Using Satellite-Based Remote Sensing Data to Assess Millet Price Regimes and Market Performance in Niger (DRAFT)

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1. Early Warning Systems and Food Security Monitoring

As a result of the horrific famines of the 1970s and 1980s, the international development community has increasingly turned to early warning systems (EWS) for monitoring food security situations around the world. Emphasis has been placed on monitoring food production systems and markets in Sub-Saharan Africa and the horn of Africa, which historically have faced some of the worst food shortages. Typically, an EWS is composed of three to five monitoring pillars: i) agricultural production monitoring (agro-climatic) and harvest forecasts; ii) market information monitoring (prices, storage, transportation costs, etc..); iii) livelihoods assessments or vulnerability profiles; iv) food and nutrition surveillance; and v) direct food aid monitoring (FAO, 2000).

In practice, many of the pillars are difficult to operationalize due to local and international infrastructural, institutional and capacity constraints. For example, detailed market information such as transaction costs are difficult to track, even in the most developed markets. Moreover, because most production systems monitored are highly dependent on local weather and environmental conditions and scant data are available on area planted or yields, many EWS rely heavily on remotely-sensed data, such as NDVI (see Hutchinson, 1991), to make timely harvest forecasts. These projections are analyzed through vulnerability profiles to make food security assessments and predictions.

Much less emphasis has been placed on analyzing and understanding market performance and exceptional price movements, which is somewhat surprising as prices alone may be one of the best indicators of famine-like conditions. This trend appears to be changing as USAID's Famine Early Warning System Network (FEWS NET) Markets and Trade Strategy for 2005-2010 explicitly calls for methods and models analyzing the behavior of market system (FEWS NET 2008). While this change is much welcomed, the process faces considerable challenges as economic models available to study and diagnose market behavior may be greatly limited by the availability of data. Moreover, traditional spatial price analysis itself may only provide confirmation or rejection of hypotheses (see Barrett, 1996; McNew and Fackler, 1997; Fackler and Goodwin, 2000; Rashid and Minot 2010). In Niger, for example, millet prices exhibit tremendous inter and intra annual variation, which may well be an indicator of poorly integrated markets. Spatial price analysis tools, such as correlation analysis, Granger-causality tests, and co-integration models, may help confirm or reject the presence of market integration. But test results alone may be of limited use to policy makers (Rashid and Minot, 2010). EWS workers are more interested in models that can link the observed biophysical state with economic outcomes, help forecast exceptional price movements, and explain how production shocks affect price dispersion.

This explicit link between the agro-climatic monitoring pillar and the market information systems pillar appears to be a vital missing link in the EWS toolkit. FAO (2000) notes this shortcoming attesting that one of the constraints of EWS is that data from different pillars are often monitored independently and not appropriately linked. Previous work has shown that Normalized Difference Vegetation Index (NDVI) data can be used to detect deviations in production conditions and is correlated with net primary production and crop yields (Tucker et al., 1981; Prince, 1991; Fuller, 1998). But there remains a gap in understanding how NDVI data co-moves with millet prices and if it can be used to generate reliable forecasts, particularly in isolated markets located in or near weather-driven production zones. Because prices are one of the best indicators of famine-like conditions, research is needed to understand this link and to create models that can ingest real-time data and accurately predict price movements based on established relationships among past NDVI anomalies and prices.

In this exploratory paper, we propose a novel method for bridging this gap by linking satellite-based agro-climatic data to millet price movements in Niger. By exploiting the link between weather-related production conditions, which serve as a proxy for millet yields, and variations in millet prices, we propose a simple probability model that provides forecasts on the direction of millet price changes for the most food insecure areas of Niger. This research is among the few studies that attempts to link explicitly remotely-sensed agricultural production monitoring indicators, using varying buffer sizes, with commodity prices at the market-level. The ability to predict accurately staple food price movements is crucial for combating food security and ensuring the timely delivery of food aid. In addition to the understanding the potential benefits of NDVI in a forecasting framework, we also seek to understand the limitations. This latter point may well be as important as modern food security analysts may be easily overwhelmed with data from each EWS monitoring pillar and thus rely on the use of few metrics. In fact, Brown and Brickley (2012) recently found that current FEWS NET analysts use rainfall data (84% of the time) much more frequently than remote sensing (28% of the time) data.

With these questions in mind we proceed as follows. The following section provides an overview of the potential benefits of NDVI in a food security context. The third and fourth sections briefly review the literature and summarize the existing hypotheses concerning NDVI and millet markets in Niger. The fifth section presents our preliminary empirical approach and the sixth section discusses various aspects of the data. Results are presented in section seventh and the final part concludes and discusses a roadmap for future research.

2. Limitations of Price Data and Benefits of NDVI in an Early Warning Context

In developing economies, Niger in particular, markets are often not well integrated (or efficient[1]) due to inadequate provision of public goods, such as infrastructure and telecommunication systems, inefficient flows of information, and missing institutions (Rashid and Minot, 2010). When these types of

[1] Market integration here is taken to be the integration the degree by which a shock in one market is transmitted to another market. Market efficiency refers the allocation of resources and welfare (see Fackler and Goodwin 2001). In a spatial sense, one can think of this as implying that no further arbitrage opportunities exist for spatial traders.

market failures are present the appropriate price signal may not be transmitted down the marketing chain (Baulch, 1997a). Storage information may be incomplete (or unavailable), and expectations about future price movements may be more dependent on rumors than on facts. Under these conditions, satellite-based remote-sensing data, which reflect actual production/environmental conditions on the ground and are not subject to the influence of rumors or political manipulation, can be a powerful tool for informing an analyst of the impending price movements, and even food aid starting or stopping points. This issue is particularly salient in Niger where millet prices exhibit extreme variation.

Figure 2, in the appendix, tracks the historic deviation (1993-2012) of average millet prices (in black) and the rolling twelve year, monthly deviation of NDVI measurements for the major millet production zones (in green and brown) in Niger. When millet prices are above the vertical axis at zero, this indicates that prices are abnormally high. On the other hand, NDVI values above the vertical axis at zero indicate an abnormally above average period of photosynthetic activity. Focusing on the fall of 2004, we see that millet price deviations, averaged across 29 markets, were steadily above their expected value. As prices continued to incorporate information throughout the fall and into the winter, we see the deviations climb in magnitude. In fact, by July 2005, prices were nearly 100 CFA (25 percent higher than their 10-year average) above their long-run, expected value. At this point in time, no purely price-driven econometric model could provide an adequate picture as to how prices would move in the future, given how far off the expected path prices already were. Moreover, from a food security standpoint, it would have been tremendously difficult to know whether more food aid was needed or not given the enormous price anomalies.

However, shifting focus to the green shaded figures, which represent positive NDVI anomalies, we can see two clear pictures emerge. First, the NDVI anomalies clearly show that from August of 2003 through May of 2005, Niger had experienced abnormally low levels of photosynthetic activity throughout the year, with a particularly poor growing season during May-October of 2004. Second, focusing on the 2005 growing seasons, particularly in July and August, vegetative vigor across all of Niger surged to levels far above the expected value. In fact, in terms of historical rankings, NDVI from July of 2005 was the second highest in the past 12 years for Niger. At the same time, in the Malian and Nigerian breadbaskets NDVI readings were at their highest levels in the past 12 years. These positive NDVI anomalies, which are a strong indicator of above average yield potential, occurred well before millet prices fell in the fall of 2005. Even with the advent of cell phones in Niger, no one trader could have known for this to be true across the whole market and region at that point in time. In this situation, incorporating NDVI into a forecasting framework could deliver benefits in two foreseeable ways.

