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

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Chapter 4
Impact of Floods on Farmers' Livelihoods in the Semi-arid Zone of Benin

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Abstract Fluvial flooding is a common and devastating natural disaster that causes significant economic and social damage. Since 2007, Benin has experienced frequent floods. In the semiarid zone of Benin, the last flood occurred in August 2012, and many farmers lost most of their crops. However, no study was conducted to show the effects of recent flooding on the livelihoods of farmers. To fill this gap in knowledge, a survey was conducted in Benin, a small country located in the south of the Sahel. Two municipalities, Malanville and Karimama, were chosen because of their locations at the downstream of the Benin part of the Niger basin and the harsh effects experienced by the farmers during the flooding in 2012. Within these municipalities, we focused on the villages near the four rivers of the basin. Within

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the 19 villages targeted, the sampling rate was 14.67%, and the sample size was 228 farmers. The econometric framework adopted was the Rubin causal model with simple linear regression using ordinary least squares. The results show that the 2012 flood had significant impacts. An increase of 1% in flooding duration was found to correspond to a loss in agricultural income of approximately 0.40%. When a farmer stated that the severity of flooding in 2012 was major, his household agricultural income was reduced by approximately 1.44% compared to a farmer who stated that the flooding was minor. An increase of 1% in the cultivated area that was flooded corresponded to a loss in agricultural income of approximately 0.27%. The introduction of water-resistant species to withstand the effects of flooding should be encouraged in the study area. Future researches will focus on the estimation of flood insurance premiums, the design of the insurance, and the implementation of the insurance.

Keywords Flooding • Semiarid zone • Livelihoods • Agriculture • Ordinary least squares • Off-farm income • Benin

4.1 Introduction

River flooding is a common and devastating natural disaster that causes significant economic and social damage (Walker et al. 2005). According to Ago et al. (2005), Benin has recently been affected by changes in seasonal patterns, which are reflected in the occurrence of new stresses and/or increased climate variability. State institutions are often unable to deal with the effects of recent climate changes, either by providing adequate advice about agriculture or adequate support in the case of a crisis like a flood (Baudoin et al. 2013). Since 1970, Benin has experienced frequent floods (World Bank 2011). For example, floods occurred in Benin in 1970, 1983, 1985, 1995, and 1999, and the total flood-related damage at the country level for each year is shown in Fig. 4.1 (EM-DAT 2016). In the semiarid zone of Benin, the last flooding occurred in August 2012, and many farmers lost most of their crops. The objective of this study was to investigate the impact of floods on crops, livestock, and off-farm activities.

The effects of flooding on the livelihoods of affected farmers have previously been assessed. These previous studies have yielded contrasting results. In some cases, floods were found to have a positive impact on the livelihoods of affected farmers, while other studies found negative impacts. The positive effects on farmer livelihoods have been acknowledged by many authors. Cuñado and Ferreira (2011) found that flood shocks tend to have a positive impact on the growth rate of the gross domestic product (GDP) and that the increase in agricultural growth in the year after a flood is larger and more persistent in developing countries that typically rely on more traditional, less intensive forms of agriculture. For example, during flooding, the Nile River brings nutrients that are beneficial to Egyptian agriculture from the river to the

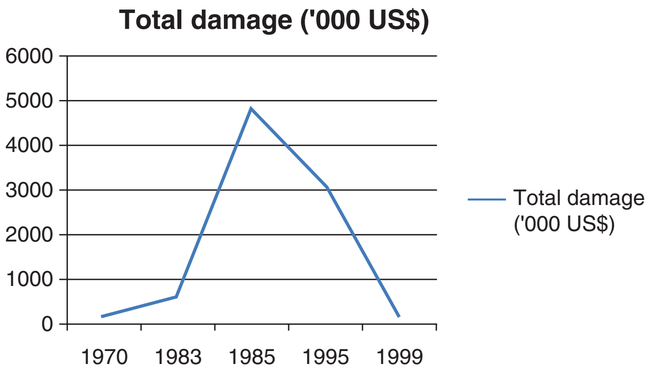

Fig. 4.1 Total damages caused by past floods at the country level

flooded area (Nixon 2003). Flooding is very beneficial for fishing (Nixon 2004). Moreover, in a flood year, farms that are not flooded benefit from the increase in prices caused by low supply with respect to demand, ceteris paribus (Dorosh 2001).

The negative effects of floods are numerous. The intensity and severity of natural disasters are exacerbated by rising atmospheric concentrations of greenhouse gases (GHGs), having immediate impacts on the poor (UK Department for International Development 2004). Many floods are caused by climate change, which is primarily attributed to anthropogenic GHG emissions (Intergovernmental Panel on Climate Change 2014). Climate change is likely to affect the temporal and spatial patterns of moisture delivery along with the physical form and quantity of moisture delivered over a given period of time. These changing patterns will probably lead to more frequent (and possibly more extreme) droughts and floods (IPCC 2014). The floods in Mozambique in 2000 caused a decline of 7% in the real annual growth rate, killed 700 people, washed away 150,000 homes, and affected numerous livelihoods (DFID 2004). Based on the repeated sampling of historical events, Pauw (2011) found that 1.7% of Malawi's GDP is lost each year as a result of the combined effects of drought and flood. After the 2010 flood in Benin, the economic loss at the country level was approximately USD 100 million (World-Bank 2011). In Asia, the flooding in Jiangxi, China, in 1998 caused great damage, and the economic loss amounted to HK$156 billion (Zong and Chen 2000).

