The 2004 Niger Food Crisis: What Role Can Price Discovery Play in Famine Early Warning Systems?

By

Jeffrey Vitale[1] and David A. Bessler[2]

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[1] Assistant Professor, Oklahoma State University. jdvitale@msn.com.
[2] Professor, Texas A&M University. d-bessler@tamu.edu .

ABSTRACT

The 2005 food crisis centered in Niger received worldwide attention and extensive media coverage. Crops suffered from poor rainfall and were plagued by locusts throughout the growing season. Malnutrition flourished with the sudden disruption in food supplies. One-fifth of Niger’s children suffered from moderate to severe forms of malnutrition by the summer of 2005. In an era of increased awareness and the introduction of famine early warning systems, the development community was left wondering why they were for the most part caught off guard by the food crisis. This paper tests whether market prices and price discovery could have played an active role in detecting the food crisis. Directed acyclic graphs are used to test whether price discovery mechanisms within Niger’s millet markets were ahead of the early warning systems. Results suggest that as early as October 2005 markets in Arlit and the Dosso province had price anomalies that appeared to begin signaling the upcoming food crisis. This market based discovery came about two months earlier than the warnings issued by the regional early warning networks.

INTRODUCTION

The recent food crisis centered in Niger received worldwide attention during the summer of 2005. An estimated three million persons were affected by the crisis in Niger alone, with an additional million affected in the neighboring country of Mali (FEWSNET 2005). With only fragile safety-nets to fall back on the rural communities were hard hit. Caloric intake fell by as much as one-third in areas already prone to chronically low levels of food consumption. Malnutrition flourished as households were forced to cutback on meals and shift to low quality substitutes. One-fifth of Niger's children suffered from moderate to severe forms of malnutrition by the summer of 2005 (WHO 2005). Although an official death toll has not been announced, all of the major relief agencies reported deaths due to starvation amidst the food crisis.

The rains came late and left early in the 2004 growing season (Eilerts 2005). Crops that managed to ward-off drought succumbed to locusts, which often ate better than humans. In Niger national food production fell by 11 percent, but plummeted severely in the areas least equipped to handle adversity. Food production in the northern and eastern provinces dropped by as much as 35 percent in 2004 (FEWS NET). As bad as these numbers sound Niger has averted crises under similar shocks to its food production. Most agree that the 2004 crisis was caused more by high prices and a lack of money in consumers' pockets than by a shortage of food in markets (*The Economist* 2005). Consider for instance that other countries in the region suffered even worse crop production losses[3] (GIEWS NET 2005).

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[3] "*.. cereal production, compared to the previous year's good levels, was estimated to have decreased by 66 percent in Cape-Verde, 44 percent in Mauritania, 35 percent in Chad and 27 percent in Senegal. In spite of severe localized damage, decreases compared to the five-year average were relatively limited in Burkina*

Staple food markets react poorly to scarcity and are prone to volatility in this region of the world. A lack of substitutes creates a nearly inelastic demand schedule that sends prices skyward under even modest supply shocks. The 11 percent drop in Niger's food production caused on average a doubling of staple food prices from the fall of 2004 through the summer of 2005 (USAID 2005). Rural households were priced out of the staple food markets even in areas where food aid was being injected at subsidized prices. Purchasing power continued to weaken as livestock markets collapsed under such strong selling pressure (Sánchez-Montero 2005). Making matters worse were restrictions placed on exports by neighboring countries Mali, Nigeria, and Burkina Faso (*The Economist* 2005).

Early warning systems were designed to forecast food crises and famines looming on the horizon. A properly functioning system should be able to look-ahead and predict events two to three months in advance to grant relief agencies adequate lead time. Donors have invested in a famine early warning network (FEWS NET) that operates throughout the West African Sahel. FEWS is a modern system that monitors a variety of information linked to food security including production, income, and food prices. Warnings are issued by FEWS when indicators signal upcoming shocks to food supply.

Market prices are a potentially useful source of information for monitoring food security. The region has undergone structural adjustment in its staple food markets leaving most of the markets under private control (Jones 1995). Economic agents form price expectations using forecasting techniques and engage in the process of price discovery that cause market prices to react to future events. While agents' forecasting

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Faso, Niger (11 percent) and Mali, the major cereal producing countries in the region." Excerpt taken from GIEWS 2005.

methods are not fully understood it's that they could be more accurate than early warning systems such as FEWS. So analyzing how discoveries in staple food market prices behaved before, during, and after the crisis provides food security analysts with important information.

The purpose of this paper is to investigate the role that price discovery could have played in alerting food security analysts of the impending crisis in Niger. In particular this paper tests a working hypothesis that economic agent-based price discovery mechanisms in the food markets were better able to forecast the crisis than FEWS, a formally structured price monitoring system. This research is not intended to place blame or point fingers. Rather this paper attempts to add insight, through gathering empirical evidence, on the value of incorporating more detailed market based information into early warning systems such as FEWS.

BACKGROUND

Niger is a land locked country located in the West African Sahel, an area characterized by its aridness and proximity to the Saharan desert[4]. Agricultural production remains highly dependent on rainfall. Irrigation is available only in limited areas along the Niger River provides, leaving most of the country vulnerable to drought (Figure 1). Even in an average production year Niger cannot feed itself. Average cereal production hovers around 11 million kg of cereals, enough in principle to provide only about 91.6 kg to each of its 12 million inhabitants. This requires an on-going need for food imports from neighboring countries and the rest-of-the-world (typically food aid).

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[4] The Sahel is taken from the Arabic word *Sahil*, which refers to a border or shore. Here it distinguishes the Sahel as the region that borders the Saharan desert.

