Tracking Vulnerability

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Introduction

While starvation is mostly the consequence of structural poverty and deficient infrastructures (roads, access to water, communication systems…) combined with more or less important entitlement shocks, only major disasters (Tsunami, earthquakes, droughts or floods) or conflicts are highlighted. The reason for that is twofold: catastrophes have an incredible positive impact on audience ratings and it is extremely difficult to locate those who suffer the most and explain or understand the reasons for such situation. Even specialized agencies are not able to accurately and precisely detect food insecurity in space and time. But they are not to be blamed. Indeed, potential food insecure populations cover huge territories and represent billions of people in the developing countries. Moreover, in spite of the fact that anybody naturally understands what hunger means, there is no “gold standard” measure for food security (Maxwell et al. 1999).

This context engenders the need for a sound theoretical methodology to spatially predict food vulnerability using all available source of information. Among the statistical sciences two major schools deal with spatial prediction: spatial-econometrics and geostatistics. The former uses causal relationships to predict the interest variable while the latter takes benefit from the spatial dependence of the studied phenomenon. As different methods have diverse advantages and flaws both will bring useful information when predicting food vulnerability. The uniqueness of this paper is to efficiently merge information coming from two spatial prediction models through the Bayesian data fusion (BDF) methodology recently developed by Bogaert and Fasbender (2006). Then, our purpose is to maximize accuracy and precision of the predictions in what we call the econometric-kriging-bayesian (EKB) approach.

Niger seems to be the perfect study case for our methodology. Indeed, food vulnerability is widespread in its vast territory (1,267,000 km^2) as a consequence of complex interactions between structural poverty, huge market inefficiencies and poor infrastructures associated with local droughts or locust attacks. Consequently, it is extremely expensive to early evaluate the situation in remote zones and to establish precise priorities for food assistance programs. The proposed methodology seeks to solve both problems: to find out the food vulnerability determinants that are observable before the harvest and to detect where food insecure populations are located, efficiently using no more than the available data.

Potential benefits for the less developed country in the world (UNDP, 2006) are numerous: budget savings, efficient interventions, no neglected populations, less market price distortions induced by inconsistent interventions, policies for vulnerability reduction, and so on. Those gains are sizeable all the more the aggregation units are thinner in the EKB methodology than the currently employed by the Famine Early Warning Systems (FEWS) or its domestic counterpart SAP (Sytème d'Alerte Précoce). While the latter is at the best the *arrondissement*, which surfaces varies from 2,215 km^2 (Matameye) up to 278,818 km^2 (Bilma), the aggregation unit here adopted is the village. This is possible thanks to the GIS data that provides information about regressors for the majority part of the set of Nigerien villages. The gains in terms of targeting benefits are obvious as *arrondissements* are not even more considered as homogenous areas. Moreover, the estimated coefficients of the econometric analysis will not incur the negative effects of the information loss engendered bu the aggregation procedure (Orcutt et al., 1968).

The next section briefly describes the available data and gives evidence for extreme food insecurity in Niger. Section 3 is subdivided in four parts that outline the choice of a food security indicator as well as the three steps of the EKB methodology: econometrics (spatial error model, Anselin 1988), kriging (Cressie 1988, Cressie 1990, Schabenberger and Gotway, 2005) and Bayesian data fusion (Bogaert and Fasbender, 2006). Results obtained from those three steps are presented in section 4. Potential improvements are discussed in section 5 while section 6 concludes.

The Data

As a consequence of the 2005 food crisis, the need for a regular monitoring of households vulnerability became an evidence for the Nigerien government. The crisis demonstrated that despite all efforts the existing early warning systems were not able to accomplish their mission basing their diagnostics on data collected only at the macro level (market prices, remote sensing, pluviometry, yield estimations…). The lack of information about households led the government to finance a biannual food security survey in collaboration with the main agencies acting on this domain in the country[1]. Surveys are taking place around November (one month after the harvest) and around April-Mai (just before the beginning of the agricultural season). Villages are stratified at the region and department levels and between rural and peripheral urban areas. Afterwards, they are selected with a probability proportional to the number of households living in the village. Twenty households per village are randomly selected. The household data we have comes from the first survey that was conducted in April 2006 and covered 528 villages for a total of 10,564 households[2].

This survey (Enquête sur la Conjoncture et la Vulnérabilité Alimentaire des Ménages), collected information about the composition of the household, its consumption, debts, agricultural production and livestock as well as about sales, purchases and transfers carried out. Moreover, few questions about the coping strategies adopted by the household were asked. The main descriptive statistics are summarized in table 1. The food insecurity that characterises the country can easily be noticed: (i) less than 6% of the households consider

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[2] The Bilma department was excluded from this survey due to budgetary constraints as well as Niamey city, structurally considered as the less vulnerable region in the country. For further details on the stratification methods and the main results of the survey, see INS-Niger et al. 2006.

their production sufficient to feed their families during the whole year, (ii) 60% are still in debt as a consequence of the 2005 food crisis and the average debt is about 427 kg of cereals (millet, sorghum, maize and rice) plus 44,000 FCFA while (iii) only 5.5% benefited from an average food aid of 154 kg of cereals and (iv) in average a Nigerien take less than 3 meals a day consuming vegetables only one day out of two and animal proteins two days out of three. Moreover, the revenues of more than 20% of the households comes from only one activity (mostly agriculture, trade or livestock) and almost 40% of them have at least 80% of their revenue that comes from only one activity. In this context, 47% of the households sold livestock and 36% personal belongings to buy food while 31% consumed wild and poorly digestible plants.

Table 1 – Households characteristics and food insecurity in Niger.

Variable	Obs	Mean	Std. Dev.
Average size	10564	7.02	4.87
Months the current cereals storage can cover	10497	0.85	2.71
Tropical Livestock Units	10564	1.74	5.5
Debt (Kg of cereals)	6377	427.5	2717.5
Debt (FCFA)	6377	43628	75071
Aid received (Kg of cereals)	573	154.18	878.41
Meals per day	10554	2.43	0.72
Different cereals consumed per day	10564	1.78	0.68
Different proteins sources consumed per day	10564	0.65	0.63
Different vegetables/tuber consumed per day	10564	0.48	0.55

Variable	Obs	% HH	Std. Dev.
Harvest is enough for a year	9137	5.63	23.04
In debt	10564	60.37	48.91
Benefited from food aid	10564	5.42	22.65
Whole revenue comes from one activity	10564	20.09	40.07
At least 80% of the rev. comes from one activ.	10564	37.91	48.52
Sold livestock to buy food	10558	46.8	49.9
Sold personal goods because of food insecurity	10558	36.21	48.06
Ate wild plants during the last month	10561	31.29	46.37

In addition to the household level data, GIS data coming from different sources were also used:

- General Census of Population 2001 conducted by the Institut Naional de Statistique (INS) that has listed 28,308 villages (from which 23,321 are georeferenced) for a counted total population of 11,060,291 inhabitants (9,309,523 for the georeferenced villages).

- Global Insight Plus (source: Europa Technologies) database that provides information about roads and major drainage features.
- Classification of the territory in major food economy zones obtained from FEWS Net. The initial classification that subdivided the country in 10 zones[3] was simplified in three main zones: pastoral (a-d), agro-pastoral (e) and agricultural (f-j).
- *Arrondissement* vulnerability indicator made by the SAP for 2004-2005 agricultural season that should capture any residual effect of the previous and recent crisis.
- Remote sensing data: Spot-4/5 Vegetation Data (1x1 km resolution) 10 days mean composites from 1 January 2000 to 31 December 2006 (Vancutsem et al, 2007).

