

# INTEGRATED ASSESSMENT OF FOOD AND WATER SECURITY USING VEGETATION AND PRECIPITATION ANOMALY DETECTION

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## ABSTRACT

The AVHRR Pathfinder database and the Global Precipitation Climatology Center gridded precipitation database are coupled to estimate global patterns of vegetation and precipitation stress. These patterns are incorporated in a Geospatial Indicators model to identify the risk and likelihood of food emergencies. An anomaly detection tool estimates stress relative to historical averages for any period of time. The anomaly surfaces, available for any location on Earth, are coupled with estimates of vulnerability to food and water insecurity to estimate the risk to which a population is exposed as a result of drought, or other conditions that may affect food production. This paper explores research undertaken to evaluate results using vegetation metrics with precipitation anomaly estimates and other measures of carrying capacity in an integrated assessment of exposure to food and water insecurity based on the Geospatial Indicators model. Using food emergency statistics reported by the UN Food and Agriculture Organization, eighty percent of African food emergencies over a 12-year period were correctly identified with an 11 percent false alarm rate.

## 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; Cicone, 2002; and Miller, 2002). 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 an eleven percent false alarm rate (Parris, 2001). These results demonstrate the plausibility of these indicators for monitoring food and water stress.

### Indicator Descriptions

Food balance was computed as the difference between the local supply and demand for food. Supply was estimated using a model of distributed imports and an estimate of local food production. Demand is estimated using a minimum threshold of 2,000 calories per person weighted local population density. The result is the imbalance between local food supply and demand. Regions in which there is a deficit are assumed to be more vulnerable to food emergencies.

Water balance was computed as the difference between the local supply and demand for freshwater. Water supply was estimated using a block parameter hydrological model estimating fresh water loading as a result of average annual precipitation, expressed for each third level watershed. Demand is estimated using reported average domestic, industrial, and agricultural consumption rates. Regions in which freshwater consumption relative to supply is large are assumed to be more vulnerable to food emergencies.

Governance is computed as the average of six indicators published by the World Bank (Kaufmann, 1999): vice and accountability, political instability and violence, government effectiveness, regulatory burden, rule of law, and graft. 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. "Good" governments – defined as those with low vice, high accountability, low instability and violence, high effectiveness, low regulatory burden, strong rule of law, and low

graft – are assumed to have more capacity with which to overcome short-term stressors and prevent food emergencies.

Infrastructure intensity was created using a cartographic model that defines the relative access of each square kilometer to central places and transport infrastructure. The model parameters consider proximity to rail, roads, and settlements. The relative density of the road and rail pattern also weights their proximity. For example, areas of multiple roads intersecting have a greater service potential than just two roads intersecting. Cities and settlement patterns are sorted by size into five different classes by area using a combination of lights at night and Digital Chart of the World settlement areas. Larger urban areas exert a greater and more highly weighted proximity effect than small settlements. The resulting indicator measures the relative accessibility to combined infrastructure. Regions with relatively easy access to infrastructure are assumed to have more capacity with which to overcome short-term stressors and prevent food emergencies.

To estimate changes in precipitation, average monthly precipitation is computed using time series data dating back to 1986 (GPCC, 2002). Precipitation anomalies are computed as the ratio of the current year precipitation compared to the average precipitation over time. Regions with low precipitation relative to the historical average are assumed to be under greater stress. The monthly variance is also computed to illustrate regions where a deficit in any given month is likely to occur. Precipitation loadings (total precipitation) can be easily calculated for any time period of interest by simply adding the reported monthly precipitation.

Vegetation anomalies are computed as the ratio of the current year vegetation as measured by the Advanced Very High Resolution Radiometer (AVHRR) satellite sensors, compared to the average vegetation over time (GSFC, 2002). Regions with low vegetation relative to the historical average are assumed to be under greater stress. 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. Cumulative greenness is calculated for any time period of interest by adding the computed index over that period. Annualized or seasonal deficits are examined by comparing cumulative vegetation in a given period to average cumulative greenness.

## METHODS

To evaluate the performance of GI, we undertook a statistical analysis of indicators of risk, which examines inherent structural components of natural and social capacity such as climate, and indicators of likelihood, that consider dynamic factors such as weather. The structural component of our analysis 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 capacity and social dependence. The dynamic component then adds factors based on precipitation and vegetation development that change rapidly over time in order to assess the likelihood a particular region will experience an undesirable event in a given year.

