

# GEOSPATIAL INDICATORS OF FOOD SECURITY

**Richard Cicone, Douglas Way, Thomas Parris**  
ISciences, LLC  
Ann Arbor, Michigan  
info@isciences.com

**Jeffrey Miller, David Cunningham, Gregory Koeln**  
Earth Satellite Corporation  
Rockville, Maryland  
info@earthsat.com

## ABSTRACT

Geospatial Indicators (GI) is an exploration into the use of GIS, remote sensing and spatial reasoning methods to identify regions at risk due to inadequate food and water resources that are a result of inherent environmental scarcity, stress due to environmental dynamics and change, or inadequate social capital. The purpose is to lay an evidentiary foundation to assess risk on a global basis as a result of unmitigated environmental scarcities. This paper focuses on first results in Continental Africa and validation of those results using UN/FAO reported food emergencies over the past decade. GI process models are constructed using basic factors like population, land cover, and topography, to estimate inherent environmental capacity to supply sufficient food and water resources to meet expected demand. This inherent natural capacity, based on time history and/or representative data, depicts *vulnerability* to food or water insecurity. This vulnerability is then modulated using estimates of environmental dynamics derived from near real time measures of precipitation, vegetation development (based on AVHRR Land Pathfinder), and risk to natural hazards. Such dynamics depict additional *stress* to which the natural system is then exposed. Subsequent food and water balance surfaces are compared to measures of regional social *capacity*. Social capacity metrics reflect a region's resilience to scarcity as a function of governance, wealth, and infrastructure. The interplay of these computed factors of *vulnerability*, *stress*, and *capacity* provide estimates of the *risk* and *likelihood* of food and water insecurity.

## INTRODUCTION

Geospatial Indicators (GI) is a method developed to provide evidence-based indicators of the *risk* and *likelihood* of food and/or water insecurity over broad regions on a subnational scale (Cicone, 2001). The capability provides an opportunity to screen for evidence of stress derived from the historical record, weather dynamics, and social capacity. First, risk is estimated using models of food production and water availability that provide maps of expected natural performance relative to the social capacity to reap and distribute the resources available. Likelihood of insecurity at a given time is estimated by including precipitation and vegetation dynamics. Analysis of the performance of the model revealed that 80 percent of the food emergency pixels and nearly all food emergency events of the last twelve years were identified by the likelihood indicator, with a eleven percent false alarm rate (Parris, 2001). These results demonstrate the plausibility of these indicators for monitoring food and water stress.

Determination of indicators of environmental and social well being have been a subject of much attention recently, particularly in light of the growing number of international agreements binding nations together in addressing common problems that affect developed and developing nations. Inspired by the success of the Human Development Index developed by the United Nations Development Program (UNDP, 2001) to provide a universal scale of the human condition, much effort has been devoted to the topic of indicators of sustainable development from local to global scales (IISD, 2000). Examples of national level indicators include the work of the United Nations Commission on Sustainable Development, the Consultative Group on Sustainability Indicators, the World Economic Forum, and the World Wide Fund for Nature International (UNSD, 2001; CGSDI, 2001; WEF, 2002; and WWF, 1998). Recently, efforts have been undertaken to understand the theoretical underpinnings necessary to produce appropriate global level indicators (Kates, 2001). Environmental factors influencing the failure of states has drawn the attention of prominent U.S Government studies such the State Failure Task Force (Esty, 1999). Prescott Allen proposes an overall wellbeing index composed of a human wellbeing and ecosystem wellbeing indices

(Prescott-Allen, 2001). The inclusion of environment factors heavily into the work of Lonergan in producing a Human Security Index derived from a clustering analysis of a large number of factors including social, political and economic perspectives to flag states that lack the means, capacity or will to “end, mitigate, or adapt to threats to their human, environmental, and social rights” (Lonergan, 2000)

Researchers have noted the shortcomings of global and national level indicators in reflecting the variation of conditions that a given nation may confront. Prescott-Allen argues the extensibility of the wellbeing index to subnational scales. Data problems, inherent in national level analysis, are more prominent deterrents at subnational scales. Researchers at the University of Kassel are prominent in tackling this concern producing a disaggregated (1/2 degree) model-based analysis to mark places experiencing environmental change and commensurate pressure on food and water security (Alcamo, 1999). The USAID Program’s Famine Early Warning System (FEWS) is a notable effort addressing the needs of emergency planners to understand dynamic conditions that could lead to food emergencies, relying heavily of remote sensing and weather data to identify anomalous conditions that predispose a region to food insecurity (USAID, 2002). Geospatial Indicators follows the work of Alcamo and USAID in pursuing subnational indications of factors impacting human security. Focusing first on continental Africa, GI differs from FEWS in three major ways by: 1) explicitly incorporating indicators of social, economic, and infrastructure capacity to respond to short-term stressors; 2) distinguishing between the structural factors influencing the frequency of food emergencies over time, and the dynamic factors that are associated with the likelihood of a food emergency in a specific year; and, 3) by using data that is available globally. However, GI does not include the richness of environmental data employed by the FEWS, primarily due to a self-imposed requirement for scalability.

## METHODS

### Conceptual Model.

The underlying conceptual model that had guided our development, use, and validation of indicators is shown in Figure 1 below. This model describes the fluid interaction between natural capacity and social capacity that define a region’s resilience and/or vulnerability to factors affecting outcomes of interest and concern. Unpredictable modifiers such as natural variability or civil war provide surprises that can change outcomes by reducing social capacity or inducing environmental changes.