Despite these previous attempts, replicating studies can highlight previously overlooked aspects. Replicating studies are thus a tangible way to collate data in order to empirically improve established theories or knowledge. Because impacts of flooding on the livelihoods of farmers are case-specific, it is important to undertake local data collection for effective solutions. Furthermore, past studies did not account for the effects of flood duration and the percentage of the cultivated area that was flooded on farm income.

The findings of past studies are mostly macro-level; thus, an impact assessment at the microlevel (farmer's level) is justified to provide a tool for disaster-relief programs.

While the focus of attention has correctly been on the impacts of floods on densely populated urban areas (Lokonon 2013), large tracts of rural land that were seriously affected by flooding were usually ignored. The main reason for this is that the total economic damage in the agricultural sector is frequently much lower than those in urban areas. Hence, damage evaluations in rural areas are often neglected or only accounted for using simple approaches and rough estimates (Forster et al. 2008). This study attempts to fill this gap in knowledge.

Flooding intensity is defined as the number of annual flooded days on a plot or farm (Maingi and Marsh 2002). Once a river reaches flood stage, the flood severity categories used by the National Weather Service (NWS) include minor flooding, moderate flooding, and major flooding. Each category is defined based on property damage and public threat. The impacts of the different flood severities vary. For each NWS river forecast location, the flood stage and associated severity categories are established in cooperation with public officials. The impact and severity of flooding at a given stage are not necessarily the same at all locations along a river reach because of varying channel and bank characteristics or the presence of levees on portions of the reach.

The assessment of the potential direct damage from natural hazards is important to examine the effectiveness of hazard mitigation strategies, calculate insurance premiums, and identify economic assets at risk (Messner et al. 2007). The rationale for the economic evaluation differs by case and includes (1) for public policy decisions, (2) for insurance contracts, and (3) for disaster-relief programs. Public policy evaluations tend to support decisions such as flood risk zoning. Regarding insurance compensation, the evaluation is based on previously agreed contract terms that promise different services from partial to entire functional reparation of damaged goods. Finally, a disaster-relief evaluation, which is the focus of this paper, assesses the individual need to recover after a flood that has disturbed daily practices. This paper assesses the effects of the 2012 flood in Benin on farmer household income in two municipalities of the Benin part of the Niger basin.

The main hypothesis to be tested is as follows: *Floods have negative effects on farmers' household incomes.*

4.2 Literature on Flood Impact Assessments

Methods for assessing flood damage involve two main processes: (1) quantifying the flood impacts and (2) expressing these impacts in monetary values (Penning-Rowsell et al. 2005). However, Brémond et al. (2013) reported that the correct damage indicator for economic assessment is the loss of added value or the repair cost associated with material damage. For crop damage, the loss of added value corresponds to the decrease in product minus the variation in production costs resulting from flooding. These authors also reported that the variation in product is usually directly monetized by applying the selling price to the variation in yield.

Although they are often used interchangeably in the literature, the words impact, damage, and cost are clearly distinguished (Brémond et al. 2013). Flood impacts are any effects that floods have on the system considered. Damage is restricted to the negative impacts, whereas costs refer to the monetary effects of the damage.

Various methodologies are used to evaluate floods damage. Post-disaster damage and loss assessment (DaLA) has been used widely by United Nations agencies (World-Bank 2011). Cuñado and Ferreira (2011) employed vector auto-regressions in the presence of endogenous variables and exogenous shocks to study the macroeconomic impacts of natural disasters (i.e., floods). Farinosi et al. (2012) estimated the direct and indirect socioeconomic impacts of floods using a combination of the computable general equilibrium model and spatial and multi-criteria analysis. Kramer (1995) adopted a productivity analysis approach to evaluate flood damage in terms of lost producer surplus. Merz et al. (2010) used a standard approach for the assessment of direct damage, that is, the susceptibility functions also known as damage functions. Finally, Atreya and Ferreira (2012) used a quasi-experimental approach known as the difference-in-difference method to measure the effect of large flood events on flood-prone property prices. This method requires panel data (data over many periods of time) to compute the impact. Because of a lack of data and time constraints, we had to conduct a survey on only one production year; thus, cross-sectional data were used, and the ordinary least square (OLS) method was applied.

4.3 Methodology

4.3.1 Study Area and Data

Benin, a small country situated in sub-Saharan Africa, was chosen as the focus of this study because it has experienced its worst flooding events in the last 50 years (EM-DAT 2016). Insights from this case study could be used to generate broadly relevant lessons for West Africa.

