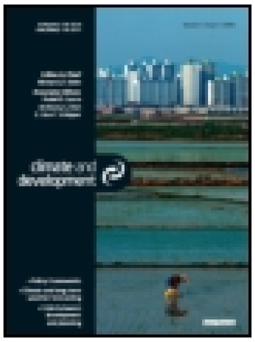

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RESEARCH ARTICLE

Farmers' vulnerability to climate shocks: insights from the Niger basin of Benin

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ABSTRACT

This paper investigates the vulnerability of farm-based livelihood systems to climate shocks in the Niger basin of Benin using a household survey dataset relative to the 2012–2013 agricultural year. The integrated approach is used to assess the vulnerability to climate shocks as function of exposure, sensitivity, and adaptive capacity, and the indices are used as a dependent variable in an Ordinary Least Squares regression. The results reveal that 57.43% of the farm households are vulnerable to climate shocks (31.74% are very vulnerable). The findings highlight that the lowest adaptive capacity does not necessarily coincide with highest exposure and sensitivity to result in the highest vulnerability. Social capital is very important in building the resilience of farm-based livelihood systems. Vulnerability of farm-based livelihoods depends on the nature of climate shocks. Indeed, the econometric estimations show that vulnerability levels increase differently with respect to the type of shock; the increase is 0.87, 0.77, 1.27, and 1.28 for droughts, strong winds, heat waves, and erratic rainfall, respectively. Floods appear to be beneficial to the farm households as they negatively influence vulnerability to climate shocks. The simulations suggest that vulnerability to climate shocks will increase in the absence of adaptation.

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KEYWORDS
Classification and Regression Tree (CART) model; econometric analysis; integrated approach; Monte Carlo analysis; resilience

1. Introduction

Climate change and variability constitutes a serious global environmental issue (Hare, Cramer, Schaeffer, Battaglini, & Jaeger, 2011; Vincent & Cull, 2014). Thus, the occurrence of climate shocks and extreme climatic events such as floods, droughts, strong winds, heat waves, earthquakes, and hurricanes is widespread.[1] The Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC, 2014) stated that climate shocks will likely have an overall negative effect on agricultural production in many African countries and regions, and this could lead to food insecurity and malnutrition exacerbation.

Unlike in developed countries, agriculture in most African countries is mainly rain-fed, and therefore is highly sensitive to climate conditions, despite its importance for these countries. For instance, Kurukulasuriya et al. (2006) found that agricultural net revenues would fall with more warming or drying in Africa. However, the extent to which climate shocks affect agricultural production differs across African regions. Roudier, Sultan, Quirion, and Berg (2011) showed that yield impact is larger in northern West Africa than in the southern part of West Africa. These adverse impacts can lead to the vulnerability of agriculture-dependent livelihoods, especially of smallholder farmers (Dixon, Smith, & Guill, 2003; IPCC, 2014).

Vulnerability to climate shocks can be exacerbated by other shocks such as poverty, unequal access to resources, food insecurity, conflict, and incidence of diseases like malaria and Ebola fever (IPCC, 2014). The combination of climate and non-climatic shocks could push farmers into the poverty trap. Farmers cannot withstand hardship without aid (from government, non-governmental organizations, or other institutions); they are on the other side of the Micawber frontier (Carter & Barrett, 2006). Therefore, they will remain permanently poor and vulnerable to climate shocks.

Assessing the vulnerability of farm-based livelihood systems to climate shocks can help identify and characterize actions towards strengthening their resilience, and achieve sustainable development goals (SDGs) (Islam, Sallu, Hubacek, & Paavola, 2014; Kelly & Adger, 2000). Indeed, one of the targets of the first SDG is to build by 2030 the resilience of the poor and vulnerable people, and lessen their exposure and vulnerability to climate-related extreme events and other economic, social, and environmental shocks and disasters. In addition, among the 5 critical priorities within the African Development Bank (AfDB) Ten-Year strategy (called the 'High 5s'), there are 'Feed Africa', and 'Improve the quality of life for the people of Africa'.[2] There is a body of papers on vulnerability to climate change and variability including climate shocks on fisheries systems (e.g. Islam et al., 2014), on agricultural livelihoods (e.g. Brooks, Adger, & Kelly, 2005; Deressa, Hassan, & Ringler, 2008, 2009; Etwire, Al-Hassan, Kuwornu, & Osei-Owusu, 2013; Madu, 2012; Pandey & Jha, 2012; Shewmake, 2008; Simane, Zaitchik, & Foltz, 2016; Vincent, 2007), and on all sectors or other sectors of the economy (e.g. Dixon et al., 2003; Dunford, Harrison, Jäger, Rounsevell, & Tinch, 2015). Three methods are commonly used in the literature, which are econometric, indicator, and simulation methods. Moreover, three major

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approaches of vulnerability analysis are identified in the literature: the socio-economic, biophysical, and integrated approaches; the integrated approach combining the socio-economic and biophysical approaches (Deressa et al., 2008). The integrated assessment can be done, either through mapping vulnerability or computing indices, and may be theory driven or data driven. Vulnerability indicators can be developed at the country level or smaller units of analysis (Vincent & Cull, 2014). However, there are some issues with the indicator approach; the weighting issue, sensitivity and uncertainty issue, issue relative to the validation of the approach, and future vulnerability issue (Alinovi, Mane, & Romano, 2009; Vincent, 2007; Vincent & Cull, 2014).

The objective of this paper is to assess the vulnerability of farm households to climate shocks in the Niger basin of Benin, using the integrated approach and an econometric regression. This assessment can help identify and characterize actions towards strengthening the resilience of farm households to climate shocks. The Niger basin of Benin is chosen because (i) Benin is located in Sub-Saharan Africa, which is considered as the most vulnerable region to climate-related shocks (IPCC, 2014); (ii) Benin is moderately to highly vulnerable to climate shocks (Brooks et al., 2005); (iii) the agricultural sector contributes 35% to the gross domestic product (GDP) and employs 70% of the active population (République du Bénin, 2014); and (iv) the Niger basin covers 37.74% of the Benin land size. This paper departs from the previous studies on vulnerability to climate-related shocks, by validating the indicator approach through a Classification and Regression Tree (CART) model (Breiman, Friedman, Olshen, & Stone, 1984), and by assessing future vulnerability through an econometric analysis. Moreover, it adds empirical evidence to the existing literature on the quantitative analysis of vulnerability of farm households to climate shocks in a region where such quantitative research is rare. It should be mentioned that there is a literature on vulnerability analysis in the study area and the whole sub-region, which literature is more oriented towards the perception of climate change and of institutions, and adaptation strategies (e.g. Baudoin, Sanchez, & Fandohan, 2014; Sanchez, Fandohan, Assogbadjo, & Sinsin, 2012).

2. Study area

The Niger basin of Benin is located in the extreme north of Benin, more specifically between latitudes 11° and 12°30' North and longitudes 2° and 3°20'40 East and has an area of 43,313 km^2 out of the 114,763 km^2 of the country (Figure 1). It belongs to the watershed of Middle Niger. The Niger River is the largest in West Africa (4200 km of length and a watershed of 1,125,000 km^2). The Niger basin of Benin covers five agro-ecological zones (AEZs) (wholly and partially) out of the eight in the country. The communes that share the same physical, biological, and social constraints are grouped together in one of the AEZs. The characteristics of the AEZs covered by the basin, which show the disparities across the zones in terms of climate, soils, and main crops, are provided in Table 1 of the Supplemental Materials.

