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Agent Model Development for Assessing Climate-Induced Geopolitical Instability

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Abstract

We present the initial stages of development of new agent-based computational methods to generate and test hypotheses about linkages between environmental change and international instability. This report summarizes the first year's effort of an originally proposed three-year Laboratory Directed Research and Development (LDRD) project. The preliminary work focused on a set of simple agent-based models and benefited from lessons learned in previous related projects and case studies of human response to climate change and environmental scarcity. Our approach was to define a qualitative model using extremely simple cellular agent models akin to Lovelock's Daisyworld and Schelling's segregation model. Such models do not require significant computing resources, and users can modify behavior rules to gain insights. One of the difficulties in agent-based modeling is finding the right balance between model simplicity and real-world representation. Our approach was to keep agent behaviors as simple as possible during the development stage (described herein) and to ground them with a realistic geospatial Earth system model in subsequent years. This work is directed toward incorporating projected climate data—including various $C0_2$ scenarios from the Intergovernmental Panel on Climate Change (IPCC) Third Assessment Report—and ultimately toward coupling a useful agent-based model to a general circulation model.

Acknowledgments

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Contents

Figures

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Agent Model Development for Assessing Climate-Induced Geopolitical Instability

1 Introduction

Research on climate change is not limited to physical models that forecast average global temperatures rising a few degrees by the year 2100. The immediate relevance of climate change includes the rapid change in local and extreme weather that has already been experienced. The near-term consequences of climate change portend an accelerating progression of higher intensity, greater frequency, and broader occurrence of extreme weather. Human history clearly demarcates the economic, social, political, and military stresses induced by such environmental change. This report considers an agent-based approach intended to address the economic and conflict dynamics associated with climate change stresses.

1.1 Climate Change, Migration, and Conflict

When extreme weather events such as floods or extended drought occur, populations have little choice but to migrate. The adjacent areas, to which the influx occurs, are often only in marginally better condition. The migration strains the local resources and threatens the perceived security or well-being of the indigenous population. Resulting tensions can easily spill over into conflict and violence. The conflicts and influx of population destroy resources, economic capacity, and lives. Populations of the previously stable areas may now be forced to all migrate or fight. Axiomatically, the forces driving population movement will exist until both areas are equally unattractive due to economic conditions (e.g., starvation risk) and/or security conditions (e.g., physical risk).

1.2 Agent Model of Spatial, Entity, and Time Interactions

The sociobehavioral dynamics caused by extreme weather have a probabilistic nature. The real and perceived impact of the events depends on how an individual experiences them. The stochastic nature of the choice an individual may make and the nonlinear characteristics of interactions amongst individuals suggest that a simulated portrayal of dynamics using aggregated (averaged) population variables is not necessarily valid. The interactions among individuals can force outcomes that are determined by the extreme of the distribution. Conflict is not generally a bulk response of a population, yet it significantly affects the entire population. Conflicts typically start when a small group encounters interactions that certain individuals feel cannot be resolved by using mutually accepted social processes. The simulation of these dynamics with agent-based modeling adds the required realism to capture emergent phenomena that are critical to understanding and potentially mitigating unacceptable consequences. Agent-based modeling of human dynamics, choices, and conflict recently obtained a larger degree of credibility and acceptance with the award of the 2005 Nobel Prize to Thomas Schellling (Schelling 1978, 1984).

Extreme weather is location dependent. The interactions among individuals (agents) depend on the physical environment in which the interactions take place. In a conceptual sense, the ability to specify physical conditions and associate them with distinct entities that can cognitively engage and move in and out of such physical (spatial) environments is a prerequisite for the broader, more-general ability to apply these methods in actual (real-world) conditions. As shown in Figure 1-1, a representative spatial grid could, for example, consider a river valley (lowlands) with surrounding highlands (hills) leading into mountainous (mountains) regions. If the river is approaching a delta (and thus very fertile land but also a flood risk), it is also possible to designate an upstream topology of improved agrarian productivity as well as heightened flood (loss of farm land) risk. Further, given the different lifestyles (and possibly cultures) associated with survival in different environments, it is possible to imagine two or more tribal distinctions, such as a red (agrarian-dominant valley ethnicity) and a blue (hunter/trader-dominant highland ethnicity). The color scheme for each cell in Figure 1-1 goes from green to brown, with green representing high relative agricultural productivity that turns to brown as the productivity declines. Each cell represents a specific physical area.

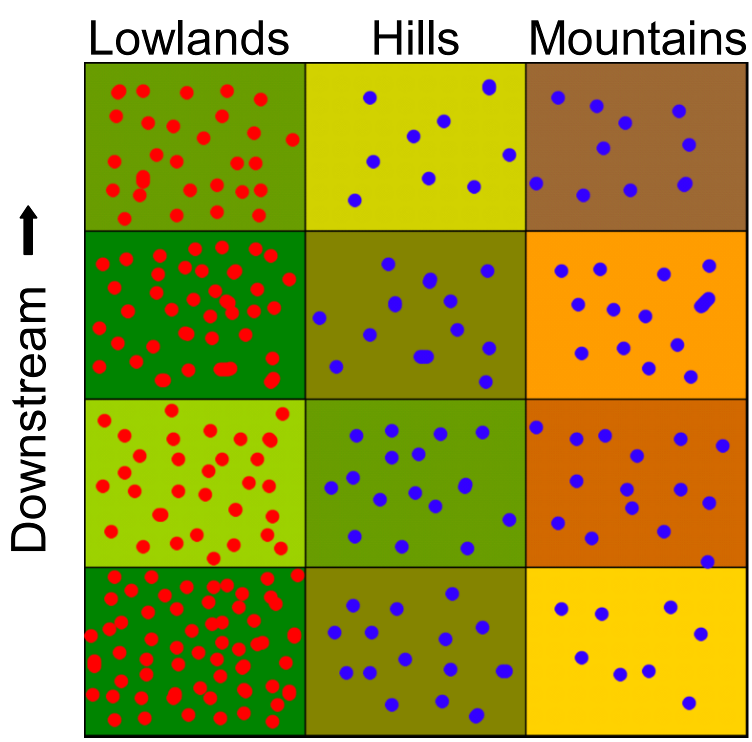

Figure 1-1. Illustrative spatial-grid logic.

Modeled agents, like real people, need time to perceive and understand their condition, time to consider their options, and time to act. A simulation is discretized into time steps that correspond to increments of information accumulation and to changes in locations and numbers of individuals. The use of differential equations and continuous but stochastic, algebraic decision rules for describing agent behaviors allows discrete agents to have a one-to-one correspondence with the measurable behaviors. As such, model parameterizations can include the real-world time constants associated with actual behavioral mechanisms and can map them to the time steps that update the simulation model.

