Understanding uptake and interrelationship of climatic agricultural innovations in rural Zambia: Evaluating seasonal climate forecast use and weather shocks

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Abstract

Due to its overreliance on rainfed agriculture, Zambia's agricultural sector is vulnerable to climatic risks. Although researchers have recommended Climate-Smart Agriculture innovations as an effective panacea to the problem, there is a nascent empirical literature supporting how seasonal climate forecast use informs the adoption of these innovations. Therefore, this study aimed to address this gap. Using the Multivariate Probit (MVP) estimation framework, the results indicate that these innovations are complementary. Additionally, demographic factors, such as household member size, age, and education, influenced adoption decisions. Other factors that have a positive impact on innovation uptake include social networking, financial inclusion, and access to extension services. Geographical and climate considerations were pivotal in shaping adoption decisions, as demonstrated by the differences in agroecological zones and climate variability, which influenced the suitability of different innovations. A shared observation of this study is that seasonal climate forecasts and financial incentives positively impact adoption. We contribute to an enhanced understanding of the factors that drive the adoption of these agricultural innovations in Zambia. In addition, the findings will inform policymakers on implementing policies geared towards interventions that encourage farmers to use complimentary portfolios through training and education programs, social networking, information dissemination, and financial inclusion.

Keywords: Climate Change, Climate Information, Climate Smart Agriculture, Sustainable Development Goals, Innovations, Economic Growth

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1. Introduction

Now more than ever, climate variability and change have severely affected agriculture and rural livelihoods across low and middle-income countries (LMICs), especially in Africa (Mulungu et al., 2021; Serdeczny et al., 2017). This is attributed to smallholder farmers' reliance on rainfed agriculture, low welfare levels, poor institutional arrangements, and a lack of early warning systems, making it challenging to manage extreme weather outcomes (Lohmann & Lechtenfeld, 2015; Nguyen et al., 2018; Trisos et al., 2022). With over 55% of the labor force absorbed in agriculture, rural livelihoods remain threatened (Trisos et al., 2022). Thus, providing climate information (CI), such as demand-driven seasonal climate forecasts, could assist smallholder farmers in responding to climate risks and curb food and nutrition insecurity more effectively (Zougmoré & Ndiaye, 2015). Climate information is a catalyst in promoting the adoption of climate smart agricultural practices which offer long term solutions for enhancing agricultural sustainability and food security under changing climate (Li et al., 2023).

In Zambia, Clarkson et al. (2021) observed that the country's demand for climate information is growing, as it underscores the importance of long-term planning and addressing immediate concerns. Through the Zambia Meteorological Department (ZMD) and other private partners, smallholder farmers in the country are empowered with access to real-time climate information to reduce their reliance on indigenous knowledge of weather forecasting, which is unreliable. This practice is envisioned to reduce farmers' welfare and resilience, and in the long run achieve sustainable development as accorded by Sustainable Development Goals one, two, eight, nine, and thirteen that address poverty, hunger, economic growth, innovation, and climate change, respectively (UNDP, 2020). Carr and Onzere (2017) noted that climate information services (CIS) have enormous potential to halt the damaging effects of climate variability and reduce vulnerability in rural farming communities. Additionally, Trisos et al. (2022) opine that demand-driven CIS, along with climate literacy, would foster households' decisions to respond to climate-induced risks by adopting climate-smart practices that would enhance the farmer's capacity to adapt to climate threats and smoothen their farm operations (Partey et al., 2020).

Providing accurate and precise climate information reduces the exposure and vulnerability of farming communities to extreme incidences of climate variability (Agyekum et al., 2022). Much as the country has demonstrated the relevance of providing climate information to farming communities, deep rooted technological and managerial aspects constrain Zambia's efforts. IFPRI (2023) notes challenges such as inadequate hydro-metrological infrastructure, funding limitations, limited technical and technological capacities, and low integration of climate change in key sectors.

