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MEASURING VULNERABILITY OF RURAL HOUSEHOLDS TO FOOD INSECURITY AND CLIMATE STRESS IN NIGER BY ECONOMETRIC AND INDICATOR METHODS

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ABSTRACT

We studied the determining factors that are significantly linked to food insecurity in rural areas. The most affected households are those having large size, those who devote a part of their expenses in the education of their children in the year preceding the food insecurity occurrence, and those who have experienced flood and drought event in the year preceding the food insecurity occurrence. From the model results, we learn that animal possession, the number of cultivated fields, expenses on agricultural tools and seeds reduce the risk of exposure to food insecurity. In view of these results, for the effectiveness of the fight against food insecurity, a political from authorities that strives to master the control factors associated with it is needed. Policies and strategies that involve the control of agricultural input prices and subsidies on chemical fertilizers and seeds are essential to sustain the fight against food insecurity.

This study is also based on vulnerability resilience indicator across regional levels following Temesgen Deressa, Rashid M. Hassan and Claudia Ringler (2008).The resilience is computed as the net effect of exposure and sensitivity on adaptive capacity and the higher net value the lesser vulnerability. The result shows that rural households living in the regions of Dosso and Tahoua are relatively less vulnerable because of their high adaptive capacity than those of the five other regions of which those of Zinder and Niamey are the most vulnerable due to their high sensitivity and exposure to climate stress.

Keywords: Food insecurity, climate stress, rural households.

JEL: Q1, Q54, R2, R3

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1. BACKGROUND

A Sahelian-landlocked country in West Africa, Niger covers an area of 1,267,000km^2. Three-quarters of the country is desert, including the Ténéré desert, which is one of the world's most austere deserts. The rainfall is characterized by a high variability in space and time from south to north as follows: The Sahel Sudan zone, which represents 1% of the total land area and receives between 600 and 800 mm of rain in normal years.It is conducive to agricultural and livestock production. The Sahelian zone covers 10% of the total land area with 350 to 600 mm of rain per year and is dominated by agro-pastoralism. The Sahel Saharan zone receives150 to 350 mm of precipitation per year on average and covers 12% of the total land area, it is characterized by moving live stock. The Saharan zone receives less than 150 mm of rain per year and extends over 77% of the total land area.

The level of vulnerability of different social groups to climate change is determined by both socioeconomic and environmental factors. The socioeconomic factors most cited in the literature include demography, gender, infant mortality, education, the level of technological development, infrastructure, institutions, and political setups (Kelly and Adger 2000; McCarthy et al. 2001). The environmental attributes mainly include climatic conditions such as precipitation and temperature, quality of soil, and availability of water for irrigation (Canadian International Development Agency [CIDA] 2003; O'Brien et al. 2004). The variations of these socioeconomic and environmental factors across different social groups are responsible for the differences in their levels of vulnerability to climate change shocks. The major impact of rainfall decline would be soil degradation, decline in agricultural production and chronic distribution of food supply weakening the capabilities of adapting populations (poverty, rapid population growth with a rate of 3.3%). The main objective of this paper is to assess the vulnerability of rural households to climate stress, based on estimating the probability that the income of rural households lies below the poverty line due to climate and socioeconomic shocks through econometric methods. We also intend to calculate the resilience of rural households to climate stress across regional levels as the net effect of adaptive capacity, exposure and sensitivity to climate stress through the vulnerability resilience indicator method. This study considers that, in addition to socioeconomic factors, vulnerability is linked to climate stress, raising the following research question: To which extent are rural households vulnerable to climate stress and what are the climate stress-related factors of vulnerability and the related regional variations?

2. LITERATURE REVIEW

Literature on climate change vulnerability assessment focuses on three conceptual and theoretical frameworks, summarized as socioeconomic or social vulnerability - describing the adaptive capacity of a system, biophysical vulnerability - describing a system's sensitivity and exposure and finally, the combination of both approaches, known as the integrated assessment approach.

Nelson et al., 2010a defines vulnerability as the susceptibility to disturbances determined by exposure to perturbations, sensitivity to perturbations, and the capacity to adopt. According to Cutter et al. (2009), vulnerability refers to the susceptibility of a given population, system, or place to harm from exposure to the hazard and directly affects the ability to prepare for, respond to, and recover from hazards and disasters.

The SAR (second assessment repot) of the IPCC (intergovernmental panel on climate change) defines vulnerability as the extent to which climate change may damage or harm a system; not only a system's sensitivity is taken into account but also its adaptive capacity (Watson, Zinyowera, & Moss, 1996). From the definition given by the IPCC TAR, vulnerability is the degree to which a system is susceptible to, or unable to cope with, adverse effects to climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity (IPCC, 2001). IPCC AR4 is consistent with the definition of vulnerability given by TAR.

Biophysical vulnerability approach

The point of view of IPCC SAR is in line with the '*end point*' analysis in which the vulnerability of people is linked with external events depending on the development of possible climate scenarios and future climate trend. Hence, the level of vulnerability follows from studying the biophysical impacts of such climate changes, and finally, any residual adverse consequences despite collective actions taken after identification of adaptive capacity options (Kelly & Adger, 2000). From the point of view of end-point analysis, exposure and sensitivity cause linear impact leading to biophysical vulnerability.

In the 'end point' analysis, researchers focus on biophysical drivers originating from extreme climatic events that are not under control of policy makers, such as drought, flood, temperature, and precipitation, and they view vulnerability as the resulting effect on the system after the climate hazard.

For instance, modeling farm income on climate variables can help measure the monetary impact of climate change on agriculture (Mendelsohn, Nordhaus, and Shaw 1994; Polsky and Esterling, 2001; Sanghi, Mendelsohn, Dinar, 1998). By the same token, modeling crop yield and climate variables can help measure the yield impact of climate change (Adams 1989; Kaiser et al. 1993; Olsen, and Jensen 2000).

Biophysical vulnerability assessment have been used in a variety of contexts, including the United States Agency for International Development (USAID), Famine Early Warning System (FEWS-NET) (USAID, 2007a), the World Food Program's Vulnerability Analysis and Mapping tool for targeting food aid (World Food Program, 2007), and a variety of geographic analysis that combine data on poverty, health status, biodiversity, and globalization (O'Brien et al., 2004; UNEP, 2004; Chen et al., 2006; Holt, 2007). The Human Development Index, for example, incorporates life expectancy, health, education, and standard of living indicators for an overall assessment of national well-being (UNDP, 2007).

