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INTEGRATED ASSESSMENT OF VULNERABILITY OF RURAL HOUSEHOLDS TO CLIMATE STRESS ACROSS REGIONS IN NIGER

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ABSTRACT

Based on household-level survey data collected from the national institute of statistics, vulnerability as an expected poverty approach (Chaudhuri et al. 2002) is used to analyse the vulnerability of households as the probability that the income of rural households falls below the poverty threshold line (minimum income) due to climate stress and socioeconomic characteristics with logistic regression model. The results reveal that a 1% increase in number of children less than 5 years, a 1% increase of household size and a 1% increase in food prices results respectively in an increase of 3.44%, 3.62% and 6.9% of vulnerability of households. A 1% increase of drought occurrence results in an increase of 4.59% of vulnerability of households. A 1% increase of access to irrigation, a 1% increase of number of cultivated fields and a 1% increase of access to cereal bank results respectively in a decrease of 3.6%, 0.48% and 4.84% of vulnerability of households.

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 livestock. 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

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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 of the IPCC 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).

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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

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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.

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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 Measuring vulnerability as expected poverty

This method is based on estimating the probability that a given shock or set of shocks will move household consumption below a given minimum level (such as a consumption poverty line) or force the consumption level to stay below the minimum, if it is already below this level (Chaudhuri et al. 2002).

$$P(y_i < \bar{y} \mid x_i)$$

Where y_i is the per capita income per day of individual i, $\bar{y}$is the existing poverty threshold in the area of concern and x_i are households' characteristics and environmental shocks.

For each household i = 1,…,n the observed endogenous variable is dichotomous and defined by a latent variable as follows:

$$Y_i = \begin{cases} 1 si Y_i^* < \bar{Y} \\ 0 si Y_i^* > \bar{Y} \end{cases} \qquad 1$$

This binary model is fitted using a logit regression by means of maximum likelihood:

$$\mathbf{Prob}(Y_i < \bar{Y} | X_i) = \frac{e^{X'\beta}}{1+ e^{X'\beta}} = \mathbf{Prob}(Y = 1 | X_i) \qquad 2$$

where β is a vector of coefficients on each of the household characteristics and environmental variables X. The equation can be normalized to remove indeterminacy in the model by assuming that β0 = 0 and the marginal effects are given by:

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$$\frac{\partial \Pr[y_i = \frac{1}{X_i}]}{\partial x_{ij}} = F'(X_i'\beta)\beta_j \qquad 3$$

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 marginal effects are interpreted instead of the coefficients.

The marginal effects measure the expected change in probability of income with respect to a unit change in an explanatory variable.

The table below gives the different independent variables and their description.

Table 1: Description and the utilized dependent and independent variables

Dependent variable	**Description**
Daily per capita income	Dummy, takes the value of 1 if below poverty line and 0 otherwise
Explanatory variables	**Description**
Socioeconomic characteristics	
Gender	Dummy, takes the value of 1 if male and 0 otherwise
Education	Dummy, takes the value of 1 if yes and 0 otherwise
Number of children less than 5 years	Discrete
Age of household head	Discrete
Household size	Discrete
Number of irrigated fields	Discrete
Number of operated fields	Discrete
Access to cereal bank	Dummy, takes the value of 1 if yes and 0 otherwise
Increase of food prices	Dummy, takes the value of 1 if yes and 0 otherwise
Climate stress perception	

Early cessation of rainfall	Dummy, takes the value of 1 if yes in the past three years and 0 otherwise
Flood occurrence	Dummy, takes the value of 1 if occurred in the past three years and 0 otherwise
Drought occurrence	Dummy, takes the value of 1 if occurred in the past three years and 0 otherwise

Source: author, 2015

Table 2 gives the log it regression results, which consists of the probability that household income falls under the minimum requirement, the regression coefficients, and the level of significance. Table 2 shows the extent to which rural households are subjected to poverty vulnerability and also the socioeconomic and climate stress underlying factors. The data used in the regression are available in Stata format.

