Impact Of Flood On Farmers´ Livelihood In Semi-Arid Zone Of Benin Republic

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Abstract

Fluvial flooding has become a widely distributed and devastating natural disaster that has caused significant damages both economically and socially. Since 2007, Benin has experienced frequent floods. 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 the 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. A total of 19 villages was chosen with 12 farmers interviewed in each village, leading to a total of 228 farmers who are interviewed. Then the sampling rate is 8.79%. The questionnaire includes open and closed questions. The econometric framework adopted is the Rubin Causal Model that has emerged as the standard approach for evaluating change effect using an observational data. Then two methods are used for comparison purpose: Propensity Score Matching Method and Instrumental Methods to measure the impact of the 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 hectares. Overall the econometric model indicates that flooding has a negative and significant impact on expected income from the harvest per hectare, about an average USD80 per farmer (Propensity Score Mtethod) and USD159 (Instrumental Variable Method). To cope with this bad situation, farmers develop many adaptation and prevention strategies as the shifting of the cultural calendar and the diversification of activities.

Keywords*: Flooding, Farmers, Impact assessment, Semi-Arid Zone*

1. Introduction

A flood is an overflow of an expanse of water that submerges land (Brémond et al., 2013). Flooding can be from a number of sources: rainfall (pluvial), coastal, tidal, sewers, groundwater, drainage and rivers (fluvial) (Walker *et al*. 2005). The latter is the focus of this study. 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).

Fluvial 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 *etal.* 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. 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 the World Bank. The damage caused by 2010 flooding amounted to XOF78.3 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 on the positive / negative impact of flooding.

The topic is well documented in the literature but most of them are at the macro level. Then, flood has a positive and negative impact on the livelihood. Positive impacts of flood consist of bringing nutrients that make very fertile farmland (Khakbazan *et al.*, 2013). Flooding shocks tend to have positive impacts on GDP growth rates. As one would expect, these positive impacts are not experienced in 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 in 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 floods 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 kilometers of land area in general and farmlands in particular (Nkeki *et al.*, 2013). Flood hazards have a 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 of historical events, at least 1.7 percent 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 small-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 river 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 income of farmers and deduce the value or cost of flood prevention.

The hypothesis to be tested in this paper is that the impact of 2012 flooding on the revenue of the farmer is significant and negative.

2. Theoretical Framework

2.1. Lowland Agriculture and Rubin Causal Model

The Rubin Causal Model developed by Rubin (1974) and surveyed in Imbens and Wooldridge (2009); Heckman (2010), has emerged as the standard method for impact evaluation using observational data when the randomization condition are not satisfied. In this analysis, we consider a typical farmer whose farms experienced fluvial flooding or not during the growing season 2012-2013. Let denote by T the hazard flooding. Then, $T = 1$ if the farmer's farm was flooded and $T = 0$ otherwise. It should be understood that within a population, each farmer will be indexed i. For any outcome variable Y, the farmer also faces two hypothetical or potential outcomes $Y_i|T_i$=1 and $Y_i|T_i$=0 with $Y_i|T_i$, the outcome of i if he experienced or not 2012 flooding. In our analysis, the outcome of interest is the agricultural income of the farmers. Then comparing the same farmer with and without the flood hazard at the same time eliminates the effect of other factors on the outcome and the difference which is the impact of the flood hazard on this outcome will due solely to the flood event. But there is the problem of counterfactual or missing value problem. So the missing value needs to be estimated through a valid control group.

Fluvial flood hazard is a natural event that occurs annually. Then the river overflow and that helps the farmers to cultivate vegetable even during the dry season. In the study area, the main method of land access is heritage. Then a farmer can inherit a land close to a river or not. This flood hazard which was beneficial to the farmers becomes now a threat because it occurs now randomly and the quantity of water is too much. Then closer the farm is to river, more likely the crops are damaged by the flood hazard. The farmers whose farms are close to the river are exposed to flooding. Then the hazard could damage partially or totally the crops.

The framework describes the mechanism explaining how the closeness to river affects T and how the latter impacts the outcomes. Obviously, the closeness to river increase the propensity of the farms to get flooded.

2.2. Flood damage assessment 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 in production costs due to flooding. The authors continue that usually, the variation of the 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, the 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. Other work has estimated the direct and indirect socioeconomic 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 two methods for comparison purpose: Propensity Score Matching Method and Instrumental Methods.