Niger's population is concentrated in the southwest portion of the country where rainfall is highest (Figure 1). In this region, where rainfall averages 500 mm per year, population densities range between 50 and 200 persons per km^2. To the north both rainfall and population density quickly drop off. There is a fairly large area where rainfall is between 200-350 mm/year, just adequate for millet production. Population densities in this area range between 3-10 persons/km^2. Above this is the pastoral region, where rainfall is inadequate for crop production. Population densities range between 0-2 persons per km^2.

METHODOLOGY

The working hypothesis is tested empirically using an econometric model. Specifically, the model tests how accurately market based agents were able to forecast the impending 2004 Niger food crisis. Directed acyclical graphs (DAG) are employed to analyze a time series of cereal price data from the West Africa region[5]. In practical terms, DAG develops a timeline of what happened before, during, and after the 2005 Niger food crisis from the perspective of the economic agents engaged in the cereal markets. The DAG method determines when market signals, through innovations in price discovery, were first sent throughout the regional markets of an impending food crisis.

The econometric results from the DAG model are then compared to the forecasts made by regional food security agencies such as FEWS. An alternative timeline is constructed based on how the early warning systems discovered and monitored the food

[5] In previous research DAG provided empirical support that cereal markets in a neighboring country, Mali, functioned adequately following liberalization and market reform (Vitale and Bessler 2006). The results from the Mali study suggest an active role for DAG in the food security context. Cereal prices were discovered primarily in the cereal deficit region of Mopti, and were found to flow to the surplus region of Sikasso.

crisis. This timeline is developed using historical records and published reports from FEWS and other food security agencies working in the region. The two timelines are compared to determine which approach was first to detect the food crisis. This provides empirical support, for or against, the working hypothesis that market based agents were better able to predict the 2004 Niger food crisis.

The empirical analysis is based on a (co-integrated) vector autoregression (VAR) model in which directed acyclic graphs are used to sort-out causal flows of price information in contemporaneous time. The econometric analysis is conducted using directed acyclical graphs (DAG). This is an approach that estimates price information flows among markets. DAG models determine in which market(s) innovations in price discovery take place, as well as the directions in which prices flow to other markets. We present our general model below in two sub-sections: ECM (error correction model) and DAG (Directed Acyclic Graphs).

The ECM

Let X_t denote a vector that includes the monthly price from each of I regions under consideration:

$$X_t = \begin{pmatrix} X_{1,t} \\ X_{2,t} \\ \cdots \\ X_{i,t} \\ \cdots \\ X_{I,t} \end{pmatrix}$$

where i is the regional market. If the series are non-stationary (which we expect for prices in a free market, we explore this below), the vector X_t can be modeled in an error correction model (ECM):

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \mu + e_t (t = 1,...,T) \quad (1)$$

Equation (1) resembles a vector autoregression (VAR) model in first differences, except for the presence of the lagged levels of X_{t-1}. There are three cases of interest: (a) if Π is of full rank, then X_t is stationary in levels and a VAR in levels is an appropriate model; (b) if Π has zero rank, then it contains no long-run information and the appropriate model is a VAR in first differences; and (c) if the rank of Π is a positive number, *r*, which is less than *p (the number of series = I)*, there exist matrices α and β, with dimensions *p* x *r*, such that $\Pi = \alpha\beta'$. In such a case, $\beta' X_t$ is stationary, even though X_t is not.

The dynamic response patterns summarized by an ECM or a VAR are difficult to interpret (Sims, 1980; Swanson and Granger, 1997). The dynamic price relationships can be best summarized through the moving average representation. Given the estimated form of equation (1) (with possible cointegrating vectors, which is applicable in this study), we can algebraically re-express equation (1) as a levels VAR. We can then solve for its moving average representation, where the vector X_t is written as a function of the infinite sum of past innovations:

$$X_t = \sum_{i=0}^{\infty} G_i e_{t-i} \quad (2)$$

where G_i is a IxI matrix of moving average parameters, which map historical innovations at lag *i* into the current position of the vector *X*.[6] In this case the matrix G_0 is generally not the identity matrix, as the elements of the vector *e* are usually not orthogonal. That is to say, there may be non-zero correlation between contemporaneous innovations. Analysis of equation (2) without making some adjustment for non-orthogonal innovations may not reflect the dynamic historical patterns present in the data (see Sims (1980)). We prefer to work with a transformed moving average representation on orthogonalized innovations $v_t = Ae_t$, where A is such that $E\{v_t v_t'\} = D$, where D is a diagonal matrix. Research workers employing VAR models have traditionally used a Choleski factorization of the (contemporaneous) innovation correlation matrix to provide a Wold causal chain on how an innovation in series *i* reacts to an innovation in series *j* in contemporaneous time. The Choleski factorization is recursive in its nature and may not reflect the "true" causal patterns among a set of contemporaneous innovations.

More recently, research workers have followed the structural factorization commonly referred to as the "Bernanke ordering" (Bernanke, 1986). This approach requires writing the innovation vector (e_t) from the estimated VAR model as: $e_t = A^{-1}v_t$, where, in our case, **A** is a 10x10 matrix and v_t is a 10x1 vector of orthogonal shocks. While the Bernanke ordering allows one to move away from the mechanically imposed constraint of recursive causal ordering embedded in the Choleski factorization, it requires research workers to actually specify a contemporaneous causal pattern among innovations. In this study we have very little information for specifying the ordering in a Choleski factorization. It is not clear if, in contemporaneous time exogenous price signals

[6] While one can actually derive the first *n* terms of equation (2) analytically, we almost always allow the computer to do this following the zero-one simulation as described in Sims (1980).

originate on the periphery or extensive limit of Millet production, in the large cities, or in the excess production regions. Accordingly, we abandon any attempt to solve the causality in current time question with a Choleski factorization of contemporaneous covariance.

