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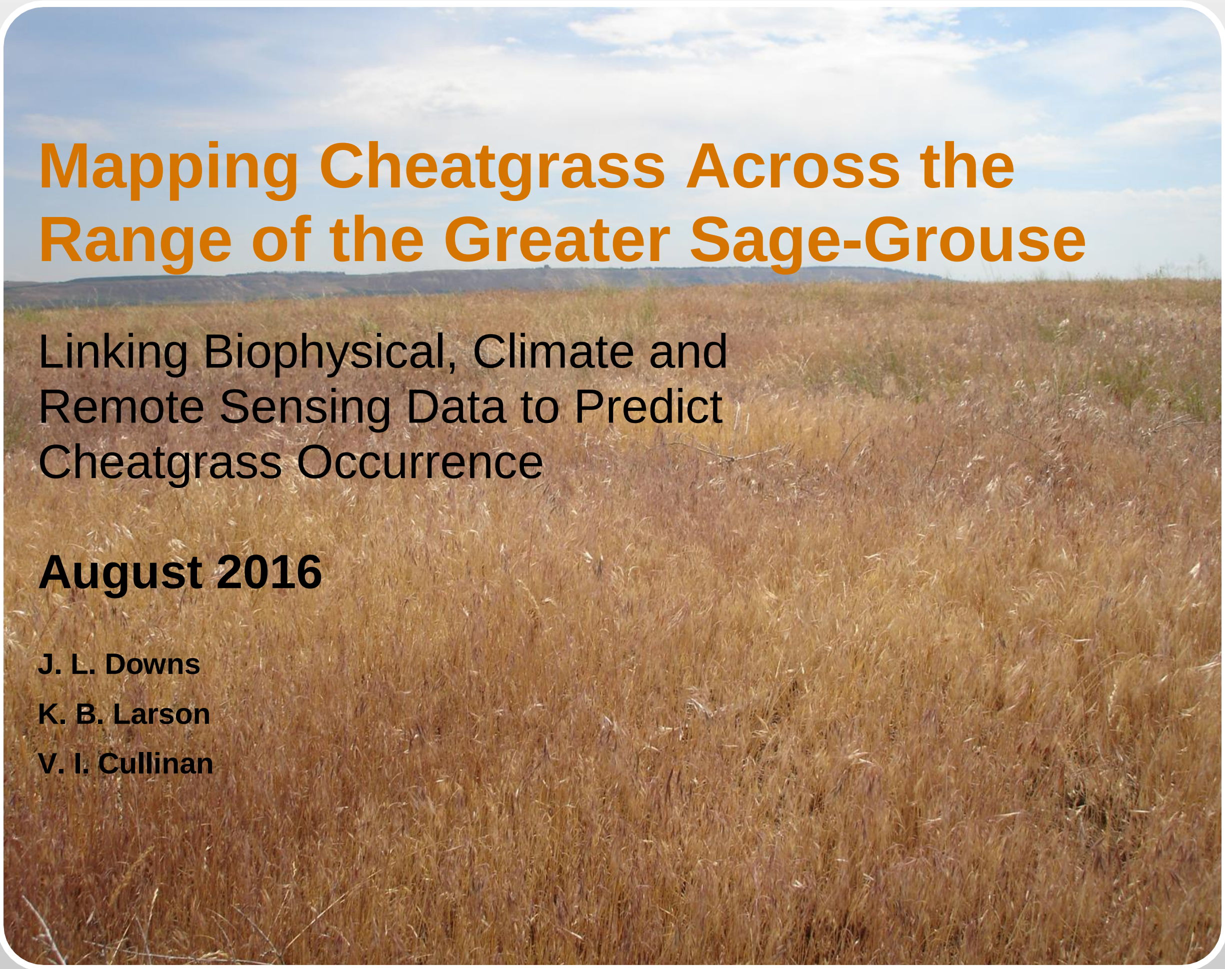

Mapping Cheatgrass Across the Range of the Greater Sage-Grouse

Linking Biophysical, Climate and Remote Sensing Data to Predict Cheatgrass Occurrence

August 2016

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U.S. DEPARTMENT OF ENERGY

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Summary

Increasing spread of invasive annual grasses, such as *Bromus tectorum* (cheatgrass), can contribute to increased fire frequency and hinder the reestablishment of native sagebrush, forbs, and grasses in subsequent years. Knowledge of the current distribution of cheatgrass on the landscape is a key component in planning and executing strategies to protect sagebrush ecosystems and sensitive wildlife species such as the Greater sage-grouse (*Centrocercus urophasianus*). Pacific Northwest National Laboratory (PNNL) worked with US Fish and Wildlife Service (FWS) to assemble and derive information to map cheatgrass occurrence across the historic range of sage-grouse. The information and map products described in this report can help land managers prioritize conservation efforts at the species' range scale.

We constructed an ecological model based on a suite of climatic and biophysical variables and satellite measures of peak NDVI (normalized difference vegetation index) – an index of vegetation greenness – to predict cheatgrass occurrence across the historic range of sage-grouse in the United States. More than 24,000 field measurements of cheatgrass cover across the study area were acquired from various agencies and research groups and reviewed for use in the modeling efforts. A subset of 6,650 field measurement points were identified and verified for use in statistical analyses. For each measurement location we derived a suite of 50 biophysical and NDVI variables correlated with cheatgrass occurrence. Pairwise correlation of variables was examined to remove highly-correlated variables from the model. A total of 13 variables were retained for use in forward-stepping discriminant analysis and modeling. Discriminant scores were used to determine probability of cheatgrass occurrence, which was broken into two relative cover classes: 0% to 2% cover and > 2% cheatgrass cover.

Section 2 of this report describes the data and methods used to develop the model and the cheatgrass occurrence map. In section 3, we provide a brief discussion of the accuracy of classification, and describe the appropriate scale of use for map results. The range-wide map of cheatgrass occurrence will be made available online for FWS and partner agencies.

