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Thesis

Ecological Impacts of the Cerro Grande Fire: Predicting Elk Movement and Distribution Patterns in Response to Vegetative Recovery Through Simulation Modeling

Los Alamos
NATIONAL LABORATORY
EST. 1943
The World's Greatest Science Protecting America

This thesis was accepted by the Department of Wildlife Science, Texas Tech University, Lubbock, Texas, in partial fulfillment of the requirements for the degree of Doctor of Philosophy. The text and illustrations are the independent work of the author, and only the front matter has been edited by the IM-1 Writing and Editing Staff to conform with Department of Energy and Los Alamos National Laboratory publication policies.

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Susan P. Rupp

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ECOLOGICAL IMPACTS OF THE CERRO GRANDE FIRE:

PREDICTING ELK MOVEMENT AND DISTRIBUTION

PATTERNS IN RESPONSE TO VEGETATIVE RECOVERY

THROUGH SIMULATION MODELING

by

SUSAN P. RUPP, B.S., M.S.

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ABSTRACT

In May 2000, the Cerro Grande Fire burned approximately 17,200 ha in north-central New Mexico as the result of an escaped prescribed burn initiated by Bandelier National Monument. The interaction of large-scale fires, vegetation, and elk is an important management issue, but few studies have addressed the ecological implications of vegetative succession and landscape heterogeneity on ungulate populations following large-scale disturbance events. Primary objectives of this research were to identify elk movement pathways on local and landscape scales, to determine environmental factors that influence elk movement, and to evaluate movement and distribution patterns in relation to spatial and temporal aspects of the Cerro Grande Fire. Data collection and assimilation reflect the collaborative efforts of National Park Service, U.S. Forest Service, and Department of Energy (Los Alamos National Laboratory) personnel. Geographic positioning system (GPS) collars were used to track 54 elk over a period of 3^{+} years and locational data were incorporated into a multi-layered geographic information system (GIS) for analysis. Preliminary tests of GPS collar accuracy indicated a strong effect of 2D fixes on position acquisition rates (PARs) depending on time of day and season of year. Slope, aspect, elevation, and land cover type affected dilution of precision (DOP) values for both 2D and 3D fixes, although significant relationships varied from positive to negative making it difficult to delineate the mechanism behind significant responses. Two-dimensional fixes accounted for 34% of all successfully acquired locations and may affect results in which those data were used. Overall position acquisition rate was 93.3% and mean DOP values were consistently in the range of 4.0 to 6.0 leading to the conclusion collar accuracy was acceptable for modeling purposes. SAVANNA, a spatially explicit, process-oriented ecosystem model, was used to simulate successional dynamics. Inputs to the SAVANNA included a land cover map, long-term weather data, soil maps, and a digital elevation model. Parameterization and calibration were conducted using field plots. Model predictions of herbaceous biomass production and weather were consistent with available data and spatial interpolations of snow were considered reasonable for this study. Dynamic outputs generated by SAVANNA were integrated with static variables, movement rules, and parameters developed for the individual-based model through the application of a habitat suitability index. Model validation indicated reasonable model fit when compared to an independent test set. The finished model was applied to 2 realistic management scenarios for the Jemez Mountains and management implications were discussed. Ongoing validation of the individual-based model presented in this dissertation provides an adaptive management tool that integrates interdisciplinary experience and scientific information, which allows users to make predictions about the impact of alternative management policies.

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CHAPTER I

INTRODUCTION

Isolation of remnant populations through habitat loss and fragmentation is a perceived threat to the conservation of biological diversity and ecological integrity (Rosenberg et al. 1997). Corridors have been proposed as a method to lower extinction rates, lessen demographic stochasticity, deter inbreeding depression, and fulfill the inherent need that animals have for movement (Noss and Cooperrider 1994, Rosenberg et al. 1997, Bennett 1999). Despite its intuitive appeal, the corridor concept has become a major battleground in conservation science (Mann and Plummer 1995). Critics argue a paucity of experimental data and weak empirical evidence supporting the use of corridors. Corridors may increase edge effect, attract predators, inadvertently serve as “sink” habitat, and act as possible conduits for disease transmission and other catastrophic events (Simberloff et al. 1992). This is further complicated by the ambiguity of the term “corridor” which has contributed to vague and often contradictory definitions (Simberloff et al. 1992, Rosenberg et al. 1997).

This controversy has led biologists to explore whether the real issue is the merit of corridors, *per se*, or the value of connectivity (Bennett 1999). Landscape connectivity has been defined as “the degree to which the landscape facilitates or impedes movement among resource patches” (Taylor et al. 1993: 571) or “the functional relationship among habitat patches, owing to the spatial contagion of habitat and the movement responses of organisms to landscape structure” (With et al. 1997: 151). Landscape connectivity, therefore, depends not only on the abundance and spatial partitioning of habitat but also on the habitat specificity and movement behavior of a species (With and Crist 1995). Noss and Cooperrider (1994) stated, "Connectivity is not just corridors" (p. 151) and advocated the pursuit of *functional connectivity,* which should be evaluated at several spatial and temporal scales, ranging from daily movements within home ranges to long-distance dispersal events connecting populations. "Connectivity is therefore a feature of a whole landscape, where the scale of the landscape is determined by the habitat use and movement scales of the organisms in question" (Tischendorf and Fahrig 2000: 633).

In addition to scale, the spatial configuration of habitats in heterogeneous landscapes is also an important determinant of connectivity (Keitt et al. 1997, Turner et al. 2001). The relationship between environmental heterogeneity and animal movements and distribution at the landscape scale can have far-reaching implications for the ecology of organisms and ecosystem function (Turchin 1998). Long-term studies on the movement patterns of species at local and regional scales are needed because those are the scales at which conservation strategies are planned and implemented (Saunders and Hobbs 1991). Designing functional corridors at the landscape scale is difficult due to limited detailed data on movements of animals through landscapes, which, in turn, inhibits accurate identification of features essential in maintaining functional connectivity.

Species' perceptions of landscape structure are determined by individual responses to spatial heterogeneity in terms of movement behavior, habitat affinities, assessment of habitat quality and, ultimately, repercussions for fitness (With et al. 1997).

The aggregative responses of individuals – the basic units of ecology (Wiens et al. 1993) – result in higher-order phenomena such as population dynamics, which are of concern when considering the ecological consequences of habitat fragmentation (With et al. 1997). It follows that the effects of corridors in facilitating movement at the population level can ultimately be explained at the level of the individual by asking how the individual orients its movements in the presence of a potential corridor (Rosenberg et al. 1997, Turchin 1998). Quantifying landscape connectivity, therefore, requires spatially explicit methods that are sensitive to the possibility of complex interactions between the behavior of individual animals and landscape structure (Pither and Taylor 1998).

Natural disturbances such fires, floods, and disease outbreaks influence habitat heterogeneity and landscape-level patch mosaics at various spatial and temporal scales. Disturbances are unique in that they both create and respond to landscape pattern (Turner et al. 2001). In addition, the resultant force can be stabilizing or disruptive depending on the spatial or temporal scale under consideration (Turner et al. 2001). "Disturbance dynamics and succession are intertwined in their effects on landscape patterns and change, and the successional changes that follow disturbance are main components of our understanding of disturbance in a landscape context" (Turner et al. 2001: 160).

Specifically, the role of fire disturbance in the natural landscape has gained much attention over the past century. Dramatic increases in the occurrence of large-scale fires following decades of fire suppression policy plague the western United States. The immense fires in Montana, Idaho, and New Mexico during the summer of 2000 are possible indications of events to come in many other western forests that are now loaded with fuels. Such fuels are normally limited through the natural occurrence of smaller fires, but fire suppression has disrupted natural fire regimes. In fact, historically anomalous, catastrophic wildfire has been classified as potentially “the most pressing forest health problem in Southwestern forests” (Swetnam and Baisan 1996: 12).

Fires strongly influence animal response at every level of ecosystem organization. Long-term faunal response is determined by changes in habitat, which influence feeding patterns, movement, reproduction, and cover (Brown et al. 2000). Variation in fire regimes alters spatial and temporal landscape patterns, which affect habitat and often produce major changes in faunal communities. Landscape-scale responses following large fire events are in constant flux, which impact fauna through (Brown et al. 2000):

- Changes in the availability of habitat patches and landscape heterogeneity;
- Transformations in the composition and structure of larger areas, such as watersheds, which provide the spatial context for habitat patches;
- Modifications in habitat connectivity.

Rocky Mountain elk *(Cervus elephus nelsoni)* have often been the focus of post-fire studies that evaluate the complex interactions between the behavior of individual animals and landscape structure. It is generally believed that fire increases biomass, nutritional quality, palatability, and digestibility of forage species consumed by elk (Peck and Peek 1991, Stein et al. 1992, Bartos et al. 1994, Tracy and McNaughton 1997) and, as a consequence, elk should prefer burned over unburned habitats (Rowland et al. 1983, Brown et al. 2000). However, many of these studies reflect effects of small-scale or prescribed burns while few studies detail the effects of extensive fires on ungulate populations due to the infrequent nature of such events.

The 1988 Yellowstone fires presented an excellent opportunity to examine the effects of large-scale fires on elk. Norland et al. (1996) studied the short-term effects of the 1988 fires on elk habitat use, forage biomass and quality, willow production, and snow characteristics in key elk habitats. Summer habitat use was indexed through the use of pellet groups and winter use was indexed through elk feeding craters in the snow. No differences were found in either summer or winter use between burned and unburned sites suggesting that elk use/behavior had not changed in response to the fire. In contrast, Singer and Harter (1996) found elk avoided burned forests during the first three winters post-fire possibly in response to deeper, denser accumulation of snow and reduced forage biomass. However, both studies stated that elk use of burned areas may increase as post-fire succession takes place. Other studies (Pearson et al. 1995, Tracy and McNaughton 1997) support this conclusion with reported preferential use of burned grasslands in Yellowstone's northern range three to four years post-fire. In addition, these studies evaluated habitat use through the use of indices and observational counts. The use of such indices as a measure of elk behavior or habitat use is debatable (Collins et al. 1978, Leopold et al. 1984) and no longer adequate given the advanced technology that is available through radio collar devices and more expensive and accurate global position system (GPS) devices.

Understanding the consequences of movement for population dynamics is practically impossible without testing and constructing empirically based, mathematical models (Turchin 1998). The use of modeling to investigate ungulate responses to large-scale fires has been explored in few instances. Turner et al. (1994) developed a spatially explicit, individual-based simulation model (NOYELP) to explore the effects of fire scale and pattern on the winter foraging dynamics and survival of free-ranging elk in Yellowstone. Search, movement, and foraging activities – which were defined as a function of initial body mass, amount of forage available, and depth and density of snow – were simulated. Simulations revealed that winter severity played an important role in ungulate survival and that spatial patterning of the fire, coupled with snow conditions, influenced predicted ungulate dynamics. The model did not address ungulate reproduction, ungulate/succession dynamics, or the effects of summer precipitation on pre-winter forage availability – all of which are important in projecting the long-term dynamics of the ecosystem (Turner et al. 1994). No models have related the effects of post-fire landscape succession on ungulate movements and distribution.

Spatial simulation models that evaluate interactions among cells in a raster-based environment provide a powerful approach to modeling spatial dynamics of complex systems based on individual-level properties (Wiens et al. 1993). However, simulation models are critically dependent on the input values for model parameters and, therefore, have the greatest value when they are coupled with field studies, both to calibrate model parameters and to test or confirm model projections (Turchin 1998). It is rare to find empirical data that directly describe key parameters of landscape connectivity, such as habitat-specific movement patterns, rates, or capabilities of animals (Pither and Taylor 1998). Even rarer are data comparing movement behaviors among landscapes that differ in structure or that describe movements occurring at spatial scales coincident with a given species' population dynamics (Pither and Taylor 1998). A more thorough understanding of landscape connectivity – and, therefore, functional corridor design – could emerge from conducting empirical studies over sufficiently large spatial scales so as to encompass the movement capabilities of the subject organisms (Thomas and Hanski 1997 *in* Pither and Taylor 1998, Rosenberg et al. 1998).

The evolution of global positioning system (GPS) devices for use in radio-marking wildlife continues to improve the quality and quantity of data that can be collected on animal movement and habitat use patterns. Spatially explicit ecosystem models coupled with detailed habitat-specific movement patterns available through GPS technology provide a unique opportunity to gain a more thorough understanding of landscape connectivity as it relates to large-scale disturbance dynamics and animal behavior. Therefore, the objectives of this research are:

- To evaluate the movement and distribution patterns of elk in relation to spatial and temporal aspects of the Cerro Grande Fire, which burned approximately 19,020 ha in the Jemez Mountains of northcentral New Mexico in May 2000;
- To integrate concurrent data collection efforts of Bandelier National Monument (BNM), Los Alamos National Laboratory (LANL), and the U.S. Forest Service (USFS) to gain more accurate insight into the movement and distribution of elk in the Jemez Mountains; and

- To provide an adaptive management tool to mitigate potential adverse impacts by elk as a result of changes in movements and distributions based on simulated conditions projected by the model.

To accomplish the above objectives, a spatially explicit, stochastic, individual-based model (IBM) was developed to simulate movement and distribution of elk in relation to projected successional changes occurring from the Cerro Grande Fire. Many methods are available for modeling animal movements and distribution (e.g., path analysis, fractal analysis, random walks, structural equation modeling). However, there has been a growing interest in the use of IBMs in ecological applications. Individual-based models are capable of modeling variation among individuals and interactions between individuals (Slothower et al. 1996). This approach to modeling animal movements addresses two fundamental principles, which are largely ignored in other modeling environments. First, it acknowledges that individuals are behaviorally and physiologically distinct because of genetic and environmental influences and second, it acknowledges that interactions among individuals are inherently localized (Slothower et al. 1996). The basic assumption in IBMs is that each action during movement (e.g., an animal's choice to start, stop, or change direction) is a mixture of stochastic and deterministic elements (Turchin 1998). An advantage to IBMs is that they do not require many of the simplifying assumptions and mathematical derivations typically needed in more aggregated models (Railsback et al. 1999), thus resulting in a more realistic representation of real-world phenomena.

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CHAPTER II

AN ASSESSMENT OF GLOBAL POSITIONING SYSTEM (GPS) COLLAR PERFORMANCE AS INFLUENCED BY FOREST STRUCTURE AND TOPOGRAPHY

Introduction

The evolution of global positioning system (GPS) devices for use in radio-marking wildlife continues to improve the quality and quantity of data that can be collected on animal movement and habitat use patterns. Despite improvements over the use of traditional very high frequency (VHF) systems, two fundamental assumptions relevant to all telemetry studies remain. First, it is assumed that the animals carrying transmitters are a representative sample of the entire population of interest and that the transmitters do not adversely affect them in any way compared to non-instrumented animals (White and Garrott 1990). Secondly, it is assumed that location estimates are accurate and free of bias (Millspaugh and Marzluff 2001). Inaccurate locations may add a source of error to a data set, which influences the statistical inferences that are drawn; this, in turn, could lead to incorrect conclusions regarding habitat use by collared animals (Moen et al. 1997) and, ultimately, erroneous management decisions. Reductions in the weight and size of transmitters have reduced the negative impacts of the former assumption on large animals such as elk, but the advent of GPS has done little to remove the problems associated with locational errors and, in fact, has introduced new concerns that must be taken into consideration when interpreting the results of telemetry studies.

Prior to May 2000, the accuracy and precision of GPS-derived locations were intentionally degraded as a security measure by the Department of Defense using a process known as “selective availability” (SA). The error associated with horizontal position estimates induced by SA was in the range of 100 m of their true location 95% of the time (Millspaugh and Marzluff 2001) but could generally be corrected to within 10 m through a process known as “differential correction” wherein the error in positional fixes is determined by recording locations at a known point (i.e., base station) and calculating the deviation from the known coordinates of the site. The resulting planimetric error recorded at the base station is then removed at a later date from the location data received at the corresponding times by the roving GPS module in the collar (Hulbert and French 2001).

In May 2000, the Department of Defense discontinued the use of SA six years ahead of schedule, although they reserve the right to reinstate it in times of national crises (Lawler 2000). Literally overnight the accuracy and precision of locations improved 10-fold, leading some researchers to believe differential correction to be obsolete. However, the process of differential correction has also been shown to remove other sources of error including satellite configuration and clock errors, ionospheric and tropospheric errors, and other sources of site and signal path error (Hulbert and French 2001, Millspaugh and Marzluff 2001, Oderwald and Boucher 2003). Hulbert and French (2001) recorded errors in locations up to 16 m and large instantaneous fluctuations (>6 m) not attributable to satellite availability or any other measure recorded at their reference station (Hulbert and French 2001), leading them to conclude that other sources of error that were masked when SA was enabled now have a major impact on precision and accuracy of locations. Hulbert and French (2001) found mean accuracy was improved by 1.4 m by removing the planimetric error after SA was turned off but concluded that differential correction may still be useful in many applications to improve precision and remove additional sources of error. Ultimately the decision to differentially correct locations in the absence of SA must be driven by the objectives of the specific research project, the level of accuracy that is needed, and the technical and financial resources available to the researcher.

Regardless of whether or not the researcher chooses to differentially correct locations in a post-SA world, no habitat-selection study is defensible without an assessment of the potential for observational bias (i.e., the possibility that GPS fixes may be more or less successful in some habitats than others). Because GPS receivers operate on a line-of-sight principle, the "visibility" of satellites under various vegetation or topographic conditions may influence the accuracy of GPS locations and whether the locations are representative of the proportion of time an animal spends within a habitat (Rempel et al. 1995, Frair et al. 2004). Location inaccuracy can lead to misclassification of habitat use dependent upon the magnitude of location error and the degree of landscape heterogeneity (Frair et al. 2004), thereby affecting all subsequent applications of the results of habitat-use studies. Inferences of animal habitat selection drawn from GPS telemetry data are generally biased toward areas of open canopy (Rempel et al. 1995, Moen et al. 1996, D'Eon et al. 2001, Di Orio et al. 2003), but topographic relief and vegetative characteristics may also contribute to missing data, which may have a more profound effect on inferences of habitat selection than inaccurate locations do since the disengagement of SA (Frair et al. 2004).

Expected accuracy of GPS locations is affected by the number of satellites from which signals are received (Rempel et al. 1995) as well as the geometric configuration of those satellites at the time the fix is taken. Positional dilution of precision (PDOP) is a unitless measure of satellite configuration often used to assess the accuracy of GPS locations (Di Orio et al. 2003). Fixes with lower PDOP values are usually more accurate because of better satellite geometry; PDOP is a more robust measure of precision than the often used horizontal dilution of precision (HDOP) values (D'Eon et al. 2001). In addition, error can be introduced in the horizontal position estimate when only three satellites are visible resulting in a 2-dimensional (2D) fix. In such cases, the elevation is determined from the last successful 3-dimensional (3D) position (i.e., ≥ 4 satellites visible) making it difficult to model animal movements because location error is a function of the change in elevation since the last 3-dimensional fix was obtained (Rempel et al. 1995). Such errors can be especially pronounced in areas of high topographic relief (Rempel et al. 1995, D'Eon et al. 2001).

Previous studies have evaluated the effect of topography and habitat type on collar performance in the Jemez Mountains of northern New Mexico (Biggs et al. 1999, Biggs et al. 2001). However, these studies focused on collars manufactured by a different company than the collars used in this research and under conditions that have drastically changed since the large 19,020-ha Cerro Grande Fire burned through the region in May 2000. The purpose of this study, therefore, was to assess general collar performance and to relate dilution of precision (PDOP for 3D, HDOP for 2D) and 2D versus 3D fixes to topographic characteristics and land cover types to identify potential biases of subsequent habitat-selection studies on which these results may depend.

Study Area

The Pajarito Plateau, located in the Jemez Mountains of north central New Mexico, was formed by an ash flow of volcanic activity about 1.4 million years ago (Wilcox and Breshears 1994). The region is classified as a wildland-urban interface and is politically segmented, making natural resource management difficult. The most conspicuous and influential government entity is Los Alamos National Laboratory (LANL; 11,200 ha). It is bordered by Bandelier National Monument (13,290 ha) to the southwest, Santa Fe National Forest to the northwest and southeast, San Ildefonso Reservation to the east, and Santa Clara Reservation to the north (Figure 2.1). In addition, the federal government purchased 37,200 ha of private land in July 2000 to the northwest that contains the Valles Caldera National Preserve (VCNP), an ancient caldera grassland that serves as the primary summering ground for the region's elk population.

The plateau is topographically complex, ranging in elevation from 1,600 m near the Rio Grande to 3,240 m near the summit of Cerro Grande. It is transected by a series of smaller canyon systems and mesas making the terrain rough and virtually inaccessible in some places. Vegetative patterns are highly dependent on elevation and topography

(Wilcox and Breshears 1994), but five main vegetative associations have been described: piñon-juniper grassland (1,600 to 1,900 m), piñon-juniper woodland (1,900 to 2,100 m), ponderosa pine grassland (2,100 to 2,300 m), mixed-conifer (2,300 to 2,900 m), and subalpine grassland (2,900 to 3,200 m). The Jemez Mountain region has a temperate, semi-arid mountain climate that is strongly influenced by elevation. Average annual precipitation is 330 to 460 mm (Davenport et al. 1996, Wilcox et al. 1996) of which about 45% occurs in July, August, and September. Average daytime temperatures range from 32.2 ^{o}C in the summer (max. = 41.1 ^{o}C) to -9.4 ^{o}C in the winter (min. = -30.6 ^{o}C).

Methods

Collar Deployment

Data were collected from fifty-four Rocky Mountain elk *(Cervus elephus nelsoni)* that were collared on Bandelier and/or LANL property in January 2001 (n = 29) or on the VCNP in November 2002 (n = 25). Of these, 50 animals were collared using Telonics, Inc., GEN-II "Store-on-Board" GPS collars equipped with Trimble Lassen™ SK-2 or SK-8 receivers and a VHF beacon transmitter. The remaining 4 animals were collared using Lotek GPS-4000 system collars, also equipped with a VHF beacon transmitter. Collars were programmed to acquire GPS positions at intervals ranging from 15 minutes to 23 hours (Table 2.1) with more fixes purposefully taken during the presumed fall and spring migrational periods.

Following a routine telemetry flight conducted in mid-August 2003, it was discovered that a number of release mechanisms (n = 29) used on GPS collars deployed on elk in January of 2001 and pre-programmed to release in July of 2003 had failed to work. The flight confirmed earlier fears that the release mechanisms might fail given that short-term collars had already failed to release. The GPS collars store the location data on-board the collar and, therefore, needed to be retrieved in order to download the information. After numerous low-cost alternatives were explored and attempted unsuccessfully, a final effort was made in mid-February of 2004 to recapture these animals using a helicopter crew from Hawkins and Powers Aviation, Inc., headquartered in Greybull, Wyoming. Numerous agencies contributed financially and logistically to this effort and 22 of 29 collars were retrieved. Of the remaining seven collars, four were no longer transmitting a signal and three were on restricted Laboratory property. Data from the retrieved collars were downloaded and processed at Los Alamos National Laboratory with the exception of four GPS collars, which had to be sent back to the company in order to retrieve the data.

In response to the initial malfunctioning of the release mechanisms in early 2002 and anticipating further problems, it was decided that cotton spacers would be used in addition to the release mechanisms during the November 2002 capture. Unfortunately, numerous collars from that deployment suffered the opposite effect and fell off animals prematurely. This resulted in a very dichotomous data set; some collars collected only a few days worth of data whereas others collected data over a period of 2 to 3 years. In addition, unseasonably warm weather prevented animals from moving off their summer range through most of the winter months of 2002 and 2003. Therefore, many of the collars that fell off prematurely failed to collect data outside the Valles Caldera National Preserve, which serves as the animals' main summering ground.

Because the purpose of this dissertation is to model movement pathways across the Jemez Mountains normally traversed during the fall/spring "migration" as well as daily movements across LANL's winter range, a decision was made to partition collars into two groups that either met/failed <u>all</u> of the following conditions:

- The collar must have ≥ 88% position acquisition rate (PAR – see below).
- The collar must have remained on the animal at least eleven months. This period was selected to: 1) allow for the inclusion of collars pre-programmed to collect locations every 15 minutes and scheduled to shut off in one year, and 2) to provide ample opportunity for an animal to traverse its annual home range.
- The 95% kernel home range (KHR) must span the Cerro Grande burn area <u>or</u> be continuous through transitional regions connecting summer/winter ranges. The 95% fixed kernel home range (Worton 1989) was calculated for each animal using the Animal Movement Analysis Extension (AMAE) in ArcView (Hooge and Eichenlaub 2000, Hooge et al. 2001). Though use of a least-squares cross validation (LSCV) smoothing parameter would have been preferable, extensive amounts of data prevented its use in favor of an ad hoc approach, which Hooge (pers. comm. 2003) believes approximates the LSCV for exploratory analysis such as this. The calculated 95% KHR with standard 50% core use areas are depicted for each of the 15 animals in Appendix B. Criteria were met by only fifteen of the fifty-four animals analyzed [see asterisks (*) in Table 2.1]. Descriptive measures (i.e., PARs) were calculated for all

fifty-four animals and detailed habitat analyses on fix type (2D versus 3D) and dilution of precision (DOP) were conducted on the fifteen collars meeting the above conditions.

Data Processing

Data were downloaded from both collar systems onto personal computers and then processed to create an Environmental Systems Research Institute (ESRI) ArcView shapefile and Microsoft Access table of collar attributes. Data files (*.dat) downloaded directly from the collars required numerous reformatting steps and application of scripts in order to put the data into a format compatible with ArcView and Access databases. Despite the potential benefits of differentially correcting locations even after the termination of selective availability, data were not differentially corrected due to time and funding constraints on personnel at Los Alamos National Laboratory. In addition, previous studies determined that differential correction of data in the Jemez Mountains actually resulted in higher error rates than non-differentially corrected data (Biggs et al. 2001). Post-SA data have a reported horizontal accuracy of <9 m (90%) and an altitudinal accuracy of <18 m (90%) for the Lassen™ SK-2 receiver (Trimble Navigation Limited 1999 – 2003©) which were determined reasonable for purposes of this study.

The goal of data processing was to create a shapefile that contained information directly related to characteristics about the physical location of each animal and an associated attribute table with GPS collection parameters (Bennett 2004, pers. comm.). Data files included the longitude, latitude, local date, local time, and a variety of information about the parameters associated with the GPS location such as dilution of precision (DOP) and the type of fix (2D versus 3D). The information contained in each file would allow further analyses of collar performance and accuracy based on topographic features.

Field names assigned by Telonics were reformatted to meet MS-DOS 8.3 file-naming convention required by ArcView software. Additional fields were added for "collar i.d." and "manufacturer" and then populated with appropriate data. Edited files were saved as comma-delimited text files and then imported into ArcView. Files were occasionally exported in dBase IV format for additional editing.

Longitude data were downloaded from the Telonics collars and required additional processing. Values were subtracted from 360 degrees to create decimal degree coordinates compatible with the shapefile format. Once this conversion was complete for each collar, individual files for each collar were imported into ArcView as an event theme and then converted to shapefiles in New Mexico State Plane Coordinates, North American Datum (NAD) 1983, using units of feet. All files were then merged into a single shapefile in order to complete data processing.

A unique record identifier field (Site_id) was created using multiple scripts that reformatted the collar identification number and appended it with the date and time of the location. To verify a unique number had been generated for each record, a script was run to flag any duplicate "site_id" numbers. Flagged records were analyzed to determine if those records were true duplicates and should be deleted or if a unique record identifier had failed to be created. The "site_id" field was then used to join information from the merged shapefile to the attribute table in various queries needed for separate analyses.

Land cover, elevation, slope, and aspect were determined by overlaying locational data from individual fixes for each animal on associated raster layers using the ArcView Spatial Analyst extension. Elevation was recorded in feet and slope and aspect were recorded in degrees using a USGS 10-m Digital Elevation Map (DEM). Land cover was assigned using the quarter-hectare smoothed, 15-m resolution version of the most recent LANL land cover map (McKown et al. 2003). Completed queries for each animal were assimilated into final data sets in Microsoft Excel and/or Access and then saved as space-delimited text files to be imported into SAS Statistical Software for analysis.

<u>Position Acquisition Rate (PAR)</u>

Biggs et al. (2001, p. 214) defined position acquisition rate as the "percentage of locations that a GPS collar successfully acquires from roving satellites based on the total number of attempts," which potentially can be affected by topography, plant cover/physiology, weather, and/or animal behavior. Coupled with an analysis of DOP and fix status (2D versus 3D), the efficacy of GPS locations can be assessed and information resulting from such analyses can be applied to future applications of collar data by potentially correcting GPS locations if bias is encountered.

Position acquisition rates were calculated for each of the 54 collars by dividing the total number of successful fixes acquired by the total number of fixes attempted for each collar regardless of fix status (2D or 3D) or DOP value. Number of fixes attempted was based on the preprogrammed interval rates during the life of the collar while deployed on the animal. Length of the data collection period was determined by examining the date the collar was deployed and either the time lapsed between collar retrieval date, the death of the animal, or the date of battery failure when positions were no longer recorded.

For consistency in application, PARs were also calculated yearly, monthly, and seasonally regardless of fix type or DOP value for comparison with Biggs et al. (2001) using a generalized linear mixed model (GLIMMIX, SAS Version 9.1, Production in March 2005) with a binomial link function and a random collar (i.e., animal) effect (McCulloch and Searle 2001). This approach accounted for the inherent distributional properties of the data as well as unreasonably large differences in sample sizes (i.e., total numbers of locations/collar). Seasons were defined as follows: spring (March and April), calving (May and June), summer (July and August), fall (September and October), and winter (November through February). In addition, PARs for 50 collars (Telonics only) were analyzed by hourly periods based on six, 4-hour time blocks: 0000 to 0400, 0400 to 0800, 0800 to 1200, 1200 to 1600, 1600 to 2000, and 2000 to 2400. Time blocks were also grouped into night-time (2000 to 0800) and day-time (0800 to 2000) periods and period means were compared. Pairwise comparisons among months, seasons, and time blocks were performed with a protected LSD test.

Effect of Slope and Elevation on DOP

Analysis of slope and elevation on dilution of precision (DOP) values were conducted on the fifteen collars that met requirements as outlined in the section "*Collar Deployment.*" Background information and PARs for these collars can be found in Table

2.1. Effects of elevation (ft/1000) and slope (degrees) on DOP were assessed using simple linear regression analyses with DOP as a dependent variable and either elevation or slope as independent variables. The null hypothesis, therefore, is that there is no linear relationship between either slope or elevation and DOP value (i.e., H_o: $\beta_1 = 0$). For each elk, n = 1 or n = 10 locations were randomly selected with replacement 1000 times to create sampled data sets used in a Monte Carlo analysis. Similar analyses were conducted by fix type (2D versus 3D), by time block (0000 to 0400, 0400 to 0800, 0800 to 1200, 1200 to 1600, 1600 to 2000, 2000 to 2400), and by the combination of fix type and time block. Due to time constraints, separate analyses were not conducted to look at all observations regardless of DOP value versus those with DOP values ≤ 12 – the default DOP mask setting for the 50 collars containing SK2 receivers according to Trimble Navigation Limited (1999). A total of 42 separate data sets were analyzed.

Regression analyses were conducted using two models that differed in assumptions about DOP for each individual animal: (1) DOP values were normally and independently distributed with homogeneous variances (“homoscedastic/independence”); and (2) DOP values were normally distributed but correlated with each other (not necessarily equally correlated) with heterogeneous variances (“unstructured”). The assumptions in the second model therefore allow for the possibility that DOP locations recorded for a given animal are not necessarily independent and/or that DOP readings for different animals may have different variances (possibly because of differences in radio-collars or animal behavior). For each analysis, DOP values among elk were considered independent of each other. When n = 1 location was used for each elk, only the "homoscedastic/independence" case applies. For n = 10 locations per animal, a null model likelihood ratio test was used to test whether the unstructured model was significantly better than the homoscedastic/independence case. Additionally, the elk effect was considered a nuisance variable that was a random effect. PROC MIXED (SAS version 9.1) was used for data analysis.

Effect of Aspect and Land Cover on DOP

Effects of aspect and land cover type on DOP were assessed on the fifteen collars that met requirements as outlined in the section "*Collar Deployment.*" A mixed model analysis of variance (with animal as a random block effect) was used to compare mean DOP values among the aspect and land cover categories. Two variance-covariance structures were tested: Mauchly's (1940) test was used to evaluate sphericity, and Box's (1950) test was used to evaluate compound symmetry. If neither of these conditions was satisfied, a univariate F statistic with the Greenhouse and Geisser (1959) adjustment to the tabular degrees of freedom was used to test for overall mean equality among the aspect or land cover categories. When the F statistic indicated differences among categories, pairwise comparisons were performed with an LSD test using error terms specific to each contrast (Kirk 1995).

Aspect was classified into nine categorical variables representing north (337.5^o to 22.5^o), northeast (22.5^o to 67.5^o), east (67.5^o to 112.5^o), southeast (112.5^o to 157.5^o), south (157.5^o to 202.5^o), southwest (202.5^o to 247.5^o), west (247.5^o to 292.5^o), and northwest (292.5^o to 337.5^o) directions as well as a category representing no aspect (i.e., flat ground). Because all fifteen animals were not found in all 32 land cover classes outlined in McKown et al. (2003), an unbalanced design resulted. Therefore, land cover was consolidated into 18 categories for this analysis. Due to limited data, an "urban" category was also removed from the analysis. Additional analyses were conducted by further consolidating the eventual 17 categories into 7 growth forms (forest, woodland, grassland, shrublands, pinyon-juniper, bare ground, and aspen) for general descriptive analysis. Separate models evaluated the combined effects of fix type (2D versus 3D), time block, and fix type and time block on DOP value for each aspect and land cover category.

Results

General Overview

A brief review of fix type indicated some striking results. Approximately 34.58% (31,646 ÷ 91,527) of fixes were 2D for all 54 animals whereas just over 34% (19,103 ÷ 55,782) were 2D fixes for the 15 collars that were used for further analysis. A comparison of Telonics (n = 50) versus Lotek (n = 4) collars indicated 39.96% (30,696 ÷ 46,122) and 6.46% (950 ÷ 14,709) of fixes were 2D, respectively. Twenty-four locations had fix types that were not interpretable as being either 2D or 3D and were excluded from the analysis.

Mean DOP values were calculated in light of the fix type results indicated above. For all 54 animals, the mean DOP value for all fixes was 4.53 (± 0.1001, range 0 – 6,060). When only considering 2D fixes, the DOP value increased to 4.59 (± 0.2890, range 0 – 6,060). For 3D fixes, the mean DOP value decreased slightly to 4.50 (± 0.105, range 0 – 50). Separating out the 50 Telonics collars resulted in a mean DOP value of 4.54 (± 0.1191, range 0 – 6,060). These results were further separated by 2D fixes ($\bar{x}$ = 4.61 ± 0.2979, range 0 – 6,060) and 3D fixes ($\bar{x}$ = 4.50 ± 0.0060, range 0 – 38). For the 4 Lotek collars, the overall mean DOP value was 4.48 (± 0.0405, range 0 – 50). The mean value for 2D fixes was 3.97 (± 0.1771, range 1.4 – 50) whereas 3D fixes counter-intuitively increased with a mean value of 4.5 (± 0.0413, range 1.2 – 50).

Position Acquisition Rates (PARs)

A total of 91,553 locations out of a possible 98,148 were recorded for all 54 animals resulting in an overall position acquisition rate of 93.3% (Table 2.1). Individual collar performance was generally acceptable with the exception of four collars (collar numbers 471946, 471961, 481468, and 481469) whose PARs were less than 80%. The overall PAR for the 15 collars used to regress DOP on slope, aspect, elevation, and land cover was 94.3%.

Position acquisition rates varied throughout the course of the year depending on month ($F_{11,319}$ = 116.60, P<0.0001), season ($F_{4,319}$ = 287.6, P<0.0001), and time of day ($F_{5,224}$ = 269.05, P<0.0001). Rates were highest during December (96.61% ± 0.6%), November (96.51% ± 0.6%) and February (95.22% ± 0.9%) and lowest in July (84.83% ± 2.5%) and August (84.18% ± 2.6%) (Table 2.2). Similarly, PARs were highest during the winter (95.92% ± 0.7%) months of November through February and lowest during the summer (84.51% ± 2.5%) months of July and August (Table 2.3). There was no difference between calving (92.39% ± 1.3%) and spring (93.23% ± 1.2%) seasons. Throughout the course of the day the highest PARs were recorded during the 0000 to 0400 time block (97.07% ± 0.5%) and the lowest PARs during the 0800 to 1200 (88.63% ± 1.8%) and 1200 to 1600 (89.3% ± 1.7%) time periods (Table 2.4). Nighttime (95.52% ± 0.8%) position acquisition rates were significantly higher than those collected during the day (92.42% ± 1.2%) ($F_{1, 224}$ = 325.89, P<0.0001; Table 2.5).

Effect of Slope and Elevation on DOP

Monte Carlo methods involving 1,000 simulations were used to assess effects of slope and elevation on DOP. Analysis of mixed statistical models requires iterative algorithms to optimize the likelihood function. Ill-conditioned data are defined as data which cause either statistical or computational difficulties in these algorithms, with the result that convergence is not achieved. Although 1,000 data sets were used in each analysis, failure to converge sometimes led to summary of simulation results based on fewer than 1,000 simulations. Convergence failures were more common for 2D locations than for 3D locations. Results from the unstructured variance/covariance matrix using a random sample of 10 locations per animal and 1,000 sample runs were considered the most robust results given the extensive number of observations used in the analysis (10 locations/animal * 15 animals * 1000 experiments = 150,000 observations) and the capability to select which test (homoscedastic and independent or unstructured/heteroscedastic) was appropriate for the underlying nature of the data. Results were further divided into total number of significant outcomes that showed a positive relationship and number of significant outcomes that showed a negative relationship between DOP value and slope or elevation out of the total number of runs that successfully converged per 1,000 experiments. In nearly all cases, the unstructured variance/covariance matrix was the appropriate test to use and discussion will, therefore, focus on these results.

Detailed results will be presented for 6 of the 42 tests run to assist the reader in interpreting tabular output. These include analyses for the effect of elevation or topographic slope on DOP regardless of fix type or time block (Tables 2.6 and 2.9, respectively), by 2D fixes regardless of time block (Tables 2.7 and 2.10, respectively), and by 3D fixes regardless of time block (Tables 2.8 and 2.11, respectively). The remaining 36 analyses examining at the effect of elevation or topographic slope on DOP given time block regardless of fix type, time block by 2D fix, and time block by 3D fix are outlined in Tables C.1 through C.36 in Appendix C. Tabular outputs for these 36 analyses are summarized through the use of charts and will be discussed in further detail below.

Nine-hundred seventy (970) of the possible 1,000 experimental runs testing the effect of elevation on DOP over all fixes and time blocks converged (Table 2.6). Of those, 926 indicated the unstructured/heteroscedastic pattern was appropriate whereas 44 indicated the homoscedastic/independence pattern was appropriate. For the 926 runs where the unstructured design was appropriate, results were significant an average of 58.5% (n = 517) of the time, far exceeding the 5% expected by chance alone. Of the significant results, 18.03% (n = 167) of the total 926 runs showed positive relationships

($\hat{\beta}_1$ = 0.4940 ± 0.2291) and 37.80% (n = 350) showed negative relationships ($\hat{\beta}_1$ = -0.6101 ± 0.3042) between elevation and DOP irrespective of fix type or time block. Regression coefficients ranged from -2.0132 to 1.4422 for all 517 significant results.

When considering only 2D fixes, 864 of the possible 1000 experimental runs testing the effect of elevation on DOP converged when time was not a factor (Table 2.7). Of those, 861 indicated the unstructured/heteroscedastic pattern to be appropriate whereas only 3 indicated the homoscedastic/independence case to be the appropriate test. Of the 861 runs where the unstructured pattern was appropriate, results were significant an average of 57.3% (n = 493) of the time exceeding the 5% expected by chance alone. Within the significant results, 21.84% (n = 188) of the total 861 runs showed positive relationships ($\hat{\beta}_1$ = 0.6472 ± 0.3216) and 35.42% (n = 305) showed negative relationships ($\hat{\beta}_1$ = -0.7107 ± 0.4000) between elevation and DOP irrespective of time block. Regression coefficients ranged from -2.1240 to 2.6426 for all 493 significant outcomes.

For 3D fixes, 934 of the possible 1000 experimental runs testing the effect of elevation on DOP converged when time block was not a factor (Table 2.8). Of those, 789 indicated the unstructured/heteroscedastic pattern to be appropriate whereas only 145 indicated the homoscedastic/independence case to be the appropriate test. Of the 789 runs where the unstructured pattern was appropriate, results were significant in 57.3% cases (n = 452), exceeding the 5% expected by chance alone. Within the significant results, 39.92% (n = 315) of the total 789 runs showed positive relationships ($\hat{\beta}_1$ = 0.3774

± 0.1792) and 17.36% (n = 137) showed negative relationships ($\hat{\beta}_1$ = -0.3212 ± 0.1425) between elevation and DOP irrespective of time block. Regression coefficients ranged from -0.9177 to 1.2202 for all 452 significant outcomes.

Significant positive and negative relationships for the effect of elevation on DOP values by time block and fix type are displayed in Figures 2.2 and 2.3. Figure 2.2 displays the mean regression coefficients by fix type (blue = all fixes, red = 2D, yellow = 3D) as well as the total number of significant positive and negative relationships given the total number of outcomes that converged (in parentheses) for each time block. Figure 2.3 presents the same data in a slightly different format by graphing the percent of significant relationships for each time block and fix type. Tabular data used to construct the figures are found in Appendix C (Tables C.1 through C.18) and follow the same format as Tables 2.6 through 2.8 described above. Pairwise comparisons between time blocks were not feasible given the statistical analyses used, but patterns in fix types across time blocks were evident.

When considering all fix types (shown in blue), as well as those within 2D (red) and 3D (yellow), the absolute value of the mean regression coefficients for negative and positive relationships were roughly equal within and across all time blocks (Figure 2.2). However, the total number of significant relationships given the total number of significant and non-significant outcomes (i.e., percent of significant outcomes) changed through the course of the day for all fix types. The percent of significant negative relationships increased through the 0800 to 1200 time block and then decreased through the remainder of the day for all fix types (Figure 2.3). Similarly, significant negative relationships for 2D fixes appeared to follow the same pattern. In contrast, the percent of significant positive relationships for 3D fixes peaked in the 1200 to 1600 time block. When the percentages of significant outcomes peaked within a given time block, the corresponding positive or negative outcomes plunged (i.e., results were a mirror image of each other). The standard errors associated with 2D fixes were the largest whereas those associated with 3D fixes were the smallest. Standard errors for all fix types taken together were intermediate in value (Appendix C, Tables C.1 through C.18).

When reviewing the effects of topographic slope on DOP values over all fixes and time blocks, 970 of the possible 1000 experimental runs converged (Table 2.9). Of those, 928 indicated the unstructured/heteroscedastic pattern to be appropriate whereas 42 indicated the homoscedastic/independence case to be the appropriate test. Within the 928 runs where the unstructured design was appropriate, results were significant an average of 53.4% (n = 491) of the time exceeding the 5% expected by chance alone. Of the significant results, 27.48% (n = 255) of the total 928 runs showed positive relationships ($\hat{\beta}_1 = 0.0570 \pm 0.0295$) and 25.43% (n = 236) showed negative relationships ($\hat{\beta}_1 = -0.0556 \pm 0.0236$) between slope and DOP irrespective of fix type or time block. Regression coefficients ranged from -0.1622 to 0.2038 for all 491 significant results.

When considering only 2D fixes, 864 of the possible 1000 experimental runs testing the effect of slope on DOP converged when time was not a factor (Table 2.10). Of those, 860 indicated the unstructured/heteroscedastic pattern to be appropriate; the homoscedastic/independence pattern was appropriate in only 4 runs. Of the 860 runs where the unstructured pattern was appropriate, results were significant an average of 55.12% (n = 474) of the time exceeding the 5% expected by chance alone. Within the significant results, 26.51% (n = 228) of the total 860 runs showed positive relationships ($\hat{\beta}_1$ = 0.0695 ± 0.0424) and 28.60% (n = 246) showed negative relationships ($\hat{\beta}_1$ = -0.0669 ± 0.0339) between slope and DOP irrespective of time block. Regression coefficients ranged from -0.2185 to 0.3499 for all 474 significant outcomes.

For 3D fixes, 934 of the possible 1000 experimental runs testing the effect of elevation on DOP converged when time was not a factor (Table 2.11). Of those, 800 indicated the unstructured/heteroscedastic pattern to be appropriate whereas only 134 indicated the homoscedastic/independence case to be the appropriate test. Of the 800 runs where the unstructured design was appropriate, results were significant an average of 74.38% (n = 595) of the time exceeding the 5% expected by chance alone. Within the significant results, 68.63% (n = 549) of the total 800 runs showed positive relationships ($\hat{\beta}_1$ = 0.0446 ± 0.0205) and 5.75% (n = 46) showed negative relationships ($\hat{\beta}_1$ = -0.0320 ± 0.0146) between slope and DOP irrespective of time block. Regression coefficients ranged from -0.0659 to 0.1160 for all 595 significant outcomes.

Significant positive and negative relationships for the effect of topographic slope on DOP values by time block by fix type are displayed in Figures 2.4 and 2.5. Figure 2.4 displays the mean regression coefficients by fix type as well as the total number of significant positive and negative relationships given the total number of outcomes that converged. Figure 2.5 presents the same data in a slightly different format by graphing the percent of significant relationships for each fix type. Tabular data used to construct the figures are found in Appendix C (Tables C.19 through C.36) and follow the same format as Tables 2.9 through 2.11 described above. Pairwise comparisons between time blocks were not feasible given the statistical analyses used, but patterns in fix types across time blocks were evident.

When considering all fix types (shown in blue), as well as those within 2D (red) and 3D (yellow), the absolute value of the mean regression coefficients for negative and positive relationships were roughly equal within and across all time blocks (Figure 2.4), although there was more variability than was found in the tests of elevation on DOP. As with elevation, the total number of significant relationships given the total number of significant and non-significant outcomes (i.e., percent of significant outcomes) changed through the course of the day for all fix types. Similar to elevation, the percent of negative significant outcomes increased through the 0800 to 1200 time block and then decreased through the remainder of the day for all fix types although the significant negative results for 2D fixes did not peak until the 1200 to 1600 time period (Figure 2.5). In contrast to the results seen with elevation, the percent of significant positive results for all fixes and 3D fixes alone diminished through the mid-day hours and increased in the early morning and late evening periods. However, the percent of positive 3D relationships far outweighed the total percentages seen in either the 2D fixes or across all fix types. When the percentages of significant outcomes peaked within a given time block, the corresponding positive or negative outcomes plunged (i.e., results were a mirror image of each other). The standard errors associated with 2D fixes were larger than the standard errors associated with 3D fixes.

Standard errors for all fix types were intermediate (Appendix C, Tables C.19 through C.36).

Effect of Aspect and Land Cover on DOP

Dilution of precision was not significantly related to aspect ($F_{2.95,38.38} = 0.69$, $P = 0.5604$) when considering all fix types (Table 2.12). However, 3D fixes showed a strong effect of aspect on DOP value ($F_{1.74,22.63} = 11.78$, $P<0.0005$; Table 2.13) whereas 2D fixes did not ($F_{2.86,36.43} = 0.76$, $P=0.5163$, Table 2.14) indicating the strong effect of 2D fixes on overall results. This is further supported by the fact that 2D fixes had relatively large standard errors when compared to 3D fixes, whereas the results for all fixes taken together show intermediate standard error values (Tables 2.12, 2.13, and 2.14). Pairwise comparisons of the 3D fixes show that lowest mean DOP values occur on flat terrain (3.86 ± 0.16) whereas all other mean values ranged from 4.47 (± 0.04) to 4.59 (± 0.06).

Similarly, DOP values were not significantly related to land cover ($F_{2.99,41.80} = 1.13$, $P = 0.3478$) or growth form ($F_{2.19, 30.71} = 0.80$, $P = 0.4689$) when considering all fix types (Tables 2.15 and 2.16, respectively). However, 3D fixes showed a strong effect of land cover on DOP value for all cover types ($F_{2.75, 38.53} = 10.77$, $P<0.0001$; Table 2.17) and differences among growth form as well ($F_{2.42, 33.83} = 11.36$, $P = 0.0001$; Table 2.18) while 2D fixes did not for either all land cover types ($F_{4.72, 65.22} = 1.17$, $P = 0.3333$; Table 2.19) or among growth forms ($F_{2.09, 28.24} = 0.88$, $P = 0.4301$; Table 2.20) indicating the strong effect of 2D fixes on overall results. This is also supported by the fact that 2D fixes had relatively large standard errors when compared to 3D fixes, whereas the results for all fixes taken together show intermediate standard error values (Tables 2.15 through 2.20).

Pairwise comparisons of the 3D fixes outlined in Tables 2.17 and 2.18 complement each other. In general, mean DOP values increased with increasing cover. The lowest values were reported in grasslands (4.43 ± 0.0468) and shrublands (4.36 ± 0.0755) and the highest values in forest (5.27 ± 0.1367) where overstory vegetation was most likely to exist in sufficient quantities to obscure satellites (Table 2.18). Similarly, the highest standard errors were also associated with forested land cover types. The lowest mean DOP value was found on Valles Caldera Grassland (4.2327 ± 0.0801) and the highest in subalpine fir *(Abies lasiocarpa)*/Engelmann-spruce *(Picea engelmannii)* forests (5.3810 ± 0.1643) (Table 2.17). Intermediary values were recorded for ponderosa pine *(Pinus ponderosa)* woodlands (Class #12, 23, and 27) and areas burned by the Cerro Grande Fire (Class #20 and 33).

Discussion

The accuracy and precision of GPS systems has misled some researchers to believe that there is negligible error associated with data acquisition when, in fact, systematic biases can occur during data collection thereby affecting all subsequent analyses (Frair et al. 2004). Inaccurate locations may result in increased Type I or Type II error rates in statistical analyses that use these data for hypothesis testing, which could lead to incorrect conclusions regarding habitat use by collared animals (Moen et al. 1997). The location accuracy of GPS units depends on fix type (2D versus 3D) and satellite geometry (Rempel et al. 1995, Trimble 1999, D'Eon et al. 2001, Dussault et al. 2001, Di Orio et al. 2003). Canopy type, percent canopy cover, tree density, tree height, and tree basal area can affect data collection efforts and may further interact with complex terrain (White and Garrott 1990, Rempel et al. 1995, Moen et al. 1996, Rempel and Rodgers 1997, D'Eon et al. 2001, Frair et al. 2004). The interactive effects of topography and vegetation are often difficult to quantify given large amounts of data and the resulting complexities in statistical analyses, but a thorough evaluation of individual effects of land features on collar performance can identify patterns and allow the researcher to more fully comprehend the issues surrounding potential application of habitat studies based on GPS telemetry.

Biggs et al. (2001) previously reported on the effect of topography, land cover, and hourly time blocks on position acquisition rates in the Jemez Mountains. Results from this study showed an increase in overall PAR to 93.3% compared to the 69% they reported. Other studies also reported lower rates of 88% (Rumble et al. nd), 85% (Bowman et al. 2000), and 70% (Dussault et al. 2001) indicating an improvement over the years in GPS technology for application in wildlife studies. However, results from PAR analyses based on hourly and seasonal time periods generally supported conclusions found in other studies. Although Biggs et al. (2001) reported PARs were generally lowest during the 0000 to 1200 time block, my results indicated the lowest PARs during the midday hours of 0800 to 1600. In addition, Biggs et al. (2001) found PARs were highest during the spring and winter months and lowest during the fall period contrary to results from this study which indicated the highest PARs occurred in winter months whereas the lowest were recorded during the summer months. Studies on moose (Moen et. al 1997, Dussault et al. 2001) and elk (Frair et al. 2004) reported similar effects of winter and summer seasons on PARs reported here. Signal interference caused by canopy characteristics affects position acquisition rates (Rempel et al. 1995, Di Orio et al. 2003) and greater frequency of unsuccessful GPS location attempts during the hottest parts of the day and year may be in response to the thermoregulatory behavior of elk seeking dense cover for shade (Merrill 1991, Moen et al. 1996, Millspaugh et al. 1998). Position acquisition rates were not calculated for different topographic features, so no comparisons with Biggs et al. (2001) could be made.

Results of analyses on fix type were more variable compared to other studies. Rumble et al. (nd) reported that 70% of fixes were 3D locations whereas results here indicated only 60% of fixes were 3-dimensional. Moen et al. (1997) reported a range of 50 to 70% of fixes being 3-dimensional when test collars were placed under tree canopies, but collar success reported here may also be attributable to topographic features or collar manufacturer. Collar manufacturer was a factor in previous studies (Di Orio et al. 2003). Because position solutions for 2D locations are calculated using the elevation from the last successful 3D position, location error is a function of the change in elevation since the last 3D fix was obtained (Rempel et al. 1995, Moen et al. 1997). Precision of 2D locations can be improved if the elevation of the GPS unit is known when the locational fix was taken (Moen et al. 1997), but this is rarely the case in wildlife studies involving wide-ranging species such as elk. Additionally, the information obtained from 2D locations can be improved if locations with lower horizontal precision of dilution (HDOP < 5.0) values are cautiously selected for use in habitat studies (Trimble 1999). It is therefore impossible to consider the effects of land cover or topography on fix type without also considering their effects given satellite geometry.

Dilution of precision (DOP) is a measure of the error caused by the geometric configuration of satellites; higher values are indicative of lower position accuracy. For differential GPS applications requiring the highest level of accuracy, Trimble (1999) suggests setting the DOP mask to 7 or below. Coupled with an analysis of fix type (2D versus 3D), data accuracy can be qualified. Results from this study are encouraging because mean DOP values were consistently in the range of 4.0 to 6.0 regardless of land cover type, slope, aspect, or elevation, leading to the conclusion that, despite statistical significance for some of these effects, collar accuracy is generally acceptable.

However, the effect of landscape features on collar performance was more difficult to interpret when both DOP values and fix type were taken into consideration. For both topographic slope and elevation effects on DOP value, fix type played a central role in determining whether regressions were positively correlated or negatively correlated. In general, elevation was twice as likely to be negatively than positively related to DOP value (i.e., as elevation increased, DOP decreased) when all fix types were considered. Likewise, 2D fixes also indicated negative relationships of elevation with DOP were roughly twice as likely to occur as positive relationships. However, the sign of the relationship changed when only 3D fixes were considered: in this case, positive relationships were twice as likely to occur. When considering slope, the effect of fix type was even more noticeable. When fix type was not considered, or when fix type was 2D, the relative proportions of significant positive and negative relationships were roughly equal. When only 3D locations were considered, the percentage of positive relationships far outweighed negative relationships (i.e., as topographic slope increased, DOP increased) by a factor of nearly 3:1 in all cases.

The effect of time block further complicated results. When considering elevation, the percentage of negative relationships for all fixes and 2D fixes increased in the 0800 to 1200 time block while positive relationships for 3D fixes were highest in the 1200 to 1600 time block. In comparison, the abundant frequency of positive relationships between slope and DOP appeared even greater in the early morning or late evening hours with fewer positive relationships occurring mid-day. Coupled with results of the analysis of elevation on DOP, this likely indicates a change in behavior or habitat use of animals during the mid-day versus crepuscular periods.

When results from PAR and DOP analyses are taken together, interpretation becomes extremely complex. The highest PARs were encountered between the 0000 to 0400 and 2000 to 2400 time blocks, suggesting that animals were likely out in the open and possibly foraging with unobstructed views of satellites. Simultaneously, DOP rates showed strong positive relationships with topographic slope suggesting the use of steeper terrain during the same time periods. If animals were traversing more complex terrain during these same time periods, one would think that PAR values would go down in conjunction with more complex topography. However, the relative change in DOP values per unit change in slope must also be considered. Regression coefficients were in the range of 0.0457 to 0.0478 during these periods, indicating for every one degree change in slope there was 0.0457 to 0.0478 units change in DOP value. Relative changes in DOP in response to slope values (as well as elevation values) were actually very small; statistical significance with these numerically small regression coefficients is in part a function of large sample sizes, which increases statistical power.

The relationship of elevation on DOP values was less clear, although a negative relationship between elevation and DOP was more likely to occur during early morning and late evening than during the mid-day hours. During the hottest parts of the day, animals likely sought thermal cover in the higher forested elevations of the Valles Caldera National Preserve, which would account for increasing DOP values as elevation increased during the 1200 to 1600 time period. This would also explain the drop in PARs during the mid-day hours.

When considering aspect and land cover across all fix types, overall results were non-significant. When 2D versus 3D fixes were analyzed separately, however, 3D locations indicated significant differences in both land cover and aspect effects on DOP value. Lower DOP values strongly corresponded to open canopy (grasslands) and flatter terrain, which likely relates to the unobstructed “view” of satellites by the GPS collar. These results are supported by other studies in which increased canopy cover was negatively related to PARs and position accuracy (Deckert and Bolstad 1996, Moen et al. 1996, Rempel and Rodgers 1997). In addition, low DOP values correspond with higher PARs observed during the early morning or late evening hours when foraging animals were most likely to be found on the flat, open grasslands of the Valles Caldera. Cautious interpretation is necessary, however, due to the potential confounding effects of slope, elevation, time block, and fix type as described in the paragraph above.

Temporal autocorrelation of consecutive radio-telemetry locations may violate independence assumptions that are central to many parametric statistics making habitat selection studies, especially those related to home range analyses, difficult to interpret (Swihart and Slade 1985, Otis and White 1999). However, some authors have argued that autocorrelation is irrelevant if the subsample of locations from an individual animal (treated as the experimental unit) is collected with a sampling design that assures unbiased temporal coverage of the animal's movement during the study period (Aebischer et al. 1993, Otis and White 1999). The approach used in this study to test for the possibility that DOP locations recorded for a given animal were not necessarily independent and/or that DOP readings for different animals may have different variances (possibly because of differences in radio-collars or animal behavior) inherently addresses these concerns. In almost all cases, the unstructured/heteroscedastic pattern of variances and covariances was appropriate. However, the design used presents an opportunity for further research to determine the effect of temporal autocorrelation on habitat use results. A comparison of the outcomes using the "unstructured" pattern versus the "homoscedastic/independence assumed" pattern when each is applied appropriately could challenge arguments about the effect of temporal autocorrelation on habitat selection studies.

Despite the relative accuracy of GPS locations, spatial inaccuracy and missing data in the form of failed location attempts contribute to locational error (Biggs et al.

2001, Frair 2004). Though no attempt was made to quantify/qualify missing locations in this study, results suggest that additional data management would need to address systematic biases in collar performance prior to application of habitat use data when location accuracy is essential for management purposes. Potential adjustments that could be made include the complete removal of all 2D fixes or some extraction of those associated with high DOP values. However, biases are often centered on data that are missing or contain habitat-dependent errors in location (Rettie and McLoughlin 1999, Biggs et al. 2001), which make such adjustments ineffective. Associated error polygons around individual locations could provide a more thorough analysis of topographic and land cover effects on PARs, fix type, and DOP values, which would then allow for adjustments to be made (Rettie and McLoughlin 1999). Rettie and McLoughlin (1999) suggested the use of error polygons related to habitat patch size and to the level of association between two or more habitat types. Studies currently in progress in the Jemez Mountains that evaluate elk habitat use related to patch size may allow for such adjustments to be made.

Other authors have suggested using more satellites in locational fixes, extracting planimetric error recorded at reference stations, and evaluating data visually to remove locations associated with large fluctuations in latitude and longitude recorded at reference stations (Hulbert and French 2001). With any approach, caution must be used when manipulating data. Simulation experiments have shown that animal locations biased to approximate GPS error led to Type II errors and incorrect conclusion of selection versus avoidance (Rettie and McLoughlin 1999, Frair et al. 2004). Furthermore, the magnitude of these effects depended on the level of data loss, how often the animal used biased vegetation types, and the degree of spatial association among vegetation types (Rettie and McLoughlin 1999, Frair et al. 2004). Unless a thorough examination of such adjustments to collar data and their associated biases can be made, it is best to approach the application of habitat use data based on a clear understanding of potential biases related to GPS radio telemetry and a thorough analysis of potential problems related to particular land cover types or topographic features.

A thorough analysis of GPS collar accuracy indicated a strong effect of 2D fixes on position acquisition rates (PARs) depending on time of day and season of year. Position acquisition rates were lower during mid-day hours and summer months indicating a possible change in animal behavior during the hottest parts of the day/season. Slope, aspect, elevation, and land cover type affected dilution of precision (DOP) values for both 2D and 3D fixes, although relationships varied from positive to negative making it difficult to delineate the mechanism behind significant responses. Two-dimensional fixes accounted for 34% of all successfully acquired locations and may affect results in which those data were used. Despite statistical significance for some of these effects, results from this study are encouraging because mean DOP values were consistently in the range of 4.0 to 6.0 regardless of land cover type, slope, aspect, or elevation, leading to the conclusion that collar accuracy is generally acceptable.

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Table 2.1. A total of 54 elk were captured over two periods (January/February 2001 and November 2002) and collared using global positioning system (GPS) collars. Sex and age were recorded when possible. Collars were preprogrammed to record locations at varying times throughout the day and season. Collars with an asterisk (*) met the following conditions: 1) PAR >= 88%, 2) collar life >= 11 months, 3) 95% kernel home range spanned areas burned by the Cerro Grande Fire or were continuous through "migrational" areas. Position acquisition rates (PARs) are calculated as the percentage of locations that a GPS collar successfully acquired versus the total number of attempts.

Collar	**Sex**	**Age**	**Start Date**	**End Date**	**Total # Months**	**#Fixes/Day (Time Interval)**	**Total # "Good" Fixes**	**# Missing Locations**	**PAR**
106*	F	unknown	11/7/2002	2/18/2004	15 months	8 (3hrs)	3698	54	0.986
107	F	unknown	11/7/2002	2/17/2004	15 months	8 (3hrs)	3685	59	0.984
108*	F	unknown	11/7/2002	2/18/2004	15 months	8 (3hrs)	3692	61	0.984
109	F	unknown	11/7/2002	2/17/2004	15 months	8 (3hrs)	3657	87	0.977
456379	F	unknown	11/6/2002	8/27/2003	9.5 months	4 (6hrs)	1144	60	0.950
456381	F	unknown	11/7/2002	6/29/2003	7.5 months	4 (6hrs)	932	44	0.955
456382	F	unknown	11/7/2002	5/7/2003	6 months	4 (6hrs) Nov - May	595	4	0.993
471923*	M	spike	1/11/2001	2/17/2004	37 months	4 (6hrs) Jan - Feb 2 (12hrs) Mar - Apr 1 (23hrs) May - Aug 6 (4hrs) Sep - Dec	3437	351	0.907
471924*	F	8	1/12/2001	2/17/2004	37 months	4 (6hrs) Jan - Feb 2 (12hrs) Mar - Apr 1 (23hrs) May - Aug 6 (4hrs) Sep - Dec	3579	208	0.945

Table 2.1. (cont.)

Collar	Sex	Age	Start Date	End Date	Total # Months	#Fixes/Day (Time Interval)	Total # "Good" Fixes	# Missing Locations	PAR
471925*	F	6	1/12/2001	7/20/2003	30 months	4 (6hrs) Jan - Feb 2 (12hrs) Mar - Apr 1 (23hrs) May - Aug 6 (4hrs) Sep - Dec	2622	196	0.930
471926*	F	2	1/11/2001	2/18/2004	37 months	4 (6hrs) Jan- Feb 2 (12hrs) Mar - Apr 1 (23hrs) May - Aug 6 (4hrs) Sep - Dec	3535	257	0.932
471927	F	1 or 2	1/12/2001	10/1/2003	21 months	4 (6hrs) Jan - Feb 2 (12 hrs) Mar - Apr 1 (23hrs) May - Aug 6 (4hrs) Sep - Dec	2893	156	0.949
471928*	F	9	1/12/2001	2/17/2004	37 months	4 (6hrs) Jan - Feb 2 (12hrs) Mar - Apr 1 (23hrs) May - Aug 6 (4hrs) sep - Dec	3517	270	0.929
471929	F	2	1/13/2001	5/10/2001	4 months	4 (6hrs) Jan - Feb 2 (12 hrs) Mar - Apr 1 (23 hrs) May	310	10	0.969
471930*	F	8	1/12/2001	2/17/2004	37 months	4 (6hrs) Jan - Feb 2 (12hrs) Mar - Apr 1 (23hrs) May _ aug 6 (4hrs) Sep - Dec	3343	444	0.883

Table 2.1. (cont.)

Collar	Sex	Age	Start Date	End Date	Total # Months	#Fixes/Day (Time Interval)	Total # "Good" Fixes	# Missing Locations	PAR
471931*	F	2	1/12/2001	2/17/2004	37 months	4 (6hrs) Jan - Feb 2 (12 hrs) Mar - Apr 1 (23hrs) May - Aug 6 (4hrs) Sep - Dec	3403	381	0.899
471932	M	spike	1/12/2001	1/6/2004	24 months	4 (6hrs) Jan - Feb 2 (12 hrs) Mar - Apr 1 (23 hrs) May - Aug 6(4hrs) Sep - Dec	3295	321	0.911
471935*	M	unknown	1/24/2001	12/18/2001	11 months	16 (15 minutes) scattered throughout days	5180	78	0.985
471936*	F	unknown	2/7/2001	12/28/2001	11.5 months	16 (15 minutes) scattered throughout days	5089	111	0.979
471938	F	unknown	11/7/2002	11/16/2002	9 dys	7 (3hrs) nov	62	3	0.954
471940*	F	unknown	1/31/2001	12/25/2001	12 months	16 (15 minutes) scattered throughout days	5090	159	0.970
471941	F	unknown	11/8/2002	5/5/2003	6 months	16 (15 minutes) Nov - May scattered throughout days	2805	75	0.974

Table 2.1. (cont.)

Collar	Sex	Age	Start Date	End Date	Total # Months	#Fixes/Day (Time Interval)	Total # "Good" Fixes	# Missing Locations	PAR
471944	F	unknown	11/7/2002	11/13/2002	6 dys	16 (15 minutes) Nov scattered throughout days	91	10	0.901
471946	F	unknown	11/7/2002	11/22/2002	15 dys	16 (15minutes) Nov scattered throughout days	166	90	0.648
471947	F	unknown	11/7/2002	5/7/2003	6 months	16 (15 minutes) Nov -Apr scattered throughout days	2746	166	0.943
471958	F	9	1/11/2001	10/15/2001	9 months	4 (6hrs) Jan - Feb 2 (12hrs) Mar - Apr 1 (23hrs) May - Aug 6 (4hrs) Sep - Dec	575	136	0.809
471959	F	9	1/11/2001	2/1/2001	1 month	4 (6hrs)	86	2	0.977
471960*	F	7	1/12/2001	2/18/2004	37 months	4 (6hrs) Jan - Feb 2 (12 hrs) Mar - Apr 1 (23hrs) May - Aug 6 (4hrs) Sep - Dec	3620	168	0.956
471961	F	8	11/7/2002	6/9/2003	7 months	6 (4hrs) Nov - Dec January=MESS! March=MESS! April=MESS! 1 (23hrs) May	280	443	0.387

Table 2.1. (cont.)

Collar	Sex	Age	Start Date	End Date	Total # Months	#Fixes/Day (Time Interval)	Total # "Good" Fixes	# Missing Locations	PAR
471962*	F	2	1/12/2001	2/18/2004	37 months	4 (6hrs) Jan - Feb 2 (12hrs) Mar - Apr 1 (23hrs) May - Aug 6 (4hrs) Sep - Dec	3634	154	0.959
471963	F	Yearling	1/12/2001	6/20/2001	5 months	4 (6hrs) Jan - Feb 2 (12hrs) Mar-Apr 1 (23 hrs) May - Jun	356	11	0.970
471966	F	7	1/12/2001	2/17/2004	37 months	4 (6hrs) Jan - Feb 2 (12 hrs) Mar - Apr 1 (23hrs) May - Aug 6 (4hrs) Sep - Dec	3582	202	0.947
481465	F	unknown	11/6/2002	2/18/2004	15 months	7 (3hrs) Nov - Dec 4-5 (5hrs) Jan - Feb 4 (6hrs) Mar - Aug 7 (3hrs) Sep - Dec	2245	266	0.894
481466	F	unknown	11/7/2002	5/7/2003	6 months	7 (3hrs) Nov - Dec 4-5 (5hrs) Jan - Feb 4 (6hrs) Mar - May	891	55	0.942
481468	F	unknown	11/7/2002	5/9/2003	6 months	7 (3hrs) nov - Dec 4-5 (5hrs) Jan - Feb 4 (6hrs) Mar - May	599	365	0.621

Table 2.1. (cont.)

Collar	Sex	Age	Start Date	End Date	Total # Months	#Fixes/Day (Time Interval)	Total # "Good" Fixes	# Missing Locations	PAR
481469	F	unknown	11/6/2002	5/7/2003	6 months	7 (3hrs) Nov - Dec 5 (5hrs) Jan - Feb 4 (6hrs) Mar - May	347	606	0.364
481470	F	unknown	11/6/2002	3/5/2003	4 months	7 (3hrs) Nov - Dec 5 (5hrs) Jan - Feb 4 (6hrs) Mar	671	30	0.957
481471*	F	unknown	11/7/2002	2/17/2004	15 months	7 (3hrs) Nov - Dec 5 (5hrs) Jan - Feb 4 (6hrs) Mar - Aug 7 (3hrs) Sep - Dec	2361	144	0.943
481472	F	unknown	11/6/2002	12/2/2002	26 dys	7 (3hrs) Nov - Dec	165	18	0.902
481473	F	unknown	11/6/2002	1/31/2003	3 months	7 (3hrs) Nov - Dec 5 (5hrs) Jan	522	19	0.965
481474	F	unknown	11/8/2002	12/2/2002	24 dys	7 (3hrs) Nov - Dec	144	31	0.823
481475	F	unknown	11/7/2002	11/21/2002	14 dys	7 (3hrs) Nov	88	4	0.957
481476	F	unknown	11/7/2002	11/25/2002	18 dys	7 (3hrs) Nov	117	10	0.921
481477	F	unknown	11/7/2002	12/4/2002	1 month	7 (3hrs) Nov - Dec	178	18	0.908
481478	F	unknown	11/6/2002	3/4/2003	4 months	7 (3hrs) Nov - Dec 5 (5hrs) Jan - Feb 4 (6hrs) Mar	630	66	0.905

Table 2.1. (cont.)

Collar	Sex	Age	Start Date	End Date	Total # Months	#Fixes/Day (Time Interval)	Total # "Good" Fixes	# Missing Locations	PAR
481479	F	unknown	11/6/2002	11/30/2002	24 dys	7 (3hrs) Nov	159	9	0.946
481480	F	unknown	11/6/2002	11/26/2002	20 dys	7 (1hr) Nov scattered intervals	128	17	0.883
4719641	F1	9	1/11/2001	5/10/2001	4 months	4 (6hrs) Jan - Feb 2 (12hrs) Mar - Apr 1 (23hrs) May	317	11	0.966
4719642	F2	unknown	11/7/2002	11/24/2002	17 dys	7 (3hrs) Nov	114	10	0.919
4719651	F1	9	1/11/2001	4/21/2001	3 months	4 (6hrs) Jan - Feb 2 (12hrs) Mar-Apr	296	4	0.987
4719652	F2	unknown	11/7/2002	11/28/2002	21 dys	6 (4hrs) Nov	117	12	0.907
4814821	F	unknown	11/7/2002	5/7/2003	1/6/1900	7 (1hrs) Nov - Dec 5 (5hrs) Jan - Feb 4 (10, 5, or 8 hrs) Mar - May	656	31	0.955
481483	F	unknown	11/7/2002	11/17/2002	10 days	7 (1hrs) Nov	78	5	0.940
481484	F	unknown	11/6/2002	11/18/2002	12 dys	7 (1hr) scattered intervals	75	11	0.872

Table 2.2. Monthly mean PAR (se) values collected from 54 elk ($F_{11, 319}$ = 116.60, P<0.0001). For each month, the total number of fixes (n) is shown.

Month	Total Fixes (n)	Mean PAR (se)	
January	10,857	0.9511 (0.008759)	b [1/]
February	10,529	0.9522 (0.008608)	b
March	7,100	0.9215 (0.01374)	d
April	6,698	0.9417 (0.01054)	c
May	4,510	0.9415 (0.01099)	c
June	4,072	0.9015 (0.01745)	e
July	4,018	0.8483 (0.02481)	g
August	4,057	0.8418 (0.02562)	g
September	9,315	0.8771 (0.02016)	f
October	9,336	0.9060 (0.01600)	e
November	14,278	0.9651 (0.006275)	a
December	13,378	0.9661 (0.006175)	a

[1/] Means followed by the same letter are not significantly different (protected LSD test, P > 0.05).

Table 2.3. Seasonal mean PAR (se) values collected from 54 elk ($F_{4, 319}$ = 287.6, P<0.0001). For each season, the total number of fixes (n) is shown.

Season	Months	Total Fixes (n)	Mean PAR (se)	
Spring	March, April	13,798	0.9323 (0.01181)	a [1/]
Calving	May, June	8,613	0.9239 (0.01342)	a
Summer	July, August	8,075	0.8451 (0.02464)	b
Fall	September, October	18,651	0.8924 (0.01783)	c
Winter	November through February	49,042	0.9592 (0.007195)	d

[1/] Means followed by the same letter are not significantly different (protected LSD test, P > 0.05).

Table 2.4. Mean PAR (se) values for 4-hour time blocks throughout the day ($F_{5,224}$ = 269.05, P<0.0001). For each time block, the total number of fixes (n) is shown.

Time of day	Total Fixes (n)	Mean (se)	
0-4	13,483	0.9707 (0.005174)	a [1/]
4-8	12,879	0.9444 (0.009439)	c
8-12	13,386	0.8863 (0.01792)	d
12-16	11,852	0.8930 (0.01706)	d
16-20	13,700	0.9453 (0.009274)	c
20-24	12,521	0.9653 (0.006068)	b

[1/] Means followed by the same letter are not significantly different (protected LSD test, P > 0.05).

Table 2.5. Mean PAR (se) values for night-time and day-time hours ($F_{1, 224}$ = 325.89, P<0.0001). For each time period, the total number of fixes (n) is shown.

Time of day	Hourly Time Periods	Mean (se)	
Night	0000-4000, 4000-8000, 2000-2400	0.9552 (0.007577)	a [1/]
Day	0800-1200, 1200-1600, 1600-2000	0.9242 (0.01240)	b

[1/] Means followed by the same letter are not significantly different (protected LSD test, P > 0.05).

Table 2.6. Effect of elevation on dilution of precision (DOP) regardless of fix or time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	-0.0110	7.4000	-186.7774	96.8283	1000	0.2141	5.3902	-32.8160	74.8383
	Pos. [4/]	22	2.5339	3.0967	0.1637	15.5192	14	2.9849	2.3151	0.5929	6.5770
	Neg. [4/]	41	-7.5494	29.1144	-186.7774	-0.4863	71	-2.2239	2.9426	-17.3255	-0.4462
Appropriate: [3/]	Full [2/]						44	-0.1919	0.2691	-0.9509	0.3297
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						9	-0.5681	0.1592	-0.9509	-0.4462
Unstructured											
Assumed: [1/]	Full [2/]						970	-0.1527	0.4632	-2.0132	1.4422
	Pos. [4/]						170	0.4957	0.2294	0.1842	1.4422
	Neg. [4/]						368	-0.6060	0.2986	-2.0132	-0.0829
Appropriate: [3/]	Full [2/]						926	-0.1506	0.4677	-2.0132	1.4422
	Pos. [4/]						167	0.4940	0.2291	0.1842	1.4422
	Neg. [4/]						350	-0.6101	0.3042	-2.0132	-0.0829

Table 2.6. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table 2.7. Effect of elevation on dilution of precision (DOP) for 2D fixes regardless of time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	-0.3904	12.3423	-197.9631	273.2727	1000	-0.1955	6.2108	-42.4336	57.3683
	Pos. [4/]	9	3.0055	6.2335	0.1468	19.5306	7	3.2980	3.4891	0.5981	10.2425
	Neg. [4/]	55	-11.7287	29.1544	-197.9631	-0.0870	86	-7.1341	8.1771	-42.4336	-0.6169
Appropriate: [3/]	Full [2/]						3	0.2692	0.0972	0.1944	0.3790
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						864	-0.1146	0.5966	-2.1240	2.6426
	Pos. [4/]						190	0.6470	0.3210	0.1846	2.6426
	Neg. [4/]						305	-0.7170	0.4000	-2.1240	-0.0988
Appropriate: [3/]	Full [2/]						861	-0.1162	0.5964	-2.1240	2.6426
	Pos. [4/]						188	0.6472	0.3216	0.1846	2.6426
	Neg. [4/]						305	-0.7170	0.4000	-2.1240	-0.0998

Table 2.7. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table 2.8. Effect of elevation on dilution of precision (DOP) for 3D fixes regardless of time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate (“Assumed”), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test (“Appropriate”). This analytical procedure was repeated N=1,000 times (“Full”) or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.1964	0.8331	-2.0322	9.8607	1000	0.1421	0.2366	-0.4490	2.0621
	Pos. [4/]	20	1.2934	1.3876	0.2596	6.9733	65	0.5972	0.3755	0.2907	2.0621
	Neg. [4/]	12	-0.9833	0.2389	-1.5006	-0.6885	7	-0.3341	0.0425	-0.4161	-0.2868
Appropriate: [3/]	Full [2/]						145	0.0571	0.1491	-0.4161	0.4228
	Pos. [4/]						7	0.3490	0.0418	0.3113	0.4228
	Neg. [4/]						2	-0.3681	0.0678	-0.4161	-0.3201
Unstructured											
Assumed: [1/]	Full [2/]						934	0.0965	0.2885	-0.9177	1.2202
	Pos. [4/]						367	0.3741	0.1728	0.0986	1.2202
	Neg. [4/]						159	-0.3239	0.1471	-0.9177	-0.0483
Appropriate: [3/]	Full [2/]						789	0.0995	0.2919	-0.9177	1.2202
	Pos. [4/]						315	0.3774	0.1792	0.0986	1.2202
	Neg. [4/]						137	-0.3212	0.1425	-0.9177	-0.0483

Table 2.8. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table 2.9. Effect of topographic slope on dilution of precision (DOP) as expressed by linear regression analysis regardless of fix type or time block. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0518	0.7354	-4.1354	16.5634	1000	0.0827	0.5403	-1.1808	7.0866
	Pos. [4/]	34	0.8856	2.8190	0.1025	16.5634	74	0.3415	0.4677	0.0423	2.3343
	Neg. [4/]	29	-0.1524	0.0765	-0.3535	-0.0016	16	-0.0598	0.0178	-0.1051	-0.0416
Appropriate: [3/]	Full [2/]						42	-0.0067	0.0240	-0.0579	0.0656
	Pos. [4/]						1	0.0655	-	-	-
	Neg. [4/]						4	-0.0517	0.0066	-0.0579	-0.0442
Unstructured											
Assumed: [1/]	Full [2/]						970	0.0012	0.0463	-0.1622	0.2038
	Pos. [4/]						262	0.0567	0.0294	0.0142	0.2038
	Neg. [4/]						247	-0.0554	0.0233	-0.1622	-0.0144
Appropriate: [3/]	Full [2/]						928	0.0016	0.0466	-0.1622	0.2038
	Pos. [4/]						255	0.0570	0.0295	0.0142	0.2038
	Neg. [4/]						236	-0.0556	0.0236	-0.1622	-0.0144

Table 2.9. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table 2.10. Effect of topographic slope on dilution of precision (DOP) for 2D fixes regardless of time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0181	0.8050	-9.6354	14.8388	1000	0.0989	0.6400	-1.4364	7.8955
	Pos. [4/]	39	0.9284	2.4112	0.0035	14.8388	71	0.6659	0.6265	0.0605	2.3267
	Neg. [4/]	25	-0.5566	1.8940	-9.6354	-0.0466	17	-0.1245	0.0623	-0.2839	-0.0592
Appropriate: [3/]	Full [2/]						4	-0.0068	0.0311	-0.0272	0.0392
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						864	-0.0013	0.0593	-0.2185	0.3499
	Pos. [4/]						229	0.0695	0.0423	0.0191	0.3499
	Neg. [4/]						246	-0.0669	0.0339	-0.2185	0.0168
Appropriate: [3/]	Full [2/]						860	-0.0013	0.0594	-0.2185	0.3499
	Pos. [4/]						228	0.0695	0.0424	0.0191	0.3499
	Neg. [4/]						246	-0.0669	0.0339	-0.2185	-0.0168

Table 2.10. (cont.)