2.3. Econometric of Disaster evaluation and application of fluvial flooding impact

The impact of flooding on the livelihood is measured through the impact on yield and production and then on livelihood and food security which affects the 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

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

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 flooding 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 about the potential sources of selection bias, Instrumental variable methods which further relaxes assumptions of 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 flooding 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, 2010; 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 flooding on any given household. However, one can estimate ATE which is the average treatment effect, namely, the mean effect of flooding on a population of households:

$$ATE = E[Yi(1) - Yi(0)] \tag{2}$$

Where E is the mathematical expectation operator, Yi represents the revenue of the 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:

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

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

$$Yi(0) \perp Ti|Xi \tag{4}$$

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 areas 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 in this study.

The annual rainfall in this basin is about 700 mm (figure 2) and the number of annual rainy days is about 35 (figure 3). Four rivers supply this watershed: Niger, Sota, Mékrou and Alibori. I used a 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 meets the observation in the field. Then the two townships located in the downstream of the basin are chosen because they are more concerned by the flooding issues within this watershed. Two (02) districts are: Malanville and Karimama. (See figure 4).

The Township of Malanville is large about 3 016 km² and its population was about 101 628 habitants in 2013 (Google, 2014). Then the density was about 33.7 habitants per km². Its Altitude is 160 meters and its Latitude is 11° 52' 0'' Nord while the Longitude is 3° 22' 60'' EST. Regarding the Township of Karimama, it is large about 6 102 km² and its population was 39 579 habitants in 2013. Then the density was 6.5 habitants per km². Its Altitude is 164 meters and its Latitude is 12° 4' 0'' Nord while its Longitude is 3° 10' 60'' EST.

3.2. Survey description: Sampling and Data

The primary data collection is done in 2014 (January-April) in four steps: census - sampling - pilot interview -survey.

The census was done and a total of 32 villages were found close to a river. Malanville district records more villages (19) crossed by river than Karimama District (13). The total of farmers recorded in the 19 villages sampled that has their farm close to the river is 2593. Since the quality of survey estimates is directly affected by survey errors that include sampling errors (due to selecting a sample rather than the whole population) and non-sampling errors (arising from data collection and processing), the efficient sampling methods developed for optimal allocation of resources to minimize sampling variance was used: the Probabilistic Method of Sampling (Duclos *et al.*, 2009). Then 9 villages in Malanville out of 19 recorded were surveyed while in Karimama, 10 out of 13 villages recorded were surveyed. Farmers were chosen in upper, middle and lower basin, from upstream to downstream. The probabilistic or random samples are made by drawing lots in the parent population for which a complete list of all the sampling units that compose it exists. Producers were selected using a two-stage stratified random sampling procedure based on two criteria: farm closeness to the river and stratum. First, farmers in each of 19 villages are divided into homogenous and mutually exclusive groups called strata (close to a river or away). In the second step, simple random sampling without replacement is used to select sample within each stratum. Randomization is a method to "unsystematise" uncontrolled effects. So, a total of 228 farmers have been interviewed and this was guided with the formula below (MRSC, 2003; Dagnelie, 1998) and also a marge above taking into account the response rate and invalid response.

$$n = \frac{Z^2\hat{p}(1-\hat{p})}{e^2 + \frac{Z^2\hat{p}(1-\hat{p})}{N}}$$

Therefore, in order to determine "n", the sample size, the following are required:

- ✓ A desired margin of error, e=0.06
- ✓ A value corresponding to a desired level of confidence, z=1.96
- ✓ The size of the population, N=2593;
- ✓ An estimate of the proportion of the population, P, falling in one of two categories, $\hat{P}$=0.75

This number is divided by 19 villages that lead to 12 farmers interviewed in each village (see table 1 and 2). Then the sampling rate is 8.79%. 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), given that the three interviewers master these languages. Questionnaire interviews lasted 1 hour to 1 hour 30 minutes. Most of the questions were closed-ended.The questionnaire includes open and closed question with seven chapters and concerned:

1.General information about each interview,

2.Socio-demographic characteristics of the household,

3.History of farmer about flooding,

4.Household farm characteristic during the rainy and dry season 2012-2013,

5.Agricultural income of the household during growth season 2012-2013,

6.Household general expenditures/ additional expenditures does flooding bring and

7. Flooding prevention and adaptation measures.

The cultures that farmer produces 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

Two methods are used for comparison purpose to measure the impact of the 2012 flood on farmers' revenue in the semi - arid zone of Benin republic. There are: Propensity Score Matching Method (Rosenbaum and Rubin 1983; Gertler, 2011) and Instrumental Methods (Angrist, 1994; Heckman, 1997; Wooldrige, 2001). The software STATA 13 is used for analysis.