Agriculture is the main activity of households in the basin. They produce for home consumption and sell a part of their crops. The production takes place from May to November

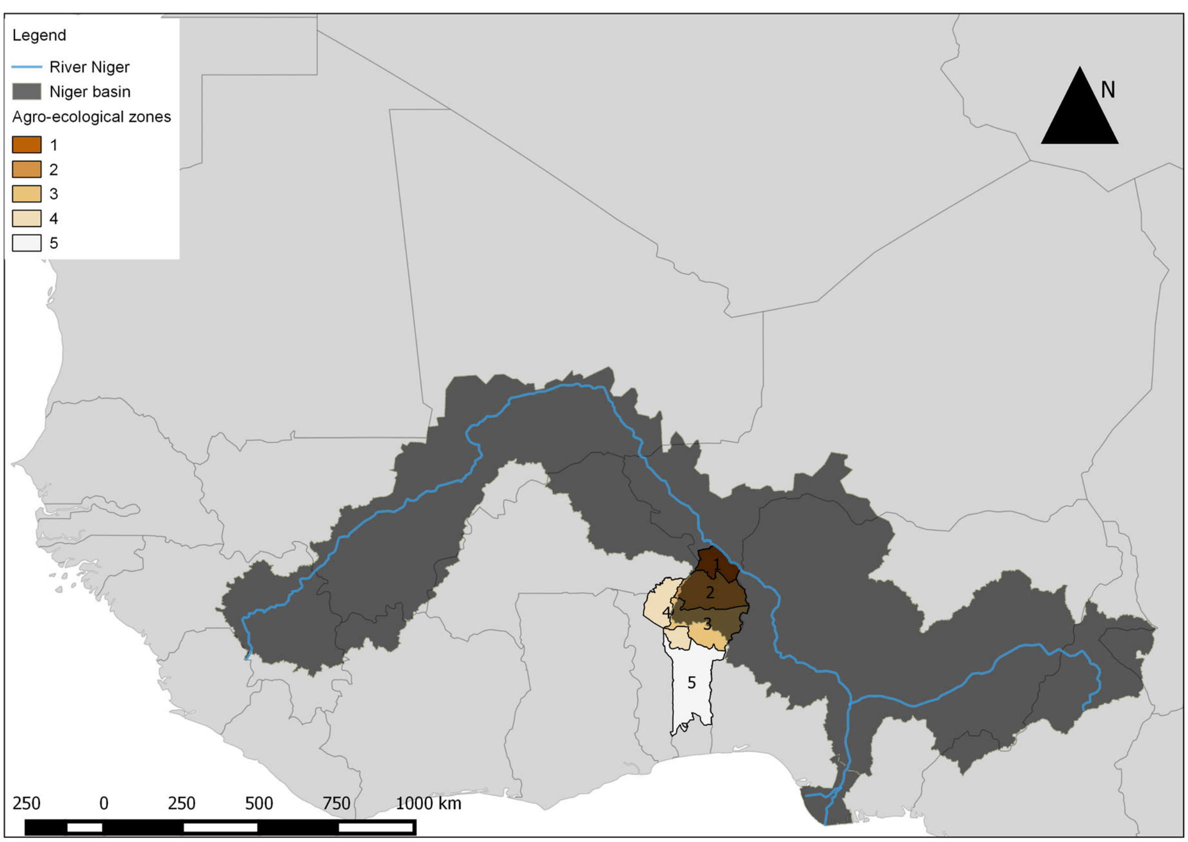

Figure 1. Map of the Niger basin.

(during the single rainy season). Cotton production is their main source of cash income. Farmers rely principally on traditional agricultural systems, which are characterized by their reliance on labour (mostly family labour) combined with limited use of improved inputs, production methods, and farm equipment. Animal traction is widespread in the eastern part of the basin due to cattle rearing. Cattle are also kept as insurance against unexpected need, catastrophes, or hardships. Small breeding (sheep, goats, and poultry) and fisheries are also developed in the basin. Though every farm household does not own cattle and plow for animal traction, some borrow them from their neighbours, to deal quickly with land preparation. Additional information on the study area is provided in Section 1 of the Supplemental Materials.

The most severe droughts that adversely affected the agricultural sector, during the past 60 years, have occurred in 1977 and 1983. However, floods occur almost every year in the basin, and affect farmers, especially those located at the vicinity of the Niger River. Actually, severe floods have been recorded in 1962, 1968, 1988, 1997, 1998, and 2010. In terms of future climate conditions, temperature is projected to increase in the basin during the twenty-first century (Hulme, Doherty, Ngara, New, & Lister, 2001). Rainfall is projected to increase during December-January-February, and to decrease during June-July-August in some scenarios (Hulme et al., 2001). Therefore, the basin will likely face difficult climate conditions and farmers will be adversely affected if they do not adapt.

3. Empirical approach, description of the variables, and data

3.1. Empirical approach

Vulnerability of farm-based livelihoods to climate shocks can be defined as their propensity or predisposition to be adversely affected (adapted from IPCC, 2014). Vulnerability of farm-based livelihood systems encompasses a variety of concepts and elements including sensitivity or susceptibility to climate shocks, and lack of capacity to cope and adapt (adapted from IPCC, 2014). It is a function of exposure, sensitivity, and adaptive capacity.

Exposure in the IPCC framework has an external dimension, whereas both sensitivity and adaptive capacity have an internal dimension (Füssel, 2007). Therefore, to assess the vulnerability of farm-based livelihood systems to climate shocks, it is necessary to understand each of the three components of vulnerability. Exposure in the context of this paper is the presence of farm-based livelihood systems in places and settings that could be adversely affected (adapted from IPCC, 2014). Exposure indicators characterize the frequency of extreme events, scale of land erosion and sea-level rise, and changes in temperature and rainfall (Islam et al., 2014). Sensitivity in this paper is the degree to which a farm-based livelihood system is affected, either adversely or beneficially, by climate shocks (adapted from IPCC, 2014). Sensitivity does not mean only negative effect, but includes also a positive one, because the occurrence of climate shocks may be beneficial to some farm-based livelihood systems. Adaptive capacity is the ability of a farm-based livelihood system to adjust to climate shocks, to take advantage of opportunities, or to respond to consequences (adapted from IPCC, 2014).

In the IPCC framework, adaptive capacity is negatively related to vulnerability. More adaptive capacity means lesser vulnerability to climate shocks in this framework. However, high adaptive capacity cannot be always associated with lesser vulnerability. A farm-based livelihood system may have high adaptive capacity and may end up being adversely affected by climate shocks, leading to high vulnerability. Moreover, low adaptive capacity can result in lesser vulnerability. As sensitivity includes also a positive effect of climate shocks, some farmers can benefit from these shocks.

Equation 14 of the Supplemental Materials is used to assess the vulnerability to climate shocks. Details on background and conceptual framework are provided in Section 2 of the Supplemental Materials. Vulnerability index is calculated as the net effect of adaptive capacity, sensitivity, and exposure:

$$v = adaptive\ capacity - (exposure + sensitivity). \tag{1}$$

One of the features of the indicator approach is to assign a weight to each indicator. Thus, two alternatives may be used: either to give them equal weight or to assign different weights, to avoid the uncertainty of equal weighting given the diversity of indicators used (Deressa et al., 2008). This paper adopts the different weighting alternative using dimension reduction methods; Principal Component Analysis (PCA), and Factor Analysis (FA) (Pearson, 1901; Spearman, 1904).

As vulnerability is a multi-dimensional concept (Vincent & Cull, 2014), all the extracted components from PCA and FA are used in computing the sub-indices. Each component from PCA and FA is weighted by its percentage of explained variance. Suppose p components are extracted, for each indicator Equation (2) is employed, before building the sub-indices:

$$Y_i^* = \frac{Var_j}{\sum_{j=1}^{p} Var_j} \times Factor_{ji} \times X_i,\ for\ all\ component\ j \tag{2}$$

where Var_j is the percentage of explained variance of the component j, $Factor_{ji}$ is the j^{th} factor score relative to the i^{th} indicator, and X_i is the i^{th} indicator.