1/ Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

2/ The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

3/ A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

4/ The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

5/ Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table 2.11. Effect of topographic slope on dilution of precision (DOP) for 3D fixes regardless of time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0399	0.0908	-0.6065	0.8808	1000	0.0345	0.0249	-0.0326	0.1761
	Pos. [4/]	94	0.1594	0.1444	0.0302	0.8808	417	0.0528	0.0222	0.0260	0.1761
	Neg. [4/]	4	-0.1045	0.0793	-0.1850	-0.0012	0	-	-	-	-
Appropriate: [3/]	Full [2/]						134	0.0271	0.0153	-0.0158	0.0674
	Pos. [4/]						58	0.0409	0.0088	0.0304	0.0674
	Neg. [4/]						0	-	-	-	-
Unstructured							934	0.0298	0.0290	-0.0885	0.1160
Assumed: [1/]	Full [2/]						632	0.0447	0.0202	0.0121	0.1160
	Pos. [4/]						50	-0.0327	0.0163	-0.0885	-0.0095
	Neg. [4/]										
Appropriate: [3/]	Full [2/]						800	0.0299	0.0292	-0.0659	0.1160
	Pos. [4/]						549	0.0446	0.0205	0.0121	0.1160
	Neg. [4/]						46	-0.0320	0.0146	-0.0659	-0.0095

Table 2.11. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table 2.12. Mean DOP values (all fix types) on 8 principle aspects and level topography. Data represent mean DOP values from a total of 55,786 fixes on 15 elk ($F_{2.95,38.38} = 0.69$, $P = 0.5604$).

Aspect	Angle (degrees)	Mean (se)	
0	(level topography)	4.4864 (0.8833)	a [1/]
1	337.5 to 22.5	4.3690 (0.2474)	a
2	22.5 to 67.5	4.8624 (0.4230)	a
3	67.5 to 112.5	4.2116 (0.1683)	a
4	112.5 to 157.5	5.2639 (0.8797)	a
5	157.5 to 202.5	4.8927 (0.5518)	a
6	202.5 to 247.5	4.2770 (0.1882)	a
7	247.5 to 292.5	4.1946 (0.1914)	a
8	292.5 to 337.5	3.9991 (0.1316)	a

[1/] Means followed by the same letter are not significantly different (protected LSD test, P > 0.05).

Table 2.13. Mean DOP values (3D fixes only) on 8 principle aspects and level topography. Data represent mean DOP values from a total of 36,677 fixes on 15 elk ($F_{1.74,22.63} = 11.78$, $P<0.0005$).

Aspect	Angle (degrees)	Mean (se)	
0	(level topography)	3.8569 (0.1593)	a [1/]
1	337.5 to 22.5	4.5240 (0.0393)	b
2	22.5 to 67.5	4.5656 (0.0381)	b
3	67.5 to 112.5	4.5616 (0.0442)	b
4	112.5 to 157.5	4.4703 (0.0424)	b
5	157.5 to 202.5	4.4956 (0.0514)	b
6	202.5 to 247.5	4.4967 (0.0521)	b
7	247.5 to 292.5	4.5895 (0.0578)	b
8	292.5 to 337.5	4.4683 (0.0406)	b

[1/] Means followed by the same letter are not significantly different (protected LSD test, P > 0.05).

Table 2.14. Mean DOP values (2D fixes only) on 8 principle aspects and level topography. Data represent mean DOP values from a total of 19,109 fixes on 15 elk ($F_{2.86,36.43} = 0.76$, $P=0.5163$).

Aspect	Angle (degrees)	Mean (se)	
0	(level topography)	5.4180 (2.1571)	a [1/]
1	337.5 to 22.5	4.2140 (0.4845)	a
2	22.5 to 67.5	5.1593 (0.8351)	a
3	67.5 to 112.5	3.8616 (0.3202)	a
4	112.5 to 157.5	6.0575 (1.7536)	a
5	157.5 to 202.5	5.2894 (1.1043)	a
6	202.5 to 247.5	4.0573 (0.3665)	a
7	247.5 to 292.5	4.7998 (1.9895)	a
8	292.5 to 337.5	3.5298 (0.2736)	a

[1/] Means followed by the same letter are not significantly different (protected LSD test, P > 0.05).

Table 2.15. Mean DOP values (all fix types) on 17 land cover classes. Data represent mean DOP values from fixes on 15 elk. Land cover classes were consolidated from an original 32 land cover classes found in the most recent version of the LANL land cover map (McKown et. al 2003). Acronyms are defined in Appendix 'B'. With the exception of combined types (Sparse Ground, PIED/JUMO, QUGA/RONE, and POTR), the original numbering system is maintained. Land cover types with the same letter are not significantly different from each other ($F_{2.99,41.80}$ = 1.13, P = 0.3478).

Class #	Land Cover	Mean	se	
1	VCNP Grassland	4.8321	0.8101	a
2	Montane Grassland	4.7487	0.5900	a
3	ABCO-PSME Woodland	5.3680	0.7959	a
4	ABCO-PSME Forest	4.7956	0.2967	a
5	Evergreen-POTR Forest	4.0597	0.1704	a
12	PIPO/BOGR-SCSC Woodland	4.0454	0.2032	a
15	Submontane Grassland	4.0541	0.2668	a
17	Other Shrubland	3.9864	0.2191	a
20	BRCA-AGTR Grassland	5.9346	1.1793	a
21	PIPO Forest	5.1698	0.4594	a
23	PIPO/QUGA Woodland	4.5460	0.2425	a
24	ALBA-PIEN Forest	5.2450	0.7823	a
27	PIPO/Other Grass Woodland	4.4656	0.2204	a
33	Sparse Ground	6.9017	2.0674	a
35	PIED/JUMO	4.7183	0.5215	a
36	QUGA/RONE Shrubland	8.5389	3.1953	a
37	POTR	4.4611	0.1686	a

Table 2.16. Mean DOP values (all fix types) on 7 growth forms. Data represent mean DOP values from fixes on 15 elk. Growth form classes were consolidated from the 17 land cover classes found in Table 2.15. Acronyms are defined in Appendix 'B'. Growth forms with the same letter are not significantly different from each other ($F_{2.19, 30.71}$ = 0.80, P = 0.4689).

Growth form	Original Classes	Mean	se	
Grasslands	1, 2, 15, 20	4.8901	0.5575	a
Woodlands	3, 12, 23, 27	4.6062	0.1940	a
Forest	4, 5, 21, 24	4.8175	0.5575	a
Shrublands	17, 36	6.2626	1.6755	a
Sparse Ground	33	6.9017	2.0674	a
PIED/JUMO	35	4.7183	0.5215	a
Aspen (POTR)	37	4.4611	0.1986	a

Table 2.17. Mean DOP values from 3D fixes, standard errors, and P values associated with pairwise comparisons of 17 land cover types ($F_{2.75, 38.53} = 10.77$, $P<0.0001$). Values in the body of the table are the probabilities associated with a comparison of land cover types in the corresponding row and column of the table. Land cover types are defined in Table 2.15.

LC	1	2	3	4	5	12	15	17	20	21	23	24	27	33	35	36	37
Mean	4.2327	4.5033	5.0045	5.3732	5.1359	4.8202	4.2781	4.2906	4.6880	5.1751	4.7015	5.3810	4.7046	4.7595	4.6854	4.4353	4.8228
Se	0.0801	0.0674	0.1331	0.1951	0.1225	0.1271	0.0681	0.1199	0.0693	0.1493	0.0729	0.1643	0.0737	0.0652	0.1321	0.0795	0.0566
1		0.0120	0.0012	0.0008	0.0003	0.0015	0.5385	0.4519	0.0001	0.0008	0.0001	0.0002	0.0008	0.0002	0.0088	0.0735	0.0001
2			0.0024	0.0010	0.0009	0.0212	0.0408	0.1083	0.0989	0.0012	0.0892	0.0002	0.0004	0.0072	0.1517	0.4292	0.0048
3				0.0118	0.4593	0.1310	0.0017	0.0068	0.0812	0.0599	0.1400	0.0336	0.0810	0.0618	0.0269	0.0007	0.3153
4					0.2081	0.0151	0.0004	0.0029	0.0132	0.0128	0.0131	0.9600	0.0033	0.0079	0.0078	0.0005	0.0293
5						0.1583	0.0001	0.0009	0.0163	0.7898	0.0029	0.0662	0.0062	0.0401	0.0678	0.0007	0.0223
12							0.0071	0.0160	0.3709	0.0380	0.5134	0.0130	0.8992	0.5735	0.1042	0.0028	0.9880
17								0.9041	0.0003	0.0005	0.0001	0.0001	0.0003	0.0013	0.0396	0.1856	0.0001
20									0.0020	0.0037	0.0028	0.0005	0.0097	0.0503	0.0458	0.3067	0.0002
21										0.0236	0.8886	0.0054	0.3257	0.4102	0.9861	0.0132	0.0769
23											0.0312	0.1066	0.0050	0.0149	0.0145	0.0003	0.0786
24												0.0020	0.3644	0.6649	0.9338	0.0477	0.0303
27													0.0004	0.0061	0.0081	0.0001	0.0089
33														0.6534	0.4401	0.0014	0.8606
34															0.4304	0.0007	0.5738
35																0.0363	0.4568
36																	0.0032
37																	----

Table 2.18. Mean DOP values from 3D fixes, standard errors, and P values associated with pairwise comparisons of 7 growth forms ($F_{2.42,\ 33.83} = 11.36$, $P = 0.0001$). Values in the body of the table are the probabilities associated with a comparison of growth forms in the corresponding row and column of the table. Acronyms are found in Appendix B.

Growth Form	Grasslands	Woodlands	Forests	Shrublands	Bare Ground	PIED-JUMO	Aspen
Mean	4.4255	4.8327	5.2663	4.3630	4.7595	4.6854	4.8228
se	0.0468	0.0606	0.1367	0.0755	0.0652	0.1321	0.0566
Grasslands		0.0003	0.0003	0.2356	0.0012	0.0835	0.0001
Woodlands			0.0017	0.0005	0.3458	0.2157	0.9255
Forests				0.0003	0.0062	0.0106	0.0169
Shrublands					0.0012	0.0284	0.0001
Bare Ground						0.4304	0.5738
PIED-JUMO							0.4568
Aspen (POTR)							----

Table 2.19. Mean DOP values (2D fixes) on 17 land cover classes. Data represent mean DOP values from fixes on 15 elk. Land cover classes were consolidated from an original 32 land cover classes found in the most recent version of the LANL land cover map (McKown et. al 2003). Acronyms are defined in Appendix 'B'. With the exception of combined types (Sparse Ground, PIED/JUMO, QUGA/RONE, and POTR), the original numbering system is maintained. Land cover types with the same letter are not significantly different from each other ($F_{4.72, 65.22} = 1.17$, $P = 0.3333$).

Class #	Land Cover	Mean	se	
1	VCNP Grassland	5.4136	1.6060	a
2	Montane Grassland	4.9941	1.1550	a
3	ABCO-PSME Woodland	5.7314	0.1531	a
4	ABCO-PSME Forest	4.2181	0.5236	a
5	Evergreen-POTR Forest	2.9836	0.2767	a
12	PIPO/BOGR-SCSC Woodland	3.2706	0.4119	a
15	Submontane Grassland	3.8301	0.5167	a
17	Other Shrubland	3.6822	0.4656	a
20	BRCA-AGTR Grassland	7.1813	3.4922	a
21	PIPO Forest	5.1645	0.9295	a
23	PIPO/QUGA Woodland	4.3905	0.4769	a
24	ALBA-PIEN Forest	5.1089	1.5516	a
27	PIPO/Other Grass Woodland	4.1265	0.4674	a
33	Sparse Ground	9.0439	4.1487	a
35	PIED/JUMO	4.5334	1.2092	a
36	QUGA/RONE Shrubland	12.6424	6.3797	a
37	POTR	4.0993	0.3803	a

Table 2.20. Mean DOP values (2D fixes) on 7 growth forms. Data represent mean DOP values from fixes on 15 elk. Growth form classes were consolidated from the 17 land cover classes found in Table 16 and 20. Acronyms are defined in Appendix 'B'. Growth forms with the same letter are not significantly different from each other ($F_{2.09, 28.24} = 0.88$, $P = 0.4301$).

Growth form	Original Classes	Mean	se	
Grasslands	1, 2, 15, 20	5.3547	1.1043	a
Woodlands	3, 12, 23, 27	4.3798	0.3971	a
Forest	4, 5, 21, 24	4.3688	0.5111	a
Shrublands	17, 36	8.1623	3.3299	a
Sparse Ground	33	9.0439	4.1487	a
PIED/JUMO	35	4.6037	1.2518	a
Aspen (POTR)	37	4.0993	0.3803	a

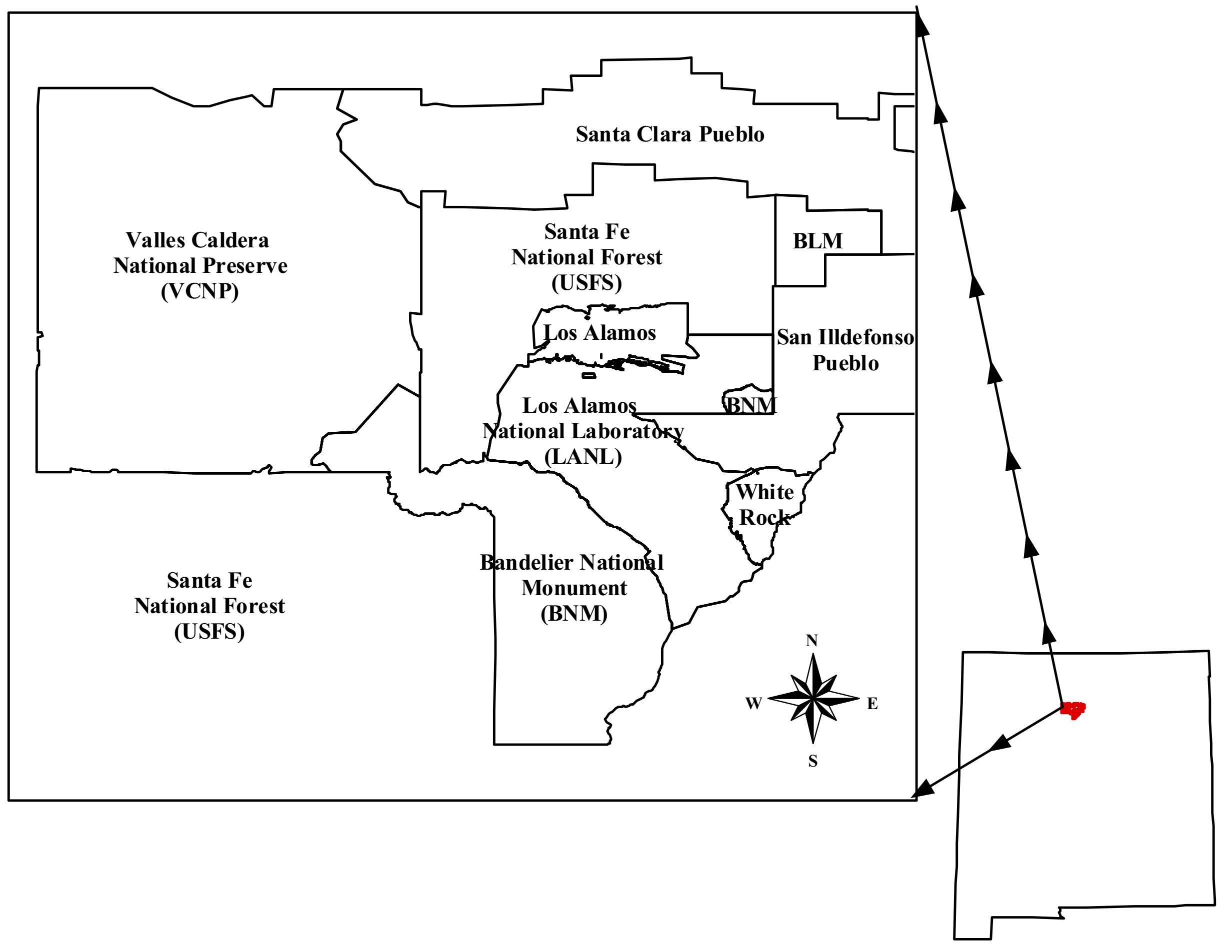

Figure 2.1. Major landowners of the Pajarito Plateau in north central New Mexico.

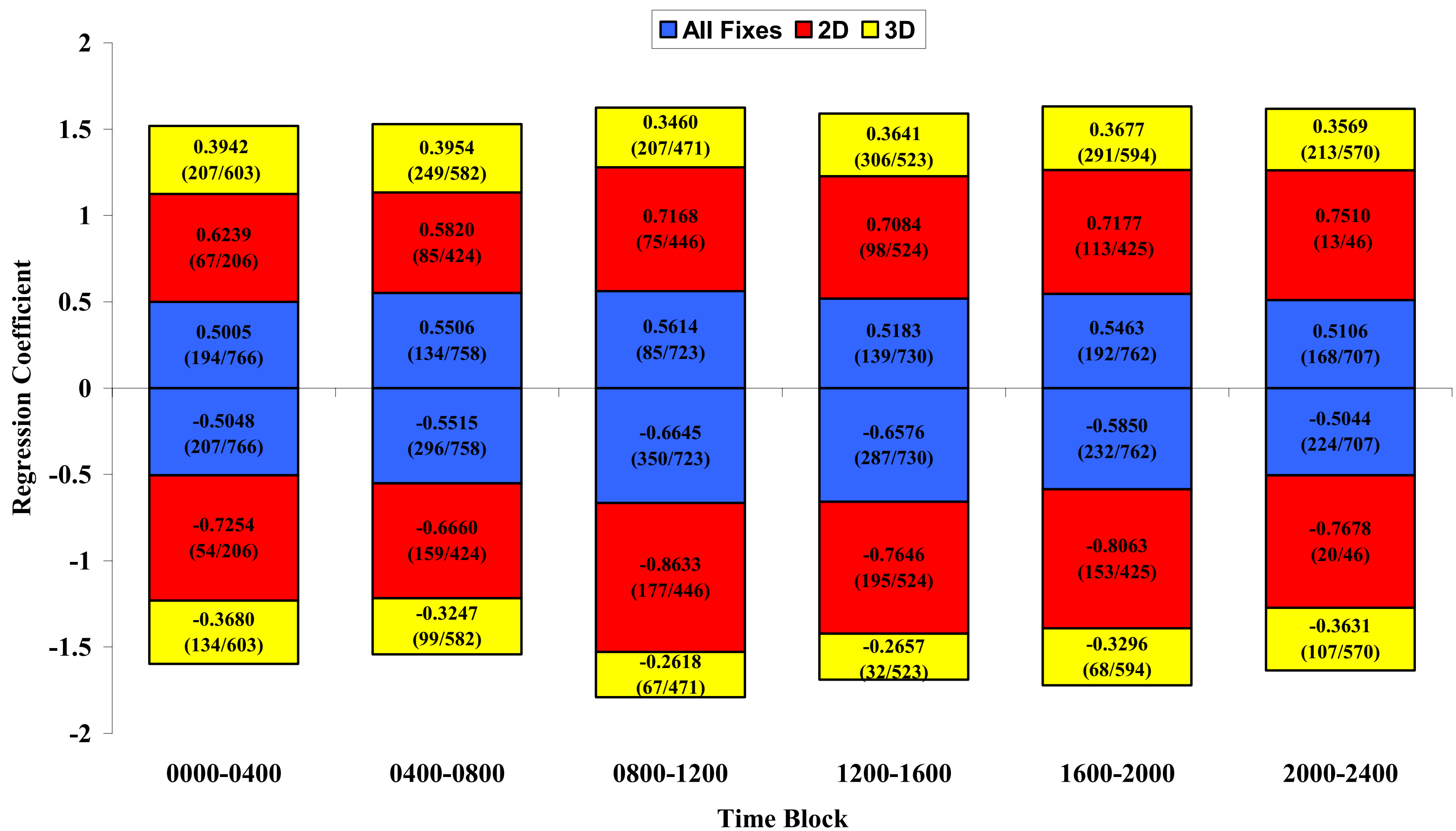

Figure 2.2. Mean regression coefficients for significant outcomes testing the effect of elevation on DOP value by fix type and time block. Shown are the mean regression coefficient regardless of fix type (blue) and the regression coefficients for the combination of fix type and time block. Total number of positive or negative significant outcomes versus all potential outcomes (significant and non-significant) are in parentheses. Elevation was measured in 1000s of feet. Standard errors for regression coefficients can be found in tables in Appendix 'C'.

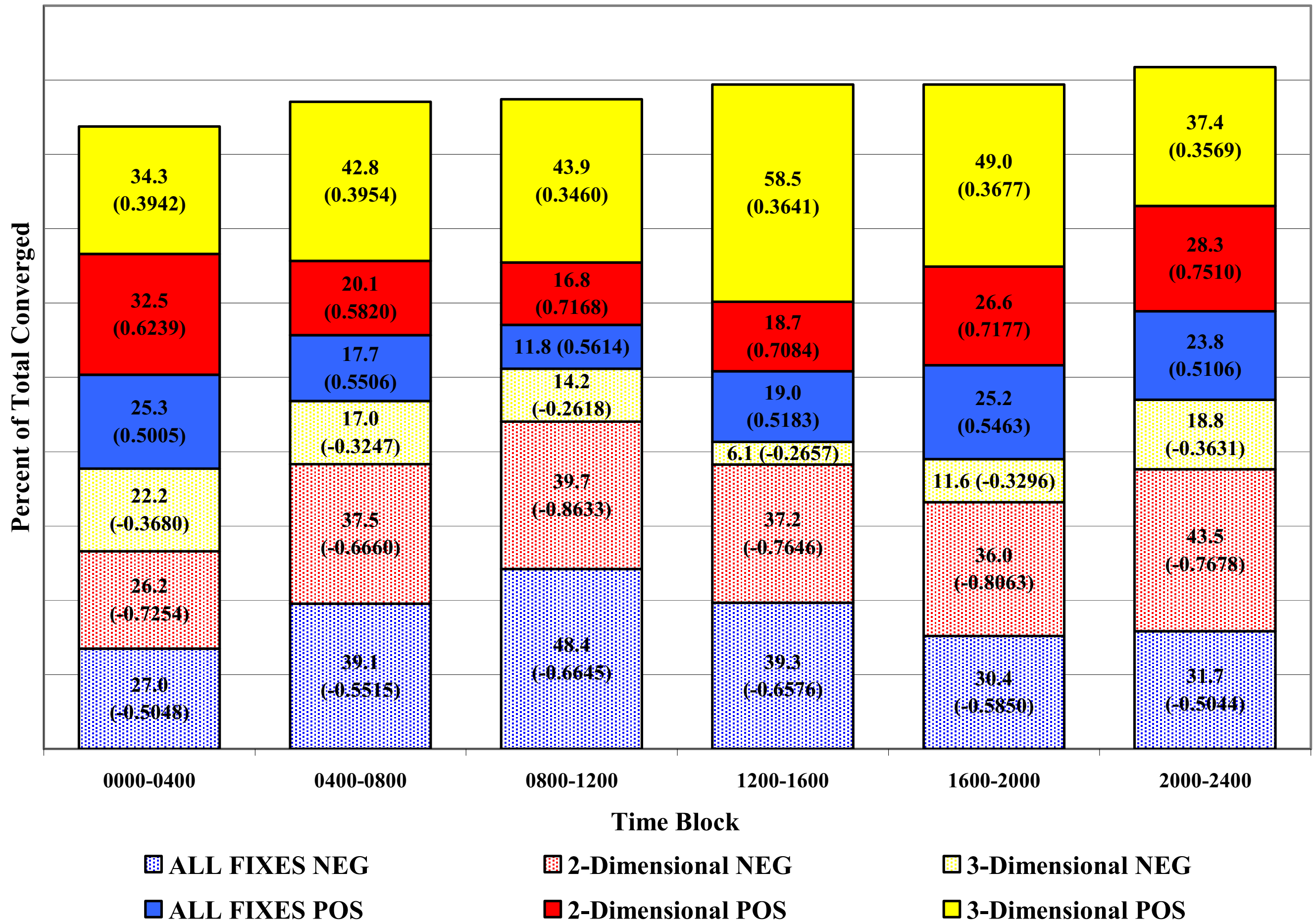

Figure 2.3. Percent of significant positive and negative relationships out of all potential outcomes (significant and nonsignificant) for the unstructured test of the effect of elevation on DOP value by fix type and time block. Average regression coefficients are shown in parentheses. Elevation was measured in 1000s of feet. Tabular output containing data for this figure can be found in Appendix 'C'.

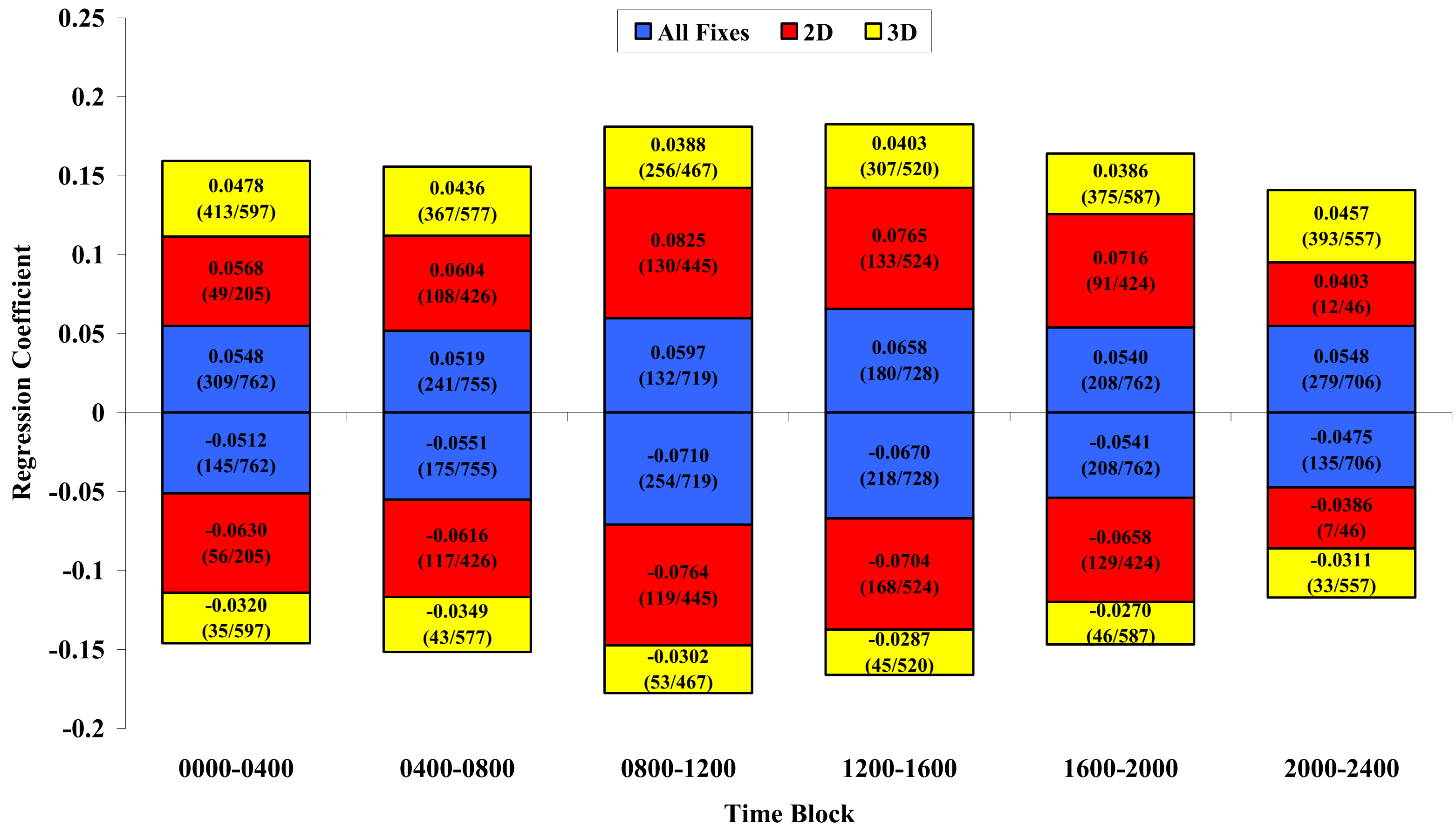

Figure 2.4. Mean regression coefficients for significant outcomes testing the effect of topographic slope on DOP value by fix type and time block. Shown are the mean regression coefficient regardless of fix type (blue) and the regression coefficients for the combination of fix type and time block. Total number of significant outcomes versus all potential outcomes (significant and non-significant) are in parentheses. Slope was measured in degrees. Standard errors for regression coefficients can be found in tables in Appendix 'C'.

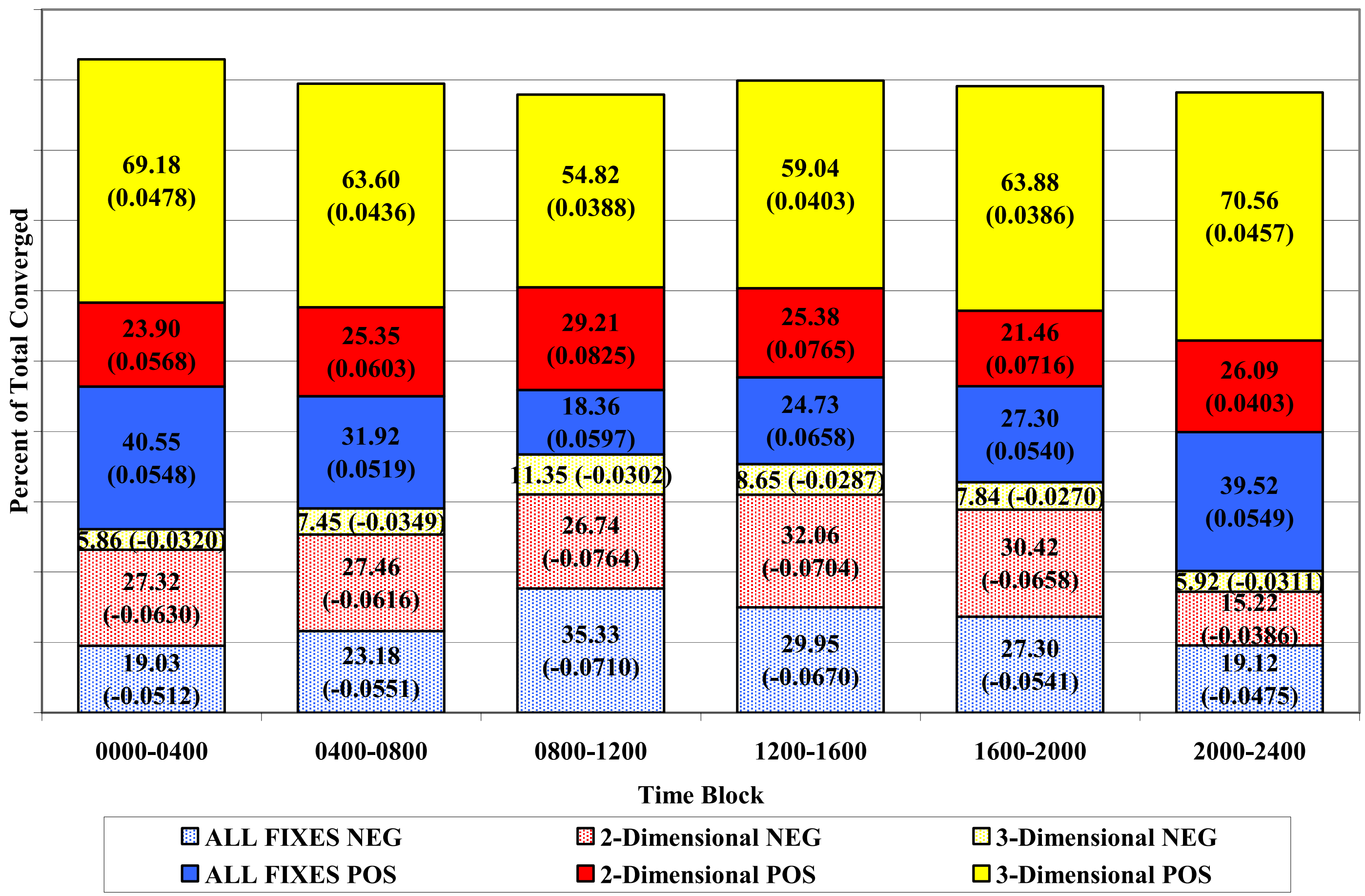

Figure 2.5. Percent of significant positive and negative relationships out of all potential outcomes (significant and nonsignificant) for the unstructured test of the effect of topographic slope on DOP value by fix type and time block. Average regression coefficients are shown in parentheses. Slope was measured in degrees. Tabular output containing data for this figure can be found in Appendix 'C', Tables C.19 through C.36.

CHAPTER III

VEGETATIVE SUCCESSION FOLLOWING THE CERRO GRANDE FIRE – MODEL SELECTION, CALIBRATION, AND EVALUATION

Introduction

Dramatic increases in the frequency and extent of large-scale fires following decades of fire suppression plague the western United States. The immense fires in Montana, Idaho, Colorado, and New Mexico in recent years are possible indications of events to come in many other western forests that are now loaded with fuels. Such fuels are normally limited through the natural occurrence of smaller fires, but fire suppression has disrupted natural fire regimes. In fact, historically anomalous, catastrophic wildfire has been classified as potentially “the most pressing forest health problem in Southwestern forests” (Swetnam and Baisan 1996: 12).

Pickett and White (1985: 7) define disturbance as “any relatively discrete event in time that disrupts ecosystem, community or population structure and changes resources, substrate availability, or the physical environment.” Understanding recovery of forest landscapes following large-scale disturbance events, such as the catastrophic wildfires that have plagued the southwest, is a challenge because of complex interactions over a range of temporal and spatial scales (He and Mladenoff 1999). Disturbance events such as these are unusual in that they both create and respond to landscape pattern (Turner et al. 2001). Environmental heterogeneity, therefore, reflects the cumulative and interactive effects of disturbance regimes, biophysical environments, and successional processes at a given temporal and/or spatial scale (Pickett and White 1985, Turner et al. 2001, Keane et al. 2002). Changes in the structure and composition of a community are associated with changes in structural and functional properties (Drury and Nisbet 1973) including, but not limited to, changes in animal movement and distribution.

Fires strongly influence animal response at every level of ecosystem organization. Individuals' responses will vary with the spatial/temporal aspects of the disturbance and subsequent recovery (Turner et al. 2001) which, in turn, can have far-reaching implications for the ecology of organisms and ecosystem function (Turchin 1998). Long-term faunal response is determined by habitat change, which influences feeding patterns, movement, reproduction, and cover (Brown et al. 2000). Therefore, any analysis of animal movement and distribution following large-scale fires must include an accurate representation of habitat resources and successional processes.

Integrated models of disturbance and succession offer a means of comparing long-term effects of fire regimes on forest vegetation and other ecosystem processes that may otherwise be difficult to observe empirically (Keane et al. 1989, Keane et al. 1996, He and Mladenoff 1999, Turner et al. 2001). In addition, successional models enable evaluation of the cumulative effects of management practices and ecosystem response in a spatial context over long time periods (Keane and Hann 1998). Several approaches have been used to model post-fire succession (Keane and Long 1998, Barrett 2001, Turner et al. 2001) but current efforts are focused on stochastic approaches that examine the relationship between fire regimes and landscape heterogeneity as well as fire-affected landscape changes through time (He and Mladenoff 1999).

In early May 2000, the Cerro Grande Fire (CGF) in north central New Mexico burned approximately 19,020 ha as well as 400 residences in the town of Los Alamos (Figure 3.1). The fire was the result of an escaped prescribed burn initiated at Bandelier National Monument (BNM) to reduce unnaturally high fuel loads resulting from decades of fire suppression. The Cerro Grande Fire, coupled with the region's unique fire history and interagency collaborations, presents a unique opportunity to study the long-term ecological consequences of large-scale fires on ungulate movements and distribution. Consequently, a "Participating Agreement" was signed by the Santa Fe National Forest (USFS), U.S. Department of Energy/University of California (LANL), and the National Park Service (BNM) to collaborate in data collection efforts to address concerns regarding potential impacts of the Cerro Grande Fire on the regional elk herd. However, before realistic assessment of elk movement and distribution following the fire can take place, post-fire successional dynamics must be simulated.

The purpose of this chapter is to briefly review and describe various post-fire successional models available in the literature and to select the model deemed most appropriate for evaluating post-fire elk movement and distribution in the Jemez Mountains. Although numerous post-fire successional models exist, only the most applicable and appropriate for the Jemez Mountains were selected for review. Potential models were evaluated with regard to specific research needs following the Cerro Grande Fire and the most appropriate model based on overall research objectives was selected.

Background information and a brief overview of the selected model components and structure are discussed. Methods outlining the development of spatial inputs, calibration using field data, and validation for application in the Jemez Mountains are detailed. Finally, issues regarding model application and needs for further research are evaluated.

Methods

Assessing Research/Model Needs

In order to select an appropriate post-fire successional model for purposes of this dissertation, overall research objectives were used as the basis for model selection and assessment. Primary research objectives are as follows:

- To evaluate the movement and distribution patterns of elk in relation to spatial and temporal aspects of the Cerro Grande Fire;
- To integrate concurrent data collection efforts of Bandelier National Monument (BNM), Los Alamos National Laboratory (LANL), and the U.S. Forest Service (USFS) to gain more accurate insight into the movement and distribution of elk in the Jemez Mountains; and
- To provide recommendations to mitigate potential adverse impacts by elk as a result of changes in movements and distributions based on simulated conditions projected by the model.

Once primary research objectives were evaluated, it was apparent the selected model must possess certain characteristics which would make it capable of meeting overall research goals. Input and output criteria as well as model performance and flexibility were addressed. Included were the need to incorporate data already available through participating agreements (input criteria), the need for a dynamic modeling atmosphere both spatially and temporally (model performance), and the need for the model to produce output variables (output criteria) meaningful for assessing elk movement and distribution following the fire. These insights led to the development of additional criteria by which models were assessed:

- Raw code for the successional model of choice must be made freely available and be modifiable with appropriate permissions.
- The chosen model must have both a temporal and spatial component to it, each of which could be modified to meet specific research needs for evaluating elk movement and distribution patterns at both regional and local scales seasonally and annually.
- The chosen model must project potential succession of understory vegetation in sufficient detail necessary to evaluate elk movement and distribution patterns.
- The chosen model should have an integrated weather component which could model snow patterns based on complex landscape features.
- The selected model should be supported in the scientific community through published reports, peer-reviewed literature, and wide-spread application.
- Emphasis should be given to models which require data inputs already made available through ongoing studies at LANL or through collaborations with other stakeholders and/or agencies participating in this research.

Model Evaluation

Following extensive literature review, six post-fire successional models were selected for further consideration: (1) Fire-BGC (Keane et al. 1996); (2) LANDSUM (Keane et al. 1997); (3) FIRESUM (Keane et al. 1989); (4) Forest Vegetation Simulator (FVS) – developed from the original "Prognosis Model for Stand Development" (Stage 1973); (5) LANDIS (Mladenoff et al. 1996); and (6) SAVANNA (Coughenour 1993). Models were independently evaluated based on a pre-determined set of questions reflecting overall research objectives (Appendix D). Model developers and subject matter experts were contacted for additional information regarding model availability, performance, structure, and computational requirements. A checklist of individual model performance based on criteria outlined above can be found in Table 3.1.

Model Selection and Description

The majority of models reviewed, although well documented, were designed specifically for evaluating forest (i.e., tree) dynamics. As a result, the temporal resolution of such models was in the range of years to decades – much longer than the daily or seasonal time step desired to evaluate elk movement across the Jemez. In addition, few models simulated the understory component or snow dynamics to the degree deemed critical for modeling elk movement and distribution. Only a single model, SAVANNA, met all criteria and, therefore, was selected to meet research objectives. A complete description of SAVANNA and its components is beyond the scope of this dissertation, but various submodels are briefly reviewed. Detailed descriptions of model development, associated algorithms, and supporting documentation for the entire SAVANNA Ecosystem Model can be found in Coughenour (1993, 2002).

SAVANNA, developed over 15+ years by Dr. Michael Coughenour and colleagues at Colorado State University, was designed specifically for evaluating herbivore dynamics within ecosystems. It is currently being applied across semi-arid and arid regions of the western United States and East Africa to address natural changes, land-use practices, and management strategies. It is inclusive by design relying upon and inviting the participation of stakeholders to make critical decisions. It has been used to model such diverse issues as global climate change scenarios and pastoral land use to the effects of habitat fragmentation on wildlife populations. Coughenour et al. (2000) gives a complete listing and description of funded projects and geographic locations where SAVANNA has been successfully implemented.

SAVANNA is a spatially-explicit, process-oriented ecosystem model that integrates computer modeling, geographic information systems, remote sensing, and field studies. The model is composed of various submodels (e.g., hydrologic, plant biomass production, plant population dynamics, ungulate herbivory/spatial distribution), which can be run independently or in combination. User-defined spatial resolution allows flexibility in application and the potential for cross-validation and detailed examination at different spatial scales. In addition, SAVANNA's weekly time step is suited to simulate seasonal dynamics unlike many models that run on an annual or decadal time step. Results can be displayed spatially and/or temporally. Once calibrated, SAVANNA can be used as an adaptive management tool to objectively explore, debate, implement, and reassess alternative policy and management strategies.

Spatial Structure. SAVANNA has a hierarchical structure that is spatially explicit (i.e., sensitive to spatial position) at the landscape scale and spatially inexplicit at patch scales. The model runs in a raster-based environment. Cell resolution (grain) is determined in part by the spatial extent of the simulated ecosystem and computer resources as well as the needs of the researcher based on the organism in question. User-defined spatial and temporal structures allow maximum flexibility to balance computational efficiency and mechanistic detail.

Within each grid cell, the model simulates vegetation patches or “facets,” which are defined by the fractional cover of herbaceous plants, shrubs and trees (Figure 3.2) and correspond to fixed distributions of physical factors such as topography and soils. Therefore, facet cover is a dynamic outcome of vegetation growth and mortality. Facet locations are not explicitly modeled, only the fractions of grid cells that are covered by the facets. The results are scaled-up to the grid-cell level by multiplying by the fractions of the grid-cell area covered by each facet (Coughenour 1993). For example, if the model simulates 100 g per square meter of plant biomass on a facet, and the facet occupies 25% of the grid cell, then the total plant biomass contributed by that facet to the grid cell is 25 g per square meter (i.e., area-weighted averaging).

The vertical spatial structure of the model is distinguished by soil and plant canopy layers (Coughenour 2002). Soils are divided into three strata with physical properties assigned to each: 1) A zone of potential bare soil evaporation (top layer), 2) a second layer (generally the deepest) that is exploited by herbaceous roots, and 3) a bottom layer that is generally occupied only by tree roots. Plant canopies are organized into herb, shrub and tree strata, which are further divided into three substrata to compute light intensity.

Submodel Overview. SAVANNA is comprised of several interacting submodels (Figure 3.3), which can be run independently or in combination. These include water budget, light interception, net primary production, plant population dynamics, litter decomposition and nitrogen cycling, ungulate herbivory, ungulate spatial distribution, ungulate energy balance, ungulate population dynamics, and wolf predation submodels. With the exception of the wolf predation submodel, which does not apply to the Jemez Mountain elk population, brief descriptions are provided below and were taken verbatim or near verbatim from Coughenour (1993, 2002).

The *water budget submodel* simulates soil moisture dynamics and use on each patch type on each grid cell. Soils map data are used in conjunction with soil properties for each soil type to determine soil water holding capacities of each facet on each grid cell. Water resources are routed through three soil layers using a simple “tipping bucket” approach that drains water in excess of field capacity to deeper layers. The water budget includes terms for precipitation, interception, run-off, run-on, infiltration, deep drainage, bare soil evaporation, and transpiration.

The *light submodel* simulates shading within and among plant canopies. On tree covered facets, incident radiation first passes through the tree canopy, then the shrub understory and finally the herbaceous understory. Light extinction follows an exponential decay function (Beer's Law), dependent on leaf area indices and a light extinction coefficient. The model tracks relative heights of woody plants in different size/age classes and apportions light accordingly.

The *net primary production (NPP) submodel* simulates plant biomass flows and dynamics. Plant biomass production is affected by light, water, temperature, nitrogen, and herbivory. The NPP submodel is explicitly linked to the water budget submodel through transpiration and plant water use efficiency. Thus, for each gram of water used by plants, a certain amount of biomass is produced. Biomass is allocated to leaves, stems, and roots. Plant tissues die because of water or temperature stress or phenological stage, and they turn over at a nominal rate that reflects their maximal longevities. The NPP submodel also simulates plant nitrogen uptake and losses due to herbivory and tissue mortality.

Plant population submodels simulate plant establishment, size, and mortality. Herbaceous plant establishment is represented by modeling seed biomass dynamics; shrub and tree establishment are modeled in simpler demographic terms. Establishment is affected by herbaceous standing crop, water, and temperature. The herb and shrub population models simulate a single variable-size class whereas the tree model simulates six fixed-size classes of plants. Mortality occurs at a nominal rate accentuated by water and temperature stress. The population submodels are explicitly linked to the NPP model.

The *litter decomposition and nitrogen cycling* submodel simulates the breakdown of dead plant materials and animal feces and urine as well as calculating the formation and turnover of soil organic matter (SOM). The decomposition submodel is formulated after the CENTURY model (Parton et al. 1987, Parton et al. 1993). The model partitions vegetation litter into a structural pool (i.e., vegetation that does not easily decompose) and a metabolic pool (i.e., vegetation that breaks down more easily). The ratio of lignin to nitrogen for a given plant (determined by plant phenology) determines if it is structural or metabolic. Decomposition and mineralization are affected, in part, by water availability within the first two soil layers, the soil temperature, and the lignin content of plant parts. SAVANNA also models the fate of nitrogen in high detail, partitioning nitrogen that is volatilized, fixed by plants, lost in drainage, and volatilized as part of animal wastes.

The *ungulate herbivory* submodel simulates ungulate foraging. Forage intake is determined by diet selection, forage abundance, forage quality, and snow cover and will increase as forage biomass increases until intake reaches a maximal value (depicted internally as a linear function) assuming snow depth does not inhibit intake. The effect of snow depth is only applied to that fraction of the plant that is covered by snow. Diet selection is based on preference indices and relative forage abundances and, therefore, responds to temporal and spatial changes. Preference indices are currently calibrated so that the diets of elk are similar to those reported by Stevens (1980), Baker and Hobbs (1982), Hobbs et al. (1981), and Singer et al. (2002). Maximum intake rates are based on Watkins et al. (1991).

The *ungulate energy balance* submodel simulates body weight of the mean animal of each species, based on differences between energy intake and energy expenditure. Energy intake depends on forage biomass intake and forage digestibility. Expenditures depend on body weight and travel patterns. The body weight of the mean animal is used to derive an animal condition index, which affects ungulate population dynamics. Metabolizable energy intake from forage consumption is in part the product of total forage intake (kg) per animal per day, the mean digestibility of the forage, and the gross energy content of digestible plant matter.

The *ungulate spatial distribution* submodel simulates how animals are dynamically distributed among grid cells over the simulated landscape or region. Animals are redistributed monthly in relationship to a calculated habitat suitability index (HSI), which has been calculated for each cell and then normalized. Habitat suitability is dynamically affected by changing forage distributions as well as topography, snow depth, tree cover, a prescribed "force" that defines a population's range at different times of the year, and a random error term in the form of a uniform random variate (0.8 to 1.0) that prevents animals from attaining an ideal free distribution.

The *ungulate population dynamics* submodel is a stage-structured model with five age/sex classes: newborns, immature females, immature males, mature females, and mature males. Recruitment rates and death rates are affected by animal condition indices (i.e., as condition index increases, recruitment rates increase, and death rates decline), which are affected by ecological conditions governing forage availability (e.g., forage production, snow depth, intraspecific competition). Animals may be culled from their respective populations in a prescribed or rule-based manner.

Model Inputs and Calibration

Following model selection, efforts were made to calibrate the model for potential use in the Jemez Mountains of north central New Mexico. Calibration was initiated with the specific aim of modifying SAVANNA's existing ungulate submodels and integrating an individual-based movement and distribution model to evaluate elk movement patterns in response to vegetation succession following the Cerro Grande Fire. Therefore, emphasis was placed on vegetative parameters and ungulate submodels were "turned off" using a flag in the simulation control (Simcon.prm) parameter file, which also designates output files and temporal resolution of model runs. The long-term goal was to integrate interdisciplinary experience and scientific information into a dynamic model that would provide a systematic process for experimentation and monitoring to compare the outcomes of alternative management actions in response to changing vegetation patterns resulting from the Cerro Grande Fire.

Though initial attempts were made to calibrate the model across individual agencies at a grain of 50 m, the final model for the eastern Jemez Mountains was constructed using maps at 150 m resolution with a total study area extent of 1739.93 km^2. The choice grain size was driven by three main factors. First, the graphical user interface (GUI) supplied with SAVANNA was designed to handle no more than 400 x 400 cells. A cell resolution less than 150 m would exceed the capabilities of the GUI. Second, larger cell sizes were needed to make the model computationally efficient. At 150 m resolution without any animals on the landscape, the model took ~3 hours to run during the 1990 to 2002 time frame used to verify weather inputs. Longer runs with animals on the landscape would be computationally inefficient. Finally, definition of cell resolution and study area extent should ultimately be driven by the needs of the researcher, the dynamics of the system being modeled, and the biology of the organism in question. A grain size of 150 m preserved rare habitat patches and also appeared reasonable for migrational processes in which elk must choose an adjacent location to move. The choice of study area extent was limited by map inputs but encompassed the majority (98%) of elk locations.

Weather. Monthly weather data are the model's most important input and, for the eastern Jemez region, are derived from a combination of LANL meteorological stations and regional SNOTEL stations established by the Natural Resources Conservation Service (NRCS) (Figure 3.4). Average monthly precipitation (mm), maximum temperature (C), and minimum temperature (C) were calculated and input along with the geographic coordinates for each station. Weather data from January 1990 through December 2002 were included in the calibration.

Each month precipitation is regressed against elevation using data from all weather stations in the study area. If the precipitation versus elevation regression produces a coefficient of determination of $r^2 > 0.2$, the elevation-corrected weather station data are spatially interpolated using inverse-distance weighting with the six nearest stations. Thus, for the i^{th} known precipitation datum and the j^{th} unknown grid cell,

$$Ppte_{(i,j)} = Ppt_{(i)} + B[E_{(j)} - E_{(i)}]$$

where Ppt_i is the known precipitation amount, E is elevation, B is the slope of the precipitation/elevation regression equation, and $Ppte_{ij}$ is the precipitation estimate. Estimates ($Ppte_{ij}$) are then weighted by the inverse square of the distance ($1/D_{ij}^2$) of the six closest stations to derive an estimate for the j^{th} unknown point. When the coefficient of determination is less than 0.2, only the inverse distance weight is used irrespective of elevation.

Stochasticity (i.e., randomness) in model outputs is generated through random sampling of years from the weather files. During each annual run of the model, a random year of data is drawn from the weather files and an additional amount of normally-distributed random variation is added to the data. The sampling and added variability are included in such a way as to affect all weather stations together, thus preserving the spatial pattern in the original data (Coughenour 2002).

Station descriptions are located in Table 3.2. The main base station was identified as TA-6, which serves as the official meteorological station for Los Alamos County and LANL (Baars et al. 1998). Missing weather data are reconstructed using regression equations between data from the main base station (i.e., TA-6, which is considered to be complete and continuous) and other weather stations in an effort to capture primary temporal and spatial patterns in the region. The occurrence of missing data was rare and, therefore, minimally impacted by such calculations.

Atmospheric water vapor content is calculated from relative humidity and temperature. Because temperature varies closely with elevation, lapse rates (change in temperature versus elevation) are calculated based on the main base station and then adjusted for slope and aspect. Solar radiation is also considered. Coughenour (2002:41) states that solar radiation "is calculated from monthly cloud cover, latitude, and day of year, correcting for slope and aspect using the methods described by Nikolov and Zeller (1992)." However, the complex terrain found in the Jemez Mountains may pose significant challenges in the accurate estimation of radiation values using such calculations which, in turn, may affect other portions of the model (e.g., snow cover and retention). Potential evapotranspiration rates are calculated using either the Priestly-Taylor (1972) or Penman-Monteith (Monteith 1965) equations as specified by the user.

Soils. A digital compilation of several soil surveys from a variety of sources was used. These data are representative of the most current geographic soil information available at the present time for the Jemez Mountain region. Original soil survey sources include: the Santa Fe National Forest Terrestrial Ecological Units layer (Miller et al. 1993), which depicts the boundaries of the Terrestrial Ecological Units on the Santa Fe National Forest and is part of the Southwestern Region Core Data Project; the Natural Resource Conservation Service's Soil Survey Geographic (SSURGO) database for Rio Arriba (NM 650) and Parts of Rio Arriba and Sandoval Counties (NM 656); and a newly-digitized map (NRCS Soil Survey Geographic Database NM 686) representing the area of San Ildefonso Indian Reservation. Because it conformed better to topographic and vegetative patterns (to which elk are more likely to respond), the USFS Terrestrial Ecological Units layer was considered the primary input layer and only supplemented with additional soil data where needed. The data are accurate to a scale of 1:20,000 for areas within San Ildefonso Reservation and 1:24,000 in all other regions.

Digital soil survey quadrangles specific to the eastern Jemez Mountains (NM650 and NM656) were downloaded from the NRCS Soil Survey Geographic (SSURGO) database website and merged to create a soil coverage of all available digital NRCS soil data for the Pajarito Plateau. Additional hard copy maps from 1973 containing NRCS soil survey spatial information for the area of San Ildefonso Indian Reservation (SSURGO NM686) were scanned into electronic TIF format using a large flat-bed scanner. Maps were individually georeferenced in ArcGIS. State Plane NAD27 coordinates were taken from each corner of each map of the hard copy maps. The georeferencing tool yielded RMS errors ranging from 0.847 to 14.37. Each soil map was screen digitized in polygon format. Soil code attributes were assigned as each polygon was digitized. Individual soil maps were then merged into one large coverage and island and sliver polygons were removed using a fuzzy tolerance of 5 feet. Quality assessment on the final NRCS coverage was done by LANL personnel.

Digital versions of USFS Terrestrial Ecological Units and NRCS Soil Surveys were then manually aligned using ArcView 3.2a and printed out in sections using a plotter. Each section depicted a portion of the border along which the NRCS and USFS soil coverages adjoined. These hard copy maps were reviewed with the assistance of the Supervisory Soil Scientist for the Albuquerque Regional Office of the U.S. Forest Service. Soil polygons were compared across boundaries and the maps were annotated so as to align polygons of similar soil type. Polygons that spanned sources were assigned a map unit symbol (musym) identifier representative of the soil type(s) being joined. In most cases, U.S. Forest Service Terrestrial Ecological Units took priority when a clear decision could not be made as to which soil type was more representative of the region in question unless the representative NRCS polygon contained a larger geographic area.

Map unit symbols (musym) for both the USFS and NRCS soil coverages are numerical identifiers unique to a given soil type. When duplicate numbers existed between the two sources of soil information, it was necessary to reclassify polygons from one source so that all soil types would have a unique numerical identifier when the NRCS and USFS soil coverages were merged. Closer inspection revealed 5 duplicate numbers between the NRCS and USFS coverages. In these cases, the NRCS numbers were given a new number and a comment was made in the attribute definitions of the metadata that states what the original NRCS number used to be. This was critical in order to preserve the original source information and naming protocols used by NRCS. On occasion, some polygons along the boundaries of the two coverages were removed whereas others were added in order to insure the two sources would eventually align in a seamless coverage. Layers were edge matched using the snapping option in ArcMap, snapping with vertex, end, and edge. Once edge matching was complete polygon continuity between the layers was established. Common attributes were defined for each layer and coverages were merged together. The merge was done using the geoprocessing wizard in ArcMap 8.3. Boundary lines were removed and the final coverage was assessed to make sure all polygons had a unique identification number.

A lookup table specifying soil properties for each soil type on the soils map was created. Each record on the file includes a list of parameters for a single soil type linked by a type index number referenced by various SAVANNA submodels. Parameters include depth of bottom layer (cm), volumetric field capacity at -1/3 bar (%), volumetric wilting point at -15 bar (%), volumetric pore space (%), minimum run-off curve number (%), maximum run-off curve number (%), and a bare soil evaporation parameter. Porosity was calculated as 1 - (bulk density/2.65 g/cc) where 2.65 g/cc is the accepted value for particle density of an unknown soil type.

Sources for data input included NRCS physical properties tables (available through the NRCS SSURGO web site), USFS personnel, a Soil Survey of Los Alamos County (Nyhan et al. 1978), and "Surface Water Management" documentation from Los Alamos National Laboratory (Lane 1984). This lookup table was then joined to the shapefile attribute table using the 'musym' in order to finalize the ArcView map for creation of appropriate metadata. A final map (Figure 3.5) and associated metadata in Federal Geographic Data Committee (1998) standard format are available through the Ecology Group at LANL (ENV-ECO).

<u>Vegetation.</u> Vegetation processes in SAVANNA are initialized through the application of a vegetation map. Following the May 2000 Cerro Grande Fire the Ecology Group at LANL, in conjunction with the Earth Data Analysis Center (EDAC) at the University of New Mexico, developed a land cover map using Landsat Enhanced Thematic Mapper Plus (EMT+) satellite imagery acquired on June 4, 2001. The extent of the area covered was approximately 1,821 km^2 and included Los Alamos County, Los Alamos National Laboratory, Bandelier National Monument, the Valles Caldera National Preserve, and parts of Santa Fe National Forest. Five hundred eighty-three training sites were acquired from field sampling, screen digitizing, and previous projects (Table 3.3)

and 242 sites were used to independently assess the accuracy of the resulting maps (McKown et al. 2003). The most accurate version – a quarter-hectare smoothed map at the association level with 30 classes (Figure 3.6) – was selected for application. The error matrix for the independent accuracy assessment is presented in Table 3.4. Area calculations by land cover type are presented in Table 3.5.

Within each grid cell, vegetation is divided into herbaceous, shrub, and tree facets, which are referenced through associated parameter files (*fac.dat files). The *fac.dat files, in turn, are used to establish the relative composition of grasses, forbs, shrubs, and trees associated with each land cover type. Plants are generically defined by life-form (e.g., deciduous shrubs, coniferous trees) with the exception of a few select, but critical, species such as aspen *(Populus tremuloides)*. Aboveground biomass (g/m^2) and percent cover for each plant type are defined within the *fac.dat files and then indexed with associated population parameter files that provide the general growth characteristics of each plant type. For purposes of this dissertation, modifications were made to the *fac.dat files in order to be representative of the newly incorporated land cover map. Because existing plant types in the latest version of SAVANNA were used (i.e., those types used to define vegetation in Yellowstone National Park), minimal changes were made to associated population parameter files.

Calibration was accomplished by incorporating field data collected from the "Forest Fuels Inventory Project" [Balice et al. (unpubl. data) 2001, 2002, and 2003] at Los Alamos National Laboratory and the "Valles Caldera National Preserve Short Term Rangeland Monitoring Project" at the United States Department of Agriculture, Agricultural Research Service (USDA-ARS), Jornada Experimental Range[1] [2002 and 2003 (unpubl. data)]. Only post-fire data were used for calibration in order to more accurately reflect the post-fire land cover map. Plots on the VCNP were run at 100-m resolution whereas LANL plots were calibrated at 50-m resolution due to constraints inherent in the spatial display of SAVANNA components using a supplied graphical user interface (SMS). Exclosure plot data from Bandelier National Monument (Rupp 2000, Rupp et al. 2001 a,b) were used empirically to corroborate findings when needed. A total of 159 field plots representative of 16 land cover types were analyzed (Figures 3.7 and 3.8).

Mean aboveground biomass for grasses/forbs (g/m^2), shrub diameter (cm), and tree height (m) were calculated for each land cover type and results were used to modify *fac.dat files. Field plots on the VCNP were scaled up from 0.25 m^2 by multiplying by four prior to averaging results. Because SAVANNA attempts to distinguish between understory vegetation (i.e., vegetation in the rooting zone of trees) and vegetation in the interstitial spaces between canopies for purposes of modeling light/water interception, best estimates were made based on personal experience. "Usually the model predicts a very low herb biomass [in the rooting zone], even if you set the initial value to what you think it is" (Coughenour 2003, pers. comm.), so exact values were not critical. Additional missing data for rare habitat types were estimated based on land cover descriptions found in the LANL Land Cover Report (McKown et al. 2003).

[1] Data sets were provided by the USDA Agricultural Research Service, Jornada Experimental Range. Funding for these data sets was provided by USDA.

Digital Elevation Model. Sixteen 7.5-minute digital elevation model (DEM) quadrangles in Spatial Data Transfer Standard (SDTS) format were downloaded from the United States Geological Survey (USGS) Earth Resources Observation Systems (EROS) Data Center website (http://edc.usgs.gov/geodata/). All 1:24,000 quadrangles are projected in Universal Transverse Mercator (UTM) coordinates, North American Datum (NAD 1927) at a resolution of 10 m. Any errors inherent in the acquired data were assumed minimal and not assessed in detail.

Once all quadrangles were downloaded, data were converted using the SDTS2ARC conversion utility available through the above website. Resulting ASCII files were imported into ERDAS Imagine (version 8.6) and then processed into a composite image using the "Mosaic" tool. Quads were then converted into meters using the "Modeler" tool as necessary and re-constructed using the "Mosaic" tool. Header information was validated and corrected as needed and slight adjustments in positioning were made to individual quadrangles to account for innate error in the data sets and to ensure proper alignment. The image was once again run through the Mosaic tool to generate a final comprehensive image (Figure 3.9).

The final DEM was then resampled to various resolutions (50 m, 100 m, 150 m, 250 m, and 500 m) using cubic convolution resampling methods available through the Spatial Analyst extension in ArcView. Because interpolation methods compute an average (Huber 2004, pers. comm.), slope and aspect maps were generated from the resampled DEMs instead of resampling the slope and aspect maps generated from the original 10 m DEM. Resultant slope and aspect maps, therefore, were also at 50 m, 100 m, 150 m, 250 m, and 500 m resolutions. Final maps used in model runs for the purposes of this dissertation were at a resolution of 150 m.

Model Validation

The plant growth (i.e., herbaceous production) model was validated by comparing model outputs to independent test sets selected from field plots sampled in 2004 by LANL and the USDA-ARS Jornada Experimental Range. Because data were limited and emphasis was placed on model calibration instead of verification in an attempt to increase the general applicability of the model across a range of topographic and weather conditions, only a single year of data was used to verify the model. In addition, safety and security concerns at LANL resulted in a “stop work” order that lasted through much of the 2004 summer season, limiting the field data collected within areas burned by the Cerro Grande Fire. Therefore, though independent field data used to validate the model reflect the grasslands of the VCNP in greater abundance than other parts of the eastern Jemez region, model corroboration should indicate proper functioning of the overall model.

Simulations were run on single cells at a 150 m resolution for all plots as this was the grain size chosen for final model runs which would eventually incorporate elk dynamics. Random weather was used during the evaluation process and was considered an additional test of the model’s reliability. Model runs require an “initialization period” before results stabilize. Therefore, the model was run beginning in January 2003, but outputs were recorded only for the year/month corresponding to selected test sets.

Ungulates were not included in the simulated ecosystem and any confounding effects from animal foraging were considered equally inherent in both the calibrated and test data systems. Comparisons were made for major land cover types across different slope, aspect, and elevational ranges, but did not necessarily represent the entire study area or all land cover types. Simulated and actual means for aboveground biomass (g/m^2) were compared using PROC GLM (SAS ver. 9.0). Levene's test (Levene 1960) tested for homogeneity of variances and means were adjusted using Welch's (Welch 1951) ANOVA when necessary. Results indicated no differences in mean aboveground biomass between simulated results and actual field data ($F_{1, 96} = 0.59$, $P = 0.4461$) for any land cover type (Table 3.6). In the Valles Caldera grasslands, simulated mean biomass (157.48 g/m^2) was very similar ($F_{1, 41.82} = 0$, $P = 0.9807$) to actual biomass (157.18 g/m^2). Because of insufficient field data and questionable methods for making accurate comparisons, shrub and tree cover will need to be validated at a future point in time.

Validation of weather data presented a challenge. Because weather is the model's most important input, all available weather data at the time was used for calibration leaving no independent test set for model verification. Therefore, a control run was used to analyze mean precipitation (mm) values over the 13 years of actual weather data to ensure model raw data were being processed correctly. PROC GLM (SAS ver. 9.0) was used to compare mean monthly and yearly precipitation values for 3 weather stations falling within the extent of the study area (Figure 3.10). Results indicate model inputs were processed correctly on both a monthly and yearly basis (Table 3.7) with no significant differences between actual and simulated mean precipitation values detected. Due to drought conditions over the past several years, snow data were not available in sufficient quantity to verify model outputs. However, spatial patterns of precipitation were realistic; precipitation and snow depth values increased with elevation (Figure 3.11) indicating the spatial interpolation algorithm was working properly.

Future Research Needs

During the calibration and validation process, several concerns arose over potential model application and evaluation. Of critical concern was the initialization of post-fire successional dynamics in areas burned by the Cerro Grande Fire. SAVANNA is capable of reading in fire severity maps during the course of a model run. However, this requires that the initial land cover map reflect pre-fire conditions. Though LANL has access to a post-fire severity map that would work in SAVANNA's modeling environment, the most recent and accurate version of the land cover map (McKown et al. 2003) was constructed using imagery acquired after the fire. Discussions with the model developer concluded we should start the run right after the fire, and initialize vegetation on lookup tables as it was after the fire (Coughenour 2004, pers. comm.), but additional work may be needed to calibrate the model so that it properly mimics post-fire succession. Ongoing field studies will continue to provide data in the burn area to update the model.

A second concern revolves around the production of snow in the study area. Though patterns of snow deposition are reasonable, actual amounts appear to be lower than observed. Though SAVANNA has been used in places like Rocky Mountain National Park and Yellowstone, the topography of the eastern Jemez Mountains is more complex than other places in which the model has been previously applied. This may pose significant challenges in the accurate estimation of solar radiation which, in turn, may affect snow deposition and retention. Additional parameters exist for wind-induced snow redistribution and stochastic snow crusting, which may also need to be further manipulated to produce realistic patterns. Drought conditions have prevented reliable testing of the snow submodel, but increased precipitation and snowfall this past winter should provide additional data with which to better calibrate this portion of the model.

Finally, because of the computational resources required to run a model of this magnitude, no work has yet been done to address issues of scale. Because disturbance events such as the Cerro Grande Fire both create and respond to landscape pattern, the spatial distribution of resources in heterogeneous landscapes can have important effects on the growth, reproduction, and movement of individuals. Though SAVANNA was calibrated at 150 m with the intent of looking at elk movement and distribution following the Cerro Grande Fire, the process of succession and how plants respond to the scale of choice within the modeling context must also be considered. Conclusions about how species respond to pattern at one scale are difficult to translate to species at another scale (Turner et al. 2001), but an initial attempt was made to strike a balance between elk responses to the environment and plant responses to post-fire succession. Considerable work remains to test these assumptions and draw conclusions about appropriate scales at which SAVANNA should be calibrated to effectively address both concerns.

Discussion

Research opportunities following extraordinary, large-scale fire events must be exploited. Because of their infrequent nature, few studies exist detailing the effects of large fires on elk movements and distribution. At present, no studies have related the effects of post-fire landscape succession on ungulate movements and distribution using dynamic modeling techniques. Though studies have evaluated the effects of fire scale and pattern on elk (Turner et al. 1994), the models used did not address ungulate reproduction, ungulate/succession dynamics, or the effects of summer precipitation on pre-winter forage availability – all of which are important in projecting the long-term dynamics of an ecosystem. Consequently, models linking the responses of herbivores to environmental heterogeneity and successional dynamics following large-scale fires are needed (Turner et al. 1994).

A primary consideration driving the conceptualization and implementation of scientific studies should be their potential value to resource managers for purposes of mitigation. As management agencies move toward the concept of adaptive management, the demand for dynamic modeling is increasing. Active adaptive management has been defined as the "systematic process of modeling, experimentation, and monitoring to compare the outcomes of alternative management actions" (Farr 2000: 2). Adaptive management aims to integrate interdisciplinary experience and scientific information into dynamic models that attempt to make predictions about the impact of alternative policies (Holling 1978, Walters 1986, Van Winkle et al. 1997). The development, calibration, and application of the SAVANNA model in the Jemez Mountains of northern New Mexico will provide such a dynamic model to be used for adaptive management applications following the Cerro Grande Fire that burned the region in May 2000.

A participating agreement was signed by the Santa Fe National Forest (USFS), U.S. Department of Energy/University of California (LANL), and the National Park Service (BNM) to collaborate in data collection efforts to address concerns regarding potential impacts of the Cerro Grande Fire on the regional elk herd. This collaborative agreement benefits agencies by providing data for mitigation purposes on the free-ranging elk herd that moves on and across agency boundaries. Data collected as part of that agreement were incorporated into the SAVANNA Ecosystem Model as part of this dissertation for further application in the Jemez Mountains.

Model predictions of herbaceous biomass, the primary forage items for elk, were consistent with available data when present and should be within levels acceptable for management applications in the Jemez Mountains (Table 3.6). Control runs for weather data from 1990 through 2002 indicated proper functioning of the model in terms of precipitation output (Tables 3.7). Additional calibration for snow components is required, but snow estimates are likely working within the bounds of current model parameters and may be reasonable across the study area in its entirety given spatial interpolations appeared to be functioning reasonably (Figure 3.11).

Shrub and tree components require additional testing to assure model outputs are within reasonable levels given the scarcity of data for model validation. Woody plants can be initialized through the application of lookup tables or woody cover/density and height maps. This option is controlled by the flags inside the parameter file that also controls maps. Currently the model is calibrated using just a land cover map, which initializes woody plants by using lookup tables that give abundance and size of trees and shrubs by life form. However, another option exists in newer versions of SAVANNA in which a second vegetation map is used to specify vegetation types by the successional stage of the tree layer. This is useful where the vegetation has been affected by disturbances which cause the tree layer to differ from the climax vegetation type on the primary vegetation map. Application of two separate maps may help to address disparities caused by the Cerro Grande Fire.

The ability to detect spatial pattern depends on the scale at which we make measurements, which, in turn, will affect an organism's ability to detect and respond to environmental heterogeneity (Wiens 1989). Because species differ in the scales at which they use resources or perceive the environment, studies of interactions among species may be especially sensitive to scale (Wiens 1989). The scale at which the SAVANNA Ecosystem Model is ultimately applied to evaluate post-fire successional processes and its affect on elk movement and distribution must balance two equally important concepts: 1) The animal's ability to perceive and use the environment at a scale applicable to the process in question (i.e., movement and distribution), and 2) the appropriate scale at which plants respond to post-fire successional processes. Understanding the responses of organisms to spatial patterns at multiple scales is in its infancy but remains a high priority for ecology (Levin 1992, Turner et al. 2001).

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Table 3.1. Criteria driving the selection of a post-fire successional model for application in the Jemez Mountains and relative performance of potential models selected. See text for discussion of model selection based on these criteria.

Criteria	FIRE-BGC	LANDSUM /CRBSUM	FIRESUM	FVS	LANDIS	SAVANNA
Raw code available?	Yes	Yes	Yes	No	No	Yes
Permission to change code?	Yes	Yes	Unknown	No	No	Yes
Complexity (low, med, high)	High	High	Med	High	High	Med
Temporal resolution ($1^{\underline{0}}$ time step)	Yearly	Yearly	Yearly	Decadal	Decadal	Weekly
Spatial resolution	Tree Stand	Tree Stand	400 m^2	Tree Stand	User-defined	User-defined
Integrated With GIS?	Yes	Yes	No	Yes	Yes	Yes
Understory vegetation modeled?	Not sufficiently	Not sufficiently	No	No	No	Yes
Snow model present?	Yes	Indirect	Indirect	No	No	Yes
Model well-documented?	Yes	Yes	Yes	Yes	Yes	Yes
Data already collected through field studies?	No	No	Yes	Yes	Unknown	Yes

Table 3.2. Descriptions of weather stations used in calibrating the SAVANNA Ecosystem Model for the eastern Jemez Mountains of northcentral New Mexico. Elevation is in meters and coordinates are in Universal Transverse Mercator (UTM), North American Datum (NAD) 1927, Zone 13 N.

STATION	ELEVATION	NORTHING	EASTING	AGENCY [1/]
QUEMAZON	2896	377078	4086683	NRCS
BATEMAN	2835	381811	4042234	NRCS
CHAMITA	2561	353084	4090394	NRCS
HOPEWELL	3049	386581	4064360	NRSC
SENORITA DIVIDE	2622	335053	3985296	NRCS
LOS ALAMOS	2683	376278	3972692	LANL
TA-49	2148	382660	3963819	LANL
TA-6 [2/]	2263	380907	3969178	LANL

[1/] NRCS = Natural Resources Conservation Service; LANL = Los Alamos National Laboratory
[2/] TA-6 serves as the main weather station for Los Alamos National Laboratory and Los Alamos County.

Table 3.3. Accuracy totals for the quarter-hectare, smoothed version of the LANL land cover map (association level). Overall classification accuracy was 88.68% (adapted from McKown et al. 2003). Plant species acronyms are given in Appendix B.

Land Cover	Training Sites	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Valles Caldera Grassland	36	37	33	91.67%	89.19%
Montane Grassland	25	23	23	92.00%	100.00%
ABCO-PSME Woodland	11	9	9	81.82%	100.00%
ABCO-PSME Forest	30	31	25	83.33%	80.65%
Evergreen-POTR Forest	15	12	10	66.67%	83.33%
Sparse-Bare Soil	12	12	10	83.33%	83.33%
Open Water	22	17	17	77.27%	100.00%
Riparian-Wetland	23	17	17	73.91%	100.00%
Sparse-Bare Rock	36	31	31	86.11%	100.00%
PIED-JUMO/BOGR Woodland	70	78	69	98.57%	88.46%
PIPO/BOGR-SCSC Woodland	14	18	14	100.00%	77.78%
QUGA Shrubland	19	19	17	89.47%	89.47%
PIED-JUMO/Sparse-Soil Woodland	13	11	11	84.62%	100.00%
Submontane Grassland	38	35	34	89.47%	97.14%
PIED-JUMO/Sparse-Rock Woodland	5	7	4	80.00%	57.14%
Other Shrubland	46	43	43	93.48%	100.00%
PIED-JUMO/ARTR Woodland	17	17	16	94.12%	94.12%
PIED-JUMO/BOER Wooded Grassland	12	12	10	83.33%	83.33%
BRCA-AGTR Grassland	6	6	4	66.67%	66.67%
PIPO Forest	29	32	28	96.55%	87.50%
PIPO/QUGA Woodland	22	19	16	72.73%	84.21%
ABLA-PIEN Forest	12	12	10	83.33%	83.33%
POTR Shrubland	4	4	4	100.00%	100.00%
POTR Forest	11	11	10	90.91%	90.91%
PIPO/Other Grass Woodland	8	10	8	100.00%	80.00%
JUMO Wooded Grassland	29	28	27	93.10%	96.43%
RONE Shrubland	3	8	2	66.67%	25.00%
PIED Forest	15	15	15	100.00%	100.00%
Urban, Vegetated	0	3	0	---	---
Urban, Paved	0	1	0	---	---
Totals	583	578	517		

	1	2	3	4	5	6	7	9	10	11	12	13	14	15	16	17	18	19	20	21	23	24	25	26	27	28	29	30	31	32	Reference Totals	Producer's Accuracy
1	**3**															2															5	60%
2	1	**3**												1																	5	60%
3																									1						1	0%
4				**17**	1						2											3									23	74%
5				3	**5**																1	2									11	45%
6						**9**													2												11	82%
7							**5**																								5	100%
9				1				**4**																							5	80%
10									**7**																						7	100%
11										**11**	1	1	1			1	3									1		1			20	55%
12									1	3	**1**			1							3							1			10	10%
13	3				1							**5**		2						1			1								13	38%
14										2			**1**			1										2					6	17%
15										2				**13**		2		1													18	72%
16									3	2																					5	0%
17										2		1				**7**					1					2					13	54%
18										3							**1**														4	25%
19										1				2																	3	0%
20						5													**4**				2								11	36%
21				4																**10**	1										15	67%
23												2								3	**2**				1			1			9	22%
24				3																		**1**									4	25%
25																							**1**	1							2	50%
26	1				3																			**6**	1						11	55%
27	1	1																													2	0%
28																1															1	0%
29	1																														1	0%
30								1		2																		**2**			5	40%
31																													**8**		8	100%
32																													1	**7**	8	88%
Classified Totals	10	4	0	28	10	14	5	5	11	28	4	9	2	19	0	14	4	1	6	14	8	6	4	7	3	5	0	5	9	7	**242**	
User's Accuracy	30%	75%	-----	61%	50%	64%	100%	80%	64%	39%	25%	56%	50%	68%	-----	50%	25%	0%	67%	71%	25%	17%	25%	86%	0%	0%	-----	40%	89%	100%	**Overall Accuracy: 55.0%**	

Table 3.4. Error matrix for the quarter-hectare, smoothed version of the LANL land cover map at the association level. Overall accuracy was 55% based on an independent sample of 242 sites.

Table 3.5. Area calculations for the quarter-hectare, smoothed version of the LANL land cover map (adapted from McKown et al. 2003). Class numbers 8 and 22 were null and, therefore, are not represented in this table. Land cover types are listed in descending order based on total area. Rank is based on total area. Plant species acronyms are given in Appendix B.

Class	Land Cover	Km^2	%	Rank
4	ABCO-PSME Forest	358.04	19.66	1
11	PIED-JUMO/BOGR Woodland	280.80	15.42	2
21	PIPO Forest	144.75	7.95	3
1	Valles Caldera Grassland	114.10	6.27	4
15	Submontane Grassland	84.86	4.66	5
23	PIPO/QUGA Woodland	84.72	4.65	6
28	JUMO Wooded Grassland	84.33	4.63	7
12	PIPO/BOGR-SCSC Woodland	76.07	4.18	8
17	Other Shrubland	70.92	3.89	9
24	ABLA-PIEN Forest	65.22	3.58	10
10	Sparse-Bare Rock	64.34	3.53	11
5	Evergreen-POTR Forest	58.13	3.19	12
13	QUGA Shrubland	45.63	2.51	13
6	Sparse-Bare Soil	44.67	2.45	14
27	PIPO/Other Grass Woodland	40.48	2.22	15
30	PIED Forest	37.85	2.08	16
3	ABCO-PSME Woodland	27.86	1.53	17
19	PIED-JUMO/BOER Wooded Grassland	23.43	1.29	18
20	BRCA-AGTR Grassland	20.30	1.11	19
2	Montane Grassland	18.17	1.00	20
26	POTR Forest	14.67	0.81	21
18	PIED-JUMO/ARTR Woodland	13.55	0.74	22
31	Urban, Vegetated	12.48	0.69	23
32	Urban, Paved	9.77	0.54	24
9	Riparian-Wetland	9.44	0.52	25
7	Open Water	4.46	0.24	26
25	POTR Shrubland	4.46	0.24	27
14	PIED-JUMO/Sparse-Soil Woodland	3.83	0.21	28
16	PIED-JUMO/Sparse-Rock Woodland	2.68	0.15	29
29	RONE Shrubland	1.13	0.06	30
	Totals	1821.14	100.00	

Table 3.6. Mean aboveground biomass values (g/m^2) comparing actual field plots to simulated results for a variety of land cover types. Means with the same letter are not statistically different within a given land cover type ($\alpha = 0.05$).

Land Cover	n	Actual	Simulated	F-Value	P-Value
Valles Caldera Grasslands [1/]	33	157.18 [a] (±8.7292)	157.48 [a] (±8.7292)	$F_{1,41.82} = 0.00$	0.9807
PIPO Forest [1/]	8	52.65 [a] (±14.3522)	5.90 [a] (±14.3522)	$F_{1,7} = 5.31$	0.0547
PIPO/Other Grass Woodland	2	92.62 [a] (±30.6744)	51.70 [a] (±30.6744)	$F_{1,2} = 0.89$	0.4451
ABCO-PSME Forest [2/]	1	77.92	2.90	----	----
ABLA-PIEN Forest [2/]	1	66.60	1.00	----	----
BRCA-AGTR Grassland [2/]	1	9.18	86.30	----	----
POTR Forest [2/]	1	88.92	24.90	----	----
RONE Shrubland [2/]	1	73.44	81.80	----	----
Sparse-Bare Ground [2/]	1	0.00	11.20	----	----
Overall	49	124.68 [a] (±10.4487)	113.38 [a] (±10.4487)	$F_{1,96} = 0.59$	0.4461

[1/] Heterongenous variances required adjustment using Welch's ANOVA.
[2/] Lack of replication prevented the use of statistical procedures to compare actual and simulated results.