The main question to be solved here is:

Impact of what (T) on what (Y) of whom (i)?

- Of what? (Input) means the variable: Farm flooding in 2012
- On what? (Output or impacted factor) means the variable: Agricultural revenue per hectare in 2012
- Of whom? (Target) means the variable: Agricultural household closeness to a river

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 an 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 to 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 neighborhood, defined based on the observable characteristics in various ways, of each flooded farmer. The average 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 into econometric language, the coefficient for the interaction term of the flood status and revenue is interpreted as the average impact of the program.

It is done through 3 steps:

Step 1: Estimate a model of being 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 neighbor matching
- Radius matching
- Interval matching
- Kernel matching

The Average Treatment effect on Treated (ATT) 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 is 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 ($T_i = 0$),

The main limitation of PSM is that it considers that the unobserved characteristics of the household do not affect the treatment variable which is: Farms get flooded.

Then the second method helps to handle the endogeneity of this treatment variable (T). So, the Instrumental Variable (IV) method is done by these steps:

First of all, the endogeneity of the treatment variable is tested by Durbin-Wu-Hausman test (Baum, 2007). Then the regression of the treatment variable (T) on the instrumental variable (Z) is done. Here the variable Z is the closeness of the household's farm to a river.

$$Ti=\delta Zi+\varphi Xi+ \mu i \quad (6)$$

After that, the predicted ($\hat{T}$) of the variable treatment is computed which contain the share of the treatment variable (T) which is affected solely by the instrumental variable (Z).

And then, replace this predicted variable in the regression model of the impacted factor: Agricultural revenue per hectare in 2012 (Y).

$$Yi=\alpha Xi + \beta iv\, \hat{T} + \varepsilon i \qquad (7)$$

The Coefficient of the treatment variable (T) in this regression is the Local Average Treatment Effect (LATE) by Wald estimation. LATE is the impact of 2012 flooding on a household randomly picked in the sub-population of household whom treatment status change when their instrumental variable (Z) change.

3.3. Empirical Specification

The explanatory variables used in computing the impact are those expected to jointly determine the probability to be flooded in 2012 and the outcome agricultural income per hectare. The focus is the determinant of income and productive assets when selecting the independent variables for computing the propensity score matching.

Below is the specification of the two models:

OLS function of agricultural income per hectare (Propensity Score Matching)

Here we assume that there is no endogeneity of the variable treatment (being flooded in 2012).

$$Y_i = \alpha_2 \; + \beta_2 flooded_i + \; X_i^{'}\delta_2 \; + \varepsilon_{i2} \qquad \textbf{(8)}$$

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 farm flooded in 2012 and 0 otherwise.

$X_i^{'}$ are vectors of observable characteristics of households,

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

ε_{i2} is the error term.

2SLS function for agricultural income per hectare (Instrumental Variable Method)

$$Yi=\alpha Xi + \beta iv\, \hat{T} + \varepsilon i \qquad (7)$$

Where Y_i is the outcome of interest which is the agricultural income per hectare in 2012,

($\hat{T}$) is the predicted of the variable treatment (T)

Xi are vectors of observable characteristics of households,

βiv is the Local Average Treatment Effect (LATE) by Wald estimation

εi is the error term

4. Results and Discussion

4.1. Descriptive statistics

The result reveals that 86.4% (197 farmers) of farmers surveyed had their farms damaged by flooding in 2012 (Figure 5). Evidence from Table 3 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 belong 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 flood farmer, 2.76 is for non-flooded farmers. In summary the variables sex, ethnic group, religion, experience in lowland, have a rice 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 4). The variable treatment "Being flooded in 2012" is determined by the variables: Experience in lowland activities, Have rice's farm, belong to Muslim and Distance between farm and river

4.2. Impact on income using mean difference

The average flooded size of farm per household after 2012 flooding is about 2.4 hectares. The 25% of the sample (57 farmers) lost almost the total cultivated area during this flooding. (See figure 6).