Acknowledgments

We would like to thank Michael Gregg (FWS) for his vision and support of this project. We would also like to thank Fred Wetzel and John Klavitter (FWS) for their assistance and guidance in initiating and completing the project. And finally, we would like to express our appreciation to the agencies and staff who shared the field measurements that made this project feasible, including Lindy Garner (FWS), Dave Pyke (USGS), Scott Schaff (USGS), and Dawn-Marie Jensen (Joint Base Lewis McChord-Yakima Training Center) as well as the SAGEMap and SageSTEP projects, and the Bureau of Land Management's Assessment, Inventory and Monitoring (AIM) program.

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1.0 Introduction

The invasion of exotic annual grasses has increased fire frequency in the Intermountain West, fragmenting the sagebrush steppe, hindering the re-establishment of sagebrush, and limiting native forbs and grasses. As part of a larger project with FWS, PNNL collaborated with the agency to investigate and apply landscape-scale approaches to map cheatgrass (*Bromus tectorum*) occurrence across the historic range of sage-grouse. Results of this mapping effort are intended to support interagency efforts to identify and manage the impacts of cheatgrass invasion in sagebrush ecosystems, including to aid in planning for cheatgrass control and restoration.

Other studies have used remote sensing and other biophysical landscape data to detect and map the abundance of invasive annual grasses, but generally at local to regional landscape scales (e.g., Boyte et al., 2015; Bradley and Mustard 2006; Bradley 2009; Peterson 2008). This study describes an effort to map cheatgrass occurrence over nearly 300 million acres covering much of the Western US. Detecting and characterizing cheatgrass occurrence this large geographic domain presents a number of challenges including the acquisition of sufficient field data for ground-truthing predictive models, as well as the variability in climate, soils, and topography.

Our approach to developing a range-wide map of cheatgrass occurrence involved three main tasks:

1. Assembling available field measurements of cheatgrass cover across the entire study area
2. Assessing key relationships between cheatgrass occurrence and climatic variables, biophysical variables, and remote sensing indices
3. Constructing a statistical model to predict and map cheatgrass

This report describes the field datasets, remote sensing indices, and the climatic datasets used in model development, and provides a brief explanation of how the model was applied to map cheatgrass occurrence. Section 2 discusses the methods used to create the map of cheatgrass occurrence, including datasets that were acquired and transformed to represent biophysical attributes relevant to cheatgrass, and statistical procedures used to develop a predictive model of cheatgrass occurrence. Section 3 summarizes results of the study and discusses potential management applications of the map and suggested use.

2.0 Methods

The study area, shown in Figure 2.1, encompasses a large part of the Intermountain West as well as portions of Montana, Wyoming, Colorado, and New Mexico east of the Rockies. The areal extent of the area identified as the historic sage-grouse range covers more than 308 million acres and includes portions of southern Alberta and British Columbia, Canada. This study focused on the U.S. portion of the sage-grouse range, which is approximately 288 million acres.

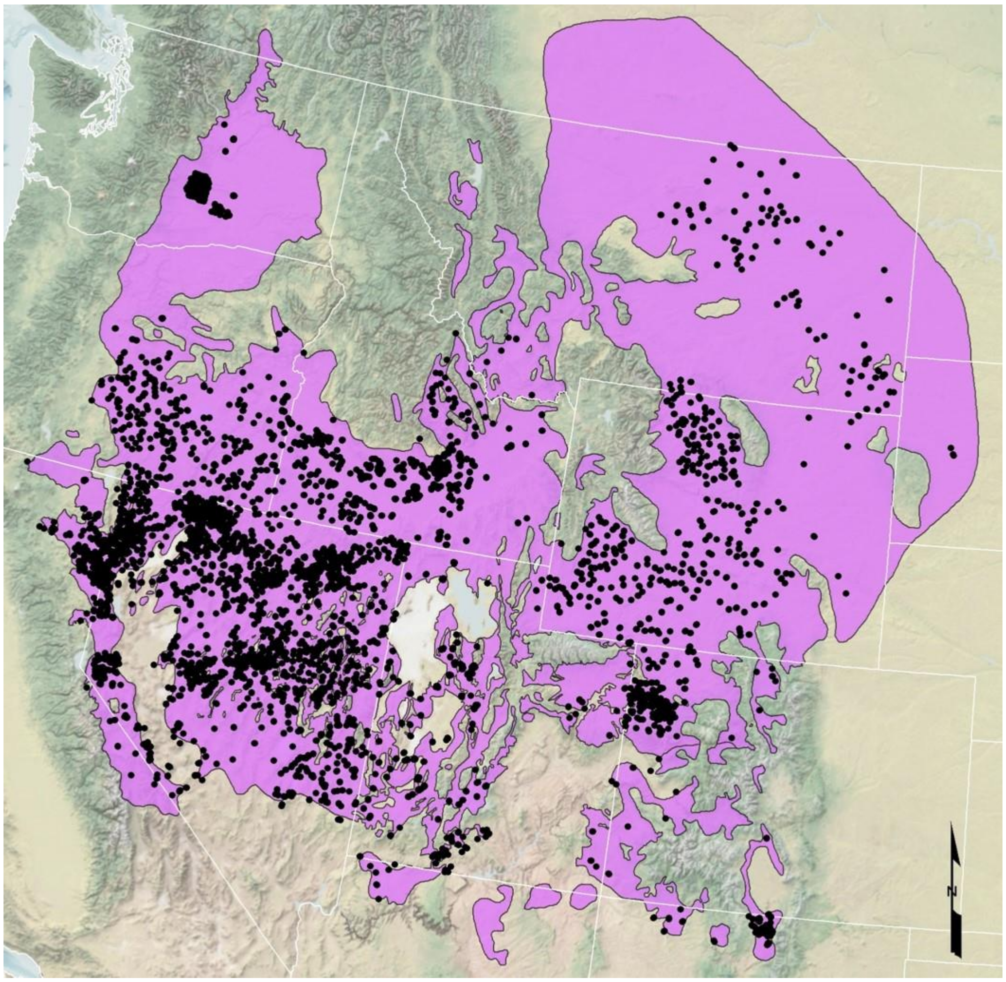

Figure 2.1. Location of Field Measurements (black dots) Within the Historical Range (purple area) for Greater Sage-Grouse.