First, in terms of millet price forecasting, NDVI could have informed analysts of the severity of environmental conditions prevailing during the steady climb of millet prices during 2004/05, and as important, it could have helped predict the precipitous decline in millet prices during the 2005 harvest. Unlike monthly millet prices, NDVI data can be processed in near real-time and on an analysts workstation in a matter of hours or days. Millet price data typically take weeks to collect and process, and are often only available on government websites with a considerable lag. Second, in terms of food aid logistics, knowing that overall environmental had been abnormal for quite some time throughout 2004 and into 2005 may have provided better insight into the urgency for food aid needed during the early part of 2005. Moreover, knowing farmers across the Sahel were having a good year in July and August would have been tremendously useful in informing donor agencies of the need for additional food aid shipments to the region. If a subsistence farmer were to experience a bumper harvest at the same time that international food aid saturated a local market, then that farmer may be even worse off depending on the magnitude of the endowment income effect.[2] Instead of being rewarded for a bumper crop, a farmer may face drastically lower than millet prices because of the oversupply in local grains caused by the untimely delivery of food aid. Thus, NDVI may not only useful in predicting impending prices movements and when to start food aid deliveries, but it can also be valuable in determining when and where to stop planned food aid deliveries to preserve the livelihoods of farmers.

From a data perspective, using NDVI alongside prices delivers other benefits. Price data alone are often fraught with missing observations and measurement error, and are often confined to a geographic region, all features which can limit the conclusions drawn from price analysis. For example, price data from two markets that are separated by geographical features (mountains or a lake) and have no trade history may appear to co-move because of similar weather (drought). In reality, the markets may not be at all integrated, but because this is not reflected in the price data, we may draw incorrect conclusions by looking only at price movements. NDVI, on the other hand, can allow us to control for the environmental conditions surrounding markets and can help in detecting the influence of varying environmental conditions on price movements. Moreover, NDVI has been measured using satellites and processed in a consistent methodology, thus the data should contain much less measurement error. NDVI is available at all points in time, is not influenced by the presence of geo-political borders, and cannot be manipulated by political figures or appointees to establish a desired trend or mask bad news. The middle point means that the analyst can peer into other breadbaskets of the Sahel and develop a sense of the vegetative vigor. This is particularly important given that, during 2000-2004, 75-85 percent of millet and sorghum imports into Niger originated from northern Nigeria (Cornea & Deotti, 2008). We now turn our attention toward a review of the literature the existing hypotheses concerning NDVI and millet markets in Niger.

[2] Recall from the Slutsky equation that a price shock to a seller will have three effects, the substitution effect, the ordinary income effect, and the income endowment effect. Depending on the magnitude of the endowment income effect, farmers may be worse or better off after a price shock.

3. A Review of NDVI Data, Market Performance, and Millet Price Forecasting Models

The use of satellite data to monitor vegetative cover dates back to the work of Tucker (1979) who formally demonstrated that combinations of red and photographic infrared radiances could be employed to monitor photosynthetically active biomass. Soon after this, Tucker et al. (1981) demonstrated that NDVI was directly related to wheat yields. Many studies, focusing on the remote sensing of biomass production in the Sahel, quickly followed (Tucker et al., 1983; Tucker et al., 1985). Prince (1991), focusing on three Sahelian countries, concludes that satellite observations of vegetative indices and seasonal primary production are strongly linked. Using a longer time series of NDVI and rangeland and agricultural data, Fuller (1998) asserts correlations between trends in maximum NDVI and field measures of rangeland and crop production are positive and statistically significant. Others (Nicholson, 1994; Tucker and Nicholson, 1999) suggest that NDVI may also be used as an indicator of precipitation.

Within the food security community, NDVI has long been part of monitoring programs (see Hutchinson, 1991). In particular, when FEWS NET was launched in 1985 it included USGS and NASA as implementing partners due to the importance of remote sensing to the monitoring task in Sub-Sahara Africa (USGS, 2010). Despite the popularity of NDVI in the EWS community, few attempts have been made to link explicitly NDVI anomalies to commodity price movements. Brown, Pinzon and Prince (2006) appear to be the first to detect a negative linear relationship between NDVI anomalies and millet prices in Burkina Faso, Mali and Niger in the 1980s and 1990s. Later work (Brown, Pinzon and Prince, 2008) highlights the importance of rainfall variations, as captured by NDVI, on the evolution of millet prices. However, the study stops short of providing an econometric-based forecasting model and does consider any spatial price analysis

Most recently, Aker (2010a) considered the impact of mobile phones on millet price dispersion in Niger. She finds that the introduction of mobile phone services reduces millet price dispersion across markets by 10 percent. In a related paper, Aker (2010b), she considers how extreme rainfall affects grain markets during 1996-2006. The study finds that drought reduces grain price dispersion. However, the study stops short of considering the converse (what is the effect of abundant rainfall on price dispersion), and the construction of the rainfall variable only incorporates rainfall data from July through September which may misrepresent the rainy season (particularly if it starts much earlier or later than expected) and instead capture the fact that during droughts unobserved transportation costs are likely much lower as normally impassable roads can be easily travelled. Additionally, Araujo, Bonjean, and Brunelin (2010), reach an opposing conclusion, using a KPSS unit root test, regarding the time series properties of select Nigerien millet price data. They find that the data are integrated of order 0 I(0), or do not contain a unit root.

Finally, regarding NDVI and forecasting models, Brown, Hintermann and Higgins (2009) developed an autoregressive millet price forecasting model that incorporates NDVI to control for local production conditions across Burkina Faso, Mali and Niger. The authors allow for market dynamics by including lagged prices and for market interaction by using lagged prices from surrounding markets. Millet prices are estimated using a fixed-effects panel model which allows them to make predictions at the market-level after controlling for unobserved time-invariant heterogeneity. While the model's overall fit is impressive, it is highly driven by lagged prices, the impact of NDVI is rather small, and the model does a poor job of forecasting peaks and valleys. Furthermore, the NDVI anomaly constructed for the study is based on a long-term anomaly rather than a rolling-anomaly. This essentially allows the model to "cheat" by incorporating information from the future.[3]

Based on the assessment of the literature, we envision our research contributing to the literature linking NDVI anomalies to commodity price movements in three of ways. First, our research will refine the approach for integrating NDVI data into a forecasting model by analyzing the effect of buffer size on forecasting model performance and by filtering NDVI data using spatial production maps. Previous research (Brown, Hintermann and Higgins, 2009) relies on a single buffer size and makes no attempt to filter NDVI data, which may introduce additional noise into the metric. Second, we construct both rolling NDVI and price anomalies so that our forecasting model only incorporates as much information as is available to an analyst at a given point in time. Third, regarding the price data, we rely on a much longer time series (1993-2012) of millet prices than has previously been used. This will allow us to capture the changing nature of millet markets across Niger. Finally, the research is expected to produce different types of fully operational forecasting models that can ingest real-time data to make projections on future price movements for early warning systems. We now turn to a review of millet production and market dynamics in Niger.

4. A Review of Millet Production and Market Dynamics in Niger

Millet production

Given its ability to thrive in the harsh climatic conditions and sandy soil of sub-Saharan Africa, millet is widely grown by households throughout Niger and is particularly important in rural areas. Under ideal conditions, millet planting should occur after the first major rain, which flushes the topsoil and activates the organic matter near the surface. Across much of Niger the best conditions for planting millet occur in May when the days are long, the sun is intense, and the heat is adequate. If a farmer can plant in

[3] For example, if the model were to generate a prediction for 2005 prices the NDVI deviation used in the predictions is constructed based on information from future NDVI readings. A more appropriate method is to construct a rolling NDVI anomaly that only incorporates information up to a given point in time.