Vulnerability index is computed for each farm household using Equation (3).

$$\begin{aligned} \hat{v}_h = & \sum_{i=1}^{na}\sum_{j=1}^{p}\frac{Var_j}{\sum_{j=1}^{p} Var_j}*Factor_{ji}*X_{ai} \\ & - \left(\sum_{i=1}^{ne}\sum_{j=1}^{p}\frac{Var_j}{\sum_{j=1}^{p} Var_j}*Factor_{ji}*X_{ei}\right. \\ & \left. + \sum_{i=1}^{ns}\sum_{j=1}^{p}\frac{Var_j}{\sum_{j=1}^{p} Var_j}*Factor_{ji}*X_{si}\right) \end{aligned} \tag{3}$$

where X_{ai}, X_{ei}, and X_{si} are the adaptive capacity, exposure, and sensitivity variables, respectively. na, ne, and ns represent the number of adaptive capacity, exposure, and sensitivity variables, respectively.

Two of the key issues of the indicator method are relative to its validation, and future vulnerability assessment (Alinovi et al., 2009; Vincent, 2007; Vincent & Cull, 2014). Alinovi et al. (2009) argued that to assess the meaningfulness of the procedure used for computing indices, a CART model may be used. Therefore, the paper uses a CART model to estimate the vulnerability decision tree and related splitting rules. CART model aids the researcher in choosing from many potentially relevant variables, and by suggesting refinements in functional form that are appropriate in subsequent parametric analysis (Larose, 2005). As the target variable is continuous (vulnerability index), CART will create a regression tree. The original indicators that are used for the computation of the vulnerability index are employed in the CART analysis.

An econometric analysis is performed to find the main factors that can significantly lessen the vulnerability to climate shocks and for simulation purposes. This is due to the major limitation of the indicator method, as it always produces normalized indicators with means zero, so it is difficult to compare the level of vulnerability over time (Alinovi et al., 2009). The vulnerability equation is specified as follows:

$$v_h = \beta_0 + X_h\beta + \gamma_h \tag{4}$$

where X_h is the set of variables belonging to the three dimensions of vulnerability, β is the vector of the coefficients to be estimated, and γ is the error term. The choice of the relevant variables for the econometric analysis is based on the CART analysis, and literature (Chaudhuri, 2003; Deressa, Hassan, & Ringler, 2009; Hoddinott & Quisumbing, 2003; Sarris & Karfakis, 2006; Shewmake, 2008). The model is estimated for all the farm households in the dataset, and also per AEZ to capture the disparities in the estimated coefficients. Sensitivity test is performed through changes and omission of certain indicators. Furthermore, Monte Carlo analysis (Metropolis & Ulam, 1949) is run to assess the uncertainty within the vulnerability index calculation model.

3.2. Description of the variables and data

Indicators are selected for each sub-index of vulnerability (Table 1). Exposure can be best represented by the frequency of climate shocks and extreme events, and changes in temperature and rainfall. In this paper, four indicators characterize exposure, under the assumption that farmers living in areas with higher changes in temperature and precipitation are most exposed to climate shocks. The geographical positing system (GPS) coordinates of each farm households were not captured in the dataset. Therefore, it was not possible to extract specific temperature and rainfall for each farm household. Nevertheless, this paper compares the subjective indicators with rainfall and temperature data for the two synoptic stations that cover the basin (Natitingou and Kandi). The subjective indicators of each household are compared with climatic variables with respect to the specific synoptic station that covers where the household is located. Figures 2 and 3 of the Supplemental Materials show the evolution of temperature and rainfall of the two synoptic stations of the basin over the period 1993-2012. Figure 2 of the Supplemental Materials shows an increasing trend in temperature. The farm households perceived in majority a change in temperature during the last 20 years.[3] Therefore, their perceptions are consistent with meteorological data. As for rainfall, Figure 3 of the Supplemental Materials shows a slight increasing trend for Natitingou, while no clear trend is observed for Kandi. Rainfall appears to be highly variable from year to year. The inter-annual variability of precipitation may be due to intra-annual variability (Fatichi, Ivanov, & Caporali, 2012), and therefore the perceptions of the farm households on rainfall are in line with observed values.

Sensitivity to climate shocks could be captured by the extent to which these shocks affect income or any proxy of livelihood (Deressa et al., 2008). However, scholars can rely on the assumption that areas experiencing climate shocks are subject to sensitivity due to loss in yields and thus in income. Thus, this paper relies on this assumption and also includes an indicator capturing the direction of changes in yields during the last 20 years or so. The relationship between the self-reported climate shocks and rainfall data was checked (Table 2 of the Supplemental Materials). To this end, May-November rainfall, its deviations from historical mean (1952–1992), and its coefficient of variation were computed for each year of the period 1993–2012, using monthly data from the two stations. Then, the averages of the three indicators were calculated to compute the coefficient of correlation between them and the self-reported climate shocks, the latter being aggregated at the village level. The relationship between them is relatively weak; it is very weak for floods and erratic rainfall. The relative low correlation can be explained by the fact that rainfall data were not specific to each village, and also were aggregated over the entire growing season. Therefore, the rainfall data may not capture the specificities of each village, and all the variabilities in rainfall across the growing season. Nevertheless, the self-reported shocks can be used as they capture more accurately the variation in climate (Shewmake, 2008). Adaptive capacity reflects the five types of capital, which are physical, institutional capital and technology, human capital, natural capital, financial capital, and social capital (Scoones, 1998). Thus, indicators are selected for each component of adaptive capacity. Definitely, farm households with more of these five types of capital are better able to cope with and adapt to the impacts of climate shocks.

The data come from the household survey, which was implemented within the Niger basin of Benin in the 2012–2013 agricultural year. The survey was conducted during April and May 2013. A three-stage sampling technique was followed to select surveyed farm households. First, communes were randomly chosen within each AEZ, based on their number of agricultural households. Second, villages were randomly selected within the selected communes. Finally, random farm households were selected within selected villages. One AEZ was disregarded (AEZ V), because only one of its communes is located within the Niger basin. The sampled size was decided as 545 for the whole basin.[4] The survey questions were designed to address the three components of vulnerability. They are relative to socio-economic and environmental attributes as well as those related to farmers' perceptions of climate change, temperature, and rainfall patterns over the past 20 years and adaptation strategies. The respondents were typically household heads. However, when the household head was not available, another adult member of the household was interviewed.[5] In

Table 1. Indicators used to assess vulnerability to climate shocks.