Table 3.7. Monthly and yearly mean precipitation (mm) and associated standard errors by station for actual versus simulated results based on a control run for the years of 1990 through 2002.

Month	Los Alamos Actual (n = 13)	Los Alamos Simulated (n = 13)	TA-6 Actual (n = 13) [1/]	TA-6 Simulated (n = 13)	TA-49 Actual (n = 13)	TA-49 Simulated (n = 13)
January	26.43 [a] (± 6.4403)	22.43 [a] (± 6.4403)	26.58 [a] (± 6.9414)	25.80 [a] (± 6.9414)	24.83 [a] (± 6.5866)	23.57 [a] (± 6.5866)
February	18.05 [a] (± 4.9155)	13.7846 [a] (± 4.9155)	18.03 [a] (± 4.9810)	17.82 [a] (± 4.9810)	17.40 [a] (± 5.2668)	16.15 [a] (± 5.2668)
March	26.36 [a] (± 4.0193)	20.20 [a] (± 4.0193)	26.50 [a] (± 4.1070)	26.02 [a] (± 4.1070)	23.16 [a] (± 3.4406)	21.44 [a] (± 3.4406)
April	24.09 [a] (± 5.6939)	21.17 [a] (± 5.6939)	23.70 [a] (± 5.7915)	23.42 [a] (± 5.7915)	22.65 [a] (± 5.3429)	21.75 [a] (± 5.3429)
May	34.10 [a] (± 7.9048)	33.14 [a] (± 7.9048)	33.59 [a] (± 8.0352)	33.44 [a] (± 8.0352)	31.84 [a] (± 7.4615)	31.60 [a] (± 7.4615)
June	38.53 [a] (± 5.9940)	38.11 [a] (± 5.9940)	37.26 [a] (± 6.4565)	35.84 [a] (± 6.2032)	31.58 [a] (± 6.5141)	31.70 [a] (± 6.5141)
July	71.57 [a] (± 9.0062)	71.00 [a] (± 9.0062)	65.01 [a] (± 7.5465)	65.08 [a] (± 7.5465)	62.76 [a] (± 9.3271)	62.81 [a] (± 9.3271)
August	87.02 [a] (± 12.3205)	85.75 [a] (± 12.3205)	87.02 [a] (± 12.2321)	86.64 [a] (± 12.2321)	79.75 [a] (± 11.3307)	79.64 [a] (± 11.3307)
September	48.11 [a] (± 7.6899)	47.21 [a] (± 7.6899)	48.11 [a] (± 7.5830)	47.94 [a] (± 7.5830)	45.57 [a] (± 7.1095)	45.39 [a] (± 7.1095)
October	38.87 [a] (± 11.1028)	37.31 [a] (± 11.1028)	38.87 [a] (± 11.0765)	38.65 [a] (± 11.0765)	36.68 [a] (± 10.8976)	36.31 [a] (± 10.8976)
November	31.12 [a] (± 5.4967)	26.38 [a] (± 5.4967)	29.85 [a] (± 5.2432)	29.50 [a] (± 5.2432)	29.59 [a] (± 5.6454)	28.21 [a] (± 5.6454)
December	21.37 [a] (± 5.2622)	18.23 [a] (± 5.2622)	21.37 [a] (± 5.3822)	21.08 [a] (± 5.3822)	20.38 [a] (± 5.4442)	19.38 [a] (± 5.4442)
Yearly Mean	465.62 [a] (± 27.5292)	434.71 [a] (± 26.7112)	450.98 [a] (± 26.6538)	451.22 [a] (± 26.3144)	426.15 [a] (± 27.8470)	417.93 [a] (± 27.5049)

[1/] Mean values for the months of January and June at TA-6 are based on 12 observations.
[a] Actual and simulated average monthly rainfall within a station followed by the same lower case letter are not significantly different.

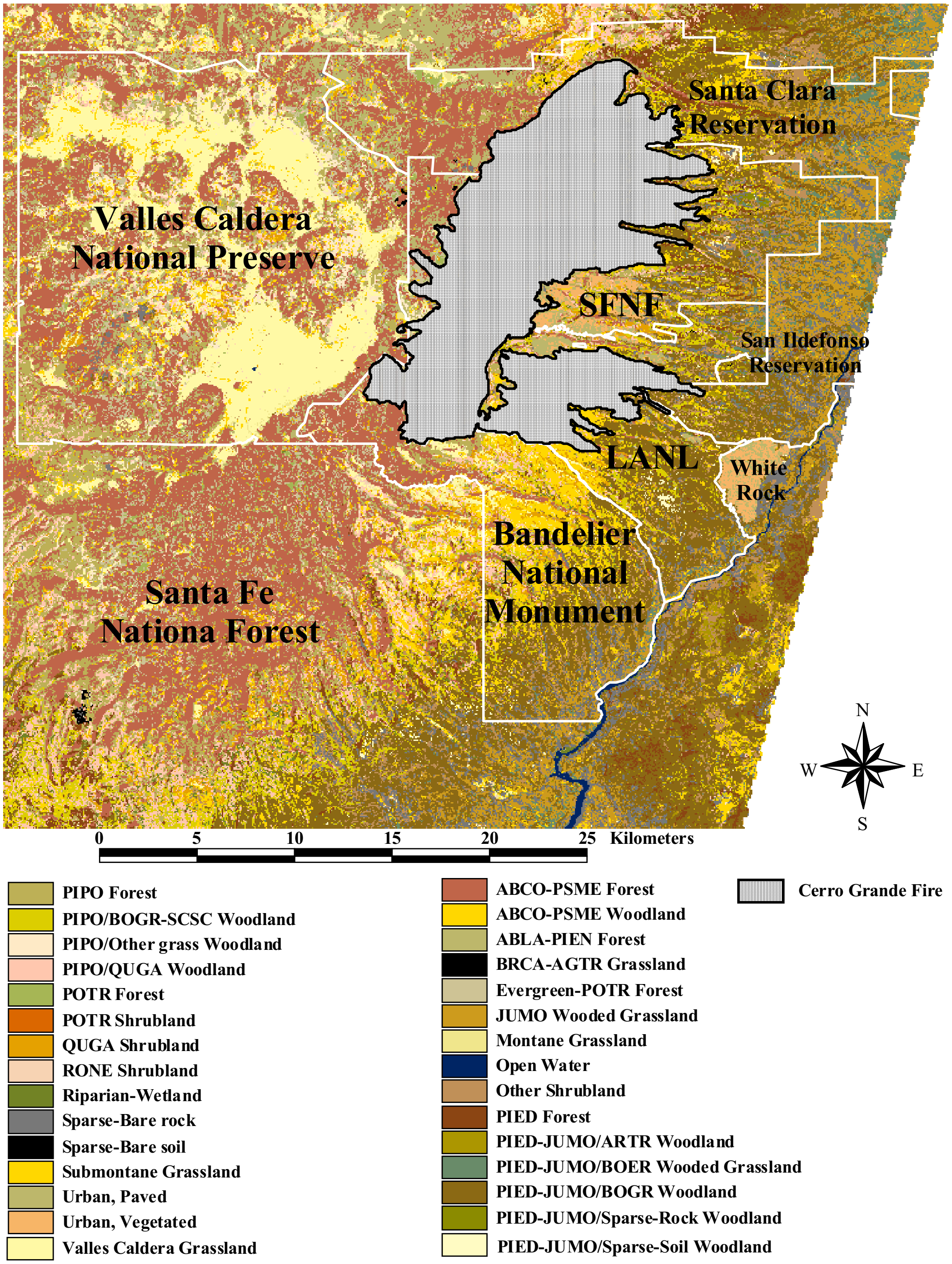
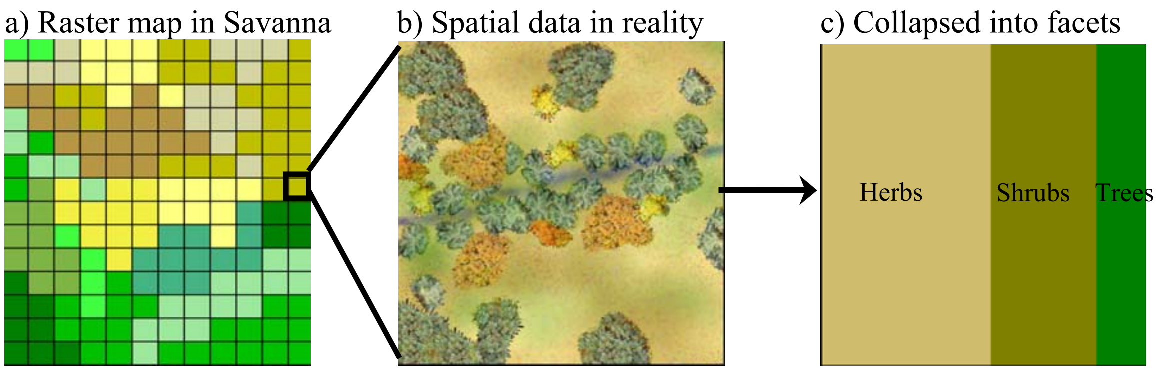


Figure 3.1. The Cerro Grande Fire burned 19,020 ha in early May 2000.

Figure 3.2. SAVANNA's representation of vegetation within a cell. A rasterized map in SAVANNA (a) represents spatial data in reality (b), which is then collapsed into three "facets" including herbs, shrubs, and trees (c) (adapted from Boone 2000).



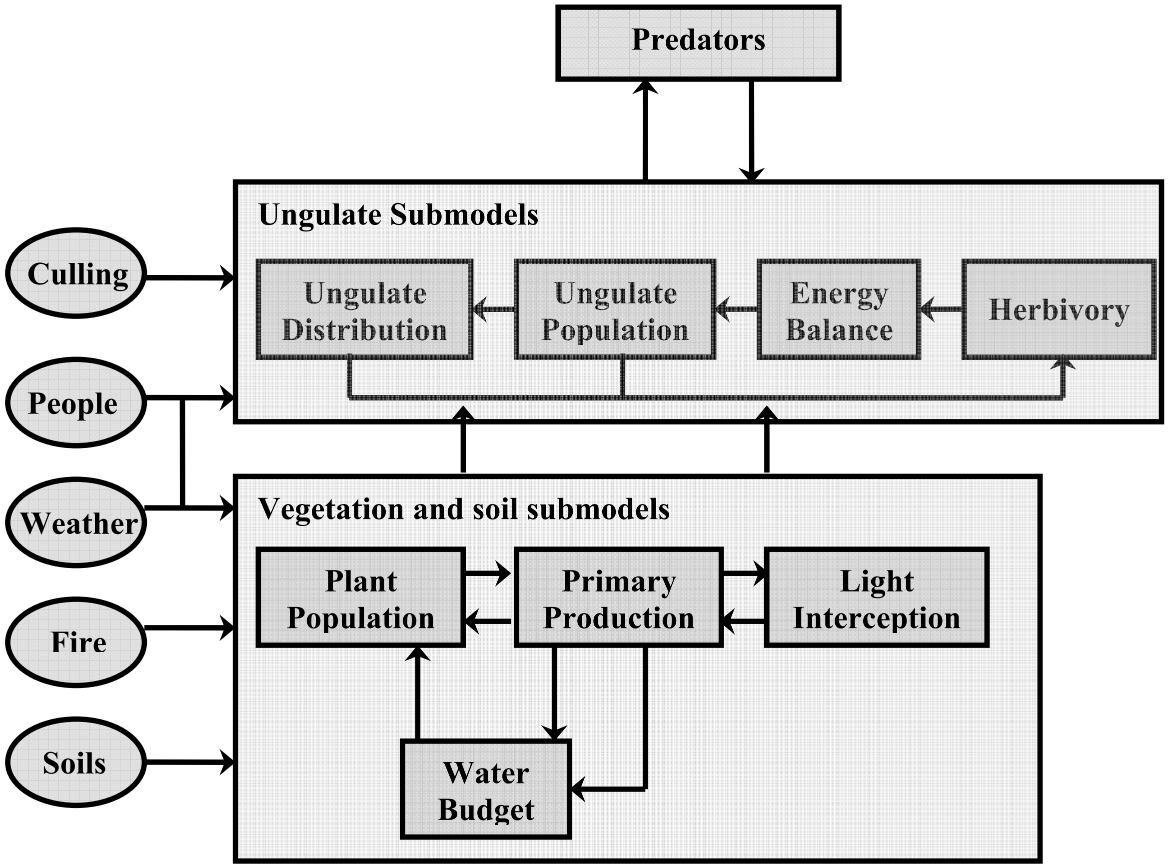


Figure 3.3. Submodels found in the SAVANNA Ecosystem Model. Submodels can be run independently or in conjunction with one another (adapted from Boone 2000).

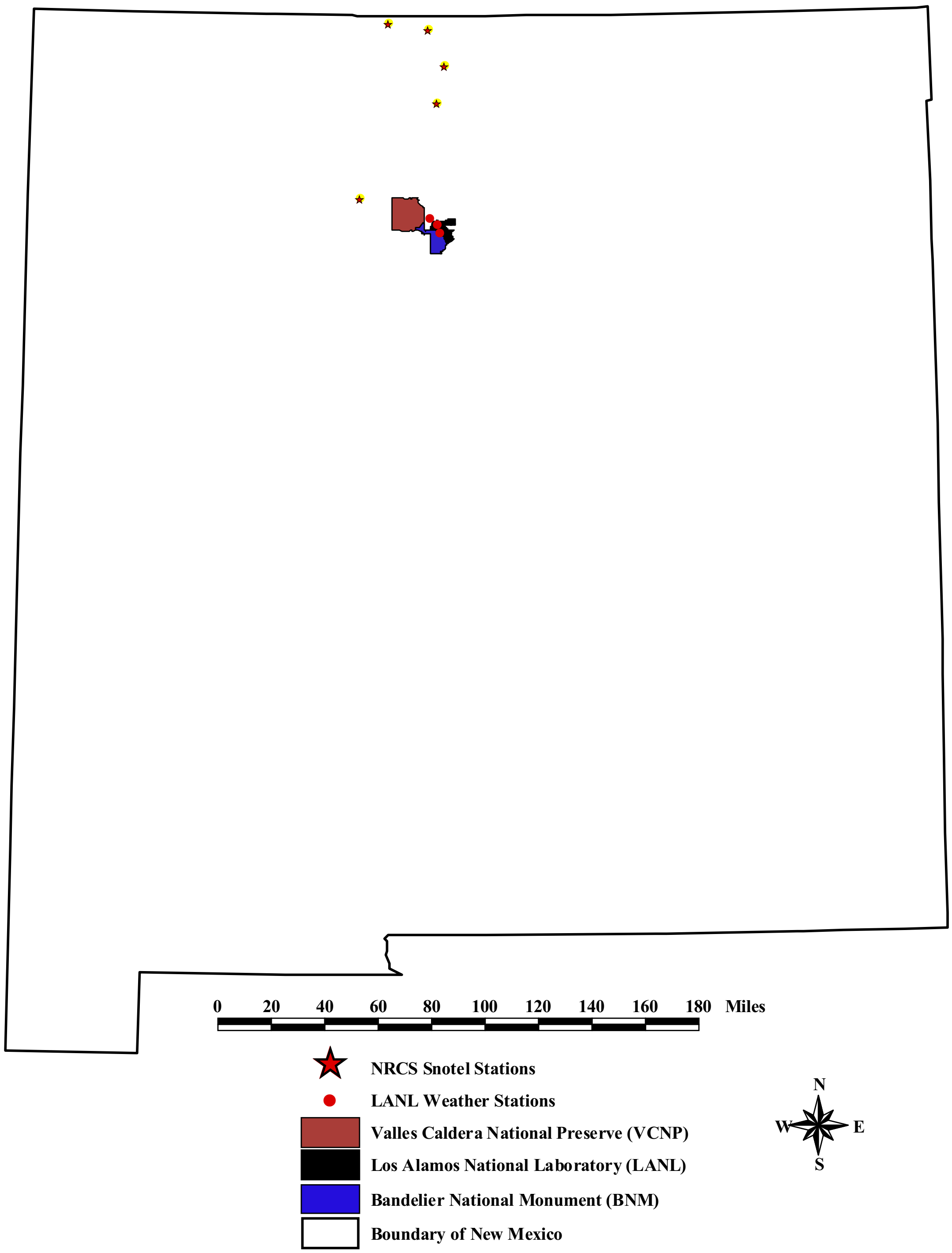


Figure 3.4. Locations of weather stations used to calibrate the SAVANNA Ecosystem Model in the Jemez Mountains of north central New Mexico.

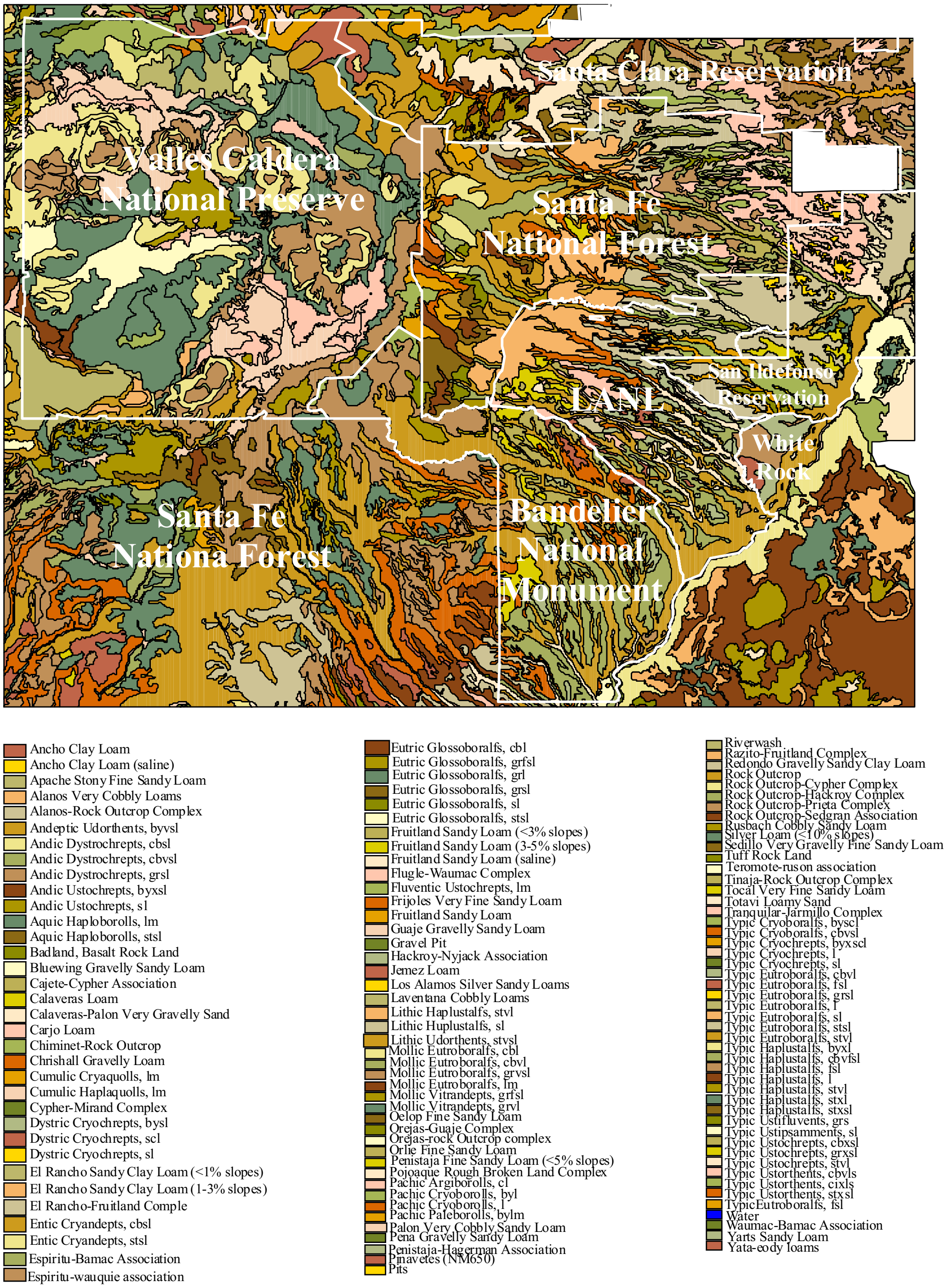


Figure 3.5. Soils of the eastern Jemez Mountains created from several sources including Santa Fe National Forest Terrestrial Ecosystem Survey, NRCS-SSURGO databases for Rio Arriba (NM 650) and Parts of Rio Arriba and Sandoval Counties (NM 656), and a newly-digitized map (NRCS Soil Survey Geographic Database NM 686) representing the area of San Ildefonso Indian Reservation. The map is 1:24000 except for the area of San Ildefonso, which is at a scale of 1:20000.

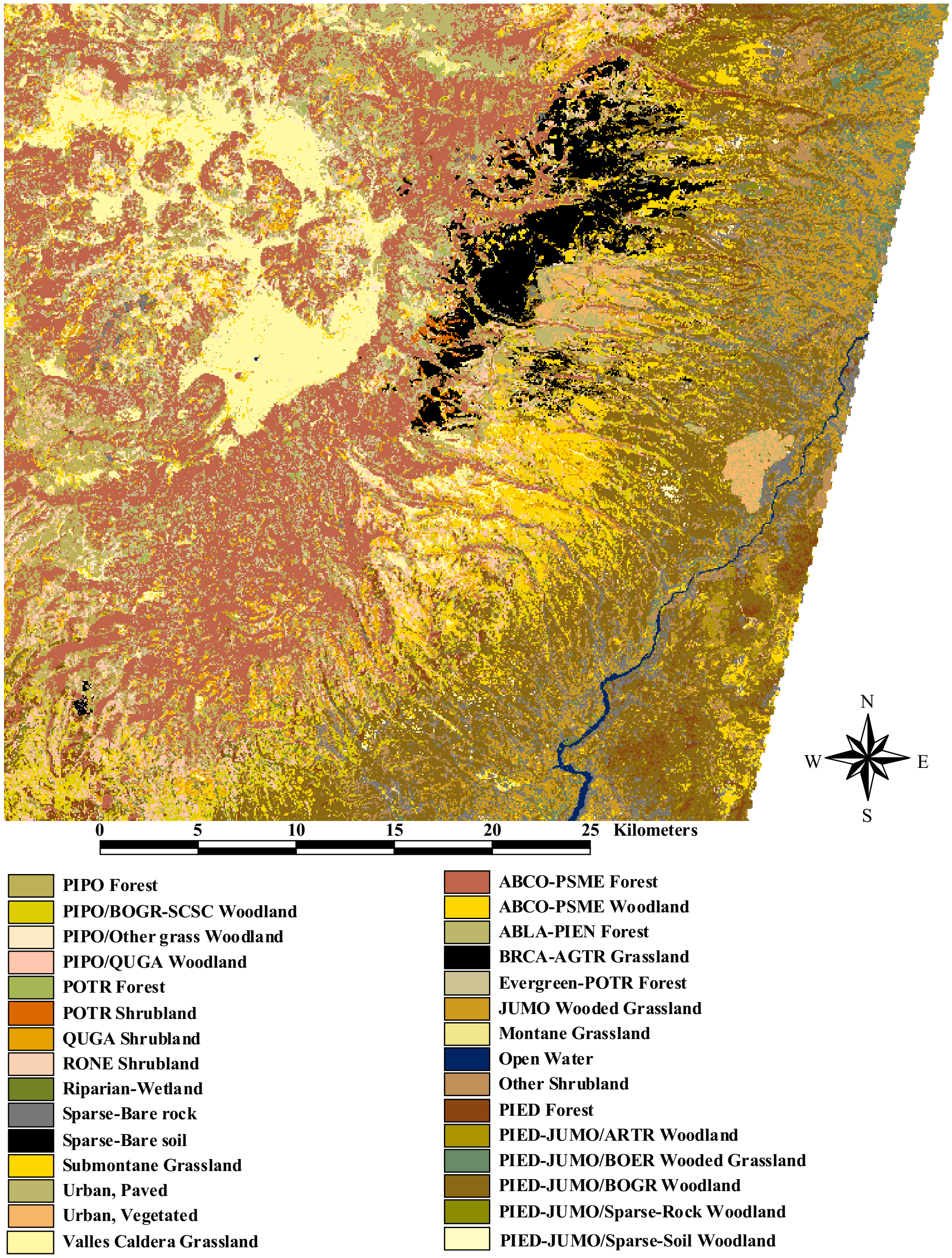


Figure 3.6. Quarter-hectare, smoothed version of the LANL land cover map created from Landsat ETM+ imagery taken June 4, 2001. The extent of the area is roughly 1,821 km^2 and includes Los Alamos County, Los Alamos National Laboratory, Bandelier National Monument, the Valles Caldera National Preserve, and parts of Santa Fe National Forest. Land cover types are delineated at the association level (n = 30). Acronyms are defined in Appendix B. Areas in black (i.e., Sparse-Bare Soil and BRCA-AGTR Grasslands) were primarily burned by the Cerro Grande Fire.

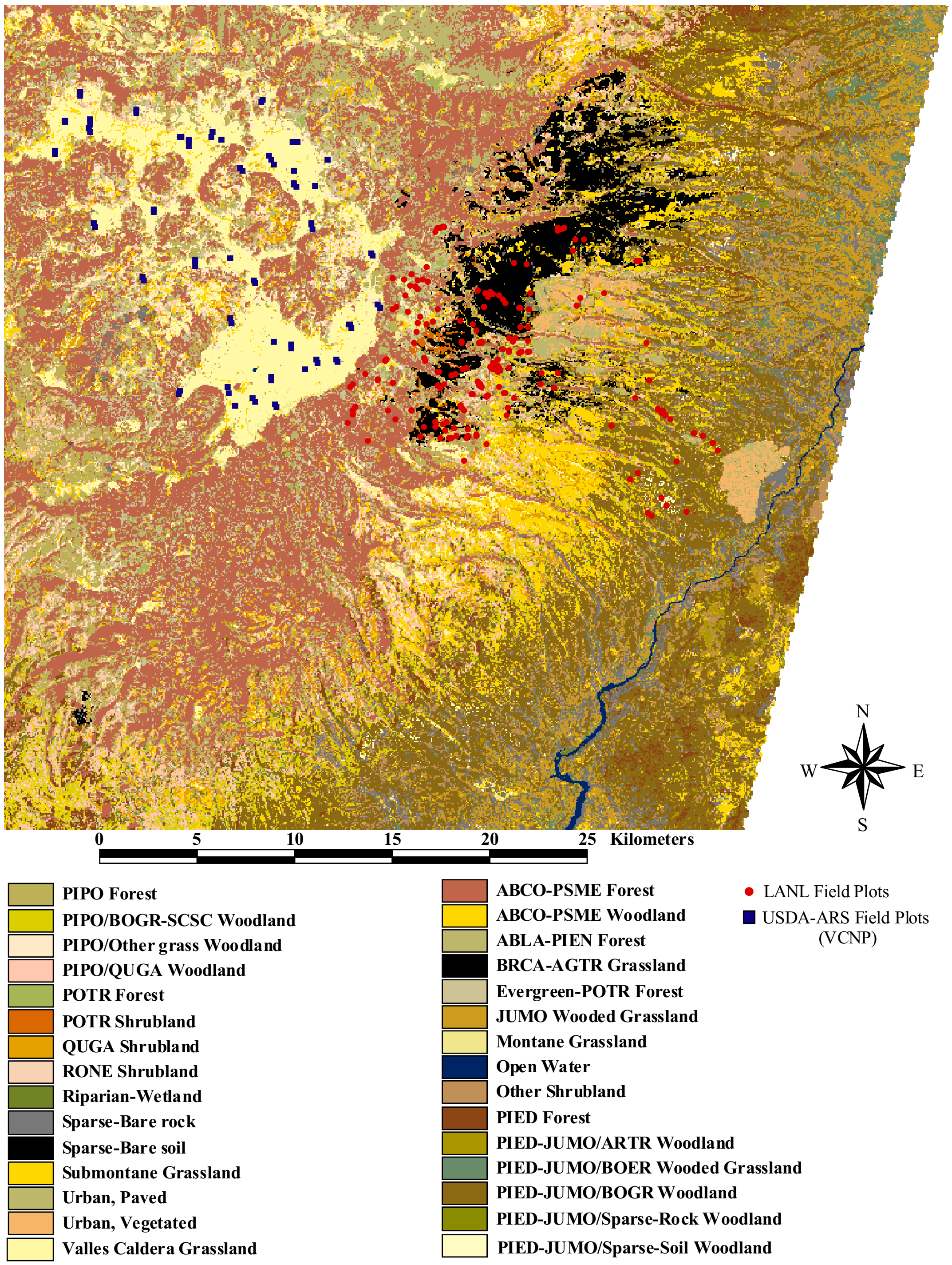


Figure 3.7. Location of field plots used to calibrate the SAVANNA Ecosystem Model for the eastern Jemez Mountains. A total of 159 plots were assessed representative of 16 land cover types.

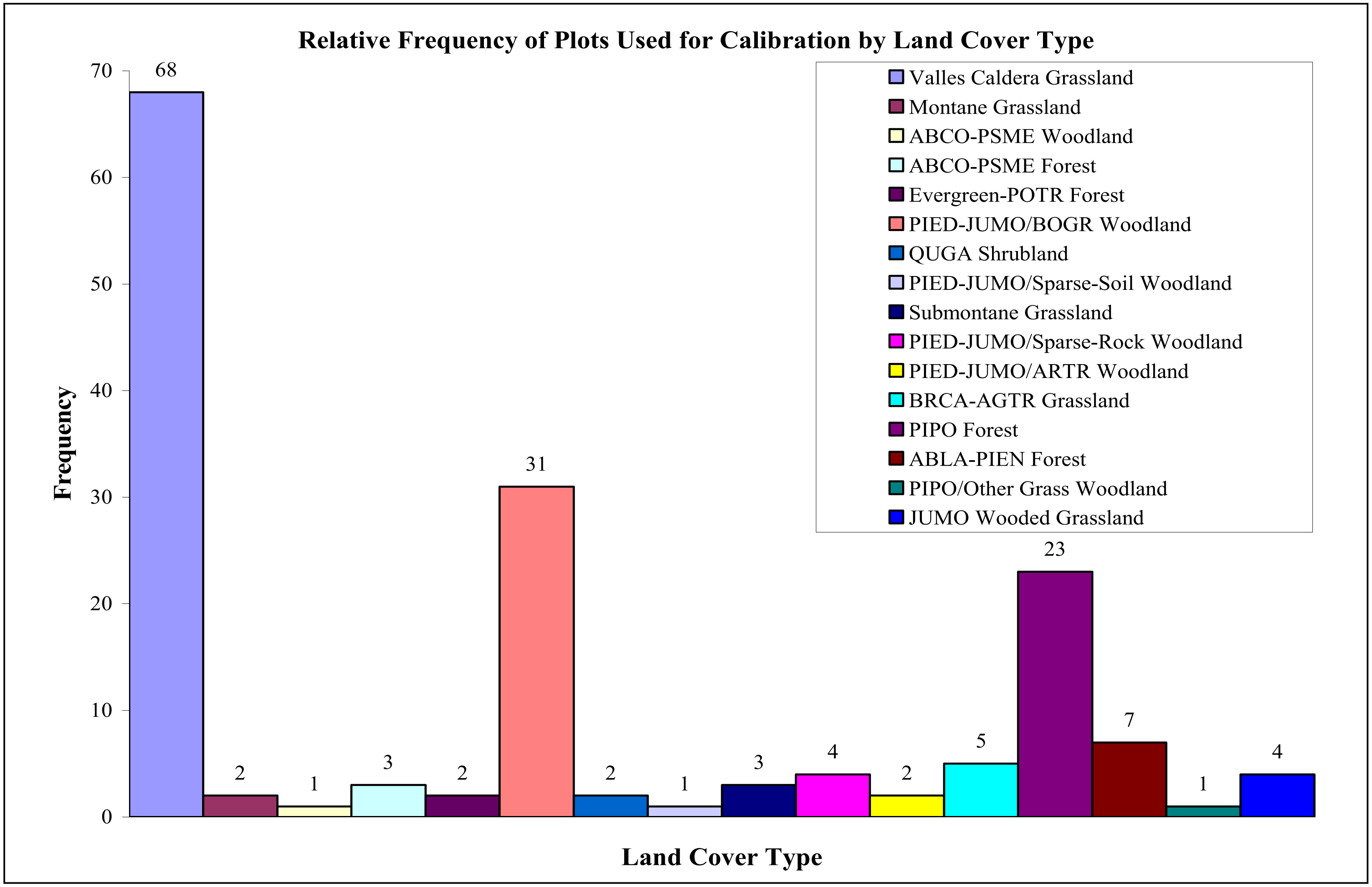


Figure 3.8. Relative frequency of survey plots by land cover type used for calibration of the SAVANNA Ecosystem Model. A total of 159 plots representative of 16 out of 30 different land cover types were analyzed and incorporated into the model.

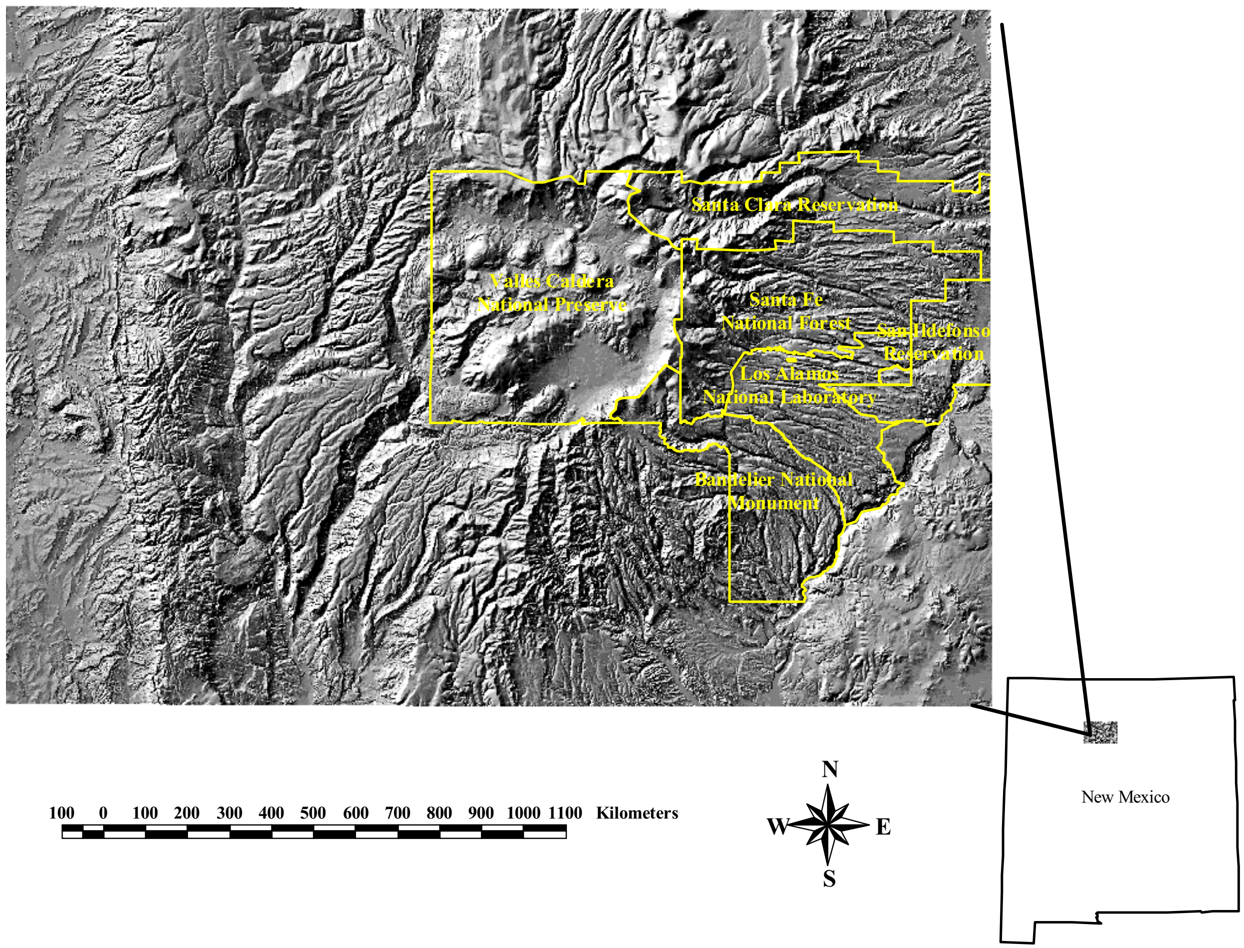


Figure 3.9. Hillshade created from DEM coverages downloaded from the United States Geological Survey (USGS) Earth Resources Observation Systems (EROS) Data Center website (http://edc.usgs.gov/geodata/). All 1:24000 quadrangles are projected in UTM coordinates, North American Datum (NAD 1927) at a resolution of 10-meters. Geographic boundaries for Los Alamos National Laboratory, the Valles Caldera national Preserve, Bandelier National Monument, Santa Clara reservation, San Ildefonso Reservation, and Santa Fe National Forest are given for spatial reference.

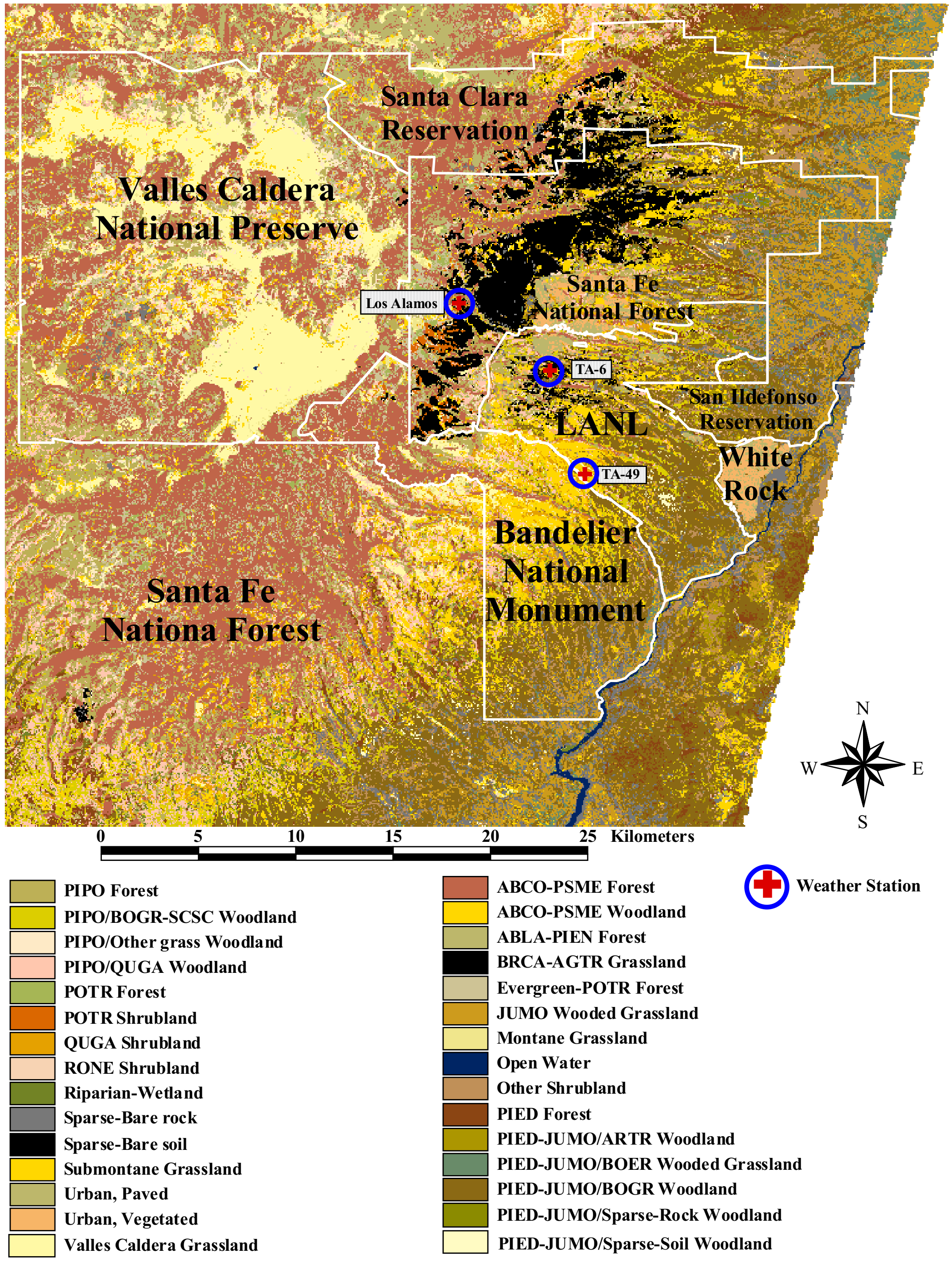


Figure 3.10. Locations of Los Alamos, TA-6, and TA-49 weather stations used in control runs to ensure weather inputs were being read correctly by the model.

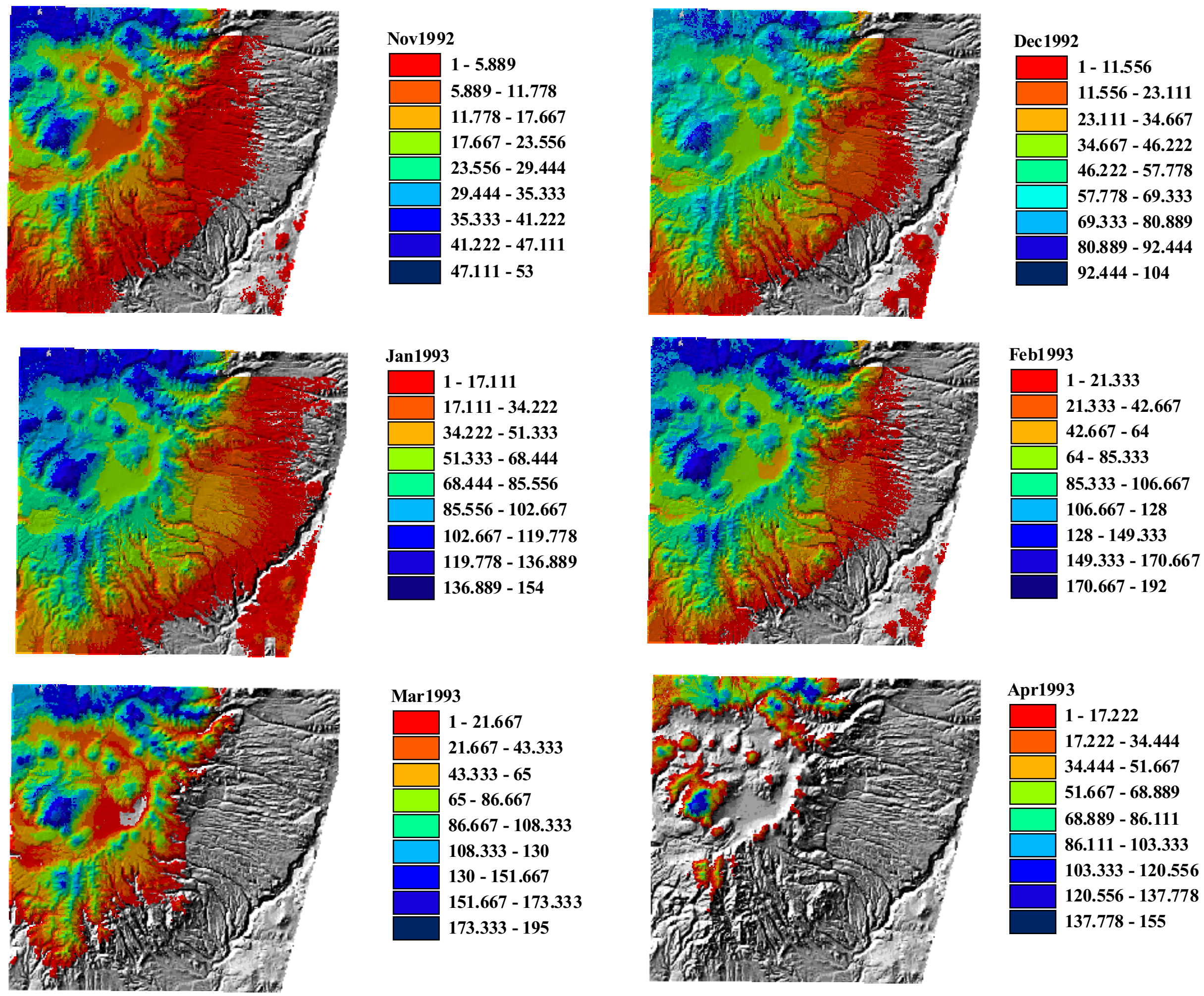


Figure 3.11. Simulated snow output for November 1992 through April 1993. Patterns of snow deposition are spatially realistic, but actual snow depth may be low indicating additional calibration for the snow submodel may be necessary. Snow depth is recorded in centimeters.

CHAPTER IV

DEVELOPMENT OF AN INDIVIDUAL-BASED MODEL TO EVALUATE ELK *(Cervus elephus nelsoni)* MOVEMENT AND DISTRIBUTION PATTERNS FOLLOWING THE CERRO GRANDE FIRE

Introduction

Quantitative models take complex ecological processes and attempt to explain them in simple mathematical terms for the purpose of exploring data, formulating predictions, and guiding research. Models serve as useful tools in cases where strongly opposed views or ethical considerations prevent field studies, at spatial or temporal scales that are logistically or economically impossible to study, or as low-cost preliminary alternatives to expensive field studies. Despite the usefulness of models, however, they are no panacea and remain an abstraction of real-world phenomena.

The modeling process is iterative and is comprised of a series of steps. These include model conceptualization, development, calibration, application, and validation/corroboration. An effective conceptual model forces the formulation of hypotheses, specification of data needs/expectations, and assessment of key components (i.e., variables and processes) of the system (Jackson et al. 2000) and usually takes the form of a block diagram or flowchart. A well-structured conceptual model will help the modeler define the type of model to be used (e.g., stochastic or deterministic, spatial or non-spatial, simulation or analytical, etc.) and the level of ecological detail to include.

Model development includes not only writing the equations and/or logical operations to be performed and interpretation of field data and/or literature for parameter estimation, but also selecting appropriate software and computer resources for model application. Model calibration refers to the iterative adjustments to inputs and parameters to improve model fit to measured output variables thus minimizing the error between predictions and observations (Turner et al. 2001). Once reasonable calibration has been achieved, model application under realistic circumstances provides an environment in which the model can be objectively evaluated. Though sometimes termed "validation," many modelers prefer to use the term "corroboration"; to validate means "to assess the truth of" and given that models are never true it is a misnomer (Johnson 2001, Turner et al. 2001). Objective testing requires an independent set of data not used in the original model development or calibration and results may be compared graphically, statistically, or in tabular form.

Many methods are available for modeling animal movements and distribution (e.g., path analysis, fractal analysis, random walks, structural equation modeling). However, there has been a growing interest in the use of individual-based models in ecological applications. "The essence of the individual-based approach is the derivation of the properties of ecological systems from the properties of individuals constituting these systems" (Łomnicki 1992, p. 4). Individual-based models (IBMs) are capable of modeling variation among individuals and interactions between individuals (Slothower et al. 1996). This approach to modeling animal movements addresses two fundamental principles, which are largely ignored in other modeling environments. First, it acknowledges that individuals are behaviorally and physiologically distinct because of genetic and environmental influences and second, it acknowledges that interactions among individuals are inherently localized (Slothower et al. 1996, Schank 2001). The basic assumption in IBMs is that each action during movement (e.g., animal's choice to start, stop, or change direction) is a mixture of stochastic and deterministic elements (Turchin 1998). An advantage to IBMs is that they do not require many of the simplifying assumptions and mathematical derivations typically needed in more aggregated models (Railsback et al. 1999) thus resulting in a more realistic representation of real-world phenomena.

Individuals usually react according to a sequence of basic rules that, when applied iteratively to many individuals over time, are capable of generating realistic and complex behavior (Slothower et al. 1996, Schank 2001). Movement rules are a critical component of spatially explicit IBMs and include both departure rules to determine when an animal leaves a location and destination rules used to select a new location (Railsback et al. 1999). Departure and destination rules are normally based on some measure of fitness (i.e., the ability of an organism to survive and reproduce viable offspring) and how fitness varies among potential locations. These rules reflect the ability of an animal to select habitat over the temporal and spatial scales used in the model.

Movement rules in IBMs can be expressed as algebraic statements, which minimize the need for more complex mathematical operations associated with other modeling approaches (Slothower et al. 1996). These statements can then be translated into the command syntax of many raster GIS packages (Slothower et al. 1996). Raster images are useful because: (1) they are compatible with remotely sensed imagery and geographic information data, (2) the structure is easy to work with conceptually and mathematically, and (3) a variety of quantitative measures are available to analyze spatial patterns in raster landscape data (Turner et al. 1994). However, in IBMs space is continuous and location is explicit whereas in raster GIS, space is discrete and location is implicit. Therefore, implementation of IBMs into raster GIS requires translating the definition of individuals, neighborhoods, and rules into the implicit locations used in raster GIS.

The use of modeling to investigate ungulate responses to large-scale fires has been explored in few instances and no models have related the effects of post-fire vegetation succession on ungulate movements and distribution. The purpose of this study is to develop a spatially-explicit, stochastic, individual-based model that can be used to identify potential movement pathways (~migration corridors) across the eastern Jemez Mountains related to spatial and temporal aspects of the Cerro Grande Fire using the SAVANNA Ecosystem model as the basis for post-fire successional dynamics. Methods (model conceptualization, assumptions, development and calibration, integration, corroboration/validation), results, discussion, and future research needs are discussed in this chapter. Model application and experimentation, which may serve as a precursor for management decisions and future alterations to the model, are presented in Chapter V.

Study Area

The Pajarito Plateau, located in the Jemez Mountains of north central New Mexico, was formed by an ash flow of volcanic activity about 1.4 million years ago (Wilcox and Breshears 1994). The region is classified as a wildland-urban interface and is politically segmented, making natural resource management difficult. The most conspicuous and influential government entity is Los Alamos National Laboratory (11,200 ha). It is bordered by Bandelier National Monument (13,290 ha) to the southwest, Santa Fe National Forest to the northwest, San Ildefonso Reservation to the east, and Santa Clara Reservation to the far north. In addition, the federal government recently purchased 37,200 ha of private land to the northwest that includes the Valles Caldera National Preserve (VCNP) – an ancient caldera grassland that serves as the primary summering grounds for the region's growing elk population.

The plateau is topographically complex, ranging in elevation from 1,600 m near the Rio Grande to 3,240 m near the summit of Cerro Grande. It is transected by a series of smaller canyon systems and mesas making the terrain rough and virtually inaccessible in some places. Vegetative patterns are highly dependent on elevation and topography (Wilcox and Breshears 1994), but five main vegetative associations have been described; piñon-juniper grassland (1,600 to 1,900 m), piñon-juniper woodland (1,900 to 2,100 m), ponderosa pine grassland (2,100 to 2,300 m), mixed-conifer (2,300 to 2,900 m), and subalpine grassland (2,900 to 3,200 m). Average annual precipitation is 330 to 460 mm (Davenport et al. 1996, Wilcox et al. 1996) of which about 45% occurs in July, August, and September. Average daytime temperatures range from 32.2 ^{o}C in the summer (max. = 41.1 ^{o}C) to -9.4 ^{o}C in the winter (min. = -30.6 ^{o}C).

In the last 30 years the Jemez Mountain region has experienced 4 major fires – the La Mesa fire in 1977, the Dome fire in 1996, the Oso fire in 1998, and the Cerro Grande Fire in 2000 (Figure 4.1). Of these, the most prominent fires were the La Mesa and the Cerro Grande burning 6,180 and 19,020 ha, respectively. These fires were centered in areas of dense, monotypic ponderosa pine forests which, in the case of the earlier fires, were converted into a more productive and diverse mosaic of grassland, shrubland, and forest communities. It is believed such conditions may have created prime wintering range, which contributed to population increases in the regional elk herd (Allen 1996).

Methods

Model Conceptualization

The development of an effective conceptual model is an iterative process and begins to take shape when specific research objectives are formulated (Jackson et al. 2000). For purposes of this study, efforts were made to balance ecological detail regarding variables and processes while still providing enough clarity to formulate questions, determine data needs, and assess key components of the system. In essence, the goal of conceptual model development was to provide a "state-and-transition" block diagram that could be critically analyzed by area experts in an effort to clarify potential biases and assumptions that may arise in the course of model development. Questions to be answered through development of the conceptual model included:

- What are the important variables and parameters that affect elk movement and distribution?
- What are the driving variables that influence model behavior, but are external to the model?
- What outputs need to be generated to answer research objectives?
- What is the appropriate level of spatial and temporal resolution of the model?
- What are the state variables (initial conditions) going to be? State variables preserve static state information in terms of variable values that are globally accessible.
- What type of model (e.g., stochastic/deterministic, dynamic/static, simulation/analytical, spatial/non-spatial) is appropriate for addressing research objectives?
- What computer hardware/software will be needed to accommodate the model?

Though basic research objectives aided the development of the conceptual model, additional questions regarding factors that influence elk movement and distribution had to be evaluated. The primary objective of the research was to analyze potential movement pathways across the Jemez typically used in "migration" and assess whether these pathways may change in response to spatial and temporal aspects of the Cerro Grande Fire. By definition, migration indicates a periodical shift from one seasonal home range to another, which can be assessed through an analysis of site fidelity within each range (Hooge 2003, pers. comm.). The elk population in the Jemez Mountains, however, is more properly referred to as "quasi-migratory" in that movements are not periodic and seasonal home ranges are difficult to delineate, but animals move in response to the best resources (food, water, shelter) available at the time. Nevertheless, it was assumed the factors that affect migratory patterns in other populations likely affect quasi-migratory behaviors as well. These may include preferred ranges, weather, snow depth, forage availability, sex and age, habitual behavior, hunting pressure, and barriers to migration (e.g., roads, buildings, fences, and other impassable barriers) (Adams 1982). Similarly, factors that influence habitat selection by elk (Table 4.1) irrespective of migration must also be considered given the quasi-migratory behavior of this population.

By definition, the process of modeling involves abstraction and simplification leading to a loss of information (Shenk and Franklin 2001) and leaving researchers to struggle with the question of how complex to make a model to effectively capture the dynamics of a given system. The natural tendency of many researchers is to include every possible variable that might explain more variation seen in the observed system. However, the result of this approach often is a model so complex that it has little use. Modeling is as much art as science – there is always a tradeoff between the amount of mechanistic detail necessary to explain a biological phenomenon and the model's tractability and transparency, which makes it more useful in the long term (Shenk and Franklin 2001). Ideally, the goal of model development should be to identify the most parsimonious model among a variety of plausible models that range from the most simple to the most complex (cf. Millspaugh and Marzluff 2001).

Initial selection of model components was kept simple and only included those variables considered necessary to the system under investigation. Following a number of iterations, a block diagram was constructed in which state variables, processes, driving variables, and dependent variables were depicted (Figure 4.2). This initial conceptual model guided expert discussion, data needs and assessment, and further introspection that led to the conclusion that numerous ecological models already existed to address various components depicted in the conceptual model. Of particular interest were models that could simulate the post-fire successional processes driving elk movement and distribution.

Extensive literature review led to the selection of the SAVANNA Ecosystem Model (Chapter III), which contained ecological components at spatial and temporal resolutions relevant to elk movement and distribution dynamics with added flexibility to manipulate these variables as necessary. Efforts were made to implement the SAVANNA Ecosystem Model in the eastern Jemez region and the conceptual model was re-written to incorporate these changes (Figure 4.3). The new conceptual model, therefore, specified the remaining variables necessary to model elk movement and distribution patterns across the eastern Jemez region. These variables, which would need to be modeled through the application of the individual-based model, can be grouped into three classes: topography, human influences (roads, buildings, fences), and habitual movement/memory. Model development, therefore, aimed to incorporate these components and integrate them with the SAVANNA Ecosystem Model.

Model Assumptions

The following fundamental assumptions are made in the development of this individual-based model for elk movement and distribution in the Jemez Mountains:

- Animal movements occur on a daily time step, but dynamic processes generated by the SAVANNA Ecosystem Model used to drive movement are updated weekly.
- Grain size is defined as 150 sq. meters in order to balance mechanistic detail with computational efficiency while working within the confines of the underlying successional model.
- The total extent of the study area (~1739.93 km^2) was driven by the availability of input data (i.e., the LANL land cover map and soil information) and not necessarily by the biology of the animals in question. However, preliminary analysis of elk locations indicated only ~2% of animal locations fell outside the final study area. Of those, only 2 of the 15 animals used in model construction were affected and they accounted for only 0.2% of total locations used in model development and calibration. Therefore, it is assumed points outside the extent of the study area would not affect overall model results and/or conclusions.
- It is assumed that study area extent and grain are representative of the scale over which elk use and select habitat.
- Factors that affect migratory patterns and habitat selection in other (migratory) populations likely affect quasi-migratory behaviors as well and are considered in this analysis.
- Primary external variables driving elk movement and distribution over time include precipitation, temperature, forage quantity and quality, and snow depth whose values are decided by the application of the Savanna Ecosystem Model (Chapter III). Any underlying assumptions and limitations of SAVANNA apply to this IBM as well.

- Food intake by elk is determined by the quantity, quality, and availability of forage in a given cell and can be influenced by the presence of other elk in that cell.
- The effect of predators (mountain lions and hunters), though likely to affect elk movement and distribution patterns, are not simulated in this system due to insufficient data at time of model development.
- Simulated elk do not have "vision" beyond the 8 cells immediately surrounding their current location and, therefore, must move through each adjacent cell to a final destination point.
- It is assumed elk move in response to spatial and temporal variation in variables associated with calculated habitat suitability indices (HSIs) in a manner that will maximize fitness.
- It is assumed that migratory pathways are, in part, a habitual behavior that may be influenced by immediate circumstances encountered during migration (Adams 1982) and are therefore modeled accordingly.
- It is recognized that elk are a gregarious species and that social interactions and group size will vary throughout the year. No attempt is made to adjust for seasonal social behaviors and no limit is placed on density of animals within individual cells; however, parameter files are capable of adjusting density of animals per cell.
- No attempt is made to distinguish variability among individuals based on size, age, sex, or other distinguishing features. Population demographics and life cycles are ignored but can be incorporated at a future point in time when additional information becomes available that allows for such distinctions.

Fifteen animals that met the following criteria were selected for model development and/or corroboration. Of these, 10 were randomly selected for model development and 5 were used as an independent test set during model corroboration. All 15 animals met the following conditions (see Chapter II):

- The collar had $\geq$ 88% position acquisition rate.
- The collar remained on the animal at least eleven months.
- The 95% kernel home range (KHR) spanned the Cerro Grande burn area or was continuous through transitional regions connecting summer/winter ranges.

Preliminary tests of GPS collar accuracy indicated a strong effect of 2D fixes on position acquisition rates (PARs) depending on time of day and season of year. Position acquisition rates were lower during mid-day hours and summer months indicating a possible change in animal behavior during the hottest parts of the day/season. Slope, aspect, elevation, and land cover type affected dilution of precision (DOP) values for both 2D and 3D fixes, although relationships varied from positive to negative making it difficult to delineate the mechanism behind significant responses. Two-dimensional fixes accounted for 34% of all successfully acquired locations and may affect results in which those data were used. Nonetheless, mean DOP values were generally in the range of 4.0 to 6.0, regardless of fix type (see Chapter II), and the application of all collar data was considered reasonable for this study.

Model Development and Calibration

Topographic Features. Sixteen 7.5-minute digital elevation model (DEM) quadrangles in Spatial Data Transfer Standard (SDTS) format were downloaded from the United States Geological Survey (USGS) Earth Resources Observation Systems (EROS) Data Center website (http://edc.usgs.gov/geodata/). All 1:24,000 quadrangles are projected in Universal Transverse Mercator (UTM) coordinates, North American Datum (NAD 1927) at a resolution of 10 m. Any errors inherent in the acquired data were assumed minimal and not assessed in detail.

Once all quadrangles were downloaded, data were converted using the SDTS2ARC conversion utility available through the above website. Resulting ASCII files were imported into ERDAS Imagine (version 8.6) and then processed into a composite image using the "Mosaic" tool. Quads were then converted into meters using the "Modeler" tool as necessary and re-constructed using the "Mosaic" tool. Header information was validated and corrected as needed and slight adjustments in positioning were made to individual quadrangles to account for innate error in the data sets and ensure proper alignment. The image was once again run through the Mosaic tool to generate a final comprehensive image and the final map was clipped to fit the extent of the study area (1739.93 km^2). Analysis of topographic features was conducted on the original 10 m maps to provide the most accurate information on habitat use, but final maps used in the IBM had a cell resolution of 150 m.

Logistic regression is often used in studies of wildlife habitat use to predict the presence or absence of an animal using independent variables which can be either categorical and/or continuous. Regression coefficients in a logistic regression equation can be used to estimate the odds ratios (Cody and Smith 1997, Keating and Cherry 2004). The odds ratio is:

$$\psi(\boldsymbol{x}|\boldsymbol{x}_{\mathrm{R}}) = \exp(\boldsymbol{\beta}'\boldsymbol{x} - \beta_0) = \exp(\beta_1 x_1 + \ldots + \beta_p x_p)$$

where $\psi(\boldsymbol{x}|\boldsymbol{x}_{\mathrm{R}})$ is the odds ratio and $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots \beta_p)$ is a vector of regression coefficients for the variables x_i, i = 1, 2, …p. Odds ratios can be used to approximate relative risk – the probability of use given $\boldsymbol{x}$ relative to the probability of use given a reference type, $\boldsymbol{x}_R$: that is,

$$\Re(\boldsymbol{x}|\boldsymbol{x}_{\mathrm{R}}) = [P(y = 1|\boldsymbol{x})]/[P(y = 1|\boldsymbol{x}_{\mathrm{R}})]$$

where $\Re$ is relative risk, $P(y = 1|\boldsymbol{x})$ is the probability of occurrence given the independent variable(s) '$\boldsymbol{x}$', and $P(y = 1|\boldsymbol{x}_{\mathrm{R}})$ is the probability of occurrence given a reference type '$\boldsymbol{x}_R$'. The odds ratio is related to relative risk as:

$$\psi(\boldsymbol{x}|\boldsymbol{x}_{\mathrm{R}}) = \Re(\boldsymbol{x}|\boldsymbol{x}_{\mathrm{R}})[1 - P(y = 1|\boldsymbol{x})]/[1 - P(y = 1|\boldsymbol{x}_{\mathrm{R}})]$$

Thus, if use is assumed to be rare everywhere (i.e., $P(y = 1|\boldsymbol{x}) \approx 0$ for all $\boldsymbol{x}$, including $\boldsymbol{x}_{\mathrm{R}}$), then $\psi(\boldsymbol{x}|\boldsymbol{x}_{\mathrm{R}}) \approx \Re(\boldsymbol{x}|\boldsymbol{x}_{\mathrm{R}})$, and the odds ratio can then be used to approximate relative risk in a case-control design (Keating and Cherry 2004). Relative risk is simply the ratio of two conditional probabilities. A relative risk of '1' indicates an event is equally probably in both groups.

The case-control design of Keating and Cherry (2004) was, therefore, applied to calculate odds ratios for topographic variables (slope, aspect, and elevation) independently and in combination. Using the Spatial Analyst extension for ArcView 3.2a, elk locations were overlaid on constructed slope, aspect, and elevation maps using the original DEM coverage and then queried to determine actual values (i.e., N_1 used locations) for each variable at each location. Because of the circular nature of aspect readings, aspect values were converted into nine categorical variables as follows: north (337.5^o to 22.5^o), northeast (22.5^o to 67.5^o), east (67.5^o to 112.5^o), southeast (112.5^o to 157.5^o), south (157.5^o to 202.5^o), southwest (202.5^o to 247.5^o), west (247.5^o to 292.5^o), and northwest (292.5^o to 337.5^o) directions as well as a category representing no aspect (i.e., flat ground). A total of 55,782 locations were recorded for the 10 animals used in model development. Thirty-four percent of these locations were 2-dimensional.

For each animal, the 95% KHR was used to define available habitat. Cells from the slope, aspect, and elevation maps that had been marked as "used" were removed and remaining cells (i.e., unused cells) were then exported from ArcView as ASCII text files into FORTRAN 90. Remaining cells were randomly sampled with replacement to create a dataset for each animal that included N_0 unused locations with associated slope, aspect, and elevation values. Aspect values were converted into categorical variables as before. Therefore, for each animal a complete dataset included N_1 used locations and equivalent number of N_0 unused locations. Data were then imported into SAS (ver. 9.0) and analyzed using PROC LOGISTIC with a stepwise procedure and aspect as a class variable. Resultant regression coefficients (beta values) were used to estimate odds ratios (≈ relative risk) for each cell at a final model resolution of 150 m in the study area based on that cell's topographic features (see raw code and associated parameter file in Tables E.1 and E.2 of Appendix E, respectively). The product was a map of "impedance values" (Figure 4.4) based on topographic features where a value of '1' indicates no selection, values less than ‘1’ indicate the cell is less likely to be used than a reference cell, and values greater than ‘1’ indicate the cell is more likely to be used.

Habitual Movement (Memory). The role that habitual behavior plays in elk migration and/or movement patterns has not been clearly defined, but likely is an integral part of migration (Adams 1982). Fall migrations are often initiated in response to snow (Vales and Peek 1996). Various authors have concluded elk utilize the same migration paths year after year (Altmann 1952, Brazda 1953, and Anderson 1958 *in* Thomas and Toweill 1982) during both the spring and fall migrations (Skinner 1925, Anderson 1958, and Compton 1975 *in* Thomas and Toweill 1982) and elk may even use the same crossing-points at places such as streams even though alternative crossings are nearby (Anderson 1958). Seasonal affinity for specific areas may be passed down from cow to calf (Murie 1951 from Wolf 2003) and some research has shown the mother-offspring relationship to be a relatively stable assemblage that persists throughout the life of the animal (Franklin and Lieb 1979). Thus migratory routes are likely established through some combination of topography and habitual use passed down through maternal relationships. In addition, one can argue that habitual migration – a learned behavior (proximate causation) that is genetically influenced and subject to natural selection – evolved because it increased evolutionary fitness over time (ultimate causation). Habitual migration/memory thus serves as an important factor to consider in destination and departure rules for development of an IBM when considering elk behavior.

Modeling habitual use/memory is a challenge. One method is to weight individual cells based on prior use (Wolf 2003) and then test results with an independent data set. However, with this approach emergent behaviors that may be elicited from an individual-based model can not be revealed. This approach also limits the potential outcomes of model runs by restricting use to certain cells. A better approach allows patterns of potential use to emerge naturally through simulation runs based on factors that influence these movements and do not change over time. Given that migratory routes are likely established through a combination of topography and habitual use as discussed above, and given that the objective *is* to model habitual use, topography remains the likely driver that influences elk memory/habitual use over evolutionary time scales. Individual animals most likely selected the path of least-resistance based on topographic features in an effort to maximize potential fitness and these paths were then passed down through each generation. Therefore, a new approach to modeling habitual habitat use is attempted here.

The map of impedance values generated through the analysis of topographic features was used as a base map for running a series of simulated animals through the landscape in order to create "memory" – a map of accumulated frequencies of simulated visits normalized between 0 and 1 that could be used as an independent variable in the final IBM. Based on actual location data from the 10 animals used in the logistic regression, 3 areas on the Valles Caldera National Preserve were subjectively defined as potential destination areas and 3 areas on LANL and/or BNM were defined as departure areas. In preliminary model runs, simulated animals randomly selected a given departure and destination area and were allowed to move freely until they reached a chosen destination regardless of the number of moves taken (i.e., no “kill cap” set). In addition, animals were not allowed to immediately return to the cell from which they just departed (i.e., no “tag backs”). The frequency of occurrence of animals within a given cell was modeled under two scenarios: 1) frequencies reflected only one occurrence by a simulated animal even if the animal returned to that cell multiple times (i.e., no “wandering”) therefore making the maximum value in a given cell the number of simulated animals run through the system, and 2) frequencies reflected multiple occurrences by a simulated animal if it returned to the cell (i.e., wandering).

Preliminary runs indicated there were three main barriers with which simulated elk had to contend. First, initial model runs indicated simulated animals were commonly crossing the Rio Grande based solely on topographic features, which did not support patterns of actual movement. Second, an intermediate area known as the “escarpment” contained a combination of slope, aspect and elevation values such that simulated animals would not traverse it without an incentive to reach more attractive summering ground on the VCNP. Finally, on occasion a simulated animal would find itself inhabiting a cell surrounded by cells that contained values of ‘0’ or ‘-9999’ making it impossible to find a way out and eventually crashing the program. The third problem was easy to resolve by allowing “tag backs” in situations where all other cells were unattractive, but the first two issues required more thought.

To address the natural barrier posed by the Rio Grande, it was decided the river would be coded as an impassable barrier to elk movement. In order to accomplish this at the 150 m resolution of the model, the river needed to be widened slightly using the "expand" function in the Spatial Analyst extension of ArcView. The river was then reassigned values of "-9999" forcing the Fortran model to exclude any data from the river and east of the river in the memory model.

The area of the escarpment was more difficult to address and required manipulation of animal movements in order to overcome this obstacle. A minimum amount of incentive (i.e., force) was applied to model runs to encourage animals to traverse the escarpment. This incentive would normally come as a response to the receding snow line as animals moved toward more attractive vegetation a higher elevation summer ranges. Because snow and vegetation were not variables in the memory model, however, this "incentive" was modeled by applying a force in the direction of the destination cells by taking the Euclidean distance between the animal's current location and the center of the chosen destination area. This distance was then compared to the Euclidean distances of the surrounding eight cells and a pre-specified force was added to the 4 cells with the lowest values. Simulated animals, therefore, responded to a combination of topography and a slight force to encourage them to move in the direction of the VCNP over less attractive areas of the escarpment. However, a small amount of stochasticity was still applied to each move made by a simulated animal by allowing the computer to randomly select a uniformly-distributed value between 0 and 1. The random number was then applied to the surrounding eight cells and the area in which it fell determined the cell that was selected. The likelihood of a given cell being selected, therefore, was a function of the normalized value (i.e., probability value) of that cell. Cells with higher values were more likely to be selected than those with lower values, but through random chance a lower value cell could still be selected.

Once the basic program was in place, simulation runs were conducted with 100, 500, 1,000, 5,000, 10,000, and 50,000 animals. Each animal was run through the matrix independently and cell counts were accumulated. Various simulations were run by modifying parameters and/or flags (i.e., a binary indicator used to determine if the condition is "on" or "off") associated with kill caps, wandering counts, tag backs, and the forced incentive value until an overriding pattern emerged that was consistent between simulations. The final map selected for incorporation into the individual-based model as a "memory/habitual use" variable, which was normalized from 0 to 1 with higher values indicating cells more likely to be used perpetually, resulted from a run of 50,000 animals using a minimum incentive of 0.05 in the direction of the VCNP with no "tag backs" and no "wandering." Examples of model runs are located in Figures 4.5 to 4.8. Model code and the associated parameter file are found in Appendix Tables E.3 and E.4, respectively.

<u>Human Influences.</u> Unlike geographic barriers, most of which elk are capable of negotiating, manmade obstacles such as roads, fences, and buildings can alter migrational patterns and restrict elk access to winter range (Adams 1982). These obstacles are obviously more prominent in areas classified as "wildland-urban interfaces" such as the Pajarito Plateau. In addition, the diversity of government agencies in the region – many with conflicting mission statements – is reflected in the prominence and overall impact of human structures and influences.

Fences. Elk behavior changes with the presence of fence lines. Bauman et al. (1999) found elk typically spend considerable time at fences up to 122 cm engaged in pacing, rubbing, and licking behaviors before finally jumping the fence. In contrast, the fences present within the bounds of Los Alamos National Laboratory typically are in the range of 228.6 cm to 243.84 cm and may (security fences) or may not (industrial fences) have an additional 61 cm of razor wire along the top. Therefore, these fences are ultimately impermeable to elk movement and were modeled accordingly by assigning all 150 m cells containing industrial or security fences a value of '0'.

Buildings. Though buildings themselves are barriers to elk movement patterns, the presence of buildings is also positively correlated with human activity in most cases. Just because a cell has a building in it, however, does not mean it is impermeable to elk. Therefore, in order to model the effect of buildings on elk movement, an assumption was made that the greater relative area occupied by buildings per m^2 the greater impact to elk movement and distribution.

An ArcView shapefile coverage of building structures across Los Alamos County was obtained that included both residential areas and technical buildings present on LANL. The coverage was converted into grid format at a resolution of 1 m in order to preserve the presence of small buildings in the study area that might otherwise be lost in the conversion to larger cell sizes. A C++ program (Table E.5 of Appendix E) was constructed to count the number of 1-m cells occupied by a building within larger grid cells at the final resolution of 150 m. The resultant map of building frequencies (i.e., total area in m^2 covered by buildings) was then normalized from 0 to 1 and inverted so that cells with values closer to 0 (i.e., those cells with more buildings) were least likely to be used and those closer to 1 were more attractive. The level of aversion or attraction to cells with these structures was assumed constant regardless of time of day.

Roads. Roads may be one of the best predictors of elk dispersion (Lyon and Ward 1982, Lyon 1983, Thomas et al. 1988, Ager and Hitchcock 1992, Hitchcock and Ager 1992, Christensen et al. 1993, Holthausen et al. 1994, Cole et al. 1997, Rowland et al. 2000, Benkobi et al. 2004), but the level of aversion depends on several factors including the kind and amount of traffic, quality of road, and density of cover adjacent to the road (Lyon and Ward 1982). To complicate matters, the level of aversion may vary with time of day (Millspaugh and Marzluff 2001). Though road density and distance from roads are commonly used as indicators of elk habitat effectiveness, the spatial patterning of roads may also have an effect (Rowland et al. 2000).

In order to effectively model the effect of roads on elk movement and distribution in the Jemez Mountains, two points had to be addressed. First, given all roads are avoided according to the literature, how much of an aversion is a particular type of road (i.e., primary, secondary/paved, or tertiary/dirt)? Second, once a basic "aversion factor" is applied to a given type of road, can portions of that road be modified to account for locations where elk appear to congregate or cross the road? Attempts were made to structure the model and provide flexibility to address both questions.

An ArcView shapefile with primary, secondary, and tertiary roads was converted into grid format at 150 m resolution. Locations from the 10 animals used in model development were overlaid on each grid and two measures were taken. First, the total number of elk occupying a cell with a given type of road was recorded. It was assumed that road cells with more elk locations were relatively more attractive than other road cells with fewer elk locations. Second, using the Animal Movement Analyst Extension (AMAE) in ArcView 3.2a (Hooge and Eichenlaub 2000, Hooge et al. 2001), movement pathways (i.e., polylines) were constructed for each animal by connecting consecutive locations. Points at which these polylines crossed roads were identified and frequencies of crossings were recorded for each road cell by differing road types. Though the time between consecutive locations could affect the accuracy of road crossings, it was assumed that a conglomeration of road crossings in a particular region was indicative of a segment of road with greater relative use (i.e., less avoidance).

In order to develop a final "aversion factor" for each cell of the study area occupied by a primary, secondary, or tertiary road, two final steps were taken. First, the total number of elk locations in a given road cell was cross-multiplied by the total number of road crossings for that same cell and normalized from 0 to 1. If cells had neither elk nor crossings, a value of '1' (i.e., a trace amount of use) was assigned to the cell prior to normalization to prevent future divisions by '0.' The resultant value was a relative "attractiveness index", indicative of portions of each road that account for locations where elk appear to congregate or cross the road. Second, the "attractiveness index" was re-normalized using a sliding scale based on road type. An associated parameter file contains maximum and minimum aversion factors (with the potential to be modified by the user) for primary, secondary, and tertiary roads. The maximum and minimum values were then used as the sliding scale to which the "attractiveness indices" were applied. Cells with the lowest attractiveness were assigned the maximum aversion while cells with the highest attractiveness were assigned the lowest aversion (Figure 4.9). On the small chance that a given cell contained a combination of primary, secondary, and/or tertiary roads, primary roads took precedence over secondary roads, which took precedence over tertiary roads. The final roads map was then imported for use in the IBM. Final code and the associated parameter file to generate the effect of roads can be found in Tables E.6 and E.7 of Appendix E, respectively.

Integration with SAVANNA: The HSI. The development of the individual-based movement model was completed with the specific intention of providing the option to replace SAVANNA's existing *ungulate distribution submodel*. A flag was added to the "Simcon.prm" file that allows the user to select SAVANNA's existing distribution model or replace it with the integrated IBM. This modification required changes to the "SVLAND.f" program, which calls submodels and sets the time step for SAVANNA's internal operations, and "MAINPROG.f" program, which initializes all of SAVANNA's subroutines.

The true integration of the IBM comes in the application of the habitat suitability index values (HSI), which integrate movement rules written for the IBM and variables modified and produced by the ecological processes run in SAVANNA. A habitat suitability index is a numerical index ranging from 0 to 1 (with the assumption there is a direct linear relationship between HSI value and carrying capacity) that represents the capacity of a given habitat to support a selected wildlife species (U.S. Fish and Wildlife

Service 1981). The HSI value is calculated in a two-step process. The first step requires the development of a “cost” map, which designates those variables that potentially inhibit movement by simulated animals:

$$\text{COST} = \text{Impedance Map} * \text{Roads Map} * \text{Fences Map} * \text{Buildings Map}$$

The “impedance map” – generated from the logistic regression based on elk use of topographic features (slope, aspect, elevation) – is modified by applying the roads and buildings maps to increase the aversion to applicable cells where buildings or roads are found. The resultant map is then further modified by masking cells wherever a security or industrial fence occurs. The resultant “cost map” is then applied to the final HSI, which is the normalized 0 to 1 product of the following:

$$HSI_F = \text{COST}*P(\text{snow})*P(\text{diet})*P(\text{forage})*P(\text{ME})*P(\text{temp})*\min(\text{shrub/thicket})*P(\text{green})*P(\text{dead})$$

where P(snow) is the functional response of elk to snow at a given depth, P(diet) is the preference-weighted forage biomass based on dietary preferences, P(forage) is based on total amounts of green and dead herbaceous biomass, P(ME) is the potential metabolic energy (MJ/kg/d) acquired by moving into a given cell, P(temp) is functional response of elk to temperature, min(shrub/thicket) uses the “Law of the Minimum” to select the lowest value between shrub and thicket cover, P(green) is the preference for green biomass, and P(dead) is the inverse-weighted avoidance of dead biomass. Each variable is controlled by a series of flags in the associated "IBM" parameter file, which allows the user to decide whether or not to include the variable. Additional variables from the original *distribution submodel* that were not used during application of the IBM for purposes of this dissertation, but were preserved for potential future use include:

- Force maps to define a population's range at different times of the year;
- Distance to water ;
- Preferred maps.

Preference values are most often generated through the application of a linear interpolation function (Alint.f) that uses x-y pairs to generate a response graph based on behavioral or physiological responses of elk to a variable. Typically, an x-value is generated either through a user-defined parameter file or an internal SAVANNA algorithm that produces a value needed for the function. A corresponding y-value is then generated, which will either be used directly in the HSI or as an input variable in another portion of the code. An example of the functional response graph for elk to snow depth is given in Figure 4.10.

<u>Movement Rules.</u> Movement rules are a critical component of spatially-explicit IBMs because movement is an essential method used to adapt to changing environmental conditions (Railsback et al. 1999). Movement includes initialization rules to determine cell origination for each animal, departure rules to determine when an animal leaves a location, and destination rules that govern when an animal selects a location. Departure and destination rules are often based on some measure of "fitness" – the ability of an

animal to survive and reproduce viable offspring. Fitness measures are often identified from optimal foraging literature in which net energy intake is further adjusted by the associated risk of mortality, which has the apparent advantage of considering both survival and growth. Because no measure of risk was identified for elk in the Jemez Mountains, fitness was assumed to be positively correlated with increasing HSI value. The potential to incorporate mortality risks (e.g., predation, harvest) using the *predation submodel* in SAVANNA can be considered at a future point in time.