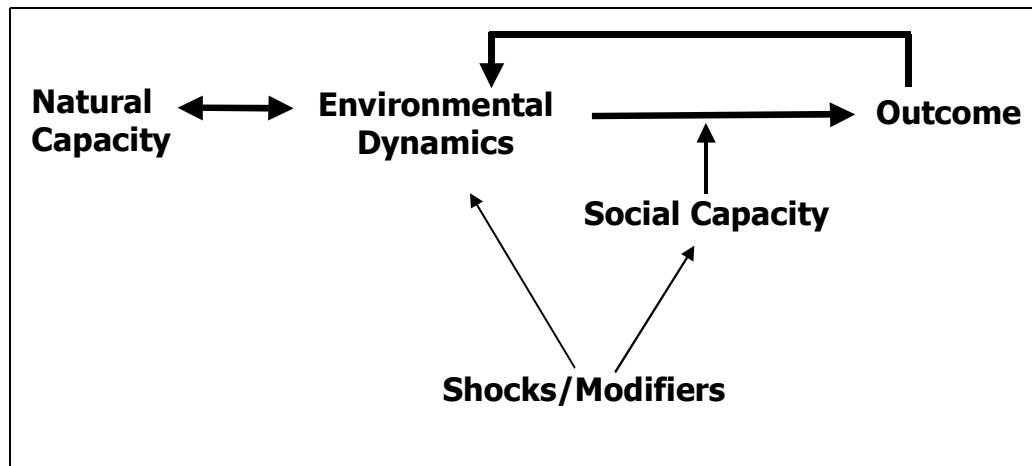
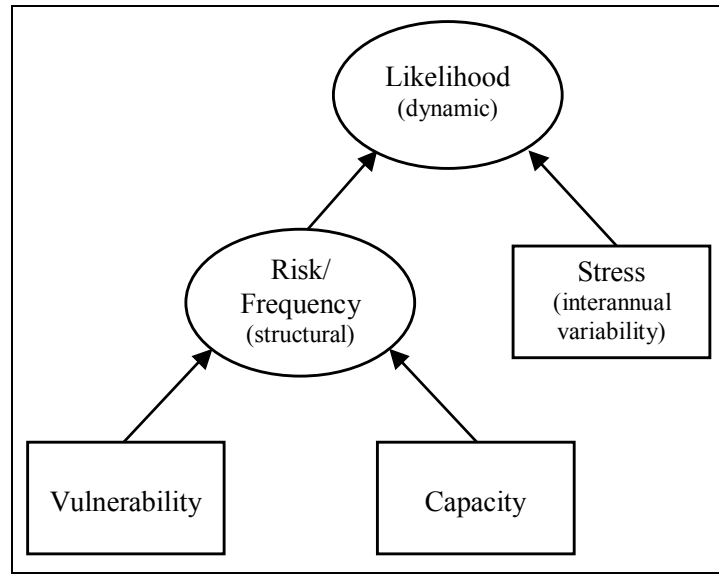


Figure 1. GI Process Model

We decompose 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 overall *risk* of undesirable outcomes such as food emergencies. It is expressed in terms of the frequency of these events. We use the term vulnerability to describe complex phenomenon such as food balance and water balance that are functions of both natural resources and social capacity. The dynamic component adds in indicators that change rapidly over time to assess the likelihood a particular region will experience an undesirable event in a given year. We rely on monthly reported precipitation and AVHRR derived vegetation development as measures of dynamics.