May they can expect two things. First, early planting makes millet less susceptible to harmful weeds (striga) and molds that commonly affect millet crops planted later in the growing season. Secondly, early planting means a farmer may also harvest his/her crop earlier in the year and thus be able to deliver it to markets ahead of the normal harvest cycle, which commonly occurs in September and October, thus earning a higher price. Early planting is not without risk. If a farmer does choose to plant early and the crop does not withstand the dry spells of May and June (false rainy starts), they may be forced to replant in July should they have adequate resources. Because millet can reach full height in 60 days, one could technically plant as late as August and still have an October harvest.[4]

In reality, most rural Nigerien households do not have access to high quality millet seeds, many of them face credit considerable credit constraints, and the majority of households rely on rudimentary agricultural inputs. Even under some of the best conditions, many households must rely on loans to purchase agricultural inputs (seeds) at the beginning of the growing season. The consequences of this action are pernicious over time as households who borrow at the start of the season are often forced to repay loans at the end of the season when millet prices are remarkably low. Further compounding the problem is the fact that most rural areas lack proper storage facilities and have less than ideal infrastructure by which markets are connected. Collectively, these issues force households to purchase millet later in the year when prices are much higher. Unfortunately, millet is the most frequently purchased grain when a household's own stocks are depleted (Brown, 2008).

Millet constitutes nearly 80 percent of all cereal output in Niger (Cornea and Deotti, 2008). Despite the historical growth in millet production (Figure 2 in the appendix), yields have remained flat and far below that of neighboring countries. Part of this can be attributed to the fact that input use is extremely limited and thus, in much of the country, millet yields are largely dependent on the prevailing weather conditions. Because of the uncertainty of crop production, many households supplement their income with livestock production, seasonal migration and low paying, off-farm activities. Millet consumption on a per capita basis is the highest in the world. Because millet is more nutritious than rice or wheat and can sustain hard physical labor longer, it is not surprising that over 75 percent of a Nigeriens daily calories are derived from millet consumption. Due to the steady demand and limited production capacity, Niger imports large volumes of millet from neighboring countries.

Grain Market Dynamics [tbc prior to August Conference]

Analysis of the millet price data shows that markets exhibit substantial intra-annual and inter-annual variation in millet prices. Figure 3, in Appendix A, shows millet price deviations from their long-term average, by harvest year, for 2000 through 2010. How does this change over time? [TBC] Many

[4] However, the plant biomass is likely to be small and the harvest low.

factors contribute to the observed volatility. Production shocks, particularly those related to droughts and pest infestations, can greatly affect yields and thus millet supplied to the market. Storage facilities are rather underdeveloped in the region and even where they exist, storage only takes place for about 45 days during a normal year (Aker, 2007). In a normal year, domestic supplies of millet may last until January or February and then are slowly replaced by imports at the beginning of the year, often from Nigeria. Because consumer demand remains relatively unchanged throughout the year, and the supply of millet tends to fluctuate, there is a tendency for prices to rise rapidly during years with production shocks. From a modeling perspective this latter points suggests that a proper model should adequately capture production shocks instead of demand shocks.

5. Empirical Strategy

[*TBC with updated data prior to August 2012*]

Our initial empirical strategy is largely driven by the desire to build a simple operational forecasting model. At this point in time, we opt for simplicity over complexity to determine the basic context in which NDVI can be used to augment a price forecasting model. Building from Aker (2010b), we divide the price data, at the market-level, into different regimes based on the anomalies observed over the course of a growing year (defined as October-September). We consider both dichotomous and polychotomous regimes. We then use a general ordered logistic regression model to create a series of predictions of the type of regime that may emerge from previous price levels and observed photosynthetic activity. Our basic model may be written as (see Williams, 2006 for a full discussion),

$$P(Y_i > j) = g(X\beta) = \frac{e^{(a_j + X_i\beta_j)}}{1 + e^{(a_j + X_i\beta_j)}}, \qquad j = 1,2, \dots, M-1 \qquad (1)$$

where M is the number of categories of the ordinal dependent variable, price regimes here, X is a vector of exogenous covariates, and alpha is an intercept. From the model above, we can determine the probabilities associated with Y when M takes the value of:

$$P(Y_i = 1) = 1 - g(X_i\beta_1)$$

$$P(Y_i = j) = g(X_i\beta_{j-1}) - g(X_i\beta_j) \quad j = 2, \dots, M-1$$

$$P(Y_i = M) = 1 - g(X_i\beta_{m-1})$$

As the name implies, the generalized ordered logistic model includes specialized sub-cases when the number of regimes is two (M=2), the logistic regression, and the ordered logistic model when the betas estimated are the same for each category values and the estimated alphas then become the cut points. The latter model is also known as the parallel lines model, which requires that the estimated coefficients be the same across regimes. Using a Brant test (1990), we test the parallel lines assumption for model validity. We consider both the logistic and ordered logistic model to estimate price regimes.

6. NDVI and Millet Price Data

Description of the NDVI Database

The NDVI time series data used in the study are based on the maximum value compositing (MVC) technique (Holben, 1986.) The method minimizes differences in the spectral properties, radiometric resolution, residual atmosphere effects, and minimizes clouds. Temporal discrepancies in the time series are reduced through a process which selects the pixel with the maximum NDVI signal and minimum atmospheric effects, usually using the same day for each sensor reading. The Advanced Very High Resolution Radiometer (AVHRR) time series data are based on maximum-value AVHRR NDVI composites from the NASA Global Inventory Monitoring and Modeling Systems (GIMMS) group at the Goddard Space Flight Center from July 1981–December 2011 (Tucker et al., 2005). To remove artifacts due to orbital drift and changes in the sun-target-sensor geometry, a post-processing satellite drift correction is applied to the dataset (Pinzon, J., Brown, M.E., and Tucker, C.J. 2005). Due to AVHRR's wide spectral bands, the imager is sensitive to water vapor in the atmosphere. As a result of this, an increase in water vapor results in a lower NDVI signal, which can be interpreted as an actual change if no correction is applied (Pinheiro et al., 2004). To lessen these artifacts, the maximum value composite technique is applied. The AVHRR time series is available at 8.0 km resolution.

To construct the rolling NDVI anomaly used in the study we first pass the raw AVHRR data through Harvest Choice's Spatial Production Allocation Model (SPAM), which contains plausible estimates of crop distribution.[5] Specifically, we use the physical area planted variable to discern areas of production from non-production. This initial filtering reduces the number of NDVI pixels considerably. The effect of the filtering exercise should help reduce distortions introduced into the NDVI signal by non-productive areas.[6] Once filtered, we then create a series of buffers, in 10 kilometer increments, around each of the 29 markets in the study. This allows us to test the sensitivity of the buffer size on forecasting performance. The smallest buffer we consider is 20 kilometers and the largest is 100 kilometers.

