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Geospatial Climate Monitoring Products:
Tools for Food Security Assessment

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by

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ABSTRACT

Geospatial Climate Monitoring Products: Tools for Food Security Assessment

Many of the 250 million people living in the drylands of Sub-Saharan Africa are food insecure—they lack access at all times to enough food for an active and healthy life. Their vulnerability is due in large measure to highly variable climatic conditions and a dependence on rainfed agriculture. Famine, the most extreme food security emergency, is caused by crop failure due to bad weather, conflict, or both. Famine is a slow onset disaster, culminating after two or more bad growing seasons. After the disastrous African famines of the 1970s and 1980s, the U.S. established the Famine Early Warning System (FEWS) to make the observations of climatic and socioeconomic variables needed for early detection of food security emergencies. Two geospatial climate monitoring products, rainfall estimate and vegetation index images derived from satellite data, are operationally used by FEWS analysts. This dissertation describes research to derive new products from them to reduce ambiguity and improve the link between early warning and early response. First, rainfall estimate images were used in a geospatial crop water accounting scheme. The resulting water requirement satisfaction index was used to estimate crop yield, and a correlation of 0.80 with conventional yield reports was obtained for the 1997 maize harvest in Zimbabwe. Thus, the agricultural significance of remotely sensed patterns of precipitation in time and space was made more clear. The second product tested was the expression of a seasonal climate forecast as a series of vegetation index anomaly images. Correlations between sea surface temperature anomalies in the equatorial Pacific and vegetation index anomalies in Southern Africa were established and predictive relationships cross-validated. Using model forecast values of Pacific sea surface temperature from the National Oceanic and Atmospheric Administration for January, February, and March, forecast images of vegetation index anomalies were prepared prior to the 1998 maize growing season. Comparison with actual vegetation index images after the season showed expected positive (wet) anomalies as expected, but wide areas of expected negative (dry) anomalies exhibited average or above-average greenness. A summary discussion identifies opportunities for further research to refine the demonstrated techniques.
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Chapter 1

Introduction

1.1 Description of the Problem

Hundreds of millions of people in the world today do not enjoy food security—they do not have “access ... at all times to enough food for an active and healthy life” (World Bank, 1986). Many of these individuals are among the quarter-billion people living in the climatically vulnerable drylands of Sub-Saharan Africa (UNSO/UNDP, 1997). Indeed, the drought of the early 1970s was responsible for 100,000 deaths in the Sahel and 200,000 deaths in Ethiopia (Sen, 1981), and was soon followed by drought in 1983-1985 that saw deaths in Ethiopia estimated to number from 400,000 to 1 million (Walker, 1989). This dissertation describes the demonstration and testing of two new climate monitoring products designed to support early detection of environmental conditions that set the stage for such food security disasters.

Famine is the most extreme food security emergency that can occur in the vulnerable areas of Africa. A practical definition of famine, offered by Cox (quoted by Field, 1993a), states that it is “the regional failure of food production or distribution systems, leading to sharply increased mortality due
to starvation and associated disease. Famine's underlying cause is crop failure brought about by bad weather, armed conflict, or both (Mellor and Gavian, 1987). As Field (1993a) describes, famine is associated with a general condition of social upheaval:

"A society experiencing famine is in disequilibrium, a state of breakdown. Crop production is abnormally low; employment opportunities shrink among the rural labor force; trade is curtailed; food prices rise as incomes decline...; the exchange rate between animal products and grain deteriorates markedly,...; and consumption is curtailed as people lose access to food. As famine unfolds, antisocial behavior — hoarding, crime, and the like — increases, social arrangements erode, people sell or abandon their assets, and out-migration accelerates. In the midst of all this, malnutrition rates soar, infectious diseases spread, and people die in unusual numbers."

Famine is a slow-onset disaster, the culmination of physical and social processes occurring over two or more growing seasons. This means that observation and detection of events leading up to famine can yield information needed to trigger responses that prepare for famine and prevent its worst effects. Even so, early warning of famine can come none too soon because "the time needed to get food to famine-stricken areas after an appeal for aid can stretch to six months or more" (Ulrich, 1993). Furthermore, early warning does not guarantee early response. The decision by relief organizations to commit large amounts of resources ordinarily demands clear evidence that, unfortunately, is often difficult to assemble in the early stages of the famine process.
Prevention of famine in climatically vulnerable regions of Africa, then, requires early and unambiguous identification of unfolding food security problems so that mitigating action can be taken. Complicating the task is the fact that, over the years, the identities and numbers of those who are food-insecure can shift in time and space. Relevant physical, social, and political forces are ever-changing. In the face of this situation, the United States Agency for International Development (USAID) created the Famine Early Warning System (FEWS) to obtain the information needed to prevent widespread human suffering due to lack of food availability and access. The FEWS mission statement is: “To provide host country and U.S. decision-makers with timely and accurate information on potential famine areas”. As the final word of this statement reveals, the information problem is in large measure geographic. Food security assessment in Sub-Saharan Africa requires monitoring the agrophysical and socioeconomic conditions of large and spatially dispersed populations. From a physical science standpoint, food security assessment requires monitoring climatic variables and modeling their implications for rainfed agriculture on an ongoing basis. Simultaneously, the human factors of famine vulnerability must be accounted for and mapped. These include, for example, population distribution, household income, prices of grain (McCorkle, 1987) and cattle (Kinsey et al. 1998), school attendance, employment opportunities, nutritional status
(Shoham, 1987; Kelly, 1993), and other variables (Reddy, 1992). Joint spatial analysis of agrophysical and socioeconomic factors is employed by analysts to produce an integrated picture of the food security situation. Field work, interviews with local experts, consultation with national early warning committees, and professional experience build upon spatial analyses to yield a synthesis of the situation in monthly bulletins and special reports (FEWS, 1999). Consumers of this information include the decision-makers in host country governments, USAID, donor countries, multinational organizations, and non-governmental organizations (NGOs) having mandates and resources for response to food security emergencies. Targeting of their responses directly benefits from FEWS analyses describing the location and intensity of food needs.

Geographically referenced (geospatial) climate monitoring products offer food security analysts succinct and practical summaries of crop growing conditions. The products are accessible in near-real time at a continental scale and are typically the most comprehensive and up to date observational data available. They have recently been supplemented by seasonal climate forecasts stemming from an improved understanding of the El Nino-Southern Oscillation (ENSO) phenomenon by the scientific community (Glantz, 1996). However, the content of these climate information products can at times be unclear and lead to more than one interpretation of food security conditions.
Current operational climate monitoring for FEWS is based primarily on Normalized Difference Vegetation Index (NDVI) maximum value composite images (Tucker and Sellers, 1986; Holben, 1986) and Rainfall Estimate (RFE) images (Herman et al., 1997) produced on a 10-day time step. The FEWS NDVI archive dates back to July 1981, while the RFE images have only been produced since 1995. Conventional rain gauge data are also analyzed, though availability of these data from country to country is quite variable, and there is a significant delay in obtaining data for many stations. These operational products are the basis for analyzing climate in the past, present, and future. Variability in the historical NDVI and rain gauge data is the basis for estimating predisposition to drought. NDVI and RFE are the principal tools for current season monitoring. Climate forecasts are usually expressed in terms of expected rainfall relative to normal over broad areas or specific precipitation stations.

While these tools for climate monitoring are based, for the most part, on high technology and are quite advanced compared with those available only 15 years ago, the pace of technological advance continues to be very rapid. Geospatial data processing methods are more powerful and inexpensive than they have ever been, and there is an increasing number of quality geospatial data sets available for continental scale studies. Meteorological
modeling produces gridded analysis fields of atmospheric state variables every six hours, and coupled ocean-atmosphere models make possible climate forecasts of unprecedented specificity. Yet at present, the FEWS project does not take full advantage of these technologies.

Because the processes of famine are "shrouded in ambiguity" (Field, 1993a) it is often difficult for early detection to be sufficiently definitive to elicit early response. Early detection and early warning must be persuasive enough to overcome the risk avoidance behaviors of bureaucrats in responsible organizations — national governments, donor agencies, international organizations, and NGOs (Cutler, 1993). Early warning systems must strive "to reduce ambiguity and thereby overcome inhibitions to taking action" (Field, 1993b). It is for this reason that FEWS food security analysts rely upon a convergence of evidence to make food security assessments. No single source of information is sufficiently authoritative and comprehensive to identify potential famine areas by itself (Mason et al., 1987; Shoham, 1987; Kelly, 1993). The contents of individual data sets and reports, be they descriptive of agrophysical, socioeconomic or nutritional variables, are unavoidably subject to ambiguity. Therefore, analysts draw their conclusions most confidently when all factors indicate a certain food security status in a region. Any reduction of ambiguity associated with data or information used
by FEWS contributes to confidence in food security assessments and an improved linkage between early warning and early response.

The research described in this dissertation is aimed at the reduction of ambiguity associated with climate information products routinely used by FEWS. Two new geospatial climate monitoring products are demonstrated and tested for Southern Africa. They build upon FEWS’ operational rainfall estimate images and the ENSO forecasts from the United States National Oceanic and Atmospheric Administration’s Climate Prediction Center (NOAA/CPC). The new products are designed to provide FEWS analysts with derivative information that speaks more directly to the food security questions that they face.

1.2 Scientific Objectives

The first science objective addressed in this dissertation is to perform a proof-of-concept trial of a geospatial method for capturing the agrometeorological significance of the RFE products. While NDVI represents an integrated response of the soil-vegetation complex to seasonal rainfall, this is not so of the RFE. The significance of a 10-day rainfall total is a function not only of quantity, but also timing relative to a crop’s phenology, and the rainfall that has occurred earlier in the season. A geospatial solution
for crop water accounting is presented that is based on the RFE, available weather forecast model output, and digital maps of the soils of Africa. The method is implemented for the case of the 1996-1997 growing season in Southern Africa as a proof-of-concept trial. Literature (e.g., Frere and Popov, 1986; Gommes et al., 1996) describing relevant agrometeorological theory and present day best practice are reviewed and used to justify the approach developed for FEWS.

Results of the geospatial crop water accounting and associated estimates of yield are evaluated using conventional agricultural statistics. Success is reported in terms of the degree of correlation between reported crop yield and estimates based on the geospatial solution. Insights gained from the test of the method are the basis of recommendations for improvement and further research.

The second science objective addressed in this dissertation research is the exploration of methods for using the African NDVI archive to express climate forecasts in a form that is easily understood by FEWS analysts. There currently exists a gap between the meteorological community and the early warning community in terms of the content of forecasts for El Nino-Southern Oscillation (ENSO) events in the equatorial Pacific. Food security analysts understand that there are teleconnections between sea surface temperature
(SST) and African crop growing conditions (Cane et al., 1994), but the language of ENSO advisories from NOAA/CPC can be unrelated to the agrometeorological concerns of a FEWS field representative (Farmer, 1997). However, evidence of the Southern Africa ENSO teleconnection as a linkage between SST anomalies and NDVI anomalies has been described in recent papers (Myneni et al., 1996; Anyamba and Eastman, 1996). These findings suggest the expression of an ENSO forecast in terms of African NDVI anomalies. Statistical relationships are developed between historical SST and NDVI anomalies for this purpose, and then applied to translate SST anomaly forecasts into forecast NDVI anomaly images. The major ENSO event of 1997-1998 provided an ideal opportunity for the conduct of this experiment.

The results of the SST-based forecast of NDVI anomalies in Southern Africa are evaluated through comparison with the actual imagery acquired during the growing season. Cross-validation techniques are applied to assess "skill", in the statistical sense, of the technique. Guidance for future applications of the method is based on these results.
1.3 Significance of the Research

The significance of the present research lies in the potential of the techniques demonstrated to reduce ambiguity in the ENSO climate forecasts and climate monitoring information used by FEWS. As a result, the information needs of disaster relief decision-makers can more confidently be met by the early warning community (Dilley, 1997). The true dimensions of an emerging disaster can then be made more clear. Mitigating actions that require commitment of large amounts of resources can be taken with greater assurance of their correctness. Ultimately, lives may be saved by more timely and directed interventions.

Vulnerability assessment is performed to locate and identify the populations most likely to experience a food security emergency in the event of a climatic or political shock. Vulnerability assessment requires a thorough review of the agrophysical, socioeconomic, health and demographic factors describing those social groups potentially at risk. The combination of highly variable growing conditions and limited coping options, for example, can combine to create a high level of vulnerability. The interpretation of seasonal forecasts and within-season monitoring, then, are guided by this a priori knowledge of the locations of at-risk populations. Vulnerability assessment is necessarily a difficult task subject to unavoidable ambiguity. If the climatic forecasts and
monitoring information which are superimposed upon the vulnerability assessment are likewise ambiguous, the task of the food security analyst can become very difficult indeed. The methods reported in this dissertation are designed to reduce the ambiguity in climatic monitoring and forecasts.

Beyond the societal significance of this work, there is significance in the technical content of the research as well. The power of a geospatial approach for synergistically combining data and information from disparate sources is demonstrated in the crop water accounting scheme. A new information product is created that speaks more directly to the question posed by FEWS, which is "How much grain will be produced this season, and where?" rather than "How much rain will fall this season, and where?".

Innovation is shown in developing a linkage between relatively new, but technically arcane, forecasts of sea-surface temperature, and a long-used, familiar geospatial climate information product, the NDVI anomaly image. A method is demonstrated for putting climate forecasts, developed at great effort and expense, into terms which more effectively communicate their content to FEWS analysts, users of important human consequence. The research presents quantitative evaluations of the experimental geospatial climate information products developed. Objective measures of their
effectiveness are presented, and firm indications of their limitations are stated.

1.4 Summary of Chapters

Following this introduction, Chapter 2 reviews the food security assessment problem and the role of early warning systems, especially FEWS. The conceptual scope and geographic scale of early warning monitoring needs are laid out. The use of a geospatial context for analysis and the importance of climate data in the analyses are described.

Chapter 3 reviews the operational FEWS rainfall estimate product and the limitations of its utility. A method is laid out for use of the RFE in conjunction with operational weather forecast data fields and the United Nations Food and Agriculture Organization (FAO) digital soil map of Africa to provide a measure of seasonal crop performance. Current agrometeorological and hydrometeorological theory and techniques are reviewed and discussed to justify the method adopted. Application of the crop moisture accounting methodology during the 1996-1997 Southern Africa growing season is described and an assessment of its effectiveness presented.
Chapter 4 reviews the value and shortcomings of conventional ENSO forecasts to the early warning community. A methodology for translating such forecasts into a product, NDVI anomaly images, that is readily understood and usable by the early warning community is described. Theoretical and technical justification for this product is drawn from remote sensing and ENSO research literature.