The benefits of CI have been well-documented in the literature. With CI, smallholder farmers can decide on short and long term decisions such as appropriate crop choices, change planting dates, and strategize when to use synthetic and organic fertilizers (Agyekum et al., 2022; Hansen, 2023; Roudier et al., 2014; Vaughan & Dessai, 2014). Therefore, in the long run, farmers would reduce their planting time, potentially generate higher yields, and improve their livelihoods, including nutrition, because of their consistency in the decision-making process. For instance, in a study conducted in Burkina Faso on cowpea and sesame production, researchers established that enhanced access to CI contributed to the adoption of CSA, as rural farmers changed their farming locations and plot sizes, while using fewer inputs in response to climate risks (Ouédraogo et al., 2015). Additionally, the CI encourages crop and livestock diversification and the adoption of other livelihood options among rural farmers (Hansen et al., 2016; Mulwa & Visser, 2020). Mapanje et al. (2020) also showed that smallholder farmers accessing tailored CI services had higher household income in Zimbabwe.

Notwithstanding benefits of CI, there is a dearth of empirical studies linking the effects of seasonal climate forecast use to CSA adoption (Djido et al., 2021). Some studies have focused on the drivers of climate information use (Muema et al., 2018; Oyekale, 2015), and there is limited literature that attempts to connect climate information and CSA adoption. McKune et al. (2018) investigated the link between CI services, CSA practices, and household food security in Kenya and Senegal. The authors found that farmers could not directly associate their adoption of CSA practices with CI because of the high coverage of climate information services (CIS) in the study regions. In a different study based on a recursive bivariate probit (RBP) regression technique conducted in Upper West Ghana, the authors observed that the use of weather and CI services hastened the uptake of water management, pest-resistant crops, and multiple cropping practices (Djido et al., 2021). In using RBP, Owusu et al. (2020) did not establish a relationship between CI and climate change adaptation measures among smallholder farmers in the upper-west of Ghana.

However, these studies (Djido et al., 2021; McKune et al., 2018; Owusu et al., 2021) overlooked the complementarity or substitutability of CSA practices, because typical rural farmers usually use and combine more than one practice on their farmlands to handle natural resources and deal with biophysical risks (Teklewold et al., 2013). In Malawi, Mulwa et al. (2017) used a multivariate probit technique to understand barriers to adaptation to climate change, which addressed complementarity/substitutability. However, their study used self-reported drought records to capture how farmers responded to climatic effects. According to Nguyen and Nguyen (2020), such records introduce biases in analyzing smallholder farmers' coping strategies when responding to climate shocks because of their endogenous nature (self-reported records). In addition, they used a set of different adaptation mechanisms to measure farmers' responses to climate stressors. Given that there is no silver bullet when applying CSA methods because they are specific to prevailing local conditions (Sova, et al., 2018), this allows for further investigation.

Therefore, this study evaluates the influence of climate information on the adoption of CSA practices among rural smallholder farmers. Specifically, we address the following questions: First, are there discrepancies between household-reported shocks and constructed weather shocks? Second, are the CSA adoption portfolio complements or substitutes? Finally, does climate information and weather shocks influence CSA adoption in rural households among smallholder farmers in Zambia?

In this paper, our main novel contribution to the literature is as follows. Using the multivariate probit (MVP) estimation framework, this is the first study to establish the relationship between seasonal climate forecast use and different climate-smart adaptation options, which allows capturing the complementarity and substitutability of these options. This is an interesting policy issue because smallholder African farming usually focuses on maximizing land use by taking advantage of different portfolios of practices, which could complement or substitute each other to mitigate risks (Kassie et al., 2015). We depart from Mulwa et al. (2017), who establish this correlation by considering access to climate information. The household's decision to access this information does not suggest using it unless it is tailored to meet its needs (Ziervogel & Calder, 2003). Other researchers, such as Djido et al. (2021) and Owusu et al. (2021), have only focused on the causal-effect relationship between climate information use and farm adaptation options. In addition, in both studies, the types of climate information were aggregated during estimation, creating challenges in understanding the existing relationship between seasonal climate forecast use and the respective adaptation strategies. Second, we used weather data shocks to ascertain their influence on the outcomes of interest because they attenuate biases and enhance precision during estimation. We extend the existing empirical literature that compares self-records and weather data (see Mulungu & Kilimani, 2023; Nguyen & Nguyen, 2020) by further disaggregating weather shocks into drought and flood shocks to gain more insight into reporting, which could be essential in policy debates. Furthermore, no other empirical studies focusing on this theme have considered our outcome variables, thus enabling the authors to contribute to the growing literature.

The remainder of this paper is structured as follows: material and methods, results and discussion, conclusions, and recommendations.