With the filtered and buffered data we then construct rolling NDVI anomalies by taking the average value of all NDVI points within a given buffer and regress them on monthly dummy variables and time variables to remove monthly and temporal effects. The leftover information, the residual, reflects the deviation (anomaly) from average for each metric at each point in time. To ensure that we do not incorporate more information than is available at a given point in time (as would be the case if we were to use the entire time series to construct the anomalies), we use a rolling regression model which

[5] http://mapspam.info/

[6] Future research will explicitly compare the potential costs and benefits of filtering and weighting NDVI data.

incorporates monthly NDVI data from the previous 12 years. That is, the October 2004 NDVI anomaly is created from the monthly time series going back to October of 1993. This rolling window method allows us to account for changes in the climate and other long-term mean or variance shifts that may affect the NDVI variables. We also create a historical ranking of each monthly NDVI anomaly by comparing it to past values at a given point in time. For example, the May 2003 NDVI ranking is calculated by looking at all NDVI anomalies for May from 1992-2003.

Description of the Millet Price Database

All millet prices used in the analysis are from USAID's Famine Early Warning System Network (FEWSNET) and the Systéme d'Information sur les Marchés Agricoles Niger (SIMA-Niger). Prices were gathered from the two sources with the most recent update from the April 2012 (Bulletin mensuel cereals) bulletin.[7] To match the historic prices from FEWSNET with the current prices available from SIMA, each market name is assigned a unique identity. Prices are matched to markets across time using the market name, the unique identifier, and a time variable. After merging all price data together, an outlier check is performed on each market price series. Each market is also assigned a latitude and longitude point using Google Earth and past datasets from SIMA.[8]

All raw price data is recorded in nominal West African CFA franc. To adjust for the influence of inflation and other macro-level factors, a number of modifications are made. First, the consumer price index for Niger, available from the International Monetary Fund's International Financial Statistics database, is downloaded and converted into Stata format. Next, the study rescales the index to a base year of 2008. All price data are then converted to 2008 terms by dividing by the price index and multiplying by 100. Because of the irregularity of price data prior to 1993 and the liberalization of markets near that time, this study focuses on price data from 1993-2012.

In total, price data are available for 79 markets. However, at the market-level many of the price series are irregular, or even missing for multiple consecutive periods. A series of tasks are undertaken to find reasonable substitutes for the missing prices points. First, all price series are exported into MATLAB along with the corresponding market latitude and longitude. An algorithm then calculates the Euclidean distance between each market and stores the results in a matrix. Price bands are constructed at the market level, with a buffer size running from 10 to 100 kilometers. Each price band consists of the average of all price points falling within a buffer surrounding a market. Price buffers are created for each market, over all time periods. The resulting data are exported into Stata and matched to the corresponding market as a new variable. To fill missing price points in all 79 markets missing price points at the market-level are replaced with neighboring millet prices using a 10 kilometer price buffer. That is, period-by-period, the

[7] http://www.sima-niger.net/publications-mois.php
[8] Markets with irregular spellings and/or coordinates were verified using http://www.nationsonline.org/oneworld/map/google_map_niger.htm

average price of all markets within a 10 kilometer band of the market with missing prices is substituted for the missing price point. This modification affects about 1,200 prices points, or about 7 percent of the universe of price points. A final round of data modifications are made using two period lags and leads to smooth out missing periods across each market. After completing these steps the data are tabulated and sorted by the number of price points per market. All markets with more than 200 price points are reserved for analysis. All markets with fewer than 200 price points are excluded from the price analysis, but used in portions of the NDVI analysis.

One potential issue in using a subset of markets is that the subset may be biased toward a particular geographic region, agro-climatic zone, population or other feature. To investigate this problem, the sub-population of markets are organized across region, agro-climatic zone, and compared to the overall population.

Table 2, in the appendix, summarizes the number of markets in the original price database, as well as each regions share of the overall population of the country. As shown in Table 2, the population of Niger tends to be relatively well distributed among the regions, with the largest share falling in Maradi and the smallest in the rural regions of Agadez and Diffa. Table 3, in the appendix, summarizes similar information focusing only on the 29 markets that are part of the final price database. The table shows that the sub-set of markets are distributed in nearly the same manner as the larger, 79-market database. The Maradi region is somewhat underrepresented and the Tillabery region somewhat overrepresented in the smaller database, but the differences are not great. We now turn to the distribution of the 29 markets across the agro-ecological zones, and compare that to the 79-market database across the same zones. Table 4, in the appendix, summarizes the two datasets. Similar to the departmental-level analysis, the distribution of the analysis database at the agro-ecological level appears to closely mirror the original price database. We calculate rolling price anomalies using a method similar to the NDVI anomalies.

Failure to account for potential unit roots in time-series data can seriously distort statistical inference. To test for unit roots in each of the 29 markets selected for analysis we use a procedure outlined by Enders (1995), who suggests estimating the least restrictive model first (usually one with a trend and drift term) and then incrementally restricting the model if unit roots are detected. Enders reasoning is based on the fact that most unit root tests have low power to reject the null hypothesis, and thus if it is initially rejected, there is little reason to proceed. Formally, we use the augmented Dickey-Fuller (1979) (ADF) test to check for unit roots:

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \alpha_2 t + \sum \beta_i \Delta y_{t-i} + \varepsilon_t \qquad (2)$$

where the delta operator indicates a first-differencing of the data, i is the number of lags, and t represents a time trend. The above regression is implemented and we test the null hypothesis, that the data contain a unit root, by looking at whether or not $\gamma = 0$. The results of our ADF test, presented in Table 5 at the end of this chapter, suggest that the majority of markets in our database do not have unit roots.

Next, we consider the panel properties of our price data and test the null hypothesis that all panels contain a unit root using the Im-Pesaran-Shin (IPS) test (2003) and a Fisher-type test. These two tests are most appropriate given the unbalanced nature of the panel dataset. Both tests strongly reject the null hypothesis and lead us to conclude that the panel dataset does not have a unit root. Because the market-level and panel-level data sets appear to be integrated of order zero, I(0), we conduct all of our analysis using data in levels rather than differences.

5. Results

Place holder - TBC with updated data prior to August 2012

[*Is NDVI useful in forecasting price outcomes? How can NDVI be used to augment price forecasting models, particularly in rural areas where prices are not readily available in a timely manner. Can NDVI contribute to the discussion of millet price movement sin Niger? Can NDVI tell us anything about market performance before and after environmental production shocks? We do not have a structural model, nor do we have a specific theory we are testing with NDIV. Our goal is simply to analyze whether or not a reduced form probability model can produce reliable forecasts on the direction of price movements for the coming year*.]

7. Discussion

Place holder – TBC prior to August 2012

a. Conclusions

b. Scope conditions/external validity

c. Policy implications

8. Next steps/research plan

Should one use to use Post-harvest NDVI?