Within the study area boundaries, we solicited more than 24,000 field measurements from various sources to gather information on cheatgrass occurrence. Table 2.1 provides the field measurement datasets and sources considered for use, although not all data sources and data were accepted for use. Data were reviewed for completeness, geographic accuracy, and quality of data source. Review of the field measurement dataset allowed us to identify 6,650 measurement points that could potentially be used for modeling. All field data were collected along transects ranging from 25m to 100 m in length. Point intercept data and plot frame (0.25 m to 1 m) data taken along the transects were summarized to calculate percent canopy cover of *Bromus tectorum* and *B. rubens*. The introduced, annual grass, red brome (*B.*

rubens) was included because it poses a very similar threat in terms of modifying fire regimes, and its life history characteristics are similar to cheatgrass.

Table 2.1. Data Source and Number of Field Measurements Evaluated.

Description	Number of Field Measurements Reviewed	Number of Field Measurements Accepted
BLM Assessment, Inventory, and Monitory Program	2043	1927
BLM Landscape Monitoring Framework	2335	2222
Global Invasive Species Information Network	4292	0
Joint Base Lewis-McCord Yakima Training Center	382	375
PNNL – Birds of Prey field campaign	92	81
PNNL – Hanford Vegetation	39	39
PNNL – Owyhee field campaign	30	29
PNNL – Shoshone field campaign	95	89
USGS SAGEMAP GIS database	820	818
Sagebrush Steppe Treatment Evaluation Project	1086	1070
U.S. Forest Service Forest Inventory Analysis	13170	0
Total	24384	6650

2.1 Climate Data

Spatially interpolated climate data (precipitation, temperature) for the study area was acquired from the PRISM (Parameter-elevation Regressions on Independent Slopes Model) Climate Group (Daly et al. 1994; Daly et al. 2008; DiLuzio et al. 2008) and the Daily Surface Weather and Climatological Summaries (DAYMET) program (Thornton et al. 1997; Thornton et al. 2014).[1] PRISM uses point measurements of climate data and a digital elevation model of terrain to estimate continuous gridded surfaces of monthly climate elements at a 4-km resolution. DAYMET provides gridded estimates of daily weather parameters for North America at a 1-km resolution, including daily continuous surfaces of minimum and maximum temperature and precipitation. PRISM 30-year mean monthly and 30-year mean annual precipitation, minimum temperature, and maximum temperature (totaling 39 separate climate variables) were obtained to explore relationships between cheatgrass occurrence and general climate patterns. We also derived several seasonal cumulative precipitation and average minimum and maximum temperature variables from PRISM data that correspond to important seasonal periods during the life history of cheatgrass. DAYMET daily minimum and maximum temperature data were acquired to calculated growing degree day index for the study area (see 2.2 Biophysical Data).

[1] PRISM website: http://www.prism.oregonstate.edu/ ; DAYMET website: http://www.daymet.ornl.gov

2.2 Biophysical Data

Biophysical datasets used for model development included the elevation, potential relative radiation index (PRR) (Pierce et al. 2005), and a growing degree day index. The PRR is a unitless index of available solar radiation for photosynthetic activity at a given location that takes into account the influence of geographic position, seasonal and daily variation in solar inclination, and topography. PRR was calculated by summing digital hillshade interpolations for a given period of interest as described by Pierce et al. (2005). Hourly hillshade interpolations were performed for daylight hours of one day of the month that most closely represents the average solar period for the month (i.e., PRR = Sum [$\text{Hillshade}_{i\text{-}j,\ m\text{-}n}$], hours *i-j* for each representative day of months *m-n*). PRR calculated for use in this study reflects the solar conditions between October and June, which encompasses the bulk of the growing season of cheatgrass across the study area (Figure 2.2).

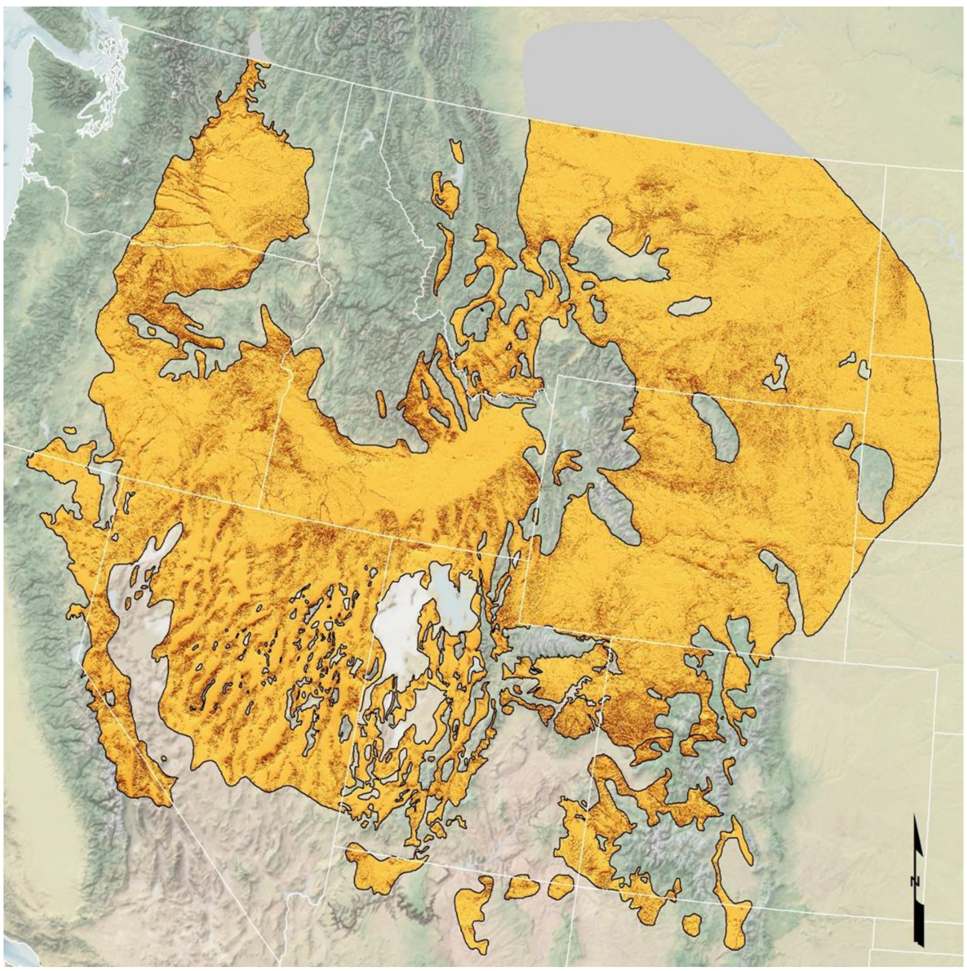

Figure 2.2. Potential Relative Radiation Index (light orange to dark orange illustrates high to low PRR).

