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Corresponding Author	Family Name	**Funk**
	Particle	
	Given Name	**Chris**
	Suffix	
	Division	
	Organization	Research Geographer, USGS EROS/UCSB Geography
	Address	93106, Santa Barbara, CA, USA
	Email	funk.cc@gmail.com

Author	Family Name	**Verdin**
	Particle	
	Given Name	**Jim**
	Suffix	
	Division	
	Organization	Research Geographer, USGS EROS/UCSB Geography
	Address	93106, Santa Barbara, CA, USA
	Email	

Abstract

A multi-institutional partnership, the US Agency for International Development's Famine Early Warning System Network (FEWS NET) provides routine monitoring of climatic, agricultural, market, and socioeconomic conditions in over 20 countries. FEWS NET supports and informs disaster relief decisions that impact millions of people and involve billions of dollars. In this chapter, we focus on some of FEWS NET's hydrologic monitoring tools, with a specific emphasis on combining "low frequency" and "high frequency" assessment tools. Low frequency assessment tools, tied to water and food balance estimates, enable us to evaluate and map long-term tendencies in food security. High frequency assessments are supported by agrohydrologic models driven by satellite rainfall estimates, such as the Water Requirement Satisfaction Index (WRSI). Focusing on eastern Africa, we suggest that both these high and low frequency approaches are necessary to capture the interaction of slow variations in vulnerability and the relatively rapid onset of climatic shocks.

Keywords (separated by '-') Early warning - Drought - Food security - Climate change - Crop modeling - Hydrology

Real-Time Decision Support Systems: The Famine Early Warning System Network

Chris Funk and Jim Verdin

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Keywords Early warning · Drought · Food security · Climate change · Crop modeling · Hydrology

1 Introduction

The rhythms of plant emergence, vegetative increase, reproduction, and grain filling still dominate and organize the activities of half the world. Cycles of good, bad, and intermediate harvests continue to help shape the fate of nations. Cycles of recurrent bad harvests punctuated by a few seasons with good harvest continue to aggravate the fate of developing countries. In many developing nations, coping with hydrologic extremes is equivalent in cost and potential outcome to war (Kates 2000). The

C. Funk (✉)
Research Geographer, USGS EROS/UCSB Geography, USA, Santa Barbara, CA, 93106
e-mail: funk.cc@gmail.com

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impacts of drought are not limited to the poorest nations. Even though only 2% of the Republic of South Africa's GDP is based on agriculture, season rainfall totals are tightly coupled to economic growth, with a correlation of 0.7 (Jury 2002). In the United States, severe drought years, such as 2002, may result in billion dollar losses. Global per capita water supplies will likely drop by a third over the next 20 years (WWD 2003), and 2 to 7 billion people may face chronic water shortages by 2050. Food crises (Natsios and Doley 2009) will continue to emerge as the world's population grows faster than crop yields (Funk and Brown 2009); per capita cereal production peaked in 1986 and will likely decline by 14% over the next 20 years. In Kenya, it's estimated that arable land is declining by 2% per year due to population growth and human settlements in key agricultural areas. This figure is very likely to increase with declining rainfall trends and associated land degradation (personal communication). At present, 1 billion people in 50 nations face chronic food shortages, with 20% or more of that population undernourished (FAO 2007). Food security early warning systems seek to mitigate shocks to these vulnerable populations. This chapter briefly discusses the work of one such system: the US Agency for International Development's Famine Early Warning Systems Network (FEWS NET).

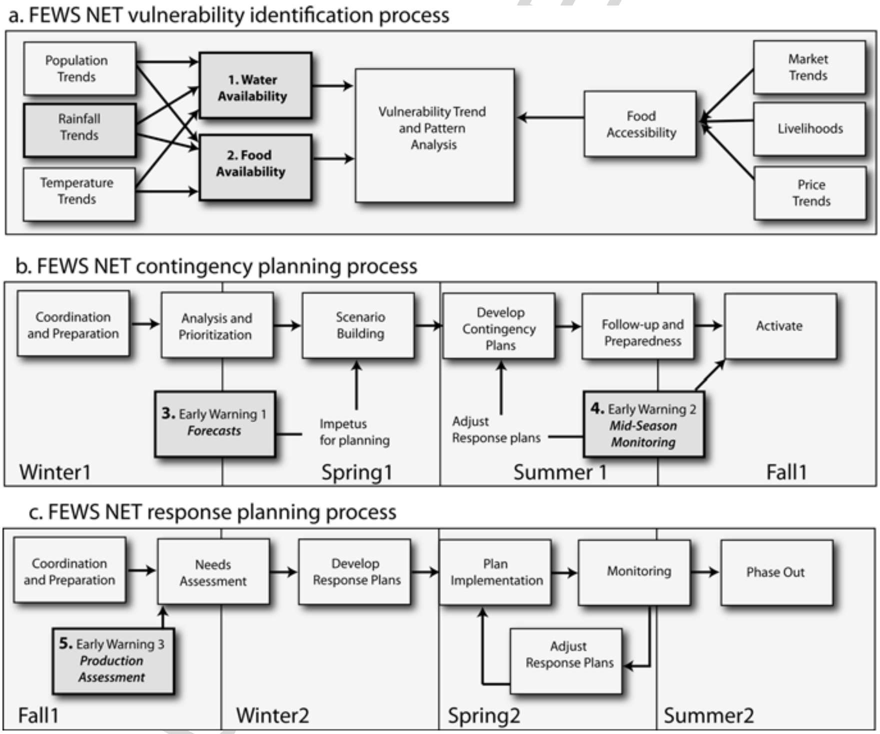

Fig. 1 FEWS NET contingency planning and response schema. Preseason, midseason, and postseason opportunities of hydrologic early warning

1.1 The Three Components of the FEWS NET Planning Process

Most food, especially in the developing world, is produced and consumed on a fairly local scale. Local food deficits related to agricultural and pastoral drought can have devastating impacts. Drought, however, is a "slow onset disaster" and, as such, is amenable to early warning applications tied to hydrologic monitoring and modeling. "Droughts," however, must be understood as a water deficit defined against a given human need. Thus, effective hydrologic early warning must evaluate changes in both demand and supply. Supply and demand will change at seasonal and decadal time scales, and effective monitoring requires modeling at both these temporal horizons.

The FEWS NET process can be conceptually divided into three components (Fig. 1). In the first process, "vulnerability identification," at-risk populations are mapped and trends in food insecurity are analyzed (Fig. 1a). This process is informed both by water and food availability studies and more detailed food economy studies focused on markets, prices, and livelihoods. The vulnerability identification stage guides long-term decision making and planning by aid agencies.

The second FEWS NET process involves the development of food security contingency plans (Fig. 1b). These contingency plans, supported by food security outlooks and forecasts, enable disaster response planners to initiate strategic planning. Seasonal rainfall forecasts and Water Requirement Satisfaction Index (WRSI) imagery play an important role in supporting agrohydrologic modeling and monitoring. The third and final FEWS NET planning process (Fig. 1c) supports and informs the design and implementation of timely and appropriate disaster relief packages. USGS FEWS NET scientists primarily support these three activities by studying trends in rainfall, food, and water availability by providing seasonal rainfall forecasts, midseason crop water assessments, and postseason crop production assessments based on Normalized Difference Vegetation Index imagery (Funk and Budde 2009). This chapter discusses our contributions to the Vulnerability Identification and Contingency Planning (Shaded boxes 1–4 in Fig. 1a and b).

1.2 Focus on Eastern African Food Insecurity in 2009

As of February 2009, 17 million eastern Africans face extremely high levels of food insecurity. These individuals live primarily in the water insecure eastern parts of these countries. These food insecurity crises have arisen through a combination of both non-climatic and climatic underlying factors, such as increasing population pressure, hyperinflation, trans-boundary human and livestock diseases, conflicts and civil insecurity, climatic constraints on water availability, anomalous climate conditions in the Indian and Pacific Oceans, and a recurrence of drought over the past several years. The "real-time" applications discussed and presented in this chapter are therefore germane to a current and grave food security crisis. After a brief discussion of the background of FEWS NET (Section 2), we describe approaches for modeling agro-hydrologic risk (Section 3) use these tools to analyze Kenyan agricultural hydrologic conditions (Section 4), and summarize our approach (Section 5).

