PLOS CLIMATE

RESEARCH ARTICLE

Comparing households' perception of flood hazard with historical climate and hydrological data in the Lower Mono River catchment (West Africa), Benin and Togo

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Citation: Dossoumou NIP, Gnazou MDT, Villamor GB, Agbossou EK, Thiam S, Wagner S, et al. (2023) Comparing households' perception of flood hazard with historical climate and hydrological data in the Lower Mono River catchment (West Africa), Benin and Togo. PLOS Clim 2(4): e0000123. https://doi.org/10.1371/journal.pclm.0000123

Editor: Bharath Haridas Aithal, Indian Institute of Technology Kharagpur, INDIA

Received: September 3, 2022

Accepted: March 20, 2023

Published: April 24, 2023

Data Availability Statement: The data is available on the repository DRYAD. The citation is as follows: NADEGE, DOSSOUMOU (2022), Comparing households' perception of flood hazard with historical climate and hydrological data in the Lower Mono River catchment (West Africa), Benin and Togo, Dryad, Dataset, https://doi.org/10.5061/dryad.6m905qg2v.

Funding: This research was funded by the German Federal Ministry of Education and Research

Abstract

The comparison of local perception of flood hazards, with hydrological and climate parameters, can give more insight and understanding on the causes of flood, its impacts and the strategies to effectively address the problem. This study examines whether households' perception of rainfall and flood occurrence are consistent with observed variation in climate parameter (rainfall) and hydrological (discharge) data in the Lower Mono River catchment (Togo-Benin, West Africa). Perceptions of the 744 households from the catchment were collected and compared to historical climatic and hydrological data using correlation analysis. The Standardized Precipitation Index was utilized to identify the extreme years in terms of precipitation. Chi-test and binary regression analyses were performed to identify the most affected communes within the catchment, and the factors that influence household perceptions on rainfall change, respectively. Findings reveal that 85% of the respondents perceived an excess in rainfall during the last 20 years and identify two particular years as the most affected by flood, which correspond to the climate data analysis. Households' perceptions on flooded months are correlated with the monthly precipitation and discharge at the upper part of the catchment while the ones at down part are not correlated. Furthermore, the chi-test analysis shows that in the perception of households, the communes at the down part are more affected by flood than those at the upper part of the catchment. It is then important for decision maker to consider local communities' perception for having insight regarding climate parameters, the causes of flood and in the decision making for implementing measures to cope with this phenomenon.

(BMBF) via the WASCAL program and CLIMAFRI project (grant number: 01LZ1710C).

Competing interests: The authors declare no competing interests.

1. Introduction

Climate related hazard and disasters have increased worldwide with huge damages on populations. Specifically, floods, storms, droughts and heat waves have become more intense and are on the rise globally [1]. It was reported by Emergency Event Database [2] that in 2020 there were "26% more storms than the annual average of 102 events, 23% more floods than the annual average of 163 events, and 18% more flood deaths than the annual average of 5,233 deaths" (page 1). The global growth in occurrence of these phenomena is linked to climate change [3]. In fact, climate change caused by the increasing of greenhouse concentration gases, contributes to making these events worse with the increasing of temperature, variability and more extreme rainfall pattern [4, 5]. These consequences of climate change lead to the increasing of extreme weather events and disaster frequency and magnitude [6] including flood [7, 8] generating intersecting disasters [9]. Floods particularly represent the disaster which occurs more (60% of the total number of major disasters events in 2020) worldwide and deadliest (41% of total disaster' deaths in 2020) type after drought [2, 10]. Recent study on satellite imaging reveals that the proportion of population exposed to flood has increased from 20 to 24% previously due to the increase of flood and migration [11]. It was shown that climate and demographic change would add 25 new countries to list of 32 that are already experiencing increasing flood globally. Furthermore, the majority of population in Asia and Africa were flooded between 2000 and 2015, and the projection give a gloomy picture with a large number of people exposed for 2030. In West Africa, flood is the top most frequent natural hazard from 1900 to 2022 among other disasters (https://public.emdat.be/mapping). In Benin and Togo, the communities in the Lower Mono River (LMR) catchment have for a several times experienced flood event. As a result of flood impacts in 2010, it causes enormous damages to the populations in Benin and Togo [12, 13]. In 2019, the communities in the LMR catchment experienced one of the most severe floods affecting thousands of people living close to the river. Indeed, in the catchment, the level of water in the river jumped a meter in four days and lead to flood which affected around 50 000 residents of Benin and Togo [14]. With the rise of extreme events, this situation is likely to worsen in the future [15]. Indeed, a study on climate and extreme rainfall events conducted in the Mono River catchment revealed that the intensity of extreme rainfall events and daily precipitation will significantly increase by 2050 [16], which could trigger future flood events in the region. Given the current context of climate change and rapid population growth, without effective adaptation strategies, the future flood damages on local communities in Lower Mono River catchment will persist and become more alarming. Therefore, proper adaptive strategies are required to deal with future flood risk, which may be numerous due to global warming and urbanization [17]. Previous studies suggest that comparing local population's perception of flood risk with historical climate data could contribute to identify efficient adaptation and improve flood management [18, 19].

Understanding how people perceive, experience and interpret climate change related hazards event is crucial for designing and implementing efficient policies and responses to this phenomena [20–22]. The way local communities perceived climate change influenced how they adapt to climate change [23, 24] compared farmers 'observations Kalapara subdistrict in Bangladesh on climate change and variability to meteorological data in order to assess the way farmers' perceptions confirm or contradict the climatic trends and analyses their adaptive strategies with a conclusion of good fit of households' perception to climate trend. Similarly, many other studies were conducted in hazard-prone areas such as various agroecological zones in Kenya, communities of the Upper East Region of Ghana, Agroecological Zones in Southern Ethiopia, hazard - prone districts of northwest Bangladesh, Kalapara subdistrict in Bangladesh, in northern Ghana and Ensaro District in Ethiopia by comparing farmers' perceptions of climate change or variability with meteorological trends and examined adaptive strategies [23, 25–30]. [31] reviewed the West African's climate trend to local perception in Burkina Faso to dig deeper insight in their decision making in response to climate change, which allowed for a better understanding of extreme events related to climate change and better guidance on adaptation strategies to be implemented in Burkina Faso. Moreover, [32] have shown the importance of local knowledge in understanding climate chnages implications in agriculture. [29] advocated for the importance of mixing approaches that integrate local perceptions with scientific evidence in order to develop effective and sustainable adaptation strategies.

Most of these studies compared specific climate parameters to household perceptions in general for determining adaptive strategies, but less attention was given to flooding. In addition, despite many studies were conducted in the Lower Mono River (LMR) catchment for analyzing the climatic and hydrological causes of flood and getting more insight in its causes in the study area [33–37], the information on local communities and stakeholders perceptions on this matter remain limited. [38] noted that local community perception is an important predictor for flood mitigation in the catchment.

Therefore, this paper aims at filling this knowledge gap by comparing local perception on flood with hydrological and climate parameters. Specifically, we looked at 1) the trends of climatic and hydrological data as well as the households' perceptions on flood trend, 2) their relationship and climate and hydrological causes of flood in the Lower Mono River catchment, and 3) factors which influence household perception on rainfall change. Establishing this information can provide insights into flood risks and inform better adaptation strategies in the region.

2. Methodology

2.1. Study area

The Lower Mono River (LMR) catchment is situated in the southern part of Mono River basin, which is a shared basin between two West African countries, Benin and Togo (**Fig 1**). It is located between 06˚30' and 7˚30'Northern latitude and 0˚ 30'and 2˚ 0' Eastern longitude and have area is 8136.78 km^2. Two dams (Nangbéto and Adjarala) were constructed on the river waterway in the Mono River basin, situated in the upper part of the LMR catchment [39].

Two types of climates are found in the LMR catchment:

- (1) Sudan tropical with one rainy season and one dry season in the upper part represented by the prefecture Ogou and Moyen Mono in the study area; and
- (2) sub-equatorial with two rainy seasons and two dry seasons in the downstream represented by the prefectures/communes of Yoto, Agome Glozoun, Lacs, Grand Popo, Athiémé and Lokossa in the study area (**Fig 2**).

