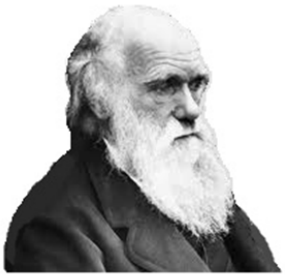
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Does place matter? Farmers' perception and adaptation to climate extremes around three dams of different sizes in Burkina Faso

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ABSTRACT

This study examines the extent to which spatial context influences farmers' perceptions of climate extremes and their adoption of adaptation strategies, beyond differences in the sociodemographic composition of farming populations. It draws on a survey of 425 farmers living around three dams of different sizes: the large Soum dam, the medium-sized Séboun dam and the small Sourgou dam and on daily rainfall and temperature records from the Ouagadougou and Boromo synoptic stations. The rainfall records cover 1980–2023, while the temperature records cover 1991–2023. The results reveal an intensification of extreme rainfall and warm extremes, particularly at the Ouagadougou station. By contrast, no statistically significant trends are detected in dry spells or in the onset, cessation or duration of the rainy season, although 57% of farmers perceive dry spells as having become longer. Variation in the adoption of the 24 adaptation strategies examined occurs mainly within villages (86% of the variance), followed by differences between villages within the same dam area (10%); differences between dams account for only 4%. Binomial multilevel models reveal no statistically detectable association between dam location, dam size and strategy adoption. Adoption is, however, associated with educational attainment and perceived climate extremes: each additional index perceived as intensifying corresponds to a 10% increase in the odds of adoption (odds ratio = 1.10). A significant village-level effect remains after individual characteristics are controlled for. These findings suggest that spatial differences in adaptation are expressed primarily at the village scale. Nevertheless, given the limited number of dams studied, a dam-specific effect cannot be ruled out.

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***Keywords*:** climate extremes, perception, adaptation, dams, spatial scale, Sahel, Burkina Faso

1. INTRODUCTION

In the Sudano-Sahelian region of West Africa, the effects of climate change on agriculture are among the most significant (IPCC, 2022; Sultan and Gaetani, 2016). The droughts of the 1970s and 1980s left a lasting imprint on the rainfall regime, and rainfall has since recovered only partially (Lebel and Ali, 2009; Nicholson, 2013). This partial recovery has been accompanied by an intensification of climate extremes. Since 1982, the frequency of the most severe Sahelian thunderstorms has tripled (Taylor et al., 2017), and heavy rainfall accounts for an increasing proportion of annual totals (Panthou et al., 2014, 2018; Sanogo et al., 2015). These extremes are commonly measured using the indices recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI), such as maximum daily rainfall (Rx1day), the number of consecutive dry days (CDD) and the frequency of hot days (TX90p) (Zhang et al., 2011).

Faced with these constraints, Sahelian farmers employ a wide range of strategies, from soil and water conservation and the use of short-cycle seeds to crop and income diversification and dry-season irrigation (Barbier et al., 2009; Kpadonou et al., 2017; Reij et al., 2009). These responses extend a long history of adjustment to rainfall variability (Mortimore and Adams, 2001; Raynaut, 2001). In Burkina Faso, dams ranging from small reservoirs to large-scale structures occupy a central place in these strategies. By storing water beyond the rainy season, they support off-season market gardening, livestock watering, fishing and other non-farm activities (de Fraiture et al., 2014; Venot et al., 2012). Much of the irrigation that develops around them is informal and farmer-led, relying on small private pumps rather than planned schemes (de Fraiture and Giordano, 2014; Woodhouse et al., 2017), and it can make a substantial contribution to household income and food security (Burney and Naylor, 2012). Reservoirs therefore broaden the range of options available to farmers, and one might expect this range, and hence adaptation, to increase with reservoir size.

Adaptation also depends on how farmers perceive climatic change. Studies conducted across Africa show that perceived changes in rainfall and temperature are associated with the adoption of adaptation strategies, alongside household characteristics such as education and farming experience (Maddison, 2007; Deressa et al., 2009; Gbetibouo, 2009; Fosu-Mensah et al., 2012). In the Sahel, farmers' perceptions generally agree with observed warming but diverge more frequently from rainfall records, particularly with regard to dry spells and the timing of the rainy season (West et al., 2008; Mertz et al., 2009; Simelton et al., 2013). The socio-cognitive model proposed by Grothmann and Patt (2005) accounts for this link by positing that adaptation depends on both risk appraisal and perceived adaptive capacity. However, most of these studies treat farmers as independent individuals and rarely examine whether perceptions and adoption differ between places once the composition of local populations has been taken into account.

This question lies at the heart of geographical analysis. Differences observed between places may reflect a genuine effect of local context or merely the differing characteristics of the people who live there (Macintyre et al., 2002; Cummins et al., 2007). Furthermore, the spatial unit chosen for analysis may itself shape the results, as the modifiable areal unit problem has

shown (Openshaw, 1984). Around reservoirs, variation may be concentrated at the level of the reservoir, the village or the individual farmer. Yet studies conducted in Burkina Faso have seldom compared perceptions and adaptation around reservoirs of contrasting sizes while explicitly distinguishing these levels.

This study therefore examines whether spatial context influences farmers' perceptions of climate extremes and their adoption of adaptation strategies beyond differences in the socio-demographic composition of farming populations. It draws on a survey of 425 farmers living around three dams of contrasting sizes in the Centre-West region of Burkina Faso, namely the large Soum dam, the medium-sized Séboun dam and the small Sourgou micro-dam, and on daily climate records from the Ouagadougou and Boromo synoptic stations. Three questions are addressed: (i) do farmers' perceptions of climate extremes correspond to the trends observed at the reference stations? (ii) at which spatial scale (dam, village or farmer) does the adoption of adaptation strategies vary most? and (iii) do dam location and dam size remain associated with adoption once farmers' characteristics and perceptions are controlled for? The article first presents the study area, data and methods, then the results, before discussing their implications for adaptation support around reservoirs.

2. MATERIALS AND METHODS

2. 1. Presentation of the study area

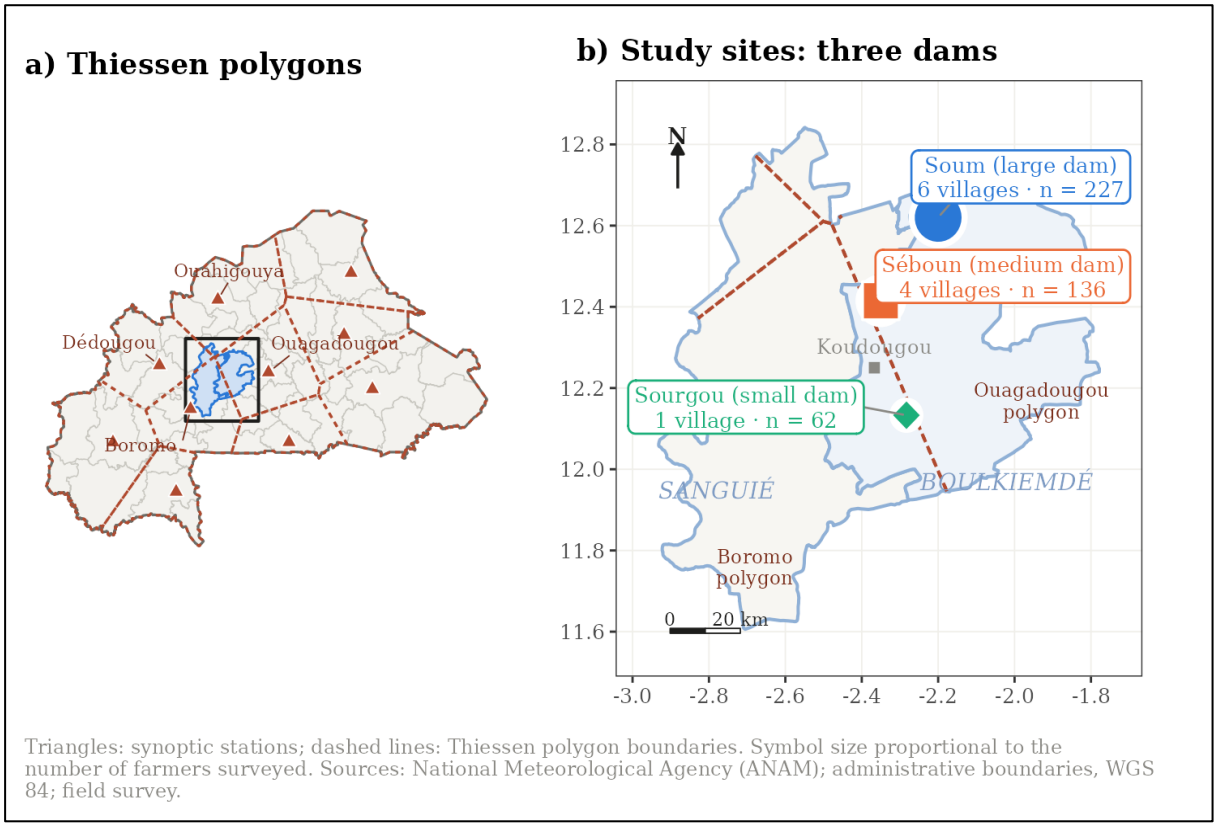


Figure 1. Study area, locations of the three dams, and Thiessen polygons of the synoptic weather stations.

The study area is located in the Centre-West region of Burkina Faso, approximately 100 km west of Ouagadougou. It covers the provinces of Boulkiemdé (4,268 km^2) and Sanguié (5,111 km^2). The climate is Sudano-Sahelian, characterised by a rainy season extending from June to September and a prolonged dry season. Agricultural activities rely primarily on rainfall, whilst water reservoirs support the development of irrigation and the diversification of economic activities.[3]

The study focuses on three water reservoirs of contrasting sizes, distributed along a north–south axis over a distance of approximately 60 km: the Soum dam, the Séboun dam and the Sourgou micro-dam (Figure 1). Located in the commune of Nanoro, the Soum dam has an estimated storage capacity of 155 million m³, an embankment length of 1,517 m and a maximum depth of 12 m. The Séboun dam, located in Boulkiemdé Province, has a storage capacity of 12,207,313.53 m^3 and an estimated sediment volume of 407,228 m^3, according to the bathymetric survey conducted by the Ministry of the Environment, Water and Sanitation (2023, p. 73). Finally, the Sourgou micro-dam, located approximately 15 km from Koudougou, has a reported storage capacity of 58,100 m^3.

