>From sandi Fri Mar 9 10:35:31 2007
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Subject: popular summary and abstract

Greetings Bob Scole:

Here is the information for this popular summary:
paper title: Using Satellite Remote Sensing in a Spatially Explicit Price Model
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Abstract in Land Economics: Famine early warning organizations use data from multiple disciplines to assess food insecurity of communities and regions in less developed parts of the world. Here we present a model that integrates information on the suitability of the growing season and millet prices in the dry central and northern areas of West Africa. The model is used to create spatially continuous maps of millet prices. By coupling the model with remote sensing vegetation data estimated one to four months into the future, we create a leading indicator of potential price movements for early warning of food crises.

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Popular Summary

Title: Connecting satellite remote sensing to food access in West Africa

Summary:

Famine early warning organizations use data from multiple disciplines to assess food insecurity of communities and regions in less-developed parts of the world. In this paper we integrate several indicators that are currently used to inform the monitoring of food security conditions and coordinating response to emergencies. The assessment uses a price model based on the relationship between the suitability of the growing season and market prices for millet grain commodity prices. This relationship is then used to create spatially continuous maps of millet prices which allow the inference of food prices in markets where no information is available. The model is applied to the dry central and northern areas of West Africa, using satellite-derived vegetation indices for the entire region. By coupling the model with satellite-derived vegetation data that has been statistically projected one to four months into the future using rainfall and humidity, maps are created of a leading indicator of potential price movements. It is anticipated that these maps can be used to enable earlier warning of food security crises due to elevated food prices and improved planning for appropriate response.

Using Satellite Remote Sensing Data in a Spatially Explicit Price Model

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Resubmitted to Land Economics, 1/9/07

Abstract:

Famine early warning organizations use data from multiple disciplines to assess food insecurity of communities and regions in less-developed parts of the World. In this paper we integrate several indicators that are available to enhance the information for preparation for and responses to food security emergencies. The assessment uses a price model based on the relationship between the suitability of the growing season and market prices for coarse grain. The model is then used to create spatially continuous maps of millet prices. The model is applied to the dry central and northern areas of West Africa, using satellite-derived vegetation indices for the entire region. By coupling the model with vegetation data estimated for one to four months into the future, maps are created of a leading indicator of potential price movements. It is anticipated that these maps can be used to enable early warning of famine and for planning appropriate responses.

1.0 Introduction

Since the food crisis of the early 1970s, national food security has been an organizing principle of development in Africa. The root of concern with food security, defined as secure access at all times to sufficient food (WorldBank, 1986), can be traced back to the Universal Declaration of Human Rights in 1948, which recognized the right to food as a core element of an adequate standard of living (UnitedNations, 1948). Determining the vulnerability of a population to food insecurity is of interest not only to prevent suffering among the local population due to food shortages but also, through early intervention, to limit the expense of ameliorating that shortfall.

The US Agency for International Development's Famine Early Warning System Network (FEWS NET) uses social science methodologies to monitor food security. Because many countries experience significant interannual rainfall variability and thus variability in food production, spatial data with country-wide coverage is essential, not just the data from the few meteorological stations that are typically available in these countries. The spatial data are obtained from satellite vegetation remote sensing and are often integrated in global information systems (GIS) for analyses. The success of famine early warning is determined by its capability of applying the data to complex decision-making, often conducted in times of crisis. Currently much of the interpretation of the data is qualitative and depends on "convergence of evidence", that is confirmation through multiple indicators that move in the same direction, to reach consensus at a variety of scales. In order to advance the skill of prediction, objective indicators are needed that integrate data using mechanistic relationships to determine the scope and extent of an emergency (Buchanan-Smith and Davies, 1995).

Early warning systems have recently integrated analysis of food access and food availability. Moseley (2001) describes this 'third wave of innovation' as an integrated approach that identifies homogeneous livelihood zones within each country with explicit knowledge regarding the sources of income and food for the demographic groups in each zone (Downing, 1991; Kennedy and Payongayong, 1992; Moseley and Logan, 2001; FEWS, 2005). By analyzing people's access to food and income as well as their other options for coping with adverse events and processes, the livelihoods approach improves judgments of the types and magnitude of the food security problems (Boudreau, 1998; Seaman et al., 2000; Mathys, 2005). For example, the livelihood of those who are reliant on rainfed agriculture for both food and income depends both on production and rising grain prices.

Early and effective intervention depends on appropriate information and preparation, including :

- Monitoring of the biophysical conditions of the growing season with satellite observations of vegetation and rainfall, interpreted qualitatively and with models such as crop models.
- Monitoring of the local economic and political situation to locate regions experiencing above-normal food prices coupled with reductions in normal coping strategies such as a reduced local or national government ability to respond.
- Contingency planning and scenario development that ensure national governments and regional organizations are prepared to respond appropriately when monitoring indicates that interventions may be beneficial.

Current food security problems are often monitored using current remote and local observations of food security conditions. These observations are used to develop immediate food aid need assessments and therefore they need to have a high degree of accuracy and precision. More sophisticated approaches such as modeling are rarely used because the focus is typically on current crises.

In the past five years planning and preparation for crises, particularly in regions that experience problems frequently, has increased in importance (FEWS, 2006). Clearly anticipation of future problems makes for better integration with humanitarian aid sources that require lengthy negotiation, early purchasing, mobilization, and shipping of food aid (personal communication, Richard Choularton, Chemonics FEWS NET, 2006). The necessary precision of the information needed for planning and forecasts of possible future food insecurity is far lower than that required to estimate current food aid needs. Recent research has enabled the projection of vegetation index dynamics up to four months into the future (Funk and Brown, 2006) that could be incorporated into operational analyses of food security. The purpose of the work presented here is to develop methods to apply the projections to planning for future food aid to enable the estimation of spatial locations and severity of future problems in regions at risk.

This research focuses on three countries in West Africa, Burkina Faso, Niger and Mali, where an important indicator of food access is the price of locally grown grains in informal village markets. Rural households in most of the Sahel sell grain in order to obtain cash for household needs (Jayne and Minot, 1989). Farmers typically sell a portion of their crop on the market directly after the harvest when the price is low, save a portion for consumption, and purchase food from the market as their own supplies diminish later in the year, usually at a much higher price. These transactions typically occur within five kilometers of the household's land because transportation is both expensive and unreliable (Platteau, 1996). Reliance on agriculture as a primary source of both income and food has led to a fundamental vulnerability to seasonal and inter-annual rainfall. Cash income is therefore important because food grown in areas with adequate rainfall can generally be purchased even if grain cannot be grown locally in some years.

Seasonal variations in food prices are a disadvantage for local producers due to food marketing patterns in infrastructure-poor economies (Barrett, 1996). While food markets are becoming more integrated, annual and interannual variations in prices are still large due to constraints in the production system and efficiency in distribution In the small, isolated, and informal markets that are typical of the region, food prices are intimately linked with local food production. Multiple variables can affect the production of cereal crops, not just whether or not adequate rain is received. These variables include area planted, insect and animal damage, soil erosion, soil infertility, and damage due to wind among other factors (Hoogmoed and Klaij, 1990; Klaij and Hoogmoed, 1993). International food trade, production imbalances between different areas of a country, and limited road networks may also influence the local prices of food (Cutler, 1984; De Waal, 1988; Deaton and Miller, 1996). Variability in the rainfall has a significant negative impact on food access, both because of reductions of grain meant for on-farm consumption and because of consequent increase in grain prices during periods of shortfall before the next harvest.