Here we apply directed graph algorithms (see the discussion given below) to place zeros on the A matrix (e.g. $v_t = Ae_t$). Directed graphs have recently been used in the literature for just this purpose in similar time series settings (see, for example, Swanson and Granger (1997) and Bessler and Kergna (2002)).

Given equation (2) (or more precisely, its estimated form) we now can write the vector X in terms of orthogonalized innovations as Equation (3):

$$X_t = \sum_{i=0}^{\infty} \Theta_i v_{t-i} \ . \tag{3}$$

Here the vector X is written as an infinite series of orthogonalized innovations, v_{t-i}. We use recent innovations in graph theory and PC algorithm (described below) to determine the causal pattern behind the correlation in contemporaneous innovations ($\Omega = E\{e_t e_t^{'}\}$) to construct orthogonal innovations (($E\{v_t v_t^{'}\} = D$).

Directed Graphs and PC Algorithm

A directed graph is a picture representing the causal flow among a set of variables. Lines with arrowheads are used to represent flows. For instance, A→ B indicates that variable A causes variable B. A line connecting two variables, C – D, indicates that C and D are connected by information flow but it's not certain whether C causes D or vice versa. The fundamental idea that enables detection of the direction of causal flow to a set of (observational) variables is the screening-off phenomena and its more formal representation as d-separation (Pearl, 2000). For three variables A, B and C, if we have variable A as a common cause of B and C so that B←A→C, then the unconditional association between B and C will be non-zero, as both have a common cause in A (this diagram is labeled a causal fork (Pearl 2000)). If we measure association (linear association by correlation) then B and C will have a non-zero correlation. However, if we condition on A, the partial correlation between B and C (given knowledge of A) will be zero. Knowledge of the common cause (A) "screens-off" association between its effects (B and C).

On the other hand, say we have variables D, E, and F such that D→E←F. Here we have E is a common effect of D and F (this diagram is labeled a causal inverted fork (Pearl 2000)). D and F will have no association (zero correlation if we constrain ourselves to linear association); however, if we condition on E, the association between D and F is non-zero (the partial correlation between D and F, given knowledge of E is non-zero). We say (in the vernacular) knowledge of the common effect does not "screen-off" association between its causes.

And if we have variables A, B and C forming a causal chain, A→B→ C, the unconditional association (correlation) between A and C will be non-zero, but the conditional correlation between A and C, given knowledge of B will be zero.

These screening-off phenomena associated with common effects and common causes have been recognized in the literature for some fifty years now; see, for example, Orcutt (1952), Simon (1953) and Reichenbach (1956). It is only recently that they have been formally introduced into the literature for assigning causal flows among three or more variables. Key to this modern re-birth is the technical work of Pearl and his associates (see Pearl 2000). Pearl and his collaborators have formalized these screening-off notions, with the idea of d-separation, which gives the connection between a causal diagram and its probability representation.

Spirtes, Glymour and Scheines (2000) and Pearl (2000) present algorithms with similar structures and outputs for inference on directed acyclic graphs from observational data. The former is labeled PC algorithm, embedded in the software TETRAD II and III (see the offering at http://www.phil.cmu.edu/projects/tetrad/ and Scheines *et al*., 1996) and described in Spirtes, Glymour and Scheines (2000); the latter is IC algorithm presented in Pearl (2000, pp.50-51). Here we offer a brief description of PC algorithm.

To begin one forms a complete undirected graph on the set of variables to be examined. Say we have three variables X, Y and Z. Form the complete undirected graph as:

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   X
 /   \
Y  —  Z
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This graph has a line (edge) connecting each variable with every other variable in a pre-determined set of variables (theory is a rich source for variable specification). Edges between variables are removed sequentially based upon vanishing unconditional correlation or higher-order partial correlation at some pre-specified significance level of normal distribution.

Edges that survive these attempts at removal are then directed by using the notion of sepset. The conditioning variable(s) on removed edges between two variables is called the sepset of the variables whose edge has been removed (for vanishing zero order conditioning information the sepset is an empty set). PC algorithm directs the edges between X and Y into variable Z if Z is *not* in the sepset of X and Y. For our X, Y, Z example, suppose we have removed the edge between X and Y not conditional on Z (that is, the unconditional correlation between X and Y is zero). We can then direct $X — Z — Y$ as $X \rightarrow Z \leftarrow Y$. Had Z been used to remove the edge between X and Y (PC algorithm removed the edge because the correlation between X and Y conditional on Z was zero) then PC algorithm would not be able to direct the edges between X, Y and Z; the underlying model may have been a causal fork $X \leftarrow Z \rightarrow Y$ or a causal chain $X \rightarrow Z \rightarrow Y$ (recall the screening off discussion given above). In such a case (the case of ambiguity) PC algorithm would leave the remaining edges undirected $X — Z — Y$.

If we have other variables in the set of variables studied (in addition to X, Y, and Z) the ambiguity illustrate above may be resolved. In our X, Y, Z example given above, PC was not able to direct edges using sepset (because of the same correlation structure for causal forks and causal chains), it may be that a fourth variable W can be used to overcome the ambiguity. Say after removing edges on the four variable set we are left with the undirected graph on X, Y, Z and W:

$$\begin{array}{c} X — Z — Y \\ | \\ W \end{array}$$

If Z is not in the sepset of X and W, but Z is in the sepset of X and Y, then using the just (or first) the sepset condition PC would return:

$$\begin{array}{c} X \rightarrow Z — Y \\ \uparrow \end{array}$$

W

However, this inverted fork relation between X, Z and W, resolves the ambiguity on the X, Z, Y directions. The causal fork possibility obviously does not hold.