In the upper part of the basin, the rainy season begin from March to October with the maximum monthly precipitation of 188.63 mm in September (prefecture of Ogou) and 160.96 mm (prefecture of Moyen Mono). It is important to notice that the prefecture of Moyen Mono tend to the Sudan tropical climate. Whereas in the lower part, the two rainy seasons are from March to July (long rainy season) and from August to November (short rainy season). During the long rainy season, the maximum monthly precipitation ranges between 177.61 mm and 210.22 mm in June depending on the prefectures or commune; whereas, during the short rainy season, the maximum monthly precipitation ranges between 145.20 mm and 147.88 mm

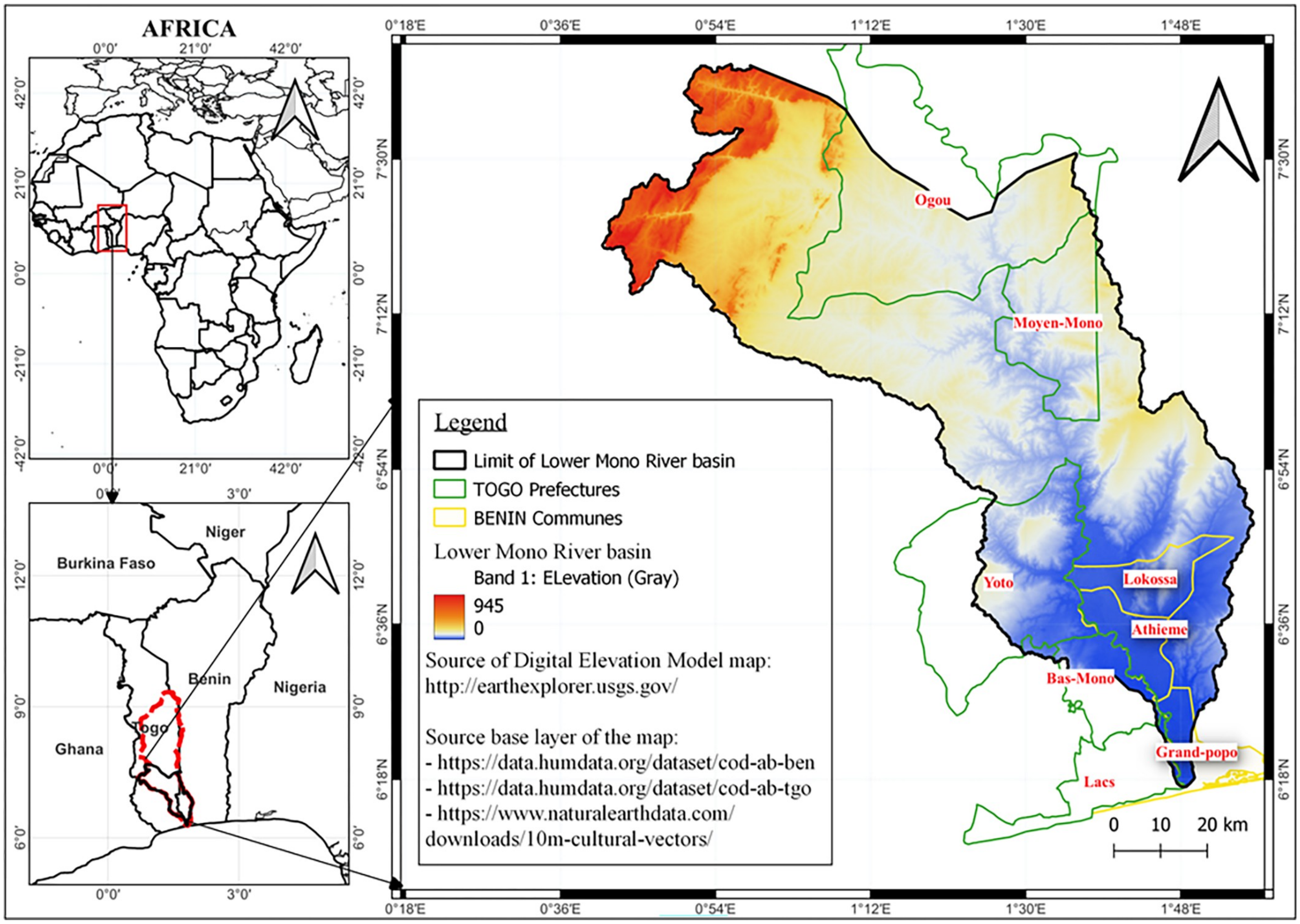

Fig 1. Location of the study area. *Source*: http://earthexplorer.usgs.gov/. Togo—Humanitarian Data Exchange (humdata.org). Benin—Subnational Administrative Boundaries—Humanitarian Data Exchange (humdata.org). Natural Earth » 1:10m Cultural Vectors—Free vector and raster map data at 1:10m, 1:50m, and 1:110m scales (naturalearthdata.com). Licenses: Data Licenses—Humanitarian Data Exchange (humdata.org).

https://doi.org/10.1371/journal.pclm.0000123.g001

in September for Athiémé, Lokossa, Bas Mono and Yoto and October for Lacs and Grand Popo.

The **Fig 3** shows the annual precipitation variation from 1979 to 2019. From the Fig 3, it can be noticed that from the upper part to the lower part of the catchment, there is a slight reduction of the annual rainfall.

2.2. Data collection

2.2.1. Ethics statement. The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board of the Center for Development Research (ZEF) (protocol code 1a-21 11/02/2021). In addition, informed consent was obtained from all subjects involved in the study.

2.2.2. Household data. A household survey was conducted in November 2020 using a questionnaire. The questionnaire was categorized according to different topics: household socio-economic characteristics, their perceptions on climate change and flood risk, their trends, causes and impacts. A multi-stage sampling was applied to select the villages where household data will be collected [40, 41]. In the first stage, communes were grouped based on

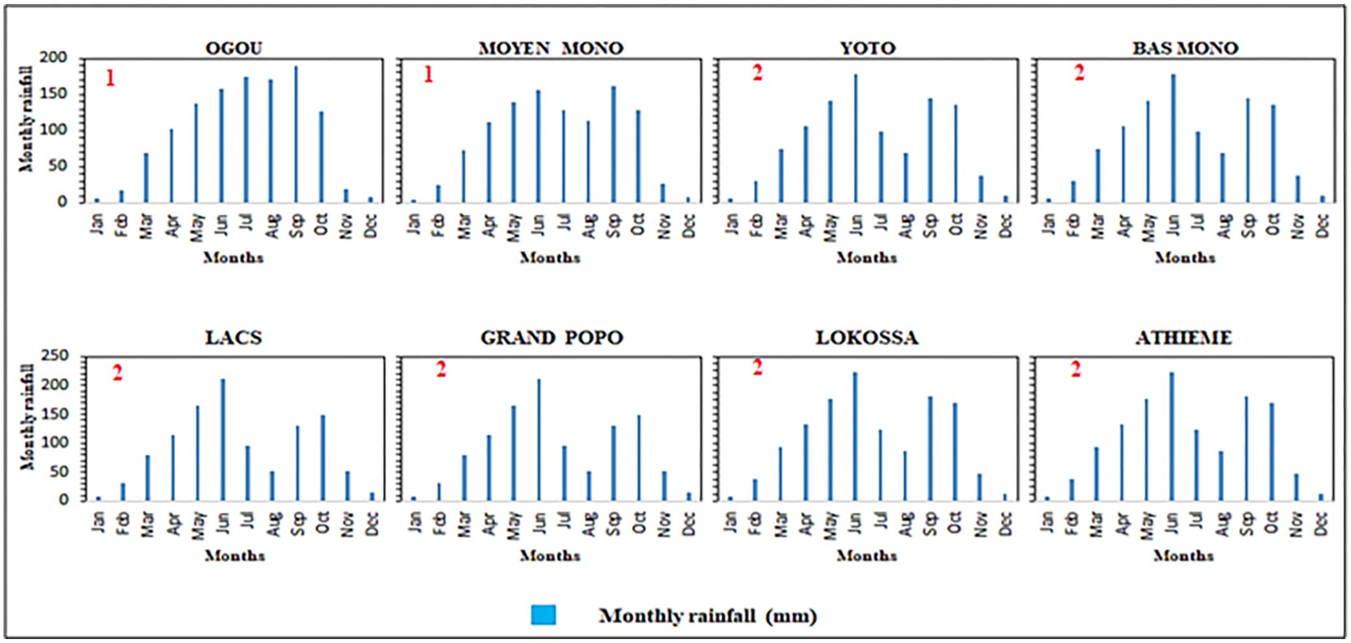

Fig 2. Monthly rainfall in the LMR catchment. 1 stand for Sudan tropical climate and 2 stand for sub-equatorial climate.