2 Simulating Conflict and Migration Dynamics

Human behavior is the process of making choices. Humans perceive information and act upon it based on previous experience and existing capabilities. Qualitative choice theory (QCT) describes the decision process, and cointegration describes the dynamics of perception and experience. These concepts are discussed in Sections 2.1 and 2.2, respectively. Both QCT and cointegration come from a unique school of economics that has recently garnered several Nobel prizes. That body of work realistically focuses on the imperfections of information and human choice. It also generalizes economics. All choice comes from a comparison of the perceived value of alternatives. The monetary component of value may play a minor role, and the mapping of perceived value to acted-upon choice will contain significant stochastic elements. The human ability to determine the relevance of information and to self-consistently act upon this information is less than perfect. Preferences may include what others might perceive as irrational or superfluous. The logic remains unaffected. The logic merely has to consider what the individual perceives as the best choice.

2.1 Qualitative Choice Theory

Although QCT originated in psychology, it was developed by economist Daniel McFadden (McFadden 1982). QCT has a long and successful history of simulating human decision making. The theory explicitly includes the uncertainty associated with decisions, responses, and the consequences of both. The theory also notes the limitations of humans to comprehend information, conditions, and stimuli, and can readily include internal preferences and beliefs in the simulation of human responses.

Independently of whether an individual is rational, irrational, profit maximizing, or satisficing, QCT applies to the decision-making process. QCT states that individuals make a choice based on their perception of utility regarding those choices. QCT causes any and all the information (preferences, tastes, culture, costs, etc.) used by the individual to define a valid (or at least functional) representation of choice behavior. QCT starts with data that reflect the conditional probability of a choice based on information that might be interacting, conflicting, and/or limited. The mathematical basis for QCT is described by Boslough et al. (2004) and reproduced in Appendix A of this document for reference as we develop our model in Section 3.

2.2 Cointegration Theory and Granger Causality

Cointegration was first conceived by Clive Granger (Granger 1981), but the development of the method was not achieved until 1987 (Engle 1987). Cointegration is now a widely accepted and used technique (Hamilton 1994; Engle 1991; Maddala 1992; Hendry 1993, 1995). It focuses on determining the dynamics of no memory, short-term memory, and long-term memory within a data-generating process. The concept of “no memory” corresponds to a set of algebraic equations. Short- and long-term memories are naturally associated with state variables (integrated levels). Short-term memory conveniently corresponds to the reinforcing feedback dynamics and long-term memory to the negative feedback dynamics. The mathematical details are provided by Boslough et al. (2004). This information is also repeated in Appendix B to provide a quick reference as we develop our model in Section 3.

3 Climate Scenario Definition and Model Design

Appendix C contains titles and links to a series of news articles that support the view that extreme weather, such as flooding, storms, and droughts, are the consequence of climate change. The articles further suggest that these changes will lead to societal and economic stress that may trigger conflict. A review of this information led to the conceptual design for an agent-based model to capture the dynamics. The inclusion of these concepts allowed the further development of the mathematical framework described below. The spatial logic assumes the topology presented previously in Figure 1-1, where a river valley and delta connect to rising highlands and mountains. For simplicity, the initial model assumes an agrarian society with access to small arms weapons—presumably whose primary use is self defense or hunting. The valley has greater agricultural productivity than the mountainous areas and, thus, a higher population density. The highlands and mountains have lower agricultural productivity and a lower population density, but the population (tribe) has better defensive/offensive skills due to hunting and a harsher environment. The framework could assume drought in the highlands causing migration into the valley or crop-destroying flooding in the valley to force migration to the highlands. For explanatory purposes, the elaboration of equation implications in the following discussion assumes a flood scenario.

The model considers two distinct tribes that each have a cohesive identity to allow an "us versus them" recognition when members of one tribe enter the area of another. The tribe members would not fight among themselves for food, but would fight an outsider. This assumption could be removed, but it would make little difference to the simulation dynamics. With stochastic variation, the agriculture productivity of the valley is, for example, initially assumed to be five times that of the mountains and two and one-half times that of the highlands. The initial randomly distributed population of an (arbitrary) 10,000 individuals assumes equilibrium full-use of all agriculture output at 2,500 calories per day. The minimum long-term adequacy of food is assumed to be 2,000 calories per day with 50% starvation rates per time period if caloric intact is only 1,000 calories. The probability of starvation varies with caloric intake.

The mountain and highland tribe is assumed, for example, to have both defensive and offensive abilities that are five times those of the valley tribe. While there is an assumption of centralized organization in this very primitive and rural setting, there is only coordinated defense. "Invasion" is just immigration to escape the conditions of the previous location. The invasions are not merely for the accumulation of land. In actual historical situations, the distinction has little meaning. Conflicts occur probabilistically as individuals interact.

The initial value of per capita conflict is zero. The memories of individuals conceive the initial food per capita and conflict per capita as a normed (average) condition. The current conditions and the norms thus initially have the same value.

3.1 Primary Forces Driving Migration

As noted previously, an individual makes a choice by comparing the alternatives. If there is no compelling need to make a choice (i.e., no internal or external motivating factors), then the highest probability is to maintain the status quo. The two compelling needs in this model are food requirements and avoidance of violent conflict. The implied scenario assumes flooding of the valley region with the consequent loss of crops and farmland. A significant portion of the valley inhabitants is forced to move or starve. When the valley tribe moves into the highlands, the tribe uses/takes a share of the existing food supply in the new area. As the food-per-capita value decreases to below minimal requirements, the in-migration threatens the lives of the highland and mountain individuals. The threat may lead to violent interactions.

Individuals combine the influence of both food and conflict conditions to determine the choice to migrate and the selection of the migration direction.

3.1.1 Extensions and Limiting Assumptions

The current framework does not include the reduction of agricultural output as the population undergoes conflict or declines. Although this detail would act to accentuate the dynamics, it was initially left out (without loss of generality) to allow a clearer delineation of the included mechanisms. The model could also include other economic activities beyond agriculture, such as industry sectors and commerce. These activities would add realistic detail, but they would not change the overall dynamics. Neglecting such complications is in keeping with our desire to keep the model as simple as possible with the expectation that insight will emerge from simplicity, following the work of Schelling (1978, 1984).

The current effort includes only two tribal distinctions with limited motivations, e.g., food and conflict levels. While the framework readily accommodates added motivations, further research is required for algorithms to accommodate several tribal distinctions.