The current work investigates whether predictions of changes in prices can be improved by incorporating remotely sensed vegetation into quantitative price models. Remotely sensed vegetation data is used qualitatively by the food security community to link vegetation indices to agricultural yields (Fuller, 1998; Funk et al., 2005; Funk and Brown, 2006). The justification for using satellite data in famine early warning activities came from research on net primary production (NPP) (Prince et al., 1990; Diallo et al., 1991; Justice et al., 1991a; Prince, 1991). At first primary production estimates from satellite data were used to determine if an area was experiencing a decline in food availability. Later, early warning organizations moved towards additional indicators based on a wide variety of locally gathered social and economic data. Unfortunately no direct connection between remotely sensed indices and food access has been established.

This paper presents a price-vegetation model that is used to create maps of price predictions using West Africa as an example. The intention is to use satellite observations of vegetation to allow regions such as West Africa to improve the functioning of their markets, information systems, and government organizations that are involved in food security. The model is presented first, with its data and outputs. Next, an analysis of the relative impacts on local prices of local conditions and millet of export regions is presented. The maps of prices across the region, that are made possible by the spatially continuous nature of remotely sensed vegetation data, are compared with specific market price observations. A generalized model that exploits the spatially continuous nature of remote sensing data is presented. The impacts of mapping forecasted prices on the ability of regional, national and international governments and organizations to respond to market movements due to environmental conditions are discussed.

2.0 Input Data

2.1 Price Data

The price data used were monthly millet prices from 445 markets in Niger, Mali and Burkina Faso. The data were obtained from local market price monitoring organizations through the USAID's Famine Early Warning System (FEWS) (May, 1991; Chopak, 1999). The data have been kept in the local currency (CFA)[1]. The data series vary in length, with all data ending in 1999, but beginning in different years (Niger in 1982, Mali in 1987 and Burkina Faso in

[1] The CFA is fixed for all three countries at the same exchange rate with the French franc. This rate varied over the period of interest, with a significant devaluation occurring in 1994.

1989). All the price datasets have similar means and standard deviations (Table 1). The 126 markets with fewer than 50 months of data out of the total possible of 215 months were excluded. 29% of the data in the three countries were either missing or could not be used due to a lack of sufficient consecutive months of data. 68,904 monthly millet price data points were available for analysis.

Although the FEWS database also includes monthly data for maize, rice, sorghum, wheat, peanuts, and a variety of other local and imported products, this study considered only millet prices. Millet is the most frequently purchased commodity in West African rural areas when own-grain production is low (Jayne et al., 1996). It is also the most widely grown and most readily available grain. Market locations are shown on a map of NPP in Figure 1.

The millet price data were deflated with a national annual consumer price index (CPI) (IMF, 1999c; IMF, 1999b; IMF, 1999a), interpolated across months. The CPI was used to relate changes of consumer's purchasing power over time in the three countries where data were used (Jayne et al., 1996). The deflation removes inflation trends from the data and corrects for the impact of 50% devaluation of the CFA in 1994.

2.2 Satellite Vegetation Data

Vegetation index data was used as a proxy for agricultural production. Normalized Difference Vegetation Index (NDVI) data have been used extensively in the Sahel to detect variations in vegetation production, and have been shown by a number of authors to be correlated to both NPP, crop yields (Tucker, 1985; Prince, 1991; Tucker et al., 1991; Fuller, 1998), and precipitation (Tucker and Nicholson, 1999). NDVI data were obtained from the NOAA Advanced Very High Resolution Radiometer (AVHRR) archive, which has 8 x 8 km spatial and monthly temporal resolutions. The data were processed by the Global Inventory

Monitoring and Mapping Study (GIMMS) group at the NASA Goddard Space Flight Center (Tucker et al., 2005). The AVHRR sensor has appropriate spatial, spectral and temporal resolutions to monitor the entire Earth, hence it is adequate to cover all West Africa (Justice et al., 1985; Townshend and Justice, 1986; Justice et al., 1991a; Justice et al., 1991b; Townshend, 1994). The mean of a five by five-pixel box (40 x 40km) centered on each market was calculated from monthly maximum value NDVI composites (Holben, 1986).

2.3 Net Primary Production Classification

A map of the means of annual NPP was used to classify the markets into those in similar agroecological potential zones, in classes of 100 grams of carbon per square meter per year (g $m^{-2}yr^{-1}$). The NPP data were obtained from the Department of Geography, University of Maryland (Prince and Goward, 1995). The nine classes range from a desert environment with an NPP of 0-100 g m^{-2} yr^{-1} (class 1) to the sub-humid Sudanian zone in the south of Burkina Faso and Mali that has an annual NPP of 800-900 g m^{-2} yr^{-1} (class 9). The NPP classes parallel latitude bands and are continuous across the landscape from East to West (Figure 1). The NPP data provided a classification of markets having similar agroecological potential. NDVI time series were used in the models instead of NPP because they provided the monthly time step that allowed relationships between the environmental characteristics and price to be derived.

3.0 Methodology

Previous work has shown that there was a negative linear relationship between vegetation productivity and millet prices in Mali, Burkina Faso and Niger during the 1980s and 1990s (Brown et al., 2006). Empirical Mode Decomposition was used here to isolate components with different cycles of fluctuations (seasonal, interannual, errors) in order to model the environmental effect on price from stochastic economic effects (Huang et al., 1998; Pinzon, 2002; Pinzon et al., 2005). By partitioning the data into components that had variations at the same timescale as the growing season, the seasonal component that is most related to crop production could be isolated. By using satellite-derived vegetation data to account for these seasonal variations instead of a dummy variable, the estimate of the modeled price was improved (Deaton and Laroque, 1992; Brown et al., 2006). The model uses Markov theory to describe the trend, since this is the component of price that is most clearly driven by economic forces. The high-frequency component, which we assume to be noise for the purposes of this analysis, was not modeled.

The Markov property can be stated as follows: the future evolution of the system depends only on its current state and it is independent of its history. This means that to predict next month's prices only the current month's prices are needed. Although the Markov property is usually expressed using probabilities, Equation 1 shows the relationship as a deterministic linear regression.

$$price_t = \alpha + \beta(price_{t-1}) + error \qquad \textbf{Equation 1}$$

A linear model was used instead of the probabilistic form of the Markov property to estimate more precisely the price dynamics. Although it is clear that the equation above will not take into account seasonal variations, this simplified equation should capture the majority of the price dynamics at one time period lag. An exploration of the use of probabilistic Markov theory for this application can be found in (Brown, 2006). The linear estimation is very similar to an autoregressive moving average model (ARMA), but the coefficients here are estimated for each market.