Table 2: Logistic regression results with reporting margins and odds ration

Dependent variable $Y = Prob(y < y_i)$ Prob> F = 0.0000	**Coef**	**P>|t|**	**Marginal effects dy/dx**	**P>|t|**	**Odds Ratio**	**P>|t|**
Explanatory variables						
Gender	-.134	0.395	-.0183	0.395	.8414	0.308
Education	-.010	0.791	-.0013	0.791	.9849	0.698
Number of children less than 5 years	.252*	0.000	.0344	0.000	1.287	0.000
Age of household head	-.001	0.785	-.0001	0.785	.9981	0.655
Household size	.265*	0.000	.0362	0.000	1.300	0.000
Number of Irrigated fields	-.263*	0.000	-.0360	0.000	.7667	0.000
Number of operated fields	-.035**	0.025	-.0048	0.025	.9648	0.024
Access to cereal bank	-.354***	0.009	-.0484	0.009	.6789	0.012
Increase in food prices	.2186***	0.069	.0299	0.069	1.231	0.082
Early cessation of rainfall	.138	0.376	.0183	0.358	1.1518	0.364
Flood occurrence	.086	0.483	.01185	0.479	1.0603	0.674
Drought occurrence	.336**	0.011	.04594	0.013	1.3492	0.043

Source: author, 2015

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

Coefficients are interpreted in absolute terms. The marginal effects measure the expected change in probability of income with respect to a unit change in an explanatory variable. Odds Ratio are the probability of the phenomenon to occur divided by the alternative probability and are

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interpreted in terms of risk: OR = P / (1 – P). For instance, if in the exposed group, OR = 0.50 < 1, P < 1 – P, there are 0.50 times more likely to be vulnerable than the alternative (not being).

Variables with positive regression coefficients are positively correlated with vulnerability status such as the number of children less than 5 years, household size and increase in food prices. A unit increase in any of these socioeconomic variables results in an increase of the vulnerability status of order of the value of the corresponding regression coefficient. The table reveal a positive correlation between drought occurrence and vulnerability status and a unit increase in drought results in an increase of household vulnerability up to 0.336 point. Variables with negative regression coefficients are negatively correlated with vulnerability status such as irrigation, number of operated fields and access to cereal bank. These variables are those that make households better off. A unit increase in any of these socioeconomic variables results in a decrease of the vulnerability status of order of the value of the corresponding regression coefficient.

In terms of marginal effects, a 1% increase in number of children less than 5 years, a 1% increase of household size and a 1% increase in food prices results respectively in an increase of 3.44%, 3.62% and 6.9% of vulnerability of households.

A 1% increase of drought occurrence results in an increase of 4.59% of vulnerability of households.

A 1% increase of number of irrigated fields, a 1% increase of number of cultivated fields and a 1% increase of access to cereal bank results respectively in a decrease of 3.6%, 0.48% and 4.84% of vulnerability of households.

The Odds Ratio OR = P / 1- P of irrigation (.7667), number of operated fields (.9648) and access to cereal bank (.6789) is lower than 1 hence, P < 1 – P meaning that a non-vulnerable household is .7667, .9648, and .6789 times less likely to be affected by climate stress than a vulnerable household. The OR of drought occurrence (1.3492) is greater than 1 hence, P > 1 – P meaning that a vulnerable household is 1.3492 times more likely to be affected by climate stress than a non-vulnerable household.

TEST

The specification tests of the model show that the model is significant because the chi-squared calculated is higher than the theoretical chi-squired (Prob> chi2).