Benin's economy shows a marked lack of diversity and is largely focused on agriculture. Agriculture accounts for 88% of Benin's export revenue and employs 70% of the country's workforce (Integrated Regional Information Networks-Africa 2013). This sector generates approximately 35.9% of the country's GDP. Cotton production remains by far the most lucrative cash crop, accounting for 40% of GDP, and there is extensive cultivation of maize, yams, sorghum, beans, cassava, rice, and other crops (Integrated Regional Information Networks-Africa 2013).

Benin is located in West Africa and lies between latitudes 6° 30′ N and 12° 30′ N and longitudes 1° E and 3°40′ E. Benin covers a land area of 114,763 km^2 and occupies a long stretch of land perpendicular to the coast of the Gulf of Guinea in West Africa. It is bordered on the north by Burkina Faso and the Republic of Niger, on the east by the Federal Republic of Nigeria, and on the west by the Republic of

Togo. With 124 km of coastline to the south, Benin stretches 672 km from north to south and 324 km from east to west at its widest point. Most of the country experiences transitional tropical conditions, with less rainfall than in other areas at the same latitude. This climate is known as the Benin variant and is marked by a dry season from November to early April and a rainy season from mid-April to October (Lawin et al. 2013). On the coast, at latitudes between 6° 25′ N and 7° 30′ N, there are two rainy seasons and two dry seasons; at latitudes between 7° 30′ N and 12° 25′ N, there is one rainy season and one dry season (White 1983).

There are five watersheds in Benin: Ouémé, Mono, Couffo, Volta, and Niger. Recall that Benin's hydrological code is 111, while the hydrological codes of the Volta and Niger watersheds are 27 and 15, respectively. As the farmers in the river catchments in the Sudan Savanna zone of West Africa are the most vulnerable to natural hazards, the relevant watersheds are the Volta and Niger watersheds. According to the World Bank (2011), the severity of floods is usually worse in the Niger watershed compared to the Volta basin. Thus, the Niger watershed is the focus of this study.

Four rivers, Niger, Sota, Mékrou, and Alibori, supply the Niger watershed. The annual rainfall in the study area is approximately 780 mm, and the number of annual rainy days is approximately 45 days. These river basins are in two municipalities, Malanville and Karimama, which are more concerned about flooding within this watershed compared to the communes Ségbana, Gogounou, and Kandi. The Malanville commune has 19 villages along the rivers, whereas the Karimama commune has 13 villages along the rivers.

A geographic tool (ArcView GIS 3.2) was used to simultaneously visualize the hydrologic map and the village/commune maps of the Niger basin. The river Mékrou crosses the commune of Banikoara and a small part of the Karimama commune, and the river Alibori crosses Malanville and Karimama. The river Sota crosses the Segbana and Malanville communes, and the river Niger crosses the Malanville commune. Malanville and Karimama, which are located downstream of the basin, were chosen because they are the most affected by the flooding issues within this watershed.

The area of the Malanville commune is approximately 3016 km^2, and its population was approximately 101,628 inhabitants in 2013; hence, the density is approximately 33.7 inhabitants per km^2. Its altitude is 160 m, and its latitude ranges from 11° 84′ N to 11° 86′ N, and its longitude ranges from 3° 37′ E to 3° 40′ E. The Karimama commune is approximately 6102 km^2 in area, and its population was 39,579 inhabitants in 2013 (density = 6.5 inhabitants per km^2). Its altitude is 164 m, and its latitude ranges from 12° 06′ N to 12° 07′ N, while its longitude ranges from 3° 17′ E to 3° 18′ E.

This study focuses on the villages near the four rivers within this region. The map of the study area is shown in Fig. 4.2.

The variability in flood exposure among the farmers who live and farm close to the river and those who live and farm further away guided the sampling.