Table 5 presents the mean difference analysis of the impact of 2012 flooding in terms of Area cultivated, Number of cultivated fields, 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 fields, 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 the harvest per hectare for flood 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 harvesting 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.

4.3. Impact on household 's agricultural income using the two methods

The empirical impact results are given in Tables 6 and 7. Overall the econometric model using Propensity Score Matching Method indicates that flooding of 2012 in the semi-arid region of Benin had a negative and significant impact on agricultural income per hectare. This flooding decreased the agricultural income of flooded farmer (ATT) by on average XOF 40,000 (USD80).

The IV model yields also a negative impact about XOF 79,282 (USD158.5). This is LATE, the impact of 2012 flooding on a household randomly picked in the sub-population of household whom flooding status change when their instrumental variable (Z) change (table 6).

The determinants of household's agricultural income 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 farm during the rainy season (table 7). 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 the 5% level, showing that a farmer in Malanville has a higher income than the one from Karimama. Finally the coefficient (51230.63) for the variable visit of extension services is positive and significant at the 5% level, which means that farmers who receive more visits will get more income.

Conclusion

The 2012 flooding has a negative and significant impact on household's agricultural income per hectare, about an average USD80 per farmer (PSM) and USD159 (IV). The determinants of household's agricultural income indicate that, apart from the variable being flooded in 2012, other variable which influence agricultural income are: vocational training, lowland agricultural, Malanville Township, public extension visits. The outcome of this research provides information to guide decision making towards the management of districts that are vulnerable to flooding. It will help them to have an idea of the revenue lost of their subjects (farmers) due to flood frequency and to elaborate on possible prevention and or mitigation alternatives like building Dams. The outcome provides also a reference or tool that an aid project or NGO managers may need to compensate or support the flooded farmer after the disaster in order to offset the consequences of the damages. On the other hand, this research contributes to the debate on the positive/negative impact of flood events. Finally, the paper contributes to ongoing discussions of impact assessment within the humanitarian sector by introducing the challenges of conducting quality impact evaluations in the disaster sector to impact evaluation practitioners.

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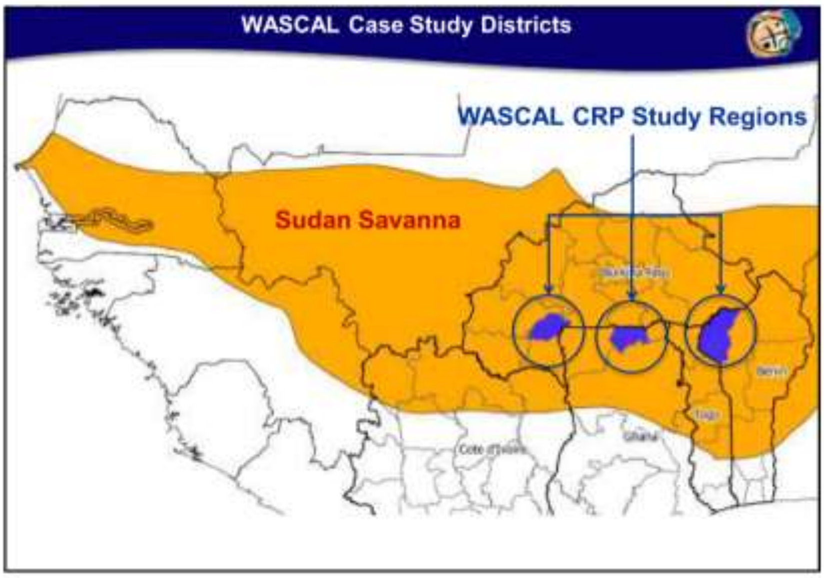