3.1 Isolating Components of Model Input

Huang et al (1998) introduced the Empirical Mode Decomposition (EMD) as an alternative to standard decomposition technique for representation of nonlinear and nonstationary data that show clear physical scales or frequency content. The Empirical Mode Decomposition technique is empirical, intuitive, direct, *a posteriori*, and adaptive, with the decomposition functions based on and derived from the data (Huang et al., 1998; Huang et al., 1999). Unlike Fourier decomposition (Wilks, 1995; Trefethen and Bau, 1997), the EMD takes the basis for the signal from the data themselves. The goal of the EMD is to decompose the signal into individual intrinsic modes of oscillation (Huang et al., 1998; Huang et al., 1999; Pinzon et al., 2001). At any given time, the data may be represented by many different, coexisting modes of oscillation, each one superimposed on the others.

The components were isolated using a sifting process repeated as many times as is required to reduce the extracted signal to an intrinsic mode function (Huang et al., 1998). The sifting allowed the expansion of the time series into modes that would reveal the principal frequencies or scales that dominate the signal. The components of an EMD are usually physically meaningful, since each mode is defined by the physical data themselves, and are additive, so summing all components recreates the original time series. The EMD technique was applied to both the NDVI and the price time series and three components were extracted from each: the trend, the seasonal component characterized by a 12-month period, and a component that consisted of high frequency oscillations with a nearly Gaussian distribution, treated here as error.

3.2 Description of the Model

The decomposition technique provided a way to isolate the portion of the price which is seasonal in nature, in that the data had a regular 12-month period. In the model, it was assumed that the seasonal price component isolated using EMD was most related to variations in the environment measured by the NDVI. Thus, the NDVI seasonal profile was used to model the price seasonal component using two linear regressions. The regressions relate the green-up of vegetation during the onset of the rainy season to the increase in prices leading to the harvest, and the senescence of vegetation to the decline in cereal prices during the harvest. This was done to associate the price with the NDVI in order to take advantage of the NDVI's spatially complete information about the variations in the environment. The coefficients from the regressions between the NDVI and price profiles were applied to the monthly time series of NDVI data to estimate the monthly price seasonal profile.

Using the EMD decomposition technique, the following procedure was used in order to model the prices (Figure 2).

1. Decomposition of both the mean NDVI of a 5x5 pixel box around each market and the accompanying millet price time series each into two components: a trend and a seasonal component.
2. A mean seasonal profile was created for NDVI and price for centered on the location of each market by averaging all available months of data from all years for each market. Linear regression was performed from May to August and from August to December between the mean price seasonal profile and the mean NDVI seasonal profile. The coefficients from these regressions were then applied to the NDVI data for all years to construct a continuous vegetation-based price seasonal time series from May to December for all years. The slope of the mean price profile from January to May was used to inform the period when the NDVI has little information due to the onset of the dry season, and the price is increasing as supply in the markets diminish.

3. The reconstructed seasonal price component was subtracted from original price data and the EMD decomposition re-run with the new price dataset, providing a new trend component and enabling the identification and removal of the noise component.
4. The trend component from step 3 represented the economic portion of the price that could not be explained by NDVI changes. The trend was predicted using the relationship between the current and next month price based on a strong Markov relationship (Equation 1).

The trend and seasonal components were then summed to reconstruct the historical price time series. By basing the portion of the price that has seasonal characteristics on the NDVI, the price reconstruction was improved over traditional economic models that either remove this portion or use an invariant climatology (see (Deaton and Laroque, 1992)). In addition, the model provided a spatially continuous map of prices derived from the satellite remote sensing data.

The model described above assumes that the local vegetation conditions are more important than the conditions in the primary millet export zones (shown in Figure 3). To evaluate the relative importance of local conditions vs conditions in the export zones, the model error of predictions made using the vegetation from local market regions was compared to the identical model using the average vegetation signal in millet regions in West Africa. Because there is significant cross-border trade, the region from Senegal through to Chad was considered as one region and included in the mean.

An additional evaluation of the integration of the markets from before and after 1994 was made by comparing model effectiveness during these two time periods. The number of observations was comparable for these two time periods, with 12,190 observations before 1994 and 13,730 after. 1994 is an important date in the region because it was the year in which all three countries devalued their currency and began market liberalization policies, which led eventually to increased market integration.

3.2 Evaluation of the Price Model

The markets were divided into training and validation sets with just over 50% of the data in the training set and the remainder in the test set. The coefficients were developed from the training set and then applied to all markets. The markets in the validation set were used to estimate the goodness of fit of the model through a comparison of the model output and the prices in the validation markets. Standard evaluation techniques such as the R-squared, F probabilities and stability of the coefficients were examined. The root mean square error (RMSE) (D'Agostino, 1986) was calculated for each market price time series and the extracted mapped price, and the normal probability plot and histogram plots by month and year were used to estimate the goodness of fit of the model. To determine if the model had a positive or negative bias, as required to use the model for applications, normal plots were summarized with the Rp statistic, a version of the Shapiro-Wilk test (D'Agostino, 1986). The Rp is a measure of the normality of the residuals, since it correlates the ordered residuals with the standard normal distribution. To determine the goodness-of-fit of the model, the RMSE and Rp were calculated for the test markets once the model was applied to the whole dataset. To compare the model's ability to predict the actual price, the actual and the predicted price for all time periods and all markets were regressed against each other and the coefficient of determination was reported. In order to save space only the RMSE is reported in this paper, but all other analyses are available upon request.

4.0 Results

The EMD decomposition of the price data allowed the separation of the overall trend from the yearly seasonal increases in price. The trend component was able to isolate non-environmentally related movements in price very effectively, reducing the errors of the linear model of price. Figure 4a shows the original price time series, the decomposed price (Figure 4b) and the actual compared with the predicted price (Figure 4c) from the market in Macina, Mali. Notice the low millet prices in 1993 and 1994, influenced by a 50% devaluation of the currency and resulting high inflation rate for the next few years in all three countries (Kelly et al., 1995; Coulibaly et al., 1998; Yade et al., 1999), and a very large millet crop as a result of one unusually wet year (Tucker and Nicholson, 1999; Nicholson, 2000).

4.1 Model Accuracy

The results of the EMD model are summarized in Table 2 using RMSE. The EMD model is compared to results using price only on raw data, as presented in the methodology, where the current month's price was used to predict the next month's price with the raw data. Note the errors for the simple, price-only model were seasonal, increasing during the harvest and post-harvest months of September – December, and were larger in the Sahel and smaller in the more humid zones. In addition to the linear model, the standard deviation of the noise component is presented, since the errors in the model should be less than the noise level present in the data (Table 2).

By modeling the seasonal cycle of prices using the seasonal information from remotely sensed vegetation data, it was possible to explain more fully the impact of differences in the environmental conditions on millet prices. When the local growing season was poor, lower millet production resulted in less price seasonality. The prices after harvest did not fall as much as normal, but instead continued to grow throughout the following year, depending on the extent of the shortfall. The EMD decomposition allocated this overall price increase to the trend portion of the price instead of in the seasonal portion, thus the small seasonality during drought years in both the price and vegetation signal was appropriate. Table 2 shows the errors of the reconstructed time series by month and by region when the prices were used as point data, decomposed and reconstructed individually.