NDVI anomaly projections for the 1997-1998 Southern Africa growing season are presented. These projections are evaluated by comparison with rainfall forecasts from the same time frame (late November-early December 1997) made by other, more conventional, climatological methods. The NDVI anomaly projections are also evaluated after the growing season by comparison with actual NDVI anomalies for the period.

Chapter 5 summarizes the findings of Chapters 3 and 4 and draws broad conclusions relative to the power of geospatial analysis in drawing the maximum information from remote sensing and modeling results, and presenting them in an unambiguous manner that increases their utility for food security decision-making. Reflections on lessons learned by undertaking this research are offered and recommendations made for follow-on work in the area of geospatial climate monitoring products.
1.5 References


Chapter 2

Institutional and Scientific Context of the Research

2.1 Early Warning Systems

While this dissertation describes research specific to USAID's Famine Early Warning System, it is important to understand the work of FEWS in the context of other early warning systems (EWS). The African drought and famine of the mid-1980s prompted a proliferation of activities aimed at systematic collection of data and information for food security purposes (Buchanan-Smith et al., 1991; Torry, 1988, and Walker, 1989). Despite their common theme of famine early warning, these systems are quite varied in their methods and goals. These systems can be compared and contrasted in terms of several conceptual dimensions (e.g., geographic coverage, input data and information, and links to response organizations).

Extent of geographic coverage is an obvious characteristic for differentiating among EWS. Mandates for individual systems range from global to local in area of concern. In between there are systems that operate at the regional and national level. Geographic scope has a strong influence on the types of data collection and analysis that can be realistically undertaken. One cannot
interview every household in Sub-Saharan Africa, but one can analyze NDVI over the whole continent. However, a single 7- to 8-km pixel may not have much to say about food aid requirements in a village, while a conversation at the local clinic may reveal a lot about nutritional status of the community.

Equally important is the continuum of activities from disaster relief to development assistance. Disaster relief focuses on emergencies related to lack of food availability, while development assistance deals more with questions of economic opportunity and food access. Each end of the continuum has a characteristic time frame of reference, with disaster response addressing short term needs (over periods measured in months) and development assistance applied to more long term, structural problems (occurring over years or decades). The scope of analysis of an EWS typically shows an emphasis towards one end or the other of the relief-development continuum, though all EWS acknowledge the full spectrum of activities.

One can also distinguish among EWS specializations in terms of the kinds of data and information dealt with, and the directions in which they flow. Some systems place an emphasis on quantification of growing conditions, food production and supply, while others pay more attention to human variables indicative of food access: household income, nutritional status, demographic
profiles, migration figures, market prices and school attendance. A top-down approach employs data collection and surveys by outsiders trying to discern current conditions, while bottom-up systems are characterized by participation of potential famine victims and advocacy by observers living among them. Local people may have a harder time seeing the benefits in sharing information with a centralized system than with a grassroots, participatory system. In the minds of local people, the latter may be more closely associated with aid in times of trouble than the former, which by contrast demands time and effort to supply information seemingly without any apparent return.

Finally, EWS differ in the nature of their links with response organizations. Such linkages ultimately determine the effectiveness of an EWS, for if early warning does not elicit early response, the system's effectiveness is put in doubt. While there are examples of an EWS housed within an organization that also dispenses aid, many EWS produce information or appeals without direct input to the food aid decision-making process. In either case, appeals must be clear and convincing to warrant the commitment of millions of dollars of aid resources. The main advantage enjoyed by an EWS operated by a donor is reduced turn-around time between warning and response, all else being equal, since fewer intermediaries are involved.
Within the conceptual space described above, Buchanan-Smith (1996) distinguishes between two types of EWS – macro and micro. Macro systems are characterized by having mandates over large areas and analytical approaches that are top down, data-oriented, and with an emphasis on questions related to food production and supply. They are centralized and operate at global, regional, and national levels, relying upon analysis of secondary data, rather than engaging in their own primary data collection. Micro systems, on the other hand, operate at the level of the village or sub-national administrative unit. They are more people-oriented than macro systems in that they deal with data and information of a qualitative nature describing vulnerable social groups and their livelihoods. Micro systems are by nature decentralized. They are also often engaged in development activities seeking to increase sustainable approaches for famine prevention through improved access to food. They are well placed to sound the alarm when food emergencies occur, and can do so in a way that permits more precise targeting of food aid than macro systems. Yet micro systems' close association with the beneficiaries of aid can mean that their warnings are greeted with a higher level of skepticism by response organizations, especially when the warnings are based on data that are subjective in nature and characterized by problems of inconsistent quality (Torry, 1993).
The Food and Agriculture Organization (FAO) of the United Nations operates the Global Information and Early Warning System (GIEWS), the only EWS taking a worldwide view (FAO, 1998). GIEWS is also the oldest of all EWS, having been established in Rome in 1975 by recommendation of the World Food Conference of 1974. GIEWS produces regular country-level summaries of supply and demand for food to identify actual or imminent shortage situations. These appear in its publication "Foodcrops and Shortages" six times per year and are also available online. GIEWS' orientation is more directed toward disaster relief than development assistance, though structural vulnerabilities are certainly recognized in its analyses. The food balance sheet is the analytical tool most closely identified with GIEWS. It is an accounting at the national level of food production, stocks, imports, and exports, vis-à-vis food requirements of the population in aggregate. GIEWS has also long used remote sensing, in the form of vegetation index and cold cloud duration images, for assessment of crop growing conditions (Snijders, 1991). These are used to estimate production for the current season and directly support the preparation of the series of reports entitled "Food Supply Situation and Crop Prospects in Sub-Saharan Africa" which communicates food aid requirements to the international community. The geographic extent of the system necessitates that GIEWS be a top-down, centralized system run by outsiders. Its national level summaries are highly regarded and carry much weight with decision-
makers. Communication with the World Food Program, the food emergency response organization of the UN, is direct and immediate, since both GIEWS and WFP are headquartered in Rome.

Multi-country, regional EWS operate at the next geographic level of monitoring coverage. The Southern Africa Development Community (SADC) operates a Regional Early Warning System (REWS) to provide “advance information on food security prospects in the region” (SADC, 1999). The REWS is composed of a Regional Early Warning Unit (REWU) based in Harare, Zimbabwe, and ten autonomous National Early Warning Units (NEWUs) in each of the original SADC member countries: Angola, Namibia, Botswana, Zambia, Tanzania, Malawi, Mozambique, Zimbabwe, Lesotho, and Swaziland. (SADC’s original formation occurred in 1980; South Africa and Mauritius joined in 1994, and Republic of Congo and Seychelles joined in 1997.) It is a top-down, regional system that puts an emphasis on the supply side of the food security question, although it does consider the question of food access through monitoring of cereal grain prices. Dekadal (10-day) monitoring of rain gauges and crop conditions, supported by remote sensing of cold cloud duration and NDVI at the SADC Regional Remote Sensing Unit, contributes to forecasts of production that are incorporated in food balance models at country and regional levels for the coming twelve months. On the demand side of the question, the REWU encourages the
consideration of household food security information in the preparation of national level food security assessments, but food access gets less attention than does food availability.

Linkage with response decision-makers is best with SADC national governments that finance and rely on the REWS for information needed to make strategic decisions regarding management and marketing of grain stocks. During severe droughts that threaten food security well beyond the resources of governments in the region, like those of 1991-1992 and 1994-1995, appeals to the international community for food aid must be made. The REWS Quarterly Food Security Bulletins, monthly bulletins, and ad hoc reports enjoy high credibility with donors and relief organizations thanks to the professionalism and technical competence of the NEWU and REWU staff. Close ties with FEWS are maintained through the presence of two FEWS Regional Representatives in Harare and FEWS Country Representatives in Malawi, Zambia, Mozambique, and Tanzania. Though short term response to food security emergencies is the priority of the REWS, long term capacity to perform the necessary monitoring functions is continuously built through the organization of regular training courses in agrometeorology, statistics and economics for member country personnel.
The nine country Comité Permanent Inter-États de Lutte contre la Sécheresse dans le Sahel (CILSS) is a formal anti-drought authority whose members are Senegal, Mali, Burkina Faso, Mauritania, Cape Verde, Gambia, Guinea-Bissau, Niger, and Chad. The CILSS does not operate an EWS per se, but rather participates in the Network for Prevention of Food Crises in the Sahel. The Network functions under the auspices of the Club du Sahel, a semi-autonomous body of the Organization for Economic Cooperation and Development (OECD) that promotes dialogue and consultation between Sahelian and donor countries (OECD, 1998). The Network depends upon the food security monitoring activities carried out by member country projects. The AGRHYMET (AGRiculture-HYdrology-METeorology) system of West Africa is one of the best known projects of the CILSS country governments.

AGRHYMET, as its name implies, is focused upon issues of agrometeorology and food production (AGRHYMET, 1999). AGRHYMET coordinates the agrometeorological and hydrological activities of national governments through data collection, synthesis, and issuance of bulletins. Stream gauge, rain gauge, meteorological and crop protection data are forwarded to the AGRHYMET Regional Center in Niamey by the National AGRHYMET Centers. There, in conjunction with the AGRHYMET Regional Center's capacity for real time reception and processing of Meteosat and
AVHRR data, a regional view of growing conditions is prepared and disseminated in bulletins issued every ten days during the months of the agricultural campaign, May through October. The AGRHYMET Regional Center’s capacity to operationally produce NDVI maximum value composites from full resolution AVHRR data, received on site, was gained through a technical cooperation arrangement with the USGS EROS Data Center, financed by USAID. The National AGRHYMET Centers, for their part, are involved with national level multidisciplinary working groups on food security, though there is considerable variation in the amount of activity from one country to another. Although centralized in structure, AGRHYMET’s formal training programs in climatology, agrometeorology, hydrology, crop protection, and maintenance of scientific equipment provide regular contact with those possessing local knowledge. These programs go beyond short courses, offering one and two year post-graduate certification. Local knowledge is enhanced through empowerment to use modern methods of observation and analysis.

The AGRHYMET system can claim success in implementing modern scientific methods in a Sahelian program, a fact that contributes to the credibility enjoyed by its bulletins and reports among the international community. AGRHYMET was born out of the drought and famine crises of the 1970s, and has an understandable orientation toward monitoring for food
security and the short term concerns of disaster relief. Its mandate was expanded, however, in 1994 to add natural resources management to its food security portfolio. This expanded mandate serves to bring the more long term perspective of sustainable development to the fore of its concerns.

The Network for the Prevention of Food Crises in the Sahel also depends heavily on the food balance sheet project of the CILSS, known as the Diagnostic Permanent project or DIAPER (OECD, 1998). DIAPER prepares current season harvest estimates and tallies these in conjunction with estimates of stocks, imports, exports, losses, and consumption requirements. DIAPER has worked closely with the agricultural and statistical services of CILSS countries to prepare figures revealing food deficits in a consistent way since its formation in 1984 (Buchanan-Smith et al., 1991).

The Club du Sahel is especially important in assuring linkage between the early warning activities of the CILSS countries and the response organizations of the member countries of the developed world and international organizations. The Club meets every November at OECD headquarters in Paris to review the just concluded crop season and evaluate the implications of the data for national food balances and food aid requirements. If needed, donor country response organizations make food aid pledges to cover food supply shortfalls that have been identified.
National EWS are implied as components of the CILSS and SADC regional systems, but in the literature there is little material discussing them directly. The descriptions of Buchanan-Smith et al. (1991), Eldridge et al. (1986), and Autier et al., (1989) do provide some detail for Ethiopia, Sudan, Mali, Chad, Burkina Faso, and Botswana. National EWS would seem to be the best positioned to bridge the gap between macro and micro systems. For one thing, they have at their disposal networks of agents (agricultural extension, statistical service, district administrators, etc.) capable of primary data collection according to food security information needs. These agents at the local level can also link with community based NGOs carrying out development projects. National EWSs in principle can link directly to national disaster response agencies, since they serve the same administration. In general, they do seek to strike a balance between a top-down, data-oriented, centralized approach focused on food supply, and a bottom-up, people-oriented, local approach emphasizing problems of food access. This is evidenced by a characteristic sequence of data analysis that national EWS attempt to follow. First, rainfall and crop growing conditions are studied as the lead indicators of a potential food security problem. Then, factors like grain prices, terms of trade between grain and livestock, and migration numbers are considered as indicators of social stress revealing the advancing process of famine. Finally, measures of nutrition and disease are
tracked to give a direct indication of human impact and suffering. Increases in malnutrition, disease, and mortality demonstrate that a food security emergency is already underway. Unfortunately, such extreme evidence is sometimes needed to prompt action by response organizations.

Although indicators of social stress are acknowledged to be needed to implement a people-oriented food access approach, these indicators can be difficult to collect and analyze in a timely manner. Nutritional surveillance data give an unambiguous measure of human suffering and need for food aid, but malnutrition is a trailing indicator. By the time there are figures available that document widespread malnutrition, it is typically too late to avoid high rates of destitution and mortality. Consequently, in times of emergency, much food aid decision making is based upon production estimates derived from knowledge of rainfall patterns, area planted, and observations of crop condition. Even so, national EWS have shown themselves to be effective enough to permit timely response in the form of food-for-work programs and fair-price food shops. These food access remedies are much preferred over traditional food aid handouts characteristic of conditions that have been allowed to advance into a state of crisis.

Local EWS are organized on the village or district level. They are community based micro systems with access to local knowledge that can identify early
signs of food insecurity and suggest responses that safeguard livelihoods long before a crisis of starvation demands massive food aid (Walker, 1992). They are in a position to differentiate between coping behaviors that are reversible, like sale of surplus livestock, and irreversible steps that cause destitution, like sale of means of production and outmigration. Livestock price supports and public works projects can be implemented instead of direct food aid. Even when food aid is required, Kelly and Buchanan-Smith (1994) suggest that knowledge of the inner workings of a community can markedly improve targeting. Rather than feed 8 people for every death averted, household level targeting might lower the ratio to 4 or 5 people fed for every death averted.