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the location within the catchment and their flood risk (low, medium and high risk). This was done by using field investigation and previous studies [42, 43], newspaper reports of flood affected areas [12, 13], and flood map from UNITAR-UNIOSAT (http://floodlist.com/africa/togo-benin-mono-river-floods-october-november-2019). A total of 8 prefectures or communes (5 in Togo and 3 in Benin) were purposely selected within the LMR catchment (along the river). For the second stage, 3 villages were selected from each prefecture or commune,

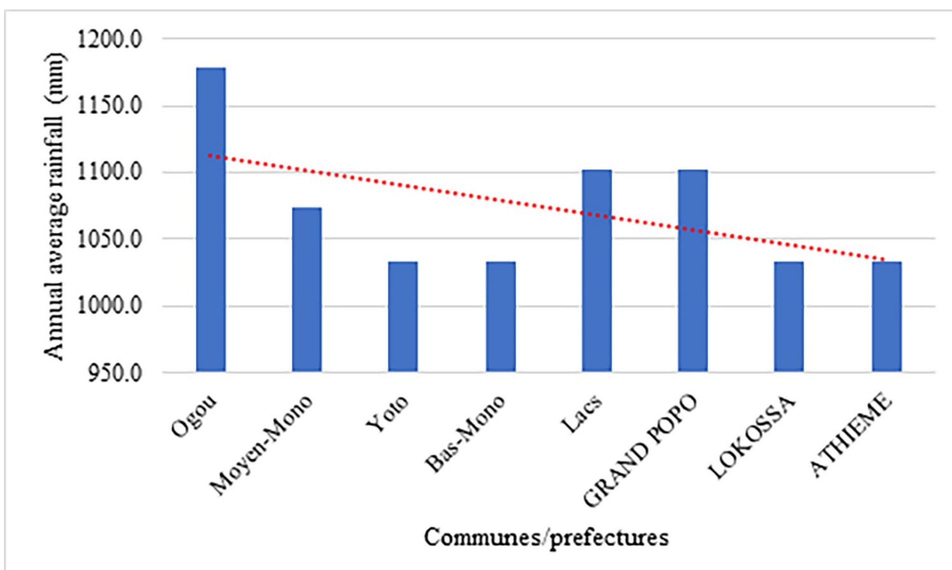

Fig 3. Annual rainfall variation per commune (1979–2019).

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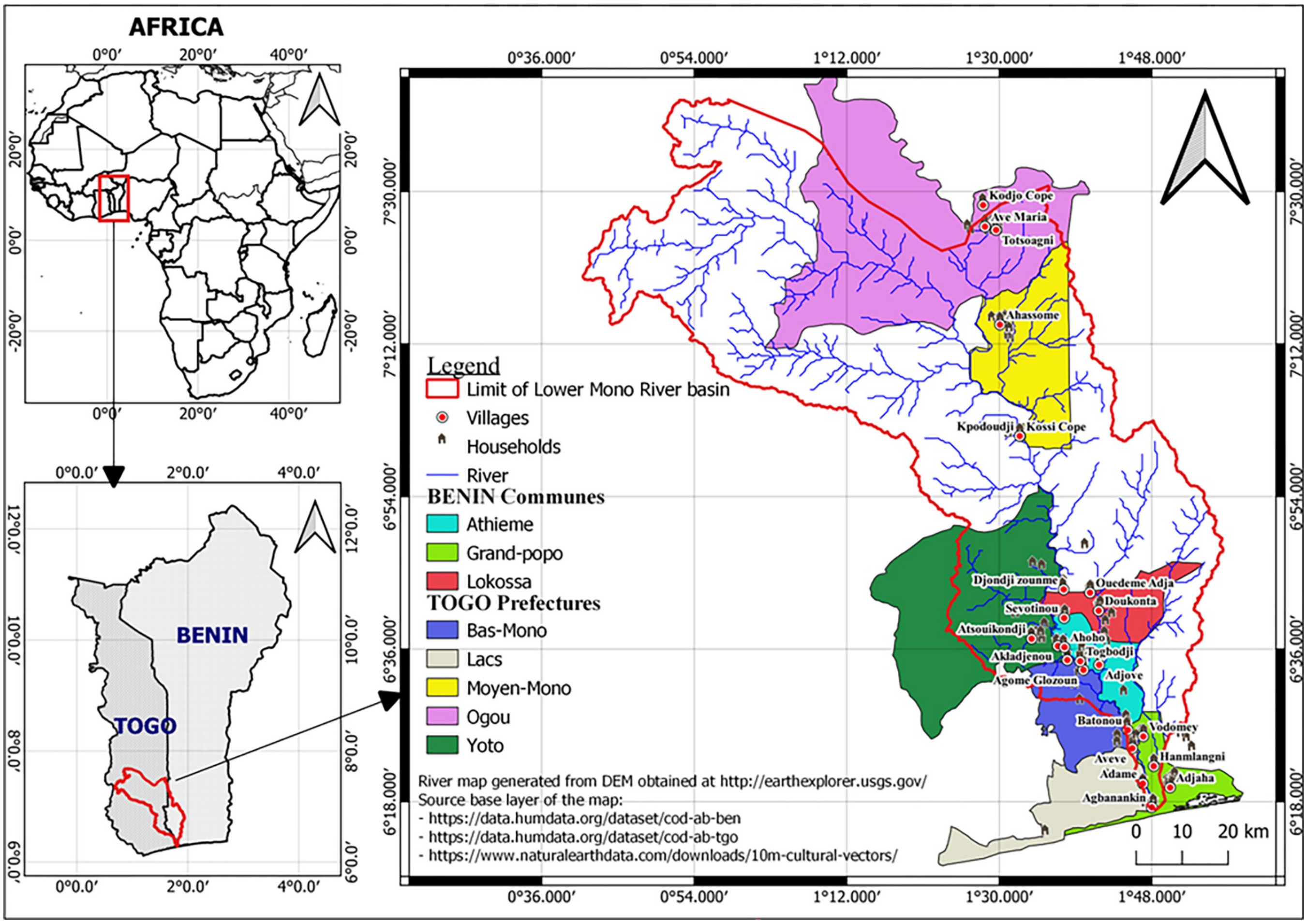

Fig 4. The location of households and villages surveyed in the study area. *Source*: *http://earthexplorer.usgs.gov/*. Togo—Humanitarian Data Exchange (humdata.org). Benin—Subnational Administrative Boundaries—Humanitarian Data Exchange (humdata.org). Natural Earth » 1:10m Cultural Vectors—Free vector and raster map data at 1:10m, 1:50m, and 1:110m scales (naturalearthdata.com). Licenses: Data Licenses—Humanitarian Data Exchange (humdata.org).

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giving a total of 24 selected villages, of which 15 villages in Togo and 9 in Benin (Fig 4). These villages were selected based on the following criteria:

- their location within the catchment;
- their proximity to the river,
- the extent of flood risks (Confirmed by the red cross during the pre-survey),
- agriculture as dominant economic activities, and
- the presence of some projects working on the issue of flood risks

A censored proportional sample with a minimum number of 10 were used to determine the sample size [44, 45]. Systematic random sampling of household was used to determine the number households to interview. A central point in the village was selected and a random direction for walking was chosen (North, East, South or West) by the interviewer [46]. Systematic interval of selecting households was chosen from the starting point into the randomly selected direction (North, East, South or West) and selects for example every 2th house. In

Table 1. Rainfall and hydrological data of selected stations.

	Country	Commune / Prefecture	Villages
Rainfall data	Benin	Grand-Popo	Djanglamey
			Adjaha
			Vodomey
		Athiémé	Adjove
			Ahoho
			Sevotinou
		Lokossa	Doukonta
			Gankpatchahoue
			Ouedeme Adja
	Togo	Ogou	Ave Maria
			Kodjo Cope
			Totsagni
		Moyen Mono	Kossi cope
			Kpodoudji
			Ahassome
		Yoto	Akladjenou
			Athshouikondji
			Kpodji
		Bas-Mono	Agome-Glozoun
			Batonou
			Togbadji
		Lacs	Agbanakin
			Adame
			Aveve
Hydrological data	Benin	Athiémé outlet	At the down part of the basin in the prefecture of Athiémé
	Togo	Nangbeto outlet	At the upper part of the basin

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case the selected house is non-residential, the interviewer selects the next house opposite the other side of the street. As a result, a total of 744 households were interviewed from the 24 villages (**Fig 4**). The data were collected using Kobo Collect tool (www.kobotoolbox.org/).