Biophysical vulnerability assessment also includes the impact of climate change on human mortality and health terms (Martens et al. 1999), on food and water availability (Du Toit, Prinsloo, and Marthinus 2001; FAO 2005; Xiao et al. 2002), and on ecosystem damage (Forner 2006; Villers-Ruiz and Trejo-Vázquez 1997). Füssel (2007) referred to this approach as a risk-hazard approach, while Adger (2000) referred to it as an approach responding to research questions such as "What is the extent of climate change problem?" and "Do the cost of climate change exceed the cost of greenhouse mitigation?"

The biophysical approach has its limitation because it only accounts for physical losses, such as yield, income etc., without mentioning particular effective reductions due to climate change for different people or regions. In other words, it focuses more on sensitivity and exposure of individuals or social groups to climate change rather than adaptive capacity, which is explained more by their inherent characteristics Adger (1999), leading to uncertainty in vulnerability assessment (Nelson et al., 2010a). This method is therefore criticized because it treats humans as passive receivers of hazards.

Socioeconomic vulnerability approach

Many of the initial studies have focused on the adaptive capacity at the national level (Haddad, 2005; Adger & Vincent, 2005; Brooks et al., 2005; Adger et al., 2004; Yohe & Tol, 2002) and few of the latter studies have been focused at the sub national level (Jakobsen, 2011; Nelson, et al., 2010b; Gbetibouo & Ringler, 2009).

Social vulnerability assessment accounts for internal socioeconomic characteristics of people (Adger, 1999; Füssel, 2007) as individuals' status varies depending on education, gender, political power, social capital, etc. Thus, people are not socially vulnerable to the same extent because of their relative human-environmental properties that allow them to cope with changes, hence, setting up vulnerability to their adaptive capacity (Vincent & Cull, 2010; Vincent, 2004; Adger & Kelly, 1999; Adger, 1999). This type of vulnerability is called 'starting point' or present day vulnerability, meaning individuals' internal characteristics before they are hit by hazard event (Allen 2003; Kelly and Adger, 2000) which itself originates from socioeconomic perturbations (Adger and Kelly, 1999). For example, Adger and Kelly (1999) used this in Vietnam when they considered environmental factors in a district to coastal lowlands as given and then measured individuals' vulnerability only depending on their intrinsic socioeconomic patterns.

Although social vulnerability approach accounts for differences among individuals in society, it has its own limitation because people do not vary only due to socioeconomic characteristics, but also to environmental factors (Deressa et al., 2008). This approach neglects the environment-based intensities, frequencies, and probabilities of environmental shocks, particularly drought and flood.

The divergence of academics' debate about the two approaches has resulted in the complexity of the term '*Biophysical*' vs. '*Social vulnerability*' (Vincent, 2004; Brooks, 2003) because the first approach cannot be completed without the latter nor the latter without the former given that hazard specificity is their common point. Therefore, combining both of them (*integrated vulnerability assessment)* simultaneously links social vulnerability (adaptive capacity) with biophysical aspects of climate change (exposure and sensitivity) to design a complete picture of vulnerability is the best methodological approach (Nelson et al., 2010b; Gbetibouo & Ringler, 2009; Cutter, 1996).

Integrated vulnerability approach

In this approach, both socioeconomic and biophysical factors are jointly considered to assess vulnerability, similarly like the example of hazard-of-place model (Cutter, Mitchell, and Scott, 2000) and mapping approach (O'Brien et al., 2004). The IPCC (2001) framework, which conceptualizes vulnerability to climate change as a function of adaptive capacity, sensitivity and exposure, is conducive with the integrated vulnerability assessment (Füssel and Klein, 2006; Füssel, 2007). Deressa et al., (2008) used the integrated vulnerability approach to assess farmer's vulnerability to climate change in Ethiopia. However, this approach has limitations. This approach does not allow for any standard method that helps combine indicators of biophysical and socioeconomic data sets. There is much to do to provide common metric for defining the relative importance of social and biophysical vulnerability and the relative importance of each individual variable. Furthermore, it does not account for the dynamism in vulnerability. To take advantage of opportunities, adaptive capacity options are to include the continual change of strategies (Campbell, 1999; Eriksen and Kelly, 2007); this dynamism is missing under the integrated assessment approach.

3. DATA AND METHODOLOGY

3.1 Data

We used secondary data from Niger's National Institute of Statistics. It is a national database drawn from the socioeconomic national survey on vulnerability to food insecurity. It includes also data on rural households' perception of climate and environmental change and resulting shocks, agricultural and livestock information, coping strategies, social networks, infant feeding and gender. The survey was conducted in 2011 in rural areas across all regions, except for the north (Agadez), because of security issues in this region located in the desert.

3.2 Methodology

3.2.1 Multinomial logistic regression model of vulnerability of households to food insecurity in Niger

3.2.1.1 Description of food insecurity scores by national institute of statistics

The methodology adopted is to identify a number of variables that characterize the three dimensions of classic analysis of food security. The variables identified for this purpose are food consumption score, livestock ownership and expenses.

- For each indicator, a reference threshold based on the existing secondary data was calculated.

The whole household was ordered increasingly against each indicator and divided into five homogeneous groups. Each group has about 20% of households. For each group of 20%, a value average was calculated. These average values are the thresholds for each indicator.

Some variables undergone preliminary transformations:

a) The food consumption score

It is calculated by combining all foods consumed in 10 groups: cereals, tubers, legumes, protein, milk, egg, vegetables, fruits, sugar, and oil.