Buchanan-Smith et al., 1991, describe decentralized, people-oriented systems in Sudan, Mali, Ethiopia, and Kenya. One such system, operated by the Sudanese Red Crescent in North Darfur, Sudan, is also described by Walker (1989) and Torry (1993). All three papers characterize it as a participatory system collecting qualitative data on grain and livestock prices, wage rates, migration, diet, rainfall and agriculture. Questionnaires used seek responses like good/average/bad, high/low, etc., on these topics, rather than quantitative data. The fact that such data could be collected cheaply by local teachers and health workers made an argument for sustainability of the system, in addition to the greater specificity of content compared to
information assembled by top-down, centralized systems. However, Torry (1993) explains that the very same grassroots characteristics giving the system participatory appeal have detracted from its effectiveness in fulfilling its role. The linkage with response organizations of the Sudanese government and the international community has been poor - not because warnings didn't reach them, but rather that they were based on data that elicited great skepticism from the donors. Torry (1993) reports that the SRC monitors avoided out-of-the-way villages and followed an ad hoc sampling approach. They systematically avoided input from women and nomads, considered untrustworthy, but did accept uncritically the estimates of village sheikhs regarding livestock ownership numbers. Unfortunately, livestock ownership is the basis for paying taxes to sheikhs, and for that reason is systematically underreported (at a level of only 20% of true value, by one estimate cited by Torry, 1993). Furthermore, farmers' estimates of cropped area tend to be overestimated by 100% and estimates of crop yield are thought to be in error by 60%. The manner in which the survey data were handled and processed also detracted from their credibility. Forms often took five or six weeks to reach the capital, some got lost on the way, and some surveys were skipped for a month or two for no apparent reason.
2.2 FEWS and Vulnerability Analysis

FEWS was born as a project of USAID in 1985. In that year, a drought-driven food security emergency prevailed in the Sahel. Emergency food aid was authorized by the Congress under Public Law 480, but USAID lacked the information needed to determine where, when, and how much to deliver. FEWS was created to fill the information void facing U.S. decision-makers. A priority was placed on collecting data regarding crop production, food stocks, and the numbers and locations of populations in need of aid as a result of the disaster. Phase I of FEWS was constituted in this way until September 1988, when the project moved into Phase II. The mandate of FEWS II was expanded to go beyond the immediate information needs of disaster relief to include monitoring problems of food access through vulnerability analysis. Vulnerability analysis addresses the predisposition of groups of people to food security emergencies as the result of shocks like drought, floods, or armed conflict – factors that interrupt ordinary livelihoods. Vulnerability is a measure of structural insecurity due to limited availability of options when primary avenues of food access are disrupted. FEWS II ended in late 1994.

FEWS is currently in Phase III, to conclude on December 31, 1999. Primary objectives of the project are now early warning, vulnerability analysis, emergency response planning, and capacity building. The latter two items
represent another expansion of the FEWS mandate. Emergency response planning is to be enhanced by the information and analyses performed by FEWS, through explicit interaction with those responsible for relief preparedness. Capacity building calls for greater training and involvement of Africans in all phases of food security assessment.

A review of the literature shows that FEWS elicited considerable criticism from the early warning community when it first came onto the scene (Buchanan-Smith et al., 1991; Field, 1993; Walker, 1989). In its early incarnation, FEWS singular dedication to informing U.S. decision-makers, to exclusion of host country governments or NGOs working on the ground, was the basis for most of this. The lack of connection with the victims of famine was seen as a major negative characteristic. Walker (1989) complained:

"FEWS is definitely not a victim-oriented warning system. It exists primarily to assist the food aid and foreign policy of the United States. Of the more than thirty people employed by the project in October 1987, only six, the country representatives, were located outside the USA. Around 250 copies of each country report are produced each month. Of these, fewer than twenty end up in the African countries they are discussing."

Buchanan-Smith et al., 1991, concurred with Walker, but with the benefit of two more years to observe FEWS in action, did concede:

"...the second phase of FEWS has sought to make the system less centralized. The Washington based staff has been halved and much more data analysis is done in country. Attempts are also being made to introduce early warning as a development concern, as an integral part of USAID's food security strategy..."
Field (1993) offered similar comments:

“...it is a sad commentary on USAID’s Famine Early Warning System (FEWS) project that its principal objective is to facilitate U.S. decisionmaking so as to trigger a more timely release of food aid. As worthy a concern as this is, it is steeped in a relief mentality and, moreover, does virtually nothing to build detection and response capacities in the participating African countries. Some movement in the right direction is evident in Phase II of the project.”

Early criticisms by these social scientists also betray a certain technophobia on their part. Perhaps they felt somewhat threatened by high technology that they did not fully understand. Buchanan-Smith et al., (1991) expressed their concerns:

“...a lot of resources in early warning have been invested in technologies such as remote sensing imagery and ever more sophisticated computer applications. ...it is time that the limitations of ... these technologies are recognized... ...they are in danger of reinforcing a centralized approach to early warning... Information collection takes on an increasingly scientific air, but is in danger of providing the illusion of knowledge, because scarce and perhaps inaccurate data are presented in such a way as to appear credible while some of the human factors which are imperative for sensible analysis are ignored. Ultimately, field level data collection and ground truthing can never be replaced if EWS are to function effectively, and this must not be overlooked in the rush to apply modern technologies.”

Walker (1989) offers a number of curious “facts” and editorial comments:

“The NDVI index has been calibrated using vegetation systems in the USA and as such the absolute values it produces may not be accurate for other areas of the world.”
"Late in 1988 IBM donated US$85 million to the United Nations Environment Program to help install their "GRID" computer/satellite information network."

"The glamour of 'high-tech', supposedly accurate data, can lead to information overkill."

The concern over remote sensing data accuracy on the part of these advocates of local, participatory EWS is ironic in view of the data quality critiques of Torry (1993) regarding the reporting of the Sudanese Red Crescent. However, in her later article, Buchanan-Smith (1996) comments positively on FEWS' "notable attempts" in "scaling-up from the micro-level...to retain those indicators which reflect the diversity and complexity of livelihoods, and still end up with a workable system." She no doubt observed that FEWS had heeded her criticisms.

FEWS III presently monitors conditions in 22 Sub-Saharan African countries (see Figure 2.1). Twenty-seven staff reside in 14 of these countries, and a staff of eleven maintain the Washington office. Most FEWS Field Representatives (FFRs) are nationals of the countries that they monitor, only about a half a dozen of them being U.S. expatriates. All are employees of Associates in Rural Development, Inc., the prime contractor for FEWS III. Their prime deliverable consists of the monthly bulletins focused on early warning, delivered as hard copy and in electronic form on the FEWS website (FEWS, 1999). Vulnerability assessment reports are also made available on
the website, as are a variety of in depth analyses, satellite image products, and graphic presentations of seasonal rainfall. Support to FEWS is provided by NOAA's Climate Prediction Center through the provision of rainfall estimate images derived from Meteosat imagery; NASA's Goddard Spaceflight Center through the provision of Normalized Difference Vegetation index images; and the USGS/EROS Data Center which provides support in terms of long term data archival, technique development, software development, and data dissemination to the general public.
Figure 2.1. Map of Africa identifying the sub-Saharan countries monitored by FEWS, including those newly-added under Phase III, 1995-1999.
FEWS is a multi-country regional EWS whose mandate requires that it be a macro system. The area to be monitored, as shown in Figure 2.2, is much too extensive to apply micro EWS methods. However, great strides have been made since the days of FEWS I to incorporate the perspectives of micro systems into FEWS operations. No longer is the simple quantification of food aid the primary concern. Vulnerability analysis, taking into account issues of food availability and food access, is applied to data for present and historical time frames. The objective is to identify areas where famine is most likely to occur and help determine which interventions are most appropriate to reduce the risk of famine (Wright et al., 1994). The conceptual model of vulnerability analysis is that of household coping behaviors in the face of food insecurity. However, since the scale of the system prohibits primary data collection to interview households directly, coping behaviors are inferred from secondary data compiled at the subnational level. Analysis is carried out using a geographic information system (GIS) approach wherein subnational administrative units are the basic elements. The smallest possible administrative unit is used for the analysis, depending on the availability of necessary data. This is typically the third or fourth level administrative unit, with mean areas ranging from 1,000 to 10,000 square kilometers. For each such geographic entity, a suite of famine vulnerability indicators is assembled.
Figure 2.2 Outline of the continental United States superimposed on a political map of Africa, at equal scale, to illustrate the extensive nature of the area monitored by FEWS.
as a set of attributes for the administrative unit polygons. These might represent agricultural production, market forces, social indicators, nutritional status, and coping options. These indicators are combined to create an overall vulnerability index that can then be mapped by the GIS to reveal areas where social groups most vulnerable to food security problems will be found. As pointed out by Hutchinson (1996) "...the most formidable problem faced by analysts...(is)...the task of selecting indicators used in an analysis and determining or specifying their relative importance." Choice of indicators will be constrained by data availability as well as relevance to the situation.

An illustrative example is provided by Wright et al. (1994) who used length and variability of growing season (based on NDVI), proximity to population centers, and relative importance of cereal crops, livestock, and cash crops to household income to assess baseline vulnerability. They then went on to assess current time frame vulnerability using quality of pasture conditions and the last three growing seasons (again, based on NDVI), millet prices, and civil insecurity restricting travel and trade. Indicators were standardized by computing differences from the mean and dividing by the standard deviation to obtain dimensionless variables. Relative weights were then applied to the variables according to the judgement of the analysts. Three maps were then prepared: baseline vulnerability, current vulnerability, and composite vulnerability. They were presented as simple choropleth maps,
with administrative units color-coded to indicate the following levels of vulnerability: much below average, slightly below average, average, slightly above average, and much above average (Wright et al., 1994).

A more recent vulnerability analysis for the Sahel went beyond the level of simply mapping vulnerable zones to the estimation of numbers of vulnerable people by social group: farmers, pastoralists, fishing households, and urban dwellers (FEWS, 1998a). Such an analysis speaks more directly to those decision-makers weighing options for intervention to prevent a food security emergency. The "Special Report on Current Food Insecurity in Southern Africa for 1998/99" (FEWS, 1998c) includes quantitative estimates of the numbers of people in three categories of food insecurity—moderate, high, and extreme. Figure 2.3 is drawn from that report.

2.3 Requirements for Climate Information

The productivity of rainfed agriculture in Sub-Saharan Africa has been a major concern of FEWS from its very beginning. Although technique development through the life of the project has put much emphasis on the increasing use of socioeconomic indicators in food security analysis, agroclimatology is still essential to the process. While it is true that food
Southern Africa—Food Insecure Areas, 1998/99 Consumption Year

Southern Africa—Food-Insecure Populations

<table>
<thead>
<tr>
<th></th>
<th>Extremely</th>
<th>Highly</th>
<th>Moderately</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Malawi</td>
<td>0</td>
<td>0</td>
<td>999</td>
<td>9</td>
</tr>
<tr>
<td>Mozambique</td>
<td>23 &lt; 1</td>
<td>697</td>
<td>4</td>
<td>2,444</td>
</tr>
<tr>
<td>Zambia</td>
<td>0</td>
<td>0</td>
<td>1,242</td>
<td>8</td>
</tr>
<tr>
<td>Zimbabwe</td>
<td>0</td>
<td>0</td>
<td>1,365</td>
<td>11</td>
</tr>
<tr>
<td>Total</td>
<td>23 &lt; 1</td>
<td>4,304</td>
<td>9</td>
<td>4,803</td>
</tr>
</tbody>
</table>

Figure 2.3. Map resulting from current vulnerability analysis of Southern Africa, identifying sub-national units where the most food-insecure people of the region were found going into the 1998/1999 consumption year.
availability doesn’t tell the food security story by itself, the situation cannot be
described without it either. Climate data are essential to understanding how
much production might occur in any given year, or in some year in particular.
Whether this potential is sufficient to meet human needs depends on
additional variables, as the discussion of vulnerability analysis has shown.
However, food security assessment remains an activity subject to much
ambiguity, and any reduction in the ambiguity associated with any variable,
including agroclimatological indicators, contributes to improving the process.

Food security analysis considers agroclimatology in the past, present, and
future. Study of past patterns of rainfall, in time and space, and their
variability over the years can provide insight into the viability of a rainfed crop
in any given year. It may be that climatic conditions in a region are of a
marginal nature, and the length of the growing season is insufficient in, say,
one out of four years. Statistical analysis of historical rain gauge data can
help reveal such conditions. Doing so for gauges throughout a region, and
mapping the results, can uncover zones of relatively high risk of crop failure
due to insufficient rainfall. Historical time series NDVI imagery can be
analyzed in a similar manner, on a pixel by pixel basis (Rowland et al., 1996).
Zones of high interannual variability, and related risk of crop failure, are
likewise revealed by the resulting image map.
With knowledge of relative vulnerability available on a spatial basis at the outset of a growing season, early warning can be served by studying patterns in agroclimatological data as they come in during a growing season. Time series traces of mean NDVI for key crop areas can be plotted versus time and compared with average or benchmark years. Depressed values relative to average conditions can alert food security analysts to the possibility of poor crop production. The same can be done with rainfall data in the form of gauge reports or remote sensing estimates (FEWS, 1999). The sooner agricultural outcomes can be forecast, the sooner the need for intervention can be identified.