To appreciate the model accuracy, sensitivity, and specificity, tests are used and are statistical measures of the performance of a binary classification test, also known in statistics as

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classification function. Sensitivity (also called the true positive rate, or the recall rate in some fields) measures the proportion of actual positives which are correctly identified as such when the vulnerability is present y = 1 (e.g. the percentage of poor people who are correctly identified as having the condition). Specificity (sometimes called the true negative rate) measures the proportion of negatives which are correctly identified as such y = 0 (e.g. the percentage of non-poor people who are correctly identified as not having the condition). These two measures are complementary to the false positive rate and the false negative rate respectively. A perfect predictor would be described as 100% sensitive (i.e. predicting all people from the poor group as poor) and 100% specific (i.e. not predicting anyone from the non-poor group as poor); however, theoretically, any predictor will possess a minimum error bound known as the Bayes error rate. Test

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Table 3: Specificity and sensitivity test and odds ration

Vulnerability status			
Test	**Present**	**Absent**	**Total**
Positive +	a = True Positive (2052)	c = False Positive (490)	a + c (2542)
Negative -	b = False Negative (23)	d = True Negative (52)	b + d (75)
Total	a + b (2075)	c + d (542)	$\boldsymbol{Pro}(\boldsymbol{y} < \overline{\boldsymbol{y}}) = 78.41\% = \frac{a}{a+b+c+d}$
Sensitivity and Specificity test			
Sensitivity	$\frac{a}{a+b} = 98.89\%$	**Specificity**	$\frac{d}{c+d} = 9.59\%$

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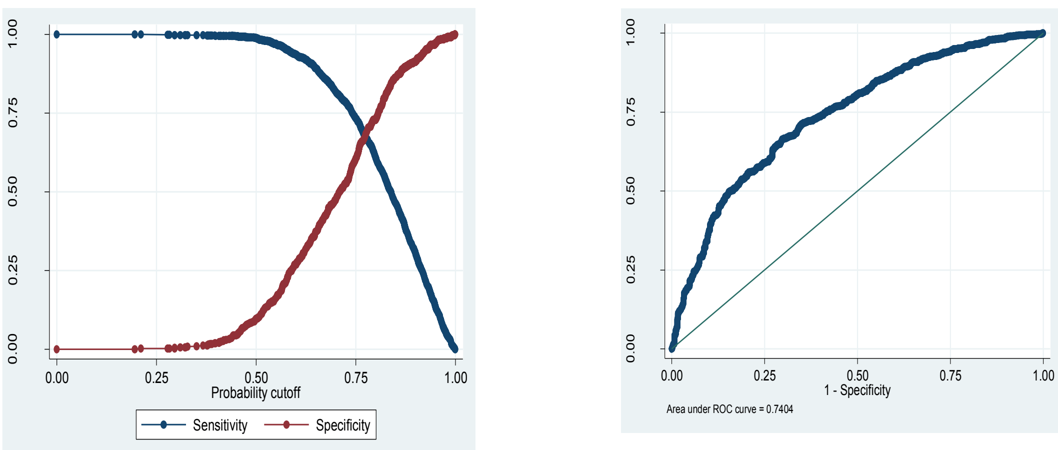
Positive Predictive Value	$\frac{a}{a+c} = 80.72\%$	**Negative Predictive Value**	$\frac{d}{b+d} = 69.33\%$

Source: author, 2015

The true positive is when the test indicates the presence of vulnerability while it is present in reality. The true negative is when the test indicates the absence of vulnerability while it is absent in reality. The false positive is when the test indicates the presence of vulnerability while it is absent in reality. The false negative is when the test indicates the absence of vulnerability while it is present in reality. The positive predicted is the probability that is present when the test is positive and vice versa.

Figure 1: ROC Curve



Source: author, 2015

The accuracy of the test to discriminate positive cases from negative cases is evaluated using Receiver Operating Characteristics (ROC) curve analysis. Each point on the ROC curve represents a sensitivity/specificity pair corresponding to a particular decision threshold. A test with perfect discrimination (no overlap in the two distributions) has a ROC curve that passes through the upper left corner. Therefore, the closer the ROC curve is to the upper left corner, the higher the overall accuracy of the test.

