

New Satellite Observations and Rainfall Forecasts Help Provide Earlier Warning of African Drought

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The poor nations of sub-Saharan Africa face a constant struggle against weather and climate. The outcome of that struggle profoundly influences these nations' economic growth, health, and social stability. Advances in climate monitoring and forecasting can help African nations and international aid organizations reduce the impact of these natural hazards. Satellites play a crucial role in this effort as they enable scientists to track climate conditions over data-sparse land and ocean areas. **In this article, I discuss how a multi-organizational group of scientists use satellite data and statistical forecasts to provide earlier and more accurate early warning of potential drought conditions.** We frame our discussion in a specific, timely context—that of probable dramatic food insecurity in Zimbabwe, Eastern Kenya, and Somalia. As this article was being prepared in mid-December, very warm conditions in the Indian Ocean appear likely to produce below normal December–January–February rainfall in both Eastern Kenya/Somalia and Zimbabwe.

Food Insecurity, Early Warning Systems, and Earth Observations

When the price of food spikes sharply—making food too expensive for poor people—famine conditions may result. These humanitarian disasters evolve slowly, and primarily take their toll by undermining nutritional condition, leading to outbreaks of disease and increased mortality. Acute malnutrition first strikes those with the most immediate and time-critical needs—such as pregnant and lactating mothers and their children. These *at-risk* populations are the first impacted by limited access to food [Natsios & Doley, 2009].

As the number of urban poor around the world rises rapidly and global grain prices soar due to increased

competition by biofuels and livestock, there has been a broad increase in three classic coping mechanisms: food hoarding, migration, and increased banditry. This expanding *food stress* disrupts societies and contributes to political unrest. Over the next decade, we are likely to see *food coups* emerge as modern counterparts to the famines of the past. While international aid, urbanization, remittances, and increasingly dense food markets are reducing the frequency of death from acute malnutrition, chronic and accelerating food shortages may contribute to rising political instability in many nations.

Early Warning Systems, such as the U.S. Agency for International Development's (USAID) Famine Early Warning Systems Network (FEWS NET), can help mitigate the political and humanitarian impacts of food shortages by identifying appropriate food, health, and market-related interventions. Satellite observations can contribute substantially to both the contingency planning and disaster response planning phases of FEWS NET (Figure 1), supporting decisions that save lives and lessen the impacts of drought. During the contingency planning phase, relatively uncertain information, such as climate forecasts [Funk et al., 2006] and climate indicators (Figure 1, Box A), can help guide scenario building and food security outlooks. This typically occurs before or during the early phase of the crop growing season. In the middle of the season (Figure 1, Box B), satellite rainfall fields may be used to monitor crop growing conditions. These simple water balance models use grids of rainfall and potential evapotranspiration [Verdin and Klaver, 2002; Senay and Verdin, 2003] to estimate whether sufficient soil moisture exists for crop growth. At the close of the crop growing season, satellite-observed vegetation may be used to assess crop production and/or yield [Funk and Budde, 2009].

Figure 1. FEWS NET Contingency Planning and Response Planning Schema. Adapted from www.fews.net. Inputs related to Earth observations are shown with shaded boxes.

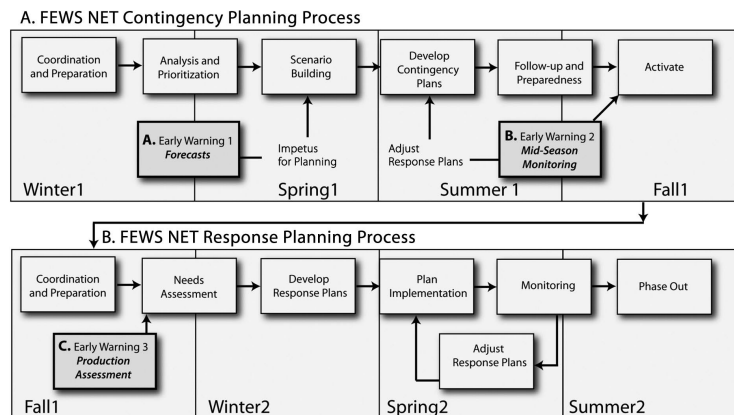


Table 1. Current food security situation and worst case scenario (from FEWS NET Executive Overview at www.fews.net)