The maximum score is 7x10 = 70. The score for each household is divided by 70 (this value may be lower if one considers less groups or greater if one considers more groups, either way the thresholds are the same). The entire household is then ordered in relation to this standard score

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and divided into 5 groups. For each group, an average of scores was calculated and resulted in the following threshold:
Very poor consumption (score between 0 and 0.27; rank = 1), poor consumption (score between 0.27 and 0.43; rank = 2), average consumption (score between 0.43 and 0.52; rank = 3), acceptable consumption (score greater than 0.52; rank = 4)

b) Livestock ownership

Livestock ownership in TLU (tropical livestock unit) for adding goats, sheep, oxen… One TLU equals to a 250kg cow; heifer beef = 0.8 TLU; bull = 0.8 TLU; young bull = 0.8 TLU; calf = 0.8 TLU; camel = 0.8 TLU; sheep = 0.8 TLU; goat = 0.8 TLU.To take account of different life system, this indicator was inversely weighted according to the weighting coefficients of the early warning system institution (0.6 for the pastoral zone, 0.32 for agro pastoral zone, and 0.06 for agricultural zone. For instance, a household having 2 TLU in pastoral zone will have a value of 2/0.6 = 3.33 and will have 2/0.06 = 33.33 in agricultural zone. The thresholds for this indicator are the following:
0 TLU does not own animals (rank = 1); between 0 and 0.05 have very few animals (rank = 2); between 0.05 and 0.21 have some animals (rank = 3); greater than 0.21 have many animals (rank = 4).

c) Household spending

The following thresholds were considered for expenses: <0.4 US $ / day / person, very expense low (rank = 1); >0.4 US $ / day / person and < 0.6 US $ / day / person, low expense (rank = 2); > US $ 0.6 and < 0.8 US $, average expense (rank = 3); > 0.8 US $ / day / person, high expense (rank = 4).

- For each household, the value for each indicator was compared with the calculated thresholds and rank has assigned.
- Principal component analysis based on the assigned ranks was calculated so as to define a set of homogeneous households based on the indicators.
- Adjustment and consolidation of households obtained on the basis of additional indicators characterizing household food security and the livelihood risk.
- Characterization household profile affected by food insecurity or risk to their livelihoods.
- Identification of departments, regions, agro-ecological zones based on the proportions of households in food insecure.

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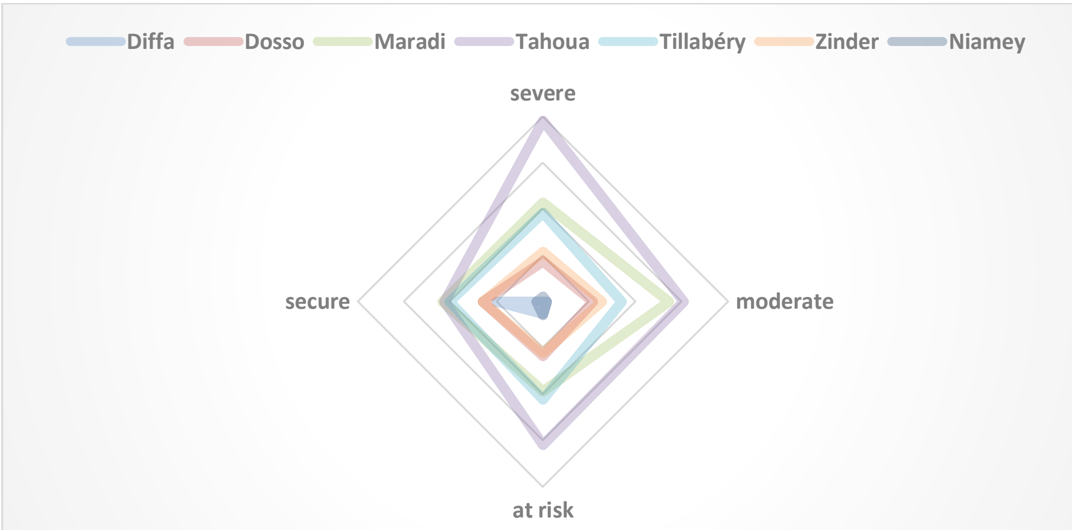
Figure1: Food insecurity in rural areas by regions



Source: author, 2015

The figure above gives the distribution of food insecurity in rural areas in the different regions. The figure shows that households in food secure are larger than those at risk and only few of them are in severe or moderate food security. Niger is ranked among the poorest in the world and its economy remains dominated by the primary sector. Despite its importance, is struggling to modernize and is largely dependent on weather conditions. In addition, the high population growth of the country is increasing pressure on land with a resulting continuous farms fragmentation and the expansion of crops on marginal land with decreasing returns. This heavy dependence on rain-fed agriculture predisposes the country to a great food vulnerability and years of low agricultural production generally result in recurrent food crisis whose breadth and depth vary depending on the level of deficit and the prevailing cyclical factors. The year 2009/2010 was a year of acute pastoral and nutrition food crisis which affected the half population of Niger. The crisis has also resulted in large losses of animals due to lack of pasture, high rainfall and flooding.

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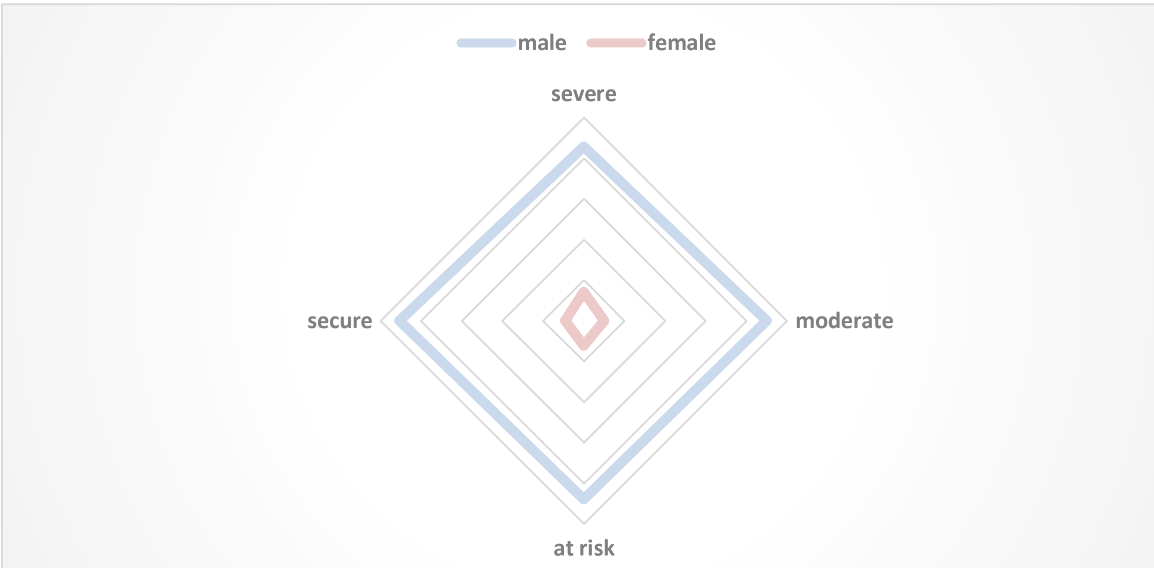
Figure2: Food insecurity and household sex



Source: author, 2015

Even although most of the surveyed households are food secure (57% of male and 49.4% of female), the situation is worrisome given the proportion of those whose food security status is at risk.