Using the DAYMET daily minimum and maximum temperature data from 1 October 2014 to 30 April 2015, the cumulative growing degree day (GDD) index was calculated to represent the relative period of time when temperatures are suitable for plant growth (Figure 2.3).

The cumulative GDD between October 1 and April 30 was calculated on a daily basis:

$$[(T_{max} - T_{min})/2] - w$$

where w is the minimum temperature for growth of cheatgrass (assumed to be 0°C or 32°F), and summed for the period. Negative values were set to 0.

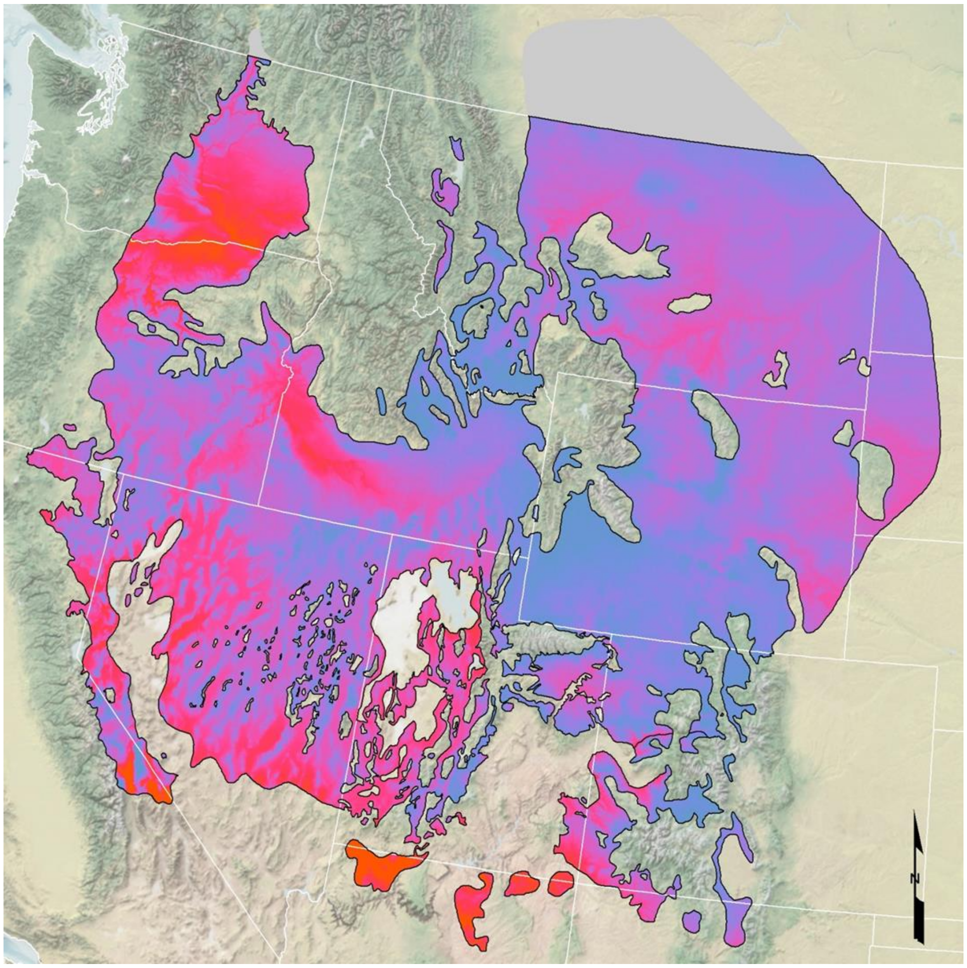

Figure 2.3. Cumulative Growing Degree Day (blue to red illustrates low to high GDD).

2.3 Remote Sensing Data

The Normalized Difference Vegetation Index (NDVI) is based on the ratio of the visible and near-infrared bands of the electromagnetic spectrum in remotely sensed imagery and represents the 'greenness' of vegetation. Generally, healthy vegetation absorbs in the spectral range known as photosynthetically active radiation (PAR), from 400-700 nm (generally in the range of visible light) and reflects a large portion of near-infrared light (~700 - 1400 nm). Unhealthy or sparse vegetation reflects more visible light and less near-infrared light. Larger differences between the near infrared and red indicates more vegetation.

NDVI is calculated by subtracting the red reflectance values (RED) from the near-infrared (NIR) and dividing by the sum of near-infrared and red bands:

NDVI= (NIR-RED) / (NIR+RED)

Weekly composite NDVI measurements derived from MODIS (Moderate Resolution Imaging Spectroradiometer) Terra satellite operated by the National Aeronautical and Space Administration (NASA). The weekly composite NDVI images are produced by U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center by combining best available pixels from daily imagery in a given week to create composite images that are largely free of clouds and other atmospheric obstruction (Jenkerson et al. 2010). Phenological products are created from daily and composite imagery by mathematically smoothing time-series NDVI data to produce temporal curves summarizing various stages that green vegetation undergoes during a complete growing season, such as the start of the growing season, peak of the season (peak NDVI) and end of the season.[2]

We developed two variables from annual peak NDVI products to include in our model: the median peak NDVI for the period 2000 through 2014, and the difference in peak NDVI in the year of maximum winter (October through March) precipitation from the long-term median peak NDVI for each pixel (ΔPeak NDVI; Figure 2.4). The ΔPeak NDVI in the year of maximum winter precipitation was derived by first determining the year of peak winter precipitation from inter-annual standard scores (i.e., Z score) from PRISM time series data, and then selecting ΔPeak NDVI values from the corresponding year. This dataset was derived to better account for the geographic and inter-annual variability in winter precipitation that occurs across the range of the sage-grouse. The resulting peak NDVI image is a composite of peak NDVI across years that is intended to improve signal-to-noise ratio for detecting cheatgrass.