2 Background

2.1 A Brief History of FEWS NET

In 1984–1985, catastrophic droughts hit Ethiopia and Sudan, leading to more than a million deaths. These large-scale famines shocked the world. Famine is a slow onset disaster. The tragic lack of timely information and intervention led to widespread human suffering. Responding to concerned citizens, the US Congress called on USAID to create the Famine Early Warning System (FEWS) in 1985.

FEWS has been implemented in roughly 5-year phases since its inception. The prime contract for implementation in each phase is awarded by USAID to a private sector firm through a competitive procurement process. Support in the form of remote sensing, modeling, forecasting, geographic information systems (GIS), data archive, training, and product dissemination is provided by US Government science agencies: The US Geological Survey (USGS), National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration (NOAA), and the US Department of Agriculture (USDA) were engaged as scientific implementing partners through interagency agreements with USAID. Since the late 1980s, FEWS has steadily evolved from being a Washington-based activity with a few expatriates in the field to one that is primarily African-based, with African professionals composing the majority of the staff. The latest phase of the activity places an emphasis on networking among individuals and institutions (governmental, inter-governmental, and non-governmental) across disciplines at the local, national, regional, and continental levels, hence the new name: FEWS NET.

USGS participation has evolved in step with the overall shift to African-based analyses. Regional scientists have been recruited for West Africa, the Greater Horn of Africa (GHA), and southern Africa. These experienced scientists are African nationals with expertise in drought monitoring, remote sensing, and GIS. They work closely with food security analysts to interpret the nature of drought and flood threats to livelihood systems (especially subsistence agriculture) and articulate their findings in bulletins and reports disseminated to the international community. The field scientists devote significant time to technical capacity building through formal and informal training on remote sensing, GIS, hydrology, agroclimatology, and other topics. They work with the following African regional institutions: Agronomy-Hydrology-Meteorology Regional Center in Niamey, Niger; IGAD Climate Predictions and Applications Centre (ICPAC) Intergovernmental Authority on Development in Nairobi, Kenya; the Regional Center for Mapping of Resources for Development (RCMRD) in Nairobi, Kenya; and the Southern Africa Development Community's Regional Remote Sensing Unit in Harare, Zimbabwe. They play a central role in research to improve techniques, algorithms, and methods of geospatial hydroclimatology. They are well positioned to provide scientific insights and local data that complement the work of US-based colleagues. They also have invaluable links to African institutions of higher education.

In 2002, USAID reorganized and moved FEWS NET out of the Bureau for Africa and into the Bureau for Democracy, Conflict, and Humanitarian Assistance. The scope of activity was expanded beyond Africa to include Afghanistan, Haiti, and four countries of Central America. The global price shocks of 2007 and 2008 have spread food security concerns across a broad swath of developing nations, and the geographic scope of FEWS NET activities is expanding as well, in synch with these spreading concerns. The twenty first century will require the effective remote monitoring of agriculture and pastoral conditions. Without a doubt, satellite rainfall estimates will play a critical role in achieving this goal.

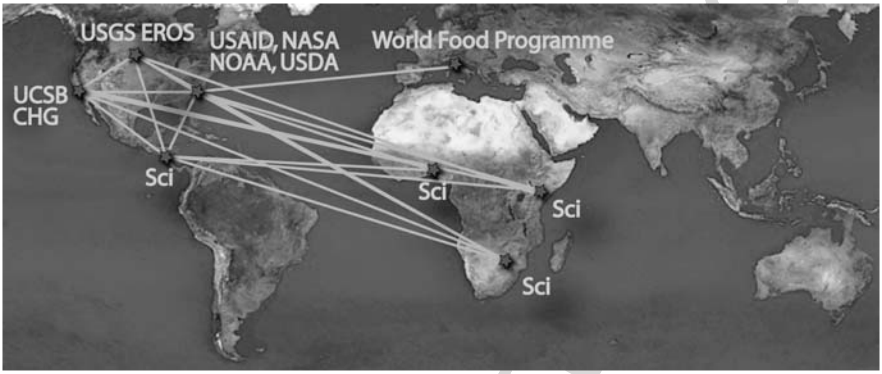

Fig. 2 The FEWS NET science network

2.2 The FEWS NET Early Warning System

The FEWS NET early warning system combines information from multiple sources into coherent food security outlooks, alerts, and briefs for decision makers. These products support decision making by the USAID Office of Food for Peace, the USAID Office of US Foreign Disaster Assistance, and the United Nation's World Food Programme (WFP) that is critical to protecting lives and livelihoods. The national governments of food insecure countries often use this information as well. Early warning can help mitigate the political and humanitarian impacts of food shortages by triggering food, health, and market-related interventions. Satellite observations can contribute substantially to both the contingency planning and disaster response planning phases of FEWS NET (Fig. 1), supporting decisions that save lives and livelihoods, and lessen the impacts of climate extremes – droughts and floods During the contingency planning phase, relatively uncertain information, such as climate forecasts (Funk, et al., 2006b; Brown, et al., 2007) and climate indicators (Box A in Fig. 1), 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 (Box B in Fig. 1), satellite rainfall fields are 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 the sufficiency of soil moisture for crop growth. At the close of the crop growing season (Box C in Fig. 1), satellite-observed vegetation is used to estimate crop production and/or yield (Funk and Budde 2009). In this report, we focus on early-to-mid-season analysis of conditions in Zimbabwe and Kenya/Somalia. While improved monitoring tools cannot make up for inadequate agricultural inputs (seeds and fertilizer) or rainfall, they can help guide the early identification of agricultural drought, which can lead to more timely and effective response to dangerous food insecurity.

The FEWS decision support system DSS process can be seen as an interactive filtering process by which enormous amounts of data are transformed into fair, objective, reproducible, and defensible analyses. For physical observations, FEWS NET relies primarily on satellite rainfall retrievals provided by the Climate Prediction Center (CPC) and the Tropical Rainfall Monitoring Mission (TRMM) a NASA product, augmented by in situ observations from the Global Telecommunications System (GTS). Other important inputs include satellite-observed Normalized Difference Vegetation Index (NDVI), snow extent, prevailing global climate conditions, and local soil and topography. Such information is used by experienced early warning analysts from USGS, NOAA, NASA, USDA, University of California, Santa Barbara UCSB, and Africa (Fig. 2) to monitor agro-hydrologic conditions. A critical component of the FEWS NET DSS is its network of in-country food security analysts. In Africa, Central America, and Afghanistan, these experts track market, vulnerability, livelihood, and agricultural conditions. These extensive analyses are compiled by a team of experts in Washington, DC (currently led by Chemonics International), who also maintain the primary FEWS NET Web portal (http://www.fews.net). Interactions between the physical and social components are vital. For example, in an area where people depend on export cash crop employment (e.g., coffee) rather than subsistence agriculture, global price shocks may be much more harmful than local drought. Availability of agricultural inputs, such as the distribution of seeds, can moderate or amplify the effects of growing season moisture deficits. Effective early warning combines a successful blend of earth observations, hydrologic modeling, food economics, weather and climate modeling, and much more. The remainder of this chapter, however, will focus on applications of satellite remote sensing to agrohydrologic early warning.

2.3 A Synopsis of USGS FEWS NET Early Warning Research

Early Warning Systems can help mitigate the political and humanitarian impacts of food shortages by supporting food, health, and market-related interventions. Satellite observations can contribute substantially to both the contingency planning and disaster response planning phases of FEWS NET (Fig. 1), supporting decisions that save lives and lessen the impacts of drought. A broad suite of early warning products (Rowland, et al., 2005) can be viewed at http://earlywarning.usgs.gov.

These products are primarily driven by satellite rainfall estimates (RFE) provided by the NOAA CPC (Xie and Arkin 1997) or the NASA TRMM multisatellite precipitation analysis (TMPA, Huffman, et al., 2007). Early work by the USGS science team involved using remotely sensed rainfall estimates to monitor the onset of rains (Verdin and Senay 2002) and generate WRSI maps (Verdin and Klaver 2002; Senay and Verdin 2003). These simple water balance models use grids of rainfall and potential evapotranspiration to estimate whether sufficient soil moisture is available for crop growth. A stand-alone version of the Geospatial WRSI (Magadzire 2009) is available from the Climate Hazard Group at the University of California, Santa Barbara (UCSB).[1] The USGS team has also developed early warning tools based on NDVI (Funk and Budde 2009).

Beginning in the late 1990s (Verdin, et al., 1999), the USGS FEWS NET team has also evaluated the impact of El Niño and Indian Ocean climate variations (Funk, et al., 2002, 2006a; Brown, et al., 2007; Funk 2009), occasionally producing ad hoc forecasts as needed to support early warning.