3.2.2 Vulnerability resilience indicator method (TemesgenDeressa, 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 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:

$$x_{1j} = y_{11}W_{1j} + y_{12}W_{2j} + \cdots + y_{1k}W_{kj}$$

… j = 1….J (2)

$$x_{k1j} = y_{k1}W_{1j} + y_{k2}W_{2j} + \cdots + y_{kk}W_{kj}$$

Where the W's are the components andthe$y$'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 $\lambda_n$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." TemesgenDeressa, 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:

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$$W_{1j} = w_{11}x_{1j} + w_{12}x_{2j} + \cdots + w_{1k}x_{kj}$$

… j = 1….J (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, 2001 and Deressa 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:

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

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

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

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:

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

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

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

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

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

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

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

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

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

RESULTS FROM PRINCIPAL COMPONENTS ANALYSIS: PCA

Running PCA on the indicators with STATA, the data set on vulnerability indicators showed five components with eigenvalues 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

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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

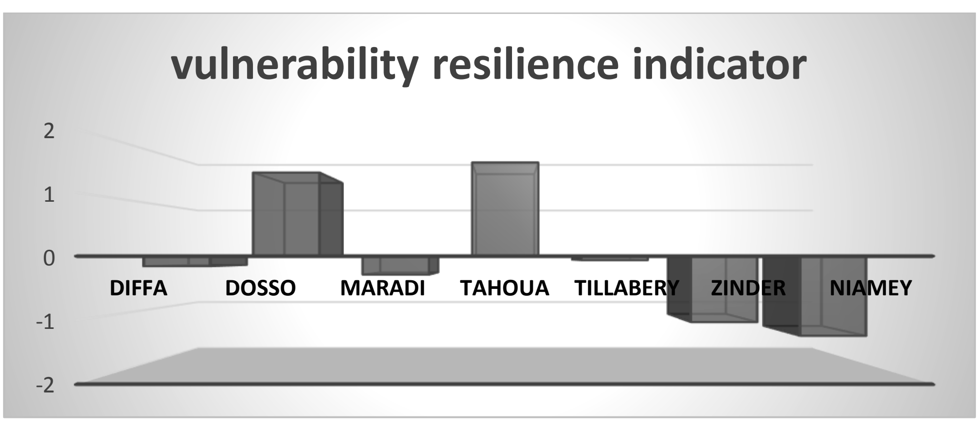
Source: author, 2015

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 2: Vulnerability resilience indicator



Source: author, 2015

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4. DISCUSSION

Graph2 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 Tillabéryis 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.

5. CONCLUSION

Based on household-level survey data collected from the National Institute of Statistics, vulnerability as an expected poverty approach is used to analyse the probability of rural households falling below the poverty line (minimum income) due to climate shocks. Logistic regression is used to estimate the proportion of rural households with income below the minimum income threshold (vulnerable households) and the result shows that 77% of rural household have their income below the threshold.

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

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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 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.

REFERENCES

Adams, R. M. 1989. Global climate change and agriculture: An economic perspective. American Journal of Agricultural Economics 71(5): 1272–1279.

Adger, W. N. 2000. Social and ecological resilience: are they related? Progress in Human Geography 24(3): 347-364

Adger, W. N., 1999. Social Vulnerability to Climate Change and Extremes in Coastal Vietnam. World Development 27 (2), 249-269, 1999.

Adger, W. N., & Vincent, K. (2005).Uncertainty in Adaptive Capacity. C R Geoscience, 337 399 - 410.

Adger, W. N., N. Brooks, G. Bentham, M. Agnew and S. Eriksen (2004). “New indicators of Vulnerability and adaptive capacity.” Norwich, UK: Tyndall Centre for Climate Change.

Adger, W. N., & Kelly, P. M. (1999). Social Vulnerability to Climate Change and the Architecture of Entitlements. Mitigation and Adaptation Strategies for Global Change, 4, 253 - 266.

ISSN: 2455-6939

Volume:02, Issue:03

Allen, K. 2003. Vulnerability reduction and the community-based approach: A Philippines study. In Natural Disasters and Development in a Globalizing World, ed. M. Pelling, 170–184, New York: Routledge.