Emergency response planning requires not only study of past agroclimatology, monitoring of current conditions, but also consideration of the probability of unfavorable conditions in the future. Climate forecasting has matured in recent years to permit the preparation of seasonal forecasts based upon modeling and observations of atmospheric and oceanic conditions. Regional climate outlook forums are now regularly organized for West, East, and Southern Africa to prepare growing season forecasts for use by society in general, including those responsible for food security. FEWS has actively participated in these meetings and incorporated them into disaster mitigation plans (FEWS, 1998b).
2.4 Existing Geospatial Climate Data and Information Used by FEWS

The primary geospatial climate monitoring products used by FEWS are derived from remote sensing data collected by meteorological satellites (Hutchinson, 1991). NDVI images produced from AVHRR imagery acquired by the NOAA polar orbiters have the longest history of use in the project (French et al., 1996). They are prepared for FEWS by the Global Inventory Monitoring and Modeling Studies research unit at the NASA Goddard Spaceflight Center in Greenbelt, Maryland, according to techniques described by Los et al. (1994). Since the NDVI signal is approximately linearly related to the area average photosynthetic capacity of the plant canopy at a location (Tucker and Sellers, 1986), it is used as an indirect measure of the condition of rainfed crops. The images are produced every 10 days and the archive for Africa dates back to July 1981. Exploitation of NDVI by FEWS for monitoring is simple and straightforward. The image for the current 10-day period, or dekad, is used to compute two difference images. The first is the difference between the NDVI for the current dekad and that of the previous dekad. This reveals areas that are greening up or drying down. The second difference is with respect to the average NDVI for the dekad in question for the 1982-1993 historical reference period. This
Figure 2.4 Sample image differencing products produced from NDVI and RFE images for Southern Africa. Differencing with previous dekad and long term average images is the most common use of remote sensing in FEWS.
reveals areas of anomalous conditions relative to average, as shown in Figure 2.4. The other operational geospatial climate products used by FEWS are the Rainfall Estimate (RFE) images produced by NOAA's Climate Prediction Center (Herman et al., 1997). They are also compiled on a dekadal basis, with each pixel's value representing an estimate of the number of millimeters of rainfall to have fallen at that location during the 10-day period. The RFE products have been produced for FEWS since 1995. Image differencing is applied to them in much the same way that it is to the NDVI images. A difference with respect to the previous dekad is calculated to show areas that are drying out or getting relief after a dry spell. A second difference with respect to long term average shows wet and dry rainfall anomalies. However, since the time series of the RFE is too short to provide a meaningful set of dekadal normals, a standard based on surface fitting of station data with long records (Hutchinson et al., 1996) is used instead. Figure 2.4 also shows an example of these routinely produced RFE difference images.

Apart from difference image products, FEWS also produces area average time series traces of NDVI and RFE for key crop growing regions. Figure 2.5 illustrates an example of these traces based on standard FEWS geospatial climate monitoring products, as available on the FEWS website (FEWS, 1999).
Figure 2.5 Area average time series traces of RFE data for crop growing regions of ten countries of Southern Africa. Such products permit a graphical evaluation of the quality of an ongoing growing season.
As far as geospatial depictions of the forecasts emanating from climate outlook forums, the illustrations provided by the participating climatologists are used directly (e.g., Figure 2.6). Color-coded maps of rain gauges showing expected patterns of dry and wet anomalies are also used (FEWS, 1997), as in Figure 2.7.

2.5 Opportunities for Developing Improved Geospatial Climate Products

Operational RFE images are of great value for FEWS monitoring because of the significance of rainfed agriculture to the livelihoods of millions of people in Sub-Saharan Africa. However, there is ambiguity associated with the RFE images and their interpretation. This would be true even if the estimates were accurate to the nearest millimeter of rainfall. That is because the sheer amount of rainfall does not directly communicate the crop condition. As any farmer might inform us, it is the timing of rainfall relative to the crop's cycle that is the determining factor. The importance of this fact to early warning was recognized by the Food and Agriculture Organization in the 1970s, and prompted the development of a simple method of crop water accounting GiEWS operations (Frere and Popov, 1986). The existence of continental scale digital soil maps and the availability of operational weather forecast modeling fields from NOAA now make possible the implementation of a
Expected Rainfall Patterns in the Greater Horn, September–December 1998

Figure 2.6 Seasonal rainfall forecast map for the Greater Horn of Africa produced by consensus at the climate outlook forum held in Mombasa, Kenya, August 31-September 4, 1998.
Figure 2.7 Color-coded rain gauge locations for Eastern and Southern Africa indicating their tendency to be wetter, drier, or normal during an El Niño event, based on historical records.
geospatial version of this technique. Such a product can reduce the ambiguity associated with the RFE products and provide a translation of the rainfall patterns depicted in agricultural terms. This is the subject of Chapter 3.

The seasonal precipitation forecast maps produced by regional climate outlook forums are likewise characterized by ambiguity when interpreted for food security purposes. The agricultural consequences are not clear. However, important linkages have been identified between anomalies of sea surface temperatures, which are a major determinant of seasonal climate forecasts, and anomalies of NDVI for certain parts of Africa (Anyamba and Eastman, 1996; Myneni et al., 1996). Because NDVI is a well understood climate variable in the early warning community, there is an opportunity to reduce the ambiguity associated with seasonal climate forecasts by expressing them as patterns of NDVI anomalies. This is the subject of Chapter 4.
2.6 References


Chapter 3

Crop Water Accounting on a Geospatial Basis

3.1 Crop Moisture Available as Rainfall

In sub-Saharan Africa, extreme food shortages are often associated with drought. Rainfall monitoring is therefore an indispensable activity for those seeking to identify potential famine areas. Rain gauge data are collected and analyzed to gain an historical perspective and to evaluate current season growing conditions. However, rain gauge data only tell the story at point locations, and many stations report only after significant delays. Two operational remote sensing products are used by FEWS to monitor agricultural areas on a near real-time, spatially continuous basis for signs of drought as well. They are Normalized Difference Vegetation Index (NDVI) images from NASA's Goddard Space Flight Center (Los et al., 1994) and Rainfall Estimate (RFE) images prepared by NOAA's Climate Prediction Center (Herman et al., 1997). Both are compiled on a nominal 10-day time step.

The NDVI time series is continuous since July 1981 and has been used routinely by FEWS analysts for over 10 years. The relationship between
NDVI anomalies and agricultural impacts is relatively well understood (Hutchinson, 1991). RFE products have been in use only since 1995, by contrast, and the implications of their information regarding crop performance are less well understood. In this chapter, the following question is addressed:

*Can crop water accounting be performed on a geospatial basis to better express the agricultural significance of RFE precipitation patterns?*

Experience with rain gauge data in crop water accounting is instructive. Only a weak relationship has been observed between seasonal rainfall station totals and agricultural yields (Frere and Popov, 1986). The amount and timing of rainfall relative to crop requirements must be accounted for. This chapter reports on the grid cell implementation of a crop water accounting system developed by the United Nations Food and Agriculture Organization (FAO).

### 3.2 Formulation of the Water Requirement Satisfaction Index for Station Data

Because conventional agricultural production figures are typically unavailable until several months after harvest, simple physically based crop water
requirement models have been devised for use with rainfall station data. These models in turn permit early estimates of crop yield and production through statistical relationships. FAO has developed the Water Requirement Satisfaction Index (WRSI) as an operational model for estimating the agricultural consequences of rainfall in water-limited areas of the world (Frere and Popov, 1986). This model's development stemmed from recognition that simple rainfall totals do not correlate well with crop yield. The timing and amount of rainfall relative to crop needs must be accounted for. Though used primarily for early agrometeorological forecasting, Mason et al. (1987) reported that the WRSI was a good predictor of malnutrition rates in Botswana. A brief explanation of the approach taken by WRSI developers follows.

Crop water accounting with the WRSI is done on a dekadal basis using sums of daily rainfall observations from a station or stations representative of conditions in a crop-reporting district. The dekad is the basic 10-day time step of agrometeorological monitoring in Africa. Each month of the year is divided into three dekads: the 1st through the 10th, the 11th through the 20th, and a final dekad of 8, 9, 10, or 11 days. "Dekad" is a technical term recognized by the World Meteorological Organization (1992). The dekad represents a compromise between a monthly time step, which is inadequate to resolve important crop growth stages, and a daily time step, which
imposes a significant data processing burden without a commensurate gain in agrometeorological information (Frere and Popov, 1986).

Usually the principal staple crop of a region is modeled with the WRSI, though calculations may be made for other crops as well. The calculations require assumption of a soil water holding capacity (WHC) that defines the volume of the conceptual "bucket" of water available for crop growth. Field data or soil maps may be consulted, but often a somewhat arbitrary value on the order of 50 to 100 mm is adopted (Frere and Popov, 1986; Farmer, personal communication). The dekad of planting must also be known. Thereafter, a simple running tally of crop water supply and demand is maintained throughout the cycle of the crop of interest.

Demand is computed from estimates of potential evapotranspiration, modified by a crop coefficient corresponding to the stage of growth of a crop. Potential evapotranspiration is computed according to the availability of necessary input data. The Penman-Monteith equation (Shuttleworth, 1992; Monteith, 1980) is the most sophisticated and demanding of input data, requiring air temperature, atmospheric pressure, relative humidity, solar radiation, and wind observations:
\[
E_{rc} = \frac{\Delta}{\Delta + \gamma^*} (R_n + G) + \frac{\gamma}{\Delta + \gamma^*} \frac{900}{T + 275} U_2 D \quad (3.1)
\]

Where

\(E_{rc}\) = reference crop evapotranspiration, mm/day

\(R_n\) = net radiation exchange for the crop cover, mm/day

\(G\) = soil heat flux, mm/day

\(U_2\) = wind speed at 2 m, m/s

\(T\) = temperature, °C

\(e_s\) = saturated vapor pressure, kPa

\[= 0.6018 \exp \left(17.27 \frac{T}{(237.3 + T)} \right)\]

\(e\) = \(e_s R_h\), kPa

\(R_h\) = relative humidity

\(D\) = vapor pressure deficit, \(e_s - e\), kPa

\(\Delta\) = slope of the temperature - saturation vapor pressure curve

\[= \frac{4098 e_s}{(237.3 + T)^2}, \text{kPa/°C}\]

\(\gamma\) = psychrometric constant = 0.0016286 \((P / \lambda)\), kPa/°C

\(P\) = atmospheric pressure, kPa

\(\lambda\) = latent heat of vaporization of water, MJ/kg

\[= 2.501 - 0.002361 T, \text{MJ/kg}\]

\(\gamma^*\) = \(\gamma (1 + 0.33 \ U_2)\)
Inadequate instrumentation often requires use of simpler equations. Long-term climatological averages are also frequently used instead of current year values. Crop coefficients are taken from published technical reports (e.g., Doorenbos and Pruitt, 1977) or are already embedded as options in software developed for calculation of WRSI on a station basis (Gommes, 1993).

Water supply consists of the dekad's rainfall plus available soil water. If precipitation exceeds the dekad's crop water requirement, it is applied to replenishment of available soil water. If soil water capacity is exceeded, water is lost to the crop as runoff or deep percolation. If crop demand exceeds precipitation in a dekad, soil water is debited to meet the requirement. If the available soil water is not enough to meet the requirement, a crop water deficit is recorded. At the end of the growing season, the WRSI is expressed as the percentage of total crop water requirement actually satisfied by rainfall or available soil moisture. A value of 100 implies full satisfaction of the requirement, and lesser values indicate the degree of shortfall. A value as low as 40 or 50 implies crop failure.

Mathematically, the change in actual seasonal cumulative crop water satisfaction, CWS, for a dekad can be expressed as:

\[
\Delta CWS_i = R_i + S_i - (K_e E_{ri})_i
\]  
(3.2)
Where

\[ \Delta CWS_i = \text{change in CWS for dekad } i, \text{ mm} \]

\[ R_i = \text{rainfall for dekad } i, \text{ mm} \]

\[ S_i = \text{available soil moisture for dekad } i, \text{ mm} \]

\[ K_c = \text{crop coefficient for dekad } l, \text{ dimensionless} \]

In the case of \( \Delta CWS_i < 0, \) (a crop water deficit)

\[ CWS_i = CWS_{i-1} + \Delta CWS_i \tag{3.3} \]

otherwise, \( CWS_i = CWS_{i-1}. \)

Available soil moisture change must also be calculated as

\[ \Delta S_i = S_i + R_i - (K_c E_{rc})_i \tag{3.4} \]

and available soil moisture is incremented

\[ S_{i+1} = S_i + \Delta S_i \tag{3.5} \]

Subject to the condition \( WHC \geq S_i \geq 0. \)
WRSI is then calculated at the end of the season as:

$$\text{WRSI} = \left[ \frac{\text{CWS}}{\Sigma(K_e \ E_w)} \right] \times 100$$ (3.6)

Which is the percentage of the seasonal total crop water requirement actually satisfied by available rainfall and soil moisture.

In order to gain an appreciation for the dependence of the WRSI on input data, a limited sensitivity analysis was undertaken using the FAOINDEX software of Gommes (1993). The case of 120-day maize at Embakasi, Kenya, is an example provided with the computer program and it was used for the analysis. Input variables were systematically varied, one at a time, to gauge the impact on the WRSI relative to the given example. Planting dekad, soil water holding capacity, precipitation, and potential evapotranspiration were each varied. Results showed that systematic over- or underestimation by 10% of precipitation or potential evapotranspiration resulted in WRSI changes on the order of +/− 5% of seasonal crop water requirement. Shifting start of season (SOS) by one dekad earlier or later had a similar effect. Increasing WHC by 25mm and 50mm had a marked impact, with WRSI increases of 10% and 16%, respectively. Table 3.1 summarizes the sensitivity analysis results.
Table 3.1. Sensitivity of the WRSI for 120-day maize to variations in SOS water holding capacity (WHC), precipitation, and PET.

<table>
<thead>
<tr>
<th>Parameter change</th>
<th>WRSI change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity of 120 day maize WHC=50mm Base WRSI=84</td>
<td></td>
</tr>
<tr>
<td>Sensitivity of 120 day maize WHC=50mm Base WRSI=84</td>
<td></td>
</tr>
<tr>
<td>SOS +1 dekad</td>
<td>3</td>
</tr>
<tr>
<td>SOS +2 dekad</td>
<td>-8</td>
</tr>
<tr>
<td>SOS -1 dekad</td>
<td>-4</td>
</tr>
<tr>
<td>WHC +25mm</td>
<td>10</td>
</tr>
<tr>
<td>WHC +50mm</td>
<td>16</td>
</tr>
<tr>
<td>Precipitation +5%</td>
<td>2</td>
</tr>
<tr>
<td>Precipitation +10%</td>
<td>4</td>
</tr>
<tr>
<td>Precipitation +15%</td>
<td>5</td>
</tr>
<tr>
<td>Precipitation -5%</td>
<td>-2</td>
</tr>
<tr>
<td>Precipitation -10%</td>
<td>-5</td>
</tr>
<tr>
<td>Precipitation -15%</td>
<td>-7</td>
</tr>
<tr>
<td>PET +5%</td>
<td>-3</td>
</tr>
<tr>
<td>PET +10%</td>
<td>-6</td>
</tr>
<tr>
<td>PET +15%</td>
<td>-9</td>
</tr>
<tr>
<td>PET -5%</td>
<td>3</td>
</tr>
<tr>
<td>PET -10%</td>
<td>6</td>
</tr>
<tr>
<td>PET -15%</td>
<td>10</td>
</tr>
</tbody>
</table>
The degree of sensitivity of the WRSI to systematic changes is approximately equal for precipitation, potential evapotranspiration, and start of season. If errors in these inputs for the geospatial solution of the WRSI are random and independent, there will tend to be a canceling of their effects among them. This assumption is not too risky to make. Although RFE and potential evapotranspiration have GDAS fields for relative humidity and wind in common, RFE is primarily driven by remotely sensed observations of cold cloud duration, while potential evapotranspiration is driven mostly by GDAS radiation calculations. The spatial distributions of cold cloud duration and net radiation are arrived at by sets of calculations that are quite independent. Start of season is a direct consequence of RFE calculations, but the threshold nature of SOS determination means that errors in RFE might affect it in only a limited number of instances.