2.2.3. Climate and hydrological data. Table 1 shows the different stations where rainfall and hydrological data were obtained to analyze the trend of climatic and hydrological trend in LMR catchment. The precipitation and discharge data were collected from the version 4 of the Climatic Research Unit gridded Time Series (CRU TS), the monthly high-resolution gridded multivariate climate dataset, and the Direction Générale de l' Eau (DGE) in Benin. The data were collected in each of the selected communes or prefectures. The Climatic Research Unit gridded time series (CRU TS) was used because of the lack of ground-based data. It was used by previous studies and presented satisfactory responses with respect to observational datasets [47, 48]. The monthly precipitation from 1979 to 2019 was collected for each commune/prefecture. The water discharges from 1979 to 2010 of the Nangbeto dam and the outlet of Athiémé were collected from the DGE.

2.3. Data analyses

Households' perception on flood represents the aggregated awareness regarding rainfall pattern and trend. Thus, households were asked about rainfall changes, the most flooded years and the rainfall characteristics of those particular years. In addition, opinions or views have been collected on flood damages and causes.

The descriptive statistics were used to summarize household perceptions on flood risk using R software version 64 4.1.1 and Microsoft Excel spreadsheet. Monthly and annual averages of rainfall and discharges were computed using Excel.

2.3.1. Standardized precipitation index (SPI). From the interannual rainfall variability, the Standardized Precipitation Index (SPI) was generated to monitor hydrological and climatological condition in river basin and to help detect and monitor droughts [49, 50]. SPI also can be applied to determine wetter than normal conditions [50]. The SPI is calculated using the following equation:

$$I(i) = \frac{x_{i-}x_m}{\sigma} \quad \text{Eq1}$$

Where, I(i), x_i, x_m and σ are the standardized index of year i, the value for the year i, the average and the standard deviation of the time series, respectively.

From the generated SPI values, drought and flood conditions were classified as shown in Table 2 based on classification by [49].

Moreover, the correlation analysis was performed to analyze the relationship between the perception of household on the flooded months and monthly rainfall, which will determine if rainfall is the main cause of flooding from household's perspective.

2.3.2. Chi-square test. The Chi-square test was performed to measure the association between the households' communes and the possibility for their houses to be affected or not by flood events. This test measures the relationship between two categorical variables using the formula as follows [52]:

$$x_c{}^2 = \sum \frac{(O_i - E_i)^2}{E_i} \quad \text{Eq2}$$

Where, *c* is the degrees of freedom; *O* is the observed value and *E* is the expected value.

The Chi-square test analysis was performed using SPSS (Statistical Package for the Social Sciences) version 26. The chi-squared statistic gives information on the difference between the observed counts of the modality of the categorical variable and the counts expected if there were no relationship at all in the population.

2.3.3. Binary logistic regression analysis. Binary logistic regression analysis was used for identifying the factors that influence the household 'perceptions of rainfall changes by using the formula below [19, 53, 54]:

$$n_{ij} = \beta_{0j} + \beta_{1j}X_{1ij} + \beta_{2j}X_{2ij} + \cdots + \beta_{pj}X_{pij} \quad \text{Eq3}$$

Table 2. Drought and flood classification by SPI.

Code for drought or flood classes	SPI values	Cumulative probability	Drought and flood classes
1	≤ - 2.0	0.0228	Extreme drought
2	(-2.0, -1.5]	0.0668	Severe drought
3	(-1.5, -1.0]	0.1587	Mild drought
4	(-1.0, -0.5]	0.3085	Near Normal
5	(-0.5, 0.5]	0.5000	Normal
6	(+0.5, +1.0]	0.6915	Near normal
7	(+1.0, +1.5]	0.8413	Mild flood
8	(+1.5, +2]	0.9332	Severe flood
9	≥ + 2	0.9772	Extreme flood

Source: [49, 51]

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where n_{ij} is the logged odds: $log\left(\frac{\emptyset_{ij}}{1-\emptyset_{ij}}\right)$, i represent the i^{th} observation in the sample. Pi is the predicted probability of households' perception which is coded as a dummy variable and take the value 1 when a household has a positive (Yes) response regarding the perception on rainfall change and 0 contrary $(1-\emptyset_{ij})$. β_0 is the intercept term, and β_1, β_2, and β_k are the coefficients associated with each explanatory variable X1, X2 and Xk. The model was performed using SPSS 26 package.

Binomial model variables were determined are follow:

2.4. Dependent variable

The dependent variable in the model is represented by the households' perception which is a dummy variable equal to 1 when a respondent was affirmative (yes) regarding the change in rainfall pattern in the last 20 years and 0 when the respondent' answer was negative (no). The binary logistic regression was also used by [19] to identify the factors that influenced farmers' perception on the long term climate change and variability in Ghana.

2.5. Explanatory variables

In most of the studies, household socio economic characteristics, institutional factors and environmental variables are used to understand the variables that influenced household's perceptions of climate change [19, 55, 56]. Therefore, in this study, we considered the following explanatory variables: age, gender of households' header, household size, household header education, household literate, household experience in agriculture, incomes of the household as the socio-economic characteristics; the fact that household in part of disaster risk management group and participate to flood training as institutional variables, the households 'plot and house elevation and the soil type as environmental variables.

3. Results

3.1. Comparison of annual historical rainfall data and household's perceptions

3.1.1. Historical annual rainfall. An analysis of rainfall records for the last 41 years showed obvious annual rainfall variability particularly in years 2019, 1979 and 2010 (**Fig 5**). The year 2019 recorded the maximum rainfall from 1360.8 to 1473.5 mm depending on the prefectures or communes followed by year 1979 (from 1295.5 to 1423 mm depending on the prefectures or communes); and year 2010 (1268 to 1404.3 mm depending on the prefectures or communes depending on the prefectures or communes).

The analysis of annual rainfall anomaly reveals that the 41 years are characterized by different drought and flood classes. The majority of the wet years are classified in the categories of near normal and mild flood in the study area. Three years especially 1979 (1.40 to 1.80), 2010 (1.36 to 1.72) and 2019 (1.78 to 2.51) were found as severe flood and extreme flood (Fig 6). The high value of the anomaly was obtained in 2019 in the commune situated in the down part of the basin. Lacs and Grand Popo recorded 2.51 while Athiémé and Yoto recorded 2.24 (Fig 6). The moving average for five years indicates variation in rainfall totals also show the upward trend in the last years.

The annual rainfall analysis shows that the years 2010 and 2019 recorded high value of rainfall and are classes as severe and extreme flooded year. These years corresponded to the ones characterized by the most flooded years in the perception of the households. Thus, rainfall may represent the causes of flood in the Lower Mono River basins.