4.2 Price Maps

As outlined in the methodology, the seasonal NDVI component was used to estimate the seasonal price time series. Figure 5a shows the average seasonal profiles calculated from the extracted seasonal price component for the nine NPP classes with the predicted curves. The curves were fairly invariant from the north to the south of the region, unlike the vegetation (Figure 5b) where increasing seasonality occurred in the NDVI year profiles towards the north. Figure 6 shows the spatial distribution of the errors from the seasonal component by market from all years. The RMSE was calculated on the residual of the actual seasonal profile for each market for all years subtracted from the calculated seasonal profile from NDVI for each year. The changing seasonality seen in Figure 5b caused larger errors in the North. Due to aridity, the NDVI does not have a clear seasonality in the northern part of the Sahel with which to model the price resulting in errors in the calculated price time series when compared to the seasonal profile calculated from the original price data.

To produce spatially varying maps of millet price, seasonal price estimates based on the by-pixel transformation of NDVI were scaled with the averaged price trends from each NPP class. Figure 7 shows the model output for the August price for 1989 through to 1999, and because the map was created using data that was corrected for inflation, it shows real prices. Large swings in food prices in the region are evident from the large variation among the years due to the averaged price trends. The variation within the year was much smaller, although the price in December was nearly always below 90 CFA/kg and the price in August was frequently above 90. For wage laborers, landless and urban dwellers, who are dependent on the market to obtain food, these large seasonal and interannual price changes significantly reduce their access to food.

4.3 Comparing Local Conditions to Millet Export Regions

The model was based on the premise that local conditions are strong determinants of local market prices. If markets are integrated, however, then prices in one market are less a function of local conditions than overall conditions in the region from which surplus, which makes it to the market, originates. Figure 8 compares the RMSE from the price only model, the EMD model using local NDVI values and millet region values, and the price derived from the maps shown in Figure 7. The raw price data were used for comparison, without removing the high frequency noise as was done for the RMSE in Table 2. The model using the NDVI from the millet production regions was slightly lower than that from the local NDVI. The errors of both models were generally below that of the price-only model. The errors derived from the price image were generally higher, but were still reasonable, and in some periods and regions approached that of the model with more precise input. Using the millet area NDVI observations reduced the errors of the model slightly indicating that the markets were integrated, but the local NDVI was still quite significant.

Whether local or regional conditions were more important depended on whether market integration increased during the period of record. To investigate this question, the RMSE for the period from before 1994 was and compared with that after 1994 for three cases: model with the local NDVI, with the regional NDVI, and the price-only model. The price-only model showed significantly larger errors in regions with low NPP during the pre-1994 period, indicating that the markets were significantly more integrated in the post 1994 period. This agreed with several report that millet markets in this region have become increasingly well integrated (Vitale and Bessler, 2006). The driest region, NPP zone 1 (0-100 $g/m^2/yr$), which even in good years was unable to produce enough millet for its populations and to fill its markets, had higher errors in both NDVI models than price alone. This was to be expected since these markets are more likely to be integrated with those that are more self-sufficient, because most of the grain in the market comes from elsewhere. NPP zones 2, 3 and 8 had the highest errors in the markets with price alone, but these were ameliorated by including NDVI in the model.

5.0 Discussion and Conclusions

Famine early warning, represented by FEWS NET, now integrates assessments of household vulnerability to shocks (Boudreau, 1998), indicators of the economic and political situation, and measures of unfavorable meteorological conditions (Verdin et al., 2005). This study shows that, by linking food prices and remotely sensed vegetation index data in quantitative relationships, the importance of rainfall-driven variations on the evolution of prices can be assessed. This relationship can be applied by providing an improved price model for areas of rainfed agriculture, which is likely to be valuable for planning purposes. Because the results of the model show that rainfall dynamics, as captured by vegetation index data, can improve the price model in some regions, the model should improve the interpretation of the input variables taken individually and provide an improved leading indicator of changes in food prices. Maps of food prices can be integrated with other data to create an enhanced leading indicator of changes to food prices for planning purposes.

Food price variations are critical to food security, both directly and as an indicator of current trends. The dynamic relationship between supply, which depends in part on rainfall, and prices observed in specific markets allows the calculation of spatially continuous maps of prices. By coupling two indicators into one map, the intensity and extent of price-induced vulnerability can be identified. This extrapolation of prices in a few markets to the entire region using satellite data could be exploited by food security organizations to enable the need for humanitarian assistance and its magnitude to be estimated for the immediate future.

The price models that use real-time vegetation observations provide information with only moderate accuracy, but adequate to be incorporated into planning responses that benefit from anticipation of need. In fact the reduction in skill by generalizing across productivity zones was found to be only moderate, but the gain in knowledge of the spatial extent of anomalous prices exchange provided by the model made the sacrifice of accuracy more than justified. Many vulnerable communities are isolated geographically and so the extension of price data from sentinel markets to provide estimates of future prices in areas that have no markets is likely to be particularly useful.

Price maps produced from this model, however, are only effective in regions that have closely coupled production and marketing systems. Regions where most of the food is imported, or in countries or times when food prices are controlled by outside events (by centrally fixing prices or during political or economic crises, for example), the model will capture less of the changes in food prices. Thus modeled millet prices are of limited accuracy in urban areas and in areas with significant trade in commodities into and out of the region.

The results of this study show that the quality of the growing season affects the price of millet at the annual and the seasonal time scales. If the growing season is characterized by erratic, sparse rainfall, higher cereal prices are the result, but with well-distributed, abundant rainfall the region experienced lower prices. The use of one time series of vegetation data from the millet export zone reduced model errors over using the local NDVI time series for the zone of shortage. The dryer the area, the greater the skill of the model runs using a unified vegetation time series from the millet export zone over local vegetation data. Coupled with an analysis of the model performance from before and after 1994, the time when market liberalization policies began in earnest, these results show that the markets have become better integrated through time. The errors were very similar between the local and millet zones vegetation signal and, although errors from price time series derived from mapped prices were generally higher, they were still sufficiently small for the estimates to be useful. Thus although vegetation information from surplus-producing zones improves the price model, using the local information to create relationships which enable these maps is reasonable.

The required accuracy of these anticipated prices is far lower than for food aid. Price projections need only give planners a general idea of which direction food prices are likely to move. This information can be used to direct the on-the-ground assessments needed to respond in an accurate and timely manner and can help food program organizations begin the large task of building up grain reserves in the most threatened areas.

Although issues of supply and demand are primary in controlling prices, improvement in estimation of prices using environmental factors can make important contributions to food security monitoring (Brown et al., 2006).

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Figure and Table Captions

Table 1. Summary of millet price data for Mali, Niger and Burkina Faso.

Table 2. Root mean square errors (RMSE) of the point model vs the actual price of millet at all markets by NPP class and month. RMSE is given in CFA/Kilogram.