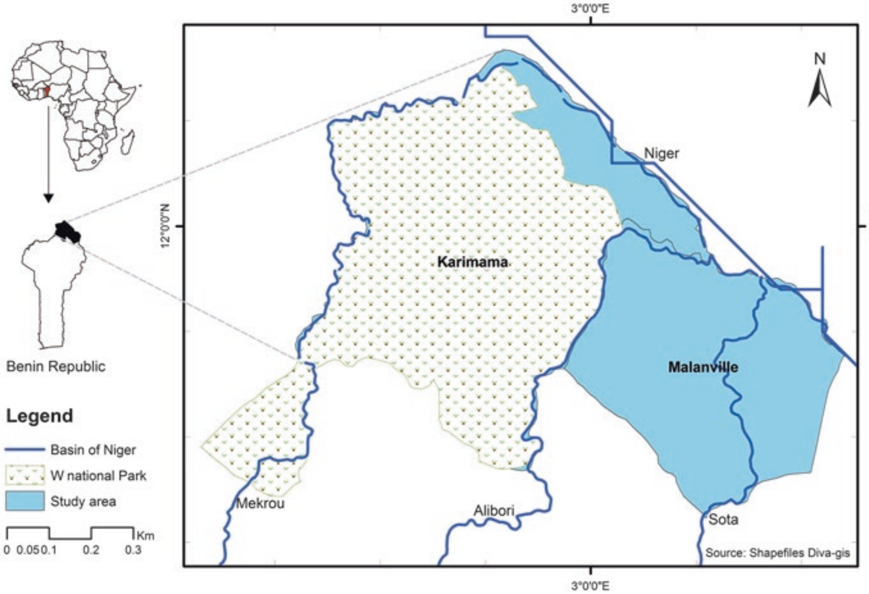

Fig. 4.2 Study area showing the two communes and four rivers

4.3.2 Sampling

The sampling rate in the study area was 14.67%, and the sample size was 228 farmers; these figures were computed by Eq. 4.1 (Minister Responsible for Statistics Canada, MRSC 2003; Dagnelie 1998).

The sampling size (n) was determined as

$$n = \frac{\hat{S}^2 Z^2}{e^2 + \frac{\hat{S}^2 Z^2}{N}} \tag{4.1}$$

where e is the desired margin of error, Z is the desired level of confidence, N is the size of the population (i.e., the total number of farmers in 19 villages that have farms close to a river), and $\hat{S}^2$ is population variability. Following MRSC (Minister Responsible for Statistics Canada) (2003) and Dagnelie (1998), we chose $e = 0.06$, $z = 1.96$, and $N = 1554$. $\hat{S}^2$, which is the hardest to obtain and is often approximated using previous studies on a similar population, was estimated. It is also possible to calculate the required sample size based on a given coefficient of variation. In this case, the required precision was specified in terms of the margin of error.

The question of whether the household's farms are close to the river or further away has a binomial distribution indicating, for example, that if p is the probability of the household whose farms are close to the river, $(1 - p)$is the probability of the household whose farms are further away from the river. The characteristic of interest was determined as the proportion of the population, P, falling in one of two above categories. For large populations, the estimated proportion $\hat{P}$ is approximately normally distributed, and the population variability of the binary characteristic y_i can be estimated as

$$\hat{S}^2 = \hat{P}\left(1 - \hat{P}\right) \tag{4.2}$$

Substituting Eq. 4.2 into Eq. 4.1 gives the following expression for n:

$$n = \frac{Z^2 \hat{P}\left(1 - \hat{P}\right)}{e^2 + \frac{Z^2 \hat{P}\left(1 - \hat{P}\right)}{N}} \tag{4.3}$$

If, prior to the survey, a good estimate of the proportion P is available, it should be used in the above equation. Otherwise, if nothing is known about the population, $\hat{P} = 0.5$ may be used, which yields the maximum sample size given the other assumptions. In this study, $\hat{P} = 0.5$. Thus, we assumed that the sample design was simple random sampling and that the response rate to the survey was 100%.

Plugging the chosen values of $\hat{P}$, N, and e into Eq. 4.3 gave the following sample size:

$$n = \frac{(1.96)^{2*} 0.5^* (1 - 0.5)}{(0.06)^2 + \frac{(1.96)^{2*} 0.5^* (1 - 0.5)}{1554}} = 227.68 \tag{4.4}$$

In summary, a total of 19 villages were chosen, and 12 farmers were interviewed in each village. Nine out of the 19 recorded villages in Malanville were surveyed, and 10 out of the 13 villages in Karimama were surveyed. A sample of 228 farmers was interviewed.

The data were collected using a questionnaire that included open- and closed-ended questions concerning sociodemographic characteristics of the household, the farmer's history of flooding, household farm characteristics during the rainy and dry seasons in 2012–2013, crop income of the household during the 2012–2013 cropping season, livestock income, and off-farm income. The crops that farmers cultivated during the rainy season were numerous and included 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 peppers, and edible leaves.

The livestock raised included cows, goats, sheep, chickens, ducks, guinea fowl, pigeons, and donkeys.

Data processing was done using Microsoft Access 2013, and data analysis was carried out using Stata 13.

4.3.3 Methods of Analysis

The total economic value of the total production of the household was used to capture the impact on whole-farm production because we could not sum the yields of different crops, livestock production, and off-farm outcome.

The economic value of cropping output was estimated by multiplying the yield of each crop (in local units) by the sale price of a local unit in 2012. The livestock income was estimated by multiplying the number of animals sold by the sale price. The off-farm income was determined as the sum of income from these different sources: farm labor on other farms, crafts, trade, transport, fisheries, healer, brick making, Koran teaching, butchery, family aids, retirement, social assistance, insurance, and loan.

Each category of income was divided by the household size to obtain per capita income. In this study, agricultural income means the income from the rainy cropping season after the 2012 flood plus the incomes from the first and second dry cropping seasons following the 2012 flood for all crops cultivated by the farmer. To allow comparison among households, the agricultural income was divided by the cultivated land size. Thus, agricultural income was computed in FCFA per ha.

