

Climate variability perception and its influence on crop diversification as an adaptation strategy among smallholder farmers in south-western Uganda

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Abstract

Smallholder farmers in sub-Saharan Africa face climate-induced threats to food and income security. While crop diversification is recognised as a sustainable adaptation strategy, its relationship with smallholder farmers' climate variability perception across seasons and agro-ecological zones (AEZs) remains underexplored. Using survey data from 583 smallholder farmers in south-western Uganda, this study examined how climate variability perception across seasons and AEZs influences crop diversification and cropland allocation. Climate variability perception differed significantly across seasons and AEZs. The long rains season was perceived as more erratic and shorter. The short rains season was perceived as prolonged. For the long rains season, climate variability perception was greatest in the water-stressed AEZ and lowest in the humid AEZ. For the short rains season, it was greatest in the water-stressed and humid AEZs and lowest in the moderately humid AEZ. Climate variability perception influenced crop diversification heterogeneously. Farmers in the water-stressed AEZ tended to diversify more during the long rains season ($\beta = 0.039$, $p < 0.10$). In the humid AEZ, farmers diversified less during the short rains season ($\beta = -0.084$, $p < 0.01$) but increased land allocation to tubers ($\beta = 2.3$, $p < 0.05$). In the moderately humid AEZ, climate variability perception was associated with crop specialisation ($\beta = -0.078$, $p < 0.05$). The findings demonstrate that crop diversification is a context-dependent adaptation strategy, varying seasonally and spatially in response to differentiated climatic risks. Adaptation interventions should account for seasonal and agro-ecological differences for climate-resilient smallholder production systems in SSA.

Keywords Agro-ecological zones · Crop diversification · Crop specialisation · Perception · Risk management · Seasonal rainfall · Smallholder farmers

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1 Introduction

Increasing climate variability is among the leading threats to the livelihoods of smallholder farmers in sub-Saharan Africa (SSA) [1, 2]. Over 70% of the population in SSA, mainly smallholder farmers, relies on agriculture—a sector that is directly dependent on and sensitive to climate [3, 4]. SSA is experiencing more frequent erratic precipitation, droughts, and temperature fluctuations, attributed to climate variability [5, 6]. These shifts have increased production uncertainties through disrupted crop phenology—the timing of biological events, cropping seasons, and heightened pest and disease pressure—leading to significant crop losses [7, 8]. Such dynamics expose smallholder farmers to food and income insecurity, necessitating the adoption of sustainable adaptation strategies.

Perception, a process by which information or phenomena are received and cognitively processed to form psychological awareness [9] plays a crucial role in shaping smallholder farmers' adaptation decisions. Climate variability perception among farmers is shaped by a complex interplay of cognitive processes, personal experiences, emotions, and socio-demographic, institutional, and biophysical factors [10–13]. Importantly, farmers' perception of climate variability occasionally diverges from the corresponding meteorological trends due to differing perspectives underlying the assessment: grounded in lived experiences for the former and instrumental measurements for the latter [14, 15]. Nevertheless, understanding how smallholder farmers characterise climate variability is fundamental to explaining their adaptation decisions, as the psychological significance they attach to experienced climate impacts influences their choice of risk management strategies [16, 17]. Empirical studies from SSA, including Uganda, show that smallholder farmers actively perceive climate variability, reporting reduced rainfall amounts, delayed rainfall onset, erratic rainfall distribution, and temperature variations, typically assessed at an annual scale [17–21].

In bimodal rainfall regions in SSA, however, climate characteristics and their variability change across seasons [22–24]. Similarly, agro-ecological zones (AEZs)—geographical areas exhibiting similar climatic conditions that determine their ability to support agriculture [25, 26] also experience distinct climate variations [27–29]. Despite these spatial and temporal climatic differences, few studies have examined how smallholder farmers' climate variability perception across seasons and AEZs influences their adoption of adaptation strategies, particularly crop diversification [16, 30, 31].

Crop diversification—the cultivation of multiple crop species across time and space— is widely recognised as a sustainable adaptation strategy to climatic risks in agricultural systems [32–35]. Rooted in the scientific discipline of agroecology, diversification enhances system resilience by increasing biological diversity within farming systems, enabling different crops and varieties to respond differently to environmental stresses [36–38]. This diversity creates a buffering effect, whereby the failure of one crop may be offset by the performance of others, thus stabilising overall production [33].

However, crop diversification may not always emerge as a uniform adaptation response. In some contexts, climate variability may also drive smallholder farmers towards crop specialisation, concentrating on a limited number of crops best suited to certain climatic conditions [39–41]. For instance, Andean smallholder farmers narrowed their crop portfolios in response to increasing intra-seasonal climate variability [42]. Similarly, higher drought frequency influenced smallholder farmers in Ethiopia to specialise in the production of the drought-tolerant enset crop [43]. Moreover, in the absence of functional insurance markets, a common limitation in SSA, smallholder farmers often rely on ex-ante production choices to mitigate several risks and safeguard livelihoods [44, 45]. Thus, the relationship between climate variability perception and crop diversification is not always linear but varies depending on how farmers perceive and evaluate risks. In practice, crop diversification or specialisation is reflected both in farmers' choice of crops grown and in how land is allocated among those crops in response to perceived climatic risks [33, 45].

This study uses Uganda, specifically south-western Uganda, to examine how climate variability perception among smallholder farmers influences crop diversification. Uganda experiences increasing intra-annual and inter-annual rainfall variability—driven by large-scale climate systems such as the El Niño Southern Oscillation

and the Indian Ocean Dipole, which continues to disrupt agricultural production [22, 23, 46]. In south-western Uganda, a region historically regarded as a national food basket [47, 48], increasingly unpredictable rainfall patterns are causing substantial crop losses, affecting over 75% of households dependent on rainfed agriculture [49]. Previous studies in the region [27, 50] have examined climate variability perception among smallholder farmers, but also at an annual scale, thereby overlooking seasonal dynamics and their implications for crop diversification.

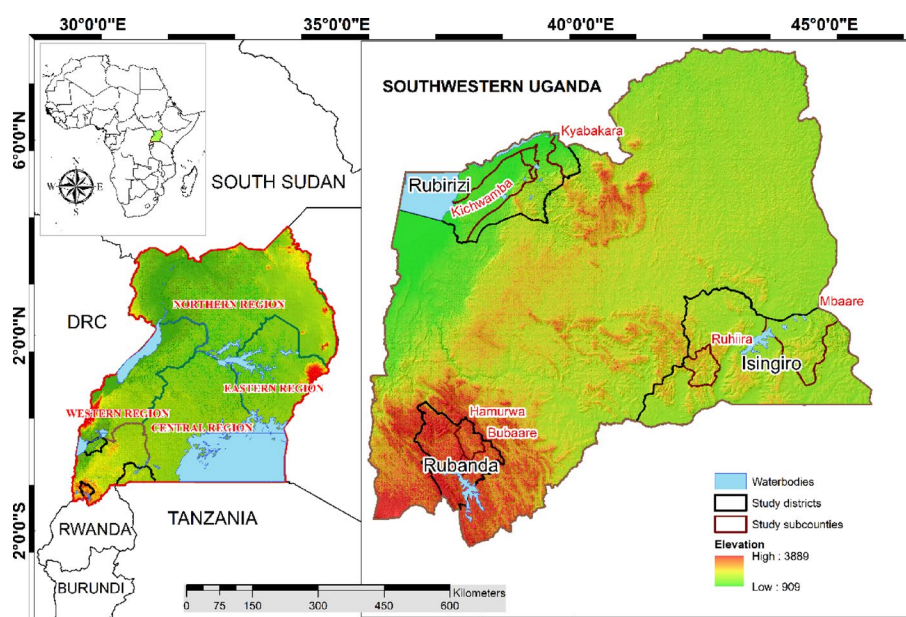
Therefore, this study uses survey data from 583 smallholder farmers in south-western Uganda to examine how smallholder farmers' perception of seasonal rainfall and temperature characteristics influences crop diversification, assessed through their crop choices and cropland allocation decisions. The study seeks to answer: i. How do smallholder farmers in south-western Uganda perceive climate variability, and how does their perception differ across seasons and AEZs? ii. How does climate variability perception among smallholder farmers influence crop diversification and cropland allocation? We hypothesize that climate variability perception among smallholder farmers in south-western Uganda differs significantly across seasons and AEZs and significantly influences crop diversification and cropland allocation. The research questions are addressed using descriptive and inferential statistics, coupled with correlated random effects (CRE) and Seemingly Unrelated Regression (SUR) models. By integrating spatial and temporal dimensions of climate variability perception, this study contributes to the adaptation literature by providing a more comprehensive understanding of how farmers perceive risks and adjust their crop portfolios. The findings offer important insights for designing evidence-based technological and policy interventions to support climate-resilient production systems among smallholder farmers in SSA.

