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Farmers' perceptions of hydroclimatic variability and climate change: survey-based insights in Northern Benin, West Africa

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Farmers in West Africa face increasing challenges from droughts and hydroclimatic variability, exacerbated by climate change. Understanding these changes and their drivers is crucial for developing effective adaptation strategies. This study investigates farming households in Northern Benin, assessing their knowledge of hydroclimatic variability and identifying the factors influencing their understanding. Using a questionnaire survey of 509 households across 96 villages in eight municipalities, we analysed both qualitative and quantitative data through statistical methods and machine learning methods. Results reveal that while 71% of farmers have a solid grasp of local hydroclimatic variability, significant gaps remain regarding its underlying causes; only 9% attributed temperature increases to global climate change. Older farmers (mean age: 55 years) and those with over 30 years of experience demonstrated higher knowledge than less experienced farmers. Conversely, formal education had little to no impact. These findings highlight the critical role of indigenous knowledge, accumulated through long-term environmental interaction, in shaping climate awareness. They underscore the need to integrate indigenous knowledge with formal education to improve the understanding of the drivers of these changes. Targeted investments in education, alongside leveraging the experiential knowledge of older farmers, can enhance climate resilience in vulnerable regions. These insights provide a novel perspective on how policymakers can bridge traditional wisdom and modern scientific approaches for more effective climate adaptation.

KEYWORDS

West Africa, farmers, hydroclimatic variability, climate change, indigenous knowledge

1 Introduction

Rural livelihoods are subject to multiple shocks and stresses that can increase household vulnerability. Climate variability is one of the pervasive stresses faced by rural farmers in Africa (Ziervogel and Calder, 2003). Adopting proper adaptation measures to hydroclimatic variability has become inevitable for people dependent on agricultural production and subsistence farming (Haile et al., 2020). Previous studies suggest that populations in dryland areas are among the most ecologically, socially, and politically marginalized. These communities often lag behind on various economic and health indices, and climate change is expected to stress these already vulnerable systems further (Verchot et al., 2007; Wilcox et al., 2019).

Recent research on human water security underscores the growing challenges posed by climate variability and change, compounded by population and economic growth, mismanaged water use, and inadequate protection of landscapes and waterways (Chaplin-Kramer et al., 2019; Harrison et al., 2016; Tickner et al., 2020). Regions with high climate variability face severe water insecurity, as hydrologic instability is closely linked to poverty and socioeconomic vulnerability (Grey and Sadoff, 2007). In arid regions like West Africa, water is a critical and limiting resource. Sustainable development efforts focus on improving water availability, access, and quality through diverse approaches, ranging from large-scale engineering solutions like water transfer projects and desalination to traditional practices such as herders' seasonal migrations, land management, and water harvesting techniques that conserve water and maintain ecosystem services. These solutions integrate indigenous wisdom, local knowledge, and modern research, contributing to multiple Sustainable Development Goals (SDGs) (Chinnasamy and Srivastava, 2021; Jain et al., 2024). A key example in Africa is the Great Green Wall initiative, which aims to combat desertification and water scarcity across the Sahel region. By restoring degraded lands, promoting agroforestry, and enhancing water conservation techniques such as rainwater harvesting and groundwater recharge, the project improves food security, livelihoods, and climate resilience for millions (UNCCD, 2020). Such integrated approaches highlight the importance of blending traditional and scientific knowledge to address climate change and water security challenges (Aguirre-Unceta, 2023; Mortimore and Adams, 2001).

However, the value of local knowledge is often underestimated in climate change studies. Farmers have valuable indigenous adaptation strategies, including early warning systems (Nyadzi et al., 2021), and they recognize and respond to climatic changes (Thomas et al., 2007). For example, local communities in the Niger River Basin have responded to variations in water availability through the use of water harvesting, irrigation, planting of drought-tolerant and early-maturing crop varieties (Jellason et al., 2021). Therefore, it has been argued that local knowledge of climate variability and adaptation measures is very valuable, particularly in the absence of reliable local observations and projections (Oyerinde et al., 2015), and some studies have demonstrated high agreement between local perceptions and observations (Oyerinde et al., 2015; Tambo and Abdoulaye, 2013; Thomas et al., 2007; West et al., 2008).

It has also been shown that integrating indigenous knowledge with scientific data can enhance climate adaptation strategies and improve resilience (Nyong et al., 2007). Indigenous knowledge refers to the understanding, skills, and philosophies developed by societies with a long history of interaction with their natural environment (Rubis, 2019). However, local perceptions and indigenous knowledge can be biased by environmental factors such as extreme droughts. For instance, in Niger, prolonged and severe droughts have strongly influenced local beliefs about climate variability. This has led many people to view the climate as consistently dry, even though observation data shows considerable variability in rainfall patterns over time (West et al., 2008). Meze-Hausken (2004) also reported that local perceptions are often based on the ability of the communities to recall key events, making them more accurate for recent climatic events (less than 30 years). Hence, there is limited understanding of how well the indigenous knowledge of rural households aligns with empirical data (Kalanda-Joshua et al., 2011).

Benin, a country in West Africa, faces significant challenges related to climate change (Badou et al., 2021; Ganni Mampo et al., 2025). The sectors most severely affected are water resources, energy, public health, agriculture, and forestry (Fadina and Barjolle, 2018). Agriculture serves as the primary occupation for almost 70% of Benin's active workforce and contributes 36% to the country's Gross Domestic Product. Climate change and environmental degradation result in declining agricultural productivity despite sustained efforts by local farmers. While smallholder farmers in rural areas are particularly vulnerable to hydroclimatic variability and climate change impacts, they possess a rich repository of indigenous knowledge and practices (Nyadzi et al., 2021). Despite growing concerns about hydroclimatic variability and climate change, little is known about how well the local perceptions of hydroclimatic variability and climate change align with empirical data, and what factors influence potential discrepancies. Understanding these differences is crucial for developing effective adaptation strategies. This study focuses on the Beninese part of the Niger River Basin in Northern Benin, aiming to answer the following research questions: (1) To what extent do local farmers' perceptions of hydroclimatic variability and climate change correspond with empirical climate and hydrological data? (2) What socioeconomic, environmental, and experiential factors influence farmers' knowledge and perception of these changes? By identifying key factors that shape local knowledge, this research will contribute to strategies that enhance adaptation and resilience to climate variability, ensuring more informed decision-making for sustainable water and land management.

2 Materials and methods

2.1 Study area

The study area is the Beninese part of the Niger River Basin in Northern Benin. Located between 1°32′ and 3°50′East and 10° and 12°30' North, it covers an area of about 48,000 km^2, i.e., 42% of the total area of Benin (Halissou et al., 2021). It is shared by 17 municipalities and includes the three catchments Sota (13,449 km^2), Alibori (13,684 km^2) and Mekrou (10,552 km^2) (Figure 1). The study area is the largest zone for cotton and vegetable production and cattle breeding in Benin. It is also home to the W-Park, which is one of the most important wildlife parks in West Africa.

