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Climate science and famine early warning

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Food security assessment in sub-Saharan Africa requires simultaneous consideration of multiple socio-economic and environmental variables. Early identification of populations at risk enables timely and appropriate action. Since large and widely dispersed populations depend on rainfed agriculture and pastoralism, climate monitoring and forecasting are important inputs to food security analysis. Satellite rainfall estimates (RFE) fill in gaps in station observations, and serve as input to drought index maps and crop water balance models. Gridded rainfall time-series give historical context, and provide a basis for quantitative interpretation of seasonal precipitation forecasts. RFE are also used to characterize flood hazards, in both simple indices and stream flow models. In the future, many African countries are likely to see negative impacts on subsistence agriculture due to the effects of global warming. Increased climate variability is forecast, with more frequent extreme events. Ethiopia requires special attention. Already facing a food security emergency, troubling persistent dryness has been observed in some areas, associated with a positive trend in Indian Ocean sea surface temperatures. Increased African capacity for rainfall observation, forecasting, data management and modelling applications is urgently needed. Managing climate change and increased climate variability require these fundamental technical capacities if creative coping strategies are to be devised.

Keywords: climate; Africa; food security; Ethiopia

1. INTRODUCTION

Food security monitoring in sub-Saharan Africa is vital because the early identification of populations at risk can enable the timely and appropriate actions needed to avert widespread hunger, destitution or even famine. The analysis is complex, requiring the simultaneous consideration of multiple socio-economic and environmental variables. Since large and widely dispersed populations depend on rainfed agriculture and pastoralism, climate monitoring and forecasting are important inputs to food security assessment.

Conventional hydrometeorological networks are sparse and often report with significant delays (Washington *et al.* 2004). Consequently, the requirements of famine early warning have inspired creative uses of remote sensing, numerical modelling and geographic information systems (GIS) to adapt traditional methods of climate monitoring. Satellite vegetation index imagery has been used since the mid-1980s to identify anomalies in seasonal landscape green-up that indicate drought (Hutchinson 1991). Satellite rainfall estimates (RFE) fill in gaps in station observations, and serve as input to drought and flood index maps and models that illustrate the implications of spatial and temporal precipitation patterns. Gridded rainfall time-series provide historical context to judge the relative significance of observed precipitation, and enable quantitative interpretation of seasonal forecasts.

In the future, many African countries are likely to see negative impacts on subsistence agriculture due to the effects of global warming: increased temperatures and enhanced evapotranspiration, without offsetting precipitation increases. Increased climate variability is forecast, with more frequent extreme events (IPCC 2001). Creative strategies will be needed to adapt livelihood systems to changing conditions. Unfortunately, scientists in the affected countries often lack the necessary resources to fully utilize available technology for characterization of the climate situation. A programme of investment in capacity building for climate science applications is needed to ensure that national policy makers have the basic climate information needed for decision making.

Ethiopia is a dramatic case in point. Complex terrain and climate mean that precipitation patterns are especially difficult to characterize. Already facing a food security emergency, with 8–10 million people at risk, troubling multi-year drying has been observed in recent years, associated with a positive trend in Indian Ocean sea surface temperatures (SSTs) that is affecting countries around the basin (§5 of this paper). The long-term viabilities of certain crops and pastoralism are called into question. In these circumstances, increased capacity to perform and apply climatic observation and forecasting is urgently needed. The country's hydrometeorological network requires expansion and

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modernization, as do systems for data capture, management and telecommunication. Managing climate change and increased climate variability require these fundamental technical capacities if creative strategies are to be devised.

2. BACKGROUND

Assessment of food security considers its three principal elements: *availability*, *access* and *utilization*. *Availability* concerns the amount, location and timing of the physical presence of food in a country. Key variables are agricultural production, stocks and cross-border trade. The question of *access* addresses the ability of households to obtain the available food that they need. Prices, market integration, employment opportunities, annual production cycles and distribution of wealth all have a bearing on access. *Utilization* of food that is accessible concerns the ability of humans to derive full biological benefit from it. It is in this area that food security analyses consider the influences of vector-borne diseases (like malaria), parasites, diarrhoea and other maladies. Basic services for clean water, sanitation and primary health care are major considerations.

The famine early warning system network (FEWS NET), an activity of the United States Agency for International Development (USAID), employs a livelihoods framework to geographically characterize vulnerability and interpret hazards (Boudreau 1998; Save the Children-UK 2000). Livelihoods analysis focuses primarily on questions of *access*. It builds an understanding of the strategies people use to meet their basic needs. By assembling information on how households access food and income, routine monitoring of rainfall, vegetation, crops and market prices is made more meaningful. Implications for key food security questions are more readily derived, such as: which population groups are facing food insecurity, and for how long? What are the best ways to mitigate adverse trends or shocks to their livelihood systems?

A first step in livelihoods analysis is developing a livelihood zone map by dividing a country into areas with relatively homogeneous patterns of natural resources and food access. Within these zones, livelihood profiles are prepared. They describe the relative importance of various sources of food and income for the principal wealth groups residing there. Finally, the amounts of food and income, as well as expenditure, are quantified and compared to minimum nutritional needs. This information provides the basis for food security scenario modelling that translates a climatic shock, say a drought-induced 50% reduction in cereal production, into consequences that can be expressed in terms of numbers of affected people and tonnes of food shortfall. It also supports assessment of the population's capacity to mitigate and manage adversity by turning to alternative sources of food and income.

Hazards monitoring provides continuous information regarding potential shocks or adverse trends affecting livelihoods. Market prices for food, livestock and cash crops are key economic variables. Climatically speaking, drought, floods and tropical cyclones are of greatest concern. Hazard information products are used as input to food security scenario modelling. Hazards are superimposed on livelihood zones, and each source of food and income for the relevant profiles is evaluated to determine if a food or income gap will result. In this way, logical and informed conclusions can be drawn in an objective and reproducible manner. Population groups at high risk of acute food insecurity can be identified and quantified, as can prospects for the duration of the problem.

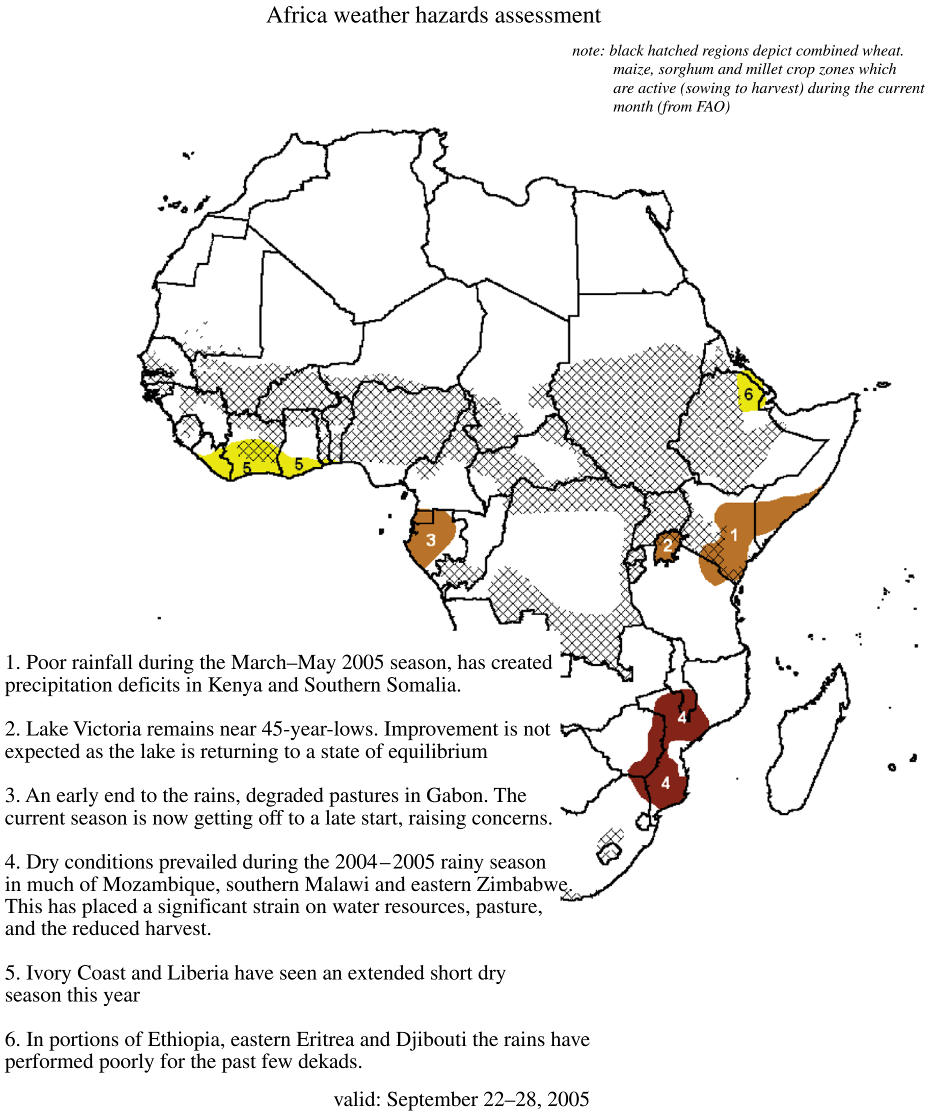
Food security projections derived from scenario modelling results are the basis of early warning. Contingency and response planning, in turn, use early warning information to identify potential actions to mitigate an emerging crisis. Better informed decisions can be made regarding the use of humanitarian interventions, such as the mobilization of direct food aid from external sources.