Methodology

The proposed methodology has the objective to generate a food security indicator for the whole set of georeferenced Nigerien villages. First, a simple but reliable indicator extracted from the INS survey was constructed as well as an agricultural season indicator based on the remote sensing data. Second, an econometric model was developed using GIS data as regressors. The fact that all regressors are observable at every point of the space ensures the applicability of the small area estimation (SAE) approach (Ghosh and Rao, 1994) at the village level. Third, kriging (Schabenberger and Gotway, 2005, pp. 226-232) was used to predict food security in non-surveyed villages, taking benefit from the spatial dependence of the phenomenon. Finally, predictions coming from the SAE approach and from kriging are merged through the Bayesian approach proposed by Bogaert and Fasbender (2006) to compose what we call an Econometric-Kriging-Bayesian (EKB) approach. Such is the structure of this section.

Food Security and Agricultural Season Indicators

[3] (a) Desert, (b) Bilma Oases, (c) Aïr Mountains Cultivation, (d) Pastoral, (e) Agro-pastoral, (f) Rainfed agriculture, (g) Rainfed agriculture high work out-migration, (h) Southern irrigated cash crop, (i) Koumadougou river and Lake Chad cash crop zone, (j) Niger River irrigated rice.

By listing up to 172 studies that seek to define and measure food security, Maxwell and Frankenberger (1992) didn't merely highlight the diversity of point of views and the complexity of the task but also induced the reader to the same conclusion than Maxwell et al. (1999) seven years later: there is a lack of 'gold standard' measure for food security, no definition or measure captures the concept accurately and completely. Indeed, even if most definitions are closely related with the World Bank's definition (1986, pp.1) which is the "access by all people at all times to sufficient food for an active, healthy life", its measurability remains problematic.

Maxwell et al. (1999) showed that indicators derived from coping strategies can be reasonable proxies for consumption and expenditure variables. However, in our opinion, this result mostly relies on the fact that the indicators were tested from surveyed households within the geographically restricted and homogenous area of Greater Accra (Ghana). In the case of Niger, the weight attributed to each coping strategy should tremendously vary between ethnicities, food economy zones, according to the proximity to markets and cities and so on. Moreover, no ranking has been established by focus groups. So we tempted instead to extract some information from the limited but available consumption and expenditure variables. First, note that the calculation of the most common and probably desirable indicator, that is to say daily caloric intake, is not possible. Indeed, consumption variables only report the number of days that each product has been consumed during the last week while expenditure variables completely ignore auto-consumed quantities. Second, as already mentioned, habits, strategies and opportunities vary significantly across the vast Nigerien territory. Consequently, the number of days that a household has consumed a given product can hardly be compared within our sample of villages. For instance, a Peul (ethnicity of herders) is expected, *ceteris paribus*, to consume meat and milk more often than a Hausa or Djerma (ethnicity of farmers) while the latter will consume more cereals. Given the absence of a reliable indicator, we decided to derive food security from an extremely simple proxy for food consumption and to evaluate the consistency of the econometric results by testing the same specification using the complex vulnerability index computed by the INS-Niger[4] (2006).

Our proxy variable groups together households in three classes, food secure, vulnerable and food insecure, using expenditures on sugar and/or on cooking oil during the last month. The idea comes from the fact that (i) sugar and cooking oil are complements to mostly of the dishes consumed in the country (they do are proxies for food consumption), (ii) they are used in a similar way by each ethnic group (no ethnical bias), and (iii) they or their substitutes are rarely produced and consumed by the same household (no omitted quantities). Table 2 shows that only 46.9% of the households have bought both commodities (food secure) and up to 25.5% has bought none (food insecure) during the previous month. Households that have bought only sugar or cooking oil are considered as vulnerable.

Table 2 – Has your household bought sugar/ cooking oil during the last month?

	Sugar		
	No	Yes	Total
Cooking oil No	25.5%	6.5%	32%
Cooking oil Yes	21.1%	46.9%	68%
Total	46.6%	53.4%	10,564 households

In spite of the fact our classification is weakly correlated with the one made by INS-Niger (polychoric correlation= 0.5 at the household level and 0.7 at the aggregated village level), econometric results obtained are robust to both regressands (see appendix 1 for the results of the regression using the INS-Niger vulnerability indicator).

Besides the vulnerability indicator that is used as dependent variable in our model, an agricultural season indicator was derived from the remote sensing data in order to be used as independent variable. Measurements of reflected light are often used for remote assessments of green biomass or vegetation physiological stresses in natural vegetation or agricultural

[4] The INS-Niger index takes into account what they call the three dimensions of the food security, that is to say availability, economic accessibility and food use. To do so, they calculated and integrated scores for food consumption, livestock ownership and household total expenditures. The methodology is explained in INS-Niger (2006, pp. 48)

plants (Tucker and Sellers, 1986). The most common indicator used in remote sensing is the normalized difference vegetation index define as

$$NDVI_i = (NIR_i\text{-}RED_i)/(NIR_i+RED_i)$$

Where RED is the intensity of the reflected light in the red band, NIR is the reflected intensity in the infra-red band and *i* is a pixel index. The use of NDVI partially solves the problems of soil influence and varying lighting conditions.

In this study, to spatially detect anomalies in vegetation growth during the 2005 rainy season, Spot-4/5 Vegetation Data (1x1 km resolution) were chosen because of their good radiometric integrity, their coarse resolution and their good temporal coverage since 1999. The data set consisted of time series of 10 days NDVI mean composites from 1 January 2000 to 31 December 2006 (Vancutsem et al, 2007). The time series, clipped to cover only Niger were processed in ArcGIS version 9.2 using the spatial analyst extension. Local statistics (per pixel) were performed to average 10 days NDVI images over the seven year period (2000-2006) to produced 36 averaged NDVI images (one per decade). For the year 2005, averaged images were subtracted from the 2005 NDVI composites for the period 1-36 producing anomalies images, a positive value indicating a denser/greener vegetation than average for the period while a negative value suggesting less green vegetation. This procedure is summarized in the following equation.

$$AI_{y,d,i} = NDVI_{2005,d,i} - \frac{\sum_{y=1}^{n} NDVI_{y,d,i}}{n}$$

Where n is the number of the years considered in the procedure, y is a year index, d a decade index and i a pixel index. This anomaly index (AI) was used to obtain agricultural season indicators at the village level. A 10 km radius buffers were created in ArcGis around all the villages to average anomaly pixels in the buffer for the periods 1-36. Standard deviation of anomalies was also calculated at the village buffer level. Different decades were tested in the econometric model. Decade 24 that on average corresponds to the NDVI seasonal peak, was used in the econometric analysis, but it is worth noting that results remain almost unchanged when decade 23 or 25 are used.