3.2.1.2 Description of the model

The dependent variable, food insecurity status is a categorical variable:
Food insecurity categories: 0 = secure; 1 = moderate; 2 = at risk; 3 = severe
In our case, it can be set as following:

$$\mathbf{Prob(Y_i = j|w_i) = \frac{e^{w_i'\alpha_j}}{\sum_{j=0}^{3} e^{w_i'\alpha_j}} = Prob(Y = 1|X_i), \boldsymbol{j} = 0, 1, \ldots, 3\ 1)}$$

The estimated equations provide a set of probabilities for the J + 1 choices for a decision maker with characteristics w_i.

Before proceeding, we must remove an indeterminacy in the model. A convenient normalization that solves the problem is $\alpha_0 = 0$. (This arises because the probabilities sum to one, so only J parameter vectors are needed to determine the J + 1 probabilities.) Therefore, the probabilities are:

$$\mathbf{Prob}(\mathbf{Y_i = j|w_i}) = \boldsymbol{P_{ij}} = \frac{e^{w_i'\alpha_j}}{1+\sum_{j=1}^{J} e^{w_i'\alpha_j}} = \mathbf{Prob}(\mathbf{Y = 1|X_i}), \boldsymbol{j}\ \mathbf{0, 1, \dots,} \boldsymbol{J}\ \mathbf{2)}$$

In this model, the coefficients are not directly tied to the marginal effects. The marginal effects for continuous variables can be obtained by differentiating (2) with respect to a particular factor w_m to obtain:

$$\frac{\partial P_{ij}}{\partial w_{im}} = ((P_{ij}\ (1(j = m)\ -\ P_{im})), m = 0, 1, \dots, J \qquad \mathbf{3)}$$

It is clear that through its presence in Pij and Pim, every attribute set w_m affects all the probabilities. One might prefer to report elasticities of the probabilities. The effect of attribute k of choice m on Pij would be:

$$\frac{\partial lnP_{ij}}{\partial lnw_{mk}} = w_{mk}(P_{ij}\ (1(j = m))\alpha_k \qquad \mathbf{4)}$$

In the multinomial logit model, we estimate a set of coefficients, α(1), α(2), and α(3), corresponding to each outcome:

$$\mathbf{Prob\ (y = 1)} = \frac{e^{w'\alpha(1)}}{e^{w'\alpha(1)}+e^{w'\alpha(2)}+e^{w'\alpha(3)}} \qquad \mathbf{5)}$$

$$\mathbf{Prob\ (y = 2)} = \frac{e^{w'\alpha(2)}}{e^{w'\alpha(1)}+e^{w'\alpha(2)}+e^{w'\alpha(3)}} \qquad \mathbf{6)}$$

$$\mathbf{Prob\ (y = 3)} = \frac{e^{w'\alpha(3)}}{e^{w'\alpha(1)}+e^{w'\alpha(2)}+e^{w'\alpha(3)}} \qquad \mathbf{7)}$$

Setting α (1) = 0, the equations become:

$$\mathbf{Prob\ (y = 1)} = \frac{1}{1+e^{w'\alpha(2)}+e^{w'\alpha(3)}} \qquad \mathbf{8)}$$

$$\mathbf{Prob\ (y = 2)} = \frac{e^{w'\alpha(2)}}{1+e^{w'\alpha(2)}+e^{w'\alpha(3)}} \qquad \mathbf{9)}$$

$$\mathbf{Prob\ (y = 3)} = \frac{e^{w'\alpha(3)}}{1+e^{w'\alpha(2)}+e^{w'\alpha(3)}} \qquad \mathbf{10)}$$

For instance the relative probability of y = 2 to the base outcome is:

$$\frac{\mathbf{Prob\ (y=2)}}{\mathbf{Prob\ (y=1)}} = e^{w'\alpha(2)} \qquad \mathbf{11)}$$

Let's call this ratio the relative risk. The relative risk ratio for a one-unit in w_i is then $e^{\alpha(2)}$. Thus the exponential value of a coefficient is **the Relative-Risk Ratio (RRR)** for a one-unit change in the corresponding variable (risk is measured as the risk of the outcome relative to the base outcome). In terms of the process for choosing the best model, it is based on the log likelihood. We used an ascending procedure starting to put in the model, among the explanatory variables, a variable which is the most associated with the dependent variable according to the bivariate descriptive analysis. Then, the other variables, are successively added to the model according to their degree of association revealed in the descriptive analysis; if the addition of a variable increases the log-likelihood it is kept in the model. The final model is one that maximizes the likelihood log and contains the maximum of variables of which at least one modality is statistically significant.

In the table below, at 10% confidence level, all the independent are associated to food insecurity except age, daily milk expense and daily meat expense. Regarding the sex of household head, female are slightly the most affected by food insecurity than male: severe 8.6% against 6.0%, moderate 7.1% against 7.5%, at risk 34.9% against 29.6%, secure 49.4% against 57%.

The table shows that households who possess the most animals are less affected by severe food insecurity than households without animals: 5.1% against 12.7%.

Table1: Bivariate descriptive analysis test between dependent and independent variables

Independent variables	**Dependent variable:** Food insecurity categories				
	Severe	Moderate	At risk	Secure	**P value Chi 2**
Household size					0.000
Age					.266
Household sex					.000
1 = Male (outcome)	6.0%	7.5%	29.6%	57%	
2 = Female	8.6%	7.1%	34.9%	49.4%	
Animal possession	5.1%	6.5%	27.8%	60.6%	.000
1 = yes	12.7%	12.3%	42.7%	32.3%	
2 = no (outcome)	6.0%	7.2%	29.9%	56.9%	
	9.4%	7.4%	31.9%	48.7%	
Number of fields / gardens operated					.000
Education spending last 12 month					.082
1 = yes	5.8%	7.9%	30.0%	55.3%	
2 = no (outcome)	6.9%	7.1%	30.2%	56.9%	
Agricultural/tools/seeds spending this year					.000
1 = yes	5.0%	5.9%	28.7%	60.3%	
2 = no (outcome)	8.0%	9.5%	31.9%	57.1%	
Flood					.000
1 = yes	9.0%%	8.1%%	30.1%	52.7%	
2 = no (outcome)	5.5%%	7.2%	30.1%	80.9%	
Drought					.000

1 = yes 2 = no (outcome)	11.5% 5.4%	6.9% 7.5%	28.5% 30.3%	53.0% 56.7%	
Daily milk consumption expense					.456
Daily fruits consumption expense					.087
Daily meat consumption expense					.293
Daily cooked food consumption expense					.002

Source: author, 2015

In the last 12 month, the following is the proportion of households in severe food insecurity: households who have operated field or gardens 6.0% against 9.4% who have not, households who have spent in education 5.8% against 6.9% who have not, households who have spent in agricultural tools or seeds 5.0% against 5.5% who have not. Households who have experienced flood over the last or the last 3 years are less food secure 52.7% than households who did not 80.9%. The severe food insecurity effects those who are the most exposed to drought occurrence 11.5% than those who are not 5.4% and are those whose households are less food secure 53.0% against 56.7%.