Climate science applications for FEWS NET are a fundamental component of hazard monitoring because many of the most food insecure groups in Africa are significantly dependent on rainfed subsistence agriculture and pastoralism. The National Oceanic and Atmospheric Administration (NOAA), US Geological Survey (USGS), National Aeronautics and Space Administration (NASA) and others (including the US Department of Agriculture, FEWS NET/Chemonics, US Agency for International Development) routinely review a suite of monitoring and forecast products to produce a weekly Africa Weather Hazards Assessment (AWHA). The AWHA is distributed to partners throughout the international food security community and posted on the web at http://www.fews.net. An example AWHA weekly hazards map is presented in figure 1.

Livelihoods analysis is extensively used to understand the implications of routine climate monitoring and weather forecasting results for food security. More recently, it has been applied to develop food security outlooks from seasonal climate forecasts, though this work is still in its early stages. Even less developed is the use of livelihoods analysis for interpretation of hazards posed by long-term climate change. As the prospects for adverse climate change become more credible and imminent, the importance of this approach will grow. Livelihoods analysis offers a practical, scientific way to inform decision makers of the strategic policy options they should be considering to deal with climate change.

3. DROUGHT MONITORING

Current season monitoring by FEWS NET makes extensive use of satellite image products to achieve early detection of drought. Vegetation index images have been used since the mid-1980s to monitor the crop and rangelands of semi-arid sub-Saharan Africa (Hutchinson 1991). The normalized difference vegetation index (NDVI) exploits the contrast between red and near-infrared reflectance of plant canopies. It is proportional to leaf area index, intercepted fraction of photosynthetically active radiation and density of chlorophyll in plants (Tucker & Sellers 1986). Maximum value composites for dekads (WMO 1992), nominally 10-day periods, are used to overcome



Africa weather hazards assessment

note: black hatched regions depict combined wheat. maize, sorghum and millet crop zones which are active (sowing to harvest) during the current month (from FAO)

1. Poor rainfall during the March–May 2005 season, has created precipitation deficits in Kenya and Southern Somalia.

2. Lake Victoria remains near 45-year-lows. Improvement is not expected as the lake is returning to a state of equilibrium

3. An early end to the rains, degraded pastures in Gabon. The current season is now getting off to a late start, raising concerns.

4. Dry conditions prevailed during the 2004–2005 rainy season in much of Mozambique, southern Malawi and eastern Zimbabwe. This has placed a significant strain on water resources, pasture, and the reduced harvest.

5. Ivory Coast and Liberia have seen an extended short dry season this year

6. In portions of Ethiopia, eastern Eritrea and Djibouti the rains have performed poorly for the past few dekads.

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Figure 1. An example of the map provided with a weekly FEWS NET Africa Weather Hazards Assessment. Brown polygons represent areas of drought, blue polygons indicate flood hazards and hatching shows areas with active growing seasons underway. Each hazard polygon is numbered and has a corresponding written narrative. Weather hazards assessments are available online at http://www.fews.net.

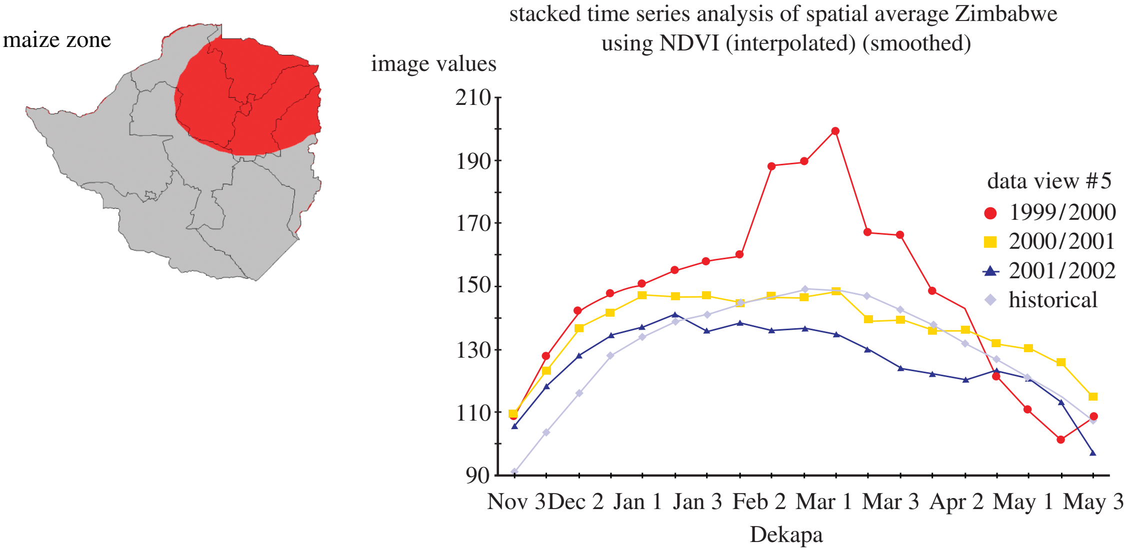

Figure 2. NOAA AVHRR NDVI seasonal traces by dekad for a key maize-growing region in Zimbabwe. The 1999/2000 was year of abundant rainfall and vigorous vegetation growth, 2001/2002 was a year of drought and poor crop performance, while 2000/2001 was about average.

cloud cover problems. Images from several different sensors are used to make the NDVI composites used by FEWS NET. They include the NOAA advanced very high resolution radiometer (AVHRR), SPOT Végétation and NASA moderate resolution imaging spectrometer (MODIS). The time-series of AVHRR NDVI images, calculated by the NASA global inventory monitoring and modelling studies group (Tucker *et al*. in press), has 8 km resolution and has been continuous since July 1981. SPOT Végétation NDVI images have 1 km resolution and have been available since 1998, while the MODIS NDVI images used by FEWS NET have 500 m resolution with a continuous series available since 2000.

Typically, a seasonal trace of mean NDVI over a crop or rangeland zone of interest is made to illustrate green-up and senescence. Traces for a long-term mean and recent years are also shown for comparison purposes. Figure 2 gives an example for an important maize growing region of Zimbabwe.

In certain parts of Africa, correlations have been noted between seasonal NDVI and El Niño indicators, such as mid-Pacific SSTs (Anyamba & Eastman 1996; Myneni *et al*. 1996; Verdin *et al*. 1999). Though the relatively short-time series of NDVI is an obstacle, efforts are underway at the International Research Institute for Climate Prediction to forecast seasonal NDVI using a general circulation model (http://iri.columbia.edu/des/figure/figure3.html). Funk & Brown (2005) recently reported that within-season projections of NDVI can be made using observed rainfall and relative humidity, a promising technique for early warning.