Figure 1. Map of the locations of the 445 markets with millet prices in Mali, Burkina Faso and Niger, overlaid on image of NPP classes of 100 gC m^{-2} yr^{-1}. Squares show locations of prices time series collected by USAID's Famine Early Warning System, www.fews.net, during the 1980s and 1990s.

Figure 2. Flow chart of price model methodology using Empirical Mode Decomposition (EMD) technique.

Figure 3. Shows the millet export regions in West Africa, according to the US Foreign Agricultural Survice.

Figure 4. Price time series example from Macina, Mali. Panel A shows original price, B shows decomposed price, and C the reconstructed price with original.

Figure 5. Averaged seasonal components from prices (A) and from NDVI (B).

Figure 6. By-market root mean square errors for price maps. RMSE given in CFA/kilogram of millet.

Figure 7. Maps of millet prices, in CFA/kilogram, for August from 1988 to 1999, the period with the most robust and complete price time series data.

Figure 8. The proportion of food sources from seven livelihood zones in Niger from purchase in the market and from the cropping activities for three income groups.

Figure 9. The proportion of food access to that of a normal year due to variations in millet prices and millet production for three income groups.

Table 1.

Country	**Burkina Faso**	**Mali**	**Niger**
Time period	1989-1999	1987-1999	1982-1999
Number of Markets	84	244	117
Number of City Markets	65	56	88
Number of Markets with more than 50 Months of data	35 (12% of total)	197 (67% of total)	63 (21% of total)
Mean (CFA/kg)	78.4	81.5	77.3
Standard deviation (CFA/kg)	26.2	33.7	31.7
Min (CFA/Kg)	3.7	15.3	22.7
Max (CFA/Kg)	185.2	300	225.6

Table 2.

NPP class $gm^{-2}yr^{-1}$	EMD model	Linear model
0-100	9.0414	15.0431
101-200	8.7617	17.3906
201-300	7.8712	13.9025
301-400	8.2227	14.0754
401-500	9.1502	13.6635
501-600	8.494	11.2062
601-700	8.7809	9.9719
701-800	9.8487	10.4214
801-900	7.0015	10.2596
Month	**EMD Model**	**Linear Model**
Jan	5.0684	9.8988
Feb	4.7132	14.9558
Mar	4.3145	10.3543
Apr	4.3715	8.6072
May	4.6919	10.114
Jun	7.442	10.383
Jul	7.8496	11.4727
Aug	10.8616	11.691
Sep	11.2781	14.3812
Oct	12.3036	18.093
Nov	11.9864	19.1073
Dec	10.3871	19.2006

Figure 1.

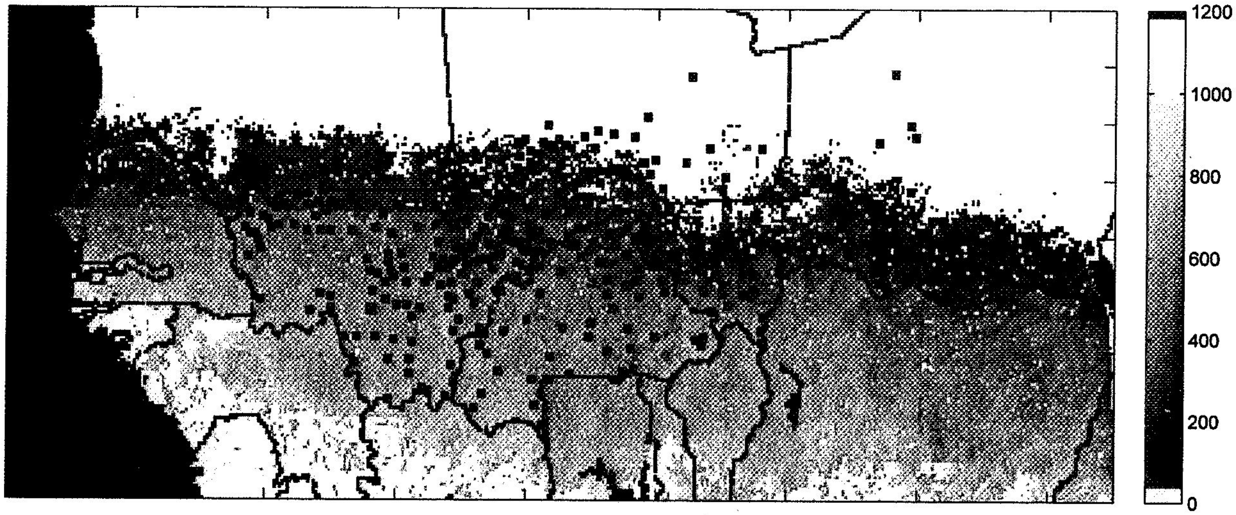
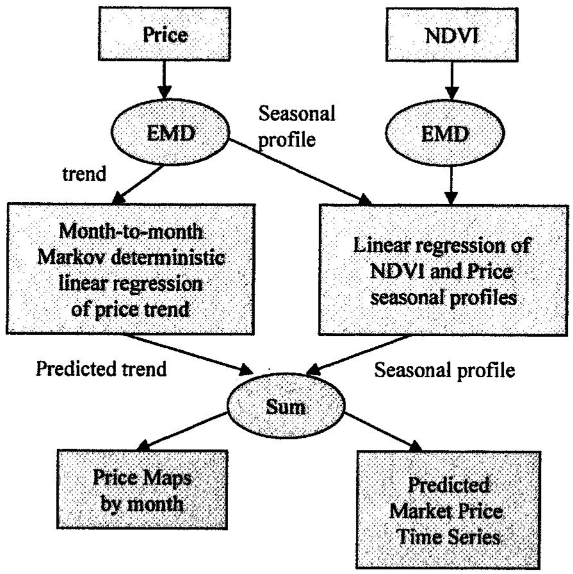


Figure 2.



Price
NDVI
EMD
Seasonal profile
EMD
trend
Month-to-month Markov deterministic linear regression of price trend
Linear regression of NDVI and Price seasonal profiles
Predicted trend
Seasonal profile
Sum
Price Maps by month
Predicted Market Price Time Series

Figure 3.

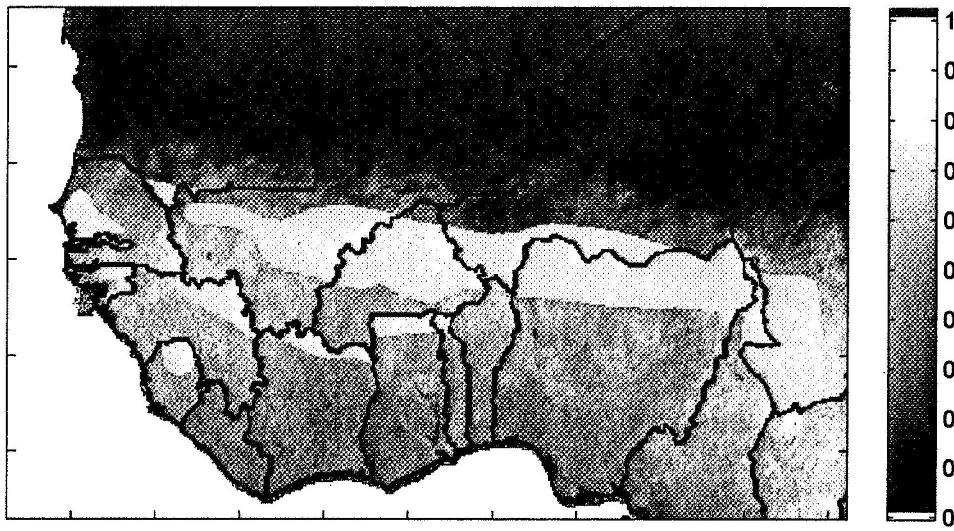


Figure 4a.