The study area has two distinct seasons. The rainy season lasts from April to October, with maximum rainfall generally occurring in August, while the dry season extends from November to March (Badou et al., 2021). Annual rainfall ranges from 780 to 1,200 mm for

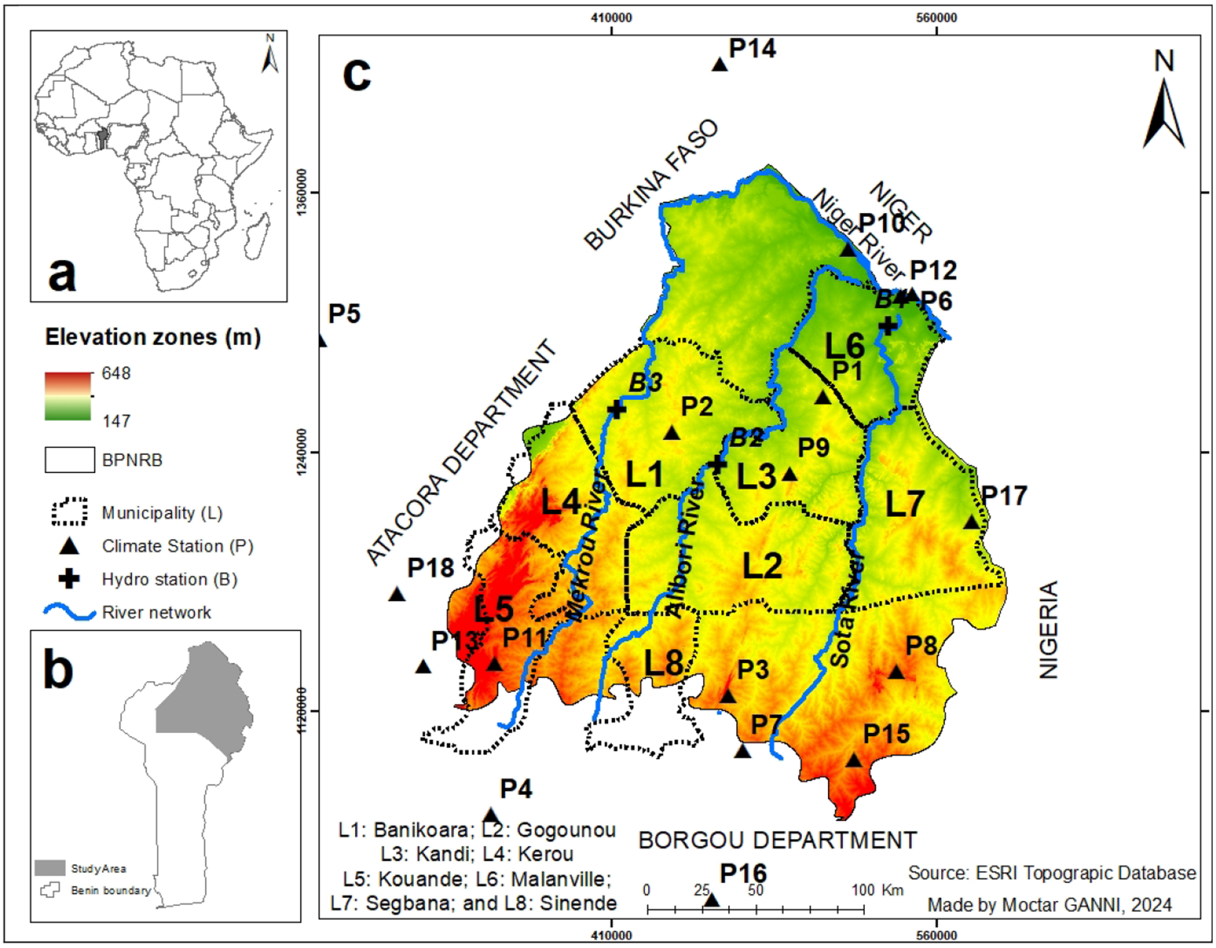

FIGURE 1
Study area Beninese part of the Niger River Basin. **(a)** Location of Benin in West Africa. **(b)** Benin including the study area. **(c)** Study area: topography, location of climate stations (P1 – P16) and discharge stations (B1 – B3), and the eight targeted municipalities (L1 – L8).

the period 1970–2020. Daily potential evapotranspiration (PET) varies between 1.6 and 10 mm, and the annual average of the daily maximum temperature is 33.8°C over the same period. The monthly average daily maximum temperature can reach around 40°C. The three rivers show large seasonal variations. The Sota River has a perennial flow regime with a low flow of about 3.6 m3/s during the dry season; the Alibori and Mekrou Rivers run dry during the dry season (Vissin, 2007).

The data collection was limited to eight municipalities (L1 to L8 in Figure 1) due to the risk of terrorism in the border areas of Burkina Faso and Niger. Isolated or sparsely populated areas were also excluded due to the potential activities of armed groups and the associated risk of kidnapping.

2.2 Data collection and survey

We conducted a survey using a household-based questionnaire to obtain data on local knowledge and perceptions of climate variability, climate change and adaptation strategies over the past 30 years. From July 13 to 16, 2023, 509 questionnaires were administered through face-to-face oral interviews by 17 well-educated and trained field interviewers. Consistent training and supervision ensured that the involvement of different interviewers did not influence the data. The respondents came from eight municipalities (Figure 1), spread over 96 villages. They were selected from these communities, with the sample weighted according to population size. All respondents are involved in farming practices, and some also engage in secondary activities, the most prominent being trading (21%), livestock production (18%), agri-food processing (9%) and coal manufacturing (8%). Indigenous knowledge is related to the duration that a person has lived in an area, to direct experience in the natural environment and to socio-cultural factors (Speranza et al., 2010), the respondents were selected based on the following criteria:

(1) Only farmer households were included.
(2) Older than 35 years, as some questions pertained to developments over the last 30 years.
(3) At least 8 years of farming experience on their farmland, enabling them to provide insights on long-term changes and yield variations.
(4) Permanent residence in the area for at least 8 years, ensuring familiarity with local conditions and practices.

The sampling method follows a purposive (criterion-based) sampling approach. Unlike random or stratified random sampling, participants were selected based on predefined criteria (age, farming experience, and residence duration), rather than through random selection from the population. We thus selected only those households whose responses were relevant to the study. Including all households would have increased the number of interviews without adding meaningful insights. The questionnaire covered demographic and socioeconomic factors such as age, gender, level of education, farming experience, secondary activities, and technology/science-oriented views. It also assessed knowledge and perceptions of climate variability and change related to changes in the rainy and dry seasons, their onset, cessation, and duration, river level changes, and temperature variations. Additionally, the questionnaire also explored adaptation measures, including the transfer of knowledge from external sources to households and the use of religious rites for economic success, specifying the types and frequency of these rites. These data were collected, coded, and deployed on kobotoolbox (Harvard Humanitarian Initiative, 2017). The survey questions were pre-tested to ensure methodological rigor. We visualized the data in RStudio, checking the range of variables such as age and experience to identify any errors or inconsistencies. To further validate the responses, we organized two focus group interviews with knowledgeable individuals, including the village chief. Their insights provided truthful responses and helped validate the survey answers.

2.3 Observations of climate change and climate variability

We collected historical records of rainfall, streamflow, and temperature to assess the accuracy of farmers' perceptions of hydroclimatic variability and climate change using actual climate data in the study area (Figure 2). For station Kandi (P9), daily rainfall and temperature data were available from 1970 to 2020. For station Malanville (P12), daily rainfall data were used for the same period. Daily streamflow data from three hydrometric stations—Couberi (B1), Yankin (B2), and Kompongou (B3)—were obtained for the three catchments from the Hydrological Service of DG-Eau in Benin.