PC will thus result in the graph:

$$X \rightarrow Z \rightarrow Y$$

$$\uparrow$$

$$W$$

PC algorithm has been studied extensively in Monte Carlo simulations in Spirtes, Glymour and Scheines (2000) and Demiralp and Hoover (2003). The algorithm may make mistakes of two types: edge inclusion or exclusion and edge direction (orientation); the latter appears to be more likely than the former. Spirtes, Glymour and Scheines write: "In order of the methods to converge to correct decisions with probability 1, the significance level used in making decisions should decrease as the sample size increases and the use of higher significance levels (e.g., .2 at sample sizes less than 100, and .1 at sample sizes between 100 and 300) may improve performance at small sample sizes." (Spirtes, Glymour and Scheines, 2000, page 116). Nevertheless, the orientation (edge direction) decision is less reliable than the edge inclusion decision in PC algorithm; results presented below should be viewed with caution and/or interpreted with other relevant information.

Data

The time series of millet price observations runs from 1990 through August of 2005 (SIM 2005). The dataset used in the analysis includes millet markets from Niger, Mali, and Burkina Faso. Observations are monthly millet prices paid by consumers. In Niger there are 45 markets that encompass the entire country. In Mali and Burkina Faso only the large urban markets were included. The Mali dataset had 7 markets and the Burkina Faso dataset had 8 markets. The FEWS operating in the West Africa region issued monthly reports on food security conditions. These agencies are responsible for monitoring food security in the West Africa region.

RESULTS

Millet prices are highest in the arid, pastoral regions to the north where rainfall is too low to support millet production (Figure 2). Millet prices typically hover about 15-25 fcfa/kg higher in markets located in the arid areas as opposed to markets located in the wetter areas in the southwest corner of Niger. The co-movement of millet prices among the markets is visually evident. Each of the market pairs illustrated in Figure 2 is barely distinguishable from one another. Even from an informal basis they appear to be responding to similar market signals.

Niger millet prices exhibit strong intra-seasonal variability (Figure 2). The run-up in millet prices during the hungry season is particularly strong in the years of food crises. In addition to the 2005 food crisis, the summer of 1999 saw almost the same level of price increases. In both the 2005 and 1998 food crises millet prices doubled from their previous levels. Price recoveries occur quickly. Following the 1998 food crisis prices returned to their long-run average level within two months in each of the markets.

The DAG analysis found that the twelve Niger markets transmit a high degree of market information flows among themselves (Figure 3). Eight co-integrating vectors were found, and all of the price series were found to be mean non-stationary. This indicates that none of the markets appear to be sluggish in how they respond to price innovations in other markets. For the most part the results of the DAG analysis are in agreement with observed market behavior. Cereals flow the southwest corner of Niger to the arid regions to the north. This behavior was captured by both the GES and PC algorithms used in the analysis (Figure 3).

Arlit and Dogondoutchi were found to be the markets where the initial price discovery innovations were detected in the fall of 2004 (Figure 4). This is apparent in the illustrations that depict the price decomposition of millet prices in Niamey (Figure 4). Both Arlit and Dogondoutchi were hard hit by the impending food crisis, but are located in very different regions. Arlit is in the arid north and Dognodoutchi is in the wetter southwestern portion.

Early Warning Systems

The early warning systems (EWS) operating in the region post monthly reports on the current status of food security through the internet and local media outlets. Under normal conditions EWS function more as information providers, detailing climatic and market conditions for a variety of stakeholders in the region. Warnings are issued, however, whenever food security reaches a critical level. The warnings serve as triggers to the international relief community food aid will be required over the short term. The warnings are separated into four categories: No Warning, Watch, Warning, Emergency.

The Niger FEWS wasn't able to detect the food crisis until November of 2004 (Figure 5). During this month a food security *Warning* was issued on their website. Prior to this the alert level had been at *No Watch* for over a year. This *Warning* level was maintained for six months. In February 2005 a clearer picture began to emerge and a food security map was posted on their website (Figure 6). The warning was upgraded to the highest level, *Emergency*, in May 2005. Neighboring FEWS in Mali and Burkina Faso also had difficulty in forecasting the upcoming food crisis.

Post-Crisis Analysis

The primary finding from the analysis is that the Niger markets were well integrated as the time series analysis found 8 co-integrating vectors. This agrees with the prevailing Sen-based explanation that food markets were in principle working, but poverty kept rural households out of the marketplace. Hindsight provides perhaps the clearest explanation for what caused the Niger food crisis. One missing factor in both the DAG model and the FEWS forecasts is the role of the wealthier coastal markets. Food prices in Cote D'Ivoire, Nigeria, and Ghana are typically much higher than in the land locked countries of Niger, Mali, and Burkina Faso. In surplus years coastal markets are better able to bid up prices. Traders are also more apt to bring cereals to the coastal areas where infrastructure is more developed and markets are less risky.

Based on the DAG analysis, it appears that private agents in the millet markets were slightly ahead of the early warning systems in detecting the impending food crisis.

Market price innovations around October 2004 were found in the Arlit and Dogondoutchi markets, but our initial findings place more of a December timeframe for when the formal warning systems detected a food crisis. This provides empirical support for the hypothesis that markets can, in certain circumstances, forecast more efficiently than more formal warning systems.

CONCLUSIONS

The integration of West African food markets has been heralded as a success. The analysis presented in this paper is in agreement with other findings from the region that the Sahelian markets have to a large extent been integrated following reform and liberalization measures. Price discovery and subsequent price information flows among markets move quickly from the food deficit to the food surplus regions.