The table shows the depth of food insecurity in rural areas whether it is severe, moderate or risky. The conclusion is that food insecurity sets apart no body when it occurs.

3.2.1.3 Results and interpretation of the Risk-Relative Ratio RRR

Table2: Multinomial logistic regression coefficients

Multinomial logistic regression — **Number of obs = 3182**; **LR chi2(39) = 278.47**; **Prob > chi2 = 0.0000**

Log likelihood = -2998.6656 — **McFadden R 2 or Pseudo R2 = 0.0444**

Independent variables	**Dependent variable:** Food insecurity categories: secure is taken as the reference category					
	Severe food insecurity		Moderate food insecurity		Food insecurity at risk	
	Coef	**P value**	**Coef**	**P value**	**Coef**	**P value**
Household size	.084*	0.000	.027	0.178	.015	0.211
Age	-.010***	0.080	-.001	0.788	-.005**	0.040
Household sex						
1 = Male (reference)						
2 = Female	.340	0.279	-.279	0.377	.173	0.290
Animal possession						
1 = yes	-1.526*	0.000	-1.032*	0.000	-1.147*	0.000
2 = no (reference)						
Number of fields / gardens operated	-.191**	0.006	-.370*	0.000	-.095*	0.001
Education spending last 12 month						
1 = yes	.494***	0.009	.509*	0.001	.332*	0.000

2 = no (reference)						
Agricultural/tools/seeds spending this year						
1 = yes	-.554**	0.002	-.753*	0.000	-.171***	0.056
2 = no (reference)						
Flood occurrence this year						
1 = yes	.647*	0.001	.751*	0.000	.073**	0.500
2 = no (reference)						
Drought occurrence this year						
1 = yes	.456**	0.050	.042	0.841	.192	0.123
2 = no (reference)						
Daily milk consumption expense	.017	0.779	-.141***	0.090	.010	0.743
Daily fruits consumption expense	-.055	0.872	.134	0.141	-.411***	0.067
Daily meat consumption expense	.064	0.641	-.379**	0.043	-.095	0.274
Daily cooked food consumption expense	-.032	0.661	.064	0.166	-.025	0.464

Source: author, 2015. *, ** and *** indicates the 1%, 5% and 10% significance level of regression coefficient for respective variables in the table.

The interpretation of our results concerns the relative risk ratios (RRR) instead of regression coefficients, the probability threshold is set at 10%.

The numerical values of the coefficients do not have direct interpretation, however their positive or negative signs are interpretable.

The sign indicates whether the probability of observing a particular category of the dependent variable is an increasing or decreasing function of the corresponding predictor or explanatory variable (all other things being equal). Thus, the results of the table above call for several comments.

The coefficient regression of household size is significantly positive: the number of household members increases the probability for a household to be severely food insecure. Age is a factor that reduces the probability for a household to be severely food insecure or at risk. The probability for a household to be severely food insecure, moderate or at risk, decreases with animal possession. The number of fields or gardens cultivated reduces the probability for a household to be exposed to food insecurity (severe, moderate or at risk). The share of household spending devoted to education exposes a household to food insecurity vulnerability. Agricultural/tools/seeds spending make household better off with against food insecurity. Experiencing climate stress event such as flood and drought increases the probability for a household to be severely food insecure, moderate or at risk. Food insecurity is moderate for households who spend in milk, fruits and meat consumption. The value of the relative risk is interpreted as follows. If the factor studied does not play a causal role, there should be no difference in incidence between those exposed and non-exposed: in this case, the relative risk must be equal to 1; if it is greater than 1, this means that the presence of factor causes an increase in the probability of occurrence of the disease (or a decrease in the probability if it is less than 1).A relative risk of 3 (or 10) should be interpreted as follows: the subjects exposed to the risk factor have a probability 3 times (10 times) higher to have the disease than the non-exposed. The term relative risk is that the incidence is a measure of the risk of disease in the population (recall that the risk is the probability of an event).

The relative risk is the ratio of two risks (the risk for the exposed and the risk the unexposed). A RRR < 1 indicates a beneficial effect, a RRR > 1 indicates a negative effect, a RRR = 1 indicates that the event frequency is the same for the exposed group and the unexposed group.

Analysis of the different climatic projections by AGRHYMET indicates that food security is far from being provided in the future. There is a visible gap between the food needs of a fast growing population and probable agricultural production. Under the influence of population pressure, the gap could, in the long term, have an exponential trend (resulting in a demand/probable production balance sheet) that will always be negative because millet, sorghum and cowpea are incredibly sensitive to their environmental conditions and production.

The major impact of rainfall decline will be soil degradation, decline in agricultural production, and chronic distribution of food supply. There is also an expected continuous large-scale movement of populations, an increase in diseases, and an important loss in terms of biodiversity.

The evolution of agricultural production in the Sahel countries, in general, and in Niger, in particular, during the last twenty years showed that one out of two years resulted in a deficit. Indeed, if the crop year 2005/2006 was characterized by a grain surplus of 21.000 tons at the national level, that of 2004/2005 recorded a deficit of about 223.000 tons.