2. Materials and Methods

2.1 Data sources, sampling techniques, and construction of weather shocks

This study used rural agricultural livelihood survey data collected by the Indaba Agricultural Policy Research Institute (IAPRI) in collaboration with the Zambia Statistics Agency (ZSA) and other partners. These data were collected in 2019, immediately after Zambia's agricultural season, and a 2010 census sampling frame was adopted. We use a stratified two-stage sampling technique, where the initial stage requires identifying the Standard Enumeration Area (SEA), the smallest administrative area consisting of at least 30 farming households. In the second phase, all listed farming households are stratified into categories A to C based on the total crop area, availability of particular crops, number of animals such as chickens, cattle, and goats, and income sources for the household. A system sampling method was then used to choose 20 agricultural farming households across the strata (A, B, and C), targeting 7,241 farming households in different study sites as indicated in Figure 1 (IAPRI, 2019).

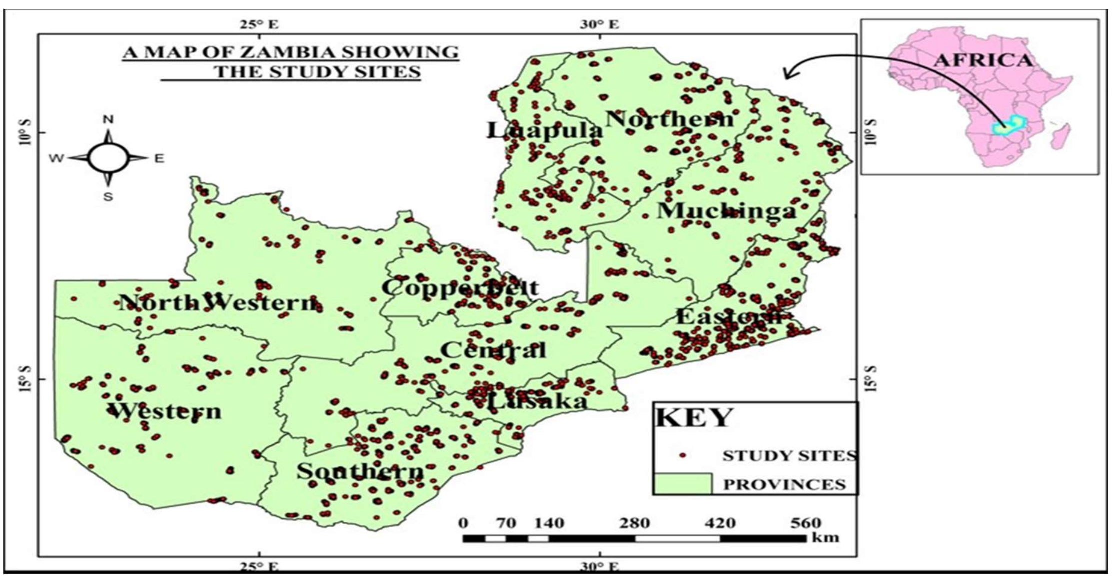

Figure 1. Distribution of the study sites

Source: Data from RALS (2019)

We merged the survey data with weather data, particularly the Climate Hazards Group Infrared Precipitation CHIRPS, using geo-referenced coordinates (GIS) to generate climate variables. Our study used satellite weather shocks because they are exogenous, whereas household-reported shocks are considered endogenous and are associated with inconsistent reporting biases (Nguyen & Nguyen, 2020). We also adapted Mulungu and Kilimani's (2023) approach to check the robustness of the constructed drought/flood shocks with household-reported shocks across farming seasons. The study generated weather shocks using the Standard Precipitation Index (SPI), as it is accurate in forecasting extreme weather occurrences and is highly associated with yields compared to other drought-monitoring indices (Mulungu & Kilimani, 2023; Vicente-Serrano et al., 2012). Since the SPI has varying time scales, we calibrated the SPI at <0.5 and >0.5, standard deviations off the 35-year long-run average to represent drought and flood risks for a specific year.