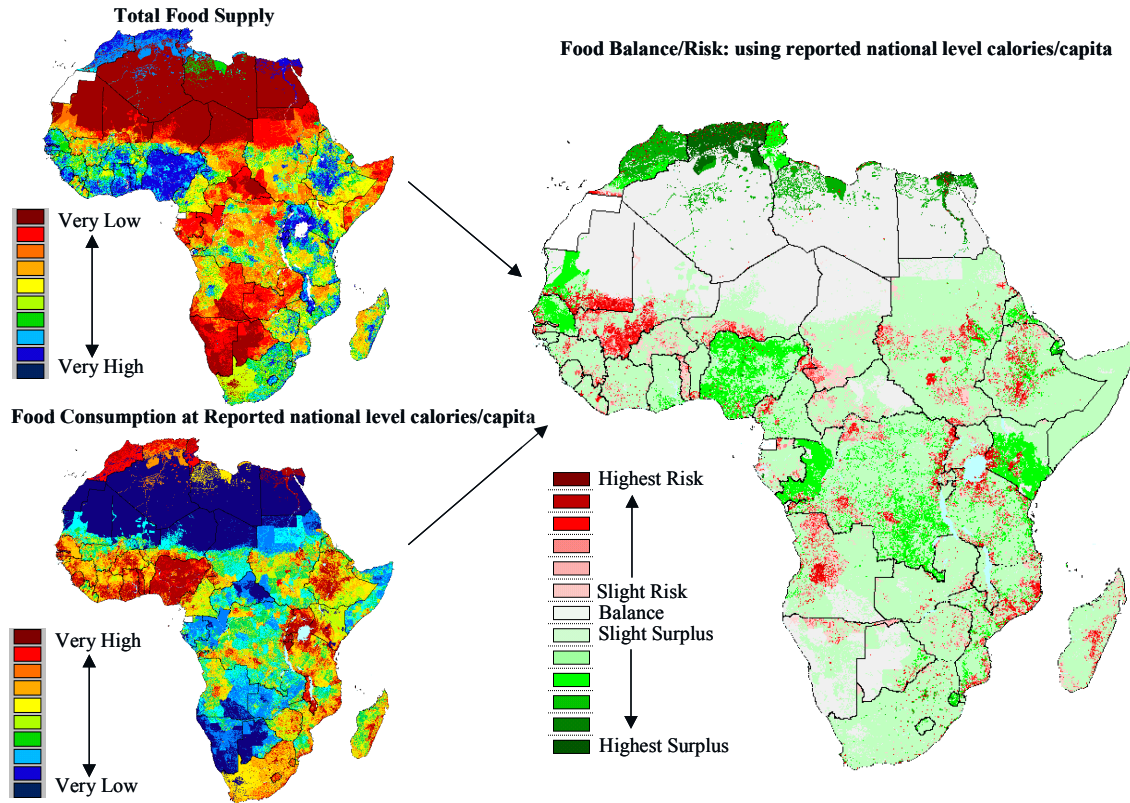


**Figure 2: Structural and Dynamic GI Model Components**

### **Estimating Natural Vulnerability To Food Insecurity**

In estimating vulnerability to food insecurity our objective is not to model in a precise way who does and does not have access to food, but to estimate in a general sense the degree of difficulty a region may have in obtaining needed food under normal conditions. Several assumptions are made in our efforts to generate a one-kilometer resolution representation of such vulnerability. First, it is assumed that local availability of food reduces vulnerability. Second, that a transportation infrastructure increases the range of access to food, thereby further reducing vulnerability. Finally, we assume that wealth preferentially provides purchasing opportunities. The last factor is complex. Income disparity, sometimes estimated in surveys and reported as the GINI index, is crucial in determining the haves and have-nots of society. However, if available at all, GINI is usually found as a national statistic. As a result, urban food stress can be approximated only in an average sense. We have no way of modeling who in a particular city may be food insecure – we can only estimate whether the city in general has local access to food products. A wealthy, modern city surrounded with rich arable land is intuitively more food secure given normal weather and growing conditions than one that is not.

We estimate vulnerability by approximating local food balance (Miller, 2002). Food balance is estimated by determining local supply versus local demand. Two components of food supply are modeled at a one-kilometer resolution – local production and imports. Local production is estimated using reported national statistics for cereal grains, root vegetables, and other food staples that are disaggregated according to an estimate of land productivity potential. Since data are unavailable regarding specific land area cultivated to non-food crops like cotton, it is assumed that any piece of arable land is likely to grow food staples. Land productivity is based on an allocation of reported production of cereal grain and other staples to primeness (or land quality). Primeness is derived from data descriptive of environmental ingredients necessary for crop production together with a consideration of other factors such as nearness to markets and agricultural scale (commercial versus subsistence). Local demand is estimated using population data and reported consumption statistics. Alternatively, demand can be estimated as a minimum consumption requirement (2000 calories is often prescribed by UN/WHO as a target minimum requirement) or some combination of local diet and minimum need. Access to locally available food is described in terms of availability within approximately one day's journey, with transportation infrastructure and wealth determining the journey's possible length – that is, how difficult it is to acquire needed food.



**Figure 3. Estimating Food Balance.** Food supply is estimated using a model of distributed imports and an estimate of local food production. Demand is estimated using reported national average food consumption rates disaggregated according to the distribution of population. Resulting risk surface illustrates imbalance between local food supply and demand. When an imbalance occurs, the area may be subject to greater food insecurity.

Determining local availability of imports is difficult. Imports reported at the national level are distributed to major cities or known food distribution centers according to regional population density. They are then locally allocated on the basis of a distribution resistance surface, which is approximated using transportation infrastructure, average income, and terrain features. It is certain that other social factors, including preferential treatment and even graft, may result in food allocation schemes more complex than addressed by the above model assumptions. However, the defined strategy does provide a first order approximation. To introduce the concept of preferential allocation, income is weighted by reported national GINI index. In this interpretation high GINI values allow larger incomes to attract more imports. That is, all other factors being equal, we make the assumption that the poor classes of nations that record high GINI value would be exposed to greater food insecurity. Many other unknown factors weigh into the distribution of food imports, such as food networks run by non-governmental organizations. In this construct, we must assume that regions dependent on such social networks as opposed to national infrastructure are exposed to greater food risk.

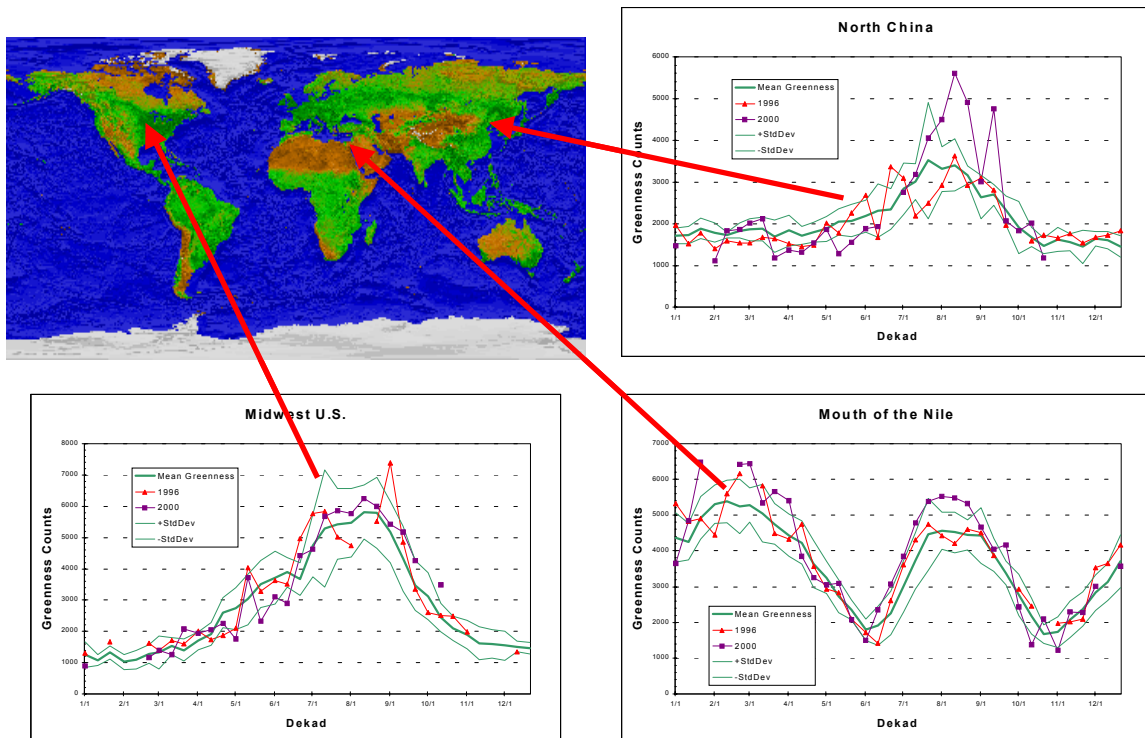
Figure 3 illustrates this process, with local food balance expressed on the right as the difference in total food supply and food demand based on reported local diet. Famine is not necessarily occurring in regions that are red. These regions would however experience greater difficulty in acquiring food to satisfy typical diet demands according to this model because of inadequate nearby agricultural capacity, poorer roads, population density, or poverty. In this depiction diet demands are reported as national averages. Such a depiction of structural food risk would be modulated each year as a function of varying agricultural production. A food scarce region may experience further risk as a result of a drought. Such dynamics are considered later in this report. Social upheaval, such as civil war in the Sudan, can also induce food insecurity. To some extent, this factor may be revealed when examining social capacity, however, because of the transient nature of such insults, it is necessary for the analyst to superimpose such effects. We undertake a similar analysis to estimate water balance in order to determine indicators for water insecurity (Cicone, 2001).