### Statistical Design

Two analysis methods are employed. The "convergence of evidence" method examines additive and multiplicative relationships of GI structural models, that is vulnerability and capacity, relative to the aggregate food emergencies over the twelve year period of available data. Convergence of evidence employs an unweighted, linear model that relies upon *a priori* knowledge of the directions for "good" and "bad" values of each indicator. The second set of analyses constructed statistical models to test our hypothesis regarding both the risk and likelihood of food emergencies in Africa. Such statistical models do not depend on *a priori* relationships and allow us to test both the structural and dynamic predictive capabilities of the indicators.

In order to assess the likelihood of food emergencies in Africa, we have applied these generic concepts as described in the following functional relationships:

1. *Likelihood*       $l_t = L(r, s_t)$
2. *Risk*               $r = R(v, c)$
3. *Vulnerability*     $v = V(f, w)$
4. *Capacity*          $c = C(e, t, g)$

Where:  $l_t$  = the likelihood of a food emergency in a given year (t);  
 $r$  = overall risk of a food emergency in terms of the number events crises per unit time;  
 $s_t$  = stress in a given year (t) (e.g., vegetation anomalies, precipitation anomalies);  
 $v$  = vulnerability to food emergencies;  
 $f$  = food balance (food availability – food demand);  
 $w$  = water balance (water availability – water demand);  
 $c$  = overall social capacity to respond to respond to food emergencies;  
 $e$  = economic capacity (e.g., GDP/capita);  
 $t$  = technical capacity (e.g., access to transportation infrastructure); and,  
 $g$  = quality of governance

The purpose of the integrated assessment was to evaluate alternative formulations for each of the functions ( $L$ ,  $R$ ,  $V$ ,  $C$ ) and indicators ( $s$ ,  $f$ ,  $w$ ,  $e$ ,  $t$ ,  $g$ ) against the recent historical record of food emergencies in Africa from 1990 through 2001. The models can be tested against this "reality" at two points. First, the computed value of  $r$  can be compared to the actual value as derived from the historical record. Second, the value of  $l_t$  can be compared to the historical record.

### **The Historical Record - Food Emergencies in Africa, 1990-2001**

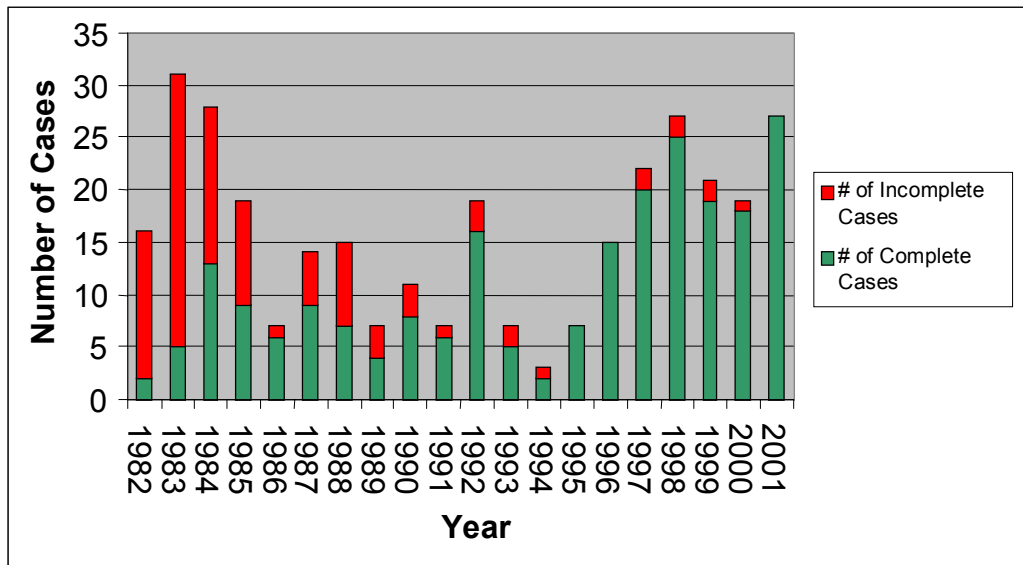
The Africa indicators effort modeled two primary vulnerabilities: food security and water security. These two vulnerabilities are most likely to be related to food emergencies – episodic shortfalls in the amount of food required to adequately feed the local population. Food emergencies generally require concerted humanitarian efforts of intergovernmental organizations (e.g., the World Food Programme), national donor governments (e.g., the U.S.), and private voluntary organizations (e.g., Oxfam) to avoid mass starvation.