Model Initialization. Before individuals can begin to move across the landscape, the model must be initialized by reading in appropriate maps and designating starting locations for each individual (Figure 4.11). During the initial steps the model reads in the cost impedance map created in the analysis of topographic features and then modifies it by overlaying maps created for roads, buildings, and fences, with each input controlled by a flag in the associated parameter file. Animals are initialized by designating the total number of individuals to be simulated across the landscape using SAVANNA's "cons4900s.dat" file and a parameter called "hpopmult," which can be read in as total numbers of individuals or density (no./km^2). A separate parameter ("startnum") was created to allow flexibility in individual animal's starting locations. The "startnum" parameter is connected to an associated parameter ("startlocs") that specifies the x-y coordinates of each individual designated in the "startnum" parameter. Additional animals have the option of starting at random locations on the summering grounds (i.e., VCNP) or across the landscape. The percent of animals to start at a random location on the summering grounds (minus the "startnum" animals) is specified and the remaining portion are then randomly distributed across the landscape in any cells considered available after masked out cells are eliminated.

Departure Rules. Some models have been designed in which animals do not depart a location until after their fitness declines to less than their average on previous days (Van Winkle et al. 1998). This approach is disadvantageous in that such rules prevent individuals from seeking locations that actually improve their fitness (Railsback et al. 1999). Railsback et al. (1999) and Railsback and Harvey (2001) apply departure rules that reflect an individual's knowledge of surrounding cells within some maximum distance, but this is computationally intensive. Therefore, a simpler version of these departure rules was applied to elk in the Jemez Mountains. Individuals were only given the "vision" to see the surrounding eight cells in their neighborhood, but a parameter allows the total number of cells moved to be adjusted based on actual movement data of the 10 animals used in model development. They also have the option of remaining in their current cell or traveling to an adjacent cell with a potentially higher HSI value resulting in more realistic movement patterns throughout the course of a day. A decision tree documenting the major steps used during the model run is found in Figure 4.12.

Given the quasi-migratory behavior of elk in the Jemez Mountains, a parameter to trigger migrational responses between distinct summer and winter ranges could not be modeled using a robust measure such as a break in site fidelity. Migration date has been defined in the literature as the median date between the last location an animal was within its seasonal home range and the next location when the animals was not on its seasonal home range (Vales and Peek 1996). Therefore, migrational responses were triggered once a simulated animal decided to leave the perimeter of the VCNP, which is considered the primary summering grounds of the Jemez Mountain elk population. Once outside the VCNP, a migration "flag" was turned on that would allow conditional modifiers to be applied to HSI values depending on the current location of a simulated animal and the conditions found in that cell. Fall migrations are often initiated in response to snow (Vales and Peek 1996); therefore, if snow was present in the cell, the inverse of the "alint" function for snow response (Figure 4.10) was applied as a force in the direction of the wintering grounds to the HSI of the 4 cells in the nine-cell neighborhood containing the shortest Euclidean distance between the current cell location and a designated cell on the wintering range. If snow was not present in the cell, a force was applied in the direction of the summering grounds (i.e., VCNP) to the 4 cells in the nine-cell neighborhood containing the shortest Euclidean distances to a designated cell on the VCNP. This approach was used in an effort to model empirical observations that elk move in response to the advancing and receding snow line.

Destination Rules. Destination habitat is selected using combinations of fractional stochasticity, exclusion of destinations that do not meet some habitat requirement (e.g., presence of fences, snow depth exceeds tolerance), and optimization of habitat variables through the application of the HSI. The fractional stochasticity, as described in the "Habitual Movement/Memory" section of the model, is applied in such a way as to allow individuals to still select cells most likely to maximize fitness.

Model Outputs. Individuals move a specified number of cells per day, but SAVANNA updates its dynamic model components on a weekly basis in order to maximize computational efficiency. Therefore, animals respond to resources available at the start of each week. All applicable spatial and temporal output files associated with SAVANNA still apply (e.g., herbaceous production, offtake, animal distribution, current annual growth for woody species, precipitation patterns, etc.).

Addition of the IBM improves the application of SAVANNA by recording individuals' movement pathways in the form of calculated x-y coordinates representing a random location within each inhabited cell on a daily stepwise basis compared to the monthly distribution routine currently used by the program. Because of the method in which information is stored, queries on specific points within the movement pathway can be used to select subsets of data according to specific management needs and then analyzed within a GIS at various temporal scales (i.e., daily, weekly, monthly, seasonally, annually) allowing maximum flexibility in data application. Model code for output data generation is found in Table E.8 of Appendix E. Final code and the associated parameter file for the IBM are found in Tables E.9 and E.10 of Appendix E, respectively.

Model Corroboration/Validation

Model corroboration acknowledges that models as abstractions of real-world systems can never be proven "true", but can be tentatively accepted until proven false (Shenk and Franklin 2001). The goal should be to establish how suitable the model is for its intended purpose, not whether the model is suitable. In this sense, model corroboration can be viewed as assembling evidence for why the IBM is valuable for its intended application. Model corroboration is classified into four basic categories: subjective assessment, visual techniques, measures of deviation, and statistical tests (Mayer and Butler 1993, Shenk and Franklin 2001, Turner et al. 2001).

"There is little sense in analyzing an IBM's system-level behavior before developing confidence that the model's individual-level behavior is acceptable, and there is no reason to expect individual behavior to be acceptable before the environmental processes that drive individual behavior have been tested" (Grimm and Railsback 2005, p. 317). By testing the underlying parts of an IBM, including the submodels representing the environment, validation proceeds from the bottom-up. Given that the SAVANNA Ecosystem Model drives the dynamic processes used in the calculation of HSI values, which are in turn the basic building blocks of this IBM, critical evaluation of the functioning of SAVANNA was a primary step in determining the validity of this IBM. Model calibration and testing of SAVANNA (Chapter III) indicated the underlying environmental processes driving the variables used for development of the HSI were within reason. Weather patterns were functioning as intended and biomass production showed no significant differences between simulated results and independent field data for a variety of land cover types. In addition spatial interpolations of snow depth were realistic, although simulated values may be low for the region. Other model functions not specifically tested were assumed reliable given the long history behind SAVANNA's development and its presence in peer-reviewed literature (i.e., face validity – see Rykiel 1996).

Uncertainty can occur in both model structure and parameter values, but for IBMs the strategy of pattern-oriented modeling is useful for separating analysis of structure from analysis of parameter values by looking beyond random variation to the IBM's underlying structural validity (Grimm and Berger unpubl. rep., Railsback 2001, Grimm and Railsback 2005). Using patterns as currency for analysis can supercede quantitative methods for evaluating the precise fit of simulated or observed patterns as long as clear criteria for qualitative patterns are established and met (Rykiel 1996, Grimm and Railsback 2005). This type of corroboration is well suited to mechanistic modeling approaches whose aim is to identify underlying processes (such as migration) and is often the primary step before more sophisticated methods of model corroboration are undertaken. Pattern-oriented modeling naturally incorporates spatial and temporal scale, guidelines to aggregate biological information, and serves as a tool by which to understand the mechanisms underlying the pattern (Grimm et al. 1996).

Observation of real data used to construct the IBM revealed stark patterns in animal behavior that served as the preliminary basis for model corroboration/validation. For purposes of modeling the quasi-migratory behaviors of elk in the Jemez Mountains it was essential for the model to reproduce these individual- and population-level responses. In particular, four distinct patterns related to movement across the eastern Jemez were identified and used for model corroboration:

1. The overall pattern of habitat use by real animals should serve as the primary basis for model corroboration. Similar patterns of habitat use across the landscape should emerge from population-level responses when simulated individuals are exposed to

realistic scenarios that mimic real-life conditions during similar time periods (i.e., visual validation/time-series analysis – see Rykiel 1996). Stray activity by one or more individuals can then be analyzed to determine if stochasticity might account for the pattern or if an underlying mechanism in the model is erroneous. Abstract patterns that emerge from model runs that are not present in the real population may be revealed and guide further model development. For purposes of this dissertation, patterns will be analyzed by visually comparing overall habitat use between real and simulated animals and analyzing density maps generated from actual locations and model results.

2. Using AMAE (Hooge and Eichenlaub 2000) in ArcView 3.2a, movement pathways were constructed for the 10 animals used in model development by connecting consecutive locations and projecting them on landscape maps. Two primary and two secondary movement corridors used to traverse the eastern Jemez Mountains were identified (Figure 4.13). Primary corridors had ≥ 4 of the 10 animals using them while secondary corridors had ≤ 2 animals using them. Emergent properties of the individual-based model should reveal use of these same corridors in roughly equal proportions to those seen in the real population.
3. When actual animal locations for the 10 animals used in model development were superimposed on interpolated maps of mean monthly snow depths generated by the SAVANNA Ecosystem Model (see Chapter III), > 68% of locations were in cells free of snow. The remaining locations where snow depth was greater than or equal to 1 cm produced a nonlinear response curve (Figure 4.14). Ninety percent of locations

were in snow less than 8 cm. Simulations should reveal similar patterns in response to snow (i.e., event validity – see Rykiel 1996).

4. In conjunction with the pattern observed in #3, animals moved to the lower elevations of BNM and LANL during months with heavy snow fall (early 2001), but this pattern was not obvious during months with little to no snowfall. Model simulations should show temporal and spatial patterns of habitat use that mimic the real population.

One method of model validation is to compare the mean of several replicate IBM runs to observed patterns (Wiegand et al. 1998, Wiegand et al. 2003). The strongest evidence of structural realism, however, is independent predictions of system properties using data not involved in model construction or parameterization (Grimm and Berger unpub. rep., Rykiel 1996). Therefore an independent test was run on 5 simulated animals to evaluate model performance compared to real-life data collected on 5 animals which were not used in model parameterization or calibration over the 2001 to 2004 period. Simulated animals were initialized on cells that contained the actual starting location of the corresponding "real" animals and runs were conducted for the length of time for which data were actually collected in the field. Animals were allowed to move up to 86 cells (~ 13,000 m/day) per day to mimic the maximum distance moved by the 10 animals used in model development. The total population of elk was set to 3,500 – a conservative estimate of elk along the eastern Jemez based on sightability estimates conducted by the New Mexico Department of Game and Fish (Kirkpatrick et al. unpub.

rep.). Actual weather data were used for 2001 and 2002 and random weather was initiated in 2003. Patterns were analyzed as outlined above.

Results

Overall patterns of habitat use by simulated animals during 2001 to 2004 were consistently similar to patterns observed in the independent test set (Figure 4.15). Because simulated animals were programmed to follow the advancing and receding snow line, they exhibited less movement down mesa tops than the real population. Overall habitat-use patterns were consistent with the real population, though simulated animal densities were higher than those of the real animals just south of the Cerro Grande burn area and not as high in the southeast portion of the Valles Caldera National Preserve (Figure 4.16). In addition, higher use was consistently exhibited by real animals in the southwest portion of the area burned by the Cerro Grande Fire. Differences in density patterns, especially in areas burned by the Cerro Grande Fire, may be due to stochasticity in simulation runs, decreased resolution of the underlying land cover map, or movement rules related to topography.

Three of four pathways identified during model development were used by the 5 independent test animals as well as the 5 simulated animals (Figure 4.17). Movement pathways of the 5 simulated animals fell within paths used by real animals in roughly equal proportions to those seen in the real population. Modeled movements were not as linear as those exhibited by real animals, however. Simulated animals tended to display more exploratory behavior. Real animals traversed single mesa tops whereas simulated animals crossed more canyon systems than their real counterparts. Therefore, movement pathways of simulated animals were not as clearly defined as in the real population though the same pathways used by the population clearly emerged.

Patterns of snow use were remarkably similar between simulated and real animals. Animals avoided cells with snow in the majority of cases (72.67% for simulated animals compared to 70.66% for the independent test set and 68.66% for animals used in model development). Ninety-one percent of simulated animals' locations were found in cells containing < 8 cm of snow compared to 90.30% of the independent test animals and 89.98% of animals used in model development. Though more simulated animals were found in cells containing > 42 cm of snow, this is likely explained through the application of the underlying SAVANNA Ecosystem Model, which may deposit "instantaneous" snow on a weekly basis.

Patterns of use in relationship to snow depth (Figure 4.18) were compared using regression analyses. The curvilinear relationships in Figure 4.18 were modeled with a power function $Y = \beta_0 \ X^{\beta_1}$ +e (where Y is percent of elk locations and X is snow depth) which was linearized by taking logarithms of both Y and X; slopes were compared between the modeled animals, the independent test set animals, and the simulated animals. Observations of snow depth > 42 cm for the simulated animals were removed from the data set; these observations were considered artifacts of SAVANNA snow generation. Simulated animals and the 10 animals used to develop the model responded similarly ($F_{1,62} = 1.18$, $P > 0.1642$) to snow depth. An even stronger test for corroboration involves a comparison between simulated animals and the 5 independent animals; in this comparison, simulated animals and real animals also responded similarly ($F_{1,52} = 0.97$, $P > 0.1265$) to snow depth. Interestingly, the 10 real animals used for model development and the 5 real animals that act as an independent data set with respect to model development responded differently ($F_{1,56} = 4.13$, $P < 0.0112$) to snow depth. Thus, although different groups of real animals vary with regard to their response to snow depth, the response of simulated animals to snow was similar to the response of real animals to snow. These results suggest that the model was functioning properly in terms of animals' response to snow depth.

In conjunction with the above results, patterns of landscape use by simulated animals during periods of heavy snowfall appeared realistic (Figure 4.19). In 2001 – the wettest year of the study period – simulated animals were at lower elevations in February and March and more scattered in November and December. December showed the greatest difference in habitat use patterns between the simulated animals and the independent test set. Simulated animals remained on the VCNP whereas actual animals moved into areas of the escarpment just below the snowline. This difference in land use was likely the result of "instantaneous snow" generated by the SAVANNA Ecosystem Model, which "trapped" simulated animals in snow-free areas of the VCNP.

Discussion and Future Research

Understanding the consequences of movement for population dynamics is practically impossible without testing and constructing empirically-based, mathematical models (Turchin 1998). Spatial simulation models that evaluate interactions among cells in a raster-based environment provide a powerful approach to modeling spatial dynamics of complex systems based on individual-level properties (Wiens et al. 1993). However, simulation models are critically dependent on the input values for model parameters and, therefore, have the greatest value when they are coupled with field studies, both to calibrate model parameters and to test or confirm model projections (Turchin 1998). It is rare to find empirical data that directly describe key parameters of landscape connectivity, such as habitat-specific movement patterns, rates, or capabilities of animals (Pither and Taylor 1998). Even more rare are data comparing movement behaviors among landscapes that differ in structure or that describe movements occurring at spatial scales coincident with a given species' population dynamics (Pither and Taylor 1998). A more thorough understanding of landscape connectivity – and, therefore, functional corridor design – could emerge from conducting empirical studies over sufficiently large spatial scales so as to encompass the movement capabilities of the subject organisms (Pither and Taylor 1998, Rosenberg et al. 1998).

There has been an increasing interest in the use of individual-based models in recent years, especially by ecologists interested in modeling movement (Turchin 1998). The traditional approach to modeling using population-based parameters has come under scrutiny because population-level parameters do not recognize the inherent variation that exists among individuals (DeAngelis et al. 2001). Individuals have long been considered the building blocks of ecological systems (Grimm and Railsback 2005). In fact, population persistence through the process of natural selection is often packaged in the form of individual-level fitness. Because natural selection works on genetic variation caused by mutation and recombination, organisms should develop optimal behavioral features that maximize fitness over time (Drickamer 1998, Rettie and McLaughlin 1999). The essence of the individual-based approach is the derivation of the properties of ecological systems from the behavioral and physiological properties of the individuals constituting the system (DeAngelis and Gross 1992, Łomnicki 1992, Slothower et al. 1996, Schank 2001).

A key principle of individual-based models is that they are more powerful if realistic behavior patterns emerge from simple, fitness-maximizing rules for individual behavior (Railsback 2001, Railsback and Harvey 2001). Attempting to model too many behaviors or individuals can strain both the capacity of the computer used to run the simulation and the human mind to interpret the results (Fahse et al. 1998, Turchin 1998). For purposes of this research, measures of fitness were implemented through the modeling of habitual migration – a learned behavior that is genetically influenced and subject to natural selection – and application of an HSI that reflected forage quality, quantity, and metabolic energy intake, among others. Adjustments to fitness measures in the form of mortality risks (i.e., predation) can be incorporated at a future point in time by implementing the *predation submodel* available in SAVANNA when additional data needed for calibration are made available through ongoing studies.

The novelty of the individual-based modeling approach in ecology has resulted in caveats about which readers should be aware. Developing IBMs is a challenge because more of the complexity of the real-world is acknowledged a priori, making model development more time consuming, complex, and difficult to communicate (Fahse et al. 1998, Grimm et al. 1999, Lorek and Sonnenschein 1999, Grimm and Railsback 2005). In IBMs higher level processes often affect lower levels; that is, not only do system dynamics arise from individual behavior, but individual behavior is affected by system dynamics (Grimm and Railsback 2005). In addition, the lack of standard terminology and widely accepted methods by which to construct IBMs makes modeling controversial, inefficient, and difficult to compare with other modeling approaches (Grimm 1999, Łomnicki 1999, Grimm and Railsback 2005). The consequence of these challenges has been the misinterpretation of models as being truly individual-based when, in fact, they lack certain defining characteristics inherent in true IBMs.

Uchmański and Grimm (1996) in Grimm and Railsback (2005) have proposed four criteria that distinguish IBMs from other models:

1. The degree to which the complexity of an individual's life cycle is modeled;
2. Whether or not the dynamics of resources used by individuals are explicitly represented;
3. Whether real or integer numbers are used to represent the size of the population;
4. The extent to which variability among individuals of the same age/cohort is considered.

Using these criteria, even the IBM developed in this dissertation falls short of being considered a true IBM, although efforts were made to address each criterion and/or provide the flexibility in the program code to modify it at a future point in time. The underlying ecosystem model (SAVANNA) used as the foundation for the integration of the IBM models dynamic ecosystem processes (Criterion #2) and, though not yet implemented, has the potential to look at life cycle dynamics (Criterion #1) based on life table information already built into the *population dynamics submodel*. The newly incorporated IBM addresses Criterion #3 by following the movements of specific individuals in the population and it meets Criterion #4, in part, by allowing stochasticity in animal movements and the ability to respond to other animals in the individual's immediate neighborhood. The overall strength of the model is its dynamic nature, which will allow alternative management scenarios to be explored with respect to temporal and spatial aspects of the Cerro Grande Fire. Future research and model development will only make the IBM approach even stronger so it can fully meet the criteria above.

Traditional methods of analyzing classical models that rely on differential equations and other mathematical derivations are often not appropriate for analyzing individual-based models. Sensitivity analysis and uncertainty analyses have limited use for analyzing complex IBMs because comprehensive analysis of all parameters is infeasible and techniques do not address how system dynamics arise from individual traits (Grimm and Railsback 2005). Goodness-of-fit to census data also has limitations in analyzing IBMs given their stochasticity and inherent variation among individuals – two of the defining characteristics of IBMs (Grimm and Railsback 2005). In addition, the arbitrary selection of numbers of model replicates, the α-value used to define significance, the degree of difference chosen among model scenarios, and the degree of variability among replicate simulations (i.e., stochasticity) within the same scenario – all of which can affect statistical significance - make the use of traditional statistics in analyzing IBMs problematic (Railsback 2001). Time series and spatial methods that consider dependence are often more appropriate than standard statistical procedures that assume independence between observations given many outputs from IBMs are not independent over space and time (Grimm and Railsback 2005). However, census data contain patterns that can be useful analyzing IBMs, such as ranges in abundance and relations between abundance and environmental conditions (Grimm and Railsback 2005). Testing models against patterns of response rather than against magnitude of observed responses allows model mechanisms to be tested comprehensively with a reasonable level of effort and expense and can lead to better understanding of how system dynamics emerge from the traits of individual agents – one of the most important problems in ecology and management (Railsback 2001).

Overall pattern analysis indicated that realistic migrational processes and habitat-use patterns were likely emerging from movement rules incorporated into the IBM in response to advancing and receding snow. Primary and secondary movement pathways emerged from the collective responses of simulated individuals. Animals responded realistically to snow patterns and overall patterns of use across the landscape were reproduced. These considerations suggest the model was adequately corroborated based on existing data and outlined objectives.

Visual observation of raw data revealed additional patterns that also deserve further consideration. An analysis of net displacement of animal locations per day (i.e., distance moved/day) on a randomly-selected subset of data indicated increased movement activity in November and April/May (Figure 4.20). This pattern was supplemented by an increase in variation in distance moved during these time periods when compared with other times of the year. Movement activity in the month of November was not sufficiently recreated with sufficient accuracy, perhaps because of hunt season activity or post-rut behavior: additionally, increased movement in April/May could be related to pre-calving activity. Obvious patterns emerged during the rutting season (i.e., September) when animals tend to congregate in typical harem groups (Figure 4.21). Additionally, grouping behavior of animals in colder months (January through March) during periods with trivial snow deposition suggests a possible thermoregulatory behavior of elk to decreasing temperatures (Figure 4.22). Given that the primary objective of model development was to recreate movement pathways no efforts were made to model such behavior. Additional research is necessary to evaluate such response mechanisms in order to sufficiently model these interactions. Caution must be used in interpretation of patterns, however. Human nature often perceives patterns even though they may not actually exist and, should a pattern truly exist, it cannot be assumed the underlying mechanism in the model is correct (Grimm and Berger, *unpubl. report*). Additional tests of the model's reliability will come as more telemetry data are collected and additional research is conducted.

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Table 4.1. Factors that influence habitat selection by elk. Adapted from Skovlin (1982).

Category of Variables	Variable Name	Category of Variables	Variable Name
Topographic		*Food*	
	Elevation		Availability
	Slope		Quality
	▪ Gradient		
	▪ Position on slope	*Cover*	
	▪ Aspect		Cover Type
	Land Features		▪ Thermal
			▪ Hiding
Meteorologic			Density
	Precipitation - snow		Composition
	▪ Depth		Site Productivity
	▪ Condition		Structure
	Temperature		Successional Stage
	▪ Solar radiation		Configuration
	➢ Radiation		
	➢ Convection	*Space*	
	Humidity		
	Barometric Pressure	*Water and Salt*	
	Wind		
	▪ Velocity	*Specialize Habitats*	
	▪ Direction		Calving
			Wallows
			Trails

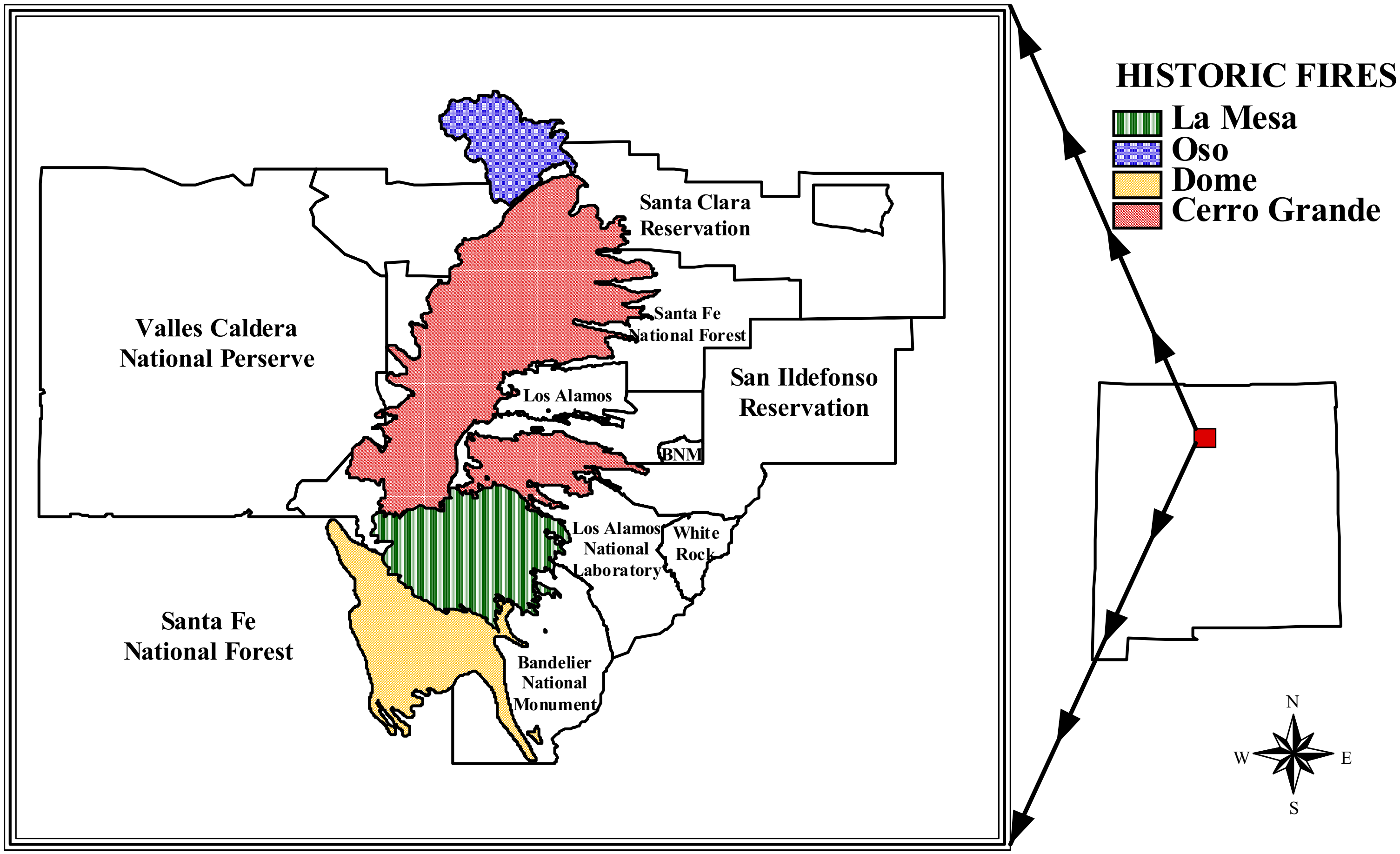

Figure 4.1. Major landowners and historic fire boundaries on the eastern slope of the Pajarito Plateau in the Jemez Mountains of north central New Mexico.

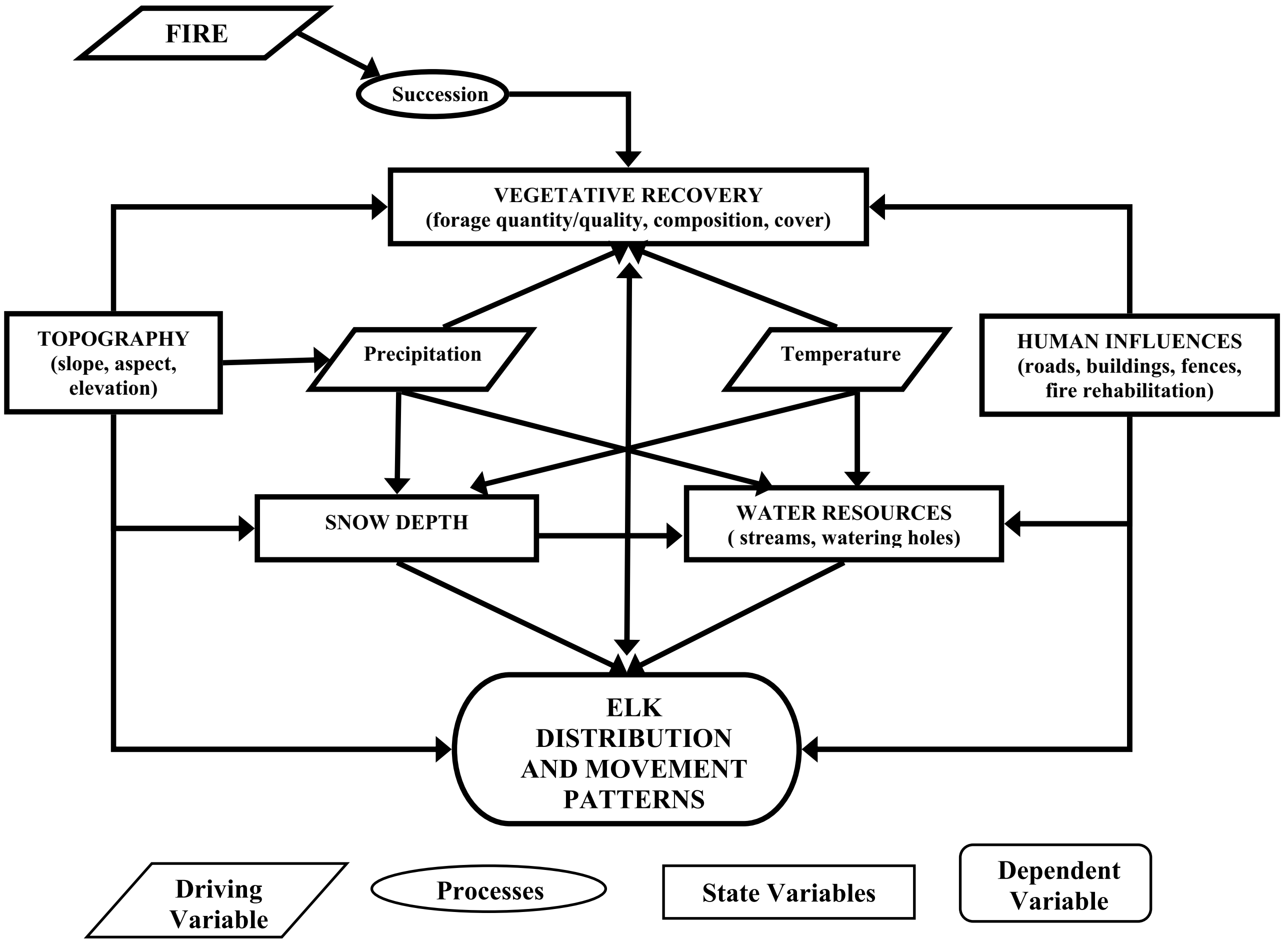

Figure 4.2. Conceptual individual-based stochastic model relating fire, succession, and associated ecosystem processes to state variables which affect potential elk distribution and movement patterns.

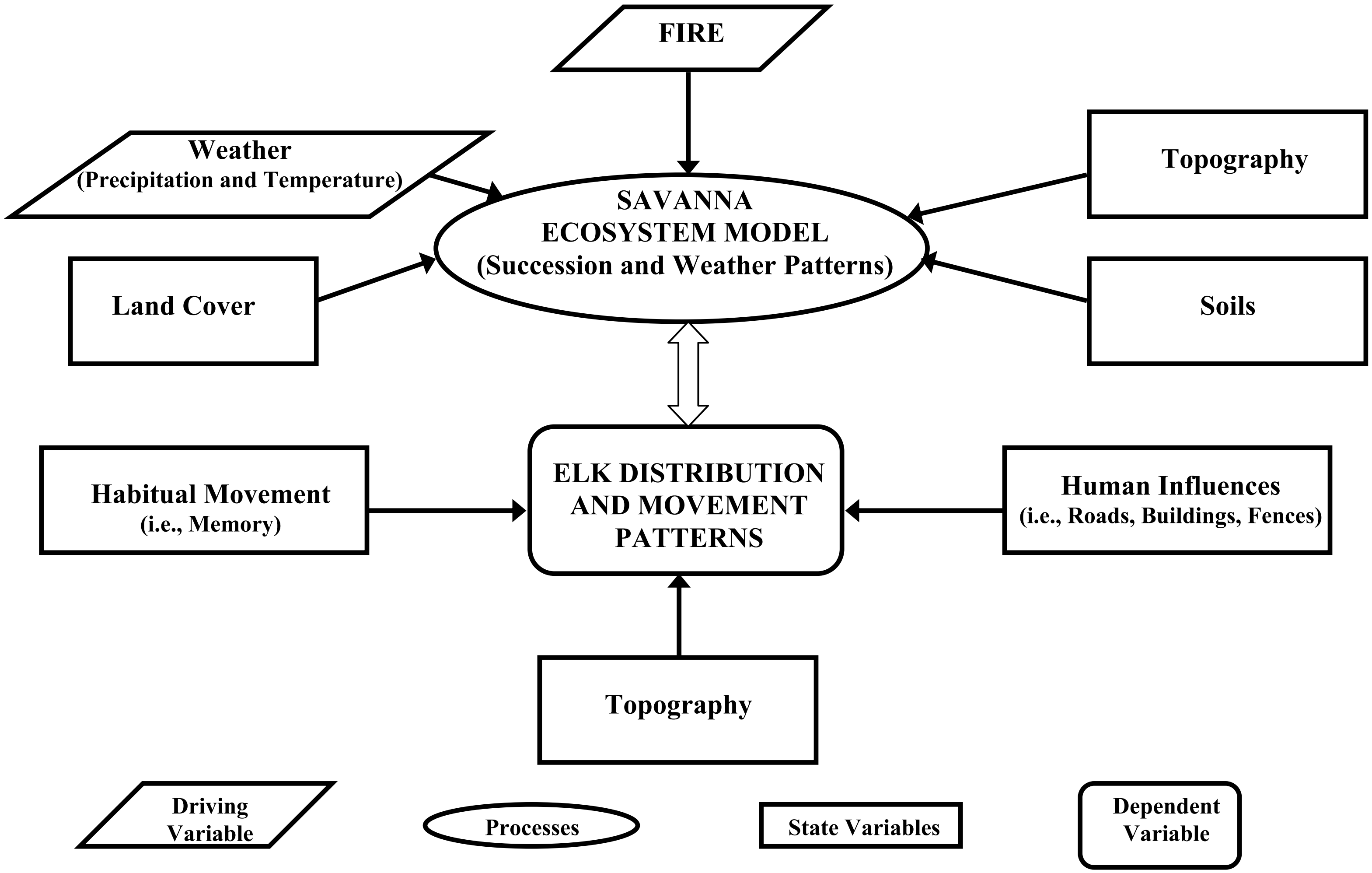

Figure 4.3. Revised conceptual model showing the integration of the SAVANNA Ecosystem Model and remaining components to be addressed through the application of movement rules in the individual-based model.

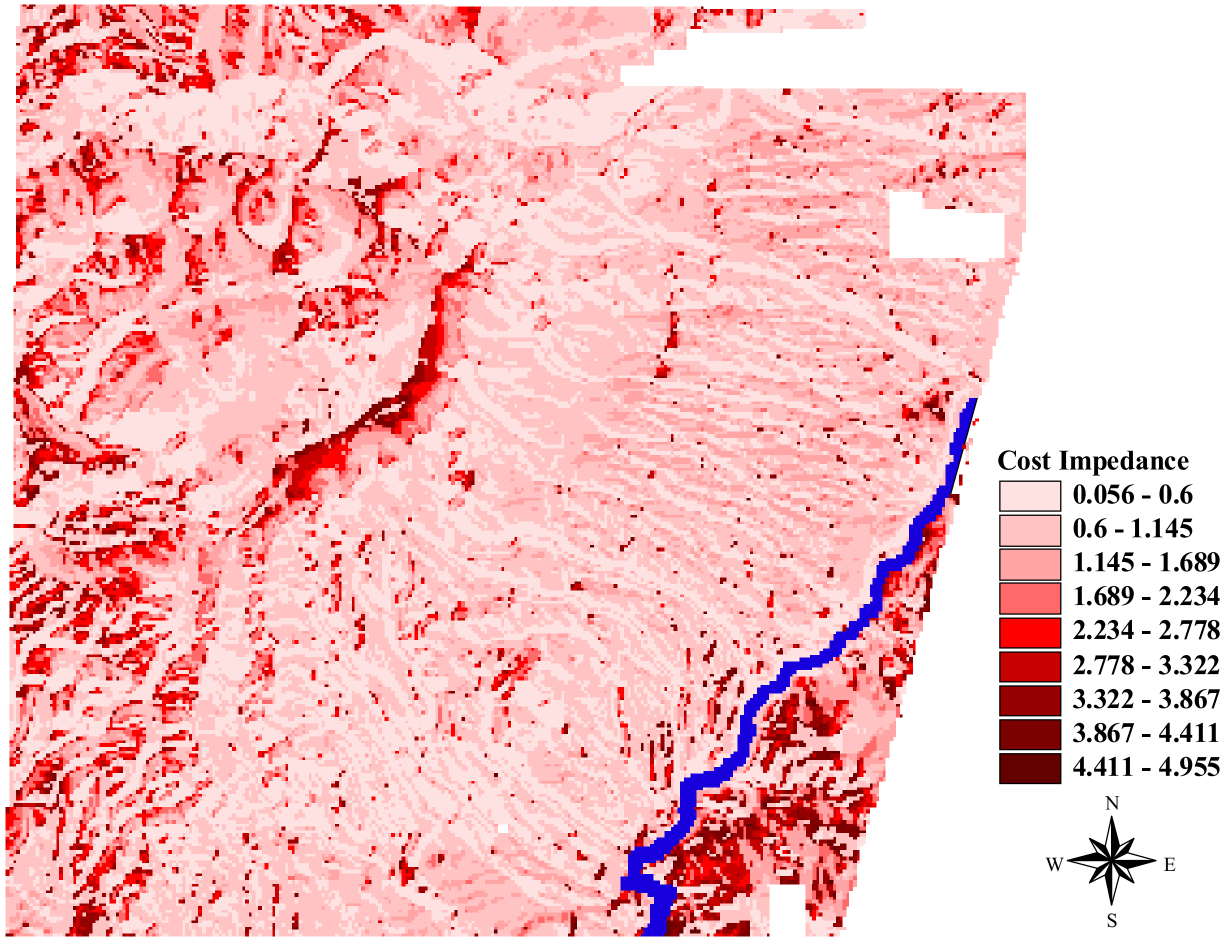

Figure 4.4. Cost-impedance surface generated from a logistic regression of slope, aspect, and elevation values. Regression coefficients (beta values) were used to estimate odds ratios (≈ relative risk) for each cell at a final model resolution of 150 m in the study area based on that cell's topographic features. Values greater than 1 indicate a greater preference for those cells. The Rio Grande (blue) was eventually used to mask out areas east of the river to prevent simulated animals from crossing.

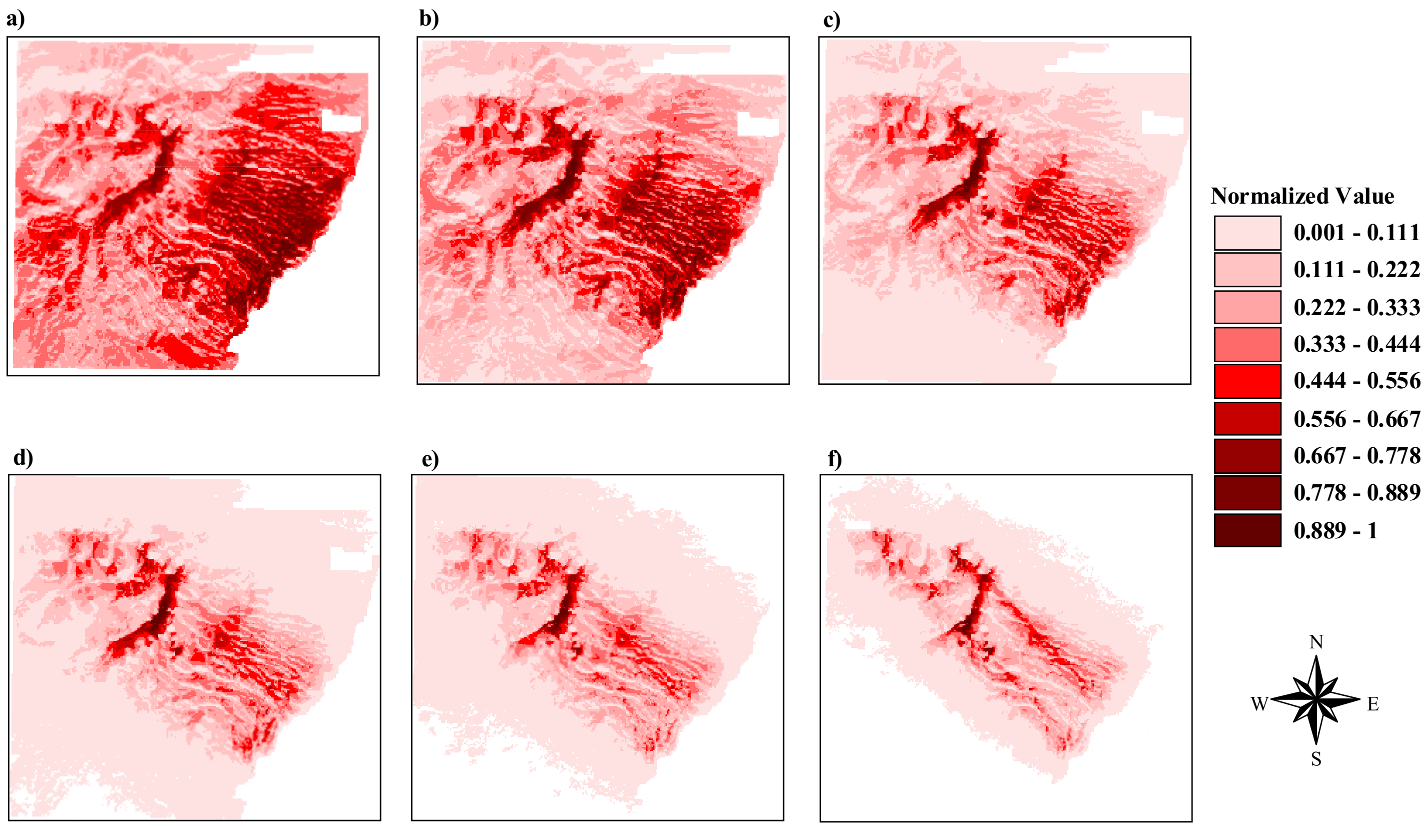

Figure 4.5. The effect of the force variable on the modeling of "Habitual Behavior/Memory" using 10,000 simulated animals, no "tag backs", and no "wandering": a) No force applied, b) 0.01 force applied, c) 0.025 force applied, d) 0.05 force applied, e) 0.1 force applied, and f) 0.25 force applied. As force increases, the overall patterns constrict and the paths of highest use become more linear. Normalized values are based on a maximum value of 10,000 potential animal observations/cell.

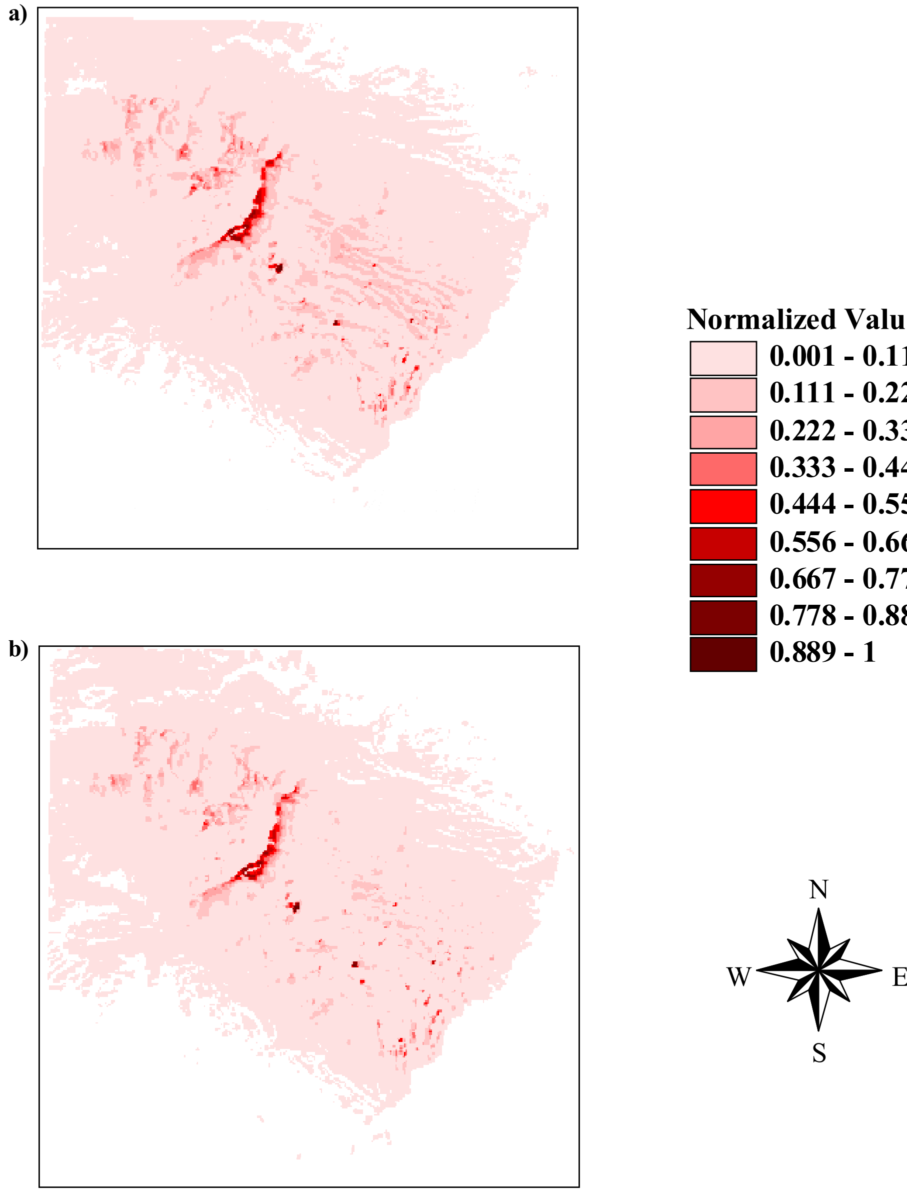

Figure 4.6. The effect of the “wandering” and “tag back” flags on the modeling of “Habitual Use/Memory” using 10,000 simulated animals. When “wandering” was turned on, simulated animals were counted every time they returned to a cell. When “tag backs” was turned on, simulated animals could immediately return to the cell from which they just departed: a) “Tag backs” turned on, but no wandering, b) “Wandering” turned on, but no tag backs. The effect of using the “tag back” and “wandering” options did not result in very realistic patterns based on actual observations and neither option was used in the creation of the final version of the habitual use/memory variable.

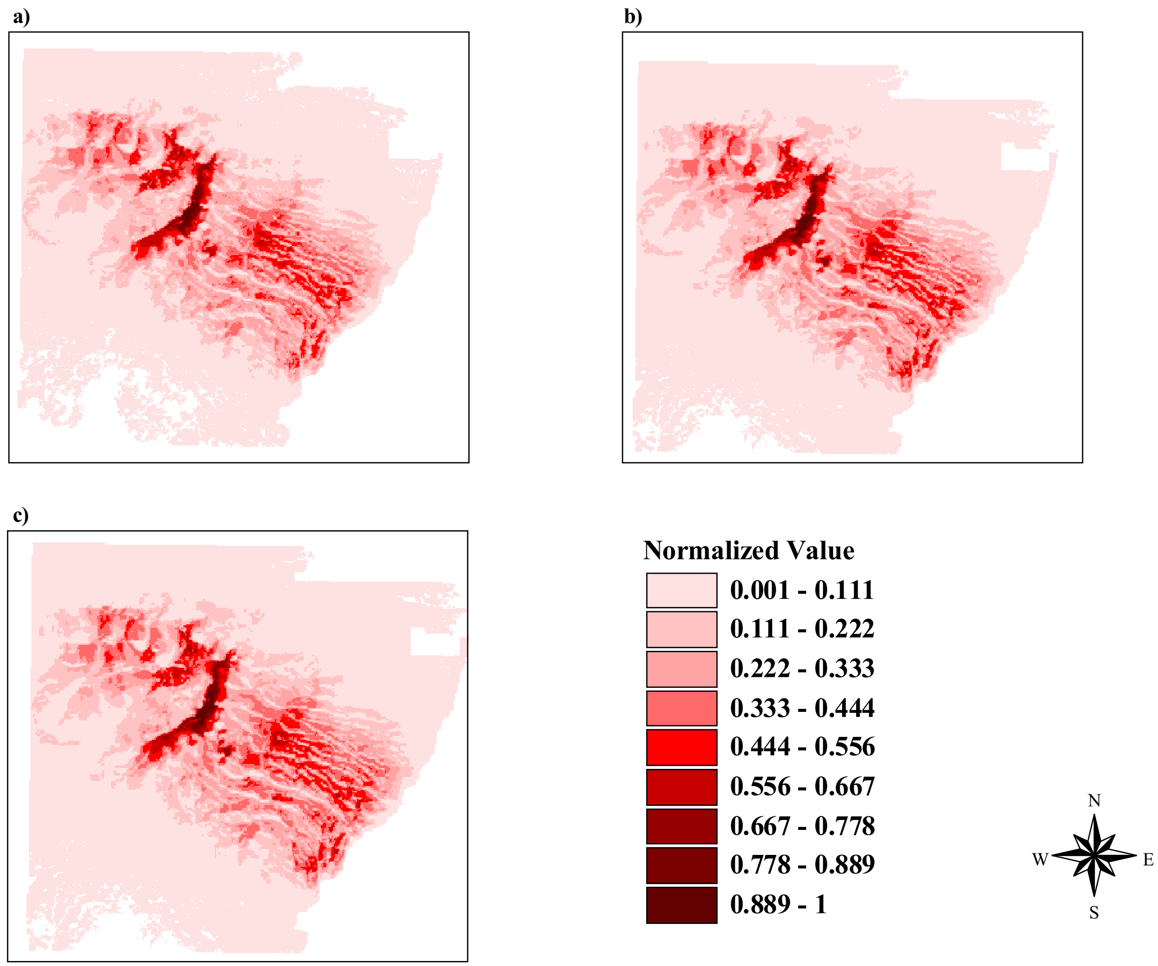

Figure 4.7. The effect of total numbers of simulated animals on the modeling of "Habitual Use/Memory" using no tag backs and no wandering at a force of 0.05: a) 1000 individuals b) 10,000 individuals, and c) 50,000 individuals. The addition of animals did not change overall patterns much, but resulted in a sharper image. The model using 50,000 animals was chosen as the final model.

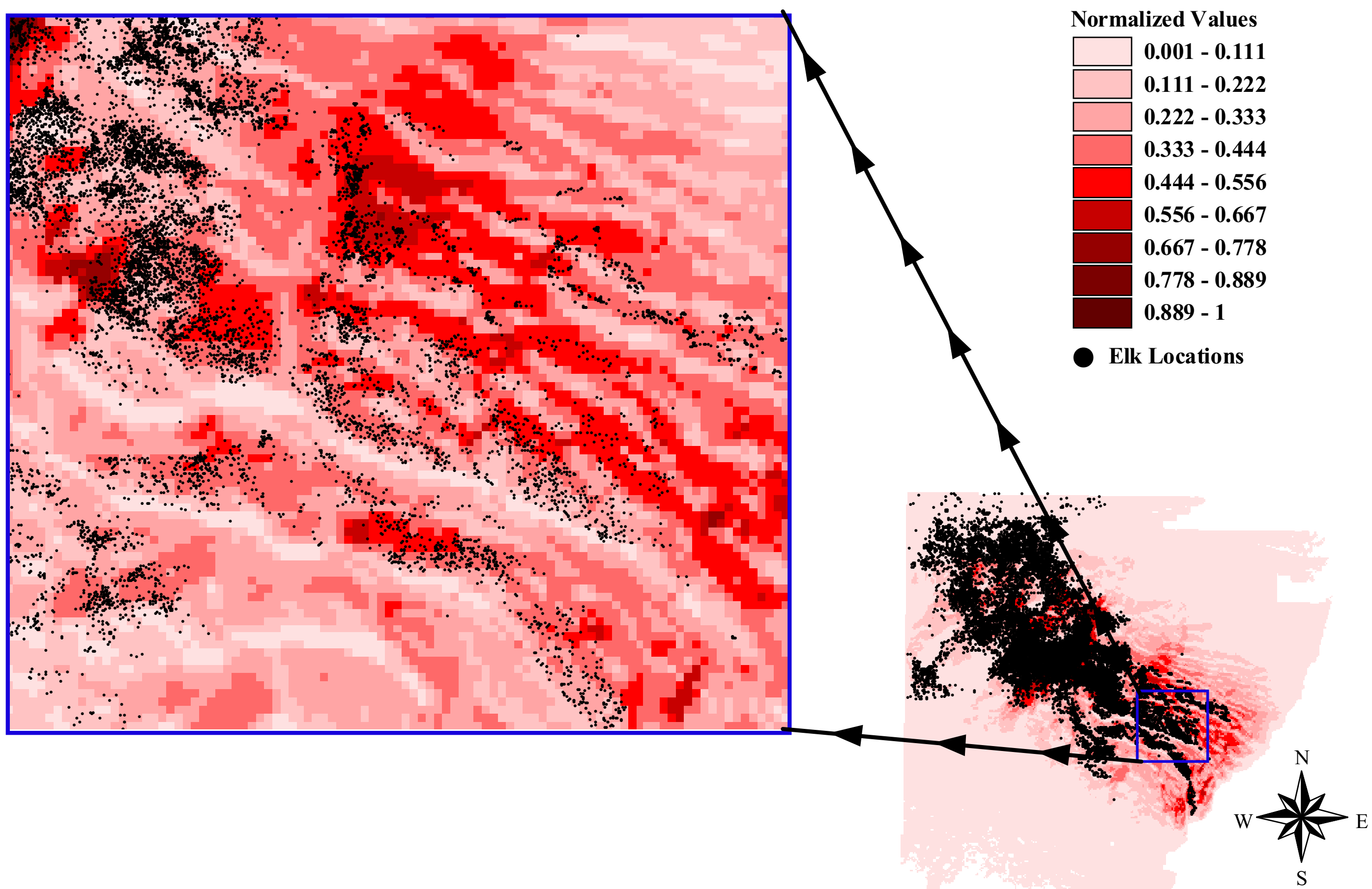

Figure 4.8. The final version of the "Habitual Use/Memory" model used in the individual-based model. Actual locations from the 10 elk used in model development are overlaid on the resultant map. The simulation run used 50,000 animals, a minimal force of 0.05, no "tag backs", and no "wandering." Maximum values for each cell were therefore 50,000 observations, but the final map was normalized from 0 to 1 with values nearest to 1 representing those cells with highest "memory." The memory variable only took effect in the final IBM when snow depth exceeded a minimum value, but was not so high as to exclude animals from a cell.

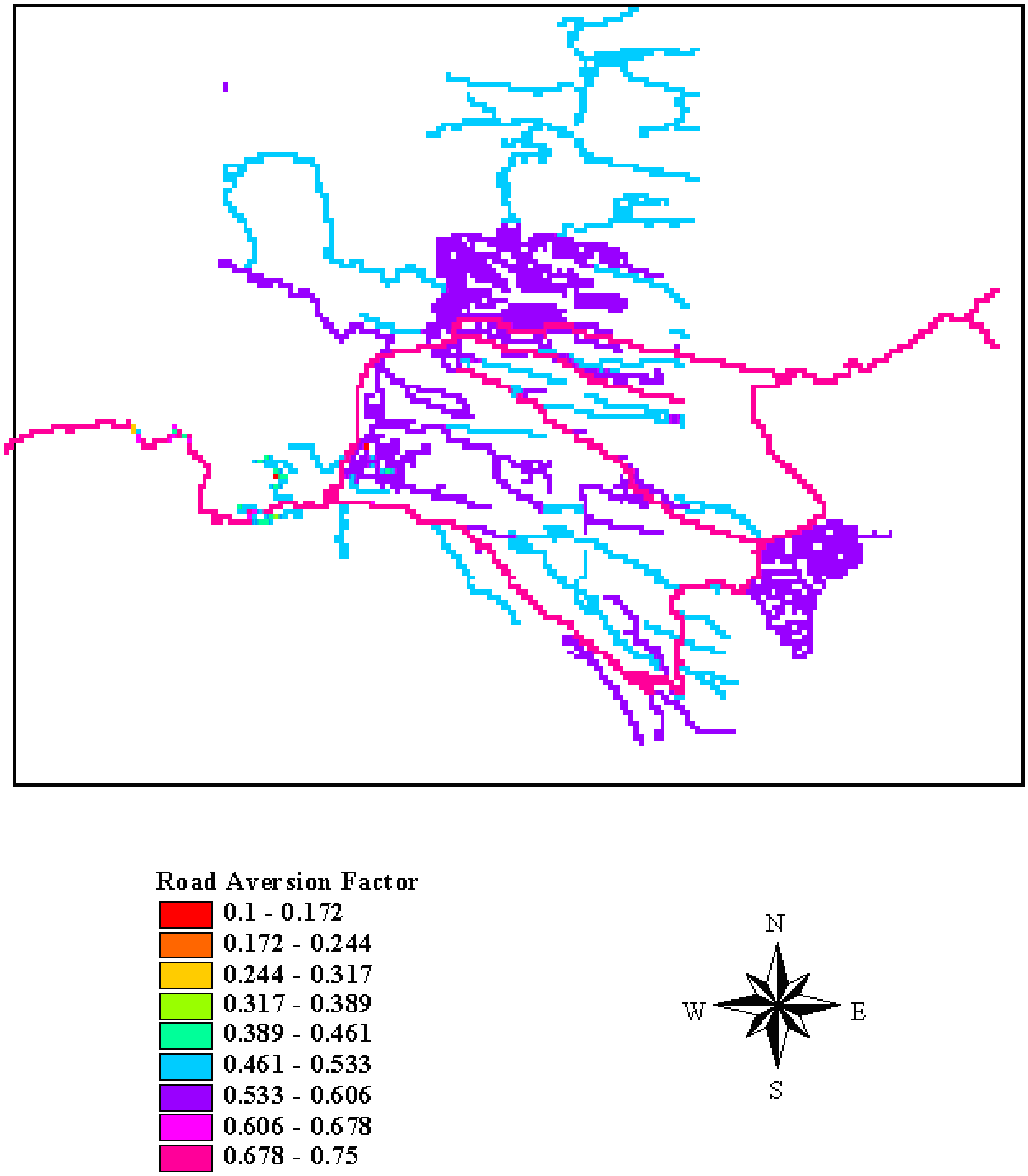

Figure 4.9. Example of final road aversion map used in the IBM. Lower values represent cells with a higher combination of elk locations and potential road crossings, which are more likely to be used by elk as the traverse the Jemez Mountains.

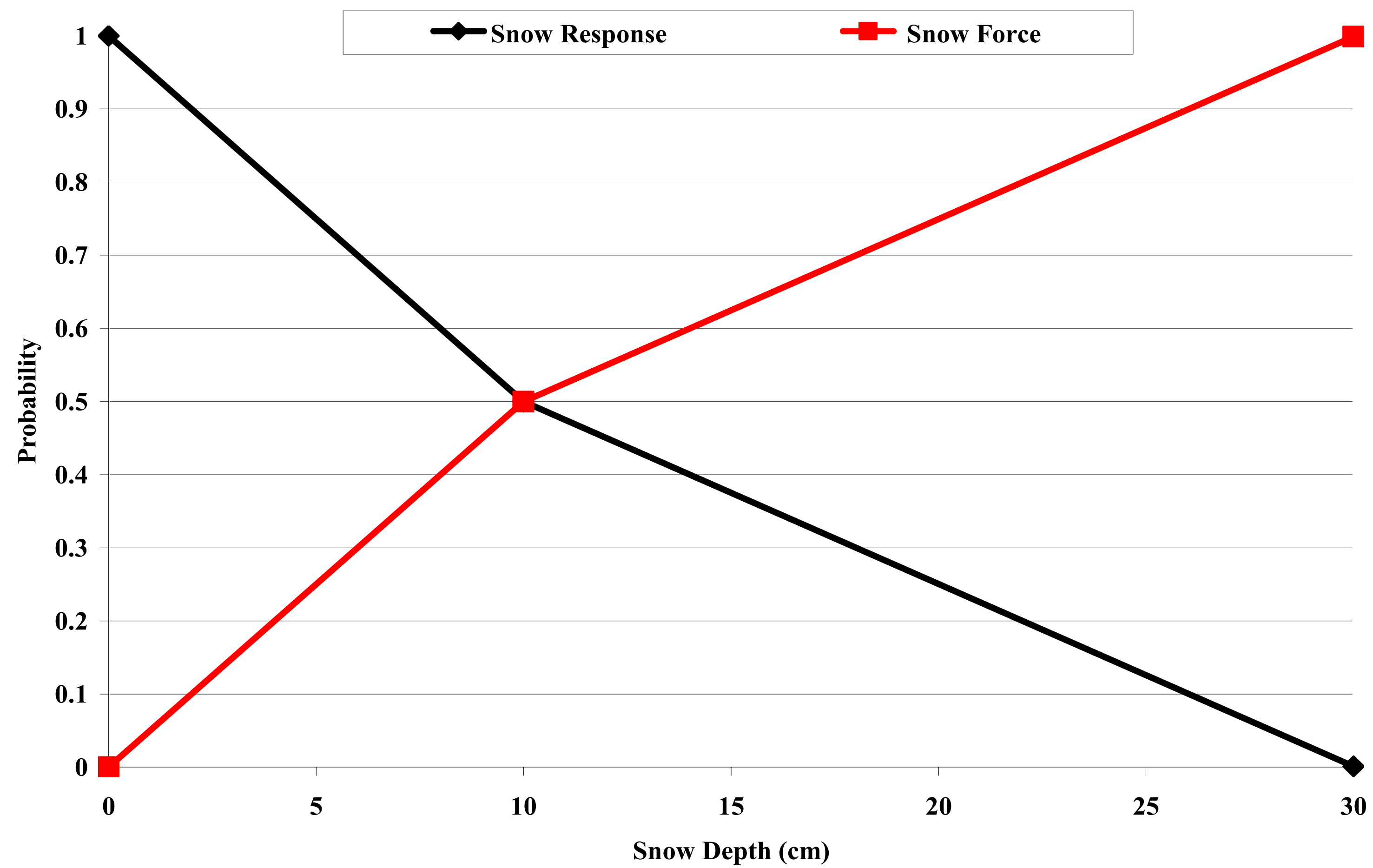

Figure 4.10. Linear interpolation function used to define elk response to snow depth (cm). Elk response (black line) to snow was used to modify HSI values while the inverse (red) was used as a force applied to the memory map in the direction of the wintering grounds.

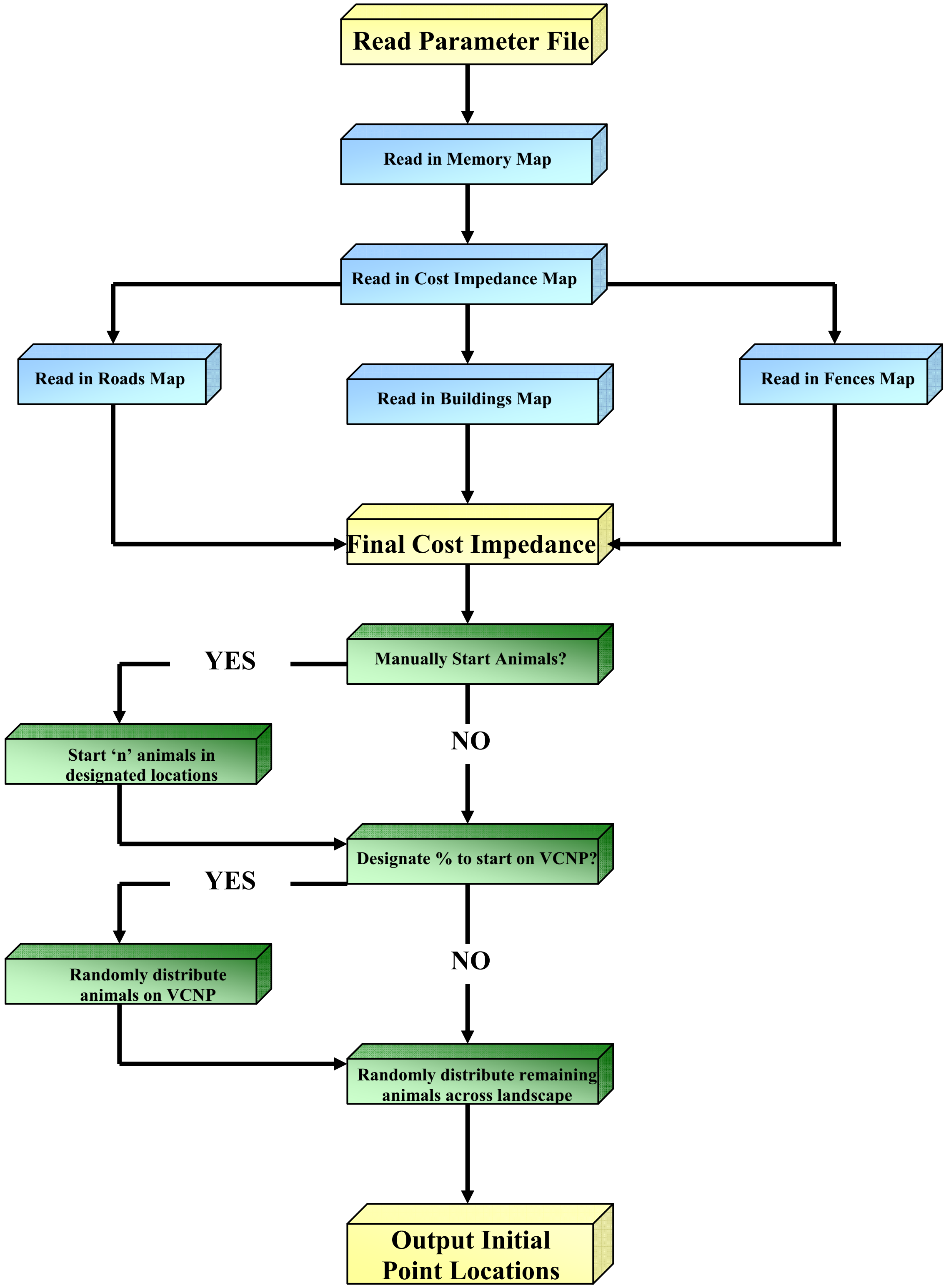

Figure 4.11. Initialization routine for the individual-based movement model.

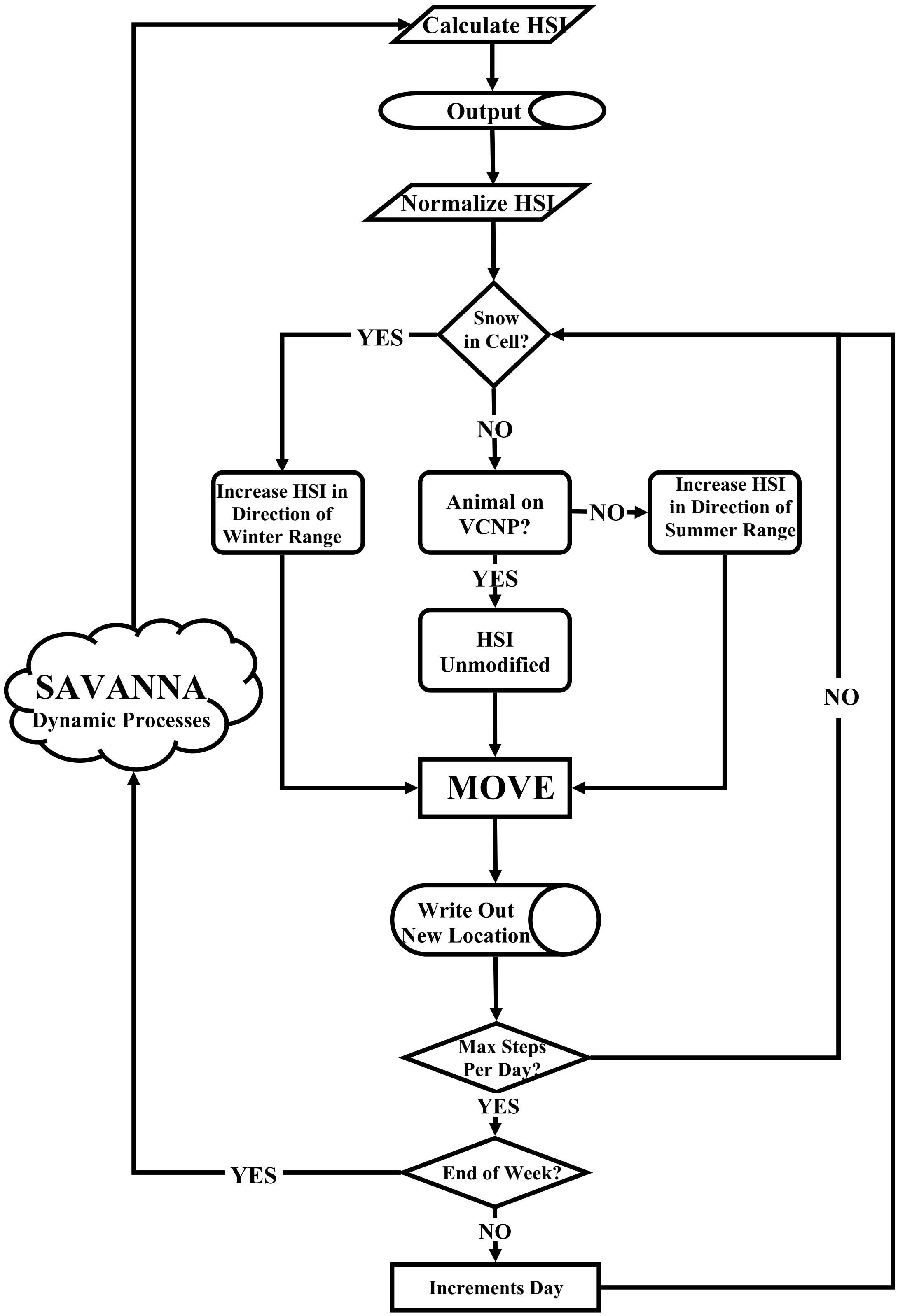

Figure 4.12. Decision tree for the individual-based movement model. At the end of each move, the total elk count in a cell is either decremented or augmented accordingly.

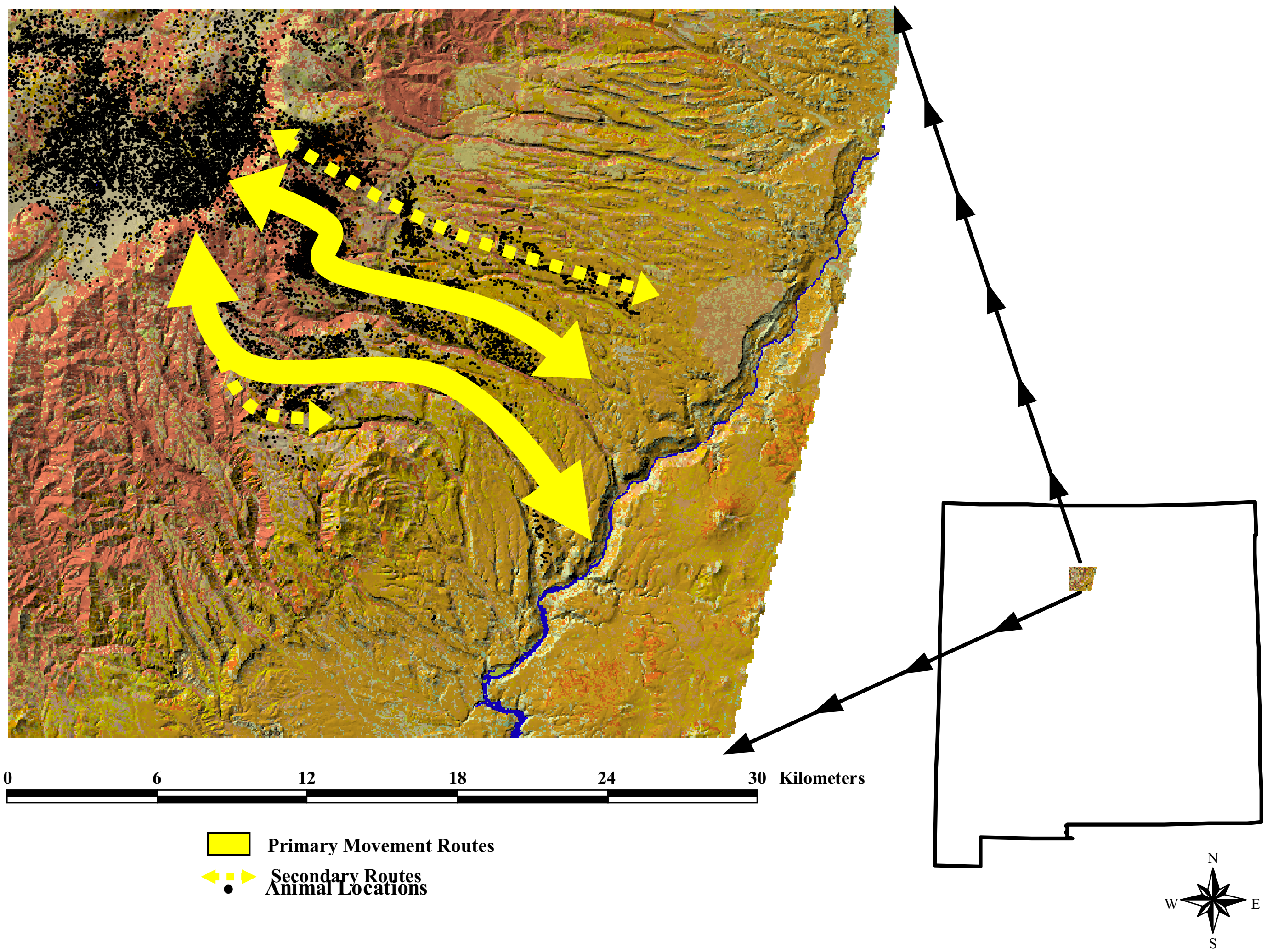

Figure 4.13. Identification of primary and secondary movement routes across the east Jemez Mountains based on 10 GPS-collared animals. Primary routes were used by ≥ 4 animals and secondary routes were used by ≤ 2 animals.

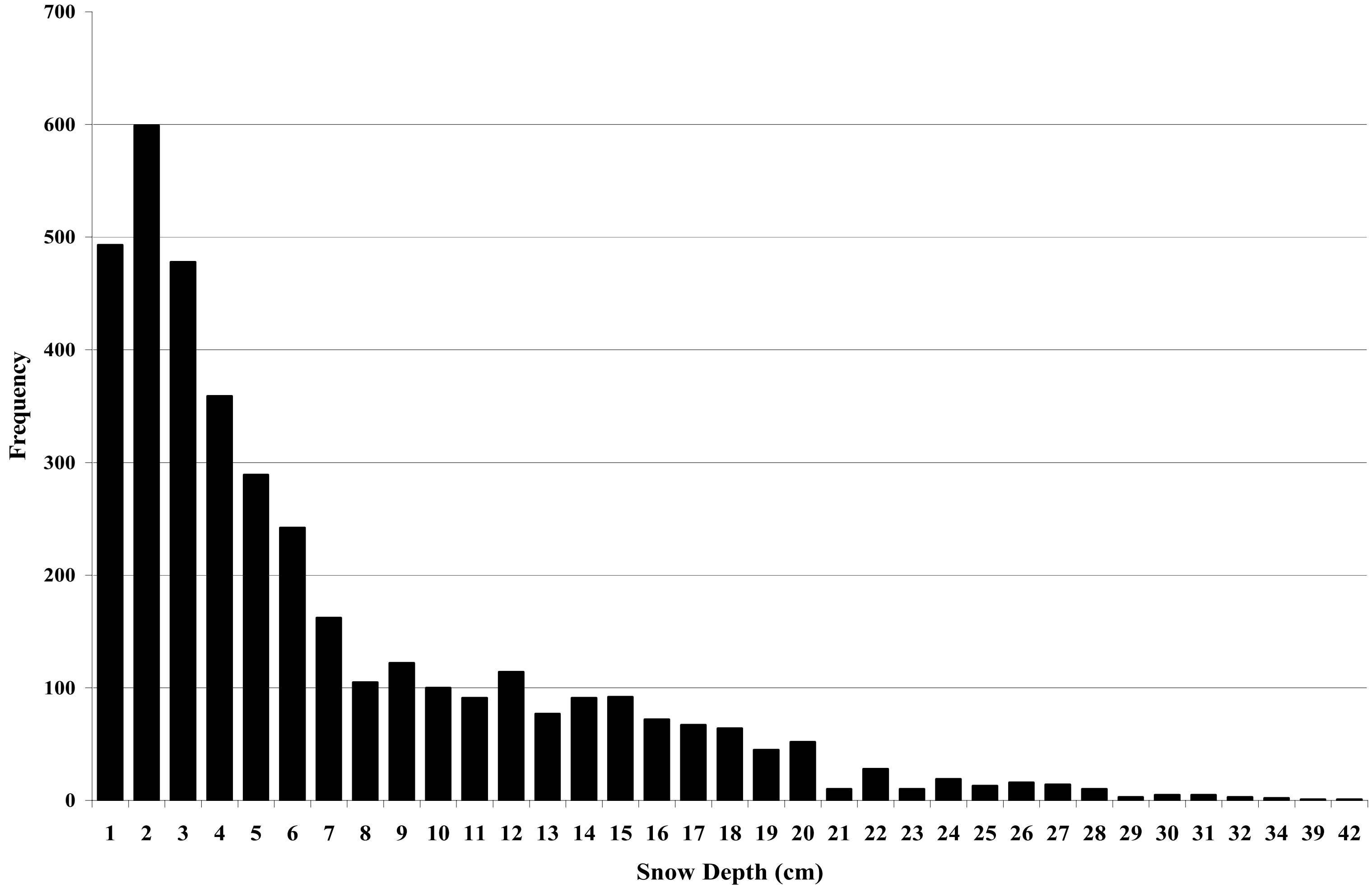

Figure 4.14. Frequency of elk occurring on ≥ 1 cm snow based on 10 animals used in model development. Mean monthly snow depth (cm) was interpolated using an internal function in the SAVANNA Ecosystem Model and actual locations of elk were superimposed on resultant maps by month. Over 68% of elk were found on cells free of snow (i.e., snow depth = 0).

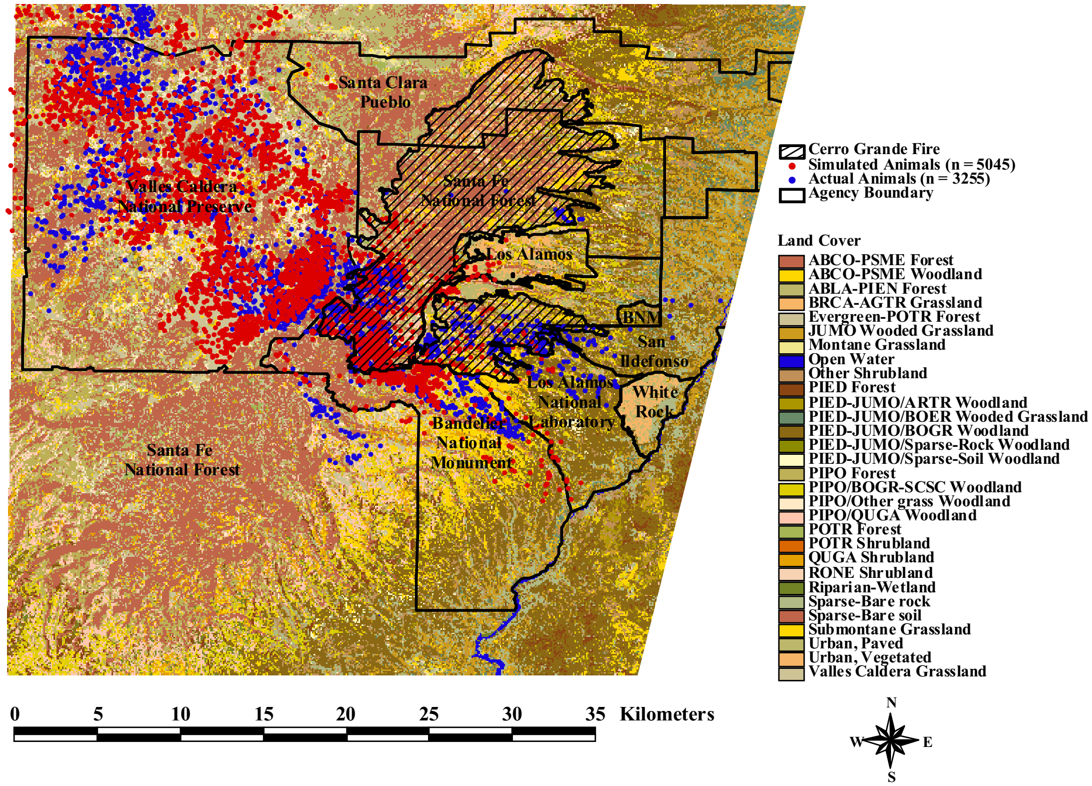

Figure 4.15. Daily locations for simulated and real animals during the time period of January/February 2001 through February 2004. A single simulation run was conducted with a total elk population of 3,500. Starting locations for simulated animals (n = 5) were matched with the capture location for the corresponding real animals (n = 5). Total numbers of locations between simulated (n = 5045) and real (n = 3255) animals differ due to missing GPS locations for the real animals. Aside from stochastic behaviors, overall patterns of habitat use between simulated and actual animals match fairly well and indicate no substantial errors in model performance. Additional simulation runs were essentially the same, which further validates model results. Acronyms for land cover types are found in Appendix B.