## Estimating Stress

Food and water risk described to this point only provide indications of structural strengths or weaknesses – a region's vulnerability, or conversely self-sufficiency as a function of its natural resources and typical weather conditions. Year-to-year and season-to-season variations in food production and water supply are obviously influenced by variability in weather. Deviations from normal patterns may foster drought conditions that could result in crop failure or inadequate fresh water supply that may not be mitigated using natural and man-made water reservoirs or food stocks. Such conditions will affect regions that are historically self-sufficient as well as exacerbate conditions in already marginal areas. Variations from the norm and specifically anomalous conditions at a given time would be of significant concern. Shocks resulting from natural hazards increase risk to food and water insecurity, sometimes dramatically. Such dynamics are difficult to predict reliably, however, historical records of volcanic activity, earthquakes, severe weather and floods, and tsunami events provide a means to evaluate the relative exposure an area may have to such insults. Other important stress factors such as civil instability, or war are not considered here.

GI utilizes three sources of information to evaluate variable, anomalous conditions and stress due to shocks. Deviations from historical averages in a given year are derived from time series vegetation cover and precipitation data. Regions that show departures from normal would then be compared to expected food and water imbalance approximations to identify regions experiencing extraordinary imbalance in a given year.

To estimate changes in precipitation, average monthly precipitation is computed using time series data dating back to 1986. Longer-term averages are used in estimating natural capacity, however, since longer term averages are based on other data sources. Here, deficits are estimated relative to this narrow weather window for internal consistency. Monthly precipitation data, reported in millimeters and geocoded at one-degree intervals across the globe, are produced by the Global Precipitation Climatology Center in Germany. These data are made available over the Internet, with postings appearing monthly with about a three-month lag time (GPCC, 2002). The vector of average monthly precipitation forms a reference for every one-degree grid cell in terrestrial regions. The monthly variance is also computed to illustrate regions where a deficit in any given month is likely to occur. Departures from normal can be computed for any location on Earth. Precipitation loadings (total precipitation) can be easily

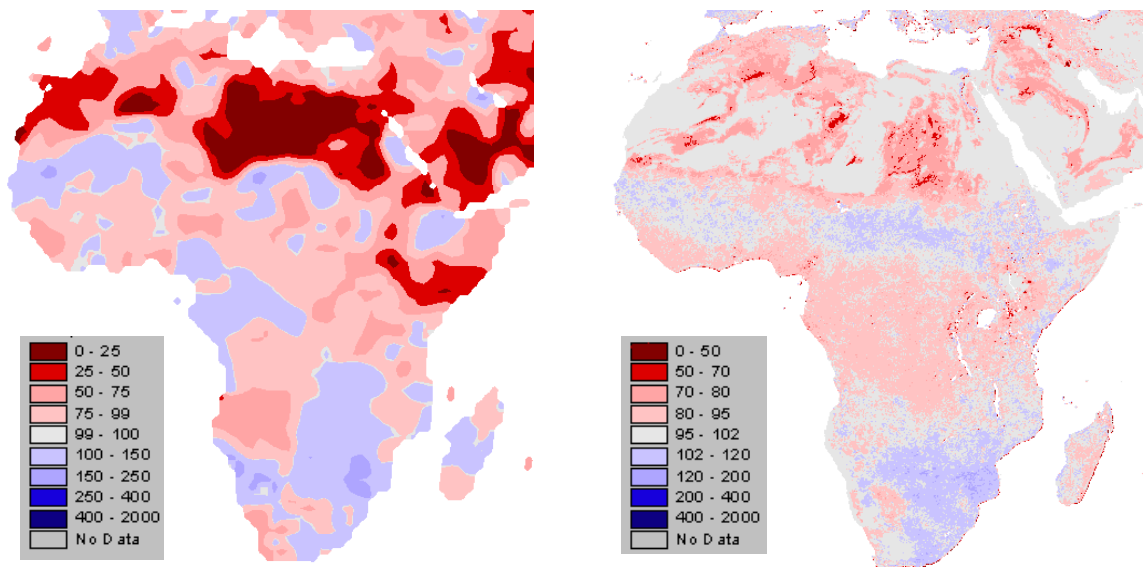


**Figure 4. Greenness Trajectories.** Vegetation greenness trajectories are depicted for three regions. Average and one standard deviation trajectories (green) are displayed with 1996 (red) and 2000 (blue) trajectories. The phenology of Midwestern corn, North China grasslands, and Nile delta double cropping are apparent.

calculated for any time period of interest (month, quarter, year, etc.) by simply adding the reported monthly precipitation over the period of interest. Hence, annualized deficits or seasonal deficits can be examined by comparing loadings to commensurate average loadings. Departures from normal are summarized as percentiles and quantized into intervals expressing departures from normal for purposes of display and comparison to structural water risk surfaces. Optionally, anomaly computations may be scaled by variance to reduce signals where variability may normally be expected.