The current framework design readily allows parallelization where a single processor can calculate the dynamics of one or more individuals. Information is topologically determined (next-neighbor grid points) and thus mitigates communication bottlenecks. Collections of more-numerous and more-sophisticated agents could overwhelm a single processor. Additional research would be required to determine the best approach for organizing the agents and their calculations to ensure scalability.

3.1.2 Food Adequacy

Individuals will migrate if they perceive the food as inadequate. Existing food per capita (*FPC*) is defined as the food in the x-y grid cell, at any given time, divided by the population at that time.

$$FPC(x,y,t) = FOOD(x,y,t) / \sum_{q} POPULATION(q,x,y,t) \tag{3.1}$$

The population is the sum of all individuals in a given x-y grid location (cell):

$$POPULATION(q,x,y,t) = \sum_{1}^{N} INDIVIDUALS(n,q,x,y,t)\,, \tag{3.2}$$

where q is the individual's tribe index and N is the total number of individuals. Note that the actual code would use only t indices for individuals. The attributes of the individual, such as tribe, x-y cell location, and remembered food/conflict conditions, would be separately contained in variables denoting those characteristics.

FPC is a mean value, and the model (as will be shown shortly) assumes a variance in the actual amount of food an individual can consume. For decision purposes, the individual learns and remembers the averaged history of the food situation (*AFPC*) in the current cell. This value is used to decide whether to go from the current cell to an alternative cell. The memory captures, for example, the fact that the average weather is most important, not year-to year-fluctuations, unless fluctuation affects long-term survivability. Conversely, one year of good harvest should not change the decision to move to where the harvests are generally better. The equation of the averaging is the cointegrated exponential delay as shown in Equation (3.3). The parameter *FAT* is the food-averaging time.

$$d(AFPC(x,y,t))/dt = (FPC(x,y,t) - AFPC(x,y,t-dt)/FAT \tag{3.3}$$

3.1.3 Conflict Threat

Similarly, the individual compares the conflict per capita (*CPC*) to the average conflict per capita (*ACPC*). The metric used for conflict is death per population due to conflict. Conflict deaths (*CDEATHS*) are calculated as the number of individuals removed from a cell in a time step (iteration) compared to the population, less any deaths due to starvation in the time period. The deaths due to starvation (*SDEATHS*) are calculated in the same fashion except that the population is that at the beginning of the time step. The filtering (averaging) time for conflict is the parameter *CAT*.

$$CPC(x,y,t) = CDEATHS(x,y,t)/\sum_{q} POPULATION(q,x,y,t) \tag{3.4}$$

$$d(ACPC(x,y,t))/dt = (CPC(x,y,t) - AFPC(x,y,t-dt)/CAT \tag{3.5}$$

3.2 Decision Hierarchy

The simulation of all decisions within the model uses QCT. The logic has a hierarchical form that first determines whether to act. Should there be a choice to change from the status quo, the method probabilistically chooses from among the alternatives. Given the choice, for example, to migrate, there is then a secondary decision that needs to determine in which direction to head. Consistent with QCT, all decisions assume imperfect information and imperfect capacity to weigh and decide on the information.

As noted previously, the model construct must also recognize the ability to act or make a decision. If an individual has starved to death, the individual cannot be included in the population that could also die or fight in a conflict. Given the sequence of events, it is assumed that being near starvation limits the ability to fight and that, in a practical sense, the rate of starvation determines the ability to fight and the ability to potentially die in conflict.

3.3 Modeled Responses

Under stress, individuals can decide to continue to maintain the status quo. They can decide to move to avoid starvation and conflict in the hopes of finding better conditions. In either case, the consequence could be starvation or dying from violent acts of conflict. The model explicitly simulates these four mechanisms, i.e., stay, go, starve, fight.

A key feature of all the decisions associated with the four mechanisms is that the knowledge of the inhabited cell is assumed to be greater than the knowledge of a remote cell. Thus, a comparison of conditions in an existing cell with those in another cell relies not on the experienced conditions of the individual's journey, but rather on the generally recognized conditions (by all parties) within the current cell.

3.3.1 Remain

A decision to migrate depends on the understanding of the threat from food scarcity and violent conflicts. The measure of the ordinal utility of migrating from food scarcity (*FMU*) depends on the ratio of the existing food condition (*FPC*) and the recognized (average) condition (*AFPC*), relative to a normed (reference) expectation of food requirements (*RFPC*), as shown in Equation (3.6). The subtraction of the ratio from unity captures the fractional (percentage) change in conditions. The use of the logarithm is a construct in QCT to accommodate proportional changes. The value is prevented from going negative because a value below zero has no added meaning beyond what it would have at zero. Taking the maximum of the value and a small number (epsilon) ensures the computational viability of the term. The food variance factor (*FVF*) captures the uncertainty associated with the decision and the stochastic nature of the food supply at the individual level.

$$\begin{aligned} &FMU(q,x,y,t) = \\ &\qquad FVF(q) * \ln(\max(\varepsilon, 1.0 - FPC(x,y,t) / \min(AFPC(x,y,t), RFPC))) \end{aligned} \tag{3.6}$$

The ordinal utility of migrating from conflict (*CMU*) depends on the existing conditions of conflict (*CPC*) compared to the recognized (average) conditions (*ACPC*) relative to a normed (acceptable) conflict intensity (*RCPC*). *RCPC* is generally defined as zero.

$$CMU(q,x,y,t) = CVF(q) * \ln(\max(\varepsilon, 1.0 - CPC(x,y,t) / \min(ACPC(x,y,t), RCPC))) \tag{3.7}$$

Using QCT, the utilities are combined to determine the net probability of migrating (*MP*). At any given population level, *MP* is the fraction of the population that will migrate. In QCT, the comparison must always be among alternatives. If there is a status quo, it is always a numaire with a utility that is neutral, i.e., zero. Thus, the reference migration utility (*RMU*), as required in Equation (3.8), is zero.

$$MP_{q,x,y,t} = \frac{e^{(FMU(q,x,y,t)+CMU(q,x,y,t))}}{(e^{RMU} + e^{(FMU(q,x,y,t)+CMU(q,x,y,t))})} \tag{3.8}$$

3.3.2 Move to New Location

Once an individual has made the choice to move (from a cell with x-y coordinates), the individual must then decide to which neighboring cell (with i-j coordinates) to transfer. The ordinal utility of this transfer (*FTU*) is defined by Equation (3.9). From a food perspective, the individual compares the existing and understood food conditions in the alternative cells (*FPC*) to the average (*AFPC*) in the existing cell relative to some reference food requirement (*RFPC*). Again, the same logic as used in the previous section for Equation (3.6) applies, with *FVF* being the uncertainty in the food conditions and the decision.