While NDVI can deliver a suite of benefits to the food security analyst, one should also be aware of its perceived limitations. Working with NDVI and prices is imperfect. NDVI can be used to capture the change in vegetative vigor occurring throughout the growing season, which serves as a proxy for yield quality. While this is useful from a food security standpoint during or at the completion of the growing season, it is not clear if NDVI should be leveraged as a tool for producing monthly price forecasts throughout the year. Month-to-month price forecasts should rely on month-to-month variation from a vector of independent covariates. However, forecasts based on post-harvest (November-March) NDVI data are questionable as they would simply be incorporating a measurement of the photosynthetically active biomass from unplanted millet fields. Where off-season NDVI it may be useful is in providing an assessment of the prevailing environmental condition at the start or completion of the growing season. This point appears to be particularly important as the continuous string of sub-normal NDVI recorded from the fall of 2003 through the spring of 2005 may have played an additional role in alerting aid organizations of the seriousness of the environmental state during this time. Moreover, as shown in our forecasting model, the previous year's overall environmental condition may reflect wider…..[tbc]

NDVI Does Not Account for Area Planted Expansion

Niger's population growth is 3% per annum. Women have, on average, around 7 children. Simply to keep up with population growth, Niger must increase millet yields by 3 percent per annum or turn to food imports to ensure that all households can meet their caloric needs. According to official production (Figure 6 in the appendix) statistics, total area planted is growing at nearly 3 percent per year, with low variability. On the other hand, total agricultural production is growing at nearly 6 percent a year, but with much greater variability. From 2003 to 2004, alone, production declined by nearly 30 percent. Combined, these statistics paint a picture of an agricultural landscape that is increasingly adding marginal lands to the production process with varying consequences. On the one hand, yields appear to be keeping pace with the booming population. However, the intensification of agriculture onto marginal lands may have dire consequences as the effects of environmental shocks will only be magnified as more and more land is introduced into the production process. While these facts can be teased out of official production statistics, NDVI does not account for the intensification or expansion of production. NDVI can only detect the vegetative vigor associated with a swath of land, processed as a rectangular pixel, and converted to an anomaly based on static data. Ideally, a model should incorporate total area planted and positively scale NDVI outcomes in a similar manner to account for the intensification of agriculture. This would mean that positive (negative) anomalies, such as 2010 (2004) would be even than greater currently measured by our NDVI metric. Future research will consider the implications of this adjustment should data become available at a disaggregated level (another round of SPAM maps).

When NDVI is Useful

TBC prior to August 2012

[Early vs. late growing season as detected by NDVI and the effects on market performance]

Demonstrated examples in the NDVI data

NDVI can be tremendously useful for detecting the onset of an early growing season as clearly document in our data. In 2003, FAO documented an early onset of the raining season starting in April and progressing during May. While this may be detected by cross-referencing rainfall data from numerous rain stations, our rolling NDVI anomaly clearly showed an early green-up. In fact, NDVI anomalies, ranked across the previous 12 years, reached a highpoint in May of 2003. From a food security perspective the early onset of the growing season is suggestive of a less severe hungry season. Early planting enables some household to harvest earlier and thus pacing the flow of millet to the market. Collaboratively, this should smooth out the drastic fall in millet prices that are normally witnessed when harvest takes place at similar times.