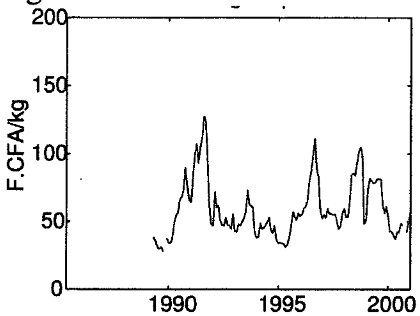


Figure 4b.

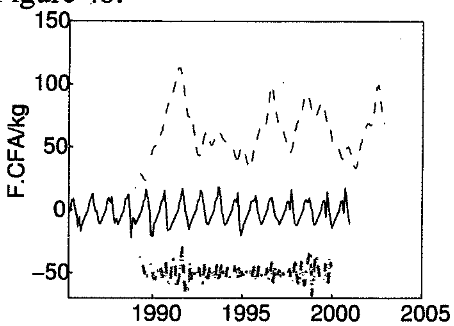


Figure 4c.

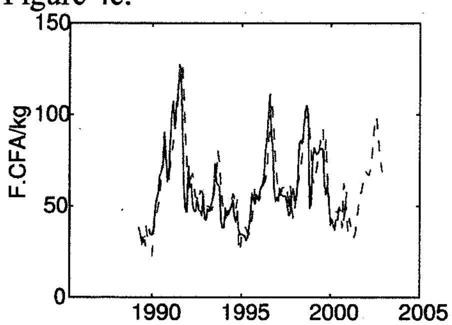


Figure 5a.

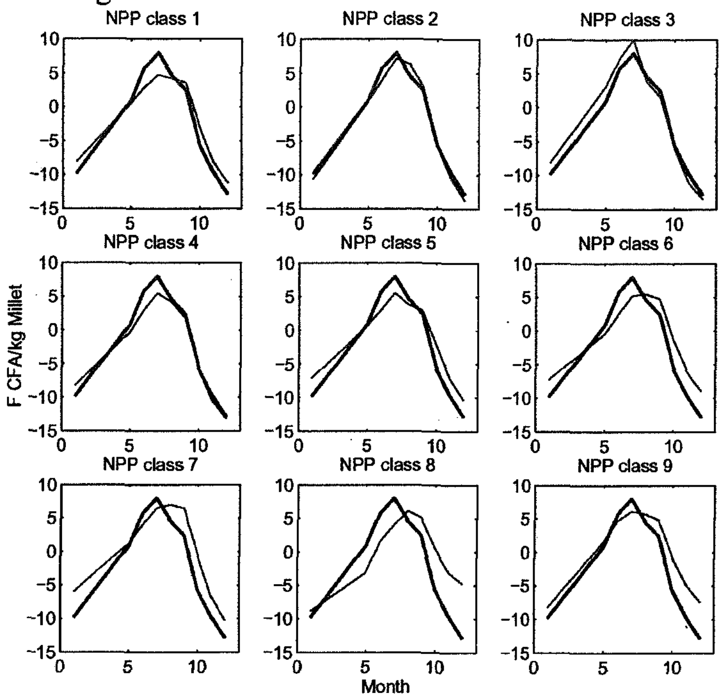


Figure 5b.

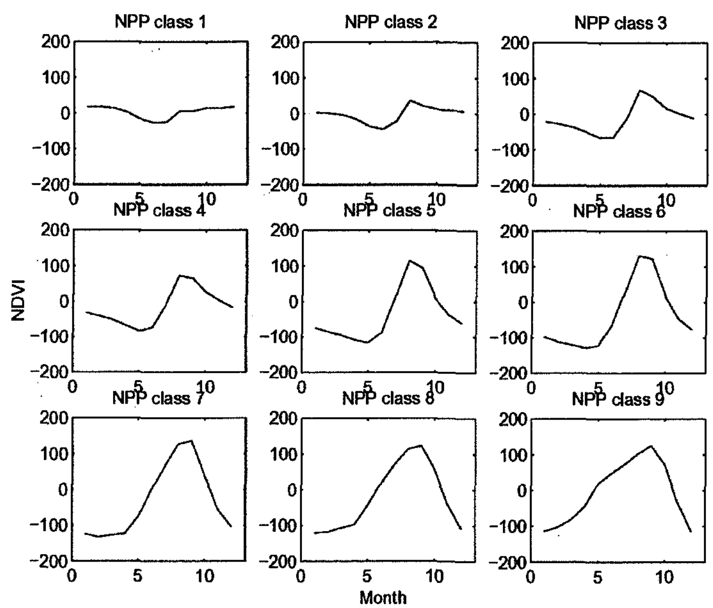
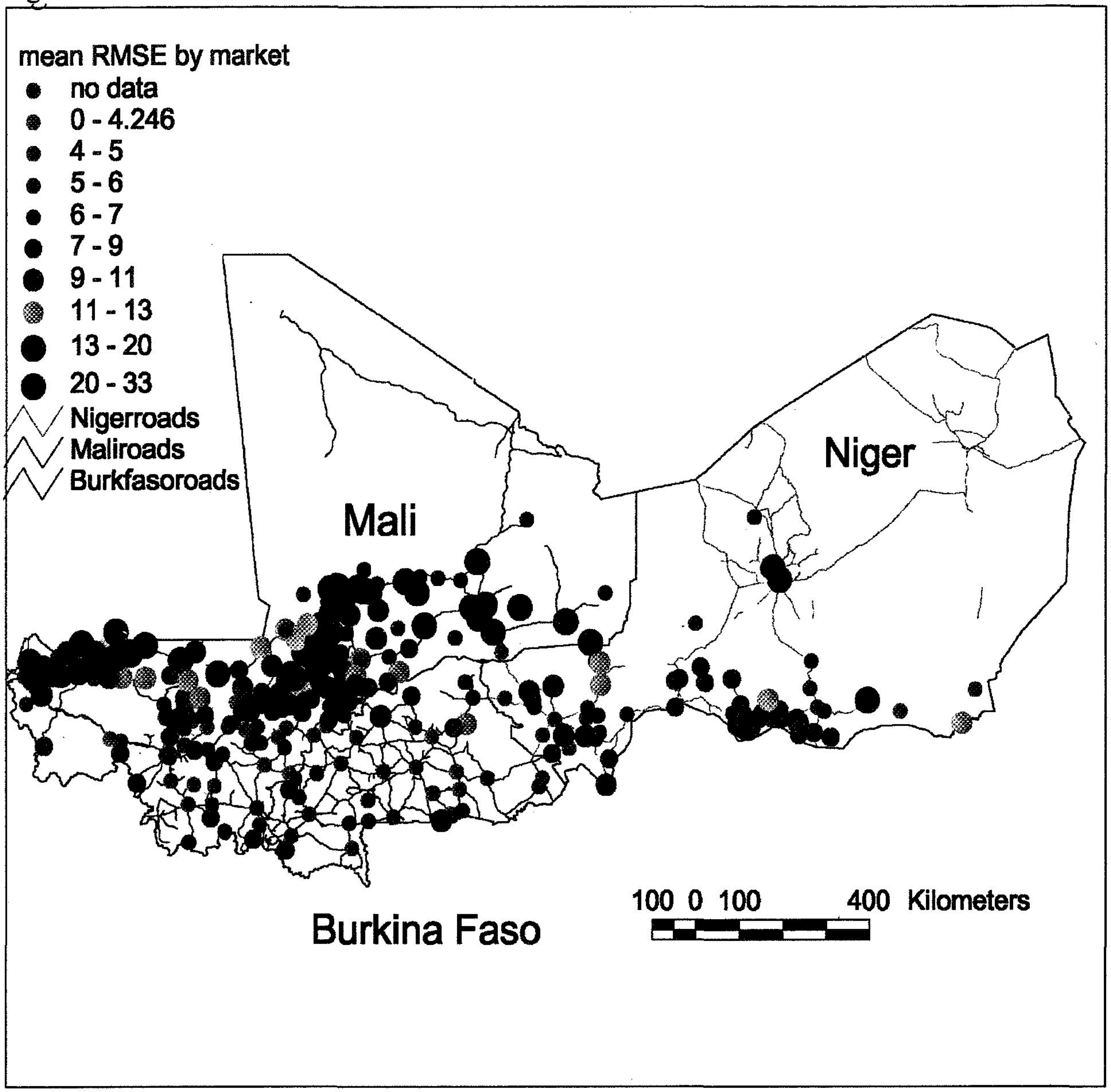