2 Materials and methods

2.1 Study area

Uganda is a country located in East Africa. This study was conducted in three districts in south-western Uganda—Isingiro, Rubanda, and Rubirizi (Fig. 1), representing the Southern drylands (SD), Southern highlands (SH), and Western highlands (WH) AEZs, respectively [51]. These districts experience a predominantly tropical climate, with a bimodal rainfall distribution. The first, also known as the long rains season, runs from March to May (MAM), while the second, also referred to as the short rains season, runs from September to November (SON)

Fig. 1 Map showing the study districts and sub-counties



[23, 52, 53]. Nevertheless, the districts differ in several biophysical and livelihood characteristics (Table 1). Isingiro district is a relatively dry area and frequently experiences high levels of water stress [54]. Rubanda, one of Uganda's highland districts, experiences a montane climate with cooler temperatures and higher humidity due to its high elevation [55, 56]. Rubirizi district lies along the uplifted border of the East African Rift Valley, and it experiences relatively humid conditions at higher elevations and drier conditions in the lowland rift valley area [57, 58]. Based on the relative moisture availability for agricultural production, Isingiro represents a water-stressed AEZ, Rubanda a humid AEZ, and Rubirizi a moderately humid AEZ [54]. Subsistence agriculture is the primary livelihood for rural communities across the three districts. Key staple crops include maize, bananas, Irish potatoes, and beans [49, 59, 60]. These districts have been exposed to several climate-related hazards, including droughts, floods, and landslides, with the latter more pronounced in Rubanda district, negatively affecting crop production [61]. These conditions make these districts suitable case studies for this research.

2.2 Sampling strategy and data collection

This study employed a quantitative research design based on a cross-sectional survey of smallholder farmers sampled across the three districts through a multi-stage probability sampling procedure. In each district, consultative meetings were conducted with the district technical teams to identify the study sub-counties and parishes. Two sub-counties per district were purposively selected (Fig. 1), and within these, three parishes were selected. The criteria for selection included the existence of a large population of smallholder farmers, predominance of crop farming systems, and the historical occurrence of climatic hazards. Within each parish, three villages were randomly selected from the lists provided by the sub-county agricultural officers through the lottery method [62]. Eighteen [18] villages were selected for each AEZ, and the total number of villages covered by the study was 54.

The sample size was calculated from the population of smallholder farmer households in the respective sub-counties [63]. The sample size determination formula described by [64] was used:

$$n = N/1 + N(e)^2 \quad (1)$$

where n = Sample size, N = Population size, 1 = Constant, e = Level of precision (10%).

Table 1 Biophysical and livelihood characteristics of the study districts

Aspect	Isingiro	Rubanda	Rubirizi
Mean annual rainfall (mm) ^{bg}	1200	1300	1233
Mean monthly temperature (°C) ^{ceg}	17–30	11–24.4	13–30
Altitude range (m a.s.l.) ^{ceg}	1200–1810	1200–3000	900–1860
Soil types ^{bdf}	Clayey, laterite loam, and sandy	Clay-loam, peat clay, and alluvium peats	Sandy-clay-loam
Total area (km ²) ^{ceg}	2,655.6	660.2	985
Population ^h	635,077	249,454	168,211
Population density (persons km ⁻²)	239.1	377.8	170.8
Population in subsistence agriculture (%) ^a	78.5	82	78.8
Major crops ^a	Banana, beans, coffee maize, sweet potato	Irish potato, beans, maize sweet potato, sorghum	Banana, coffee, maize sweet potato, beans
Major livestock ^{ag}	Cattle, goats, and pigs	Cattle, goats, sheep, and pigs	Cattle, goats, and pigs
Average land size owned (ha) ^a	1.2	0.5	1.2
Major climatic hazards ⁱ	Drought, floods, strong winds, hailstorms	Landslides, floods, hailstorms, and strong winds	Floods, drought, hailstorms, and strong winds

Source: ^a49, ^b54, ^c55, ^d56, ^e57, ^f58, ^g59, ^h60, ⁱ61. Population density was computed as a ratio of the total district population to the total district area

A total sample of 583 respondents was obtained, where 194 respondents were considered for Isingiro, 196 for Rubanda, and 193 for Rubirizi district. To select the actual respondents, sampling frames that contained all smallholder farmer households in the study area were obtained from the village leaders. Specific respondents considered for the study—those who had been residents in the area and had farming experience of more than 10 years, were selected through a random number generator using the Microsoft Excel RAND function. These were contacted in advance by the village chairpersons.

Six enumerators, fluent in the communities' local language (Runyankole-Rukiga) and with experience in conducting household interviews, were trained. The enumerators pre-tested the questionnaire, which was uploaded in SurveyCTO App, with 30 randomly selected non-targeted farmers in Isingiro district to ensure clarity of the questions. The main survey involving actual individual household interviews was conducted between January 2024 and March 2024. The average duration of the interview was three hours. In appreciation of the time committed to the survey, respondents were immediately compensated with a modest amount of Uganda Shillings 10,000 ($\approx$ \$ 2.6).

2.3 Study variables

2.3.1 Socio-demographic variables

The survey collected information on the social-demographic characteristics of households in the year 2023, as control variables impacting farmers' cropping decisions. These included household size, age of each household member, and their gender, education, marital status, main occupation, income sources, and farming experience. Household generic aspects like land owned and cultivated, rented land cultivated, number of plots cultivated, household assets (other than land), distance to the nearest market—proxied by the minutes taken to walk to the market, use of hired labor, access to agricultural information, and membership in a community group were also recorded.

2.3.2 Climate variability perception variables

This study used rainfall and temperature characteristics, as perceived by the farmers, as proxy indicators for climate variability. The assessment time-frame was the last 10 years (2013–2023), with differentiation between the MAM and SON rainfall seasons. The variables included perception of rainfall onset, rainfall consistency, rainfall amount, rainfall cessation, and hotness or coldness of each season, measured on a 5-point item-specific Likert scale (Table 2).

2.3.3 Crop variables

Data were collected on all crops grown by the household on each plot in 2023. The proportion of land allocated to each crop on each plot—reported subjectively using farmers' commonly used units: yard (20 m $\times$ 60 m) and

Table 2 Item-specific 5-point Likert scale response options for climate variability indicators

Likert scale	Response options for each climate variability perception indicator				
	Rainfall onset	Rainfall consistency	Rainfall amount	Rainfall cessation	Seasonal temperatures
1	Very late	Very inconsistent	Highly insufficient	Significantly ends earlier than expected	Extremely hotter than expected
2	Late	Inconsistent	Insufficient	Ends earlier than expected	Hotter than expected
3	On time	Neutral	Neutral	Neutral	Neutral
4	Early	Consistent	Sufficient	Ends later than expected	Cooler than expected
5	Very early	Very consistent	Highly sufficient	Significantly ends later than expected	Extremely cooler than expected

acre (40 m × 100 m) was also documented. Data for annual crops were collected separately for the MAM and SON seasons. For perennial crops, cropland allocation was recorded during the MAM season only because these crops occupied the same plot area in each cropping season. Respondents provided information on harvested yield for each crop, recorded monthly or seasonally depending on the crop type. The harvested yield was disaggregated into the quantities consumed, retained as seed, fed to livestock, and sold. The local selling price for each crop was recorded. Data on crop harvests, sales, and local selling prices were used to compute agricultural income, which was subsequently incorporated into the calculation of household income per adult equivalent (IPE).