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Appendix

Figure 1. Study Area

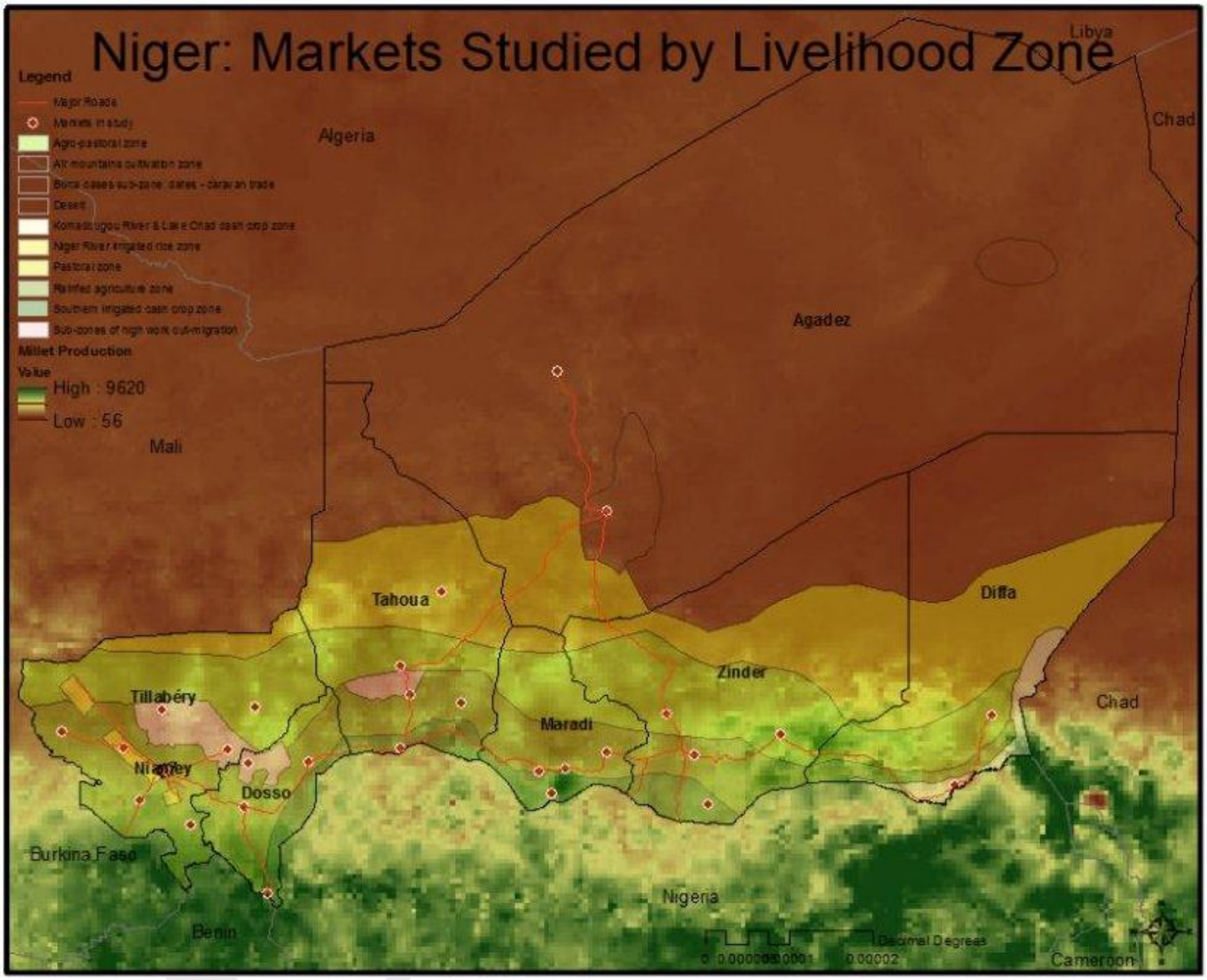


Figure 2. Long-term millet price & NDVI anomalies for selected years

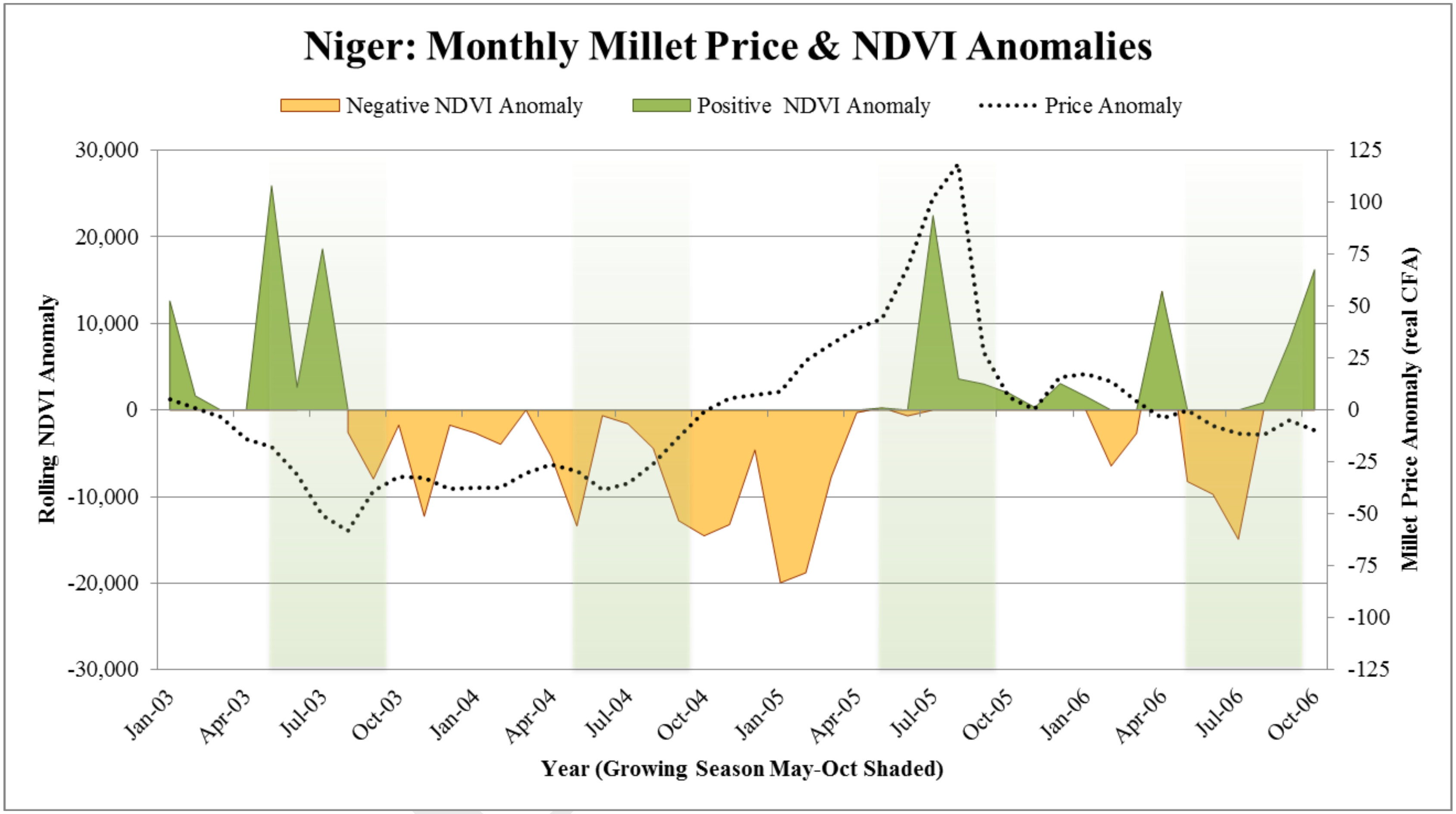


Table 1. NDVI data summary

Data Product	AVHRR NDVI	SPAM (Production Maps)
Time series	July 1981-December 2011	Based on year 2000 inputs
Data orientation	8.0 km x 8.0 km resolution Centroid-based coordinates	5km x 5km resolution
Raw data points	93,661 x 330	n.a.
Filtered data Points	33,296 x 330	n.a.

Figure 3. NDVI Buffers by Millet Physical Area Planted Intensity

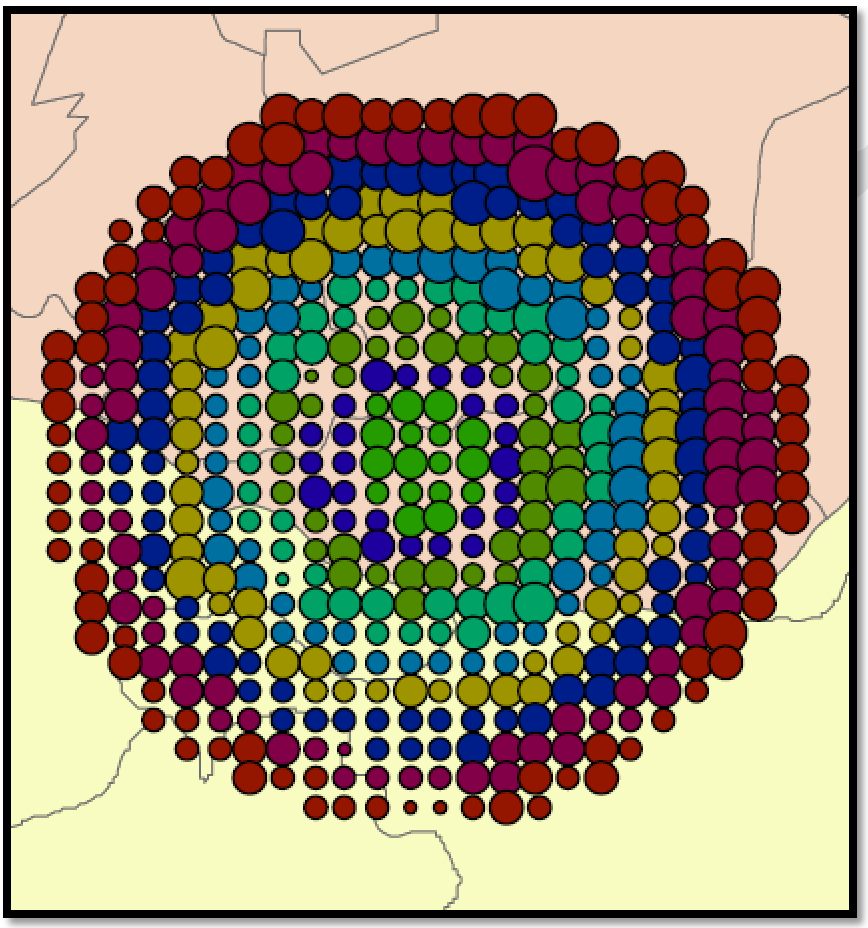


Table 2. Summary of markets in price database by region

Region	**Number of markets in original database**	**Share**	**Est. 2010 Population**	**Share**
Agadez	5	6%	487,313	3%
Diffa	5	6%	473,563	3%
Dosso	10	13%	2,016,690	13%
Maradi	17	22%	3,021,169	20%
Niamey	5	6%	1,222,066	8%
Tahoua	13	16%	2,658,099	17%
Tillabéry	12	15%	2,500,454	16%
Zinder	12	15%	2,824,468	19%
Total	79	100%	15,203,822	100%

Table 3. Summary of markets in price database by region

Region	Number of markets in analysis database	Share of sub-population
Agadez	2	7%
Diffa	2	7%
Dosso	4	14%
Maradi	4	14%
Niamey	1	3%
Tahoua	5	17%
Tillabéry	7	24%
Zinder	4	14%
Total	29	100$

Table 4. Summary of markets by agro-ecological zone

	Markets in original database	Share of total	Markets in analysis database	Share of total
Agro-pastoral zone	12	15%	5	17%
Aïr mountains cultivation zone	2	3%	1	3%
Desert	1	1%	1	3%
Komadougou River & Lake Chad cash crop zone	2	3%	1	3%
Niger River irrigated rice zone	5	6%	1	3%
Pastoral zone	4	5%	1	3%
Rainfed agriculture zone	31	39%	10	34%
Southern irrigated cash crop zone	17	22%	5	17%
Sub-zones of high work out-migration	5	6%	4	14%
	79		29	