Current season monitoring also depends heavily on satellite RFE. In Africa, the primary product used by FEWS NET is RFE 2.0 from the NOAA Climate Prediction Center. The algorithm for this product, described in Xie & Arkin (1997), involves a geostatistical blend of rainfall station data with imagery from thermal infrared and microwave sensors. Estimates of 24 h precipitation totals are made for each grid cell at 0.1° resolution (approximately 10 km) and are available the following day. There are only about 400 rainfall stations across the African continent that report each day via the World Meteorological Organization's global telecommunication system (GTS). The RFE consequently fill in what would otherwise be large spatial gaps in FEWS NET rainfall monitoring. The inclusion of those station data that are available significantly reduces bias inherent in estimates based on satellite data alone. Furthermore, RFE 2.0 estimates show better agreement with surface observations than do numerical atmospheric model precipitation fields. In a test case in western Kenya, RFE 2.0 estimates agreed with observations over a dense gauge network significantly better than did numerical atmospheric model estimates, explaining 80% of the variance, compared to 20% for atmospheric model estimates (Funk & Verdin 2003). Modelled precipitation and satellite-derived RFE need to be constrained by modest numbers of station observations.

The significance of current season rainfall patterns can be best understood in the context of past precipitation. FEWS NET first began comparing monthly and dekadal RFE totals to gridded long-term average values produced by the Australian National University (Hutchinson *et al*. 1996). While the departures from normal (in millimetres) obtained in this way were valuable, they told only part of the story. To fully appreciate the significance of a rainfall anomaly, it is necessary to know its relative size and expected frequency of occurrence as well. This would require a full 30 year time-series of RFE 2.0 grids. Unfortunately, the complete suite of required satellite input data only goes back to the late 1990s. Nonetheless, efforts have been made to create an historical time-series of gridded RFE as context for current season RFE, and a certain amount of success has been achieved.

The collaborative historical African rainfall model (CHARM) (Funk *et al*. 2003) was developed and applied to create a 36 year time-series of daily rainfall grids. The CHARM blends gridded monthly station data (Willmott & Feddema 1994; Willmott & Matsura 1995) at 0.5°, daily reanalysis precipitation fields (Kalnay *et al*. 1996) at 1.875°, and daily orographic enhancement at 0.1° (Funk & Michaelsen 2004). The objective was to create a time-series product with sub-monthly variability, constrained to match monthly station totals. Validation with independent station data at areas in Kenya and Mali showed good results in reproducing dekadal variability ($r=0.75$), but with significant bias in some regions.

An effort at the NOAA Climate Prediction Center (Thiaw *et al*. 2005) is taking an alternative approach to creating an historical context for the RFE. The African rainfall climatology (ARC) is being constructed with Meteosat thermal infrared imagery and GTS station data. The microwave imagery used in RFE 2.0 are left out, but the advantage in so doing is that it becomes possible to create a time-series dating back to 1982, since necessary inputs are available for the full period. Characteristics of the ARC are in contrast to those of the CHARM dataset. When validated with independent data for the Sahel, the structure of the mean field is well represented, but temporal variability is underestimated.

Husak (2005) took an approach that blends the strengths of the CHARM and ARC. First, for an accumulation period of interest (dekad, 1 month, 3 months, etc.), a probability distribution function was fit for each pixel over the 36-year time-series of the CHARM. The gamma or normal distribution was used, as appropriate for each pixel. Then, the corresponding mean values of the ARC were substituted for the accumulation period in question. Such an approach can be used to fuse dissimilar datasets, and is generally applicable to situations having a longer, sparser data source on the one hand and a newer, shorter (satellite era) time-series on the other. The result is a historical time-series that can provide context to current time frame RFE—provided they are calculated in the same manner as the ARC estimates, without microwave imagery as input. Consequently, an ARC-type RFE has been instituted as a by-product of RFE 2.0 processing, to create a homogeneous time-series for historical analyses. This set the stage for a valuable new drought monitoring product—a grid cell implementation of the standardized precipitation index (SPI).

The SPI (McKee *et al.* 1993) characterizes departures from normal as a number of standard deviations above or below the mean, a kind of z-score. It is calculated for a range of accumulation periods—typically 3, 6, 12 and 24 months each, to measure drought across a range of durations and intensities. It has become popular as a drought indicator throughout the world. It is an ideal accompaniment to anomalies expressed in absolute (millimetre) terms. Originally formulated for use with station data, it can now be applied to gridded rainfall datasets. Figure 3 gives an example of such an SPI map for a 3-month accumulation period.

In another approach to drought monitoring, satellite RFE have been especially useful as input to a geospatial crop water balance model that evaluates the availability of moisture to a crop relative to its needs over the course of the growing season. Frere & Popov (1986) originally developed the water requirement satisfaction index (WRSI) for calculation with rainfall station data. It has been adapted to use on a geospatial basis to facilitate wide area monitoring (Verdin & Klaver 2002; Senay & Verdin 2003). The WRSI varies from 0 to 100, and is the ratio of actual crop evapotranspiration to the amount that would occur with a full water supply. This quantity has been shown to be a good indicator of yield reduction due to water limitation (Doorenbos & Kassam 1986).

The geospatial implementation of the WRSI, in effect, treats each grid cell as if it were a station location. To do so requires gridded estimates of soil water holding capacity (WHC) and daily potential evapotranspiration (PET). The FAO digital soil map of the world is used to assign a value of WHC to each cell. Reference crop PET is calculated according to the Penman–Monteith equation (Shuttleworth 1992) using 1° analysis fields from the NOAA global data assimilation system (Kanamitsu 1989) for air temperature, atmospheric pressure at the surface, wind, relative humidity and radiation. Published crop coefficients (FAO 1998) are used to modify PET to simulate the demand for water of a staple crop of interest. The daily crop water balance calculation includes a regularly updated estimate of available soil moisture. The maps that are forthcoming from these geospatial calculations reveal zones of poor crop performance due to dry spells or drought, as corroborated by field reports. Furthermore, maize yield estimates based on WRSI (calculated with RFE) were found to agree ($r=0.8$) with official reports in a test with 1996/1997 data for Zimbabwe (Verdin & Klaver 2002). Figure 4 gives an example WRSI map for the West African Sahel.

Seasonal precipitation forecasts have come into regular use in Africa in recent years (Basher *et al.* 2001; Goddard *et al.* 2001). Prior to each rainy season, climate outlook forums (COF) are convened by region in the Greater Horn of Africa (GHA), West Africa and Southern Africa. International, regional and national experts in climate come together to review the current state and latest forecasts for the global climate system. These are blended with local knowledge and expertise to develop a regional seasonal forecast for precipitation, usually for 3-month periods. These forecasts are expressed in map form by dividing a region into 4–8 broad polygons, and associating with each polygon three tercile probability values. These values express the expected likelihood of the seasonal total rainfall being in each of three ranges: above normal, normal and below normal. These ranges refer to a rank ordering of seasonal rainfall totals for a reference 30-year period, the top ten values defining above-normal, the middle ten defining normal, and the driest ten corresponding to below-normal. (Examples can be viewed at http://www.dmcn.org/.)

Many users find tercile forecast maps challenging to relate to the specific questions of their application areas. To address this need, Husak (2005) devised an approach whereby the forecasts are expressed as rainfall totals in millimetres, while still respecting their probabilistic nature. He took advantage of the per-pixel fitting of probability distribution functions implemented for the SPI, adding a capability for re-fitting the distributions according to a Monte Carlo resampling consistent with the COF tercile forecasts. Random samples are drawn from the upper, middle and bottom thirds of the climatological distribution, proportional to the forecast probabilities, and new distribution parameters determined. The process is repeated one hundred times and the median parameter values adopted to represent the forecast distribution. Figure 5 illustrates this concept for a single pixel by comparing distributions for wet and dry forecasts with that of the standard climatology. The algorithm is implemented in the forecast interpretation tool (FIT), software developed to support FEWS NET analyses.

Figure 6 presents a standard COF forecast map and the corresponding rainfall map, for the 50% probability level, developed with the FIT. It is also possible to specify a seasonal rainfall total value and produce a map of the spatially varying probability of realizing that amount in the season ahead. Such a map can be useful if there is a known rule-of-thumb amount of rainfall associated with successfully growing a crop, or filling the reservoir of a hydroelectric dam.