Sensitivity of the WRSI to soil WHC is of a different nature since it is a permanent property of a site. In this sense, WHC is like soil fertility, which the WRSI does not account for at all, but which nonetheless has a bearing on crop yield. Since yield estimation from WRSI does not attempt to calculate yield directly in an absolute sense, but rather seeks to quantify departures from local historical average or maximum yields, site differences (other than weather) are accounted for indirectly. It would seem to be most important not to set WHC too high, lest full satisfaction of the WRSI be met too easily.
The full range of conditions that the WRSI might account for would be reduced with WHC set too high, because the capability of soil water supplies to mitigate lack of rain would be overstated. If WHC were set somewhat too low, on the other hand, this would be compensated by the empirical relationship between local variations in WRSI and local variations in departure of yield from a reference average or maximum value. Underestimation of WHC is therefore of less consequence than overestimation.

3.3 Formulation of the Water Requirement Satisfaction Index for Geospatial Data

Gaps in the network of rainfall stations for which the WRSI can be calculated leave significant areas without early crop yield estimates. However, RFE images can supplement rainfall station data, and digital maps of soils and crop reporting districts are available. Consequently, it is now possible to think in terms of a geospatial solution for the WRSI. Recent work by FAO and national early warning services report progress in this area. For example, Rojas and Amade (1998) developed a surface of WRSI values for maize in Mozambique using point solutions for crop reporting districts and a spatial interpolation program (SURFER). At FAO in Rome, surfaces are likewise fit to point values of WRSI and associated yield estimates (Gommes
and Bernardi, personal communication) though a different algorithm is used. Co-kriging (Bailey and Gatrell, 1995) is applied, with seasonal maximum value NDVI as the covariate used in the interpolation.

The approach for a spatial solution offered in this dissertation differs in two important ways from those cited above. The first is that the WRSI is calculated on a cell by cell basis, using grids of input values that correspond directly to the individual inputs of a point solution (precipitation, potential evapotranspiration, soil water holding capacity, and planting dekad). There is no statistically based spatial interpolation of the WRSI itself; rather, spatial calculation of the input variables precedes calculation of the WRSI. Fields of precipitation and potential evapotranspiration are based on remotely sensed and ground observations and physically based dynamic modeling of the global atmosphere. Soil water holding capacity is derived from digital soil maps, and planting dekad is inferred from the RFE time series. A second important difference is that no use of the NDVI time series is made. This is because an independent assessment of growing conditions is sought to corroborate patterns seen in the NDVI data. This is consistent with the “convergence of evidence” approach used by FEWS to assess food security.

The following section of this chapter reports results of an initial test of a spatial implementation of the WRSI with FEWS specifically in mind. The
estimation of maize yield in countries of the Southern Africa Development Community (SADC) was undertaken for this first test owing to the availability of necessary data and the active interest of scientists in the region.

3.4 Geospatial Implementation of the Water Requirement Satisfaction Index

The FEWS spatial implementation is based upon the 0.1-degree grid of the RFE, the spatial analog of the precipitation station data used for point calculation of the WRSI. RFE are prepared from thermal infrared images from Meteosat, acquired every 30 minutes, which are used to identify areas of cold cloud top temperatures (less than 235K). The duration of these temperatures over a day is used to make an initial estimate of convective rainfall. Then, daily rainfall totals from 760 stations that report electronically through the World Meteorological Organization (WMO) Global Telecommunication System (GTS) are used to remove bias from the cold cloud estimates. Finally, areas of “warm cloud” rainfall, associated with orography, coastal areas, and frontal activity are estimated from output fields of NOAA’s Global Data Assimilation System (GDAS), a system that integrates operational weather forecast modeling with observations of atmospheric state (Kanamitsu, 1989). Fields of wind, relative humidity, and a
digital elevation model are used to identify these areas of non-convective lifting and condensation. Figure 3.1 displays an example RFE product.

Herman et al., (1997) compared RFE estimates with independent station data for 180 rain gauges in Mali, Niger and Chad for the dekads of June through September 1995. Their analysis revealed a correlation coefficient of 0.86 for 1780 observations (some stations had missing data for certain dekads). Rojas and Amade (1998) compared RFE dekadal estimates with station values for 60 gauges in Mozambique over a 3-month period, December 1997 - February 1998. They computed correlations for each station and found values in the range of 0.65 to 0.80, or better, for stations representing about three-fourths of the country. Pockets of weaker correlations, mostly in the range of 0.45 to 0.65, accounted for the rest of the area. A tendency for underestimation was observed.

To assess the reliability of the RFE in the SADC region, spatial cross-correlations were computed with grids of monthly long term average rainfall provided by the Agrometeorology Group of FAO in Rome (M. Bernardi, personal communication). FAO prepared these grids by fitting surfaces to station data from the FAOCLIM agroclimatic database (FAO, 1997). The months of December through March of the 1996/1997 and 1997/1998
Figure 3.1 An example RFE image from NOAA's Climate Prediction Center for the last dekad of October, 1998. Intervals of rainfall totals are color coded as indicated in the legend. Small figures indicate location and amount of ground measured precipitation used in the algorithm, in millimeters.
growing seasons were examined. Correlations varied between 0.58 and 0.82, as shown in Table 3.2. These values, along with visual examination, gave confidence that the spatial patterns of the RFE are consistent with those to be expected from climatological estimates.

Table 3.2. Cross-correlation values computed between long term average precipitation grids from FAO and RFE grids for months of the 1996/1997 and 1997/1998 Southern Africa maize growing seasons.

<table>
<thead>
<tr>
<th>SADC Region Precipitation</th>
<th>Grid Cross-Correlation</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>RFE</td>
<td>FAO</td>
<td></td>
</tr>
<tr>
<td>Dec-96</td>
<td>Dec avg</td>
<td>0.74</td>
</tr>
<tr>
<td>Jan-97</td>
<td>Jan avg</td>
<td>0.73</td>
</tr>
<tr>
<td>Feb-97</td>
<td>Feb avg</td>
<td>0.82</td>
</tr>
<tr>
<td>Mar-97</td>
<td>Mar avg</td>
<td>0.58</td>
</tr>
<tr>
<td>Dec-97</td>
<td>Dec avg</td>
<td>0.72</td>
</tr>
<tr>
<td>Jan-98</td>
<td>Jan avg</td>
<td>0.78</td>
</tr>
<tr>
<td>Feb-98</td>
<td>Feb avg</td>
<td>0.75</td>
</tr>
<tr>
<td>Mar-98</td>
<td>Mar avg</td>
<td>0.72</td>
</tr>
</tbody>
</table>
In order to assess the validity of the Potential Evapotranspiration (PET) estimates for 1996/1997 and 1997/1998 in Southern Africa, they were compared with long-term average values on both a point and a spatial basis. P. Mattei (personal communication) provided files of dekadal values for 243 stations from throughout the SADC region. These same data were used to make the WRSI calculations reported in Mattei and Sakamoto (1993). The PET values for the 1997/1998 growing season were extracted from the grids computed for FEWS at the station locations, and a correlation of 0.77 was calculated. Figure 3.2 presents a scatter plot of the data pairs. Grids of monthly long-term average PET (M. Bernardi, personal communication) were also quantitatively compared with the FEWS spatial estimates by computing spatial cross-correlations. Values varied between 0.38 and 0.82, as shown in Table 3.3. It should be noted that values for December 1996 and January 1997 pre-date the availability to FEWS of 1.0 degree GDAS fields, and were instead computed with 2.5 degree GDAS fields from the NOAA archive. If these coarser resolution data are excluded, the minimum cross-correlation value increases from 0.38 to 0.66. While concurrent station values of PET would be preferred for evaluation of the FEWS grids of PET, such data are difficult to obtain. The comparisons made with climatological values, however, do nothing to discourage calculation of PET from GDAS grids.
Figure 3.2 Scatter plot of long term average dekadal PET versus 1997/1998 geospatial estimates from GDAS analysis fields for the 243 stations of Mattei and Sakamoto, 1993. The pattern illustrates the 0.77 correlation between the two data sets.

<table>
<thead>
<tr>
<th>SADC Region PET</th>
<th>FAO</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dec-96</td>
<td>Dec avg</td>
<td>0.46</td>
</tr>
<tr>
<td>Jan-97</td>
<td>Jan avg</td>
<td>0.38</td>
</tr>
<tr>
<td>Feb-97</td>
<td>Feb avg</td>
<td>0.74</td>
</tr>
<tr>
<td>Mar-97</td>
<td>Mar avg</td>
<td>0.82</td>
</tr>
<tr>
<td>Dec-97</td>
<td>Dec avg</td>
<td>0.74</td>
</tr>
<tr>
<td>Jan-98</td>
<td>Jan avg</td>
<td>0.74</td>
</tr>
<tr>
<td>Feb-98</td>
<td>Feb avg</td>
<td>0.66</td>
</tr>
<tr>
<td>Mar-98</td>
<td>Mar avg</td>
<td>0.77</td>
</tr>
</tbody>
</table>

The spatial variation of WHC is characterized using the FAO Digital Soil Map of the World (FAO, 1994). The scale of the original mapping is 1:5,000,000, and the soil polygons carry attributes which include an estimate of easily available water capacity in the upper 100 cm, based on soil physical characteristics. These are the values adopted as WHC for the FEWS spatial calculation of the WRSI, with the soil map rasterized to match the 0.1-degree RFE grid.

Comparisons of these WHC values were made with those used at the stations of Mattei and Sakamoto (1993). A scatter plot of values for the two
data sets is displayed in Figure 3.3. It can be seen that the range of values, roughly 25 mm to 150 mm, is similar in both cases but that there is not much agreement on a site-to-site basis. The somewhat arbitrary assignment of WHC values by Mattei and Sakamoto is evidenced by the clustering of sites at even values like 30, 40, 50, etc. There are especially large numbers of stations with WHC values at 50 mm, 80 mm, 100 mm, and 120 mm in their data set. By contrast, values drawn from the FAO Digital Soil Map are seen to vary in a more continuous fashion over the full range. This latter characteristic is more in line with what one would expect to observe in nature, but without any independent physical determinations of this soil property at the sites, there is no way to say which is more accurate.

The planting, or SOS, dekad is a critical input to the calculation of the WRSI, as demonstrated by the sensitivity analysis. For the geospatial implementation of the WRSI, SOS was identified on a spatial basis by processing the RFE time series for the growing season. On a per pixel basis, rainfall criteria developed at the AGRHYMET Regional Center in Niger (AGRHYMET, 1996) are applied to the RFE values. Beginning several dekads in advance of the usual SOS, each pixel is tested to identify the first dekad in which at least 25 mm of rain
Figure 3.3 Scatter plot of WHC (in millimeters) from the FAO Digital Soil Map of the World versus those of Mattei and Sakamoto (1993) for their 243 stations. Although the range of values encountered is similar for both sources, there is not much site-specific agreement.
fell. To test for failed plantings, the next two dekads’ rainfall must total to at least 20 mm. If not, testing for a planting dekad resumes.

SOS results were obtained in this way for the 1996/1997 and 1997/1998 growing seasons in the SADC countries. Figure 3.4 illustrates the estimates for the 1996/1997 season. It was possible to evaluate the 1997/1998 results by comparing them with reports from the field for maize in Mozambique (O. Rojas, personal communication). Since these reports were compiled on a district basis, the per pixel values were aggregated by taking the median pixel value within each district. The median was selected instead of the average since it is less sensitive to the influence of outlier values. The results of the comparison are presented in two forms. Figure 3.5 presents side by side color-coded district maps of Mozambique, and Table 3.4 presents a contingency table or confusion matrix. In Table 3.4, instances of agreement between RFE based estimates of SOS and field reports are tallied along the diagonal. Off the diagonal are cases of disagreement. The results are positive by both measures, which is encouraging in view of the fact that the criteria were originally developed in West Africa rather than Southern Africa.
Figure 3.4 Start of season determination through application of AGRHYMET criteria to the RFE time series for the 1996/1997 season for the SADC countries and Madagascar. Different colors represent different start of season dekads as explained in the legend.
Figure 3.5 Start of season by district for 1997/1998 in Mozambique, as reported from the field (left) and as estimated from the RFE time series (right). Different colors represent different start of season dekads as explained in the legend.
Table 3.4. Confusion matrix for comparison of SOS estimates, based on analysis of RFE, with reports from districts in Mozambique for the 1997/1998 growing season.

<table>
<thead>
<tr>
<th>Reported SOS</th>
<th>SOS Calculated from RFE</th>
<th>29</th>
<th>30</th>
<th>31</th>
<th>32</th>
<th>33</th>
<th>34</th>
<th>35</th>
<th>36</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>26</td>
<td></td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>28</td>
<td></td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>29</td>
<td></td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>30</td>
<td></td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>31</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>32</td>
<td></td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>32</td>
<td>3</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>40</td>
</tr>
<tr>
<td>33</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>17</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>24</td>
</tr>
<tr>
<td>34</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>2</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>35</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>36</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>3</td>
<td>13</td>
<td>0</td>
<td>36</td>
<td>21</td>
<td>10</td>
<td>9</td>
<td>5</td>
<td>97</td>
</tr>
</tbody>
</table>

Note that there is agreement 72% of the time (70 cases are on the diagonal out of 97 in all), and in 81 out of 97 cases the remotely sensed SOS estimate matches the field report or precedes it by one dekad. Only 3 of the 27 incorrect estimates were for a dekad later than that reported from the field.