Econometrics

The econometric approach is straightforward. Assume a food security indicator aggregated at the village level $\left\langle Z_s : s \in D \subset \Re^2 \right\rangle$ measured at locations *s* in the random spatial set *D*. Let *X*, be a set of structural variables and *Y* a set of time varying variables, both observable at every point of *D*. The following regression was run:

$$Z_s = \beta X_s + \delta Y_s + \varepsilon_s \qquad (1)$$

where $\varepsilon_s \sim G(0, \Sigma(\theta))$ are the model residuals and the parameters to be estimated are β and δ. This simple regression technique permits to distinguish the effects of structural problems or seasonal shocks on food security. Moreover, and it is the focus of this paper, predictions of food security situation can be obtained for all villages inside *D*. However, given the fact we are dealing with a spatial process, residuals are not guaranteed to be iid and this hypothesis must be tested. Residuals spatial independence was rejected by both Moran's I and Langrange multiplier statistics with a p-value<0.000[5]. Consequently, OLS estimators are no longer efficient and their estimated standard errors are biased. To solve this problem a spatial error model was adopted. Equation (1) holds but the errors are assumed to be auto-correlated:

$$\varepsilon = \lambda W \varepsilon + \mu$$

Where λ is the spatial autoregressive parameter, *W* is a spatial weight matrix and μ denotes a vector of homoskedastic and uncorrelated errors. Then, the variance-covariance matrix becomes:

[5] We are aware about the caveats raised by Schabenberger and Gotway (2005, pp.307-316) concerning the use of classic Moran's I to test spatial autocorrelation of OLS residuals. Among the proposed solutions, we've adopted the first one: "proceed with the raw residuals but understand the implications and (try to) interpret the results accordingly". In our case, it means precaution when accepting the null hypothesis of no spatial autocorrelation. Rejection is in our case beyond doubt.

$$\text{cov}(\varepsilon_s, \varepsilon_{s+d}) = \sigma^2 f(d)$$

Where ε_s and ε_{s+d} are the residuals at two locations d kilometres apart and $f(d)$ is a distance decay function with: $f(0) = 1$; $|f(d)| \leq 1$ for $\forall d$; and $f(d) = 0$ for $\forall d > \bar{d}$ the radius of considered neighbourhood. The distance decay applied is $f(d) = 1/d$ and the radius of the considered neighbourhood is 200 km.

Kriging

"Everything is related with everything else, but near things are more related to each other". The first law of geography invoked by Tobler (1970) clearly raises the main characteristic of every spatial process, that is to say spatial autocorrelation. For econometricians, it represents a problem to be solved, contrary to geostatisticians who see an opportunity to be seized. The divergence comes from the fact that causality is the major concern for the former while spatial prediction is the central question for the latter. Different methodologies for univariate spatial prediction are available in the classic geostatistician toolbox. As a whole, they share the same general formulation when predicting a random variable $Z(s_0)$ at an unobserved location s_0 based on a set of observations $Z(s_\alpha)$ in the neighbourhood of s_0:

$$Z^*(s_0) = m(s_0) + \sum_{\alpha=1}^{n_0} \lambda_{\alpha,0} \left(Z(s_\alpha) - m(s_\alpha) \right)$$

Where $Z^*(s_0)$ is the predicted value for the random variable at location s_0, $m(s_i)$ is the expected value for the random variable at the location s_i and $\lambda_{\alpha,0}$ is the weight assigned to the observation at location s_α. Divergences between methods come from: (i) the assumptions about $m(s_i)$, (ii) the distance function used to generate the weights; and (iii) the loss function used when estimating the weights. The most widespread adopted predictor is without any doubt kriging that is referred as the Best Linear Unbiased Predictor (BLUP) under square error loss function (Cressie, 1990). Moreover, kriging is an extremely flexible technique that allows nugget effects and polynomial specifications for $m(s_i)$, it accommodates anisotropy[6] and it can "honor" or "smooth" the data. But the success of this technique probably comes from the fact that its distance decay function for spatial weights is estimated from the data and not imposed by the modeller[7]. For those reasons kriging was chosen as the second spatial predictor in our methodology.

As second-order spatial stationarity is a required assumption for the meaningful interpretation of the estimated semivariogram[8], the first step is to remove any macro-trend in the spatial process of our interest variable Z_i. This is done by assuming $m(s_i)$ to vary on the spatial domain D following the same quadratic specification than in the econometric model. Thus, the empirical semivariogram $\hat{\gamma}(d)$ of the remaining spatial process is calculated:

$$\hat{\gamma}(l) = \frac{1}{2|N(l)|} \sum_{N(l)} \{Z(s_i) - Z(s_j)\}^2$$

where l denotes a spatial lag or a distance interval, $N(l)$ and $|N(l)|$ respectively represents all pairs of observations $\lfloor Z(s_i); Z(s_j) \rfloor$ and the number of pairs inside l. The next step consists in fitting the semivariogram $\hat{\gamma}(d)$ with an appropriate function. Given the obtained empirical semivariogram (Graph 1, section 4), the following exponential model was chosen:

$$\gamma(d) = \theta_{ps}\left(1 - \exp\left(-3\frac{d}{\theta_r}\right)\right) + n\theta_{ps}$$

Where θ_{ps} is the partial sill parameter, θ_r the range parameter, d is the distance between two observations and $n=0$ if $d=0$ and $n=1$ otherwise. It is worth noting that the

[6] A spatial process is said to be anisotropic if spatial dependencies are not identical in all directions. For a brief discussion about accommodating anisotropy, see Schabenberger and Gotway (2005, pp. 151-152).
[7] For a general discussion about kriging methods and spatial prediction see Schabenberger and Gotway (2005) chapter 5.
[8] The semivariogram estimates how the dissimilitude between two spatial observations increases with the distance separating them.

coordinate system was transformed in order to accommodate anisotropy before distances and lags have been calculated.

Bayesian data fusion

Finally, information coming from the econometric model and from kriging should be merged in a sound theoretical framework. Indeed, both models bring pertinent and complementary predictions for unsampled villages. In one hand, the econometric approach above described is based on causal relationships between food security and structural and seasonal variables. Consequently, predictions are consolidated by the economic theory and the magnitude of the effects is estimated by using Best Linear Unbiased Estimators (BLUE). Standard errors of the predictions depend on the values of the exogenous variables at the prediction location. Consequently, predictions are more reliable for average villages. Despite the fact it is a desirable characteristic (interventions should not be based on outliers), it can mislead interventions if vulnerability is associated with marginality. On the other hand, kriging is based on the spatial autocorrelation between observations. Here there is no direct causality relationship. However, as the autocorrelation is spatially structured, kriging takes benefit from the locally observed data and generates region specific BLUP predictions. Predictions' standard error varies with the density of the observations in its neighbourhood. They are expected to be smaller (larger) than those coming from the econometric approach if the prediction is situated in a densely (sparsely) sampled area.

Following the Bayesian data fusion approach proposed by Bogaert and Fasbender (2006), the predictions derived from both models can efficiently be merged. Starting from a simple error model of the form Z=g(Y)+E, where Y is a set of observable variables and Z is the interest variable and the authors, the authors derived the following naïve Bayes' fusion rule of individual posterior predictors given by $f\left(z_0 \middle| y_{0,j}\right)$:

$$f\left(z_0 \middle| y_0\right) \propto \frac{1}{\left(f\left(z_0\right)\right)^{m-1}} \prod_{j=1}^{m} f\left(z_0 \middle| y_{0,j}\right)$$

By assuming that:

$\varepsilon_j \sim G\left(\mu_j, \sigma_j^2\right)$

$E_{reg} \perp E_{kri}$

The following simple fusion rule applies:

$$\mu_{fus} = \sum_{j=1}^{m} \frac{1/\sigma_j^2}{\sum_{k=1}^{m} \left(1/\sigma_k^2\right)} \mu_j \qquad\qquad \sigma_{fus}^2 = 1 \Big/ \sum_{j=1}^{m} \frac{1}{\sigma_j^2}$$

The first hypothesis directly follows from the properties of the residuals from both Kriging and the Spatial-error regression model. Testing the second hypothesis is beyond the scope of this paper, but it is justified by the fact that it is the hypothesis that maximises the entropy of the system.