$$FTU(q,x,y,i,j,t) = FVF(q) * \ln(\max(\varepsilon, 1.0 - FPC(i,j,t) / \min(AFPC(x,y,t), RFPC))) \tag{3.9}$$

Similarly, the impact of conflict on the decision of where to transfer (*CTU*) follows the logic of Equation (3.9) and the variable dependency of Equation (3.7).

$$CMU(q,x,y,i,j,t) = CVF(q) * \ln(\max(\varepsilon, 1.0 - CPC(i,j,t) / \min(CFPC(x,y,t), RFPC))) \tag{3.10}$$

The probability of transfer (*TP*) compares the ordinal utility of all alternative choices using the basic QCT construct. This decision uses the conditional probability (*MP*) that the individual will move and there is no numaire. The choice process is controlled by the logic that produced Equation (A.1) (see Appendix A) in the summary of QCT. A Kronecker-delta function is included in the formulation to ensure (in the computational sense) that there are no values for a nonsensical transfer from a cell to the same cell.

$$TP_{q,x,y,i,j,t} = \frac{MP_{q,x,y,t} * e^{(FTU(q,x,y,i,j,t)+CTU(q,x,y,i,j,t))} * \delta_{x,y,i,j}}{\sum_{k,l} e^{(FMU(q,x,y,k,l,t)+CMU(q,x,y,k,l,t))}) * \delta_{x,y,k,l}} \tag{3.11}$$

Starting with any neighboring cell and summing the *TP* in a sequence around the neighboring cells, a random number is compared to the sum of *TP* at that point. If the random number is less than the summed *TP*, the individual moves to that neighboring cell.

3.3.3 Death from Starvation

The probability of loss/death due to starvation (*PS*) depends on a stochastic comparison of the food per capita (*FPC*) to the level of starvation food per capita (*SFPC* —a parameter). The variance driving the stochastics is assumed to be a fixed parameter (*SVF*).

$$PS_{x,y,t} = \frac{1}{(1+(FPC(x,y,t)/SFPC)^{SVF})} \tag{3.12}$$

Numerically, a random number is compared to this probability for each individual in each tribe in each cell. If the random number is less than *PS*, the individual dies of starvation. The summation of the victims then determines the *SDEATHS* value noted previously.

3.3.4 Death from Conflict

The risk of dying in a conflict has several aspects. The model construct contains the assumption that all members of the tribe within a cell either stochastically exhibit the qualities of the tribe or act in unison with other members of the tribe to demonstrate those same characteristics. Given its lifestyle, each tribe has differing military defensive (*MDA*) and offensive (*MOA*) abilities—under normal heath conditions. As noted previously, the *MDA* and *MOA* of the highland and mountain tribe are assumed to be much higher than those of the valley tribe. The total defensive ability (*DA*) or offensive ability (*OA*) then depends on *MDA* and *MOA* with the populations available to counter invaders (immigrants) or to direct an attack against them.

$$OA(q,x,y,t) = MDA(q) * POPULATION(q,x,y,t) \tag{3.13}$$

$$DA(q,x,y,t) = MOA(q) * POPULATION(q,x,y,t) \tag{3.14}$$

The level of health determines the ability (*CA*) to successfully defend or attack an adversary. The degradation of physical and mental ability due to lack of nutrition is assumed to be the same for both tribes. (If data so suggest, it would not be difficult to have a different response to nutrition levels for each tribe.) The measure of the level of nutrition compares the current food per capita (*FPC*) to the starvation food per capita (*SFPC*). The health variance factor (*HVF*) recognizes the distribution in a population of the decreased ability due to lack of nutrition, and it further allows the use of the qualitative choice logic in describing the impact.

$$CA_{x,y,t} = \frac{1}{(1+(FPC(x,y,t)/SFPC)^{HVF})} \tag{3.15}$$

The potential for conflict (*PC*), given the basic mechanisms included in the model, comes from a threat to the indigenous population at the tribal level due to the immigrating population reducing the local food supply below acceptable (reference) levels (*RFPC*).

An individual's perception of the threat and the stochastic decision to respond with conflict is a function of preferences and culture that gives rise to the variance (*OVF*) of responses among a population. Note that the "outbreak" variance factor in Equation (3.16) contains the *q* index to designate that it is a function of the tribe and its culture.

$$PC_{q,x,y,t} = \frac{1}{(1+(FPC(x,y,t)/RFPC)^{OVF(q)})} \tag{3.16}$$

Military ability (*MA*) is a relative concept that compares the offensive ability (*OA*) of one tribe to the defensive ability (*DA*) of another. If the offensive ability is less than the defensive ability, then there is (stochastically) no net military ability to execute a mission. Given that the *MA* will be used in a probabilistic qualitative-choice framework, a negative value of military ability has no meaningful value and is limited to a small number, ε, that approximates zero for computational purposes. The use of q versus $3 - q$ in Equation (3.17) is specific to a two-tribe system. A multiple-tribe system would require significant alteration to the model logic.

$$MA(q,x,y,t) = \max(\varepsilon, OA(3-q,x,y,t)/DA(q,x,y,t)-1.0) \tag{3.17}$$

The probability of loss/death due to conflict (*PCL*) depends on a stochastic comparison of the military ability (*MA*) to the reference ability numaire (defined as unity according to QCT). The variance driving the stochastics is assumed to be a fixed parameter (*MVF*). The ability to fight/defend (*CA*) and the probability of conflict (*PC*) multiplicatively contribute to the ultimate probability of casualties from conflict (*PCL*), as shown in Equation (3.18).

$$PCL_{q,x,y,t} = \frac{PC(q,x,y,t) * CA(x,y,t)}{(1+(RMA/MA(q,x,y,t)^{MVF})} \tag{3.18}$$

Numerically, a random number is compared to this probability for each individual in each tribe in each cell. If the random number has a value below *PCL*, the individual becomes a victim of the conflict. The summation of the victims produces the *CDEATHS* value noted previously.

3.4 Stylized Model Response

The model assumes an initial condition where the valley tribe (red) lives in the valley and the blue tribe lives in the hills and mountains. This situation is illustrated in the left-hand side of Figure 3-1.