2.4 Methods

To investigate farmers' understanding of hydroclimatic variability, we selected 14 questions (Table 1) that allow a clear comparison between the farmers' perceptions and observed climate data. Each respondent was assigned a knowledge score based on the degree to which their responses to these 14 questions matched observations. These questions were either binary (wrong, right) or more nuanced (wrong, mostly wrong, mostly right, right). Each answer was assigned to one of these classes and then the knowledge of the respondent for each question was determined (questions with 2 options: wrong = 0; correct = 1; questions with 4 options: wrong = 0; mostly wrong = 0.33; mostly correct = 0.67; correct = 1). The assignment of the answers to these classes is given in Table 1. In a second step the results for all 14 questions were averaged. Thus, a respondent who answers all question correctly will obtain a knowledge score of 1, whereas a respondent who gives only incorrect answers will receive a knowledge score of 0.

We aim to identify those factors that enhance people's understanding of hydroclimatic variability, climate change and appropriate adaptation measures. Potential factors that were included in our survey are gender (male, female), age, experience (number of years of farming practices), education level (none, primary, high), secondary work engagement (yes, no), location (municipalities L1 to L8), and technology/science-oriented view (yes, mixed, no). The latter factor was not asked directly to the respondents, but was inferred from their answers to questions that were related to their farming practices and their approaches to increase their agricultural yields. Households that used pesticides and agricultural equipment were classified as favorable to a technology/science-oriented view. Households that relied on community-based practices and the use of religious rites in their farming activities, were classified as not technology/science-oriented. The mixed class was assigned to those farmers who used both types of approaches, such as using pesticides and religious rites.

To understand the relationships between the variables surveyed, we calculated the Spearman correlation coefficient (r_s) (Ellis, 2011) for the continuous variables (age, experience, and knowledge):

$$r_s = 1 - \frac{6\sum d_i^2}{n\left(n^2 - 1\right)} \tag{1}$$

Where:

- $d_i^2 = R\left(X_i\right) - R\left(Y_i\right)$ is the difference between the ranks of each pair of values in the two datasets.
- n is the number of observations.
- $R\left(X_i\right)$ and $R\left(Y_i\right)$ are the ranks of X_i and Y_i, respectively.

For the categorical variables, we used the Mann–Whitney U test for the binary variables (gender, secondary work) to determine whether there is a significant difference between the two groups. For two independent groups A and B, the U statistic is calculated as:

$$U = n_1 n_2 + \frac{n_1\left(n_1 + 1\right)}{2} - R_1 \tag{2}$$

or

$$U = n_1 n_2 + \frac{n_2\left(n_2 + 1\right)}{2} - R_2 \tag{3}$$

Where:

- n_1 and n_2 are the sample sizes of groups A and B, respectively.
- R_1 and R_2 are the sums of ranks for groups A and B, respectively.
- The smaller U value is used for statistical significance testing.

Z-score for significance testing:

$$Z = \frac{U - \mu_U}{\rho_U} \tag{4}$$

Where:

- $\mu_U = \frac{n_1 n_2}{2}$ is the mean of U

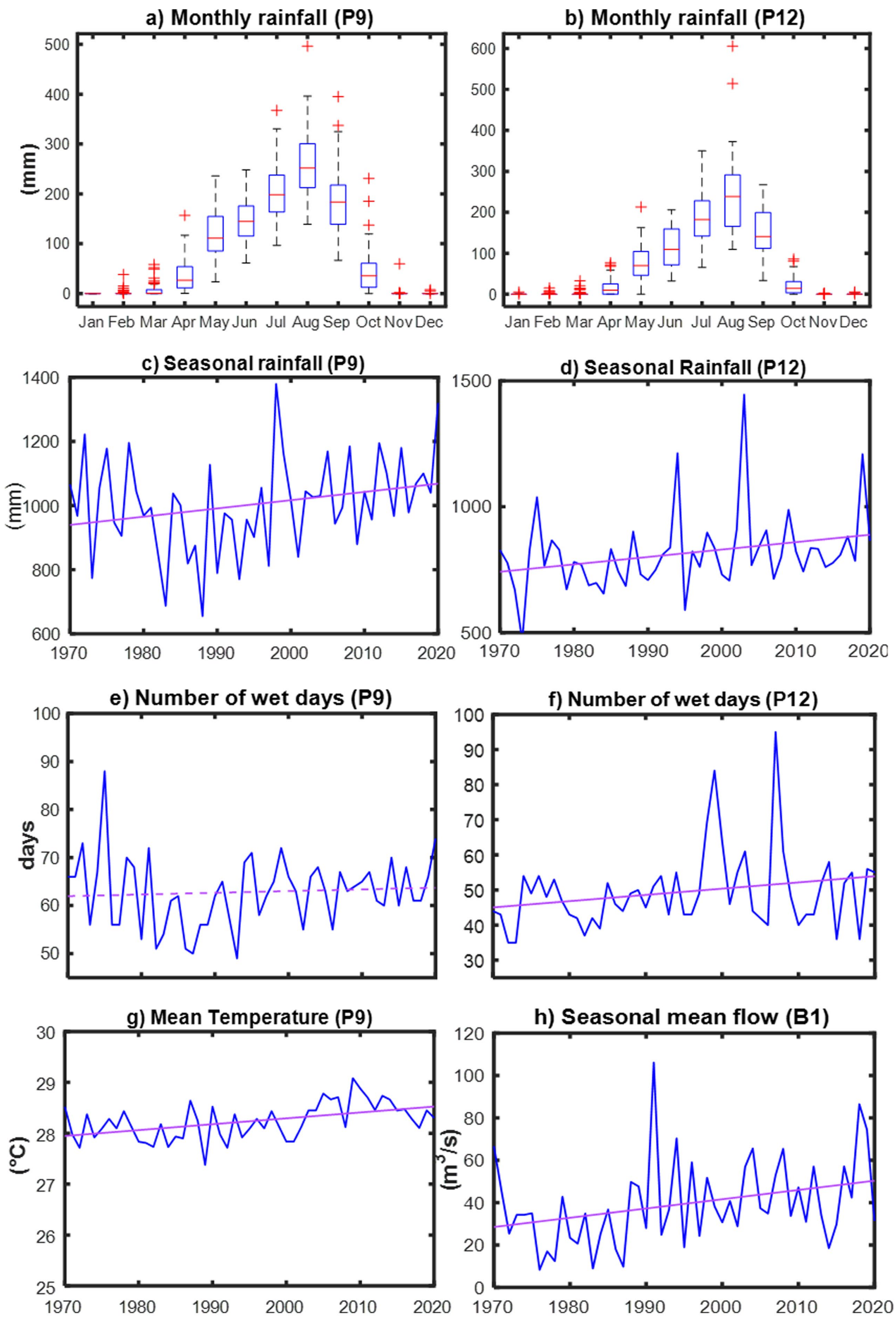

FIGURE 2
Observations of rainfall, streamflow and temperature: **(a,b)** Boxplots of monthly rainfall showing the median (red line), the interquartile range IQR (box), the range of the data (whiskers, ≤ 1.5 IQR) and outliers (red cross). **(c,d)** Total rainfall in the rainy season. **(e,f)** Number of wet days in the rainy season. **(g)** Mean annual temperature. **(h)** Mean daily streamflow in the rainy season. Trends are calculated using Sen's slope (Sen, 1968). Significance of trends is calculated using the Mann-Kendall test (Kendall, 1975; Mann, 1945). Significant trends at the 5 and 10% level are shown with solid and dashed lines, respectively. Locations of the stations are given in Figure 1.

TABLE 1 The 14 selected questions that were used to quantify the knowledge of the farmers and the assignment of knowledge scores to the answers given.