Brooks, N., W. N. Adger, and P. M. Kelly. 2005. The determinants of vulnerability and adaptive Capacity at the national level and the implications for adaptation. Global Environmental Change 15(2): 151–163.

Brooks, N. (2003). Vulnerability, Risk and Adaptation: A Conceptual Framework. Working Paper 38. Norwich: Tyndall Centre for Climate Change Research.

Campbell, D. J. 1999. Response to drought among farmers and herders in southern Kajiado District, Kenya: A comparison of 1972–1976 and 1994–1995. Human Ecology 27: 377-415.

Chaudhuri, S., J. Jalan, and A. Suryahadi. 2002. Assessing household vulnerability to poverty: A Methodology and estimates for Indonesia. Department of Economics Discussion Paper 0102-52. New York: Columbia University.

Chen, J.T., Rehkopf, D.H., Waterman, P.D., Subramanian, S.V., Coull, B.A., Cohen, B., Ostrem, M., Krieger, N., 2006. Mapping and measuring social disparities in premature mortality: The impact of census tract poverty within and across Boston neighborhoods, 1999-2001. Journal of Urban Health 83, 1063-1084.

Cutter, S. L., Emrich, C. T., Webb, J. J., & Morath, D. 2009. Social Vulnerability to Climate Variability Hazards.

Cutter, S. L. (1996).Vulnerability to Environmental Hazards. Progress in Human Geography, 20(4), 529 - 539.

Cutter, S. L., J. T. Mitchell, and M. S. Scott. 2000. Revealing the vulnerability of people and Places: A case study of Georgetown County, South Carolina. Annals of the Association of American Geographers 90(4): 713–737.

Du Toit, M. A, S. Prinsloo, and A. Marthinus. 2001. El Niño-southern oscillation effects on Maize production in South Africa: A preliminary methodology study. In Impacts of El Niño and climate variability on agriculture, eds. C. Rosenzweig, K. J. Boote, S.

Eriksen, S. H., and P. M. Kelly. 2007. Developing credible vulnerability indicators for climate Adaptation policy assessment. Mitigation and Adaptation Strategies for Global Change 12(4): 495–524.

Forner, C. 2006. An introduction to the impacts of climate change and vulnerability of forests. Background document for the South East Asian meeting of the Tropical Forests and Climate Change Adaptation (TroFCCA) project. Bogor, West Java (May 29–30).

Füssel, H.-M., and R. J. T. Klein. 2006. Climate change vulnerability assessments: An Evolution of conceptual thinking. Climatic Change 75(3): 301–329.

Füssel, H. 2007. Vulnerability: A generally applicable conceptual framework for climate change Research.

Gbetibouo, G. A., & Ringler, C. (2009). Mapping South African Farming Sector Vulnerability to Climate Change and Variability. A Sub national Assessment. IFPRI Discussion Paper 00885. Washington, DC: International Food Policy Research Institute (IFPRI).

Haddad, B. M. (2005). Ranking the adaptive capacity of nations to climate change when socio-Political goals are explicit. Global Environmental Change, 15, 165-176.

IPCC, Intergovernmental panel on Climate Change. 2001. Climate change 2001: Impacts, Adaptation and Vulnerability. Cambridge University Press.

Jakobsen, K. (2011). Livelihood asset maps: a multidimensional approach to measuring risk-Management capacity and adaptation policy targeting-a case study in Bhutan. DOI 10.1007/s10113-012-0320-7.

Kaiser, H. M., S. J. Riha, D. S. Wilks, D. G. Rossiter, and R. K. Sampath. 1993. A farm-level Analysis of economic and agronomic impacts of gradual warming. American Journal of Agricultural Economics75: 387–98.

Kelly, P. M., and W. N. Adger. 2000. Theory and practice in assessing vulnerability to climate Change and facilitation adaptation. Climatic Change 47(4): 925–1352.