Results

Econometrics

In Africa, structural problems account more for food insecurity than conjunctural shocks (Platteau 1990). Niger, where food crises are endemic, is not an exception to the rule (Aïssetou and Boureima, 2006). Consequently and as expected, the econometric model run shows the crucial role played by long-term variables on food security. However, before the interpretation of the results, it is worth noting that the 2005 agricultural season was fairly good with a national cereal production surplus of 21.000 tonnes (INS-Niger et al., 2006). Thus, it is important to bear in mind that the measured vulnerability can be the result of (i) structural constraints, (ii) local rainfall failure during rainy season or (iii) the reminiscence of the previous food crisis; in a generally favourable domestic context. Different results would be obtained in severe or moderate drought years.

Table 3 – Description of the regressors

Variable	Range	Description
LDistRoad	[0;5.16[	Logarithm of the Euclidean distance in kilometres to the nearest paved road plus 1
LDistDrain	[0;4.46[	Logarithm of the Euclidean distance in kilometres to the nearest river, lake or irrigated zone plus 1
Irrigated	[0;1]	1 if the village is inside an irrigated zone, 0 if not
Latitude	]11.88;16.79 [	Village's latitude in decimal degrees
Longitude	]0.78;13.06[	Village's longitude in decimal degrees
InvPop	]0.004;1.11[	Inverse of the population density in inhabitants per km^2
Agri	[0;1]	1 if the village is inside the agricultural zone, 0 if not
Agropast	[0;1]	1 if the village is inside the agro-pastoral zone, 0 if not
dMoy_NDVI_24	]-0.07;0.05[	Average vegetation (NDVI) anomaly in a buffer of 10 km radius around villages for the 24th decade of the year.
LdStd_NDVI_24	]0.005;0.61[	Standard deviation of the vegetation (NDVI) anomaly in a buffer of 10 km radius around villages for the 24th decade of the year.
Vulne2005	]0.01;0.033[	Inverse of the food security index calculated by the Système d'Alerte Précoce during the 2005 crisis for each "arrondissement"

In spite of recent efforts of the local government and international agencies, the vast Nigerien territory remains poorly covered by paved roads. Remote villages suffer from little scope for labour and production specialization, hard access to agricultural inputs and weakly integrated cereal markets (Platteau, 1990; Gaspart and Marinho, 2007). The variable LDistRoad shows that those factors do have a negative impact on food security in villages. However, the magnitude of this effect is probably smaller than one could expect. A village situated 26 km from the nearest paved road, which is the average distance for our set of villages, has an expected average food security indicator 0.071 unit smaller than a village where the road passes through, and 0.1 smaller if the distance is 100 km. In spite of that, it is important to note that the dilapidation of the roads and the laterite roads have not been considered. The omission of both variables is likely to engender a downward bias of LDistRoad coefficient. On one hand, damaged roads can not have the same positive effect on food security than a newly built one. The estimated coefficient consequently is the effect of an average Nigerien paved road. On the other hand, as laterite is a fairly good substitute to asphalt, the measured effect is partially the marginal difference between a paved and a laterite road. Thus, before making any policy recommendation, this result should be reconsidered by including roads quality and laterite roads in the analysis. Unfortunately, this data is not available and we do recommend agencies willing to understand food security process in Niger to finance such data collection.

Water is with soil nutrient, the main constraint to agricultural production in the country. Moreover, access to this resource plays a crucial role in sanitation and nutrition. Consequently, distance to the nearest river, lake (both perennial or not) or irrigated zone has an impact on food security. Indeed, it is a good estimator of how deep plants and above all men should go to find water. This is corroborated by the negative sign of the estimated coefficient of the variable LDistDrain. Again, the measured effect is quite moderate. Indeed, the average distance between a village and the nearest water source (excluding wells) is around 18km what implies an expected food security indicator 0.052 units smaller than a village situated on the border of an irrigated zone. However, the difference between villages falling inside an irrigated zone and the others villages is quite important. Indeed the coefficient of Drain is 0.18, which represents near to 10% of the total range of variance of our interest variable.

Table 4 – Spatial error model for food insecurity in Niger

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Spatial error model                                   Number of obs   =       394
                                                      Variance ratio  =     0.407
                                                      Squared corr.   =     0.533
Log likelihood = -136.96777                           Sigma           =      0.34
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	Coef.	Robust Std. Err.	P>|z|	[95% Conf.	Interval]
Longitude	-.0681638	.0990926	0.492	-.2623818	.1260541
Londitude^2	.0097493	.008382	0.245	-.0066792	.0261778
Latitude	.4589602	.7207138	0.524	-.953613	1.871533
Latitude^2	-.0117009	.0255424	0.647	-.0617631	.0383614
LDistRoad	-.049416	.0171324	0.004	-.082995	-.015837
LDistDrain	-.0398449	.0192148	0.038	-.0775052	-.0021846
Irrigated	.183209	.0853859	0.032	.0158558	.3505622
InvPopulDens	.1084599	.1857424	0.559	-.2555885	.4725083
Agri	-.7119844	.1340024	0.000	-.9746244	-.4493444
Agropast	-.3797673	.1209934	0.002	-.61691	-.1426247
dMoy_NDVI_24	3.360474	1.039625	0.001	1.322847	5.398102
LdStd_NDVI_24	-1.103054	3.75401	0.769	-8.460778	6.254671
Vulne2005	-15.2257	7.295702	0.037	-29.52501	-.9263828
Constant	-1.877354	5.080569	0.712	-11.83509	8.080378
lambda	.8488023	.1137167	0.000	.6259216	1.071683

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Wald test of lambda=0:                  chi2(1) =  55.714 (0.000)
Lagrange multiplier test of lambda=0:   chi2(1) =  44.155 (0.000)

Acceptable range for lambda: -2.786 < lambda < 1.000
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In terms of population density, our findings plead either the reconciliation of the simplistic and apparently opposed Malthusian and Boserup theories or the refutation of both. Population density does not have an impact in food security at the village level in Niger, and this is a robust result[9]. Malthus supporters should assume overpopulated zones to be more food insecure as a consequence of the scanty of the resources, while the opposite is true for Boserup that expect more technical progress and lower per capita investment cost in highly populated areas. The truth is probably somewhere in between, and the compromise is the outcome of widespread migration practice. The density map (appendix 1) shows that Nigeriens are concentrated in zones with favourable physical characteristics to agricultural activities and livestock rising, in what we should call a spatial Malthusian equilibrium. However, in spite of the recurrent food insecurity, that corroborates the Malthus thesis, the Nigerien population has grown 3.3% in average per year between 1988 and 2001 (INS-Niger et al., 2006) and 3.6% in 2005 (UNDP, 2005), showing an increasing carrying capacity of the environment due to investments in infrastructures (roads, irrigation systems, wells, health centres…) and progress in agricultural techniques (use of fertilizers, phytosanitary products, improved grains…). Those improvements are mostly concentrated in highly populated zones, following Boserup's theory. In short, thanks to its high mobility, population seems to be optimally distributed in the Nigerien territory.