No	Content of questions	Answers given	Assignment of knowledge score
Q1	How many rainy seasons do you have in your area?	1 rainy season	1
		2 rainy seasons	0
Q2	In which month does the rainy season start in your locality?	April	1
		May	1
		June	0
Q3	How many months (n) does the rainy season last?	0 < n < 3	0
		3 ≤ n < 4	0.33
		4 ≤ n ≤ 5	0.67
		6 ≤ n ≤ 7	1
Q4	Has the start date of the rainy season changed?	Yes	1
		No	0
Q5	During the rainy season, are there days when it does not rain?	Yes	1
		No	0
Q6	If so, what is the average number of days (n) without rain?	0 < n < 3	0
		3 ≤ n < 7	0.33
		7 ≤ n < 10	0.67
		10 ≤ n	1
Q7	How many months (n) does the dry season last?	5 ≤ n ≤ 6	1
		others	0
Q8	In which month does the dry season begin in your locality?	October	1
		others	0
Q9	Do you think it is warmer than it used to be?	Yes	1
		No	0
Q10	If yes, what is the cause of the increase in temperature?	God's will; any religious or cultural beliefs that people assume as cause	0
		Bush fire, agriculture	0.33
		Deforestation, desertification, decline in rainfall	0.67
		Climate change, global warming	1
Q11	Has the average level of the rivers (B1, B2 and B3) fallen or risen compared with 30 years ago?	Fallen	0
		Risen	1
Q12	Do rivers dry up during the dry season?	Yes	1
		No	0
Q13	If yes, give the frequency with which the rivers dry up.	Every year	1
		Others	0
Q14	Did these rivers dry up with the same frequency 30 years ago?	Yes	0
		No	1

Questions with 2 options: wrong = 0; correct = 1; questions with 4 options: wrong = 0; mostly wrong = 0.33; mostly correct = 0.67; correct = 1.

- $\rho_U = \sqrt{\dfrac{n_1 n_2 \left(n_1 + n_2 + 1\right)}{12}}$ is the standard deviation of U

We applied the Kruskal-Wallis H test for the variables with more than two categories (level of education, location, technology/science-oriented view). The Kruskal-Wallis H test checks if at least one of the groups has a different median compared to the others. The H statistic is calculated as:

$$H = \left(\frac{12}{N\left(N+1\right)}\right)\sum_{i=1}^{k}\frac{R_i^2}{n_i} - 3\left(N+1\right) \quad (5)$$

Where:

- K is the number of groups
- N is the total number of observations across all groups
- n_i is the number of observations in group i
- Ri is the sum of ranks for group i

For large sample sizes ($n_i > 5$), the H statistic follows a chi-square distribution with k-1 degrees of freedom.

Both tests analyze whether the populations from which the samples are drawn are different.

To understand whether and how a certain factor contributes to farmers' understanding of hydroclimatic variability and climate change, represented by the knowledge score over all 14 questions, we applied the Random Forest and Accumulative Local Effects methods. Random Forest is a robust machine-learning algorithm known for its ability to handle large datasets and complex interactions among variables (Breiman, 2001). A Random Forest is an ensemble of many regression trees. Each regression tree is trained on a random subset of the data, which helps to ensure that the trees are uncorrelated and reduces the risk of overfitting. The Random Forest method is particularly suitable for our analysis due to its flexibility and high accuracy in classification and regression tasks. Random Forests perform well compared to many other methods, including discriminant analysis, support vector machines, and neural networks (Liaw and Wiener, 2002). The data set of 509 records was split into a training set, which consisted of a random subset representing 80% of the data, and a holdout set, comprising the remaining 20%. A random forest was generated using 500 conditional inference trees as base learners (Hothorn et al., 2015), which are unbiased toward variables with numerous potential split points, unlike regular regression trees (Hothorn et al., 2006). Model performance was assessed using out-of-bag (OOB) predictions, providing conservative accuracy measures akin to cross-validation for multiple linear regression models (Liaw and Wiener, 2002). The random Forest package in R was used to fit random forest models to the training data (Liaw and Wiener, 2002).

Random Forests are black-box models that do not allow to understand how a certain predictor influences the target variable. To shed light on these influences, we used accumulated local effects (ALE) plots (Apley and Zhu, 2020; Robette, 2020). ALE plots estimate the change in model predictions across small intervals of each predictor, unaffected by collinear input variables (Molnar, 2021). They thus show how each predictor influences, possibly in a non-linear way, the target variable.

Figure 3 illustrates the steps of our analysis.

3 Results

3.1 Farmers' understanding of hydroclimatic variability and climate change

The understanding of the surveyed farmers of different aspects of hydroclimatic variability and climate change is summarized in Figure 4. Averaged over all 14 questions, we find a 20.2% error rate and a 71% accuracy rate. This result reflects a substantial alignment between local perceptions and observed data. However, there are specific areas where knowledge is lacking, such as the link between global climate change and temperature increase (question 10). Here, more than 70% of the respondents were classified as wrong or mostly wrong. Our results also suggest that farmers have difficulties in understanding past changes in streamflow (questions 11, 12).

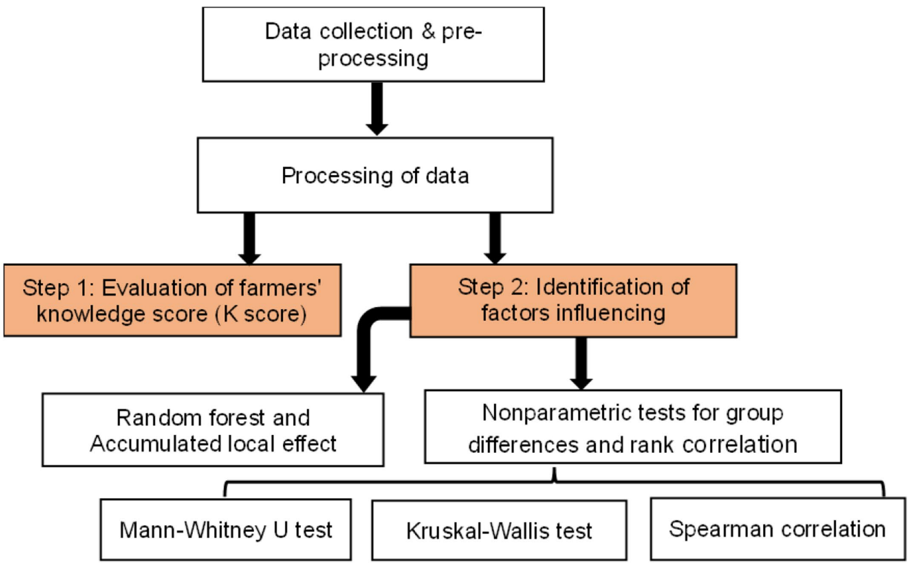

FIGURE 3
Flowchart outlining the steps of the analysis.