Vulnerability components		Indicators	Nature
Exposure		Change in rainfall period during the last 20 years	Categorical (Yes = 1, No = 2, and I do not know = 3)
		Increase regarding the intensity of rainfall throughout the years	Categorical (Yes = 1, No = 2, and I do not know = 3)
		Increase regarding the length of dry spells during the rainy season	Categorical (Yes = 1, No = 2, and I do not know = 3)
		Change in temperature during the last 20 years	Categorical (Yes = 1, No = 2, and I do not know = 3)
Sensitivity		Having encountered floods throughout the last 20 years	Dummy (Yes = 1, and No = 2)
		Having encountered droughts throughout the last 20 years	Dummy (Yes = 1, and No = 2)
		Having encountered strong winds throughout the last 20 years	Dummy (Yes = 1, and No = 2)
		Having encountered heat waves throughout the last 20 years	Dummy (Yes = 1, and No = 2)
		Having encountered erratic rainfall throughout the last 20 years	Dummy (Yes = 1, and No = 2)
		Having encountered heavy rainfall throughout the last 20 years	Dummy (Yes = 1, and No = 2)
		Change in planting dates throughout the years	Categorical (Yes = 1, No = 2, and I do not know = 3)
		Change in yield	Categorical (Increase = 1, Decrease = 2, and I do not know = 3)
Adaptive capacity	Financial capital	Fertilizer use value	Continuous (CFA F)[a]
		Herbicide use value	Continuous (CFA F)
		Insecticide use value	Continuous (CFA F)
		Yearly income from agricultural off-farm activities	Continuous (CFA F)
		Yearly income from non-agricultural off-farm activities	Continuous (CFA F)
		Yearly income from cropping	Continuous (CFA F)
		Yearly income from livestock	Continuous (CFA F)
	Natural capital	Bush and valley bottom land use size	Continuous (ha)
		Compound land use size	Continuous (ha)
		Supplementary irrigated land use size	Continuous (ha)
		Irrigated land use size	Continuous (ha)
	Human capital	Household head age	Continuous (Years)
		Household head formal education level	Continuous (Validated years)
		Number of men	Continuous
		Number of women	Continuous
		Number of children	Continuous
	Physical, institutional capital and technology	Tractor use	Dummy (Yes = 1, and No = 2)
		Plow use	Dummy (Yes = 1, and No = 2)
		Livestock value	Continuous (CFA F)
		Amount of credit obtained	Continuous (CFA F)
		Frequency of access to extension services	Continuous
		Distance from dwelling to food market	Continuous (km)
		Distance from dwelling to paved or tarred road	Continuous (km)
		Access to electricity	Dummy (Yes = 1, and No = 2)
		Asset value	Continuous (CFA F)
	Social capital	Membership in labour sharing group	Dummy (Yes = 1, and No = 2)
		Membership in farmers' organization	Dummy (Yes = 1, and No = 2)
		Amount of financial assistance received	Continuous (CFA F)
		Value of in-kind assistance received	Continuous (CFA F)
		Moral assistance	Dummy (Yes = 1, and No = 2)
		Number of relatives within the village	Continuous
		Labour mobilized from relatives, and friends within the community	Continuous (Man-days)
		Number of close friends	Continuous
		Number of people the household could turn to who would be willing to lend money	Categorical (No one = 1, One or two = 2, Three or four = 3, Five or more = 4)
		Whether the household can rely on neighbours to take care of children when they are travelling	Categorical (Definitely = 1, Probably = 2, Probably not = 3, Definitely not = 4)
		Working for the benefit of the community during the last 12 months	Dummy (Yes = 1, and No = 0)
		Believing that people that do not participate in communities' activities will be criticised	Categorical (Very likely = 1, Somewhat likely = 2, Neither likely or unlikely = 3, Somewhat unlikely = 4, Very unlikely = 5)
		Proportion of people in the community that contribute time towards common development goals	Categorical (Everyone = 1, More than half = 2, About half = 3, Less than half = 4, No one = 5)

[a]On average, 1US$=510.53 CFA F in 212.

addition to the primary data, the research benefited from the monthly climatic data from the World monthly surface station climatology data (National Climatic Data Center et al., 2012).

This paper relies on the assumption that cross-sectional variability captures temporal variability similar to the early literature on the Ricardian model used to assess the impact of climate

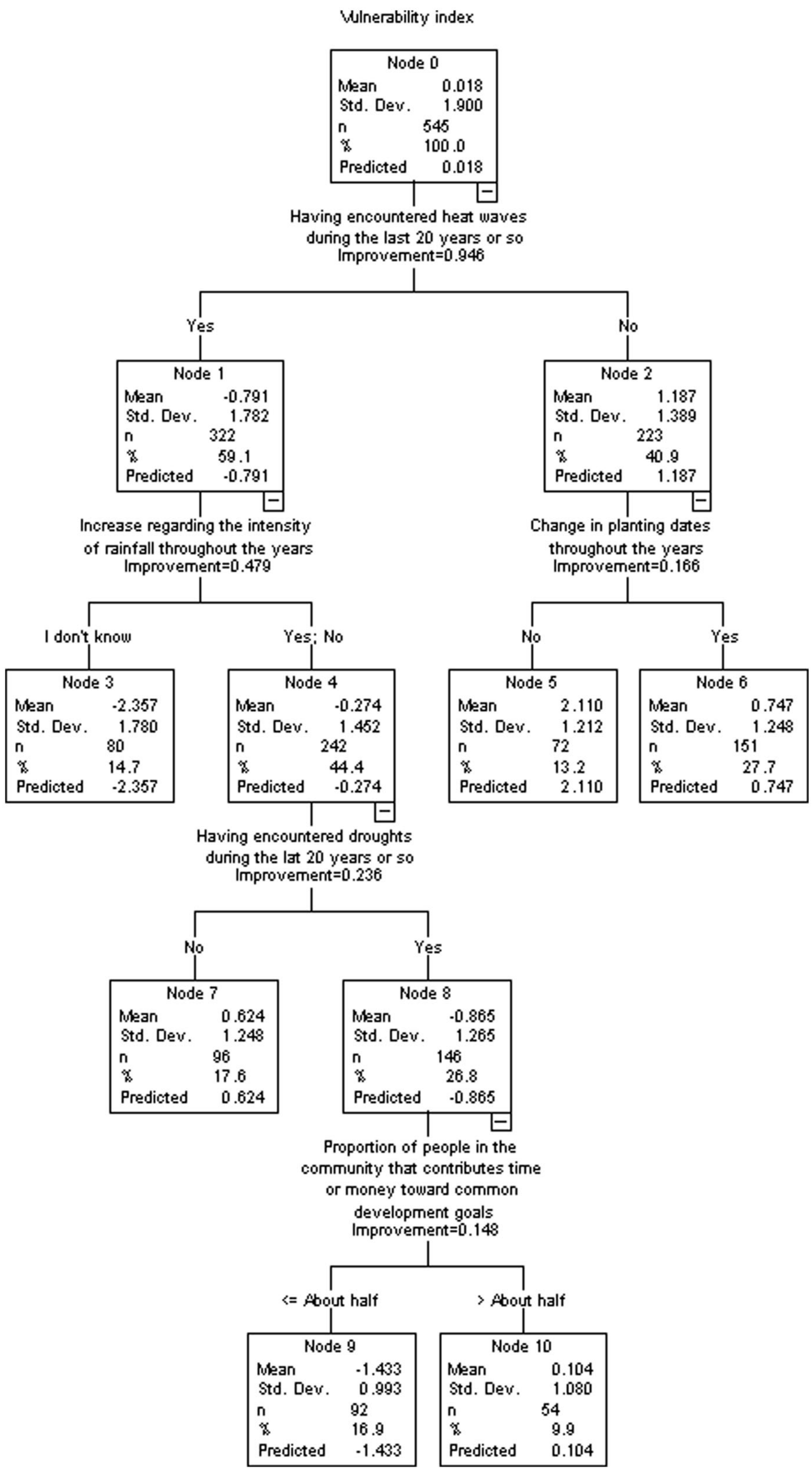

Figure 2. Regression tree of vulnerability to climate shocks.

change on agriculture (e.g. Kurukulasuriya et al., 2006). Normally, panel data should be used to capture the evolution of each indicator over time, due to the dynamic aspect of vulnerability. Moreover, only climate shocks are considered, even though climate shocks and other shocks such as illness are interrelated. Nonetheless, the paper provides useful insights into the vulnerability levels of the farm households to climate shocks.