2.4 Data processing

2.4.1 Calculating household income and income per adult equivalent

This study considered household gross income, calculated as the sum of agricultural and non-agricultural income sources. Agricultural income included crop and livestock revenues from marketed products and the market value of products retained for household consumption, seed, livestock feed, and other uses, valued at local market prices. It also included revenue from the sale of trees. Seasonal harvest data were summed for the MAM and SON seasons, while for perennial crops, harvest data were aggregated based on annual harvesting patterns. Non-agricultural income included earnings from off-farm employment, transfers, rentals, savings groups, and asset sales. Income (IPE) was computed by dividing total household gross income by household adult-equivalent size [65]. Adjustments for age differences in household composition followed the individual classification by the Uganda Bureau of Statistics [60].

2.4.2 Constructing a composite climate variability perception indicator

To understand the general trend of climate variability perception, the 5-point response categories of each indicator were transformed into a more uniform 3-point Likert scale to obtain comparable scores across indicators [66, 67]. This transformation followed established approaches for rescaling and aggregating indicators into a composite index [67]. It was adopted to reflect the magnitude of deviations from expected climatic conditions on a harmonised scale, where changes in either direction impact agricultural production. Thus, options 1 and 5 in the original scale were transformed into scale 3 (Very variable), 2 and 4 into scale 2 (Variable), while 3 (Neutral) into scale 1, and remained neutral. A different form of transformation was considered for rainfall consistency. Response option 1 (Very inconsistent) was transformed into 3, option 2 (Inconsistent) into 2.5, option 3 (Neutral) into 2, option 4 (Consistent) into 1.5, and option 5 (Very consistent) into 1. This transformation ensured that higher scores were assigned to response options that depicted variability in climate conditions and lower scores to options that reflected more stable conditions.

Following scale transformation, internal consistency of the transformed indicators was tested using McDonald's omega total composite reliability measure ($\omega_t = 0.79$). McDonald's omega was used because it is flexible and provides a more reliable estimate of reliability in cases where indicators of the latent construct do not yield equal factor loadings, a strict assumption under Cronbach's alpha [68, 69]. A composite climate variability perception indicator was constructed for each season by generating mean values of the transformed variables for the MAM and SON rainfall seasons separately [70, 71].

2.4.3 Quantifying crop diversification

This study used a diversity index to quantify households' crop diversification. Shannon–Wiener's diversity index was used due to its strength in capturing both crop richness and the relative abundance of each crop based on cultivated area in a single measure [45, 72, 73]. Shannon–Wiener's diversity index is calculated using the following formula:

$$H' = - \sum p_i \cdot \ln p_i \quad (2)$$

where H' = Shannon–Wiener’s diversity index, and p_i = proportion of the area allocated to crop i out of the total cultivated area, and $\ln$ denotes the natural logarithm.

Additionally, the crops grown were categorised into seven categories: Banana (*Musa spp*), legumes, cereals, tubers, beverages, fruits, and vegetables [74]. The aggregate areas allocated to each crop category were computed as the outcome variables for analysing how smallholder farmers’ climate variability perception influenced cropland allocation. The Shannon–Wiener diversity index and cropland allocation were computed separately for the MAM and SON seasons, where the proportion of land allocated to perennial crops was held constant across seasons.

2.5 Data analysis

2.5.1 Descriptive and inferential statistics

Data analysis was performed using Stata software (version 17) for descriptive and inferential statistics and R (4.3.0, 2023-04-21) for graphical summaries. Before analysis, all variables were screened for completeness. No missing observations were identified in any of the variables included in the analyses. Chi-square tests were applied to examine associations between categorical variables across AEZs. Differences in climate variability perception and crop diversification between seasons were analysed using the Wilcoxon signed-rank test. A Kruskal–Wallis test was conducted to identify significant differences across AEZs, and where detected, pairwise comparisons were performed using the Mann–Whitney U test.

2.5.2 Estimating the influence of climate variability perception on crop diversification: empirical model

This study employed the correlated random effects (CRE) model [75], to examine the influence of climate variability perception on crop diversification across seasons and AEZs. The CRE approach was selected because it simultaneously estimates the effects of time-varying and time-invariant household characteristics, while accounting for unobserved household-specific factors that may be correlated with the explanatory variables [76, 77]. In the CRE model, the household-level means of time-varying variables and their deviations from these means are modelled in a single regression, enabling simultaneous estimation of within-household and between-household effects. In this study, the within-household effect captures how seasonal changes in climate variability perception influence crop diversification within the same household. The between-household effect reflects how differences in average climate variability perception levels across households are associated with differences in crop diversification. The CRE model was estimated with the following formula:

$$Y_{it} = \beta_0 + \beta_1 TV_{it} + \beta_2 V_i + \beta_3 TIV_i + \varepsilon_{it} \quad (3)$$

where Y_{it} is the crop diversity index for household i in season t . TV_{it} is the vector of time-varying variables, including the season-specific composite climate variability perception indicator, the cultivated area, the number of plots cultivated, and hired labor. V_i captures the means of the time-varying variables for household i , TIV_i captures the time-invariant socio-demographic variables for household i . β denotes the estimated coefficients, and ε_{it} captures the error term. All continuous variables were standardised to facilitate comparison of the estimated coefficients. Before model estimation, multicollinearity among explanatory variables was assessed using variance inflation factors (VIF). All variables that showed VIF values below 3, indicating no evidence of multicollinearity, were considered in the model [78].

Since the crop diversification indices were lower-bounded at zero, where zero values represented households that cultivated only one crop in a given season, the CRE regression was estimated with a Tobit model [79]. The Tobit model accounts for the lower-bound nature of the dependent variable. Its suitability was further assessed

using a likelihood-ratio test to verify the model assumptions regarding the constant variance of the error terms [80]. Tobit model is presented by the following equation:

$$Y_{it}^* = X_{it}\beta + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma^2) \quad (4)$$

where $Y_i = 0$ if $Y_{it}^* \leq 0$ and $Y_i = Y_{it}^*$ if $Y_{it}^* > 0$.

Y_{it}^* = Latent (unobserved) crop diversification index for household i and season t .

X_{it} = Vector of predictor variables for household i and season t .

β = Vector of coefficients for the predictor variables.

ε_{it} = Error term, assumed to be normally distributed with mean 0 and constant variance.

Y_i = Observed crop diversification index for household i .

2.5.3 Estimating the influence of climate variability perception on cropland allocation

This study applied the Seemingly Unrelated Regression (SUR) model [81] to examine the influence of climate variability perception on cropland allocation across the broad crop categories recorded. SUR is suitable for this analysis because it jointly estimates separate regression equations for each crop category while accounting for correlations among their error terms. This approach establishes how unobserved household-level factors may simultaneously influence the proportions of land allocated to different crop categories. To assess whether the effect of climate variability perception on cropland allocation differed across AEZs, interaction terms between climate variability perception and AEZ were included in the model. A bootstrap approach (1,000 replications), which is robust to violations of normality, was applied to correct for the skewed distribution of land allocation across crop categories to obtain robust statistical inferences [82]. The estimated SUR is presented in Eq. 5:

$$Y_{it} = \beta_0 + \beta_1 CV_{ij} + \beta_2 AEZ_{ij} + \beta_3 (CV_{ij} \times AEZ_{ij}) + X_{ij}\beta_j + \varepsilon_{ij} \quad (5)$$

where: for household i and crop category j , Y represents the percentage of land allocated to a crop category, CV represents the composite climate variability indicator, AEZ represents the agro-ecological zone, $CV \times AEZ$ represents their interaction, X is the vector of control variables described in Eq. 3, β represents the estimated coefficients, and ε is the error term.