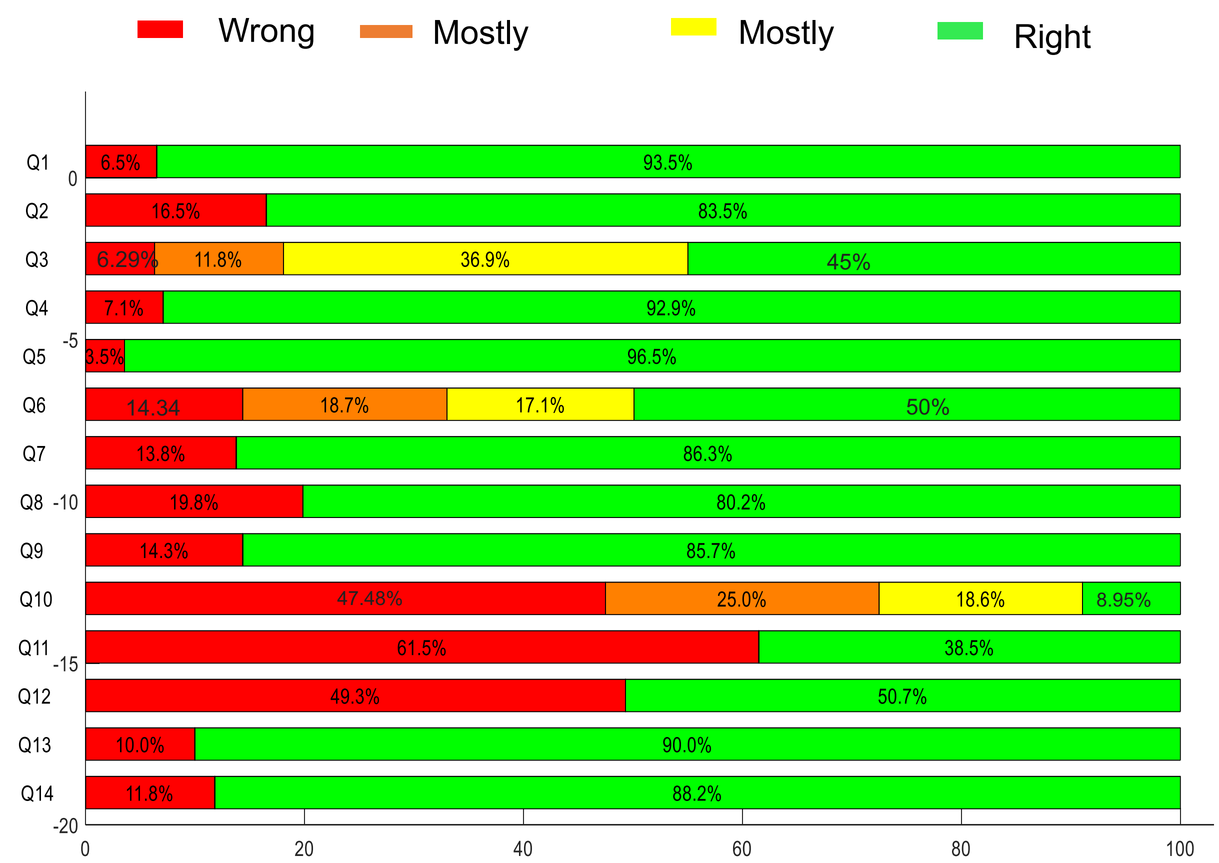

FIGURE 4
Correctness of the answers, averaged across all 509 farmers, to the 14 selected questions that allow a comparison with observed hydroclimatic data.

3.2 Factors that contribute to the farmers' understanding

3.2.1 Distributions of the factors and the target variable

Before analyzing which factors influence how well the farmers understand hydroclimatic variability and climate change, we present how these factors and the target variable, i.e., the knowledge score, are distributed among the 509 respondents (Figure 5). More than 90% of the farmers are men, highlighting a significant gender imbalance in the agricultural sector (Figure 5a). The majority of respondents are between 35 and 60 years old (Figure 5b), with their experience in farming generally spanning from 10 to 40 years (Figure 5c). The age distribution indicates that a significant proportion of the farmers are in their mid-to-late careers. However, this distribution is influenced by the age restrictions applied in the selection of the respondents (older than 35 years). Education within the agricultural sector remains a challenge, as 63% of the farmers are either uneducated or have only completed primary school, while those with higher education (high school or university) are less involved in agricultural activities, leaving farming largely to the uneducated (Figure 5e). 38% of the surveyed households engage in secondary activities to supplement their livelihoods, which is encouraged by the nature of rain-fed agriculture (Figure 5f). The seasonal nature of farming allows for other income-generating activities during the off-season. This diversification helps mitigate risks from crop failure due to climate variability, improving financial stability and household resilience (Ozor, 2010). The large majority (77%) of the farmers show a technology/science-oriented view toward farming (Figure 5g). Due to the poor quality of harvests, often attributed to climate variability, land degradation, and soil infertility, farmers seem to recognize the need for modern agricultural tools, fertilizers, and pesticides to improve yields. The distribution of the knowledge score indicates that many farmers in Northern Benin are well aware of hydroclimatic variability, with an average knowledge score of 0.67 (Figure 5h).

TABLE 2 Spearman correlation coefficient between knowledge, age and experience using Equation 1.

Variables	Knowledge	Age	Experience
Knowledge	1	0.09 (0.04)	0.19 (<0.01)
Age	0.09 (0.04)	1	0.53 (<0.01)
Experience	0.19 (<0.01)	0.53 (<0.01)	1

p-values are given in brackets. All correlations are significant at the 5% level.

3.2.2 Relationships between the variables surveyed

The Spearman correlation analysis shows that age and experience are positively correlated with the knowledge score, significant at the 5% level (Table 2). Hence, older and more experienced farmers tend to have more knowledge about hydroclimatic variability and climate