It's likely that food markets may be too well integrated in the region. The 2005 Niger food crisis raises previous concerns over the tenuous nature of regionally integrated markets. The evidence suggests that imports from neighboring countries shrank precisely at the time when they were most needed. Whether the neighboring countries became reluctant to export cereals into Niger or the wealthier coastal countries were successful in "outbidding" the Niger markets for the surplus grains is still unclear. In either event the 2004 food crisis points out that affected areas were unable to allocate for themselves enough food through the free market system. a common theme that free markets won't . Either through hoarding or government mandate, the Malian and suggest, however,.

The results suggest that more emphasis should be placed on price expectations contained within market prices. One approach would be to better integrate FEWS with market information systems (SIM) in the West African region. Including a formal price forecasting engine, such as the DAG method used in this paper, is expected to increase the predictive power of the FEWS NET throughout the West African region.

The results of this paper also imply the need for better integration among the FEWS network operating in the region. This will also require some monitoring of food prices in countries outside the FEWS network, particularly those on the neighboring coastal countries.

Further studies will be required to assess the impacts of market integration. The results of this study suggest that market integration concentrates its benefits among the wealthier coastal countries. Arid regions within the poorer land locked countries appear even more vulnerable to food insecurity than they were prior to market reform.

Future research should focus on a wider range of prices. It’s possible that the co-movement between livestock and cereal prices would be an even better predictor of impending food insecurity. The pastoral areas hard hit by the 2005 food crisis rely heavily on livestock to safeguard themselves in years when crops fail. The time when animals begin entering markets may turn out to be the pest predictor that a food crisis looms on the horizon.

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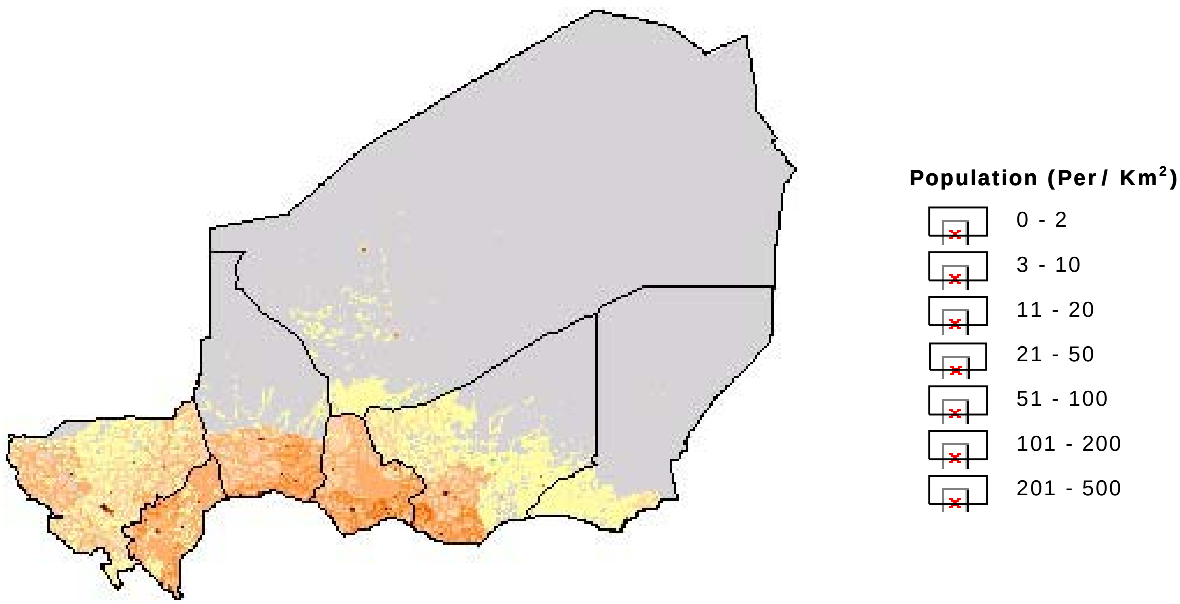
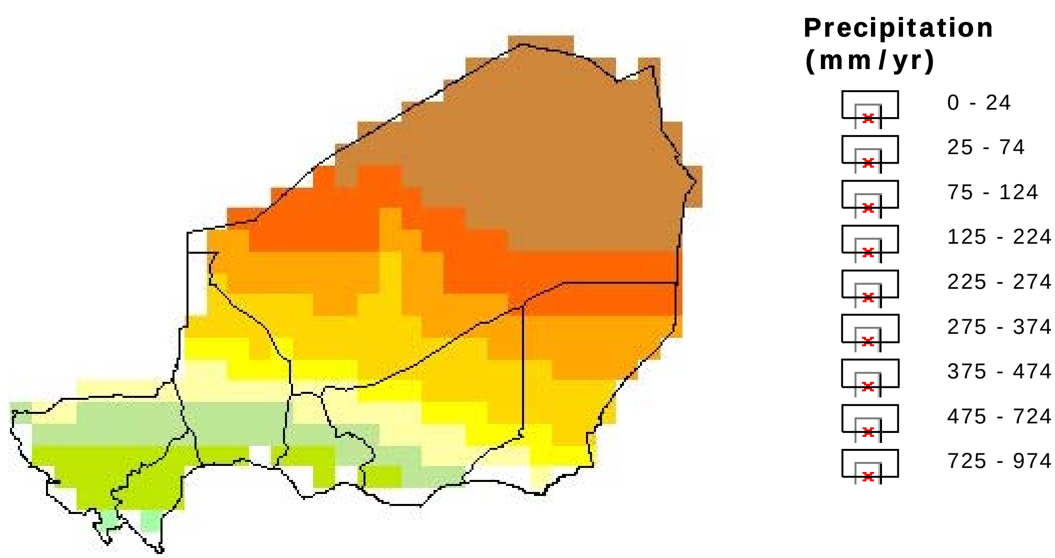
FIGURES



(a) Population density



(b) Rainfall

Figure 1 Population density and mean annual rainfall in Niger (FAO 1996).