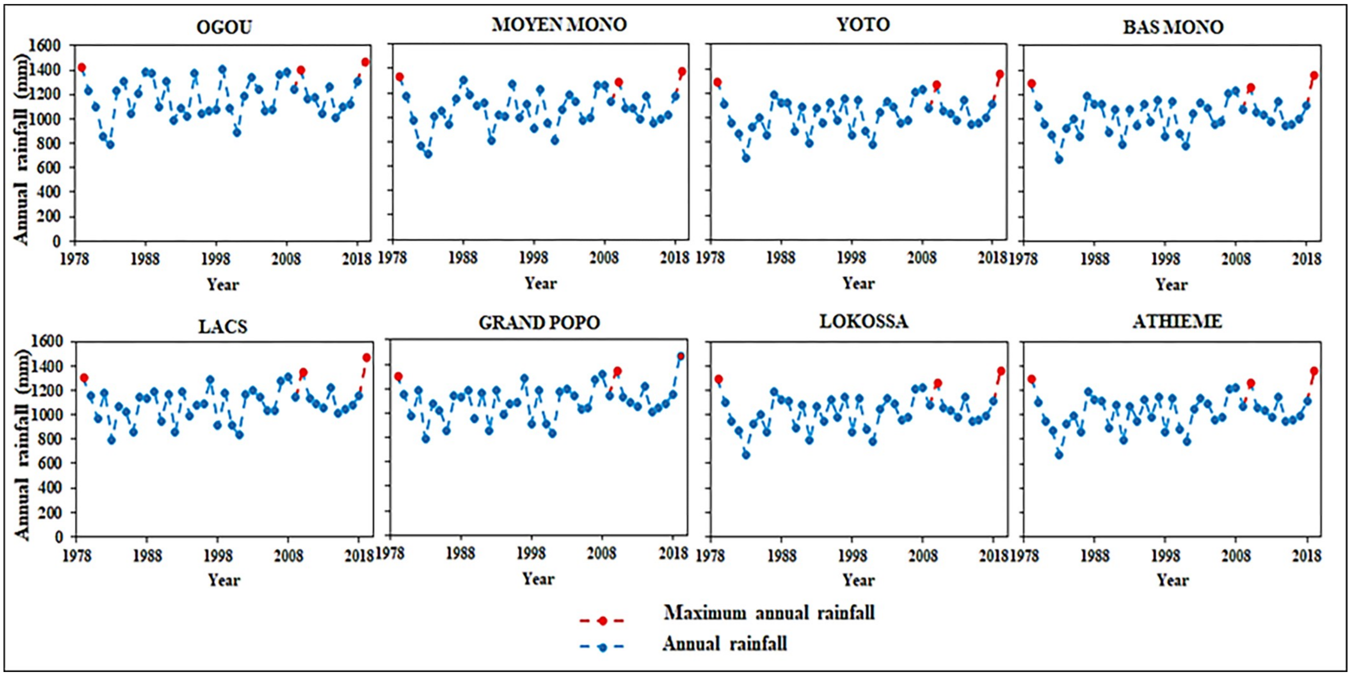

Fig 5. Annual rainfall in Lower Mono River basin (1979–2019).

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3.1.2. Monthly rainfall and discharge variation. The comparison of the monthly rainfall pattern and discharge at the upper and down part of the basin shows that the maximum value of the discharge is reached in the month of September (Fig 7). September corresponds to the maximum rainfall month in the communes of Ogou and Moyen Mono at the upper part. Regarding the lower part, September and October are the months of maximum rainfall. Rainfall may lead to increased discharge, causing the river overflow and flooding in surrounding households.

3.1.3. Households' characteristics and perception on rainfall change. Sixty percent (60%) of the respondents were male whereas 40% percent are female, and 50% of them are literate. They are generally married (88%) and the majority of them (63%) are in the middle age

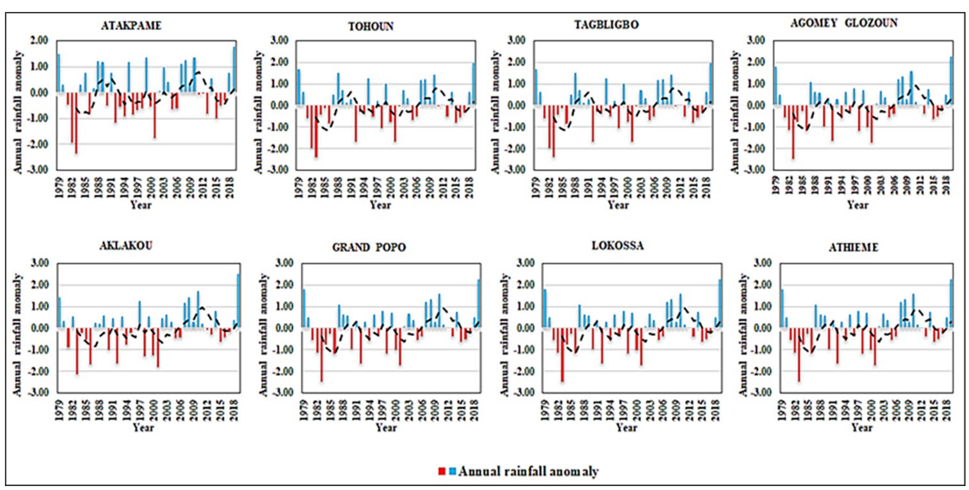

Fig 6. Annual rainfall anomaly (1979–2019).

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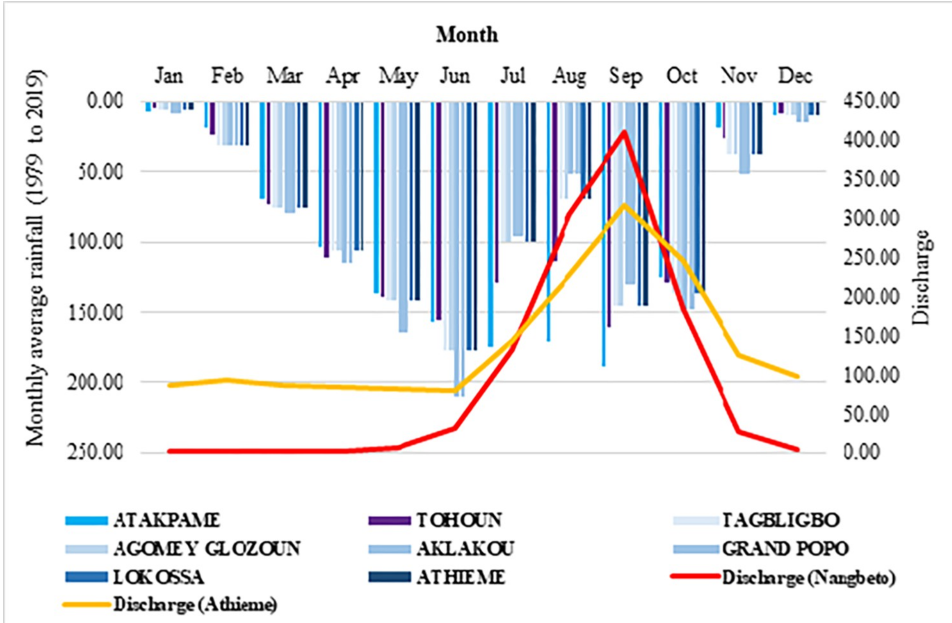

Fig 7. Monthly precipitation and discharge.

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(25–50 years). Around 79% of the respondents have household size of 5. With regards to access to education, 61% of the respondent (households header) who have access.

The respondents considered the years of 2010 and 2019 were the most flooded years during the last 20 years. This was reported by 30% and 27% of the total respondents for 2010 and 2019, respectively (Fig 8).

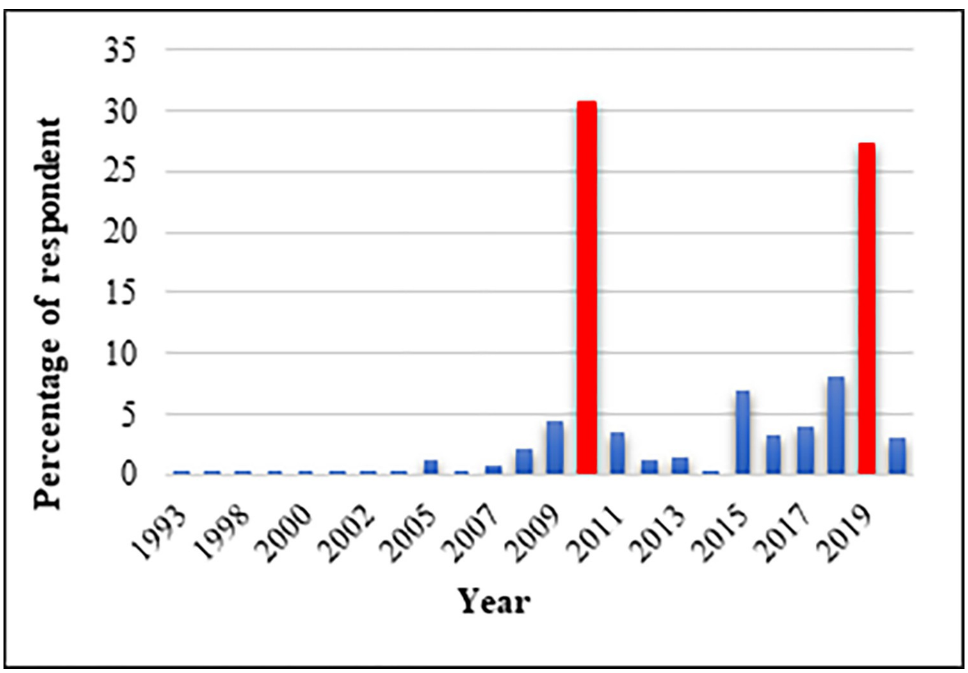

Fig 8. Severe flood years.