Region	Current Food Security Situation	Potential Worst Case Scenario
Eastern Africa	“Fifteen to 18 million people are currently highly or extremely food insecure due to below-normal rains, poor crop and pasture production, civil conflict and insecurity, abnormally high food prices ... Near-normal October to December rains would improve livestock production, but high/extreme food insecurity would remain.”	“Below-normal October-December rains provide marginal, short-lived improvements in pasture and water availability in pastoral areas and crop failure in agro-pastoral areas of East Africa. The January-March dry season will thus be more severe than normal, reducing prospects for improvements in child malnutrition and overall food security.”
Zimbabwe	“Approximately four million people are food insecure in Zimbabwe due to poor 2008 harvests, slow progress of food imports, weak internal distribution, hyperinflation, high unemployment, shortages of foreign and local currencies, and political instability.”	“Over five million people will be dependent on emergency food assistance in Zimbabwe and, in the worst case, if commercial and humanitarian imports are inadequate, they could become highly food insecure. Maize planting is expected to be delayed and, in key cropping areas, followed by inadequate rainfall at critical growth stages.”

In this report we will focus on early-to-mid-season analysis of conditions late in 2008 in Eastern Kenya, Somalia, and Zimbabwe. While improved monitoring tools cannot compensate for inadequate *agricultural inputs* (i.e., seeds and fertilizer) or rainfall, they can help guide the early identification of agricultural drought—leading to more timely and effective intervention.

Current Food Security Conditions in Eastern Kenya, Somalia, and Zimbabwe

In December 2008, two highly food insecure regions are in the midst of their main growing seasons. Eastern Africa, following the twice-yearly passage of the sun, has two main growing seasons, known as the *long* and *short* rains and covering March-July and October-December, respectively. For Eastern Kenya and Somalia, the *short* rains tend to be the most important. Southern Africa, on the other hand, has a different climate, and typically has a single monsoonal rainy season, during the Southern Hemisphere summer (October–April). In this area, most of the moisture necessary for flowering and grain growth and, hence, successful harvests falls during the latter half of the rainy season (i.e., during December–January–February).

Both Eastern Africa and Zimbabwe currently face dangerous food availability challenges. Excerpts from a recent (November 26, 2008) FEWS NET Executive Overview are shown in **Table 1**. FEWS NET country-level analyses (based on reports by in-country food security analysts) indicate that Kenya faces unprecedented escalations in the price of corn (*maize*), the main food crop. In Ethiopia, significant price inflation has also occurred since 2007, and the southeastern Somali region is still extremely food insecure. In Somalia, October–November rains were near normal, but high prices and civil unrest persist. In Zimbabwe, poor harvests in 2006–07 and 2007–08 have combined with hard

currency shortages and outbreaks of cholera. Agricultural inputs for the current season are limited, and the pipeline of food aid may experience breaks in January. Availability of seeds and fertilizer has been very poor, almost ensuring very low crop production.

Monitoring the Current Climate

While rainfall is only one factor in a complex tableau of factors that influence global climate, it plays an important role in regulating the climate of Eastern and Southern Africa. Satellites help us monitor the climate by tracking atmospheric conditions over the Indian Ocean, which strongly influences rainfall in this part of the world. Using satellites, we can also estimate rainfall over land and observe vegetation responses in crop growing areas.