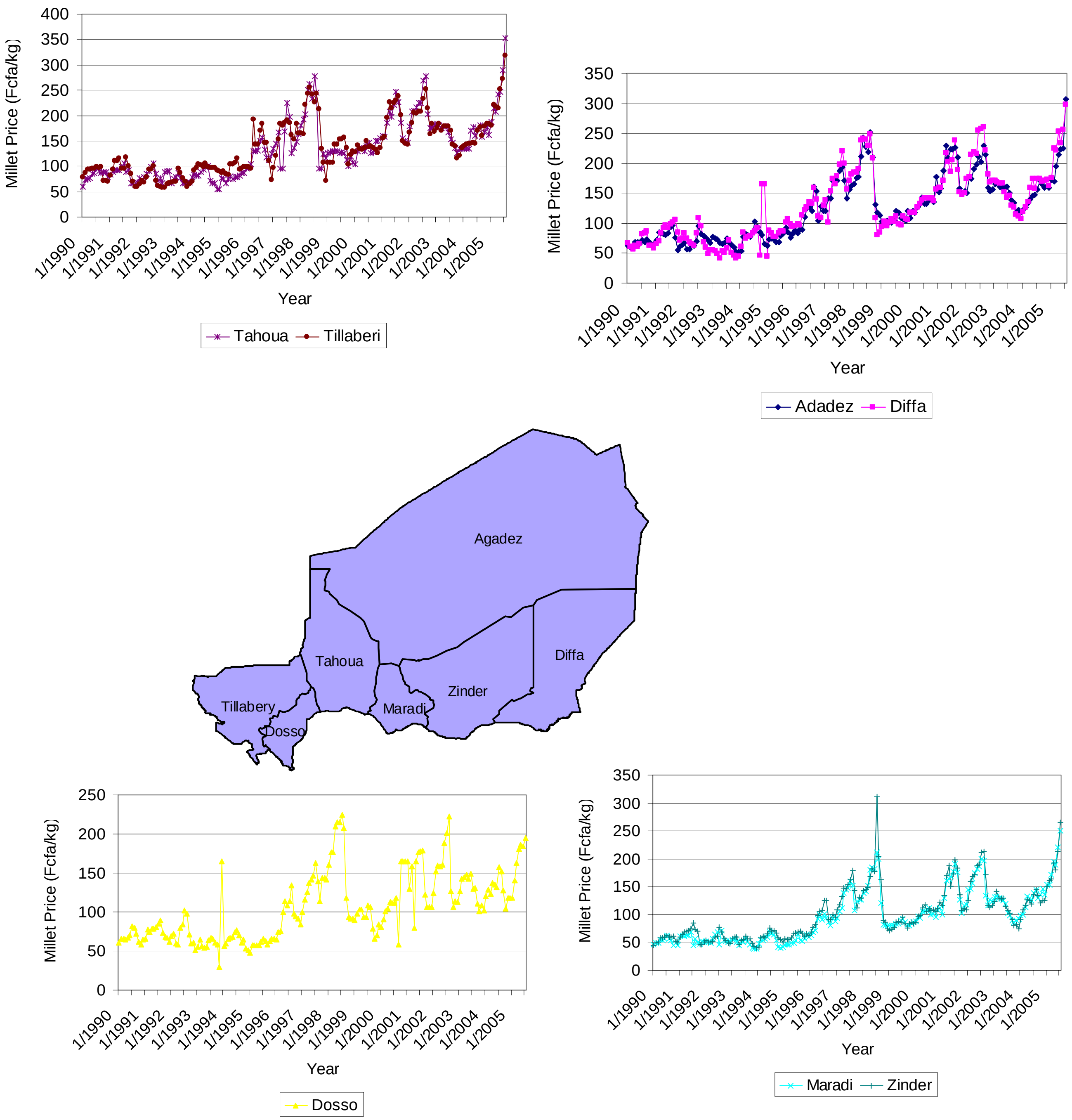
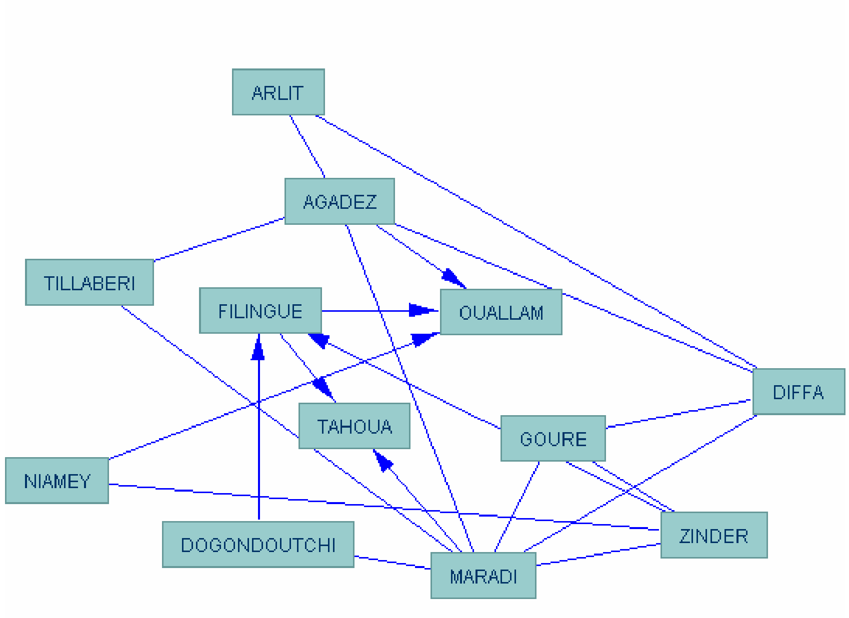
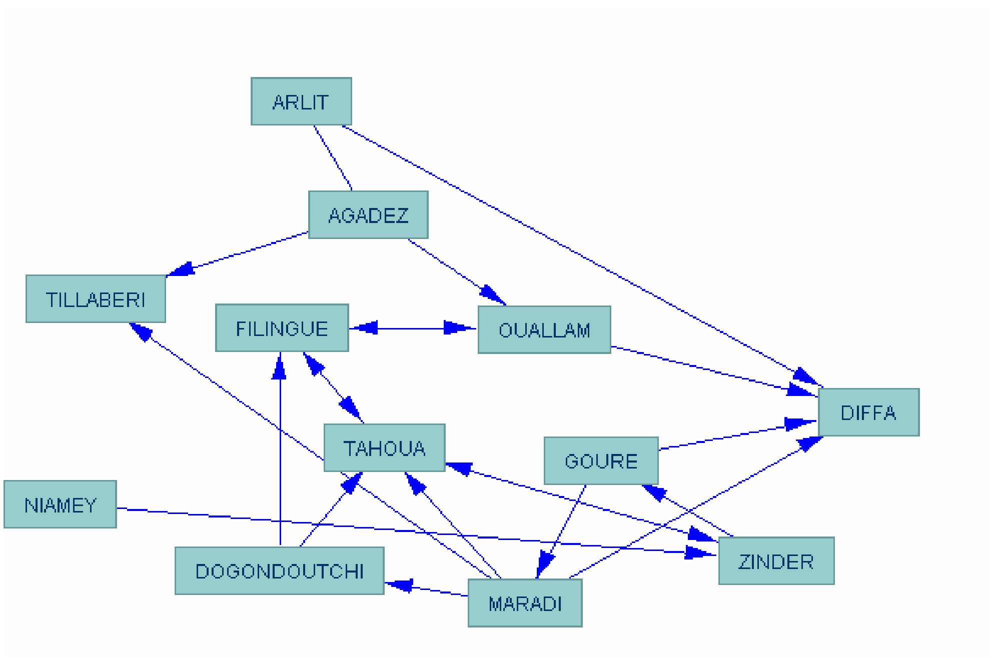