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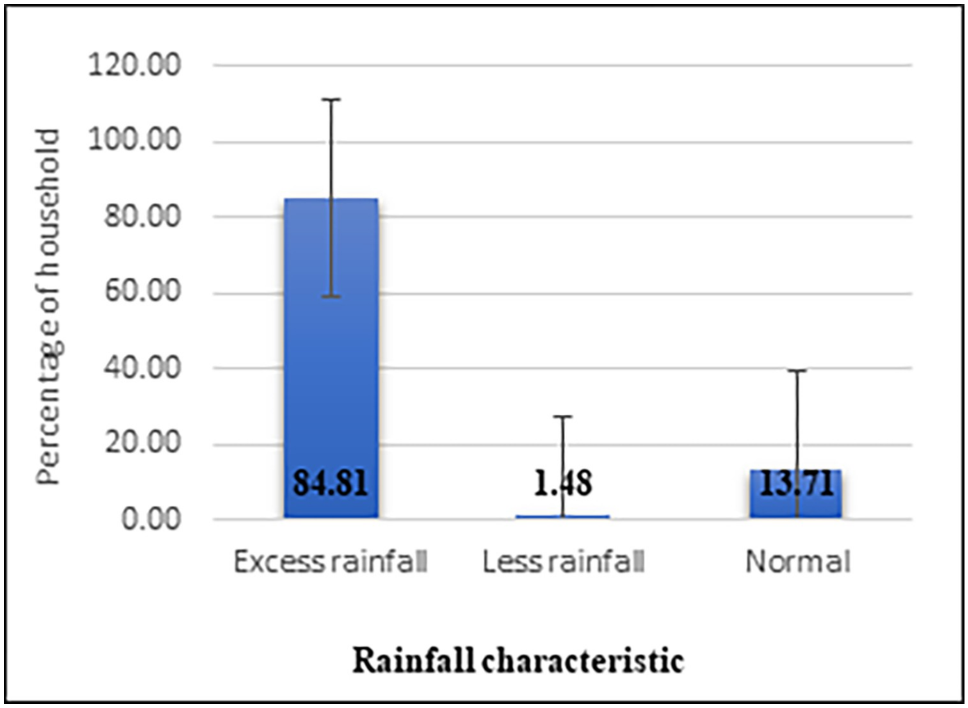

Fig 9. Perceived rainfall changes.

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In terms of rainfall pattern, 85% reported the having excess rainfall in the last 20 years (Fig 9). In contrast, 1% of respondents reported normal rainfall. Since the average age of the interviewers is at middle age (25–50 years), the 1979 extreme rainfall was not capture from the respondents' answers (Fig 9).

3.1.4. Variable influencing household perception on rainfall change. Tables 3 and 4 present the descriptive statistic of the variables used for the binary regression and the factors that influence household's perception in rainfall change, respectively. It reveals that 87% of the respondents had observed change in the rainfall pattern. The binary regression result is statistically significant at 5% (with the p-value = 0.000). Among the dependent variables are: household size (p = 0.034), experience in agriculture (p = 0.043), incomes (p = 0.002), agricultural plot soil type (p = 0.002) and households' houses altitude (p = 0.000) are significantly associated with household's perception in rainfall change.

These results imply that large size of household is more likely to perceive change in rainfall than the one with fewer members. Households with agricultural experience between 11 and 20 years represent the ones who identify more change in rainfall pattern than the others. Also, households with a less income (less than 100 000 FCFA in a year which is equivalent to 153.06 USD$) are more likely to identify change in rainfall than income level. Soil type (i.e., Dystric Nitosols) of household agricultural plot influence household perception on rainfall change. Furthermore, households with homes located at higher elevation are more likely to notice a change in rainfall.

3.2. Relationship between monthly rainfall with the household perceptions on flooded months

The result of correlation analysis shows a positive correlation between household perceptions on flooded months and the recorded rainfall data in specific prefectures (Ogou, Moyen Mono,

Table 3. Descriptive statistic of variables.

Variables		Frequency	Percentage
Age	<25 years	30	4.0
	25–50 years	472	63.5
	>50 years	242 744	32.0 100
	Total		
Household size	Small (1–4 persons)	162	21.8
	Medium (5–8 persons)	355	47.7
	Large (>8 persons)	227	30.5
	Total	744	100
Rainfall characteristic	No	102	13.7
	Yes	642	86.2
	Total	744	99.9
Gender	Female	296	39.7
	Male	448	60.1
	Total	744	99.9
Communes/ Prefectures	Athieme	89	11.9
	Bas-Mono	134	18.0
	Grand Popo	75	10.1
	Lacs	136	18.3
	Lokossa	84	11.3
	Moyen-Mono	92	12.3
	Ogou	41	5.5
	Yoto	93	12.5
	Total	744	99.9
Household incomes	No response	20	2.7
	Less than 100 000	140	18.8
	> 100 000 to 200 000	173	23.2
	> 200 000 to 300 000	185	24.8
	More than 300 000	226	30.3
	Total	744	99.9
Household agriculture experience	Less than 10 ye	118	15.8
	11–20 years	252	33.8
	21–30 years	176	23.6
	More than 30 ye	197	26.4
	Total	743	99.7
Membership in disaster risk management	No	414	55.6
	Yes	330	44.3
	Total	744	99.9
Participation in flood training	No	521	69.9
	Yes	223	29.9
	Total	744	100
Farm plot soil type	Dystric Nitosols	287	38.5
	Eutric Gleysols	212	28.5
	Chromic Vertisols	98	13.2
	Eutric Nitosols	30	4.0
	Gleyic Luvisols	78	10.5
	Total	705	94.6

https://doi.org/10.1371/journal.pclm.0000123.t003

Table 4. Factors influencing household's perceptions on rainfall change (n = 744).

Variables	B	S.E.	Sig.	95% C.I.for EXP(B)	
				Lower	Upper
Gender (Female)	.326	.277	.240	.805	2.383
Header age	.008	.013	.516	.983	1.034
Household size	.070	.033	.034**	1.005	1.144
Household experience in agriculture (Less than 10 years)	.706	.507	.164	.750	5.470
Household experience in agriculture (11–20 years)	.783	.388	.043**	1.023	4.682
Household experience in agriculture (21–30 years)	.166	.331	.616	.617	2.258
Household incomes (No response)	1.497	1.068	.161	.551	36.242
Household incomes (Less than 100 000)	1.428	.466	.002***	1.673	10.385
Household incomes (100 000 to 200 000)	.324	.327	.322	.728	2.625
Household incomes (200 000 to 300 000)	.017	.303	.956	.561	1.843
Membership in disaster risk management (No)	-.278	.280	.320	.437	1.311
Participation in flood training (No)	-.295	.288	.305	.423	1.309
Soil type of household agricultural plot (Dystric Nitosols)	1.195	.391	.002***	1.535	7.116
Soil type of household agricultural plot (Eutric Gleysols)	.578	.395	.143	.823	3.863
Soil type of household agricultural plot (Chromic Vertisols)	-.350	.544	.519	.243	2.045
Soil type of household agricultural plot (Eutric Nitosols)	-.637	.607	.293	.161	1.736
Household header education level (No education)	-.221	1.132	.845	.087	7.378
Household header education level (Primary)	.104	1.109	.925	.126	9.748
Household header education level (Secondary)	-.654	1.108	.555	.059	4.560
Household house elevation	.012	.003	.000***	1.007	1.018

Model Summary Step -2 Log likelihood = 487.026a; Nagelkerke R Square = .157

Df = 1; Yes (N = 589), No (N = 90). *** and **, indicate significant level at 1% and 5% respectively.

https://doi.org/10.1371/journal.pclm.0000123.t004

Yoto), which are located in the low part of the catchment (Fig 10). Indeed, even though there was a positive correlation between local knowledge and rainfall data in some areas, the relationship was not strongly significant (maximum $R^2 = 0.56$). These findings indicate that rainfall induces the increase in water flow at the upper part of the catchment and represents one of flood causes. However, at the lower part, rainfall seems to be not the main cause of flooding according to respondents' perception.