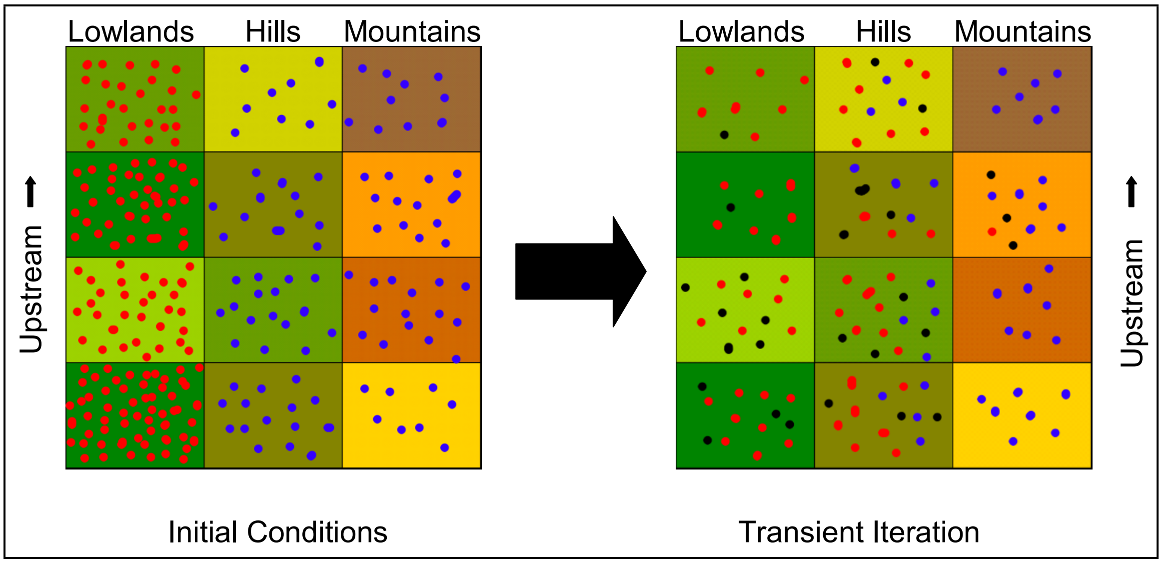

Figure 3-1. Illustrative model dynamics.

An assumed flood could cause a migration from the valley into the lands of the blue tribe. Some of those who remain behind die of starvation (as designated by black dots on the right-hand side of Figure 3-1). Minimal conflict would occur as long as food in the blue-tribe region remains adequate. As the influx of red-tribe individuals strains the food supply in the blue-tribe areas, death occurs by both starvation and conflict. Blue-tribe individuals migrate from their home cells to other cells (including possibly to formerly red-tribe areas) to avoid conflict and/or starvation. Red-tribe individuals may migrate from one cell to another, continuously trying to avoid conflict and starvation that are exacerbated by their own movement. As the death rates climb, the demand for food declines and conflict declines.

A new equilibrium may occur that includes a mixed population or cells that have changed their ethnic color. If the model contained an added propensity to maintain preference for the original "homeland," it is possible that the net affect would again lead to a condition where a reduced red population inhabits only the valley—with some emigrated red individuals ultimately returning. A modestly reduced blue tribe would then maintain its cell occupation with a small contingent of red-tribe individuals. If memory times are long, even after the threat of starvation has passed, conflict would still arise until the red and blue become totally isolated again.

Implementation of this modeling approach has the potential to reproduce, and add understanding to, many social phenomena associated with resource-initiated conflict—

including apparent ethnic cleansing and territorial dynamics. An elaboration of the model might also show the means to mitigate the conflict and to recognize constraints on the policy options. For example, in this simple model, added food supply would temporarily relieve conflict tension until the valley region is again available for full habitation. Given the long-term nonsustainability of accommodating large populations in the highlands and mountains, the long-tem solution would not include the permanent residence of numerous red-tribe individuals in the blue-tribe area.

4 Summary

This first-year effort provides the conceptual development of a dynamic, multiregion, agent-based prototype model of conflict caused by migration due to extreme weather. Real data indicate that China and surrounding countries may suffer the impacts of extreme weather more than, for example, India. Tensions leading to conflict are easily imagined. The growing Chinese need for raw materials already affects several South American countries. The rapidly growing demand of the Chinese economy for oil will also affect the Western nations. Extreme weather can clearly exacerbate these dynamics. Future national security may be closely tied to understanding the link between conflict and climate change. Implementation of agent-based models and the coupling of these models to general circulation models may provide useful insight.

The use of QCT allows meso-level historical data to be used to estimate agent-level parameters. The model can then validly represent actual situations as long as the model contains the significant mechanisms that determine the dynamics. The logic described in this report readily allows the arbitrary addition of more mechanisms. This approach could lead to the generalized multiscale ability to use meso-level models/data for parameterizing agent-based models and, conversely, to use agent-based models to develop aggregate mechanisms for use in meso-level models. The meso-level results can then be applied at the macro level, based on existing techniques. While this work focused on social and economic behaviors, the same logic could apply to physical systems.

QCT (behavioral) and cointegration (statistical) methods have shown their validity and value in many areas of behavioral research. The activity of this LDRD effort has helped to further improve the capabilities of Sandia National Laboratories in using these critical methods.

Lastly, the array-based and minimal information flow approach used for modeling indicates large agent-based systems can be produced with excellent scalability characteristics.

As globalization and the extremist response to it grows, agent-based modeling of the sociopolitical mitigation of conflict may become more a part of ensuring national security than solutions using military hardware.

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Appendix A: Qualitative Choice Theory

A.1 Probabilistic Decisions under Imperfect Conditions

At the individual level, QCT represents the probability that a particular decision will be made. It is thus directly applicable to a multiple-agent perspective (for example, the Los Alamos National Laboratory EpiSims model [Barrett et al. 2005]). Theoretically, any form of the probability distribution can act as the basis for the analysis. In practice, the Weibul distribution has the greatest numerical ease-of-use and has shown itself to be empirically and theoretically the most likely shape of the actual distribution. The Weibul distribution is skewed to the left with a broad tail to the right. This implies that while individuals consider higher "cost" or lower "value" options, they tend to focus on the lower "cost" and higher "value" options.

People do not have perfect information. A sampling of the population shows different perceptions of actual costs and personal preferences. The choice made is called random utility maximization, or RUM (McFadden 1986). Figure A-1 shows an example distribution of perceived price for three technologies (choices). Preferences are not included to simplify the example.