In many regions of Africa, there is a useful correlation between seasonal rainfall totals and end of season WRSI for a principal staple crop. In these instances, rainfall total maps from the FIT can be re-expressed again as expected WRSI outcome maps, at specified levels of probability. Such maps serve as useful input to food security scenario modelling, by combining them with livelihood zone maps and profiles. Earlier warning can be had than with the use of monitoring products, though the level of confidence in the scenario is necessarily lower, being based on forecast climate rather than observed climate.

Figure 7 presents an example of forecast maize WRSI and the livelihoods zone map of Kenya used in interpreting the food security consequences of the climate scenario (IRI 2004). Though a new area of activity, food security outlook forums are now being organized routinely in conjunction with COFs for the GHA.

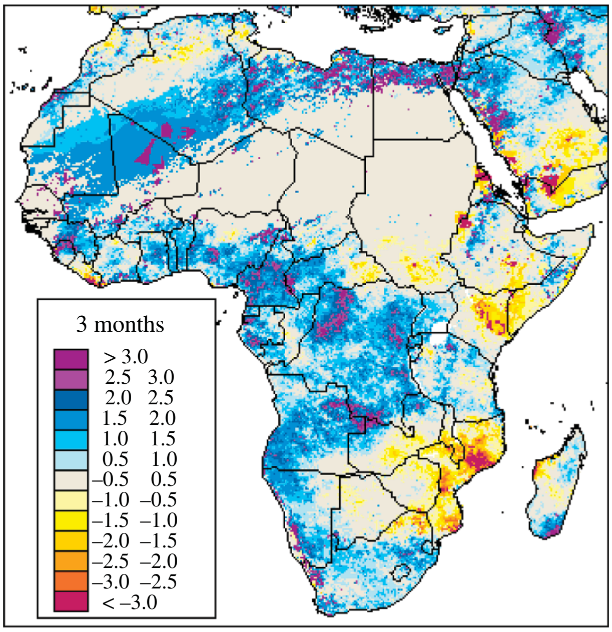

Figure 3. A map of the standardized precipitation index (SPI) based on time-series gridded rainfall data with per-pixel fitting of probability distribution functions. Scores compare the 3-month period January–March, 2005, with the same months of a climatological time-series for 1961–1996. Recent growing season dryness in Mozambique is highlighted.

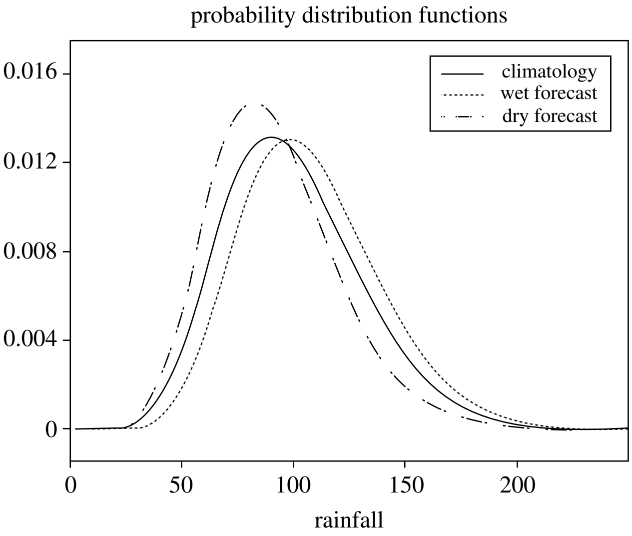

Figure 5. Examples of modified probability distribution functions for a single pixel both wet and dry forecasts, using the resampling algorithm implemented in the forecast interpretation tool (FIT) software. Note the shifts relative to the normal climatology curve (Husak 2005).

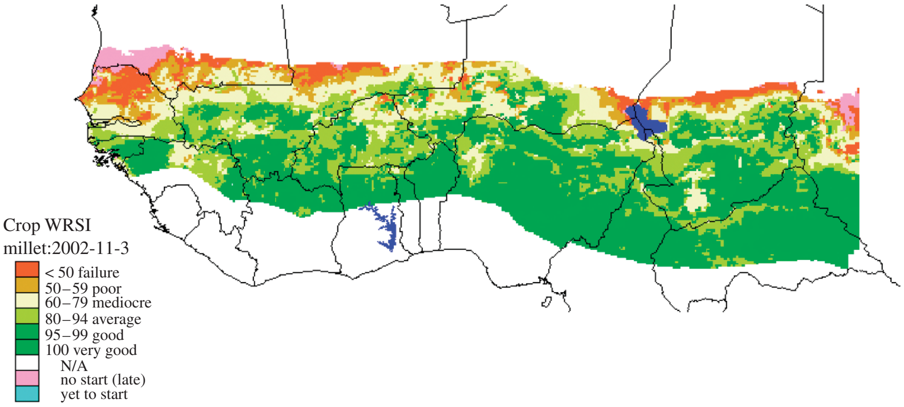

Figure 4. Map of the water requirement satisfaction index (WRSI) for the Sahelian countries of West Africa 2002. Intervals of WRSI correspond to levels of crop performance. Growing conditions for millet that year were especially poor for northern Senegal and southern Mauritania.

4. FLOOD MONITORING

Satellite RFE have been used by FEWS NET since 1999 to monitor flood hazards in Africa that potentially pose a threat to food security. The initiative was prompted by the massive flooding that occurred in the GHA in late 1997 and 1998, causing extensive loss of life and property, with serious negative impacts on food security in the region. Impacts were especially severe in Somalia, where flooding of the Juba and Shabelle Rivers not only destroyed crops in the field, but also caused the loss of major food stocks. Further impetus was provided by the flooding disasters of 2000 in Southern Africa, caused by the successive landfall of three tropical cyclones on the Mozambican coast.

Due to the data sparse nature of these settings, conventional stream gauging and river forecasting approaches practiced in the US could not be applied. Instead, development of new monitoring and modelling methods was undertaken to devise solutions suited to available data: limited surface stations (precipitation and stream flow); satellite remote sensing; numerical weather prediction models; and global land cover, topographic and soils datasets. The objective was the early identification of regional scale flooding due to sustained heavy rains over wide areas, and geographic characterization of impacts.

Implementation involved new technique development in four areas: (i) the arrangement of internet access to gridded representations of daily rainfall totals (both observed and forecast) from NOAA, the US Air Force Weather Agency and NASA; (ii) use of precipitation grids in conjunction with land cover (from USGS), soils (from FAO) and topography (from USGS and NASA) to make simple daily monitoring products—basin excess rainfall maps