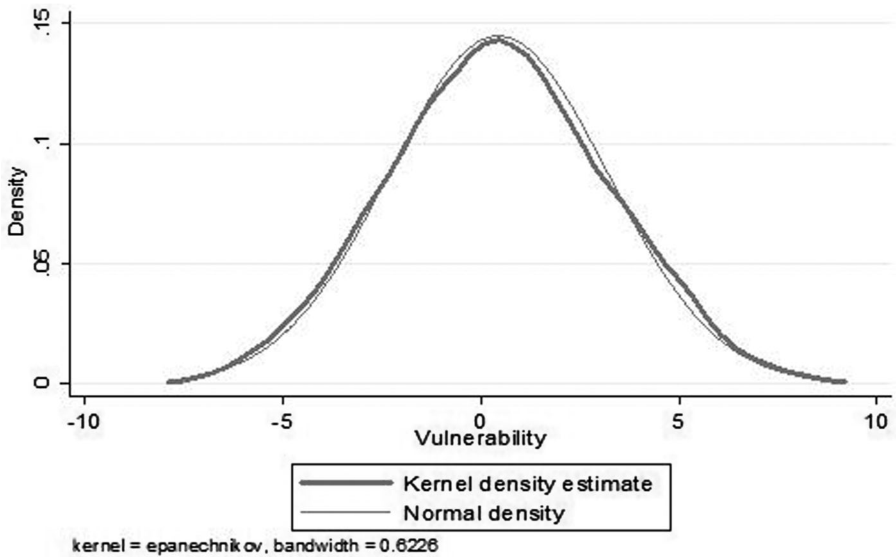

Figure 3. Kernel density of the generated vulnerability index.

4. Results

The surveyed households reported to have encountered many climate shocks throughout the last 20 years. The major climate shocks that farmers faced in all the four AEZs were strong winds, followed by erratic rainfall, heavy rainfall, heat waves, floods, and finally droughts. AEZ I farmers faced floods more often than the remaining farmers. These floods were mostly due to the overflows of the Niger River. Descriptive statistics are provided in Tables 3–5 of the Supplemental Materials.

4.1. Vulnerability

Lower values of the index show more vulnerability, and higher values depict less vulnerability (more resilience).[6] More than half of the farm households (57.43%) are vulnerable to climate shocks. Among these vulnerable farm households, 55.27% (37.74% of the sample) are in critical situation (very vulnerable to climate shocks). It should be mentioned the classification was made by organizing the data in 10 intervals of the same bin width. Then, those with vulnerability index lower than 0.42 are considered as vulnerable to climate shocks, and farmers with an index lower than −0.81 are classified as very vulnerable to these shocks. The most vulnerable household is in AEZ II, whereas the least vulnerable household is in AEZ I, where farmers mostly practice irrigation. The differences among the AEZs' vulnerability levels are all significant ($p < 0.05$), except between AEZs II and IV, and between AEZs III and IV. On average, farmers in the AEZ I are the least vulnerable, followed by those in AEZs III, IV, and II (Tables 2). The findings highlight that the highest vulnerability to climate shocks does not necessarily coincide with the highest exposure and sensitivity, and the lowest adaptive capacity. For instance, farm households in AEZ II, which are the most vulnerable, have the lowest adaptive capacity, but are not the most sensitive and the most exposed to climate shocks. Education also appears to be somewhat correlated with vulnerability. A higher formal education level of the household head is associated with lower vulnerability to climate shocks. Moreover, among farm households whose heads completed less than six validated school years, those that are able to read and write in local languages are less vulnerable than those whose heads cannot either read or write in any language.

As previously mentioned, this paper assesses the meaningfulness of the procedure used for computing indices, using a CART model. The optimal tree generated by the CART model has six terminal nodes (Figure 2). The model's predictions are relatively good, because the within-node variance is 1.629, and the proportion of variance explained is 0.55. This result confirms the meaningfulness of the method used to compute the indices. The interpretation of the CART model result is provided in Section 4 of the Supplemental Materials.

Moreover, the method used turned out to be sufficiently robust in terms of sensitivity and uncertainty. Indeed,

Table 2. Indices and sub-indices of vulnerability across agro-ecological-zones.

Indices	Agro-ecological zone I	Agro-ecological zone II	Agro-ecological zone III	Agro-ecological zone IV	All households	Standard deviation
Sub-index of exposure	0.01	0.02	−0.08	0.26	0	1.12
Sub-index of sensitivity	−0.60	0.18	−0.01	0.34	0	1.33
Sub-index of financial capital	0	0.07	−0.03	−0.07	0	0.15
Sub-index of physical, institutional capital and technology	0.07	0.09	−0.01	−0.18	0.02	0.17
Sub-index of human capital	0	−0.01	0	0.03	0	0.10
Sub-index of natural capital	0.09	0	−0.02	−0.03	0	0.07
Sub-index of social capital	0.02	−0.41	0.14	0.68	0	1.18
Sub-index of adaptive capacity	0.18	−0.26	0.07	0.43	0.02	1.16
Index of vulnerability	0.76	−0.47	0.17	−0.16	0.02	1.90

regarding sensitivity, the values of some indicators have been changed or some indicators are simply disregarded to explore the impact on the vulnerability index. Regarding the Monte Carlo analysis, the vulnerability index was computed 1000 times to map its probability distribution. For each sub-index of vulnerability, random values were generated between its minimum and maximum values. The distribution of the generated vulnerability index corresponds to a Gaussian distribution (Figure 3). The reliability of the originally calculated vulnerability index is estimated through determination of the range of the standard deviation around the mean. The Student test showed that the original vulnerability index lies within the range ($p < 0.01$).

4.2. Exposure

Farmers in AEZ IV are more exposed to climate shocks, followed by AEZ II, AEZ I, and AEZ III (Table 2). It was not possible to distinguish exposure between AEZs, except between AEZs III and IV ($p < 0.01$). The exposure level of farmers in AEZ IV is due to the combination of three elements: (i) the fact that most of the farmers (82%) faced a change in the rainfall period during the last 20 years prior to the year of the interview; (ii) they faced an increase regarding the intensity of rainfall throughout the years (69%); and (iii) only 38% of them faced a change in temperature. If most of the farmers in AEZ IV faced a change in temperature during the last 20 years, they would be the lowest exposed to climate shocks like farmers in AEZ III. The situation of farm households in AEZs II and I is similar and is between those of AEZs IV and III.

4.3. Sensitivity

Sensitivity is highest among farm households in AEZ IV, followed by AEZs II, III, and I (Table 2). It varies significantly between (i) AEZs I and II ($p < 0.01$), (ii) AEZs I and III ($p < 0.01$), (iii) AEZs I and IV ($p < 0.01$), and (iv) AEZs III and IV ($p < 0.1$). The highest sensitivity of farmers in AEZ IV is due to the fact that all of them were obliged to change the planting date during the last 20 years. Moreover, 47% and 2% of these farmers experienced a decrease and an increase in yield due to climate shocks, respectively, whereas 51% of them were not able to indicate precisely the direction of the change in yields. Though farmers in AEZ I experienced more floods than the remaining farmers, they have the lowest sensitivity to climate shocks. This is due to the fact that they practice irrigated and supplementary irrigated agriculture than the remaining farmers, and 61% of them changed the planting date (80%, 82%, and 100% of farm households changed planting date in AEZs II, III, and IV, respectively).

4.4. Adaptive capacity

On average, farmers in AEZ IV have the highest adaptive capacity, followed by farmers of AEZs I, III, and II (Table 2). Adaptive capacity varies significantly between (i) AEZs I and II ($p < 0.01$), (ii) AEZs II and III ($p < 0.01$), (iii) AEZs II and IV ($p < 0.01$), and (iv) AEZs III and IV ($p < 0.1$). Though farmers in AEZ IV lack financial capital, physical, institutional capital and technology, and natural capital, they have the highest adaptive capacity due to their highest human and social capital. The lowest adaptive capacity of farmers in AEZ II is due to the lack in human and social capital. Therefore, the five components are jointly important in building adaptive capacity, because a lack in one lowers adaptive capacity.