To facilitate interpretation of the interaction terms, marginal effects (ME) were estimated to quantify the effect of climate variability perception on cropland allocation for each AEZ [83, 84]. The main effect of climate variability perception represented its effect in the reference AEZ, while the interaction terms indicate how this effect differed across the other AEZs. Wald χ^2 tests were conducted to assess the statistical significance of the estimated marginal effects and determine whether the effects differed significantly across AEZs. Marginal effects were estimated as linear combinations of the coefficients in Eq. 5 and were computed using Eq. 6 below:

$$ME_{AEZ_n} = \beta_1 + \beta_3 (AEZ_n) \quad (6)$$

where n is the respective agro-ecological zone.

3 Results

This section reports the empirical findings of the study. Descriptive statistics of the socio-demographic profile of the sampled households, patterns of climate variability perception, and crop diversification are presented. It further presents the CRE and SUR analyses assessing how climate variability perception among smallholder farmers in south-western Uganda influences crop diversification and cropland allocation.

3.1 Socio-demographic profile of the sampled households

Table 3 presents the socio-demographic profile of the sampled households. The average household size was 5.4 persons. The mean age of household heads was 51.5 years; most were male, had attended primary school as their highest level of education, and the majority were married. The average annual gross income (IPE) was UGX 1.9 million ($\approx$ 530 USD). Crop farming was the main occupation for most households. Households owned an average of 1.6 acres (0.65 ha), while the average area cultivated was 1.7 acres, including rented land. Access to agricultural information was high, and membership in community groups was also common.

Overall, the socio-demographic profile of respondents was broadly similar across AEZs, although slight differences were evident. Crop farming as the main livelihood activity was most prevalent in WH; average household

Table 3 Socio-economic and farm characteristics of the study households for the pooled sample and by agro-ecological zone

Continuous variables	Mean (standard deviation)				Statistical tests
	Pooled sample (n = 583)	SD (n = 194)	SH (n = 196)	WH (n = 193)	Kruskal–Wallis test
Household size	5.4 (2.1)	5.5 ^a (2.1)	5.0 ^b (1.8)	5.6 ^a (2.3)	**
Age (years) of HHH	51.5 (13.2)	50.9 (13.0)	52.8 (13.4)	50.8 (12.8)	ns
Farming experience (years)	26.9 (13.5)	26.4 ^a (13.1)	29.8 ^b (14.4)	24.7 ^a (12.5)	***
Land size owned (acres)	1.6 (1.0)	1.7 (1.1)	1.6 (1.1)	1.5 (1.0)	ns
Total area cultivated (acres)	1.7 (1.1)	1.9 ^a (1.1)	1.5 ^b (1.1)	1.8 ^a (1.1)	****
Number of plots cultivated	2.7 (1.3)	2.3 ^a (1.2)	3.4 ^b (1.4)	2.5 ^a (1.1)	****
Proportion of plots rented (%)	14.2 (22.3)	18.6 ^a (24.6)	6.0 ^b (15.0)	18.0 ^a (23.8)	****
Gross annual income–IPE (million SHS)	1.9 (2.0)	2.1 ^a (1.8)	1.8 ^b (2.1)	1.7 ^b (1.9)	****
Distance to the nearest market (minutes)	80.1 (64.0)	81.9 (60.3)	79.4 (66.1)	78.9 (65.7)	ns
Altitude (m)	1577.2 (425.7)	1449.9 ^a (177.5)	2110.0 ^b (153.2)	1163.9 ^c (126.1)	****
Categorical variables	Percentage (frequency)				Chi-square test
Gender of HHH					ns
Male	73.4 (428)	73.2 (142)	75.5 (148)	71.5 (138)	
Female	26.6 (155)	26.8 (52)	24.5 (48)	28.5 (55)	
Education of HHH					ns
No formal education	26.0 (151)	27.8 (54)	25.0 (49)	24.9 (48)	
Primary level	56.4 (329)	55.7 (108)	53.1 (104)	60.6 (117)	
Secondary level	13.0 (76)	12.4 (24)	15.8 (31)	10.9 (21)	
Above secondary level	4.6 (27)	4.1 (8)	6.1 (12)	3.6 (7)	
Marital status of HHH					ns
Married	73.6 (429)	73.2 (142)	76.0 (149)	71.5 (138)	
Widow/Widower	21.4 (125)	21.1 (41)	21.4 (42)	21.8 (42)	
Separated	5.0 (29)	5.7 (11)	2.6 (5)	6.7 (13)	
Occupation of HHH					****
Crop farming	66.4 (387)	68.0 ^a (132)	56.1 ^b (110)	75.1 ^a (145)	
Mixed farming	27.4 (160)	29.4 ^a (57)	36.2 ^a (71)	16.6 ^b (32)	
Off-farm self-employment	4.0 (23)	2.1 (4)	4.1 (8)	5.7 (11)	
Other forms	2.2 (13)	0.5 (1)	3.6 (7)	2.6 (5)	
Households that rented in land	32.1 (187)	39.7 ^a (77)	16.4 ^b (33)	39.9 ^a (77)	***
Households that rented out land	3.1 (18)	2.1 ^a (4)	1.5 ^b (3)	5.7 ^c (11)	*
Households that used hired labor	35.5 (207)	25.8 ^a (50)	47.5 ^b (93)	33.2 ^a (64)	****
Access to agricultural information	91.8 (535)	92.3 ^a (179)	95.4 ^a (187)	87.6 ^b (169)	**
Membership in a community group	93.4 (545)	97.9 ^a (190)	96.4 ^a (189)	86 ^b (166)	****

Asterisks *, **, *** and ****, represent significance levels; $p < 0.1$, $p < 0.05$, $p < 0.01$ and $p < 0.001$ respectively. ns represents non-significant differences

Different superscript letters within a row indicate statistically significant pairwise differences, and values sharing the same letter in the same row are not significantly different

HHH represents household head. SD denotes Southern drylands, SH, Southern highlands, and WH, Western highlands agro-ecological zones; n represents the number of households

Fig. 2 Smallholder farmers' responses for their perception of rainfall onset (a), rainfall consistency (b), rainfall amount (c), and rainfall cessation (d) in the MAM and SON rainfall seasons