Correlation analysis was used to ascertain the disparities between respondent-reported drought/flood shocks and constructed drought/flood shocks across different seasons. To quantify the distinctions between drought or flood shocks reported by households and those we constructed, we assessed the agreement (disagreement) proportion of self-reported drought or flood shocks and constructed droughts or floods from the rainfall data. Because several tests, including the predictive (positive/negative) values, odds ratio, and kappa statistics, can be used to determine the proportion of agreement and disagreement (Nguyen & Nguyen, 2020), we used kappa statistics for its wide applicability in different fields, such as medicine and social sciences (Kennedy et al., 2010; Kriegsman et al., 1996; Mulungu & Kilimani, 2023). The test was calibrated using different scales. For example, a kappa (k) value less than 0.40 means poor-fair agreement, moderate agreement is 0.41 to 0.60, substantial agreement (0.61-0.81), near-perfect agreement is 0.81- 1, and a kappa value with a negative sign indicates disagreement (Machón et al., 2013; Mulungu & Kilimani, 2023).

2.2 Econometric estimation strategy

Agricultural households often encounter a range of CSA options to optimize land use. These options, in our case, include agroforestry (A), crop rotation (C), intercropping (I), minimum tillage (M), and drought-resistant seed varieties (D), which can be combined in various ways to maximize expected utility while mitigating risks associated with climate change. However, employing a univariate probit (logit) model involves estimating five separate probit/logit equations, disregarding the potential correlations and interdependencies among these practices. This fails to estimate the interrelationship caused by identical unobservable factors among these practices, resulting in biased and inefficient parameter estimates (Greene, 2012; Gujarati, 2015; Kassie et al., 2015). Therefore, employing a multivariate probit (MVP) model acknowledges the presence of correlated binary responses to multiple practices, enabling us to capture our CSA portfolio simultaneously (Hahn & Soyer, 2005). As a result, the MVP model helps identify complementary or substitute practices that occur when there is a positive or negative association in the equations' error terms (Khanna, 2001). Mathematically, the model is specified as:

$$\begin{aligned} y_{i1} &= \beta_1 x'_{ik1} + \varepsilon_{i1} \\ y_{i2} &= \beta_2 x'_{ik2} + \varepsilon_{i2} \\ y_{i3} &= \beta_3 x'_{ik3} + \varepsilon_{i3} \\ y_{i4} &= \beta_3 x'_{ik4} + \varepsilon_{i4} \\ y_{i5} &= \beta_4 x'_{ik5} + \varepsilon_{i5} \end{aligned} \qquad (\mathrm{k} = \mathrm{A, C, D, I, M}) \quad \ldots\ldots (1)$$

where i indexes the identification of the smallholder farmer, $y_{i1} = 1$ if the farmer used agroforestry in their plots, and 0 otherwise. $y_{i2} = 1$, if the farmer used crop rotation (0 is otherwise); $y_{i3} = 1/0$, if the farmer used a drought-resistant variety (0 otherwise); $y_{i4} = 1/0$, if the farmer practiced intercropping on their farms; $y_{i5} = 1/0$, if the farmer adopted minimum tillage (i.e., zero tillage, planting basins, and ripping); x'_i is the vector of covariates influencing the uptake of CSA portfolio; β_k denotes the vector of unidentified parameter estimates $(k = 1, 2, 3, 4, 5)$, and ε denotes the residuals.

To estimate the influence of seasonal climate forecasts on various CSA portfolios, we adapted a multivariate probit model, as specified in equation 2, to test the underlying hypothesis:

$$y_{i1} = x'_{ik}\beta_k + \varepsilon_{ik} \quad \ldots\ldots (2)$$

Where $y_{i1}(k = 1...., 5)$ reflects the five CSA portfolios adopted by the farmer, x'_{ik} shows the vector of covariates influencing the farmers' decision-making, β_k indicates the vector of unmeasured parameters, and ε_{ik} represents the residuals. This study assumes that the stochastic residuals ($k = 1...m$ options) are multivariate and normally distributed around zero, and the variance is normalized to unity, rendering the symmetric variance-covariance matrix to be specified as follows (equation 3):

$$\Omega = \begin{bmatrix} 1 & \rho_{AC} & \rho_{AI} & \rho_{AM} & \rho_{AD} \\ \rho_{CA} & 1 & \rho_{CI} & \rho_{CM} & \rho_{CD} \\ \rho_{IA} & \rho_{IC} & 1 & \rho_{IM} & \rho_{ID} \\ \rho_{MA} & \rho_{MC} & \rho_{MI} & 1 & \rho_{MD} \\ \rho_{DA} & \rho_{DC} & \rho_{DI} & \rho_{DM} & 1 \end{bmatrix}^{+} - \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