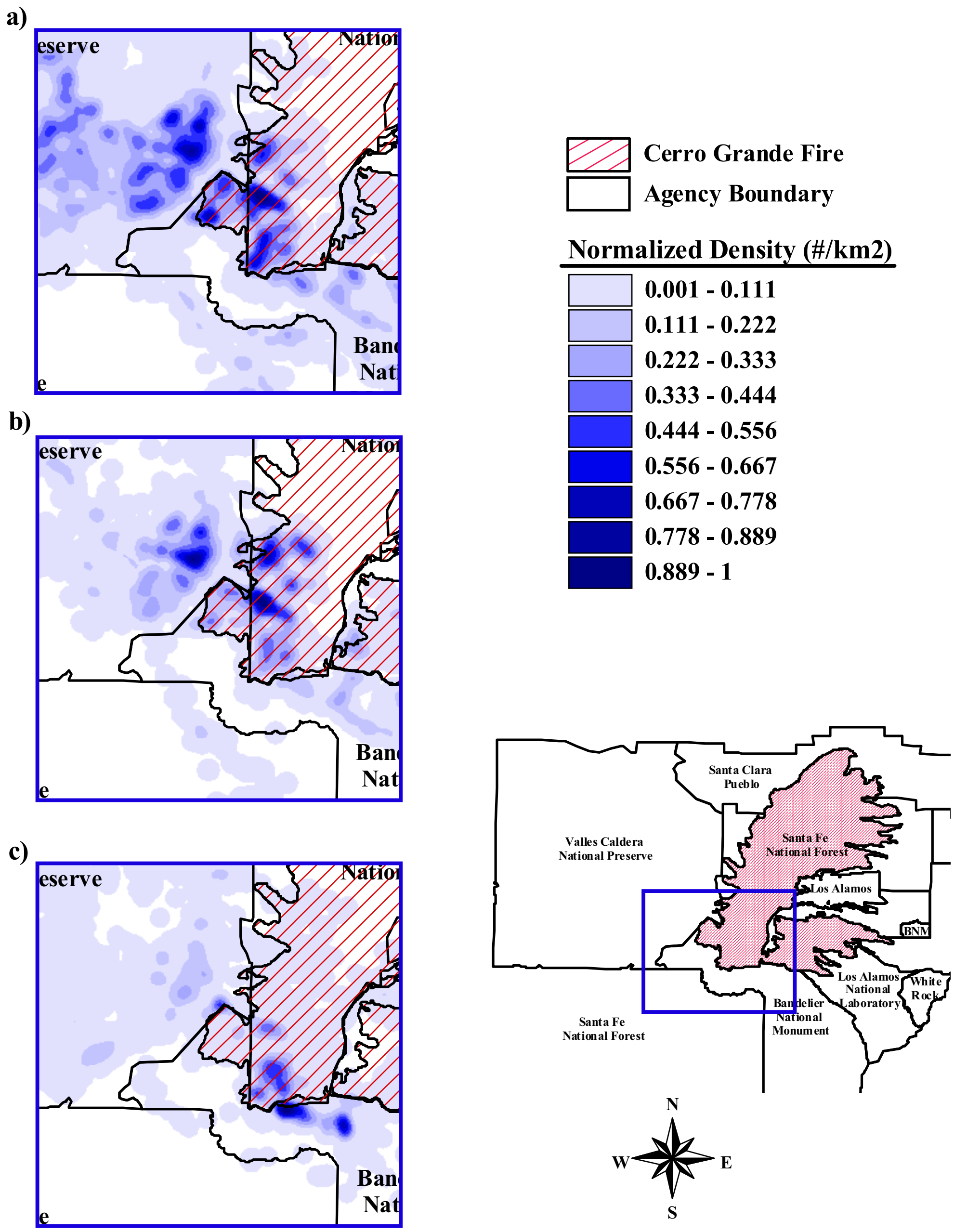

Figure 4.16. Normalized density (number/km^2) for the ten animals used in model development (a), the 5 independent test animals used in validation (b), and 5 animals generated through a single simulation run (c). Though simulated animals exhibited similar habitat-use patterns, densities were higher just south of the Cerro Grande burn area and not as high in the southeast portion of the Valles Caldera National Preserve. Differences in density patterns, especially in areas burned by the Cerro Grande Fire, may be due to stochasticity in simulation runs, decreased resolution of the underlying land cover map, or movement rules related to topography.

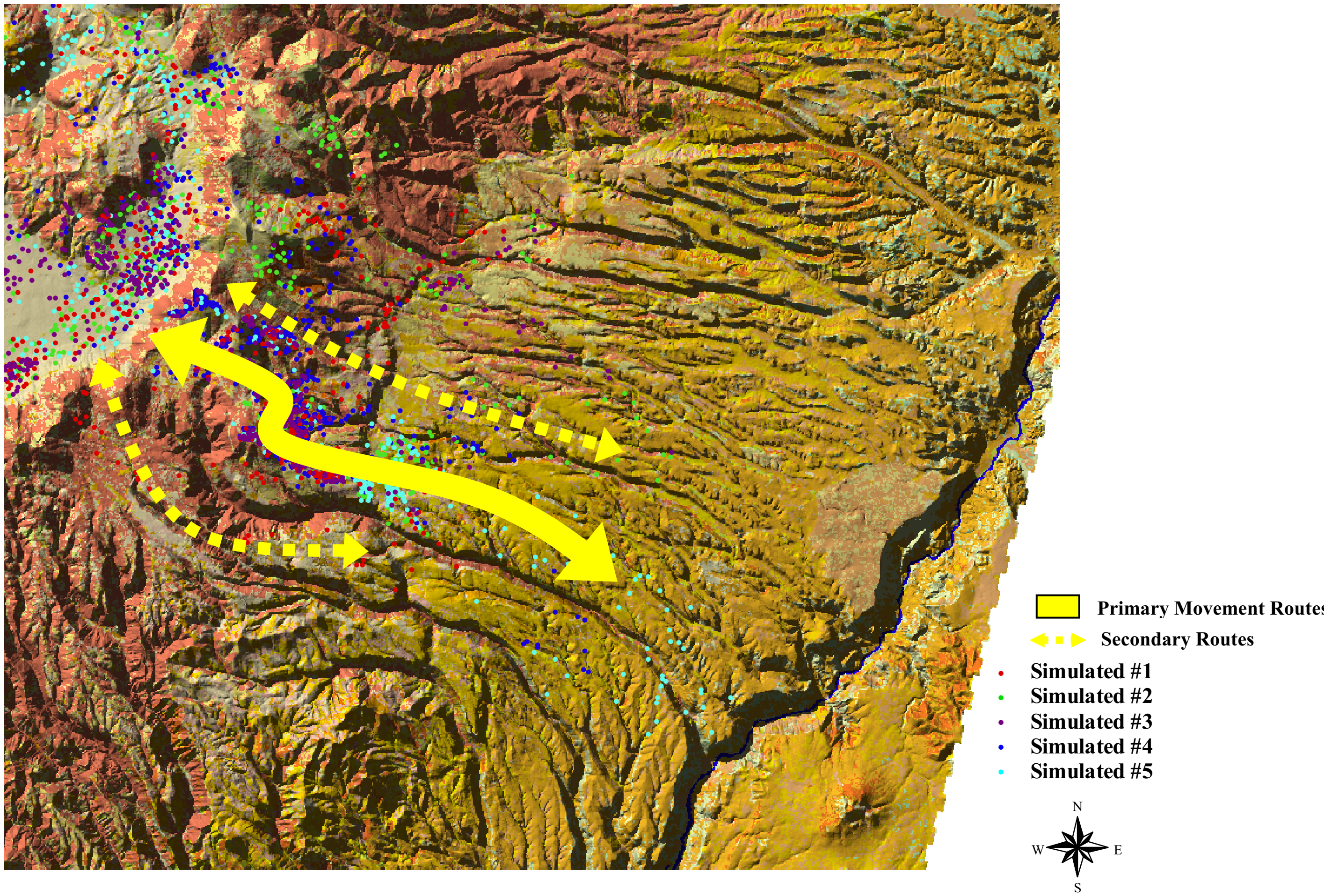

Figure 4.17. Movement pathways of 5 simulated animals used in validation revealed use of 3 of the 4 pathways identified during model development. The southernmost route did not correspond to the independent test animals, but fell within a primary corridor identified during model development. The primary movement route was used by 4 of 5 simulated animals and secondary routes were used by ≤ 2 animals. The goal of model validation was to recreate pathways in roughly the same proportions used by real animals and that was accomplished.

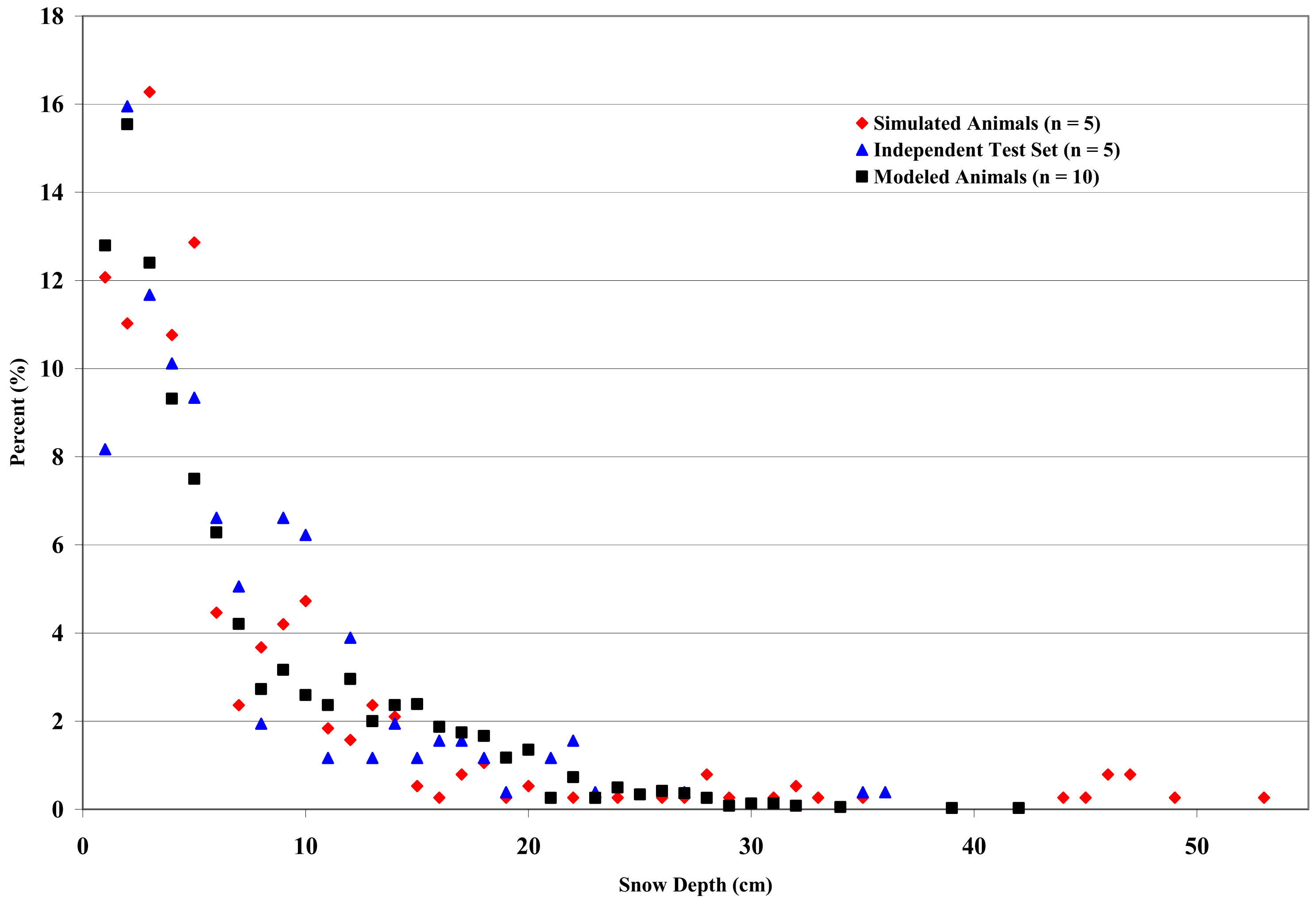

Figure 4.18. Percent of elk locations for snow depths ≥ 1 cm for simulated animals compared to an independent test set as well as animals used in model development. Overall patterns of use were remarkably similar.

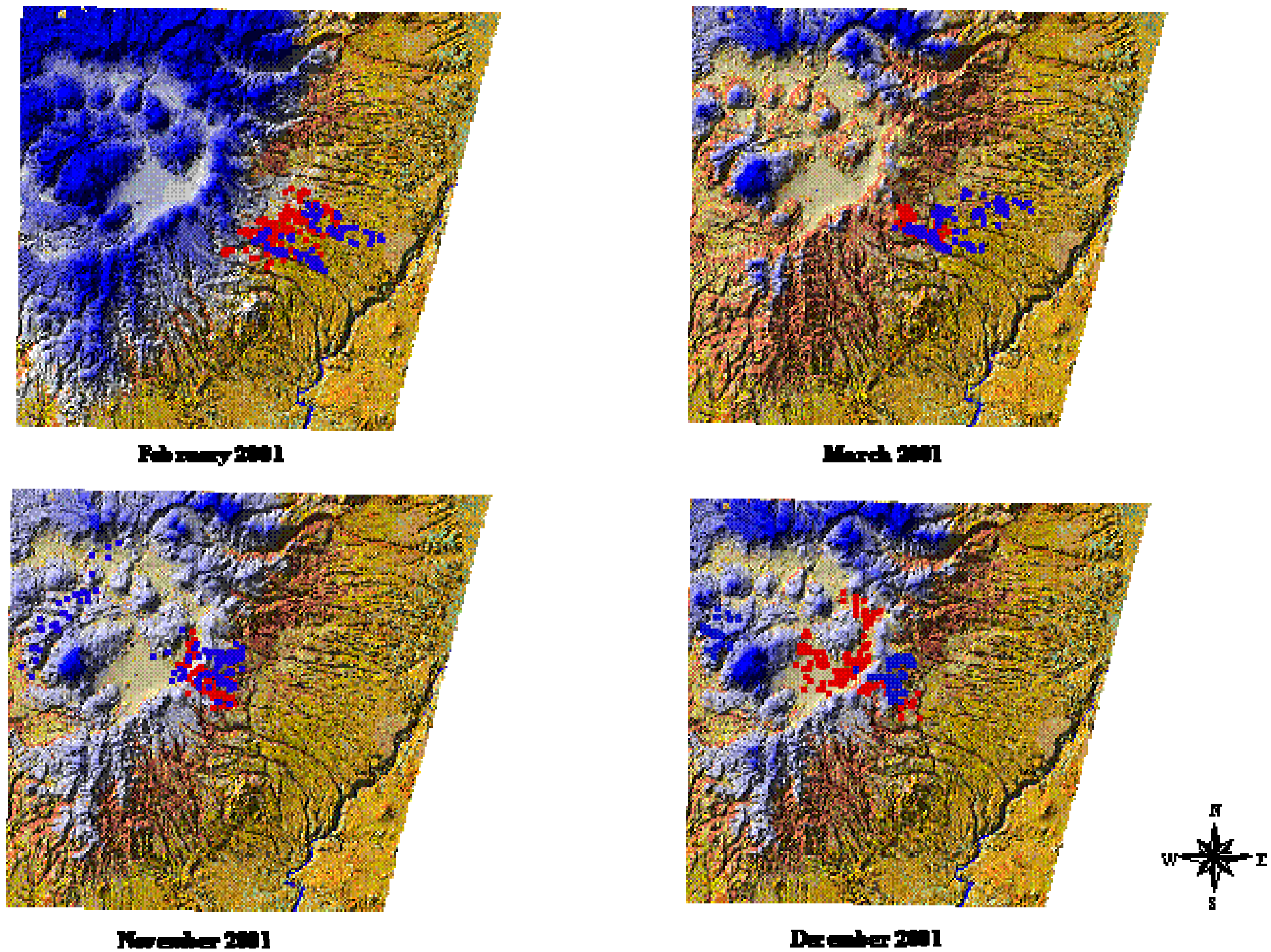

Figure 4.19. Response of animals to periods of snowfall. Shown are mean monthly snow depths (cm) for February, March, November, and December 2001 – the wettest year of the study period. Darker shades of blue indicate more snow. Simulated animals (red) appear to respond realistically when compared to an independent test set (blue) with the exception of some random variation in both populations. Differences in December are likely due to the "instantaneous" production of snow by the SAVANNA Ecosystem Model, which resulted in simulated animals remaining on the Valles Caldera.

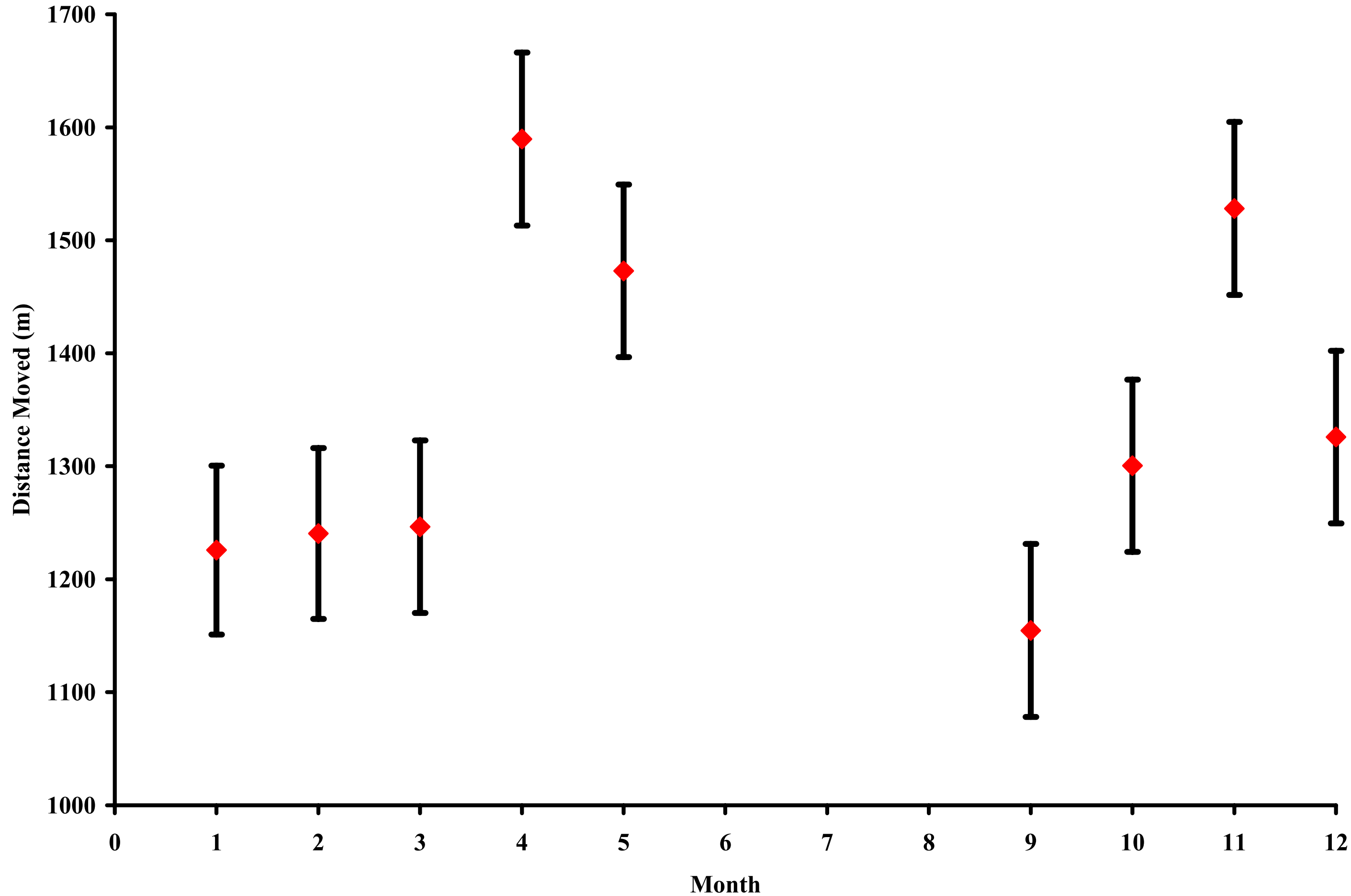

Figure 4.20. Mean daily movement (m) and associated standard errors by month for the 10 animals used in model development. Patterns indicate increased movement activity in April/May and November, which may be tied to pre-calving behavior and hunting activity, respectively. Such patterns were not modeled in the current IBM, but will drive future model development.

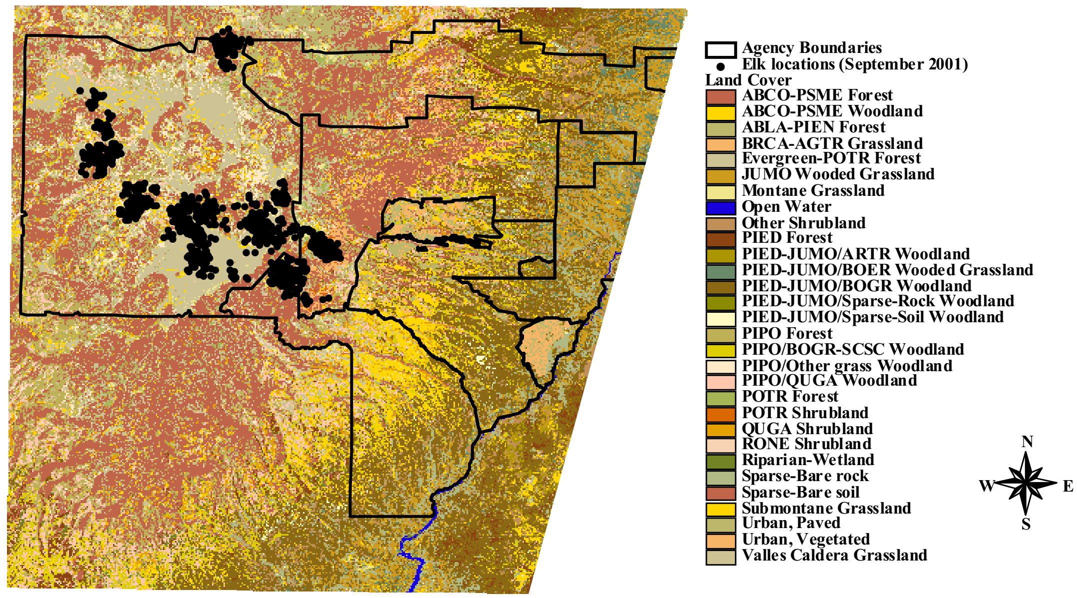

Figure 4.21. The individual-based model was not designed to capture behavior seen by animals during the rutting season when animals typically form harem groups as seen in this map of animal locations from September 2001. Acronyms for land cover types are listed in Appendix B.

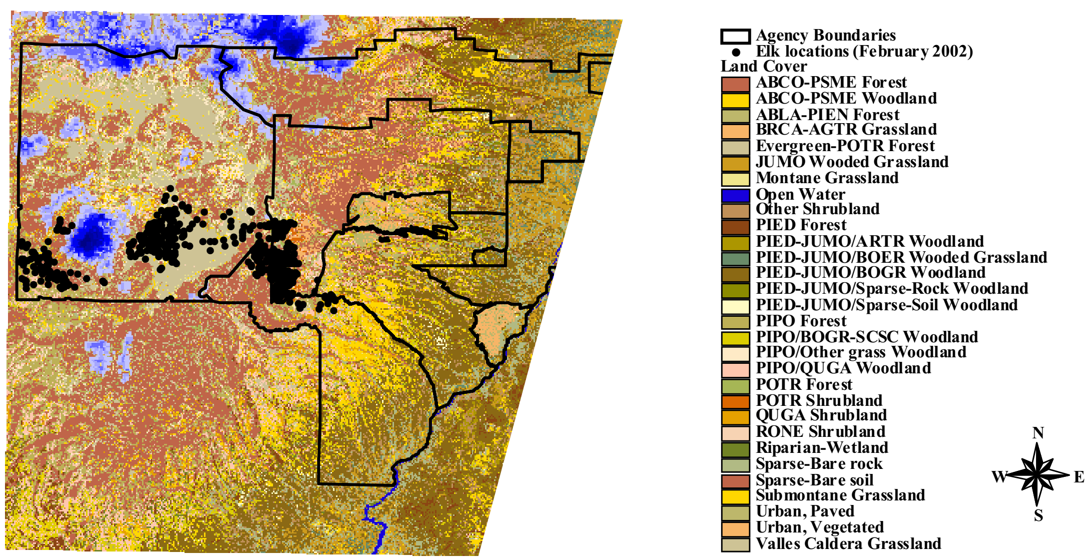

Figure 4.22. Animals congregated during colder months in which there was little snow. Shown are all animal locations for February 2002. Snow cover is depicted in shades of blue and ranges from 0 (lighter) to 57 cm (darker). This pattern of behavior was not sufficiently captured by the individual-based model and deserves further consideration. Acronyms for land cover types are listed in Appendix B.

CHAPTER V

APPLICATION OF AN INDIVIDUAL-BASED MODEL TO ASSESS ELK *(Cervus elephus nelsoni)* MOVEMENT AND DISTRIBUTION PATTERNS FOLLOWING THE CERRO GRANDE FIRE

Introduction

In early May 2000, the Cerro Grande Fire (CGF) in northcentral New Mexico burned approximately 17,200 ha and 400 residences in the town of Los Alamos. The fire was the result of an escaped prescribed burn initiated at Bandelier National Monument (BNM) to reduce unnaturally high fuel loads resulting from decades of fire suppression. National Park Service (NPS) policy states that rehabilitation guidelines for newly burned areas will be implemented to mitigate short- and long-term detrimental consequences of severe wildland fires (National Park Service 2001). The specific goal of this policy is to prevent further degradation of resources following wildland fire, and mitigate threats to life, property, and natural and cultural resources. This cannot be achieved without sound, scientific research that evaluates the effects of large-scale fires on landscape succession and ecosystem recovery. The recent Cerro Grande Fire, coupled with the region's unique interagency collaborations, presents a rare opportunity to study the long-term ecological consequences of large-scale fires through the use of simulation modeling.

It is generally believed that fire increases biomass, nutritional quality, palatability, and digestibility of forage species consumed by elk (Peck and Peek 1991, Stein et al.

1992, Bartos et al. 1994, Tracy and McNaughton 1997) and, as a consequence, elk should prefer burned over unburned habitats (Rowland et al. 1983, Brown et al. 2000). However, many of these studies reflect effects of small-scale or prescribed burns: few studies detail the effects of extensive fires on ungulate populations due to the infrequent nature of such events. Despite the lack of information, it is certain that large-scale wildfires influence the availability of habitat patches and change landscape heterogeneity and habitat connectivity (Brown et al. 2000), which affects the distribution and movement patterns of ungulates.

The effect of large-scale fires on elk has not been adequately investigated. Norland et al. (1996) studied the short-term effects of the 1988 Yellowstone fires on elk habitat use, forage biomass and quality, willow production, and snow characteristics in key elk habitats. Summer habitat use was indexed through the use of pellet groups and winter use was indexed through elk feeding craters in the snow. No differences were found in either summer or winter use between burned and unburned sites, suggesting that elk use/behavior had not changed in response to the fire. In contrast, Singer and Harter (1996) found elk avoided burned forests during the first three winters post-fire, possibly in response to deeper, denser accumulation of snow and reduced forage biomass. However, both the Singer and Harter (1996) and Norland et al. (1996) studies stated that elk use of burned areas may increase as post-fire succession takes place. Other studies also support this conclusion (Pearson et al. 1995, Tracy and McNaughton 1997) with reported preferential use of burned grasslands in Yellowstone's northern range 3 to 4 years post-fire. In addition, habitat use in the former studies was evaluated through the use of indices and observational counts. The use of such indices as a measure of elk behavior or habitat use is debatable (Collins et al. 1978, Leopold et al. 1984) and no longer adequate given the advanced technology that is available through radio collar devices and more expensive and accurate global position system (GPS) devices.

The eastern Jemez Mountains of northcentral New Mexico are not new to the impacts of large-scale fires. In the last 30 years the Jemez Mountain region has experienced 4 major fires – the La Mesa fire in 1977, the Dome fire in 1996, the Oso fire in 1998, and the Cerro Grande fire in 2000. Of these, the most prominent fires were the La Mesa and the Cerro Grande burning 6,180 and 17,200 ha, respectively. These fires were centered in areas of dense, monotypic ponderosa pine forests, which, in the case of the earlier fires, were converted into a more productive and diverse mosaic of grassland, shrubland, and forests. It is believed such conditions may have contributed to population increases in the regional elk herd, which has previously been estimated to have an annual growth rate of 21.3% and doubling time of 3.6 years (Allen 1996).

The purpose of this chapter is to apply a spatially explicit, stochastic, individual-based model (IBM) and assess its use as a flexible, cost-effective adaptive management tool following the Cerro Grande Fire. Efforts will be made to evaluate changes in movement and distribution patterns of elk in relation to spatial and temporal aspects of the fire under two potentially realistic model scenarios given elk dynamics and management concerns in the Jemez Mountains. Pattern-oriented analysis following methods outlined in Chapter 4 will be used to assess changes in movement and distribution from baseline conditions. Management implications as a result of changes in movements and distributions based on simulated conditions projected by the model will be discussed.

Study Area

Los Alamos National Laboratory (LANL) is situated on the eastern edge of the Jemez Mountains in north-central New Mexico along the Pajarito Plateau – an area formed by an ash flow of volcanic activity about 1.4 million years ago (Wilcox and Breshears 1994). LANL covers 112 sq km (43 sq mi) and is approximately 120 km (80 mi) north of Albuquerque and 40 km (25 mi) west of Santa Fe (Bennett et al. 1997). It is bordered by Bandelier National Monument to the southwest, Santa Fe National Forest to the northwest, San Ildefonso Pueblo to the east, and Santa Clara Pueblo to the north. In addition, the federal government recently purchased 37,200 ha of private land that contains the Valles Grande – an ancient caldera grassland that serves as the primary summering ground for the region's growing elk population.

The territory is topographically complex ranging in elevation from 1,631 m near the Rio Grande to 3,199 m at the crest of Sierra de los Valles (Balice et al. 2000) and is transected by a series of smaller canyon systems and mesas making the terrain rough and virtually inaccessible in some places. Five main vegetative associations have been described (Foxx et al. 1999). Pinyon-juniper grassland is found along the Rio Grande on the eastern border of the plateau and extends upward on the south-facing sides of canyons between 1,700 and 1,900 m. Elevations between 1,900 and 2,100 m are characterized as pinyon-juniper woodland, which include moderate stands of pinyon pine *(Pinus edulis)* and one-seed juniper *(Juniperus monosperma)* with understory shrubs of wavy leaf oak *(Quercus undulata),* Apache plume *(Fallugia paradoxa),* and mountain mahogany *(Cercocarpus montanus)*. Ponderosa pine communities range in elevation from 2,100 to 2,300 m and are characterized by an overstory of ponderosa pine *(Pinus ponderosa)* and understory of Gambel oak *(Quercus gambelii),* New Mexican locust *(Robinia neomexicana),* and mountain mahogany. Typical grasses in the transitional zone include mutton grass *(Poa fendleriana),* June grass *(Koeleria cristata),* and mountain muhly *(Muhlenbergia montana)*. Mixed-conifer, at an elevation of 2,300 to 2,900 m, has a variety of overstory species that include Douglas fir *(Pseudotsuga menziesii),* white fir *(Abies concolor),* blue spruce *(Picea pungens),* and quaking aspen *(Populus tremuloides)*. Gambel oak, rock spirea *(Holodiscus dumosus),* and waxflower *(Jamesia americana)* are typical understory shrubs and slender wheatgrass *(Agropyron trachycaulum),* Canada bluegrass *(Poa compressa),* Parry oatgrass *(Danthonia parryi),* and blue grama *(Bouteloua gracilis)* are common grasses in the mixed-conifer zone. Subalpine grasslands are found at elevations of 2,900 to 3,200 m and are characterized by intermittent stands of spruce-fir.

The Jemez Mountain region has a temperate, semi-arid mountain climate that is strongly influenced by elevation. Average annual precipitation on the Pajarito Plateau is 330 to 460 mm (Davenport et al. 1996, Wilcox et al. 1996) of which about 45% occurs in July, August, and September. Average daytime temperatures range from 32.2^{o}C in the summer (max. = 41.1^{o}C) to -9.4^{o}C in the winter (min. = -30.6^{o}C).

Methods

In traditional field ecology, hypothesis testing is typically accomplished by creating several replicates of ≥ 2 treatments in which 1 or more independent variables are manipulated and then analyzed for significant differences among treatments. The same approach can be used to analyze an IBM: treatments (a.k.a. "scenarios") are different versions of the IBM in which ≥ 1 independent variable(s) are manipulated and replicates are generated via stochastic events in the IBM (Grimm and Railsback 2005). However, traditional hypothesis-testing statistics are often inappropriate to analyze IBM scenarios (see "Discussion," Chapter IV). An alternative approach is followed here, whose first (and sometimes sufficient) step is to present the degree of difference among scenarios using visual observation techniques and pattern-oriented analysis (Rykiel 1996, Grimm and Berger unpub. rep., Grimm and Railsback 2005).

Model Scenarios

It is clear that an infinite numbers of possible scenarios could be created through the collective manipulation of 1 or more independent variables and/or parameters in the individual-based model or the underlying successional model (SAVANNA – see Chapter 3). In this chapter, an attempt at simple, yet realistic, applications was pursued. Selection of model scenarios arises from a comprehensive understanding of elk biology and issues faced by managers in the Jemez Mountains.

In 1948, the New Mexico Department of Game and Fish (NMGF) released 21 cows/calves and seven bulls imported from Yellowstone National Park into the Jemez

Mountain region (Allen 1996). Since then, it is believed that the population has exhibited an exponential increase, partially in response to the 1977 La Mesa fire when thousands of hectares of wintering range were created (Wolters 1996). By 1997, management of the elk herd in the Jemez Mountains had become controversial enough that the New Mexico Department of Game and Fish increased the number of elk licenses in the region, reducing the population by 30% within 2 years (Kirkpatrick et al. unpub. rep.).

Since 1999, sightability surveys have estimated the Jemez Mountain elk population to be roughly 3,500 to 5,000 animals (Kirkpatrick et al. unpub.rep.). The potential for an increase in the Jemez Mountain elk population remains a management concern. Studies estimated an annual population growth rate of 21.3% and doubling time of 3.6 years (Allen 1996) for the region. Other studies have also reported annual growth rates of elk exceeding 20% (McCorquodale et al. 1988). Local residents of Los Alamos and White Rock report an increased number of elk/vehicle accidents on roads (Parker 1997). About 70% of Bandelier's cultural resources are being damaged by erosion (Allen 1996) and there is concern that elk impacts to the area may accelerate erosion due to excessive trampling and loss of herbaceous cover resulting from grazing (Rupp et al. 2001a,b).

An obvious application of the IBM developed in this research, therefore, is to evaluate possible changes in elk movement and distribution following the Cerro Grande Fire in conjunction with a potential increase in the population. Individuals will likely respond to an increase in the population in one of two ways: 1) they will exhibit increased tolerance for their intraspecific counterparts by increasing the number of animals per unit area, or 2) they will limit their number per unit area in response to increased intraspecific competition resulting in different disbursal patterns. Given plant response to defoliation is partially defined by the intensity (amount of plant material removed) and frequency (the number of times a plant is defoliated) of use which, in turn, affects both the quality and quantity of forage produced (Motazedian and Sharrow 1990), these two scenarios may substantially impact successional processes following the Cerro Grande Fire and affect the movement and distribution patterns of elk. Two scenarios were modeled:

- *Scenario 1* - A current population of 3,500 animals assuming no population growth and no limit on the number of animals occupying a single cell.
- *Scenario 2* - An "instantaneous" doubling of the elk population to 7,000 animals and no limit on the number of animals occupying a single cell.

Though the doubling of the population to 7,000 animals appears low given the potential doubling-time reported in the region and substantiated in the literature, a conservative approach was taken under the assumption the regional population will not be allowed to increase beyond the 8,000 animals seen in the late 1980's (Kirkpatrick et al. unpub. rep.). Pressure on resources, however, will remain constant given the population will not be allowed to fluctuate.

Each scenario was run in a computer simulation for a period of 20 years beginning in June 2000 and concluding in May 2020. Animals were initialized by randomly scattering them through their summering range on the Valles Caldera National

Preserve. Maximum number of steps per day was set at 86 cells per day to (~ 13,000 m/day) to mimic the maximum observed distance moved by the 10 animals used in model development. In order to initialize vegetative processes following the fire in the most realistic way possible, actual weather data were used from June 2000 through December 2002 and random weather was initiated in January 2003. The HSI described in Chapter 4 was used without modification for the entire length of each run. Quasi-migratory behavior was triggered by the emigration of individuals from the VCNP and return to the summering ground was determined by the presence or absence of snow as outlined in Chapter 4.

Evaluation of Results

In order to properly assess potential changes in movement and distribution patterns of elk following the Cerro Grande fire, baseline conditions must first be established. The most robust measure of current behavioral conditions exhibited by the Jemez Mountain elk population arises from GPS locational data used in development of the individual-based movement model (Chapters 2 through 4). Therefore, the 10 animals used in development of the IBM will serve as the baseline conditions for animal movements and distribution immediately following the Cerro Grande Fire. Movement was assessed through analysis of primary and secondary pathways and distribution was assessed through the application of density maps.

Preliminary assessment of movement pathways revealed two primary and two secondary movement corridors used to traverse the eastern Jemez Mountains (Figure

5.1). Primary corridors had ≥ 4 of the 10 animals using them whereas secondary corridors had ≤ 2 animals using them. The role that habitual behavior plays in movement patterns has not been clearly defined (Adams 1982), but fidelity to [migratory] movement patterns appears strong (Altmann 1952, Brazda 1953, and Anderson 1958 *in* Thomas and Toweill 1982). Shifts in movement pathways as succession proceeds would, therefore, be a conspicuous behavioral response worthy of additional study and consideration.

In addition, animal densities were extremely high in the southeast portion of the Valles Caldera National Preserve and southwest portion of the area burned by the Cerro Grande Fire (Figure 5.2). It is generally believed that fire increases biomass, nutritional quality, palatability, and digestibility of forage species consumed by elk (Peck and Peek 1991, Stein et al. 1992, Bartos et al. 1994, Tracy and McNaughton 1997) and, as a consequence, elk should prefer recently burned over unburned habitats (Rowland et al. 1983, Brown et al. 2000). High densities in the southwest portion of the Cerro Grande Fire in the first three years following the fire may reflect these factors or be related to creation of edge habitat and/or focused reseeding efforts. Visual observation revealed high densities of elk along edge habitat adjoining highest burn severities where reseeding efforts were focused (Figure 5.3).

Daily movements were extracted in groups of 10 random individuals using the output program developed in Chapter 4 (Table E.8 of Appendix E) and overall patterns were subjectively analyzed to determine consistent changes in movement and distribution patterns following the 20-year run for each model scenario. One set of ten randomly-selected animals judged to best exhibit consistent overall patterns with the simulated population was chosen for analysis and discussion. Movement pathways were constructed using the Animal Movement Analyst Extension (AMAE) in ArcView 3.2a (Hooge and Eichenlaub 2000) and projected on landscape maps for a visual analysis of primary and secondary pathways as outline in Chapter 4. In addition, density maps (locations/km^2) were created and compared to baseline conditions. Cumulative annual net primary production (ANPP) and animal offtake/consumption (normalized in kg/ha) were extracted from the SAVANNA Ecosystem Model following each model run and used to further clarify changes in movement and distribution patterns. Deviation from patterns of habitat use exhibited by the 10 animals used in model development will be considered as consequences of changes in landscape conditions following the fire.

Results

Scenario 1

When no increase in the elk population was assumed and group size was not limited within individual cells, distinct changes in habitat and movement patterns in relation to spatial and temporal aspects of the Cerro Grande Fire resulted. As expected, ANPP increased in the central portion of the Cerro Grande Fire 20 years post-burn (Figure 5.4). Locations from GPS-collared animals 1-year post-fire indicated concentrated behavior along forest edges next to severely burned areas (Figure 5.3). Behavior of simulated animals 20-years post-fire also showed activity along forest edges next to areas that were severely burned, but overall distribution patterns were not as concentrated (Figures 5.3 and 5.4). Twenty years following the fire simulated animals began exploring more central portions of the burn where fire severities were at their highest, but activity was still largely limited to edges of these areas. Though not related to the burn itself, it was also noted that ANPP decreased over 20 years in the southeastern portion of the VCNP where historical elk use was at its highest.

A map of elk densities based on the 10 simulated animals corresponded with the increased activity just east of the tip of Bandelier National Monument (Figure 5.5). The region of highest density within the burn area corroborates findings based on burn severity discussed above. In addition, animals expanded northward 20 years following the fire compared to 1-year post-fire (Figures 5.2. and 5.5). Areas of increasing density also showed the highest levels of consumptive activity (Figure 5.6).

An analysis of movement pathways substantiated patterns seen in distributional behavior (Figure 5.7). Though the two primary and southern-most secondary pathways used by animals immediately following the fire continued to be used 20 years post-fire (Figures 5.1 and 5.7), a shift in activity northward resulted in the upgrading of the northern-most pathway from secondary to primary. In addition, a potential new secondary pathway emerged to the far north.

<u>Scenario 2</u>

When the elk population was doubled and group size was not limited within individual cells, distinct changes in habitat and movement patterns in relation to spatial and temporal aspects of the Cerro Grande Fire resulted but differed from those seen in

Scenario 1. Annual net primary productivity increased in the central portion of the Cerro Grande Fire 20 years post-burn (Figure 5.8), but overall production was lower in the southern-most portion of the Cerro Grande Fire when compared to *Scenario 1* (Figures 5.4 and 5.8). Behavior of simulated animals 20-years post-fire also showed activity along forest edges next to areas that were severely burned, but overall distribution patterns were less concentrated than those observed in *Scenario 1*. In addition, simulated animals explored more central portions of the burn area and moved less distance to the southeast than seen in the original population or the simulated population from *Scenario 1*. Though not related to the burn itself, it was also noted that ANPP decreased over 20 years in the southeastern portion of the VCNP as it did in *Scenario 1*.

A map of elk densities based on the 10 simulated animals corresponded with the expanding activity further north into the burned area (Figure 5.9). In addition, animals expanded northward 20 years following the fire compared to 1-year post-fire (Figures 5.2. and 5.5). In contrast to patterns seen in *Scenario 1*, however, few "hot spots" of activity existed inside the burned area and overall densities were more dispersed. This was reflected in the map of consumption (Figure 5.10). Though more consumptive activity was recorded for the central section of the burn, the greatest offtake was seen in the far northwestern portion of the fire where burn severities were varied creating a patchy mosaic often attractive to elk.

An analysis of movement pathways substantiated patterns seen in distributional behavior (Figure 5.11). Though the two primary and southern-most secondary pathways used by animals immediately following the fire continued to be used 20 years post-fire

(Figures 5.1 and 5.10), a shift in activity northward resulted in the upgrading of the northern-most pathway from secondary to primary. In addition, a potential new secondary pathway emerged to the far north. These patterns were also seen in *Scenario 1* indicating a true pattern may be emerging as a result of changes occurring in conjunction with spatial and temporal aspects of the Cerro Grande Fire.

Discussion

Landscape-scale responses following large fire events are in a state of constant flux, which can impact elk through (Brown et al. 2000):

- Changes in the availability of habitat patches and landscape heterogeneity;
- Transformations in the composition and structure of larger areas, such as watersheds, which provide the spatial context for habitat patches;
- Modifications in habitat connectivity.

Ecotones produced by changes in landscape heterogeneity often result in a preferred combination of forage and cover (Skovlin 1982). Elk winter ranges are often concentrated in areas historically impacted by fires or burned for management purposes (Irwin and Peek 1983, Peck and Peek 1991) and may be related to animal energetics. Rowland et al. (1983) found elk weighed significantly more and blood samples indicated better energy status for elk wintering on the burn following the 1977 La Mesa Fire. In addition, use of burned areas can persist beyond the initial increases of early successional herbaceous growth (Wolf 2003) thus affecting long-term ecosystem dynamics.

The use of modeling to investigate ungulate responses to large-scale fires has been explored in few instances. Turner et al. (1994) developed a spatially explicit, individual-based simulation model (NOYELP) to explore the effects of fire scale and pattern on the winter foraging dynamics and survival of free-ranging elk in Yellowstone. Simulations revealed that winter severity played an important role in ungulate survival and that spatial patterning of the fire, coupled with snow conditions, influenced predicted ungulate dynamics. The model did not address ungulate reproduction, succession dynamics, or the effects of summer precipitation on pre-winter forage availability – all of which are important in projecting the long-term dynamics of the ecosystem (Turner et al. 1994).

My application of a dynamic, spatially explicit individual-based model is an extension of and possible improvement to the model developed by Turner et al. (1994). Results were evaluated through subjective evaluation and pattern-seeking; more thorough model corroboration (as was done in Chapter 4) is clearly needed, and will be a focus of future research.

As with other studies, spatial patterning of the fire coupled with snow conditions influenced the response behaviors of simulated animals. In addition, successional processes altered movement and distribution patterns observed following the fire. Areas of greatest density were often focused along forest/grassland edges in areas that were severely burned and, in general, populations expanded to the north. The magnitude of behavioral response was dependent on the total number of simulated animals. Doubling the population caused expansion of habitat use, increased activity (movement and distribution, consumption) in the central portion of the Cerro Grande burn, and decreased ANPP in the southern-most portion of the Cerro Grande Fire. These results might suggest ecological carrying capacities were reached and/or intraspecific competition encouraged the expansion of animals into new territory.

Though correlation does not imply causation, multilevel models yield information about parameters within and between levels of organization and allow us to discover heuristic principles for generating predictions about systems and possibly principles for manipulating them (Schank 2001). Prior to the Cerro Grande Fire, the eastern Jemez region was already concerned about potential increases in the regional elk population. Application of this model and analysis of its results will allow managers to project where on the landscape elk may be most likely to aggregate, paths of movement/migration, and sites potentially vulnerable to erosion. Furthermore, LANL and Los Alamos County are concerned about increases in elk/vehicle collisions. Model predictions may identify potential "hotspots" of elk activity along roadways and relate this information to pre- and post-fire vegetative characteristics. Displacement of animals as a result of the fire will no doubt alter mitigation efforts in this area as well. Finally, the model can be used as a predictive tool to determine the potential impacts of management activities (e.g., post-fire tree thinning and increased human activity, reseeding efforts) on potential elk distribution and movement patterns. The development, calibration, continued validation, and application of this IBM will provide a dynamic tool to be used for adaptive management applications for many years to come.

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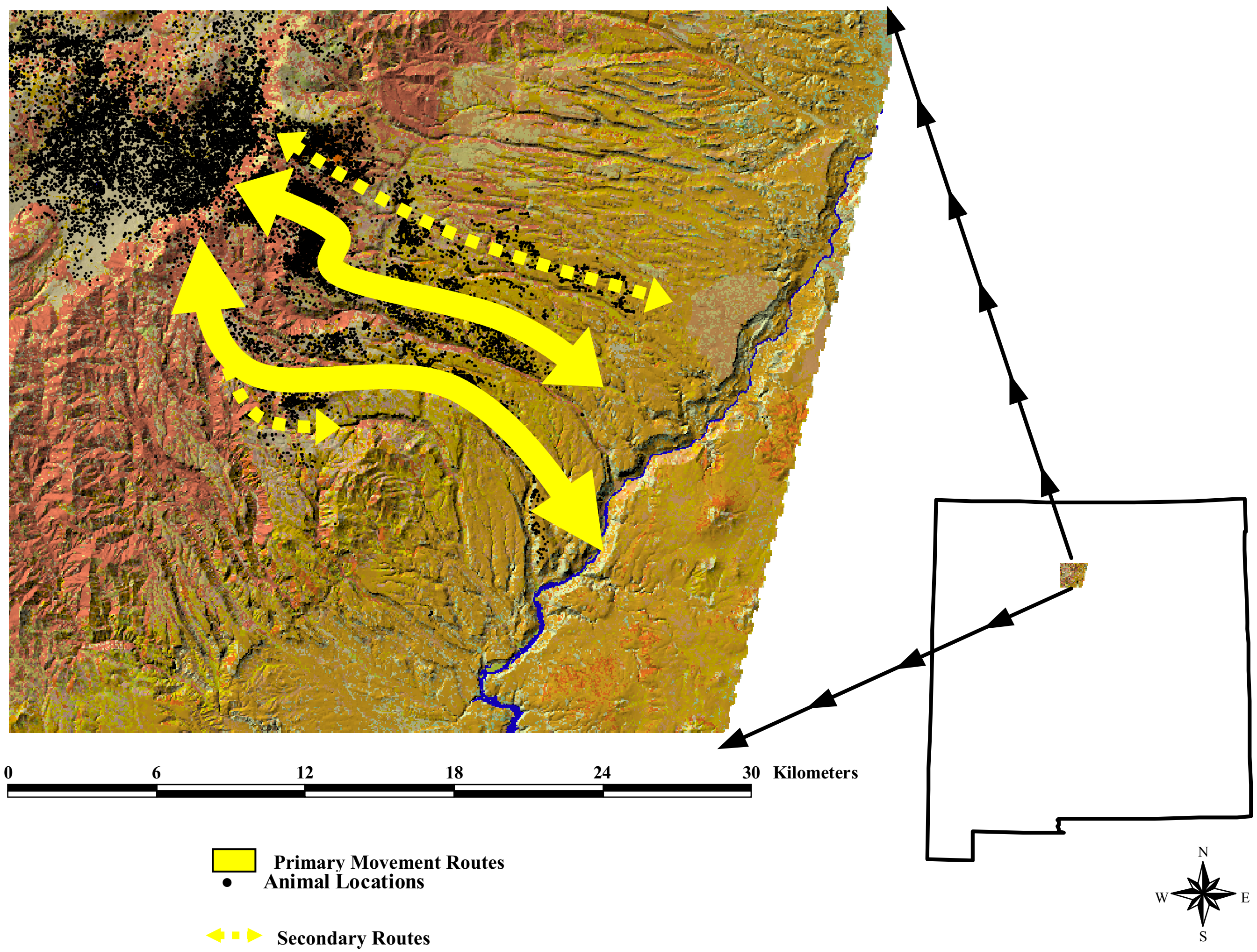


Figure 5.1. Identification of primary and secondary movement routes across the east Jemez Mountains based on 10 GPS-collared animals. Primary routes were used by ≥ 4 animals and secondary routes were used by ≤ 2 animals. These routes serve as baseline conditions to analyze changes in elk movement in relation to spatial and temporal aspects of the Cerro Grande Fire.

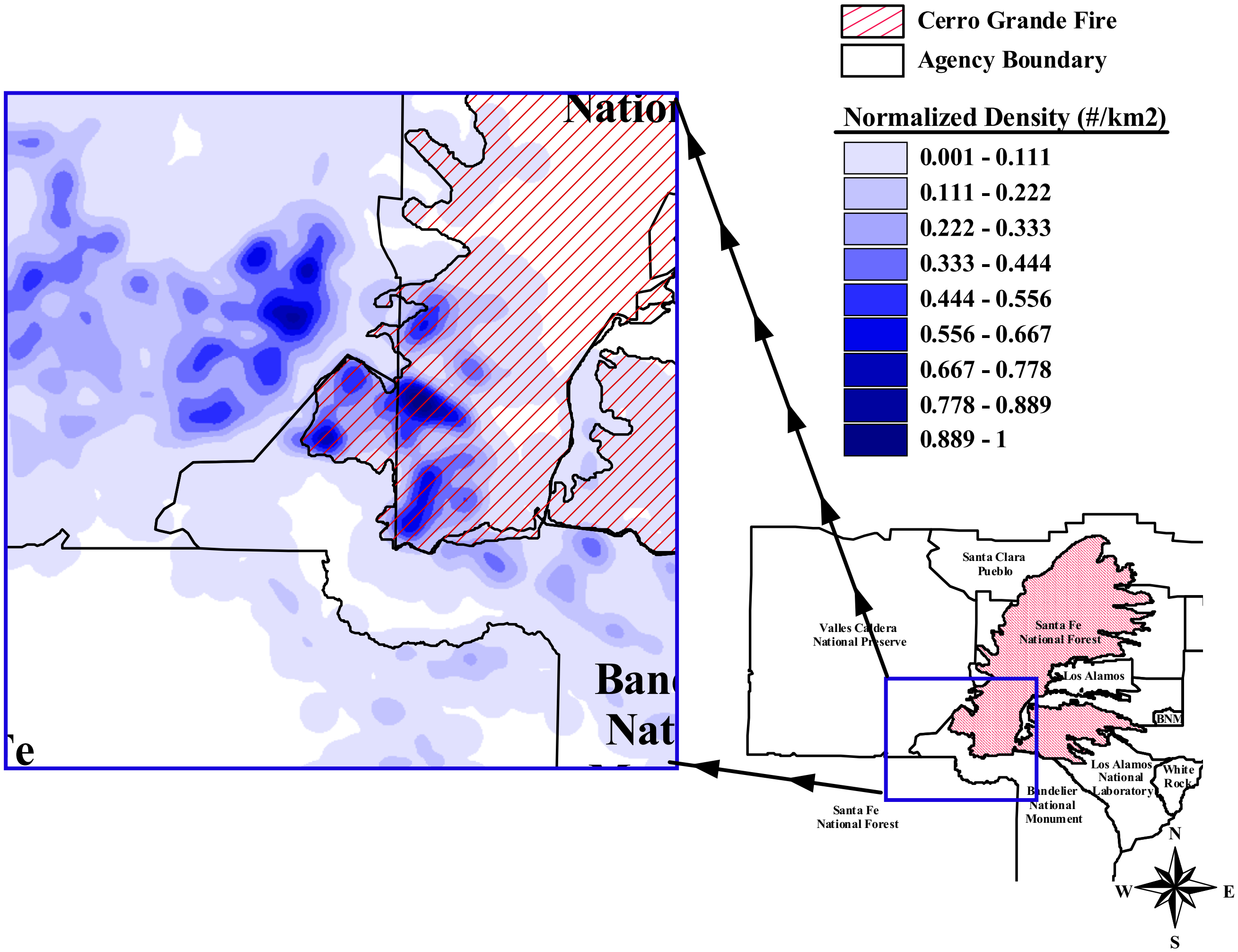


Figure 5.2. Animal densities in the first 3 years following the fire showed high use of the southwestern portion of the Cerro Grande Fire. Densities are based on 10 collared animals and represent a total of 10,812 locations taken on a daily basis.

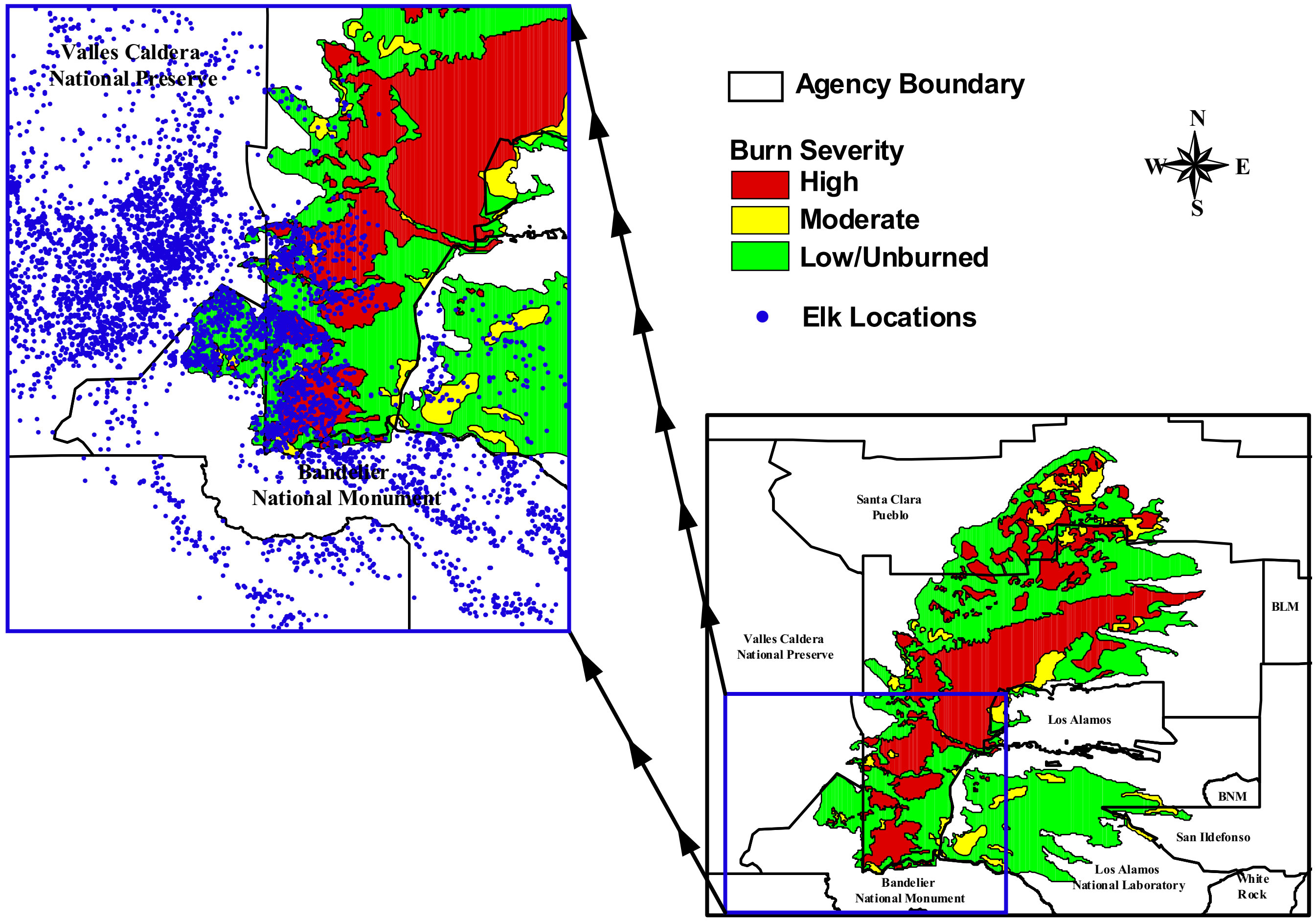


Figure 5.3. Cerro Grande Fire burn severity map with associated elk locations based on 10 GPS-collared animals for the period of 2001 through 2004. Hot spots of activity may be related to increased biomass, nutritional quality, palatability, and digestibility of forage species, creation of attractive edge habitat, and/or reseeding efforts in regions with the highest burn severity. Density patterns serve as baseline conditions to analyze changes in elk distribution in relation to spatial and temporal aspects of the Cerro Grande Fire.

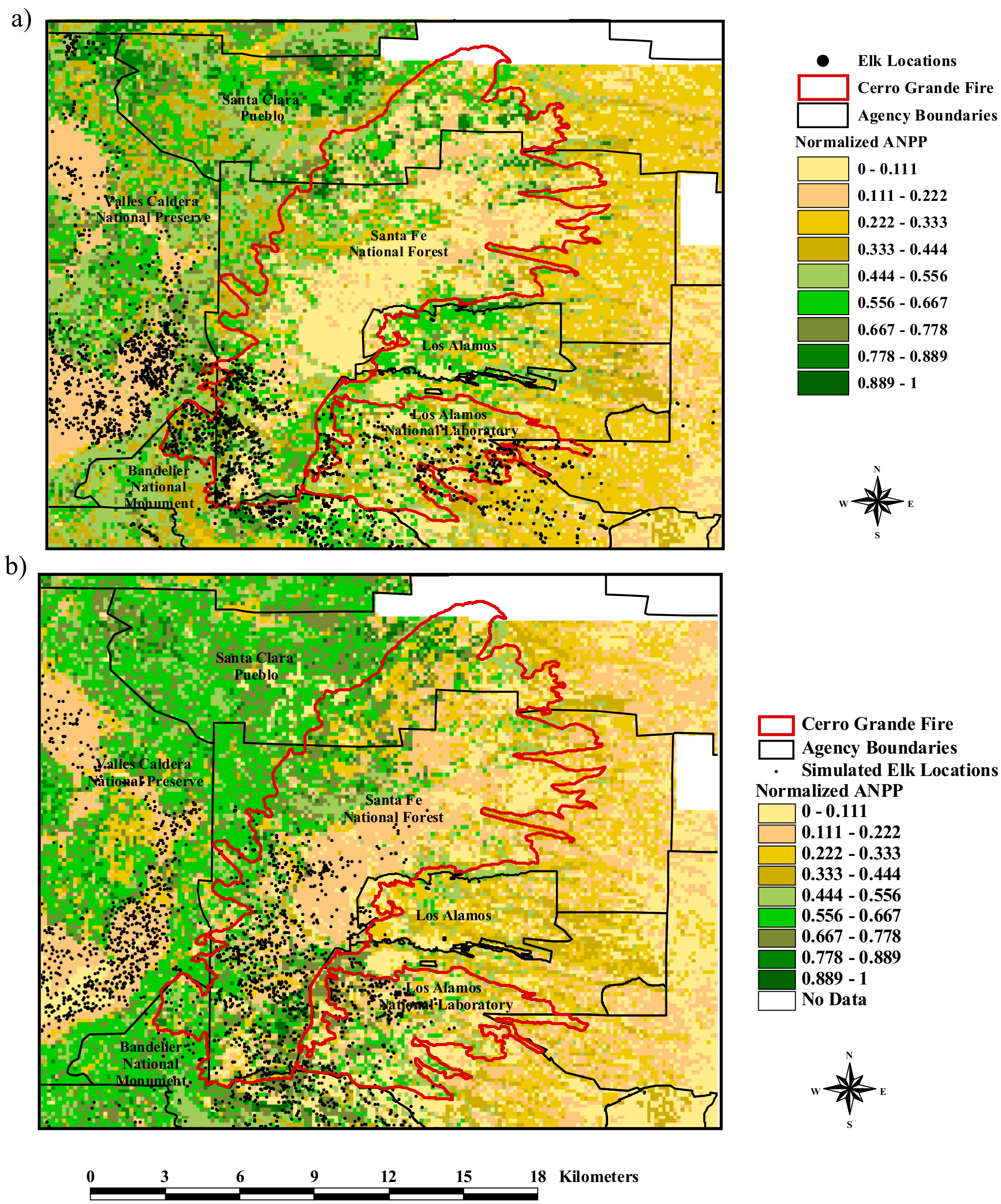


Figure 5.4. Total annual net primary production 1-year post-fire with actual locations for 10 GPS-collared animals (a) and 20-years post fire (b) with 10 simulated animals (*Scenario 1)*. In both cases animals appeared to prefer edge habitat. Note the increased production in the central portion of the Cerro Grande burn and the decreased production in the southeastern portion of the Valles Caldera National Preserve.

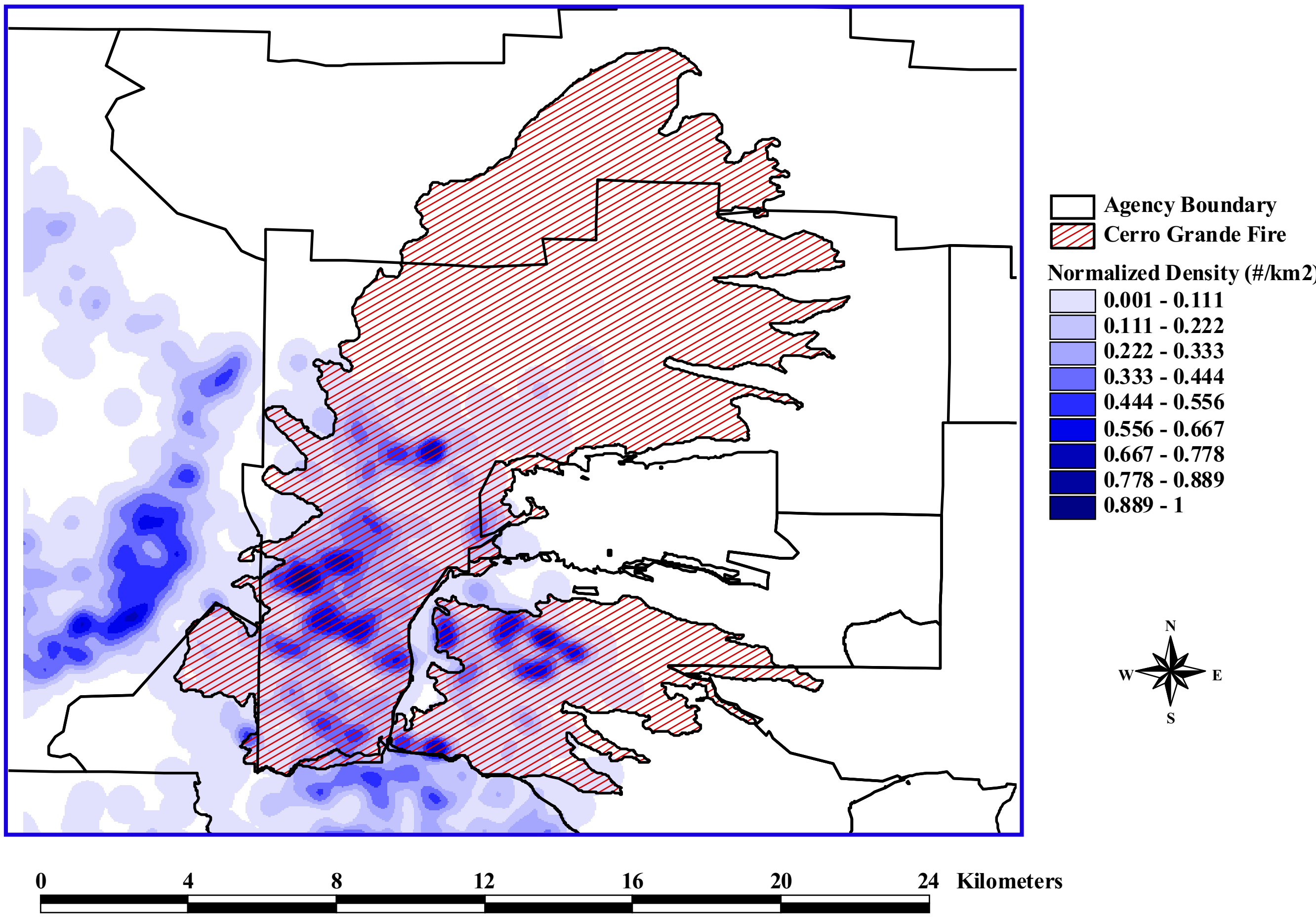


Figure 5.5. Density (#/km^2) for a random sample of 10 animals based on a simulation run of 3,500 animals for 20 years assuming no population growth and no limit on the number of animals occupying a single cell *(Scenario 1)*. Results indicate increased densities just north of where previous densities were highest 20 years prior (compare to Figure 5.2) plus an overall shift in habitat use further north than previously seen.

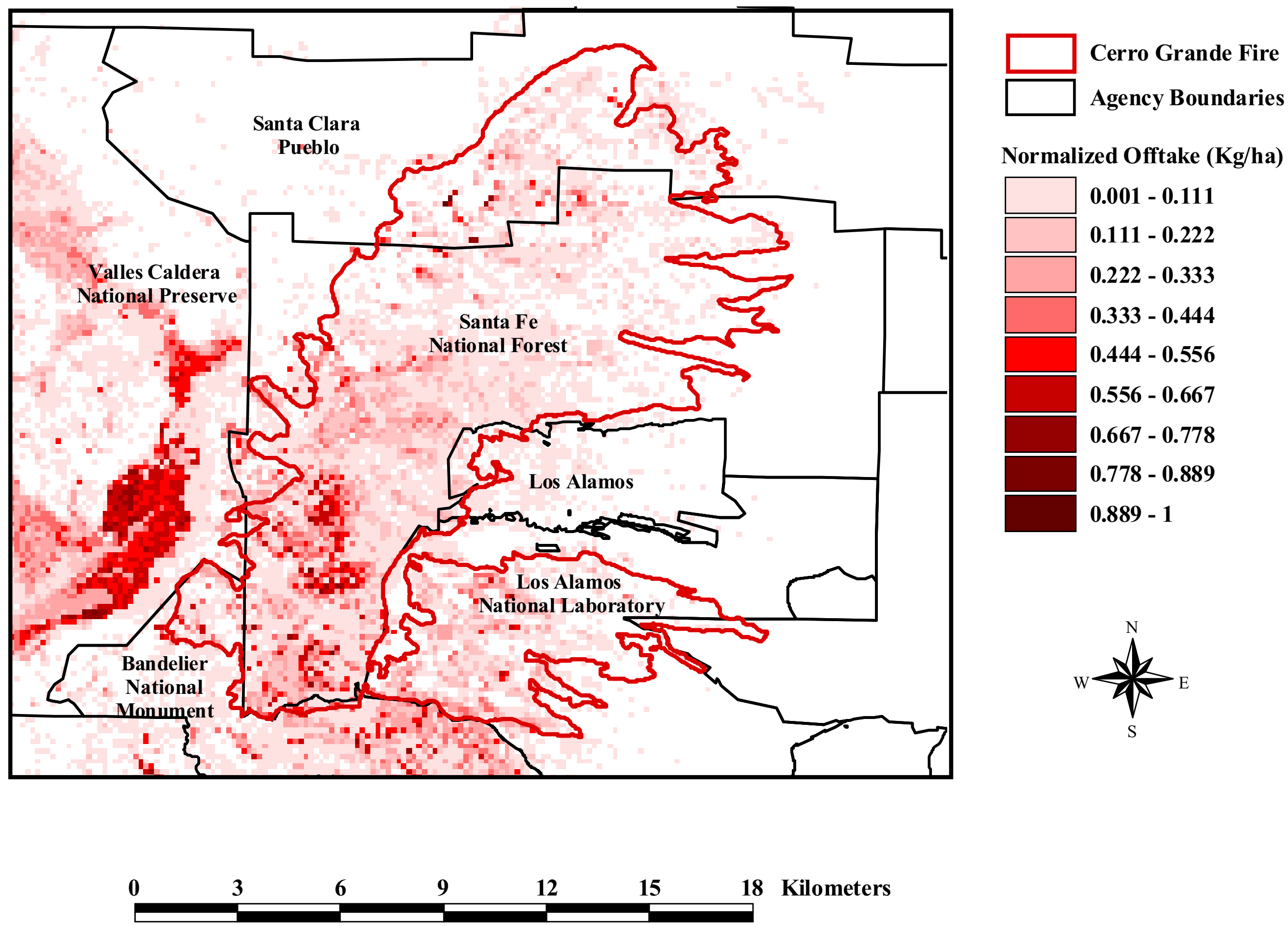


Figure 5.6. Normalized consumptive offtake (kg/ha) for simulated elk under *Scenario 1* 20-years post-fire. The highest levels of consumptive offtake were found just east of the tip of Bandelier National Monument, which corresponded with high elk densities (Figure 5.5). In addition, elk habitat use expanded northward when compared to use 1-year post-fire (Figure 5.5), but animals continued to concentrate along edges classified as high burn severities (Figure 5.3).

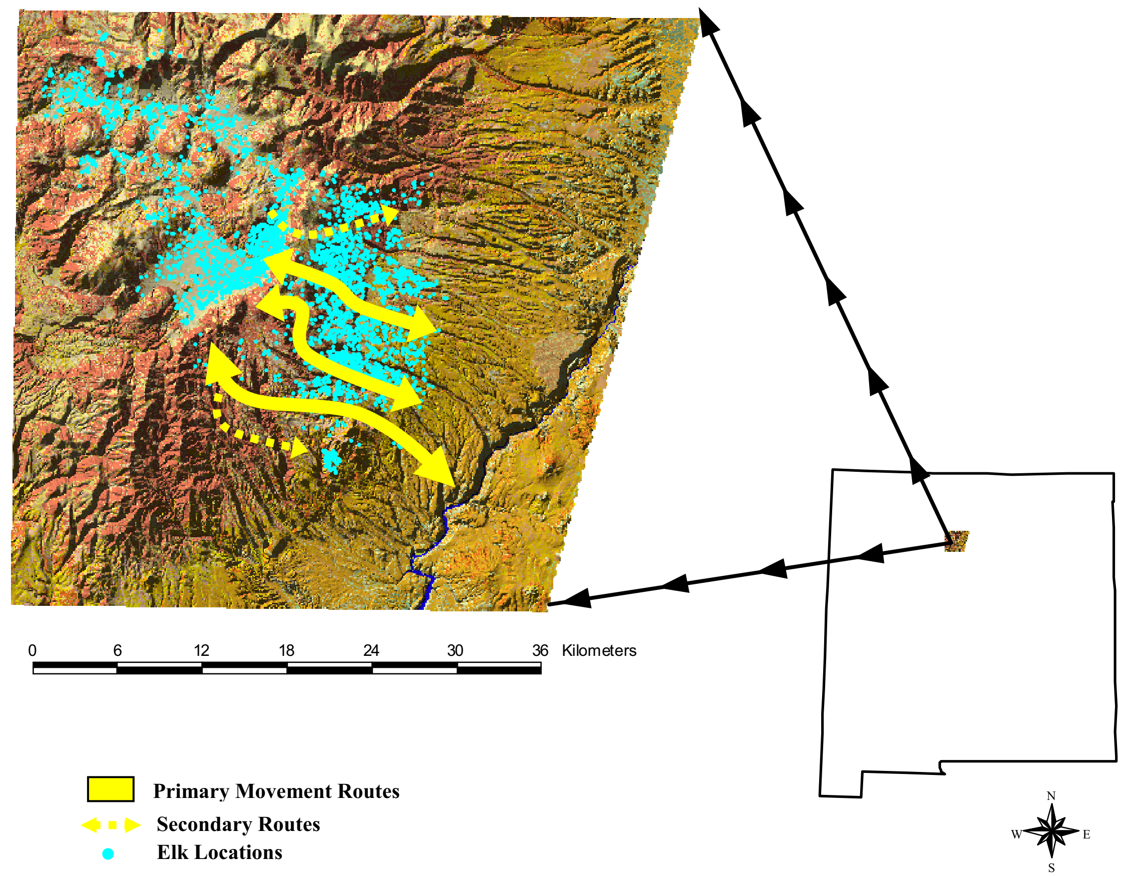
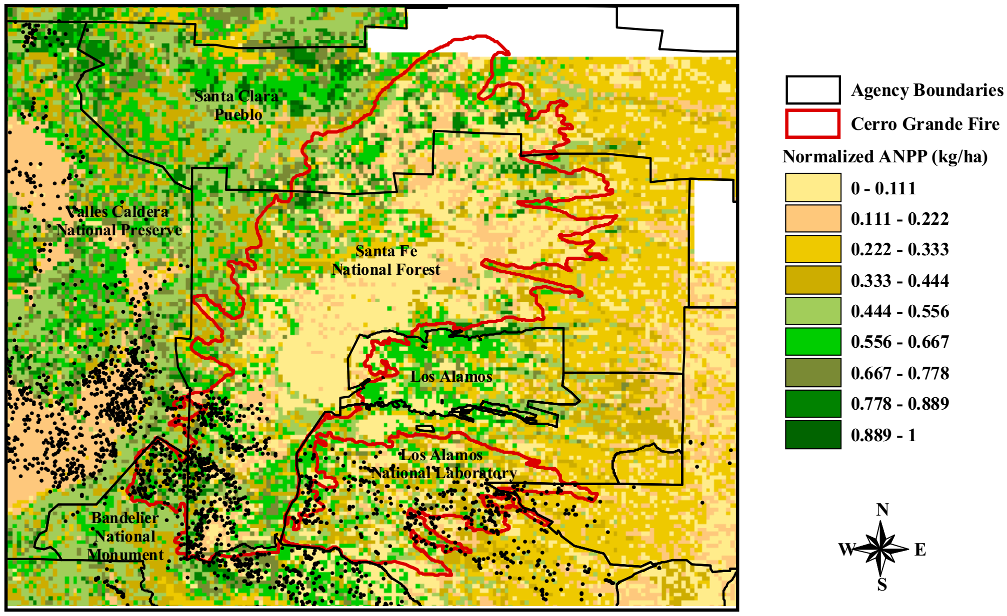


Figure 5.7. Potential primary and secondary movement routes based on a simulation run of 3,500 animals for 20 years assuming no population growth and no limit on the number of animals occupying a single cell *(Scenario 1)*. Primary routes were used by ≥ 4 animals and secondary routes were used by ≤ 2 animals. Results indicate a potential new primary movement route emerging from a secondary route 20 years prior (compare to Figure 5.1) and a new secondary route at the far north.

a)



b)

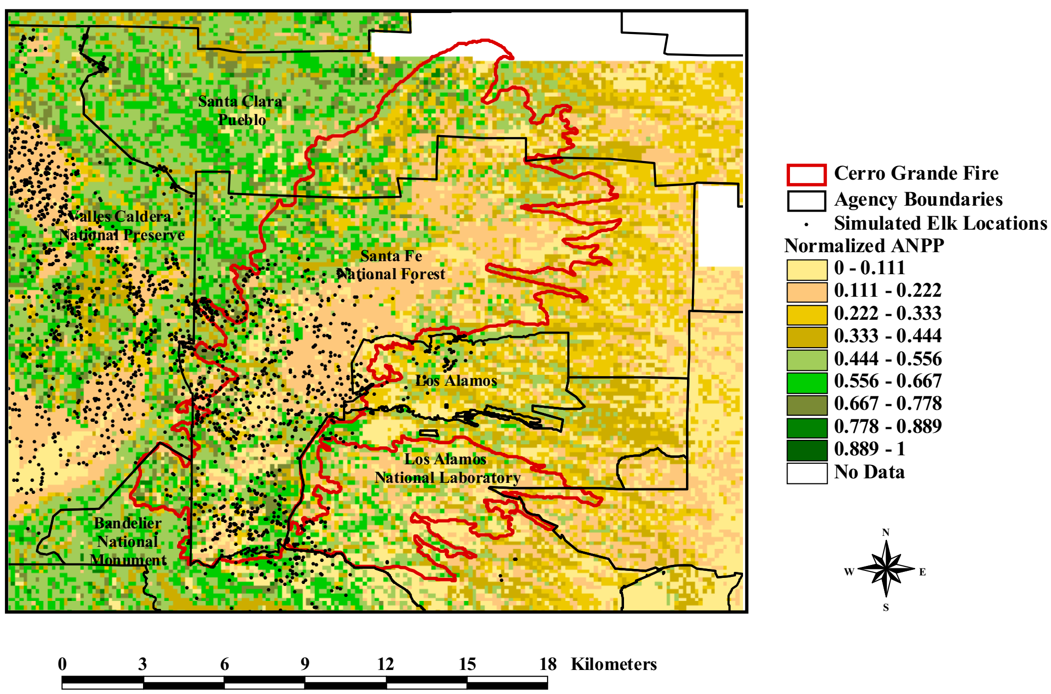


Figure 5.8. Total annual net primary production 1-year post-fire with actual locations for 10 GPS-collared animals (a) and 20-years post fire (b) with 10 simulated animals (*Scenario 2)*. In both cases animals appeared to prefer edge habitat. Unlike *Scenario 1*, more animals exhibited exploratory behaviors near the central part of the Cerro Grande Fire area where burn severities were high in May 2000. Close inspection also reveals more areas denuded of vegetation in the south part of the burn where densities were initially high post-fire.

