Geospatial Modeling to Identify Populations Vulnerable to Natural Hazards

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Abstract – A geospatial model has been developed to identify areas of human population vulnerable to natural hazards. These areas tend to be locations where disasters have occurred frequently, and populations lack the social and economic infrastructure to mitigate or adequately respond to effects of disaster events. In this paper we examine an application of this model in continental Africa. An evaluation of the AVHRR Land Pathfinder database and time series precipitation data from the Global Precipitation Climatology Center was undertaken to identify anomalies indicative of adverse natural conditions. These conditions were used to modulate the vulnerability index to identify vulnerable populations..

INTRODUCTION

With geospatial modeling we examine interactions between natural and human systems to assess the vulnerability of the human populations to natural disasters. Exposure to both acute and chronic events are considered by examining historical records of events, or evaluating anomalous environmental conditions derived from field measurement and remote sensing sources. Vulnerability is determined by considering the degree that social capacity may mitigate impacts of environmental stress by comparatively examining their geospatial distribution.

Vulnerability can be thought of as the degree to which a population may suffer harm as a result of exposure to change or stress. A new field of study focusing on vulnerability analysis is emerging called "sustainability science" which is attempting to broaden the analytical framework of traditional risk-hazards (RH) or pressure-and-response (PAR) approaches that have been dominant for the past four decades in disaster related research and analysis (Turner, 2003). First, sustainability science addresses *coupled ecological-human systems*. It recognizes that interactions are highly complex, with many feedback mechanisms. In addition, sustainability science concerns itself with transformations within the coupled systems that interact with the systems' sensitivity and resilience when exposed to stress. The terms coping capacity and adaptive capacity are used to describe a systems ability to avoid, mitigate, rebound or adapt to adverse conditions. The overall framework is referred to as "vulnerability-exposure-sensitivity-resilience" (VESR).

An understanding of social capacity is critical to evaluating vulnerability to exposure to an acute perturbation (like severe storm) or chronic stressor (like drought or environmental degradation). Following analysis guidelines emerging from sustainability science methods, a geographic information system was developed at a one kilometer resolution utilizing data from natural and social science sources and applied in Continental Africa to develop an index identifying populations vulnerable to natural disasters.

MODEL

Conceptual Model. The underlying conceptual model pictured in Figure 1 that guides this effort is derived from previous work, Geospatial Indicators (GI), wherein the risk to food or water insecurity as a result of environmental factors and social capacity is estimated (Cicone, 2003; Parris, 2003). The model assumes that natural systems, social capacity, and their ongoing interaction define a region's sensitivity and resilience to factors leading to outcomes of concern, like food or water insecurity. Acute disasters enter into the system as shocks that impact both environmental conditions, and social capacity. Chronic conditions, such as drought, behave as environmental dynamics that affect the natural resource base and modulate capacity.

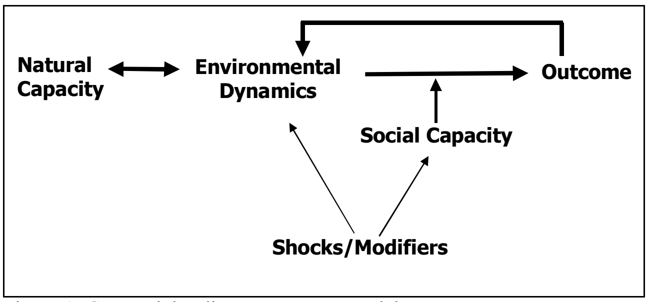

Figure 1. Geospatial Indicators Process Model.

GI decomposes this conceptual model into structural and dynamic components as shown in Figure 2. The structural component focuses on indicators of natural and social capacity that change slowly over time to assess the inherent *risk* of undesirable outcomes such as food emergencies. It is assumed that frequent exposure to acute natural disasters increases overall structural risk. This effect is introduced by estimating the historical frequency of severe weather, earthquakes, tsunamis, and volcanic activity. The dynamic component introduces factors that change more rapidly over time to assess the likelihood that a particular region will experience an undesirable event in a given year. Monthly reported precipitation and AVHRR derived vegetation development provide measures of such dynamics.

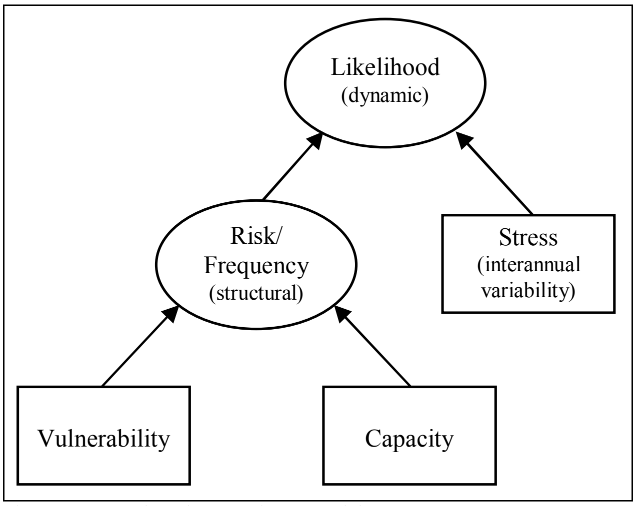

Fig. 2: Structural And Dynamic GI Model Components.