Figure 1: WASCAL Core Research Program Study Regions

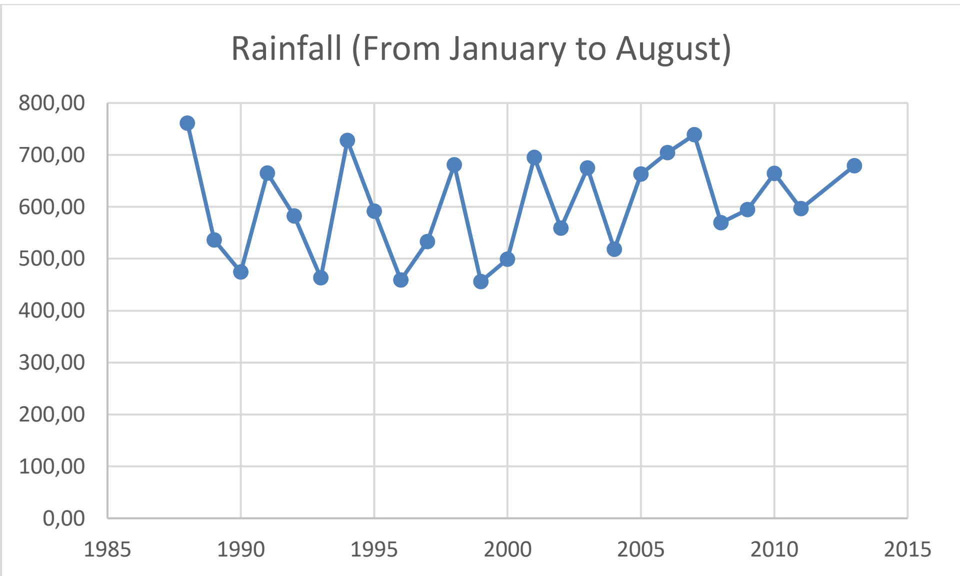

Figure 2: Rainfall of the study area

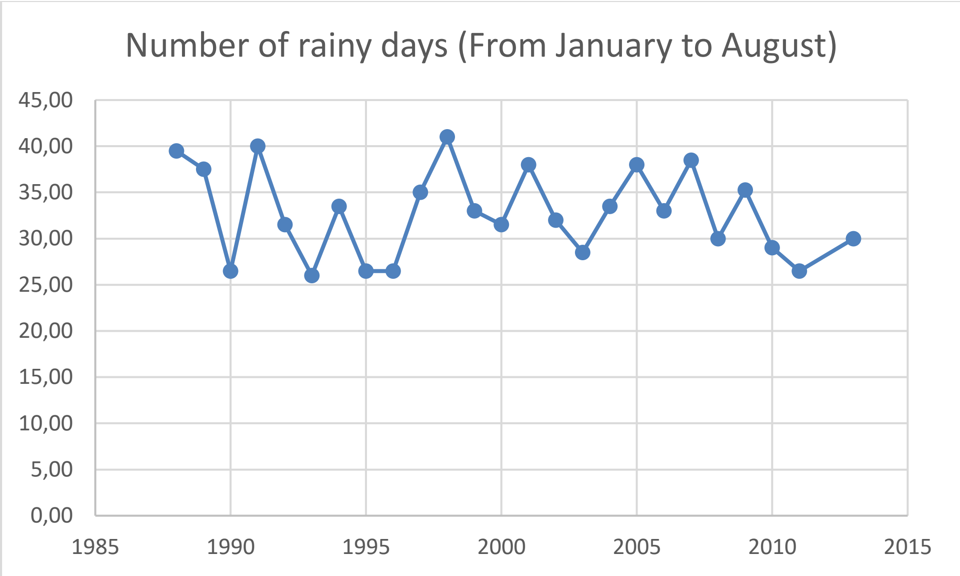

Figure 3: Number of rainy days

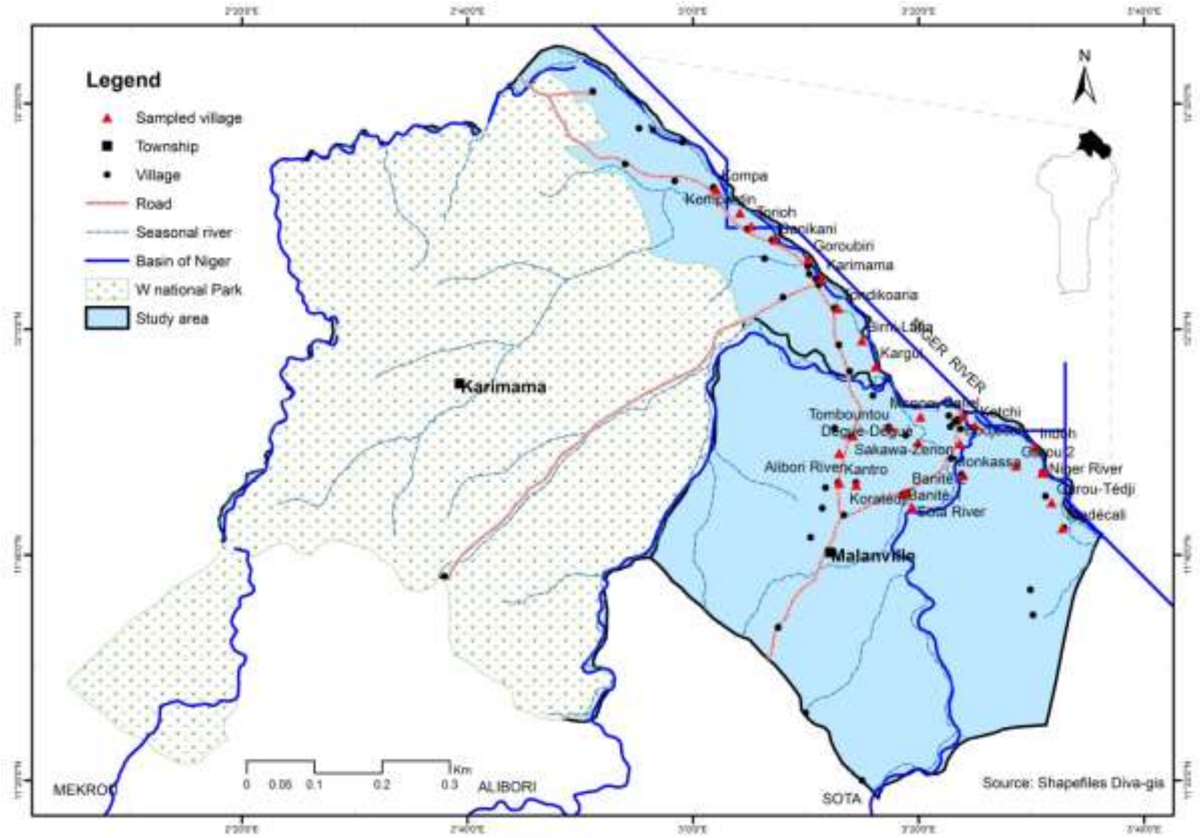

Figure 4: Study area showing the two communes and the villages and the rivers

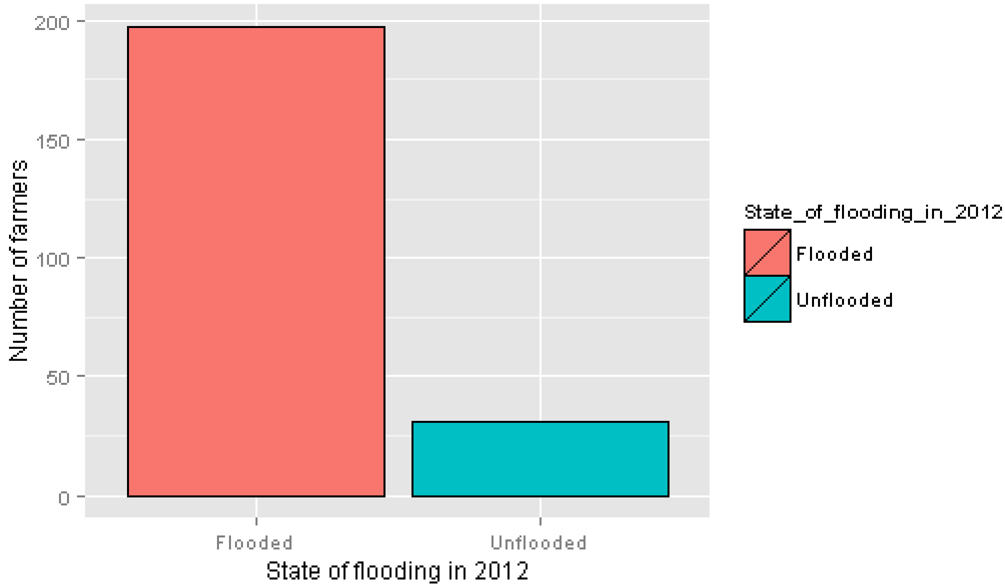

Figure 5: Number of farmers flooded and unflooded in 2012

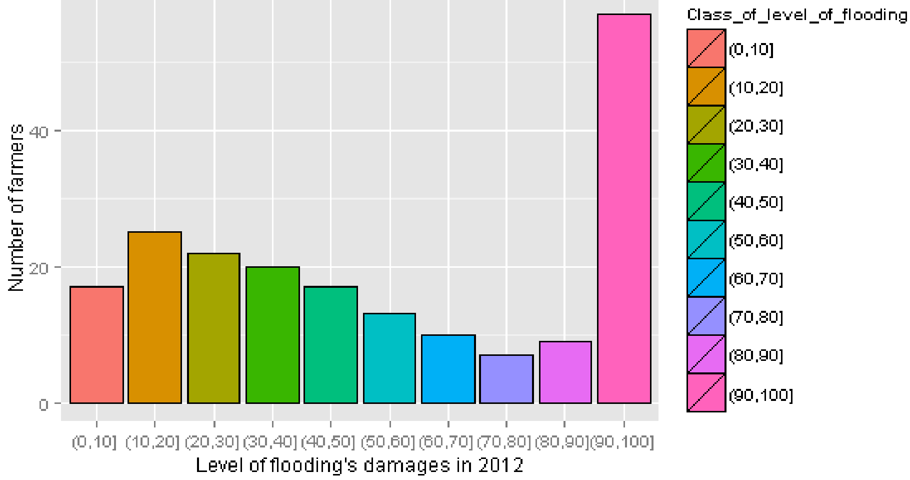

Figure 6: Number of farmers per categories of flood damages in 2012

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

District	Village/City	Total of recorded farmers	Total of surveyed farmers
	Monkassa	46	12
Garou			**12**
	Bodjecali	413	12
	Galiel	86	12
	Kotchi	44	12
	Monney	374	12
Malanville			**48**
	Banite 1	28	12
	Banite 2	90	12
	Kantro	61	12
Guene			**36**
	Sakanwa Zenon	30	12
Toumboutou			**12**
Total		**1172**	**108**