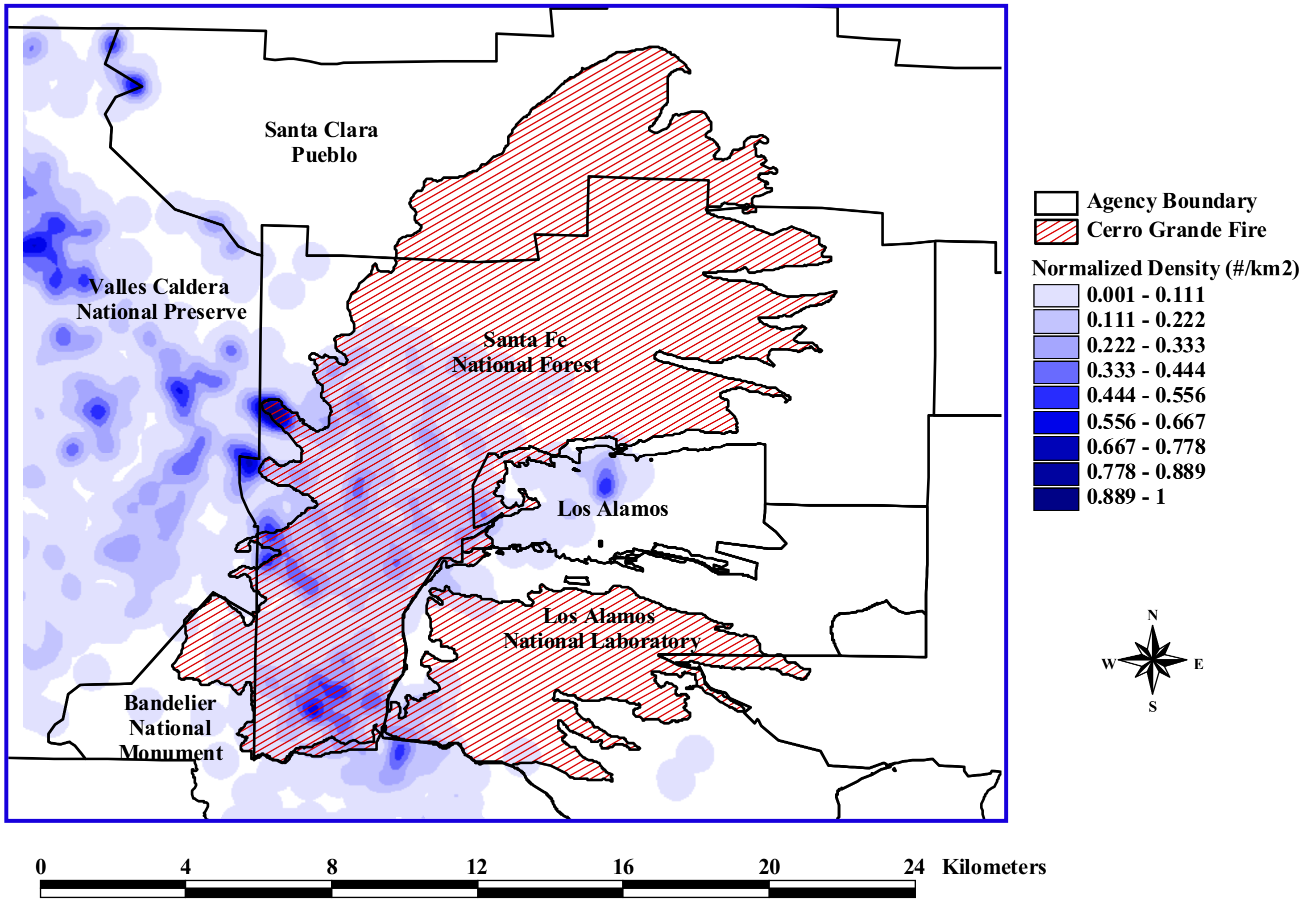


Figure 5.9. Density (#/km^2) for a random sample of 10 animals based on a simulation run of 7,000 animals for 20 years assuming no population growth and no limit on the number of animals occupying a single cell *(Scenario 2)*. Results indicate increased densities north of where previous densities were highest 20 years prior (compare to Figure 5.2) but with a more equitable disbursement in pattern when compared with *Scenario 1* (Figure 5.5).

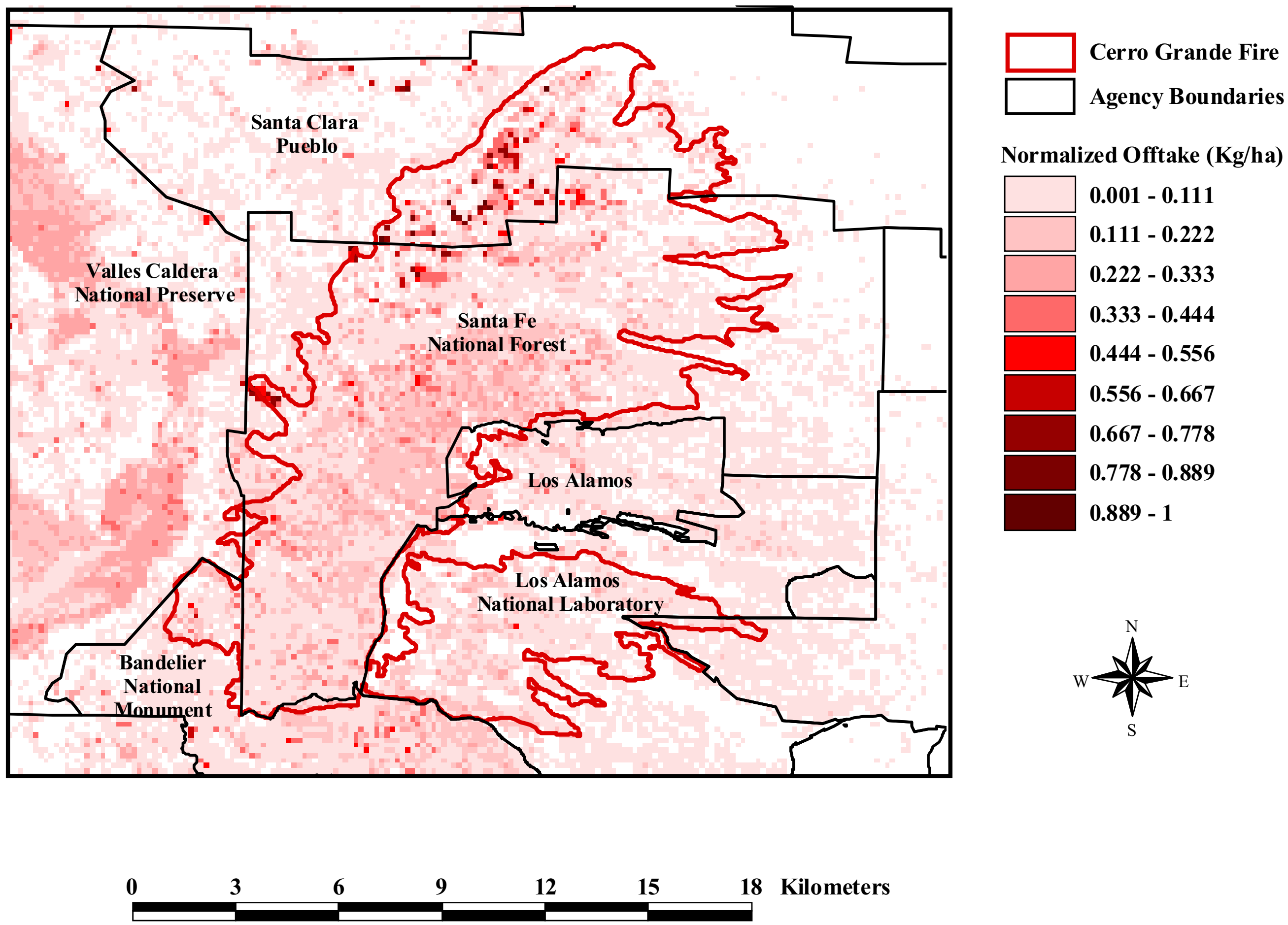


Figure 5.10. Normalized consumptive offtake (kg/ha) for simulated elk under *Scenario 2* 20-years post-fire. When compared to offtake in *Scenario 1* (Figure 5.6), patterns were more evenly distributed but showed higher use in central portions of the Cerro Grande burn. In addition, new areas of elk habitat use emerged in the far northwest portion of the Cerro Grande burn where fire severities varied (see Figure 5.3) creating a patchy mosaic attractive to elk.

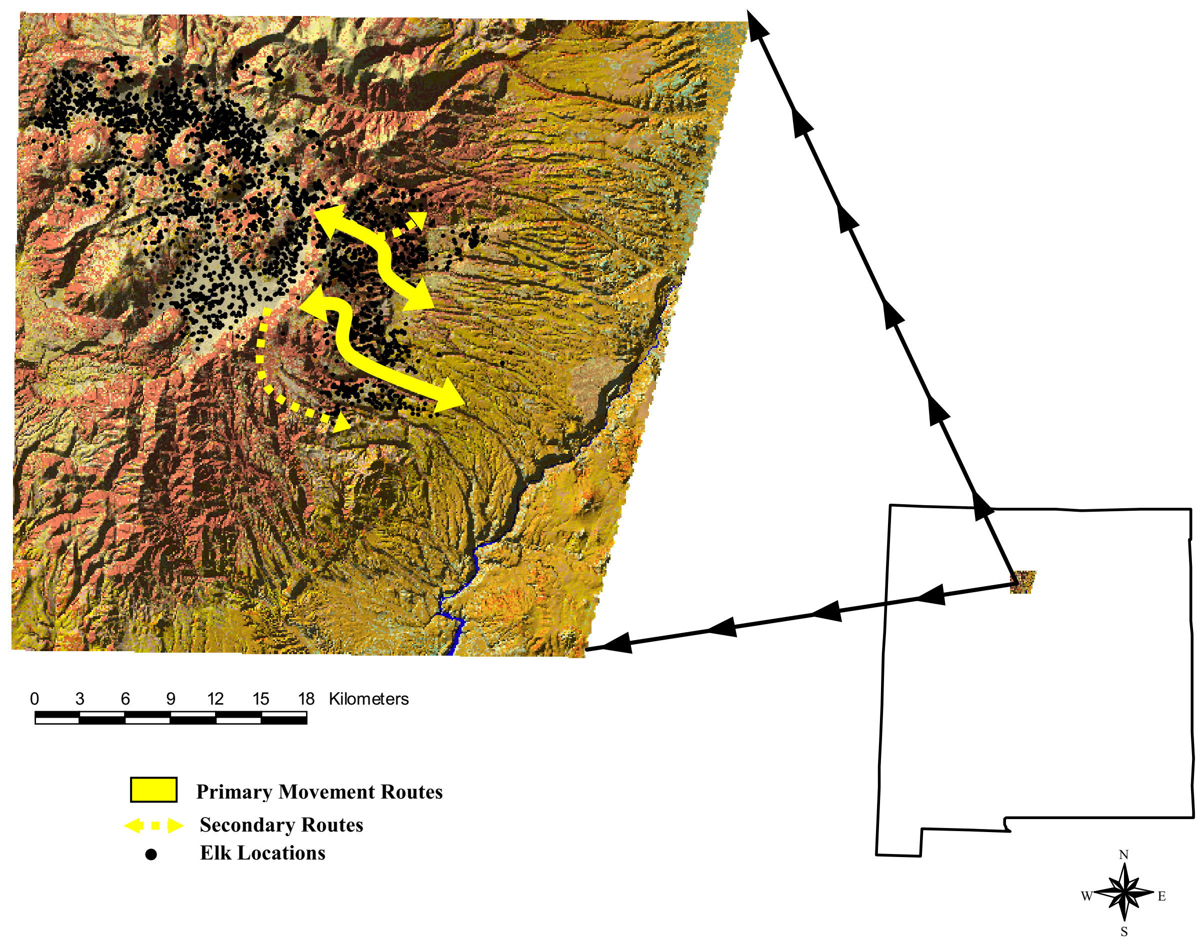


Figure 5.11. Potential primary and secondary movement routes based on a simulation run of 7,000 animals for 20 years assuming no population growth and no limit on the number of animals occupying a single cell *(Scenario 2)*. Primary routes were used by ≥ 4 animals and secondary routes were used by ≤ 2 animals. Results indicate a potential new primary movement route emerging from a secondary route 20 years prior (compare to Figure 5.1) and a new secondary route at the far north in close proximity to those identified in *Scenario 1*.

CHAPTER VI

CONCLUSION AND DISCUSSION

A primary consideration driving the conceptualization and implementation of scientific studies should be their potential value to resource managers for purposes of mitigation. As management agencies move toward the concept of adaptive management, the demand for dynamic modeling is increasing. Active adaptive management has been defined as the "systematic process of modeling, experimentation, and monitoring to compare the outcomes of alternative management actions" (Farr 2000: 2). Adaptive management aims to integrate interdisciplinary experience and scientific information into dynamic models that attempt to make predictions about the impact of alternative policies (Holling 1978, Walters 1986, Van Winkle et al. 1997).

Quantitative models take complex ecological processes and attempt to explain them in simple mathematical terms for the purpose of exploring data, formulating predictions, and guiding research. Habitat selection models are widely used to evaluate habitat quality and predict effects of habitat alteration on animal populations. Habitat quality is typically measured by observing the frequency with which animals use various habitat types in relation to the availability of habitat. Such approaches have come under intense criticism in recent years because animal density does not necessarily translate into critical habitat necessary for the survival and reproduction (i.e, "fitness") of an individual (Van Horne 1983, Rettie and McLoughlin 1999). In addition, application of telemetry data commonly employed to assess habitat selection involves a number of implicit assumptions (Rettie and McLaughlin 1999).

Population persistence through the process of natural selection is often packaged in the form of individual-level fitness. Because natural selection works on genetic variation caused by mutation and recombination, organisms should develop optimal behavioral features that maximize fitness over time (Drickamer 1998, Rettie and McLaughlin 1999). The aggregative responses of individuals – the basic units of ecology (Wiens et al. 1993) – result in higher-order phenomena such as population dynamics, which are of concern when considering the ecological consequences of habitat fragmentation (With et al. 1997). It follows that movement at the population-level can ultimately be explained at the level of the individual (Rosenberg et al. 1997, Turchin 1998). Quantifying landscape connectivity, therefore, requires spatially explicit methods that are sensitive to the possibility of complex interactions between the behavior of individual animals and landscape structure (Pither and Taylor 1998).

The individual-based approach to modeling animal movements applied here addresses these principles that are largely ignored in other modeling environments. First, it acknowledges that individuals are behaviorally and physiologically distinct because of genetic and environmental influences. Second, it recognizes that interactions among individuals are inherently localized (Slothower et al. 1996, Schank 2001). However, individual-based (bottom-up) approaches are not mutually exclusive from traditional population-based (top-down) approaches and ecological theory would be better served by analyzing IBMs with tools developed for state variable models and comparing results to determine joint interactions (Grimm 1999).

By definition, landscape connectivity is a species-specific characteristic determined by the interaction between movement potential of each species and landscape structure (Mönkkönen and Reunanen 1999). Long-term studies on the movement patterns of species at local and regional scales are needed because those are the scales at which conservation strategies are planned and implemented (Saunders and Hobbs 1991). Designing functional corridors at the landscape scale is difficult due to limited detailed data on movements of animals through landscapes, which, in turn, inhibits accurate identification of features essential in maintaining functional connectivity.

The evolution of global positioning system (GPS) devices for use in radio-marking wildlife continues to improve the quality and quantity of data that can be collected on animal movement and habitat use patterns. With the discontinuance of selective availability (SA) in May 2000, the accuracy of GPS increased 10-fold. As a result, many researchers regard differential correction as obsolete, yet many underlying sources of error in locations may still exist. Regardless of whether or not the researcher chooses to differentially correct locations in a post-SA world, no habitat-selection study is defensible without an assessment for observational bias that may result from changes in animal behavior or a malfunction of the collar system and lead to misapplication of results (Rempel et al. 1995, Moen et al. 1997, Frair et al. 2004).

A thorough analysis of GPS collar accuracy (Chapter 2) indicated a strong effect of 2D fixes on position acquisition rates (PARs) depending on time of day and season of year corresponding with other studies cited in the literature. Position acquisition rates were lower during mid-day hours and summer months indicating a possible change in animal behavior during the hottest parts of the day/season. Slope, aspect, elevation, and land cover type affected dilution of precision (DOP) values for both 2D and 3D fixes, but significant relationships varied from positive to negative making interpretation difficult. Additional biases centered on data that are missing or contain habitat-dependent errors in location (Rettie and McLoughlin 1999, Biggs et al. 2001) may be countered through the application of associated error polygons related to habitat patch size and studies are currently underway in the Jemez Mountains to address these concerns. Nonetheless, thorough analysis of GPS collar accuracy indicated an overall position acquisition rate (PAR) of 93.3%, higher than that typically seen in the literature, and mean DOP values consistently in the range of 4.0 to 6.0 – well below the 7.0 DOP setting suggested for best accuracy by the manufacturer (Trimble 1999) – leading to the conclusion that collar performance was acceptable for purposes of this research.

In addition to potential bias introduced through GPS telemetry, some authors have argued that temporal autocorrelation of consecutive radio-telemetry locations may violate independence assumptions that are central to many parametric statistics making habitat selection studies difficult to interpret (Swihart and Slade 1985, Otis and White 1999). However, others have stated that when individual animals are treated as the experimental unit, the dependencies between relocations are not an issue because we are interested in the trajectory of space used by an animal (Aebischer et al. 1993, Millspaugh and Marzluff 2001). Attempts were made to address these concerns through the application of statistical procedures to test for the possibility that DOP locations recorded for a given animal were not necessarily independent and/or that DOP readings for different animals may have different variances. Furthermore, this approach presents an opportunity for further research to determine the effect of temporal autocorrelation on habitat use results thus challenging arguments about the effect of temporal autocorrelation on habitat selection studies.

Simulation models are critically dependent on the input values for model parameters and, therefore, have the greatest value when they are coupled with field studies, both to calibrate model parameters and to test or confirm model projections (Turchin 1998). A primary need for the development of an IBM to study fire effects on elk movement and distribution was a model to simulate successional patterns following disturbance. SAVANNA, which has survived rigorous testing and peer-review for 15+ years, was designed specifically for evaluating herbivore dynamics within ecosystems (Chapter 3). Inputs to the SAVANNA Ecosystem Model included a detailed land cover map developed from LANDSAT images, long-term Natural Resource Conservation Service (NRCS) and LANL weather data, NRCS soil maps, and U.S. Geological Survey digital elevation models – all of which have been independently validated by these agencies as well as corroborated here. These data were assimilated and augmented with 159 additional vegetation plots to further calibrate and validate the model. Model predictions of herbaceous biomass were consistent with available data and control runs for weather data from 1990 through 2002 indicated proper functioning of the model in terms of precipitation output. Therefore, weather and vegetation output worked within the bounds of model parameters and spatial interpolations of snow were considered reasonable for this study.

Dynamic outputs generated through the application of the SAVANNA Ecosystem Model were used as inputs to develop a spatially-explicit, stochastic, individual-based model to assess potential changes in elk movement and distribution patterns related to spatial and temporal aspects of the Cerro Grande Fire (Chapter 4). Static variables in the form of roads, buildings, fences, and habitual use/memory were used to modify a map of impedance values based on the logistic regression of slope, aspect, and elevation. Integration with SAVANNA came through the application of a habitat suitability index (HSI), which integrated movement rules written for the IBM and variables modified and produced by the ecological processes run in SAVANNA. Fitness – the ability of an animal to survive and reproduce viable offspring – was assumed to be positively correlated with increasing HSI value.

A key principle of individual-based models is that they are more powerful if realistic behavior patterns emerge from simple, fitness-maximizing rules for individual behavior (Railsback 2001, Railsback and Harvey 2001). Overall pattern analysis indicated that realistic migrational processes and habitat-use patterns were likely emerging from movement rules incorporated into the IBM in response to advancing and receding snow. Primary and secondary movement pathways emerged from the collective responses of simulated individuals. Using regression analyses, no significant differences between simulated animals and animals used in either model development or an independent test set revealed any differences in response to snow patterns. These considerations suggest the model was adequately corroborated based on existing data and outlined objectives.

Increases in the Jemez Mountain elk population are a concern to local managers and residents. Over the years Los Alamos County has reported an increase in elk/vehicle collisions (Parker 1997). Intensive browsing has largely destroyed aspen (*Populus tremuloides*) suckers from upland portions of the La Mesa fire and the headwaters of the Frijoles watershed (Allen 1996). Mature aspen trees are heavily barked in many areas. Meadows appear to be kept in the early stages of succession by excessive elk use (Wolters 1996). About 70% of Bandelier's cultural resources are being damaged by erosion (Allen 1996) and there is concern that elk impacts to the area may accelerate erosion due to excessive trampling and loss of herbaceous cover resulting from grazing (Rupp et al. 2001a,b). To add confusion to an already intense political situation surrounding management of the Jemez Mountain elk population, changes in movement and distribution patterns are anticipated as a result of the May 2000 Cerro Grande Fire. Coupled with the region's unique interagency collaborations, simulation modeling presents a rare opportunity to study the long-term ecological consequences of large-scale fires on elk movement and distribution patterns. The development, calibration, and ongoing corroboration/validation of the individual-based model presented in this dissertation provides an adaptive management tool that integrates interdisciplinary experience and scientific information, which allows users to make predictions about the impact of alternative policies (Holling 1978, Walters 1986, Van Winkle et al. 1997).

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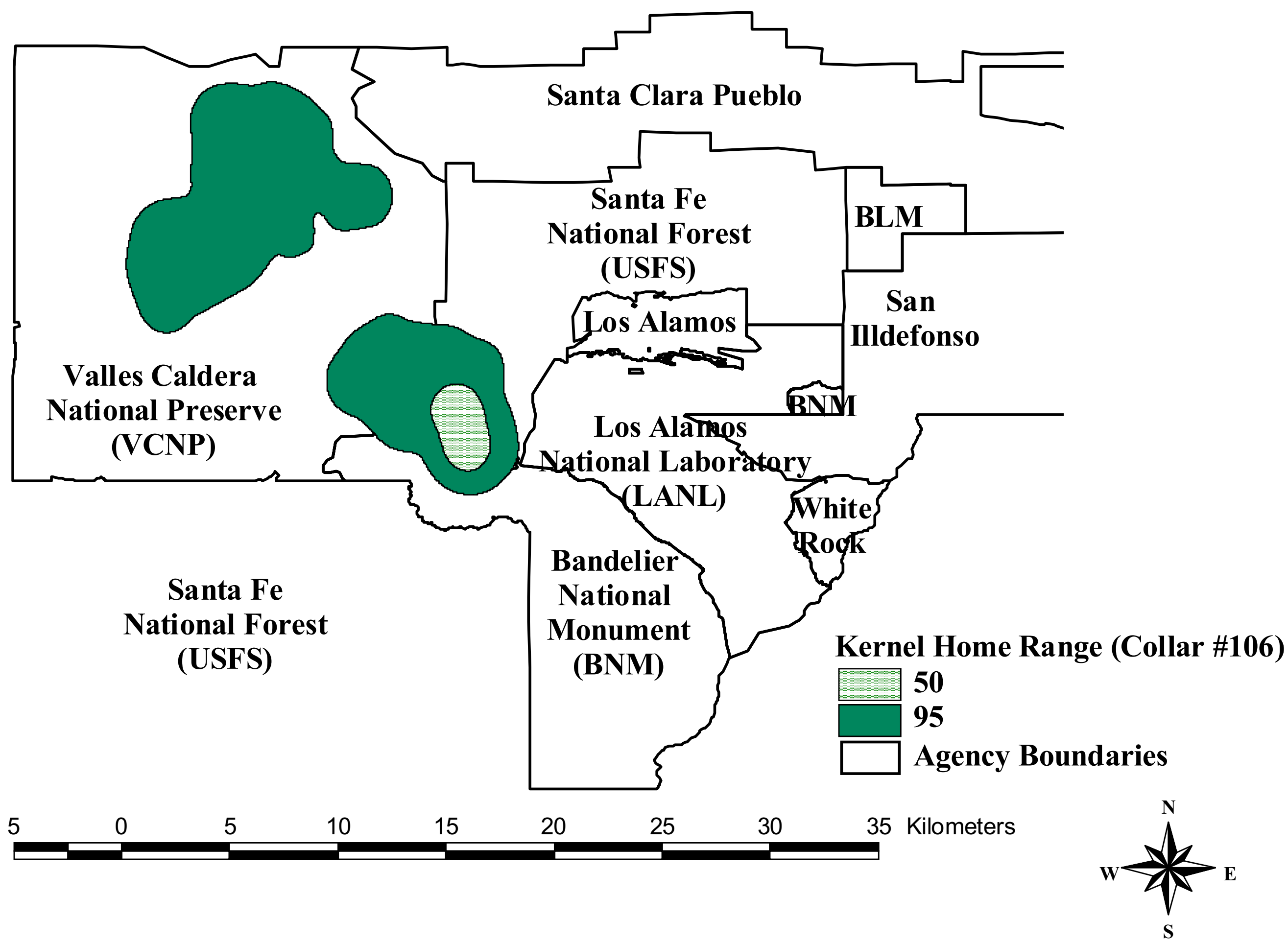
APPENDIX A

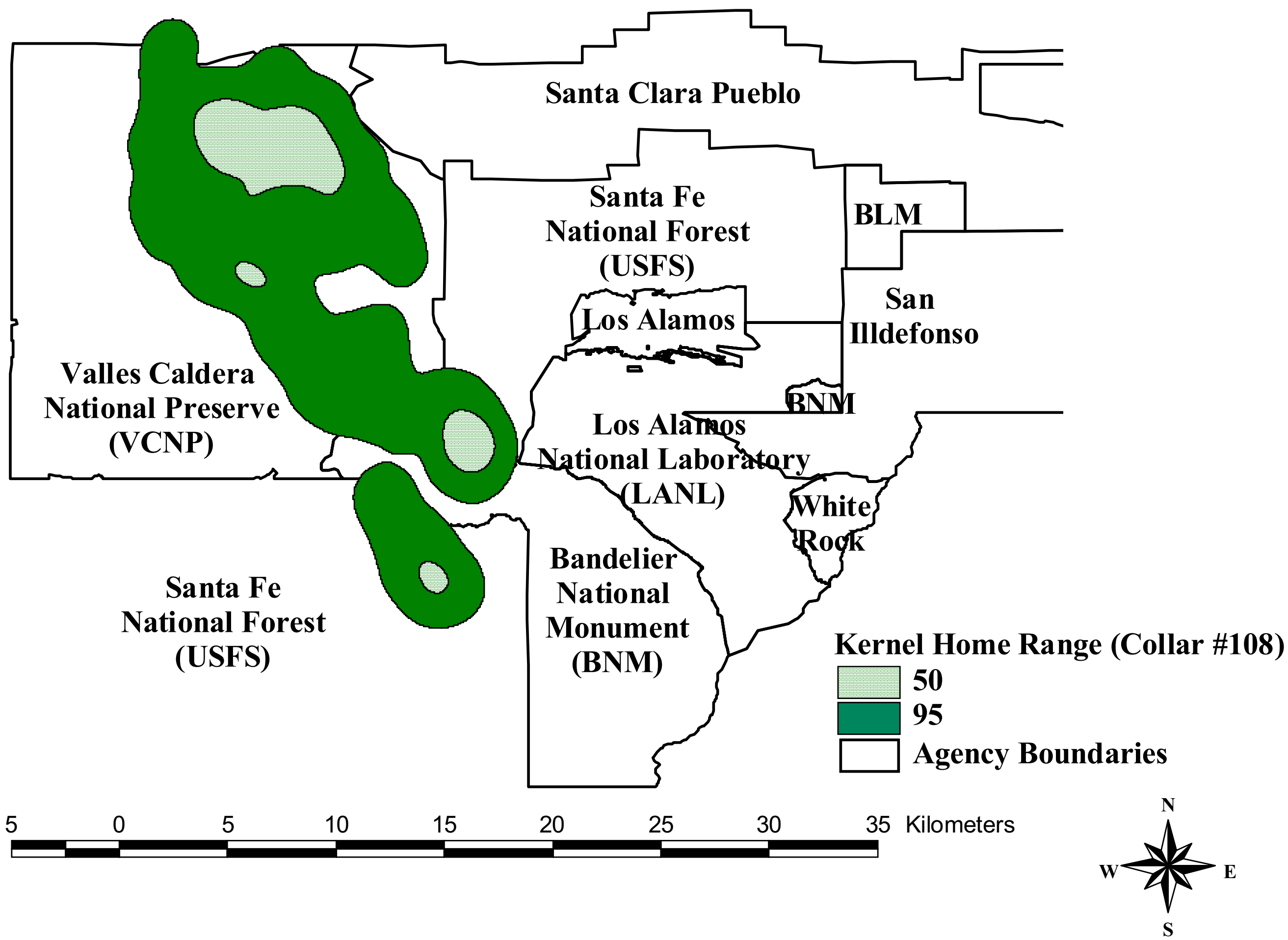
HOME RANGE MAPS FOR ANIMALS

USED IN MODEL DEVELOPMENT

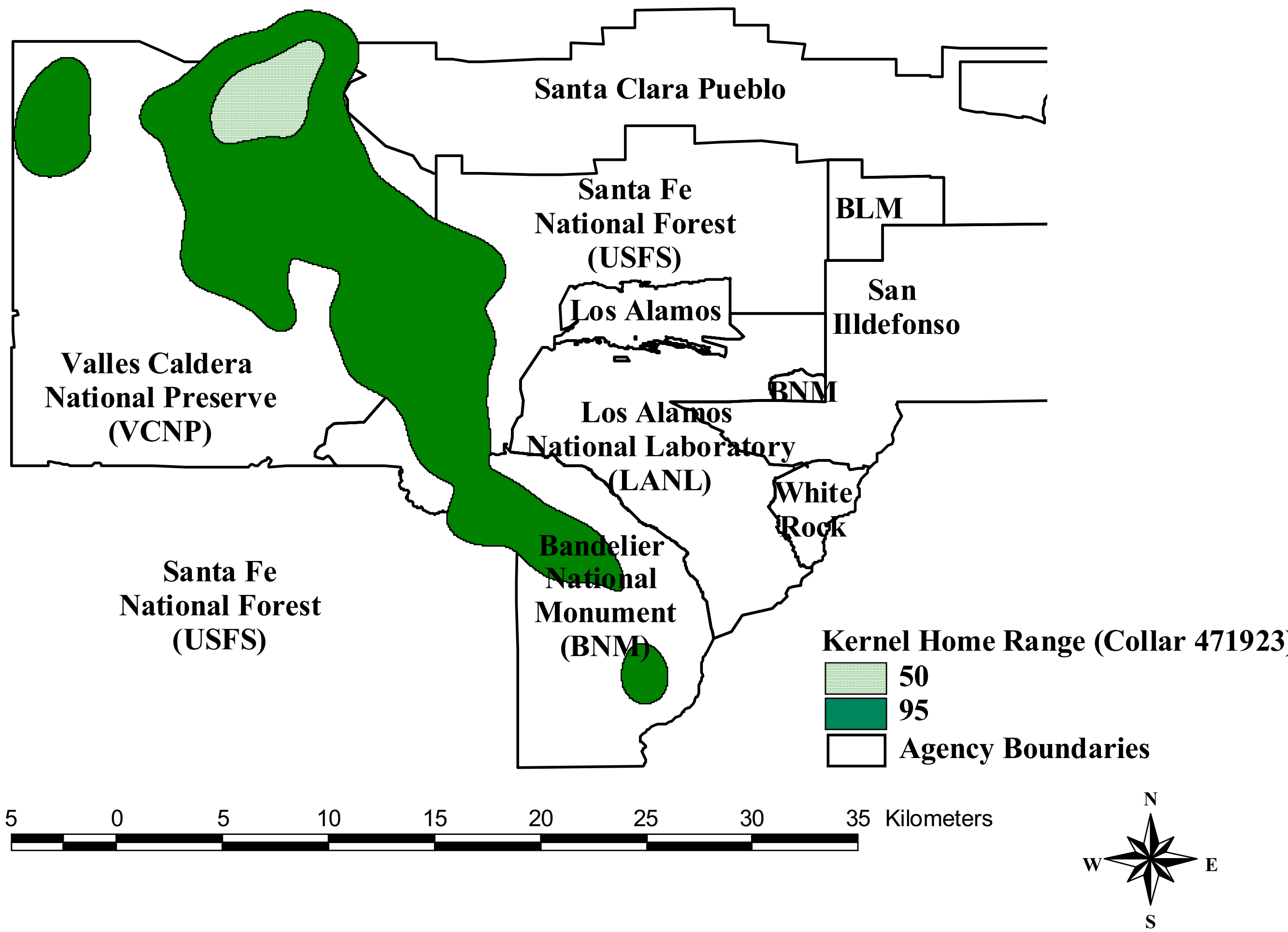
OR VALIDATION



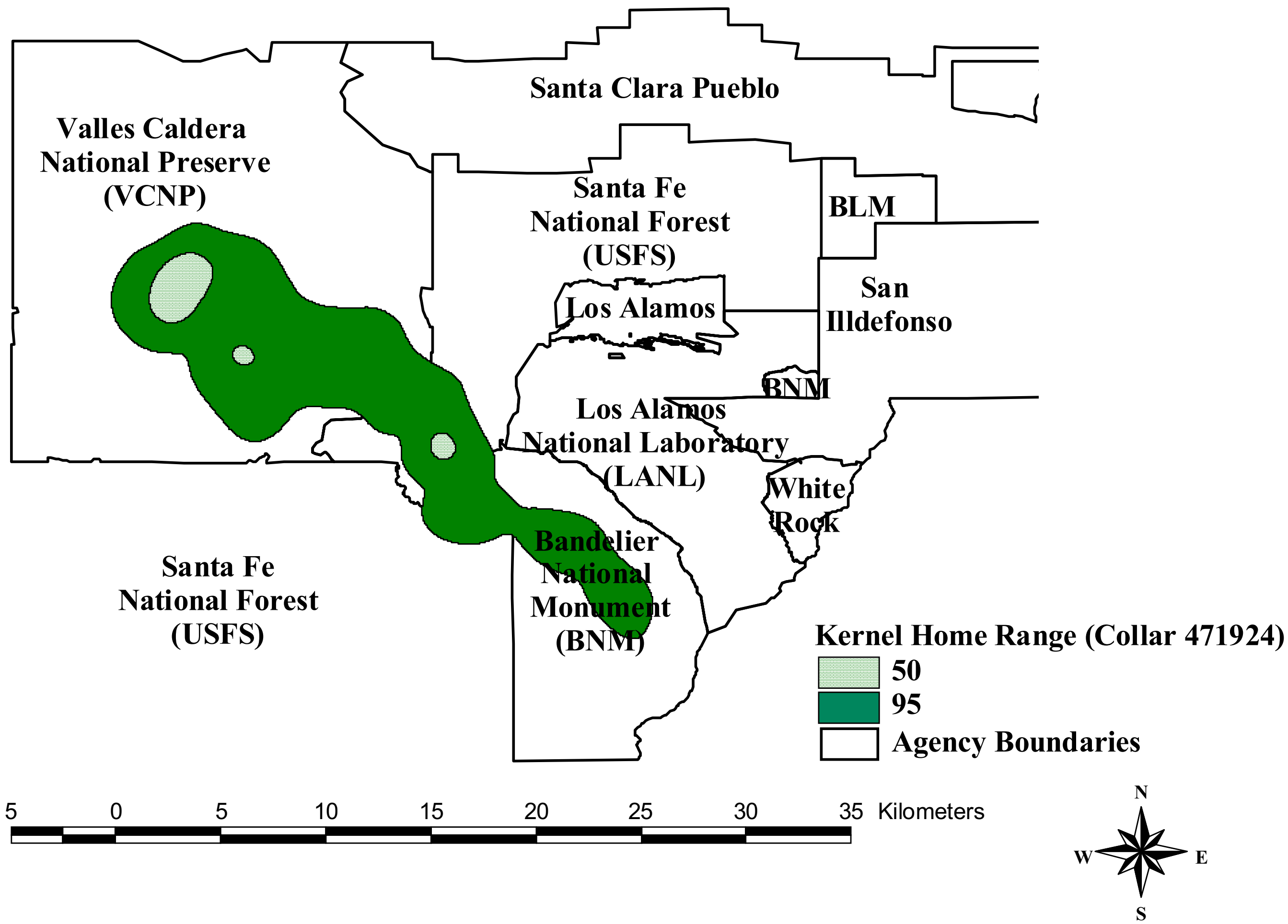
Appendix A.1. Kernel home range for animal #106. Both the 95% activity area and 50% core use area are shown.



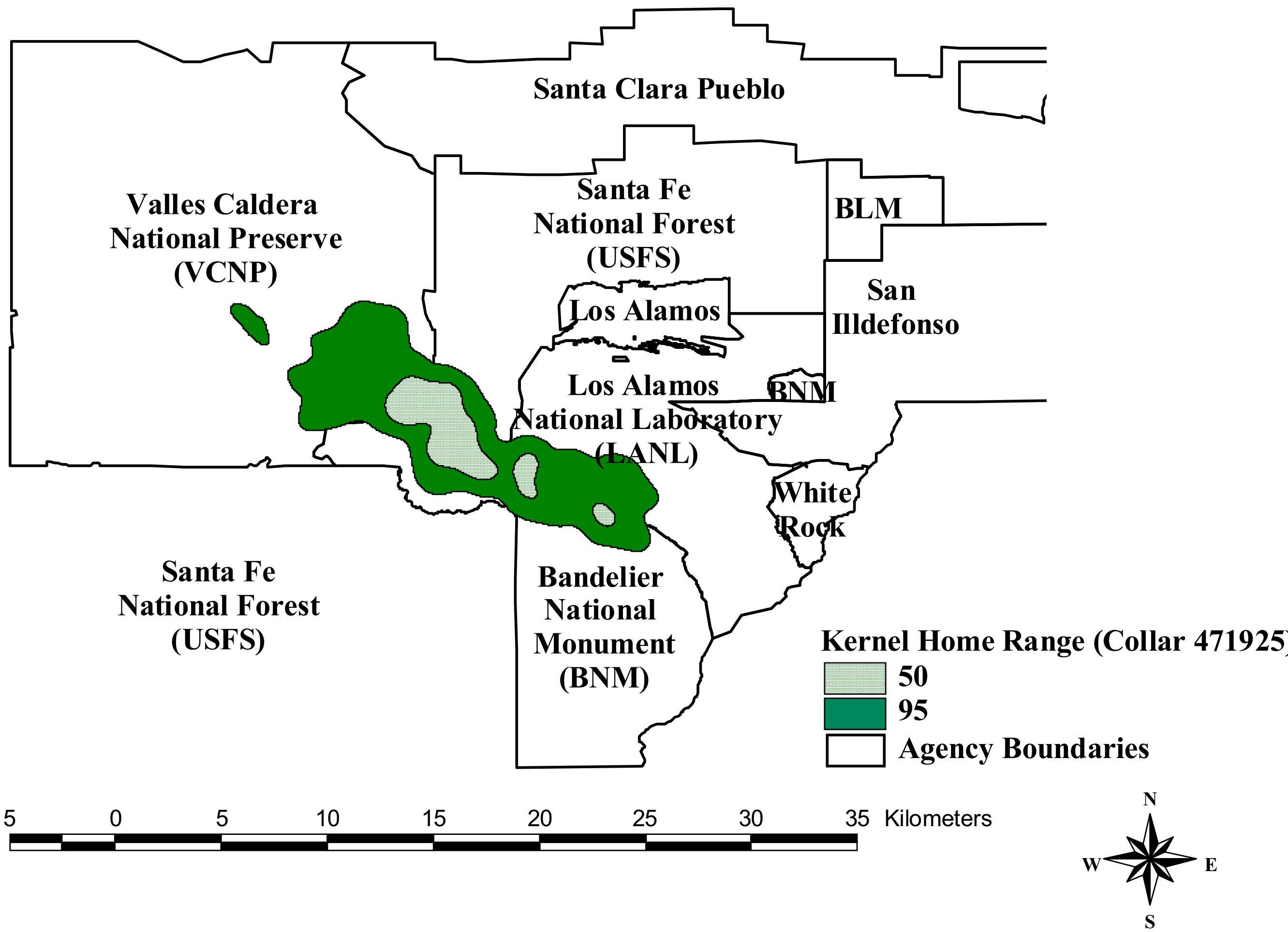
Appendix A.2. Kernel home range for animal #108. Both the 95% activity area and 50% core use area are shown.



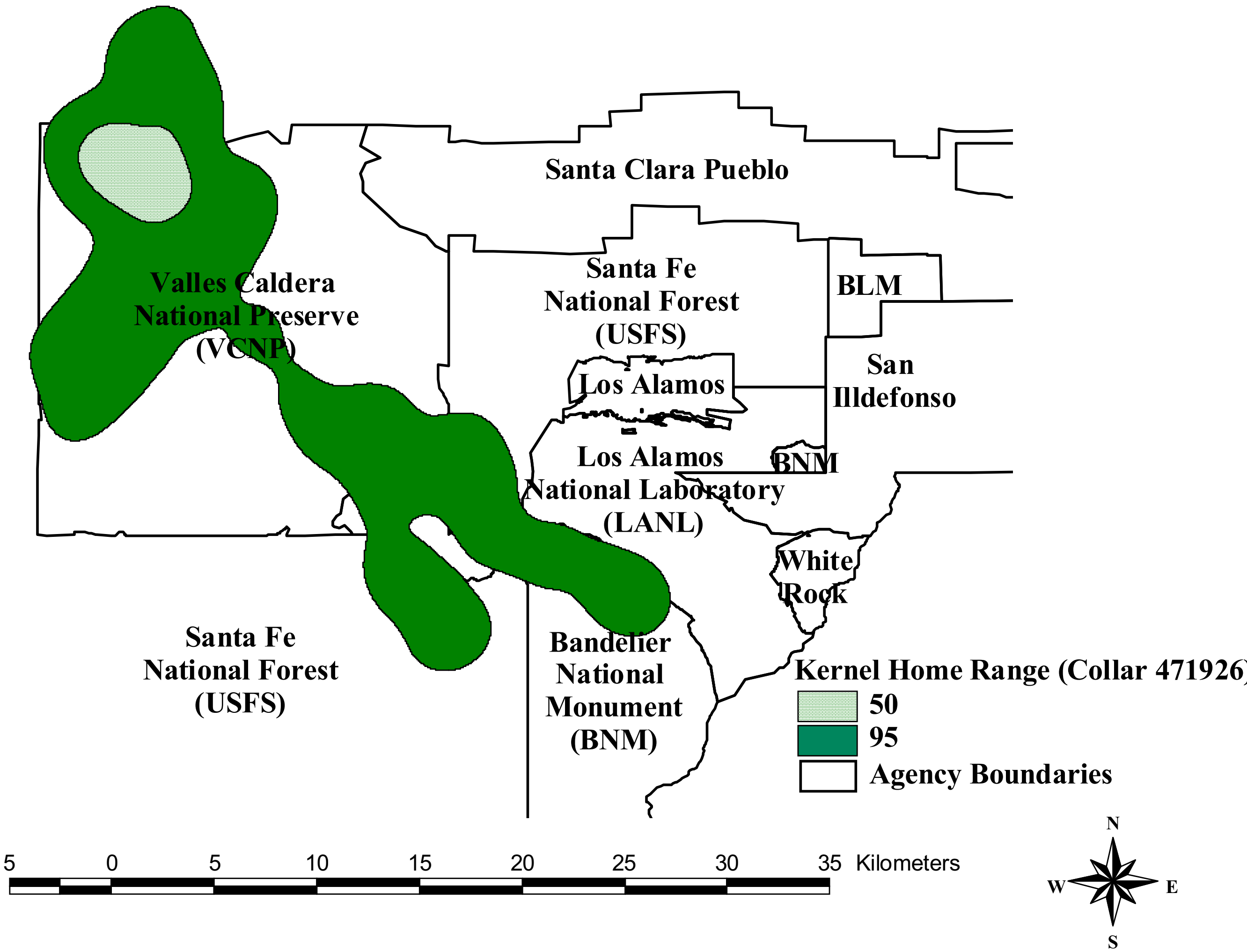
Appendix A.3. Kernel home range for animal #471923. Both the 95% activity area and 50% core use area are shown.



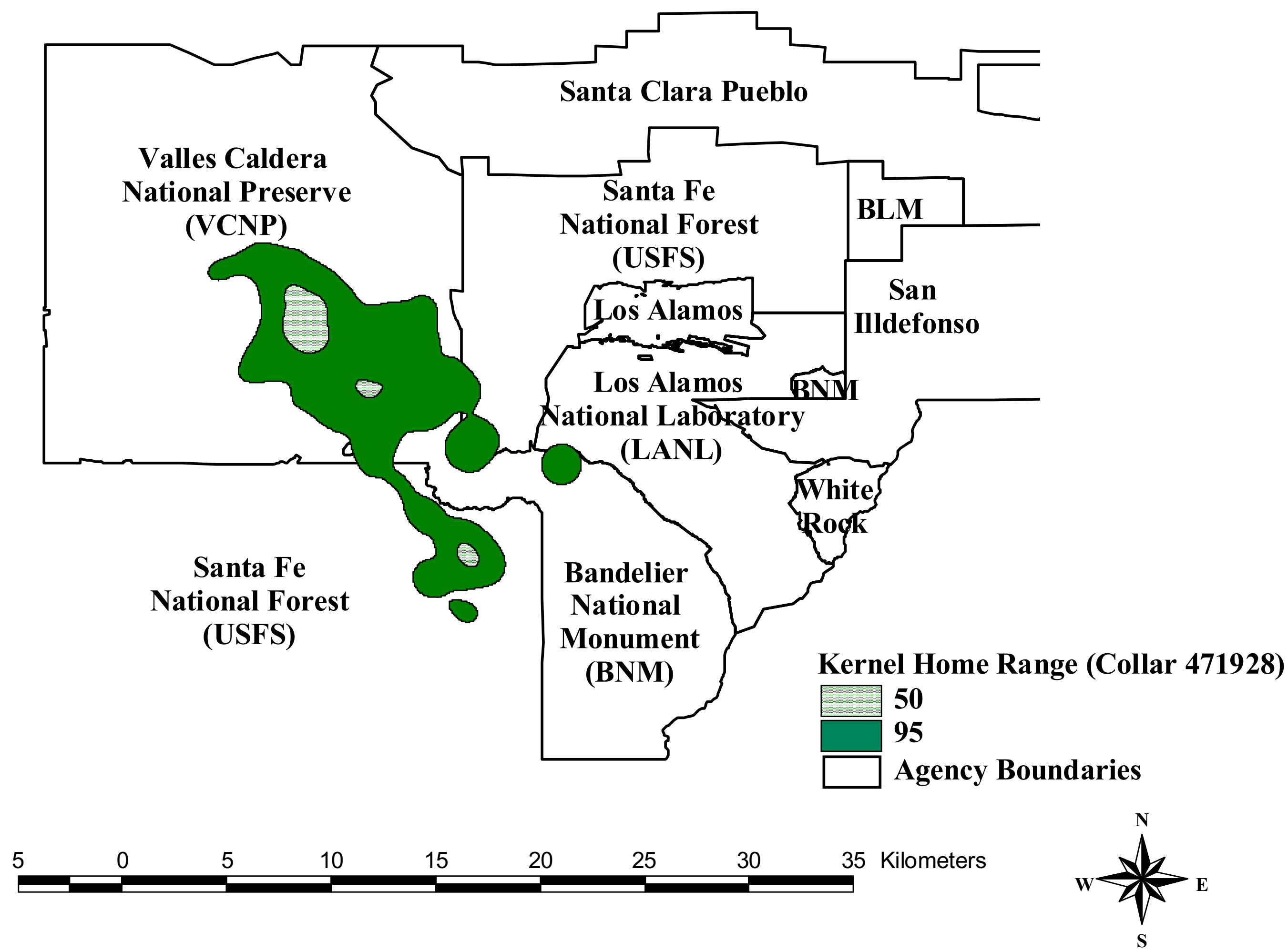
Appendix A.4. Kernel home range for animal #471924. Both the 95% activity area and 50% core use area are shown.



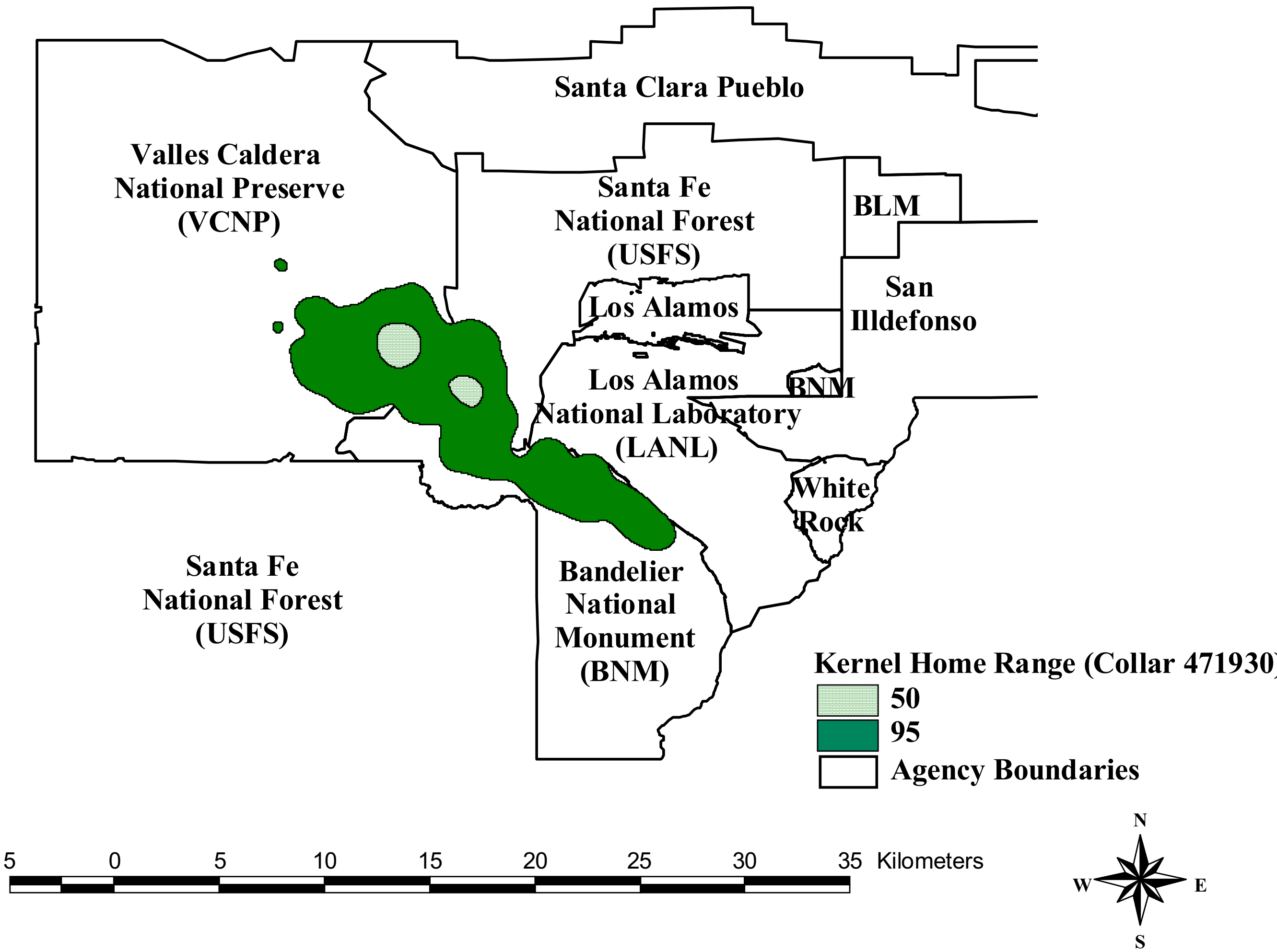
Appendix A.5. Kernel home range for animal #471925. Both the 95% activity area and 50% core use area are shown.



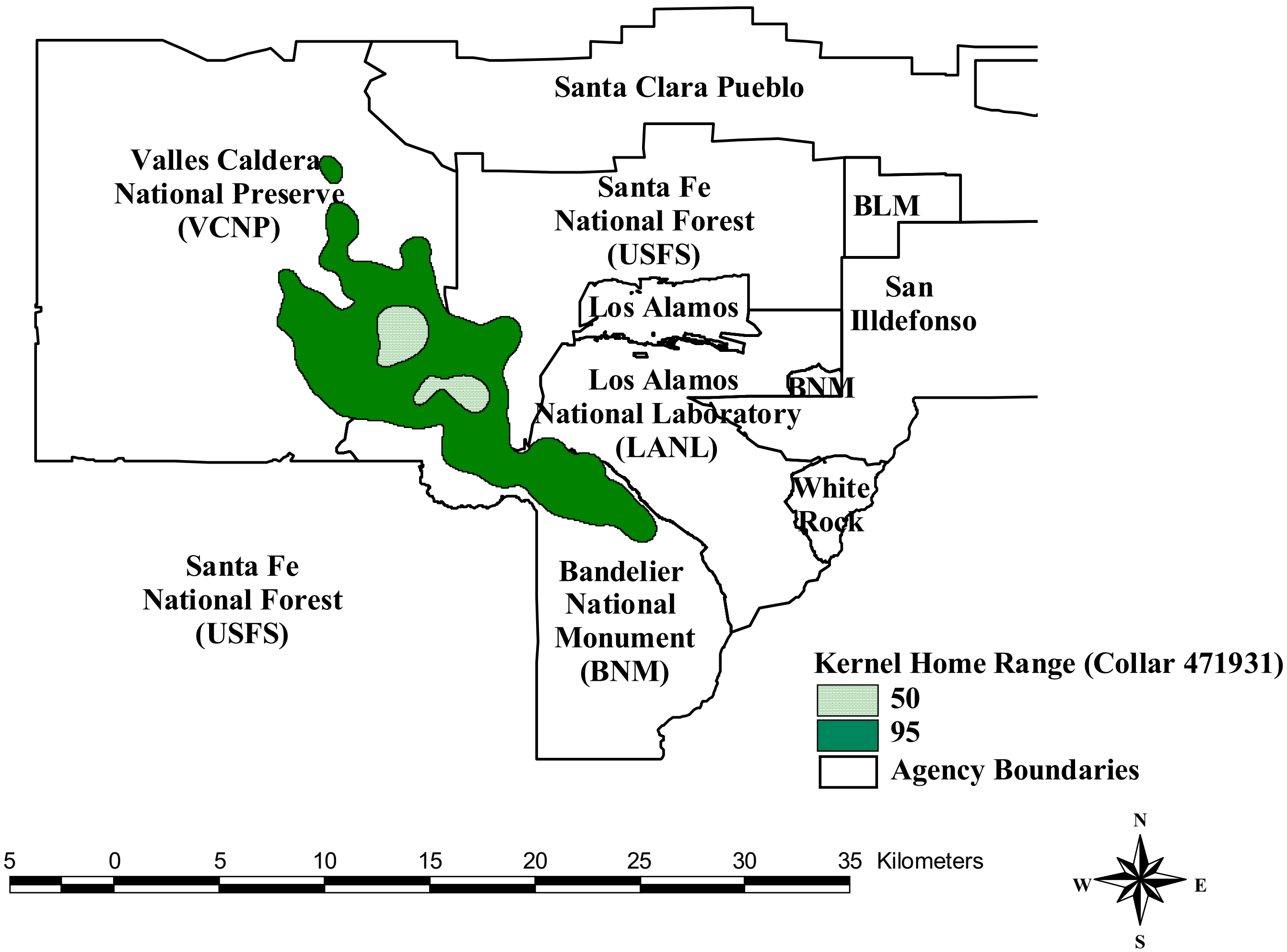
Appendix A.6. Kernel home range for animal #471926. Both the 95% activity area and 50% core use area are shown.



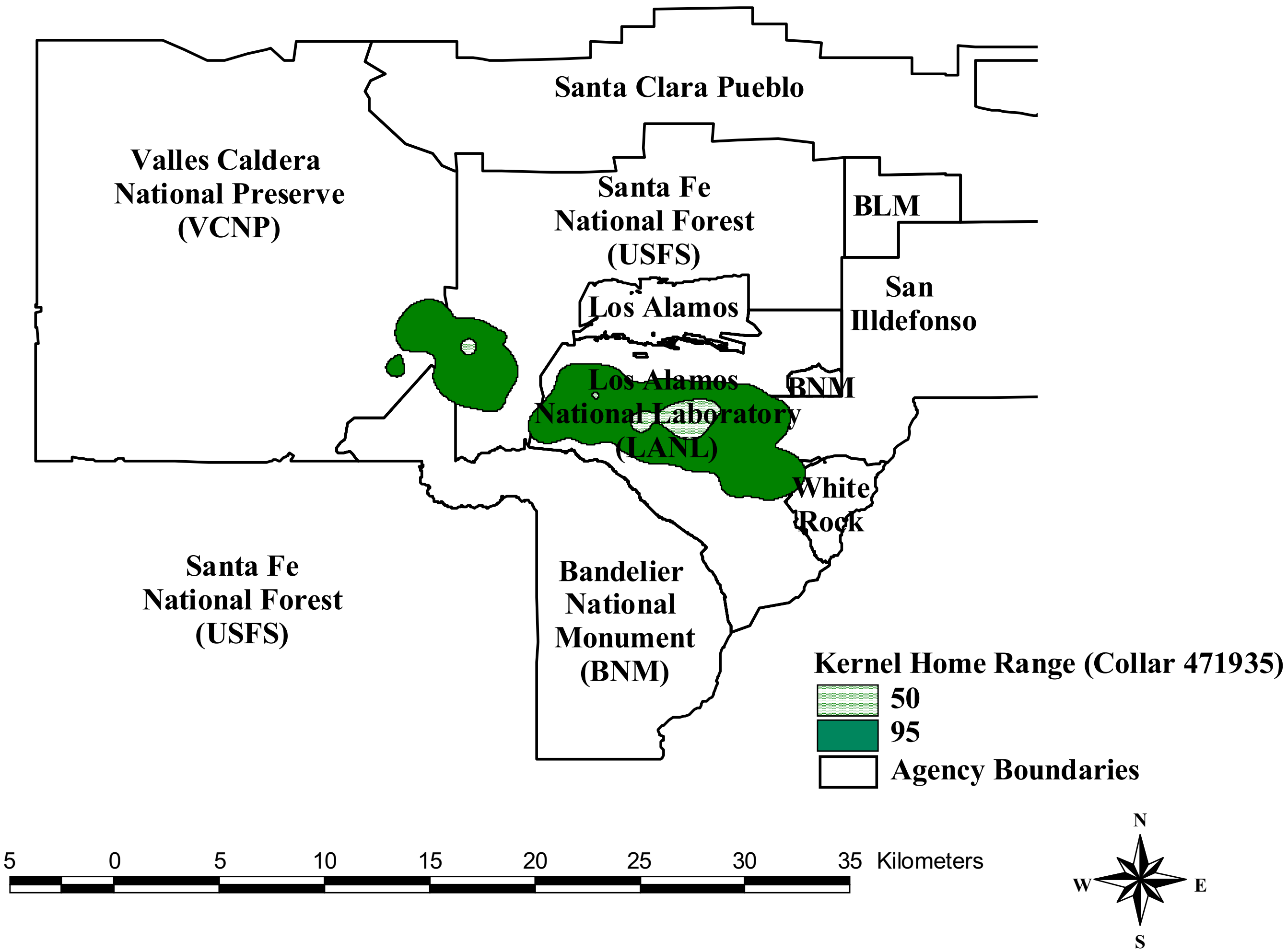
Appendix A.7. Kernel home range for animal #471928. Both the 95% activity area and 50% core use area are shown.



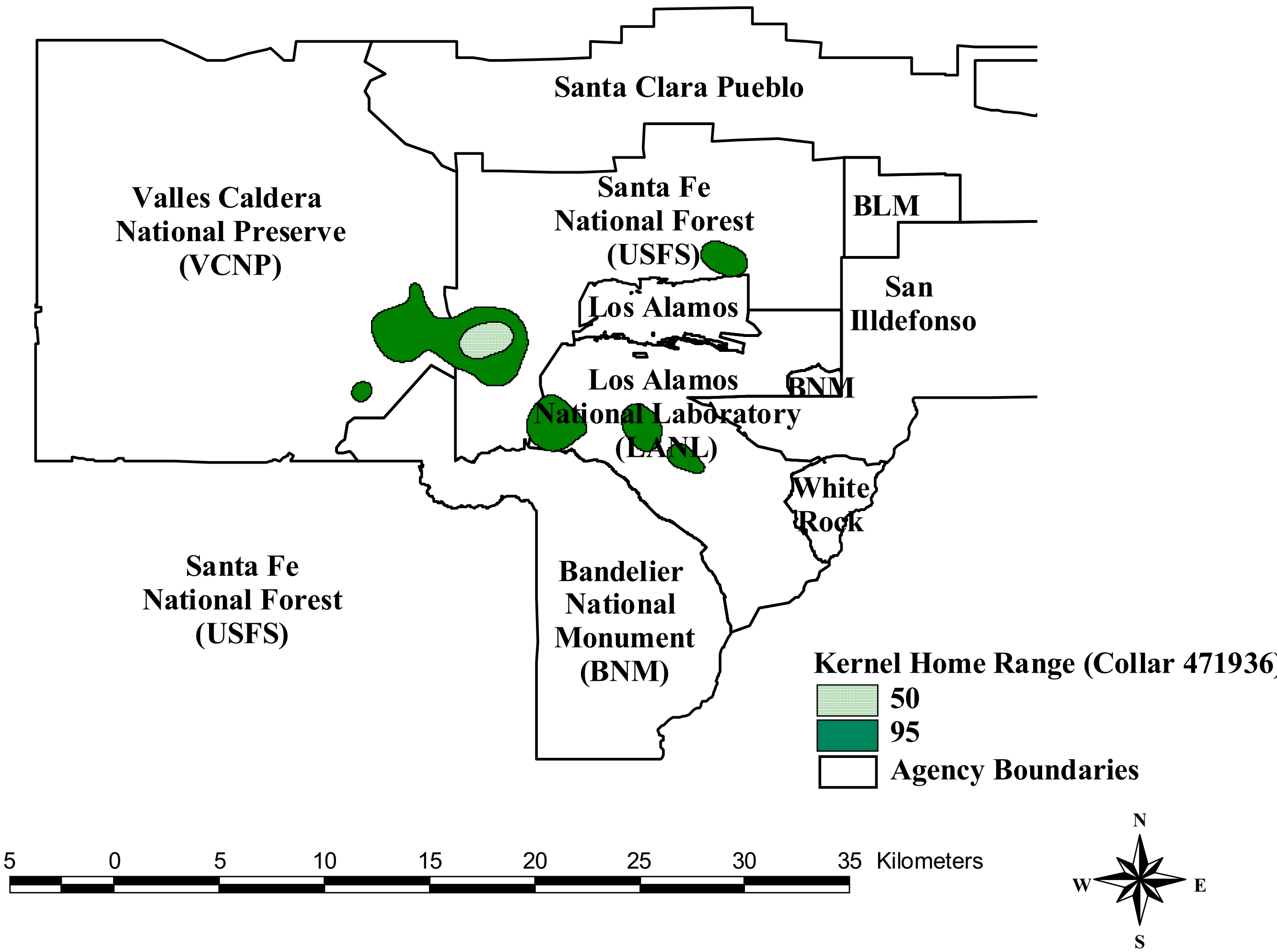
Appendix A.8. Kernel home range for animal #471930. Both the 95% activity area and 50% core use area are shown.



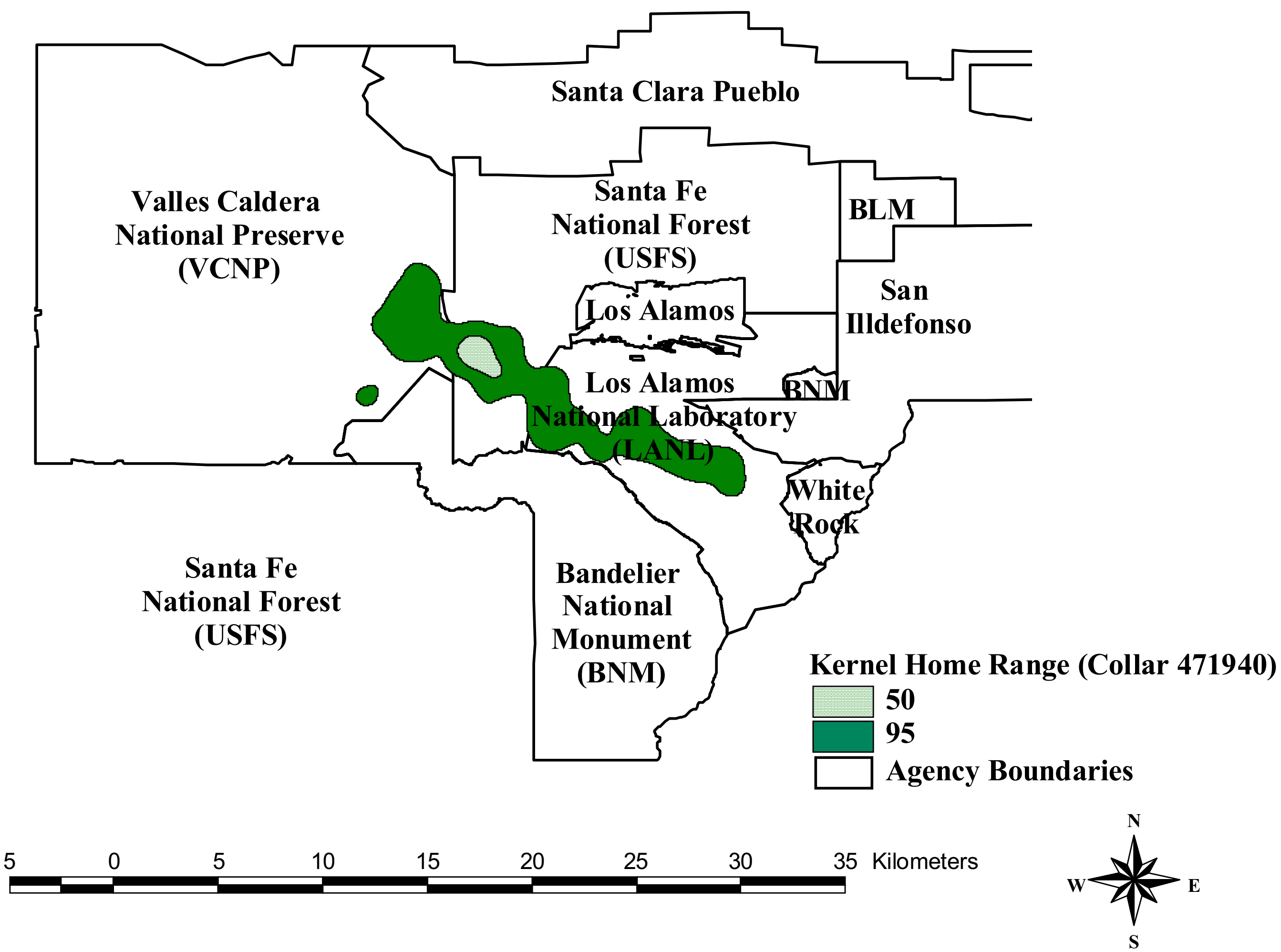
Appendix A.9. Kernel home range for animal #471931. Both the 95% activity area and 50% core use area are shown.



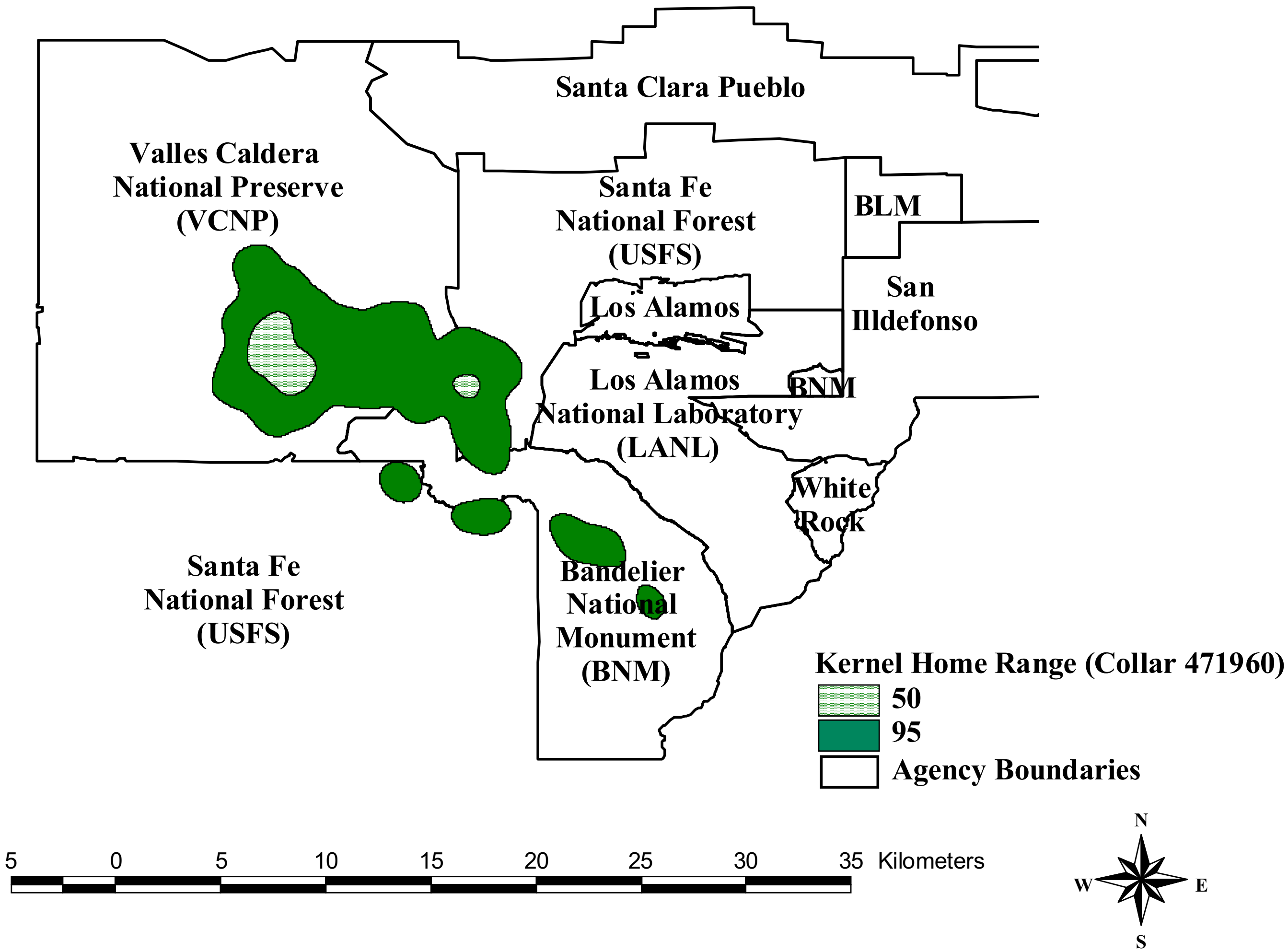
Appendix A.10. Kernel home range for animal #471935. Both the 95% activity area and 50% core use area are shown.



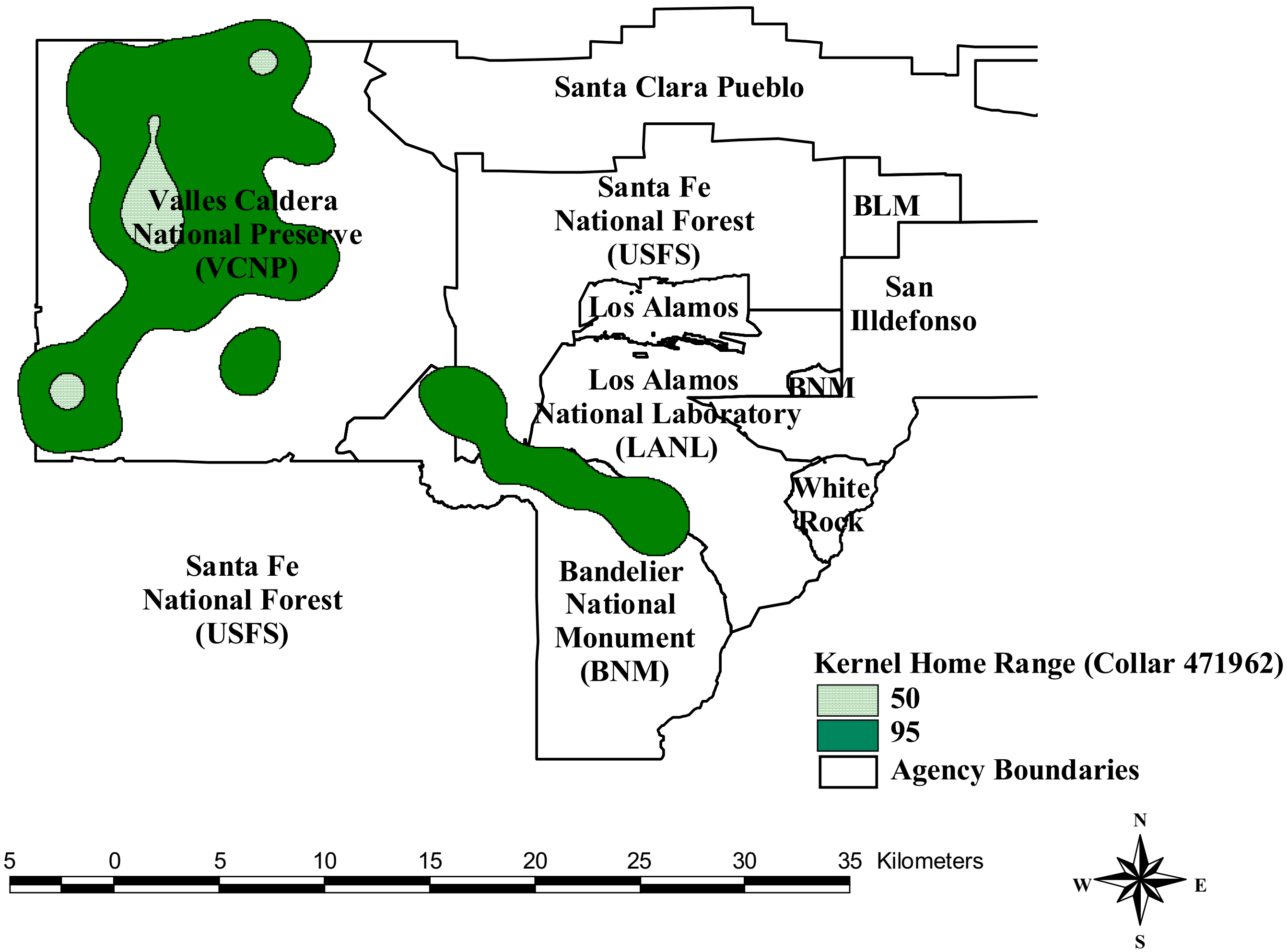
Appendix A.11. Kernel home range for animal #471936. Both the 95% activity area and 50% core use area are shown.



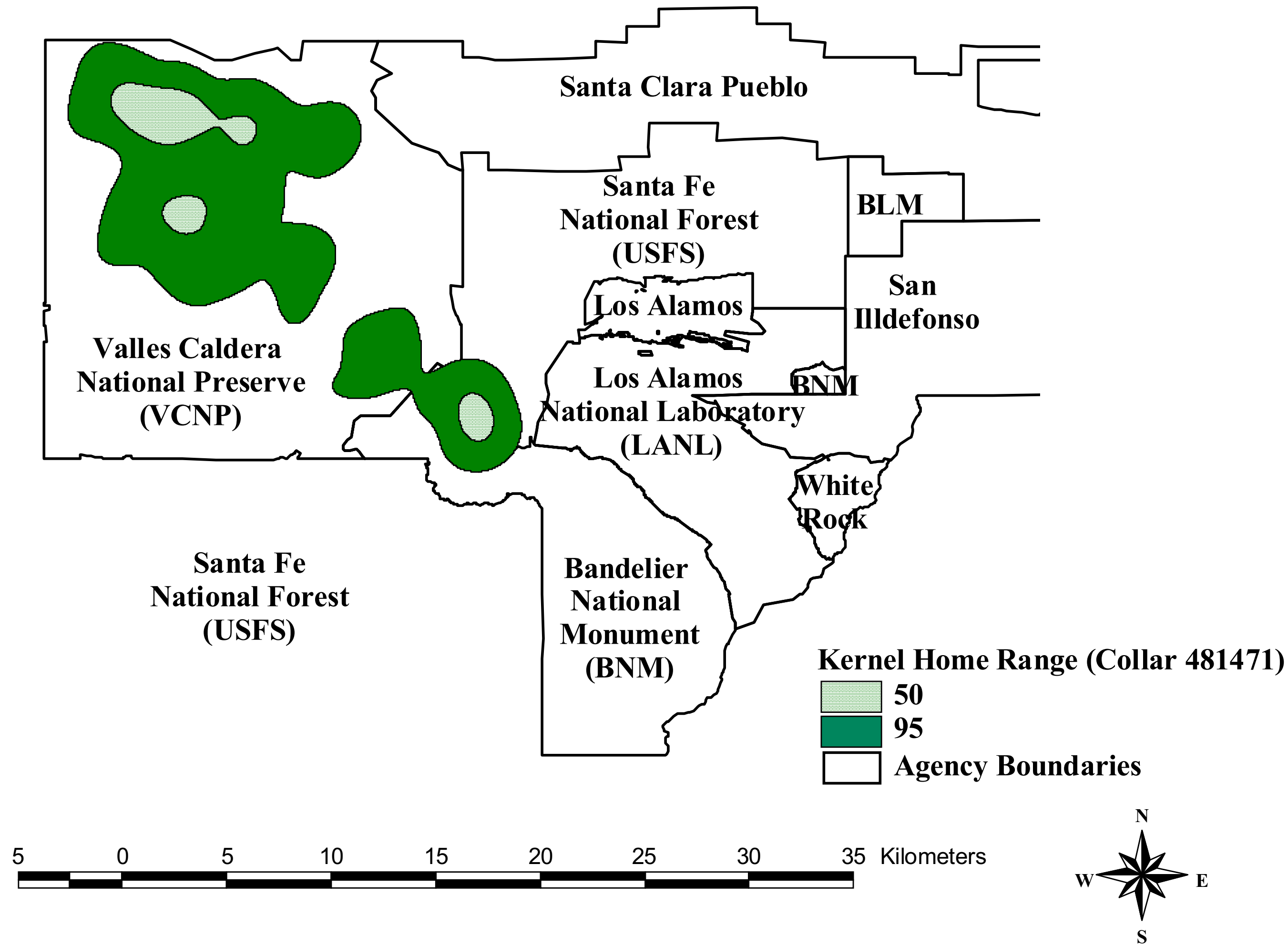
Appendix A.12. Kernel home range for animal #471940. Both the 95% activity area and 50% core use area are shown.



Appendix A.13. Kernel home range for animal #471960. Both the 95% activity area and 50% core use area are shown.



Appendix A.14. Kernel home range for animal #471962. Both the 95% activity area and 50% core use area are shown.



Appendix A.15. Kernel home range for animal #481471. Both the 95% activity area and 50% core use area are shown.

APPENDIX B

ACRONYMS USED IN THE TEXT

Table B.1. Acronyms used in the text.