Before looking at the current climate anomalies (mid-December 2008), we need to briefly review *normal conditions* for the Indian Ocean. **Figure 2** shows satellite-observed Global Precipitation Climatology Project rainfall and surface winds for December–January–February. The rainy intertropical front typically stretches from Southern Africa east across the southern tropical Indian Ocean, with rainfall peaks near Indonesia and Madagascar. Across the northern Indian Ocean the monsoonal winds blow from north to south (black arrows pointing toward the Equator in **Figure 2**). Along the southern Indian Ocean steady easterly trade winds (another black arrow in **Figure 2**) bring moisture into Southern Africa, feeding the main rainy season. In recent years, surface winds have tended to flow southward (gray arrows in **Figure 2**), into the warming south-central Indian Ocean and away from Africa. We have suggested that this *warm south-central Indian Ocean* pattern is related to recent greenhouse gas-related global warming [Funk et al., 2008]. This climate shift tends to draw moisture away from Africa, reducing December–January rains in parts of Southern Africa and March–May rains in parts of Eastern Africa.

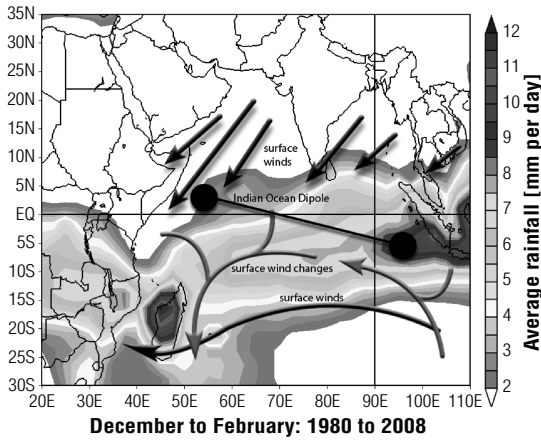


Figure 2. Average rainfall (shading) and surface wind conditions (black arrows) for December–January–February. Also shown are recent changes (1993–2007 minus 1979–2002) in surface winds. Images were obtained from the Climate Diagnostic Center.

The large connected black dots in **Figure 2** demarcate a second important source of climate variation in these regions: the *Indian Ocean Dipole*. When sea surface temperatures are relatively warm in the northwestern Indian Ocean and cold in the southeastern Indian Ocean, Eastern Africa is relatively wet and Southern Africa is relatively dry—and vice versa. Taken together, the *warm south-central Indian Ocean* and *Indian Ocean Dipole* patterns can tell us a lot about December–January–February rainfall in Eastern and Southern Africa. Some seasons, we shall see, are affected by warming in both the south-central and south-eastern Indian Ocean.

Satellite Observations of November Climate Conditions

As part of our ongoing research for USAID’s FEWS NET activity, the U.S. Geological Survey, and NASA, we have been using two new satellite data products to track moisture and wind conditions over the Indian Ocean and Africa. These new observations allow us to examine water vapor over the land and ocean, as well as the direction and speed of surface winds over the ocean. **Water vapor images tell us where the atmospheric water is, while surface wind observations over the oceans tell us where it’s going.** The combination helps

us understand *cause and effect*, and anticipate hydrologic conditions in the coming months.

The left panel of **Figure 3** shows water vapor observations from the Atmospheric Infrared Sounder (AIRS). Launched in 2002 aboard the Aqua satellite, AIRS provides 3-dimensional (3-d) maps of air temperature, water vapor, cloud properties, and greenhouse gases. Adding up all the water vapor from the surface to the top of the atmosphere gives us *total precipitable water*. This is the amount of liquid water that would fall to the ground if all the water vapor in the sky suddenly precipitated. To quickly compare different regions, we can express the total precipitable water vapor as standardized anomalies.

These are calculated by: i) subtracting the monthly inter-annual mean from the current monthly average; and ii) dividing the resulting anomaly by the inter-annual standard deviation. These maps, in units of *standard deviations* or σ , allow us to quickly identify abnormally wet and dry locations. Locations with more than $\pm 1\sigma$ are exceptionally wet or dry. In the left panel of **Figure 3**, dark areas indicate regions of below-normal water vapor while white areas depict areas with above-normal water vapor.

The right panel of **Figure 3** depicts November *surface wind anomalies* (i.e., observed monthly winds minus the average monthly observed winds) obtained from the SeaWinds scatterometer aboard NASA’s QuikSCAT mission. SeaWinds is a radar sensor used to measure the reflection or scattering from the surface of the world’s oceans. The instrument has been specially designed to retrieve surface wind direction and speed.