In order to test the relationship between the GI modeled vulnerabilities and food emergencies, a database describing all known food emergencies on the African continent was constructed by coding (or recoding) data from the following sources:

1. *Food Supply Situation and Crop Prospects in Sub-Saharan Africa Special Report* (FAO-GIEWS, 1990-1995);
2. *Food Crops and Shortages Report* (FAO-GIEWS, 1996-2001); and,
3. EM-DAT: The OFDA/CRED International Disaster Database (CRED, 2001).

Food emergencies were defined by whether a population experienced hunger/starvation in distinguishable areas within each country for a given year. For instance, if a country experienced food emergencies in two geographically disjoint regions (e.g., the Northern-most province and the Southern-most provinces), then each emergency was recorded as a separate event. The year, database source, as well as the location, cause (i.e. drought, civil conflict, refugees, etc.), and total number of persons affected for a famine event was noted at the provincial level when possible.

The majority of the cases in the database originated from the EM-DAT maintained by Centre for Research on the Epidemiology of Disasters (CRED) at Université Catholique de Louvain. These events were verified by checking the cause of the famine, total number of persons affected, and location information with the FAO-GIEWS reports or by conducting a Lexis-Nexis Academic Universe News Wire search. Food emergencies not accounted for by CRED but reported by the FAO-GIEWS were added to the composite dataset. Figure 1 illustrates the number of reported food emergencies in Africa by year. The green portion of each bar indicates the number of cases for which we were able to construct complete descriptions. The red area shows the number of cases with incomplete descriptions. In order to reduce systematic biases due to incomplete information contained in cases from 1982 through 1989, the time period of the study was restricted to 1990-2001. The resulting dataset contains 189 individual food emergencies from 1990 to 2001.



**Figure 1: Food Emergencies in Africa 1982-2001**

These 189 food emergencies were then consolidated into multi-year events for a given region based on two criteria: (1) an event “ends” when there is one full year without famine and (2) the consecutive events occur in the same general area of the country. The magnitude for each consolidated event was the maximum of the total number of persons affected for all years of the event. Each consolidated event was geocoded by assigning both a central latitude/longitude and a bounding polygon constructed from the boundaries for one or more affected provinces. In order to provide some conceptual uniformity, the famine classes were grouped into 3 categories: (1) crop failure (drought, infestation, flood, fires, and other weather), (2) migration (refugees, returnees, internally displaced persons), and (3) conflict (international, civil). The consolidated famine event could therefore be represented by a total of eight famine classes since a given famine may fall into multiple categories. There were 91 consolidated multi-year events, each represented by a unique event ID. The result is pictured in Figure 2. In this figure, each region is shaded by the number of years it experienced food emergencies in the 12-year period from 1990 through 2001.

## RESULTS

Convergence of evidence based analysis reveals a strong correspondence between the aggregate food emergency events over the subject 12 year period and indicators of risk. Statistical models identified those factors that are most prominent and revealed the potential to predict specific food emergency events. These results are described in the following.

### Convergence of evidence

While GI uses both additive and multiplicative models, we restrict our discussion to the multiplicative form for convergence of evidence. That is we examine whether (vulnerability x capacity) is a predictor of the number of food emergencies to occur in any region. The multiplicative model shown in Figure 3 is based on the assumption that regions with *both* high vulnerability and low capacity are at greatest risk. Hence, risk was modeled as the product 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 computed model results were then validated against the historical record of food emergencies. This was accomplished by computing the average model score for the 12 non-contiguous regions defined by the frequency of food emergencies. The average model result for each region was then plotted against the number of food

emergencies (non-populated regions were excluded from the analysis). For example, the pixels in regions that did not experience any food emergencies received an average modeled risk score of approximately 28 (where high scores are considered "good"), whereas the pixels in regions that experienced 11 years of food emergencies received an average modeled risk score of approximately 13. A good model would show that regions with high risk (as computed by the model) would more frequently experience food emergencies. Figure 3 shows that this is indeed the case. A simple correlation between the average model result and the number of event-years resulted in an  $R^2$  of 0.72, with a strongly linear relationship depicted.