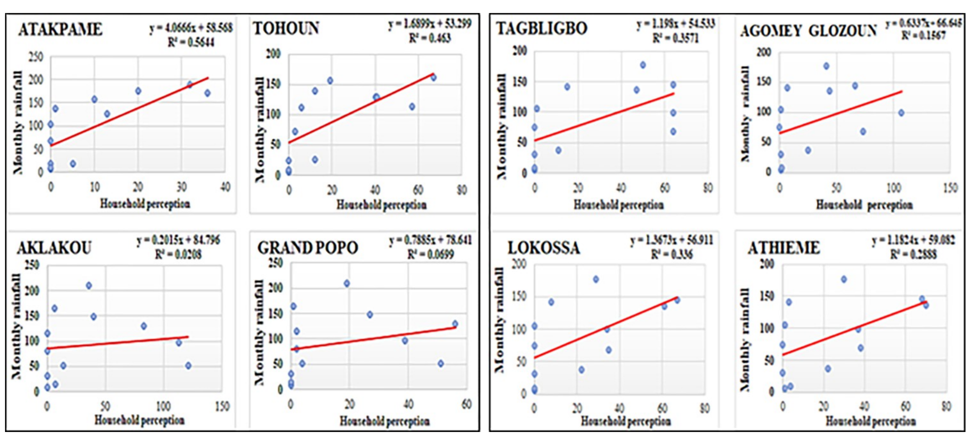

Fig 10. Correlation between monthly rainfall and household perceptions.

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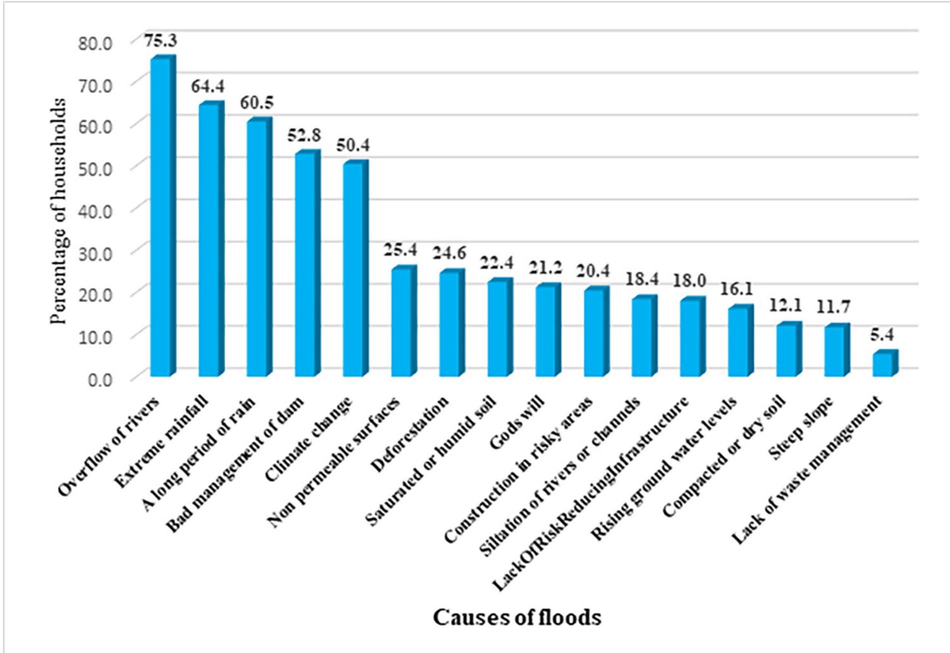

Fig 11. Household's perceptions on causes of floods in LMR catchment.

https://doi.org/10.1371/journal.pclm.0000123.g011

3.3. Perceived causes of floods in the LMR catchment

According to the respondents, several factors are causing flooding in their localities (Fig 11). Fig 11 shows that apart from the rainfall change, other factors were considered as major causes of floods in the LMR catchment. Among the top three perceived causes are: river overflow, extreme rainfall and bad management of the dams, especially the release of water. Respondents believe that the installation of the Nangbeto dam induced flood events in their villages every time its releases water. They feel that the Nangbeto dam construction caused floods in their villages every time it releases water. Indeed, the opening of the Nangbeto dam spillway, combined with extreme rainfall and short rainy season, causes water to accumulate in the communes in the lower part of the basin, making them more vulnerable to this phenomenon.

3.4. Most perceived affected localities

The Chi-test results revealed that there is strong a relationship between communes (location of households) and whether they are affected or not by flood (Chi square = 69.183; df = 7; p value = 0.000) (Table 5). The communes of Athiémé, Grand Popo, Lacs and Yoto (15.6%, 13.5%, 23.7% and 16.8%, respectively) recorded the highest percentage of respondents' house affected by flood and represent the group "**A**". The communes of Bas Mono and Moyen Mono recorded 14.9% and 8.6%, respectively of respondents affected by flood and represent group "**B**". The communes of Lokossa and Ogou recorded 17% and 19% of respondents affected by flood, respectively and constitute the group "**C**". Communes from Group **A** are the most affected by flood whereas the least affected are communes from Group C.

Overall, most affected communes are all located in the downstream of the basin. In spite of this, the communes of Bas Mono and Lokossa, located in the lower part of the basin were classified as averagely affected and less affected, respectively. It is important to notice that a protective dam is installed in Bas Mono. Also, Lokossa is located after the commune of Athiémé and

Table 5. Relationship between commune and the fact that household are affected by flood.

			Communes							
			Athiémé	Bas-Mono	Grand_Popo	Lacs	Lokossa	Yoto	Moyen Mono	Ogou
Households' houses affected by flood	No	Count	7_a	56_b	4_a	12_a	67_c	5_a	47_b	$22_{b, c}$
		Expected Count	26.3	39.6	22.2	40.2	24.8	27.5	27.2	12.1
		% of No Within Households' houses affected by flood	3.2	25.5	1.8	5.5	30.5	2.3	21.4	10.0
	Yes	Count	82_a	78_b	71_a	124_a	17_c	88_a	45_b	$19_{b, c}$
		Expected Count	62.7	94.4	52.8	95.8	59.2	65.5	64.8	28.9
		% of Yes Within Households' houses affected by flood	15.6	14.9	13.5	23.7	3.2	16.8	8.6	3.6
Total		Count	89	134	75	136	84	93	92	41
		Expected Count	89.0	134.0	75.0	136.0	84.0	93.0	92.0	41.0
		% Within Households' houses affected by flood	12.0	18.0	10.1	18.3	11.3	12.5	12.4	5.5

Each subscript letter denotes a subset of Prefecture new categories whose column proportions do not differ significantly from each other at the .05 level. No = Not affected by flood; Yes: affected by flood; Count: Count or number of households which responded Yes or No for being affected by flood

https://doi.org/10.1371/journal.pclm.0000123.t005

therefore far from the main line of the river. This may explain the fact that households are less affected in these communes. Comparing with the perception of flood risks, the consistent ones are the fact that rainfall contribute to the increasing of the river' discharge and cause the flood risk in the upper part of the basin while the lower part of the basin received accumulation of water and make the communities in this part the most affected by flood. In addition, the lower part is situated in the southern part of the countries which is characterize with the ground water not too deep.

4. Discussion

This study compares household perception of flood to climate (rainfall) with hydrological data in the Mono river catchment. The annual rainfall analysis for the 8 localities purposely selected for this study revealed that the years 2010 and 2019 had recorded high rainfall values and were classified as severe and extreme flooded years. These same years were characterized by households as the most flooded years, which shows that households' rainfall perception is in good tracked with climate data. Similar finding was reported by [57] in Bangladesh. Also, it appears that rainfall is the principal cause of flooding in the region, shown both by the empirical data and the household perceptions. This result corroborates with many studies and reports conducted in the study area, which have also shown how hydro metrological event, especially floods, have caused huge damage to local population [58–61].