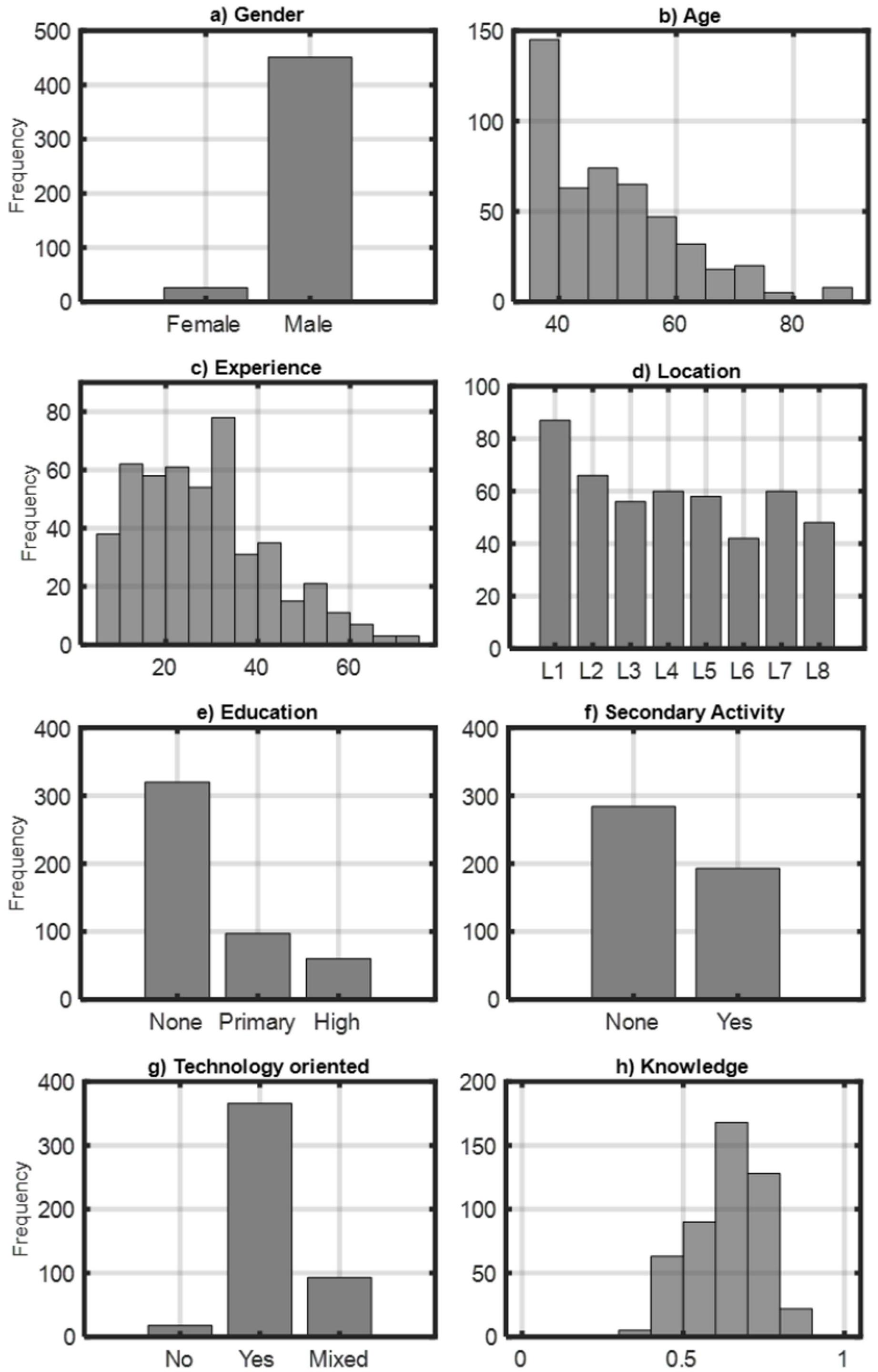

FIGURE 5
Distribution of the factors gender **(a)**, age **(b)**, farming experience **(c)**, location of the household **(d)**, level of education **(e)**, secondary activity besides farming **(f)**, technology/science-oriented view **(g)**, and knowledge score **(h)** of the 509 households surveyed.

change. However, the correlation coefficients are small, and age and experience can only explain a small part of the variation in knowledge.

The Mann–Whitney U test and the Kruskal-Wallis test found significant differences between the groups for the categorical factors location and level of education (Figure 6). The null hypothesis 'the medians of all groups are equal' can therefore be rejected for these two factors. The knowledge scores vary significantly between the municipalities. It ranges from the lowest knowledge score of 0.55 (median value) for L5 to the highest value of 0.75 for L2. The level of education has a slightly negative influence on knowledge, suggesting that higher formal education does not necessarily translate into greater indigenous knowledge in this context. The remaining categorical factors (gender, technology/ science-oriented view, secondary work) have no statistically

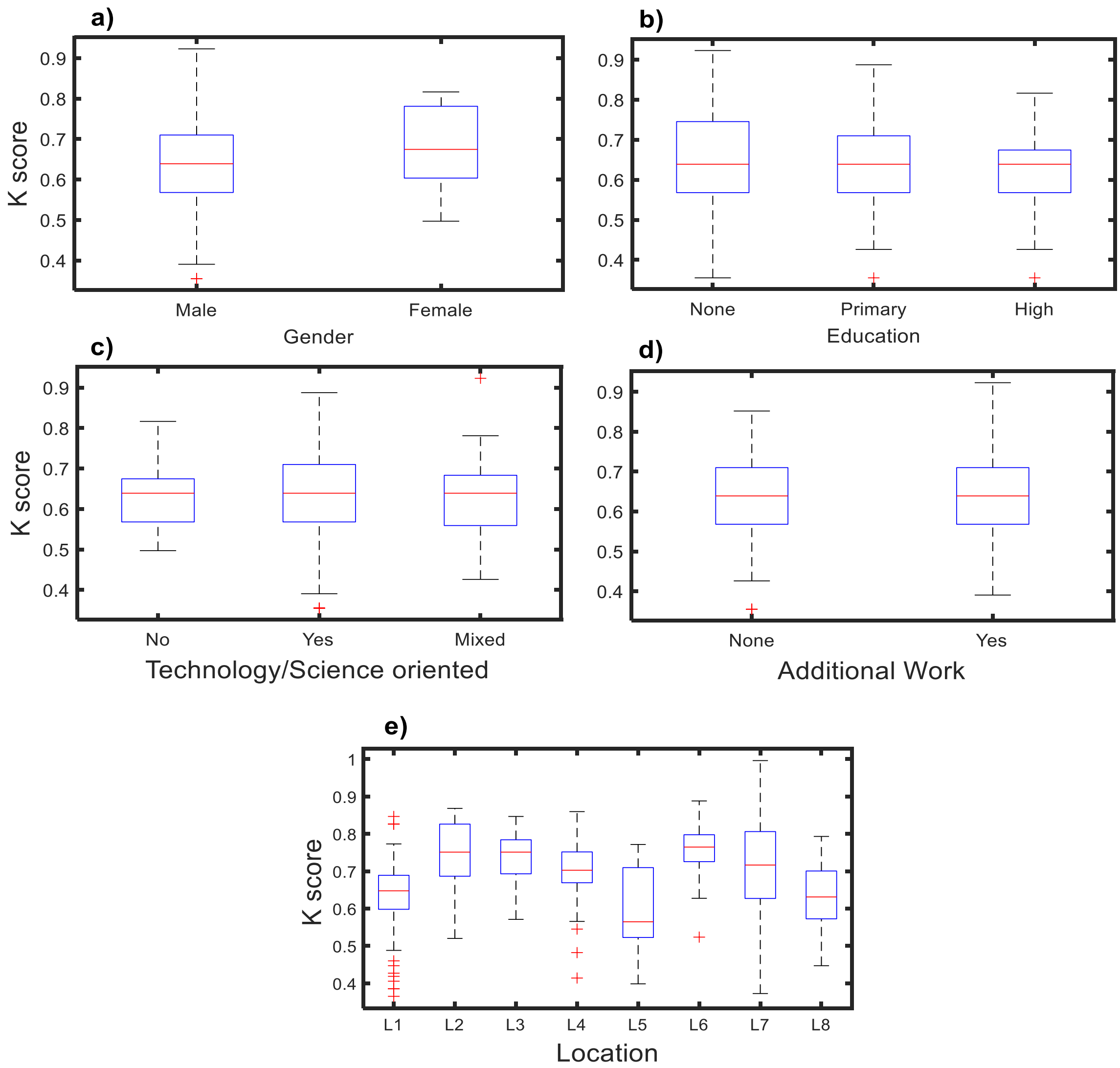

FIGURE 6
Boxplots of the knowledge score separated into different groups: **(a)** gender; *p*-value: 0.14, **(b)** level of education, *p*-value: 0.04, **(c)** Technology oriented view, *p*-value: 0.16, **(d)** secondary work, *p*-value: 0.15, and **(e)** location of household, *p*-value: <0.01. *p*-values are calculated using the Mann–Whitney U test for the binary factors gender and secondary work, and the Kruskal-Wallis test is used for the remaining factors.