Modeling Vulnerability to Natural Disasters. The vulnerability of a population in a given area to a natural disaster is a function of the population's sensitivity and resilience to an exposure. We estimate vulnerability by considering social and environmental factors that impinge on a region's coping capacity, the most significant determinant of sensitivity, and its resilience, measured by accessibility to food and water resources. Coping capacity is modeled using disaggregated measures of a regions overall social capital (simply called capacity in the GI construct), including governance, wealth and technical development. Resilience is approximated using measures of food and water security estimated by GI. We estimate a population's relative vulnerability as follows:

$V_t = [P \times (10\text{-}C) \times I \times E_t]^{1/4}$ where:

P is population density

C is capacity estimated by GI (GI estimates capacity as a function of wealth (disaggregated GDP), infrastructure (nearness to roads and central places) and governance)

I is food and water insecurity (GI estimates the imbalance of supply and demand for food and water)

E_t is the exposure to acute and/or chronic events at time t

Since each indicator is scaled from zero to ten, the fourth root is a scaling term. The multiplicative model acts as an "and" function. High capacity would reduce the affect of insecurity or exposure.

DATA

Core data sources included the Oak Ridge National Laboratory Global Population of the World, GTOPO30, IGBP Land Cover Characteristics Database, the AVHRR Land Pathfinder Database, the Digital Chart of the World (DCW), and gridded historical precipitation from the Global Precipitation Monitoring Center. Key variables included population density, gross domestic product, terrain, vegetation, lines of communication, state boundaries, governance, vegetation greenness and accumulated precipitation (Miller, 2002).

Figure 3 illustrates the distribution of population across continental Africa in 1998 as estimated by ORNL with one kilometer resolution. Figure 4 is a composite of relative historical exposure to natural disasters. The composite is derived from historical records of earthquakes, volcanoes, tsunamis, and severe storms, with flood and desertification potential. The integration of Figure 3 and 4 would provide a classic "Risk-Hazard" surface indicating population at risk based on historical exposure. This type of analysis ignores a population's coping capacity and resilience, key factors introduced in this exercise.

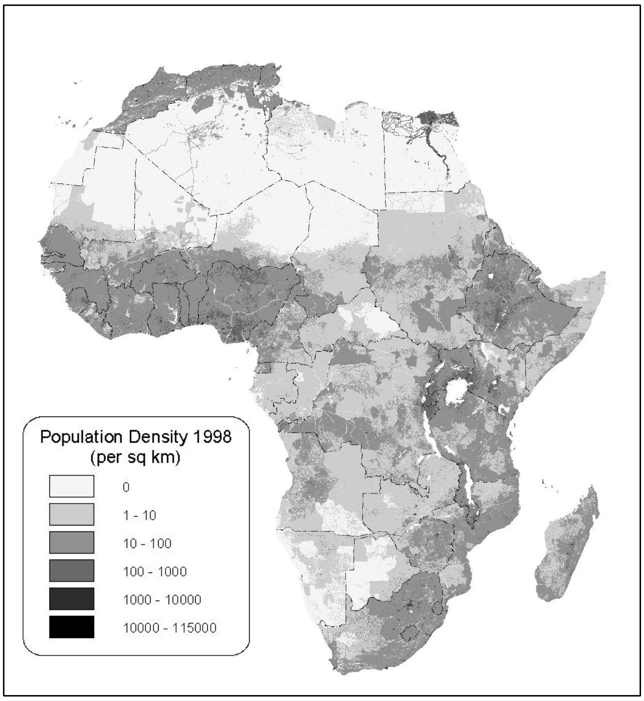

Figure 3. Population Density (Source: ORNL Global Population 1998). Data are disaggregated from population reported by administrative units based on contextual information, including topography, land cover, land use, hydrology, culture, central places.