Table 3: Relative risk associated to food insecurity

Multinomial logistic regression	**Number of obs = 3182**					
	LR chi2(39) = 278.47					
	Prob > chi2 = 0.0000					
Log likelihood = -2998.6656	**McFadden R 2 or Pseudo R2 = 0.0444**					
Independent variables	**Dependent variable:** Food insecurity categories: secure is taken as the reference category					
	Severe food insecurity		Moderate food insecurity		Food insecurity at risk	
	RRR	P value	**RRR**	P value	**RRR**	P value
Household size	1.087*	0.000	1.028	0.178	1.015	0.211
Age	.989***	0.080	.998	0.788	.994**	0.040
Household sex						

1 = Male (reference)						
2 = Female	1.405	0.279	.756	0.377	1.188	0.290
Animal possession						
1 = yes	.217*	0.000	.356*	0.000	.317*	0.000
2 = no (reference)						
Number of fields / gardens operated this year month	.825*	0.006	.690*	0.000	.908*	0.001
Education spending this year						
1 = yes	1.640*	0.009	1.665*	0.001	1.394*	0.000
2 = no (reference)						
Agricultural/tools/seeds spending						
this year	.574**	0.002	.470*	0.000	.842***	0.056
1 = yes 2 = no (reference)						
Flood occurrence this year						
1 = yes	1.910*	0.001	2.120*	0.000	1.076**	0.500
2 = no (reference)						
Drought occurrence this year						
1 = yes	1.577**	0.050	1.043	0.841	1.212	0.123
2 = no (reference)						
Daily milk consumption expense	1.017	0.779	.868***	0.090	1.010	0.743
Daily fruits consumption expense	.945	0.872	1.144	0.141	.662***	0.067
Daily meat consumption expense	1.066	0.641	.684**	0.043	.908	0.274
Daily cooked food consumption expense	.968	0.661	1.066	0.166	.974	0.464

Source: author, 2015. *, ** and *** indicates the 1%, 5% and 10% significance level of regression coefficient for respective variables in the table.

All other things being equal, compared with food security, households with higher size have a probability 1.087 times higher to be severely food insecure in the exposed group than in the unexposed group. Compared with food security, heads of household with higher age have a probability .989 times lower to be severely food insecure and a probability .994 times lower to be at risk in the unexposed group than in the exposed group respectively. Compared with food security, the probability is .217 to .356 times lower to be food insecure or at risk for households possessing animals than households without animals. Compared with food security, households with higher number of cultivated fields are more than .9 times less likely to be severely food insecure, moderate or at risk in the unexposed group than in the exposed group. Compared with food security, households who spend in the education of their children in the last 12 months have a probability more than 1.394 higher to be affected by severe food insecurity, moderate or at risk than households who devote any part of their budget in the education of their children in the last 12 months. Compared with food security, the probability of being in severe food insecurity, moderate or at risk, is more than 0.470 lower for households who spent in agriculture in the year than households who spent any part of their budget in agriculture. Compared with food security, households who experienced flood occurrence in the year, have a probability 1.910 times higher, 2.120 times higher and 1.076 times higher to be affected by food insecurity whether it is severe, moderate or at risk respectively than households who did not suffer from flood occurrence in the year. Compared with food security, households who suffered from drought occurrence in the year, have a probability 1.577 times higher to be severely food insecure than households who did not experience drought occurrence in the year. Compared with food security, households with higher daily milk consumption expense are .868 less likely to be affected by food insecurity (moderate) in the unexposed group than in the exposed group. Compared with food security, households with higher daily fruits consumption expense are .662 less likely to be affected by food insecurity (at risk) in the unexposed group than in the exposed group. Compared with food security, households with higher daily meat consumption expense are .684 less likely to be affected by food insecurity (moderate) in the unexposed group than in the exposed group.

3.2.1.4 Discussion

This study shows that the number of individuals to feed exposes a household to severe food insecurity. This situation is due to the fact that more than seven in ten households live in poverty in poverty, in rural areas, the majority of households (71%) have their income below the poverty line (Illa, 2014) and poor households are the most exposed to food insecurity (Kimani Murage-EW et al, 2014; Chinnakali P. et al, 2014; Vogt and Tarasuk V. J, 2009). Any policy encouraging the reduction of household members can increase the probability for the household to be food secure. The age of the household head has positive and significant relationship with household food security (Fekadu Beyene and Mequanent Muche, 2010). Age is a factor that reduces vulnerability to food insecurity because of the experiences accumulated in the past in agricultural practices. Animal possession and number of fields operated make households better off as they can sale few animals and/or fields as coping strategies to protect themselves against food insecurity. In rural areas, larger livestock and/or fields are important indicator of wealth. Households possessing larger livestock and fields are found to be less vulnerable to food insecurity in Ethiopia (Fekadu Beyene and Mequanent Muche, 2010). Extending arable and grazing land area can contribute to reduce the probability of households to be food insecure. Education expenses are a burden for food insecure households, this seems logical since the education expenses reduce the share of food expenditures for households who struggle to achieve food security. Agricultural expenditure on seeds and fertilizers improve soil fertility and crop yields resulting in food insecurity reduction. In Ethiopia, (Fekadu Beyene and Mequanent Muche 2010), found that the use of fertilizers has a positive impact on land and livestock productivity and hence resulting in food security improvement. Policy implication granting seed and fertilizer subsidies will increase the probability of households to be food secure. Drought and flood are constant threats to food insecurity affecting several sectors and resulting in income losses. The supply reduction causes food prices to rise making it difficult for the households to meet the food needs of its members. Food insecurity has become more frequent in recent years because of drought and flood occurrence with many severe impacts including crop losses, lower yields in both crop and livestock production, land degradation and soil erosion.

3.2.2 Vulnerability of households to climate stress: vulnerability resilience indicator method (Temesgen Deressa, Rashid M. Hassan, Claudia Ringler, 2008)

In the IPCC framework the resilience is net effect of vulnerability as following:

$$\text{Vulnerability} = \text{adaptive capacity} - (\text{exposure} + \text{sensitivity}) \qquad (1)$$

PCA (Principal Components Analysis) is run on the indicators of exposure, sensitivity and adaptive capacity with STATA software and then weights from the component that explains the most of the total variance were assigned.

"PCA is a technique for extracting from a set of variables those few orthogonal linear combinations of variables that most successfully capture the common information. Intuitively, the first principal component of a set of variables is the linear index of all the variables that capture the largest amount of information common to all the variables. Assuming that we have a set of k-variables ($x_{1j} to\ x_{kj}$) that represent k-variables (attributes) of each region j; PCA starts by specifying each variable normalized by its mean and standard deviation.