Acronym	Scientific Name	Common Name
VCNP	----	Valles Caldera National Preserve
ABCO	*Abies concolor*	White fir
PSME	*Pseudotsuga menziesii*	Douglas fir
POTR	*Populus tremuloides*	Aspen
PIPO	*Pinus ponderosa*	Ponderosa pine
BOGR	*Bouteloua gracilis*	Blue grama
SCSC	*Schizachyrium scoparium*	Little bluestem
BRCA	*Bromus carinatus*	California brome
AGTR	*Agropyron trachycaulum*	Slender wheatgrass
QUGA	*Quercus gambelii*	Gambel oak
ABLA	*Abies lasiocarpa*	Subalpine fir
PIEN	*Picea englemannii*	Engelmann spruce
PIED	*Pinus edulis*	Colorado pinyon
JUMO	*Juniperus monosperma*	Oneseed juniper
RONE	*Robinia neomexicana*	New Mexican locust

APPENDIX C

ASSESSING GPS COLLAR PERFORMANCE:

ANALYSIS OF SLOPE AND ELEVATION

ON DILUTION OF PRECISION (DOP)

Table C.1. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for the 0000 to 0400 time block regardless of fix type as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.4107	4.9609	-28.6668	103.5435	1000	0.4568	1.5668	-4.4489	12.0875
	Pos. [4/]	46	3.5720	7.8746	0.1616	41.5836	42	2.2455	2.1440	0.4914	6.5496
	Neg. [4/]	45	-2.2061	4.2467	-28.6668	-0.0337	18	-1.7748	1.6252	-4.4489	-0.4330
Appropriate: [3/]	Full [2/]						28	-0.0408	0.1753	-0.4737	0.4067
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						1	-0.4737	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						794	-0.0109	0.4050	-1.4200	1.2113
	Pos. [4/]						200	0.4968	0.2192	0.1522	1.2113
	Neg. [4/]						210	-0.5039	0.2154	-1.4200	-0.1528
Appropriate: [3/]	Full [2/]						766	-0.0129	0.4090	-1.4200	1.2113
	Pos. [4/]						194	0.5005	0.2202	0.1522	1.2113
	Neg. [4/]						207	-0.5048	0.2166	-1.4200	-0.1528

Table C.1. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.2. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for the 0400 to 0800 time block regardless of fix type as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.8796	25.8063	-44.3716	786.8106	1000	2.0013	11.8402	-4.7638	149.2534
	Pos. [4/]	31	1.3772	1.2002	0.0046	5.6545	5	0.9355	0.3357	0.5213	1.3564
	Neg. [4/]	43	-2.2404	4.3994	-29.2274	-0.0358	39	-0.6933	0.6863	-4.7638	-0.3878
Appropriate: [3/]	Full [2/]						58	-0.1362	0.2059	-0.6079	0.3548
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						3	-0.5190	0.0793	-0.6079	-0.4553
Unstructured											
Assumed: [1/]	Full [2/]						816	-0.1323	0.4491	-1.6424	1.6351
	Pos. [4/]						141	0.5482	0.2696	0.1405	1.6351
	Neg. [4/]						323	-0.5476	0.2513	-1.6424	-0.1394
Appropriate: [3/]	Full [2/]						758	-0.1274	0.4536	-1.6424	1.6351
	Pos. [4/]						134	0.5506	0.2733	0.1405	1.6351
	Neg. [4/]						296	-0.5515	0.2557	-1.6424	-0.1394

Table C.2. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.3. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for the 0800 to 1200 time block regardless of fix type as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	-0.4211	3.4021	-58.0643	11.6070	1000	-0.8534	3.5170	-35.0377	1.5153
	Pos. [4/]	20	2.2911	2.3498	0.0136	10.0782	0	-	-	-	-
	Neg. [4/]	74	-4.2359	9.2240	-58.0643	-0.0552	107	-3.8226	6.4498	-35.0377	-0.4423
Appropriate: [3/]	Full [2/]										
	Pos. [4/]						20	-0.2469	0.1688	-0.5227	0.0500
	Neg. [4/]						0	-	-	-	-
							2	-0.5102	0.0177	-0.5227	-0.4978
Unstructured											
Assumed: [1/]	Full [2/]						743	-0.2719	0.4963	-1.9814	1.5377
	Pos. [4/]						85	0.5614	0.2533	0.1659	1.5377
	Neg. [4/]						359	-0.6634	0.3237	-1.9814	-0.1553
Appropriate: [3/]	Full [2/]						723	-0.2705	0.5003	-1.9814	1.5377
	Pos. [4/]						85	0.5614	0.2533	0.1659	1.5377
	Neg. [4/]						350	-0.6645	0.3267	-1.9814	-0.1553

Table C.3. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.4. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for the 1200 to 1600 time block regardless of fix type as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0400	2.5544	-37.2811	25.532	1000	-0.0009	1.4418	-8.1795	7.0514
	Pos. [4/]	22	0.8954	0.7070	0.0148	2.3489	2	1.1510	0.0816	1.0933	1.2087
	Neg. [4/]	49	-2.4779	5.4979	-37.2811	-0.0207	52	-2.6979	2.4268	-8.1795	-0.4868
Appropriate: [3/]	Full [2/]						32	-0.0863	0.2337	-0.5511	0.3710
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						1	-0.5511	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						762	-0.1622	0.4937	-1.9323	1.4347
	Pos. [4/]						144	0.5196	0.2228	0.2390	1.4347
	Neg. [4/]						284	-0.6591	0.2972	-1.9323	-0.1192
Appropriate: [3/]	Full [2/]						730	-0.1658	0.4960	-1.9323	1.4347
	Pos. [4/]						139	0.5183	0.2244	0.2390	1.4347
	Neg. [4/]						278	-0.6576	0.2983	-1.9323	-0.1192

Table C.4. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.5. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for the 1600 to 2000 time block regardless of fix type as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	-0.0105	9.6642	-208.6154	210.2720	1000	-0.1438	1.8509	-8.4828	14.1376
	Pos. [4/]	35	1.6023	1.6995	0.0058	7.8648	16	1.0261	0.3955	0.5681	2.1131
	Neg. [4/]	39	-3.7545	5.5676	-20.7768	-0.1458	64	-2.4852	1.8117	-8.4828	-0.3951
Appropriate: [3/]	Full [2/]						29	-0.0578	0.1978	-0.4663	0.2205
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						1	-0.4663	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						791	-0.0459	0.4798	-1.7843	1.9568
	Pos. [4/]						195	0.5494	0.2732	0.1416	1.9568
	Neg. [4/]						241	-0.5831	0.2823	-1.7843	-0.1050
Appropriate: [3/]	Full [2/]						762	-0.0451	0.4817	-1.7843	1.9568
	Pos. [4/]						192	0.5463	0.2731	0.1416	1.9568
	Neg. [4/]						232	-0.5850	0.2847	-1.7843	-0.1050

Table C.5. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.6. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for the 2000 to 2400 time block regardless of fix type as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	-0.2867	3.9743	-82.2179	30.1404	1000	0.3105	6.0540	-22.6728	65.2259
	Pos. [4/]	23	1.3012	1.3338	0.0293	6.2106	4	0.6206	0.1402	0.4286	0.7339
	Neg. [4/]	69	-2.5461	3.6890	-22.7139	-0.0168	68	-3.8135	6.0745	-22.6728	-0.3553
Appropriate: [3/]	Full [2/]						39	-0.1054	0.2134	-0.5599	0.3425
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						2	-0.4903	0.0985	-0.5599	-0.4206
Unstructured											
Assumed: [1/]	Full [2/]						746	-0.0489	0.4227	-1.6833	1.8409
	Pos. [4/]						171	0.5094	0.2491	0.0544	1.8409
	Neg. [4/]						235	-0.5006	0.2450	-1.6833	-0.1140
Appropriate: [3/]	Full [2/]						707	-0.0451	0.4293	-1.6832	1.8409
	Pos. [4/]						168	0.5106	0.2507	0.0544	1.8409
	Neg. [4/]						224	-0.5044	0.2492	-1.6833	-0.1140

Table C.6. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.7. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for 2-dimensional fixes during the 0000 to 0400 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate (“Assumed”), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test (“Appropriate”). This analytical procedure was repeated N=1,000 times (“Full”) or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.7847	7.1232	-46.5128	147.0993	1000	0.5883	1.9719	-7.5076	12.8551
	Pos. [4/]	114	4.3786	9.5960	0.0148	68.1143	56	4.1340	2.5842	0.8064	12.8551
	Neg. [4/]	64	-2.8700	5.2999	-26.4205	-0.0168	25	-4.3119	1.2719	-7.5076	-3.2164
Appropriate: [3/]	Full [2/]						0	-	-	-	-
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						206	0.0109	0.6034	-2.1305	1.6369
	Pos. [4/]						67	0.6238	0.3349	0.1812	1.6369
	Neg. [4/]						54	-0.7254	0.4095	-2.1305	-0.2022
Appropriate: [3/]	Full [2/]						206	0.0109	0.6034	-2.1305	1.6369
	Pos. [4/]						67	0.6239	0.3349	0.1812	1.6369
	Neg. [4/]						54	-0.7254	0.4095	-2.1305	-0.2022

Table C.7. (cont).

1/ Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

2/ The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

3/ A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

4/ The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

5/ Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.8. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for 2-dimensional fixes during the 0400 to 0800 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	3.6028	44.9825	-70.9332	836.4965	1000	4.5675	15.1526	-4.9680	133.6018
	Pos. [4/]	49	10.5725	57.8592	0.0401	406.0156	1	0.8708	-	-	-
	Neg. [4/]	74	-3.5083	8.5895	-70.9332	-0.0480	35	-1.2786	1.1651	-4.9301	-0.4857
Appropriate: [3/]	Full [2/]						4	-0.3157	0.4586	-0.8866	0.2299
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						1	-0.8866	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						428	-0.1405	0.5401	-2.1476	1.6791
	Pos. [4/]						86	0.5821	0.2873	0.1096	1.6791
	Neg. [4/]						161	-0.6644	0.3521	-2.1476	-0.1671
Appropriate: [3/]	Full [2/]						424	-0.1413	0.5403	-2.1476	1.6791
	Pos. [4/]						85	0.5820	0.2890	0.1096	1.6791
	Neg. [4/]						159	-0.6660	0.3537	-2.1476	-0.1671

Table C.8. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.9. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for 2-dimensional fixes during the 0800 to 1200 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	-2.7409	28.1705	-650.8810	19.9692	1000	-2.4597	7.5387	-70.7824	1.8180
	Pos. [4/]	41	1.0301	1.1861	0.0807	6.6407	0	-	-	-	-
	Neg. [4/]	93	-21.3209	76.6991	-650.8810	-0.0537	172	-12.3213	13.8752	-70.7824	-0.6459
Appropriate: [3/]	Full [2/]						0	-	-	-	-
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						446	-0.2372	0.6618	-2.2174	1.9535
	Pos. [4/]						75	0.7168	0.3790	0.2445	1.9535
	Neg. [4/]						177	-0.8633	0.4126	-2.2174	-0.1644
Appropriate: [3/]	Full [2/]						446	-0.2372	0.6618	-2.2174	1.9535
	Pos. [4/]						75	0.7168	0.3790	0.2445	1.9535
	Neg. [4/]						177	-0.8633	0.4126	-2.2174	-0.1644

Table C.9. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.10. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for 2-dimensional fixes during the 1200 to 1600 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5]					Locations/animal = 10 Regression Coefficient [5]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1]	Full [2]	1000	-0.4807	8.6989	-153.3957	64.6235	1000	-0.3674	2.3104	-19.1164	12.9251
	Pos. [4]	45	2.7329	7.8287	0.0392	53.1647	4	4.0277	5.9342	-0.8134	12.9251
	Neg. [4]	108	-9.3141	20.9074	-153.3957	-0.0094	113	-4.4521	3.3779	-19.1164	-0.7648
Appropriate: [3]	Full [2]						2	-0.6091	0.8995	-1.2451	0.0270
	Pos. [4]						0	-	-	-	-
	Neg. [4]						1	-1.2451	-	-	-
Unstructured											
Assumed: [1]	Full [2]						526	-0.1595	0.6231	-2.6080	2.1594
	Pos. [4]						99	0.7083	0.3974	0.1375	2.1594
	Neg. [4]						195	-0.7646	0.3781	-2.6080	-0.1945
Appropriate: [3]	Full [2]						524	-0.1618	0.6229	-2.6080	2.1594
	Pos. [4]						98	0.7084	0.3995	0.1375	2.1594
	Neg. [4]						195	-0.7646	0.3781	-2.6080	-0.1945

Table C.10. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.11. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for 2-dimensional fixes during the 1600 to 2000 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate (“Assumed”), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test (“Appropriate”). This analytical procedure was repeated N=1,000 times (“Full”) or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	-0.6370	10.1760	-93.5735	176.4256	1000	-0.6000	2.5765	-11.3502	14.5740
	Pos. [4/]	51	2.0615	2.4535	0.0077	9.7097	5	1.1925	0.3082	0.6687	1.4793
	Neg. [4/]	83	-8.4543	14.8426	-93.5735	-0.0193	106	-3.8238	2.0088	-10.7437	-0.5488
Appropriate: [3/]	Full [2/]						1	-0.0162	-	-	-
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						0	-	--	-	-
Unstructured											
Assumed: [1/]	Full [2/]						426	-0.1112	0.7013	-2.9300	2.3543
	Pos. [4/]						113	0.7177	0.3946	0.1056	2.3543
	Neg. [4/]						153	-0.8063	0.4644	-2.9300	-0.2253
Appropriate: [3/]	Full [2/]						425	-0.1120	0.7019	-2.9300	2.3543
	Pos. [4/]						113	0.7177	0.3946	0.1056	2.3543
	Neg. [4/]						153	-0.8063	0.4644	-2.9300	-0.2253

Table C.11. (cont).

1/ Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

2/ The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

3/ A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

4/ The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

5/ Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.12. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for 2-dimensional fixes during the 2000 to 2400 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate (“Assumed”), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test (“Appropriate”). This analytical procedure was repeated N=1,000 times (“Full”) or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	1.0803	38.9389	-201.9384	986.0600	1000	0.2079	8.7648	-32.2684	49.8801
	Pos. [4/]	119	14.2955	98.3387	0.0704	986.0600	3	2.4417	2.4052	0.8394	5.2074
	Neg. [4/]	153	-7.7504	26.8974	-201.9384	-0.0107	96	-10.3290	7.2984	-32.2684	-0.8516
Appropriate: [3/]	Full [2/]						0	-	-	-	-
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						46	-0.1273	0.7102	-1.3089	1.8193
	Pos. [4/]						13	0.7510	0.4758	0.3035	1.8193
	Neg. [4/]						20	-0.7678	0.2706	-1.3089	-0.1444
Appropriate: [3/]	Full [2/]						46	-0.1273	0.7102	-1.3089	1.8193
	Pos. [4/]						13	0.7510	0.4758	0.3035	1.8193
	Neg. [4/]						20	-0.7678	0.2706	-1.3089	-0.1444

Table C.12. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.13. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for 3-dimensional fixes during the 0000 to 0400 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.1284	0.8596	-2.7409	13.9717	1000	0.0848	0.2677	-0.9128	1.2851
	Pos. [4/]	39	1.2199	2.1549	0.0589	13.9717	36	0.7073	0.3508	0.3113	1.2851
	Neg. [4/]	35	-0.7444	0.4427	-1.7090	-0.0316	11	-0.5033	0.2494	-0.9128	-0.2964
Appropriate: [3/]	Full [2/]						114	0.0258	0.1578	-0.3794	0.3809
	Pos. [4/]						3	0.3472	0.0323	0.3164	0.3809
	Neg. [4/]						1	-0.3794	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						717	0.0593	0.3211	-1.0208	0.9617
	Pos. [4/]						240	0.4004	0.1922	0.1053	0.9617
	Neg. [4/]						155	-0.3690	0.1654	-1.0208	-0.0996
Appropriate: [3/]	Full [2/]						603	0.0599	0.3211	-0.9222	-0.9617
	Pos. [4/]						207	0.3942	0.1927	0.1053	0.9617
	Neg. [4/]						134	-0.3680	0.1599	-0.9222	-0.0996

Table C.13. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.14. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for 3-dimensional fixes during the 0400 to 0800 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.1371	0.8155	-2.9971	9.9987	1000	0.1399	0.2336	-0.4641	1.3021
	Pos. [4/]	44	1.3279	1.8115	0.0278	9.9987	57	0.5902	0.2748	0.3063	1.3021
	Neg. [4/]	29	-0.9448	0.5795	-2.0338	-0.0762	6	-0.3632	0.0614	-0.4458	-0.2978
Appropriate: [3/]	Full [2/]						98	0.0466	0.1572	-0.3466	0.5035
	Pos. [4/]						5	0.3892	0.0686	0.3318	0.5035
	Neg. [4/]						1	-0.3466	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						680	0.1175	0.3055	-0.9001	1.1652
	Pos. [4/]						282	0.3965	0.1958	0.0552	1.1652
	Neg. [4/]						108	-0.3252	0.1439	-0.9001	-0.1024
Appropriate: [3/]	Full [2/]						582	0.1179	0.3105	-0.9001	1.1652
	Pos. [4/]						249	0.3954	0.1960	0.0552	1.1652
	Neg. [4/]						99	-0.3247	0.1464	-0.9001	-0.1024

Table C.14. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.15. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for 3-dimensional fixes during the 0800 to 1200 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate (“Assumed”), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test (“Appropriate”). This analytical procedure was repeated N=1,000 times (“Full”) or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.1712	0.5635	-1.1547	4.4350	1000	0.1268	0.1568	-0.3848	0.8025
	Pos. [4/]	63	0.7153	0.6167	0.0337	3.6418	41	0.3704	0.0759	0.2497	0.5565
	Neg. [4/]	41	-0.4271	0.3047	-1.1547	0.0251	4	-0.3153	0.0691	-0.3848	-0.2378
Appropriate: [3/]	Full [2/]						45	0.0853	0.1013	-0.0928	0.2954
	Pos. [4/]						3	0.2731	0.0194	0.2610	0.2954
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						516	0.1261	0.2491	-0.6904	1.0011
	Pos. [4/]						219	0.3447	0.1724	0.0940	1.0011
	Neg. [4/]						69	-0.2614	0.1214	-0.6904	-0.0634
Appropriate: [3/]	Full [2/]						471	0.1276	0.2547	-0.6904	1.0011
	Pos. [4/]						207	0.3460	0.1736	0.0940	1.0011
	Neg. [4/]						67	-0.2618	0.1230	-0.6904	-0.0634

Table C.15. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.16. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for 3-dimensional fixes during the 1200 to 1600 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.2110	0.6099	-2.2520	8.0776	1000	0.2208	0.1749	-0.3575	0.8564
	Pos. [4/]	79	0.6818	0.4809	0.0131	2.4942	178	0.3881	0.1145	0.2329	0.8564
	Neg. [4/]	29	-0.3597	0.3159	-1.0965	-0.0013	0	-	-	-	-
Appropriate: [3/]	Full [2/]						74	0.1447	0.1294	-0.1592	0.4946
	Pos. [4/]						15	0.3346	0.0634	0.2561	0.4946
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						597	0.2015	0.2382	-0.7104	0.8948
	Pos. [4/]						345	0.3582	0.1620	0.0839	0.8948
	Neg. [4/]						35	-0.2677	0.1419	-0.7104	-0.0853
Appropriate: [3/]	Full [2/]						523	0.2061	0.2436	-0.7104	0.8948
	Pos. [4/]						306	0.3641	0.1658	0.0839	0.8948
	Neg. [4/]						32	-0.2657	0.1472	-0.7104	-0.0853

Table C.16. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.17. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for 3-dimensional fixes during the 1600 to 2000 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.1715	0.7106	-2.7991	9.7519	1000	0.1742	0.2271	-0.4676	1.6130
	Pos. [4/]	36	1.2463	1.2861	0.0042	6.6737	86	0.6071	0.3068	0.2648	1.6130
	Neg. [4/]	27	-0.6755	0.3896	-1.4318	-0.0548	0	-	-	-	-
Appropriate: [3/]	Full [2/]						90	0.0789	0.1333	-0.1484	0.5056
	Pos. [4/]						3	0.4258	0.1019	0.3110	0.5056
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						684	0.1481	0.2710	-0.8135	1.2659
	Pos. [4/]						319	0.3659	0.1744	0.0631	1.2659
	Neg. [4/]						75	-0.3284	0.1508	-0.8135	-0.0606
Appropriate: [3/]	Full [2/]						594	0.1530	0.2775	-0.8135	1.2659
	Pos. [4/]						291	0.3677	0.1756	0.0631	1.2659
	Neg. [4/]						68	-0.3296	0.1547	-0.8135	-0.0606

Table C.17. (cont).

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.18. Effect of elevation (measured in 1000-foot units) on dilution of precision (DOP) for 3-dimensional fixes during the 2000 to 2400 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and elevation was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0344	0.6361	-4.5389	4.0234	1000	0.0005	0.1710	-0.6537	0.5878
	Pos. [4/]	33	0.8211	0.6704	0.0276	2.8670	18	0.3772	0.0619	0.2854	0.5240
	Neg. [4/]	50	-0.7852	0.6869	-3.8540	-0.0301	10	-0.3496	0.0607	-0.4913	-0.2743
Appropriate: [3/]	Full [2/]						106	-0.0059	0.1474	-0.3929	0.4513
	Pos. [4/]						2	0.3698	0.1152	0.2884	0.4513
	Neg. [4/]						1	-0.3929	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						676	0.0645	0.2950	-1.1264	1.0751
	Pos. [4/]						239	0.3640	0.1625	0.1338	1.0751
	Neg. [4/]						127	-0.3621	0.1751	-1.1264	-0.0633
Appropriate: [3/]	Full [2/]						570	0.0665	0.2956	-1.1264	0.8942
	Pos. [4/]						213	0.3569	0.1552	0.1338	0.8942
	Neg. [4/]						107	-0.3631	0.1822	-1.1264	-0.0633

Table C.18. (cont).

1/ Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

2/ The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

3/ A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

4/ The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

5/ Analyses were conducted for elevation measured in ft/1000. Thus, a regression coefficient of -0.2 can be interpreted as follows: for a 1000-ft increase in elevation, DOP decreases 0.2 units.

Table C.19. Effect of topographic slope on dilution of precision (DOP) for the 0000 to 0400 time block regardless of fix type as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0297	0.4598	-10.9954	3.9052	1000	0.0282	0.1870	-1.1762	0.9574
	Pos. [4/]	62	0.2442	0.2775	0.0023	1.4012	99	0.1667	0.1676	0.0420	0.7573
	Neg. [4/]	30	-0.1369	0.0776	-0.2988	-0.0044	3	-0.0591	0.0128	-0.0706	-0.0454
Appropriate: [3/]	Full [2/]						32	0.0057	0.0275	-0.0387	0.0908
	Pos. [4/]						4	0.0602	0.0212	0.0420	0.0908
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						794	0.0133	0.0456	-0.1707	0.2063
	Pos. [4/]						319	0.0551	0.0279	0.0138	0.2063
	Neg. [4/]						151	-0.0509	0.0268	-0.1707	-0.0169
Appropriate: [3/]	Full [2/]						762	0.0133	0.0456	-0.1707	0.2063
	Pos. [4/]						309	0.0548	0.0274	0.0138	0.2063
	Neg. [4/]						145	-0.0512	0.0272	-0.1707	-0.0169

Table C.19. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.20. Effect of topographic slope on dilution of precision (DOP) for the 0400 to 0800 time block regardless of fix type as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate (“Assumed”), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test (“Appropriate”). This analytical procedure was repeated N=1,000 times (“Full”) or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.1560	3.0509	-1.7142	94.0398	1000	0.2085	0.9297	-0.1585	11.0445
	Pos. [4/]	43	0.4067	1.0971	0.0054	7.1923	101	0.5028	0.6305	0.0437	2.3495
	Neg. [4/]	24	-0.1167	0.0961	-0.4027	-0.0003	7	-0.0585	0.0128	-0.0851	-0.0450
Appropriate: [3/]	Full [2/]						61	0.0042	0.0229	-0.0374	0.0536
	Pos. [4/]						4	0.0493	0.0039	0.0454	0.0536
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						816	0.0045	0.0456	-0.1923	0.1688
	Pos. [4/]						257	0.0526	0.0254	0.0140	0.1688
	Neg. [4/]						186	-0.0551	0.0317	-0.1923	-0.0142
Appropriate: [3/]	Full [2/]						755	0.0045	0.0457	-0.1923	0.1688
	Pos. [4/]						241	0.0519	0.0255	0.0140	0.1688
	Neg. [4/]						175	-0.0551	0.0319	-0.1923	-0.0142

Table C.20. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.21. Effect of topographic slope on dilution of precision (DOP) for the 0800 to 1200 time block regardless of fix type as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	-0.0171	0.2208	-2.2462	1.6290	1000	0.0102	0.2073	-0.2443	2.4829
	Pos. [4/]	37	0.3110	0.3426	0.0025	1.6290	34	0.5305	0.8216	0.0625	2.4829
	Neg. [4/]	48	-0.1705	0.1346	-0.8033	-0.0098	27	-0.1000	0.0449	-0.2396	-0.0539
Appropriate: [3/]	Full [2/]						24	-0.0183	0.0268	-0.0733	0.0358
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						3	-0.0617	0.0103	-0.0733	-0.0539
Unstructured											
Assumed: [1/]	Full [2/]						743	-0.0150	0.0535	-0.1852	0.1797
	Pos. [4/]						134	0.0597	0.0254	0.0158	0.1797
	Neg. [4/]						261	-0.0708	0.0335	-0.1852	-0.0187
Appropriate: [3/]	Full [2/]						719	-0.0149	0.0539	-0.1852	0.1797
	Pos. [4/]						132	0.0597	0.0256	0.0158	0.1797
	Neg. [4/]						254	-0.0710	0.0338	-0.1852	-0.0187

Table C.21. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.22. Effect of topographic slope on dilution of precision (DOP) for the 1200 to 1600 time block regardless of fix type as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0027	0.3763	-3.0429	3.6337	1000	-0.0151	0.1401	-0.8580	0.9967
	Pos. [4/]	45	0.3970	0.7637	0.0095	3.6337	49	0.2612	0.2210	0.0555	0.9967
	Neg. [4/]	33	-0.2025	0.2376	-1.2964	-0.0135	13	-0.1084	0.0465	-0.2400	-0.0540
Appropriate: [3/]	Full [2/]						34	0.0186	0.0281	-0.0435	0.0722
	Pos. [4/]						4	0.0616	0.0076	0.0555	0.0722
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						762	-0.0025	0.0560	-0.1861	0.1865
	Pos. [4/]						192	0.0660	0.0330	0.0153	0.1865
	Neg. [4/]						222	-0.0670	0.0311	-0.1861	-0.0142
Appropriate: [3/]	Full [2/]						728	-0.0037	0.0560	-0.1861	0.1865
	Pos. [4/]						180	0.0658	0.0329	0.0153	0.1865
	Neg. [4/]						218	-0.0670	0.0314	-0.1861	-0.0142

Table C.22. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.23. Effect of topographic slope on dilution of precision (DOP) for the 1600 to 2000 time block regardless of fix type as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient 5/					Locations/animal = 10 Regression Coefficient 5/				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: 1/	Full 2/	1000	0.0465	1.0832	-6.6509	32.2901	1000	0.1181	0.7534	-0.8784	6.3023
	Pos. 4/	55	0.4191	0.7893	0.0053	3.7707	53	0.3253	0.2074	0.0483	0.7508
	Neg. 4/	39	-0.1780	0.1274	-0.8107	-0.0217	9	-0.0731	0.0232	-0.1184	-0.0492
Appropriate: 3/	Full 2/						29	-0.0115	0.0212	-0.0739	0.0351
	Pos. 4/						0	-	-	-	-
	Neg. 4/						1	-0.0739	-	-	-
Unstructured											
Assumed: 1/	Full 2/						791	-0.0007	0.0456	-0.1639	0.1310
	Pos. 4/						211	0.0537	0.0253	0.0076	0.1310
	Neg. 4/						221	-0.0548	0.0259	-0.1639	-0.0141
Appropriate: 3/	Full 2/						762	0.0002	0.0453	-0.1639	0.1310
	Pos. 4/						208	0.0540	0.0254	0.0076	0.1310
	Neg. 4/						208	-0.0541	0.0254	-0.1639	-0.0141

Table C.23. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.24. Effect of topographic slope on dilution of precision (DOP) for the 2000 to 2400 time block regardless of fix type as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0322	0.2657	-3.0300	2.0862	1000	0.0986	0.5526	-0.3893	5.8700
	Pos. [4/]	89	0.3978	0.4782	0.0014	2.0143	136	0.1341	0.0851	0.0361	0.4389
	Neg. [4/]	30	-0.1156	0.0719	-0.3348	-0.0154	0	-	-	-	-
Appropriate: [3/]	Full [2/]						40	0.0119	0.0246	-0.0380	0.0720
	Pos. [4/]						5	0.0514	0.0142	0.0361	0.0720
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						746	0.0128	0.0442	-0.1846	0.1789
	Pos. [4/]						291	0.0547	0.0292	0.0118	0.1789
	Neg. [4/]						143	-0.0468	0.0230	-0.1846	-0.0109
Appropriate: [3/]	Full [2/]						706	0.0130	0.0446	-0.1846	0.1789
	Pos. [4/]						279	0.0548	0.0296	0.0118	0.1789
	Neg. [4/]						135	-0.0475	0.0235	-0.1846	-0.0109

Table C.24. (cont.)

1/ Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

2/ The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

3/ A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

4/ The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

5/ Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.25. Effect of topographic slope on dilution of precision (DOP) for 2-dimensional fixes during the 0000 to 0400 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0553	0.6388	-11.9454	5.5895	1000	0.0301	0.2213	-1.6028	0.5810
	Pos. [4/]	148	0.4205	0.5500	0.0340	4.2330	119	0.2063	0.1283	0.0862	0.5810
	Neg. [4/]	31	-0.2109	0.1589	-0.6907	-0.0086	6	-0.1336	0.0552	-0.2233	-0.0808
Appropriate: [3/]	Full [2/]						1	-0.0369	-	-	-
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						206	-0.0038	0.0505	-0.2448	0.1698
	Pos. [4/]						49	0.0568	0.0277	0.0170	0.1698
	Neg. [4/]						56	-0.0630	0.0364	-0.2448	-0.0170
Appropriate: [3/]	Full [2/]						205	-0.0039	0.0506	-0.2448	0.1698
	Pos. [4/]						49	0.0568	0.0277	0.0170	0.1698
	Neg. [4/]						56	-0.0630	0.0364	-0.2448	-0.0170

Table C.25. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.26. Effect of topographic slope on dilution of precision (DOP) for 2-dimensional fixes during the 0400 to 0800 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.3959	3.7866	-3.2717	66.2638	1000	0.4792	1.2425	-0.2686	9.5734
	Pos. [4/]	67	1.2174	3.3730	0.0065	18.6498	90	1.0180	0.6800	0.0495	2.9396
	Neg. [4/]	43	-0.1428	0.1592	-0.8929	-0.0007	6	-0.0969	0.0404	-0.1739	-0.0657
Appropriate: [3/]	Full [2/]						2	-0.0120	0.0001	-0.0121	-0.0119
	Pos. [4/]						0	-	-	-	
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						428	-0.0020	0.0510	-0.1760	0.1958
	Pos. [4/]						108	0.0604	0.0333	0.0150	0.1958
	Neg. [4/]						117	-0.0616	0.0297	-0.1760	-0.0212
Appropriate: [3/]	Full [2/]						426	-0.0020	0.0511	-0.1760	0.1958
	Pos. [4/]						108	0.0604	0.0333	0.0150	0.1958
	Neg. [4/]						117	-0.0616	0.0297	-0.1760	-0.0212

Table C.26. (cont.)

1/ Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

2/ The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

3/ A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

4/ The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

5/ Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.27. Effect of topographic slope on dilution of precision (DOP) for 2-dimensional fixes during the 0800 to 1200 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate (“Assumed”), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test (“Appropriate”). This analytical procedure was repeated N=1,000 times (“Full”) or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.1237	1.3249	-1.7442	28.8109	1000	0.0782	0.4267	-0.5306	4.4997
	Pos. [4/]	79	0.9644	2.8739	0.0038	18.4654	82	0.9252	1.0217	0.0647	4.4997
	Neg. [4/]	54	-0.2184	0.2580	-1.3183	-0.0073	14	-0.2342	0.1185	-0.5306	-0.0908
Appropriate: [3/]	Full [2/]						1	-0.0423	-	-	-
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						446	0.0040	0.0689	-0.2262	0.2834
	Pos. [4/]						130	0.0825	0.0455	0.0189	0.2834
	Neg. [4/]						120	-0.0765	0.0382	-0.2262	-0.0220
Appropriate: [3/]	Full [2/]						445	0.0042	0.0688	-0.2262	0.2834
	Pos. [4/]						130	0.0825	0.0455	0.0189	0.2834
	Neg. [4/]						119	-0.0764	0.0384	-0.2262	-0.0220

Table C.27. (cont.)

1/ Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

2/ The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

3/ A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

4/ The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

5/ Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.28. Effect of topographic slope on dilution of precision (DOP) for 2-dimensional fixes during the 1200 to 1600 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	-0.0247	0.5717	-5.7027	4.0044	1000	-0.0401	0.1790	-0.9753	0.7724
	Pos. [4/]	71	0.4236	0.7911	0.0033	4.0044	40	0.3321	0.1848	0.0766	0.7724
	Neg. [4/]	68	-0.2984	0.6769	-5.4081	-0.0004	17	-0.1281	0.0608	-0.3306	-0.0720
Appropriate: [3/]	Full [2/]						2	-0.0276	0.0319	-0.0502	-0.0051
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						526	-0.0035	0.0638	-0.2510	0.2808
	Pos. [4/]						134	0.0763	0.0419	0.0198	0.2808
	Neg. [4/]						169	-0.0703	0.0362	-0.2510	-0.0188
Appropriate: [3/]	Full [2/]						524	-0.0035	0.0639	-0.2510	0.2808
	Pos. [4/]						133	0.0765	0.0420	0.0198	0.2808
	Neg. [4/]						168	-0.0704	0.0363	-0.2510	-0.0188

Table C.28. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.29. Effect of topographic slope on dilution of precision (DOP) for 2-dimensional fixes during the 1600 to 2000 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.1279	3.4227	-10.1814	96.7012	1000	0.2397	1.0350	-1.6734	5.9172
	Pos. [4/]	53	0.5877	0.9176	0.0057	3.5602	62	0.4321	0.2089	0.0662	1.0184
	Neg. [4/]	51	-0.2658	0.5175	-3.2759	-0.0022	16	-0.1359	0.0569	-0.2454	-0.0554
Appropriate: [3/]	Full [2/]						2	-0.0040	0.0305	-0.0256	0.0176
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						426	-0.0055	0.0564	-0.1877	0.2407
	Pos. [4/]						91	0.0716	0.0358	0.0189	0.2407
	Neg. [4/]						129	-0.0658	0.0338	-0.1877	-0.0226
Appropriate: [3/]	Full [2/]						424	-0.0055	0.0566	-0.1877	0.2407
	Pos. [4/]						91	0.0716	0.0358	0.0189	0.2407
	Neg. [4/]						129	-0.0658	0.0338	-0.1877	-0.0226

Table C.29. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.30. Effect of topographic slope on dilution of precision (DOP) for 2-dimensional fixes during the 2000 to 2400 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.1317	1.8840	-4.4258	34.5985	1000	0.0794	0.4488	-0.5080	3.1585
	Pos. [4/]	111	0.5796	2.6803	0.0011	28.0200	29	0.1994	0.0585	0.0853	0.3051
	Neg. [4/]	140	-0.1342	0.1988	-1.7053	-0.0006	3	-0.0775	0.0272	-0.1051	-0.0506
Appropriate: [3/]	Full [2/]						0	-	-	-	-
	Pos. [4/]						0	-	-	-	-
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						46	0.0049	0.0294	-0.0673	0.0636
	Pos. [4/]						12	0.0403	0.0147	0.0189	0.0636
	Neg. [4/]						7	-0.0386	0.0174	-0.0673	-0.0171
Appropriate: [3/]	Full [2/]						46	0.0049	0.0294	-0.0673	0.0636
	Pos. [4/]						12	0.0403	0.0147	0.0189	0.0636
	Neg. [4/]						7	-0.0386	0.0174	-0.0673	-0.0171

Table C.30. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.31. Effect of topographic slope on dilution of precision (DOP) for 3-dimensional fixes during the 0000 to 0400 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0358	0.1007	-0.5753	1.3000	1000	0.0375	0.0295	-0.0349	0.2422
	Pos. [4/]	95	0.1538	0.1438	0.0009	1.0575	416	0.0574	0.0308	0.0284	0.2422
	Neg. [4/]	11	-0.0345	0.0313	-0.1075	-0.0042	0	-	-	-	-
Appropriate: [3/]	Full [2/]						120	0.0296	0.0163	-0.0117	0.0721
	Pos. [4/]						55	0.0432	0.0098	0.0304	0.0721
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						717	0.0316	0.0312	-0.0864	0.1520
	Pos. [4/]						488	0.0475	0.0221	0.0106	0.1520
	Neg. [4/]						40	-0.0323	0.0148	-0.0864	-0.0125
Appropriate: [3/]	Full [2/]						597	0.0322	0.0317	-0.0864	0.1520
	Pos. [4/]						413	0.0478	0.0227	0.0106	0.1520
	Neg. [4/]						35	-0.0320	0.0148	-0.0864	-0.0125

Table C.31. (cont.)

1/ Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

2/ The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

3/ A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

4/ The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

5/ Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.32. Effect of topographic slope on dilution of precision (DOP) for 3-dimensional fixes during the 0400 to 0800 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient 5/					Locations/animal = 10 Regression Coefficient 5/				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: 1/	Full 2/	1000	0.0388	0.0861	-0.2783	1.5100	1000	0.0373	0.0262	-0.0241	0.1475
	Pos. 4/	106	0.1304	0.1571	0.0041	1.5100	405	0.0563	0.0252	0.0268	0.1475
	Neg. 4/	9	-0.0663	0.0875	-0.2783	-0.0013	0	-	-	-	-
Appropriate: 3/	Full 2/						103	0.0272	0.0144	-0.0179	0.0558
	Pos. 4/						42	0.0404	0.0072	0.0309	0.0558
	Neg. 4/						0	-	-	-	-
Unstructured											
Assumed: 1/	Full 2/						680	0.0256	0.0301	-0.0936	0.1306
	Pos. 4/						427	0.0429	0.0204	0.0077	0.1306
	Neg. 4/						47	-0.0347	0.0193	-0.0936	-0.0116
Appropriate: 3/	Full 2/						577	0.0262	0.0309	-0.0936	0.1306
	Pos. 4/						367	0.0436	0.0210	0.0077	0.1306
	Neg. 4/						43	-0.0349	0.0199	-0.0936	-0.0116

Table C.32. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.33. Effect of topographic slope on dilution of precision (DOP) for 3-dimensional fixes during the 0800 to 1200 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0236	0.0745	-0.2626	0.7179	1000	0.0169	0.0210	-0.0349	0.1154
	Pos. [4/]	97	0.1049	0.0886	0.0010	0.5708	123	0.0452	0.0146	0.0280	0.1154
	Neg. [4/]	34	-0.0458	0.0398	-0.1364	-0.0013	0	-	-	-	-
Appropriate: [3/]	Full [2/]						49	0.0156	0.0128	-0.0131	0.0482
	Pos. [4/]						8	0.0361	0.0076	0.0280	0.0482
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						516	0.0178	0.0281	-0.1045	0.0967
	Pos. [4/]						275	0.0385	0.0166	0.0119	0.0967
	Neg. [4/]						57	-0.0302	0.0181	-0.1045	-0.0098
Appropriate: [3/]	Full [2/]						467	0.0183	0.0287	-0.1045	0.0967
	Pos. [4/]						256	0.0388	0.0169	0.0119	0.0967
	Neg. [4/]						53	-0.0302	0.0187	-0.1045	-0.0098

Table C.33. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The "Full" data represents 1,000 samples of n=1 or n=10 locations per elk for the" homoscedastic/independence assumed" case; for the "homoscedastic/independence appropriate" case, "Full" represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the "Unstructured assumed" case, "Full" represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the "Unstructured appropriate" case, "Full" indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as "appropriate" derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The "Positive" and "Negative" results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.34. Effect of topographic slope on dilution of precision (DOP) for 3-dimensional fixes during the 1200 to 1600 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0256	0.0812	-0.4561	0.8444	1000	0.0265	0.0263	-0.0537	0.1474
	Pos. [4/]	83	0.1206	0.1472	0.0029	0.8444	285	0.0535	0.0215	0.0255	0.1474
	Neg. [4/]	33	-0.0570	0.0450	-0.1511	-0.0006	0	-	-	-	-
Appropriate: [3/]	Full [2/]						77	0.0207	0.0165	-0.0102	0.0748
	Pos. [4/]						22	0.0416	0.0104	0.0287	0.0748
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						597	0.0219	0.0282	-0.0630	0.1254
	Pos. [4/]						345	0.0406	0.0187	0.0113	0.1254
	Neg. [4/]						50	-0.0302	0.0127	-0.0630	-0.0110
Appropriate: [3/]	Full [2/]						520	0.0221	0.0280	-0.0630	0.1254
	Pos. [4/]						307	0.0403	0.0183	0.0113	0.1254
	Neg. [4/]						45	-0.0287	0.0116	-0.0630	-0.0110

Table C.34. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.35. Effect of topographic slope on dilution of precision (DOP) for 3-dimensional fixes during the 1600 to 2000 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0252	0.0727	-0.4400	0.7119	1000	0.0253	0.0205	-0.0466	0.1338
	Pos. [4/]	82	0.1165	0.0989	0.0031	0.7119	322	0.0449	0.0154	0.0219	0.1338
	Neg. [4/]	18	-0.0695	0.0557	-0.2430	-0.0003	0	-	-	-	-
Appropriate: [3/]	Full [2/]						97	0.0231	0.0142	-0.0049	0.0615
	Pos. [4/]						35	0.0380	0.0086	0.0263	0.0615
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						684	0.0234	0.0266	-0.0730	0.1142
	Pos. [4/]						425	0.0392	0.0183	0.0089	0.1142
	Neg. [4/]						48	-0.0273	0.0136	-0.0730	-0.0094
Appropriate: [3/]	Full [2/]						587	0.0233	0.0268	-0.0730	0.1142
	Pos. [4/]						375	0.0386	0.0184	0.0089	0.1142
	Neg. [4/]						46	-0.0270	0.0133	-0.0730	-0.0094

Table C.35. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

Table C.36. Effect of topographic slope on dilution of precision (DOP) for 3-dimensional fixes during the 2000 to 2400 time block as expressed by linear regression analysis. A random sample of n=1 or n=10 locations was selected from each of 15 collared elk. For each sample, the relationship between DOP and topographic slope was estimated under two model scenarios involving assumptions about the distribution of DOP observations for a given elk: (1) DOP values were assumed to be homoscedastic and independent, or (2) DOP values were assumed to have an unstructured variance-covariance matrix (heteroscedastic, correlated). For each analysis, observations among elk were assumed to be independent. For each model scenario, results include number of experimental data sets (N), average, standard error, minimum and maximum regression coefficients for these experiments. A null model likelihood ratio test was used to test whether the model using an unstructured variance-covariance matrix was a significant improvement over the model using the homoscedastic/independence variance-covariance matrix for data sets with n=10 locations per elk; results are presented for analyses when each variance-covariance structure was assumed to be appropriate ("Assumed"), and for when each variance-covariance structure was appropriate based on the null model likelihood ratio test ("Appropriate"). This analytical procedure was repeated N=1,000 times ("Full") or for subsets of the full data set for which significant relationships were detected.

		Locations/ animals = 1 Regression Coefficient [5/]					Locations/animal = 10 Regression Coefficient [5/]				
Analysis	Data Set	N	Ave.	Stderr	Min	Max	N	Ave	Stderr	Min	Max
Homoscedastic/ Independence											
Assumed: [1/]	Full [2/]	1000	0.0301	0.1119	-2.4062	0.6997	1000	0.0350	0.0235	-0.0479	0.1653
	Pos. [4/]	120	0.1146	0.0638	0.0009	0.3949	475	0.0513	0.0186	0.0260	0.1653
	Neg. [4/]	18	-0.0692	0.0505	-0.1720	-0.0006	0	-	-	-	-
Appropriate: [3/]	Full [2/]						119	0.0318	0.0160	-0.0067	0.1110
	Pos. [4/]						57	0.0442	0.0129	0.0292	0.1110
	Neg. [4/]						0	-	-	-	-
Unstructured											
Assumed: [1/]	Full [2/]						676	0.0308	0.0292	-0.0630	0.1454
	Pos. [4/]						470	0.0452	0.0203	0.0124	0.1454
	Neg. [4/]						40	-0.0308	0.0129	-0.0630	-0.0056
Appropriate: [3/]	Full [2/]						557	0.0315	0.0297	-0.0630	0.1454
	Pos. [4/]						393	0.0457	0.0209	0.0124	0.1454
	Neg. [4/]						33	-0.0311	0.0140	-0.0630	-0.0056

Table C.36. (cont.)

[1/] Results are for an analysis that *assumed* that the specified variance-covariance structure applied to the data.

[2/] The “Full” data represents 1,000 samples of n=1 or n=10 locations per elk for the” homoscedastic/independence assumed” case; for the “homoscedastic/independence appropriate” case, “Full” represents the number of times that this variance-covariance structure was adequate to describe the relationship; for the “Unstructured assumed” case, “Full” represents the number of times out of 1,000 samples that a solution was possible (solutions were not possible when, for example, the iterative fitting algorithm used by SAS to derive maximum likelihood estimates of the regression parameters resulted in a nonpositive definite Hessian matrix); for the “Unstructured appropriate” case, “Full” indicates the number of times that this covariance structure was appropriate for the data.

[3/] A null model likelihood ratio test was used to test whether the unstructured variance-covariance structure was better than the homoscedastic/independence variance-covariance structure; for n=10 locations per elk, this test had 54 df. Thus, results labeled as “appropriate” derive from analyses for which the indicated variance-covariance structure was appropriate.

[4/] The “Positive” and “Negative” results represent subsets for which there was a significant positive or negative relationship between DOP and slope. For n=1 location per elk, error df = 13; for n=10 locations per elk, error df = 14 and 134 for the unstructured and homoscedastic/independence analyses, respectively.

[5/] Analyses were conducted for slope measured in degrees. Thus, a regression coefficient of -0.056 can be interpreted as follows: for a 1-degree increase in slope, DOP decreases 0.056 units.

APPENDIX D

POST-FIRE MODEL EVALUATION FORM

APPENDIX D
POST-FIRE MODEL EVALUATION FORM

MODEL NAME: ____

1. Level of complexity? Low Med High

2. If complex, can it be easily simplified? YES NO

Explain: ____

____

3. Type of model (stochastic, IBM, etc.): ______________________

4. Briefly describe the model's objectives: ______________________

____

____

5. Are there associated submodels? YES NO

Describe: ____

____

____

6. Does it include an understory component? ______________________

7. Is there a climate component? ______________________

Describe: ____

____

____

8. Integrated into GIS already? YES NO

9. If NO to #8, can it be? ______________________

10. If YES to #8, is it raster-based? ______________________

11. What is the spatial resolution/scale?______________Temporal?______________

12. Can the resolution be modified? ______________________

13. Is the source code available? YES NO

14. Can it be modified with permissions? YES NO

15. Programming Language: ______________________________

16. Hardware Requirements: ______________________________

17. Input Data Needed:

Variable Name	**COLLECTED @ LANL?**	
	YES	**NO**

NOTES:

18. Output Data Generated:

Variable Name	**Description**

NOTES:

19. Give your overall opinion about the model and if it will meet our requirements:

20. OVERALL RATING: Excellent Good Fair Poor Undecided

Reviewed By: ______________________ Date: __________

APPENDIX E

RAW CODE AND PARAMETER FILES

Table E.1. FORTRAN 90 raw code for development of a “cost impedance” map based on a logistic regression of topographic features (slope, aspect, and elevation). The cost impedance map served as the basis for the generation of an independent variable (Memory) that was used in the habitat suitability index (HSI) to reflect habitual use as well as the response of elk to slope, aspect, and elevation as independent variables in the final HSI calculated through the application of the SAVANNA Ecosystem Model (Code copyright 2005, Acorp Computers, Paul Rupp – owner).

```
!  LogReg.f90
!
!  FUNCTIONS:
!  LogReg      - Create Cost Impedance Surface Map
!

!****************************************************************************
!
!  PROGRAM: LogReg (Logistic Regression)
!
!  PURPOSE: This program creates the cost impedance surface map, and exports/saves
!                  it in the output subdirectory.  Inputs are received from LogReg.PRM,
!                  which needs to be located in the same directory as the executable.  The
!                  Parameter file consists of the name of the Slope Map, the name of the
!                  Aspect Map, the name of the Elevation Map, and the name to use for the
!                  output map.  The parameter file also includes the Beta values used to
!                  calculate the Cost Impedance Surface Map.
!
!****************************************************************************
```

Table E.1. (cont.)

```
program LogReg

  implicit none

  ! Variables
  Real (Kind=16)::Beta(28),XVals(28),Results(28),odds
  INTEGER :: Aspect(0:8,8)
  INTEGER :: nrow,ncol,cellw,nodata,i
  REAL :: xllcrnr,yllcrnr
  INTEGER :: Animals,x,y,count,RandX,RandY
  REAL, ALLOCATABLE, DIMENSION(:,:)  :: SlpIn,AspIn,DemIn
  CHARACTER(30) :: SlpFName,AspFName,DemFName,OutFName,InDirName,OutDirName

  100   FORMAT(<ncol>I4)
  200   FORMAT(A,I5,A,I5)
  300   FORMAT(2(A,I4))
  400   FORMAT(1X, A20)

  Aspect=0
  ! The following section of codes sets up the Aspect array as a series of 1's and 0's
  ! Aspect0 = 1 0 0 0 0 0 0 0
  ! Aspect1 = 0 1 0 0 0 0 0 0
  ! Aspect2 = 0 0 1 0 0 0 0 0
  ! Aspect3 = 0 0 0 1 0 0 0 0
  ! Aspect4 = 0 0 0 0 1 0 0 0
  ! Aspect5 = 0 0 0 0 0 1 0 0
```

Table E.1. (cont.)

```
! Aspect6 = 0 0 0 0 0 0 1 0
! Aspect7 = 0 0 0 0 0 0 0 1
do x=0,8
   do y=1,8
      if (x==(y-1)) Aspect(x,y)=1
   end do
end do

! Aspect8 = -1 -1 -1 -1 -1 -1 -1 -1
Aspect(8,:)=-1

! Read directories and input/output map names from Parameter File (LogReg.PRM)
open(1,file="LogReg.PRM")
read(1,*) InDirName
read(1,*) OutDirName
read(1,*) SlpFName
read(1,*) AspFName
read(1,*) DemFName
read(1,*) OutFName

write(*,*) InDirName,OutDirName,SlpFName,AspFName,DemFName,OutFName

! Read BETA values from Parameter File
do i=1,28
   read(1,*) Beta(i)
end do
close(1)
```

Table E.1. (cont.)

```
! Open Input Maps
open(2,file=(Trim(InDirName) // Trim(SlpFName)))
open(3,file=(Trim(InDirName) // Trim(AspFName)))
open(4,file=(Trim(InDirName) // Trim(DemFName)))

! Read the Slope, Aspect, and Elevation Map Headers
! Make sure the dimension of all maps is the same, break if not
call headerin(nrow,ncol,xllcrnr,yllcrnr,cellw,nodata,2)
RandX=ncol
RandY=nrow
call headerin(nrow,ncol,xllcrnr,yllcrnr,cellw,nodata,3)
if ((RandX .ne. ncol) .or. (RandY .ne. nrow)) then
   Pause
   Stop "Rows/Cols don't match up..."
end if
call headerin(nrow,ncol,xllcrnr,yllcrnr,cellw,nodata,4)
if ((RandX .ne. ncol) .or. (RandY .ne. nrow)) then
   Pause
   Stop "Rows/Cols don't match up..."
end if

! Allocate Memory for Slope, Aspect, and Elevation Maps
allocate (SlpIn(ncol,nrow),AspIn(ncol,nrow),DemIn(ncol,nrow))

! Read the Slope, Aspect, and Elevation Maps into memory
```

Table E.1. (cont.)

```
do y=1,nrow
   read(2,*)(SlpIn(x,y),x=1,ncol)
   read(3,*)(AspIn(x,y),x=1,ncol)
   read(4,*)(DemIn(x,y),x=1,ncol)

end do
close(2)
close(3)
close(4)

! Open Output File (Cost Impedence Surface Map) and write header info
open(1,file=(Trim(OutDirName) // Trim(OutFName)))
call HeaderOut(nrow,ncol,xllcrnr,yllcrnr,cellw,1)

do y=1,nrow
   do x=1,ncol
      ! Pass any "NO DATA" cells from underlying maps through to new Cost Impedence Surface Map
      if ((AspIn(x,y)==-9999) .or. (SlpIn(x,y)==-9999) .or. (DemIn(x,y) ==-9999)) then
         odds=-9999
      else
         ! Create the "X" values to multiply against the Beta Values
         XVals(1)=0
         XVals(10)=SlpIn(x,y)
         XVals(11)=DemIn(x,y)
         XVals(28)=SlpIn(x,y)*DemIn(x,y)
         ! Convert Aspect into one of the arrays as defined above, place it in the "X" values array
         if ((AspIn(x,y) .ge. 0.00) .and. (AspIn(x,y) .le. 22.50)) XVals(2:9)=Aspect(1,:)
```

Table E.1. (cont.)

```
        if ((AspIn(x,y) .gt. 22.50) .and. (AspIn(x,y) .le. 67.50)) XVals(2:9)=Aspect(2,:)
        if ((AspIn(x,y) .gt. 67.50) .and. (AspIn(x,y) .le. 112.5)) XVals(2:9)=Aspect(3,:)
        if ((AspIn(x,y) .gt. 112.5) .and. (AspIn(x,y) .le. 157.5)) XVals(2:9)=Aspect(4,:)
        if ((AspIn(x,y) .gt. 157.5) .and. (AspIn(x,y) .le. 202.5)) XVals(2:9)=Aspect(5,:)
        if ((AspIn(x,y) .gt. 202.5) .and. (AspIn(x,y) .le. 247.5)) XVals(2:9)=Aspect(6,:)
        if ((AspIn(x,y) .gt. 247.5) .and. (AspIn(x,y) .le. 292.5)) XVals(2:9)=Aspect(7,:)

       if ((AspIn(x,y) .gt. 292.5) .and. (AspIn(x,y) .le. 337.5)) XVals(2:9)=Aspect(8,:)
        if ((AspIn(x,y) .gt. 337.5) .and. (AspIn(x,y) .le. 360.0)) XVals(2:9)=Aspect(1,:)
        if (AspIn(x,y) .eq. -1.00) XVals(2:9)=Aspect(0,:)
        XVals(12:19)=XVals(2:9)*SlpIn(x,y)
        XVals(20:27)=XVals(2:9)*DemIn(x,y)
        ! Calculate Logistic Regression
        Results=Beta*XVals
        odds=exp(Sum(Results))
      end if
      ! Write Cost Impedence Surface Map Cell to output file
      write(1,'(F12.5)') odds
    end do
  end do
  close(1)

  end program LogReg
```

Table E.2. Associated parameter file for use with the logistic regression program (Table E.1) used to generate a cost-impedance surface map. The main purpose this file serves is to input associated beta values generated through the logistic regression of slope, aspect, and elevation using PROC LOGISTIC with a stepwise procedure and aspect as a class variable in SAS version 9.0 (Code copyright 2005, Acorp Computers, Paul Rupp – owner)

```
C:\SAVANNA\PROJ\JEMEZ\                  ! Input Subdirectory
C:\SAVANNA\PROJ\JEMEZ\                  ! Output Subdirectory
slp150_UTM.asc                          ! Slope Map
asp150_UTM.asc                          ! Aspect Map
dem150_UTM.asc                          ! Elevation Map
cost150_UTM.asc                         ! Cost Impedance Output Map
0.25556390856224                        ! Beta Values
-3.72970021285766
0.908289812803
0.47714403573645
0.17912811236401
-0.10238587110499
-1.21075360790451
-0.24780776763488
1.9444552756285
-0.20967088123136
0.00001638758918
-0.19251538469185
0.02615273380824
0.03201311634105
0.03947718534524
0.03915524929864
0.02444280731408
0.02239622634565
0
0.00040852863859
-0.00012338987055
-0.00004988084828
-0.0000156493932
0.00001669264503
0.00016080820617
0.00002760406254
-0.00020326152888
0.00001641583175
```

Table E.3. FORTRAN 90 raw code for generation of the elk memory/habitual use map to create the variable “memory” used in the individual-based movement model (Code copyright 2005, Acorp Computers, Paul Rupp – owner).

```
!  Husker_Du.f90
!
!  FUNCTIONS:
!  Husker_Du      - Elk Memory Map Creator Program
!

!****************************************************************************
!
!  PROGRAM: Husker_Du
!
!  PURPOSE: This program creates a memory map for Elk.  It does so by
!          running a number of elk simulations across the study area,
!          with nothing but topographic features.  This program is
!          used to generate the most likely path Elk will take across
!          the study area, based on prior history.  The compilation of
!          this data will be fed back in to the Individual Based
!          Movement Model for the Elk as "memory."  Given two equally
!          attractive movement choices, Elk tend to migrate the same
!                  way they always have.
!
!****************************************************************************

    program Husker_Du

    implicit none
```

Table E.3. (cont.)

```
! Variables
include "HuskerDu.inc"

INTEGER :: nrow,ncol,cellw,nodata
REAL :: xllcrnr,yllcrnr

CHARACTER(LEN=50) :: QualFileNameIn,QualFileNameOut,MapElkOut
CHARACTER(LEN=2) :: DayPart

INTEGER :: Time(8),count,StartCount(3)=0,EndCount(3)=0
REAL, ALLOCATABLE, DIMENSION(:,:)  :: MapIn,MapOut,MapElk
INTEGER :: Times,x,y,i,t,ct,ThisStart,ThisEnd,Success,MaxMoves,MinMoves
INTEGER (KIND=8) :: TotalMoves
INTEGER :: CurrentLoc(2),StartLoc(2),EndLoc(2),EndLocUL(2),EndLocLR(2)
INTEGER :: PriorLoc(2),Choice(2),ChoiceLocs(9,2),n(2)
REAL :: Choices(9)
REAL :: TopVal,r,s,cNow,cMove,cSmall,aNow,bNow,aMove,bMove
LOGICAL :: Flag

100   FORMAT(I4)
200   FORMAT(A,I5,A,I5)
300   FORMAT(2(A,I4))
400   FORMAT(1X, A20)

   ! Body of Husker Du

! Read Control Parameters
```

Table E.3. (cont.)

```
! The Init_Vars Namelist is set up and the variable types are defined
! in the "HuskerDu.inc" include file.
! Variables set in the "HuskerDu.PRM" parameter file are read into the
! Init_Vars Namelist with the "read" statement below.

! Since "HuskerDu.PRM" is one level above the "DEBUG" directory, where
! this program is run from, I have to move up one directory level to find
! the "HuskerDu.PRM" file, hence the "..//" before the filename.

if (iomsg.ge.1) write(*,*) "Opening parameter file (HuskerDu.PRM) for Read..."

! Add "..//" before filename for RELEASE version
open(8,file=("HuskerDu.PRM"))
read(8,nml=Init_Vars)
close(8)
open(8,file="h-log.txt")

if (iomsg.ge.1) write(*,*) "Parameter file values read and accepted."

! Assemble our qualified path and filename, assuming a starting directory of "Debug"
! Add "..//" at the beginning of the filenames for RELEASE version
QualFileNameIn = trim(InFileDir) // "//" // trim(InFileName) // ".asc"
QualFileNameOut = trim(OutFileDir) // "//" // trim(OutFileName) // ".asc"

! Output information/diagnostic messages to the screen if turned on
if (iomsg.ge.1) then
   write (*,*) "Simulation will run ",RunCount," times, and"
   write (*,*) "the output file name will be ",trim(QualFileNameOut)
```

Table E.3. (cont.)

```
    write (*,*) "The Path and Filename for the input map is: ",trim(QualFileNameIn)
    write (*,*)
    write (*,*) "Opening Cost Impedance Surface map for header read..."
  end if

  ! Open the GIS Cost Impedence Surface Map Header and test for error
  open(9,file=(QualFileNameIn))

  ! Read the GIS Cost Impedence Surface Map Header
  call headerin(nrow,ncol,xllcrnr,yllcrnr,cellw,nodata,9)

  ! Spit out some information on the Surface Map
  if(iomsg.ge.1)then
    write(*,*)"Map Name: ",QualFileNameIn
    write(*,*)"Total domain of Cost Impedance Surface Map (rows,cols): ",nrow,ncol
    write(*,*)"Geographic Coordinates (X,Y): ",xllcrnr,yllcrnr
  end if

  ! Allocate the Input and Output Map Arrays
  allocate (MapIn(MaxX,MaxY),MapOut(MaxX,MaxY),MapElk(MaxX,MaxY))

  ! Initialize Random Number Seed
  call random_seed

  ! Read the GIS Cost Impedence Surface Map
  ! The read statement reads in a row at a time, hence the first do-loop,
  ! and puts each value read from the input file into the array.
  ! The "x=1,MaxX" handles the Columns portion of the array, so we don't
```

Table E.3. (cont.)

```
! need another do-loop for that.  Essentially we read Y Records, with each record
! containing X elements.  So, you can say that we read Y Rows, and each row
! contains X Columns.
do y=1,MaxY
   do x=1,MaxX
      read(9,*)MapIn(x,y)
   end do
end do
close(9)

! Initialize Program Variables
i = 1
MapOut = 0
Times = 0
Success = 0
if (KillCap) then
   MinMoves = KillCap
else
   MinMoves =5000000
endif
MaxMoves = 0
TotalMoves = 0

Open(4,file=trim(OutFileDir) // "//" // trim(OutFileName) // ".log")
write(4,*)"Husker Du Model Run Summary Information: "
write(4,*)
Call Date_and_Time(Values=Time)
DayPart="AM"
```

Table E.3. (cont.)

```
  if (Time(5)>12) then
      Time(5)=Time(5)-12
      DayPart="PM"
   endif
   write(4,'(A,I2,A,I2,A)')"Started at ",Time(5),":",Time(6),DayPart
   write(4,'(A,I5,A)')"Simulation will run ",RunCount," time(s)"
   write(4,'(A,I4,A,I4)')"Total domain of Cost Impedance Surface Map (rows,cols): ",nrow,",",ncol
   write(4,*)

   write(*,'(A,I2,A,I2,A)')"Started at ",Time(5),":",Time(6),DayPart

   Do While (i <= RunCount) ! All Elk Loop
      ! Initialize and increment variables for each run
      write(*,*)"Elk: ",i
      MapElk = 0
      ThisStart = 0
      ThisEnd = 0
      Times = 0
      i = i + 1

      ! Randomly choose a starting and ending area for Elk
      ! If we only have one start/end area, we get that area, no randomness
      ! If we have two start/end areas, there is a 50-50 chance we get one or the other
      ! If we have three start/end areas, each one has a 33% chance of being selected
      CALL Random_Number(r)
      ThisStart=StrtAreas*r+1
      CALL Random_Number(r)
      ThisEnd=EndAreas*r+1
```

Table E.3. (cont.)

```
! Find out the Max X and Max Y of each area,
! then randomly choose a cell somewhere in that area
SELECT CASE( ThisStart )
   CASE( 1 )
      StartLoc(1)=Str1LRCoord(1)-Str1ULCoord(1)
      CALL Random_Number(r)
      StartLoc(1)=(r*StartLoc(1)+1)+Str1ULCoord(1)
      StartLoc(2)=Str1LRCoord(2)-Str1ULCoord(2)
      CALL Random_Number(r)
      StartLoc(2)=(r*StartLoc(2)+1)+Str1ULCoord(2)
   CASE( 2 )
      StartLoc(1)=Str2LRCoord(1)-Str2ULCoord(1)
      CALL Random_Number(r)
      StartLoc(1)=(r*StartLoc(1)+1)+Str2ULCoord(1)
      StartLoc(2)=Str2LRCoord(2)-Str2ULCoord(2)
      CALL Random_Number(r)
      StartLoc(2)=(r*StartLoc(2)+1)+Str2ULCoord(2)
   CASE( 3 )
      StartLoc(1)=Str3LRCoord(1)-Str3ULCoord(1)
      CALL Random_Number(r)
      StartLoc(1)=(r*StartLoc(1)+1)+Str3ULCoord(1)
      StartLoc(2)=Str3LRCoord(2)-Str3ULCoord(2)
      CALL Random_Number(r)
      StartLoc(2)=(r*StartLoc(2)+1)+Str3ULCoord(2)
END SELECT

SELECT CASE( ThisEnd )
   CASE( 1 )
```

Table E.3. (cont.)

```
     EndLocUL(1)=End1ULCoord(1)
     EndLocLR(1)=End1LRCoord(1)
     EndLocUL(2)=End1ULCoord(2)
     EndLocLR(2)=End1LRCoord(2)
     EndLoc(1)=End1LRCoord(1)-End1ULCoord(1)
     CALL Random_Number(r)
     EndLoc(1)=(r*EndLoc(1)+1)+End1ULCoord(1)
     EndLoc(2)=End1LRCoord(2)-End1ULCoord(2)
     CALL Random_Number(r)
     EndLoc(2)=(r*EndLoc(2)+1)+End1ULCoord(2)
   CASE( 2 )
     EndLocUL(1)=End2ULCoord(1)
     EndLocLR(1)=End2LRCoord(1)
     EndLocUL(2)=End2ULCoord(2)
     EndLocLR(2)=End2LRCoord(2)
     EndLoc(1)=End2LRCoord(1)-End2ULCoord(1)
     CALL Random_Number(r)
     EndLoc(1)=(r*EndLoc(1)+1)+End2ULCoord(1)
     EndLoc(2)=End2LRCoord(2)-End2ULCoord(2)
     CALL Random_Number(r)
     EndLoc(2)=(r*EndLoc(2)+1)+End2ULCoord(2)
   CASE( 3 )
     EndLocUL(1)=End3ULCoord(1)
     EndLocLR(1)=End3LRCoord(1)
     EndLocUL(2)=End3ULCoord(2)
     EndLocLR(2)=End3LRCoord(2)
     EndLoc(1)=End3LRCoord(1)-End3ULCoord(1)
     CALL Random_Number(r)
```

Table E.3. (cont.)

```
        EndLoc(1)=(r*EndLoc(1)+1)+End3ULCoord(1)
        EndLoc(2)=End3LRCoord(2)-End3ULCoord(2)
        CALL Random_Number(r)
        EndLoc(2)=(r*EndLoc(2)+1)+End3ULCoord(2)
    END SELECT

    if (.not. EndPoint) then
      EndLoc(1)=ABS((EndLocUL(1)-EndLocLR(1))/2)
      EndLoc(1)=EndLocUL(1)+EndLoc(1)
      EndLoc(2)=ABS((EndLocUL(2)-EndLocLR(2))/2)
      EndLoc(2)=EndLocUL(2)+EndLoc(2)
    endif

    ! Our Starting Location is also our Current Location,
    ! and will become our Prior Location as soon as we move
    CurrentLoc=StartLoc;PriorLoc=StartLoc

    write (4,200)"Elk #",i-1," of ",RunCount
    write (4,200)"Started from Area",ThisStart
    write (4,300)"Cell: ",StartLoc(1),",",StartLoc(2)
    if (EndPoint) then
      write (4,300)"Going To: ",EndLoc(1),",",EndLoc(2)
    else
      write (4,'(A,I1,5(A,I4))')"Going to area ",ThisEnd,": (",EndLocUL(1),",",EndLocUL(2),") x -
      (",EndLocLR(1),",",EndLocLR(2),")"
    endif
    write(4,*)
```

Table E.3. (cont.)

```
! Keep Statistics for how many elk start/end at each location
StartCount(ThisStart)=StartCount(ThisStart)+1
EndCount(ThisEnd)=EndCount(ThisEnd)+1

! Write this individual's map, if we are keeping it, and the
! entire simulation map.
MapElk(StartLoc(1),StartLoc(2)) = 1
! Begin searching for the end point
Do While ((Times <= KillCap) .or. (KillCap == 0)) ! One Elk Loop
   ! Reset and Increment Variables
   ! (Times: Number of times this elk has moved)
   ! (t: 1-9 of the cells available to this elk)
   ! (ChoiceLocs: (Col,Row) Index of cells 1-9)
   ! (Choices: Desirability of cells 1-9)
   Times=Times+1
   t=0
   Choices = 0
   ChoiceLocs = 0
   cSmall=5000000
   ct=0
   if(ForceEnd) then
      aNow=(CurrentLoc(1)-EndLoc(1))**2
      bNow=(CurrentLoc(2)-EndLoc(2))**2
      cNow=aNow+bNow
      cNow=SQRT(cNow)
   endif
```

Table E.3. (cont.)

```
! Each time through this loop is one cell move
do x = CurrentLoc(1)-1,CurrentLoc(1)+1
   do y = CurrentLoc(2)-1,CurrentLoc(2)+1
      ! Increment Choice Index
      t=t+1
      ! Reset Flag to default state
      Flag = .true.

      ! Set ChoiceLocs to correspond to coordinates of cell we are evaluating
      ChoiceLocs(t,1)=x
      ChoiceLocs(t,2)=y

      ! Check to make sure Column is in-bounds high/low
      ! If not in-bounds set desirability to zero
      if ((x > MaxX) .or. (x < 1)) then
         Choices(t)=0
         Flag=.false.
      endif

      ! Check to make sure Row is in-bounds high/low
      ! If not in-bounds set desirability to zero
      if ((y > MaxY) .or. (y < 1)) then
         Choices(t)=0
         Flag=.false.
      endif
```

Table E.3. (cont.)

```
! Check to make sure this isn't our "TagBack" cell, if we are not allowing them
! Though we don't technically allow tagbacks, the situation could occur where an
! elk moves to a cell which is surrounded by all zero option choices.  In this
! case, an elk would be "trapped" forever and eventually crash the program.  By
! setting the value of our tagback cell to a very small number instead of zero,
! we allow the elk to "escape" from a no alternative situation, since .01
! compared to 0 is still a better choice.
if (NoTagBack) then
   if (x==PriorLoc(1) .and. y==PriorLoc(2)) then
      Choices(t)=.000001
      Flag = .false.
   endif
endif

! Check to see if we are evaluating the cell we are already in
! If so, set desirability to zero
if ((x==CurrentLoc(1) .and. y==CurrentLoc(2))) then
   Choices(t) = 0
   Flag = .false.
endif

! Check to make sure that this isn't a "No Data" cell
if (Flag) then
   if (MapIn(x,y)==-9999) then
      Choices(t) = 0
      Flag = .false.
```

Table E.3. (cont.)

```
      endif
   endif


   ! If none of the special cases above apply,
   ! read the desirability of this cell from the Map
   if (Flag) then
      Choices(t)=MapIn(x,y)

      ! Even if cell has a desirability of zero, it still has a statistical
      ! chance of being selected, so increase desirability to .01
      ! This does not apply to cells forced to zero above, only to cells read from map as zero
      if (Choices(t)==0) Choices(t)=.01

      ! If we are forcing Elk to migrate, do that here
      if (ForceEnd) then
         aMove=(x-EndLoc(1))**2
         bMove=(y-EndLoc(2))**2
         cMove=aMove+bMove
         cMove=SQRT(cMove)
         if (cMove<CNow) then
            if(iomsg)then
               write(4,*)"Force Exert Applied..."
               write(4,*)"on cell: ",CurrentLoc(1),",",CurrentLoc(2)
               write(4,*)"going to: ",Endloc(1),",",EndLoc(2)
               write(4,*)"force applied to: ",t,"(",x,",",y,")"
               write(4,*)"cMove is: ",cMove
```

Table E.3. (cont.)

```
                endif
                Choices(t)=Choices(t)+(ForceExert)
                if (cMove<CSmall) then
                   cSmall=cMove
                   ct=t

                endif
             endif
          endif
       endif
    end do
 end do
 ! The desirability of our cell choices needs to add up to 100%
 ! Have to mask where Choices > 0 to avoid divide by zero error
 Where (Choices > 0) Choices=Choices/SUM(Choices)

 ! Pick a cell at "random" based on the desirability of all the cells avail
 ! Call random number generator
 Call Random_Number(r)
 if (iomsg.ge.2) then
    do t=1,9
       write(4,*)"     Choice #",t,"=",Choices(t),"Loc= ",
-                                  ChoiceLocs(t,1),ChoiceLocs(t,2)
    end do
    if(sum(Choices).eq.0)write(4,*)"The problem started here, all choices are zero!"
    write(4,*)"     My Random number is: ",r
 end if
```

Table E.3. (cont.)

```
! See which cell matches the random number (It will be in 't')
do t=1,9
   r=r-Choices(t)
   if (r<=0) exit
end do


! It is possible that we ran through the loop above, and because of REAL number
! problems we completed the loop, which would leave t=10, and cause subscript
! problems.  So, if t>9, reset it to 9.
if (t>9) t=9

if (iomsg.ge.2) write(4,'(A,I1,3(A,I4))')"      I selected choice ",t,
-                  " which is location: (",ChoiceLocs(t,1),",",ChoiceLocs(t,2),")"
if(ChoiceLocs(t,1).gt.334)then
   write(4,*)"*****************--PROBLEM--*****************"
   write(4,*)"     Choices: ",(choices(x),x=1,9)
   do x=1,9
      write(4,*)"     Choice(x,y) ",ChoiceLocs(x,1),ChoiceLocs(x,2)
   end do
endif
if (WanderCount) then
   MapElk(ChoiceLocs(t,1),ChoiceLocs(t,2)) = MapElk(ChoiceLocs(t,1),ChoiceLocs(t,2)) + 1
else
   MapElk(ChoiceLocs(t,1),ChoiceLocs(t,2)) = 1
endif
if (iomsg.eq.1) then
   write(*,'(A,I10,A)')"I have moved: ",Times," times."
```

Table E.3. (cont.)

```
            write(*,300)"On Cell: ",ChoiceLocs(t,1),",",ChoiceLocs(t,2)
            write(*,300)"Prior Cell: ",PriorLoc(1),",",PriorLoc(2)
            write(*,300)"Started From: ",StartLoc(1),",",StartLoc(2)
            write(*,300)"Going to: ",EndLoc(1),",",EndLoc(2)
            write(*,*)
         endif


         ! Update all of my location arrays
         PriorLoc = CurrentLoc
         CurrentLoc(1)=ChoiceLocs(t,1)
         CurrentLoc(2)=ChoiceLocs(t,2)

         ! If EndPoint is true, looking for the random point in the end area determined above
         ! If EndPoint is false, we are looking for any point within the end area
         ! If we reached our "end point", then we're done!
         if (EndPoint) then
            if (CurrentLoc(1) == EndLoc (1)) then
               if (CurrentLoc(2) == EndLoc(2)) exit
            endif
         else
            if (CurrentLoc(1)>=EndLocUL(1) .and. CurrentLoc(1)<=EndLocLR(1)) then
               if (CurrentLoc(2)>=EndLocUL(2) .and. CurrentLoc(2)<=EndLocLR(2)) exit
            endif
         endif
      end do  ! One Elk Loop

      if (iomsg.ge.1) then
```

Table E.3. (cont.)

```
      write (*,300)"Started From: ",StartLoc(1),",",StartLoc(2)
      write (*,300)"Went To: ",EndLoc(1),",",EndLoc(2)
      write (*,'(A,I7,A)')"In ",Times," moves."
    endif

    ! Check if Times < KillCap; if so or no KillCap, add MapElk to MapOut
    if ((Times < KillCap) .or. (KillCap == 0))  then
      Success=Success+1

      if (Times>MaxMoves) MaxMoves=Times
      if (Times<MinMoves) MinMoves=Times
      TotalMoves=TotalMoves+Times
      MapOut = MapOut + MapElk
      ! If we are tracking individual Elk Runs, then write MapElk
      if (ElkOutFile) then
        MapElkOut="MapElk.asc"
        where (MapIn==-9999) MapElk=-9999
        open(10,File=(MapElkOut))
        call HeaderOut(nrow,ncol,xllcrnr,yllcrnr,cellw,10)
        write(10,*)((MapElk(x,y),x=1,MaxX),y=1,MaxY)
        close(10)
      endif
    else
      if (.not. CountKilled) i=i-1
    endif
  end do  ! All Elk Loop

  write(4,*)"Completion Rate: ",Success," out of ",RunCount
```

Table E.3. (cont.)

```
write(4,*)"Elk starting from Start Area 1: ",StartCount(1)
write(4,*)"Elk starting from Start Area 2: ",StartCount(2)
write(4,*)"Elk starting from Start Area 3: ",StartCount(3)
write(4,*)"Elk going to End Area 1: ",EndCount(1)
write(4,*)"Elk going to End Area 2: ",EndCount(2)
write(4,*)"Elk going to End Area 3: ",EndCount(3)
write(4,*)"Combined moves for all elk: ",TotalMoves
write(4,*)"Minimum Number of moves for any one elk: ",MinMoves
write(4,*)"Maximum Number of moves for any one elk: ",MaxMoves

TopVal=TotalMoves/Success
write(4,*)"Average Number of moves for all elk: ",(TopVal)
write(4,*)
Call Date_and_Time(Values=Time)
DayPart="AM"
if (Time(5)>12) then
   Time(5)=Time(5)-12
   DayPart="PM"
endif
write(4,'(A,I2,A,I2,A)')"Simulation ended at ",Time(5),":",Time(6),DayPart

! Write MapOut to disk here
where (MapIn==-9999) MapOut=-9999
write(*,*) "MaxX=",MaxX,"MaxY=",MaxY
open(10,file=(QualFileNameOut))
write(10,*)((MapOut(x,y),x=1,MaxX),y=1,MaxY)
close(10)
open(10,file=trim(OutFileDir) // "//" // trim(OutFileName) // "-Table.prn")
```

Table E.3. (cont.)

```
    count=0
    do y=1,MaxY
        do x=1,MaxX
            count=count+1
            write(10,*) RunCount,count,MapOut(x,y)
        end do
    end do
    close(10)

    Where (MapOut/=-9999) MapOut=MapOut/MaxVal(MapOut)


!    write(4,*)MaxVal(MapOut)
    close(4)

    if(MarkAreas)then
        do y=Str1ULCoord(2),Str1LRCoord(2)
            do x=Str1ULCoord(1),Str1LRCoord(1)
                MapOut(x,y)=8888
            end do
        end do
        do y=Str2ULCoord(2),Str2LRCoord(2)
            do x=Str2ULCoord(1),Str2LRCoord(1)
                MapOut(x,y)=8888
            end do
        end do
        do y=Str3ULCoord(2),Str3LRCoord(2)
            do x=Str3ULCoord(1),Str3LRCoord(1)
```

Table E.3. (cont.)

```
            MapOut(x,y)=8888
         end do
      end do
      do y=End1ULCoord(2),End1LRCoord(2)
         do x=End1ULCoord(1),End1LRCoord(1)
            MapOut(x,y)=8888
         end do
      end do
      do y=End2ULCoord(2),End2LRCoord(2)
         do x=End2ULCoord(1),End2LRCoord(1)
            MapOut(x,y)=8888
         end do

      end do
      do y=End3ULCoord(2),End3LRCoord(2)
         do x=End3ULCoord(1),End3LRCoord(1)
            MapOut(x,y)=8888
         end do
      end do
   end if

   open(10,file=trim(OutFileDir) // "//" // trim(OutFileName) // ".asc")
   call HeaderOut(nrow,ncol,xllcrnr,yllcrnr,cellw,10)
   write(10,"(F12.5)")((MapOut(x,y),x=1,MaxX),y=1,MaxY)
   close(10)

   end program Husker_Du
```

Table E.4. Associated parameter file for the elk memory/habitual use program ("Husker-Du" - Table E.3). Raw code was written on FORTRAN 90 (Code copyright 2005, Acorp Computers, Paul Rupp – owner).

```
&Init_Vars
MaxX =          334             !/Set to the maximum number of columns (Should conincide or exceed GIS input map)
MaxY =          286             !/Set to the maximum number of rows (Should conincide or exceed GIS input map)
iomsg = 0                       !/0=No Diag/info messages, 1=Diag/info messages to screen, 2=Diag/info messages to file
RunCount =      100             !/Number of times/number of elk to run the program with
KillCap =       0               !/Kill an elk/run that reaches this many moves without finding endpoint
                                !/      (0 = No limit; if limited, should be about 5,000,000 for this extent)
CountKilled=.FALSE.             !/If TRUE, killed elk count toward the total RunCount
NoTagBack=.TRUE.                !/If TRUE, prevent elk from returning to immediately prior cell
WanderCount=.FALSE.             !/If TRUE, count every time a cell is entered (by the same animal)
                                !/      if FALSE, only count each unique cell entered
ElkOutFile=.FALSE.              !/If TRUE, create individual outfile maps for each elk/run
StrtAreas=3                     !/Indicate the number of possible Start Areas (Max = 3)
EndAreas=3                      !/Indicate the number of possible End Areas (Max = 3)
EndPoint=.FALSE.                !/If TRUE, Elk must find a randomly selected point within the End Area
                                !/If FALSE, Elk just needs to enter the End Area
Str1ULCoord =233,153            !/(X,Y) ordered coordinate pair for Upper Left of Start Point 1
Str1LRCoord =253,169            !/(X,Y) ordered coordinate pair for Lower Right of Start Point 1
Str2ULCoord =215,174            !/(X,Y) ordered coordinate pair for Upper Left of Start Point 2
Str2LRCoord =239,195            !/(X,Y) ordered coordinate pair for Lower Right of Start Point 2
Str3ULCoord =194,216            !/(X,Y) ordered coordinate pair for Upper Left of Start Point 3
Str3LRCoord =214,230            !/(X,Y) ordered coordinate pair for Lower Right of Start Point 3
End1ULCoord =18,37              !/(X,Y) ordered coordinate pair for Upper Left of Start Point 1
End1LRCoord =40,45              !/(X,Y) ordered coordinate pair for Lower Right of Start Point 1
End2ULCoord =89,45              !/(X,Y) ordered coordinate pair for Upper Left of Start Point 2
End2LRCoord =110,58             !/(X,Y) ordered coordinate pair for Lower Right of Start Point 2
End3ULCoord =82,112             !/(X,Y) ordered coordinate pair for Upper Left of Start Point 3
End3LRCoord =115,132            !/(X,Y) ordered coordinate pair for Lower Right of Start Point 3
ForceEnd =.TRUE.                !/If TRUE, force elk toward end-point (ForceExert must have a value > 0 if TRUE)
```

Table E.4. (cont.)

```
Normalize=.TRUE.                          !/If TRUE, normalize map on high value


MarkAreas=.FALSE.                         !/If TRUE, mark starting and ending areas on map
                                          !/        [This will OVERWRITE ALL ELK DATA in those areas!]
ForceExert =.25                           !/If ForceEnd is TRUE, ForceExert is added in the direction of the end-point

OutFileDir="C:\\SAVANNA\\PROJ\\JEMEZ"     !/Directory to write output files to
InFileDir="C:\\SAVANNA\\PROJ\\JEMEZ"      !/Directory to read input files from
ElkFileName =  "Elk-"                     !/Output Map filename for each individual elk/run (Sequential numbers appended)
OutFileName = "mem150_utm"                !/Output Map filename for the complete run
InFileName =    "costmask150_utm"         !/Input Map filename for the Surface Dependency Map
/
```

Table E.5. C++ raw code to count the number of 1-m cells occupied by a building within larger grid cells at the final resolution of 150 m. The resultant map of building frequencies (i.e., total area in m^2 covered by buildings) was then normalized from 0 to 1 for use in the habitat suitability index (Code copyright 2005, Acorp Computers, Paul Rupp – owner).

```
// BuildScaleUp.cpp : Scales up buildings from 1m to 150m cell size
//
#include "stdafx.h"
#include <iostream>
#include <fstream>
using namespace std;

int _tmain(int argc, _TCHAR* argv[])
{
	int val=0;
	int count=0;
	int x=0;
	int y=0;
	int x1=0;
	int y1=0;
	char readin[25];
	int BuildOut[333][285];

	for (y=0;y<285;y++)
	{
		for (x=0;x<333;x++)
		{
	BuildOut[x][y]=0;
		}
	}
```

Table E.5. (cont.)

```
ifstream buildings;
ofstream buildingsout;
buildings.open("C:\\TRX\\IN\\bldgs_1m.asc", ios::in);  // declare and open
for (y=1;y<=12;y++)
{
        buildings >> readin;
        cout << readin << endl;
}
for (y=0;y<42271;y++)
{
        for (x=0;x<49497;x++)
        {
                count=count+1;
                buildings >> val;
                if (val != -9999)
                {
   cout << "Value Read: " << val << " at location: " << count << " (x,y): " << x << "," << y << endl;
   x1=(x/151);
   y1=(y/151);
   cout << "Setting Array Location x1,y1: " << x1 << "," << y1 << endl;
   BuildOut[x1][y1]=BuildOut[x1][y1]+val;
                }
        }
}
buildings.close();
buildingsout.open("bldgs_150m.asc",ios::out);
for (y=0;y<=y1;y++)
{
```

Table E.5. (cont.)

```
                for (x=0;x<=x1;x++)
                {
        buildingsout << BuildOut[x][y];
                }
        }
        buildingsout << endl;
        buildingsout.close();
        return 0;
}
```

Table E.6. FORTRAN 90 raw code to calculate the aversion factor for roads in the study area. Cell values were determined by combining numbers of elk observed along the roads and number of times elk crossed roads and then weighting these values by an associated aversion factor depending on the type of road (primary, secondary, or tertiary). Code copyright 2005, Acorp Computers, Paul Rupp – owner.

```
!  RoadCrossings-Norm.f90
!
!  FUNCTIONS:
!  Road Aversion - Calculate Aversion factor for roads/crossings (Normalized)
!

!****************************************************************
!
!  PROGRAM: Road Aversion Normalized
!
!  PURPOSE:  This program accepts the input from three maps.  These maps contain
!            values everywhere there is a road.  These values are based on the
!            calculation of the number of elk crossings in that particular cell.
!            The road maps are then multiplied against a map of elk locations on
!            these roads to obtain an aversion number that elk have to each cell
!            containing a road.  Finally, the map is rescaled against an average
!            aversion factor for that type of road using a linear interpolation.
!            Output will be a map containing real values which will be multiplied
!            against the underlying cell values (Cost Impedance) at a later time.
!
!  REVISION: This is the final version of the "Road Crossing" programs.
!            This revision matrix multiplies Elk Locations * Road Crossings
!            after first converting any zeros in either matrix to one's.
!            The resulting map is then rescaled on the minimum/maximum aversion
!            factor for each type of road.
!
!****************************************************************
program RoadAversion

   implicit none

   INTEGER :: nrow,ncol,cellw,nodata
   REAL :: xllcrnr,yllcrnr
   CHARACTER(50) :: Roads(3),ElkIn,RoadsOut,InDirName,OutDirName
   INTEGER,ALLOCATABLE,DIMENSION(:,:) :: Elklocs
   REAL,ALLOCATABLE,DIMENSION(:,:) :: RoadFactors
```

Table E.6. (cont.)

```
REAL,ALLOCATABLE,DIMENSION(:,:,:) :: XRoads
INTEGER ::  x,y,t,Cols,Rows
Logical (Kind=1) :: iomsg
REAL :: Aversion(2,2,3),alint
      write(*,*) "Starting program run..."
      write(*,*)
      iomsg=.FALSE.
! Read in the Road Crossings Parameter File- this file will contain ten fields
!     1) File Input Directory
!     2) File Output Directory
!     3-8) Primary, Secondary, and Tertiary Road Maps/Aversion Factors
!     9) The name of the Elk Locations Map
!     10) The name for the Road Factors Output Map
write(*,*) "Reading RoadCrossing.PRM"
open(1,file="RoadCrossing.PRM")
read(1,*) InDirName
read(1,*) OutDirName
do t=1,3
   read(1,*) Roads(t)
   read(1,*) (Aversion(2,x,t),x=1,2)
end do
read(1,*) ElkIn
read(1,*) RoadsOut
close(1)

do t=1,3
   open(t,file=(Trim(InDirName) // Trim(Roads(t))))
end do
open(4,file=(Trim(InDirName) // Trim(ElkIn)))

! Read Road Crossing and Elk Location Map Headers,
! and make sure they are all the same size
call headerin(nrow,ncol,xllcrnr,yllcrnr,cellw,nodata,4)
Cols=ncol
Rows=nrow
do t=1,3
   call headerin(nrow,ncol,xllcrnr,yllcrnr,cellw,nodata,t)
   if ((Cols .ne. ncol) .or. (Rows .ne. nrow)) then
      Pause
      Stop "Rows/Cols don't match up..."
   end if
```

Table E.6. (cont.)

```
  end do

  ! Allocate Memory for Road Crossing Maps, Elk Locations, and Output Map
  if(iomsg)write(*,*)"Allocating memory..."
  allocate (XRoads(3,Cols,Rows),ElkLocs(Cols,Rows),RoadFactors(Cols,Rows))

  ! Default Output Map to "No Value"
  if(iomsg)write(*,*)"Initializing RoadFactors array..."
  RoadFactors=-9999

  ! Read the Road Crossing and Elk Location Maps into memory
  if(iomsg)write(*,*)"Loading maps..."
  do t=1,3
     if(iomsg)write(*,*)"Reading RoadCrossing Map #",t," and ElkLocs..."
     do y=1,Rows
        read(t,*)(XRoads(t,x,y),x=1,Cols)
        if (t.eq.1)read(4,*)(ElkLocs(x,y),x=1,Cols)
     end do
  end do
  close(1)
  close(2)
  close(3)
  close(4)

  ! Replace all zeros in all Road Crossing Maps with one's
  ! While this introduces a small error, specifically:
  ! (zero elk/zero crossings) = (zero elk/one crossing) = (one elk/zero crossings)
  ! which is not technically correct, it solves the larger problem of making sure
  ! that every cell containing a road recieves an aversion factor, as per the literature.
  if(iomsg)write(*,*)"Replacing zero's in maps with one's..."
  do t=1,3
     Where (XRoads(t,:,:)==0) XRoads(t,:,:)=1
  end do
  Where (ElkLocs==0) ElkLocs=1

  ! Order is important here.  Since primary roads will have a higher aversion factor than
  ! secondary and tertiary roads, we apply road factors in descending order of aversion.
  ! Matrix Multiplication is so much fun...
  do t=3,1,-1
     write(*,*) "Matrix Multiplication for Roads/Crossings",t
```

Table E.6. (cont.)

```
    ! Multiply Roads/Crossings by ElkLocs everywhere there is a road (mask by -9999)
    Where (XRoads(t,:,:).ne.-9999) XRoads(t,:,:)=XRoads(t,:,:)*ElkLocs

    ! Determine the Minimum and Maximum values from the multiplication above
    ! These will be used in the linear interpolation to scale the values from min to max
    ! aversion for each road type.  The min/max aversion factor is read in from PRM file
    Aversion(1,1,t)=MinVal(XRoads(t,:,:),MASK=(XRoads(t,:,:).ne.-9999))
    Aversion(1,2,t)=MaxVal(XRoads(t,:,:))

    ! Application of the linear interpolation function to the entire matrix at once
    ! Using "Where" doesn't work, so have to use the old fashioned double-do loop
    do y=1,rows
      do x=1,cols
        if(XRoads(t,x,y).gt.0) then
          XRoads(t,x,y)=alint(XRoads(t,x,y),Aversion(1,1,t),2)
        end if
      end do
    end do

    ! Place Results in the RoadFactors Array
    Where(XRoads(t,:,:).ne.-9999)RoadFactors=XRoads(t,:,:)
  end do

  ! Open File for output map
  open(6,file=Trim(OutDirName) // Trim(RoadsOut))

  ! Write ArcView Header
  call HeaderOut(nrow,ncol,xllcrnr,yllcrnr,cellw,6)
  write(6,'(F12.5)') RoadFactors
  close(6)

  ! Update command line status for user
  write (*,*) "This program is done, please check your output files..."

end program RoadAversion
```

Table E.7. Associated parameter file for the road aversion program (Table E.6). Code copyright 2005, Acorp Computers, Paul Rupp – owner.