Figure 2 Millet prices in Niger from January 1990 through July 2005



(a) GES Algorithm



(b) PC Algorithm

Figure 3 Pattern of information flow on 1990–2005 innovations on Niger Millet Prices from the GES and PC algorithms.

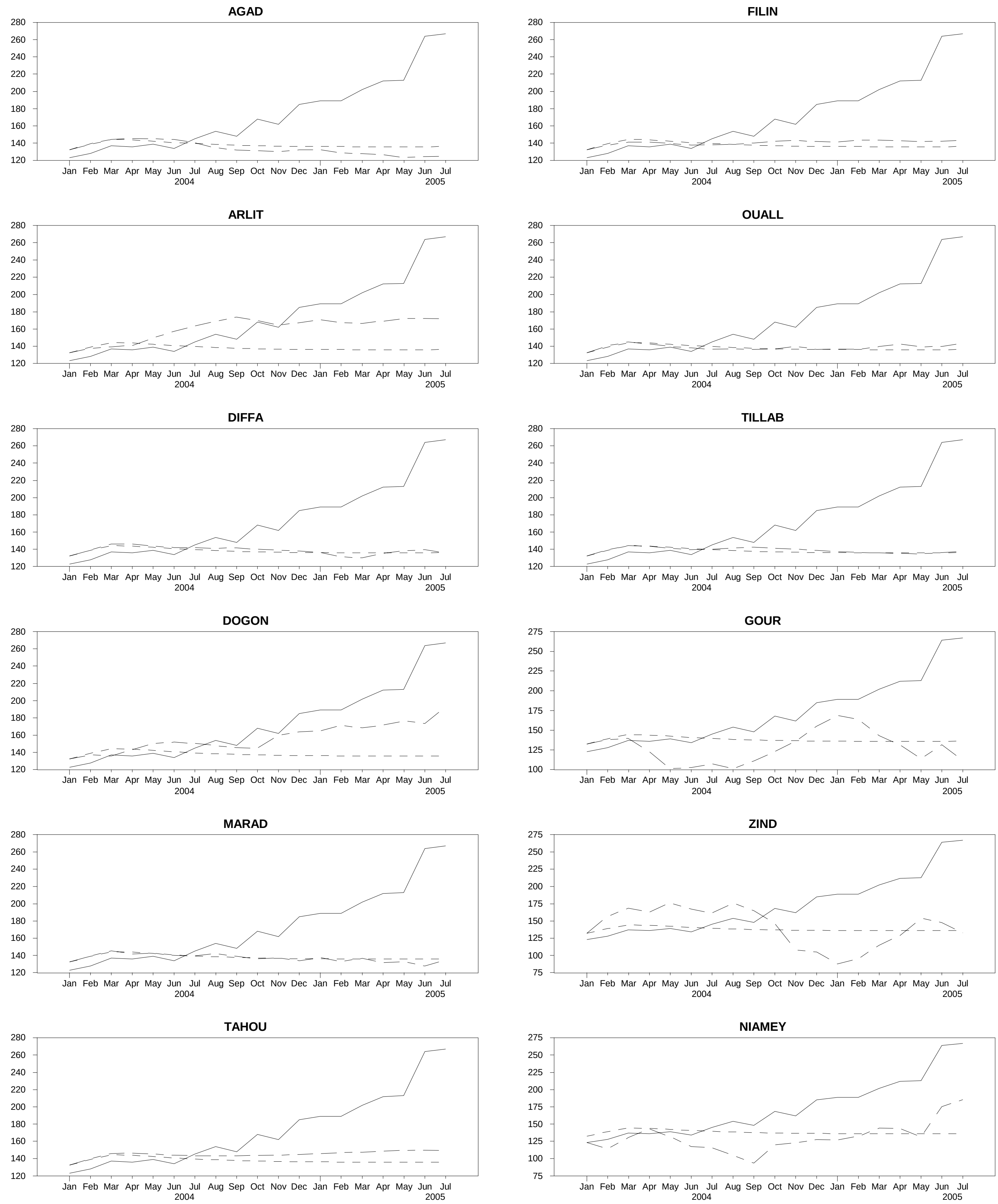


Figure 4 Historical Decomposition of millet price in Niamey (Fcfa/kg)