These three infrastructures therefore exhibit considerable differences in storage capacity, providing a relevant comparative framework for analysing the relationships between reservoir characteristics, access to water, agricultural practices and farmers' adaptation strategies. The study also examines the influence of local contexts and complementary economic activities on the livelihoods of communities living around these reservoirs.

2. 2. Farmers' survey and climate data

The sample size was determined using Cochran's (1977) formula for a proportion. Its precision was then corrected for the cluster effect described by Kish (1965):

$$n = \frac{z^2\, p\,(1-p)}{e^2}, \qquad n_{\text{eff}} = \frac{n}{1 + (\bar{m} - 1)\,\rho} \qquad (1)$$

where: z = 1.96, p = 0.5, e is the margin of error, $\bar{m}$ is the mean number of respondents per village, and ρ is the intraclass correlation coefficient. For a margin of error of 5%, the formula yields a sample size of 384 farmers. A total of 425 completed questionnaires were processed and analysed, corresponding to a margin of error of 4.75% under simple random sampling assumptions. Respondents were allocated proportionally to the number of farmers living near each reservoir (227 at Soum, 136 at Séboun and 62 at Sourgou) and randomly selected within the villages.

The surveys were conducted between 2024 and 2025. The questionnaire covered farmers' socio-demographic characteristics, types of crops grown and secondary activities, crop sensitivity to climatic extremes, perceptions of changes in 13 climate extreme indices, perceived impacts, and the adoption of 24 adaptation strategies. With approximately 39 respondents per village and an intraclass correlation coefficient of 0.16 for adoption intensity, the effective sample size was close to 60, corresponding to a margin of error of approximately 13 percentage points for a proportion. Consequently, village-level clustering was taken into account in the comparisons and statistical models.

Observed climatic conditions were characterised using daily rainfall data (1980–2023) and daily maximum and minimum temperature records (1991–2023) from the ten synoptic stations in the national network, supplied by Burkina Faso's National Meteorological Agency

(ANAM). All ten stations were used to delineate Thiessen polygons. Only the two stations associated with the reservoirs were included in the trend analysis.

2. 3. Comparison of farmers across reservoirs

To compare the three reservoirs, Pearson's chi-squared test (Pearson, 1900) and Cramér's V coefficient (Cramér, 1946) were used to assess differences in categorical variables. The Kruskal–Wallis test (Kruskal and Wallis, 1952) was applied to quantitative variables that did not follow a normal distribution, as assessed using the Shapiro–Wilk test (Shapiro and Wilk, 1965).

These statistical tests assume that observations are independent. However, farmers from the same village are likely to share common characteristics and local conditions. Consequently, comparisons must account for the clustering of respondents within villages. To address this issue, Rao–Scott chi-squared tests (Rao and Scott, 1984) were used for categorical variables, while linear mixed-effects models with village-level random intercepts and Satterthwaite's approximation for the F-test (Kuznetsova et al., 2017) were applied to the indices. Only differences that remained significant after accounting for village-level clustering were interpreted (Table 1).

2. 4. Perceived and observed climate extremes

In this study, 16 indicators were selected to assess extreme climate events, including heavy rainfall, heatwaves and strong winds. These indicators were grouped into four main categories: extreme rainfall (Rx1day, Rx5day, R95p, R99p, SDII, R10mm and R20mm); dry and wet spells (CDD and CWD); temperature extremes (TX90p, TN90p, TX10p and TN10p); and strong winds (frequency, duration and intensity).

Farmers were asked to indicate whether each indicator had increased, decreased or remained unchanged over the previous 20 years. For the purposes of this study, each response was coded as $x_{ij} = 1$ when it indicated an intensification (an increase, or a decrease in cold days and cold nights), and 0 otherwise. The perception index was calculated as the sum of these responses.

$$\mathrm{PERC}_i = \sum_{j=1}^{16} x_{ij}\,, \qquad 0 \le \mathrm{PERC}_i \le 16 \qquad (2)$$

The index is a measurement tool designed to assess the extent of perceived intensification. In this study, a productive impact index (IMPACT, 0–23) and a socio-economic impact index (0–16) were constructed using the same approach, based on reported effects of heat, flooding, strong winds and drought.

Internal consistency was assessed using Cronbach's alpha (Cronbach, 1951). In this model, k represents the number of items, σ_i^2 denotes the variance of item i, and σ_T^2 represents the variance of the total score. According to Nunnally (1978), a value above 0.70 is generally considered acceptable.

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_T^2}\right) \qquad (3)$$

The perception index exhibits low internal consistency (α = 0.55). Furthermore, internal consistency is even lower within each indicator group, ranging from 0.55 for extreme rainfall to 0.03 for strong winds. Farmers therefore do not perceive climate extremes as a single coherent phenomenon. Accordingly, the index is interpreted as a measure of the breadth of perceived intensification rather than as a unidimensional scale. The robustness of the findings is assessed using the extreme rainfall indicators alone. The productive impact index, which has very high reliability (α = 0.92), owes part of this reliability to a ceiling effect, as revealed by the study findings.

The same ETCCDI indices, excluding wind-related indicators, were calculated for the Ouagadougou and Boromo stations, following Zhang et al. (2011) and Klein Tank et al. (2009). The station records contain no missing data over the periods considered. Percentile thresholds for rainfall indices were based on the 1981–2010 reference period, while those for temperature indices were based on 1991–2020. For temperature indices, the bootstrap procedure developed by Zhang et al. (2005) was applied.

CDD and CWD were calculated over the May–October period, as annual CDD values in the Sahel mainly reflect the dry season. To better understand dry-spell dynamics, the onset of the rainy season was also examined. This was defined as the first day after 1 May on which the three-day cumulative rainfall reached 20 mm, provided that no dry spell lasting more than seven days occurred during the following 30 days. This was followed by the end of the rainy season, defined as the first rainy day after 1 September followed by 20 consecutive dry days. The length of the rainy season and the number of dry spells lasting at least 7, 10 and 15 days during the season were also calculated (Sivakumar, 1988).

For the purposes of this study, each reservoir was assigned to the meteorological station within whose spatial influence it falls. This allocation was determined using Thiessen polygons (Thiessen, 1911). These polygons define the spatial domain V_k associated with each station s_k, comprising all locations closer to that station than to any other station in the network.

$$V_k = \{ x : d(x, s_k) \leq d(x, s_j),\ \forall j \neq k \} \qquad (4)$$

The Thiessen polygon method showed that Soum and Séboun are located within the Ouagadougou polygon, as illustrated in Figure 1, whereas Sourgou falls within the Boromo polygon, with a sample of 62 respondents. The use of an area-weighted average of the meteorological stations was ruled out, as this approach would have smoothed the extreme climate indices and assigned Boromo a weight disproportionate to the distribution of respondents. To assess trends, Sen's method (1968) was applied. This method involves calculating the median of all pairwise slopes derived from the time series.

$$\hat{\beta} = \text{median}\left(\frac{y_j - y_i}{j - i}\right), \qquad i < j \qquad (5)$$

In this study, the statistical significance of the data was assessed using the Mann (1945)–Kendall (1975) test, as modified by Hamed and Rao (1998). This method was selected for its ability to account for autocorrelation, which is particularly important when analysing time series. A Benjamini–Hochberg (1995) correction was applied to the 13 indices at each station to account for multiple testing. Furthermore, trends were estimated over the 20-year period covered by the survey (2004–2023), and potential change points were identified using Pettitt's

test (1979). Within a given Thiessen polygon, agreement between perceived and observed trends was established when the majority of producers reported an intensification and the corresponding observed trend was statistically significant in the expected direction, or when neither perception nor observation indicated a significant change.

2. 5. Adoption intensity and scales of variation

Adoption intensity is defined as the number of adaptation strategies simultaneously implemented by an individual farmer. The 24 strategies examined in this study are intended to address drought, flooding and strong winds. Of these, 14 target drought, ranging from the use of short-cycle crop varieties and stone bunds to irrigation wells and the mulching of seeds with straw. A further four strategies address flooding, including raised planting beds, off-season crop production, field drainage and rice cultivation in flood-prone areas. The remaining six strategies are designed to mitigate the effects of strong winds, focusing on the construction of planting mounds, staking and earthing up, as well as leaf tying, the use of dwarf varieties and mulching. For farmer *i*, if strategy *s* is adopted, the corresponding binary variable is assigned a value of $y_{is} = 1$.

$$\mathrm{ADAPT}_i = \sum_{s=1}^{24} y_{is} = \mathrm{SECH}_i + \mathrm{INOND}_i + \mathrm{VENT}_i \qquad (6)$$

In this study, SECH_i, INOND_i and VENT_i are defined as the number of strategies adopted to address each of the aforementioned hazards. The internal consistency of these data was assessed using several statistical methods, including Cronbach's alpha (Equation 3), the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy (Kaiser, 1974), and Bartlett's test of sphericity (Bartlett, 1954).

The adoption index demonstrated high reliability ($\alpha = 0.86$) and comprises internally consistent strategies (KMO = 0.76; Bartlett's chi-square = 4,655.3, df = 276, $p < 0.001$).

Furthermore, the drought sub-index ($\alpha = 0.82$; KMO = 0.74) and the strong-wind sub-index ($\alpha = 0.79$; KMO = 0.77) also demonstrate comparable levels of reliability and sampling adequacy. By contrast, the flooding sub-index ($\alpha = 0.10$; KMO = 0.36) exhibits a different pattern. The four strategies included in this sub-index represent alternative rather than complementary options. For example, field drainage is incompatible with rice cultivation in flood-prone areas. Consequently, this sub-index is treated as a count of available options rather than as a measurement scale.

To identify the spatial scale at which adoption varies, the total sum of squares (SS_T) was partitioned into between-dam variation (SS_D), between-village variation within each dam, and between-farmer variation within villages (Snijders and Bosker, 2012). In addition, the village-level contribution was estimated using the intraclass correlation coefficient (ICC) derived from a random-intercept model:

$$\eta_D^2 = \frac{SS_D}{SS_T}, \quad \eta_{V|D}^2 = \frac{SS_V - SS_D}{SS_T}, \quad \eta_W^2 = 1 - \frac{SS_V}{SS_T}, \qquad \rho = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2} \qquad (7)$$

where: SS_V denotes the sum of squares between villages, while σ_u^2 and σ_e^2 represent the between-village and within-village variances, respectively. This decomposition makes the

choice of spatial scale explicit, a consideration that is particularly important given the sensitivity of geographical results to the spatial units used (Openshaw, 1984).