Where ρ indexes the pairwise correlation coefficients of the stochastic error terms for any paired system equations. If there is a relationship in the residuals, then the matrix's off-diagonal values will be nonzero, implying that equation 2 is an MVP model. On the other hand, if the value of ρ is positive, our CSA portfolios are complements, and the converse implies substitutes. Therefore, we use a simulated maximum likelihood approach to obtain the parameter estimates in equation 2. This study's independent explanatory variables were drawn from previous adoption studies on agriculture practices, including household characteristics (Ng'ombe et al., 2014, 2017), institutional factors (Kassie et al. 2015; Khonje et al., 2018). Other institutional factors include social network variables, which include farmer group, savings group, and kinship ties (Mulwa et al., 2017), location characteristics such as distances (Manda et al., 2015), and climatic variables such as agroecological zones, rainfall variability, and weather shocks (Ngoma et al., 2016).

3.0 Results and Discussion

3.1 Differences between self-reported shocks and satellite weather shocks

Table 1 shows the level of agreement and disagreement between self-reported drought or flood shocks and weather-constructed drought or flood risks for four consecutive agricultural seasons from to 2015/2016 to 2018/2019. The results indicate that the kappa statistics are very low for both drought and flood shocks. Our findings suggest that drought risk experiences in the 2015-2016 season had the highest level of agreement (0.0670), whereas disagreement in drought experiences was lowest at -0.0017 in the 2017-2018 farming season. On the other hand, flood shock agreement was highest in the 2018-2019 season at 0.0510 and lowest at 0.0139 during the 2015-2016 season, indicating very poor agreement between self-reported drought or flood shocks and satellite drought or flood shocks. These results suggest that there are still differences between self-reported drought or flood shocks and weather records. These findings corroborate those of Nguyen and Nguyen (2020), whose yearly and regional kappa statistics ranged between 0.03-0.13 and -0.15-0.14, respectively. In addition, Mulungu and Kilimani (2023) reported low kappa statistics after comparing majority – objectively defined shocks (0.042) with self-reported objectively defined shocks in Malawi. On the contrary, a study in medicine by Machón et al. (2013) found moderate and substantial kappa statistics ranging from 0.35 and 0.75, respectively.

3.2 Detecting the presence of multicollinearity

As part of the pre-estimation test, we tested for multicollinearity among the variables that could affect farmers' decision-making process in the model (multivariate probit). There are several techniques for detecting multicollinearity in the data, such as a higher r-squared with fewer significant t-ratios, higher pairwise corrections among the observed covariates, and high Variance Inflation factor (VIF) values exceeding an absolute value of 10 (rule of thumb) (Gujarati, 2015; Gujarati, 2003). Following Okello (2021), this study used the variance inflation factor (VIF) on continuous covariates to measure multicollinearity and pairwise correlations on dummy and/or categorical variables. As indicated in Table 2, the VIF for each observed continuous variable was less than 10, suggesting that multicollinearity among the continuous variables was absent.

Table 12: Agreement or disagreements between self-reported drought/flood shocks and constructed drought/flood shocks

Farming season		Satellite weather shocks		
Nature of shocks	Self-reported	Yes	No	Kappa
Drought 2018-2019	Yes	1,823	2,627	-0.0172
	No	1,196	1,595	
Drought 2017-2018	Yes	11	3,055	-0.0017
	No	21	4,154	
Drought 2016-2017	Yes	3	1,424	-0.0046
	No	29	5,785	
Drought 2015-2016	Yes	421	611	0.0670
	No	1,900	4,309	
Floods 2018-2019	Yes	269	799	0.0510
	No	1,192	4,981	
Floods 2017-2018	Yes	517	390	0.0348
	No	3,107	3,227	
Floods 2016-2017	Yes	428	362	0.0148
	No	3,246	3,205	
Floods 2015-2016	Yes	94	552	0.0139
	No	849	5,746	

Note: Self-reported refers to households reporting the occurrence of drought or flood shocks. Satellite weather shocks refer to drought and flood shocks generated from the SPI using rainfall data.