2.4 Model Development

Forward stepping discriminant analysis was used to construct a predictive model (Generalized Additive Model) of cheatgrass occurrence:

$$y = \beta_0 + f_1(x_1) + f_1(x_1) + f_1(x_1) + \cdots + f_i(x_i)$$

A random sample of 80% of the field-measured cheatgrass cover data was used for model development and remaining observations were used for model validation. A total of 50 variables (described in Sections 2.1, 2.2, and 2.3) were considered for model-building. Upon further investigation of the field and climate data, we chose to group some of the monthly temperature and precipitation data into seasonal periods that are important in the life history of cheatgrass. This included average maximum winter (Nov-Feb) temperature and cumulative winter (Dec-Feb) precipitation. For mapping cheatgrass occurrence, we chose two cover classes based on an evident separation in cheatgrass cover in the field data: ≤ 2% (low cover or absent) or cover > 2% (high cover or present (Figure 2.5). Use of these classes provided better ability to distinguish cheatgrass with respect to the variables included in the model.

[2] USGS Remote Sensing Phenology products: http://phenology.cr.usgs.gov/methods_metrics.php

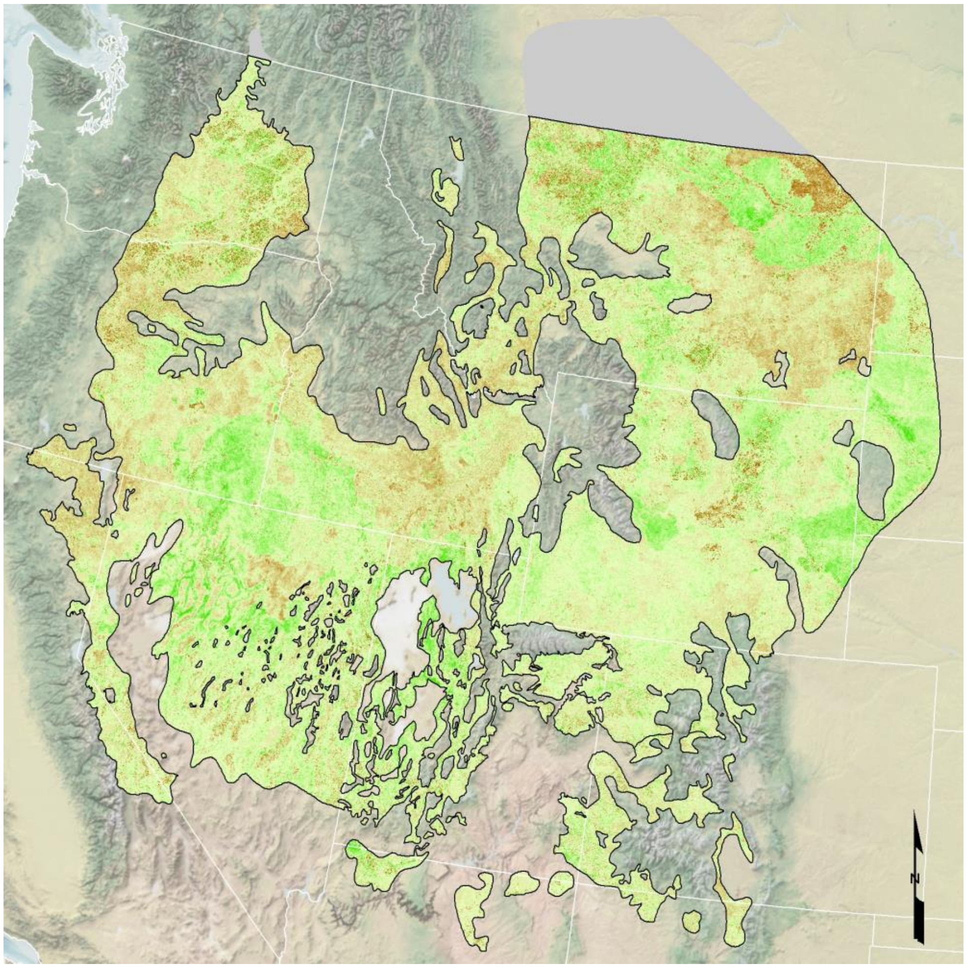

Figure 2.4. Peak NDVI for the Year of Maximum Winter Precipitation (brown to green illustrates low to high peak NDVI).

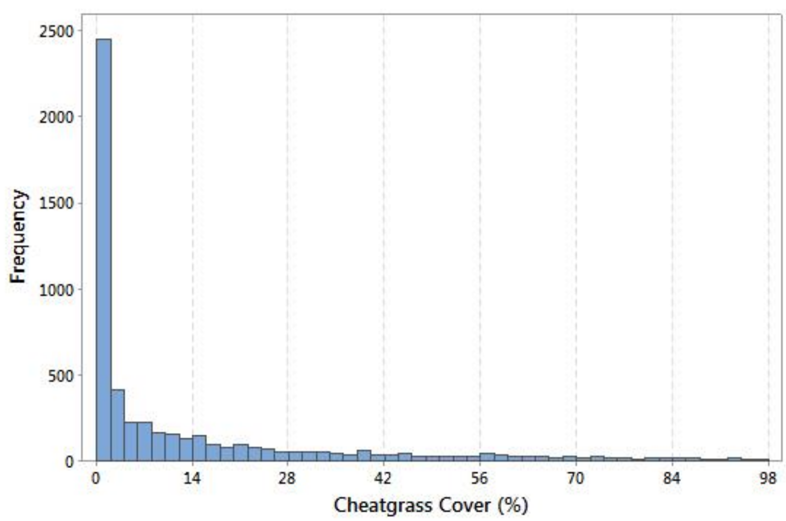

Figure 2.5. Histogram Showing Distribution of Cheatgrass Cover Values Measured at Field Locations

Variables used in model development were standardized by subtracting the mean and then dividing by the standard deviation before discriminant analysis. One of each pair of variables was deleted from model-building when the pair-wise correlation exceeded r = 0.8. Variables selected for model-building (Table 2.2; n = 13) were less correlated, had smaller interquartile ranges for the ≤ 2% cover class among competing variables, and greater separation between the ≤ 2% and > 2 % cover class quartiles. To increase the separation between cover classes, observations with cover greater than 2% but less than or equal to 10% were excluded from model development.