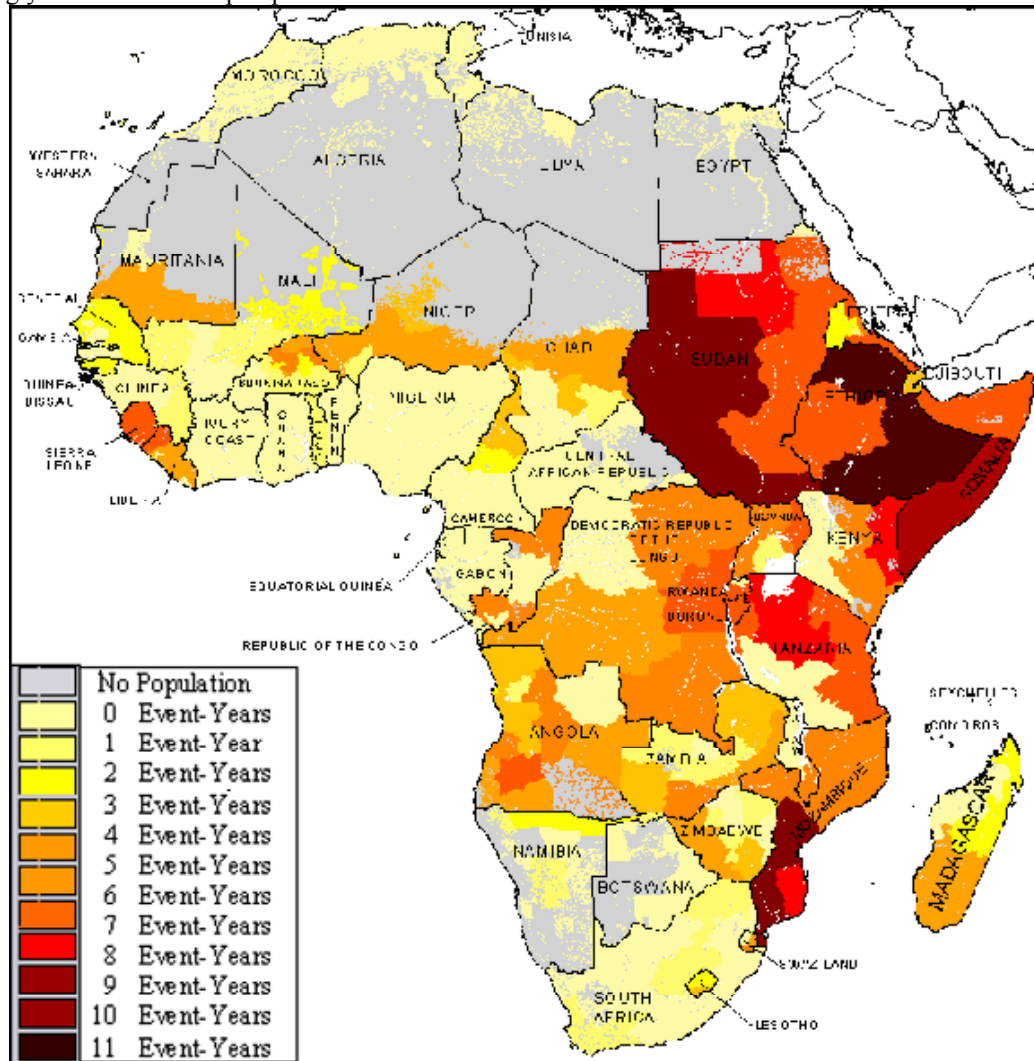


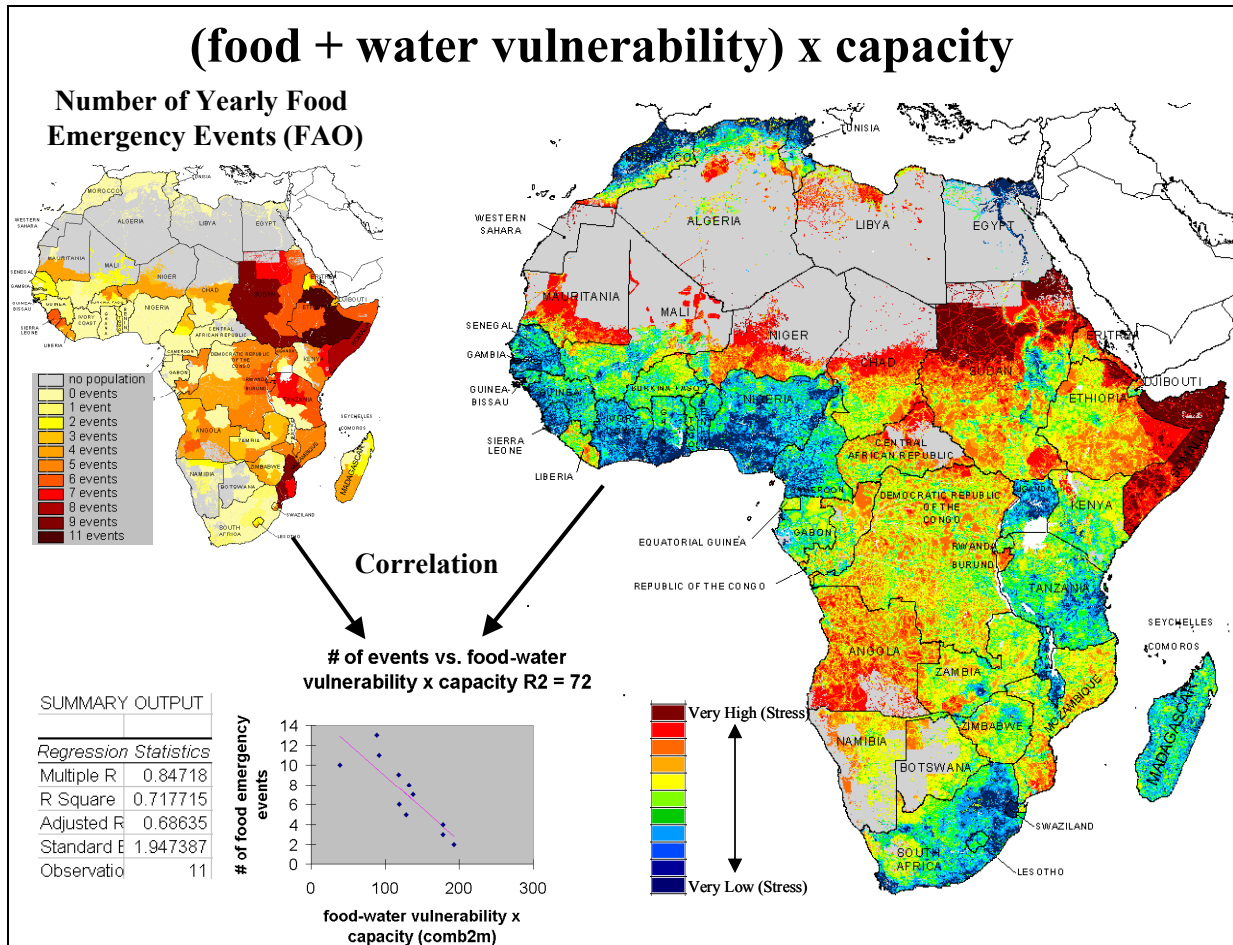
Figure 2. Incidence of Food Emergencies in Africa 1990-2001

### Statistical analysis of Structural Models

The statistical validation of the structural models uses 24km x 24km pixels as the basic unit of analysis. Africa GI data was aggregated from its native 1km x 1km structure using a median block filter (i.e., the value for each 24km x 24km pixel was computed as the median of its 576 constituent 1km x 1km pixels). The analysis excluded non-populated places (primarily the Sahara) because it is impossible to have a food emergency without people. We also excluded data within 16km of a national boundary to minimize the effect of alignment errors between the national boundaries contained in the Digital Chart of the World and the province boundaries contained in the ESRI Data & Maps collection. The resulting dataset contained 32,971 24km x 24km pixels.

The distribution of the number of years pixels experienced food emergencies during the period 1990-2001 was heavily skewed toward zero. Hence, all of the models described below use a modified dependent variable,  $d = \ln(nfe + 1)$ , where  $nfe$  is the number of years a given pixel experienced food emergencies during the period 1990-2001 as the dependent variable. Table 1 describes the independent variables tested in the models.