Another explanation for the fact that population density does not have a significant coefficient can be derived from Boubacar (2000) that ascertains that more populated zones are inclined to have weaker social networks and more unequal land tenure systems. Following the author, when land becomes scarce local populations try to impose Islam's laws that are more individualistic over traditional power, weakened during the colonisation period. This shows

[9] This result is robust to any tried specification when using our FSI and regressand. However, if it is replaced by the INS-Niger vulnerability indicator, populated areas appears as significantly more food secure corroborating the Boserup thesis.

that agricultural system intensification resulting from Boserup theory does not directly imply higher food security, as traditional mutual insurance diminishes while inequality increases.

As rural population tries to adapt their activities to their environment, different agro-pastoral systems can be found following the latitudinal pluviometry gradient, going from 700-800 mm/per year in the south till 0 mm in the Sahara desert. Three main systems can be distinguished: agricultural, agro-pastoral and pastoral. Agricultural zone is situated in the south, where rainfall is relatively abundant, rural revenues come mostly from cereal and cash crops (millet, sorghum, beans, peanuts, onions…) even if livestock also plays an important role in terms of savings and risk diversification. In the north, the pastoral area is populated by nomads that rely on livestock breeding (cattle, goats, lambs, dromedary camels…) for living. Mixed agro-pastoral systems can be found in between, where settled nomads take benefit from the abundant quantities of manure produced by their animals to improve soil fertility and insure an efficient use of the water by the crops; while traditional cereal producers try to increase their livestock for the same reasons. Variables Agri and Agropast capture the differences between those 3 systems in terms of food security. Pastoral zone appears as the most food secure while the opposite is true for the agricultural area. This is the result of a relatively good 2005-2006 crop season that improved the livestock-cereal terms of exchange. But it doesn't mean that nomad populations are less vulnerable in the long-term. On the contrary, when a drought takes place, cattle losses are significant and moreover the livestock-cereal terms of exchange collapses. Then, the estimated differences between the three zones are an evidence of the risk premium paid (through demographical pressure) by agricultural households to live in a riskier environment.

Concerning the agricultural season indicators, the coefficient of the variable *dMoy_NDVI_24* is highly significant showing that useful information can be derived from remote sensing data in order to improve vulnerability diagnostics. Its positive coefficient shows that when the average NDVI around a given village in the 24^{th} decade is above (under) its inter-annual average, the food distress of its population is lower (higher). This result is promising, all the more this indicator is extremely simple. Indeed, as better indicators of agricultural production can be derived from remote sensing data (see Dorigo et al., 2006 for a review), much can be expected from the integration of this kind of data in econometrics models aiming to spatially predict food insecurity. Moreover, as the indicator can be obtained before the harvest, emergency agencies will have more time to plan their interventions. However, the coefficient of the disparities inside the village indicator, *LStd_NDVI_24*, is not significantly different from zero, although it has the expected negative sign and that result is robust do different specifications. The explication for that is threefold: (i) the anomaly indicator (AI) here employed may be too simple, and more robust results can merge when using a better AIs; (ii) mutual insurance schemes may be able to ensure households their minimal needs even if revenues are not completely smoothed; (iii) auto-insurance strategies, such as the spatial dispersion of the farmers' plots, may undermine the pertinence of this variable. Further research on those topics is needed.

Finally, the 2004-2005 food crisis is still perceptible despite humanitarians efforts and the following good rainy season. And the remaining effects are sizeable. According to the SAP, Tera, Tillabery and Keita were the three *arrondissements* that suffered the most during the crisis. As a consequence of that, our food security indicator is on average and respectively 0.32, 0.23 and 0.21 smaller in the villages of those *arrondissements* than in villages from Gaya, the less affected zone. This finding is extremely important for many reasons. First, food crises in the recent past have to be taken into account when predicting food security in a given period. Indeed, households can remain vulnerable two years after a production shock. Second, a good harvest can not insure households to recover food security. Third, in spite of the fact that humanitarian aid prevented many deaths during the 2004-2005 food crisis, there is a lack of social net programs that help households to find food security again. In other words, short-term humanitarian actions are palliative measures for emergency problems and do not really contribute to medium and long-term problems.

Figure 1: Food insecurity spatial predictions generated by the spatial error model.

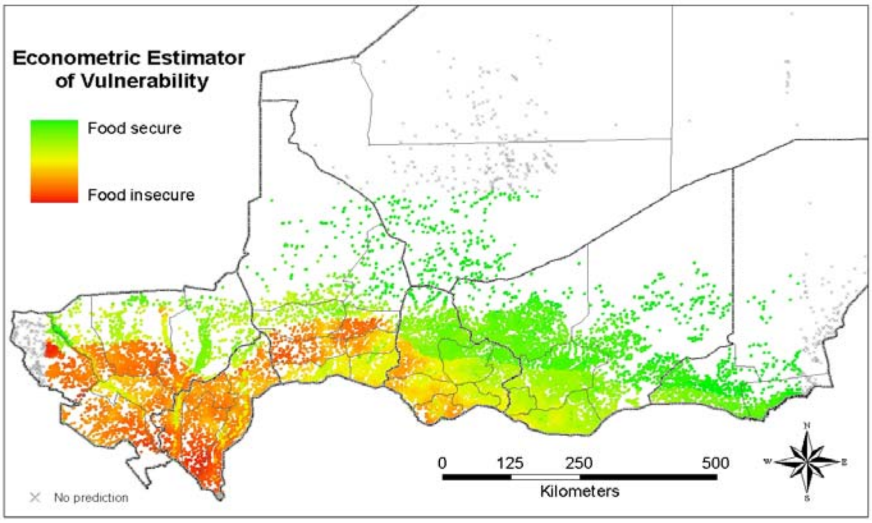
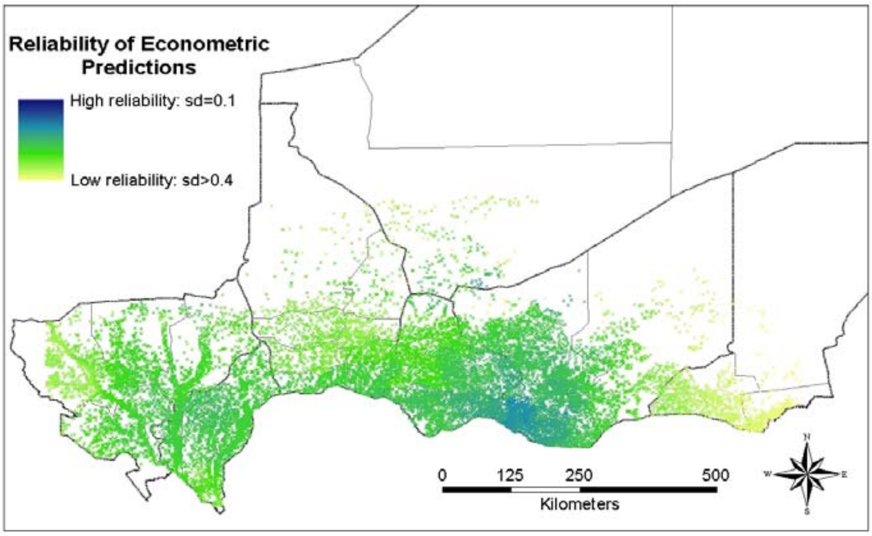


Figure 2: Standard errors of the food insecurity spatial predictions generated by the spatial error econometric model.