Crop coefficients (Kc) needed to modify PET in each dekad according to crop phenology can be obtained from the FAOINDEX software (Gommes, 1993) or other suitable reference (e.g., Doorenbos and Pruitt, 1977). FAOINDEX values for 120-day maize, the most widespread staple in the SADC region, have been used for this first spatial implementation of the WRSI.
3.5 Geospatial WRSI Results and Maize Yield Estimation

Following verification of the input spatial data sets, the WRSI itself was calculated for all of the SADC countries for the 1996/1997 and 1997/1998 seasons. This was done by means of a program written in the Arc Macro Language (Klaver et al., 1997) for use with the ARC/INFO GRID software.

The WRSI output grids are presented in Figure 3.6. It is important to recall that what has been modeled is the impact of water limitation on 120-maize if it had been planted at a given location. Whether the crop was indeed present, and how many hectares were planted, are questions that must be answered independently of the WRSI solution. Observed patterns do reflect favorable conditions that generally prevail in the traditional maize-growing regions of the SADC countries. However, note the sharp difference between the two seasons for Tanzania, consistent with field reports. In April 1997 it was announced that the Government of Tanzania would release 10,000 metric tons of maize from its Strategic Grain Reserves to cope with drought-related food shortages (FEWS, 1997). By contrast, in June, 1998, above-average production and dropping food prices were reported (FEWS, 1998). In the maize growing region of northeastern Namibia, the opposite sequence was observed. A good harvest was had in 1997, but significant drought impacts were suffered in 1998.
There typically exists proportionality between the WRSI and reported crop yields. This proportionality is used to develop local regressions for estimation of crop yield that have WRSI as the independent variable. They are capable of effective early discrimination between good and poor crop yields. Relationships with coefficients of determination ($r^2$) on the order of 0.75 are commonly reported (Frere and Popov, 1986; Mattei and Sakamoto, 1993; Rojas, 1994; Gommes et al., 1996). Both linear and exponential models have been used. These regression models of yield, along with field observations of planted area, are used to make estimates of crop production immediately at harvest, months before conventional figures become available. (In some countries, estimates of this kind are the only available figures.) The timeliness of these estimates is a clear advantage for early warning systems.

Development of useful regressions requires a large number of observations, with a good range of both wet and dry conditions represented. This large number can be partially achieved by having data from many widespread locations, however, there are large differences in soil fertility and farming practices from place to place over a large region like Southern Africa. As a consequence, a given value of the WRSI might be associated with a wide
Figure 3.6. Water Requirements Satisfaction Index (WRSI) for the 1996/1997 and 1997/1998 growing seasons in the SADC countries and Madagascar. Dark green represents good growing conditions while tan to brown areas represent areas of potential crop failure.
range of maize yield values. For this reason it has usually proven necessary to normalize yield data relative to a long-term local average or historical maximum for purposes of a developing regression model (Frere and Popov, 1986). It is also desirable to have data representing several years of record available for calculation of statistical relationships. Thirty years of record is a common standard for climatological studies. In the case of spatial WRSI, the short period of record for newly available inputs, like RFE and GDAS 1-degree fields, presents a significant obstacle.

In order to develop maize yield estimates from the FEWS spatial implementation of the WRSI, an existing regression estimator based on station calculations of WRSI was used. It is a SADC-wide estimator developed by Mattei and Sakamoto (1993). It is of the form:

\[ Y = 3.58 \text{ WRSI}_{\text{avg}} - 258.6 \]  

(3.7)

Where \( Y \) is yield as a percentage of the district historical average yield and \( \text{WRSI}_{\text{avg}} \) is current period WRSI expressed as a percentage of the district historical average WRSI. The estimator was developed using data from 206 points, has a coefficient of determination of 0.74, and correlation coefficient
of 0.86, and a standard error of estimate of 26.6. Figure 3.7 illustrates the results as a map of maize yield for the 1996/1997 growing seasons.

In order to test the maize yield estimates derived from the geospatial WRSI, it was possible to obtain a limited number of Zimbabwean maize yield reports for the 1996/1997 growing season. These figures were compiled on a communal land basis, the fifth level administrative unit of that country. Reports were only used from locations common to the Mattei and Sakamoto (1993) data base, since their quality control demonstrated that these locations historically reported reliable figures. Figure 3.8 is a scatter plot of estimated versus reported maize yield for these 14 communal lands, and illustrates the correlation of 0.80 that was computed between the two sets of figures.
Figure 3.7 Maize yield map for the SADC countries and Madagascar for the 1996/1997 growing season. Yellow areas are characterized by estimated yields around average. Tan and brown areas have below average estimated yields, and the green areas saw conditions favoring above average yields.
Figure 3.8. Scatter plot of estimated versus reported 1996/1997 maize yields, expressed as tons per hectare, for 14 communal lands of Zimbabwe, illustrating the 0.80 correlation observed.
3.3 Discussion

The need for agrometeorological monitoring of crop growing conditions for food security in sub-Saharan Africa and the use of the WRSI for this purpose has been reviewed. A geospatial version of the WRSI that uses grids of input data as an alternative to computing the index on a point by point basis has been explained. Input grids were compared with independent measures of the same variables to establish credibility for them, though concurrent station data were available to only a limited extent. Comparison with grids representing climatological conditions had to suffice, for the most part. In spite of this, the favorable nature of the results of these comparisons justified the use of these spatial inputs.

This trial has focused on maize, by far the most important staple in the region from a food security point of view. However, application of appropriate crop coefficient values would permit modeling other crops in the same way.

While the technique has been illustrated through application to eleven SADC countries, plus Madagascar, for two growing seasons, only limited field reports of yield were available from Zimbabwe for one season, 1996/1997, for validation. Comparison of these field reports and the estimates based on
the geospatial WRSI has shown reasonable agreement, with a correlation coefficient of 0.80. Given the many factors contributing to the uncertainty of both the geospatial estimates and the reports from the field, this correlation is encouraging. However, it is recognized that 14 points are insufficient for a conclusive validation. Further consultation of field scientists is planned. This will be accomplished in an effort to obtain more quality-controlled maize yield reports to extend the validation.
AGRHYMET, 1996. Methodologie de suivi des zones a risque. AGRHYMET
FLASH, Bulletin de Suivi de la Campagne Agricole au Sahel, Centre
Regional AGRHYMET, B.P. 11011, Niamey, Niger 2 (0/96): 1-2.

Bailey, T., and A. Gatrell, 1995. Interactive Spatial Data Analysis. Addison

Irrigation and Drainage Paper No. 24, Food and Agriculture Organization of
the United Nations, Rome, Italy 144 p.

FEWS Bulletin, April 25. Available from Famine Early Warning System
Project, 1611 North Kent Street, Suite 1002, Arlington, Virginia 22209 USA,
and http://www.fews.org/

Famine Early Warning System Project, 1998. Above-average Production in
System Project, 1611 North Kent Street, Suite 1002, Arlington, Virginia
22209 USA, and http://www.fews.org/


Chapter 4

Expression of Seasonal Climate Forecasts as Patterns of NDVI Anomalies

4.1 Seasonal Climate Forecasts and Early Warning Systems

Pacific Ocean waters offshore Peru are characteristically cold and nutrient-rich due to the presence of a major coastal upwelling. These conditions favor the growth of phytoplankton that sustain fish populations and, in turn, human fishing activities. Long ago, Peruvian fishermen noted the seasonal displacement of cold coastal waters by warmer waters, ordinarily beginning around Christmas and lasting for just a few months. Because of the association of the onset of warm waters with Christmas, this warm current was named El Niño, the Spanish name for the Christ child (Wyrtski et al., 1976; Cane, 1983; Ramage, 1986; Glantz, 1996). On occasion the warm waters would persist well into the next year, adversely impacting the fishermen's livelihoods. It is now understood that these irregularly recurring events along the coast of South America are part of a much broader anomalous warming of the central and equatorial Pacific Ocean that has impact on weather around the world. The term El Niño has gained popular
acceptance as the name for this warming of the Pacific and the associated changes in weather patterns.

In his quest to find a method to predict failure of the Indian monsoon, the British mathematician Sir Gilbert Walker studied records of sea level atmospheric pressure from around the Indian and Pacific Oceans, among many other meteorological phenomena. In 1924 he first used the term "Southern Oscillation" to describe the see-saw variation in pressure he observed across the south Pacific (Rasmusson and Wallace, 1983; Cane, 1983; Glantz, 1996). Normally, the western equatorial Pacific is an area of low pressure with atmospheric convection and warm sea surface temperatures. The central and eastern Pacific, by contrast, enjoy high pressure and fair skies and cooler sea surface temperatures. However, there are periodic changes in this pattern and they display a clear inverse relationship. That is, when atmospheric pressure goes up in the western Pacific, it goes down correspondingly in the eastern Pacific. These changes are monitored through calculation of the Southern Oscillation Index (SOI), which is simply the difference in atmospheric pressure between Tahiti, in French Polynesia, and Darwin, Australia. Generally, the SOI is positive (Tahiti minus Darwin), but there are episodes when it becomes negative for months at a time. These are the same periods when warm waters persist for unusually long periods off the coast of Peru. As it turns out, both are
indicators of the same basin-wide phenomenon in the Pacific. The warm pool of water in the western Pacific that feeds moisture into convective cells of the atmospheric low pressure system is displaced eastward to the central Pacific. High pressure, favoring the onset of drought, moves in over Indonesia and northern Australia. The prevailing easterly trade winds of the equatorial Pacific are reversed and connection of the warm pool with similarly warm waters off Peru occurs. Normally dry conditions on the west coast of South America are replaced by low pressure, and heavy rains and flooding result. Recognition that El Niño and the Southern Oscillation represent oceanic and atmospheric elements of the same general condition is made through the use of the combined term El Niño/Southern Oscillation or ENSO (Rasmusson and Wallace, 1983; National Research Council, 1996).

The anomalous patterns of sea surface temperature (SST) and atmospheric pressure in the Pacific that characterize an ENSO event are correlated with unusual climatic events around the world. Examples include drought in the Northeast of Brazil, wet weather in California, and warm winters in the Northern Great Plains. The maps of Figure 4.1 show the temperature and precipitation anomalies associated with the 1982-1993 ENSO event, one of the strongest of this century. These correlations are known as "teleconnections" (Kerr, 1982; Brown and Katz, 1991; Blench and Marriage, 1998), a term first used in the scientific literature by Angstrom (1935).
Teleconnections, where they have been demonstrated to exist, contribute significantly to seasonal climate forecasting. One such area is Southern Africa (Figure 4.2). A number of studies, notably those of Ropelewski and Halpert (1987), Barnston et al., (1996), and Nicholson and Kim (1997), have pointed out the occurrence of anomalous rainfall patterns in Southern Africa during ENSO events. Increased rainfall is seen in the north and northeast (especially parts of Tanzania and Zambia), and decreased rainfall characterizes the southeast (especially southern Zimbabwe, southwestern Mozambique, and northeastern South Africa). Cane et al. (1994) went further and showed that the variations in Zimbabwe rainfall patterns associated with ENSO have a marked impact on maize yields, the primary rainfed staple crop of the region. In fact, they reported that Pacific SST anomalies show a stronger correlation with maize yield than they do with rainfall. Furthermore, the possible lead time for a maize yield estimate based on Pacific SST ranges up to a year. The implications for early warning systems are clear. The potential contribution of drought to the creation of extreme food shortages in Southern Africa can be forewarned, to the benefit of preparedness and prevention, if ENSO indicators are tracked and used to prepare seasonal forecasts (Rosenzweig, 1994).
Figure 4.1. Climatic anomalies characteristic of an ENSO event during Northern Hemisphere winter months (excerpted from Ropelewski, 1992).
Figure 4.2 Countries of Southern Africa and Madagascar for which NDVI and SST anomalies were analyzed.
The 1991-1992 Southern Africa drought is considered by many to have been the worst of this century in terms of adverse food security impacts (Rook, 1997). Cereal grain production fell to less than half of normal output in the region, and the countries in the region that are ordinarily looked to for surplus production and exports, Zimbabwe and South Africa, suffered large reductions. The food security of an estimated 40 million people was directly affected. The resulting shortfall in food stuffs had to be met by the importation of over 10 million metric tons of food over a mere 12 month time span at a cost of $4 billion, with an additional $440 million spent on shipping costs (Rook, 1997; Glantz et al., 1997). Although an ENSO forecast for drought during the 1992 growing season (January-March) existed as early as March 1991, widespread dissemination of an alarm to the SADC countries by their Regional Early Warning System did not occur until December 1991. Most national declarations of a drought disaster and appeals for food aid were made in February and March of 1992, and the regional appeal was made in June. Grain imports began arriving in significant amounts in April 1992, and they peaked during September-November 1992. This latter fact is consistent with the rule of thumb that foreign donor food aid shipments take about six months to organize and deliver to the inland locations where they are needed. In their case-scenario study of the 1991-1992 Southern Africa drought, Glantz et al. (1997) assert that earlier action would have yielded significant savings. For example, they estimated that Zimbabwe could have
saved $41 million by halting maize exports in April 1991. Furthermore, shipping costs to Zimbabwe and Zambia might have been reduced by $20 million through greater use of ports in Mozambique, instead of the more expensive and more distant ports in South Africa. This option would have been possible had shipping begun in January 1992.

The obstacles to early action based on ENSO forecasts are many, including the insistence on hard evidence of drought-related food shortages by governments and humanitarian aid donors. Responsible persons naturally hope that conditions will improve before a full-blown disaster develops, avoiding the politically unpalatable requirement that a government admit to a food security emergency. Unfortunately, this means waiting until well into the growing season when poor rains and failing crops are plain for all to see. One part of the problem, however, involves the use of ENSO forecasts by the early warning community itself. They are often couched in terms of purely climatological descriptions of atmospheric and oceanic conditions in the equatorial Pacific. It is left up to food security analysts to interpret their meaning. Recent moves to organize regional climate outlook forums have addressed this to some extent by producing probabilistic maps of seasonal rainfall totals. However, the food security community has asked for significantly more. Higher spatial and temporal resolutions, for example, were specifically identified by Farmer (1997) as needed improvements to
reduce ambiguity and achieve greater utility for famine early warning systems. As we shall see, recent papers in the remote sensing literature report a correlation between Southern Africa NDVI and Pacific SST time series anomalies (Anyamba and Eastman, 1996; Myneni et al., 1996). The objective of the research reported in this chapter, then, is to address the following science question:

*Given reports in the literature of a correlation between anomalies of Southern Africa NDVI and equatorial Pacific SST, can forecasts of ENSO SST anomalies be more usefully expressed as patterns of NDVI anomalies?*

### 4.2 Relationships between SST and NDVI Anomalies

From its very beginning, USAID’s FEWS has looked to imagery from the AVHRR instruments on the NOAA polar orbiting satellites to get a timely view of broad areas of sub-Saharan Africa (Walsh, 1986; Henricksen, 1986). NDVI images in particular, computed from the AVHRR data, are used to monitor crop growing conditions over semi-arid agricultural regions (LeComte, 1989; Hutchinson, 1991). NDVI has been shown to be correlated with a number of measures of the relative abundance of green biomass, including leaf area index (LAI), intercepted fraction of photosynthetically active radiation (FPAR), density of chlorophyll in plants, and total biomass production (Sellers, 1985; Tucker and Sellers, 1986). NDVI has been also
been used to predict crop yields (Rasmussen, 1992; Groten, 1993; Unganai and Kogan, 1998) and demonstrates a significant correlation with annual and monthly rainfall totals (Malo and Nicholson, 1990; Nicholson and Farrar, 1994). The potential for the use of such correlations led to its adoption by FEWS as an operational indicator for food security monitoring.