As with the "convergence of evidence" approach we tested two sets of models. The first set 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. The second set is based on the alternative assumption that regions with *both* high vulnerability and low capacity are at greatest risk. The latter proved more accurate.



**Figure 3. Multiplicative Convergence of Evidence**

The initial set of additive models tested all six concepts listed in table 1 using the three alternate variables for food balance. The best of these models used food balance relative to 2,000 calories/capita demand (imp2kcd) resulted in an  $R^2$  of 0.3709. This makes sense given that people who live on less than 2,000 calories per day are undernourished and most vulnerable to food emergencies. In contrast, the other two variables measure supply relative to national average consumption, and demand in surplus of 2,000 calories per day. While all variables are highly significant, this is to be expected given the large number of observations. What is curious is that GDP/capita (totgdpi) is much less significant than the other variables and positively correlated with the frequency of food emergencies. As a result, we tested a model without the totgdpi variable. This model had almost the same predictive value ( $R^2=0.3683$ ).

We then tested several models with a variety of interaction terms. These terms test the multiplicative relationships between the two components of vulnerability and the three components of capacity. The best model to emerge is summarized in Table 3. This model only adds one interactive term, the product of governance and food balance. This results in an  $R^2$  of 0.411. The interesting aspect of this model is that by adding the interaction between governance and food balance, the sign of the coefficient for governance by itself changes. This actually makes quite a bit of sense. Good government in the presence of an adequate food supply significantly diminishes the risk of a food emergency. However, a "good" government in the presence of an inadequate food supply is more likely to call upon the international community for assistance (by declaring a "food emergency") than a "bad" government.

| Category      | Concept        | Indicator   | Variable Name |
|---------------|----------------|---|---------------|
| Vulnerability | Food balance   | Food balance with imports, average national demand          | imp2keplUSD   |
|               |                | Food balance with imports, 2K-calory/capita demand          | imp2kcd       |
|               |                | Food balance with imports, 2K-calory+rising demand          | impnac        |
|               | Water balance  | Water balance normalized to 3 <sup>rd</sup> level watershed | inflowai      |
| Capacity      | Governance     | Average of 6 World Bank governance indicators               | governance    |
|               | Wealth         | GDP/Capita  | totgdp        |
|               | Infrastructure | Infrastructure intensity                                    | trans.acc     |

**Table 1. Independent variables tested in structural models**

The R2 of 0.411 reported above is expectedly less than that achieved using convergence of evidence, due to the granularity of analysis here. It is still a respectable result. However, it is even more impressive when considered in the context of the inherent errors in geocoding food-emergencies. The reporting of food emergencies is only specific to the province level. However, in many cases, the true extent of the food emergency is somewhat less than the full extent of the province (e.g., specific localities within the province). Given this degree of error in the geocoding, the R2 of 0.411 is even more significant.

```
Call: lm(formula = log(sof + 1, base = exp(1)) ~ inflowai + imp2kcd +
governance + trans.acc + (governance * imp2kcd), data = AfricaSub, na.action
= na.exclude)
Residuals:
  Min 1Q Median 3Q Max
-2.143 -0.507  0.1094  0.5066  1.946

Coefficients:
value          Std. Error t value Pr(>|t|)
intercept      2.7955      0.0310  90.1115 0.0000
inflowai      -0.0231      0.0005 -47.7394 0.0000
imp2kcd       -0.0408      0.0015 -27.9616 0.0000
governance     0.0333      0.0009  35.4521 0.0000
trans.acc     -0.0074      0.0005 -16.0955 0.0000
governance:imp2kcd -0.0023      0.0000 -48.8433 0.0000

Residual standard error: 0.6982 on 32965 degrees of freedom
Multiple R-Squared: 0.411
F-statistic: 4600 on 5 and 32965 degrees of freedom, the p-value is 0

Correlation of Coefficients:
intercept      inflowai imp2kcd governance trans.acc
inflowai      -0.4105
imp2kcd       -0.9338  0.1674
governance    -0.7087  0.0959  0.6954
trans.acc     -0.0834 -0.2141  0.0031  0.1949
governance:imp2kcd 0.7132 -0.0895 -0.7379 -0.9783 -0.2088
```