The intraclass correlation coefficient calculated in this way from the adoption scores differs from that derived from the binomial model (Equation 8), which is expressed on the latent logistic scale of an individual strategy and is inherently lower by construction (Nakagawa and Schielzeth, 2010).

2. 6. Models of the factors associated with adoption

ADAPT represents the number of successful adoptions across 24 possible strategies, with many farmers approaching the maximum score. It was therefore modelled using a multilevel binomial model (Bates et al., 2015):

$$\text{logit}(\pi_{iv}) = \beta_0 + \sum_{k=1}^{K} \beta_k x_{ikv} + u_v + e_{iv}, \qquad u_v \sim N(0, \sigma_u^2), \quad e_{iv} \sim N(0, \sigma_e^2) \qquad (8)$$

In this study, π_{iv} represents the probability that farmer i in village v adopts a given strategy. The term u_v denotes a village-level random intercept, while e_{iv} represents an observation-level random effect that accounts for overdispersion (Harrison, 2014). The coefficients are expressed as odds ratios with 95% confidence intervals.

Three nested models were fitted to test the composition hypothesis. The first model (M1) considers the dam alone. The second (M2) incorporates farmers' characteristics, while the third (M3) additionally includes perceptions and perceived impacts. Model comparisons were conducted using likelihood ratio tests to assess the statistical significance of successive additions. In particular, the likelihood ratio statistic, $LR = 2(\ln \hat{L}_1 - \ln \hat{L}_0)$, follows a chi-squared distribution with degrees of freedom equal to the number of additional parameters, according to Wilks (1938). Multicollinearity was assessed using the variance inflation factor (VIF) (O'Brien, 2007).

The control variables included the number of crops cultivated (out of 14) and the use of agricultural inputs (organic fertiliser and chemical pesticides, scored from 0 to 2).

Robustness was assessed through several re-estimations of M3: restricting the sample to farmers with more than ten years of farming experience; using a perception index limited to extreme rainfall events; and fitting a model based on the 24 responses provided by each farmer, incorporating random effects for farmers, villages and strategies.

A fixed-effects ordinary least squares model with village fixed effects was also fitted. Its p-values were obtained using a wild cluster bootstrap, an approach suited to settings with a small number of clusters (Cameron et al., 2008). Perception was decomposed into the deviation of each farmer's score from the village mean and the village mean itself, thereby distinguishing within-village from between-village associations (Mundlak, 1978; Bell and Jones, 2015).

Differences between dams were also expressed in terms of the number of strategies adopted, using linear mixed-effects models. Their coefficients remain comparable across models, unlike odds ratios, which are affected by the rescaling of coefficients in non-linear models (Mood, 2010).

The village effect was assessed using a likelihood ratio test. Finally, dam size was introduced as an ordered gradient (small Sourgou dam = 1, medium-sized Séboun dam = 2, large Soum dam = 3), allowing a linear trend to be tested with a single degree of freedom.

However, with only three dams, size remains confounded with the other characteristics specific to each reservoir. All analyses were conducted using R version 4.4 (lme4 package) and Python version 3.13.

3. RESULTS

3. 1. Socio-demographic profile of farmers by reservoir

3. 1. 1. Age, farming experience and educational attainment

The socio-demographic composition of the farming populations differs considerably across the three reservoirs. Table 1 compares the main socio-demographic characteristics of farmers, expressed as percentages, according to the reservoir with which they are associated. The comparisons are based on Pearson's chi-squared test, Cramér's V and a statistical test adjusted for village-level clustering. This approach highlights the distinctive characteristics of the farming populations across the three reservoirs, whilst also identifying characteristics for which no statistically significant differences are observed.

The socio-demographic characteristics of farmers reveal substantial differences across the three reservoir areas, particularly in terms of age, farming experience and educational attainment (Table 1).

Gender composition and land tenure status do not differ significantly across the three sites after adjustment for village-level clustering. Women account for 28.6% of farmers around Soum, 24.3% around Séboun and 33.9% around Sourgou. Similarly, the proportion of migrant farmers ranges from 20.6% to 25.8%, suggesting relatively comparable land tenure profiles across the three areas.

Educational attainment exhibits marked descriptive differences. The proportion of farmers with no formal education is considerably higher around Soum (56.4%) than around Séboun (25.7%) and Sourgou (21.0%). Conversely, primary and lower secondary education are more prevalent in the latter two areas. Although the unadjusted chi-squared test indicates a significant association ($\chi^2 = 73.3$; $p < 0.001$; $V = 0.29$), this difference is no longer statistically significant after accounting for village-level clustering (adjusted $p = 0.091$).

Age profiles also differ across the three reservoirs. Farmers around Soum are predominantly younger, with 55.1% aged between 30 and 40 years. In contrast, the largest age group around Séboun is 40–50 years (54.4%). Sourgou has a comparatively older farming population, with 27.4% of farmers aged over 60. These differences remain statistically significant after adjustment (adjusted $p = 0.020$).

Farming experience displays the strongest association with reservoir location. Around Soum, 52.0% of farmers have between one and ten years of experience, whereas this proportion falls to 20.6% at Séboun and 8.1% at Sourgou. Conversely, farmers with 20–30 years of experience account for 50.7% of the sample at Séboun, compared with 11.0% at Soum and 33.9% at Sourgou. The association is statistically significant even after adjustment for village-level clustering ($\chi^2 = 108.0$; $V = 0.36$; adjusted $p = 0.010$).

Overall, the results indicate that the three reservoir areas are characterised by distinct age and farming experience profiles, whereas gender composition and land tenure status are relatively similar. These differences provide important socio-demographic context for examining farmers' perceptions of climatic extremes and their adoption of agricultural adaptation strategies.

Table 1. Farmers' profile by dam (%).

Variable	Category	Soum (n = 227)	Séboun (n = 136)	Sourgou (n = 62)	Test
Gender	Women	28.6	24.3	33.9	$\chi^2 = 2.0$; p = 0.359; V = 0.07; adj. p = 0.102
Land tenure status	Non-native	23.3	20.6	25.8	$\chi^2 = 0.7$; p = 0.693; V = 0.04; adj. p = 0.841
Educational attainment	No formal education	56.4	25.7	21.0	$\chi^2 = 73.3$; p < 0.001; V = 0.29; adj. p = 0.091
	Primary	9.3	26.5	32.3	
	Lower secondary	10.1	28.7	14.5	
	Upper secondary	11.9	14.0	16.1	
	University	12.3	5.1	16.1	
Age	30–40 years	55.1	14.7	19.4	$\chi^2 = 85.4$; p < 0.001; V = 0.32; adj. p = 0.020
	40–50 years	24.2	54.4	41.9	
	50–60 years	7.0	19.9	11.3	
	Over 60 years	13.7	11.0	27.4	
Farming experience	1–10 years	52.0	20.6	8.1	$\chi^2 = 108.0$; p < 0.001; V = 0.36; adj. p = 0.010
	10–20 years	23.3	16.9	48.4	
	20–30 years	11.0	50.7	33.9	
	Over 30 years	13.7	11.8	9.7	

Statistical tests: Gender, $\chi^2 = 2.0$, p = 0.359, V = 0.07, adjusted p = 0.102; land tenure, $\chi^2 = 0.7$, p = 0.693, V = 0.04, adjusted p = 0.841; education, $\chi^2 = 73.3$, p < 0.001, V = 0.29, adjusted p = 0.091; age, $\chi^2 = 85.4$, p < 0.001, V = 0.32, adjusted p = 0.020; farming experience, $\chi^2 = 108.0$, p < 0.001, V = 0.36, adjusted p = 0.010.

Source: Field survey, n = 425. Adjusted p-values (p adj.) are based on the Rao–Scott chi-squared test, accounting for clustering of farmers within villages.

3. 2. Perceptions of climate extremes

3. 2. 1. Perceived climate extremes and observed trends

The intensification of climate extremes is widely perceived by farmers. However, these perceptions vary according to the indicators considered and the reservoir areas concerned. Figure 2 shows, for each indicator, the proportion of farmers in each reservoir area who perceive an intensification of the corresponding climatic phenomenon. Table 2 subsequently compares these proportions, Thiessen polygon by Thiessen polygon, with the observed trends recorded at the corresponding meteorological station.

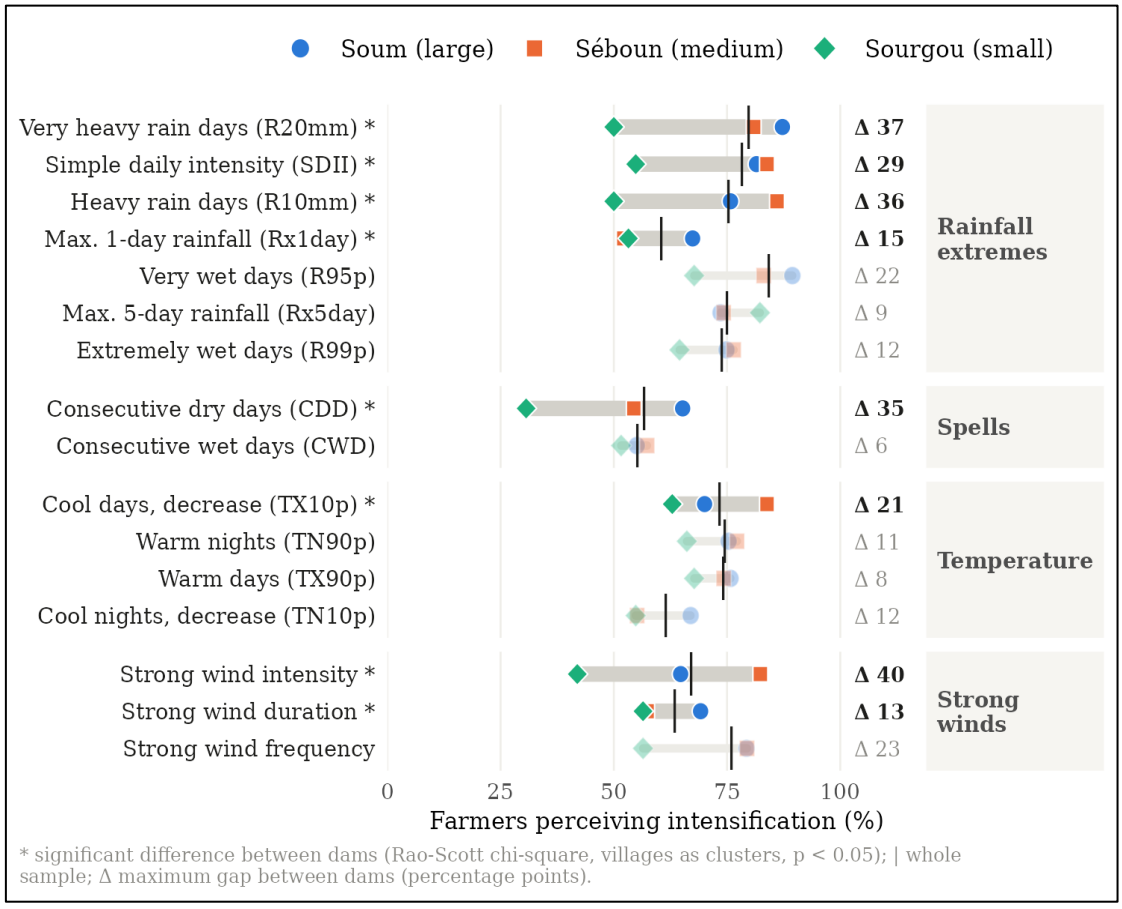


Figure 2. Farmers' perceptions of the intensification of extreme climatic events according to reservoir size (Soum, Séboun and Sourgou).