2.4 A Synopsis of FEWS NET-Related Climate Change and Food Security Research

One focus of our FEWS NET research has been the evaluation of climate change and vulnerability trends in food insecure eastern and southern Africa. This work began with the creation of historical rainfall time series for Africa (Funk, et al., 2003b; Funk and Michaelsen 2004). In 2003, FEWS NET evaluated the predictive potential of early growing season rainfall in Ethiopia and provided USAID with food balance projections (Funk, et al., 2003a). That analysis revealed two disturbing tendencies. First, agriculturally critical regions of Ethiopia had experienced substantial precipitation declines. Second, population growth and food balance analyses suggested that Ethiopia faces chronic and increasing food deficits.

FEWS NET followed up on this study with a careful study of thousands of eastern African rainfall gauge observations. The analysis suggested that a warming Indian Ocean was likely to produce increasing dryness in extremely vulnerable areas of eastern and southern Africa. These results were presented in an extensive FEWS NET report (Funk, et al., 2005). The work was also published by the United Kingdom's Royal Society (Verdin, et al., 2005) and presented in 2005 at its meeting on Climate Change and Agriculture. Lord May, the President of the Royal Society, referred to this work in an open letter to the G8 Ministers, asking them to "recognize the impacts of increasing drought conditions in Ethiopia . . . that may already be occurring due to climate change, and to agree to further action to combat greenhouse gas emissions."[2] Satellite observations of vegetation greenness also reveal these declines (Funk and Brown 2005).

[1] http://chg.geog.ucsb.edu/wb/geowrsi.php

[2] http://www.royalsociety.ac.uk/news.asp?id=3833

Over the past several years, FEWS NET has continued multidisciplinary research on this topic. Reporting in the *Proceedings of the National Academy of Sciences* (Funk, et al., 2008) suggests that the dangerous warming in the Indian Ocean is likely to be at least partially caused by anthropogenic greenhouse gas emissions. Thus, further rainfall declines across parts of eastern and southern Africa appear likely. These drought projections run counter to the recent 4$^{\text{th}}$ Intergovernmental Panel for Climate Change (IPCC) assessment. The authors have suggested in *Science* that climate change assessments, based on inaccurate global climate precipitation fields, probably understate the agricultural risks of the warming Pacific and Indian Oceans (Brown and Funk 2008). The interaction of growing populations and limited potential water and cultivated areas increases food and water insecurity, amplifying the impacts of drought. A more recent paper, for the new journal *Food Security*, focuses on global risks implied by these tendencies (Funk and Brown 2009).

3 Techniques for Evaluating Hydrologic Risk

3.1 Low Frequency and High Frequency Models for Food Security Risk Monitoring

In general terms, we can represent the risk of food insecurity (r) as a function of shocks (s) and vulnerabilities (v).

$$r = F(s,v) \tag{1}$$

In this equation, shocks represent any serious disruption of food availability or access. Shocks may be related to global price increases, fertilizer shortages, political instability, or outbreaks of epizootic diseases such as Rift Valley Fever. For many semiarid areas dependent on rainfed agriculture, however, soil moisture deficits are commonly a potential shock. Shocks alone, however, do not create risks. The underlying vulnerability of livelihoods determines the impact of a given shock, such as agricultural drought. Complex economies, integrated into world markets, have the means to transport food (virtual water), making up for local rainfall deficits. In many parts of Africa, Asia, and Central and South America, where most people still subsist by farming, local rainfall deficits often translate into local food shortages.

In examining food security risks, it is important to consider both low frequency (years-to-decades) and high frequency (weeks-to-seasons) changes in shocks and risks. Theoretically, we can write a somewhat more complicated equation for risk.

$$r = F(s_{\text{low}} + s_{\text{high}}, v_{\text{low}} + v_{\text{high}}) \tag{2}$$

In this revised formula, hydrologic shocks might arise as a function of both weather and slowly varying changes in growing conditions. This latter category might include deleterious tendencies of declining rainfall and increasing temperatures, or degrading soil conditions. Shifts in agricultural practices (crop selection, fertilizer use, water retention, and harvesting practices) will also modify a shock. In a similar fashion, globalization, urbanization, biofuel usage, economic development and growth, and the burden of diseases such as HIV/AIDS and malaria act to slowly change baseline vulnerability patterns. We discuss techniques for evaluating the patterns in the next two Sections 4.1 and 4.2.

3.2 Evaluating Low Frequency Changes in Food Security Risks with Food and Water Balance Models

While they can often miss the complexity of individual food or water insecurity crises, at low frequencies, simple water and food balance calculations can usefully represent the slow evolution of risk, especially in less economically developed societies. It often holds, both in space and in time, that food and water vulnerability are strongly coupled to per capita supply. This is especially true in landlocked, poor, semiarid countries with nominal food and water transport infrastructures. Most food is used near where it is produced, and most rainfall is used near where it falls. Understanding this fact allows us to relate low frequency spatial and temporal variations in vulnerability (v_{low}) to basic per capita food and water balances.

$$v_{\text{low}} \infty \text{supply} \cdot \text{person}^{-1} \tag{3}$$

In this equation, supply may typically be cereal grain production, total caloric production, or available water. While these balance equations clearly miss a great deal of the local variations between societies and governments, they do help define significant variations in the geography of food and water insecurity. Insecurity often arises from limited food and water availability, and balance equations provide a first order approximation of vulnerability.

Figure 3 shows an example drawn from an updated version of a 2003 FEWS NET analysis. This report provided USAID with historical and projected estimates of a "theoretical number of people without food" based on an assumed per capita cereal requirement. Historical trends in this food balance (Fig. 3.a) indicated increasing levels of food insecurity. Projections based on flat production trends and a population growth of 1.8 million people per year (Fig. 3.b) suggested that the theoretical number of people in Ethiopia without food would increase by some 1.5 million per year. In fact, since 2003, the number of people in Ethiopia has increased from 7 to 12 million, an increase of about 1 million per year.

Spatial per capita water availability measures can also provide useful guidance. In 2005 (Funk, et al., 2005), runoff built on the water harvest potential mapping work of Senay and Verdin (2004) was used to evaluate per capita water availability for Ethiopia. This work used the SCS Curve Number method to estimate annual runoff. The derivation of the curve numbers can be found in Artan, et al., (2001).

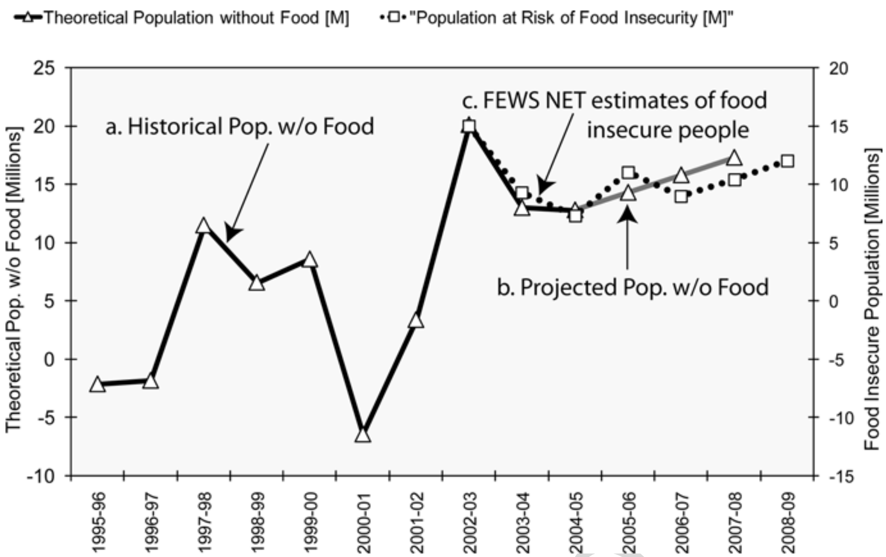

Fig. 3 Theoretical food balance results from our 2003 FEWS NET report (1995–2008, left axis), superimposed with actual FEWS NET food insecurity estimates (2002–2008, *right axis*). Historical population without food estimates (*a*) were based on observed crop production and population data. Projected population without food estimates (*b*) assumed constant crop production and a growing population. The *dashed line* (*c*) shows actual FEWS NET estimates of acutely food insecure people. These FEWS NET estimates are based on extensive in-country analysis, and are one important basis for international food aid requests

Daily RFE2 data were used to derive annual mean runoff values for 10 km grid cells. This mean runoff was divided by gridded population (Dobson, et al., 2000) to estimate spatial patterns of household water availability (Fig. 4). This map is presented with a reference unit volume of 1000 m^3 of water, after considering evaporation and seepage losses from reservoirs. The 1000 m^3 is suggested based on the amount of water that can be used to grow enough grain and biomass to support an average farm family in Africa. Taking into account system inefficiencies, regions with two or fewer units may be labeled as highly vulnerable. Areas with 2–4 units may be considered vulnerable. In general, Ethiopia may be roughly partitioned into three sections: water insecure areas with low rainfall (Fig. 4a), relatively wet areas with high population densities (Fig. 4b), and relatively wet areas with water surpluses (Fig. 4c).