Table 2.2. Variables Included in Final Model.

Model Variables
Elevation
Potential Solar Radiation Index
Cumulative Growing Degree Days (Oct-Apr)
Median Annual Peak NDVI (14-yr)
Deviation of Peak NDVI (Year of Maximum Winter Precipitation) from 14-yr Median NDVI
Cumulative Winter Precipitation (Dec-Feb)
Mean March Precipitation
Mean June Precipitation
Mean July Precipitation
Average Maximum Winter Temperature (Nov-Feb)
Mean Minimum March Temperature
Mean Minimum November Temperature
Mean Maximum May Temperature

Forward-stepping discriminant analysis determined the coefficients for canonical variables, which were used to calculate discriminant scores for all pixels within the study area. Next for each pixel, we calculated two values representing the distance of the score from the centroid of each of the scores of the field data for each cover class.

After calculating the distance variables for each pixel, the probability of membership in each class was determined by calculating the probabilities as a function of the distances:

Class 1: Probability(≤ 2%) = 1 - Distance(Class 1) / [Distance(Class 1) + Distance(Class 2)]

Class 2: Probability(≥ 2%) = 1 - Distance(Class 2) / [Distance(Class 1) + Distance(Class 2)]

These probabilities were then used to assign each pixel to one of the two cover classes. If the probability value for the a class was greater than the probability of the other class (i.e., if P > 0.5) then the pixel was classified as high. The resulting map with two classes was then masked to leave out areas such as cultivated agricultural land, pasture and hay lands, closed canopy deciduous and evergreen forests types, urban/developed lands, and water as defined in the 2015 release of the USDA-NASS Cropland Data Layer and the 2011 release of the Multi-Resolution Land Characteristics (MRLC) Consortium National Land Cover Database. [3]

[3] National Cropland Data Layer: https://www.nass.usda.gov/Research_and_Science/Cropland/Release ; National Land Cover Database; http://www.mrlc.gov/nlcd11_data.php

3.0 Results and Management Implications

The model was applied in a GIS to create a map predicting two classes (0% to 2%, >2%) across the historic range of the sage-grouse (Figure 3.1). The map indicates the differences in cheatgrass occurrence at the regional and sub-regional scales and confirms the broad niche of cheatgrass with respect to the variables evaluated for model development. Both the field data used to develop the model, and the model predictions suggest that cheatgrass occurrence in the eastern portion of the sage-grouse range is locally isolated. The map depicts several large portions of the sage-grouse range where cheatgrass invasion is more widespread, including the Columbia Plateau in Washington and Oregon, Snake River Plain in southern Idaho, and central and southern portions of the Great Basin (Figure 3.2). Table 3.1 summarizes acreages of predicted cheatgrass occurrence (>2% cover) by ecoregions that intersect the historic range of sage-grouse.

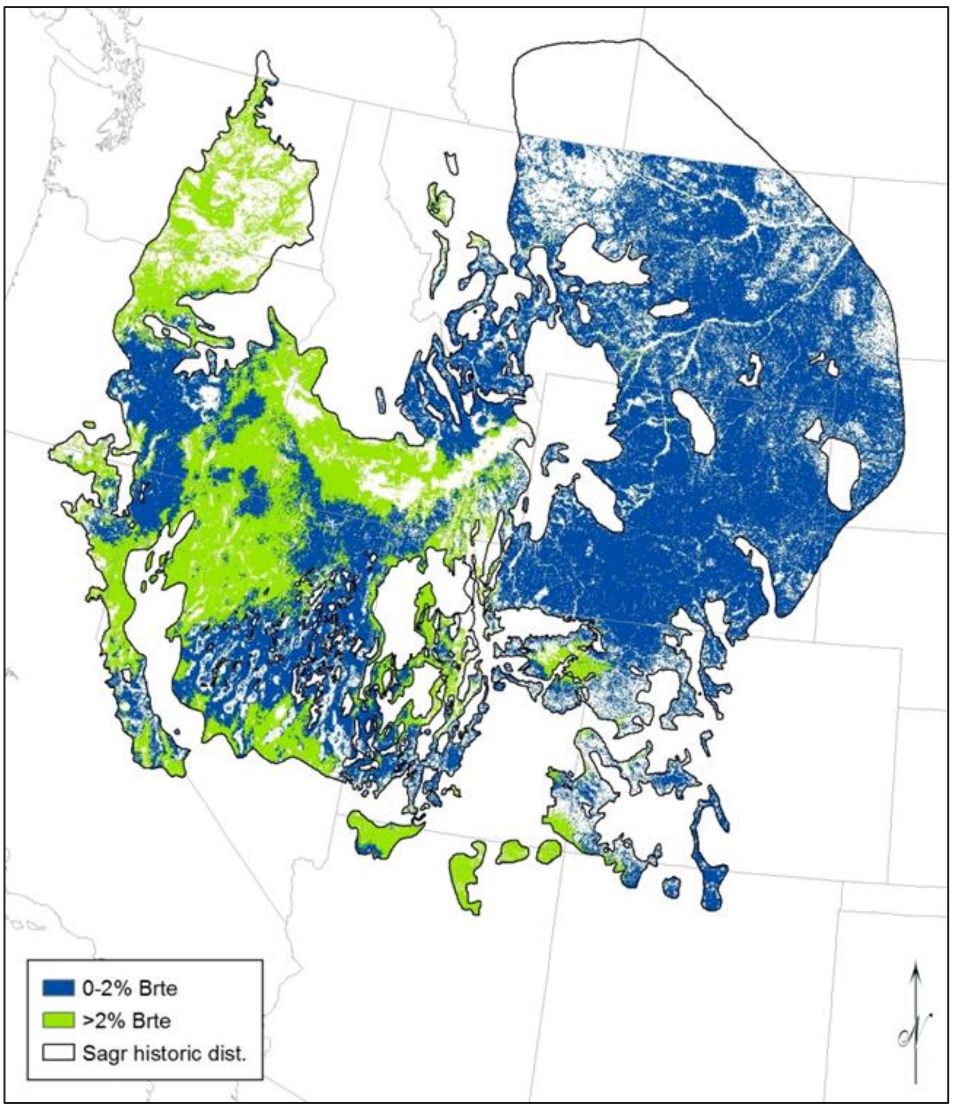

Figure 3.1 Predicted Occurrence of Cheatgrass Across the Historic Range of Sage-Grouse.