The most widely perceived extreme weather events are heavy rainfall (R95p, 84%), very heavy precipitation days (R20mm, 80%) and rainfall intensity (SDII, 78%). After accounting for village-level clustering, perceptions differ between reservoir areas for 8 of the 16 indicators (11 according to the unadjusted chi-squared test). Notably, farmers in Sourgou generally report lower levels of perceived intensification. For example, 31% consider dry spells to have become longer, compared with 65% in Soum, while 50% perceive an increase in very heavy precipitation days, compared with 87% in Soum.

Table 2. Perceived and observed trends in climate extremes by Thiessen polygon.

Index	Ouaga.: perceived (%)	Ouaga.: trend	p	Agreement	Boromo: perceived (%)	Boromo: trend	p	Agreement
Rx1day (mm)	62	+4.51*	0.021	Yes	53	+1.36	0.407	No[a]
Rx5day (mm)	74	+10.06*	0.002	Yes	82	+4.86	0.160	No[a]
R95p (mm)	87	+54.30*	< 0.001	Yes	68	+20.13	0.082	No[a]
R99p (mm)	75	+3.46*	0.002	Yes	65	0.00	0.472	No[a]
SDII (mm/day)	82	+0.77*	< 0.001	Yes	55	+0.29*	0.036	Yes
R10mm (days)	80	+1.54*	< 0.001	Yes	50	+1.04*	0.004	No[b]
R20mm (days)	85	+1.15*	0.002	Yes	50	+0.51	0.169	Yes
CDD May–Oct. (days)	61	0.00	0.992	No[a]	31	0.00	0.927	Yes
CWD May–Oct. (days)	56	+0.25*	0.022	Yes	52	0.00	0.486	No[a]
TX90p (%)	75	+3.58*	< 0.001	Yes	68	+0.66	0.486	No[a]
TN90p (%)	76	+3.45*	< 0.001	Yes	66	+3.21*	< 0.001	Yes
TX10p (%)	75	−1.94*	< 0.001	Yes	63	−0.84	0.150	No[a]
TN10p (%)	63	−2.30*	< 0.001	Yes	55	−2.59*	< 0.001	Yes
Season onset (days)	–	+0.74	0.849	–	–	+1.52	0.263	–
Season cessation (days)	–	0.00	0.879	–	–	+0.40	0.769	–
Season length (days)	–	−0.35	0.847	–	–	+1.06	0.800	–
CDD ≥ 7 days	–	0.00	0.842	–	–	0.00	0.362	–
CDD ≥ 10 days	–	0.00	0.137	–	–	0.00	0.381	–
CDD ≥ 15 days	–	0.00	0.729	–	–	0.00	0.907	–

Perceived: proportion of farmers within each Thiessen polygon reporting an intensification (Ouagadougou: Soum and Séboun, n = 363; Boromo: Sourgou, n = 62). Trend: Sen's slope per decade; * indicates statistical significance (modified Mann–Kendall test, following Hamed and Rao, 1998, $p < 0.05$). a Perceived intensification reported by the majority but not observed; b observed trend but not perceived by the majority. Sources: Field survey; National Meteorological Agency (ANAM), rainfall data (1980–2023) and temperature data (1991–2023).

Ouagadougou, the reference meteorological station for Soum and Séboun, exhibits statistically significant trends for 12 of the 13 indices, and these trends remain significant after

correction for multiple testing. Observations indicate a significant increase in heavy precipitation (R95p), at a rate of 54 mm per decade. This trend is accompanied by a slight lengthening of wet spells, an increase in the number of hot days and nights, and a decrease in the number of cold days and nights.

At Boromo, the reference station for Sourgou, only SDII, R10mm and the two minimum-temperature indices (TN90p and TN10p) exhibit statistically significant trends.

Dry spells constitute a notable exception at both stations. No statistically significant trends are observed in the wet-season CDD, the number of dry spells lasting at least 7, 10 or 15 days, or the onset, cessation or duration of the rainy season ($p \geq 0.13$). Nevertheless, 61% of farmers in Soum and Séboun perceive dry spells as having become longer.

In Ouagadougou, change points are identified between 2002 and 2007 for most extreme rainfall indices and between 2005 and 2010 for temperature indices. These periods broadly coincide with the beginning of the 20-year period covered by the farmers' survey.

Table 2 compares, indicator by indicator, the proportion of farmers perceiving an intensification with the trend recorded at the corresponding meteorological station. Agreement is established when a majority perceives an intensification and the observed trend is statistically significant in the expected direction, namely a decrease in cold days and nights (TX10p and TN10p), or when neither perceived intensification nor a significant observed trend is detected. Within the Ouagadougou polygon, perceptions and observations agree for 12 of the 13 indicators. In contrast, within the Boromo polygon, a majority of farmers in Sourgou perceive an intensification for seven indicators for which the meteorological station records no statistically significant trend. The only disagreement in Ouagadougou concerns dry spells (CDD), whereas Boromo exhibits only five instances of agreement. In particular, the increase in the number of heavy rainfall days (R10mm) is detected in the meteorological records but is not perceived by the majority of farmers.

Seasonal indicators and the number of dry spells per rainy season, which were not included in the perception questionnaire, show no statistically significant trends. Owing to a lack of data, violent winds could not be included in the comparison.

3. 3. Perception and impact scores

Perceptions and self-reported impacts were summarised using composite scores. Figure 3 presents the original data for each reservoir, including the proportion of farmers corresponding to each value of the perception index and the production-related and socio-economic impact indices. It also reports the mean, mode and an F-test comparing the reservoirs while accounting for village-level clustering. This analysis aims to determine whether the observed differences between reservoirs reflect an overall shift in the distribution or are attributable to a small number of atypical farmers.

At Sourgou, the distribution of perception scores is shifted downwards (mean 9.1 and median 9, compared with 11.6–11.7 and 12 at Soum and Séboun). However, this difference is not statistically significant when village-level clustering is taken into account (mixed-effects model, $p = 0.116$). Furthermore, the distributions overlap considerably: 23% of producers at Sourgou perceive at least 12 indicators, while 18% of those at Soum perceive nine or fewer.

Productive impacts exhibit a ceiling effect, with between 46% (Séboun) and 79% (Sourgou) of producers reporting all 23 impacts. By contrast, socio-economic impacts are lower at Sourgou (11.6 compared with approximately 15; $p = 0.002$, accounting for village-level clustering) and almost uniform at Séboun, where 93% of producers report a score of 15.

At Séboun, producers also attribute crop abandonment to a short rainy season less frequently (72%, compared with more than 95% at the other sites; Rao–Scott test, $p < 0.001$).

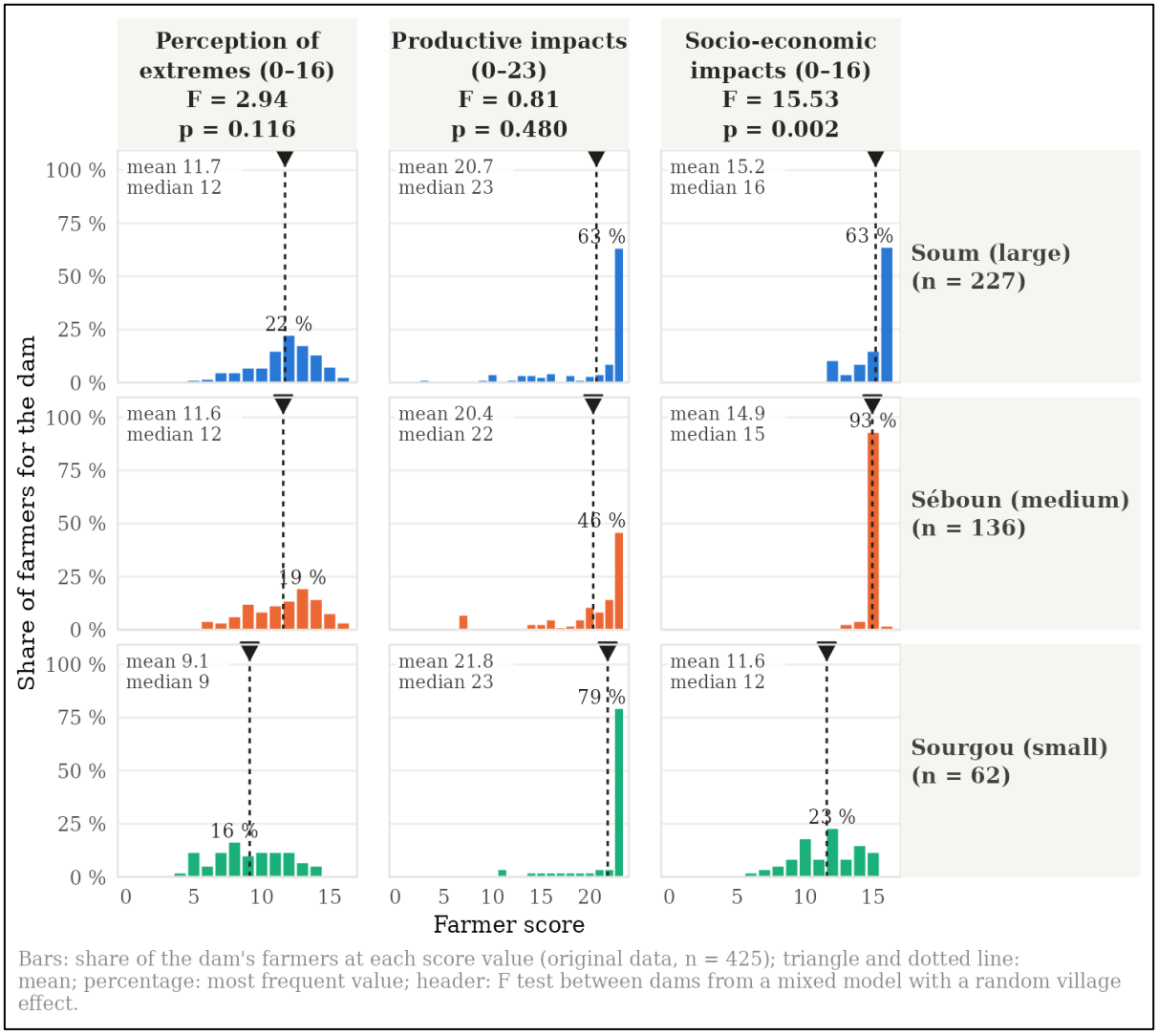


Figure 3. Distribution of perception and impact scores by dam

When examined as a gradient of dam size, perception scores show a modest increase from the smallest to the largest dam (+1.0 indicator per size category; $p = 0.091$), whereas socio-economic impact scores increase more substantially (+1.4 points per size category; $p = 0.009$).