Spatially, there is a very strong correspondence between areas of low rainfall and water availability (Fig. 4a) and areas in eastern Ethiopia currently experiencing chronic food insecurity (red areas in Fig. 5). These food insecure conditions have arisen through a combination of increasing population pressure (Fig. 3), climatic constraints on water availability (Fig. 4), and recurrent drought. The next section evaluates this latter tendency using a combination of downscaled 2.5° long-term

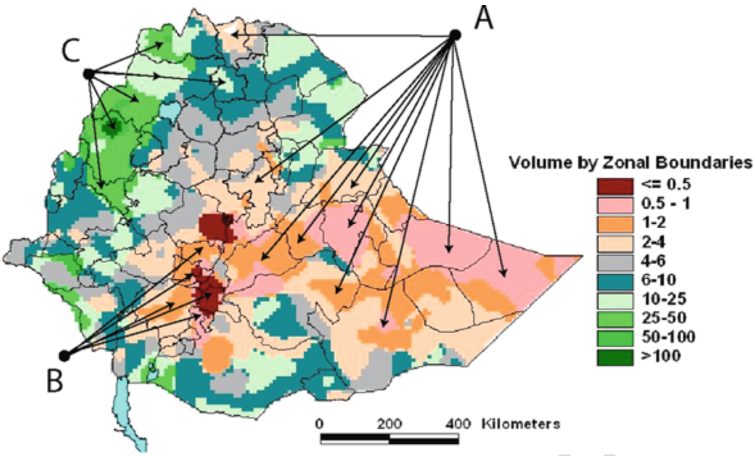

Fig. 4 Volume of potentially available annual surface water per family in 1,000 m^3 units (assumes 7 persons per family)

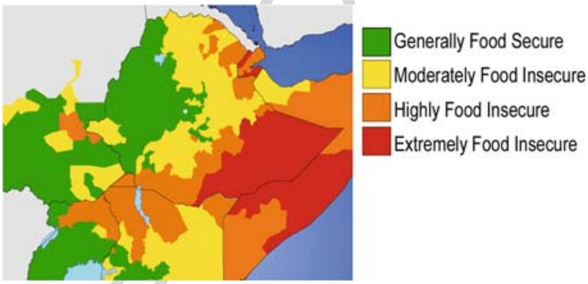

Fig. 5 FEWS NET estimated food security conditions, October–December 2008. Image obtained from http://www.fews.net

(1979–2005) Global Precipitation Climatology Project (GPCP, Adler, et al., 2003) monthly rainfall fields and RFE2 precipitation.

3.3 Combining Long-Term and Real-Time Satellite Rainfall Records

While extremely useful for crop modeling and early warning applications, high resolution satellite products, such as the RFE2 (Xie and Arkin 1997) and the TMPA (Huffman, et al., 2007), have relatively short periods of record. To overcome this limitation, we have developed two analogs to the satellite estimates: the 1960–1996 Collaborative Historical African Rainfall Model (CHARM) time series (Funk, et al., 2003b) and a gauge-enhanced downscaled version of the GPCP (Funk, et al., 2008). The CHARM time series used a reanalysis-driven model of orographic rainfall (Funk and Michaelsen 2004). Unfortunately, the reanalysis model data can produce spurious trends in the resulting CHARM data. For this reason, our new work focuses on the enhanced GPCP product. We describe this product here, evaluate its accuracy in Kenya, and use the combination of enhanced GPCP and RFE2 data to examine recent rainfall trends and anomalies in Kenya, where the station support for both products is quite high, and current food insecurity is very substantial, with more than 10 million people at risk.

The GPCP enhancement procedure began with the creation of a set of high quality, monthly 0.1° resolution long-term mean fields. These orographically enhanced mean fields were produced by combining three sources of information: (i) 0.1° long-term average monthly satellite rainfall estimate (RFE2, Xie and Arkin 1997) grids $\bar{p}$, (ii) 0.1° grids of elevation e and slope s, and (iii) observations ($\bar{o}$) of long term mean rainfall measured at a large number of stations. The use of satellite rainfall averages as a basis for deriving improved gridded climatologies, as far as we know, is new. This innovation grows naturally out of the fact that there are strong local regressions between station normals and monthly mean satellite precipitation ($\bar{p}$). Because variations in infrared and microwave emissions covary in space with rainfall, these estimates represent well large scale precipitation gradients. Local variations within these large scale climate gradients are often induced by topography, and strongly related to the product of $\bar{p}$ and the local elevation e and slope s. The term $\bar{p}s$ describes the multiplicative interaction of local slopes and satellite rainfall estimates. The term $\bar{p}e$ describes the interaction of elevation and mean satellite rainfall. The observed station normals ($\bar{o}$) can be reasonably fit by local regressions of the form $\bar{o} \approx b_o + b_1\bar{p} + b_2\bar{p}e + b_3\bar{p}s$.

Because these models use long term monthly mean rainfall $\bar{p}$ and the interaction of these rainfall mean fields with topography ($\bar{p}e, \bar{p}s$), they benefit from the ability of satellite rainfall estimates to capture spatial gradients in rainfall. These models were fit as described in Funk and Michaelsen (2004), except that a series of moving spatial windows with a 7° radius (~770 km) were used to develop localized regression models, based on distance-weighted subsets of 6965 FAOCLIM2.0 precipitation. The period represented by these climate normals varies by station but typically corresponds to the 1950–1980 era. These moving window regressions produced 12 monthly 0.1° grids of average rainfall. Block kriging was then used to interpolate the 6,965 at-station differences (residuals) between the FAOCLIM2.0 climate normals and regression estimate grids. The regression estimates and kriged anomalies were combined yielding 12 monthly FEWS NET climatology fields (FCLIM). The at-station accuracy of the FCLIM monthly long-term mean fields was evaluated numerically by comparing the regression estimates at each of the 6965 points to the observed value for each month. The error statistics were promising, with a coefficient of determination of 0.9, a mean bias error of 0.06 mm month^{-1}, and mean absolute error of 18 mm month^{-1}. As a reference, the mean monthly rainfall in sub-Saharan Africa is 80 mm month^{-1}, and typically ranges between 0 and 200 mm month^{-1}.

In the second step of the GPCP enhancement procedure, the monthly, 0.1°, African (20°W-55°E, 40°S-40°N) FCLIM fields were used to downscale the 2.5° 1979–2005 GPCP dataset. Monthly GPCP data were translated into fractions of their long-term means, downscaled to 0.1° degree fields via cubic convolution interpolation, and multisplied against the corresponding 0.1° FCLIM grids. This produced monthly, 1979–2005, 0.1° downscaled GPCP fields. The second stage of the GPCP enhancement used a modified inverse distance weighting procedure to blend a moderately dense, quality controlled set of rain gauge observations with the downscaled GPCP fields. Some of these gauges would have been included in the 2.5° GPCP estimates. We will refer to the blended gauge-GPCP-FCLIM dataset as the "enhanced GPCP."

Figures 6 and 7-top panel show March-April-May validation results for the enhanced GPCP dataset. The validation is based on 22 years (1979–1998) of a large number (73) of high-quality daily gauge observations located the western edge of Kenya between 34.15°E and 35.55°E and 1°S and 1°N. While the study site has an area equal to 45% of a GPCP grid cell, the downscaled enhanced GPCP means correspond fairly well at 0.1° resolution (Fig. 6), and the spatial R^2 of these fields is about 0.65. Temporally, the enhanced GPCP and validation data track very well (Fig. 7), with a seasonal R^2 of 0.87. The monthly 0.1° mean absolute error of the data is 14 mm month^{-1}, and the mean bias is 0 mm month^{-1}. This compares favorably with error statistics from the first set of rainfall estimates used by FEWS NET AQ1 (the RFE1, Herman et al. 1997). Previous analysis for this area found monthly 0.1° mean absolute errors of 20 mm month^{-1}, and mean bias values of 15 mm month^{-1}, Funk and Verdin 2003).