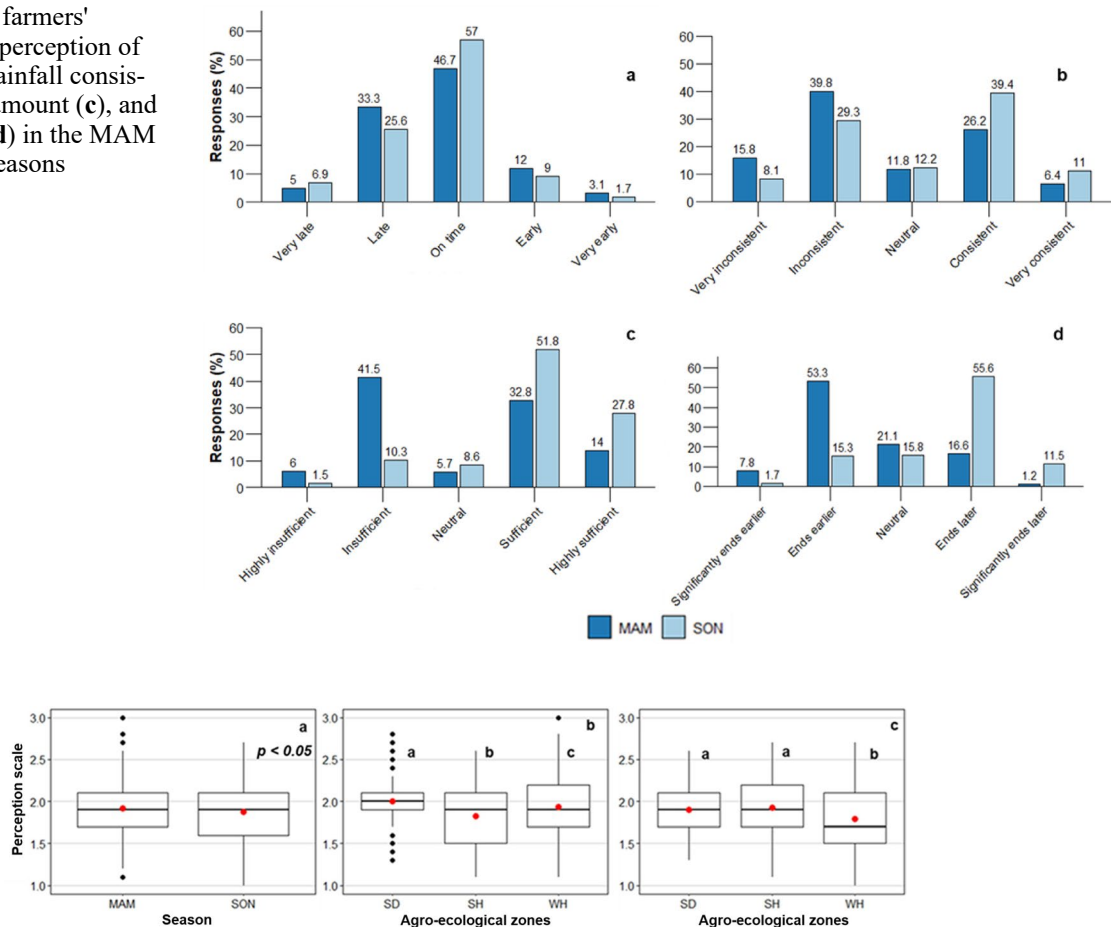


Fig. 3 Boxplots of composite climate variability perception indicators by season (a), perception by agro-ecological zones for the MAM season (b), and for the SON season (c). The horizontal lines represent the median perception score, while the red dots represent the mean perception score. Boxes sharing the same letters are not significantly different. SD denotes Southern drylands, SH denotes Southern highlands, and WH denotes Western highlands

income was higher in SD; and access to agricultural information and community group participation were comparatively lower in WH. These findings suggest that, despite the generally similar socio-demographic characteristics of households across AEZs, differences in livelihood dependence, economic capacity, and institutional support may influence how farmers adopt crop diversification as an adaptation strategy to perceived climatic risks.

3.2 Climate variability perception across seasons and agro-ecological zones

Climate variability perception among smallholder farmers manifested in different ways across the MAM and SON seasons (Fig. 2) (detailed results of rainfall and temperature characteristics are presented in electronic supplementary material (ESM) 1). While rainfall onset was perceived as timely in both seasons, other indicators showed contrasting patterns. In the MAM season, rainfall was perceived as inconsistent, insufficient, and ending earlier than expected, while in the SON season, it was viewed as more consistent, sufficient, and ending later than expected. Seasonal temperatures were perceived to be hotter in the MAM season but stable in the SON season. These seasonal differences were statistically significant ($p < 0.05$), with the MAM season depicting a more climatically variable pattern than the SON season (Fig. 3a). These findings indicate that the MAM season

is perceived to be characterised by more erratic climatic conditions, posing higher risks for crop production, whereas the SON season is relatively stable.

Across AEZs, climate variability perception among smallholder farmers showed both similar and contrasting patterns (ESM 1), but generally, values of the composite climate variability perception indicators differed significantly across AEZs in both the MAM and SON seasons ($p < 0.05$). In the MAM season, farmers in SD showed the greatest climate variability perception, while those in SH showed the lowest (Fig. 3b). In the SON season, climate variability perception was comparatively greater in SD and SH, and this was significantly greater than in WH (Fig. 3c). These patterns indicate that climate variability perception among smallholder farmers is spatially differentiated, influenced by agro-ecological differences in climatic conditions.

3.3 Crop diversification patterns across seasons and agro-ecological zones

This study recorded 36 crop types grown by smallholder farmers (ESM 2). Characterisation of the recorded crops into crop diversity indices revealed significant seasonal and spatial differences in crop diversification ($p < 0.05$). Crop diversification was significantly higher in the MAM season than in the SON season (Fig. 4a). Across AEZs, SD and WH showed similar levels of crop diversification in the MAM season, both significantly higher than in SH (Fig. 4b). In the SON season, crop diversification differed significantly across all AEZs (Fig. 4c). These significant seasonal and spatial differences in crop diversification suggest that crop diversification patterns in south-western Uganda are shaped by both seasonal and agro-ecological variation in production environments.

3.4 Crop diversification and the influence of climate variability perception

Table 4 presents the results of the CRE model that assessed whether the observed patterns of crop diversification were influenced by climate variability perception. Results from the pooled sample showed that climate variability perception among smallholder farmers in south-western Uganda did not significantly influence crop diversification. However, at the AEZ level, the influence was marginally significant in SD, highly significant in SH, and moderately significant in WH, as reflected in the within-household and between-household effects. The absence of a significant pooled association compared with the AEZ-specific results implies that the direction and magnitude of the associations differed across AEZs, revealing that the relationship between climate variability perception and crop diversification is spatially heterogeneous.

In SD, a positive but marginal within-household effect was observed. These findings suggest that farmers in SD may have responded to greater climatic risks in a season they perceived as more climatically variable by growing a more diversified crop portfolio. In contrast, SH exhibited a strongly significant negative within-household effect, indicating that when climatic variability was perceived to be greater in a particular season, farmers tended to reduce the number of crops grown. However, SH also exhibited a strongly significant positive between-household effect, indicating that households with consistently greater climate variability perception

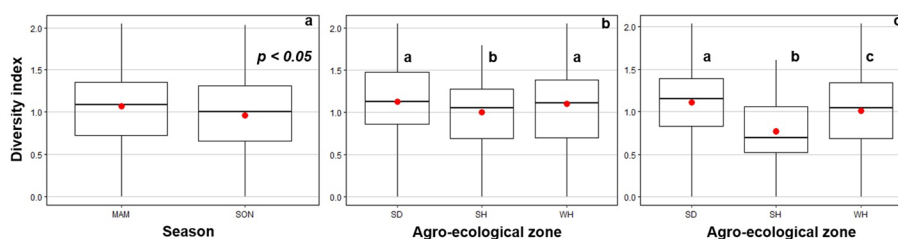


Fig. 4 Boxplots of Shannon–Wiener’s crop diversity indices by season (a) by agro-ecological zones (AEZs) for the MAM season (b), and for the SON season (c). The horizontal lines represent the median crop diversity index, while the red dots represent the mean crop diversity index. Boxes sharing the same letters are not significantly different. SD denotes Southern drylands, SH denotes Southern highlands, and WH denotes Western highlands

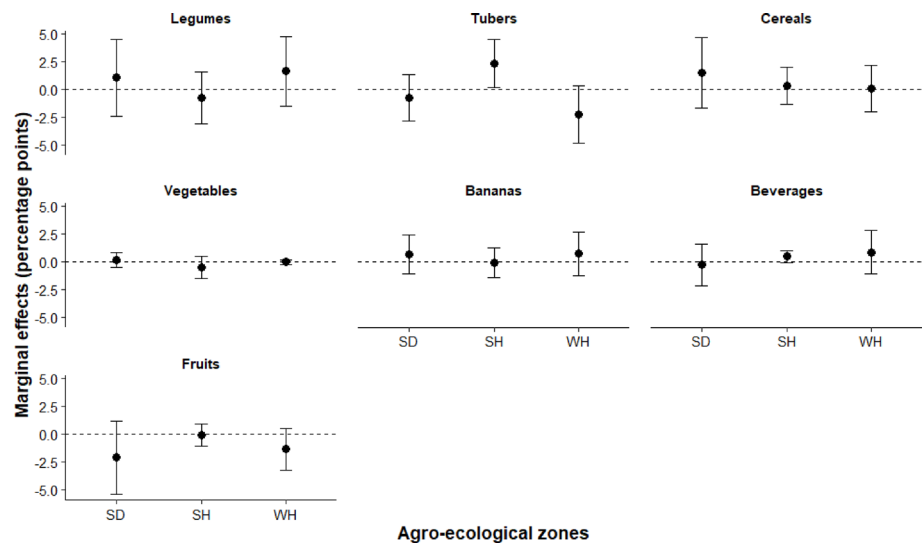
Table 4 Influence of climate variability perception and households' socio-demographic factors on crop diversification: Pooled and AEZ-specific CRE estimates