The dynamic of monthly rainfall and discharge at the upper and down part of the basin revealed that both maximal monthly rainfall and discharge are obtained in the same month (October). In the same line with that, the study conducted by [62] on the hydrometeorological analysis of floods in the Mono watershed in West Africa with a conceptual rainfall-runoff model shows that the discharge at the entrance as well as at the exit of the dam has a seasonal regime between the months of June and October. Similarly, the rainfall-runoff model, HBV-light (Hydrologiska Byråns Vat- tenbalansavdelning) was used in the study conducted by [63] whereby the satellite rainfall data were used to assess the utility of the satellite data in runoff modelling, flood forecasting and climate change impact assessment. This study reveals that there is concordance between the discharge simulated (except of the Climate Hazards Group

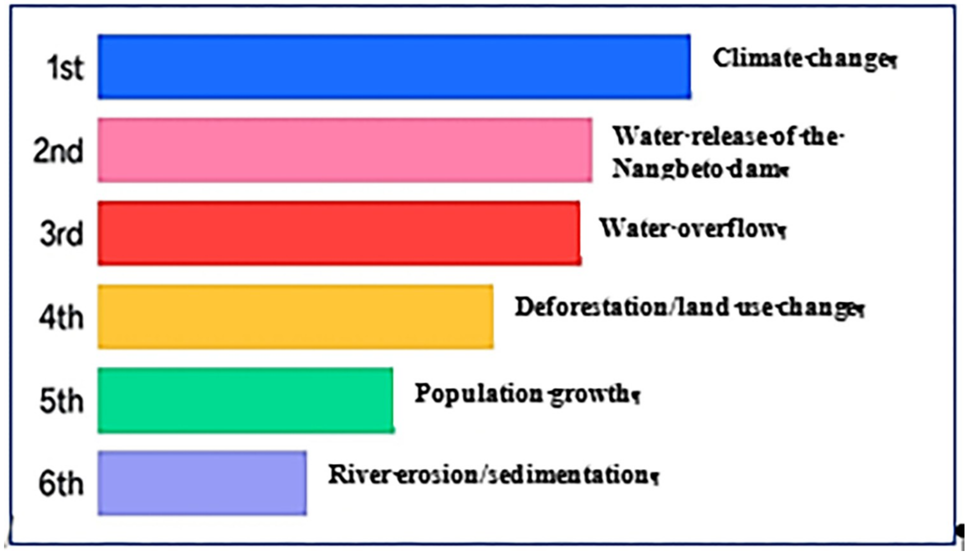

Fig 12. Perception of stakeholders on flood drivers (source: stakeholders' workshop, CLIMAFRI 2022).

https://doi.org/10.1371/journal.pclm.0000123.g012

Infrared Precipitation with Station data version v2.0) with the observed value of discharge within the basin.

Furthermore, the monthly precipitation is correlated with the household perception of flooded months reported by the respondents from the upper part of the basin, and opposite from the respondent from the lower part (with no correlation). Then, it raises the question of whether household perceptions vary according to their location within the catchment, or whether households are more interested in dealing with other flood causes than rainfall because of religious beliefs (e.g., some believe that rainfall and floods are God' will and that have no control over them, see Fig 12). In the view of household, at the upper part, rainfall is link to flood while in the down part flooding are less associated to rainfall and other factors such as dam management contributes to flooding. On other hand, the most flood-affected communes including Athiémé, Grand Popo, Lacs and Yoto, which are situated in the lower part of the basin [64, 65]. The communes of Bas-Mono and Moyen Mono were considered averagely flood affected whereas the communes of Ogou and Lokossa were less affected. However, it can be noticed that the communes of Lokossa and Bas Mono, which are in the down part of the basin are considered as averagely and less affected based on perception of households. This observation is due to the location of protective dam in Bas-Mono. Also, Lokossa is located after the commune of Athiémé and therefore far from the main line of the river. This could be the results of the extreme rainfall that lead to increased discharge, causing the river to overflow and affecting the surrounding households [66]. In addition to extreme rainfall, other major causes of flooding such as the Nangbeto dam management was also reported by respondents. Indeed, the communes in the lower part of the basin receive the accumulation of water due to the opening the Nangbeto dam releases combined with the short rainy season, which increases their vulnerability to this phenomenon. This statement was also confirmed by stakeholders during our workshop organized on March 2022 on drivers to flood risk (forthcoming publication) (Fig 12). They classified climate change through extreme rainfall and Nangbeto water release as the first principal cause of flood. According to Red Cross during the CLIMAFRI workshop in 2022, the fact that households in the down part of the basin are more affected by the flood is due to the fact that they received the accumulation of water and runoff through the river coming from the upper part of the basin. It was also reported that, in 2021, some communes were affected by flood without experiencing extreme rainfall event (2019). This was also mentioned by, official press agency of the government of Benin (Agence Bénin Presse (ABP)) that "*the flooding was exacerbated by dam releases at Nangbéto and Anié in the Plateaux Region of Togo. Several small tributaries of the Mono have also flooded*" [67].

Similarly, [68] reported that communities at higher elevation are less at risk than the ones at the low altitude and concluded the causes of flood risk in the lower part of the catchment do not only come from the extreme rainfall but also the result of the bad regulation of Nangbeto dam. Our study corroborates with the study of [38], that the population at the lower part of the catchment ranked the "release of water by the Nangbeto dam" as the main cause of flooding in the target study communities. Furthermore, [69] showed that stakeholders perceived the flood duration, depth, velocity and spatial extent in the LMR catchment are associated with the discharge at Nangbeto. This has been observed in in a Transboundary River Basin in Korean Peninsula showed that the released of water from the dam constructed on the river represents the principal cause of flood in the downstream part [70].

Regarding the factors affecting household's perception on rainfall change, our findings corroborate with other studies. For example, [71] showed that the increasing size of the household lead to an increase in the level on climate change perception of farmer. Others studies have the same conclusion such as of [72, 73]. Households with agricultural experience between 11 to 20 years represent the ones who identify change rainfall pattern compared to the other categories. This can be explain by the fact that, majority of the respondents (88%) are in their middle age (25–50). [56] found that increases in farming experience permit the increasing of awareness in rainfall change. This result is also confirmed by others studies [71, 74]. Also, household income may constitute a factor which make household vulnerable to the impact of extreme or less rainfall as more households' incomes is small, more household are aware of change in rainfall pattern. In addition, the soil type (Dystric Nitosols) of household agricultural plot and the households 'house altitude represents variables which permit to household to identify a change in rainfall pattern. Dystric Nitosols can be find at the lower altitude [75]. Finally, households with homes located at higher elevations are more likely to notice a change in rainfall.

5. Conclusion

Flood is one of the disasters which occurs more in the transboundary basin shared between Benin and Togo. Despite the plan set up by the governments of each country to cope with that phenomenon, the risk is still high, and the projections are worst. Adaptation strategies are therefore necessary to reduce the risk of flooding and improve the living conditions of communities. In order to identify an efficient and sustainable strategy, it is important to know the perception of the households for understanding the flood' causes. It is within this context that this study has been conducted. This study reveals that respondents perceive the year 2010 and 2019 as the year they were most affected by flood, these years are perceived as the excess rainfall years in term of rainfall. Households' perception on flooded month is correlated with the monthly precipitation and discharge in some commune. This show that rainfall induces the increase of discharge and subsequently in some communes. Adaptive strategies need to pay more attention on combining structural and non-structural measure to reduce the impact due to flood in the Lower Mono River catchment. From the findings, the perception of the local communities is important for having more insight in the real causes of the flood. The local perception can also guide decision makers in taking the best measures to tackle flood risk in the Mono river catchment. Climate and hydrologic data show that all the communes or prefectures at the down part of the catchment are more vulnerable because of the fact that they received the accumulation run off water. But in the perception of households, some communes are not because there are some hydraulic infrastructures. This denotes the importance of considering local communities need to be considered for choosing the efficient measures in order to cope with flood risk. Therefore, proposition of efficient adaptive strategies needs to pay more attention on local communities' participation to reduce the impact of flood in the Lower Mono River catchment. Future work could concentrate on the utility or efficiency of installing hydraulic infrastructures in the most vulnerable prefectures. This article represents the result of my thesis work.

Acknowledgments

This work would not have been possible without the financial support and capacity building of West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL) and Implementation of Climate-sensitive Adaptation Strategies to Reduce the Flood Risk in the Catchment Area of the Cross-border Lower Mono River (CLIMAFRI) project. A big thank to the Center for Development Research (ZEF) support.

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