Putting the precipitable water and wind images together (as we do in **Figure 3**), we see strong moisture *convergence* to the east of Madagascar and to the north-west of Australia—meaning that the wind is acting to “pile up” moisture in these areas. Of particular interest are those anomalies near the equator (the equator is shown with a black line in **Figure 3**). Low-latitude anomalies have a strong influence on tropical Africa. The strong ($> +1\sigma$)

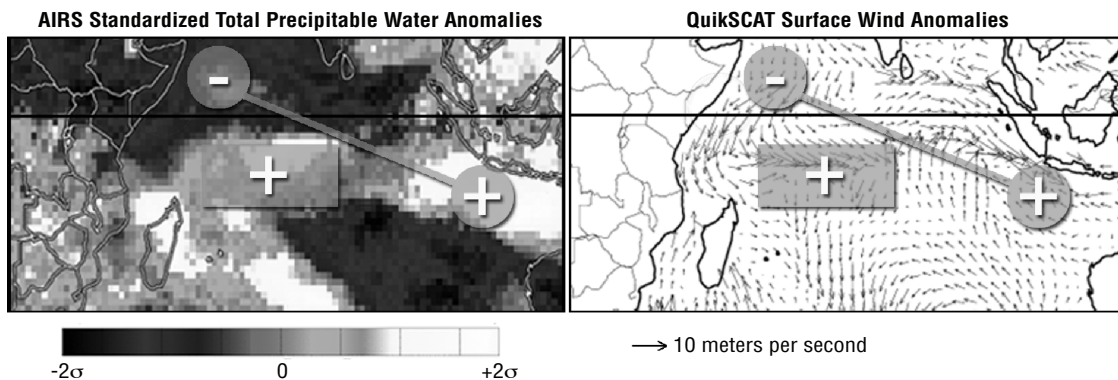


Figure 3. The panel on the left shows standardized November precipitable water anomalies from AIRS on Aqua. The panel on the right shows near-surface wind anomalies from SeaWinds on QuikSCAT. These data were mapped by Pete Peterson, University of California Santa Barbara.

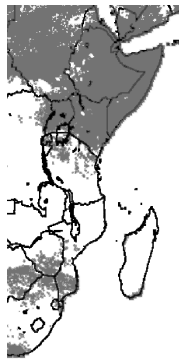


Figure 4. Shaded areas have November 17th–December 18th rainfall of less than 50% of normal. Source: www.cpc.noaa.gov.

precipitable water anomalies to the east of Madagascar (the gray boxes in **Figure 3**) correspond with a strong *warm south-central Indian Ocean event*, linked to drought across Southern Africa [Funk et al., 2008]. The strong ($> +1\sigma$) precipitable water anomalies to the north of Australia, combined with the -1σ precipitable water anomalies to the east of Kenya, correspond to a fairly vigorous Indian Ocean Dipole structure. **Thus, the above-normal moisture convergence in both the south-central and south-eastern Indian Ocean could result in below-normal rainfall for both Eastern Africa and Southern Africa.**

Over Eastern Africa, both the precipitable water image (see **Figure 3**) and recent satellite-observed rainfall (shown in **Figure 4**) have been very low ($<50\%$ of normal) across Kenya, southern Somalia, Uganda, and southern Ethiopia. For eastern Kenya, north-eastern Tanzania, and southern Somalia, the *short rainy season* has been diminished. Over Southern Africa, rainfall (shown in **Figure 4**) has been less than half of normal across the *drought alley* stretching across southern Mozambique, southern Zimbabwe, the northern portion of the Republic of South Africa's *maize triangle*, and into Botswana—see **Figure 4**.

A logical next question: *Are these dryness tendencies likely to persist?* To assess this risk, we turn to statistical rainfall forecasts, based on November rainfall data—i.e., using the conditions the month before December–January–February to estimate what will come.