Econometric modeling (simple linear regression or OLS) was completed using the following steps:

Step 1: Choice of endogenous variable

The endogenous variable is the variable used to explain or forecast. In this paper, the endogenous variable was agricultural income.

Step 2: Choice of the explanatory or exogenous variables

In this study, the exogenous variables might include flood intensity, flood severity, formal education level of the farmer, interval between two floods, gender, vocational training, lowland agricultural activities, location, and public extension visits. Among these, the exogenous variables of interest in this study were the intensity and severity of flooding in 2012. The intensity was measured as the number of days that the farm was flooded in 2012 (flood duration). The severity was determined as either the percentage of the farm that was flooded or the farmer's perception of the level of damage. Farmer's perceptions of flood severity were divided into three levels: minor, average, and major.

Step 3: Data collection

At least 30 observations are required for a regression. In this study, the number of the observations was either 197 households or 228 households. Among the 228 total farmers interviewed, 197 experienced flooding in 2012, while 31 did not. Some data (i.e., flood intensity and severity) concerned only the 197 farmers who experienced flooding. Other data (i.e., the impacts of the 2012 flood on crops, livestock, off-farm activities, and total household income) concerned the entire sample of 228 households.

Step 4: Choice of model

In this paper, the Rubin causal model was adopted as the econometric framework. This model has emerged as the standard approach for evaluating influential factors using observational data. We used simple linear regression with the OLS method (Khandker et al. 2010; Imbens and Angrist 1994) and assumed that there was no endogeneity in the variables of interest.

Step 5: Estimation of parameters of the model

Parameters were estimated by OLS and interpreted economically. The coefficient of determination (R^2) for regression was calculated and interpreted.

Step 6: Validation of the model

Some tests were done before validating the model.

The specification of the empirical model is calculated below:

$$Y_i = \alpha_1 + \beta_1 flooded_i + X_i^{'}\delta_1 + \varepsilon_i \quad (4.5)$$

where Y_i is the outcome of interest (per capita farm income) for household i; $flooded_i$ is the variable of interest used to measure either the intensity or severity of flooding; α_1, β_1, and δ_1 are the regression coefficients; $X_i^{'}$ is a vector of the other exogenous variables (see Table 4.1); and ε_i is the error term. The model is a log-log model

Table 4.1 Variables of control used to compute the impact of flooding on income and their expected signs

Variable	Expected effect on income	Why?	References
Interval between two floods in years	+	A bigger interval between floods will have a lower effect on agricultural income	–
Number of years of formal education in years	+	An educated farmer will have good production	Griliches and Mason (1972), Muller (2002), and Nzabakenga et al. (2013)
Gender (male = 1)	+	Males are more efficient than females	Bobbitt-Zeher (2007) and Nzabakenga et al. (2013)
Vocational training (yes = 1)	+	A trained farmer will have a good production	–
Lowland agriculture experience in years	+	The more a household is experienced in lowland activities, the more they master production and the higher the income will be	–
Location (Karimama commune = 1)	–	Malanville has more access to the factors of production than Karimama, which is not easy to access	Bohne (2009)
Public extension visits (annual number) (log)	+	Visits from extension services positively affect agricultural income	–

meaning that the continuous variables are in the log (logarithm) form; thus, the coefficients of the variables in the model are interpreted as elasticity.

4.4 Results and Discussion

4.4.1 The Impact of the 2012 Flood on Crops, Livestock, Off-Farm Activities, and Total Household per Capita Income

The crops that were flooded included rice, maize, millet, sorghum, cotton, groundnut, bean, tomato, pepper, onion, okra, and gourd. Figure 4.3 shows the distribution of the size of farmland use which gets flooded, based on the sample. In other words, Fig. 4.3 shows the percentage of total farm area that was flooded (total area lost in ha) by crop. Among the crops, rice was the most affected by flooding and represented approximately 38% of the total flooded farm area.

Figure 4.4 shows household per capita income from crops during the rainy and dry cropping seasons, livestock, and off-farm activities along with the total annual household income. The income is shown per category of household: the households whose farms were flooded in 2012 and the households whose farms were not. In each case, except for the rainy cropping season, the household income of farmers that experienced flooding was higher than the household income of non-flooded