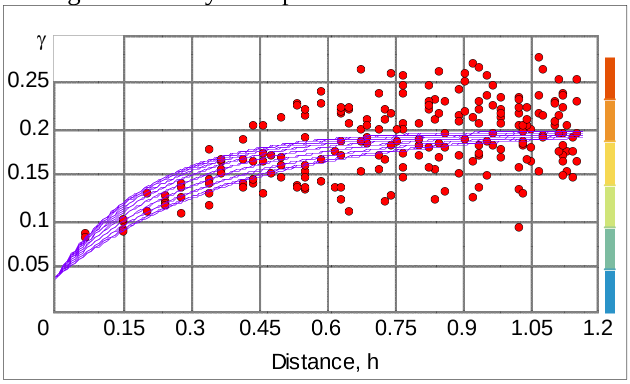
Kriging

The first step for the Kriging methodology we've applied is to remove the macro spatial trend of the food security indicator. It is worth noting this trend will be re-added to the estimated values at the end of the methodology. The quadratic specification generates the following trend removal surface:

S=12.77154+0.0172277*x^2-0.1208476*x+0.0720861y^2-1.84618*y

that reaches its minimum in the department of Dosso around Dosso, Zabori and Karakara *arrondissements*.

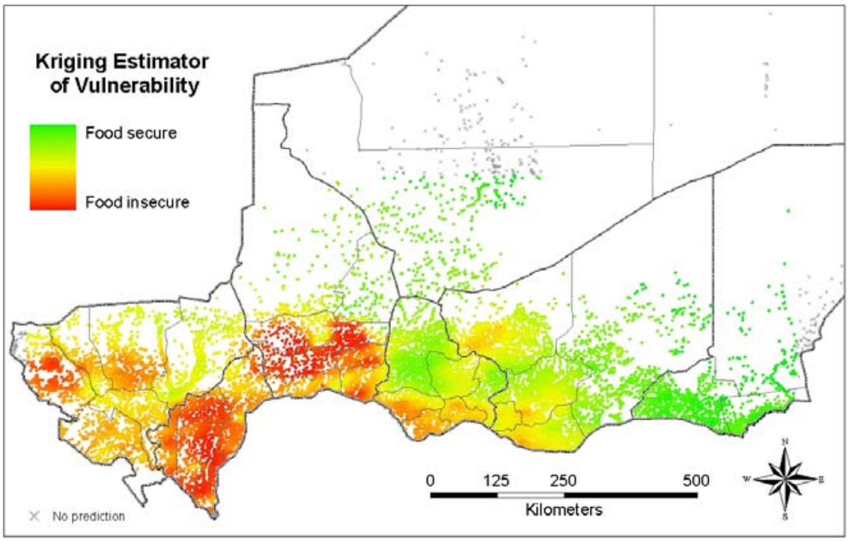
Graph 1 – Anysotropic semivariogram fitted by an exponential model



Than, the semivariogram can be estimated following equation (X). Graph 1 shows a set of semivariogram points and the estimated exponential semivariogram functions. Twelve spatial lags of 0.098 decimal degrees (approximately 10km) have been used to fit the exponential model (X). Evidence for anisotropy has been found. The major range azimuth direction is 80°2’, showing as expected a higher longitudinal spatial dependence. This can be explained by the above mentioned South-North rainfall gradient and the major road axis linking Niamey to Zinder. Precisely, the estimated major range is 1.8 times bigger than the orthogonally directed minor range. Food security spatial independence is achieved if two villages are 1.16 decimal degrees apart in the azimuth direction of 80°2’ and 0.64 decimal degrees in the orthogonal direction.

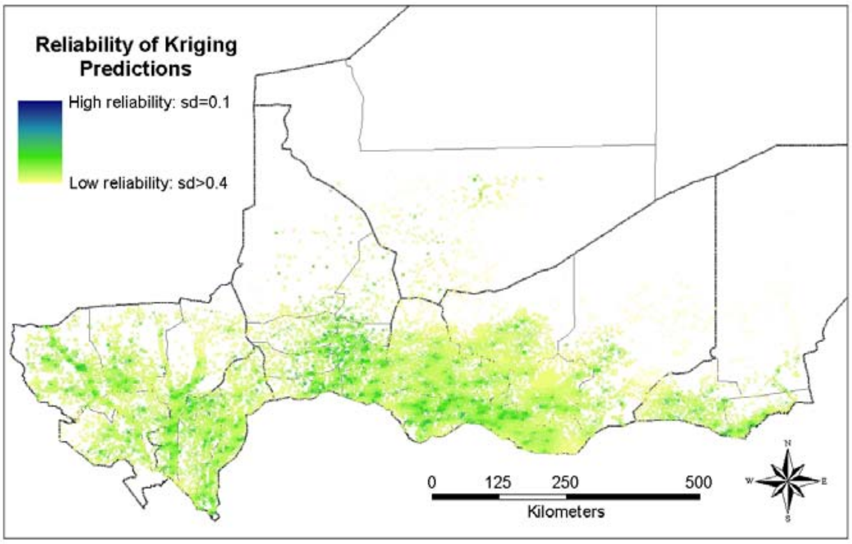
The estimated partial sill parameter is 0.163 and the nugget effect is 0.034. Interpretation for the nugget effect is twofold: on one hand it can be seen as a micro-structure in the spatial process that can not be captured by the model given the minimum distance between the surveyed villages and on the other hand, it can represent a measurement error of our interest variable. We suspect the nugget effect to mostly be the consequence of a measurement error. First, because we are dealing with an aggregated indicator based only 20 household interviews per village as an estimation of the food security in the whole village. The standard error of this estimator averaged in our set of villages is 0.031, which is extremely close to our nugget effect. Second, many surveyed villages are not more than 5 km apart from each other, what usually represents the minimum distance between two villages. Consequently, it is rather implausible that a spatial micro process is hidden in the nugget effect and it has completely been attributed to a measurement error. As a consequence of that, predictions standard errors are smoother in the space and smaller in average.

Figure 3 – Food insecurity spatial predictions generated by the kriging



Figures 3 and 4 show the predicted food vulnerability and the predictions' standard errors. Unfortunately and not surprisingly, they confirm that food security is rarely achieved in the country. Food insecure households are concentrated in the south of Tahoua, with a very thin band near the Nigerian boarder where the situation seems better, in the west of Tillabery and in almost the whole department of Dosso, while Maradi and Zinder appears as fairly food secure departments. But those general remarks hide the main contribution of those figures: it is the first time that food security in Niger is shown regardless department and *arrondissement* boarders. Here it is important to notice the existence of pockets of food (in)security, that could not be taken into account by the classical methodologies till now employed by the FEWS. This information is precious when optimizing spatial utilisation of scarce resources to fight vulnerability. If it is correctly used, every village in need can be detected and moreover no superfluous intervention should take place.

Figure 4 – Standard errors of the spatial predictions generated by the kriging



But the quality of kriging predictions is not spatially constant. Higher precision is obtained in densely surveyed and consequently populated areas. Even if this represents a desirable feature for an estimator that seeks to correctly predict food security in a maximum of villages, precision in remote areas is also fundamental. Indeed, logistic costs of interventions in isolated and sparsely populated areas are particularly high. In this context, incertitude about predictions can lead international agencies, NGOs or the local government that try avoid waste of the resources, to neglect them. The next sub-section provides a solution to this problem by merging information generated by the kriging and the econometric model.

Bayesian

Accuracy and precision are *sine quo non* conditions for efficient food assistance interventions. As human lifes directly depend on that, our two prediction models represent an inestimable source of information. However, as far as they estimate vulnerability following completely different approaches, divergences between predictions (even if marginal) are expected and ambiguities in the results should be vanished. That is the key contribution of the EKB methodology: to merge predictions in order to increase both their accuracy and precision. The results obtained by the Bayesian data fusion are shown in figures 5 and 6.