Development of vegetation cover is approximated using features derived from the NOAA Advanced Very High Resolution Radiometer (AVHRR). The NASA/NOAA AVHRR Land Pathfinder Data Set provides a twenty-year radiometric record of every eight by eight kilometer grid cell on terrestrial surfaces with postings for each ten-day interval. Data are composed from daily AVHRR collections over the ten-day period to provide a relatively cloud free representation of terrestrial surfaces of the whole Earth. In addition to cloud free representation, the data are geometrically corrected and conditioned to minimize effects such as sun angle and viewing angle by NASA's Goddard Space Flight Center (GSFC). Postings are available over the Internet from Goddard's Distributed Active Archive Center for each ten-day period within one month of the date of scene acquisition (GSFC, 2002).

AVHRR collects data in both reflective and emissive regions of the electromagnetic spectrum. Two measurements in the reflective region, one in the visible region and one in the near infrared region, are particularly responsive to soil color and the presence of vegetation. Two vegetation features are derived from these two measurements: vegetation greenness (the difference between the infrared and visible values) and normalized greenness (known as the normalized vegetation difference index or NDVI).



**Figure 5. Precipitation and Vegetation Anomalies.** Precipitation deficits over the one-year period from January to December 2000 can be compared to cumulative vegetation deficits over the same period.

NDVI is computed by scaling vegetation greenness by the sum of the two measurements (this value is pre-computed by GSFC and made available with original AVHRR measurements). Figure 4 illustrates one-year trajectories of vegetation greenness for three areas, each depicting useful characteristics of the phenological development pattern of the vegetation within each grid cell. Users may choose to examine either NDVI or Greenness as a matter of preference. NDVI is reputed to be less sensitive to calibration and other viewing geometry and atmospheric effects, while greenness provides a more linear approximation of biomass throughout the entire vegetation development cycle.

To estimate changes in vegetation development, average vegetation indices are computed for each ten-day interval using time series data dating back to 1981. The vector of average monthly precipitation forms a reference for every grid cell in terrestrial regions. The monthly variance is also computed to illustrate regions where greenness deficit in any given month is likely to occur. Departures from normal vegetation can be computed for any location on Earth, for any reported time period. Temporal accumulation of greenness signals has been shown to be well

correlated to net primary productivity (NPP), itself an indicator of total biomass. We make the assumption that loss in net primary productivity indicates potential loss of fruit production in the plant system.

Cumulative greenness can be easily calculated for any time period of interest (month, quarter, year, etc.) by simply adding the computed index over the period of interest. Hence, annualized deficits or seasonal deficits can be examined by comparing cumulative vegetation realized in a given period to commensurate average cumulative greenness. However, the vegetation greenness metric (either NDVI or Greenness) is influenced by soil color and condition. So in low vegetation cover conditions deviations may be less well correlated to changes in vegetation cover. As a result, departures from normal are modified with a multiplier whose value is zero for values of average greenness up to the estimated “soil line” (discounting any detected difference); one for values that exceed an estimated greenness value associated with about fifty percent vegetation cover; and the cube root of greenness between those two extremes. Departures from normal are summarized as percentiles and quantized into intervals expressing percentage departures from normal for purposes of display and comparison to structural water risk surfaces. Optionally, anomaly computations may be scaled by variance to reduce signals where variability may normally be expected. Figure 5 provides an illustration of precipitation and vegetation departures from normal over the African Continent in 2001.

### **Estimating Social Capacity**

Societies mitigate exposure to environmental risk by building social capacity to accommodate and deal with that risk. Societies that lack arable land will trade for food by building industry and products that are of value to food producers. In turn they invest in education and health to insure a competent work force to build the needed products. Various studies have noted that factors such as infant mortality, trade openness, and governance are important indicators of state failure, and premises statistical models on such factors (SFTF, 2000). When negative values of such factors are present in combination with high values of food or water risk, short of failing, the society may lack the wherewithal to mitigate the problem that it confronts and may suffer other consequences. One may also assume that positive social capacity does provide means to mitigate structural scarcities, that abundance is compromised by lack of capacity, and so on. Such indicators provide a useful means to visualize social capacity. GI attempts to provide a sub-national depiction of social capacity and is constructed primarily around four key indicators: national governance, technical infrastructure, local wealth, and income disparity (though one may substitute any number of other indicators using a tool that builds a capacity map). Governance and income disparity are two measures available only at national level. Income disparity is particularly problematic. Notwithstanding the ambiguities associated with the term “wealth”, local wealth is estimated by disaggregating reported national level GDP using first order approximations of the industries and resources that most likely generate wealth. Infrastructure intensity is also estimated using surrogate measures such as transportation networks.

*Governance:* The World Bank publishes a set of Aggregate Government Indicators for nations of the world that include six factors: vice and accountability, political instability and violence, government effectiveness, regulatory burden, rule of law, and graft (Kaufmann, 1999). A principal component analysis of the factors revealed that 80 percent of the variability among measures is explained by the average of all six indicators. Hence, the average of these government factors is used to provide a metric of governance.

*Technical infrastructure:* A disaggregated representation of infrastructure capacity is generated by computing a transportation and industrial intensity (or infrastructure density) surface based on estimates of industrial density derived from persistent lights data and depictions of road, rail, and airports from the DMA Digital Chart of the World, and night lights. (See Cicone, 2001 for further explanation.)