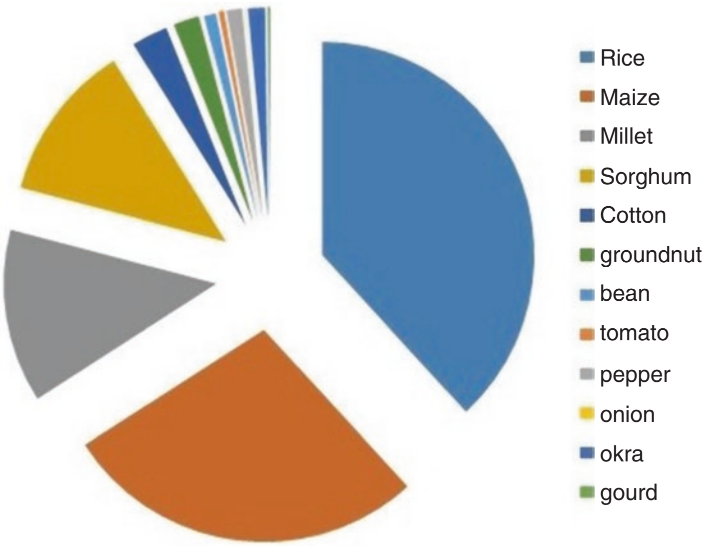

Fig. 4.3 Distribution of the size of farmland use which gets flooded

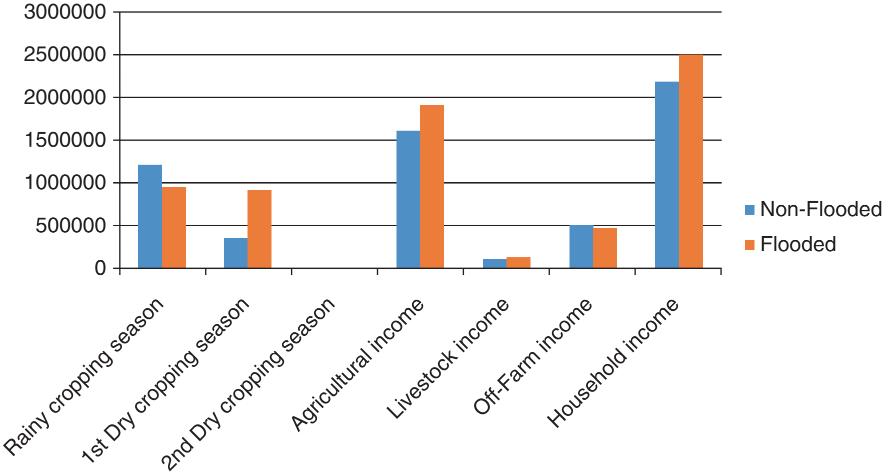

Fig. 4.4 Household incomes from crops, livestock, and off-farm activities and total household incomes for flooded and non-flooded households

farmers. In the rainy cropping season, the household income of farmers that experienced flooding was lower than that of non-flooded farmers. This means that after the 2012 flood, the households of farms that were flooded earned less income from crop activities and sold more animals and participated in more off-farm activities to make up the difference. Regarding the result in the dry cropping season, after the 2012 flood, the high output from the subsequent cropping season was beneficial for the farmers that experienced flooding. These results also highlight the fact that household incomes from the second dry cropping season were low, approximately 2364.33 FCFA for non-flooded farmers and 5249.7 FCFA for flooded farmers. The rainy cropping season extends from June to October. During this season, farmers cultivate rice, maize, millet, sorghum, cotton, groundnut, bean, tomato, pepper, onion, okra, gourd, sweet potato, cassava, banana, orange, mango, and edible leaves. Flooding occurred during August and September, and the first dry cropping season is from November to January. During the first dry cropping season, farmers produce rice, maize, tomato, pepper, onion, okra, gourd, hot and red peppers, and vegetable. The second dry cropping season is from February to May. In this season, farmers produce rice, tomato, pepper, onion, and okra.

The mean outcomes of the flooded and non-flooded households were compared using two sample t-tests with equal variances. The results indicated that the difference was only significant in the first dry cropping season (Table 4.2). These results did not account for other observable and unobservable factors that may influence income; thus, they are less reliable. The next section will account for additional factors by using an advanced econometric methodology.

Table 4.2 Comparison of mean incomes from the first dry cropping season between flooded and non-flooded households using two sample t-tests with equal variances

	Mean	Std. dev.	95% confidence interval
Non-flooded (31)	27,158.09	45,194.27	10580.7; 43735.48]
Flooded (197)	0249.73	117352.9	[53760.56; 86738.9]
Difference	−43091.64		[−85171.61; −1011.664]
t-test statistics	−2.01		
P-value	0.04		
Degrees of freedom	226		

4.4.2 Impact of Flood Duration on Farm Income

The results show that 86.4% (197 farmers) of farmers surveyed had their farms damaged by flooding in 2012, while 31 farms were not flooded (Fig. 4.5). According to the farmers, the average time between two successive floods was 3 years; the minimum response was 1 year, and the maximum was 7 years. The farmlands in Malanville and Karimama were flooded in August 2012, when most crops were almost mature and ready for harvesting. The farmers reported that water stayed on the farmlands for an average of 42 days, and responses varied from day 1 to 3 months (Table 4.3).

The most frequently reported impacts of the flooding in 2012 were crop damage and the associated loss in yield. Based on the sample and taking all crops into account, 476 ha of crops were flooded out of a total of 1256 ha cultivated (37.89%). Many farmers reported that the costs of damage were high because of the long duration of surface flooding and water logging.