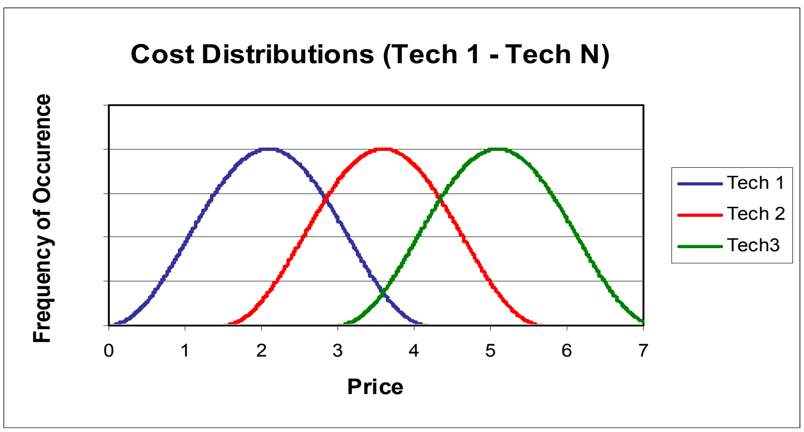

Figure A-1. Illustrative choice distribution.

Maximum-likelihood estimation (MLE) methods determine the shape of the distribution as a function of costs and preferences in the model (McFadden 1986). The actual market share is determined by mathematical integration over the distributions (McFadden 1974). Nonetheless, the physical process can be understood intuitively. Most individuals will perceive technology 1 as less expensive and select it. However, several individuals will perceive technology 2 competitive with technology 1 and select technology 2. Finally, a small few will perceive technology 3 as the least expensive and select it.

The market share of technology 1 would be as shown in Figure A-2, as its price varies relative to the prices of the other choices. The price ratio depicts the weighted price of the other alternatives divided by the price of technology 1. As the price of technology 1 becomes small compared to the other choices, the market share of technology 1 would go to unity. If the uncertainty is large (as in a residential decision), the slope is gradual. If there is significant effort to reduce costs (have less uncertainty), the curve is steeper, as shown for industrial choices. If there is perfect information, as assumed in an unconstrained linear programming (L-P) framework, then the market share would jump from 0.0 to 1.0 with the smallest of price differentials.

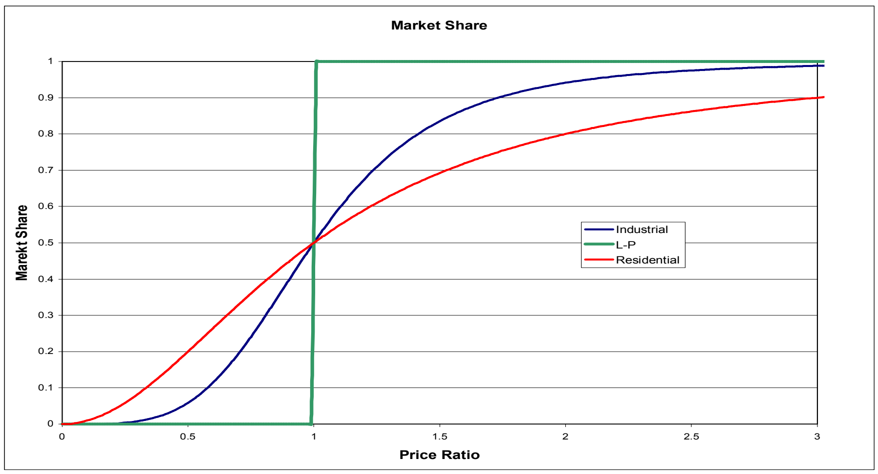

Figure A-2. Illustrative market-share response.

A.2 Mathematical Basics

The integration of Figure A-1 produces the probability of the choice, or in the aggregate, the market share, of the *i*'th choice (MS_i) per Figure A-2. For a Weibul distribution, this integral has a closed-form solution:

$$MS_i = \frac{e^{U_i}}{\sum_{j=1}^{N} e^{U_j}}, \tag{A.1}$$

where U_i is the utility of choice *i* and *e* is the base of the natural logarithm. The utility function is often written, for example, as a simple linear function of price (P_i) with the constant (nonprice) term noted by Train (1986):

$$U_i = A_i + B * P_i \,. \tag{A.2}$$

In this case, *A* would be (assumed constant) nonprice factors of taste and preference for the *i*'th choice. *A* can also capture the ability to make the choice (e.g., the limitation of physician selection in an insurance plan) or the availability of the choice (e.g., the availability of corn in the Sahel). Note that *B* does not have a subscript. It is directly related to the uncertainty of the choice—how well the information of the choice *set* is known and understood. The uncertainty of the decision process is the same for all choices in a set because it is an ordinal, and not a cardinal, process that compares all options at once.

There can be a hierarchy of choice, like a binary tree, but the logic is called nesting because the decision process is represented as a nested hierarchy of decisions. Each level is a choice among all the options of that level (e.g., choosing the flavor of ice cream to eat occurs after choosing which place to go for the snack after the decision to go for a snack.) Each decision level is self-contained but can be conditional on the level below it.

The derivation of the theory of QCT requires that all choices at any level are mutually exclusive (e.g., the decision to live in Kashmir or migrate to India). Empirically this limitation is nonbinding. A classic example is the addition of travel choice by painting half of all the buses green and the remaining buses blue. There really has been no change in the choices—taking the green bus is no different from taking the blue bus. The *A* of Equation (A.2) can capture this fallacy by simply multiplying the blue-bus and green-bus choices, in this example, by 0.5. The same process can often allow the complicated nested equations to be reduced to a single layer called a "comb" that requires only the single use (and estimation) of Equation (A.1).

Reducing the uncertainty, increasing the understanding of the choices, and making better decisions (as contained in the *B* term of Equation [A.2]), takes time and effort. The benefit may not be worth the effort. When buying a house, a purchaser may want to know the price within 1% or less. For a candy bar, a 200% variance in uncertainty is tolerable. The consequences of purchasing a house are much more momentous than those of purchasing a candy bar. The magnitude of *B* appears to vary directly with the importance of the decision. That importance is the cost of the decision compared to the value of the entire output (a labor-year of income for a person and the revenue for a company).

Data indicate the linear function of Equation (A.2) works well for small variations of the input variables, but the actual underlying function is logarithmic. Equation (A.3) is a simple logarithmic enhancement of Equation (A.2):

$$U_i = A_i + B*\ln(P_i). \tag{A.3}$$

The use of the logarithm indicates that people can determine relative proportionality but not absolute differences in price (or other components of utility). This implication is consistent with the previous discussion that *B* is proportional to the percentage impact it has on total outcome.