4.5. Econometric analysis of vulnerability and simulations

The variance inflation factors are all very low, so there is no multicollinearity problem with the explanatory variables (Table 3). The model was estimated for the whole data set and then for each AEZ by the Ordinary Least Squares (Table 4). The results of the regression display some differences across AEZs. One variable was disregarded for AEZ IV due to multicollinearity (change in planting dates throughout the years).

Having noticed an increase and no trend in the intensity of rainfall throughout the years is beneficial for the livelihoods of the farm households in all the four AEZs. Actually, it

Table 3. Variance inflation factors.

Variable	VIF	1/VIF
Increase in the intensity of rainfall throughout the years (Base: I do not know)		
Yes	1.88	0.532591
No	1.75	0.570667
Having encountered floods throughout the last 20 years (1 = Yes and 0 = No)	1.24	0.803260
Having encountered droughts throughout the last 20 years (1 = Yes and 0 = No)	1.39	0.719900
Have encountered strong winds throughout the last 20 years (1 = Yes and 0 = No)	1.05	0.953866
Having encountered heat waves throughout the last 20 years (1 = Yes and 0 = No)	1.33	0.750750
Having encountered erratic rainfall throughout the last 20 years (1 = Yes and 0 = No)	1.15	0.869757
Having encountered heavy rainfall throughout the last 20 years (1 = Yes and 0 = No)	1.33	0.752041
Change in planting dates throughout the years (Base: I do not know)		
Yes	8.62	0.115949
No	9.16	0.109216
Proportion of people in the community that contribute time or money toward common development goals (Base: No one)		
Everyone	1.98	0.504152
More than half	3.03	0.330211
About half	2.18	0.459049
Less than half	2.52	0.396765
Frequency of access to extension services	1.05	0.954985
Mean VIF	2.64	

Table 4. Regression results of vulnerability.

Dependent variable: vulnerability index					
Independent variables	All households	Agro-ecological zone I	Agro-ecological zone II	Agro-ecological zone II	Agro-ecological zone IV
Increase in the intensity of rainfall throughout the years (Base: I do not know)					
Yes	2.217***	1.536***	2.593***	1.948***	1.982***
	(0.133)	(0.262)	(0.211)	(0.236)	(0.450)
No	2.340***	2.097***	2.425***	2.076***	2.515***
	(0.152)	(0.331)	(0.270)	(0.260)	(0.520)
Having encountered floods throughout the last 20 years (1 = Yes and 0 = No)	0.443***	0.509*	0.280*	0.554***	0.803**
	(0.091)	(0.296)	(0.161)	(0.158)	(0.332)
Having encountered droughts throughout the last 20 years (1 = Yes and 0 = No)	−0.873***	−1.466***	−0.510***	−1.063***	−0.858**
	(0.100)	(0.253)	(0.156)	(0.161)	(0.337)
Have encountered strong winds throughout the last 20 years (1 = Yes and 0 = No)	−0.774***	−1.022***	−0.754***	−0.627**	−1.101***
	(0.158)	(0.267)	(0.201)	(0.273)	(0.210)
Having encountered heat waves throughout the last 20 years (1 = Yes and 0 = No)	−1.268***	−0.720***	−1.618***	−1.074***	−0.911***
	(0.098)	(0.237)	(0.153)	(0.163)	(0.246)
Having encountered erratic rainfall throughout the last 20 years (1 = Yes and 0 = No)	−1.282***	−1.363***	−1.308***	−1.125***	−1.363***
	(0.124)	(0.267)	(0.166)	(0.318)	(0.475)
Having encountered heavy rainfall throughout the last 20 years (1 = Yes and 0 = No)	−0.076	−0.215	0.035	−0.225	0.126
	(0.122)	(0.352)	(0.216)	(0.170)	(0.368)
Change in planting dates throughout the years (Base: I do not know)					
Yes	−1.315***	−2.102***	1.370***	−1.188**	
	(0.476)	(0.753)	(0.264)	(0.490)	
No	−0.194	−0.849	2.302***	−0.161	
	(0.483)	(0.771)	(0.330)	(0.516)	
Proportion of people in the community that contribute time or money toward common development goals (Base: No one)					
Everyone	−1.892***	−1.141***	−1.853***	−2.460***	−1.504***
	(0.179)	(0.411)	(0.321)	(0.321)	(0.501)
More than half	−1.933***	−1.600***	−1.919***	−2.366***	−1.181***
	(0.159)	(0.343)	(0.270)	(0.271)	(0.409)
About half	−1.498***	−0.997**	−1.668***	−1.807***	−0.647*
	(0.176)	(0.420)	(0.270)	(0.303)	(0.371)
Less than half	−0.696***	−0.427	−0.512*	−0.968***	−0.580
	(0.169)	(0.365)	(0.281)	(0.291)	(0.449)
Frequency of access to extension services	0.025**	0.049	0.024	0.016	−0.011
	(0.012)	(0.114)	(0.018)	(0.017)	(0.593)
Constant	3.427***	4.609***	0.597	3.668***	1.354
	(0.516)	(1.045)	(0.522)	(0.613)	(0.816)
Adjusted R^2	0.742	0.857	0.794	0.660	0.683
Observations	545	80	175	235	55

Note: ***, **, * Significant at the 1%, 5%, and 10% levels, respectively. Numbers in parentheses are robust standard errors. Lower values of the dependent variable (vulnerability) indicate improvement in vulnerability.

lessens significantly their vulnerability levels compared with those that were unable to notice a change in the intensity of rainfall. Certainly, an increase in the intensity of rainfall means more precipitation, and it is beneficial to farmers if it does not lead to floods. On average, contributing time or money towards common development goals of the community appears to not be beneficial for the farm households, ceteris paribus. This could be explained by the fact that contributing money to development goals decreases the financial means of farmers, and the goals do not match what is required to lessen vulnerability.[7] On average, the frequency of access to extension services influences significantly the vulnerability level.

Climate shocks seem to have the expected impacts on vulnerability. The vulnerability of farm households that experienced droughts, strong winds, heat waves, and erratic rainfall is respectively 0.87, 0.77, 1.27, and 1.28 points significantly higher than the vulnerability of the remaining farmers, ceteris paribus. The effect of erratic rainfall is the highest. However, floods appear to be beneficial to the farm households in terms of vulnerability, and the direction of effect is consistent across AEZs. It is worth noting that although heavy rainfall leads to an increase in vulnerability levels, the effect is not statistically significant. Farmers resort to several means including income and social capital to cope with climate shocks. Therefore, climate shocks apart from floods negatively influence the livelihood of farmers, which strengthens vulnerability to these shocks. This may push some farm households in the poverty trap (Carter & Barrett, 2006). On average, having experienced either a change or no change in planting dates throughout the years strengthens the vulnerability levels of farm households compared to experiencing both, with the effect being statistically significant in the case of experiencing a change. However, it lessens significantly the vulnerability levels of farm households in AEZ II.

Using the regression results, Table 5 shows predictions of the level of vulnerability as a function of two climate shocks (droughts and heat waves). All the other variables of the models are held equal to their mean. Four scenarios are simulated for climate shock. It is worth noting that the simulations do not take into account the remaining four climate shocks as the proportion of farm households that experienced three of them was already high, and it does not allow the four levels of scenarios. Moreover, floods are disregarded because those that have encountered them are less vulnerable than the remaining farm households (econometric estimation results). The level

Table 5. Predictions of vulnerability index.