The Matched Filter Forecast Technique

In remote sensing applications, *matched filters* are sometimes used to measure the strength of a given target signal [Funk et al., 2001]. In simple cases, the optimal filter

is very similar to a correlation calculation. Standardized versions of the data and the signal are multiplied against each other and normalized by a constant. Building on this concept (shown schematically in **Figure 5**), we can *filter* a set of climate fields—e.g., surface wind observations—to isolate variability associated with our “target of interest”. In this case, our “targets” are December–January–February rainfall in Zimbabwe and Eastern Kenya/Somalia. We use sea surface temperatures and winds and rainfall (obtained from www.cpc.noaa.gov) as our predictors. We next standardize the time series of predictors at each grid cell by first subtracting the mean and then dividing by the standard deviation. All predictors now have a mean of zero and a standard deviation of 1. Next, each predictor time series is scaled by its correlation with the target time series—i.e., either Zimbabwe or Eastern Kenya/Somalia rainfall. This dampens the variance of locations historically unrelated to our target. Finally, two standard statistical manipulations (*principal components* and *regression*) are then used to produce forecasts for all seasons. Accuracy assessments are carried out by *take-one-away cross-validation*. (This means that for the analysis of each year, November’s data are removed, the entire estimation procedure recalculated, and the corresponding December–January–February seasonal rainfall estimated.) This *cross-validation* provides a relatively unbiased way to assess forecast accuracy.

Figure 6 shows time series of our forecasts for Eastern Kenya, Somalia, and Zimbabwe for late 2008 and early 2009. The forecasts are based on November climate data. We have expressed the December–January–February totals as *Standardized Precipitation Index* (SPI) values, with an average of zero and an inter-annual standard deviation of 1. Values of $\pm 1\sigma$ indicate particularly good or bad seasons. **While the cross-validated forecasts do not catch every good and bad season, they do capture the sign of the rainfall anomalies, and have reasonably good skill, with a cross-validated forecast correlation of ~ 0.6 for both regions.** The standard error for both estimates is about ± 0.8 , indicating a modest level of precision sufficient to bracket the likely outcome. For both regions, the statistical forecasts for the 2008–2009 season are moderately pessimistic (about -0.5σ) with a level of uncertainty that embraces both well-below and slightly-above normal rainfall totals (see dark vertical bars at far right of each graph, indicating the 2008–2009 forecast).

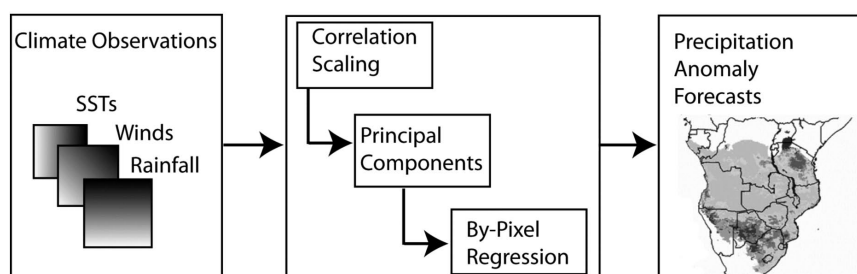


Figure 5. Matched Filter Forecast technique.