For instance, $x_{1j}^* = (x_{1j} - \overline{x_1})/\sigma_{x_1}$where $\overline{x_1}$ is the mean of the first indicator x_{1j} across regions and σ_{x_1} is its standard deviation. The selected variables are expressed as linear combination of a set of underlying components for each region j:

$$x_{1j} = y_{11}W_{1j} + y_{12}W_{2j} + \cdots + y_{1k}W_{kj}$$
$$\ldots \qquad j = 1\ldots.J \qquad (2)$$
$$x_{k1j} = y_{k1}W_{1j} + y_{k2}W_{2j} + \cdots + y_{kk}W_{kj}$$

Where the W's are the components and the$y$'s are the coefficients on each component for each variable (and do not vary across regions). Because only the left side of each line is observed, the solution to the problem is indeterminate. PCA overcomes this indeterminacy by finding the linear combination of the variables with maximum variance (the first principal component: W_{1j}), then finding a second linear combination of the variables orthogonal to the first and maximum remaining variance, and so on. Technically, the procedure solves the following equation$(R - \lambda I)V_n = 0$ for λ_n and V_n, where $R$is the matrix of correlations between the scaled variables,x and V_n is the vector of coefficients on the nth component for each variable. Solving the equation yields the characteristic roots of R, λ_n (also known as eigenvalues), and their associated eigenvectors (V_n). The final set of estimates is produced by scaling the eigenvectors (V_n) so that the sum of their squares sums to the total variance-another restriction imposed to achieve determinacy of the problem." Temesgen Deressa, Rashid M. Hassan, Claudia Ringler, 2008 (pp.11-12)

The scoring factors from the model are recovered by inverting the system implied by equation (2). This yields a set of estimates for each of the k-principal components:

$$W_{1j} = w_{11}x_{1j} + w_{12}x_{2j} + \cdots + w_{1k}x_{kj}$$
$$\ldots \qquad j = 1\ldots.J \qquad (3)$$
$$W_{kj} = w_{k1}x_{1j} + w_{12}x_{2j} + \cdots + w_{kk}x_{kj}$$

where the w's are the factor scores. Following Filmer and Pritchett, 2001andDeressa et al., 2008, the first principal component, expressed in terms of the original (unnormalized) variables is an index for each region in Niger based on the following expression:

$$W_{1j} = w_{11}(x_{1j} - \overline{x_1})/\sigma_{x_1} + \cdots + w_{1k}(x_{kj} - \overline{x_k})/\sigma_{x_k} \qquad (4)$$

Finally the index formula for a region j is given by:

$$I_j = \sum_{i=1}^{k} w_i(x_{ij} - \overline{x_i})/\sigma_{x_i} \qquad (5)$$

Where w_i is the weight for the i^{th} indicator in the PCA model, x_{ij} is the j^{th} region's value for the i^{th}indicator, $\overline{x_i}$ and σ_{x_i} are the mean and standard deviation respectively of the i^{th} indicator for all regions. From the equation (5) we can generate the associated index for adaptive capacity, exposure and sensitivity:

Adaptive capacity index of region j for the i^{th} indicator:

$$A_j = \sum_{i=1}^{k} w_i^A(x_{ij}^A - \overline{x_{ij}^A})/\sigma_{x_i}^A \qquad (6)$$

Exposure index of region j for the i^{th} indicator:

$$E_j = \sum_{i=1}^{k} w_i^E(x_{ij}^E - \overline{x_{ij}^E})/\sigma_{x_i}^E \qquad (7)$$

Sensitivity index of region j for the i^{th} indicator:

$S_j = \sum_{i=1}^{k} w_i^S (x_{ij}^S - \overline{x_{ij}^S})/\sigma_{x_i}^S$ (8)

Vulnerability resilience indicator of region j for the i^{th} indicator:

$$VRI_j = A_j - (E_j + S_j)$$

$$VRI_j \quad \left\{ \sum_{i=1}^{k} \frac{w_i^A \left(x_{ij}^A - \overline{x_{ij}^A}\right)}{\sigma_{x_i}^A} - \left[\frac{w_i^E \left(x_{ij}^E - \overline{x_{ij}^E}\right)}{\sigma_{x_i}^E} + \frac{w_i^S \left(x_{ij}^S - \overline{x_{ij}^S}\right)}{\sigma_{x_i}^S}\right] \right\} \qquad (9)$$

The data used for the computation of the index is the percentage (%) of respondents except income and tropical livestock unit.

3.2.2.1 Results from Principal Components Analysis: PCA

Running PCA on the indicators with STATA, the data set on vulnerability indicators showed five components with eigen values greater than 1 and explains 95.01% of the total variation in the data set.

The first principal component explained most of the variation (34.70%), the second principal component explained 27.53% of the variation, the third principal component explained 14.72% of the variation, the fourth principal component explained 11.5% of the variation, and the fifth principal component explained 6.56% of the variation.

As the first principal component explains most of the variation in the data set, the weights used in constructing vulnerability indices are those of that component, given the initial argument when it comes to the use of PCA.

The factor analysis shows that the first principal component correlates positively with almost all indicators related to adaptive capacity and correlates negatively with all related to exposure and sensitivity.

Table 4:Variables and factor scores loaded from the first principal components

Vulnerability indicators	Factor scores
Adaptive capacity indicators	
Tropical livestock unit	-0.1064
Income	0.1283
Mobile phones	-0.1825
Animal- ploughs	0.1621
Primary school	0.2985
Secondary school	0.2522
Health center	0.1423
Improved drinking water source	-0.1948
Vet box	0.1717
Market	0.3027
Cereal bank aid	0.3218
Supply of fertilizers and seeds	0.2041
Community system for support for women	-0.1358
Infant nutritional rehabilitation center	-0.1194
Community system for responding to climate shocks	0.2628
Exposure indicators	
Drought	0.2676
Flood	-0.0445
Sensitivity indicators	
Presence of malnourished children	0.0786
Increase of food prices	-0.0366
Increase of agricultural inputs	-0.2176
Insect infestation	-0.2346
Low crop yield	0.2265
Income decline	0.3144