3. 4. Adoption of adaptation strategies

3. 4. 1. Intensity of adoption by dam

Statistical analysis reveals that producers adopt an average of 17.1 out of the 24 strategies, demonstrating widespread and diversified adaptation. The original adoption data are presented in Figure 4, which illustrates the distribution of producers according to the number of strategies

adopted, both overall and for each climatic hazard. It also reports the mean values and the F-test comparing the three dams, while accounting for village-level clustering. As each axis covers the full range of the corresponding sub-index, the figure makes it possible to assess how producers' adoption levels relate to the minimum and maximum possible scores.

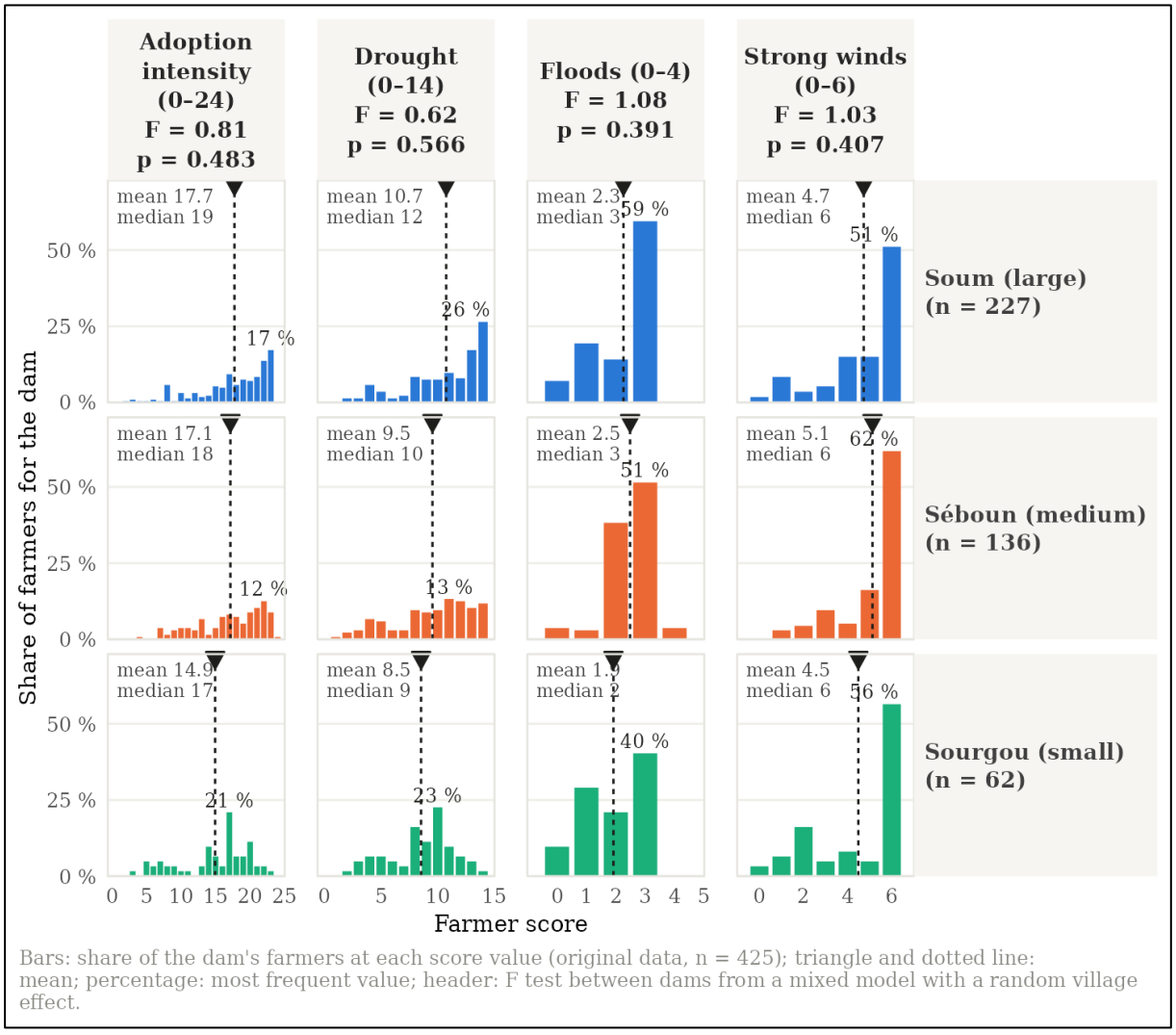


Figure 4. Distribution of adaptation adoption intensity scores by dam.

Analysis of Figure 4 shows that Sourgou has a lower mean adoption intensity (14.9 strategies) than Soum (17.7 strategies) and Séboun (17.1 strategies), particularly in relation to drought adaptation strategies (median scores of 12, 10 and 9, respectively). By contrast, the adoption of strategies addressing strong winds is concentrated at the maximum score of six across all three dams, with 51–62% of producers adopting all six strategies.

However, once village-level clustering is taken into account, these differences are no longer statistically significant (mixed-effects model, F = 0.81; p = 0.483; drought adaptation, p = 0.566). This result should be interpreted cautiously, as Sourgou is represented by only one

village. Although mean adoption decreases from the large Soum dam to the small Sourgou dam, this size gradient is not statistically significant (+0.5 strategy per size category; p = 0.639).

The distributions also overlap considerably. Adoption scores at Soum range from 2 to 23. The lower adoption intensity at Sourgou does not therefore reflect a distinct group of poorly adapted producers, but rather a shortage of highly adapted producers: only 5% adopt at least 22 strategies, compared with 31% at Soum. The flood adaptation sub-index, meanwhile, rarely exceeds three strategies, with only five producers adopting all four options, confirming their largely alternative rather than complementary nature.

It should be noted that the aggregate index does not reveal differences in the adoption of individual strategies. Figure 5 therefore presents a matrix showing the adoption rate of each strategy by dam, ranked according to statistical significance and the maximum difference between dams. The colour of the difference bar indicates the dam where each strategy is most widely adopted.

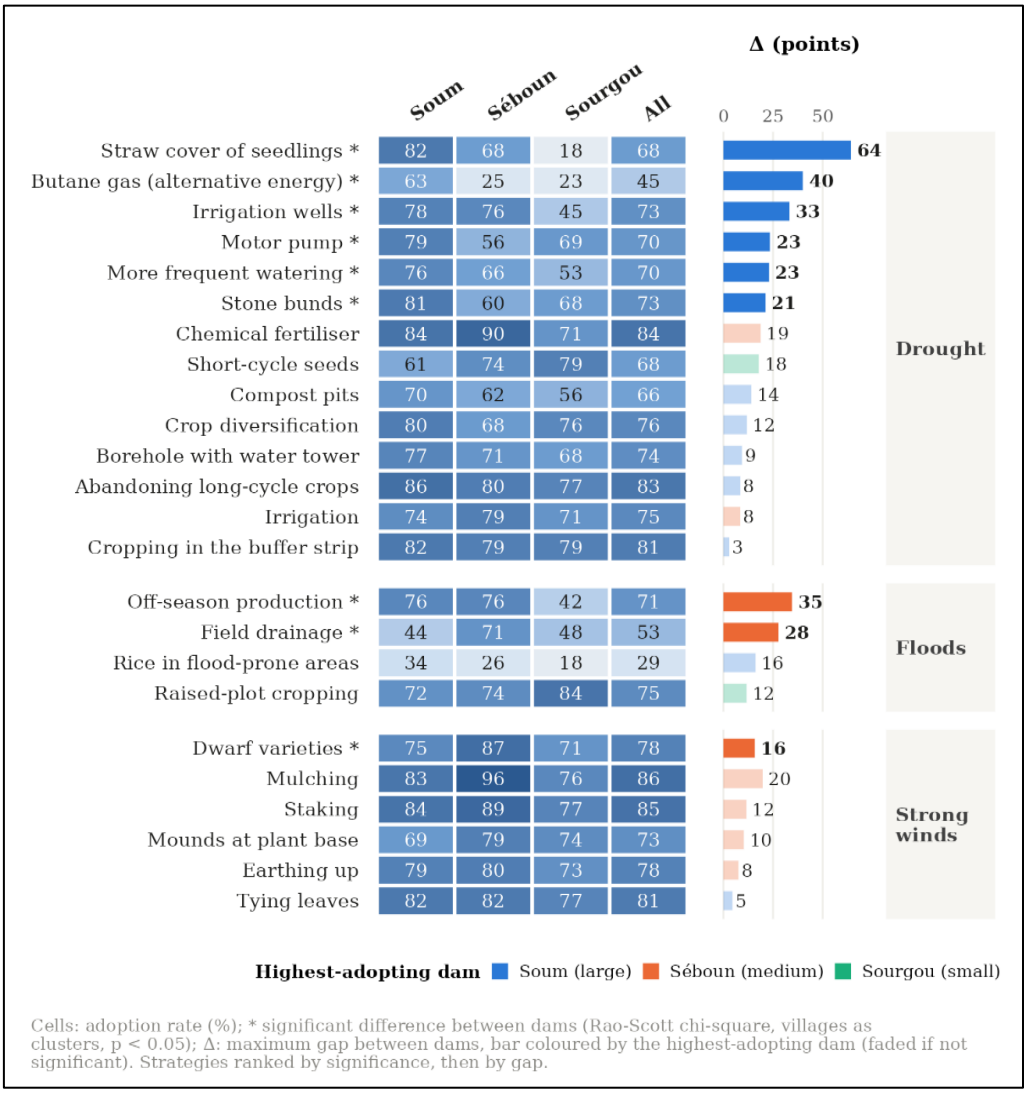


Figure 5. Adoption rates of the 24 adaptation strategies by dam.