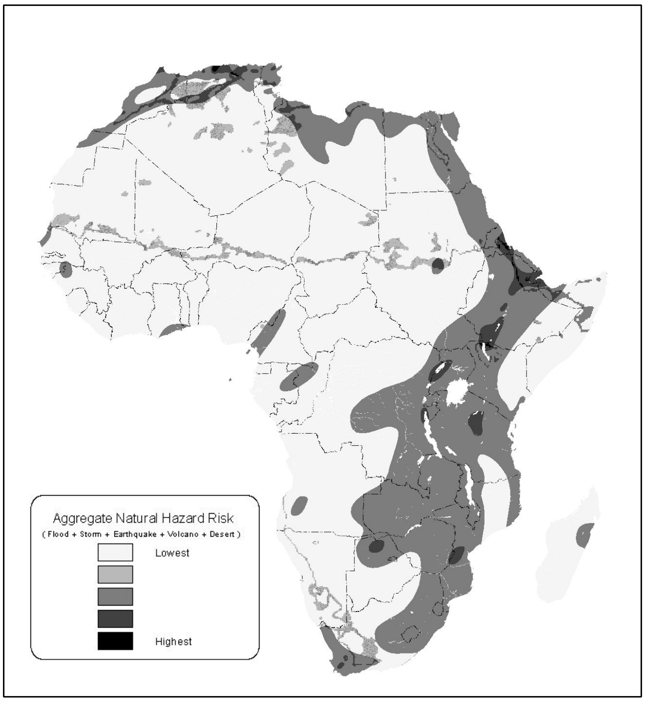

Figure 4. Composite Historical Hazards (severe storm, earthquake, volcano, desertification, tsunami, flooding) Source: ISciences & Earthsat.

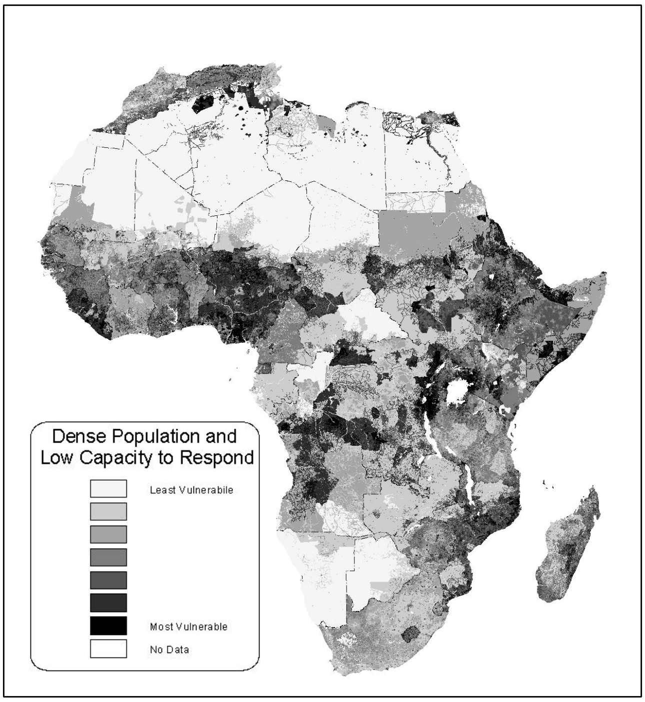

Figure 5. Coping Capacity (from governance, infrastructure intensity and disaggregated GDP). A measure of capacity is inverted and multiplied by population density to produce a measure of sensitivity. Red regions are dense populations with low capacity.

RESULTS

We present the results of our estimation of vulnerability by building the index one factor at a time, introducing capacity, then insecurity, and finally exposure. In this case we examine the vulnerability of continental Africa to anomalous weather conditions in the year 2000. Figure 5 illustrates the effect of the capacity index. Our estimate of capacity is based on three contributing factors. First a measure of governance provides a national level indicator of a given nation's political will to provide essential services. Second, we introduce a measure of a region's general economic development based on an index that examines the industrial and transportation complexity in the neighborhood of each one kilometer pixel. Third, national level GDP are disaggregated to one kilometer using measures of land use, natural resources, and industrial development to provide a crude measure of local wealth. Nigeria's population density, and poor governance counterbalance its generally positive industrial capacity. Its coping capacity is in effect inadequate to serve the needs of the size of its population, implying a sensitivity toward exposure to natural disaster.

We use indicators of food and water security as an index of general "resilience" to a natural disaster, with the assumption that sufficient access to these essential resources would increase resilience and thereby reduce vulnerability to natural disasters. Figure 6 illustrates the effect of the introduction of this factor, producing a surface that can be thought of as a general measure of a region's sensitivity and resilience. Note that southern Nigeria is typically food secure, reducing its overall vulnerability. The scores in Somalia, Ethiopia, and the Great Lakes regions increase as a result of less adequate food and water resources.

We estimate exposure to natural hazards by examining anomalies in normal precipitation and vegetation development in 2000. Precipitation anomalies are estimated by examining the aggregate level of precipitation over the twelve month period as compared to historical averages. Outliers are identified in terms of their departure from average measured in standard deviations. Vegetation anomalies are identified using cumulative AVHRR Greenness over the same period of time. Outliers are identified in terms of the absolute value of their departure from average in terms of percent. Other studies found that this non-linear metric reflects negative impacts due to both anomalous dry and wet events (Parris, 2002).