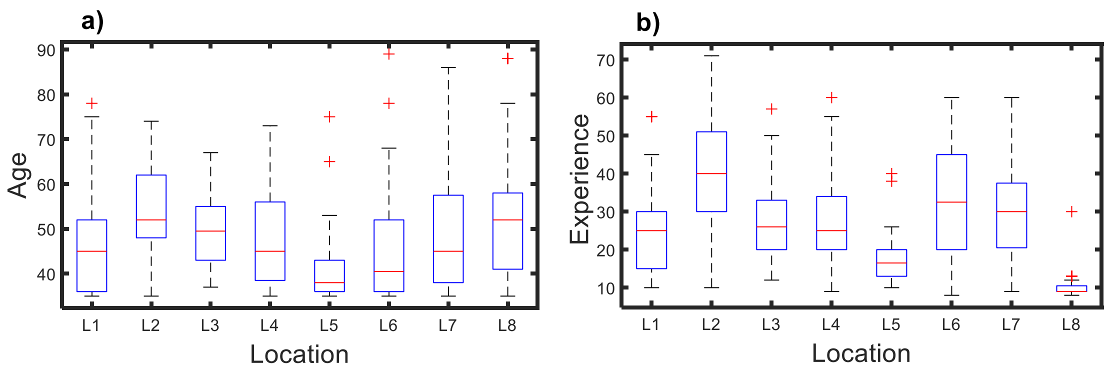

FIGURE 7
Boxplots of age **(a)** and farming experience **(b)** separated into the eight municipalities. Statistical significance (*p*-value for age: <0.01, *p*-value for farming experience: 0.01) is calculated using the Kruskal-Wallis test.

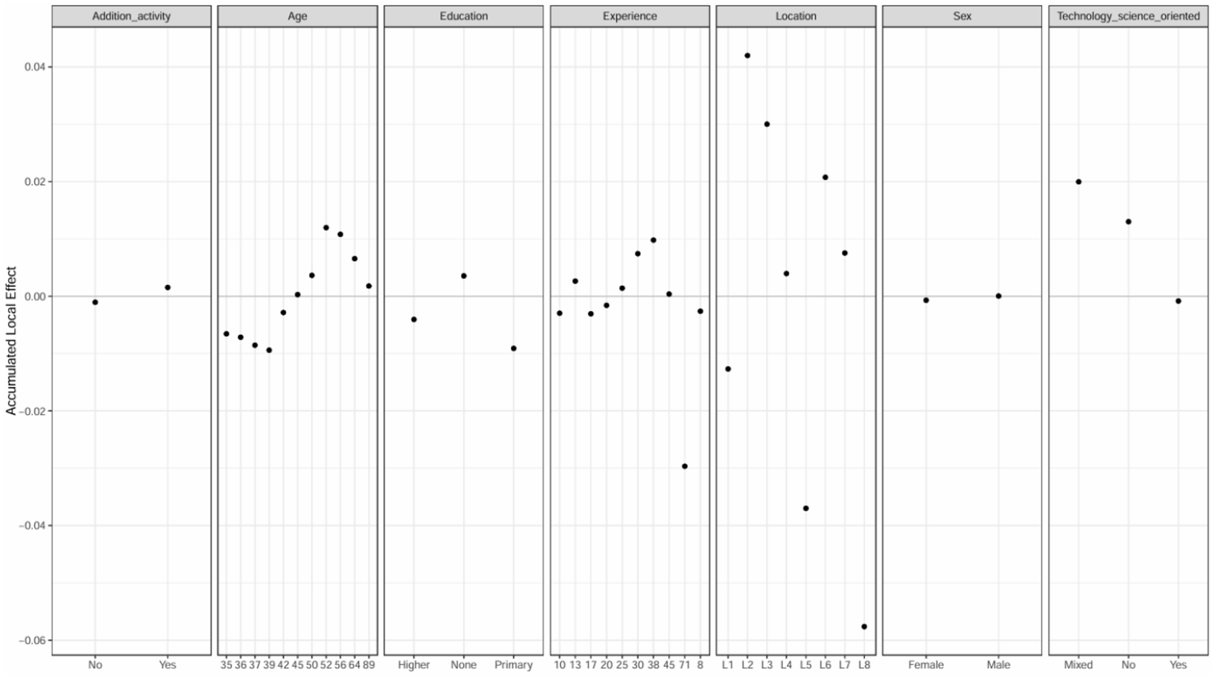

FIGURE 8
Accumulated local effects (ALE) of all seven factors. The ALE plots illustrate how the model outcome, i.e., knowledge score, deviates from the mean prediction of the random forest model across the range of a predictor. Positive ALE values indicate a positive influence of the range of the predictor on the knowledge score.

significant influence on the knowledge score, and p-values are larger than 10% (Figure 6).

Besides the relationships between the different factors and the knowledge score, we also checked whether those factors, that show a significant influence on the knowledge score, are cross-correlated. We find a significant correlation of 0.53 between age and farming experience (Table 2). We also find statistically significant differences in the distribution of age and farming experience between the different municipalities (Figure 7). For instance, the municipality L2 with the highest average knowledge scores has also the highest values in age and farming experience.

3.2.3 Influences of the factors on the knowledge score

To assess the extent to which a non-linear, multi-dimensional model is able to explain the variation in knowledge scores, we built a random forest model with 300 trees. Using all seven factors as predictors for the knowledge in the random forest model, we obtain a modest R^2 value of 28% between the observed and simulated knowledge scores. We then applied the Accumulative Local Effect (ALE) method to understand and visualize how the different factors influence the knowledge score (Figure 8).

The ALE plots show that the non-linear random forest model identifies roughly the same factors as important predictors as were found when looking at the relationships between knowledge scores and the seven factors surveyed (section 4.2.2): Location is the dominant predictor, followed by age and experience and then, less important, level of education. In the ALE plot, the factor technology/science-oriented view features much higher. However, its distribution is very skewed (Figure 8g), and most values fall into the class ‘Yes’. This imbalance can lead to biased predictions (Siddiqui and Ali, 2016). The factor age shows an interesting non-linear pattern: farmers from 35 to 42 years old have lower knowledge scores, then the knowledge scores increase with age until the age of 52 years, after which they decrease again. Experience shows a similar pattern.

4 Discussion

Our survey highlights a number of challenges and opportunities for Benin’s agricultural sector. The distribution of the households surveyed shows that women are severely under-represented in the agricultural labor force, with less than 10% of the farming population being female. Women tend to have fewer opportunities for income, decision-making roles, and access to resources such as land, credit, and training. This limits not only their economic empowerment but also their influence within their communities. Similar patterns across West Africa link this disparity to cultural norms and limited access to resources, restricting women’s economic opportunities and affecting household food security (Doss, 2018). There also remains a significant educational challenge, as the majority of farmers have little formal education. More educated people tend to avoid agriculture, which could limit innovation. This gap could hinder the adoption of sustainable farming practices, as formal education often correlates with the ability to engage with modern technologies (Awojobi, 2018).

The survey results reveal that farmers in Northern Benin have overall a good knowledge of the region’s hydro-climatology and its changes over time. While previous studies in West Africa, including Benin (Fadina and Barjolle, 2018; Loko et al., 2013; Tossa et al., 2016), Ghana (Fosu-Mensah et al., 2010; Hammond Antwi et al., 2018; Yaro, 2013), Niger (Ado et al., 2019), Nigeria (Oyerinde et al., 2015; Ozor, 2010) and South Africa (Thomas et al., 2007; Topp and Thesis, 2020), have documented farmers' intricate understanding of local climatic patterns based on long-term observations and experiences, there remains a gap in investigating the knowledge of the specific hydroclimatic changes in Northern Benin. This study addresses that gap, providing new insights into the high consistency between farmers' perceptions and observed climatic data in this region.

However, the survey also reveals gaps in understanding hydroclimatic changes. Notably, the link between global climate change and regional temperature increases remains poorly understood. Nearly half of the respondents explained rising temperatures in the region over the recent past by divine will or other religious or cultural beliefs, while only 9% attributed it to global climate change. Such perspectives are often shaped by long-standing spiritual beliefs and traditional knowledge systems that differ from scientific explanations. The persistence of these beliefs can be attributed to limited access to climate science education and low scientific literacy, especially in rural areas. Moreover, religious and cultural worldviews can significantly influence how communities perceive environmental changes.