Nine of the 24 strategies exhibit statistically significant differences between dams after accounting for village-level clustering, compared with 14 strategies according to the conventional chi-square test.

Strategies addressing strong winds are the most widely adopted and show the greatest degree of consistency across the three sites. Mulching (86%) and staking (85%) are particularly widespread, with adoption rates exceeding 75% across all three dams.

However, clear differences emerge in agricultural practices around the reservoirs. At Soum, 82% of producers use straw to cover seeds, compared with only 18% at Sourgou. Similarly, the use of watering wells is considerably less common at Sourgou (45%) than at Soum (78%).

Séboun stands out for the widespread use of field drainage (71%), whereas Soum is characterised by greater reliance on bottled gas as an alternative energy source (63%, compared with 23–25% at the other sites). These findings suggest that producers develop adaptation strategies in response to the specific constraints and opportunities associated with each reservoir.

3. 4. 2. Variation between producers, villages and dams

These contrasts become less pronounced when village-level clustering is taken into account, highlighting the need to identify the spatial scale at which adaptation varies. Figure 6 illustrates the distribution of variance in perception and adaptation adoption across dams, between villages within the same dam area, and among producers within villages. It thereby identifies the spatial level at which differences between producers are most strongly concentrated.

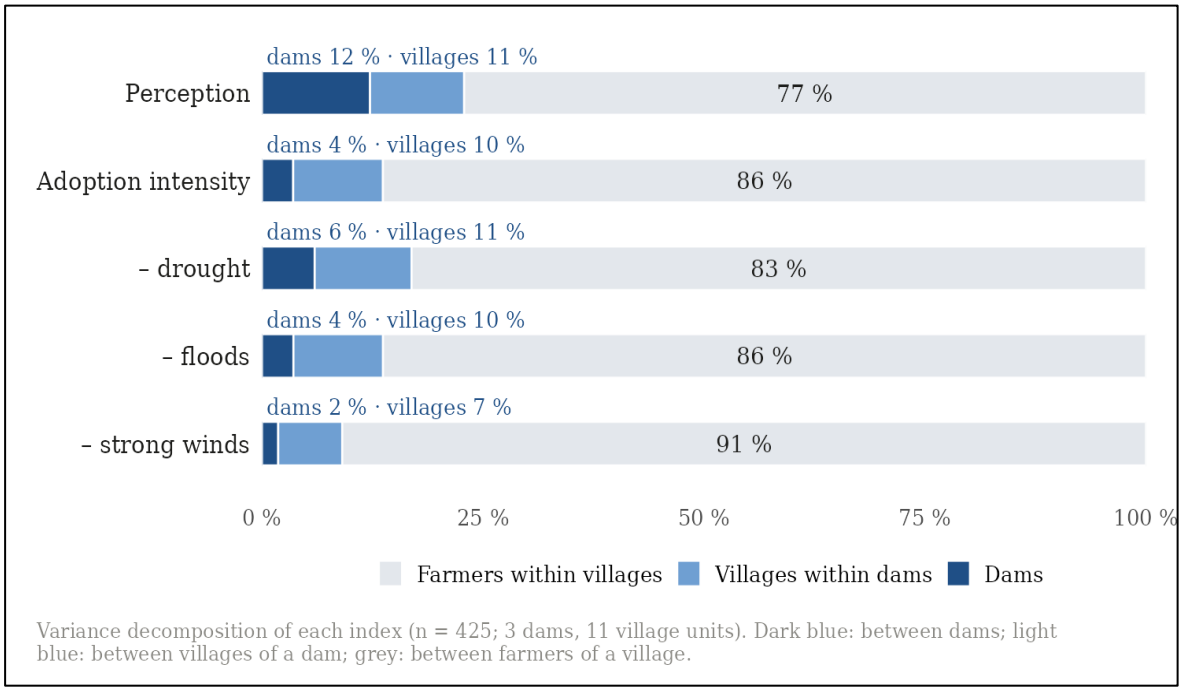


Figure 6. Variance decomposition of perception, adaptation adoption intensity and climate hazard indices across dams, villages and producers.

Statistical analysis shows that the largest share of variation in adaptation adoption occurs between producers within the same locality (86%), followed by differences between localities within the same dam area (10%). Differences between dams account for only 4% of the total variance. This finding is confirmed by the F-test for villages within the same dam area ($F = 6.09$; $p < 0.001$) and an intraclass correlation coefficient (ICC) of 0.16.

Perception, by contrast, is more strongly structured by dam location (12%) than adaptation adoption. The sub-indices for individual climatic hazards follow a similar pattern, with between-dam variance ranging from 2% for strong winds to 6% for drought. Overall, variation in adaptation adoption at dam level remains negligible.

The village-level scale offers a more direct perspective on the dynamics underlying these differences. Figure 7 presents the mean adoption intensity for each village with at least ten surveyed producers, together with its 95% confidence interval. A coloured reference line indicates the mean for each dam, making it possible to compare differences between villages with those observed between dams.

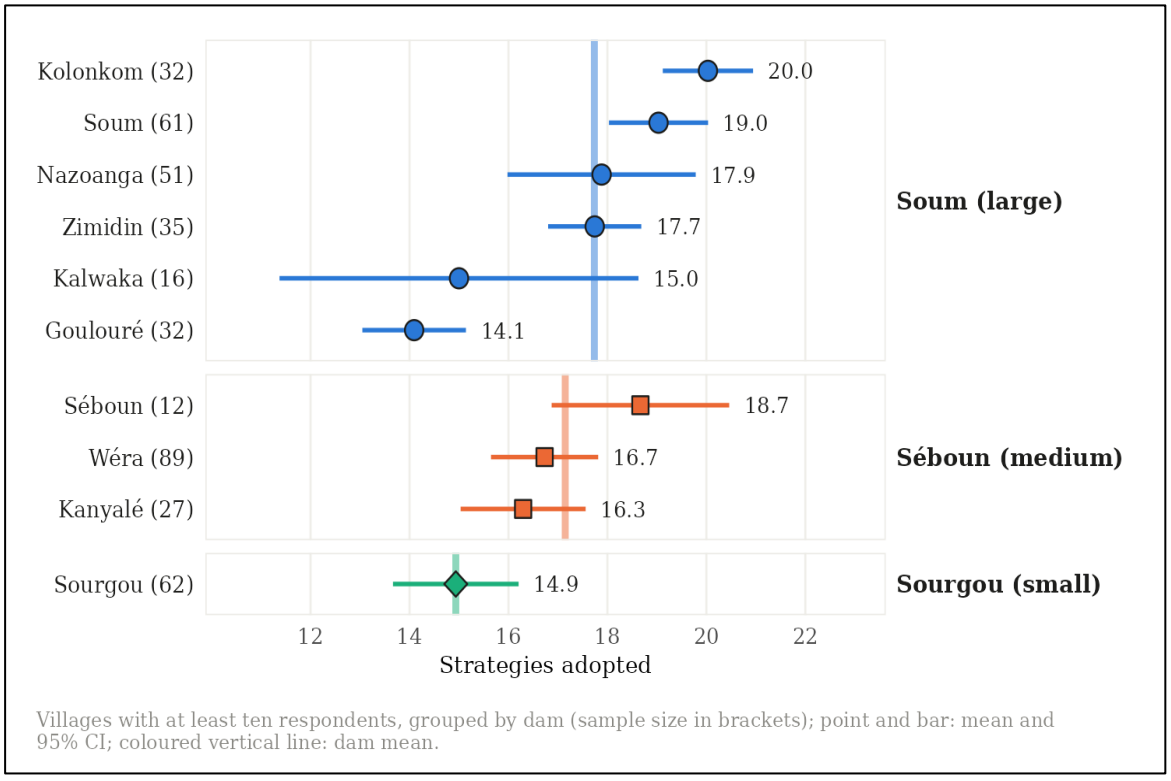


Figure 7. Mean adoption intensity by village.

The Soum dam exhibits greater variation between villages than that observed between the overall dam means (14.9–17.7), with mean adoption intensity ranging from 14.1 in Goulouré to 20.0 in Kolonkom. Around the Séboun dam, village-level mean scores range from 16.3 in Kanyalé to 18.7 in Séboun.

Several confidence intervals overlap with the mean values of other dams. Village-level contexts therefore appear to play a more important role than dam-level differences in explaining

adoption patterns. This helps explain why differences in adoption between dams become less pronounced once village-level effects are incorporated into the statistical models.

These differences between producers may be partly explained by variations in their perceptions of climate extremes. Figure 8 illustrates mean adoption intensity according to the number of climate extremes perceived as having intensified, for each dam. Perceived extremes are classified into three categories: nine or fewer, 10–12, and 13 or more. Comparing producers within the same dam makes it possible to distinguish the influence of climate perception from that of geographical location.