Kappa (k) formula: (2(hk-ij))/((h+i)(i+k)+(j+k)(h+j))

Table 13: Variance Inflation Factor (VIF) for observed continuous predictor variables

Variable	VIF	1/VIF
Age	1.04	0.96371
Household member number	3.23	0.30961
Prime age (15-59)	3.24	0.30865
Farm income	1.00	0.99819
Productive assets	1.00	0.99758
Farm size (Hectares)	1.00	0.99919
Distance to Boma (Km)	1.91	0.52238
Distance to markets (Km)	2.03	0.49287
Distance to agricultural camp (Km)	1.32	0.75894
Rainfall variability	1.01	0.99373
Mean VIF	1.68	

3.3 Variables, measurements, and summary statistics

Table 3 shows the explanatory variables used in the multivariate probit model during the analysis and how the variables were measured. In addition, it shows the summary statistics of the general sample that adopted smart climate practices. Regarding the uptake of climate smart resilient practices, 64%, 49%, 42%, 40%, and 11% of the households practiced intercropping (I), agroforestry (A), crop rotation (C), used drought-resistant seed varieties (D), and minimum tillage (M) on their farms, respectively. The results showed that most smallholder farmers used intercropping (64%), whereas minimum tillage (11%) was the least practiced among the farmers. A plausible explanation could be that intercropping is a conventional method that farmers have practiced for a long time and has become a part of their lifestyle. Smallholder farmers might also perceive intercropping as a channel to achieve food diversity, which is critical for enhancing food and nutrition security in farming households. At the same time, farmers perceive minimum tillage as a labor-intensive method, causing hurdles in adopting the practice entirely. As shown in Table 2, the average age of the households involved in agricultural activities that are climate resilient is 52 years. This is attributed to the level of experience that comes with old age in farm management. This finding is supported by Ng'ombe et al. (2017), who observed that elderly farmers embraced more conservation farming as a result of amassing adequate wealth, both socially and physically, thereby enabling them to meet their needs. Table 2 also shows that the average size of a farming household was five, and about three people were in their productive ages, suggesting that there could be scarce labor availability in rural households to execute farm management activities related to adopting these practices.

Table 14:Variables, measurements, and summary statistics for means and standard deviations

Variables	Measurement	Mean	SD
Dependent variables			
Agroforestry	1 if hh adopted A, 0 otherwise	0.49	0.50
Crop rotation	1 if hh adopted C, 0 otherwise	0.42	0.49
Intercropping	1 if hh adopted I, 0 otherwise	0.64	0.48
Drought-resistant variety	1 if hh adopted D, 0 otherwise	0.40	0.49
Minimum Tillage	1 if hh adopted M, 0 otherwise	0.11	0.32
Independent variables			
Age	Years	52.0	14.3
Household members	number	5.30	2.46
Prime age (15-59)	number	3.09	1.82
Household head education	0=none, 1=primary level, 2=secondary level, 3=college, 4=university	1.65	0.68
Household head married	1 if Married, 0 otherwise	0.76	0.43
Female head	1 if household is female, 0 otherwise	0.24	0.43
Female decision-maker	1 if female, 0 otherwise	0.086	0.28
Farm income	Zambian Kwacha	49574.6	1017261.4
Productive assets	Zambian Kwacha	45570.0	616814.1
Phone	1 if Yes, 0 otherwise	0.71	0.46
Television	1 if Yes, 0 otherwise	0.27	0.44
Access to radio	1 if Yes, 0 otherwise	0.57	0.50
Access to financial credit	1 if Yes, 0 otherwise	0.20	0.40
Farm size (Hectares)	Hectares	5.47	15.6
Agriculture extension	1 if Yes, 0 otherwise	0.85	0.36
Farmer group	1 if Yes, 0 otherwise	0.52	0.50
Savings group	1 if Yes, 0 otherwise	0.13	0.34
Kinship	1 if Yes, 0 otherwise	0.48	0.50
Distance to government offices (Km)	Kilometers	38.8	34.1
Distance to markets (Km)	Kilometers	24.1	30.7
Distance to agricultural camp (Km)	Kilometers	13.2	23.0
Agroecological zone (AEZ)	0=AEZ I, 1=AEZ II, 2=AEZ III	1.28	0.67
Use of weather forecast	1 if Yes, 0 otherwise	0.32	0.47
Rainfall variability	proportion	0.50	0.40
Drought risk$_t$	1 if Yes, 0 otherwise	0.42	0.49
Flood risk$_t$	1 if Yes, 0 otherwise	0.20	0.40
Flood risk$_{t-1}$	1 if Yes, 0 otherwise	0.50	0.50
Drought risk$_{t-2}$	1 if Yes, 0 otherwise	0.0044	0.066
Flood risk$_{t-2}$	1 if Yes, 0 otherwise	0.51	0.50
Flood risk$_{t-3}$	1 if Yes, 0 otherwise	0.13	0.34
Drought risk$_{t-3}$	1 if Yes, 0 otherwise	0.32	0.47
Sample Size (n)		7241	

Note: ZMK = Zambian Kwacha currency; \$ 1 = ZMK13.24 exchange rate at survey time.