The regression results indicate that the intensity of flooding was negatively correlated with the agricultural income of farmers in 2012 (Table 4.4). The longer that the farm was waterlogged, the more the farm income was reduced. A 1% increase in flooding duration corresponded to a loss in per capita agricultural income of approximately 0.40%. As the mean flooding duration was 42 days and the mean agricultural income was 144512.3 FCFA per capita, when the water stayed on the farm for 42 days, the agricultural income was reduced by 57804.92 FCFA per household member.

The interval between two floods was also negatively correlated with income, although the effect was not statistically significant. Formal education, lowland agricultural activities, and being located in Karimama were negatively correlated with agricultural income, with the effects of formal education and being located in Karimama being statistically significant. Thus, relatively well-educated farmers earned less income from agriculture. However, vocational training, male-headed households, and public extension visits were beneficial for income. Income was significantly higher in male-headed households compared to female-headed households.

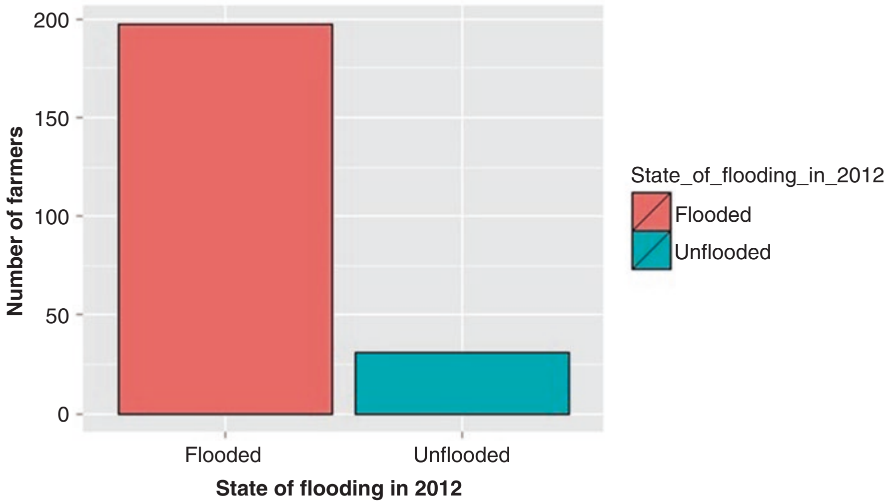

Fig. 4.5 Number of flooded and unflooded farmers in 2012

Table 4.3 Descriptive statistics

Variable	Observation	Mean	Std. dev.	Min	Max
Flood duration in 2012 (days)	197	42.72	27.90	1	120
Time between two successive floods (years)	197	3.07	1.6	1	7
Percentage of cultivated area flooded	197	55.65	34.61	1.23	100
Agricultural income (FCFA per capita)	197	144,512.3	199,074.6	0	1,242,083
Agricultural income (FCFA per ha)	197	240,608.4	248,169.8	0	1,607,097

Source: Field work, 2014

4.4.3 Impact of Flood Severity on Farm Income

As mentioned earlier, two indicators were used to measure flood severity: farmer perception of flood severity and the percentage of cultivated area that was flooded.

4.4.3.1 Farmer Perceptions of Flood Severity

Farmers were asked to rank the 2012 flood in terms of severity (minor, moderate, or major), with the baseline being minor. The result below shows that the severity of flooding in 2012 negatively impacted farmer agricultural income (Table 4.5). The

Table 4.4 Effect of the flood intensity (annual flooded days) on agricultural income

Factors affecting agricultural income (log)	Coefficient/elasticity	Std. err.	t-statistic
Number of days the farm was flooded in 2012 (log)	**−0.40**	**0.21**	**−1.87***
Interval between two floods (log)	−0.14	8584.14	−1.05
Number of years of formal education (log)	−0.36	0.19	−1.85*
Gender (male = 1)	1.26	0.52	2.43**
Vocational training (yes = 1)	0.44	0.41	1.06
Lowland agricultural activities (log)	−1.20	0.41	1.06
Location (Karimama commune = 1)	−1.14	0.31	−3.87***
Public extension visits (log)	0.23	0.21	1.09
Constant	15.38	1.31	11.67***
Number of observations	197		
F statistic (8, 188)	6.09***		
R^2	20.59%		

Source: Field work, 2014
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 4.5 Results for farmer perceptions of flood severity

Factors affecting agricultural income (log)	Coefficient/elasticity	Std. err.	t-statistics
Perception of famers: major severity	**−1.44**	**0.65**	**−2.21****
Perception of famers: moderate severity	**−0.29**	**0.67**	**−0.43**
Number of years of formal education (log)	−0.25	0.19	−1.35
Gender (male = 1)	1.10	0.51	2.15**
Vocational training (yes = 1)	0.09	0.41	0.24
Lowland agricultural activities (log)	−1.27	0.30	−4.20***
Location (Karimama commune = 1)	−1.37	0.36	−3.72***
Public extension visits (log)	0.28	0.21	1.36
Constant	15.19	1.15	13.13***
Number of observations	197		
F statistic (8, 188)	7.29 ***		
R^2	23.69%		

Source: Field work, 2014
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

household per capita agricultural income for farmers that reported flood severity to be major in 2012 was approximately 1.44% lower than for farmers who reported minor flood severity. The corresponding decrease in income for farmers reporting moderate flood severity was approximately 0.29%.