Predictors	Main predictors	Pooled coefficients (Robust std. errors)	Coefficients (Robust std. errors) by AEZ		
			SD	SH	WH
Continuous variables	Climate variability perception ^w	−0.016(0.014)	0.039*(0.022)	−0.084*** (0.030)	0.000(0.018)
	Climate variability perception ^b	0.005(0.022)	−0.039(0.040)	0.128*** (0.038)	−0.078** (0.031)
	Household size	−0.009(0.015)	−0.001(0.027)	−0.012(0.024)	−0.002(0.022)
	Age	−0.031** (0.015)	−0.034(0.029)	0.005(0.020)	−0.048* (0.025)
	Income PAE	0.049*** (0.016)	0.006(0.032)	0.072*** (0.021)	0.054* (0.028)
	Area cultivated ^w	0.421*** (0.025)	0.465*** (0.035)	0.376*** (0.049)	0.378*** (0.039)
	Area cultivated ^b	−0.257*** (0.025)	−0.343*** (0.039)	−0.242*** (0.048)	−0.190*** (0.038)
	Plots cultivated ^w	0.013(0.023)	−0.044(0.029)	0.007(0.066)	0.051* (0.030)
	Plots cultivated ^b	0.035(0.029)	0.125*** (0.045)	0.050(0.069)	−0.084** (0.043)
	Distance to the nearest market (minutes)	0.023(0.013)	0.070** (0.027)	−0.020(0.019)	0.050** (0.021)
Categorical variables					
Gender	Male	0.079(0.065)	0.127(0.116)	−0.012(0.121)	0.046(0.088)
Education level	Primary level	0.017(0.036)	0.019(0.063)	0.105** (0.053)	−0.015(0.056)
	Secondary level	−0.035(0.053)	0.020(0.103)	−0.018(0.072)	0.028(0.086)
	Above secondary level	0.032(0.077)	−0.020(0.148)	0.046(0.102)	0.058(0.131)
Marital status	Widow or widower	0.068(0.071)	0.201(0.126)	−0.042(0.124)	−0.087(0.099)
	Separated	0.009(0.083)	0.120(0.147)	−0.205(0.168)	−0.040(0.109)
Occupation	Mixed farming	−0.091*** (0.033)	−0.194*** (0.060)	−0.063(0.042)	0.000(0.061)
	Off-farm self-employment	−0.201*** (0.074)	−0.182(0.195)	−0.235** (0.099)	−0.164(0.097)
	Other forms	−0.071(0.098)	−0.468(0.359)	0.091(0.113)	−0.226(0.138)
Use of hired labor	Hired labor (Yes) ^w	0.075* (0.045)	0.030(0.071)	0.124(0.090)	0.051(0.058)
	Hired labor ^b	0.001(0.059)	0.155(0.114)	−0.157(0.102)	0.158* (0.085)
Sources of agricultural information	Extension officers	0.020(0.034)	−0.028(0.062)	0.127** (0.051)	0.005(0.052)
	Fellow farmers	0.022(0.033)	−0.022(0.062)	−0.016(0.049)	0.057(0.050)
	Television	−0.099** (0.049)	−0.157* (0.086)	−0.109(0.089)	−0.109(0.068)
	Radio	0.018(0.031)	−0.043(0.055)	0.034(0.045)	0.018(0.050)
	Agricultural exhibitions	−0.077(0.075)	−0.010(0.127)	−0.319** (0.159)	0.027(0.101)
	Printouts	0.187(0.154)	−0.117(0.284)	0.119(0.201)	0.927*** (0.301)
	Training	−0.041(0.029)	0.020(0.052)	−0.046(0.043)	−0.091** (0.045)
	Phone	−0.096(0.069)	−0.142(0.114)	−0.210(0.165)	−0.110(0.093)
Social network	Group membership	0.037(0.060)	0.040(0.180)	−0.098(0.105)	0.011(0.069)
AEZ	SH	−0.201*** (0.042)	—	—	—
	WH	−0.058(0.036)	—	—	—
	Constant	1.434*** (0.107)	1.589*** (0.242)	1.407*** (0.179)	1.273(0.131)
Model summary	Wald χ^2	498.23***	232.14***	167.70***	287.20***
	Observations (N)	1166	388	392	386

Asterisks *, **, *** and ****, represent significance levels; $p < 0.1$, $p < 0.05$, $p < 0.01$ and $p < 0.001$ respectively. Superscript w denotes the within-household (seasonal) effect, b denotes the between-household effect. SD denotes Southern drylands, SH, Southern highlands and WH, Western highlands agro-ecological zones (AEZs). In the pooled sample, SD is the reference AEZ

maintained more diversified cropping systems across seasons. In WH, the moderately strong and significant negative between-household effect indicates that households with consistently greater perception of climate variability opted to specialise in fewer crops over time. Overall, these findings suggest that crop diversification and crop specialisation are plausible responses to perceived climatic risks among smallholder farmers across AEZs, reflecting season-specific coping and longer-term adaptation strategies.

Fig. 5 Marginal effects of climate variability perception on cropland allocation across crop categories and agro-ecological zones. Points show estimated marginal effects, error bars represent 95% confidence intervals, and the dashed line indicates the null effect. SD represents Southern drylands, SH represents Southern highlands, and WH represents Western highlands



3.5 Socio-demographic and institutional drivers of crop diversification

Crop diversification by smallholder farmers in south-western Uganda was also associated with several socio-economic and institutional factors, with notable differences across AEZs and with evident within- and between-household effects (Table 4). Cultivated area showed the strongest association across AEZs. The positive and highly significant within-household effect suggests that households tended to cultivate a more diversified crop portfolio in seasons when they expanded the area under cultivation. In contrast, the highly significant negative between-household effect indicates that households that consistently cultivated larger areas tended to specialise in fewer crops. Distance to the nearest market was positively associated with crop diversification in SD and WH, suggesting that households located farther from market infrastructure may have diversified their crops more. Income–IPE showed a moderately positive association in the pooled model and in SH and a marginal association in WH, indicating that households with higher income tended to diversify their crops more. Most other socio-demographic and institutional variables showed significant effects only in the pooled model or a single AEZ, indicating limited spatial influence in their association with crop diversification.

3.6 Influence of climate variability perception on cropland allocation

The results of the SUR model complement the CRE analysis by examining whether climate variability perception influenced land allocation among the crop categories that constituted the diversity index. Generally, climate variability perception exhibited limited associations with land allocation across most crop categories (ESM 3), indicating that perceived climatic risks do not generally alter household cropland allocation decisions. However, an exception was observed for tuber crops in the SH, where greater climate variability perception was associated with a 2.3 percentage-point increase in land allocated to tubers. This positive association was particularly evident during the SON season (ESM 4).

This result complements the CRE finding that greater climate variability perception was associated with lower within-household crop diversification in SH. The pattern was also consistent with the descriptive results: farmers in SH perceived the SON season as more climatically variable, while the Shannon–Wiener index indicated lower crop diversification during the same season. Taken together, these findings indicate a coherent pattern of greater specialisation in tuber production in SH rather than widespread reallocation across several crop categories.

Figure 5, presenting the marginal effects, showed that the positive association with tuber allocation was specific to SH. No significant association was observed in SD, whereas the marginal effect was negative in WH.

The post-hoc Wald test indicated a marginal difference between SH and SD ($p < 0.1$) and a significant difference between SH and WH ($p < 0.01$), suggesting spatial heterogeneity in the influence of climate variability perception on tuber crop allocation across AEZs.