Variables	Scenarios[a]	All households	Agro-ecological zone I	Agro-ecological zone II	Agro-ecological zone III	Agro-ecological zone IV
Baseline		0.018	0.758	−0.465	0.169	−0.163
Droughts	0.05	−0.026	0.684	−0.491	0.116	−0.206
	0.10	−0.069	0.611	−0.516	0.063	−0.249
	0.15	−0.113	0.538	−0.542	0.010	−0.292
	0.20	−0.157	0.464	−0.568	−0.044	−0.335
Heat waves	0.05	−0.045	0.722	−0.546	0.115	−0.209
	0.10	−0.109	0.686	−0.627	0.062	−0.255
	0.15	−0.172	0.650	−0.708	0.008	−0.300
	0.20	−0.235	0.614	−0.789	−0.046	−0.346

[a]The scenarios refer to the increases of the proportion of farm households that experience climate shocks.

of vulnerability varies for each climate shock. On average, the effects of heat waves will be the highest. With droughts, farmers will shift early from cropping to non-agricultural off-farm activities, including migration. However, during heat waves they will be waiting for rainfall and they will only decide late to look for income from other activities to cropping. However, the pattern differs across AEZs. For AEZ I farmers, the effects of droughts are the highest. These findings suggest that an increase in the occurrence of droughts and heat waves will lessen the resilience of farm households in the absence of relevant policies.

5. Discussion

5.1. Exposure, sensitivity, and adaptive capacity

Farm households of the AEZs are differently exposed to climate shocks. Farm-based livelihoods of AEZ IV have the highest exposure to climate shocks. Sensitivity of livelihoods to climate shocks is determined by dependency on rain-fed agriculture, because of lack of financial capital and access to water to implement irrigation, lack of institutional support through extension services, access to credit, etc. for livelihood improvement and diversification, lack of human capital for livelihood diversification. Farm households rely on social capital when they lack the remaining four kinds of capital. Therefore, the components of vulnerability to climate shocks are interrelated. The increase of physical capital or livelihood diversification cannot be possible when households lack financial capital (Islam et al., 2014). Lowest adaptive capacity does not necessarily coincide with highest exposure and sensitivity. Climate shocks appear to affect farm households in different ways. The results are in line with those of Islam et al. (2014) that found the most exposed communities are not necessarily the most sensitive and the least able to adapt.

5.2. Vulnerability

It appears that poverty and vulnerability to climate shocks are linked, and this is in line with previous studies (e.g. Shewmake, 2008; Deressa et al., 2008, 2009; Islam et al., 2014). Vulnerability levels depend also on the types of shocks farm-based livelihood systems face. Farm households that are similarly exposed to climate shocks and that have the same sensitivity level do not necessarily have the same vulnerability level. Therefore, vulnerability levels vary relatively across farm households' characteristics (Shewmake, 2008). Farm households headed by women are less vulnerable than those headed by men ($p < 0.10$). Female-headed households invest relatively less than men-headed households in highly climate-dependent activities and this leads to their lowest vulnerability to climate shocks. They develop non-agricultural off-farm activities such as the transformation of soybean, groundnut, and millet. Goh (2012) argued that the gender-differentiated impacts of a change in the climate are not at all times inflexible, clear, or predictable; they depend on the context and may be mediated by the socio-cultural, economic, ecological, and political factors.

The findings suggest that education also appears to be somewhat correlated with vulnerability. Through a higher level of education, farmers have access to information in terms of appropriate adaptation strategies that can be developed to cope with climate shocks. These findings are in line with those of previous studies (e.g. Deressa et al., 2008; Etwire et al., 2013) that found the lesser vulnerability is associated with high literacy rate. However, access to relevant information in terms of appropriate adaptation strategies depends also on communication infrastructure, settlement location, access to communication devices such as mobile phones, etc. It should be noted that Ostrom and Ahn (2007) argued that social capital may end up enhancing the well-being of a few at the expense of others. The findings reveals that the more the farm households have access to extension services, the more they are better off in terms of vulnerability to climate shocks, and this is in line with previous studies (e.g. Asfaw et al., 2016).

6. Conclusion

This paper analyses vulnerability of farm-based livelihoods to climate shocks using indicators combined with an econometric analysis. In addition, CART analysis was used to assess the meaningfulness of the approach used to build the indices. Moreover, uncertainty analysis was run through a Monte Carlo analysis, and the sensitivity of the indices to changes and omission of some variables was checked. The findings show that 57.43% of the farm households are vulnerable to climate shocks. About one-third of the farm households appear to be very vulnerable (31.74%). The degree of vulnerability to climate shocks differs across farm households' characteristics and AEZs. Farm households that are highly exposed and highly sensitive to climate shocks do not necessarily have the lowest adaptive capacity to be the most vulnerable. Therefore, the lowest adaptive capacity does not necessarily coincide with the highest exposure and sensitivity to result in the highest vulnerability. Adaptive capacity is disaggregated in financial capital, physical, institutional capital and technology, human capital, natural capital and social capital, and differs significantly across AEZs. Social capital is very important in building the resilience of farm-based livelihood systems; they rely on it when they lack the other four kinds of capital. Vulnerability of farm-based livelihoods depends also on the nature of climate shocks. The vulnerability of farm households that experienced droughts, strong winds, heat waves, and erratic rainfall is respectively 0.87, 0.77, 1.27, and 1.28 points significantly higher than the vulnerability of the remaining farmers, ceteris paribus. Floods appear to be beneficial to the farm households as they negatively influence vulnerability to climate shocks. The simulations suggest that vulnerability to climate shocks will increase in the absence of adaptation.

This study gives important information that can improve our understanding of drivers of vulnerability to climate shocks, and therefore to global climate change that is in some extent responsible for the increase of the probability of occurrence of climate shocks. Based on the findings, building resilience of farm-based livelihood systems should be through each of the three components of vulnerability which are exposure, sensitivity, and adaptive capacity. Adaptive capacity should be strengthening through financial capital, physical, institutional capital and technology, natural capital, human capital, and social capital. A particular emphasis should be put on the strengthening of the frequency of access to extension services, as it leads to less vulnerability. Weather forecasts and early warning systems can be useful in exposure and sensitivity reduction, and can increase opportunities. The specificities of the AEZs should be taken into account in building resilience to climate shocks.

Notes

1. However, it is not easy to attribute any extreme weather event and climate shock to a change in the climate, as a wide range of extreme events and climate shocks are expected in most regions of the world, even under unchanging climate (IPCC, 2013).
2. The AfDB is committed to improving food security and rural livelihoods by tackling the most important constraints on agricultural productivity, and to building resilience to climate change (AfDB, 2016).
3. They were asked to give their perception relative to a period of 20 years prior to the survey. However, those that do not have 20 years of experience were supposed to state their perception based on their actual experiences which are less than 20 years. In the paper, during the last 20 years means during the last 20 years or so.
4. The sample size was determined analytically based on the number of farm households within the basin with a margin of error of about 5%, and a response rate of 90%.
5. The number of respondents that were not household heads amounts to 71 (13.03% of the respondents).
6. The factor scores and percentage of explained variances used to compute the indices are not reported, but they are available upon request.
7. Among the common activities in the communities there are roads and places surrounding schools clearing, taking care of the water wells, and contributing liquidity to finance school activities such as the payment of the salary of local recruited teachers. For most of the activities apart from liquidity contribution, the frequency of occurrence increases during the rainy season, and this competes with working in own farms.

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References

AfDB. (2016). *Annual Development Effectiveness Review 2016: Accelerating the pace of change*. Abidjan: African Development Bank Group.

Alinovi, L., Mane, E., & Romano, D. (2009). *Measuring household resilience to food insecurity: Application to Palestinian households*. Rome: Food and Agriculture Organization of the United Nations. Working Paper.

Asfaw, S., McCarthy, N., Paolantonio, A., Cavatassi, R., Amare, M., & Lipper, L. (2016). *Diversification, Climate Risk and Vulnerability to Poverty in Rural Malawi*. Abidjan: African Development Bank. Working Paper No. 236.