Figure 6.



mean RMSE by market
no data
0 - 4.246
4 - 5
5 - 6
6 - 7
7 - 9
9 - 11
11 - 13
13 - 20
20 - 33
Nigerroads
Maliroads
Burkfasoroads
Mali
Niger
Burkina Faso
100 0 100 400 Kilometers

Figure 7.

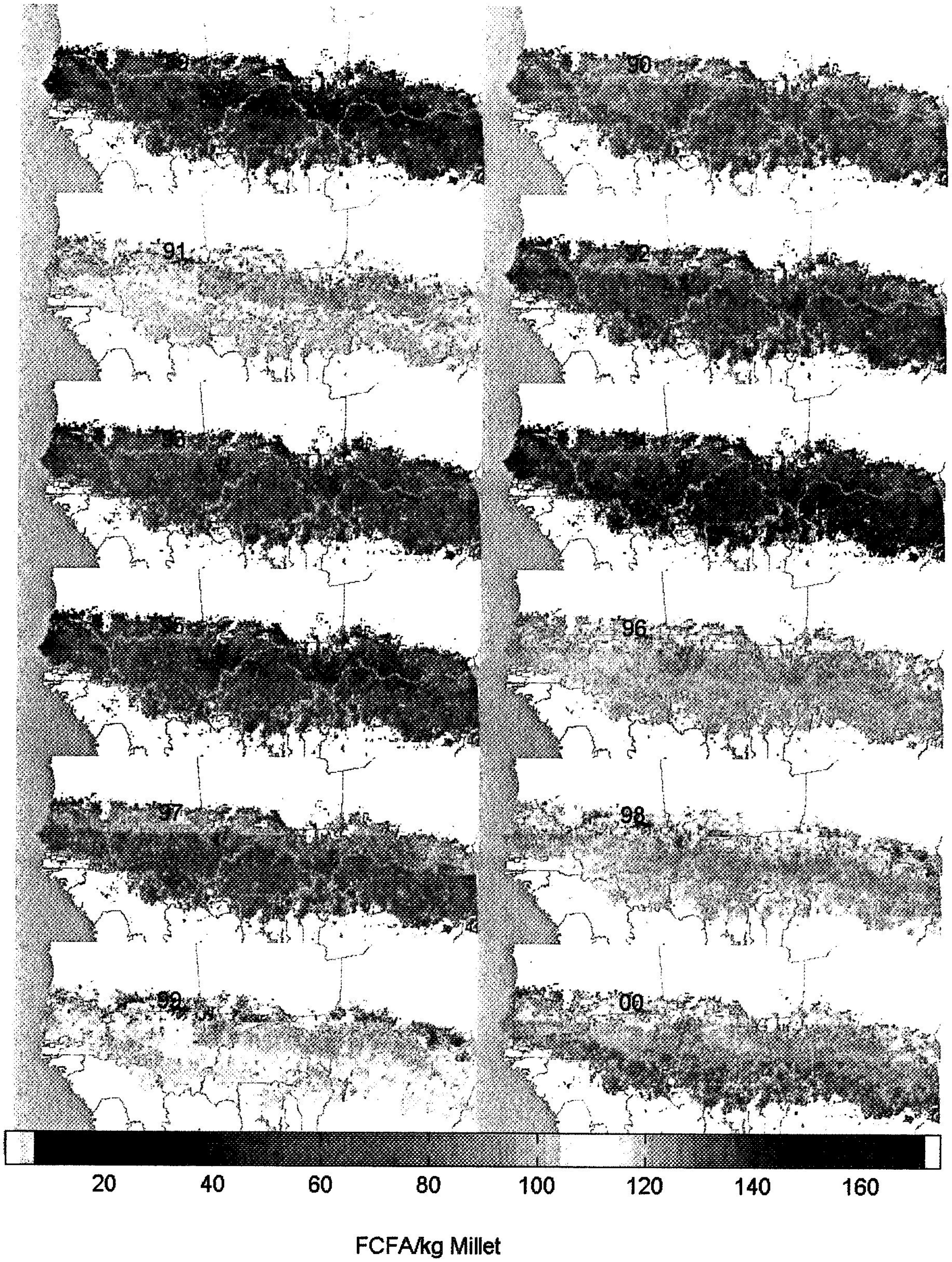


Figure 8.