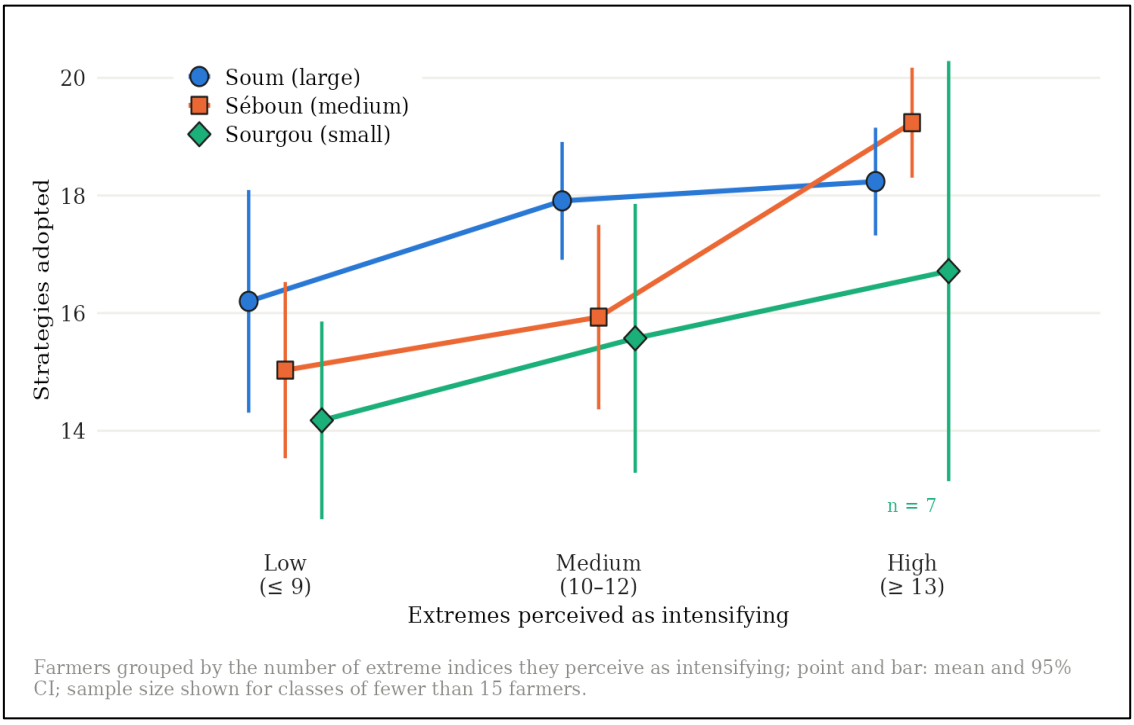


Figure 8. Adoption intensity according to the level of perceived intensification and the dam.

Across all the dams studied, it was observed that adoption tends to increase with the number of extremes perceived as intensifying. Statistical analysis reveals a significant variation in the producers' use of strategies. Indeed, the average stands at 15.2 strategies among those who perceive up to nine indices, whereas among those who perceive at least 13, this average rises to 18.6. This statistical relationship proves significant within villages ($r = 0.25$; $p < 0.001$), while no notable correlation is observed between the averages of the ten villages ($r = -0.14$; $p = 0.69$). Perception therefore distinguishes neighbouring producers rather than locations, even though in Sourgou the high-perception class comprises only seven producers.

3. 5. Factors associated with adoption

3. 5. 1. Dam, village and producer effects

In order to verify whether the dam remains associated with adoption once composition is controlled for, it is necessary to use three nested multilevel models. Table 3 presents the odds

ratios with their 95% confidence intervals, the standard deviation of the village effect and the likelihood ratio test associated with each addition. When the odds ratio exceeds 1, the probability of adopting a given strategy is higher than in the reference category.

Table 3. Multilevel models of adoption intensity.

Variable	M1: Dam	M2: + Characteristics	M3: + Perceptions
Soum (ref. Sourgou)	1.86 [0.68–5.08]	1.73 [0.65–4.66]	1.36 [0.47–3.95]
Séboun	2.20 [0.76–6.36]	1.49 [0.55–4.05]	1.34 [0.46–3.92]
Women	–	0.88 [0.70–1.09]	0.82 [0.66–1.02]
Non-native	–	1.20 [0.92–1.56]	1.14 [0.89–1.48]
Primary (ref. none)	–	0.57 [0.42–0.78]***	0.59 [0.44–0.79]***
Lower secondary	–	1.75 [1.26–2.41]***	1.59 [1.16–2.18]**
Upper secondary	–	0.81 [0.58–1.13]	0.83 [0.60–1.15]
University	–	0.48 [0.32–0.71]***	0.47 [0.31–0.69]***
40–50 years (ref. 30–40)	–	1.22 [0.93–1.58]	1.30 [1.01–1.68]*
50–60 years	–	1.45 [0.97–2.16]	1.67 [1.13–2.46]*
Over 60 years	–	0.66 [0.47–0.92]*	0.74 [0.54–1.03]
Experience 10–20 years (ref. 1–10)	–	0.76 [0.56–1.02]	0.82 [0.61–1.10]
Experience 20–30 years	–	1.17 [0.88–1.56]	1.18 [0.89–1.55]
Experience over 30 years	–	0.68 [0.46–0.98]*	0.73 [0.51–1.05]
Number of crops grown	–	0.98 [0.94–1.02]	1.00 [0.95–1.04]
Agricultural inputs	–	0.93 [0.52–1.69]	0.99 [0.55–1.78]
Perception of extreme events (PERC)	–	–	1.10 [1.05–1.15]***
Perceived production impacts (IMPACT)	–	–	1.03 [1.00–1.05]*
Standard deviation of village-level effect	0.45	0.42	0.45
AIC	2,416.6	2,354.9	2,333.2
Likelihood ratio test	$\chi^2(2) = 2.0$; $p = 0.373$	$\chi^2(14) = 89.7$; $p < 0.001$	$\chi^2(2) = 25.7$; $p < 0.001$

Source: Field survey, n = 425. Multilevel binomial models (24 strategies) with random intercepts at village and observation levels; odds ratios [95% confidence intervals]; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Likelihood ratio tests: M1 versus the null model, M2 versus M1, and M3 versus M2. Latent village-level intraclass correlation coefficient (null model): 0.06; maximum variance inflation factor (VIF) (M3): 3.85.

Once village-level effects are accounted for, the dam is not significantly associated with adoption, even in the absence of other explanatory variables (M1: $\chi^2(2) = 2.0$; $p = 0.373$). In terms of the number of strategies, the differences between dams, estimated using linear mixed-

effects models, amount to +2.4 strategies for Soum and +3.2 for Séboun, relative to Sourgou, without adjustment for other variables. When farmers' characteristics and perceptions are introduced, these differences decrease to +0.9 and +1.1, respectively, with confidence intervals of approximately ±6 strategies. Furthermore, the available data do not allow us to conclude either that there is no difference or that a substantial difference exists. By contrast, the village effect is statistically significant ($\chi^2(1) = 16.9$; $p < 0.001$), and the standard deviation remains unchanged across the models (0.45 in both M1 and M3). This effect remains significant when the eight farmers from Sourgou assigned to the Séboun dam are excluded ($p = 0.005$); their mean adoption level is 22.4 strategies. When included as a continuous gradient, dam size is likewise not associated with adoption (odds ratio of 1.15 [0.72–1.84] per size category in M1 and 1.12 [0.69–1.84] in M3).

The statistical analysis incorporating farmers' characteristics reveals a significant improvement in model fit ($\chi^2(14) = 89.7$; $p < 0.001$). Educational attainment shows the strongest association, although this relationship is not linear (overall test: $\chi^2(4) = 43.4$; $p < 0.001$). Specifically, farmers with primary and university education have approximately half the odds of adoption compared with those with no formal education (0.59 and 0.47, respectively), whereas those with lower secondary education have higher odds (1.59).

Furthermore, the inclusion of perception variables leads to a further improvement in model fit, as indicated by the likelihood ratio test ($\chi^2(2) = 25.7$; $p < 0.001$). Each additional perceived intensification indicator is associated with a 10% increase in the odds of adoption (odds ratio: 1.10 [1.05–1.15]), equivalent to approximately half an additional strategy relative to the sample mean.

3. 5. 2. Robustness of the associations

It should be noted that the measurement of perceptions and the treatment of village-level effects may influence these associations. The main odds ratios from M3 were therefore compared across four alternative specifications.

These included a sample restricted to farmers with more than ten years of farming experience, a perception index restricted to extreme rainfall events, a strategy-specific model, and a village fixed-effects model with a wild cluster bootstrap. In addition, perception was decomposed into each farmer's deviation from their village mean and the village-level mean itself. An association is considered robust if it retains the same direction and statistical significance across all specifications.

Across the four multilevel specifications examined, the association between perception and adoption remains consistent, with odds ratios ranging from 1.10 to 1.11. This association is entirely attributable to each farmer's deviation from their village mean (1.10 [1.06–1.15]). By contrast, the village-level mean perception is not associated with adoption (0.86 [0.63–1.17]).

Furthermore, the statistical analysis shows that the most conservative inference approach with eleven clusters, namely the village fixed-effects model combined with a wild cluster bootstrap, no longer provides sufficient evidence of a statistically significant association between perception and adoption (+0.39 strategies per index unit; $p = 0.107$). Nevertheless, this same analysis confirms that the associations with lower secondary education ($p = 0.023$) and university education ($p = 0.032$) remain statistically significant.

The associations of adoption with gender and perceived production impacts are statistically significant only in some of the specifications. Moreover, these associations are not robust and should therefore not be interpreted.

4. DISCUSSION

4. 1. Dams differentiated primarily by off-farm activities

The comparative analysis of the three dams reveals only partial differences between their respective populations. Age, farming experience and, most notably, secondary economic activities distinguish farmers across the three dam sites, even after accounting for village-level effects. Importantly, gender and land tenure status do not constitute distinguishing factors. Differences in educational attainment and most differences in crop choices, with the exception of rice and maize, do not remain significant after controlling for these factors. This finding is consistent with the sustainable livelihoods approach, which conceptualises adaptation in terms of household capital assets (Scoones, 1998; Ellis, 2000), as well as with the interplay between ecological and social diversity observed at fine spatial scales in the Sahel (Raynaut, 2001). The population of Soum, characterised by its younger age profile and more limited farming experience, contrasts with the older farmers and longer-standing farming presence in Sourgou and Séboun. This dichotomy points to settlement histories that remain to be investigated.

With regard to secondary economic activities, the differences between the dam sites are almost complete. Diversification beyond the agricultural sector is shaped by local constraints and opportunities (Reardon, 1997; Barrett et al., 2001). However, a systematic and critical approach is needed, as the responses obtained for each dam often display a degree of uniformity that warrants further investigation. This pattern may be interpreted either as a reflection of collective practices specific to each reservoir or as a potential interviewer effect. The absence of differences in land tenure status may be surprising, given that land rights are traditionally governed by local rules and customary arrangements (Platteau, 1996).