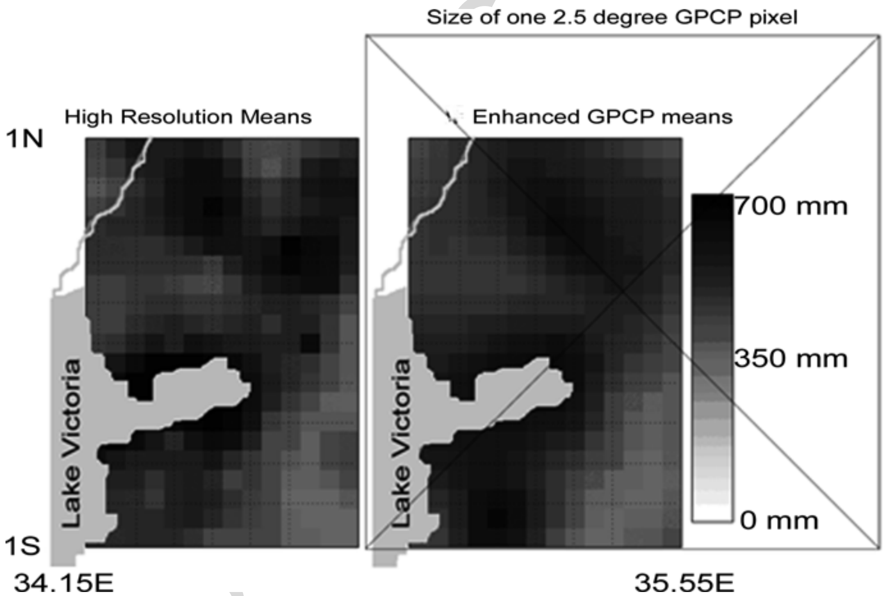

Fig. 6 Monthly March–April-May mean 1979–1998 high density gauge and enhanced GPCP rainfall estimates over the Kenya test site

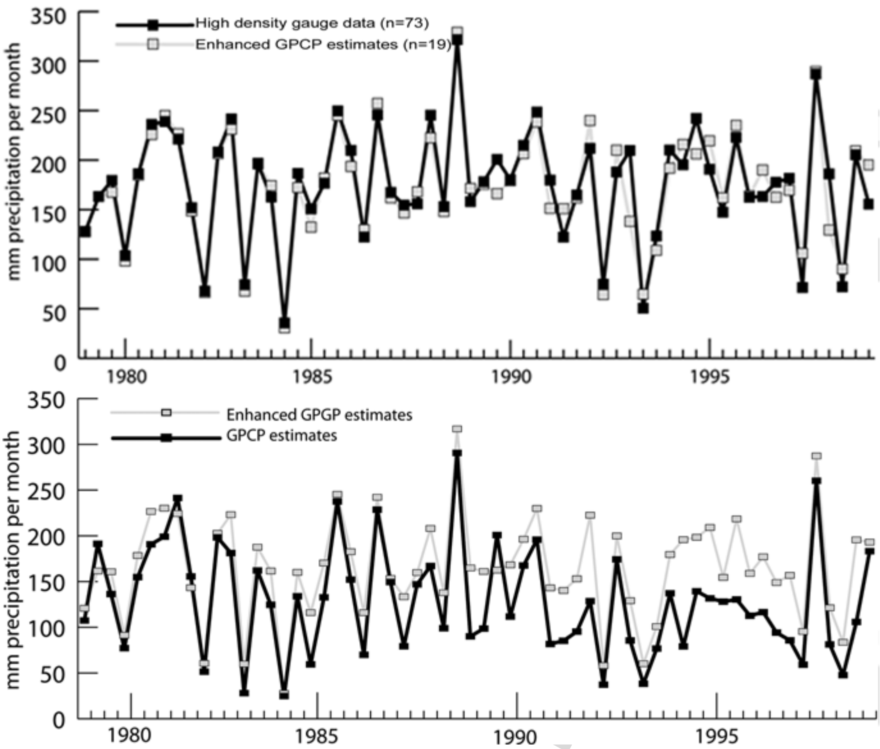

Fig. 7 Regionally averaged 1979–1998 March–May rainfall over the western Kenya test site. The first three *boxes* represent 3 months from 1979 (March–May). Each consecutive set of three *boxes* represents one of the following years. The *top panel* shows high density gauge observations and enhanced GPCP time series. The *bottom panel* shows the GPCP data and enhanced GPCP time series

Comparison between the enhance GPCP and raw GPCP data (Fig. 7, bottom panel) show substantial discrepancies between the two data sets: the GPCP tends to be substantially lower than the enhanced GPCP data, especially after 1986. This shift in performance is likely due to the degradation of the publically available station data sets over the past 20 years.

Further validation can be achieved by comparing the enhanced GPCP and RFE2 data. These results, evaluated across provinces in Kenya, are shown in Table 1 for the two main growing seasons. The long rains are centered on March–May. The short rains are centered on October–December. In general, the correlations are high (over 0.8), especially during the short rains. A very small province (Nairobi) has a low correlation (0.49) during March–May. This is likely due to a difference in spatial scale and underlying station support. The low correlation for the coastal province's March–May time series may be attributable to the low station density here in the RFE2 and the known difficulty with rainfall retrievals near the coast.

Table 1 Correlations between 2001 and 2005 enhanced GPCP and RFE2

Province	Correlation March–May	Correlation October–December	Correlation with long rains yields
Eastern	0.81	0.97	0.66
North Eastern	0.83	0.86	NA
Coast	0.61	0.97	0.38
Nairobi	0.49	0.98	0.12
Central	0.85	0.85	0.60
Rift Valley	0.91	0.97	0.58
Nyanza	0.93	0.99	0.87
Western	0.98	0.94	0.95

3.4 Monitoring High Frequency Shocks Using Water Requirement Satisfaction Index Maps

The primary agrohydrologic monitoring tool used by USGS FEWS NET is a gridded version of the WRSI.[3] Originally developed by the FAO (1977, 1979, 1986), the WRSI is a measure of how much moisture is available to a crop relative to the crop's phenologically changing demands. The USGS FEWS NET team (Verdin and Klaver 2002; Senay and Verdin 2003) has created a spatially explicit version of the WRSI, driven by gridded estimates of satellite rainfall (Xie and Arkin 1997; Huffman, et al., 2007) and potential evapotranspiration (PET) derived using the Penman-Monteith equation (Shuttleworth 1992; Verdin and Klaver 2002; Senay, et al., 2008) which uses numerical weather prediction model data. In addition to rainfall and PET, the WRSI also uses grids of soil parameters and length of the crop growing season (Senay and Verdin 2003). This last parameter is determined by examining the ratio of rainfall and PET and may vary from 60 days for very fast maturing crops in arid zones to 180 days in moist high-altitude locations. In addition to these grids of data, the WRSI requires crop-specific water demand coefficients (K_c) as a function of the current phenology of the crop.

Before looking at the specifics of the WRSI calculation, it is worth a quick review of crop phenology. To represent this, we show time-series data from an early study (Tucker 1979) of vegetation index observations of a cornfield in the United States (Fig. 8). As the plants mature, plant height, percent cover, vegetation index values, and the crop coefficient increase linearly out to about 80 days. At this time, the first tassels appear, and the plants go from the vegetative to reproductive stage. The mass of cereal grains increases during the reproductive stage, so this transition is important. Soil water deficits during this critical grain filling period are the most

[3] This section builds strongly on the FEWS NET readme (http://earlywarning.usgs.gov/adds/readme.php?symbol=ws), written by Gabriel Senay, as well as the GeoWRSI technical manual, written by Tamuka Magadzire.