**Table 3. Baseline Structural Model With Interaction Terms**

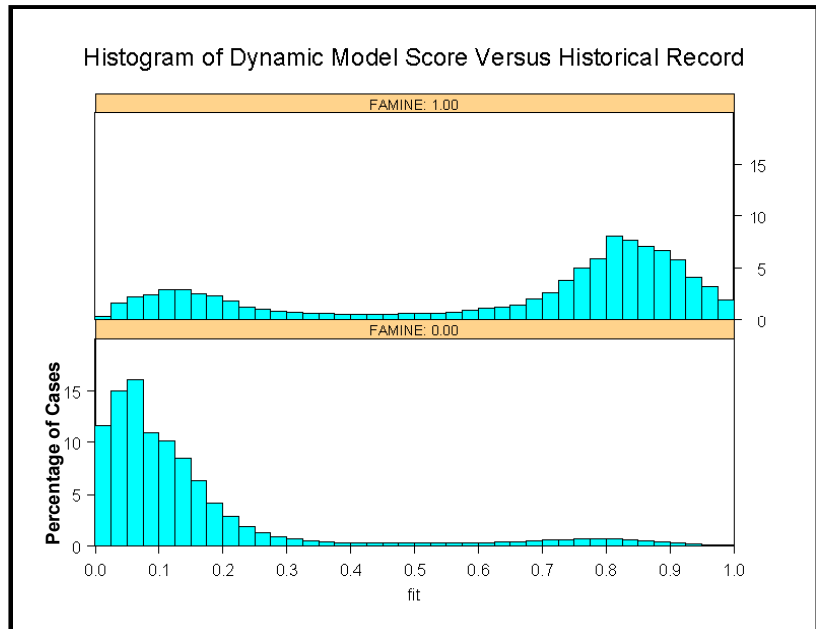
## Statistical Analysis of Dynamic Models

Once the baseline structural model, shown in Table 3, was established, we changed the goal of the modeling effort from predicting the frequency of food emergencies, to predicting the presence of a food emergency in a given year using logistic regression. In this modeling context, the unit of analysis is a pixel-year, where pixels are defined as the same set of 24km x 24km pixels used in the structural analysis. This yields a total of 395,652 observations (32,971 pixels x 12 years). In order to prove that these models are better than the simple default prediction that tomorrow will be like today, the baseline structural model was augmented to include a one-year lagged version of the dependent variable (LFAMINE). We then improved upon this baseline model by adding year-specific stress variables derived from precipitation anomalies and vegetation anomalies as summarized in Table 4.

Based upon our experience with the "convergence of evidence", the stress variables were tested using linear, quadratic and piece-wise linear functional forms. The first step was to find the best indicator/formulation for each concept (vegetation anomalies and precipitation anomalies) independently. The best indicator of vegetation anomalies to emerge from this analysis was current year vegetation as a fraction of the historical norm (GPCSTAVG1). The fact that the best fit used a quadratic form indicates that both vegetation deficits and vegetation surpluses create stress relative to food emergencies. At first glance this may seem counterintuitive. How can surplus vegetation contribute to food emergencies? Vegetation is not the same as agricultural productivity. The same environmental factors that may cause lush natural vegetation may be detrimental to agricultural production. Surplus vegetation anomalies are indicative of inter-annual environmental variability (e.g., El Niño, La Niña). If the agricultural communities are not prepared for these stresses, they will be likely to have planted the wrong crops at the wrong time and experience poor yields. Indeed, this is precisely why there is so much interest in developing reliable seasonal forecasts.

The best precipitation anomaly to emerge was the difference between current year precipitation and historical norms, measured in standard deviations (PNSTDDEV1). As with vegetation anomalies, this was best fit using a quadratic form. Just as too little precipitation (i.e. drought) creates food stress, so does too much precipitation (i.e. floods). This is precisely the situation encountered in Malawi and Mozambique in 2000.

A final model was then tested using both stress indicators (GPCSTAVG1 and PNSTDDEV1). Both stress variables retained their predictive power in this combined model summarized in Table 5. Figure 4 illustrates how this model performs relative to the historical record. The histogram at the top of this figure shows the distribution of the modeled likelihood for pixel-years that experienced food emergencies. As one would expect, the majority of the distribution is clustered at high model values. The histogram at the bottom of this figure shows the distribution of the modeled likelihood for pixel-years that did not experience food emergencies. Again, as one would expect, the majority of the distribution is clustered at low model values.