According to de Fraiture et al. (2014) and de Fraiture and Giordano (2014), the development of privately managed irrigation systems around reservoirs in Burkina Faso has been observed. These systems are financed by the farmers themselves. Dams, ranging from the large Soum dam to the smaller Sourgou dam, play a key role in organising water territories. They help structure spaces characterised by diversified uses. According to Venot et al. (2012), the performance of these irrigation systems is influenced by both their water-use rules and their technical characteristics. Unequal access to irrigation has implications for resource management and livelihoods, as highlighted by Burney and Naylor (2012), Tittonell et al. (2010) and Woodhouse et al. (2017). Each dam can therefore be regarded as a distinct socio-hydrological territory. However, data on these reservoirs, particularly their storage capacities, irrigated areas and water-use arrangements, remain insufficiently documented

4. 2. Perceptions and observed trends

In the Ouagadougou polygon, perceptions and observed trends are largely consistent. The results of this analysis reveal agreement between local perceptions and observed trends for 12 of the 13 indices examined, whereas in the Boromo polygon, agreement is found for only five indices. In Ouagadougou, the intensification of rainfall, widely perceived by farmers, corresponds to a marked increase in all rainfall extremes. This correspondence is consistent with the intensification of Sahelian rainfall documented by Panthou et al. (2014, 2018), Sanogo et al. (2015) and Taylor et al. (2017). The detected breakpoints in the early 2000s are consistent with the return of rainfall and increased variability reported by Lebel and Ali (2009) and Nicholson (2013). Perceived warming also corresponds to the observed increase in hot days

and nights, a trend documented in several regions worldwide and confirmed by the IPCC's regional assessment (Seneviratne et al., 2021).

It is worth noting that the most pronounced discrepancies between perceived and observed trends concern dry spells.

The definition of CDD (consecutive dry days) is not, in itself, responsible for this discrepancy, since no significant changes are observed either in the number of dry spells during the rainy season or in the onset, cessation or duration of the rainy season. West et al. (2008) demonstrated, in their study of the Central Plateau of Burkina Faso, that farmers' perceptions only partially correspond to observed rainfall trends. According to Simelton et al. (2013), farmers primarily perceive changes affecting their crops, such as the onset of the rainy season and dry spells, rather than changes reflected in rainfall statistics. In their detailed analysis, Thomas et al. (2007) highlight farmers' responses to intra-seasonal rainfall patterns, which are not adequately captured by the conventional indices commonly used. Vegetable production, which has higher water requirements, may also make dry spells more damaging without necessarily increasing their duration. According to Maddison (2007) and Gbetibouo (2009), perceptions are influenced by individual experience and household characteristics. Roncoli et al. (2002) showed that farmers in Burkina Faso rely on local indicators to interpret rainfall patterns. These indicators are based more on the assessment of seasonal climatic conditions than on statistical rainfall data.

In Sourgou, the assignment of dams to weather stations helps partly explain the narrower range of perceptions observed. In Boromo, rainfall has shown an increase, albeit modest and statistically non-significant, whereas farmers in Sourgou reported a lower degree of intensification than those in Soum and Séboun. Although this approach is relevant in its own right, it has inherent limitations that need to be taken into account. Indeed, farmers in Sourgou perceive a greater intensification of rainfall than is recorded by the corresponding weather station. The data analysis shows that differences in perceptions between the dam sites diminish when village-level effects are taken into account. Furthermore, Sourgou is located at almost equal distances from Boromo and Ouagadougou (82 and 86 km, respectively). Zampaligré et al. (2014) established that perceptions vary across agro-ecological zones in Burkina Faso. Our findings suggest that these perceptions may also reflect finer-scale spatial differences, which are poorly captured by weather stations located 80–90 km apart. Socio-economic impacts are less pronounced in Sourgou, where fishing and trading activities provide opportunities for income diversification. This observation is consistent with the relationship identified by Sahelian farmers between climate change and socio-economic factors (Mertz et al., 2009).

4. 3. The village as the main scale of variation

The village emerges as a more important scale of variation in adoption than the dam. The statistical analysis reveals that adoption variance is greater between villages within the same dam catchment (10%) than between different dams (4%). This pattern is also observed when variance components are estimated using restricted maximum likelihood (REML), with 16% of the variance attributable to villages and 0% to dams, as well as when the eight farmers from Sourgou assigned to the Séboun dam are excluded (8% and 4%, respectively). The data analysis shows that the mean difference between Sourgou and the other dams is not statistically significant once village-level clustering is accounted for. As demonstrated by Openshaw (1984), results depend on the spatial units considered. Multilevel approaches (Snijders and Bosker, 2012) make it possible to identify explicitly where variation occurs. An adaptation

analysis restricted to the dam level could therefore lead to an overestimation of territorial homogeneity and of disparities between reservoirs. Indeed, as highlighted by Below et al. (2012), farming practices vary according to local contexts, while soil and water conservation techniques are often adopted in combination (Kpadonou et al., 2017). In this context, assessing the intensity of farming practices appears particularly relevant.

Field observations revealed a wide diversity of strategy combinations. These findings therefore appear to corroborate responses to local challenges documented by previous research in the Sahel. In this study, we observe the gradual intensification of farming practices (Mortimore and Adams, 2001), agro-environmental transformation based on locally developed techniques (Reij et al., 2009), and the spread of conservation practices, such as stone bunds, adopted by 81% of farmers in Soum (Kaboré and Reij, 2004), as well as the combination of soil conservation and livelihood diversification in northern Burkina Faso (Barbier et al., 2009). Nevertheless, some strategies continue to distinguish between dams even after accounting for village-level effects, such as seed mulching in Soum and drainage in Séboun. This finding suggests that combinations of strategies are specific to each water territory.

This adaptation remains essentially incremental. Indeed, Sahelian strategies generally seek to adjust production systems without fundamentally altering their underlying vulnerability (Mertz et al., 2011). If intensive watering were to deplete the shared water resources of reservoirs to the detriment of more vulnerable users (Eriksen et al., 2011), it could constitute maladaptation in the sense defined by Barnett and O'Neill (2010). In Sourgou, a lower level of adoption does not necessarily indicate greater vulnerability. Adaptation is also shaped by cultural and social choices (Nielsen and Reenberg, 2010). In Sourgou, fishing and trading activities provide alternative livelihood strategies for managing risk.

4. 4. Dams, farmers' characteristics and perceptions

In the absence of a detectable association between the dam and adoption, the explanation based on population composition cannot be ruled out, but neither can it be confirmed. Incorporating farmers' characteristics and perceptions substantially reduces the difference relative to Sourgou, from +2.4 to +0.9 strategies for Soum. It should be noted, however, that the confidence intervals remain compatible with differences involving several strategies.

The study design, which covers three dams, with Sourgou represented by only one village, can detect only differences in the order of six to eight strategies. The size gradient, from the large Soum dam to the small Sourgou dam, is not associated with adoption, but it is associated with reported socio-economic impacts, which are greater around larger infrastructure. With only three dams, however, dam size cannot be disentangled from the other characteristics of each reservoir. The interpretation proposed here, in terms of population composition, is consistent with frameworks that place household resources at the heart of adaptive capacity (Adger, 2006; Smit and Wandel, 2006), as well as with the distinction between compositional and contextual effects (Macintyre et al., 2002). However, Cummins et al. (2007) call for this distinction to be reconsidered, suggesting that population composition is itself shaped by the history of places.

The village effect, which is statistically significant, does not diminish when farmers' characteristics are introduced into the analysis. This points to an unmeasured village-level context, potentially attributable to access to water, mutual support networks or agricultural extension services. Other explanations are also possible, including an interviewer effect or irrigation infrastructure, which may be captured by several of the strategies examined.

Vulnerability is conceptualised as a 'hazard of place' (Cutter, 1996), in which the interaction between exposure, sensitivity and adaptive capacity (Turner et al., 2003) is essential, and in which biophysical and social dimensions are closely interconnected (Eakin and Luers, 2006).

The relationship between education and adoption is statistically significant, although non-linear, reaching its highest level among farmers with lower secondary education. Indeed, studies conducted by Deressa et al. (2009) in Ethiopia and Nhemachena and Hassan (2007) in southern Africa report positive and monotonic effects associated with access to information. In the sample examined here, farmers with university education have approximately half the odds of adoption of those with no formal education. An explanation based on engagement in non-agricultural economic activities is plausible, but cannot be verified, since fishing and trading, practised almost exclusively in Sourgou, are closely linked to the dam. It should be noted that adoption is influenced by socio-economic variables, although these relationships are not universally consistent (Knowler and Bradshaw, 2007; Fosu-Mensah et al., 2012). Access to credit and land also plays a determining role in this process.

When analysing the factors associated with adoption, perceptions must be treated as a variable requiring cautious interpretation. The socio-cognitive model developed by Grothmann and Patt (2005) posits that adaptation depends on risk appraisal and perceived adaptive capacity. However, the association observed here is entirely driven by each farmer's deviation from their village mean. It loses statistical significance when village fixed effects and a cluster bootstrap are applied. In other words, it distinguishes between neighbours rather than between places, and the data provide no basis for interpreting it as a mechanism through which the dam influences adoption. Furthermore, the direction of the relationship between perception and adoption remains uncertain. The adoption of water management techniques may increase farmers' awareness of dry periods. In addition, undocumented household-specific characteristics may bias naïve estimates, as demonstrated by Abdulai and Huffman (2014). Importantly, the perception, impact and adoption indices, all assessed through the same questionnaire, are based on affirmative responses. Consequently, a tendency towards acquiescence may also contribute to this correlation.

According to Bassett and Fogelman (2013), adaptation research frequently overlooks the underlying social factors contributing to vulnerability. The findings of this study suggest that adaptation to climate change is influenced by a range of factors, including individual characteristics and the context in which people live within their communities.

5. CONCLUSIONS

This study draws on a survey of 425 farmers living near three dams of different sizes in the Nando region of the Centre-West of Burkina Faso, together with observed climate time series. Farmers' perceptions are consistent with the observed intensification of rainfall and hot extremes at the Ouagadougou weather station. They are considerably less consistent with the trends recorded at Boromo. Furthermore, the perceived lengthening of dry spells is not reflected in any of the available indicators. The dams considered differ substantially in terms of farmers' age, farming experience and economic activities. However, once village-level clustering is taken into account, no detectable differences in adoption intensity remain. Adoption varies primarily between neighbouring farmers, in relation to their level of education and perceptions of extreme events, as well as between villages. From a geographical perspective, the village

emerges as the most relevant spatial scale for understanding these patterns. The disparities observed between locations can be attributed, in part, to differences in the demographic composition of their respective populations. These findings call for a more geographically targeted approach to adaptation support, involving interventions at the level of villages bordering each reservoir, rather than across the reservoir as a whole. Further research should seek to identify the factors shaping village-level contexts, document the characteristics of the reservoirs more comprehensively, and follow farmers over time.

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