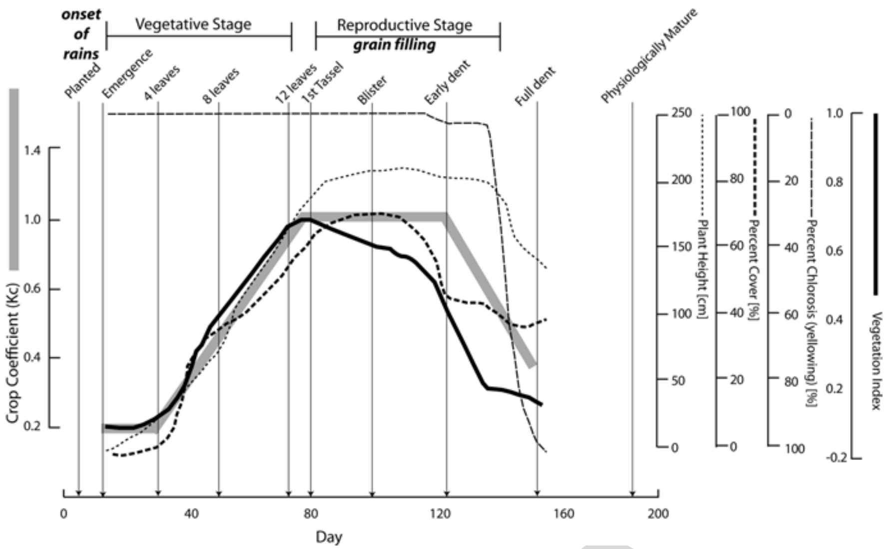

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Fig. 8 Crop phenology for a maize plot, modified from Tucker (1982)

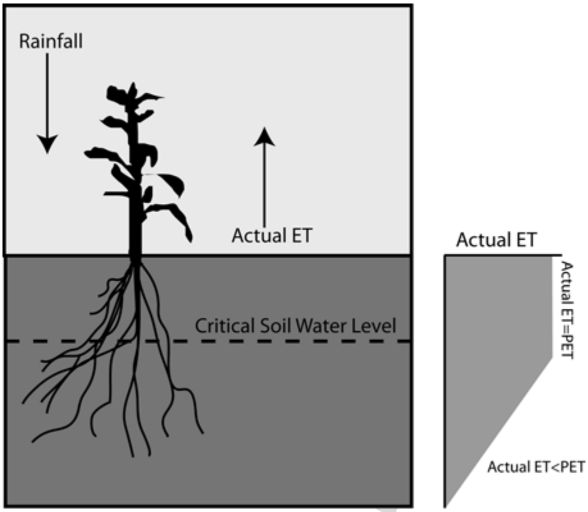
damaging. Conversely, late season soil water deficits, after the grain biomass accumulation is complete, may actually lead to higher yields by protecting the grains from loss due to disease, insects, and mold.

Because of the different water needs of the plant at different phenological stages, timing is critical to the successful calculation of the WRSI, which measures the relative crop water availability from the Start of the Season (SOS) to the End of the Season (EOS). This time period corresponds to the typical phenological curve shown in Fig. 8. Standard FEWS NET WRSI modeling is done using ~10 day (dekadal) accumulations. Each month's rainfall is divided into the sum of the first 10 days, the middle 10 days, and the remaining 8–11 days. The SOS date is then determined by finding the first dekad with more than 25 mm of rain, followed by two dekads with a total rainfall of at least 20 mm. This threshold is linked to the necessary moisture availability triggering the crop's emergence. The EOS date is a function of the length of growing period, LGP (EOS=SOS+LGP).

For a given grid cell, calculation of the WRSI initializes several months before the SOS date with a standard water balance calculation. Once at SOS dekad, the WRSI calculation begins. At this, and each following dekad d, up to the EOS, the WRSI estimates the running ratio of actual plant evapotranspiration (AET_c) to the full plant water requirement (WR).

$$\mathrm{WRSI} = 100\frac{\sum_{t=\mathrm{SOS}}^{d} \mathrm{AET}_c}{\sum_{t=\mathrm{SOS}}^{d} \mathrm{WR}} \tag{4}$$

Fig. 9 WRSI soil water balance



The WR value is a function of the PET and the phenologically dependent crop coefficient (K_c), and the WRSI index is accumulated from the SOS to a given dekad (d).

$$WR = PET \cdot K_c \tag{5}$$

The K_c parameter peaks during the reproductive stage of the crop (Fig. 8). The WR is a measure of how much water the crop would need under ideal growing conditions. Full satisfaction of WR constitutes growing conditions without water stress, that is, WRSI values of 100. When WRSI falls below 50, a crop is considered to have failed. This threshold of 50 is based on empirical analysis (FAO 1986, Senay and Verdin 2003).

AET_c is determined by a modified water balance calculation, with the AET_c value representing the water withdrawn from the soil water reservoir (Fig. 9) at each time step. Depending on the soil water level, root depth, and WR, AET_c may be equivalent, or less, than WR. Please refer to Senay and Verdin (2003) for details. Each time AET_c is less than WR, the WRSI value lowers, indicating increasing water stress. It is standard practice to produce "extended WRSI" predictions. These extended WRSI maps continue integrating the WRSI value forward in time from dekad d using long-term average rainfall and PET. This provides an approximation of the final crop water status of the crop. These projections will become increasingly accurate as the EOS date approaches and are typically quite stable by the middle to the end of the reproductive stage. Since this date is typically several months before the crops are harvested, the WRSI provides a valuable early warning tool.

Operational WRSI runs are hosted at the USGS early warning portal.[4] A stand-alone version of the GeoWRSI (Magadzire 2009) has been created for PCs and is available at the Climate Hazard Group Web site: http://chg.geog.ucsb.edu.

4 Analysis of Kenyan Agricultural Hydrologic Conditions

4.1 WRSI Anomalies for the 2007 and 2008 Long and Short Rains

Using 2nd generation satellite rainfall estimates (RFE2) from NOAA CPC, Penman-Montieth PET (Shuttleworth 1992, Senay, et al., 2008) fields from the USGS,[4] and the stand-alone GeoWRSI tool obtained from the Climate Hazard Group Web site,

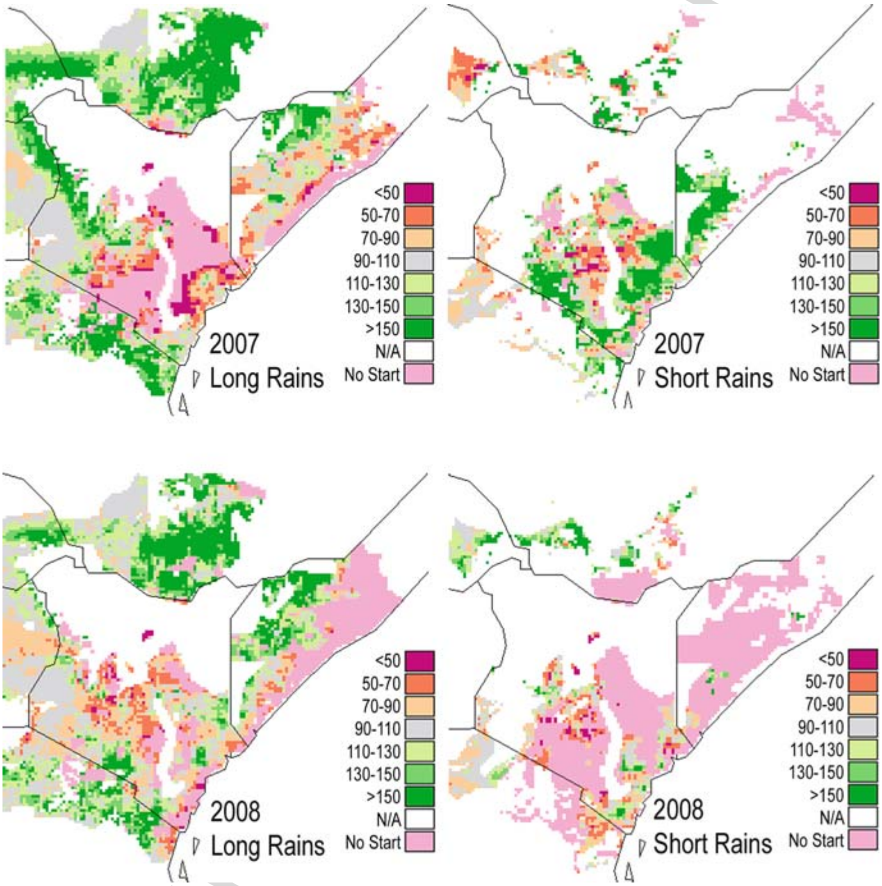


Fig. 10 GeoWRSI end-of-season maize percent anomalies for the long rains (March–September) and short rains (October–February)

[4]http://earlywarning.usgs.gov

we have calculated the 2007 and 2008 maize WRSI anomalies for the long (March–September) and short (October–December) rainfall seasons (Fig. 10). These figures show the end of season WRSI, expressed as percent deviations from the long-term mean (2001–2007). In general, the arid northern parts of Kenya depend on pastoral livelihoods. These areas are masked in the WRSI runs and shown in white in Fig. 10. Across the southern two-thirds of the country, the western parts rely more upon the long rains, and the eastern parts depend more upon the less reliable short rainy season. In general, the rainfall performance for the 2007 long, 2008 long, and 2008 short seasons was very poor across the entire eastern half of the country. Many areas never received sufficient moisture to even initialize the WRSI model with an "onset of rains" signal. This could indicate that the 25 mm SOS-threshold, originally developed for the Sahel during the 1970s, might not be appropriate in eastern Kenya. More research into this component of the model seems warranted.