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

District	Village/City	Total of recorded farmers	Total of surveyed farmers
	Birni Lafia	183	12
	Kargui	165	12
	Tondikoaria	185	12
Birni Lafia			**36**
	Mamassi Gourma	162	12
	Torioh	93	12
Bogo Bogo			**24**
	Kompa	263	12
	Kompanti	18	12
Kompa			**24**
	Goroubiri	20	12
	Karimama-Centre	162	12
	Mamassi Peulh	170	12
Karimama			**36**
Total		**1421**	**120**

Table 3: 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***
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 4: Logistic regression of the treatment variable: being flooded

Being flooded	Coef.	Std. Err.	z-statistics
Experience in the 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 observations		228	
LR chi2(4)		47.38***	
Pseudo R^2		26.14%	

[1]mean(Non-flooded) – mean(Flooded).

Table 5 : 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 fields (average)	1.71 (0.9)	2.03 (1.06)	1.98 (1.04)	-0.31
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 6: The impact of 2012 flooding on agricultural income of household

Impact	PSM (ATT)				IV (LATE)
	Nearest Neighbor Matching	Radius Matching	Kernel Matching	Stratification Matching	
ATT (XOF)	-39,300	-61,700	-61,700	-104,000	-79282
ATT ($)	-78.6	-123.4	-123.4	-208	-158.56
Flooded size	197	197	197	196	105
Control group size based on pscore	21	31	31	24	123
Standard Error	52515	29298	30424.41	46651	5079969

Table 7: Estimated coefficients of the 2SLS function for agricultural income per hectare

Agricultural income	Coef.	Std. Err.	t-statistics
Being flooded in 2012	-57737.12	53370.51	-1.08 **
Farmers have received vocational training	51838.01	26042.88	1.99**
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	
Wald chi2(4)		30.81***	
Log likelihood		-3143.75	

[2]mean(Non-flooded) – mean(Flooded).