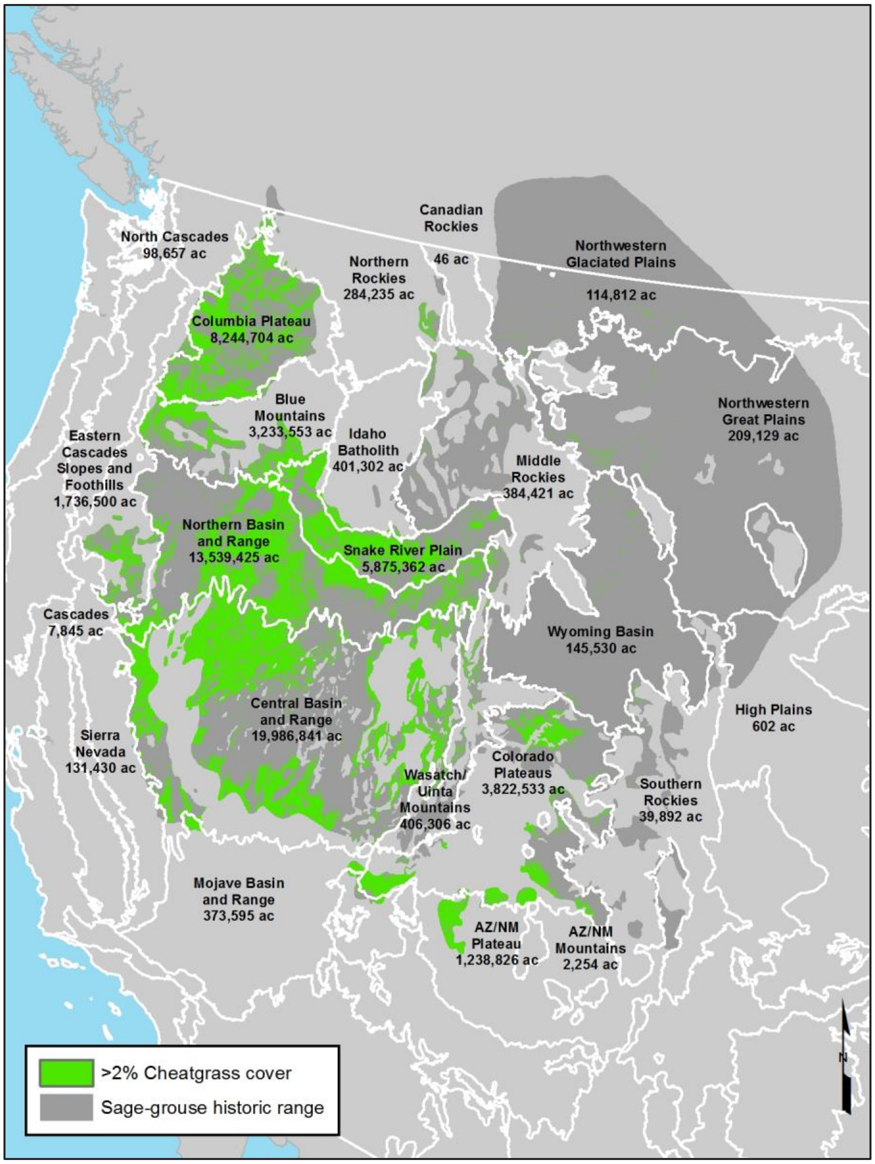

Figure 3.2. Acreage of Predicted Cheatgrass Occurrence by US EPA Level III Ecoregions.

Table 3.1. Acreages of Predicted Cheatgrass Occurrence by Ecoregion.

Ecoregion Name	Acreage		
	Ecoregion	Sage-Grouse Range[1]	Cheatgrass (>2% Cover)[2]
Arizona/New Mexico Mountains	27,406,376	6,795	2,254
Arizona/New Mexico Plateau	36,289,720	2,813,070	1,238,826
Blue Mountains	17,522,603	7,085,694	3,233,553
Canadian Rockies	4,665,288	22,301	46
Cascades	14,543,149	42,209	7,845
Central Basin and Range	76,303,734	51,521,764	19,986,841
Colorado Plateaus	33,748,531	14,665,123	3,822,533
Columbia Plateau	20,542,147	17,820,591	8,244,704
Eastern Cascades Slopes and Foothills	13,160,143	4,382,309	1,736,500
High Plains	71,245,347	2,830,413	602
Idaho Batholith	14,896,340	950,853	401,302
Middle Rockies	40,639,356	15,105,329	384,421
Mojave Basin and Range	31,552,809	423,511	373,595
North Cascades	7,510,777	171,029	98,657
Northern Basin and Range	34,643,702	34,142,167	13,539,425
Northern Rockies	20,252,915	914,807	284,235
Northwestern Glaciated Plains	43,214,181	20,472,778	114,812
Northwestern Great Plains	88,360,818	58,632,663	209,129
Sierra Nevada	13,121,963	382,368	131,430
Snake River Plain	13,251,404	12,849,688	5,875,362
Southern Rockies	36,003,642	7,132,459	39,892
Wasatch and Uinta Mountains	11,291,082	4,294,679	406,306
Wyoming Basin	32,786,525	32,303,333	145,530
Total	702,952,552	288,965,933	60,277,800

[1] Area of the sage-grouse historic range within a given ecoregion.
[2] Total area of predicted cheatgrass occurrence (>2% cover) within the historic range of sage-grouse in a given ecoregion.