**Figure 4 Dynamic Model Score Versus Historical Record**

Finally, Table 5 illustrates the percentage of correct and incorrect classifications using an arbitrary cut point of 0.5. The final dynamic model correctly predicts 80% of the food emergency pixel-years and 89% of the no food emergency pixel-years. We hypothesize that most of the errors (missed predictions and false hits) are due to differences in the predicted and actual extents of food emergencies, rather than a failure to correctly capture the fact that an event occurred. This is likely given the fact that using province level boundaries almost certainly overstates the extent of many food emergencies. Even so, these results are encouraging and validate the concepts upon GI is based.

| Category | Concept                 | Indicator  | Variable Name |
|----------|-------------------------|--|---------------|
| Stress   | Vegetation Anomalies    | Current year vegetation as fraction of historical norm.  | GPCTAVG1      |
|          |                         | Difference of current year vegetation from norm, measured in number of standard deviations.    | GNSTDDV1      |
|          | Precipitation Anomalies | Current year precipitation as fraction of historical norm.                                     | PPCTAVG1      |
|          |                         | Difference of current year precipitation from norm, measured in number of standard deviations. | PNSTDDV1      |

**Table 4. Stress Variables Tested in Dynamic Models**

```

FAMINE ~ LFAMINE + imp2kcd + inflowai + trans.acc + governance +
imp2kcd:governance + poly(PNSTDDV1, 2) + poly(GPCTAVG1, 2)

Residual Deviance: 256884.7 on 362670 degrees of freedom

Terms added sequentially (first to last)
      Df      Deviance Resid. Df Resid. Dev
NULL              362680 440072.2
LFAMINE             1 151649.5      362679  288422.7
imp2kcd             1   8146.7      362678  280276.0
inflowai           1  2121.6      362677  278154.3
trans.acc          1  1052.7      362676  277101.6
governance         1   2954.6      362675  274147.0
poly(PNSTDDV1, 2)  2   7895.0      362673  266252.0
poly(GPCTAVG1, 2)  2   5905.4      362671  260346.6
imp2kcd:governance 1    3461.9      362670  256884.7

```

**Table 5. Dynamic Model Using Both Precipitation and Vegetation Anomalies**

| Historical Record        | Score<=0.5                         | Score>0.5                            | Score=NA        | Row Total        |
|--------------------------|------------------------------------|--------------------------------------|-----------------|------------------|
| <b>Food Emergencies</b>  | <b>Misses</b><br>30,441<br>(11%)   | <b>Correct</b><br>76,602<br>(80%)    | 6,835<br>(21%)  | 113,878<br>(29%) |
| <b>No Food Emergency</b> | <b>Correct</b><br>236,116<br>(89%) | <b>False Hits</b><br>19,522<br>(20%) | 26,136<br>(79%) | 281,774<br>(71%) |
| <b>Column Total</b>      | 266,557                            | 96,124                               | 32,971          | 395,652          |

**Table 6. Summary of Dynamic Model Results** (Percentages are column percentages)

## CONCLUSIONS

The Geospatial Indicators effort attempts to systematically model food emergencies over time for the continent of Africa based on independent evidence of the natural and social capacity of nations, modeled at a sub-national scale. Such efforts are important because they create tools with which the international humanitarian assistance

community can plan for, and possibly prevent, food crises in the future. The positive results of the validation exercise reported here points to the promise of deploying GI as a capability to guide analysts in their assessment of security issues that derive from perturbations in the availability of necessary food and water resources.

There were three key features to this analysis. First, it explicitly incorporates indicators of social, economic, and infrastructure capacity to respond to short-term stressors. Second, it distinguishes 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. Third, it relies solely on data that can, in principle, be produced on a global scale. This initial effort for continental Africa is, therefore, a proof of concept, for a global food emergency early warning system.

The results of this analytic framework are positive. Models based on the indicators were able to perform well in predicting both the *risk* (frequency over time) of food emergencies and the *likelihood* of a food emergency in a specific year. The best statistical model correctly predicts 80% of the food emergencies on a per pixel basis, and 89% of the no food emergency cases on a per pixel basis, providing a degree of validation to the overall GI concept.

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