The 2007 short rainy season provided some relief near the coast, but not further inland. Substantial agrohydrologic shortages have contributed significantly to the current food insecurity (Fig. 5). Using 2001–2006 long rains maize FEWS NET yield data pooled across the eastern provinces, we can establish a reasonable relationship to the log of seasonal March–May rainfall (R^2=0.63). This simple relationship, in turn, can be used to make estimates of very low long rain yields across the eastern provinces (Fig. 11). Because the main rainy season ends several months before the actual harvest, satellite rainfall can be a good early warning trigger. In February 2009, maize prices in Kenya are almost twice the 2003–2008 average. Without assistance, the food security situation there is likely to degrade substantially.

4.2 The 2007 and 2008 Seasons in Historical Context

How uncommon is the multiseason combination of crop water deficits presented in Fig. 10? To address this question, we extracted long (March-April-May) and short

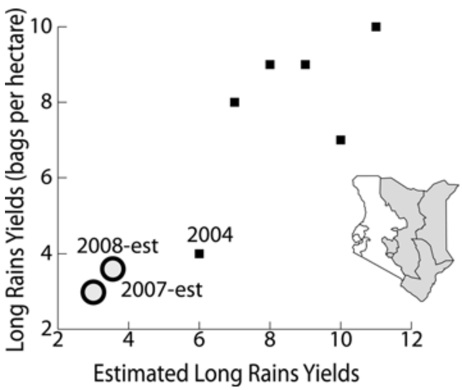


Fig. 11 Actual yields and estimated long rain maize yields for the eastern provinces of Kenya (the area *shaded* in the map above). Actual 2001–2006 yields (y-axis) were obtained from FEWS NET collaborators in Kenya. Yield estimates (x-axis) based on the log of March–May rainfall (R^2=0.63). No yield estimates were available for 2007 and 2008 – the values shown are estimated from rainfall

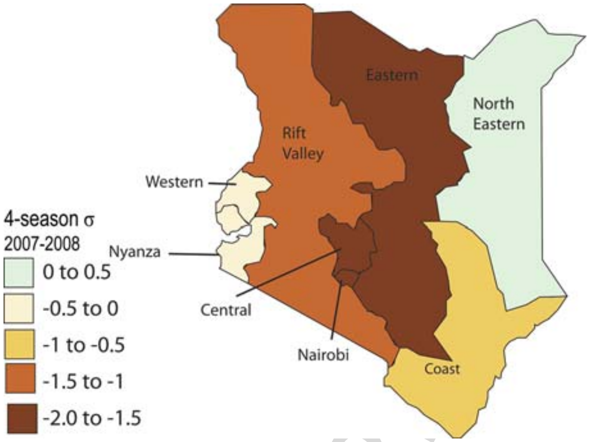


Fig. 12 Combined rainfall performance for last four seasons (2007 MAM, 2007 OND, 2008 MAM, 2008 OND), measured as standard deviations over the 1979–2008 era

(October–December) province-scale rainfall time series. The well-correlated RFE2 data (Table 1) were bias corrected using the period of overlap (2001–2005) and the 2006–2008 seasons to produce a complete 1979–2008 record. For each season, and for each province, the ratio of the 3-year (2002–2005) enhanced GPCP and RFE2 average was estimated. The 2006–2008 RFE2 values were multiplied by this scalar, and added to the end of the enhanced GPCP time series.

The rainfall data were next transformed into ranks, which minimized the impact of a few extremely wet short rainy seasons associated with El Niño years. Time series of 4-season averages were then calculated and expressed as standard deviations from the average. These sigma (σ) values range from about –2 to +2, with values above ±1 denoting exceptional 4-season groupings. Figure 12 shows the sigma values for the combined 2007 long, 2007 short, 2008 long, and 2008 short seasons. In the middle of Kenya (the Eastern, Central and Nairobi provinces), four-season rainfall performance has been extremely poor, compared to 1979–2008 records, with sigma values of less than –1.5. The Rift Valley province, by far Kenya's most productive crop growing region, is not far behind, with a sigma of –1.4. In the arid pastoral North Eastern province and in the tropical Western province, four-season rainfall performance has been near normal. The Coast Province received modestly below normal rainfall in each of the four 2007 and 2008 seasons, resulting in a 4-season sigma of –0.8.

4.3 1979–2008 Trends in Kenyan Rainfall and WRSI

We can use the enhanced GPCP and RFE2 rainfall grids to examine trends in rainfall and WRSI. These results are presented in Figs. 13 and 14. In order to run the GeoWRSI over the 1979–2001 era, dekadal rainfall estimates were derived by equally dividing each months total into three dekadal estimates. Correlation analysis

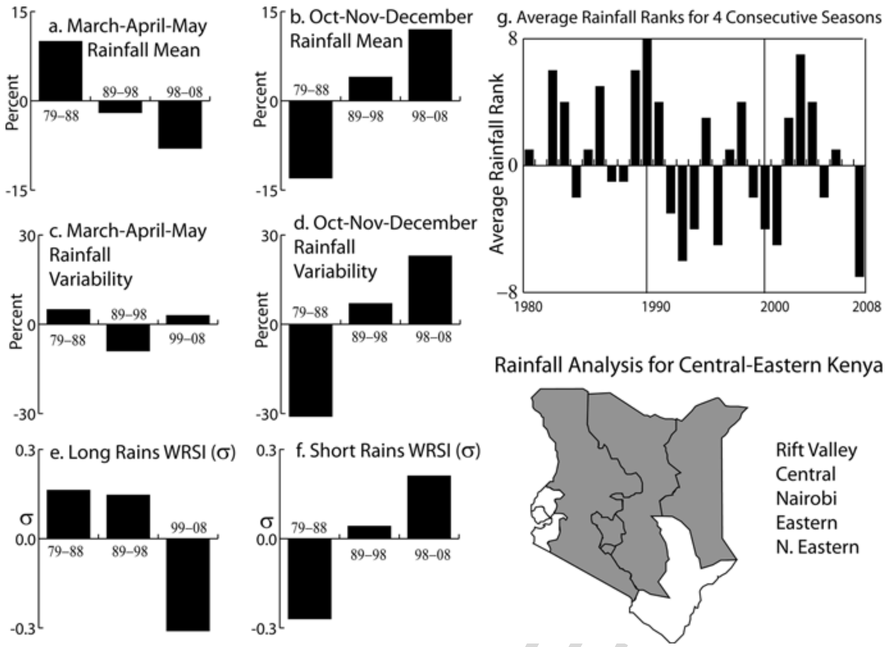


Fig. 13 Long-term rainfall and WRSI analysis for Central-Eastern Kenya. The area analyzed is *shaded* in the map of Kenya

of the seasonal provincial rainfall time series indicated strong homogeneity (1979–2008 correlations of > 0.8) among the Rift Valley, Nairobi, Central, Eastern, and North Eastern provinces. Hence, these regions have been pooled (Fig. 13). Coastal Kenya displayed different interannual variations, so it is presented alone (Fig. 14). The humid Western and Nyanza provinces displayed little decadal variation, so results for these provinces are not displayed here.