Remote sensing research has also been directed toward the question of ENSO impacts in Southern Africa. As early as 1990, NDVI was proposed as a new climatic variable suited to monitoring seasonal fluctuations of vegetation and crops (Gallo, 1990). Since then, the extension of the available period of record for analysis makes NDVI even more suited to the application of traditional methods of climatological analysis. Time series NDVI data have been analyzed for expressions of the ENSO signal. For example, patterns illustrating the spatial propagation of drought through the region have been shown through the application of principal components analysis (Anyamba and Eastman, 1996) to monthly images for the period 1986-1990. One principal component in particular was identified as the continental scale ENSO indicator. It showed high correlations with established ENSO indicators: the Southern Oscillation Index, Pacific SST, and Outgoing Longwave Radiation. In a similar manner, negative NDVI anomalies in Southern Africa, indicative of drought, have been shown to be
associated with positive (warm) Pacific SST anomalies (Myneni et al., 1996) through analyses on a monthly time step for the period 1982-1990.

The present study was undertaken in late 1997, when the largest ENSO warming event of the century was firmly established and the Southern Africa maize growing season was about to begin. It was recognized that the situation presented the opportunity to explore the predictive value of the SST-NDVI correlation reported in the literature, if used in conjunction with forecasts of Pacific SST anomalies from NOAA's Climate Prediction Center. Experimental forecast NDVI anomaly images were produced for January, February, and March of 1998. The intent was to respond to the call of the early warning community for climate forecasts with greater spatial and temporal resolution, in a readily useable format (Farmer, 1997). This chapter reports on the data and methods used, the level of agreement between forecast and actual NDVI anomaly images for the period, and the results of a statistical cross-validation to assess the expected skill of the method in any given year.

4.3 Data

A time series of 16 years (1982-1997) of monthly maximum-value NDVI composite images (Holben, 1986) was prepared for January, February, and
March. These are the core months of the Southern Africa maize growing season (FEWS, 1995). Each image array was made up of 550 lines of 630 samples each, with dimensions of 0.0625 degree of latitude and longitude (about 6 kilometers) to give full coverage of Southern Africa and Madagascar. The images for the years 1982-1993 were provided by the NASA/Global Inventory Monitoring and Modeling Studies (NASA/GIMMS) group (Los et al., 1994). Processing techniques employed at NASA/GIMMS screen data for elimination of pixels with temperature less than 285 K (presence of clouds) and off-nadir viewing angle greater than 42 degrees.

Channel 1 (red) and channel 2 (near infrared) radiances are normalized by Lambert cosine law to the case of solar zenith angle of zero, and the NDVI is calculated using the resulting values according to the formula:

\[
\text{NDVI} = \frac{(r_1 - r_2)}{(r_1 + r_2)} \quad (4.1)
\]

Where \( r_1 \) and \( r_2 \) are the normalized radiances for channels 1 and 2. The NDVI data are then mapped to a plate carré (latitude-longitude) coordinate system and correction for sensor degradation is applied to the NDVI values according to techniques, described by Los (1993), that use ocean and desert targets.
Each month's time series through 1997 was completed using NDVI images in the FEWS archive at USGS for the 1994-1997 period. These images were also originally produced by NASA/GIMMS, though the compositing period was 10 days, instead of one month, and the coordinate system was a 7.4-km grid in the Hammer–Aitoff projection. USGS performed maximum value compositing of the dekadal images to obtain monthly maximum-value composites, and re-projected the data to the 0.0625 degree plate carré coordinate system. This completed a 1982-1997 time series for each of the three months analyzed (January, February, and March). Mean monthly NDVI "normal" images were based on the years 1982-1993, to be consistent with FEWS operational methods. NDVI anomaly images were then prepared by computing the difference between the individual monthly images and their respective monthly normal images.

For data processing purposes, the inherent decimal values of the NDVI were scaled from −0.30 to 0.67 to byte values of 2 to 254. Anomaly values were computed by the formula

$$\text{NDVI}_{\text{anomaly}} = \frac{(\text{NDVI}_{\text{average}} - \text{NDVI}_{\text{current}} + 256)}{2} \quad (4.2)$$
According to this scheme, values greater than 128 indicate negative NDVI anomalies, and values less than 128 indicate positive NDVI anomalies. Both of these byte scales have a long history of use in the FEWS project (Pfirman and Hogue, 1998).

The eastern equatorial Pacific from 5°S to 5°N latitude and 90°W to 150°W longitude, known as the "NINO3" region, is an area whose SST anomalies are widely tracked as an ENSO indicator. A time series of monthly SST anomaly values, dating back to 1950, has been developed by NOAA's Climate Prediction Center (CPC) and is continually updated (Woodruff et al., 1993). Monthly NINO3 SST anomaly data for the 16 year period were downloaded from the NOAA/CPC World Wide Web site. Forecast NINO3 SST anomalies for 1998 were also provided by NOAA/CPC (J. Kousky, personal communication). Figure 4.3 illustrates the SST anomaly time series, byte-caled by the formula \((ssta*10) + 128\), where \(ssta\) is the original expression of the SST anomaly in degrees C. Also depicted in the figure is the time series byte-NDVI anomaly trace for an example pixel in Mozambique that has shown signs of drought during NINO3 SST warming events.
Figure 4.3. Time series trace of byte-scaled NINO3 SST anomalies alongside a similar trace of NDVI anomalies for a point in Mozambique at 31° 41' East, 22° 04' South, characterized by drought during ENSO warming events.
4.4 Methods

The time series of 16 images each for January, February, and March were partitioned into groups of 5 and 11 images. The group of five images represented years of ongoing ENSO warm events (1983, 1987, 1988, 1992, and 1995) and the group of eleven represented the other years. Presumably, areas without a teleconnection would have similar means for a month for both groups. On a pixel-by-pixel basis, a two-tailed t-test was applied to identify locations having significantly different NDVI anomalies during ENSO warm events than during other years, at the 0.01 confidence level. For each month, regions of wet (greener than average) and dry (less green than average) pixels were identified.

Within each of the monthly wet and dry regions, mean NDVI anomaly was calculated for each of the 16 years of record. These values were used to develop regression estimators of mean regional NDVI anomaly using NINO3 SST anomalies as the independent variable. Six estimators were developed, one for each wet and dry region for each month (January, February, and March). Coupled model forecast SST anomalies were then substituted into the regressions to obtain estimates of mean NDVI anomaly in the wet and dry regions for the upcoming 1998 season.
During the course of the 1998 season, actual NDVI images from FEWS operations were collected and processed into monthly NDVI anomaly images. These were compared with the forecast NDVI anomaly patterns to evaluate them.

Cross-validation (Michaelsen, 1987) was also used to determine a skill statistic for each NDVI anomaly estimator. Including data for 1998 to obtain a 17-year time series, one year at a time was withheld and its NDVI anomaly estimated by regression using the remaining 16 data points. Skill was calculated as

\[ R = [1 - (\text{MSE}/\text{MSA})]^{1/2} \quad (4.3) \]

where \( R \) is the skill statistic, MSE is the mean square error in estimating withheld points, and MSA is mean square anomaly, or variance, of the data set. The MSA can be interpreted as the error incurred by simply forecasting the long term mean NDVI. Positive skills range up to 1.0 for perfect forecasts. Negative skills occur when the forecasts are outperformed by the long term mean.
4.4 Forecast NDVI Anomaly Images for 1998

The t-test images (left column of Figure 4.4) show the spatial pattern of pixels that were significantly wetter (in green) or drier (in red) during warm ENSO event years. These patterns change substantially from month to month. In January, the ratio of the number of wet to dry pixels was 1.32, indicating an aggregate increase in precipitation in Southern Africa. There is a rough north-south pattern to the distribution of wet/dry pixels, with South Africa, Mozambique and Zimbabwe being mostly dry, and Angola, Zambia and Tanzania being generally wet. The wet/dry dichotomy appears to shift north over the next two months; by March only Tanzania and Angola exhibit significantly greener than average conditions, and the ratio of the number of wet to dry pixels is 0.34.

Table 4.1 summarizes the correlation coefficients (r), coefficients of determination ($r^2$), and cross-validated skill statistics (R) for the six regression estimators, along with forecast and observed mean NDVI anomaly values for the t-test regions. For January and February, all three measures suggest that increased greenness is more readily predicted than drought. For all three months, the cross-validated skills (R) for wet regions varied between +0.36 and +0.39, a range recognized to be of practical value.
Figure 4.4 Forecast (left) and actual (right) NDVI anomaly patterns for (top to bottom) January, February, and March of 1998. Red areas are drier (lower NDVI) than average and green areas are wetter (higher NDVI) than average.
for preparation of seasonal climate forecasts (Barnston et al., 1996). The estimates for the dry region exhibited negative skills for all months. The performance of the regression estimators for 1998 confirms this finding. The wet region estimates are of the same sign and order of magnitude as the observed values, while the dry region estimates were off by up to 0.08 NDVI, predicting considerable drought for areas that actually showed average greenness.

Table 4.1. Summary description of monthly regression estimators for dry and wet t-test regions, with forecast and actual mean NDVI anomaly values for 1998.

<table>
<thead>
<tr>
<th></th>
<th>January</th>
<th>February</th>
<th>March</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>wet</td>
<td>dry</td>
<td>wet</td>
</tr>
<tr>
<td>( r )</td>
<td>0.54</td>
<td>-0.41</td>
<td>0.62</td>
</tr>
<tr>
<td>( r^2 )</td>
<td>0.30</td>
<td>0.17</td>
<td>0.38</td>
</tr>
<tr>
<td>( R ) (skill)</td>
<td>0.39</td>
<td>-----</td>
<td>0.39</td>
</tr>
<tr>
<td>forecast SST anomaly (C)</td>
<td>3.2</td>
<td>2.7</td>
<td>2.1</td>
</tr>
<tr>
<td>forecast NDVI anomaly</td>
<td>0.07</td>
<td>-0.07</td>
<td>0.05</td>
</tr>
<tr>
<td>actual NDVI anomaly</td>
<td>0.04</td>
<td>0.00</td>
<td>0.02</td>
</tr>
<tr>
<td>forecast NDVI anomaly</td>
<td>0.04</td>
<td>0.00</td>
<td>0.02</td>
</tr>
<tr>
<td>actual NDVI anomaly</td>
<td>0.04</td>
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<tr>
<td>actual NDVI anomaly</td>
<td>0.04</td>
<td>0.00</td>
<td>0.02</td>
</tr>
</tbody>
</table>

120
4.5 Assessment of the NDVI Forecast Images

The t-test forecast images on the left side of Figure 4.4 show wet/dry patterns that are consistent with previous work dividing the subcontinent into Southern African and Eastern Equatorial regions (Nicholson and Kim, 1997; Ropelewski and Halpert, 1987) in terms of ENSO response. Forecast NDVI anomaly patterns strongly resemble the consensus forecast of the Southern Africa Regional Climate Outlook Forum (SARCOF) (FEWS, 1998). However, both the SARCOF and NDVI forecasts predicted drought for regions that in fact experienced average to above-average rainfall in 1998. Cross validation skill better foretold observed NDVI forecast performance in this regard than did simple correlation statistics. Areas forecast to be wet generally were wetter than average, while vast areas forecast to be drier than average did not experience drought.

The correlation values of Table 4.1 are quite comparable to values reported in similar studies carried out with conventional climatological data, (Nicholson and Kim, 1997). However, cross-validation statistics suggest that NINO3 SSTs are better predictors of increased greenness in the north than they are decreased greenness in the south. Comparison of forecast and actual NDVI anomaly patterns for 1998 reinforce this finding. The t-test images
suggested an initial core of drought in January that would expand north in
February and March. Most of Tanzania, northern Zambia, and southwestern
Angola were forecast to have wet anomalies. In 1998, these latter areas did
exhibit wet anomalies, but as part of a broader phenomenon. Expected
widespread drought in the south was replaced by widespread above-average
greenness. Northeastern South Africa and Namibia were the exception,
showing drought patterns not unlike those forecast.

Ward et al. (1998) performed a check of the SARCOF forecast for January-
March rainfall totals by imposing a two-degree grid over the region and then
comparing observed and forecast rainfall spatial patterns. The forecast was
expressed in terms of tercile ranges of seasonal rainfall totals. For each of
250 stations, thirty-three years of record (1961-1994) were ranked and
divided into three groups, or terciles, of 11 values. At each station, the
terciles defined a characteristic range of seasonal rainfall totals. The middle
tercile was considered normal, and the other two called above and below
normal. The SARCOF forecast assigned regions to tercile ranges,
sometimes specifying two possible terciles (e.g., normal to above). Ward et
al. (1998) compiled actual seasonal totals for the same stations and compiled
equivalent tercile maps. Figure 4.5 illustrates their work, and reveals
regional patterns very much like those of Figure 4.4. The suggestion is clear
– projecting patterns of NDVI anomalies based on SST forecasts performed
as well as conventional climatological methods during January-March 1998 in Southern Africa. Unfortunately, this fact is overshadowed by the fact that neither forecast did a very compelling job of foretelling seasonal patterns in this instance.