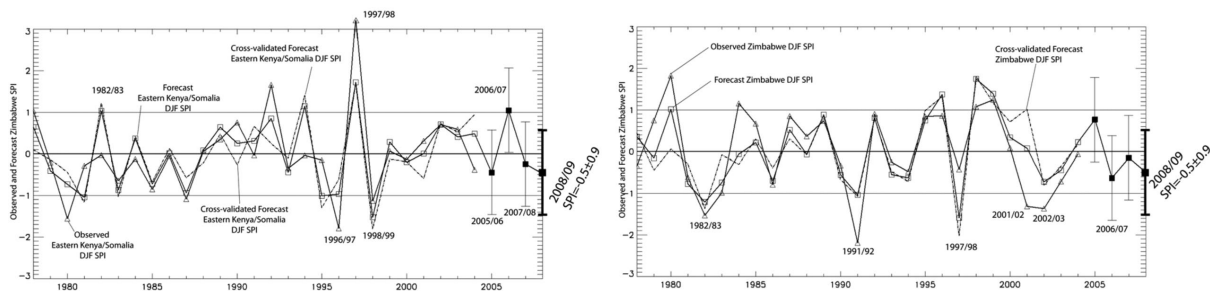


Figure 6. Time series of December-January-February rainfall totals for Eastern Kenya/Somalia (left panel) and Zimbabwe (right panel). Rainfall time-series are expressed in terms of the SPI with a mean of zero and standard deviation of 1. Observed data are marked with triangles, and end in 2004 or 2005. See Funk *et al.*, 2008 for details. Full matched filter forecasts are marked with boxes. Cross-validated estimates are shown with dashes.

Conclusions

While the future is always uncertain, we can learn from patterns of the past. As Mark Twain put it, “History doesn’t repeat itself, but it does rhyme.” Using a combination of satellite-based Earth observations and historic rainfall archives, we are slowly learning to reveal those patterns in climate and follow the complex interplay of mass and energy within tropical ocean-atmosphere dynamics. New observations of atmospheric water vapor and near-surface winds (Figure 3) help us watch the seasons reveal their character, and we can now peek ahead, making educated guesses about the next few months (Figure 5 and Figure 6).

When these forecasts and satellite-observed rainfall (Figure 4) are combined with in-country analyses of prices, grain stores, political conditions, and agricultural inputs, we can provide effective early warning of potential food shortages related to drought.

The food aid community has already mitigated the impact of very large droughts (such as that of 2002–03 in Ethiopia—an event similar in magnitude to the 1984–85 event that cost a million lives). While these are real and positive steps forward—putting Earth observations into service for the poorest nations on earth—we must remember that humanitarian crises are fundamentally caused by a failure of human institutions. True progress will require improving the agricultural capacity and early warning systems of these African nations. This will allow them to better harness the power of satellites, improving their food security and resilience. Rising food costs and drought induced by a warming Indian Ocean make these objectives increasingly important.

List of Related Web Sites

- eosps0.gsfc.nasa.gov/eos_observ/pdf/Nov_Dec08final.pdf: Previous article written by Molly Brown describing the Famine Early Warning System that appeared in the November–December 2008 issue of *The Earth Observer* [Volume 20, Issue 6, pp. 4–9].

- www.fews.net: Central FEWS NET website, where information from a large network of in-country observers and satellite observations is synthesized.
- earlywarning.usgs.gov: USGS web site containing satellite observations and crop/pasture model analyses.
- www.cpc.ncep.noaa.gov/products/fews/briefing.html: NOAA Climate Prediction Center website containing satellite rainfall and related weather analysis.
- www.cdc.noaa.gov: NOAA Climate Diagnostic Center, where reanalysis data are archived and climate conditions monitored.
- airs.jpl.nasa.gov/ and winds.jpl.nasa.gov/: NASA satellite websites describing the AIRS and QuikSCAT winds.
- www.pnas.org/content/105/32/11081.full.pdf+html: Link to our *Proceedings of the National Academies* paper on climate change and agricultural capacity trends.

References

- Funk, C. and M. Budde. 2009. Phenologically-tuned MODIS NDVI-based production anomaly estimates for Zimbabwe, *Remote Sensing of Environment*, 113 (1), doi:10.1016/j.rse.2008.08.015
- Funk, C., M.D. Dettinger, M.E. Brown, J.C. Michaelsen, J.P. Verdin, M. Barlow, and A. Hoell. 2008. Warming of the Indian Ocean threatens eastern and southern Africa, but could be mitigated by agricultural development, *Proc. of the Nat. Academy of Sci.*, 105: 11081–11086.
- Funk, C., Verdin, J., and Husak, G. 2006. Integrating observation and statistical forecasts over sub-Saharan Africa to support Famine Early Warning, American Meteorological Society (AMS) meeting, Extended Abstract.