The three main vulnerability pockets detected by the kriging and the spatial error model are still visible in figure 5: the south but not the extreme south of Tahoua, the middle and the south of Dosso and the west of Tillaberi. This means that predictions of both econometric and kriging are consistent with each other. However, the vulnerability appears more structured in space as a consequence of the information brought by the econometric prediction. Indeed, they depend less on neighbouring observations, and consequently are less exposed to the above discussed measurement errors. Per example, the Niger River valley that benefits from water and a paved road clearly appears as less vulnerable than surrounding areas. If crossed with the population and intervention costs maps, those more accurate predictions can represent a powerful decision making tool. It allows the optimisation of interventions taking into account the exact emplacement of vulnerable populations. However, even the best predictions still are random variables. Consequently, optimal decisions can only be taken if the predictions expected errors are also taken into account.

Figure 5 – Final food insecurity spatial prediction, obtained by the Bayesian fusion of the predictions coming from the spatial error model and kriging

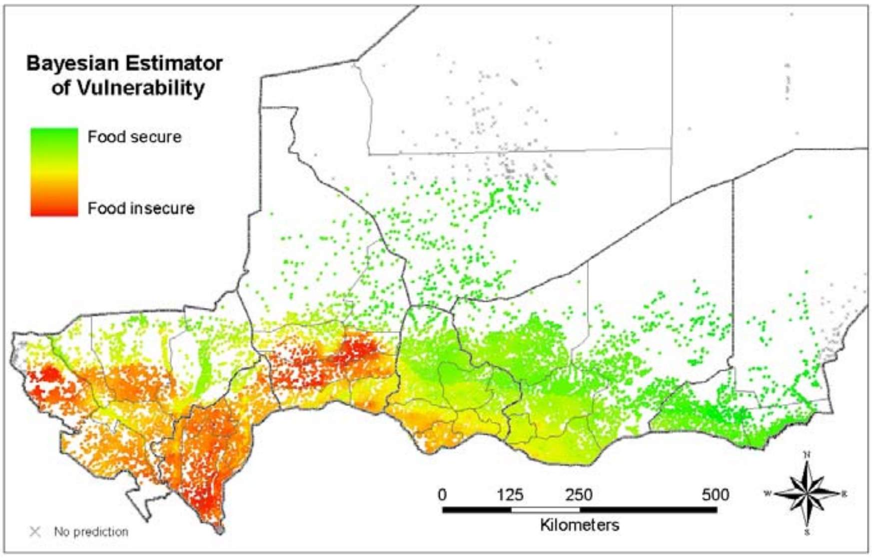


Table 5 shows how the final average standard errors of the predictions decreased from the kriging and econometric estimations. The average decrease is about 16% from the econometric model and 46% from the kriging model. This gain in reliability should not only amplify food assistance program success but also reduce inefficiencies engendered by arbitrary interventions and agencies' wariness of unnecessary interventions. Moreover the spatial variability of those errors also decreased from the econometric and kriging approaches by 20% and 41% respectively. As above mentioned, it should reduce the number of villages that were neglected not because they were expected to be food secure, but because too much uncertainty was attributed to the food insecure diagnostic. Finally, figure 6 highlights villages where predictions are still imprecise. They are located in sparsely populated and marginal (in terms of average regressor values) areas with the exception of the extreme west of Tillabery where regression predictions could not be done and only kriging predictions were available. To solve this problem, more villages should be selected in isolated areas of Diffa, Zinder and Agadez; and regressors need to be available to the whole Nigerian territory.

Table 5 – Descriptive statistics of the standard errors of the spatial food insecurity predictions coming from the spatial error model, kriging and their fusion

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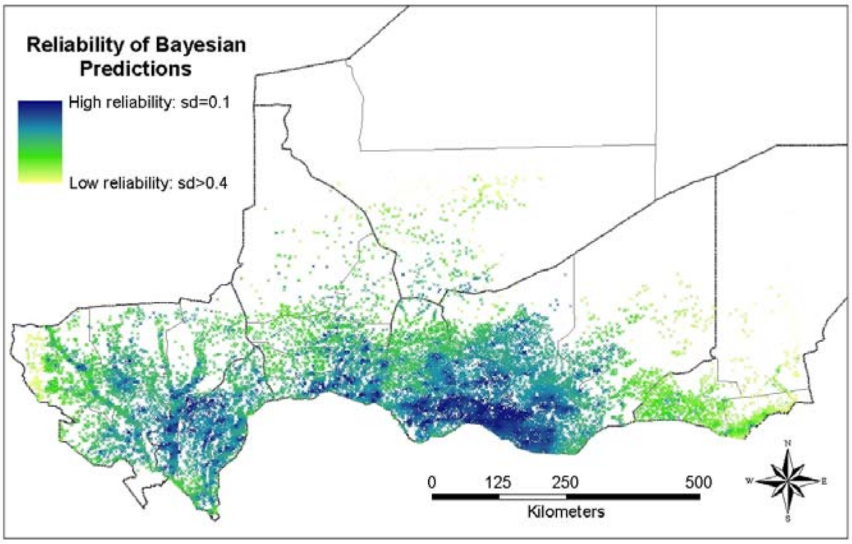
Variable	Obs	Mean	Std. Dev.	Min	Max
Spatial error model	22687	.1761861	.0406649	.135336	.883925
Kriging	22914	.2743449	.0556888	.134377	.453979
Bayesian data fusion	23041	.1476929	.0326382	.102154	.453979

Figure 6 – Final standard errors of the predictions obtained by the Bayesian data fusion



Discussion and perspectives

Encouraging results in terms of spatial prediction of food vulnerability have been obtained by the proposed EKB approach. It has been shown that an efficient use of the available information is possible in a sound theoretical framework. Potential improvements in terms of food security are numerous. First, a better targeting of villages implies on one hand less superfluous interventions, what not only is a waste of resources but can also have harmful effects on local economies such as production and market distortions (Marinho, 2007), aid dependence or corruption. On the other hand, the number of suffering people will inevitably decrease with the number of neglected villages.

Second, confidence building in a coherent, certain and timely food assistance should help farmers to increase their expected yields by an increased adoption of techniques they consider too risky in the present context (Skees et al. 2002). However, moral hazard becomes a danger, especially in the poorest zones where agricultural potential is merely enough to ensure survival. Even if this eventuality should be deeply considered in a case based analysis, two features of our methodology should limit that risk: (i) villages and not households are targeted, what implies that individuals always have an incentive to produce more than the average villager; (ii) the econometric model being based only on variables that can not be controlled by the household, interventions should weakly be function of individual action. Third, this methodology can represent the missing puzzle piece for the creation of private famine insurance in Niger. Information asymmetry represents the main constraint for this contract to be concluded. Specifically, an objective measure of vulnerability is required. That is why much is expected from weather insurance markets (Sakurai and Rerdon 1997, Skees 2000). But, without an explicit link between weather conditions and food insecurity, vulnerable households will not receive the needed help even if weather insurance contracts are signed. The EKB methodology provides such a link. Forth, this tool reduces subjectivity on famine diagnostics and consequently facilitates the mobilization of international funds when they are needed. Moreover, interventions based on donor surpluses shall reduce, at least if donors are willing to adopt an objective criteria to justify their interventions.