Figure 7 illustrates the result and provides an overall disaster vulnerability surface. The model points to vulnerable populations in the region of Somalia and Eritrea, and Western Ethiopia, affected by severe drought

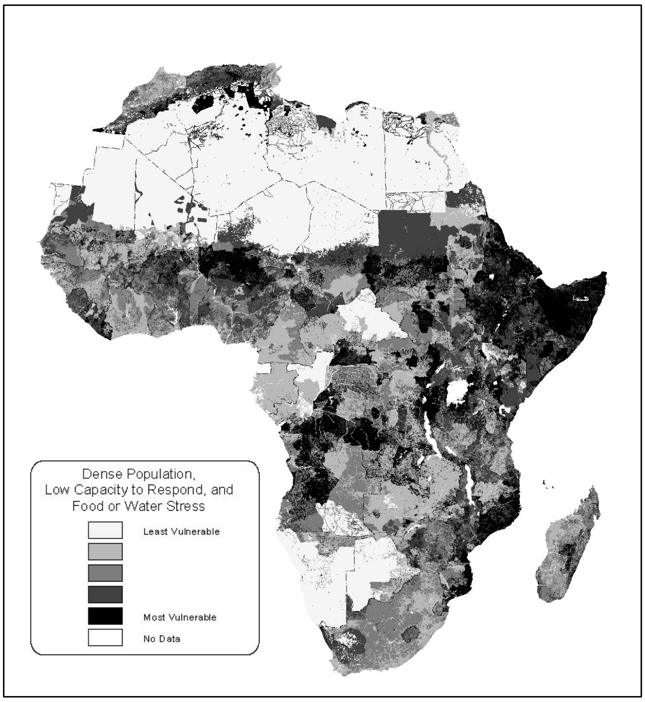

Figure 6. Sensitivity/Resilience (from coping capacity, food and water security). Availability of food and water is a critical factor influencing a regions resilience to chronic or acute natural disasters.

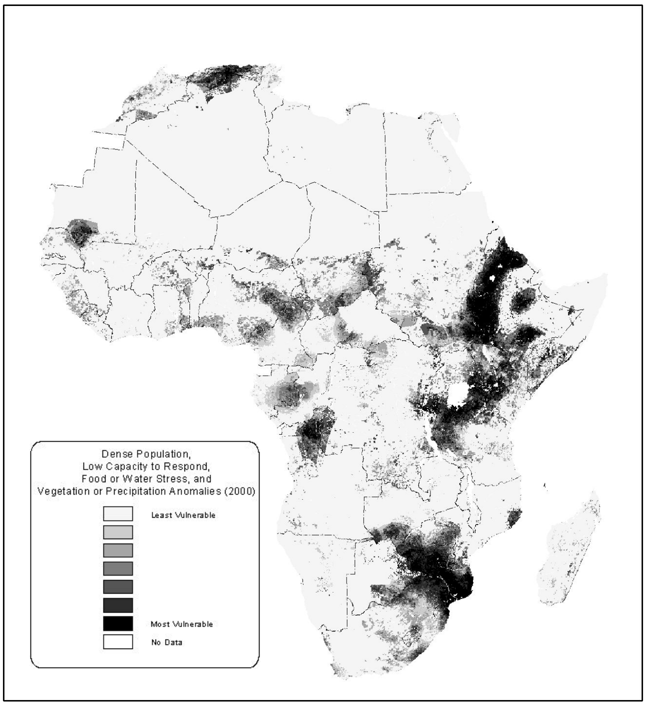

Figure 7. Vulnerability to drought, severe weather in 2000. Cumulative greenness from AVHRR, and precipitation levels reported to the World Meteorological Organization are analyzed to determine anomalous conditions in the year 2000. Sensitivity/ resilience are used to modulate the impact on populations illustrating the regions most vulnerable to these adverse natural conditions.

conditions, and in the region of Mozambique affected in 2000 by severe weather. Anomalous conditions existed elsewhere, however their impact was mitigated by as a result of social capacity to cope and overall resilience (see Figure 4).

CONCLUSIONS

An estimate of the vulnerability of populations to anomalous conditions in 2000 was created in continental Africa by considering exposure to adverse weather conditions derived from remote sensing and direct measurement sources. Mitigating factors, derived from measures of social sensitivity (coping capacity) and resilience, modulate the effect that would have been produced through a simple estimation of populations exposed to anomalous conditions. The indices used, all derived from social and environmental factors that were modeled to a scale of one kilometer resolution, demonstrate the potential of geospatial methods to portray disaster vulnerability surfaces on a continental scale. Specific identification of measures that thoroughly describe a population's sensitivity and resilience to natural disasters was beyond this paper's scope. However, indices were available as a result of other studies that provide a credible step toward estimation of vulnerability that considers social the interaction of social and environmental factors that influence vulnerability.

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