3.1 Classification Accuracy

Table 3.2 shows both the overall accuracy and accuracy by class as determined by comparing model predictions to observed cheatgrass cover at field measurement locations. Overall classification accuracy was 71-72%. Preliminary evaluation of the field data and the false-positive errors indicate that errors may be associated with the seasonal variability in temperature and precipitation, as well as the variability in NDVI response in years of high winter precipitation. Although we used an NDVI value corresponding to the year of maximum precipitation between 2000 and 2014 to reflect favorable growing conditions for cheatgrass, it may have not reflected the maximum peak NDVI for that pixel due to other factors that may have affected growth that particular year. For example, the combination of temperature and precipitation in another year with high winter precipitation may have resulted in more favorable growing conditions for cheatgrass, higher NDVI and potentially a stronger spectral signal. Further investigation of the relationships between cheatgrass occurrence and these variables could feasibly improve modeling results using NDVI in similar mapping efforts, but this investigation was beyond the scope of the current study.

Table 3.2. Accuracy of Predicted Cheatgrass Occurrence Map.

	Classification Accuracy of Field Data	
Cover Class	**Development Data**	**Validation Data**
0-2%	74%	74%
>2%	70%	69%
Combined	**72%**	**71%**

When assessing these types of classification errors, map users should consider the context of factors that contribute to errors. These factors include the artificial assignment of categories, the scale of the field sampling compared to the mapping scale, and the accuracy of registration of the imagery and field points. First, the class categories are discrete and create an arbitrary boundary whereas the actual cheatgrass cover data are continuous, potentially resulting in classification errors where the difference between actual and predicted cover is small. For example, a ground truth point mapped as 0-2% cover class with a measured value of 2.3% will be counted as an error. Second, the measured cheatgrass cover along a 25 m or 50 m transect, although representative of cover along the transect, may not be representative of cheatgrass cover at larger scales such as the scale of the data used in mapping and the final map resolution (250 m ground sample distance in this study). We also found numerous cases where field measurements of low (0-2%) cover were adjacent to measurements of greater than 2% cover, indicating that cheatgrass cover can vary considerably at smaller scales and potentially confound error estimation and accuracy. Third, the registration accuracy for this type of sensor data is usually no better than ± 1 pixel, which can contribute to the overall classification error where field measurement locations are at the edge between the two cheatgrass cover classes.

Other factors limiting the classification accuracy include the structure of the available field data. The strong skew toward very low cheatgrass cover in the field measurements limited the analysis of underlying relationships between model variables. The geographic and physical variability across the study area were also a challenging factor in developing a more accurate classification. For example, elevations within the Columbia Basin where cheatgrass is prevalent vary between 200 and 2,000 ft while elevations where cheatgrass occurs on the eastern side of the Rockies start at 5,000 ft and rise to nearly 10,000 ft. This wide range of variation in physical and climate conditions illustrate the very broad niche of cheatgrass.

3.2 Map Use and Management Implications

We consider this range-wide map and the underlying model to be appropriate for assessing cheatgrass occurrence to inform and prioritize restoration and conservation actions at regional and sub-regional scales. For example, the map may be helpful for prioritizing cheatgrass management actions within Sage-Grouse Management Zones (SGMZs), sage-grouse Priority Areas of Conservation (PACs), or other agency or inter-agency management regions. This map also may help inform regional planning processes and future research needs, particularly those requiring multi-agency coordination aimed to address long-term, large-geographic-scale management objectives. It can also be combined with other geospatial products such as the cheatgrass ‘resistance/resilience’ mapping (Chambers et al. 2014; Maestas and Campbell 2015) based on soils information to better support management decisions. The map also represents a range-wide baseline of cheatgrass occurrence at the time it was created, and may be used to assess cheatgrass expansion at a similar scale in future years.

The map of predicted cheatgrass occurrence for the historic range of the sage-grouse represents a starting point for approaches to evaluate cheatgrass occurrence at local scales and, more importantly, cheatgrass relative abundance at finer spatial scales. The underlying data used in this mapping effort may be leveraged in combination with finer spatial and temporal resolution remote sensing imagery and additional biophysical data to support development of finer scale maps of cheatgrass occurrence and abundance. The range-wide map can be utilized to identify areas where additional field data may need to be collected to support local, fine-scale cheatgrass maps that can be used at the district or refuge scale. A standardized method for collecting cheatgrass cover data at scales that could better support modeling applications utilizing remote sensing data would also be helpful.

Future efforts to improve our understanding of cheatgrass distribution across the range of sage-grouse would be aided by development of cheatgrass abundance maps that are specific to each ecoregion such as that developed by Boyte et al. (2015) for the Northern Great Basin and research that would allow better understanding of the potential niche of cheatgrass in each ecoregion. Data developed and integrated to support this range-wide mapping effort could be readily utilized to identify and map those factors comprising the ecological niche (habitat suitability) of cheatgrass. This type of analysis would be useful to identify those areas that may be vulnerable to cheatgrass invasion and could be expanded to better understand how cheatgrass invasion may proceed under future climate conditions.

Users of this data set should note that this mapping effort presents a snapshot in time describing the distribution and occurrence of cheatgrass using field and remote sensing information from 2000 through 2014. If feasible, updates to the model and map should be scheduled on a 5-year rotation. Updates would need to incorporate new field data in the model along with additional remote sensing data spanning the 5-year period.

In summary, the range-wide map of cheatgrass occurrence aligns with multiple management objectives:

- supports efforts to prioritize and focus management and restoration actions to control and prevent cheatgrass invasion throughout the range of sage-grouse
- supports efforts to prioritize and focus management actions among sage-grouse and other inter-agency related management regions
- helps inform regional planning processes and future research needs pertaining to cheatgrass and sage-grouse habitat management

The range-wide cheatgrass occurrence map serves as a basis for additional scientific investigations to support cheatgrass management, including assessing cheatgrass expansion in future years under future climate conditions, and assessing cheatgrass abundance or niche suitability at finer spatial scales that can better support local land management decisions.

3.3 Points of Contact

For additional assistance regarding the content of this report, development of the described model, or use of resulting map products please contact the report authors:

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