Our data suggests that, while farmers have a good understanding of climate, weather and the hydro-climatological general trends in their region, their knowledge of the underlying causes is very limited. This lack of knowledge might hinder their ability to implement effective long-term adaptation measures. Closing this knowledge gap is essential for preparing rural communities to address rising temperatures and shifting rainfall patterns.

It is important to understand why (some) farmers have less knowledge. Understanding which factors influence the level of knowledge can inform strategies to close existing knowledge gaps. However, analyzing the factors explaining variations in the knowledge between farmers found only relatively weak relationships. The strongest influence was location, followed by age and experience. Older and more experienced farmers tended to have better knowledge. This result points to the importance of long-term exposure to environmental changes in shaping farmers' understanding. Older farmers, with decades of experience, have likely observed multiple cycles of climate variability, allowing them to develop more intuitive knowledge of weather patterns, soil conditions, and seasonal shifts.

The result that location had the strongest impact on the knowledge score is partially explained by the age and experience, as those municipalities where the age and experience distribution showed higher values had higher knowledge scores. However, age and experience explained only a modest share of the variability in knowledge. Other differences between the municipalities seem to play a role, which could not be investigated given the information in our survey. Variables such as access to training programs, farmer networks, and media exposure may significantly shape farmers' knowledge and merit further investigation.

A counterintuitive finding is that formal education had a weak or even a slightly negative impact on knowledge. Formal education, particularly in its traditional form, often emphasizes standardized, theoretical knowledge, which may not always align with the practical, context-specific understanding essential for hydroclimatic systems. This mismatch can create a negative relationship between formal education and hydroclimatic knowledge in specific contexts. According to Maldonado et al. (2016), formal education sometimes overlooks indigenous and local knowledge systems, which tend to be more attuned to local environmental realities. Consequently, individuals with higher formal education may possess knowledge that is less relevant or disconnected from local climate conditions.

However, Jain et al. (2024) and previous research (Belfer et al., 2017; Etchart, 2017; Makondo and Thomas, 2018) emphasize the complementary roles of indigenous knowledge and formal education in addressing climate challenges, particularly in combating desertification. They suggest that indigenous knowledge can enhance climate resilience, particularly in regions heavily dependent on natural resources. Jain et al. (2024) also acknowledge that formal education plays a critical role in bridging gaps in understanding and facilitating the application of new technologies and approaches. While indigenous knowledge offers practical, context-specific solutions, formal education helps scale these solutions and integrate them into broader climate policy frameworks. In comparison to earlier studies, for instance, Jain et al. (2024) emphasize the challenges faced by marginalized communities, who, despite their reliance on indigenous knowledge, often struggle to transform this knowledge into actionable policies due to limited resources, education, and infrastructure. This finding resonates with Maldonado et al. (2016), who highlight that communities with limited access to formal education are often the least adaptable to climate change and desertification.

Our study highlights the multifaceted nature of knowledge acquisition and its dependence on various demographic and socio-cultural factors. By recognizing and addressing these factors, it is possible to develop more effective and contextually relevant climate adaptation strategies that enhance the resilience of rural communities in West Africa. The vast experience of older farmers provides them with a deeper understanding of hydroclimatic variability. Programs that capitalize on the experience of older farmers could be particularly effective in transferring valuable indigenous knowledge to younger and less experienced farmers. Moreover, the slightly negative relation between formal education and hydroclimatic knowledge suggests that integrating indigenous knowledge systems into formal education curricula could be beneficial. In Kenya, indigenous farming practices are taught in schools through agriculture classes where students learn about traditional crop rotation, soil conservation, and native plants from local farmers. This hands-on approach connects students to sustainable practices rooted in their communities' heritage. The result that the causes of observed temperature increases were attributed to global warming by only a small fraction of households surveyed suggests the need for integrating scientific information with indigenous knowledge to address these knowledge gaps (Oyerinde et al., 2015). Based on our finding, Table 3 proposes some actionable strategies for integrating indigenous knowledge into education systems. This study is among the first of its kind in West Africa, offering a unique contribution by combining statistical and machine learning methods to analyze hydroclimatic knowledge among farmers. Previous studies in Africa have primarily focused on qualitative insights (Nyadzi et al., 2021) or farmer perceptions without advanced modeling (Kabore et al., 2023). By integrating machine learning, this study moves beyond basic correlations to identify key predictors of hydroclimatic knowledge, aligning with recent calls for data-driven

TABLE 3 Implications and actionable strategies for integrating indigenous knowledge into education systems.

Key area	Implications	Actionable strategy	Supporting References
Curriculum Development	Indigenous knowledge is often undervalued in formal education systems. Its integration can improve climate literacy.	Develop hybrid curricula that incorporate traditional climate indicators alongside scientific methods. Train educators on culturally relevant teaching approaches.	Jumba and Mwendwa Mwiti (2022), Petzold et al. (2020), Sarker et al. (2023)
Community-Based Monitoring	Farmers rely on experiential knowledge, but hydrological data could improve decision-making.	Establish local hydrologic monitoring stations to validate traditional observations. Engage farmers in data collection and interpretation.	Möller González (2019), Singhal et al. (2024)
Climate Risk Awareness	Farmers recognize hydroclimatic variability but often lack an understanding of global climate drivers.	Organize farmer extension workshops combining indigenous climate perceptions with climate science. Strengthen outreach programs.	del Pozo et al. (2019), Gao et al. (2022)
Policy and Decision-Making	Indigenous knowledge can complement scientific data in environmental planning and policy.	Advocate for policies that promote the integration of indigenous knowledge into national education strategies.	Wheeler and Root-Bernstein (2020)

approaches to assess climate adaptation in sub-Saharan Africa (Mertz et al., 2011).

5 Conclusion

The survey results indicate that farmers in Northern Benin generally possess a good understanding of the region's hydro-climatology, but that a significant gap exists in linking regional temperature increases to global climate change. This disconnect may limit their ability to adopt long-term adaptation strategies, underscoring the need for targeted interventions.

The study also highlights that age and farming experience are key determinants of hydroclimatic knowledge, whereas formal education had little to no impact. This suggests that indigenous knowledge remains central to farming practices in North Benin. Older and more experienced farmers tend to possess better knowledge, while the level of formal education does not improve the knowledge. These results suggest that indigenous knowledge plays an important role in the daily life of farming households in Northern Benin. These insights emphasize the importance of demographic, socio-cultural, and experiential factors in shaping climate awareness. Strengthening context-specific education and integrating scientific and indigenous knowledge can enhance the climate resilience of rural communities in West Africa.

Our findings are based on data collected from a limited number of municipalities in Norther Benin, which may limit their generalizability to other regions of Benin or broader West Africa. Future research could include a more diverse set of locations to better capture regional differences. The strong variation in knowledge found between the locations calls for a broader set of factors to be collected.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the [patients/ participants OR patients/participants legal guardian/next of kin] was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

OG: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. KG: Conceptualization, Methodology, Supervision, Writing – review & editing. BM: Conceptualization, Validation, Methodology, Supervision, Writing – review & editing. HY: Conceptualization, Methodology, Supervision, Writing – review & editing. EM: Conceptualization, Methodology, Supervision, Writing – review & editing. AA: Conceptualization, Methodology, Supervision, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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