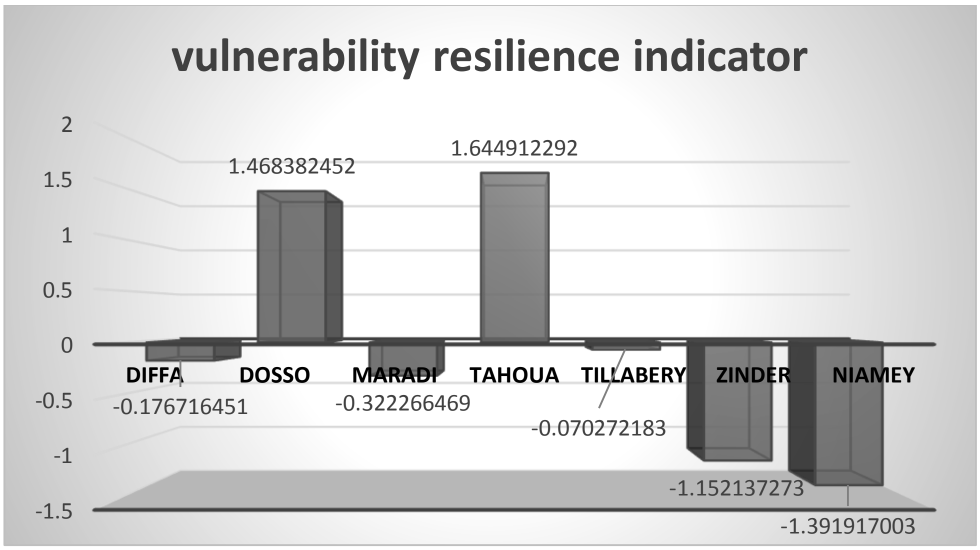
Source: author, 2015

As indicated earlier, factor scores from the first principal component are employed to construct indices for each region. For instance, the vulnerability index for Diffa is calculated as follows: is calculated as follow:

$$\begin{pmatrix} (-0.1064*2.225)+(0.1283*1.336)+(-0.1825*0.060)+ \\ (0.1621*0.619)+(0.2985*-1.111)+(0.2522*-0.339)+ \\ (0.1423*-1.354)+(-0.1948*-0.931)+(0.1717*1.017)+ \\ (0.3027*-0.563)+(0.3218*-0.525)+(0.2041*-0.838)+ \\ (-0.1358*0.876)+(-0.1194*0.334)+(0.2628*-0.896) \end{pmatrix} - \begin{pmatrix} (0.2676*-1.363)+(-0.0445*-1.170)+ \\ (0.0786*-1.010)+(-0.0366*-0.780)+ \\ (-0.2176*-0.664)+(-0.2346*0.347)+ \\ (0.2265*-1.041)+(0.3144*-1.340) \end{pmatrix} = -0.177 \quad (10)$$

The calculation for the rest of the regions follows the same procedure.

Graph 3: Vulnerability resilience indicator



Source: author, 2015

The vulnerability resilience indicators of Niamey, Zinder, Tillabery, Maradi and Diffa are negative which indicate their lower resilience and meaning that rural households living in that regions are extremely vulnerable to climate stress. The vulnerability resilience indicators of Dosso and Tahoua show a lower vulnerability to climate stress and greater resilience.

3.2.2.2 Discussion

Graph3 shows that rural households in the regions of Dosso and Tahoua reveal a positive net effect of adaptive capacity, exposure and sensitivity, while the other regions reveal a negative net effect. This result means that Dosso and Tahoua are relatively less vulnerable than Diffa, Maradi, Tillabéry, Zinder and Niamey, which are very sensitive and highly exposed to climate stress. The lesser vulnerability of Dosso and Tahoua could be explained by their relatively high access to primary and secondary schools, health centers, vet boxes (vetinary clinics), markets and community systems for responding to climate shock. Rural households living in the regions of Zinder and Niamey are the most vulnerable because of their relatively lower levels of collective actions, social networks and social capital. The vulnerability of rural households in Maradi and

Diffa is mainly associated with their relatively lower level of development of primary and secondary schools, health centers, improved drinking water sources, market access and community systems for responding to climate shocks. The vulnerability index of Tillabéry is approximately zero, meaning that this region is more or less a climate prone area. This is because it is located in the Sahel Sudan area which represents 1% of the total land area and receives between 600 and 800 mm of rain in normal years, so it is conducive to agricultural and livestock production. However, despite its natural advantages, this region is also prone to irregular floods as it is located along the Niger River.

4. CONCLUSION AND POLICY IMPLICATION

This study has showed the determining factors that are significantly linked to food insecurity in rural areas. The most affected households are those having large size, those who devote a part of their expenses in the education of their children in the year preceding the food insecurity occurrence, and those who have experienced flood and drought event in the year preceding the food insecurity occurrence. From the model results, we learn that animal possession, the number of cultivated fields, expenses on agricultural tools and seeds reduce the risk of exposure to food insecurity. In view of these results, for the effectiveness of the fight against food insecurity, a political from authorities that strives to master the control factors associated with it is needed. Policies and strategies that involve the control of agricultural input prices and subsidies on chemical fertilizers and seeds are essential to sustain the fight against food insecurity. The lack of such a policy could make it difficult for households to purchase agricultural inputs if there is a rise of input prices because of the depletion of food supply as a result of drought or flood.It is important to study the determinants of food insecurity but it is also interesting, for further research, to find out what are the strategies developed firstly by households in food security to address food insecurity and secondly by those who suffer.

This study has analyzed the climate stress vulnerability of rural households across regional levels in Niger within the context of climate change under the IPCC (2001) framework, which consists of adaptive capacity, exposure and sensitivity. Positive signsare assigned to adaptive capacity indices and negative signsare assigned to exposure and sensitivity, based on the literature review. Vulnerability is computed as the net effect of exposure and sensitivity on adaptive capacity. The results indicate that rural households in Zinder and Niamey are relatively more vulnerable regions and this can be attributed to the relatively lower level of interactions in rural communities. These two regions are followed in terms of vulnerability of rural households by Maradi and Diffa, in particular due to the lack of technology and infrastructure. The geographic location of Tillabéry makes its rural households more or less vulnerable, despite the fact that it is

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conducive to farming. The high development of infrastructure, institutional and social networks in rural areas located in Dosso and Tahoua regions explains their relatively lesser vulnerability to climate stress.

Non-governmental organizations aiming at sustainable rural development can both help people overcome poverty and hedge against climate change, especially rural areas in the regions of Niamey and Zinder. Moreover, community systems for responding to climate shocks such as drought, and floods, and to high prices for food and agricultural materials, can save rural households from hunger and food insecurity by granting them a supply of fertilizers and seeds, water harvesting, investment in technology and infrastructure and other natural resources. These are actions that may boost the adaptive capacity in rural areas while lowering the exposure and sensitivity to climate risk.

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