If Equation (A.3) is substituted into Equation (A.1) and *m* is defined as

$$m_i = \exp(A_i), \tag{A.4}$$

then Equation (A.2) becomes

$$MS_{(i)} = \frac{m_i P_i^B}{\sum_{j=1}^{N} m_j P_j^B}. \tag{A.5}$$

Equation (A.5) is consistent with the engineering assessment of options according to the distribution of (estimated) cost versus (estimated) performance. The uncertainty of the estimate (B) is also a function of the importance of accuracy. This is the only example known where engineering/scientific theory and economic theory agree.

While MLE is required for the unbiased estimation of Equation (A.5), within a feedback system, ordinary least-square estimation often produces adequate parameterization to generate accurate forecasts.

Note that because the decision process is always ordinal, there is no absolute concept of preference. Therefore, one of the m_i must be arbitrarily selected as the numaire and set to unity.

The use of QCT seems to force a rigor and a method for defining the implicit or explicit decisions associated with a simulation hypothesis. Experience indicates that QCT forces a self-consistency of thought and theory that always has a causal description consistent with empirical data.

A.3 Multiscale Properties

A unique feature of QCT is that it is valid across scales. At the individual level, the results represent the probability of a choice. At a societal (or even tribal) level, the probability translates to the fraction of the population making a particular decision. Numerical experiments also show that the summation of individual responses (aggregation) produces a smooth relationship whose estimated response curve also matches the QCT formulation.

Appendix B: Cointegration Theory And Granger Causality

B.1 Mathematical Basics

Cointegration discusses dynamics in terms of variables being jointly integrated (or differenced). To statisticians, the effort is to find stationarity in the residual error term. That is, they want the variables to stay related without the error term growing over time.

B.1.1 Stationarity

Differencing of a series with serial correlation will always result in stationarity if differenced enough times. An undifferenced equation is designated $I(0)$, a first difference $I(1)$, etc.

A general introductory cointegrated equation would be

$$\Delta Y_t = B0 + \sum B_i * \Delta X_{i,t} + Bn * (Y_{t-1} - \boldsymbol{F}(X_{i,t-1})) + u_t\,, \tag{B.1}$$

where Δ is the difference operator: $\Delta X = (X_t - X_{t-1})$, and u_t is the error term. A problem with econometrics is that the time interval always coincides with the data collection interval. In the "delta t" limit, the difference equations are differential equations. The distinction between a "true" difference (discrete) equation and the "true" differential/integral equation will result in an anomalous Δ term that is "without physical interpretation" in the cointegrated equation. $\boldsymbol{F}(X_{i,t-1})$ is the asymptotic value of Y when X is held constant. A nonzero $B0$ distorts this definition and is often restricted to a 0.0 value. The $Bn * (Y_{t-1} - \boldsymbol{F}(X_{i,t-1}))$ term is called the error-correction mechanism (ECM). An example of $\boldsymbol{F}(X_{i,t-1})$ could be

$$\boldsymbol{F}(X_{i,t-1}) = A0 + A1 * X1 + A2 * X2\,. \, . \, . \, . \tag{B.2}$$

The use of a nonzero $B0$ means that the $A0$ in Equation (B.2) becomes $A0 = A0 + B0 / Bn$. As noted above, u_t is the classical "error term." Cointegration ensures that this term is never serially correlated.

B.1.2 Unit Roots

The determination of cointegration is based on the concept of a unit root. Equation (B.3) is a simple autoregressive equation that highlights the cointegration logic.

$$Y_t = \rho Y_{t-1} + \varepsilon_t\,. \tag{B.3}$$

In Equation (B.3), ε is the error term but, unlike u in Equation (B.1), it might be serially correlated. If ρ is greater than unity, there is a positive feedback situation. If it is less than unity, there is a negative feedback situation. This makes sense by rewriting the equation to look a bit more like a systems dynamics smoothing logic:

$$Y_t = Y_{t-1} + dt * (\rho - 1) * Y_{t-1} . \tag{B.4}$$

The smoothing logic captures the accumulation and filtering of information.

$$\Delta Y = dY = (\rho - 1) * Y = \alpha Y \tag{B.5}$$

The sign of α determines the feedback-loop polarity. The polarity depends on the value of ρ compared to unity. If α is thought of as a positive growth rate, as in population growth, then ρ is greater than 1.0. The equation is not cointegrated. It only has short-term memory. The level changes slowly as other possible inputs affect it. A simple system-dynamics delay, as shown in Equation (B.6), with its long-term, cointegrating memory that parrots human-memory dynamics will clarify the unit-root significance (Sterman 2000)

$$Y_t = Y_{t-1} + dt * (S_t - Y_{t-1}) / T \tag{B.6}$$

or

$$\Delta Y_t = (S_t - Y_{t-1}) / T , \tag{B.7}$$

where S is the input variable to be smoothed and T is the averaging time.

In general cointegration terms,

$$\Delta Y_t = B0 + B1 * \Delta S_t + B2 * (S_{t-1} - Y_{t-1}). \tag{B.8}$$

Equation (B.8) looks like the original cointegration equation (Equation [B.1]) above. By comparing Equations (B.4) and (B.6) to Equation (B.8), *B1* and *B2* have the definitions below.

$$B2 = 1 / T , \tag{B.9}$$

$$B1 = (\rho - 1) . \tag{B.10}$$

The $(\rho - 1)$ term is comparable to its use in Equation (B.5) above.

Note the minor issue of the time-subscript change on S between the difference equation (B.8) and the implied differential equation (B.4). This is not statistically significant, but it does change the causal interpretation of estimation results.

The regression of Equation (B.8) corresponds to Equation (B.1) or (B.3) only if ρ is unity—the unit root. The unit root indicates the reinforcing loop limit. The value of ρ just needs to be unity from a statistical perspective. A value of less than unity will do as well in most cases. There is a problem if ρ is much above unity. The test that ρ is statistically unity is then not the conventional t statistic for $(\rho - 1)$ being nonzero, but rather a modified distribution that is heavily skewed toward values below zero. The verification of the unit root is called the augmented Dickey-Fuller (ADF) test, in cointegration jargon. A delay (memory) function is perfectly cointegrated.

A population-growth equation is not cointegrated. The serial correlation of the error term can be removed by simply assuming a growth rate. A growth-rate equation has the *Bn* of Equation (B.1) equal to 0.0 and the B_i not all equal to 0.0.

B.2 Granger Causality Mathematical Basics

The explicit use of lagged values determines "causality." In cointegration, the test (Granger causality) is not to prove causality, but to verify when there is not causality. If Y_t is a well-correlated function of $X_{i,t-1}$, the X_i could be causing Y; but if Y_t is more correlated with a function of $X_{i,t+1}$ (note the "+"), then the X_t does not Granger-cause Y. Another perspective on Granger causality is to say that Y is explained better by order-n [l(n)] lags of X than by lags of Y alone.