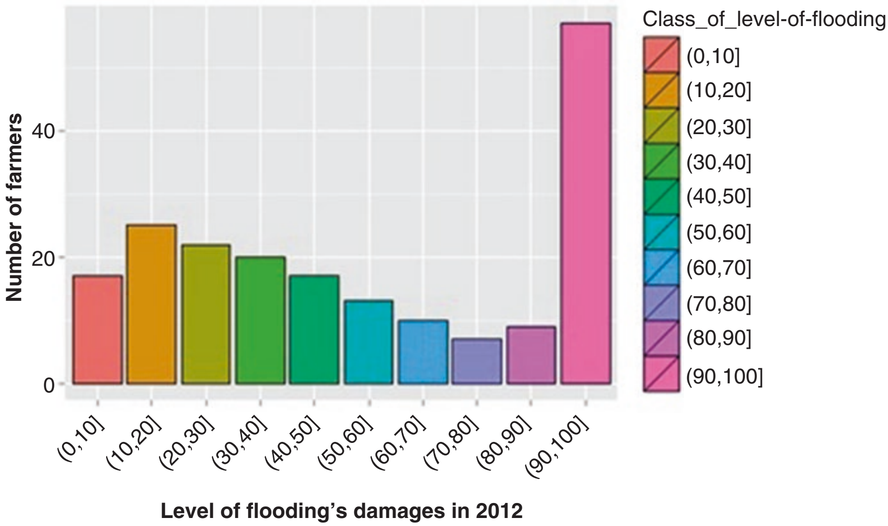

Fig. 4.6 Number of farmers per severity of flooding in 2012

4.4.3.2 Result on the Percentage of the Cultivated Area Which Was Flooded

A total of 57 farmers (25% of the sample) reported losing almost 100% of their total cultivated area during the flooding in 2012 (Fig. 4.6). A 1% increase in flooded cultivated area corresponded to a loss in agricultural income of approximately 0.27% (Table 4.6). Given that the average agricultural income was 240608.4 FCFA/ha, the damage associated with a 1% increase in flooded area was 650 FCFA/ha. Given that the economies in the study area are heavily dependent on agriculture, damage to food production systems by floods reduces household income and the ability to buy food and, consequently, justifies the starvation that follows periods of floods.

The outcome of this study provides information to guide the management of the municipalities that are vulnerable to flooding. The findings will help these communities understand the extent to which citizens (farmers) have lost revenues because of flooding. This may help decision makers identify possible prevention and mitigation strategies (e.g., building dams). Furthermore, this study provides a reference to aid project or NGO (nongovernmental organization) managers in compensating or supporting farmers affected by flooding. In addition, this study outlines the positive and negative impacts of flood events. Finally, this paper contributes to ongoing discussions of impact assessment within the humanitarian sector by highlighting the challenges of conducting quality impact evaluations in the disaster sector to the practitioners of impact evaluation research.

Table 4.6 Results for the percentage of cultivated area flooded

Factors affecting agricultural income (log)	Coefficient/elasticity	Std. err.	t-statistics
Percentage of cultivated area which is flooded (log)	**−0.27**	**0.11**	**−2.45****
Number of years of formal education (log)	−0.19	0.17	−1.13
Gender (male = 1)	0.82	0.48	1.68*
Vocational training (yes = 1)	0.12	0.36	0.33
Lowland agricultural activities (log)	−0.39	0.21	−1.82*
Location (Karimama commune = 1)	−1.34	0.32	−4.19***
Public extension visits (log)	0.20	0.19	1.06
Constant	12.73	0.81	15.65***
Number of observations	228		
F statistic (7, 220)	6.46***		
R^2	17.05%		

Source: Field work, 2014
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

4.5 Conclusion

The results of this study show that 86.4% (197 farmers) of the surveyed farmers were affected by flooding in 2012, whereas 31 farmers' farms were not flooded. According to the farmers, the average time between successive floods was 3 years. Farmers reported that water stayed on farmlands for 1 day to 3 months, with an average of 42 days. Among all crops, 476 ha of crops were flooded out of 1256 ha of cultivated farmland. By comparing the household incomes of flooded and non-flooded farmers, we found that the household income of farmers that experienced flooding was higher than that of non-flooded farmers, except for the rainy cropping season. A 1% increase in flooding duration corresponded to a loss in agricultural income of approximately 0.40%. When a farmer stated that the severity of the 2012 flood was major, his household agricultural income was reduced by approximately 1.44% compared to a farmer who stated that the 2012 flood was minor. An increase of 1% in the cultivated area that got flooded was found to correspond to a loss in agricultural income of approximately 0.27%. Based on the results, efforts should be made to withstand the effects of flooding in the study area (e.g., avoiding farming in the floodplain and introducing water-resistant species). The design of insurance contracts will be a focus of future research.

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