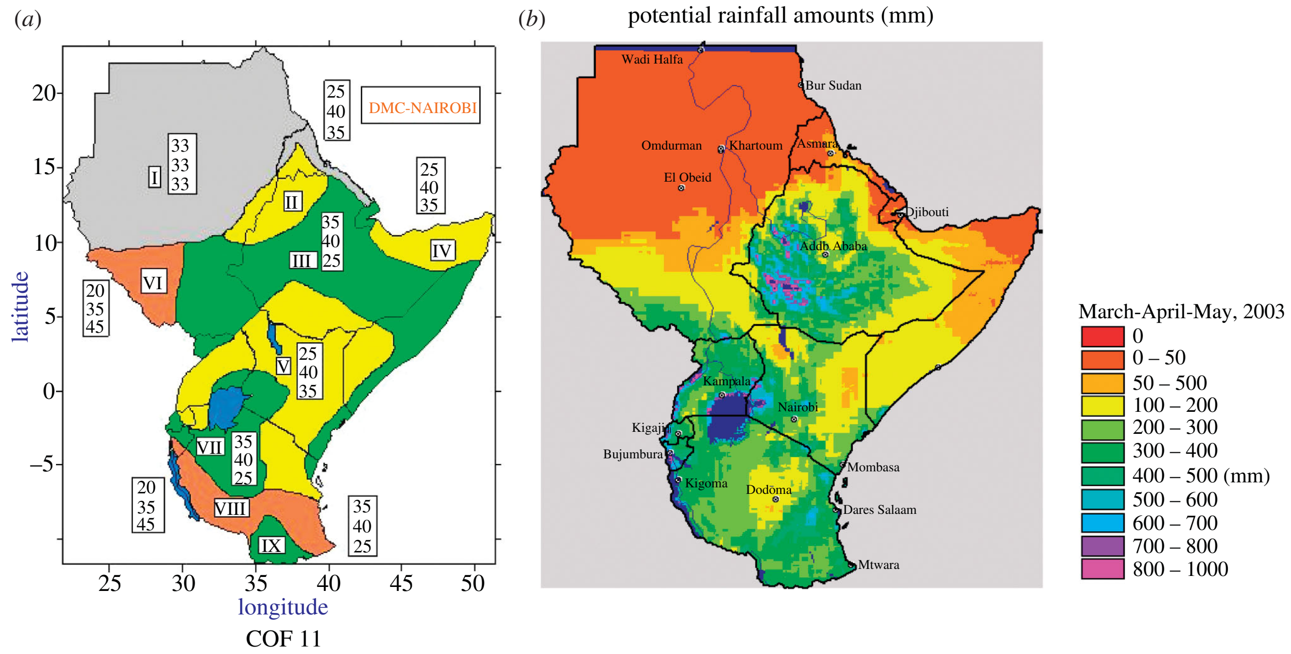

Figure 6. (*a*) Standard tercile forecast map from a climate outlook forum and (*b*) the corresponding map of forecast rainfall totals at the 50% probability level of occurrence, developed using the forecast interpretation tool.

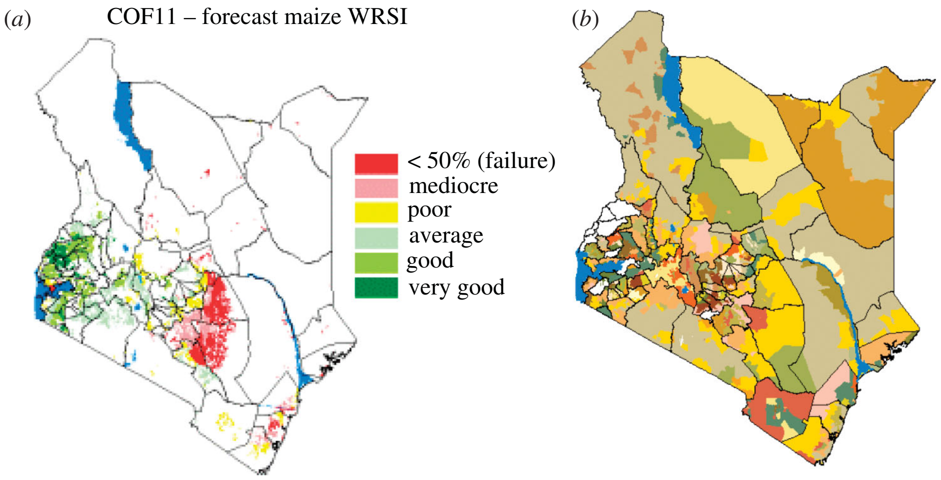

Figure 7. (*a*) Forecast maize growing conditions based on COF forecast rainfall, application of FIT software and WRSI correlations with seasonal rainfall and (*b*) the livelihood zones Kenya, based on socio-economic data collected at 6631 sub-locations. Such data sets are used in developing scenarios at food security outlook forums, organized in conjunction with COFs.

(BERM) and runoff estimate maps; (iii) application of hydrological principles in a GIS environment to produce the geospatial stream flow model (GeoSFM), which has routing calculations to provide hydrographs (plots of river discharge versus time) for hundreds of locations over a region and (iv) development of methods for using digital elevation models to estimate the inundation patterns associated with observed and modelled river flows.

BERM are made by straightforward use of NOAA RFE 2.0 images in conjunction with USGS digital maps of river basins. The basins were derived from 1 km resolution topographic data, and are part of a topologically coded (Verdin & Verdin 1999) global dataset known as HYDRO1K (http://edcdaac.usgs.gov/gtopo30/hydro/index.html).

RFE are summed over river basin areas and accumulated for the season. These sums are divided by the corresponding values for long-term average conditions (Hutchinson 1995), and excess rainfall scores are assigned to basin areas accordingly—the higher the ratio, the greater the score. Maps are then produced with colour codes indicating relative levels of excess precipitation. BERM products are made on both a daily and a dekadal basis. They reveal situations of sustained heavy regional rains that adversely affect food security through flooding and consequent widespread disruption of agriculture, transportation and market systems. The maps highlight sub-basins (out of approximately 3000 across the continent) receiving above-average precipitation by colour coding the relevant polygons. The daily BERM is more sophisticated than the dekadal BERM, in that it takes into account current SPI and maintains a running soil water balance calculation.

Satellite RFE are also used to make a daily runoff estimates according to the curve number method of the Soil Conservation Service (SCS 1972). The method was adapted to be applied on a geospatial basis to support a study of water-harvest potential, as described by Senay & Verdin (2004). The method has also proven useful for application on an operational basis, highlighting basins in Africa that experience high soil moisture and runoff conditions.

Satellite RFE can be used to forecast river flows (Artan *et al.* 2001; Grimes & Diop 2003). Regional scale modelling with the GeoSFM is performed both at USGS and in Nairobi, Kenya, with output for the GHA displayed on the web. The Southern Africa Development Community also displays GeoSFM output on its hazards website for major rivers including the Limpopo, Zambezi, Save and Rovuma. In partnership with FAO, GeoSFM output supports flood warning to communities on the Juba and Shabelle Rivers in Somalia. In Kenya, modelling of the Tana helps inform NGOs working with vulnerable communities on that river. In Mozambique, the national government uses the GeoSFM operationally to estimate river levels at key locations on the Limpopo and Incomati rivers. River levels at gauging stations have accompanying inundation maps for contingency and response planning by the national disaster management agency.

Tests of the GeoSFM in Kenya found correlations between observed and modelled flows in the range of 0.64–0.82; in South Africa correlations ranged between 0.72 and 0.99 (Artan *et al.* 2001).

5. CHANGING CLIMATE AND FOOD SECURITY: FOCUS ON ETHIOPIA

Rising concentrations of carbon dioxide (CO_2) in the atmosphere are associated with increased global mean surface temperatures, already observed, as well as prospects for further increases in the future. Global warming threatens to undermine the stability of the Earth's climate system, disrupting the human populations and ecosystems that depend upon it (IPCC 2001). Africa is no exception. The continent has warmed in the last 100 years and faces possible future increases of 2–6 °C (Hulme *et al.* 2001). Indeed, Hare (2005) recently observed that 'Africa seems to be consistently among the regions with high to very high projected damages' across a range of global warming scenarios. These changes will tend to impact the most vulnerable populations first.

Home to semi-arid regions where crops are already near their thermal maxima, higher temperatures will depress yields and place increasing limitations on pasture, yields and water availability in semi-arid regions. Increased air temperatures will also raise rates of evapotranspiration and crop water requirements in regions, where rainfall is already scarce. More frequent occurrences of extreme hydroclimatic events are foreseen as well. These changes imply increased occurrence of crop failure and livestock losses due to lack of sufficient pasture and water resources and, consequently, greater food insecurity among subsistence farmers as well as pastoral and agro-pastoral households highly vulnerable to such shocks.

Rural Africa will have to adapt to withstand the effects of changing climate. Tieszen *et al.* (2004), have shown that promotion and adoption of natural resources management practices can help mitigate the impacts on subsistence farmers. Stemming the loss of woody biomass while increasing fallow, manure applications and water conservation practices can increase soil organic carbon and lead to positive intensification of agriculture, instead of destructive extensification. The benefits of increased carbon sequestration are threefold: food and water supplies are enhanced, greenhouse gas emissions are mitigated and desertification is reversed. These practices will have to be part of a broad spectrum of adaptive measures. Timely identification of such measures, however, requires basic climate data and information to identify and quantify trends. Unfortunately, in many countries of Africa, climate data networks, data management systems, telecommunications and modelling capacity are not adequate to meet the challenge. In fact, in the last 40 years there has been a major decline in the number of active stations (IRI 2005). Priority must be given to investments that will empower African climate scientists and engineers with the technology they need to fully apply their knowledge to meet the challenges at hand (Washington *et al.* 2004). Indeed, this is an international responsibility under the implementation plan for the global climate observing system (WMO 2004).