The test of whether Y_t is a function of $X_{i,t}$ occurs in the first pass of the two-stage cointegration regression process. The first stage estimates the long-term (asymptotic) solution, and the second stage estimates the dynamic ΔX contribution. Note that higher-order ΔY [$I(n)$] components can also be added to Equation (B.1).

Granger causality seeks to falsify the X-causality by testing whether all the ε_i are 0.0. This process requires comparison to the autocorrelation Equation (B.12) with the inclusive Equation (B.11):

$$Y_t = c + \sum_{i=1}^{p} \alpha_i * Y_{t-i} + \sum_{i=1}^{p} \beta_i * X_{t-i} + \mu_t \,, \tag{B.11}$$

$$Y_t = c + \sum_{i=1}^{p} \gamma_i * Y_{t-i} + \varepsilon_t \,. \tag{B.12}$$

Let $R1$ be the sum of squared residuals for Equation (B.11), and let $R2$ be it for Equation (B.12):

$$R1 = \sum_{1}^{N} \mu_t^2 \,, \tag{B.13}$$

$$R2 = \sum_{1}^{N} \varepsilon_t^2 \,. \tag{B.14}$$

If N is the number of observations, the test is then

$$N * (R2 / R1 - 1) = \chi^2 (p) . \tag{B.15}$$

B.3 Norms, Status Quo, And Feedback

Cointegration regularly verifies assumptions about simultaneous relationships/interactions and feedback. Cointegration analyses have falsified such accepted assertions as the price of a commodity being a function of current supply and demand (Hendry 2000, 2001), and that current weather drives current conflict (Boslough et al. 2004). Thus, cointegration supports the agent-based–simulation view that interactions are caused by previous conditions or by long-term assets/perceptions associated with previous conditions. The historical relevance of interacting variables, as determined via cointegration analyses, then, further implies that feedback dominates any relevant agent-based–model process. Cointegration analyses reveal the limited impact of simultaneous processes and the dominance of feedback, and thereby establish the key state variables that drive agent behavior. Therefore, cointegration and agent-based modeling methods are integrally tied together.

The verification of cointegration within an agent-based model indicates the existence of “memory” within the agents and among the behavioral responses they produce. Conversely, if the feedback processes associated with “memory” act to drive the system toward any goal or balanced condition (negative feedback), then processes within the model must be cointegrated. The use of the delay/smoothing process, noted above, to capture information accumulation and filtering produces a reference norm or status quo to which new information is compared. The information driving a norm may be the consequence of previous decisions affected by the norm. Thus, the norm is often part of a feedback (cointegration) process that perpetuates initial choices.

Appendix C: Reference News Releases

This appendix includes the "fair use" presentation of climate change articles that support the conceptualization of the modeling scenario.

Impact of global warming on weather patterns underestimated EurekAlert AAAS: 21 September 2005, http://www.eurekalert.org/pub_releases/2005-09/uoea-iog092005.php (There will be more extreme weather.)

Report says global warming could spark conflict Reuters: 23 September 2005, http://www.planetark.com/dailynewsstory.cfm/newsid/32631/story.htm (Climate change causes many triggers of conflict.)

Environmental decay may prompt refugee surge-study Reuters: 11 October 2005, http://www.alertnet.org/thenews/newsdesk/L10622231.htm (Extreme weather causing migration requires the definition of a new category of environmental refugees, according to a recent study by the United Nations.)

Millions 'will flee degradation' BBC: 11 October, 2005,
http://news.bbc.co.uk/1/hi/sci/tech/4326666.stm (By 2010, there may be up to 50 million environmental refugees in the world.)

Climate change linked to rise in malaria, asthma Reuters: 1 November 2005, http://www.usatoday.com/weather/climate/2005-11-02-climatechange-disease_x.htm (The secondary affects of weather change will drive demographic changes.)

Warmer Seas, Wetter Air Make Harder Rains as Greenhouse Gases Build
NCAR: October 13, 2005, http://www.ucar.edu/news/releases/2005/hardrain.shtml (Analysis and data indicate increasing extreme weather.)

Where will they go when the sea rises? New Scientist Magazine: 7 May 2005, http://www.eurekalert.org/pub_releases/2005-05/ns-wwt050405.php (Developed countries may have the greater burden when it comes to accepting immigrants displaced because of climate change.)

As Polar Ice Turns to Water, Dreams of Treasure Abound New York Times: October 10, 2005,
http://www.fromthewilderness.com/free/ww3/101905_world_stories.shtml (The opening Arctic causes economic and political tensions.)

Global warming drying out source of China's mighty Yellow River
AFP: 10 October 2005, http://www.terradaily.com/news/climate-05zzzzze.html (Climate change may crash Chinese expectations.)

Katrina rings alarms on climate change: World Bank Reuters: 8 September 2005, http://www.climateark.org/articles/reader.asp?linkid=45972 (The World Bank is fearful of impacts of climate-induced extreme weather.)

British scientist criticizes 'climate loonies' Reuters: 22 September 2005, http://www.msnbc.msn.com/id/9444878/ (Climate change is linked to extreme weather.)

The 100-Year Forecast Stronger Storms Ahead LiveScience: 13 October 2003, http://www.livescience.com/forcesofnature/051013_stronger_storms.html (Data and models link extreme weather to climate change.)

Climate change hurts Africa most: Scientists Reuters: 23 September 2005, http://www.planetark.com/avantgo/dailynewsstory.cfm?newsid=32630 (Climate will further strain developed countries through impacts within undeveloped ones.)

Spain gets first tropical storm - Vince AFP: 11 October 2005, http://www.terradaily.com/2005/051011190620.48hh225v.html (This is the first eastern Atlantic hurricane ever. Last year, the South Atlantic got the first ever.)

Hurricane Vince one for record books The Virginian-Pilot: 10 October 2005, http://home.hamptonroads.com/stories/story.cfm?story=93419&ran=182423 (New weather seems to defy conventional weather.)

Global Warming 'Past the Point of No Return' The Independent / UK: 16 September 2005, http://www.zmag.org/content/showarticle.cfm?SectionID=57&ItemID=8761 (Continued climate change and extreme weather are now inevitable.)

2005 set to be second hottest year on record Reuters: 14 October 2005, http://www.rame-cornwall.co.uk/newspages/hot2005.htm (2005 is just the next in the recent list of hottest years.)

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