C:\\SAVANNA\\PROJ\\JEMEZ\\	!Input Directory (Use \\ for subdirectories and make sure it includes a trailing \\)
C:\\SAVANNA\\PROJ\\JEMEZ\\	!Output Directory
X1Rds150_UTM.asc	!Primary Roads Input Map
.75,.25	!Maximum/Minimum aversion to Primary Roads (Decimal Percentage)
X2Rds150_UTM.asc	!Secondary Roads Input Map
.60,.15	!Maximum/Minimum aversion to Secondary Roads (Decimal Percentage)
X3Rds150_UTM.asc	!Tertiary Roads Input Map
.50,.10	!Maximum/Minimum aversion to Tertiary Roads (Decimal Percentage)
ElkLocs150_UTM.asc	!Elk Locations Input Map
XRrds150_.asc	!Road aversion output map

Table E.8. FORTRAN 90 raw code used to output locations for individual simulated animals run through the individual-based movement model. The resultant program allows flexibility in data extraction, which allows the user to look at elk response by individual days, seasons, months, or years (Code copyright 2005, Acorp Computers, Paul Rupp – owner).

```
!  ElkData.f90
!
!  FUNCTIONS:
!  ElkData      - Extract movement data from file.
!

!****************************************************************************
!
!  PROGRAM: ElkData
!
!  PURPOSE:  Program to extract movement data from file
!
!****************************************************************************
    program ElkData

    implicit none

    integer herds,days,months,years,xll,yll,cell,narea,startyear,stopyear,stopmon,step,t
    integer herd,animal,day,month,year,maxX,maxY,x,y,lowrange,highrange,startmon
    integer,allocatable,dimension (:) :: steps,pop,stepfac,dayfac,monfac,yearfac
    integer(Kind=8) i,n
    character*50 Output,Output1,Input
    character*20 FName
    integer iyear,imonth,iday,istep,ianimal,times,hmonhigh,hmonlow
    integer anilow,anihigh,yearlow,yearhigh,monlow,monhigh,daylow,dayhigh,steplow,stephigh
```

Table E.8. (cont.)

```
    logical(Kind=1) simflag,msgscrn,badin

    common/grid/maxX,maxY,x,y,narea,xll,yll,cell,startyear,startmon,simflag
    common/range/lowrange,highrange,badin,input

    call random_seed()

    simflag=.true.
    msgscrn=.false.

    if(.not.simflag)open(12,file="Testout.txt")

    write(*,*) "File name (omit extension and path):"
    Read(*,*) FName

    open(1,file="C://SAVANNA//PROJ//JEMEZ//SITE//OUT//" // Trim(adjustl(FName)) // ".hdr")
    if(simflag)open(2,file="C://SAVANNA//PROJ//JEMEZ//SITE//OUT//" // Trim(adjustl(FName)) //
-           ".OUT",access="Direct",recl=1)
    read(1,*)startyear,startmon,months,days,herds,maxX,maxY,xll,yll,cell

    years=0

    i=months
    do while(i.gt.12)
       i=i-12
       years=years+1
    end do
```

Table E.8. (cont.)

```
write(*,*)"Months Tot",months,"= Months/Years =",i,years

stopmon=(months-(years*12))-1
stopmon=stopmon+startmon

if(stopmon.eq.0) then
   stopmon=12
   years=years-1
endif
if(stopmon.gt.12) then
   years=years+1
   stopmon=stopmon-12
endif

stopyear=startyear+years
write(*,*)"Run ",months," months."
write(*,*)"Start: ",startmon,"/",startyear
write(*,*)"End: ",stopmon,"/",stopyear

allocate(steps(herds),pop(herds),stepfac(herds),dayfac(herds),monfac(herds),yearfac(herds))
do t=1,herds
   read(1,*) steps(t),pop(t)
   ! Setup index factors
   stepfac(t)=pop(t)
   dayfac(t)=steps(t)*stepfac(t)
   monfac(t)=dayfac(t)*days
   yearfac(t)=monfac(t)*12
```

Table E.8. (cont.)

```
   end do
   close(1)

   Write(*,*) "Specify the information you wish to extract using the fields below."
   write(*,*) "    To extract all records in a certain field, use ALL in that field"
   write(*,*)
   times=0

10    times=times+1
   herd=1
   write(output,*)times
   if(simflag)open(10,file="C://SAVANNA//PROJ//JEMEZ//SITE//OUT//" // Trim(adjustl(FName)) // "-" //
-         Trim(adjustl(output)) // ".txt")
   if(simflag)write(10,fmt='(7(A10,","),A10)')"Index","Animal","Year","Month","Day","Step","X-Coord","Y-Coord"

   write(output,*)pop(herd)
110    print *, "Animal # (Max= ",trim(adjustl(output)),") [ALL for all animals]: "
   call charcon(1,pop(herd))
   if(badin)goto 110
   anilow=lowrange
   anihigh=highrange
   animal=(anihigh-anilow)

   write(output,*)months
120    write(*,*) "Month (Min=1, Max=",trim(adjustl(output)),") [ALL for all months]:"
   call charcon(1,months)
   if(badin)goto 120
   monlow=lowrange
```

Table E.8. (cont.)

```
   monhigh=highrange

130   write(*,*) "Day # (Max= 28) [ALL for all days]:"

   call charcon(1,28)
   if(badin)goto 130
   daylow=lowrange
   dayhigh=highrange
   day=dayhigh-daylow

140   write(output,*)steps(herd)
   write(*,*) "Step # (Max=",trim(adjustl(output)),") [ALL for all steps]:"
   call charcon(1,steps(herd))
   if(badin)goto 140
   steplow=lowrange
   stephigh=highrange
   step=stephigh-steplow

   write(*,*) "Include origination points for selected animals (Y/N)?"
   read (*,*) input
   if(input.eq."y".or.input.eq."Y")then
      do animal=anilow,anihigh
         call fileread(animal,0,0,0,0,0,0,0)
      enddo
   endif

   write(*,*)"Loop check: "
   write(*,*)" anilow,anihigh=",anilow,anihigh
```

Table E.8. (cont.)

```
 write(*,*)" monlow,monhigh=",monlow,monhigh
 write(*,*)" daylow,dayhigh=",daylow,dayhigh
 write(*,*)" steplow,stephigh=",steplow,stephigh


 do animal=anilow,anihigh
   do month=monlow,monhigh
     do day=daylow,dayhigh
       do step=steplow,stephigh
         call fileread(animal,step,day,month,pop(herd),stepfac(herd),dayfac(herd),monfac(herd))
       enddo
     enddo
   enddo
 enddo

 close(10)
 write(output,*)times
 write(*,*)"File Written: C:\SAVANNA\PROJ\JEMEZ\SITE\OUT\" // Trim(adjustl(FName)) // "-"
-        // Trim(adjustl(Output)) // ".txt"
 write(*,*)
 write(*,*) "    'X' To exit, any other key to continue..."
 read(*,*)output
 if(output.ne."x".and.output.ne."X")goto 10
 write(*,*)" ** EXITING Elk Data Read program **"
 close(2)
 close(12)
 end program ElkData
```

Table E.8. (cont.)

```
subroutine FileRead(ani,st,dy,mn,pop,sf,df,mf)
   integer ani,yr,mn,dy,st,mf,df,sf,pop
   real r
   integer n,iyear,imonth,iday,istep,east,north
   integer maxx,maxy,narea,x,y,xll,yll,cell,startyear,startmon

   logical(kind=1) simflag

   common/grid/maxX,MaxY,narea,x,y,xll,yll,cell,startyear,startmon,simflag

  if (mn.eq.0) then
      i=ani
   else
      i=pop+(ani)+(sf*(st-1))+(df*(dy-1))+(mf*(mn-1))
   endif

   n=i
   if(mn.eq.0)then
      iyear=0
      imonth=0
      iday=0
      istep=0
   else
      istep=st
      iday=dy
      iyear=startyear
      imonth=startmon+(mn-1)
      do while (imonth.gt.12)
```

Table E.8. (cont.)

```
         iyear=iyear+1
         imonth=imonth-12
      end do
   endif

   if(simflag) then

     read(2,rec=i)narea
      x=mod(narea-1,maxX)+1
      y=maxY-(int((narea-1)/maxX))
      x=x-1
      y=y-1
      east=((x-1)*cell)+xll
      call random_number(r)
      r=(r*(cell-1)+1)
      east=east+(int(r))
      north=((MaxY-y)*cell)+yll
      call random_number(r)
      r=(r*(cell-1)+1)
      north=north+(int(r))
      write(10,fmt='(7(I10,","),I10)')i,ani,iyear,imonth,iday,istep,east,north
      if(msgscrn)then
         write(*,fmt='(A10,5(A7),2(A9),A6)')"Record","Animal","Year","Month","Day","Step","Easting","Northing","narea"
         write(*,fmt='(I10,5(I7),2(I9),I6)')i,ani,iyear,imonth,iday,istep,x,y,narea
         write(*,*)"----------------------------------------------------------------------"
      endif
   else
      write(12,fmt='(A10,5(A7),2(A9),A6)')"Record","Animal","Year","Month","Day","Step","Easting","Northing","narea"
```

Table E.8. (cont.)

```
        write(12,fmt='(I10,5(I7),2(I9),I6)')i,ani,iyear,imonth,iday,istep,x,y,narea
        write(12,*)"----------------------------------------------------------------------"
    endif
    return
end

Subroutine charcon(min,max)


    character*20 input,low,high
    integer lowrange,highrange,s,min,max
    logical(Kind=1) badin
    common/range/lowrange,highrange,badin,input

    badin=.false.
    read(*,*)input
    if(input.eq."ALL".or.input.eq."all".or.input.eq."All") then
        lowrange=min
        highrange=max
    else
        s=index(input,"-")
        if(s.eq.0) then
            read(input,fmt='(I8)') lowrange
            highrange=lowrange
        else
            low=input(1:s-1)
            high=input(s+1:)
            read(low,*)lowrange
```

Table E.8. (cont.)

```
            read(high,*)highrange
        endif
    endif
    if(lowrange.lt.min.or.highrange.gt.max) then
        write(*,*)" ** ERROR - Response must be ",min,"-",max," **"
        badin=.true.
    endif
    return
end
```

Table E.9. Raw code for generation of the individual-based movement model. Due to the long history behind SAVANNA and the need to integrate this IBM with that ecosystem model, the code below is a combination of FORTRAN 77 and FORTRAN 90 (Code copyright 2005, Acorp Computers, Paul Rupp – owner).

```
      subroutine IBM(init,ntim,idum)
c Individual Based Movement Model for Elk
c Elk move across the landscape responding to HSI,
c where hsi is based on forage and physical factors
      include 'arraysiz.inc'
      include 'state.inc'
      include 'statec.inc'
      include 'statew.inc'
      include 'stateh.inc'
      include 'runcon.inc'
      include 'grdvar1.inc'
      include 'grdvar2.inc'
      include 'grdvar3.inc'
      include 'grdvar4.inc'
      include 'grdvar5.inc'
      include 'grdvar6.inc'
      include 'grdvar7.inc'
      include 'grdvar8.inc'
      include 'grdvar9.inc'
      include 'imgmx.inc'
      include 'cvars.inc'
      include 'wdprm.inc'
      include 'species.inc'
      include 'plprm.inc'
      include 'sppmix.inc'
      include 'cdistr.inc'
      include 'cdiscnt.inc'
      include 'consprm.inc'
      include 'filenam.inc'
      include 'pathname.inc'
      include 'anmsk.inc'
      include 'baseppt.inc'

      integer nspherd(nsphx)
      integer ifrcprb(nsphx)
      real ansimilar(nsphx,nsphx)
      real pelevmn(12,nsphx),pelevmx(12,nsphx)
      real xpopsv(nsphx,ncellx)
      character*4 endmark
```

Table E.9. (cont.)

```
      real emmigrants(nsphx),displeft(nsphx)
      INTEGER :: Times,iter,day,x,y,x1,y1,t,startnum(nsphx),xloc,yloc
      INTEGER :: CurrentLoc(2),ChoiceLocs(9,2)
      INTEGER :: ULStartX(nsphx),ULStartY(nsphx),
     -         LRStartX(nsphx),LRStartY(nsphx),
     -         MidX(nsphx),MidY(nsphx),yr,mon,mem
      INTEGER,ALLOCATABLE,DIMENSION(:,:) :: StartLocs
      REAL :: Choices(9),vcstart(nsphx),r,cNow,MigForce
      LOGICAL :: MigFlag,Flag,Problem,Skipsav,WriteData
      CHARACTER*80 :: FName,FileName
      CHARACTER*10 :: MonName,WeekName,YearName,HSIType
      integer*2 shadecvr(ncellx),thickcvr(ncellx)
      REAL :: cellsz,xllcrnr,yllcrnr,EucDist,Lint(2,3),NowDist,RadDist

      common/watsup/wsuplt,wdemt

      common/rangeknow/irangeexp(nsphx),prknow(nsphx),know(nsphx,ncellx)
      integer*2 know

      data ifrcprb/nsphx*0/

c initialize species similarities with respect to habitat
        if(iomsg.eq.1)write(*,*)'Opening ansimilr.prm'
        open(2,file=adjustl(parmpath//'ansimilr.prm'))
        read(2,*)nsppc
        if(nsppc.ne.nspcon)then
          write(*,*)'# species on ansimilr.prm ne. nspcon '
          pause
          stop
        end if
        do nscn=1,nsppc
          read(2,*)ndum,(ansimilar(nscn,nscn2),nscn2=1,nspcon)
        end do
        close(2)
c initialize total herbivore populations
        if(iomsg.eq.1)write(*,*)'Opening IBM.prm'
        open(2,file=adjustl(parmpath//'IBM.prm'))

c read number of consumer species
        read(2,*)nsppc
c Possibility of entering a zero value cell
        read(2,*)stoch
```

Table E.9. (cont.)

```
! Read IBM Outfile name
      read(2,*)FName
c flag to override all with a uniform distribution
      read(2,*)iuniform
c initialize habitat preference functions by consumer species
c first, flag which ones are used
      read(2,*)ihdfd
      read(2,*)ihdme
      read(2,*)ihdwc
      read(2,*)ihdsl
      read(2,*)ihdel
      read(2,*)ihdcost
      read(2,*)ihdroad
      read(2,*)ihdbuild
      read(2,*)ihdfence
      read(2,*)ihdmem
      read(2,*)ihdfc
      read(2,*)ihdzone
      read(2,*)ihdpr
      read(2,*)ihdmig
      read(2,*)ihden
      read(2,*)ihsnw
      read(2,*)ihgreen
      read(2,*)ihdead
      read(2,*)ihtemp
      read(2,*)ihrngexp
      read(2,*)ihemmigr
      read(2,*)hsipower

      if(hsipower.lt.0..or.hsipower.gt.0.)then
       ihpower=1
      else
       ihpower=0
      end if

      if(ispatial.eq.0)then
         write(*,*)'Nonspatial run - ignoring all options to use'
         write(*,*)'spatial data to calculate animal distribution'
         ihdfd=0
         ihdme=0
         ihdwt=0
```

Table E.9. (cont.)

```
      ihdwc=0
      ihdsl=0
      ihdel=0
      ihdfc=0
      ihden=0
      ihsnw=0
      ihgreen=0
      ihdead=0
      ihtemp=0
    end if

c parameters for reporting total grazing pressure
    read(2,*)(itgrzsp(nscn),nscn=1,nspcon)
    read(2,*)(anunit(nscn),nscn=1,nspcon)
    read(2,*)iauacc

c read parameters for each species, using approp herd/consumer index
    nherdt=0
    do nsp=1,nsppc
     nherdt=nherdt+1
     read(2,*)nherd
     read(2,*)(nspherd(nh),nh=1,nherd)
     nscn=nspherd(1)
     if(nscn.gt.nsphx)then
      write(*,*)'Exceeding max number of animal pops ',nsphx,
  -   'on IBM.prm, species/herd-',nsp,nherd
      pause
     end if
     read(2,*)((pforage(i,j,nscn),i=1,2),j=1,3)
     read(2,*)((emetintk(i,j,nscn),i=1,2),j=1,2)

c the following 4 vars must range 0-1 since all in an amin1 function below
     read(2,*)((pshcv(i,j,nscn),i=1,2),j=1,2)
     read(2,*)((pthcv(i,j,nscn),i=1,2),j=1,2)
     do j=1,2
      if(pshcv(2,j,nscn).gt.1..or.pthcv(2,j,nscn).gt.1)then
       write(*,*)'pshcv or pthcv must be <=1 in IBM.prm'
       pause
       stop
      end if
     end do
```

Table E.9. (cont.)

```
      read(2,*)((pslope(i,j,nscn),i=1,2),j=1,3)
      do j=1,3
        if(pslope(2,j,nscn).gt.1.)then
          write(*,*)'pslope must be <=1 on IBM.prm'
          pause
          stop
        end if
      end do

      read(2,*)pelev(1,1,nscn),pelev(1,2,nscn)
      read(2,*)(pelevmn(m,nscn),m=1,12)
      read(2,*)(pelevmx(m,nscn),m=1,12)
      read(2,*)prfgmn(nscn)
      read(2,*)prefam(1,nscn),prefam(2,nscn)
      read(2,*)((psnow(i,j,nscn),i=1,2),j=1,3)
      read(2,*)((pgreenhb(i,j,nscn),i=1,2),j=1,2)
      read(2,*)((pdeadhb(i,j,nscn),i=1,2),j=1,2)
      read(2,*)((ptemper(i,j,nscn),i=1,2),j=1,4)
      read(2,*)((esnowemmig(i,j,nscn),i=1,2),j=1,2)
      read(2,*)((ecrustemmig(i,j,nscn),i=1,2),j=1,2)
      read(2,*)vcstart(nscn)
      read(2,*)startnum(nscn)
      if(startnum(nscn).ne.0) then
        do t=1,startnum(nscn)
           read(2,*)x,y
           narea=((nrow-y)*ncol)+x
           elkloc(nscn,t)=narea
           hpop(nscn,narea)=hpop(nscn,narea)+1
        end do
      end if
      read(2,*)ulstartx(nscn),ulstarty(nscn)
      read(2,*)lrstartx(nscn),lrstarty(nscn)
      read(2,*)daystep(nscn)
      read(2,*)((winrange(nscn,j),j=1,2))
      read(2,*)((sumrange(nscn,j),j=1,2))
      read(2,*)((radius(nscn,j),j=1,2))
      read(2,*)MigForce

c do not allow zero values - set to a very low value
c otherwise could simulate an area with all 0's, leaving no animals even though they are there
```

Table E.9. (cont.)

```
c in the normal case, the very low value will translate into essentially 0 animals
      ylow=1.e-6
      i=2
      do j=1,2
        emetintk(i,j,nscn)=amax1(emetintk(i,j,nscn),ylow)
        pgreenhb(i,j,nscn)=amax1(pgreenhb(i,j,nscn),ylow)
        pdeadhb(i,j,nscn)=amax1(pdeadhb(i,j,nscn),ylow)
        pshcv(i,j,nscn)=amax1(pshcv(i,j,nscn),ylow)
        pthcv(i,j,nscn)=amax1(pthcv(i,j,nscn),ylow)
        esnowemmig(i,j,nscn)=amax1(esnowemmig(i,j,nscn),ylow)
        ecrustemmig(i,j,nscn)=amax1(ecrustemmig(i,j,nscn),ylow)
      end do

      do j=1,3
        psnow(i,j,nscn)=amax1(psnow(i,j,nscn),ylow)
        pforage(i,j,nscn)=amax1(pforage(i,j,nscn),ylow)
        pslope(i,j,nscn)=amax1(pslope(i,j,nscn),ylow)
      end do

      do j=1,4
        ptemper(i,j,nscn)=amax1(ptemper(i,j,nscn),ylow)
        pelev(i,j,nscn)=amax1(pelev(i,j,nscn),ylow)
      end do

c for each species fill in other remaining herds
      if(nherd.gt.1)then
        do nh=2,nherd
          nherdt=nherdt+1
          nscn2=nspherd(nh)
          prfgmn(nscn2)=prfgmn(nscn)
          prefam(1,nscn2)=prefam(1,nscn)
          prefam(2,nscn2)=prefam(2,nscn)
          do m=1,12
            pelevmn(m,nscn2)=pelevmn(m,nscn)
            pelevmx(m,nscn2)=pelevmx(m,nscn)
          end do
          do i=1,2
            do j=1,2
              pshcv(i,j,nscn2)=pshcv(i,j,nscn)
              pthcv(i,j,nscn2)=pthcv(i,j,nscn)
              pgreenhb(i,j,nscn2)=pgreenhb(i,j,nscn)
```

Table E.9. (cont.)

```
              pdeadhb(i,j,nscn2)=pdeadhb(i,j,nscn)
              emetintk(i,j,nscn2)=emetintk(i,j,nscn)
              esnowemmig(i,j,nscn2)=esnowemmig(i,j,nscn)
              ecrustemmig(i,j,nscn2)=ecrustemmig(i,j,nscn)
             end do
             do j=1,3
              psnow(i,j,nscn2)=psnow(i,j,nscn)
              pforage(i,j,nscn2)=pforage(i,j,nscn)
              pslope(i,j,nscn2)=pslope(i,j,nscn)
             end do
             do j=1,4
              pelev(i,j,nscn2)=pelev(i,j,nscn)
              ptemper(i,j,nscn2)=ptemper(i,j,nscn)
             end do
            end do
          end do
         end if
        end do
        read(2,221)endmark
221     format(a4)
        if(endmark.ne.'-999')then
         write(*,*)'Wrong end of file mark for IBM.prm '
         write(*,*)'There must be a -999 in cols 1-4 of last line'
         write(*,*)'Press Enter'
         read(*,*)
         stop
        end if
        close(2)

! Initialize Random Number Generator
        call random_seed()

        if(nherdt.ne.nspcon)then
         write(*,*)'Number of consumer spp. in IBM.prm '
     -   //'not equal nspcon '
         pause
         stop
        end if

! Cost Impedence Surface Map
        if(ihdcost.eq.1)then
```

Table E.9. (cont.)

```
         if(iomsg.eq.1)write(*,*)
     -      'Opening cost impedance surface map ',costmap
         call mapread(costmap)
         ! Cost Impedence Surface Map is a map of continuous real values
         ! representing the logistic regression and interaction of
         ! slope, aspect, and elevation.
         ! 0 value cells are deemed to be inaccessible to elk
         ! The cost impedance surface map is the underlying map which
         ! the following maps build on
         do narea=1,nareat
            elkcost(narea)=(rarray(narea))
         end do
         ! We want all no-data cells to be functionally masked out on the HSI
         where(elkcost.lt.0)ElkCost=0
      else
         elkcost=1
      endif

! Memory Map
      if(ihdmem.eq.1)then
         if(iomsg.eq.1)write(*,*)'Opening memory map ', memorymap
         call mapread(memorymap)
         ! Memory Map is a map of continuous real values
         ! representing the memory of migration routes
         ! 0's will have no effect on the underlying map
         ! Other values will be multiplied with the underlying map,
         ! then added back in so that positive cells less than one
         ! will be viewed more favorably
         ! ** Memory is only "turned on" during snowfall, so the
         ! ** application of this map occurs during movement
         ! Remove the Normalization for Memory Map1
!           Where(rarray.gt.0)rarray=rarray/(MaxVal(rarray))
         Where(rarray.gt.0)elkcost=elkcost+rarray
      end if

! Roads Map
      ! Roads Map is a map of continuous real values
      ! representing roads and road crossings
      ! 0 values (no roads) are masked out, and the remaining
      ! values are inverted then cross multiplied with the
      ! Cost Impedance Map so that higher values (which
```

Table E.9. (cont.)

```
      ! indicate more crossings) have a less adverse impact
      ! on the underlying map than lower positive numbers.
      if(ihdroad.eq.1)then
         if(iomsg.eq.1)write(*,*)
     -      'Opening road map ',roadmap
         call mapread(roadmap)
         Where(rarray.gt.0)elkcost=elkcost*(1-rarray)
      endif

! Buildings Map
      ! Buildings Map is a map of continuous real values
      ! We invert and normalize because 0's (no buildings) should
      ! become 1's and have no effect on the underlying map, and
      ! values closer to one (many buildings) should function to
      ! decrease HSI
      if(ihdbuild.eq.1)then
         if(iomsg.eq.1)write(*,*)
     -      'Opening buildings map ',buildmap
         call mapread(buildmap)
         ! Normalize Buildings Map
         where(rarray.gt.0)rarray=rarray/maxval(rarray)
         ! Invert and cross multiply with cost impedance map
         where(rarray.ne.-9999) elkcost=elkcost*(1-rarray)
      endif

! Fence Map
      ! Fence Map is a 1/0 presence/absence map
      ! and 0's (fences) should be masked out
      if(ihdfence.eq.1)then
         if(iomsg.eq.1)write(*,*)
     -      'Opening fence map ',fencemap
         call mapread(fencemap)
         where(rarray.ne.-9999) elkcost=elkcost*rarray
      endif

c zonal maps
      if(ihdzone.eq.1)then
        open(2,file=adjustl(parmpath//'zonemap.prm'))
        if(iomsg.eq.1)write(*,*)'Opening zone map ', zonemap
        call mapread(zonemap)
        do narea=1,nareat
```

Table E.9. (cont.)

```
          nzone(narea)=int(rarray(narea))
        end do
        wtzone=1.
        read(2,*)nzonet
        do n=1,nzonet
          read(2,*)nscn,nz,wtzone(nz,nscn)
        end do
      end if

      if(ihrngexp.eq.1)then
        call rangeexp(1)
      end if

      if(ihdfd.eq.4)then
        call logistic(1,0,0,0,prob)
      end if

c hard code uniform distribution
      if(iuniform.eq.1)then
        write(*,*)'Overriding distribution data in IBM.f to'
        write(*,*)'achieve uniform herbivore distributions '
      end if

c Open file to track individual animal movements and write header
      open(96,file=adjustl(outpath//Trim(adjustl(FName))//'.hdr'))
      write(96,*)nystrt,mstrt,int(nmnths),28,nsppc,ncol,nrow,
     -  nint(xllcrnr),nint(yllcrnr),150
      do iter=1,nsppc
         write(96,*)int(daystep(iter)),
     -      int(hpopt(iter))
      end do
      close(96)
      open(96,file=adjustl(outpath//Trim(adjustl(FName))//'.out'),
     -        access='Direct',status='Replace',recl=4)
      ibmout=0
      vctype=0

! Determine where the VC land cover is if we have animals starting on the VC
! We check here both to make sure it is VC, and that it isn't masked out
! on the cost impedance map
      if(MaxVal(vcstart).gt.0)then
```

Table E.9. (cont.)

```
           do narea=1,nareat
              if(vegtype(1,narea).eq.1) then
                 vctype=vctype+1
                 rarray(vctype)=narea
              endif
           end do
           allocate(startlocs(vctype,2))
        endif

! Loop through all species
        do nscn=1,nsppc
         j=1
         do iter=1,vctype
           narea=rarray(iter)
           x1=mod((narea-1),ncol)+1
           y1=nrow-(int(narea-1)/ncol)
           if((x1.ge.ulstartx(nscn).and.x1.le.lrstartx(nscn)).and.
    -        (y1.ge.ulstarty(nscn).and.y1.le.lrstarty(nscn)))then
              startlocs(j,1)=x1
              startlocs(j,2)=y1
              j=j+1
           endif
         end do

! Determine center point of Summer Range
!         midX(nscn)=int((LRStartX(nscn)+ULStartX(nscn))/2)+
!    -     ULStartX(nscn)
!         midY(nscn)=int((LRStartY(nscn)+ULStartY(nscn))/2)+
!    -     ULStartY(nscn)
        TopDist(nscn)=EucDist(SumRange(nscn,:),WinRange(nscn,:))

c read in maps of emmigration area
         if(emmigareamap(nscn)(1:4).ne.'    '.and.
    -    emmigareamap(nscn)(1:4).ne.'NONE'.and.
    -    emmigareamap(nscn)(1:4).ne.'none')then
         if(iomsg.eq.1)write(*,*)'Opening emmigration areas map ',
    -     emmigareamap(nscn),nscn
           call mapread(emmigareamap(nscn))
           do narea=1,nareat
             emmigar(nscn,narea)=int(rarray(narea))
           end do
```

Table E.9. (cont.)

```
        end if

! Set Elk Starting Locations for each herd
! Distribute VCStart% of animals on Valle Caldera Land Cover Type
        y=(hpopt(nscn)-startnum(nscn))*vcstart(nscn)
        x=y
        if(iomsg.ge.3)open(40,file='elkinit.txt')
        if(y.gt.0) then
         do iter=1,y
           call random_number(r)
           ! Select a random cell within the VC area
           ! Max selection choice is J, the number of
           ! VCNP cell types on the Caldera
           r=(r*(j-1)+1)
           x1=startlocs(int(r),1)
           y1=startlocs(int(r),2)
           narea=((nrow-y1)*ncol)+x1
           hpop(nscn,narea)=hpop(nscn,narea)+1
           elkloc(nscn,iter+startnum(nscn))=narea
         end do
        endif

! Distribute remaining animals elsewhere on the map randomly
        y=(hpopt(nscn)-startnum(nscn))-y
        do while (y.gt.0)
         call random_number(r)
         ! Select a random cell somewhere on the map
         r=int(r*(nareat-1)+1)
         ! Make sure it isn't masked out
         if(nstp(1,r).ne.0.and.elkcost(r).ne.0) then
           ! Decrease the number of animals left to distribute
           y=y-1
           ! Increase the animal "index" number
           x=x+1
           hpop(nscn,r)=hpop(nscn,r)+1
           elkloc(nscn,x+startnum(nscn))=r
           if(iomsg.ge.3)write(40,*)"Ani=",int(x),
     -        "Cell=",int(r),
     -        "Cell Pop=",int(hpop(nscn,r))
         end if
        end do
```

Table E.9. (cont.)

```
! Put Elk Population in an array that won't get lost
        elkpop=hpop

! Write elk starting points to IBM.out
        if(iomsg.ge.3)then
          write(40,*)"Max Cell Pop",
    -      int(MaxVal(hpop))," in cell",
    -      int(MaxLoc(hpop))
          close(40)
        endif
        do iter=1,hpopt(nscn)
          ibmout=ibmout+1
          write(96,rec=ibmout)int(ElkLoc(nscn,iter))
!          write(97,*)int(ElkLoc(nscn,iter))
        end do
      end do

      return
    end if


c end intialization
c ----------------------------------------------------------------------

! Bring in Elk Population Distribution from a persistant array
      hpop=elkpop
      write(*,*)"Start Elk IBM..."



!     iomsg=3
!       open(40,"hsicomp.txt")

c read data off a file if running distrib only
c store data in arrays that are not used in this kind of run
    if(idistrd.eq.1)then
      nrto=nlrow-nfrow+1
      nvarsv=nv_not_con3+2*nspcon
      do nr=nfrow,nlrow
          do nvar=1,nvarsv
```

Table E.9. (cont.)

```
          nrec= (nrto*nvarsv*(nimgsv-1)) + (nvar-1)*nrto +
     -          (nr-nfrow+1)
          read(64,rec=nrec)(ldat3(nvar,nc),nc=nfcol,nlcol)
        end do
        do nc=nfcol,nlcol
          na=idcel(nr,nc)
          wdcvr(1,na)=ldat3(1,nc)/100.
          shcvr(1,na)=ldat3(2,nc)/100.
          shadecvr(na)=ldat3(1,nc)
          thickcvr(na)=ldat3(2,nc)
          snwdp(na)=ldat3(3,nc)
          ncrust(na)=ldat3(4,nc)
          gbiom(1,na)=ldat3(5,nc)
          dedb(1,na)=ldat3(6,nc)
          meantemp(na)=ldat3(7,nc)
          do n=1,nspcon
            tforage(n,na)=float(ldat3(nv_not_con3+n,nc))/10.
            metabintk(n,na)=ldat3(nv_not_con3+nspcon+n,nc)
          end do
        end do
      end do
     end if

     if ((MaxVal(snwdp).le.0).and.(MaxVal(meantemp).le.0)) then
       Write(*,*)"Meantemp & Snow Depth for entire area <=0..."
       pause
     endif


c call range expansion monthly - at ntim=4 so works w. distrib-only run
     if(ihrngexp.eq.1)then
       if(ntim.eq.4)then
         call rangeexp(0)
       end if
     end if

c Loop over a single animal herd/species at a time
     do 1 nscn=1,nspcon
     if(skipsav)goto 888
!          fname="elkstart-"
!          write(fname,*)ntim
```

Table E.9. (cont.)

```
!          fname=fname//".txt"
!          write(fname,*)"elkstart-",ntim,".txt"
!          open(40,file=fname)
!          write(40,*)"Population Check #'s: "
!          write(40,*)"    Theoretical=",hpopt(1)
!          write(40,*)"    hpop array=",sum(hpop)
!          write(40,*)"    elkpop array=",sum(elkpop)
!          i=nscn
!          do x=1,hpopt(i)
!          narea=idcel(elkloc(i,x+startnum(i),2),
!    -      elkloc(i,x+startnum(i),1))
!             write(40,*)"Ani=",int(x),"Cell=",int(narea),"X,Y=",
!    -         int(elkloc(i,x+startnum(i),1)),
!    -         int(elkloc(i,x+startnum(i),2)),
!    -         "Cell Pop=",int(hpop(i,narea))
!          end do
!             write(40,*)"Total Pop=",sum(hpop)," Max Cell Pop",
!    -         MaxVal(hpop)," in cell",MaxLoc(hpop)
!             close(40)


c forced movements may be scheduled
c find if different map now based on date and if so, read in new map
c nfmap(nscn) is the map index currently in use for species nscn
c nfmapt(nscn) is the total number of maps for the species
c only do at beginning of month
      if((ihdfc.eq.1.and.ntim.le.1).or.idistrd.eq.1)then
        nmap=0
        do n=1,nfmapt(nscn)
          if(nyear.ge.nyrfrc(1,n,nscn).and.
     -       nyear.le.nyrfrc(2,n,nscn).and.
     -       monfrc(month,n,nscn).eq.1)then
               nmap=n
          end if
        end do
        if(nmap.eq.0.and.nfmapt(nscn).gt.0)then
          write(*,*)'Warning - no force map found for current time'
          write(*,*)'year/month',nyear,month,'   herd/species ',nscn
        end if
        if(nmap.ne.0.and.nmap.ne.nfmap(nscn).and.nfmapt(nscn).ne.0)
     -   then
```

Table E.9. (cont.)

```
          nfmap(nscn)=nmap
          if(iomsg.eq.1)write(*,*)'Opening force map ',nmap,
    -      'herd ',nscn ,frcmap(nmap,nscn)

          call mapread(frcmap(nmap,nscn))
c check force map values
          nn=1
          iok=0
          do narea=1,nareat
            nn=nn+rarray(narea)
c            allow non-data codes of -99 etc to be non-force (0)
            rarray(narea)=amax1(rarray(narea),0.)
            force(nscn,narea)=int(rarray(narea))
            if(force(nscn,narea).gt.0)iok=1
          end do
          if(iok.eq.0.and.hpopt(nscn).gt..001.and.ifrcprb(nscn).ne.1)
    -       then
            ifrcprb(nscn)=1
            write(*,*)
            write(*,*)'Warning'
            write(*,*)'  No cells within specified force map for '
    -        ,'animal population',nscn
            write(*,*)'  - yet population size is >0 '
            write(*,*)'  Results will be spurious (CI will not change'
    -        ,', intake will =0, etc.)'
            write(*,*)
          end if
        end if

      end if

c assess forage level in preferred area (eg. wet season concentration area)
c to include green leaves and stems of herbs and CAG of woodies only
      if(ihdpr.eq.1)then
        prfhbg(nscn)=0.
        nprarea=0
        do narea=1,nareat
          if(nstp(1,narea).gt.0)then
            if(prefar(narea).eq.1)then
              if(ihdfc.eq.0.or.(ihdfc.eq.1.and.
    -         force(nscn,narea).gt.0))then
```

Table E.9. (cont.)

```
          nprarea=nprarea+1
          do nsp=1,nspmx
            nspt=nspec(nsp,nf)
            if(nspt.gt.0)then
              if(prfsp(nspt,nscn).gt.0.)then
                if(nwdysp(nspt).eq.0)then
                  do nsub=1,nsubar
                    do nfac=1,nfacet
                      prfhbg(nscn)=prfhbg(nscn)+gbiom(nsp,nf)+
     -                 wood(nsp,nf)
                    end do
                  end do
                else
                  do nsub=1,nsubar
                    do nfac=1,nfacet
                      prfhbg(nscn)=prfhbg(nscn)+cagw(nsp,nf)
                    end do
                  end do
                end if
              end if
            end if
          end do
        end if
      end if
    end if
  end do
  if(nprarea.gt.0)then
    prfhbg(nscn)=prfhbg(nscn)/float(nprarea)
  end if

end if


ndrow=nfrow
ndcol=nfcol-1

c calculate preference value for each cell

hsit=0.
hsitw=0.
```

Table E.9. (cont.)

```
      do 3 narea=1,nareat

       hsi(nscn,narea)=0


c for image output - row and column, zero arrays or fill with miss value code
       if((imgcon.ne.0.and.imgmon(month).eq.1).or.
     - (idistrd.eq.1.and.nscn.eq.1))then
        ndcol=ndcol+1
        if(ndcol.gt.nlcol)then
          ndcol=nfcol
          ndrow=ndrow+1
        end if

        if(nstp(1,narea).eq.0)i=-999
        if(nstp(1,narea).ne.0)i=0
        if(nscn.eq.1)then
          do nvar=1,nv_not_con3
            ldat3(nvar,ndcol)=i
          end do
        end if
        ldat3(nscn+nv_not_con3,ndcol)=i
        ldat3(nscn+nspcon+nv_not_con3,ndcol)=i

       end if




c assess shade and thicket cover one time per month
c do for whole area, unless want to determine what is in the ranges of all species (need
for image3.img)

       if(nscn.eq.1.and.ihdwc.eq.1.and.ntim.le.1.
     - and.idistrd.ne.1)then
        if(nstp(1,narea).ne.0)then
          thcv=1.e-6
          trcv=1.e-6
          do nsub=1,nsubar
            if(subcvr(nsub,narea).gt.0.)then
              do nfac=1,nfacet
```

Table E.9. (cont.)

```
                nf=nfpnt(nfac,nsub,narea)
                do nsp=1,nspmx
                  nspt=nspec(nsp,nf)
                  if(nspt.ne.0.and.nwdysp(nspt).gt.0)then
c                    could use species ht here, but then would only save spp. 1
c                    thcv and shcv to image3 (which is used by distrib-only runs)
                    do n=1,6
                      if(tnum(nsp,n,nf).gt.0.)then
                        nsiz=npsize(n,nsp,nfac,nsub)
                        plsiz=wdsize(nsp,n,nf)*1.e6/tnum(nsp,n,nf)
                        if(nsiz.eq.1)then
                          canar=xyinter(plsiz,0.,sbsize(nsiz,nspt),
     -                     0.,wcarea(nsiz,nspt))
                        else
                          canar=xyinter(plsiz,sbsize(nsiz-1,nspt),
     -                      sbsize(nsiz,nspt),wcarea(nsiz-1,nspt),
     -                      wcarea(nsiz,nspt))
                        end if
c                        m2 area/m2 ground = trees/km2 * 1.e-6km2/m2 * m2 area/tree
                        cancvr=tnum(nsp,n,nf)*1.e-6*canar
                        if(canbot(nsiz,nspt).gt.2.)then
                          trcv=trcv+cancvr
                        else
                          thcv=thcv+cancvr
                        end if
                      end if

                    end do
                  end if
                end do
              end do
            end if
            shadecvr(narea)=trcv*100
            thickcvr(narea)=thcv*100
          end do
        else
          if(idistrd.ne.1)then
            shadecvr(narea)=0
            thickcvr(narea)=0
          end if
        end if
```

Table E.9. (cont.)

```
      end if

c branch around if masked
      if(nstp(1,narea).eq.0)go to 330

c herbaceous green and dead biomass
      if(ihgreen.eq.1.or.ihdead.eq.1)then
        if(idistrd.ne.1)then
          hbgrn=1.e-6
          hbded=1.e-6
          do nsub=1,nsubar
            if(subcvr(nsub,narea).gt.0.)Then
              cvrsub=subcvr(nsub,narea)
              do nfac=1,nfacet
                nf=nfpnt(nfac,nsub,narea)
                do nsp=1,nspmx
                  nspt=nspec(nsp,nf)
                  if(nspt.gt.0)then
                    if(nwdysp(nspt).eq.0)then
                     hbgrn=hbgrn+(gbiom(nsp,nf)+wood(nsp,nf))*cvrsub
                     hbded=hbded+dedb(nsp,nf)*cvrsub
                    end if
                  end if
                end do
              end do
            end if
          end do
c distrib run -
        else if(idistrd.eq.1)then
c          gbiom(1,) will have live leaf+stem all herbs stored in it
c          dedb(1,) will have dead of all herbs stored in it
c          both will have been scaled up to grid-cell already
          hbgrn=gbiom(1,narea)
          hbded=dedb(1,narea)
        end if
      end if

      if(ihgreen.eq.1)then
        pgrnhb=alint(hbgrn,pgreenhb(1,1,nscn),2)
      else
        pgrnhb=1.
```

Table E.9. (cont.)

```
        end if

        if(ihdead.eq.1)then
          pdedhb=alint(hbded,pdeadhb(1,1,nscn),2)
        else
          pdedhb=1
        end if


c branch around if not in use area
        if(ihdfc.eq.1.and.force(nscn,narea).eq.0)go to 330

c branch around if not known
        if(irangeexp(nscn).eq.1)then
          if(know(nscn,narea).ne.2)go to 330
        end if

c forced movements due to threat, fencing, rotation, fixed migration etc.
c frc can be scaled any way (0 or 1, 0-100) since it is multiplicative on hsi
        if(ihdfc.eq.1.and.nfmapt(nscn).gt.0)then
          frc=float(force(nscn,narea))
        else
          frc=1.
        end if

c zone map
        if(ihdzone.eq.1)then
          n=nzone(narea)
          if(n.gt.0)then
            zonewt=wtzone(nzone(narea),nscn)
          else
            zonewt=1.
          end if
        else
          zonewt=1.
        end if

c preferred area
        if(ihdpr.eq.1)then
c if forage is good in the preferred area (prfhb > prfgmn)
          if(prfhbg(nscn).gt.prfgmn(nscn))then
```

Table E.9. (cont.)

```
              if(prefar(narea).eq.1)parea=prefam(1,nscn)
              if(prefar(narea).ne.1)parea=prefam(2,nscn)
            else
              parea=1.
            end if
          else
            parea=1.
          end if


c forage -
          if(ihdfd.eq.1)then
            for=alint(tforage(nscn,narea),pforage(1,1,nscn),3)
c tforage computed differently for ihdfd=2,3 in dietpatc
          elseif(ihdfd.eq.2)then
            for=tforage(nscn,narea)
          elseif(ihdfd.eq.3)then
            for=tforage(nscn,narea)
          elseif(ihdfd.eq.4)then
            call logistic(0,nscn,narea,ntim,for)
          else
            for=1.
          end if
          for=amax1(for,.001)


c metabolic energy intake - convert KJ/kg/d to MJ/kg/d
c note, this has implicitly the effects of forage biomass, digestible energy,
c and snow in it, so could actually use this in place of all the others
c furthermore, because shrubs may have forage available despite snow
c depth, it may be a better way to represent snow effect
          if(ihdme.ge.1)then
            tmetin=float(metabintk(nscn,narea))/1000.
            eme=alint(tmetin,emetintk(1,1,nscn),2)
          else
            eme=1.
          end if
          eme=amax1(eme,.001)
```

Table E.9. (cont.)

```
c slope
      if(ihdsl.eq.1)then
        sl=alinti2(slope(narea),pslope(1,1,nscn),3)
      else
        sl=1.
      end if

c woody cover - shade trees vs. thicket, based on height of canopy bottom
      if(ihdwc.eq.1)then
        if(idistrd.ne.1)then
          shcvrx=float(shadecvr(narea))/100.
          thcvrx=float(thickcvr(narea))/100.
        else if(idistrd.eq.1)then
          shcvrx=wdcvr(1,narea)
          thcvrx=shcvr(1,narea)
        end if

        sh=alint(shcvrx,pshcv(1,1,nscn),2)
        th=alint(thcvrx,pthcv(1,1,nscn),2)
      else
        sh=1.
        th=1.
      end if

c elevation
      if(ihdel.eq.1)then
        pelev(2,1,nscn)=pelevmn(month,nscn)
        pelev(2,2,nscn)=pelevmx(month,nscn)
        el=alinti2(elev(narea),pelev(1,1,nscn),4)
      else
        el=1.
      end if

c snow   - depth is in cm
      if(ihsnw.eq.1)then
        sd=float(snwdp(narea))
        snw=alint(sd,psnow(1,1,nscn),3)
      else
        snw=1.
      end if
```

Table E.9. (cont.)

```
c temperature
        if(ihtemp.eq.1)then
          t=float(meantemp(narea))
          tmp=alint(t,ptemper(1,1,nscn),4)
        else
          tmp=1.
        end if

c Cost Impedance Surface Map (Includes any modifiers)
        if(ihdcost.eq.1)then
          cost=elkcost(narea)
          if (cost.eq.-9999) cost=1
        else
          cost=1.
        end if

c total habitat suitability/preference wt
!       sl=slope
!       el=elevation
!       sh=shrub cover
!       th=thicket cover
!       (Law of the minimum on above- only use the lowest)
!       frc=force
!       snw=snow
!       tmp=termperature
!       zonewt=zone weight
!       cost=cost impedance
        phys=amin1(sl,el,sh,th)*frc*snw*tmp*zonewt*cost

c the final HSI
!       for=forage
!       eme=metabolic energy
!       phys=physical factors (listed above)
!       pwat=distance to water
!       parea=preferred area
!       pgrnhb=preference for green biomass
!       pdedhb=preference for dead biomass
        hsi(nscn,narea)=for*eme*phys*parea*pgrnhb*pdedhb
!           write(40,*)"for=",for
!           write(40,*)"eme=",eme
!           write(40,*)"parea=",parea
```

Table E.9. (cont.)

```
!           write(40,*)"pgrnhb=",pgrnhb
!           write(40,*)"pdedhb=",pdedhb
!           write(40,*)"HSI=",hsi(nscn,narea),"narea=",narea
!           write(40,*)"----------------------------------------"

c using a power<1 will dampen effect of multiplying many fractions together
        if(ihpower.ne.0)then
          hsi(nscn,narea)=hsi(nscn,narea)**hsipower
        end if

        hsit=hsit+hsi(nscn,narea)
        hsitw=hsitw+hsi(nscn,narea)

c branch here if cell is masked out or not in use area
330     continue


c save temporally varying habitat factors for image output -
c and for use in driving the distrib model by itself
c set imgcon=0 for no output
c non-varying factors elev,slope can be obtained from GIS data
c force and prefar can also seen in GIS data
        if(nimgsv.ne.0.and.imgmon(month).eq.1.and.imgcon.ne.0)then
          if(nstp(1,narea).gt.0)then
            if(nscn.eq.1)then
              ldat3(1,ndcol)=shadecvr(narea)
              ldat3(2,ndcol)=thickcvr(narea)
              ldat3(3,ndcol)=snwdp(narea)
              ldat3(4,ndcol)=ncrust(narea)
              ldat3(5,ndcol)=hbgrn
              ldat3(6,ndcol)=hbded
              ldat3(7,ndcol)=meantemp(narea)
            else

            end if
            if(force(nscn,narea).eq.0.)then
              ldat3(nscn+nv_not_con3,ndcol)=0
              ldat3(nscn+nspcon+nv_not_con3,ndcol) =0
            else
              ldat3(nscn+nv_not_con3,ndcol)=tforage(nscn,narea)*10
              ldat3(nscn+nspcon+nv_not_con3,ndcol)=
```

Table E.9. (cont.)

```
     -          metabintk(nscn,narea)
              end if
c         ldat3(nscn+nspcon+nv_not_con3,ndcol)=know(nscn,narea)

             else
              if(nscn.eq.1)then
               do nvar=1,nv_not_con3
                ldat3(nvar,ndcol)=i
               end do
              end if
              ldat3(nscn+nv_not_con3,ndcol)=i
              ldat3(nscn+nspcon+nv_not_con3,ndcol)=i
             end if

c write row of image output if on last cell in the row
             if(ndcol.eq.nlcol)then
c write out variables which do not vary by animal species - once
              if(nscn.eq.1)then
               call imagesv3(ndrow,1,nv_not_con3)
              end if
c write out variables that do vary by animal species - for each species
              n=nscn+nv_not_con3
              call imagesv3(ndrow,n,n)
              n=nscn+nspcon+nv_not_con3
              call imagesv3(ndrow,n,n)
             end if

            end if

3       continue

!        close(40)
        ! Use HSIMax to Normalize on highest HSI Value, or hsit to normalize on total HSI
        hsimax=MaxVal(hsi(nscn,:))

c normalize hsi
        do narea=1,nareat
         if(nstp(1,narea).gt.0)then
          if(ihdfc.eq.0.or.(ihdfc.eq.1.and.
     -     force(nscn,narea).gt.0))then
c           if hsimax is 0, probably no habitat here, out of force range
```

Table E.9. (cont.)

```
          if(hsimax.eq.0.)then
            hsi(nscn,narea)=0
          else
            if(hsi(nscn,narea).gt.0.)then
              hsi(nscn,narea)=hsi(nscn,narea)/hsimax
            else
              hsi(nscn,narea)=1.e-30
            end if
          end if
        end if
      end if
    end do

! Move Elk across landscape based on HSI as modified by snow/memory
!       write(fname,*) "elkmove",nscn,"-",ntim,".txt"
!       open(40,file=fname)
!         write(*,*)"Ani-1",ElkLoc(nscn,1)
!         write(*,*)"Ani-6",ElkLoc(nscn,6)

888     do day=1,7                      !Loop through seven days/one week
          do Times=1,daystep(nscn)      !Loop through the max elk daily step
            tzcnt=0
              do iter=1,hpopt(nscn)     !Loop through entire elk population
            ! Reset and Increment Variables
            ! (ChoiceLocs: (Col,Row) Index of cells 1-9)
            ! (Choices: Desirability of cells 1-9)
            Choices=0
            ChoiceLocs=0
            narea=elkloc(nscn,iter)
            x=mod((narea-1),ncol)+1
            y=nrow-(int(narea-1)/334)
            MigFlag=.False.
            t=0
            writedata=.false.

            ! Special modifiers can be applied to a cell-
            ! 1) If there is snow in a cell, apply a force inversely proportional to the result
            !       of the alint function for that depth of snow, or
            ! 2) If there is no snow in the cell, and we aren't in our Summering Range then
            !       apply memory as a directional force to return to home range.
```

Table E.9. (cont.)

```
            ! In this section we also calculate the distance to summer/winter ranges from
our
            ! current location
            if(ihdmig.eq.1)then
               sd=float(snwdp(narea))
               ! We will be migrating, either to Winter Range or to Summer Range, so set
flag true
               MigFlag=.True.
               ! Set the first pair of lint to be the (x,y) coordinates of our current location
               lint(1,2)=x
               lint(2,2)=y
               if(sd.gt.0)then
!                    sd=sd*2
                  ! Since it is snowing in our cell, we head to the Winter Range
                  ! We need to decide how much force to exert toward the Winter Range
                  !   The amount of force is based on the inverse of the linear interpolation
function which
                  !   controls how elk respond to snow- the more snow, the more force we
apply toward Winter Range
                  ForceExert=(1-alint(sd,psnow(1,1,nscn),3))
                  lint(1:2,1)=WinRange(nscn,1:2)
                  ! cNow is the distance from where we are now, to the Winter Range
                  ! We have to set cNow, because we compare against it later to figure out
where to go!
                  cNow=EucDist(lint)
                  RadDist=0
!                   writedata=.true.
!                   write(*,*)"------------------------------------"
!                   write(*,*)"X,Y=",x,y
!                   write(*,*)"Snow=",sd,"Force=",ForceExert
               else
                  ! Since it isn't snowing in our cell, we head back to the Summer Range
                  ! cNow is the distance from where we are now, to the Summer Range
                  ! We have to set cNow, because we compare against it later to figure out
where to go!
                  lint(1:2,1)=SumRange(nscn,1:2)
                  cNow=EucDist(lint)
                  ! If we leave lint(1:2,2) set to the Summer Range coordinates, we
effectively have no boundary,
                  ! and Elk are forced, albeit a gradually declining force, all the way to the
```

Table E.9. (cont.)

```
Summer Range
                    ! If we set lint(1:2,2) to a coordinate other than the Summer Range
coordinates,
                    ! force will not be applied once Elk come within a distance to the Summer
Range equal to or less
                    ! than the distance between the Summer Range and the boundary
coordinate
!                    lint(1:2,2)=SumRange(nscn,1:2)
                    lint(1:2,2)=Radius(nscn,1:2)
                    RadDist=EucDist(lint)
                    ! Set up Linear Interpolation Function to determine how much force to
apply to elk movements
                    ! First Pair- lint(1:2,1)= The distance from SumRange where force should
no longer be applied
                    !   Lint(1,1)=RadDist=The distance the radius/boundary is from Summer
Range
                    !   Lint(2,1)=0=No force applied if within this distance of Summer Range
                    !   If no boundary, this should be (0,0), otherwise it should be (radius,0),
                    !   where radius is the euclidian distance of the boundary from the Summer
Range.
                    lint(1,1)=RadDist
                    lint(2,1)=0.0
                    ! Second Pair- lint(1:2,2)= The force to be applied at the maxium distance
(Summer Range to Winter Range)
                    !   Lint(1,2)=TopDist(nscn)=The distance from SumRange to WinRange
                    !   Lint(2,2)=Maximum force to be applied at this distance [Currently Max
Force=.1]
                    lint(1,2)=TopDist(nscn)
                    lint(2,2)=MigForce
                    ! We are currently located somewhere along the continum between
Summer and Winter Ranges
                    !   Find the force (currently between 0 and .1) related to the distance we
are from the Summer Range
                    ForceExert=alint
    -                (float(cNow),Lint,2)
                    ! Use the following two lines for a force related to Temperature
!                    ForceExert=alint(float(meantemp(narea)),
!    -                ptemper(1,1,nscn),4)
!                    write(*,*)"Force=",ForceExert
                    ! We need to leave the first pair set up for use later, when we apply the
force determined in the step above
```

Table E.9. (cont.)

```
                    ! In this case, lint(1:2,1) is the X,Y coordinate pair of the Summer Range
(Where we are headed)
                    lint(1:2,1)=SumRange(nscn,1:2)
!                    write(*,*)"cNow,RadDist,TopDist,ForceExert=",
!    -                 cNow,RadDist,TopDist(nscn),ForceExert
!                    pause
                    ! If we are exerting no force, it is pointless to do any migration, so simply
clear the migration flag
                    if(ForceExert.le.0)MigFlag=.False.
                 endif
              endif

              if(iomsg.ge.6)write(*,*) "Day=",day," Animal=",iter
              if(iomsg.ge.6)write(*,*) "   From (X,Y)=",x,y,
     -         " narea=",narea," pop=",int(hpop(nscn,narea))

              ! Need to take elk out of old cell
              hpop(nscn,narea)=hpop(nscn,narea)-1
              if(hpop(nscn,narea).lt.0)then
                 write(*,*)"PROBLEM-- ELK POP is NEGATIVE"
                 write(*,*)"Elk=",iter," x,y=",x,y," narea=",narea,
     -            " pop=",int(hpop(nscn,narea))
                pause
                stop
              endif

              ! Each time through this loop is one cell move
              do x1=x-1,x+1
                 do y1=y-1,y+1
                 ! Convert (x,y) to narea
                 narea=((nrow-y1)*ncol)+x1

                 ! Increment Choice Index
                 t=t+1

                 ! Set ChoiceLocs to correspond to coordinates of cell we are evaluating
                 ChoiceLocs(t,1)=x1
                 ChoiceLocs(t,2)=y1

                 ! Informative
                 if(iomsg.ge.6)write(*,*) "   Evaluating (X,Y)=",
```

Table E.9. (cont.)

```
-             x1,y1," narea=",narea

            ! Make sure narea is within the map
            ! If not in-bounds set desirability to zero
            if (narea.lt.1.or.narea.gt.nareat) then
               Choices(t)=0
               if(iomsg.ge.6)write(*,*)
-               "Cell out of bounds/narea."
               cycle
            end if

            ! Check to make sure Column is in-bounds high/low
            ! Under most circumstances narea check is not enough
            ! If not in-bounds set desirability to zero
            if ((x1 > ncolx) .or. (x1 < 1)) then
               Choices(t)=0
               if(iomsg.ge.6)write(*,*)"Cell out of bounds/X"
               cycle
            end if

            ! Check to make sure Row is in-bounds high/low
            ! Under most circumstances narea check is not enough
            ! If not in-bounds set desirability to zero
            if ((y1 > nrowx) .or. (y1 < 1)) then
               Choices(t)=0
               if(iomsg.ge.6)write(*,*)"Cell out of bounds/Y"
               cycle
            end if

            ! Check to make sure cell isn't masked on soil type map
            if (nstp(1,narea).eq.0) then
               Choices(t)=0
               if(iomsg.ge.6) then
                  write(*,*)"Cell mask/Soiltype"
                  write(*,*)"Cell Vegtype=",
-                  vegtype(1,narea)
               end if
               cycle
            end if

            ! Check to make sure cell isn't masked on cost impedance map
```

Table E.9. (cont.)

```
          if (ihdcost.eq.1) then
             if(elkcost(narea).eq.0) then
                Choices(t)=0
                if(iomsg.ge.6)then
                  write(*,*)"Cell masked/Cost Impedance map"
                  write(*,*)"Cell Vegtype=",vegtype(1,narea)
                endif
                cycle
             end if
          end if

          ! Check to make sure cell isn't masked on force map
          if (ihdfc.eq.1) then
             if(force(nscn,narea).eq.0) then
               Choices(t)=0
               if(iomsg.ge.6)write(*,*)"Cell mask/force map"
               cycle
             end if
          end if

          ! Check to make sure we don't already have too many elk in this cell
          if (ihden.gt.0) then
             if(hpop(nscn,narea).gt.ihden) then
                Choices(t)=0
                cycle
             end if
          end if

          ! If none of the special cases above apply,
          ! read the desirability of this cell from the Map
          Choices(t)=hsi(nscn,narea)
!          if(iomsg.ge.6)
!          write(*,*)"Cell(",t,") HSI=",Choices(t)

          ! Even if cell has a desirability of zero, it still has a statistical
          ! chance of being selected, so increase desirability to value set in parm file.
          if (Choices(t)==0) then
             Choices(t)=stoch
             if(iomsg.ge.2)write(*,*)"+Stochastic=",stoch
          else
!              write(*,*)"Non-zero",narea,x1,y1,hsi(nscn,narea)
```

Table E.9. (cont.)

```
                endif

                ! Special modifiers applied to a cell if migrating
                ! ForceExert is determined above, as is the migration direction
                ! (Winter or Summer) in the xMig,yMig variable
                if (MigFlag) then
                   ! Here we want to see if this prospective cell (x1,y1) is closer to our goal
                   !   (either Winter Range or Summer Range, decided above) than where we
currently are
                   !   or not.  lint(1:2,1) contains Winter/Summer Range, lint(1:2,2) our
possible location (x1,y1)
                   ! The distance of this prospective cell from the Winter/Summer Range will
be compared to the
                   !   distance of our current cell from the Winter/Summer Range.  If this
prospective cell is
                   !   closer than our current cell, we will make it more attractive by a force
determined above.
                   lint(1,2)=x1
                   lint(2,2)=y1
                   ! If this cell is closer to where we want to go, then we want to make it
more attractive
                   !   and more likely to be selected.  We will increase its desirability by
memory and the
                   !   force calculated above.
                   if (EucDist(lint)<cNow) then
!                      if(writedata)then
!                      write(*,*)"X/Y=",x1,y1,
!    -                  "Choice(",t,")= ",
!    -                  Choices(t),"Force=",ForceExert
!                      write(*,*)"Dist to Range=",EucDist(lint),
!    -                  "Current to Range=",cNow
!                      endif
                      total=ForceExert
                      if(cNow.lt.RadDist)
     -                 total=total/1.25
                      Choices(t)=(Choices(t)*total)+Choices(t)
!                     if(writedata)then
!                         write(*,*)"PostForce=",Choices(t),
!    -                     "Force=",total
!                         pause
!                      endif
```

Table E.9. (cont.)

```
              endif
            endif
          end do   !(Y1 Loop)
        end do      !(X1 Loop)

        ! Normalize choices
        r=SUM(Choices,Mask=Choices.gt.0)
        if(iomsg.ge.6)write(*,*)"Total of positive choices=",r,
  -      "Total of ALL choices=",SUM(Choices),"Choices=",Choices
        Where (Choices > 0) Choices=Choices/r
        if(iomsg.ge.6)write(*,*)"Normalized Choices=",Choices
        if(r.eq.0)then
          write(*,*)"Error in IBM- no valid locations,"
  -        // " so elk can't move..."
          write(*,*)"In Cell (x,y)=",x,y
          pause
          stop
        end if

        ! Pick a cell at random based on the desirability of all avail cells
        ! Call random number generator
        Call Random_Number(r)
        if (iomsg.ge.6) write(*,*)"My Random number is: ",r

        ! See which cell matches the random number (It will be in 't')
        ! We subtract each successive choice from the random number we generated
        ! When the number becomes less than or equal to zero, that is our choice
        do t=1,9
          if(Choices(t).gt.0)r=r-Choices(t)
          if (r<=0) exit
        end do

        ! It is possible that we ran through the loop above, and because of REAL
number
        ! problems we completed the loop, which would leave t=10, and cause
subscript
        ! problems.  So, if t>9, reset it to 9.
        if (t>9) t=9

        if (iomsg.ge.6) write(*,'(A,I1,3(A,I4))')
  -     "I selected choice ",t," which is location: ("
```

Table E.9. (cont.)

```
     -         ,ChoiceLocs(t,1),",",ChoiceLocs(t,2),")"

               ! Update population map
               x=ChoiceLocs(t,1)
               y=ChoiceLocs(t,2)
               narea=((nrow-y)*ncol)+x
               hpop(nscn,narea)=hpop(nscn,narea)+1

               ! Update my Elk Location Array
               elkloc(nscn,iter)=narea
!               write(40,*) "   To (X,Y)=",x,y,
!     -           " narea=",narea," pop=",int(hpop(nscn,narea))

             ! Write selection to output file
             ibmout=ibmout+1
             write(96,rec=ibmout)int(narea)
!             write(97,*)int(narea)
           end do          !(Population Loop)
        end do             !(Daystep Loop)
      end do               !(Day Loop)
      t=nint(sum(hpop))
      write(*,*) "  Population= ",int(t)
!       write(40,*)"POP=",t," MaxCellPop=",MaxVal(HPOP)," at cell:",
!     -      MaxLoc(HPOP)
!      close(40)
      elkpop=hpop

c end of big species loop
1     continue

c override everything except force map, to get a uniform distribution
c or one affected by force values only
c (for experiments or debugging)
      if(iuniform.eq.1)then
        do nscn=1,nspcon
          tot=0
          do narea=1,nareat
            if(nstp(1,narea).gt.0)then
              if(ihdfc.eq.1)then
                if(force(nscn,narea).gt.0)then
                  frc=float(force(nscn,narea))
```

Table E.9. (cont.)

```
              hsi(nscn,narea)=frc
              tot=tot+hsi(nscn,narea)
             end if
            else
             hsi(nscn,narea)=1.
             tot=tot+1.
            end if
           end if
          end do
          do narea=1,nareat
           if(nstp(1,narea).gt.0)then
            if(tot.gt.0.)then
             hpop(nscn,narea)=hpopt(nscn)*hsi(nscn,narea)/tot
            else
             hpop(nscn,narea)=0
            end if
           end if
          end do
         end do
        end if


c total grazing pressure array - once a month
        if(ntim.eq.ndtmn)then
         do narea=1,nareat
          if(nstp(1,narea).gt.0)then
           tot=0.
           do nscn=1,nspcon
            if(itgrzsp(nscn).eq.1)then
             if(ihdfc.eq.0.or.(ihdfc.eq.1.and.
     -        force(nscn,narea).gt.0))then
              tot=tot+hpop(nscn,narea)*anunit(nscn)
             end if
            end if
           end do
c convert to animal units per km2 * 10
           tot=tot/cellsz * 10.
           if(iauacc.eq.1)then
            tgpress(narea)=tgpress(narea)+tot
           else
            tgpress(narea)=tot
```

Table E.9. (cont.)

```
          end if
        end if
      end do
    end if

c an output file of animal numbers within a set of cells
    if(ioutanmask.ge.1)then
      if(ntim.gt.0)then
        totanmsk=0
        do narea=1,nareat
         if(outanmsk(narea).ge.1)then
            n=outanmsk(narea)
            do nscn=1,nspcon
              totanmsk(nscn,n)=totanmsk(nscn,n)+hpop(nscn,narea)
            end do
          end if
        end do
c output monthly
        if(idtanmask.eq.1)then
          if(ntim.eq.ndtmn)then
            write(88,880)month,nyear,(totanmsk(nmskpop(ncat),
     -       nmskarea(ncat)),  ncat=1,nanmskcats)
880          format(i2,',',i4,',',50(f7.1,','))
          end if
        end if
c output weekly
        if(idtanmask.eq.2)then
          xmon=float(month)-1.+(float(ntim)/4.)
          write(88,881)xmon,nyear,(totanmsk(nmskpop(ncat),
     -     nmskarea(ncat)),  ncat=1,nanmskcats)
881        format(f5.2,',',i4,',',50(f7.1,','))
        end if
      end if
    end if

! Put Elk Population in an array that won't get lost
!      elkpop=hpop

c close image output file
    if(imgcon.gt.0)close(20)
    write(*,*) "Finish Elk IBM"
```

Table E.9. (cont.)

```
      return

      end

      Function EucDist(data)
        dimension data(2,2)
!         write(*,*)"x=",data(1,1)
!         write(*,*)"y=",data(2,1)
!         write(*,*)"x1=",data(1,2)
!         write(*,*)"y1=",data(2,2)
        a=(data(1,1)-data(1,2))**2
        b=(data(2,1)-data(2,2))**2
        EucDist=SQRT(a+b)
!         write(*,*)"Funct Val=",eucdist
        return
      end
```

Table E.10. Associated parameter file for the individual-based model (IBM.f – Table E.9). The parameter file allows for the inclusion/exclusion of maps and other variables that go into the calculation of habitat suitability index (HSI) values (Code copyright 2005, Acorp Computers, Paul Rupp – owner).

1	/nsp - Number of parameter blocks (usually species) on this file (herds/species are defined on consume.prm)
0	/stoch - Random possibility to enter zero value cells
Valid2	/IBM Output Datafile name
0	/iuniform - if 1=flag to impose a uniform distribution, overriding everything (for experimental or debugging purposes)
2	/ihdfd -flag to use 1-forage biomass and pforage function, 2 -pref weight times biomass index (2),
	/ 3 - snow-free forage or 4 -logistic in Determining Herbivore Distribution
1	/ihdme - flag to use metabolic energy intake rate
1	/ihdwc - flag to use woody cover (tree and thicket)
0	/ihdsl - flag to use slope
0	/ihdel - flag to use elevation
1	/ihdcost - flag to use cost impedance map
1	/ihdroad - flag to use road map
1	/ihdbuild - flag to use buildings map
1	/ihdfence - flag to use fence map
1	/ihdmem - flag to use memory map
0	/ihdfc - flag to use force maps
0	/ihdzone - flag to use zones
0	/ihdpr - flag to use preferred area
1	/ihdmig - flag to use migration force
0	/ihden - flag to use density (0 not used, other number = maximum elk population density in any give cell)
1	/ihdsnw - flag to use snow
1	/ihgreen - flag to use herbaceous green biomass
1	/ihdead - flag to use herbaceous dead biomass
1	/ihtemp - flag to use mean daily temperature
0	/ihrngexp - flag to use range expansion
0	/ihemmigr - flag to use emmigration

Table E.10. (cont.)

0	/hsipower - take this power of the resultant hsi, or set to 0 to not use it,
	/<1 will spread animals out, >1 will compress them
1	/itgrzsp - flags to include herds/populations in total grazing pressure maps on image1
1	/anunit - conversion factors for including in total herbivore map (eg to convert to AUMs)
1	/iauacc - flag 1=output cumulative grazing pressure AUM/km2, 2- output total grazing pressure for timestep
1	/ELK //nherd - number of herds of this species
1	/indices of herds for this species
0,1,200,1,300,1	/pforage -- if ihdfd=2 is not used - if ihdfd=1 or 3 is foraging Efficiency vs. Forage Biomass
	/ (X-Y Pairs)(g/m**2 vs. index)
0,1,.25,1	/emetintk - effect of ME intake rate on HSI, 0-1 index vs. MJ/kg/d
0,1,1,1	/pshcv -- Habitat Preference Index vs. Cover Fraction of trees with canbot>.8*reachht
.7,1,1,1	/pthcv -- Habitat Preference Index vs Cover Fraction of thicket-forming bush/trees
	/ with canbot <.8*reachht –
15,1,30,.7,45,0	/pslope -- Habitat Preference Index vs. Slope (X-Y Pairs)(% vs. index)
1000,5000	/elevmn,elevmx - elevations at the min and max pref indices
12*1	/pelevmn - value of pref index at elevmn, by month
12*1	/pelevmx - value of pref index at elevmx, by month
0	/prfgmn -- Critical Herbaceous Amount to Utilize Preferred Areas (on map PREFAR)(g/m**2)
0	/prefam -- Preferred Area Habitat Preference Index Multiplier (? Why 2)()
0,1,10,.3,30,.001	/psnow -- Effect of Snow Depth on HSI (cm for Snow Depth)
5,.01,100,10	/pgreenhb -- Effect of Herbaceous Green biomass on habitat Suitability(index vs. g/m2)
0,1,100,1	/pdeadhb -- Effect of herbaceous dead biomass on HSI (0-1 vs. g/m2)
0,.001,7,1,15,1,30,.001	/ptemper -- Effect of mean daily temperature on HSI (0-1 vs. deg. C)
65.,0.,75.,.17	/esnowemmig (from Coughenour 5/18/2005 email - YNP)
0.,0.,1.,.17	/ecrustemmig based on 34% in 88/89 (from Coughenour 5/18/2005 email - YNP)
1.	/VCStart (Decimal Percentage of elk to start randomly on V.C. 1=100%, .2 = 20%, etc.)
1	/StartNum/StartLocs: Number of elk to start in a particular cell and corresponding (x,y) pairs
219,157	

Table E.10. (cont.)

1,1	/Upper Left coordinate of start area [ulstartx,ulstarty]
93,113	/Lower Right coordinate of start area [lrstartx,lrstarty]
86	/DayStep: Number of cells an elk can move through in a day
334,286	/WinRange: (X,Y) pair defining an approximate winter range
1,1	/SumRange: (X,Y) pair approximate center point of summer range
20,1	/Radius: (X,Y) pair defining a boundary from Summer Range within which to reduce migration force
0.4	/Force: Amount of force to apply when migrating toward Summer Range [MigForce]
-999	/end of file mark