Full explanation of these results requires an improved understanding of the climatic mechanisms underlying the Southern African and Eastern Equatorial teleconnections. It appears likely that the two regimes are governed by different physical processes, with the northern region dominated by interannual variations in the intertropical convergence zone (ITCZ), and the southern region having rainfall levels modulated by fluctuations in SST of the nearby Indian and Atlantic oceans. The former is likely more directly linked with equatorial Pacific SST (the ITCZ being an equatorial phenomenon itself), and is therefore better predicted by NINO3 SST anomalies. The latter regime suggests that a fruitful path for follow-on research would be in the area of canonical correlation analysis (CCA), as described by Barnston et al. (1996) wherein global fields of SST are used as for prediction, rather than a single window in the equatorial Pacific. In this way, the influence of the Indian Ocean and South Atlantic are permitted to come into play. Furthermore, substitution of NDVI for precipitation as the predicted variable in CCA would
result in a new forecast product of greater relevance to the needs of the
famine early warning community.
Figure 4.5 Comparison of the Southern Africa Regional Climate Outlook Forum forecast for January-March, 1998, with actual rainfall totals (from Ward et al. (1998)).
4.7 References


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Chapter 5

Conclusions and Recommendations

5.1 Crop Water Accounting on a Geospatial Basis

The science question addressing reduction of ambiguity in the use of remote sensing estimates of rainfall for food security monitoring was posed as:

*Can crop water accounting be performed on a geospatial basis to better express the agricultural significance of the RFE precipitation patterns?*

A preliminary answer to this question is "yes". The use of the WRSI on a station basis to make early estimates of crop production has been successfully applied for many years by FAO and is an accepted operational field practice (Gommes, 1983; Frere and Popov, 1986). This dissertation has demonstrated that credible geospatial versions of the fundamental WRSI station inputs (soil water holding capacity, dekadal precipitation, and dekadal potential evapotranspiration) can be assembled from digital maps, remote sensing, and an operational numerical weather forecast model. Calculations to determine start of season, apply crop coefficients, and create maps of the WRSI within a GIS have likewise been demonstrated. Furthermore,
substitution of geospatially calculated values of WRSI in a regression estimator for maize yield produced results in substantial agreement ($r = 0.80$) with 1997 field reports of maize yield from 14 communal lands of Zimbabwe. These results, though favorable, must be qualified as preliminary due to the limited number of independent maize yield reports available for comparison.

Conventional reports of crop yield are subject to many sources of uncertainty (e.g., visual estimates of area planted and expected production) and are therefore less than ideal standards for evaluating estimates made from geospatial climate monitoring products. There are few good alternatives except to apply quality control procedures to identify and eliminate districts with abnormal reporting histories (Mattei and Sakamoto, 1993). Another option is to seek the recommendation of reliable districts from long term users of yield data (Eilerts, personal communication).

Crop production figures by district are often more reliable than yield figures, since they are based on more direct measures like counts of truckloads of grain or data from marketing organizations. More easily verifiable results might be obtained by using geospatial methods to estimate crop production instead of crop yield. If good estimates of planted area can be obtained in the form of land cover maps or figures compiled in some reliable manner by reporting district, their use in conjunction with geospatial estimates of yield
can give crop production estimates suitable for comparison with conventional production figures. This was the approach taken recently by Reynolds (1998), who implemented a GIS-based crop water balance for Kenya similar to the one described in Chapter 3. He reported a correlation coefficient of 0.94 for maize production estimates compared with government figures for 41 districts over 5 years. Prospects for the availability in the near future of reliable, up to date planted area estimates for East Africa are good, thanks to the efforts of the FAO Africover Project (Di Gregorio, personal communication).

There are three key areas for recommended future research for improved early estimates of crop production through geospatial crop water accounting. First, there is room for improvement in the remote sensing estimates of rainfall. Second, the season-specific timing of crop water demand, as expressed by SOS and crop coefficient values, can be better modeled with available data. Finally, difficulties of relating WRSI to crop yield can be addressed by means of crop yield functions instead of regression estimators.

The RFE produced for FEWS by the method of Herman et al. (1997) have been reported to show a good correlation with station data in the Sahel and somewhat weaker performance in Mozambique (Rojas and Amade, 1998), with a tendency for underestimation. A strength of the method is the
integration of rain gauge data with the remote sensing estimates, however, there is reliance on a single cold cloud temperature threshold value for the entire African continent, regardless of region or season. By contrast, the Tropical Applications of Meteorological Satellites (TAMSAT) group at the University of Reading varies the cold cloud threshold between -50° C and -70° C, depending upon geographic zone and time of year (Snijders, 1991), but makes no use of rain gauge data in preparing its estimates. A recent comparative study by the TAMSAT group for Southern Africa (Thorne et al., 1999) concluded that optimum results might be obtained by combining local calibration of threshold temperature with the merging of rain gauge data with remotely sensed data. This should be pursued by FEWS, and indeed, prospects for this happening are good. The Intergovernmental Authority on Development (IGAD), in the context of its current project “Strengthening Remote Sensing for Early Warning, Food Security, and Environmental Monitoring in the IGAD Countries”, has approached both TAMSAT and FEWS for this purpose and gotten a positive response in both cases (M. Haile, personal communication). Participation of the national meteorological services of Kenya, Ethiopia, and Uganda should significantly enhance opportunities for success.

Another prospect for achieving improvements in satellite remote sensing estimates of rainfall in Africa lies with NASA's Tropical Rainfall Measuring
Mission (TRMM). TRMM carries three rainfall observing instruments: a precipitation radar, a microwave imager, and a visible/infrared scanner. Although the low inclination (35°) orbit provides relatively infrequent (once or twice a day) observations, as compared with geostationary satellite systems like Meteosat (observations every 30 minutes), TRMM data provide unprecedented detail on the structure and intensity of precipitation events. By using TRMM data in conjunction with data collected by geostationary platforms, it appears that relatively crude estimates of rainfall based on cold cloud top temperature can be "calibrated" using the detailed TRMM observations, to obtain more accurate daily and dekadal gridded rainfall estimates (C. Kummerow, TRMM Project Scientist, personal communication). As soon as such improved rainfall estimate products are available to FEWS, test applications for crop water accounting should be investigated.

Determination of the start-of-season dekad, the assumed length of growing period, and the variation of crop coefficient values during the season have a direct effect on the calculated value of the WRSI. Reliance on the RFE alone for identification of the SOS dekad is subject to error due to inaccurate rainfall estimates. A complementary method of SOS determination makes use the operational NDVI imagery available to FEWS (Lee, 1997). Two consecutive dekads with increases of at least 0.02 NDVI mark the beginning
of the season. Comparative studies of these two methods of SOS
determination are recommended. It is likely that a joint use of the two
methods would improve crop water accounting. Areas of persistent cloud
cover would benefit from the RFE approach, and areas of poor local
calibration of the RFE would benefit from a determination of SOS based on
NDVI increases. Length of growing season and associated crop coefficients
are presently assumed from incomplete knowledge of local practices and use
of standard reference documents. Studies based on experimental plots have
shown that a crop's requirement for water throughout its cycle can be better
determined by direct observation of ambient conditions. Inference of a crop
coefficient can be made from a vegetation index based on remotely sensed
reflectance measurements (Neale et al., 1989; Bausch, 1993) or by
maintaining an account of cumulative growing-degree-days (Sammis et al.,
1985). Either of these might be investigated for FEWS. Available NDVI data
could be used in the former case, and fields of surface air temperature from
GDAS could be used in the latter. A growing-degree-day approach probably
has more promise, since air temperature is less spatially variable than crop
canopy reflectance properties, and is therefore better suited to
characterization with available systems. The NDVI of a 7.4-kilometer pixel
represents the signal from a mixture of land cover types, not just the crop of
interest. The 1-degree cell size of the GDAS is cruder by an order of
magnitude, but model temporal frequency of 6 hours and relative uniformity
of temperature over growing regions would be expected to compensate for this.

Results of a sensitivity analysis have been presented for one season’s data for one station in Kenya. This is not enough to assess the behavior of the WRSI under the variety of conditions present in FEWS countries. More years of data and more stations need to be studied. In particular, the key role of soil water holding capacity needs to be better understood by means of more extensive sensitivity analyses.

We have seen that calculating regression equations to estimate crop yield from WRSI requires large numbers of observations that can be subject to error and difficult to assemble. For this dissertation, it was necessary to use a previously developed regression (Mattei and Sakamoto, 1993). Crop yield functions, an attractive alternative, relate the WRSI to reductions in yield relative to a local average yield. They are based on the findings of experimental water balance studies (Doorenbos and Kassam, 1986) and were successfully applied by Reynolds (1998) in Kenya. Investigation of their use for a variety of important crops in other African countries is recommended.
5.2 Seasonal Climate Forecasts Expressed as NDVI Anomaly Patterns

In Chapter 4, experimental NDVI anomaly forecast images were presented and analyzed to address the science question:

*Given reports in the literature of a correlation between anomalies of Southern Africa NDVI and equatorial Pacific SST, can forecasts of ENSO SST anomalies be more usefully expressed as patterns of NDVI anomalies?*

The results presented in Chapter 4 support an answer of "yes" to this question, particularly the t-test and cross-validation statistical measures. NDVI is a more familiar climate variable than Pacific SST for the African food security community, so there is clear benefit in expressing SST anomaly forecasts in terms of probable patterns of NDVI anomalies based on these statistical relationships. The improved spatial and temporal resolutions, when compared with conventional climate outlook forecast maps (Figure 2.6), are also advantageous. Probable impacts on specific crop growing areas and stages of crop phenology can be inferred more readily. However, this greater specificity must be tempered by knowledge of the probabilistic nature of any given seasonal climate outlook. The weakness of the underlying relationships does not justify their use as categorical predictions.
Seasonal climate outlooks will show benefit through long term use, but in specific instances can be quite inaccurate. They are best considered as one of many tools to be used in decision making and risk management, rather than a definitive procedure that can foretell the future (Australian Bureau of Meteorology, 1999). The use of information of such quality is quite consistent with the convergence of evidence approach used by FEWS. Use of seasonal climate outlooks that recognize the uncertainty associated with them is also consistent with the pioneering research that revealed the teleconnection between anomalies in Southern Africa precipitation and equatorial Pacific SST anomalies.

Ropelewski and Halpert (1987), Kiladis and Diaz (1989), and Nicholson and Kim (1997) not only described the Southern Africa teleconnection, they also detailed its consistency and cited historical instances in which observed Southern African precipitation was the opposite of that expected from the prevailing Pacific SST anomaly patterns. For example, Ropelewski and Halpert (1987), for the period 1877-1980, found Southeastern Africa to be wetter than normal during 5 of 22 ENSO warm events. Kiladis and Diaz (1989) found a percent consistent signal of about 80% for Harare, Zimbabwe, for the period 1877-1988, but cited 1925, 1939, 1965, and 1976 as years of warm ENSO events with positive precipitation anomalies. Nicholson and Kim (1997), for the period 1901-1990, considered 75% consistency as their
criterion for a robust ENSO signal but identified 1951, 1977, and 1987 as ENSO episodes in which continental scale rainfall response was inconsistent with expectations based on the Pacific SST teleconnection. The point here is that comparison of expected and actual NDVI anomaly patterns in Southern Africa will likely show a substantially incorrect forecast, as it did for January-March 1998, about one fourth of the time.

The improvement of skill in developing maps of expected seasonal NDVI anomaly patterns for Southern Africa lies with the identification of predictor variables in addition to NINO3 SST anomalies. Walker (1990) demonstrated the importance of SST variations in the Southwest Indian Ocean and the South Atlantic for explanation of interannual variations in austral summer rainfall in South Africa. The application of canonical correlation analysis using global SST patterns as predictors (Barnston et al., 1996), instead of the NINO3 window alone, would insure that data from these areas are taken into account as researchers seek improved statistical explanations of Southern Africa rainfall patterns. Researchers at NOAA’s Climate Prediction Center, in fact, have expressed their willingness to train the CCA model to forecast NDVI anomaly patterns for this purpose, on an experimental basis (Wassila Thiao, personal communication). The complexity of the subcontinent’s climate patterns (Tyson, 1986), though, will require future researchers to look beyond SST as an indicator. Indeed, Hastenrath et al. (1995) found their
greatest success in modeling the austral summer rainfall of Southeastern
Africa through the use of Southwest Indian Ocean SST, zonal winds in the
equatorial Indian Ocean, and stratospheric winds over Singapore (nine
months earlier!) as independent variables.

5.3 Concluding Remarks

The broadly stated goal of the research described in this dissertation has
been to demonstrate how the application of geospatial analytical methods
can contribute to the reduction of ambiguity associated with climate
information products used by analysts involved in FEWS activities. Two
specific examples were taken up, operational rainfall estimates based on
remote sensing and seasonal climate outlooks based on ENSO monitoring of
Pacific sea surface temperatures. Results have been positive, and follow-on
investigations are already underway which involve the active participation of
FEWS partner organizations beyond the author’s home agency, the U.S.
Geological Survey. The findings of Chapter 3 are being built upon through
cooperative efforts with FEWS analysts in Africa and Washington, FAO field
agrometeorologists, and the U.S. Department of Agriculture’s Agricultural
Research Service. NOAA’s Climate Prediction Center and Office of Global
Programs are supporting work that builds upon the findings of Chapter 4.
The interest and dedication of resources by these organizations are evidence of the significance of the findings.

It should not be terribly surprising that this is so. We live in a period in which rapidly advancing technologies present ever-increasing opportunities to the geographer to contribute to humanitarian assistance and the achievement of sustainable development. The continuing trend for decreasing cost and increasing power of computing hardware, software, and telecommunications networks expands these opportunities every year. At the same time, a profound lack of current information describing human and environmental conditions in the developing world continues to persist. There are even situations where this information gap is growing because financial hardship and armed conflict have curtailed established activities to collect rainfall and agricultural production data in African countries. The implication is clear. The investment of a tiny fraction of donor agency budgets can make possible the effective application of current technology to remedy gaps in information through the creative application of geospatial analysis. Disparate data sets, stemming from modeling, remote sensing, digital mapping, and ground surveys can be combined to respond to the practical questions of disaster preparedness and long-term development. The unprecedented communications opportunities afforded by the expansion of the internet mean that these activities can be carried out by partnerships that balance high
technology resources and local know-how. Realization of these opportunities awaits only their articulation by geographic information scientists who are in a position to know that the need for such initiatives is all too obvious.
5.4 References


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