Control variables also exhibited limited and crop-specific associations with cropland allocation. While a few variables, such as age, education, income, gender, and access to extension services, were significantly associated with individual crop categories, most control variables showed no significant associations across the majority of crop groups (ESM 3). Together with the generally limited associations observed for climate variability perception, these findings suggest that cropland allocation among smallholder farmers in south-western Uganda is relatively stable, with adjustments occurring only under specific production circumstances rather than as a routine response to perceived climatic risks.

4 Discussion

This study examined climate variability perception among smallholder farmers in south-western Uganda across seasons and AEZs, and how it influenced crop diversification and associated cropland allocation. The findings highlight the importance of seasonal and spatial differences in climate variability perception for understanding crop diversification and cropland allocation decisions among smallholder farmers in SSA in response to perceived climatic risks.

4.1 Perception of climate variability across seasons and agro-ecological zones

The results of climate variability perception reveal clear contrasts in how smallholder farmers in bimodal rainfall regions interpret climate variability. The long rains season of MAM is perceived as more variable, with inconsistent rainfall distribution, insufficient amount, early cessation, and higher temperature, indicating a drier and shorter growing season. In contrast, the short rains season of SON is perceived as less variable, but the late rainfall cessation suggests wetter conditions and a prolonged growing season. The uniformity in perception of early rainfall cessation in the long rains season and the late cessation in the short rains season across AEZs may reflect widespread shifts in seasonal boundaries. These perceptions align with the recorded climatological trends across East Africa, which show that the long rains season has become drier, characterised by reduced rainfall, frequent dry spells, and a shortened growing season, while the short rains season has become longer [22, 85]. This seasonally contrasted climate variability perception signals distinct climatic crop production risks, where the erratic rainfall in the long rains season may be associated with crop moisture stress and pest pressure, while prolonged rainfall in the short rains season may be linked to disease outbreaks, flooding, and post-harvest challenges [8, 19].

Across AEZs, climate variability perception was consistently greater, although the season in which it was most pronounced differed among the zones. Since AEZs represent broader and distinct climate-driven livelihood systems [26], the interpretation of the results from this study is extended beyond the studied AEZs to understanding their implications in a regional adaptation context.

In the water-stressed SD and the moderately humid WH, climate variability perception is greatest during the long rains season, which is characterised by more erratic rainfall patterns. This pattern suggests that farmers in water-stressed and moderately humid regions may be more sensitive to disruptions in rainfall patterns, where modest variability can rapidly translate into noticeable production impacts. In contrast, in the humid SH, climate variability perception is highest in the short rains season, with delayed rainfall cessation, which may imply more sensitivity to excess-moisture conditions rather than water scarcity. Similarly, studies by [29, 86] show that farmers in water-stressed regions are more sensitive to disruptions in rainfall patterns, which have been associated with immediate negative impacts on crop production compared to humid regions. These findings indicate that climate variability perception is not uniform but is shaped by localized exposure to seasonal climate stresses, bearing important implications for designing regionally specific adaptation strategies.

4.2 Crop diversification and the influence of climate variability perception

The pooled CRE estimates indicated that climate variability perception was not significantly associated with crop diversification among smallholder farmers in south-western Uganda. This absence of an overall association suggests that the relationship between climate variability perception and crop diversification is not uniform in direction and magnitude across the study area. At the AEZ level, however, the findings revealed spatial heterogeneity in the association between climate variability perception and crop diversification, with significant relationships observed in different directions across AEZs.

In the water-stressed SD, the positive marginal within-household effect suggests that smallholder farmers in those regions tend to diversify their crops slightly more, consistent with a coping mechanism for season-specific anticipated risks. Although the association was marginally significant ($p < 0.10$), it may indicate a meaningful pattern [87] in the water-stressed AEZ, where crop production is inherently sensitive to climatic variability. The observed effect size therefore warrants cautious interpretation rather than dismissal. Within this AEZ, crop diversification is more pronounced during the long rains season, which farmers perceive as more climatically variable. Under such conditions of production uncertainty, crop diversification may present a risk reduction strategy that smallholder farmers can adopt to spread production risks across multiple crops [32, 45, 88, 89].

In contrast, the humid SH exhibit a significant negative within-household effect, meaning that greater perception of seasonal variability is associated with reduced crop diversification. This pattern is particularly evident in the short rains season, which farmers perceive as more variable due to delayed rainfall cessation. In such inherently humid regions, delayed rainfall cessation may be associated with reduced diversification by exacerbating waterlogging and hindering field operations [90–92]. These conditions may encourage farmers to concentrate on fewer crop types that are better able to withstand excessive moisture conditions. In contrast, the significant positive between-household effect shows that households with consistently greater climate variability perception tend to diversify more. This pattern suggests that farmers may opt for crop diversification as a longer-term adaptation strategy to accumulated experience with climatic risks. Previous studies show that when farmers consistently anticipate recurring climate stress, they often adopt crop diversification over the long term to enhance their resilience towards climatic risks [40, 93]. Thus, while greater climate variability perception within households across seasons may constrain crop diversification, households with consistently greater climate variability perception appear more likely to adopt crop diversification as a longer-term adaptation strategy.

In the moderately humid WH, the significant negative between-household effect reveals a tendency of crop specialisation among households with persistently greater climate variability perception. As shown in ESM 2, next to banana crops, farmers in WH cultivate a relatively greater diversity of high-value perennial crops for Uganda, such as coffee, cassava (*Manihot esculenta*), cotton (*Gossypium hirsutum*), and fruit crops, especially avocado (*Persea americana*) [94]. This pattern suggests that adaptation to perceived climate variability may also occur through crop specialisation, where farmers may channel limited resources to growing high-value, climate-resilient crops [43, 95].

It is important to note that, although crop diversification is presented as a plausible adaptation strategy, its impacts are not uniformly positive for smallholder farming households. While greater crop diversification may reduce climate-induced crop losses, it can also shift production toward low-risk, low-value crops, potentially constraining household income [96, 97]. This trade-off appears more relevant in the water-stressed SD and humid SH AEZs. As shown in ESM 2, farmers in these AEZs diversify into several low-value annual crops, such as sweet potato (*Ipomoea batatas*) and vegetable crops, which are outside the nationally prioritised high-value crops, that benefit from public investment and market support [94, 98]. Similar patterns are observed in water-stressed regions in Ethiopia and Burkina Faso, where smallholder farmers respond to climatic shocks by diversifying into low-risk but low-return food crops, a pattern associated with crop-based poverty traps [45, 99].

Conversely, greater crop specialisation in climate-resilient high-value crops, as observed in the moderately humid WH, has been associated with economic returns for smallholder farming households when supported by

favorable market conditions [32]. These contrasting pathways suggest that the benefits of crop diversification depend on the climatic context and the market opportunities for smallholder production systems.

Therefore, these findings indicate that adaptation policies may be more effective if they recognise that the suitability of crop diversification and crop specialisation differs across agro-ecological contexts. Our findings reveal that crop diversification may be a more appropriate adaptation strategy in water-stressed regions, whereas strategic crop specialisation may provide greater livelihood benefits in humid and moderately humid regions.

4.3 Socio-demographic and institutional drivers of crop diversification

Besides climate variability perception, crop diversification among smallholder farmers is also associated with several socio-demographic and institutional factors. This discussion is mainly focused on drivers that showed strong and consistent associations in all or at least two AEZs, and these include cultivated area and access to markets.

In all AEZs, the significant positive within-household effect of cultivated land indicates that a seasonal increase in the land committed to crop production is associated with higher crop diversification, as farmers expand their crop portfolios when more land is available. This pattern is consistent with previous studies that also reveal that, other factors held constant, expanded arable land facilitates crop diversification to meet household welfare needs [32, 40]. However, the negative between-household effect of cultivated land suggests that households that consistently cultivate larger land areas tend to diversify less, possibly reflecting specialisation strategies to exploit economies of scale and reduce the costs of managing multiple crops [32, 39]. These temporal and long-term land allocation dynamics illustrate smallholder farmers' trade-offs between crop diversification and specialisation to realise their production goals.