Table 5. Augmented Dickey-Fuller Unit Root Test Results

Market ID	Market Name	Test Stat	1%	5%	10%	Status
325001	AGADEZ	-14.181	-4.003	-3.435	-3.135	1 %
325003	ARLIT	-14.551	-4.003	-3.435	-3.135	1 %
325004	BADAGUICHIRI	-15.447	-4.003	-3.435	-3.135	1 %
325005	BAKIN-BIRGI	-14.656	-4.003	-3.435	-3.135	1 %
325006	BALEYARA	-14.728	-4.003	-3.435	-3.135	1 %
325008	BIRNI KONNI	-14.81	-4.003	-3.435	-3.135	1 %
325009	BOUZA	-15.247	-4.003	-3.435	-3.135	1 %
325011	DAN-ISSA	-14.232	-4.003	-3.435	-3.135	1 %
325012	DIFFA	-14.016	-4.003	-3.435	-3.135	1 %
325013	DOGONDOUTCHI	-15.26	-4.003	-3.435	-3.135	1 %
325014	DOSSO	-14.721	-4.003	-3.435	-3.135	1 %
325015	DUNGASS	-15.424	-4.003	-3.435	-3.135	1 %
325018	FILINGUE	-15.551	-4.003	-3.435	-3.135	1 %
325019	GAYA	-14.777	-4.003	-3.435	-3.135	1 %
325020	GOTHEYE	-15.473	-4.003	-3.435	-3.135	1 %
325022	GOURE	-14.591	-4.003	-3.435	-3.135	1 %
325027	KIRTATCHI	-15.157	-4.003	-3.435	-3.135	1 %
325030	KOUNDOUMAWA	-15.007	-4.003	-3.435	-3.135	1 %
325031	LOGA	-15.633	-4.003	-3.435	-3.135	1 %
325034	MARADI	-14.607	-4.003	-3.435	-3.135	1 %
325036	N'GUIGMI	-14.451	-4.003	-3.435	-3.135	1 %
325043	OUALLAM	-15.355	-4.003	-3.435	-3.135	1 %
325049	TAHOUA	-15.037	-4.003	-3.435	-3.135	1 %
325051	TCHINTABARADEN	-14.647	-4.003	-3.435	-3.135	1 %
325053	TERA	-14.691	-4.003	-3.435	-3.135	1 %
325054	TESSAOUA	-15.094	-4.003	-3.435	-3.135	1 %
325129	TCHADOUA	-14.725	-4.003	-3.435	-3.135	1 %
325132	TORODI	-14.356	-4.003	-3.435	-3.135	1 %
325134	COMPLEX/Bonkaney	-14.414	-4.003	-3.435	-3.135	1 %

Table 6. Summary of Millet Prices

	Overall		May-Aug		Sep-Apr		
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Observations
AGADEZ	196.26	47.03	210.75	54.25	196.26	47.03	230
ARLIT	204.61	41.37	216.90	45.12	204.61	41.37	230
BADAGUICHIRI	167.60	47.72	190.80	55.13	167.60	47.72	230
BAKIN-BIRGI	140.43	43.53	160.18	50.13	140.43	43.53	230
BALEYARA	197.92	43.08	215.71	47.73	197.92	43.08	230
BIRNI KONNI	170.97	45.73	190.73	52.67	170.97	45.73	230
BOUZA	173.10	43.83	193.02	48.78	173.10	43.83	229
COMPLEX/Bonkaney	201.00	39.82	213.78	46.03	201.00	39.82	230
DAN-ISSA	147.43	48.15	166.80	57.50	147.43	48.15	230
DIFFA	196.92	53.28	212.07	60.12	196.92	53.28	230
DOGONDOUTCHI	163.95	43.26	185.26	48.79	163.95	43.26	229
DOSSO	201.54	48.10	221.94	53.67	201.54	48.10	230
DUNGASS	147.77	51.26	168.75	62.00	147.77	51.26	230
FILINGUE	189.76	49.98	213.44	55.37	189.76	49.98	227
GAYA	183.65	53.83	206.64	60.87	183.65	53.83	230
GOTHEYE	200.09	55.33	217.58	63.94	200.09	55.33	230
GOURE	170.63	46.58	188.23	56.22	170.63	46.58	230
KIRTATCHI	183.98	48.68	205.40	50.29	183.98	48.68	226
KOUNDOUMAWA	145.44	47.04	167.73	53.25	145.44	47.04	230
LOGA	177.87	46.33	202.54	49.44	177.87	46.33	230
MARADI	152.90	44.09	170.03	51.22	152.90	44.09	230
N'GUIGMI	216.04	56.79	228.14	63.32	216.04	56.79	230
OUALLAM	214.82	50.79	234.88	53.81	214.82	50.79	227
TAHOUA	209.36	51.70	228.11	60.87	209.36	51.70	230
TCHADOUA	144.79	43.69	161.27	50.55	144.79	43.69	226
TCHINTABARADEN	209.45	51.03	226.17	60.19	209.45	51.03	230
TERA	183.70	47.02	200.42	48.95	183.70	47.02	230
TESSAOUA	146.08	47.05	165.58	52.75	146.08	47.05	230
TORODI	177.40	45.18	192.81	51.02	177.40	45.18	230
Overall	179.84	47.63	198.47	53.93	179.84	47.63	229.45

Figure 4. Millet Price Anomaly Distributions by Regime Type

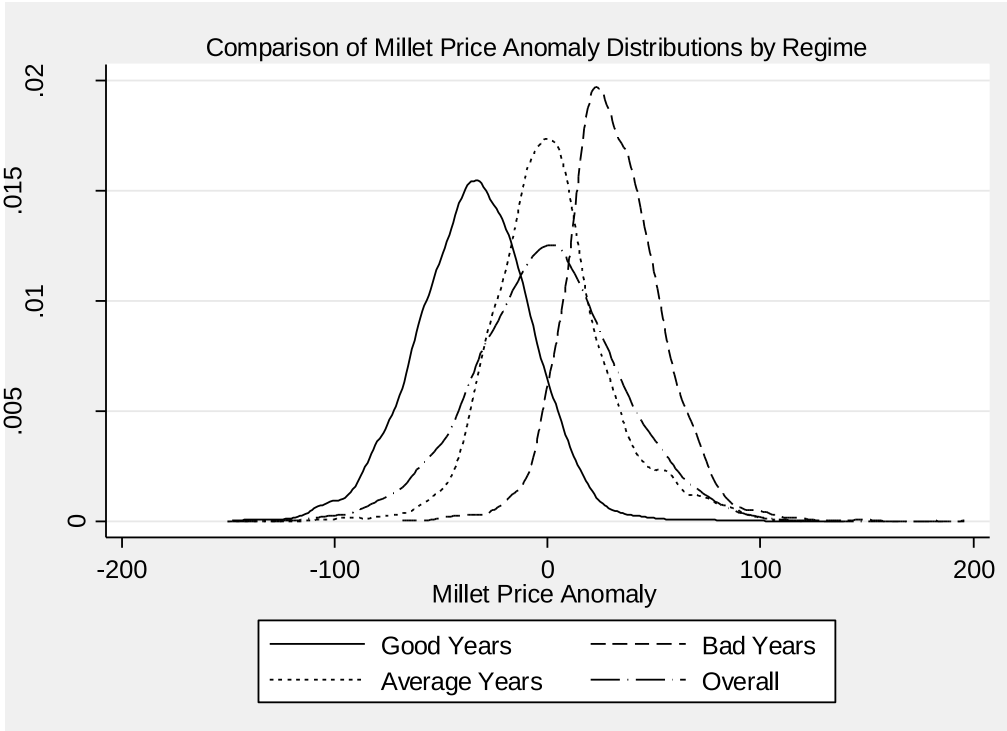


Figure 5.Graphical Representation of Rolling NDVI Anomalies & Millet Price Anomalies (1993-2012)