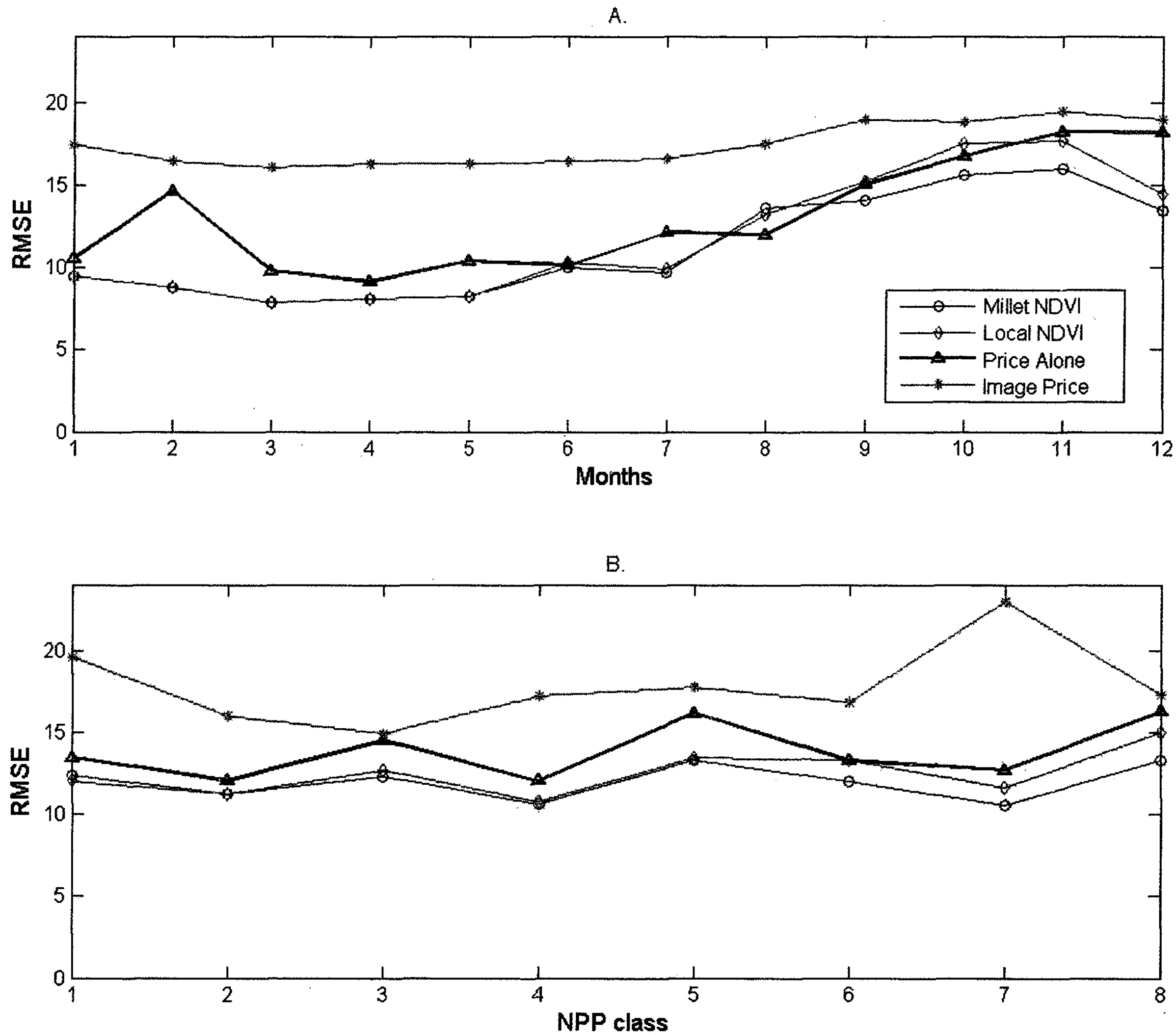
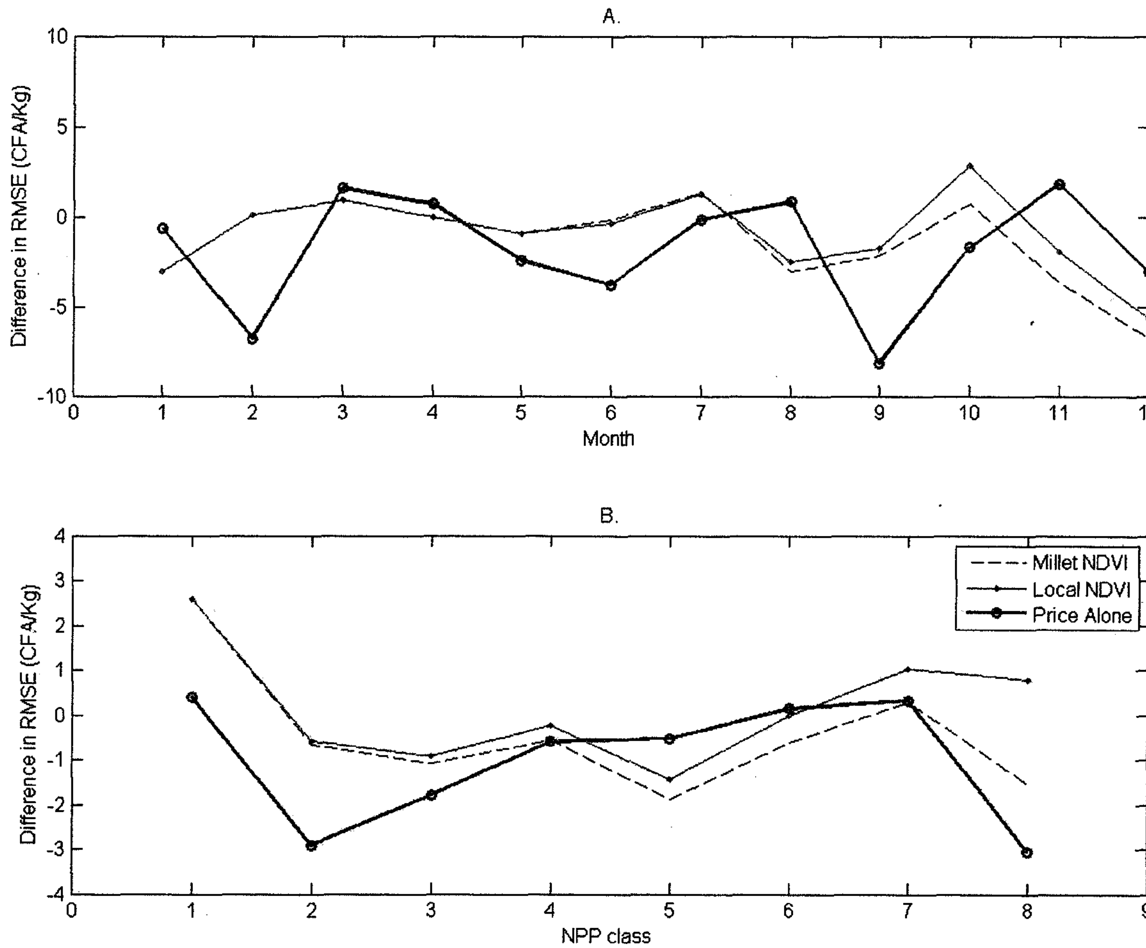

A.
RMSE
Months
Millet NDVI
Local NDVI
Price Alone
Image Price
B.
RMSE
NPP class

Figure 9.


A.
10
5
0
-5
-10
Difference in RMSE (CFA/Kg)
0
1
2
3
4
5
6
7
8
9
10
11
12
Month
B.
4
3
2
1
0
-1
-2
-3
-4
Difference in RMSE (CFA/Kg)
0
1
2
3
4
5
6
7
8
9
NPP class
Millet NDVI
Local NDVI
Price Alone