Besides its practical implications, EKB methodology opens promising doors for future research on food security. Possible enhancements to our study case are numerous. In terms of vulnerability indicator, daily caloric intake should be used as universal benchmark in our opinion. However, as collection of those data is time consuming and often subjected to a high degree of incertitude, researchers and above all decision makers should base their diagnostics and carefully validate their results by using other indicators. Per example, anthropometric measures are easy to collect and even if they are not early indicators, if time dynamics are introduced in the model early warnings are possible based on previous observations. Coping strategies represents a reliable indicator (Maxwell et al. 1999) but they are meaningful only in homogenous areas. The last option is the use of simple proxies as the one above adopted but in this case it is crucial to validate the results using a different and independent indicator. Improvements can also be obtained when extracting information from remote sensing data. Finally, it is also important to spatially collect information about other variables which are likely to play a role in the vulnerability mechanism and to introduce them in a similar econometric specification. Pluviometry, market prices, conflict zones, locust invasion and NGOs presence composes a list far from being exhaustive.

Spatial econometrics being a recent sub-field of econometrics (see Anselin et al. 2004 for recent advances in this topic), we anticipate major advancements on this component of the EKB methodology. In our opinion, the most promising models are Geographically Weighted Regressions (GWR) proposed by Brusdon (1998) and already adopted for spatial vulnerability predictions (Kam et al. 2005, Benson et al. 2005, Farrow et al. 2005), Micro-Level Estimation (Elbers, 2003) and Spatial-VAR (Beenstock and Felsenstein, 2007). When the methodology is to be applied on wide territories, coefficients of some variables are expected to vary over space as a consequence of different agro-ecological, socio-economical, and political systems, and GWR should bring useful information about local vulnerability mechanisms and significantly improve the econometric prediction power. However, several theoretical questions, such as the estimation of the prediction's standard error (that are requested for the Bayesian fusion) and local multicollinearity (Wheeler and Tiefelsdorf, 2005), have to be elucidated before its generalized application. Conversely, if predictions are to be made for more populated villages or cities (the average population in our sample is 400 inhabitants per village), and the available census data provides information about wealth of each household, Micro-Level Estimation should be adopted. In this case, intra-village variability can be such that village level predictions become meaningless without a pertinent inequality estimator.

Moreover, a better integration of the methods used on geostatistics and by econometricians seems to be an important path still to be explored. More specifically, the semivariogram may be used in order to estimate the spatial dependence of the residues of the econometric models. Indeed, this procedure is much more general and adapted to spatial process than those till now developed in the spatial econometrics field.

Time dynamics is one of the key issues of any Early Warning System. Consequently, the fact that INS-Niger collects information about households' vulnerability twice a year represents an opportunity that should be seized. First by trying to predict vulnerability on April based on the situation on November. And as the surveyed villages are not the same, it will also represent a validation of our spatial predictions. Second, as EKB generates predictions for every point in the space, Spatial-VAR should be accommodated in order to estimate spatio-temporal coefficients and impulse functions that will generate predictions to be merged by the same Bayesian approach.

Finally, it is important to underline that food assistance program failures can be the result of institutional and political constraints as well as a lack of accurate and precise information (Buchanan-Smith et al. 1994). In this context, the EKB methodology can represent a tool that not merely generates information but also solve political and institutional problems between food security actors. First, as the methodology is extremely flexible, it can be applied in any country taking benefit from the available data and generating results that can be objectively compared between countries. International agencies should consequently proceed to interventions coherent with the needs of populations in different countries and not based on political relations. Second, the econometric analysis helps to understand the famine process and can be used by other national or international institutions working on long-term vulnerability reduction in a profitable cooperation with the FEWS. Third, any vulnerability prediction model can be incorporated by the BDF methodology. Consequently, local government, international agencies and NGOs can contribute to the vulnerability spatial prediction bringing information at different scales and in different zones. By doing so, it can facilitate a centralized decisions that are derived from the cooperation of different actors with different knowledge.

Conclusion

Major improvements can be achieved in the existing early warning systems thanks to an efficient use of the available data. The proposed Econometric-Kriging-Bayesian methodology merges spatial predictions generated by two different estimators, one based on causal relationships, the other on the spatial correlation inherent of every spatial process. In a context where accuracy and precision of spatial predictions are vital, this tool allows a better targeting of vulnerable populations but also can improve food assistance programs through different channels: better understanding of the vulnerability mechanism, improved cooperation between different actors working in different spatial and temporal scales, budget savings, less abusive interventions and so on.

In terms of results, on one hand the output maps show that predictions generated by the econometric model are fairly spatially correlated with those derived from kriging. However, as the predicted values are linear combinations of different variables, the econometric predictions are more structured in the space while those coming from kriging are flexible to local specificities. Moreover, better predictions are obtained for different areas. Consequently, the final predictions are structured in the space but can take into account local phenomenon, and their standard errors are smaller and more homogenous in the space. On the other hand, the econometric approach showed that structural variables (roads, access to water, agro-pastoral systems) are extremely important determinants of food security, while a food crisis can continue to be felt one year latter. The results also corroborate the idea that NDVI can be used as a proxy for agricultural production by establishing a link between remote sensing and food vulnerability.

The present article is first attempt at our best knowledge that tries to integrate geostatistics and spatial-econometrics in a sound-theoretical framework. Consequently, it opens many doors for future research in terms of spatial predictions. Specifically, as the Bayesian approach allows the modeller to separate the problem and to take benefit from advancements in both disciplines, even if they take place independently.

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Appendix

```
Weights matrix
 Name: W
 Type: Distance-based (inverse distance)
 Distance band: 0.0 < d <= 2.0
 Row-standardized: Yes

Spatial error model                                Number of obs   =       394
                                                   Variance ratio  =     0.382
                                                   Squared corr.   =     0.366
Log likelihood = -176.94667                        Sigma           =      0.38

------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
```

```
-------------+----------------------------------------------------------------
class_vu_m   |
           x |  -.1184724   .0788887    -1.50   0.133    -.2730915    .0361466
          x2 |   .0147331   .0057912     2.54   0.011     .0033826    .0260835
           y |   .2651968   .8486379     0.31   0.755    -1.398103    1.928497
          y2 |  -.0087793   .0303515    -0.29   0.772    -.0682672    .0507085
Ldistdrain~1 |  -.0376854   .0193464    -1.95   0.051    -.0756037    .0002329
      drainp |   .0937602   .1046745     0.90   0.370    -.1113981    .2989186
Ldistroadkm1 |  -.0462491   .0193637    -2.39   0.017    -.0842012   -.008297
   invdstpop |  -.8545499   .3114785    -2.74   0.006    -1.465037   -.2440633
  isagricole |  -.6761415   .1922043    -3.52   0.000    -1.052855   -.299428
     agropas |  -.4470052   .1678141    -2.66   0.008    -.7759149   -.1180956
   moy_b1_24 |   1.865021   1.092261     1.71   0.088    -.2757713    4.005813
   Lstd_b1_24 |  -1.971169   4.245945    -0.46   0.642    -10.29307    6.350731
  invsec2005 |  -19.24868    7.10391    -2.71   0.007    -33.17208   -5.325271
       _cons |   2.179044   5.917251     0.37   0.713    -9.418554    13.77664
-------------+----------------------------------------------------------------
      lambda |   .7695457   .1209887     6.36   0.000     .5324122    1.006679
------------------------------------------------------------------------------
Wald test of lambda=0:                 chi2(1) =  40.456 (0.000)
Lagrange multiplier test of lambda=0:  chi2(1) =  37.908 (0.000)

Acceptable range for lambda: -2.786 < lambda < 1.000
```

Population density map: