IMPACT OF FLOOD ON THE LIVELIHOOD OF FARMERS IN SEMI-ARID ZONE OF BENIN REPUBLIC

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Abstract

River flooding has become a widely distributed and devastating natural disaster that has caused significant damages both economically and socially. According to different studies, Benin has recently been affected by changes in seasonal patterns, reflected in the occurrence of new stresses, and /or increased climate variability. As people cultivate more land than before, and a greater proportion of this new land is located near to the river, and so more liable to flooding, locals are now more susceptible to the devastating effects of floods. Since 2007, Benin has experienced frequent floods. The recent and severe one occurred in August 2010 when 55 townships out of 77 were affected. In semi-arid zone of Benin republic, the last flooding events occurred in August 2012 and 2013, when many farmers lost most of their crops. Yet, no studies were conducted to show the effect of these frequent flooding events on the livelihood of farmers. To fill in this gap, a survey is conducted in Benin, a small country south of the Sahel. Two townships are chosen: Malanville and Karimama because of their location in downstream. In this region, our focus is the villages near a river. Then 9 villages in Malanville out of 19 recorded were surveyed. While in Karimama, 10 out of 13 villages recorded were surveyed. A stratified random sampling procedure is applied to strata with high, medium and low flood probabilities. A total of 19 villages were chosen with 12 farmers interviewed in each village, leading to a total of 228 farmers are interviewed. That represents 3.82% of the total farmers recorded in the 32 villages recorded. The questionnaire includes open and closed questions. A quasi-experimental approach known as a Propensity Score Matching (PSM) is used to measure the impact of 2012 flood on farmers' revenue in semi-arid zone of Benin republic. Results show firstly, that 86.4% (197 farmers) of farmers surveyed had their farms damaged by flooding in 2012. In this subset, the average flooded size of farm per household after 2012 flooding is about 2.4 hectare. The 25% of the sample (57 farmers) lost almost the total cultivated area during this flooding. The average expected income from harvest per hectare for flooded farmers after 2012 flooding is XOF 136,544 ($US273) while it is XOF 198,257 ($US396.5) for non-flooded farmers. Overall the econometric model indicates that flooding has a negative and significant impact on expected income from harvest per hectare, about on average USD80 per farmer. The determinants of household agricultural income as given by the Propensity Score Matching Method indicate that, apart from the variable being flooded in 2012, other household socio-demographic variables significantly explain the change in household income. These variables include: Farmers have received vocational training, Farmer is from Malanville township and Number of public extension visits to the farmer during the rainy season. To cope with this worse situation, farmers develop many adaptation and prevention strategies as the shifting of the cultural calendar and the diversification of activities. The outcome of this research provide information to guide decision making towards management of districts that are vulnerable to flooding. It will help them to have an idea of revenue loss of their subjects (farmers) due to flood frequency and to elaborate on possible prevention and or mitigation alternatives like "Green Dams".

***Key words**: Flooding, Impact assessment, adaptation, Propensity Score Matching, Semi-Arid*

Zone

1. Introduction

River flooding has become a widely distributed and devastating natural disaster that has caused significant damages both economically and socially. According to different studies, Benin has recently been affected by changes in seasonal patterns, reflected in the occurrence of new stresses, and /or increased climate variability (Ago *et al.* 2005). State institutions' incapacity to deal with recent climate changes, either by providing adequate advice regarding agriculture, or adequate support in case of crisis such as severe floods, is outlined (Baudoin et al. 2013). As people cultivate more land than before, and a greater proportion of this new land is located next to the river, and so more liable to flooding, locals are now more susceptible to the devastating effects of floods (Cuni-Sanchez et al. 2012). Since 2007, Benin has experienced frequent floods. In Benin floods have always taken place, and they are not always related to heavy rains in the local area but sometimes to heavy rain upstream (Cuni-Sanchez et al. 2012). The recent and severe one occurred in August 2010 when 55 townships out of 77 were affected. Agricultural experts had warned of huge damage to land and livelihoods in rural communities. Relief agencies and the government of Benin have appealed for US$46.8 million to help the nation recover from the worst flooding in nearly 50 years (IRIN 2013). The impact of these floods on Benin's economy was captured through the Analysis of Damage and Losses done by World Bank. The damage caused by 2010 flooding amounted to XOF 78.3 billion (about USD 160 million) and was related to total or partial destruction of assets including buildings and what they contain, infrastructure, inventory, etc. The losses amounted to XOF 48.8 billion (approximately USD 100 million) (World-Bank, 2011). In semi-arid zone of Benin republic, the last flooding events occurred in August 2012 and 2013, when many farmers lost most of their crops. Yet, no studies were conducted to yield comprehensive data on the level of damage local communities have gone through after the flooding of 2012. Then the agricultural economic impact of flood at household levels is needed in order to contribute to the scientific debate of positive/negative impact of flooding.

Flood has positive and negative impact on the livelihood.

Positive impacts of flood consist of bringing nutrients that makes very fertile farmland (Khakbazan *et al*., 2013). Flood shocks tend to have positive impacts on GDP growth rates. As one would expect, these positive impacts are not experienced on the year of the flood. The delay in the overall growth response seems to be driven by the agricultural sector likely due to potentially beneficial effects of floods on land productivity that manifest on the following harvest cycle (Fomby *et al*., 2010). The increase on agricultural growth in the year after the flood is larger and more persistent in developing countries which typically rely on more traditional, less intensive forms of agriculture (Cuñado *et al*., 2011).

The negative effects of flood are numerous. The frequency and severity of natural disasters, exacerbated by rising GHG atmospheric concentrations have immediate impacts on the poor. In Africa, following the 2000 floods in Mozambique the real annual growth rate fell by 7%, 700 people were killed, 150,000 homes were washed away, and numerous livelihoods were affected (DFID, 2004). Recently, it displaced millions of people in Nigeria and submerged several square kilometres of landed area in general and farmlands in particular (Nkeki *et al.*, 2013). Flood hazards have negative effect on socioeconomic activities leading to decrease in the productivity of the people (Ojeh *et al.,* 2012). Another study shows that, based on repeated sampling from historical events, at least 1.7 per cent of Malawi's gross domestic product (GDP) is lost each year due to the combined effects of droughts and floods. The authors further stressed that smaller-scale farmers in the southern region of the country are worst affected (Pauw *et al*., 2011). Finally in South of Benin maize can no longer be efficiently grown during the short rainy season because the soil is flooded when it should be sown (due to excessive rainfalls or rivers' floods); (Baudoin *et al.,* 2013). In Asia, the flooding in Jiangxi of China in 1998 caused great damage. The economic loss was HK$156 billion, 400 buildings surrounding the lake were inundated, leaving more than 1 million people homeless. Severe floods have also killed some 200 people in India and Bangladesh and left millions homeless and in starvation (Google, 2013).

The objective of this paper is to assess the impact of 2012 flooding on the agricultural revenue of farmers and deduce the value of preventing flood. The hypothesis to be tested in this paper is thet the impact of 2012 flooding on the revenue of farmer is significant and negative.

2. Impact partway framework

Flood damage assessment methods rely on two main stages: 1) quantifying flood impacts, 2) expressing these impacts in monetary values (Penning-Rowsell *et al*., 2005). But Brémond *et al*., 2013 thinks that the correct damage indicator for economic assessment is the loss of added value or the reparation costs for material damage. For crop damage, the loss of added value corresponds to the decrease in product less the variation of production costs due to flooding. The authors continue that usually, the variation of product is directly monetized by applying the selling price to the variation of yield.

Whereas they are often indifferently used in the literature, we make a clear distinction between the words impact, damage, and cost (Brémond *et al*., 2013). Flood impacts are any effects flood may have on the system considered, damage is a restriction to the negative impacts, and costs are the evaluation in monetized term to some damage.

Cuñado *et al*. (2011) employ vector auto-regressions in the presence of endogenous variables and exogenous shocks to study the macroeconomic impacts of natural disasters i.e., floods. Another work has estimated the direct and indirect socio-economic impacts of flood using a combination of Computable General Equilibrium model and spatial and Multi-Criteria Analysis (Farinosi *et al*., 2012). Finally Atreya *et al.* (2013) used a quasi-experimental approach known as a Difference-In-Difference (DD) method to measure the effect of a large flood event on flood prone property prices. This method needs a panel data to compute the impact. As we have time constraint we focus on cross-sectional data and then we use in this study a quasi-experimental method based on assumptions known as Propensity Score Matching methods (PSM) method. The impact of flooding on livelihood is measured in this study through the impact on yield and production and then on livelihood and food security with affects food supply curve.

Ex post Impact Evaluation (IE) seeks to measure the impact of flood exposure on an outcome of interest only due to the flood. IE is basically a causal inference issue. It tries to relate observed changes in an outcome to the extreme event. Formally its value is:

Equation 1: Ex Post Impact Evaluation Framework

$$\boldsymbol{Gi} = (\boldsymbol{Yi}|\boldsymbol{Ti} = \mathbf{1}) - (\boldsymbol{Yi}|\boldsymbol{Ti} = \mathbf{0}) \quad \textbf{(1)}$$

Where Gi is the impact of flood exposure on household (i), Yi is the outcome of household (i), Ti is a dummy variable equal to 1 when household (i) experienced flood and 0 otherwise.
Comparing the same household with and without flood event eliminates the effect of other factors. Then, Gi is due only to flooding. But there is a problem of missing data because the realization of the two outcomes above is mutually exclusive for any household (Rubin, 1974; Diagne, 2003). Without information on the counterfactual, we need to estimate it by finding a comparison group which mimics the counterfactual of flooded group. If there is any systematic difference between the 2 groups, the estimated impact will be biased. The basic objective of a sound impact assessment is then to find ways to get rid of selection bias (B = 0) or to find ways to account for it.
Two broad approaches help to do that:
(1) Modify the targeting strategy of the flood itself to wipe out differences that would have existed between the treated and non-treated groups before comparing outcomes across the two groups (experimental methods or randomized evaluation);
(2) Create a comparator group through a statistical design: quasi experimental methods (Rosenbaum & Rubin, 1983). The latter include: Propensity score matching methods, Double-

difference methods in the context of panel data, which relax some of the assumptions on the potential sources of selection bias, Instrumental variable methods which further relaxes assumptions self-selection, Regression discontinuity design and pipeline methods which exploit the design of the program itself as potential sources of identification of program impacts.

Randomized evaluation is the best method because it avoids the problem of selection bias from unobserved characteristics (Linnemayr *et al.*, 2011). However it is difficult to use it because it may not always be feasible, particularly in the case of extreme event like flood which occurs naturally. So in such cases, researchers then turn to so-called non experimental methods based on assumptions in order to avoid bias. Then, Propensity Score Matching methods (PSM) deal with the self-selection bias (Mendola, 2007) problem but assume that selection bias is based only on observed characteristics and unobserved characteristics do not have a significant effect on treatment. However, the PSM method fails to deal appropriately with the selection on unobservable problem which may be handled by the DD. Regarding Double-difference methods (Khandker *et al.*, 2009), they allow for unobserved heterogeneity between groups but assume that its effect is time-invariant over the course of the evaluation. However, like PSM, they do not deal appropriately with the problem of non-compliance. Concerning Instrumental Variable methods (IV), they allow for endogeneity in individual flood experience, flood risk, or both (Abadie, 2003; Dontsop Nguez *et al.*, 2011; Adekambie *et al.*, 2009). They can be applied to cross-section or panel data, and in the latter case they allow selection bias on unobserved characteristics to vary with time. Instrumental variable (IV)-based methods (Heckman and Vytlacil, 1999, and 2005; Heckman and Robb, 1985; Manski and Pepper, 2000; Imbens, 2004; Abadie, 2003; Imbens and Angrist, 1994) are used in order to remove both overt and hidden biases and deal with the problem of endogenous treatment. The IV-based methods assume the existence of at least one variable z called instrument that explains treatment status but is redundant in explaining the outcomes y_1 and y_0, once the effects of the covariates x are controlled for. Different IV-based estimators are available, depending on functional form assumptions and assumptions regarding the instrument and the unobserved heterogeneities. Finally, Regression discontinuity and pipeline methods are extensions of instrumental variable and experimental methods. All these non-experimental methods have their own strengths and weaknesses and hence are potentially subject to bias for various reasons. In reality, no single assignment or evaluation method may be perfect, and verifying the findings with alternative methods is wise. This study uses the Propensity Score Matching methods (PSM).

The equation (1) cannot measure the individual effect of flood on any given household. However, one can estimate ATE which is the average treatment effect, namely, the mean effect of flood on a population of households:

$$ATE = E[Yi(1) - Yi(0)] \quad (2)$$

Where E is the mathematical expectation operator, Yi represents the revenue of farmer (outcome of interest) for household i and Ti is the variable of flood exposure. For flooded farmer, Ti= 1, and the value of Yi under treatment is represented as Yi (1). For non-flooded farmer, Ti= 0, and Yi can be represented as Yi (0). One can also estimate ATE1 (or ATT or TOT) which is the Average Treatment Effect on the Treated (flooded) (or Treatment effect On the Treated), namely, the mean effect of flood on the sub-population of flooded:

$$ATE1 = E[Yi(1) - Yi(0)|Ti = 1] \quad (3)$$

To estimate the TOT as opposed to the ATE, a weaker assumption (unconfoundedness) is needed (Rosenbaum and Rubin 1983):

$$Yi(0) \perp Ti|Xi \quad (4)$$

Where Xi are a set of observable covariates that are not affected by treatment Ti.

3. Materials and methods

3.1 Study Area

Benin, a small country south of the Sahel, was chosen as the focus of this research because it has experienced its worst flooding events in the last 50 years. Insights from this case study will be used to generate broadly relevant lessons for West Africa. There are 5 watersheds in Benin (hydrological code=111): Ouémé, Mono, Couffo, Volta (code=27) and Niger (code=15). As WASCAL project is concerned by River Catchments located in the Sudan Savannah Zone of West Africa (see figure 1) and considering that farmers in those area are the most vulnerable to extreme events, it remains only the Volta and Niger watersheds. After the literature review, the severity of flood is usually important in the Niger watershed compared to Volta Basin. Then the Niger watershed is retained for this study. The annual rainfall in this basin is about 700 mm (figure 3) and the number of annual rainy day is about 35 (figure 4). Four rivers supply this watershed: Niger, Sota, Mékrou and Alibori. I used geographic tool (ArcView GIS 3.2) to visualize simultaneously the hydrologic map and village/commune map of the Niger Basin. Then I identify that the river Mekrou crosses Banikoara Township and a small part of Karimama while the river Alibori crosses Malanville and Karimama. Regarding the river Sota, it crosses Segbena and Malanville while the river Niger crosses Malanville Township. These information meet the observation in field. Then the two townships located in the downstream of the basin are chosen: Malanville and Karimama (see figure 2). Two (02) districts are more concerned by flooding within this watershed: Malanville and Karimama. Malanville district records more villages (19) crossed by river than Karimama District (13). Farmers were chosen in upper, middle and lower basin, from upstream to downstream.Then a total of 19 villages were chosen for this survey purpose with 9 villages in Malanville and 10 villages in Karimama district. 12 farmers interviewed in each village, leading to a total of 228 farmers interviewed (see table 1 and 2). That represents 3.82% of the total farmers recorded in the 32 villages. The primary data collection is done in 2014 in four steps: census – sampling – pilot interview – survey. During the survey itself (March-April 2014), three interviewers were used apart from the researcher herself. The questionnaire was written in French but the interviews were entirely conducted in farmers' local languages (Dendi, Gourmantche and Fulani). Questionnaire interviews lasted 1 hour to 1 hour 30 minutes. Most of the questions were closed-ended.The questionnaire includes open and closed question and concerned: socio-demographic characteristics of the household, History of farmer about flooding, household farm characteristic during the rainy and dry season 2012-2013, agricultural income of household during growth season 2012-2013, additional expenditures does flooding bring and flooding prevention and adaptation measures. The cultures that farmer produce during the rainy season are numerous: rice, maize, millet, sorghum, cotton, groundnut, bean, soybean, Tomato, pepper, onion, okra, sweet potato, cassava, potato, Banana plantain, banana, orange tree, mango, gourd, Hot and red pepper, edible leaves.

3.2 Data Analysis

A quasi-experimental approach known as a Propensity Score Matching (PSM) is used to measure the impact of 2012 flood on farmers' revenue in semi-arid zone of Benin republic (Gertler *et al.*, 2011) using stata 13.

Since propensity score matching is not a real randomized assignment method, but tries to imitate one, it belongs to the category of quasi-experimental methods based on assumptions. In this case of flooding of 2012, as evaluator who comes in 2014, we come after the event.

We need to satisfy 2 conditions before using Propensity Score Matching method:

- The main hypothesis here is that the unobserved characteristics do not have a significant effect on the treatment (flooding),
- A large sample of non-flooded farmers is available in order to have a common support. The common support is the area where the distributions of the Pscore of the 2 groups overlap.

In practice, matching methods are typically used when randomized selection, regression discontinuity design, and difference-in-differences options are not possible (Gertler et al, 2011). Many authors use so-called ex-post matching when no baseline data are available on the outcome of interest or on background characteristics

Then Propensity Score Matching develops a control group similar to the treatment (flooded) group in terms of observed characteristics, finds a large group of non-flooded farmers, matches each flooded farmer to the most similar non-flooded based on some observed characteristics and then compute the difference in mean outcome which is the impact of the flooding. The PSM method allows us to isolate the effect attributable to this flood event from the effect of other contemporaneous variables that might have influenced the revenue (Mendola, 2007). It is applicable for a cross-sectional data set. The basic idea of matching is to construct the counterfactuals for the flooded farmers with the non-flooded ones without imposing strong assumptions on model specification. Intuitively, the matching untreated agents come from the neighbourhood, defined based on the observable characteristics in various ways, of each flooded farmer. The mean impact of the flood is the average of the differences in outcomes between the matched flooded and non-flooded farmers. From this revenue effect, we calculate the value of preventing flooding: value transfer.

Put in econometric language, the coefficient for the interaction term of the flood status and revenue is interpreted as the mean impact of the program.

It is done through 3 steps:

Step 1: Estimate a model of been flooded

We pool the flooded and non-flooded farmers together and estimate propensity score using a binary model (probit, logit).

Step 2: Define the region of common support

The observations with a pscore outside the region of common support are dropped out of the evaluation. Here a balancing test is done to make sure that the mean of the pscore and the mean of the observable characteristics are the same across the 2 group using Student test (t test).

Step 3: Matching flooded to comparable unflooded in terms of pscore

There are several matching approaches:

- Nearest neighbour matching
- Radius matching
- Interval matching
- Kernel matching

The Average Impact of the flooding on the flooded farmer is G:

Equation 2: Propensity Score Matching Method

$$G = \frac{1}{N^T}\left\{\sum_{i=1}^{N^T} y_i^T - \sum_{j\epsilon J} w(i,j)\, y_j^C\right\} \quad (5)$$

Where N^T is the number of flooded farmers.

$w(i,j)$ is the weight which 1 for flooded and $\frac{p(x)}{1-p(x)}$ for non-flooded.

J is the number of non- flooded farmer used.

P(x) is propensity score which is the probability of being flooded $PS = P_r(T_i = 1|_X) = P(x)$

y_i^T is outcome for the flooded farmer ($T_i = 1$)

y_j^C is the outcome for non-flooded ($T_i = 0$)

3.3. Empirical Specification

The explanatory variables used in computing the propensity scores were those expected to jointly determine the probability to be flooded in 2012 and the outcome agricultural income per hectare. We focused on the determinants of income and productive assets when selecting the independent variables for computing the propensity score matching.

Below are the specification of the two models

Logistic regression of the treatment variable: being flooded

$$flooded_i = a + bdistan_i + \delta_1 v_i {}_{+\varepsilon_{i1}} \quad \textbf{(6)}$$

OLS function for agricultural income per hectare

$$Y_i = \alpha_2 + \beta_2 flooded_i + X_i'\delta_2 + \varepsilon_{i2} \quad \textbf{(7)}$$

Where Y_i is the outcome of interest which is the agricultural income per hectare,

$flooded_i$ is a dummy variable equal to 1 if the household is flooded in 2012 and 0 otherwise,

$distan_i$ is the distance between the farm and the river of each household which is like an instrumental variable,

v_i and X_i' are vectors of observables characteristics of households,

a,b, δ_2, α_2 , β_2, δ_2 are the regression coefficients.

ε_{i2} and ε_{i1} are the error term.

The observables characteristics of households used in the two regressions are summarized in table 3.

4. 5. Results and Discussion

4.5.1. Descriptive statistics

Result reveals that 86.4% (197 farmers) of farmers surveyed had their farms damaged by flooding in 2012 (Figure 5). Evidence from Table 4 reveals that all female farmers in the sample (33) are flooded. At the time of the survey, the average age of the farmers was 41 years. The average household size of flooded respondents was 15 while it is 13 for non-flooded. The respondents have spent on average 40 years in their villages. 81.58% of farmers belongs to the ethnic group Dendi and 96.93% are Muslim. The educational level of the household's head was the same across the 2 groups. The flooded farmers have more experience in lowland agricultural activities (23 years). The distance between the farm and the river is significantly different between the flooded and non-flooded farmers. Whereas this distance is on average 0.53 km for flooded farmer, 2.76 is for non-flooded farmers. In summary the variables sex, ethnic group, religion, experience in lowland, have a rice's farm, and the distance between farm and river are the six variables which make difference between flooded and non-flooded farmers. This is confirmed by the regression model (table 5). The variable treatment "Being flooded in 2012" is determined by the variables: Experience in lowland activities, Have a rice's farm, belong to Muslim and Distance between farm and river

4.5.2. Impact on income using mean difference

The average flooded size of farm per household after 2012 flooding is about 2.4 hectare. The 25% of the sample (57 farmers) lost almost the total cultivated area during this flooding. (See figure 2).

Table 6 presents the mean difference analysis of the impact of 2012 flooding in terms of Area cultivated, Number of cultivated field, Total Agricultural Income during Rainy Season, Expected Income from total harvest and Expected Income from harvest per hectare between flooded and non-flooded farmers.

The result shows that while there is a significant difference between the Expected Income from harvest per hectare of flooded and non-flooded farmers, there was no significant difference in the other 4 variables (Area cultivated, the Number of cultivated field, the Total Agricultural Income during Rainy Season and the Expected Income from total harvest) between flooded and non-flooded farmers. The average expected income from harvest per hectare for flooded farmers after 2012 flooding is XOF 136,544 ($US273) while it is XOF 198,257 ($US396.5) for non-flooded farmers.

We call Expected Income from harvest per hectare the total harvest of the farmer (in local unit) time the price per local unit divided by the total cultivated size. The idea is if the farmer should sell the whole production without self-consumption, which amount of money he should earn.

The mean differences in Expected Income from harvest per hectare, and other household farmers indicate that flooded are worse than non-flooded. However, the differences in observed mean outcomes between flooded and non-flooded cannot be attributed entirely to 2012 flooding due to the problem of self-selection (Heckman and Vytlacil, 2005; Imbens and Angrist, 1994). The impact of 2012 flooding on income levels is discussed in the next section.

4.5.3. Impact on household agricultural income using Propensity Score Matching and its determinants

The empirical impact results are given in Tables 7 and 8. Overall the econometric model indicates that flooding of 2012 in the semi-arid region of Benin had a negative and significant impact on expected income from harvest per hectare. This flooding decreased the agricultural income of flooded farmer by on average XOF 40,000 (USD80) (table 7). The determinants of household agricultural income as given by the Propensity Score Matching Method indicate that, apart from the variable being flooded in 2012, other household socio-demographic variables significantly explain the change in household income. These variables include:

Farmers have received vocational training, Farmer is from Malanville township and Number of public extension visits to the farmer during the rainy season (table 8). The coefficient (51838.01) for the variable vocational training reception is positive and significant, indicating that farmer who receives a vocational training have higher income than those who does not. The coefficient (72425.49) of the household location is positive and significant at 5% level, showing that farmer in Malanville farmers have higher income than those from Karimama. Finally the coefficient (51230.63) for the variable visit of extension services is positive and significant at 5% level, which means that farmers who receive more visit will get more income.

Conclusion

197 farmers of farmers surveyed had their farms damaged by flooding in 2012. 25 % of the sample (57 farmers) lost almost the total cultivated area during 2012 flooding. Flooding has a negative and significant impact on agricultural income per hectare, about on average USD80 per farmer. The determinants of household agricultural income indicate that, apart from the variable being flooded in 2012, other variable which influence income are: vocational training, lowland agricultural, Malanville Township, public extension visits. To cope with, strategies as the shifting of the cultural calendar and the diversification of activities. The outcome of this research provide information to guide decision making towards management of districts that are vulnerable to flooding. It will help them to have an idea of revenue loss of their subjects (farmers) due to flood frequency and to elaborate on possible prevention and or mitigation alternatives like building Dams.

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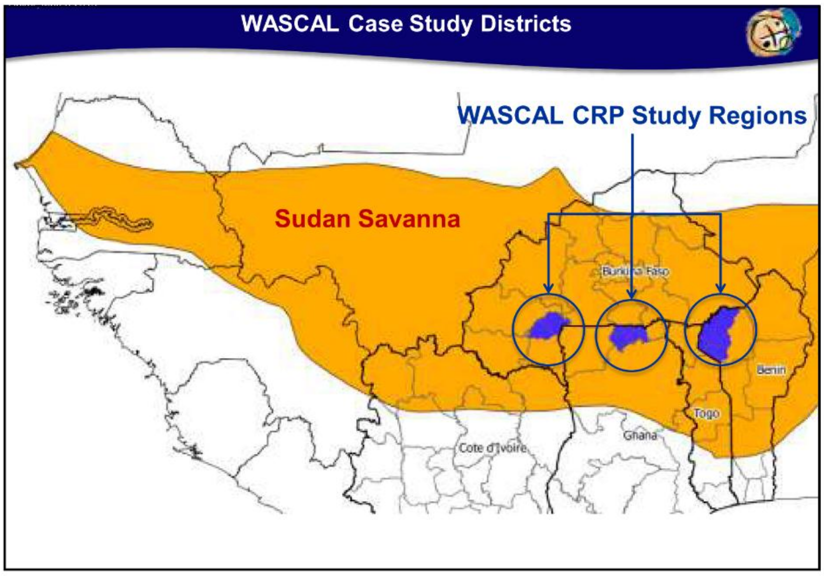

Figure 1: WASCAL Core Research Program Study Regions

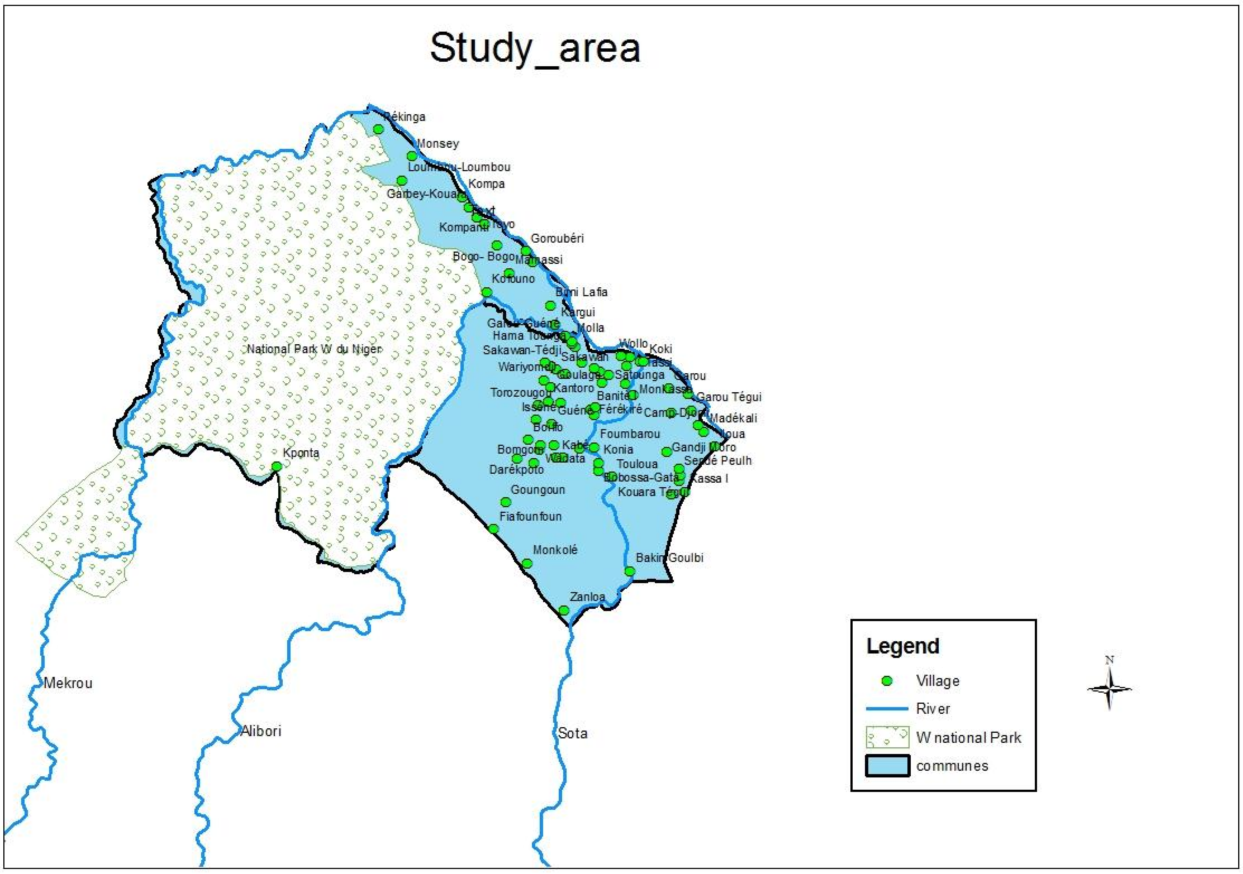

Figure 2: Study area showing the two communes and villages and rivers

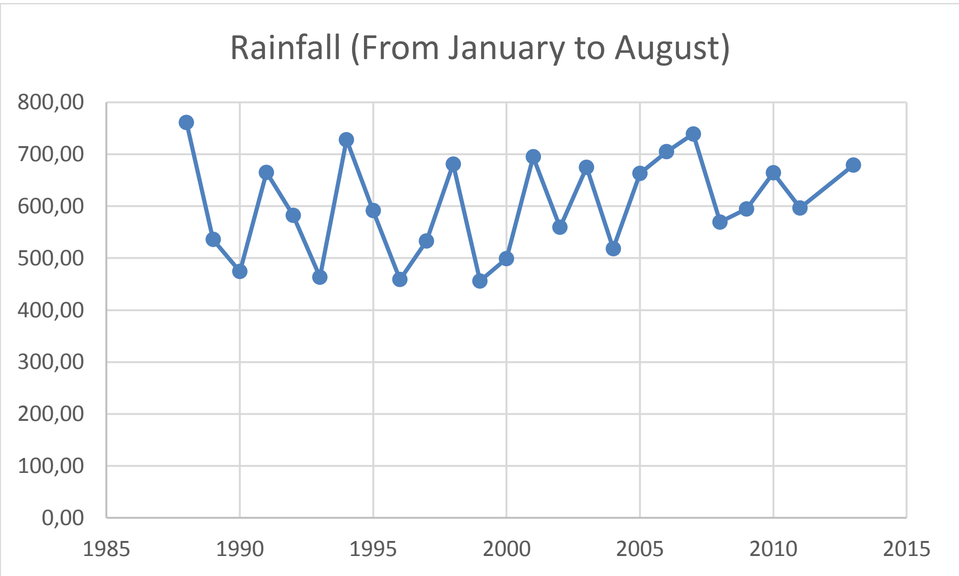

Figure 3: Rainfall study area

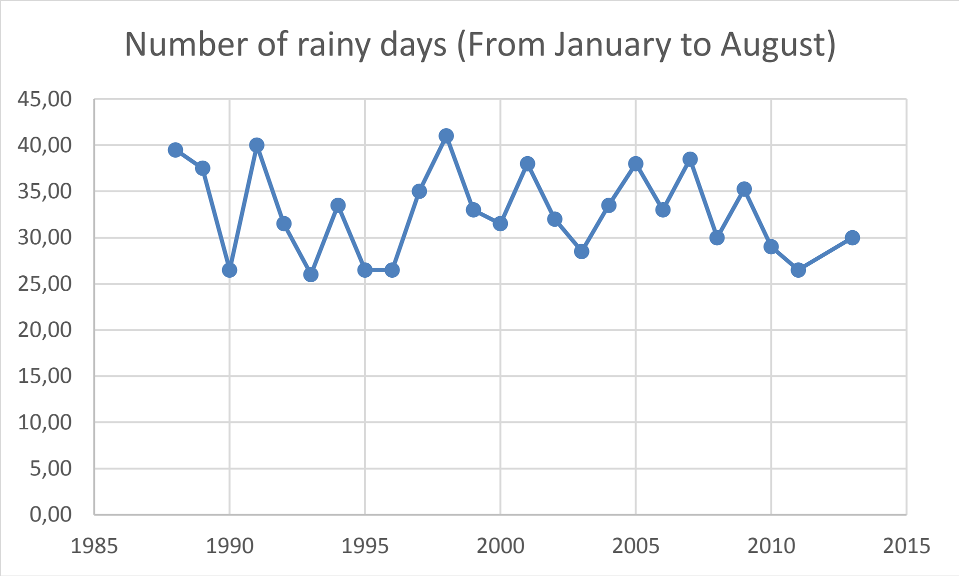

Figure 4: Number of rainy days

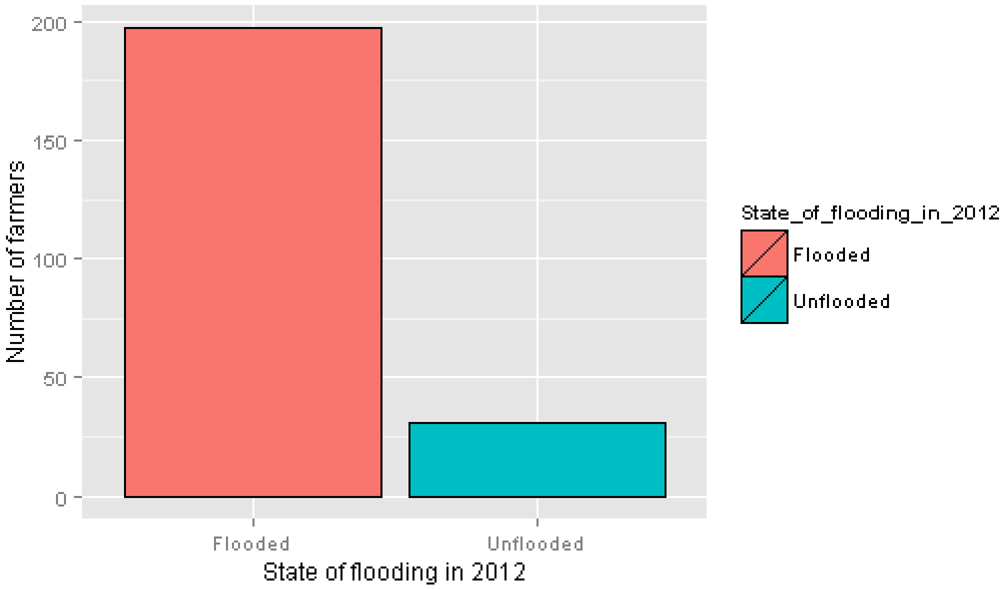

Figure 5: Number of farmers flooded and unflooded in 2012

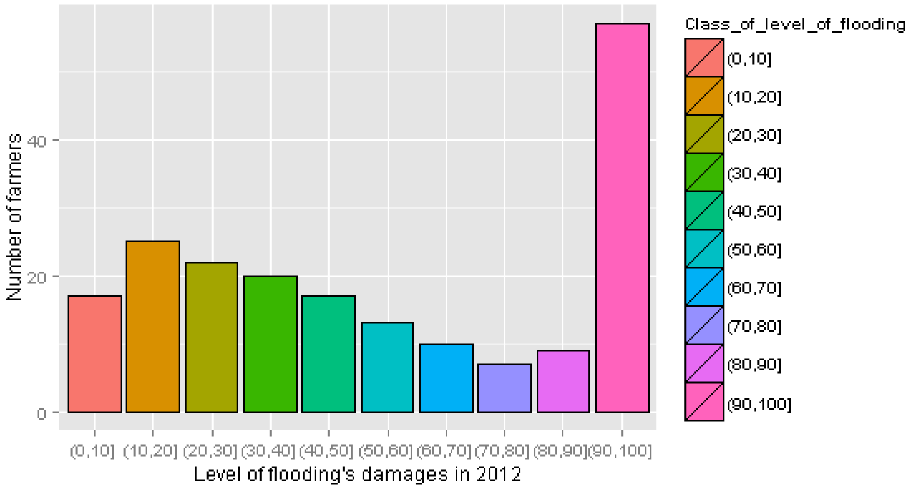

Figure 6: Number of farmers per categories of flooding damages in 2012

Table 1: Sample size with the village surveyed in the Municipality of Malanville

District	Village/City	Total of surveyed farmers
	Monkassa	12
Garou		**12**
	Bodjecali	12
	Galiel	12
	Kotchi	12
	Monney	12
Malanville		**48**
	Banite 1	12
	Banite 2	12
	Kantro	12
Guene		**36**
	Sakanwa Zenon	12
Toumboutou		**12**
		108

Table 2: Sample size with the village surveyed in the Municipality of Karimama

District	Village/City	Total of surveyed farmers
	Birni Lafia	12
	Kargui	12
	Tondikoaria	12
Birni Lafia		**36**

	Mamassi Gourma	12
	Torioh	12
Bogo Bogo		**24**
	Kompa	12
	Kompanti	12
Kompa		**24**
	Goroubiri	12
	Karimama-Centre	12
	Mamassi Peulh	12
Karimama		**36**
		120

Table 3: Variables Used to compute Propensity Scores and their Expected Signs

Variable	Expected Impact on being flooded in 2012	Why?	Expected sign on agricultural income per hectare	Why?
Experience in lowland activities	-	More households are experienced in lowland activities, less they are vulnerable to flooding because they will master a bit the occurrence frequency of flood		
Have a rice's farm	+	Lowland rice farming means that the farm will be close to wetland and the probability to get flooded will be higher		
Muslim	+			

Distance between farm and river	-	Closeness of farm to river increase the probability to get flood since when the river will overflow, the farm will be flooded quickly		
Being flooded in 2012			-	
Farmers have received vocational training			+	
Number of years in lowland agricultural activities			+	
Being in malanville township			+	
Number of public extension visits in rainy season			+	

Table 4: Household socio-economic characteristics by flooding status

Characteristic	Non flooded (31)	Flooded (197)	Total (228)	Difference[1] Test
Socio-demographic factors				
Proportion of male farmers (%)	100	83.25	85.53	16.75**
Proportion of female farmers (%)	0	16.75	14.47	-16.75**
Age (average)	41 (11.88)	41 (12.76)	41 (12.62)	0.4
Household composition (average)	13 (8.32)	15(10.72)	15 (10.42)	-1.52
Number of years of residence (average)	41 (11.90)	39 (13.78)	39 (13.52)	1.68
Proportion of Dendi farmers (%)	58.06	85.28	81.58	-27***

[1]mean(Non-flooded) – mean(Flooded).

Proportion of Muslim farmers (%)	87.1	98.48	96.93	-11.38***
Education and experience in rice farming				
Number of years of formal education (average)	1.93	1.93	1.93	0
Have an informal education (%)	25.81	20.30	21.05	5.5
Number of years in lowland agricultural activities (average)	14.48 (11.34)	23.12 (12.67)	21.94 (12.82)	-8.63***
Proportion of farmers that receive vocational training (%)	32.26	31.47	31.58	0.78
Have a rice farm (%)	54.84	81.22	77.63	-26.37***
Distance between farm and river (average)	2.76 (3.43)	0.53 (0.98)	0.83 (1.72)	2.23***
Institutional factors				
Public Extension visits in rainy season (average)	1.32 (1.49)	1.89 (2.57)	1.82 (2.46)	-0.57

NB: The T-test was used to test for difference in socio-economic/demographic characteristics between flooded and non- flooded.
Standard deviation in parentheses.
Legend: * significant at 10%; ** significant at 5% and *** significant at 1%

Table 5: Logistic regression of the treatment variable: being flooded

Being flooded	**Coef.**	**Std. Err.**	**z-statistics**
Experience in lowland	0.03	0.01	1.82*
Have a rice's farm	1.10	0.49	2.25**
Religion Muslim	1.79	0.89	2.01**
Distance between farm and river	-0.52	0.12	-4.25***
Number of observation		228	
LR chi2(4)		47.38***	
Pseudo R^2		26.14%	

Table 6 : Descriptive analysis of the impact of flood

Characteristic	**Non flooded (31)**	**Flooded (197)**	**Total (228)**	**Difference[2] Test**
Area cultivated (average)	6.22 (6.08)	6.39 (6.57)	6.36 (6.5)	-0.15
Number of cultivated field (average)	1.71 (0.9)	2.03 (1.06)	1.98 (1.04)	-0.31

[2]mean(Non-flooded) – mean(Flooded).

Total Agricultural Income Rainy Season (average)	593,625 (902,525)	527,139 (1,039,592)	536,179 (1,020,457)	66485.93
Expected Income from total harvest (average)	1,201,075 (1,309,077)	973,037 (1,479,371)	1,004,042 (1,456,804)	228037.7
Expected Income from harvest per hectare (average)	198,257 (144022)	136,544 (193,103)	144,935 (188,115)	61712.59**

NB: The T-test was used to test for difference in socio-economic/demographic characteristics between flooded and non- flooded.
Standard deviation in parentheses.
Legend: * significant at 10%; ** significant at 5% and *** significant at 1%

Table 7: The impact of 2012 flooding on agricultural income of household

Parameters	**By Matching Methods**			
	Nearest Neighbor Matching	**Radius Matching**	**Kernel Matching**	**Stratification Matching**
ATT	**-39,300**	**-61,700**	**-61,700**	**-104,000**
Flooded size	197	197	197	196
Control group size based on pscore	21	31	31	24
Standard Error	52515	29298	30424.41	46651

Table 8: Estimated coefficients of the OLS function for agricultural income per hectare

Agricultural income	**Coef.**	**Std. Err.**	**t-statistics**
Being flooded in 2012	-71218.04	35570.63	-2.00**
Farmers have received vocational training	51838.01	26042.88	1.99**
Number of years in lowland agricultural activities	-1160.41	951.007	-1.22
Being in malanville township	72425.49	24705.93	2.93**
Number of public extension visits in rainy season	51230.63	19894.16	2.58**
Number of observation		228	
F(5, 222)		6.81***	
R-squared		13.30%	