Both the central-eastern and coastal areas exhibit substantial shifts in seasonality, with long rains decreasing (panel a) and short rains increasing (panel b) by 20–30%. This shift has been previously noted by the regional FEWS NET scientist (Galu 2008), who has also suggested that the intraseasonal variability of the rainfall has increased in recent years, leading to less reliable crop performance. We test this hypothesis by estimating the 3-month standard deviation for each long and short rain season. The standard deviation estimated from the monthly 1979 rainfall for March, April, and May represents the variability for that season. These values, broken out by region, decade, and season, are shown in panels c and d in Figs. 13 and 14. For the March-April-May season, no increase in variability is apparent. For the October–December rains, on the other hand, there does appear to be a large (>30%) increase in the intraseasonal rainfall variability, from about 38 mm month^{-1} in 1979–1988 to about 50 mm month^{-1} in the 10 years between 1999 and 2008. The combination of panels b and d suggests that while October-November-December

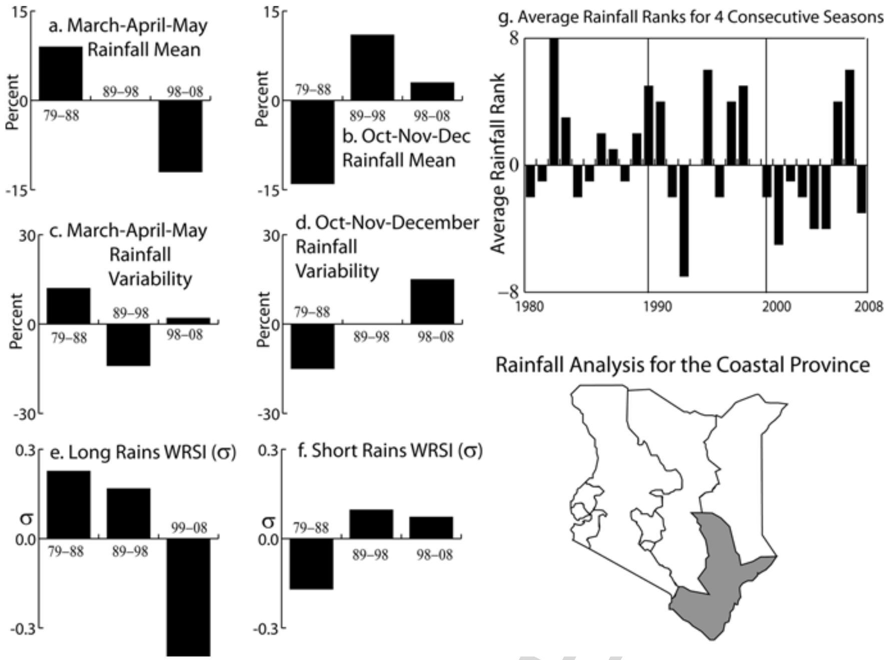


Fig. 14 Long-term rainfall and WRSI analysis for the Coastal Province of Kenya. The area analyzed is *shaded* in the map of Kenya

rainfall has been increasing, on average this rainfall tends to arrive poorly distributed throughout the season (again, as suggested by Gideon Galu, 2008). We can examine the impacts of intraseasonal rainfall variations by running the WRSI model over the 1979–2008 era, expressing the end-of-season WRSI values as standard deviations (σ), and estimating decadal averages. As expected, long rain WRSI values (panel e in Figs. 13 and 14) appear to have dropped substantially across both Central-Eastern and Coastal Kenya. In Central-Eastern Kenya, short rain WRSI (Fig. 13f) has increased, in line with recent rainfall increases (panel Fig. 13d). The case in coastal Kenya, however, appears quite different. While both the short and WRSI seem to have increased by a small amount, the increase in variability appears much more substantial.

Figures 13 and 14 also show time series displaying successive 2-year combinations of long and short rainy season. The first bar on the left in panel g represents the combined performance of the 1979 long and short rains together with the 2008 long and short rains. The last bar on the right represents the most recent 4 seasons: the 2007 long and short rains and 2008 long and short rains. The intervening dry seasons are not included. The data have been ranked to minimize the effect of a few extremely wet El Niño October–December seasons. For each season, ranks for the past 30 years have been calculated from lowest to highest and offset by 15. A value of –15 indicates the worst season on record, 0 a median season, and 15 the best on record. For the areas analyzed, these individual ranks were then averaged, producing values between –8 (very low 4-season rainfall) and 8 (very good 4-season rainfall). For central and eastern Kenya (i.e., most of the country), the tendency toward poorer rainfall is apparent. In the early 2000s, rainfall performance was quite good, but the combined 2007–2008 long-short rains appear to be the worst over the period analyzed. Coastal Kenya also exhibits a downward tendency, again driven by the decreasing long rains. Except for a few positive years, linked to wet 2006 long and short rains, the average rainfall performance for Coastal Kenya has been substantially below normal.

5 Summary and Discussion

In Africa, 90% of farmers are smallholders, reliant on small plots of land, limited technological inputs, and rainfed agriculture (Rockstrom 2000). These farmers and their societies are tightly coupled to the environment and climate. This makes them vulnerable to hydrologic extremes. Satellite rainfall estimates, especially when linked to agrohydrologic models, such as the WRSI, can provide valuable early indication of weather-induced shocks. The WRSI filters the rainfall data in space and time. The particular impact of midseason rainfall receipts will vary by the soil characteristics, the length of growing period, the crop type, antecedent rainfall and PET, and the phenological stage of the plant. The most damaging crop water deficits arise during the reproductive stage of the crop (Fig. 8), when the cereal plants switch from growing leaves to growing grains. Late planting (Funk and Budde 2009) or midseason water deficits (Senay and Verdin 2003) can dramatically reduce yields. The WRSI allows these disruptions to be identified months before the actual harvest date, providing early warning and time to develop disaster response strategies (Fig. 1).

Food security responses by USAID and partner agencies are saving thousands of lives. A good example would be the 2002–2003 food crisis in Ethiopia. Rainfall performance was very poor (Funk, et al., 2003a, 2005), perhaps analogous to conditions accompanying the devastating 1984–1985 famine. This dryness, combined with low planted area due to low cereal prices, produced a large spike in food insecurity (Fig. 3). This food crisis provided a benchmark test for the international food security organizations, and effective response prevented widespread hunger, disease, and social disruption. These responses were enhanced substantially by real-time satellite rainfall applications.

In addition to effective early warning, agrohydrologic modeling can also inform long-term food security decision making through water and food budget analysis. This perspective helps explain, in part, the increasingly chronic food insecurity in eastern Africa. The Ethiopian 2002–2003 food crisis in Ethiopia was associated with about 15 million food insecure individuals. Recent food insecurity levels appear to be trending toward this amount at a rate of about 1 million people per year. Growing population and stagnant yields help create this problem (Fig. 3), as has the low water availability across the more arid parts of eastern Africa (Fig. 4).

Focusing on Kenya, we have shown that the WRSI model, driven by satellite rainfall fields, can effectively monitor anomalous hydrologic conditions (Fig. 10). Across most of Kenya, hydrologic growing conditions for the 2007 and 2008 long rains and the 2008 short rains were very poor, indicating failure or near-failure of maize crops, as suggested by our empirical estimation of yields (Fig. 11). Performance of the 2008 short rains was mixed but poor in the center of the country.

The combination of these 4 seasons appears unusually bad, indicating that a rare and intense multiyear drought has impacted most of the country (Fig. 12). Examination of pooled enhanced GPCP/RFE2 data support the assertion (Galu 2008) that a shift in seasonality may be occurring. Consistent with our previous research (Funk, et al., 2005; Verdin, et al., 2005; Funk, et al., 2008), March–May rainfall appears to be decreasing by almost 10% a decade (Figs. 13 and 14), producing a –0.5σ reduction in WRSI over the 1979–2008 era over both coastal and central-eastern Kenya.

The October–December short rains, on the other hand, appear to be increasing. There appears to have been a substantial increase in intraseasonal variability in the October–December short rains across central-eastern and coastal Kenya, and the March–May long rains in coastal Kenya. Increasing intraseasonal variability tends to reduce crop performance due to the occurrence of midseason dry spells. WRSI analysis suggests that this increasing variability may be reducing the beneficial impact of rainfall increases in coastal Kenya (Fig. 13f), consistent with reports coming from Kenya (Galu 2008).

We suggest that satellite observations can contribute to both short- and long-term monitoring of food security in Africa. Furthermore, we believe that both these perspectives are necessary. As the number of urban poor rises rapidly and global food prices soar due to increased consumption by biofuels and livestock, there has been a broad increase in three classic coping mechanisms (Natsios and Doley 2009): food hoarding, migration, and increased banditry. This expanding food stress disrupts societies and creates political unrest; over the next decade we are likely to see "food coups" emerge as modern counterparts to the famines of the past. We have shown that agricultural development can help reduce these impacts (Funk, et al., 2008; Brown and Funk 2008; Funk and Brown 2009). Without addressing the key issues of resource scarcity, short-term food aid responses may in fact act to create future risk, moving African societies into imbalance and helping to create greater need. More analysis of the shift in seasonality, discussed briefly here, could help guide future agricultural development strategy.

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Chapter 17

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