In the water-stressed SD and moderately humid WH, distance to markets is positively associated with crop diversification. This pattern suggests that in such regions, limited market access may encourage subsistence-oriented risk management through on-farm crop diversification, a similar pattern documented among smallholder farmers in Sudan [100].

Importantly, most socio-demographic characteristics, including age, education, occupation, consistent engagement of hired labor, and access to agricultural information through different channels, showed inconsistent associations across AEZs. This pattern suggests that their influence on crop diversification is context-dependent and varies by local agro-ecological and livelihood conditions. Similar context-specific effects of socio-demographic characteristics on agricultural adaptation have been reported by [11, 101, 102].

4.4 Influence of climate variability perception on land allocation across crop categories

Climate variability perception showed limited associations with cropland allocation across most crop categories, indicating that its influence on land allocation was generally weak. However, disaggregated analysis by AEZ revealed that in the humid SH, greater climate variability perception is associated with increased land allocation to tuber crops, particularly in the short rains season, where delayed rainfall cessation is experienced. This pattern is consistent with an adaptive response where smallholder farmers allocate more land to the production of the higher moisture-demanding tuber crops under generally favorable growing conditions [103]. Importantly, tubers are a major source of food and income for rural communities in humid regions in SSA [49, 104, 105]. Thus, greater land allocation to tuber crops under perceived favorable climatic conditions may contribute to household food security and income stability, alongside boosting resilience to climate variability.

In contrast, in the moderately humid WH, greater climate variability perception may be associated with reduced land allocation to tuber crops. The perceived erratic and insufficient rainfall, especially in the long rains season, may be hindering farmers from engaging in greater production of tuber crops. Tuber crops are sensitive to moisture stress, especially during germination and tuber development, leading to reduced yields and quality [106,

107]. The marginal difference in the influence of climate variability perception on tuber land allocation across AEZs suggests that farmers' adaptation strategies to climate variability are heterogeneous.

Control variables showed heterogeneous associations across crop categories, with significant effects confined to particular crop groups and no variable exhibiting a consistent association across all categories. Together with the generally limited associations between climate variability perception and cropland allocation, these findings suggest that cropland allocation decisions are influenced by multiple interacting socio-economic and biophysical factors. Given the limited landholdings and competing food and livelihood objectives of smallholder farmers, major reallocations of cropland may be uncommon, with adjustments occurring only under specific circumstances.

Overall, the findings indicate that climate variability perception across seasons and AEZs influences smallholder farmers' adaptation in different ways. While crop diversification responses differed across AEZs, changes in cropland allocation were generally limited and occurred only for a specific crop category. These contrasting adaptation pathways highlight the complexity of farmers' responses to perceived climatic risks and suggest that adaptation strategies are shaped by the interaction between local climatic conditions and production constraints.

4.5 Limitations of the study

This study provides insights into the relationship between climate variability perception and crop diversification, together with the associated cropland allocation decisions among smallholder farmers. These findings should be interpreted in light of this study's limitations. First, this study relies primarily on farmers' perception to understand climate variability in the study area. While farmers' perception is crucial for understanding their lived experiences, its subjective nature may not fully align with objective climatic observations. Despite the referenced meteorological-based findings [22, 85] a comparison of farmers' perception with historical climate data would have enabled validation of subjective assessments against objective climatic observations. However, the local dataset of daily rainfall and temperature for the reference period of this study is not readily available.

Second, whereas analysis of seasonal differences in crop diversification as influenced by climate variability perception uses a longitudinal approach, this study was based on a cross-sectional design. This limits a full understanding of the trend of crop diversification and its determinants but also limits causal inference. While the analyses controlled for a range of observed household and farm characteristics, residual endogeneity arising from unobserved characteristics, such as farmers' innovativeness, risk preferences, or farm managerial ability, cannot be ruled out. These factors may influence both climate variability perception and crop diversification decisions, potentially introducing selection bias into the estimated associations. Thus, longitudinal data would enable a more robust assessment of the causal relationship between climate variability perception and crop diversification decisions.

Third, while this study focuses on crop diversification as an adaptation strategy, it does not evaluate the outcomes of such a mechanism, especially its direct contribution to livelihoods and food security. This makes it difficult to assess its effectiveness for smallholder farmers.

5 Conclusion

This study examined whether climate variability perception among smallholder farmers in south-western Uganda differed significantly across seasons and AEZs, and whether it influenced crop diversification and cropland allocation. The findings showed that climate variability perception differed significantly across seasons and AEZs. When all AEZs were considered together, climate variability perception was not significantly associated with crop diversification and showed limited influence on cropland allocation across most crop categories. However, the disaggregated analysis revealed that its influence was non-uniform and context-dependent, with heterogeneous associations across AEZs.

5.1 Main findings and scientific contributions

Climate variability perception is greater for the long rains MAM season and is mostly associated with rainfall deficits. In the short rains SON season, it is associated with prolonged rainfall. These differences shape smallholder farmers' diversification decisions differently across AEZs. In the water-stressed SD, where climate variability perception is mostly associated with rainfall deficits, smallholder farmers tend to diversify their crops more as a coping mechanism to season-specific climatic risks. In the humid SH, where greater climate variability perception is associated with prolonged rainfall, smallholder farmers reduce crop diversification in the more variable SON season, but enhance production of higher-water-demanding crops, particularly tubers. However, households in this zone, with consistently greater climate variability perception, adopt diversification as a longer-term adaptation strategy. In WH, persistently greater climate variability perception appears to encourage smallholder farmers to respond to potential production risks by specialising in a few high-value crops and limiting land allocation to tuber crops.

The absence of a significant pooled association between climate variability perception and crop diversification, together with the limited influence of perception on land allocation across most crop categories, indicates that perception alone does not universally shape adaptation decisions. Instead, it operates alongside structural factors, particularly land availability and market access. These findings advance understanding of perception-based adaptation by demonstrating that farmers' responses to climatic risks are highly context-dependent and may only become evident through disaggregated analyses across seasons and agro-ecological settings.

5.2 Policy recommendations and future research

From a policy perspective, this study presents the following recommendations. First, season-sensitive adaptation strategies are needed to enable smallholder farmers to respond to the seemingly shifting seasonal boundaries. Second, adaptation interventions that address the contrasting climatic risks across AEZs are needed. These include irrigation and soil moisture conservation interventions for water-stressed AEZs, effective drainage systems, erosion control, and investment in water-tolerant crops for humid AEZs and climate-resilient high-value crops for moderately humid AEZs. Third, extension services should provide season- and AEZ-specific guidance on balancing crop diversification and specialization to strengthen food security and income stability. This should recognise the trade-off between reducing production risks through diversification and maintaining the income potential of high-value crops. Fourth, future research should support the development and evaluation of climate-resilient crop portfolios suited to the contrasting moisture conditions across AEZs. Finally, given the important role of the size of cultivated land and market access in shaping diversification decisions, adaptation programmes should include improving farmers' access to markets and support the efficient use of available cultivated land.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s43621-026-04621-8>.

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Author contributions D.N.: Conceptualisation of the study, data collection, analysis, drafting, and revision of the manuscript. L.V., G.K.R., and M.K.: Conceptualisation and supervision of the study, and overall guidance throughout all stages of the research and manuscript development. H.B., J.N., R.W., and I.N.: Conceptualisation, critical review, and substantive revisions of the manuscript. R.M. and J.B.N.: Data analysis, critical review, and substantive revisions of the manuscript. All authors reviewed and approved the final manuscript.

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Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate This study was conducted with approval from the Research Ethics Committee of Mbarara University of Science and Technology and the Uganda National Council of Science and Technology. In accordance with these approvals, the study was carried out following the ethical principles and guidelines for the protection of human subjects of research outlined in the Belmont Report. All respondents were informed about the purpose of the study, the confidentiality of their responses, and the use of data in aggregated form. Written informed consent was obtained from all participants before data collection.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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