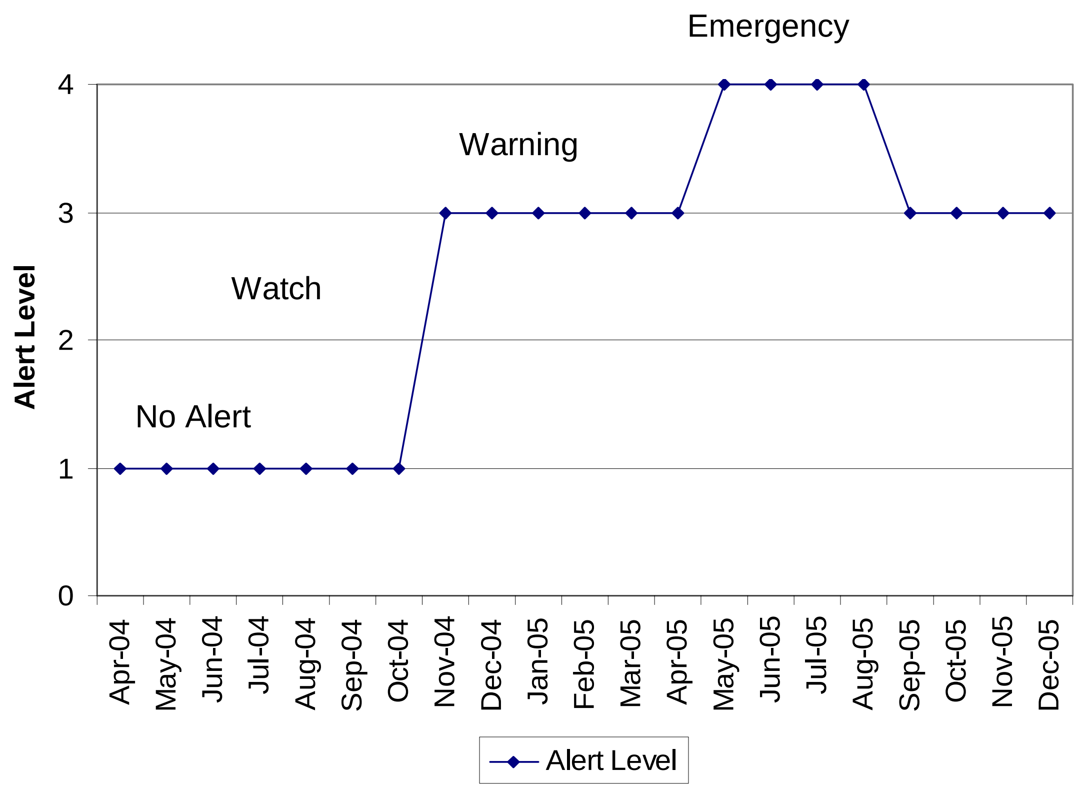
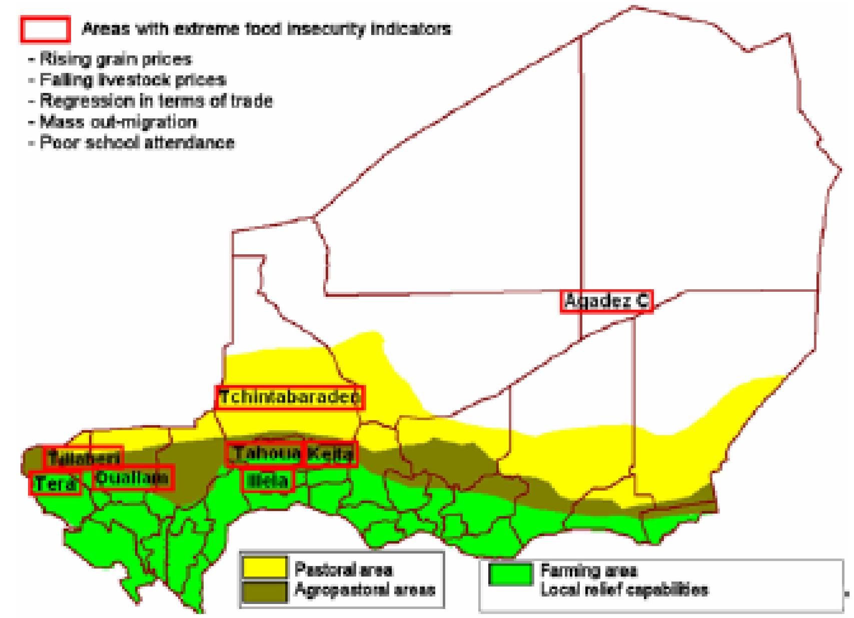


Figure 5 FEWS NET alert levels posted on their websites: April 2004 through December 2005.
Source: FEWS NET Niger.

Figure 1: Conditions in extremely food-insecure areas



Source: Joint mission; Graphic by FEWS NET

Figure 6 FEWS NET map of insecurity regions posted on their website in February 205
Source: FEWS NET, Niegr, February 2005.