Martens, P., R. Kovats, S. Nijhof, P. de Vries, J. Livermore, D. Bradley, et al. 1999.Climate Change and future populations at risk of malaria. Global Environmental Change 9(1): 89–107.

McCarthy, J., O. F. Canziani, N. A. Leary, D. J. Dokken, and C. White, eds. 2001. Climate Change 2001: Impacts, adaptation, and vulnerability. Contribution of Working Group II to the Third assessment report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press.

Mendelsohn, R., W. Nordhaus, and D. Shaw. 1994. The impact of global warming on Agriculture: A Ricardian analysis. American Economic Review 84: 753-771.

Nelson, R., Kokic, Crimp, S., Meinke, H., &Howden, S. M. 2010a. The vulnerability of Australian Rural Communities to Climate Change Variability and Change.

Nelson, R., Kokic, P., Crimp, S., Martin, P., Meinke, H., Howden, S. M., et al.(2010b). the Vulnerability of Australian Rural Communities to Climate Variability and Change: Part II - Integrating Impacts with Adaptive Capacity. Environmental Science and Policy, 13, 18 -27.

O'Brien, K., Leichenko, R., Kelkar, U., Venema, H., Aandahl, G., Tompkins, H., Javed, A., Bhadwal, S., Barg, S., Nygaard, L., West, J., 2004.Mapping vulnerability to multiple Stressors: climate change and globalization in India. Global Environmental change 14, 303-313.

Olsen, J. E., P. K. Bocher, and Y. Jensen. 2000. Comparison of scales of climate and soil data for Aggregating simulated yields in winter wheat in Denmark. Agriculture, Ecosystem and Environment 82(3): 213–228.

Polsky, C., and W. E. Esterling. 2001. Adaptation to climate variability and change in the US Great Plains: A multi-scale analysis of Ricardian climate sensitivities. Agriculture, Ecosystem and Environment 85(3): 133–144.

Sanghi, A., R. Mendelsohn, and A. Dinar. 1998. The climate sensitivity of Indian agriculture. In measuring the impact of climate change on Indian agriculture, ed. A. Dinar et al. (Technical Paper 402). Washington, DC: World Bank.

TemesgenDeressa, Rashid M. Hassan and Claudia Ringler. 2008. Measuring Ethiopian Farmer's Vulnerability to Climate Change across Regional States.

UNDP, 2007.Human development reports. http://hdr.undp.org/en/ (accessed 25 December 2007).

UNEP, 2004.Poverty-biodiversity mapping applications. In: Presented at: IUCN World Conservation Congress, Bangkok, Thailand, 17-25 November 2004.

USAID, 2007a.Famine Early Warning Systems-NETwork (FEWS-NET). http://www.fews.net/ (Accessed 24 December 2007).

Villers-Ruiz, L., and I. Trejo-Vázquez. 1997. Assessment of the vulnerability of forest Ecosystems to climate Change in Mexico. Climate Research 9(December): 87–93.

Vincent, K. (2004). Creating an index of social vulnerability to climate change for Africa. Working Paper 56. Norwich: Tyndall Center for Climate Change Research.

Vincent, K., & Cull, T. (2010). A Household Social Vulnerability Index (HSVI) for Evaluating Adaptation Projects in Developing Countries. Paper presented in PEGNet Conference 2010, Policies to Foster and Sustain Equitable Development in Times of Crises, Midrand, 2nd -3rd September 2010.

Watson, R. T., Zinyowera, M. C., & Moss, R. H. 1996. Adaption and Mitigation of Climate Change.

World Food Program, 2007. Vulnerability Analysis and Mapping tool for targeting food aid.

Xiao, X., et al., 2002. Transient climate change and potential croplands of the world in the 21st Century. Massachusetts Institute of Technology, Joint Program on the Science and Policy of Global Change, Report No. 18. Cambridge: MIT

Yohe, G., & Richard S.J Tol (2002).Indicators for social and economic coping capacity-moving toward a working definition of adaptive capacity. Global Environmental Change 12 (2002) 25-40.