Baudoin, M.-A., Sanchez, A. C., & Fandohan, B. (2014). Small scale farmers' vulnerability to climatic changes in southern Benin: the importance of farmers' perceptions of existing institutions. *Mitig Adapt Strateg Glob Change*, *19*(8), 1195–1207.

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). *Classification and Regression Trees*. Belmont, CA: Wadsworth.

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

Carter, R. M., & Barrett, B. C. (2006). The economics of poverty traps and persistent poverty: An asset-based approach. *The Journal of Development Studies*, *42*(2), 178–199.

Chaudhuri, S. (2003). *Assessing vulnerability to poverty: Concepts, empirical methods and illustrative examples*. Columbia: Department of Economics, Columbia University.

Deressa, T. T., Hassan, R. M., & Ringler, C. (2008). *Measuring Ethiopian Farmers' Vulnerability to Climate Change Across Regional States*. Washington, DC: International Food Policy Research Institute. Discussion Paper 00806.

Deressa, T. T., Hassan, R. M., & Ringler, C. (2009). *Assessing Household Vulnerability to Climate Change: The Case of Farmers in the Nile Basin of Ethiopia*. Washington, DC: International Food Policy Research Institute. Discussion Paper 00935.

Dixon, R. K., Smith, J., & Guill, S. (2003). Life on the edge: Vulnerability and adaptation of African ecosystems to global climate change. *Mitigation and Adaptation Strategies for Global Change*, *8*(2), 93–113.

Dunford, R., Harrison, P. A., Jäger, J., Rounsevell, M. D., & Tinch, R. (2015). Exploring climate change vulnerability across sectors and scenarios using indicators of impacts and coping capacity. *Climatic Change*, *128*(3), 339–354.

Etwire, P. M., Al-Hassan, R. M., Kuwornu, J. K., & Osei-Owusu, Y. (2013). Application of Livelihood Vulnerability Index in Assessing Vulnerability to Climate Change and Variability in Northern Ghana. *Journal of Environment and Earth Science*, *3*(2), 157–170.

Fatichi, S., Ivanov, Y. V., & Caporali, E. (2012). Investigating Interannual Variability of Precipitation at the Global Scale: Is there a Connection with Seasonality? *Journal of Climate*, *25*, 5512–5523. doi:10.1175/JCLI-D-11-00356.1

Füssel, H.-M. (2007). Vulnerability: A generally applicable conceptual framework for climate change research. *Global Environmental Change*, *17* (2), 155–167.

Goh, A. H. (2012). *A literature review of the gender-differentiated impacts of climate change on women's and men's assets and well-being in developing countries*. Washington, DC: Collective Action and Property Rights (CAPRi). Working Paper No. 106.

Hare, W. L., Cramer, W., Schaeffer, M., Battaglini, A., & Jaeger, C. C. (2011). Climate hotspots: key vulnerable regions, climate change and limits to warming. *Regional Environmental Change*, *11*(Suppl 1), S1–S13.

Hoddinott, J., & Quisumbing, A. (2003). *Methods for Microeconometric Risk and Vulnerability Assessments*. Washington, DC: World Bank. Social Protection Discussion Paper No. 0324.

Hulme, M., Doherty, R., Ngara, T., New, M., & Lister, D. (2001). African climate change: 1900-2100. *Climate Research*, *17*, 145–168.

IPCC. (2013). *Climate Change 2013: The Physical Science Basis. Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge University Press.

IPCC. (2014b). *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. (V. R. Barros, C. B. Field, D. J. Dokken, M. D. Mastrandrea, K. J. Mach, T. E. Bilir, . . . L. L. White, Eds.) Cambridge, UK: Cambridge University Press.

Islam, M. M., Sallu, S., Hubacek, K., & Paavola, J. (2014). Vulnerability of fishery-based livelihoods to the impacts of climate variability and change: Insights from coastal Bangladesh. *Regional Environmental Change*, *14*(1), 281–294.

Kelly, M., & Adger, W. N. (2000). Theory and practice in assessing vulnerability to climate change and facilitating adaptation. *Climatic Change*, *47*(4), 325–352.

Kurukulasuriya, P., Mendelson, R., Hassan, R., Benhim, J., Deressa, T., Diop, M., … Dinar, A. (2006). Will African Agriculture Survive Climate Change? *The World Bank Economic Review*, *20*(3), 367–388.

Larose, D. (2005). *Discovering Knowledge in Data: An Introduction to Data Mining*. Hoboken, NJ: John Wiley & Sons.

Madu, I. A. (2012). *Spatial vulnerability of rural households to climate change in Nigeria: Implications for internal security*. Austin, TX: Robert S. Strauss Center for International Security and Law, University of Texas. Working Paper No. 2.

Metropolis, N., & Ulam, S. (1949). The Monte Carlo Method. *Journal of the American Statistical Association*, *44*(247), 335–341.

National Climatic Data Center. (2012). NESDIS, NOAA, Department of Commerce, Havard College Observatory, Havard University, . . . University Corporation for Atmospheric Research. (1981, updated yearly). World Monthly Surface Station Climatology, 1738-cont. (C. a. Research Data Archive at the National Center for Atmospheric Research, Compiler) Retrieved 09 27, 2013, from http://rda.ucar.edu/datasets/ds570.0.

Ostrom, E., & Ahn, T. K. (2007). *The Meaning of Social Capital and its Link to Collective Action*. Bloomington: Indiana University, Workshop in Political and Policy Analysis.

Pandey, R., & Jha, S. (2012). Climate vulnerability index - measure of climate change vulnerability to communities: a case of rural Lower Himalaya, India. *Mitig Adapt Strateg Glob Change*, *17*, 487–506.

Pearson, K. (1901). On lines and planes of closest fit to systems of points in space. *Philosophical Magazine*, *2*, 559–572.

République du Bénin. (2014). *Analyse Globale de la Vulnérabilité et de la Sécurité Alimentaire*. Cotonou: INSAE.

Roudier, P., Sultan, B., Quirion, P., & Berg, A. (2011). The impact of future climate change on West African crop yields: What does the recent literature say? *Global Environmental Change*, *21*(3), 1073–1083.

Sanchez, A. C., Fandohan, B., Assogbadjo, A. E., & Sinsin, B. (2012). A countrywide multi-ethnic assessment of local communities' perception of climate change in Benin (West Africa). *Climate and Development*, *4* (2), 114–128.

Sarris, A., & Karfakis, P. (2006). *Household Vulnerability in Rural Tanzania*. Paper Presented at the CSAE Conference 2006: Reducing Poverty and Inequality: How can Africa be included? Held on 19–21 March 2006, St Catherine's College, Oxford.

Scoones, I. (1998). *Sustainable Rural Livelihoods: A Framework for Analysis*. Brighton: Institute of Development Studies. Working Paper 72.

Shewmake, S. (2008). *Vulnerability and the Impact of Climate Change in South Africa's Limpopo River Basin*. Washington, DC: International Food Policy Research Institute. Discussion Paper 00804.

Simane, B., Zaitchik, B. F., & Foltz, J. D. (2016). Agroecosystem specific climate vulnerability analysis: Application to the livelihood vulnerability index to a tropical highland region. *Mitigation and Adaptation Strategies for Global Change*, *21*(1), 39–65.

Spearman, C. (1904). General Intelligence," Objectively Determined and Measured. *The American Journal of Psychology*, *15*(2), 201–292.

Vincent, K. (2007). Uncertainty in adaptive capacity and the importance of scale. *Global Environmental Change*, *17*(1), 12–24.

Vincent, K., & Cull, T. (2014). Using Indicators to Assess Climate Change Vulnerabilities: Are there Lessons to Learn for Emerging Loss and Damage Debates. *Geography Compass*, *8*(1), 1–12.