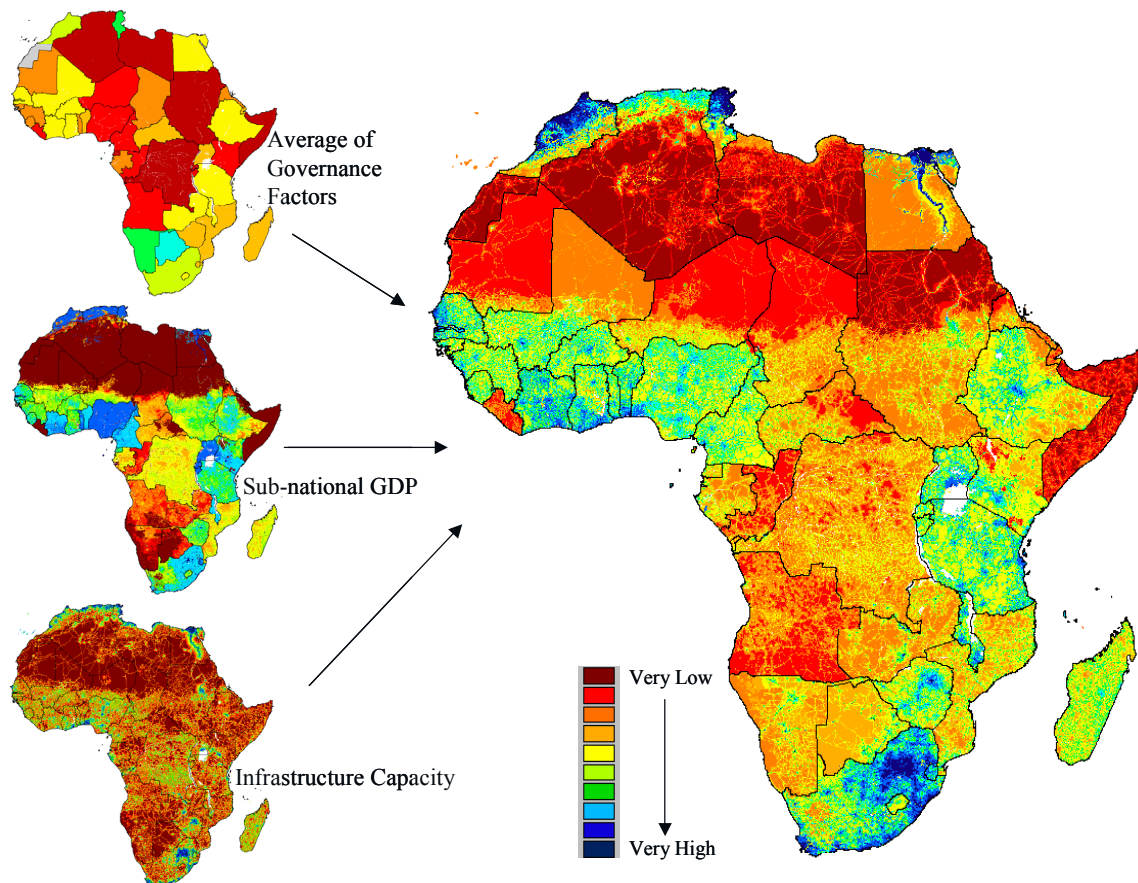
*Distributed GDP:* Gross domestic product is reported in the World Bank’s World Development Indicators for the industrial, domestic and agricultural sectors of the world’s nations. Population, land cover, agricultural primeness, and persistent lights (a surrogate for industrial infrastructure) are used to allocate GDP according to income generating units.

*Income Disparity (GINI):* Income distribution surveys, often reported as GINI indices, are generally local or national surveys. No single index exists that estimates GINI for all nations of the world due to the complexity of designing a survey of such a magnitude. The UN University World Institute for Development Division for Economic Research has published a collection of over 3000 income surveys reported in the last several decades (WIDER, 2000). By grouping surveys of similar design, estimates of income disparity were produced for many nations of the world. Because of the lack of consistent data, the index was not directly introduced into the capacity indicator. However, the index was used to differentiate buying power of different nations in algorithms that estimated food distribution alternatives. GINI remains a critical, though apparently unattainable, parameter in estimating social capacity.

Figure 6 illustrates the scheme employed to combine social capacity indicators into a single metric. In the absence of the availability of a rigorous model to guide the construction of the metric, the three available indicators were combined with equal weights. Provided software tools allow analysts to substitute or include additional indicators and modify weights.

## RESULTS

Using the conceptual models described above, we performed an integrated assessment of the risk and likelihood of food emergencies in Africa. This assessment was performed using a "convergence of evidence" methodology. This method uses *a priori* knowledge about how each indicator is likely related to food emergencies. Using this knowledge, we recast the indicators to a common scale in which 10 is the "best" possible value (the value least likely to be related to food emergencies) and 0 is the "worst" possible value (the value most likely to be related to food emergencies). Table 1 summarizes the indicators used in the integrated assessment, and the *a priori* direction of the scale assigned to each indicator. We then combined the individual indicators into overall scores using two structural models and one dynamic model. The first structural model assumed an additive relationship between vulnerability and capacity, whereas the second assumed a multiplicative relationship. The dynamic model used annual precipitation anomalies as the stress variable.



**Figure 6. Social Capacity.** Governance, disaggregated GDP, and Infrastructure Intensity are combined with equal weight to provide a representation of social capacity in regions of continental Africa. Somalia, Angola, Liberia, and nations of the Sahel will likely be less resourceful than South Africa, Egypt, Morocco, and other nations that exhibit greater social capacity to deal with environmental scarcities.

## Estimation of Risk and Likelihood of Food Emergencies

We define risk to be the vulnerability to food insecurity mitigated by the social capacity to cope with risk. Likelihood considers dynamic factors Additive and multiplicative relationships were examined. The additive structural model is based on the assumption that *either* high vulnerability or low capacity is associated with the regional frequency of food emergencies. Hence, risk was modeled as the sum of vulnerability and capacity. Vulnerability was computed as the sum of the rescaled food and water balance indicators, and capacity was computed as the sum of the rescaled governance, GDP/capita, and infrastructure intensity variables.

The multiplicative model is based on the alternative assumption that that regions with *both* high vulnerability and low capacity are at greatest risk. The idea is that capacity to prevent food emergencies only comes into play in regions that are vulnerable to begin with. Hence, in this model risk is modeled as the product of vulnerability and capacity where vulnerability and capacity are computed as above.