Ethiopia is an extreme case in point. The country faces the same general problems that confront sub-Saharan Africa, as described above, but has acute problems of its own. It is in the midst of an ongoing food security emergency, where 8–10 million people will not be able to meet their minimum food requirements this year with out external assistance. The last 10 years have seen massive increases in destitution due to multiple causes.

Beginning in 1997, the world price for coffee began to decline, reducing employment opportunities that formerly provided a prime coping mechanism for withstanding crop and livestock losses. The El Niño of 1997/1998 brought floods and crop losses, as well as outbreaks of rift valley fever. The disease caused livestock losses and more importantly led to a seven-year export ban which undermined the principle mechanism that pastoral households use to access food—the sale of livestock to purchase cereals. The disruptions of the 1998–2000 war with Eritrea were compounded by drought that was felt especially hard in pastoral areas. Then, a bumper crop in 2000 led to a market crash in 2001 due to poor market infrastructure and lack of effective demand in food deficit areas of the country. Farmers responded by reducing planted area in 2002, only to be struck by the worst drought in 40 years. An unprecedented food security crisis ensued in 2002/2003, when 13.2 million people required emergency food aid (22% of the population). Recovery from that crisis has been slow. Ethiopia now has 5.1 million people who are chronically food insecure, and another 3.7 million who will need emergency assistance this year. Another million or more might become food insecure in the months ahead.

Malaria is the number one health problem in Ethiopia, with an estimated 65% of its 70 million people exposed at some point in their lifetimes. Each year there are more than 5 million malaria cases in the country. Morbidity and mortality are high in the adult population, and school absenteeism spikes when epidemics occur. Malaria discourages settlement in potentially productive low-lying parts of the country, while the malaria-free highlands have suffered widespread environmental degradation, deforestation and soil erosion as the population continues to grow rapidly. When there are malaria epidemics, health services are overwhelmed and inadequate to meet the challenge. Precipitation, temperature and other environmental variables are highly correlated with malaria transmission rates (Connor 2002; WHO 2002; Hay *et al.* 2003; Morse *et al.* 2005). Yet, there is no programmatic use of climate monitoring to help guide the application of limited malaria-control resources.

Pasture and crop production is highly dependent on climate, and therefore, vulnerable to climate variability. Most of the rains in Ethiopia come in the period March to September, with a pause in many parts of the country around the end of May or beginning of June. The Belg rains come in March–May, and the Kiremt rains in June–September. Crops grown in the Belg season account for 5–10% of national production, while those associated with the Kiremt rains make up 40–45% of production. These are short cycle crops, typically wheat, teff and barley. Long-cycle crops, mostly maize and sorghum, are grown through the full March–September period. They account for 50% of national production. The Meher harvest includes all crops harvested after rains end in September, both short and long-cycle varieties. Long-cycle crops are quite sensitive to the performance of Belg rains. A FEWS NET (2003) study showed that April–May rainfall totals could explain 50% of the variance of long-cycle WRSI, revealing that this is a critical stage when rainfall deficits can negatively impact yields of crops harvested in September–December.

The Climate Hazards Group at the University of California, Santa Barbara, recently completed a study of rainfall variability in Ethiopia for the period 1960–2004, with a focus on the key growing seasons. Monthly data from 162 stations of the National Meteorological Service Agency were supplemented with observations from the Global Historical Climate Network and archives of the FAO and FEWS NET. In all, 186 stations within Ethiopia, and 373 in neighbouring countries, were used.

Block kriging (Bailey & Gatrell 1996) was used to interpolate the station data and create spatial averages for level 3 administrative units (zones). The administrative units were then grouped into four regions based on similarity of their rainfall patterns. Figure 8 illustrates these regions, along with time-series of seasonal rainfall totals for each, with 7-year running means superimposed to reveal trends. Seasonal plots of rainfall for the country as a whole are also shown, for March–May (Belg), June–September (Kiremt) and March–September periods.

Examination of figure 8 shows that, nationally, Kiremt rains have been quite consistent since 1960, with 7-year trends staying within ±50 mm of the long-term mean of 760 mm. Belg rains, on the other hand, have fallen off consistently since 1996. This decrease is seen to carry through in the graph of national rainfall totals for the full March–September season, though the downward turn is less dramatic. Turning to the regions, the annual rains in the northwest are seen to be most stable. The southwest, on the other hand, shows a steady decline throughout the entire period examined. Fortunately, rains are still abundant there and there are no adverse implications for crops. The northeast and southeast give cause for concern. In the former case, we see dryness since 1996, and in the latter, dryness persists since about 1980.

These rainfall tendencies have serious food security implications. Since 1996, there is a correlation at the 0.79 level ($r^2=0.62$) between millions needing food aid and national rainfall anomalies (figure 9). The impacts and responses to rainfall deficits, however, will vary greatly depending on location and livelihood. The largest impacts are likely to occur in northeastern and southeastern Ethiopia. These regions already exhibit very high rural population densities, more than 100 people per km^2, and low water availability in Ethiopia. In southeastern Ethiopia, the belg rains constitute a greater proportion of the annual rainfall. Geographically, impacts and adaptation will vary with elevation. Highland areas are associated with more rainfall and more agriculture than the surrounding lowlands. In lowland areas most people depend on pastoral livelihoods.

Lowland areas, such as Afar to the north and Shinile and Jigjiga to the south, have suffered from the recent livestock export ban. They possess a limited capacity to respond to climate shocks, and will likely be the first affected by increasing temperatures, recent decreases in rainfall and a potential increase in climate variability. If annual rainfall totals continue to decline and persist below 300 mm yr^{-1}, pastoral life in these regions may become untenable.

Highland areas in the east, generally, rely on rainfed agriculture (e.g. East and West Harargue, East Tigray, South Tigray, North Wello). In these regions reduced Belg harvests seem likely, as do reduced long-cycle yields. Reduced long-cycle yields may also be likely in the relatively wet southwest. Such crops are vulnerable to drought in April–May that is increasingly common in the last 10 years. We may be seeing an expression of this in the variation of national figures for those in need of food aid. In these areas, a shift away from long-cycle crops might improve food security. Although reliance on the short-cycle crops has been practised by the local farmers as a coping mechanism to the failing of the long-cycle crops, the low-yielding nature of traditional short-cycle crops such as teff means an overall reduction in production. This highlights the need for more research and extension to introduce appropriate high-yielding short-cycle crops into these regions.

Reduced Belg rains in Ethiopia appear to be part of a larger set of climate changes in the Indian Ocean basin. SSTs in the central Indian Ocean are among the