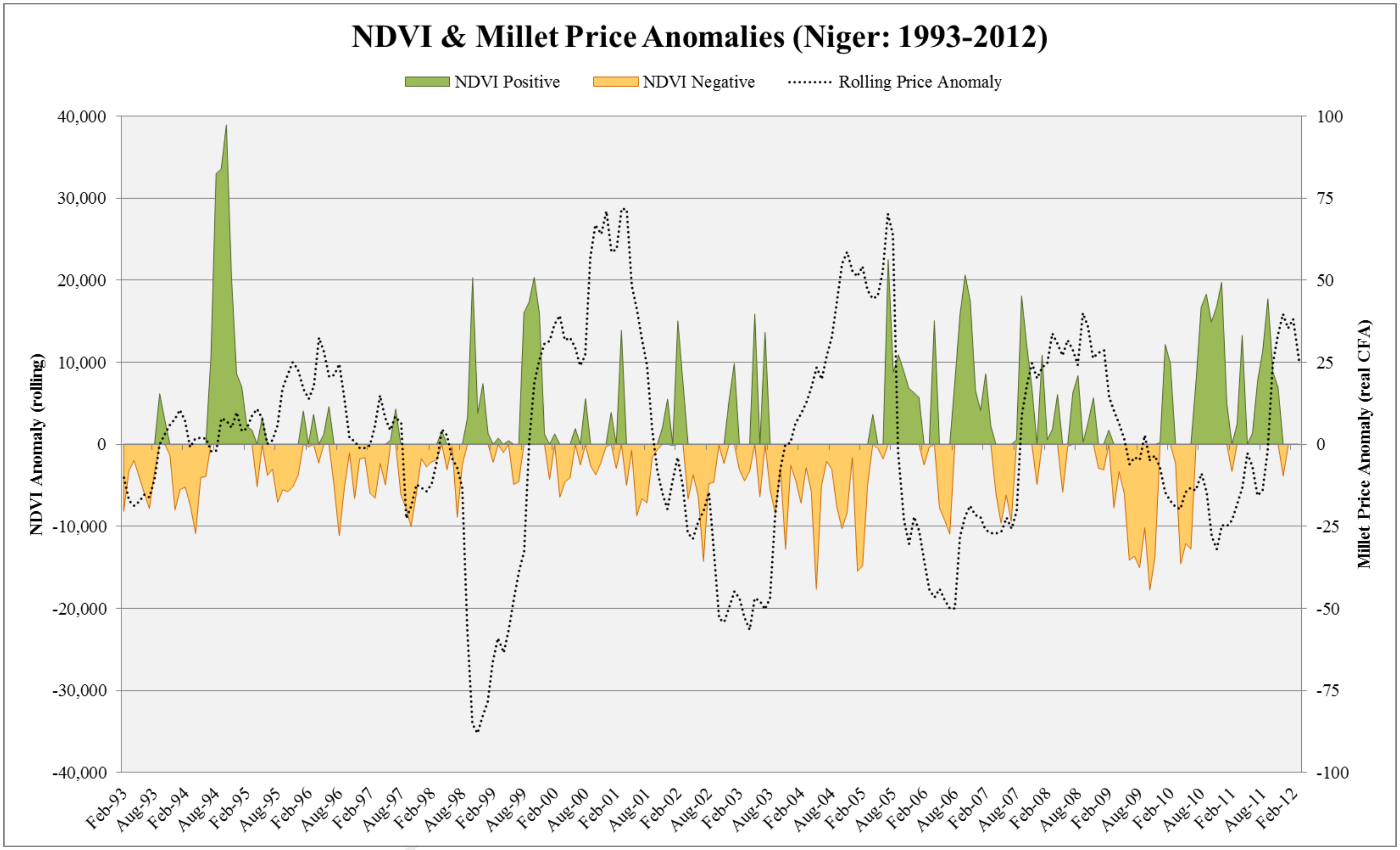
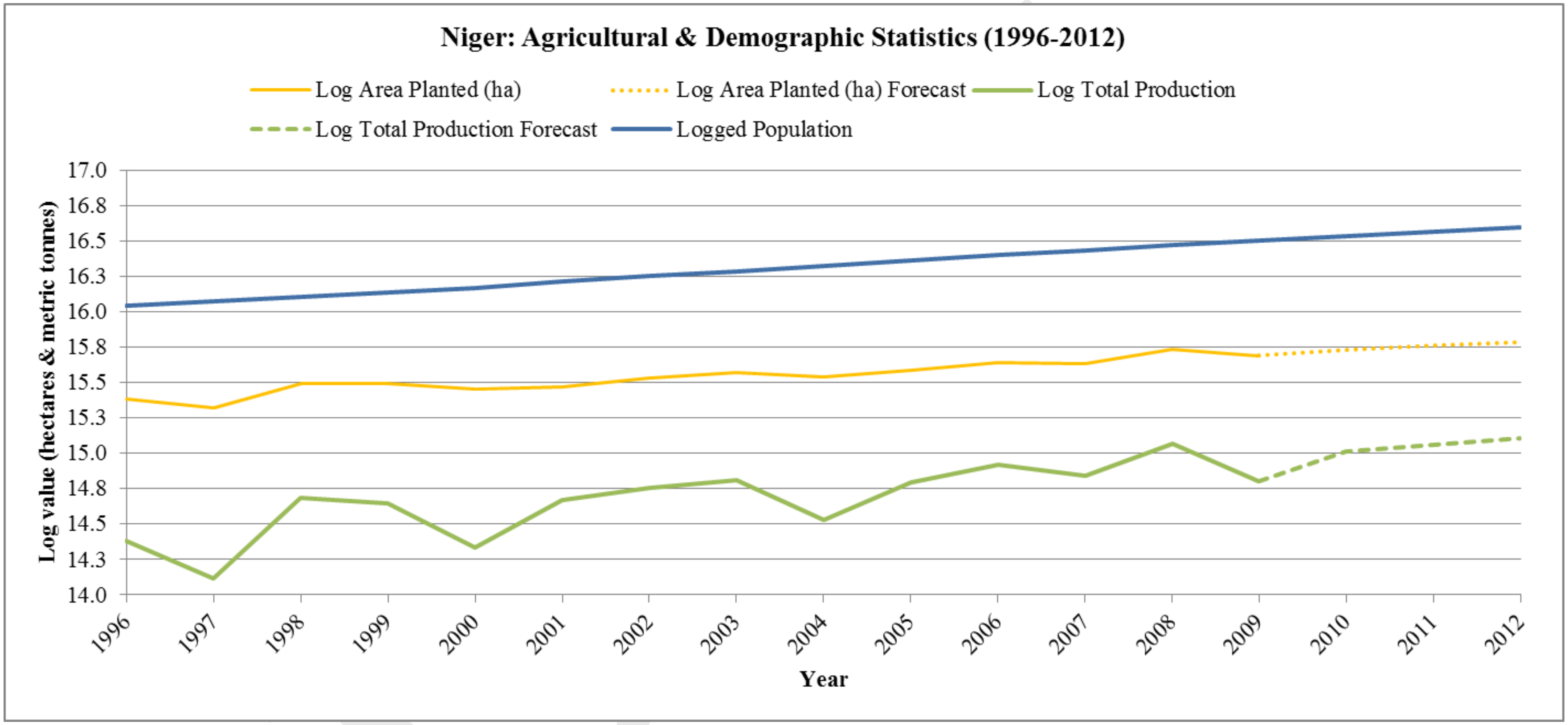


Figure 6. Select Agriculture Statistics from Niger



Source: FEWS NET Niger/Government of Niger