Estimating likelihood begins with the risk (either additive or multiplicative) and adds in stress variables (precipitation anomalies and/or vegetation anomalies). Illustrative results for the year 2000, using the additive structural model and precipitation anomalies, are shown in Figure 7. The upper left figure illustrates the additive vulnerability to food and water insecurity. Variability due to precipitation This assessment of likelihood works reasonably well for the drought driven food emergencies in East Africa, but misses flood driven food emergencies in Southern Africa (e.g., Malawi and Mozambique). This result led us to evaluate quadratic – or "U" shaped relationships – for precipitation and vegetation anomalies that proved to be a better predictor (Parris, 2002).

Category	Indicator	Direction of Scale
Vulnerability	Food balance (including imports) relative to 2K-calorie/capita demand.	Surplus is "good" (10) Deficit is "bad" (0)
	Water balance (normalized to 3 <sup>rd</sup> level watershed)	Low utilization is "good" High utilization is "bad"
Capacity	Governance	Good government is "good" Bad government is "bad"
	Wealth (GDP/capita)	High wealth is "good" Low wealth is "bad"
	Infrastructure Intensity	Easy access to infrastructure is "good" Difficult access to infrastructure is "bad"
	Annual Precipitation Anomalies	Normal or above normal precipitation is "good" Deficit relative to normal is "bad"
	Annual Vegetation Anomalies (not used in this step)	Normal or above normal vegetation is "good" Deficit relative to normal is "bad"

**Table 1: Summary of Indicators Used in Integrated Assessment**

## CONCLUSIONS

We have described a method to assess the risk and likelihood of food and/or water insecurity based on an assessment of vulnerability, stress and capacity factors that determine a society's ability to produce, acquire and distribute food supplies. The model is based on a geospatial analysis of factors ranging from topography, land use, vegetation growth patterns to governance and wealth. The study resulted in the ability to illustrate regions at risk at continental scales. The overall performance of the model in identifying risk and likelihood indicators for historical

food emergencies. over continental Africa is described elsewhere (Parris, 2002). Those results indicate significant promise for extending the model globally.

Future development of GI will benefit from the availability of refined data that are being derived from remote sensing. For example, GeoCover – Land Cover (Cunningham, 2002), will provide a means to describe land cover at improved scales. A preliminary version of GeoCover–LC for continental Africa revealed promise in this application by aggregating land cover classes to one-kilometer resolution providing a percentage land use scale per pixel. The decay of the POES AVHRR series has left a gap in coverage of vegetation data since September 2001. The use of MODIS is feasible, but will require inter-calibration of the two data sets in order to take advantage of the existing twenty year history of the AVHRR Land Pathfinder data set.

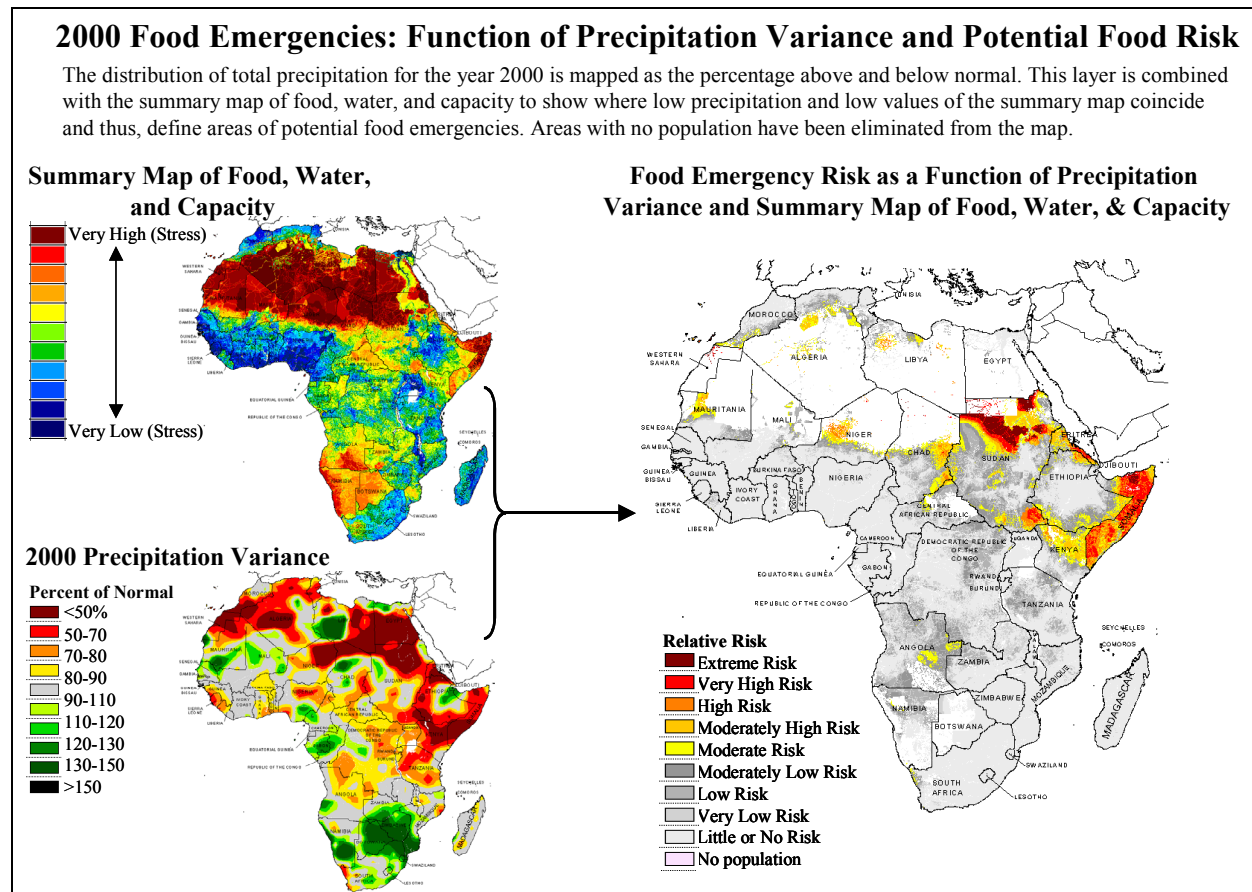


Figure 7. Integrated Assessment of vulnerability, risk and social capacity.