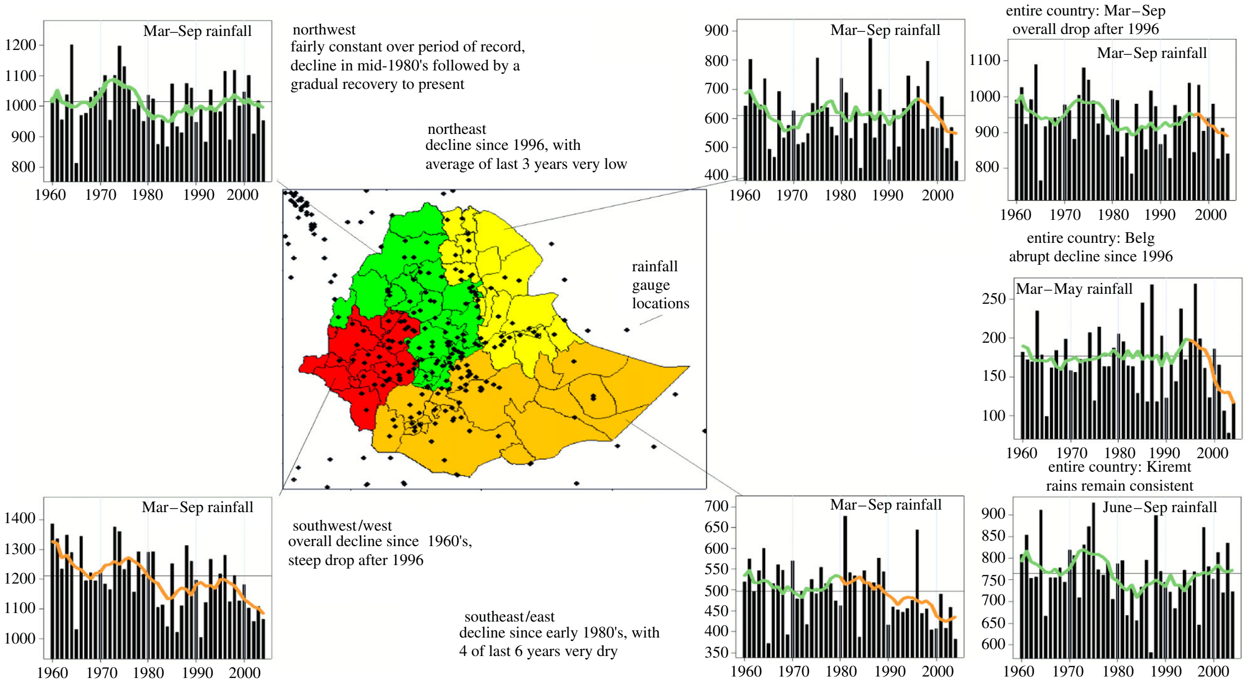

Figure 8. National and regional graphs of seasonal rainfall totals, with 7-year running means as a linear trace, for the period 1960–2004. See text for discussion.

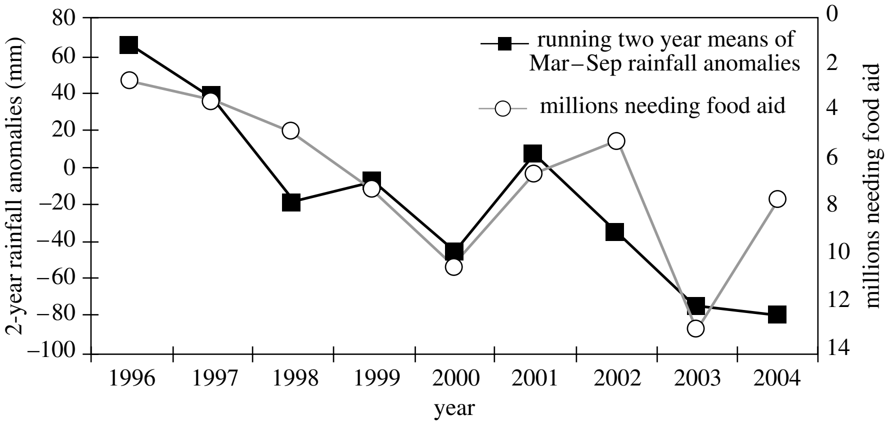

Figure 9. Correlation between millions needing food aid and 2-year running average national precipitation for March–September. The rainfall time-series has a strong relationship to food aid ($r2=0.62$).

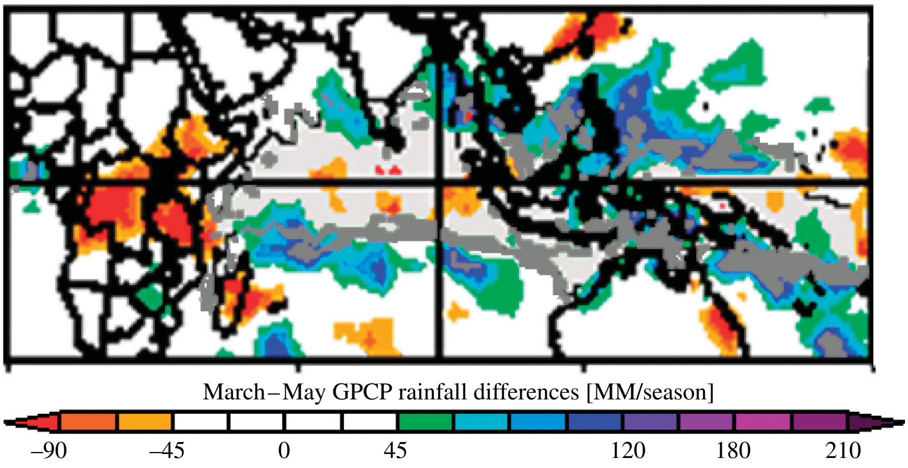

Figure 10. Regions with recent warm SSTs and GPCP precipitation anomalies. Dark grey shading specifies regions which had averages of SSTs of less than 29 °C over the 1980–1996 period, and over 29 °C between 1997 and 2004. Blue–purple shading denotes regions with enhanced recent (1997–2004) precipitation. Red shades indicate reduced recent rainfall. A 1980–1997 baseline was used to define anomalies.

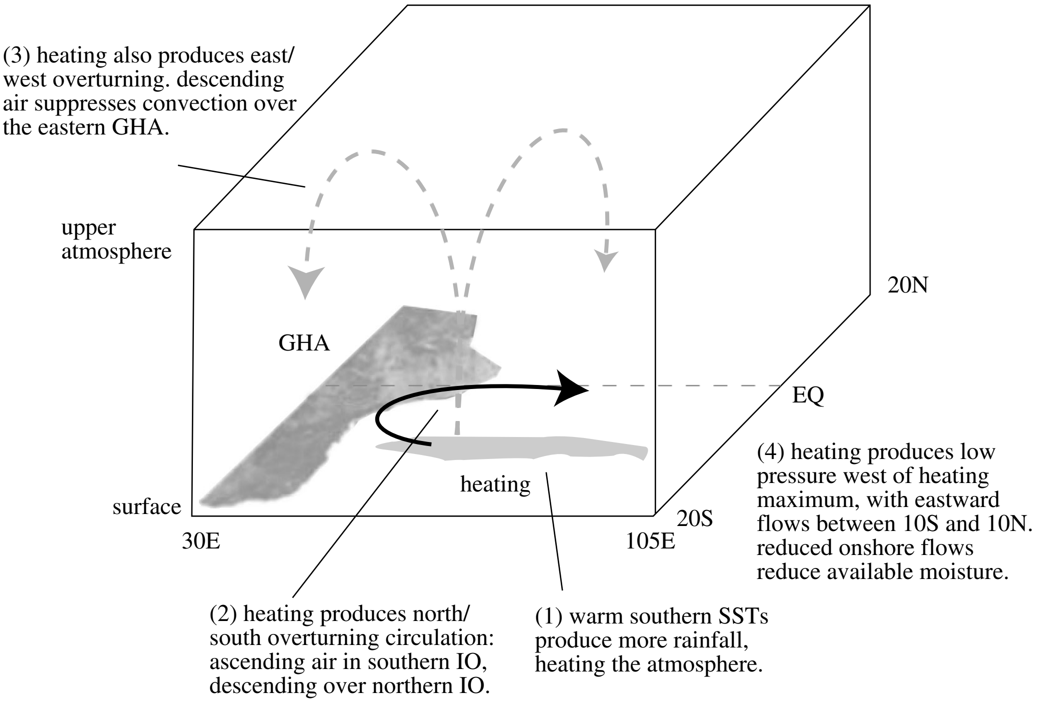

Figure 11. March–May circulation schema based on the Gill (1982) model.

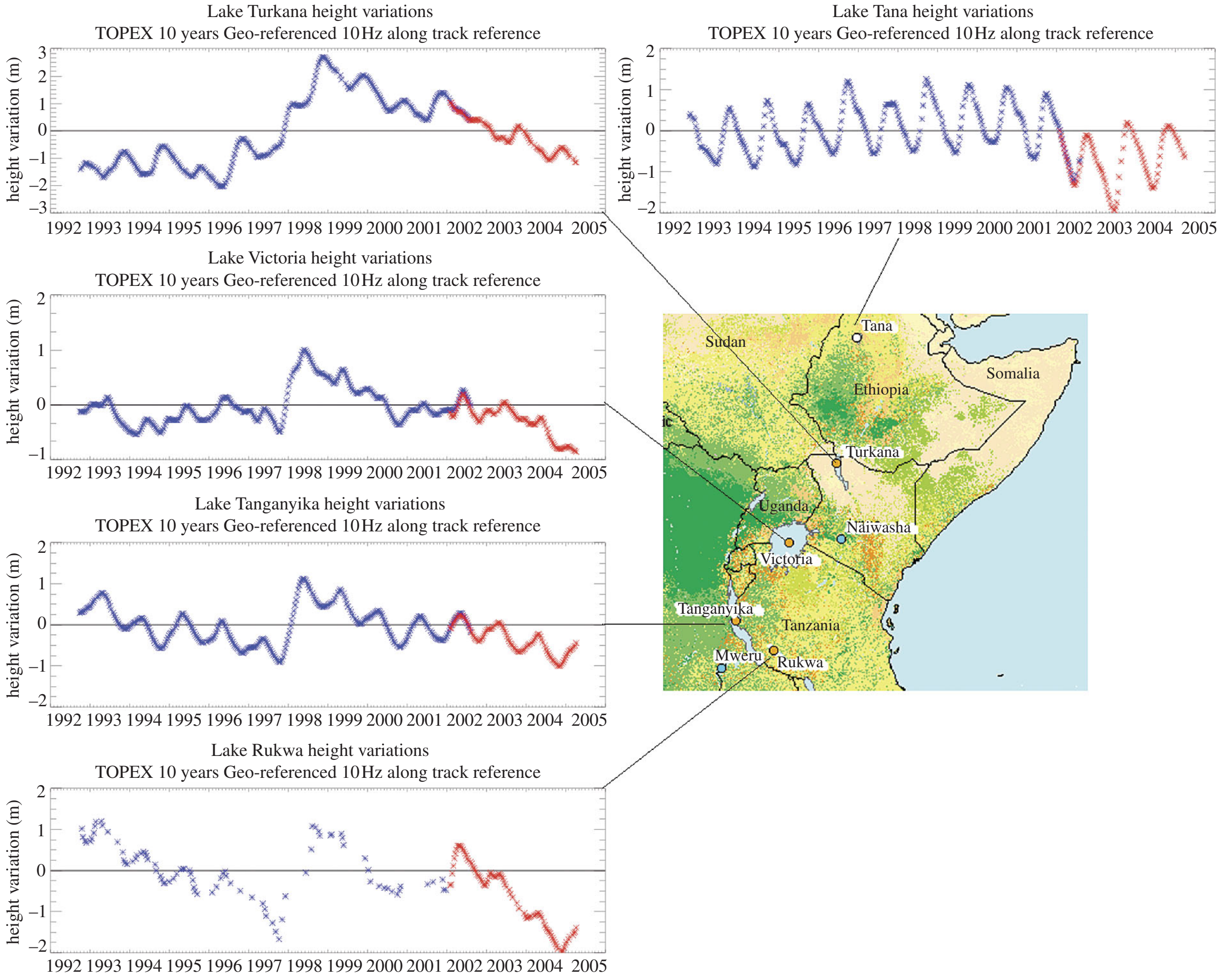

Figure 12. Topex Poseidon/Jason 1 Lake levels for five lakes in the Greater Horn. Time-series and imagery obtained from the USDA PECAD crop explorer: http://www.pecad.fas.usda.gov/cropexplorer/global_reservoir/.

highest in the world. In concert with summer heating of the Eurasian land mass, they help set up wind patterns that each year bring moisture to the GHA, the Middle East and India (Camberlin & Philippon 2002). A warming trend in these SSTs increasingly places them in a dynamically active range that may be changing regional circulations over the Greater Horn. When SSTs approach 30 °C, large-scale convection and precipitation can occur, drawing in moisture from surrounding areas. The Indian Ocean is particularly warm in the boreal spring, when the basin is relatively cloud free. Analysis of recent (1997–2004) March–May SSTs and precipitation fields show new areas of very warm water and increased convection across the southeastern Indian ocean. The diabatic heating from these anomalies is consistent with reduced rainfall over central eastern Africa.

Dark grey polygons in figure 10 denote ‘new’ very warm regions in the southeastern Indian Ocean. This figure compares March–May composites for the 1980–1996 and 1997–2004 periods. Grey areas denote areas that had average 1997–2004 SSTs of over 29 °C, and average 1980–1996 SSTs of less than 29 °C. Red-to-blue shading depicts March–May GPCP differences (1997–2004 minus 1980–1996) showing associated increases in precipitation just to the south of these very warm waters. Reductions in precipitation are also apparent over a good deal of Central Africa.

Our premise is that warm SST anomalies in the southern equatorial Indian Ocean produce an anomalous circulation (Gill 1982, pp. 466–472) that reduces rainfall over parts of the Greater Horn. Figure 11 shows the salient elements of such a circulation, which is driven by a heating anomaly near 10S. A surface low forms to the immediate west of the heat source, and the associated pattern impacts eastern Africa by: (i) creating eastward (offshore) surface wind anomalies near the equator and (ii) setting up vertical circulations that bring hot dry descending air down over the Horn and northwestern Indian ocean. Reanalysis fields (not shown) do in fact support this hypothesis, showing a marked tendency towards increased subsidence *over* and reduced moisture transport *into* the Greater Horn over the 1997–2004 period, consistent with recent decrease in Belg rains shown in figure 8. Time-series of satellite measurements of lake levels (figure 12) also suggest a pattern of recent dryness across the central-eastern Greater Horn. Following a large jump in 1998 associated with ENSO, decreases in lake levels are apparent in Lake Rukwa, Tanganyika, Victoria and Turkana. Lake Tana, in Northern Ethiopia, shows a substantial anomaly beginning in 2002.

In summary, station data, satellite precipitation estimates, reanalysis fields and lake levels all suggest recent dryness in Eastern Africa, primarily during the Belg (March–May) season. The associated circulation changes appear consistent with the expected response to diabatic heating in the southeastern Indian Ocean.

Studies of this kind are needed for early identification and quantification of climate shifts and trends. Ethiopia has qualified scientists and a station network that can provide the basis for these studies, but only if investments are made to bolster data collection and analysis. The hydrometeorological network requires expansion and modernization and satellite RFE are needed to supplement station observations. The country’s complex precipitation patterns (Gissila *et al.* 2004) require these measures if they are to be characterized and understood. Historical context, as we have seen, is also essential to understanding the climate patterns of today. To this end, Ethiopia’s climate station observation records must be digitized to make them useable for modern methods of analysis. These methods include numerical modelling, remote sensing, geostatistics and GIS. Their implementation will require new computer hardware and software. Scientific and technical staff will require training in the use of these analytical tools. Investment is also needed in education to increase the number of qualified scientists, engineers and technicians using modern technology for climate studies.

6. CONCLUDING REMARKS

Food security monitoring in sub-Saharan Africa provides the early warning needed to save lives and livelihoods in the face of a wide range of potential socio-economic and environmental shocks. Climate monitoring and forecasting are especially important given the large number of rural people dependent on subsistence agriculture and pastoralism. Because conventional climate station networks are sparse, remote sensing and modelling methods have been developed to support food security assessment.

The global climate is forecast to change significantly as a consequence of increasing concentrations of greenhouse gases in the atmosphere, and scenarios for Africa are consistently negative. Increased probability of crop and livestock losses implies increased food insecurity for vulnerable pastoralists and subsistence farmers. Changes in agricultural practices and improved natural resources management techniques will be needed to adapt to new conditions. However, adaptation strategies cannot be developed and implemented until trends and shifts in climate have been identified. The case of Ethiopia is instructive. The country confronts a food security emergency, where 8–10 million people cannot meet the annual food needs without external assistance. A wide range of reforms and restructuring are urgently required. In agriculture, there is a need to strengthen the research and extension work in the introduction of high-yielding short-cycle crops, to compensate for consistently poor Belg rains. The apparent shift in rainfall patterns since 1996 coincides with a steady warming trend in SSTs that is affecting countries all around the Indian Ocean. However, people are only now becoming aware of the nature of this shift in climate, not because Ethiopia lacks qualified scientists (though more could certainly be used) but because they lack access to modern methods of data capture, data management, telecommunications, modelling and analysis. The developed countries must act now to transfer advanced climate science and technology to African counterparts, for it is in the hands of those with local knowledge that creative adaptation strategies will be forthcoming.

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