## REFERENCES

- Alcamo, J., Endejan, Kaspar, Rosch (1999). "The Glass 1 Model: A Concept for Global Modeling of Environment and Security", 1999 Open Meeting of Human Dimensions of Global Environmental Change Research Community, Kanagawa, Japan.
- Cicone, R., D. Way, J. Metzler, J. Miller, D. Cunningham (2001). Geospatial Indicators: Assessing Risk of Food and Water Insecurity, ISciences Technical Report, MI\_USA.
- Consultative Group on Sustainable Development Indicators (CGSDI) (2001). The Dashboard of Sustainability (Version 2.0). Winnipeg, Canada: International Institute for Sustainable Development. [On-Line] Available:<<http://iisd1.iisd.ca/cgsdi/dashboard.htm>>

Cunningham, D (2002). "GeoCover LC - A Moderate Resolution Global Landcover Database." 2002 ESRI User's Conference Proceedings.

Esty, D., J. Goldstone, T. Gurr, B. Harff, M. Levy, G. Dabelko, P. Surko, A. Unger (1999). "State Failure Task Force – Phase II Findings", Woodrow Wilson Center Environmental Change and Security Project, Issue 5. International Institute for Sustainable Development (IISD). (2000). Compendium of Sustainable Development Indicator Initiatives and Publications. [On-Line]. Available: <<http://iisd.ca/measure/compindex.asp>>.

Global Precipitation Climatology Center (GPCC) (2002). Gridded datasets of monthly total precipitation. [On-Line] Available: <<http://www.dwd.de/research/gpcc/e06.html>>.

United Nations Development Program (2001). *Human Development Report, 2001*. [On-Line] Available: <<http://www.undp.org/hdr2001/>>.

Kates, R. W., W. C. Clark, R. Corell, J. M. Hall, C. C. Jaeger, I. Lowe, J. J. McCarthy, H. J. Schellnhuber, B. Bolin, N. M. Dickson, S. Faucheux, G. C. Gallopin, A. Gruebler, B. Huntley, J. Jäger, N. S. Jodha, R. E. Kasperson, A. Mabogunje, P. Matson, H. Mooney, B. Moore III, T. O'Riordan, and U. Svedin (2001). "Sustainability science." *Science* 292:641-42.

Kaufmann, D., A. Kraay, and P. Zoido-Lobaton (1999). "Governance Matters." World Bank Working Paper No. 2196. [On-Line]. Available: <<http://econ.worldbank.org/view.php?topic=13&type=5&id=919>>

Loneragan, S., Gustavson, Carter (2000). "The Index of Human Insecurity", Aviso, International Human Dimensions Program on Global Environmental Change, Issue 6. [On-Line] Available: <<http://www.gechs.org/aviso/AvisoEnglish/six.shtml>>

Miller, J., D. Cunningham, G. Koeln, D. Way, J. Metzler, R. Cicone (2002). Global Database for Geospatial Indicators, Proceedings of the Pecora 15/Land Satellite Information IV Conference/ISPRS Commission I Mid-term Symposium.

NASA Goddard Space Flight Center (GSFC) (2002). Normalized Difference Vegetation Index (NDVI) and AVHRR channel radiance data sets, 1981-present, [On-Line]. Available: <[http://daac.gsfc.nasa.gov/CAMPAIGN\\_DOCS/LAND\\_BIO/GLBDST\\_Data.html](http://daac.gsfc.nasa.gov/CAMPAIGN_DOCS/LAND_BIO/GLBDST_Data.html)>.

Parris, T., D. Way, S. Manley, R. Cicone, S. Metzler (2002). Geospatial Indicators: Integrated Assessment of Food Security in Africa, ISciences Technical Report, MI-USA.

Parris, T., D. Way, J. Metzler, R. Cicone, S. Manley, S. Metzler (2002). Integrated Assessment of Food and Water Security Using Vegetation and Precipitation Anomaly Detection, Proceedings of the Pecora 15/Land Satellite Information IV Conference/ISPRS Commission I Mid-term Symposium.

Prescott-Allen, R. (2001). *The Wellbeing of Nations: A Country-by-Country Index of Quality of Life and the Environment*. Island Press (Washington, DC).

United Nations Division for Sustainable Development (UNSD) (2001). Indicators of Sustainable Development: Framework and Methodologies. Background Paper No. 3 for the Ninth Session of the Commission on Sustainable Development (New York, 16-27 April 2001). DESA/DSD/2001/3. [On-Line]. Available: <[http://www.un.org/esa/sustdev/csd9/csd9\\_indi\\_bp3.pdf](http://www.un.org/esa/sustdev/csd9/csd9_indi_bp3.pdf)>

US Agency for International Development (USAID) (2002). Famine Early Warning System Network (FEWS NET). [On-Line]. Available: <<http://www.fews.net/>>.

World Institute for Development Economics Research (WIDER) (2000). *World Income Inequality Database V1.0*. [On-Line] Available: <<http://www.wider.unu.edu/wiid/wiid.htm>>.

World Economic Forum (WEF) (2002) 2002 Environmental Sustainability Index. Global Leaders for Environment Tomorrow Task Force. World Economic Forum: Annual Meeting 2002. [On-Line]. Available: <<http://www.ciesin.columbia.edu/indicators/ESI/>>

World Wildlife Fund for Nature (WWF) (1998). Living Planet Report 1998: Overconsumption is driving the rapid decline of the world's natural environments. Gland Switzerland, WWF International. [On-Line]. Available: <<http://www.panda.org/livingplanet/lpr/>>