The majority (76%) of household heads, who are primarily the main decision-makers, were married and went through formal education, mainly secondary education, implying that households with a higher level of literacy and awareness of climate resilient practices would understand, articulate, and use smart climate practices to improve their productivity and mitigate climate extremes. Gikonyo et al. (2022) provides evidence to prove that formal education had positive significant influence on adoption of CSA practices among smallholder farmers in Kenya while Asante et al. (2024) confirms that one-year increase in education of the married household head increases probability of adoption of a combination of CSAs among smallholders in Ghana.

On average, smallholder farmers have a household income equivalent to ZMK 49 574.6 and ZMK45 570.0 in productive assets. Regarding communication devices, 71%, 51%, and 27% owned phones, radio, and television, respectively. This indicates that resource-endowed households can purchase important devices for information delivery services related to smart climate practices and climate change. Regarding access to financial incentives, only 20% of smallholder households that adopted CSA had formal access to credit. Financial access enables farmers to purchase inputs, such as seed varieties with drought-resistant traits, fertilizers, and other equipment to foster their adoption of sustainable practices. Additionally, financial inclusion enables smallholder farmers to invest in more expensive practices.

The average size of cultivated land was five hectares, showing that this study targeted smallholder farmers susceptible to the changing climate. This result is confirmed by Chapoto and Chisanga (2016), who found that over 90% of smallholder farmers in Zambia possessed less than five hectares of farmland. Alidu et al. (2022) also observed that most smallholder farming households that adopted climate adaptation practices owned approximately 2 ha of cultivated land in Ghana.

Most (85%) of the farmers surveyed received extension services, which aligns with the findings of (Alidu et al., 2022; Anang et al., 2021; Anang et al., 2020), who noted that most smallholder farmers accessed extensive services on various innovative agricultural strategies to support the adoption of climate-smart practices and productivity. As suggested by Manda et al. (2016), extension services play a vital role in increasing the adoption of CSAs because they expose smallholder farmers to information related to new technologies, input delivery, and credit.
Social capital is important for spurring the uptake of agricultural innovations among smallholder farming households. Over 50% of the farmers belonged to farmer groups, and 48% and 13% were associated with kinship ties and savings groups, respectively. Kassie et al. (2013) opined that belonging to social networks is crucial in facilitating information exchange, making it easier to access farming inputs and overcome credit limitations.

The average distances to the district center (Boma), markets, and agricultural camps were 38.8 km, 24.1 km, and 13.2 km, respectively. These distances are associated with transaction costs, market access, smallholder access to new agrarian innovations, financial institutions, and information exchange (Kassie et al., 2013; Manda et al., 2015). Rainfall variability was equivalent to 50%, and only 32% of smallholder households used seasonal weather forecasts to mitigate weather shocks during the 2018-2019 season. Additionally, weather shocks ranged from 51% to 0.4% in the past four consecutive farming seasons (2018/2016 to 2016/2016).

3.4 Correlation analysis of the response variables
Rural farmers are usually faced with deciding to pursue more than one CSA practice in their agricultural activities, suggesting that a correlation exists between the CSA portfolios of their choice. Using a pairwise correlation approach, we tested for associations in the residuals of the five CSA usage equations. Table 4 shows that the seven paired correlation coefficients in the residuals of the MVP model were statistically significant, indicating that the practices were interdependent. Additionally, these results lend credence to the idea that the residuals of the CSA equations are associated. The LR test [(Chi2(10) = 435.641, Prob>chi2 = 0.000)] results of the null hypothesis of independent residuals of the five equations (minimum tillage, crop rotation, intercropping, agroforestry, and drought-tolerant seed variety) were rejected, justifying the use of the multivariate probit model rather than the univariate probit model. We also find that the coefficients are positive, indicating that the portfolios are complementary.

Table 15:Correlation coefficient parameter estimates for Multivariate Probit (MVP)

Climate Smart practices	Minimum Tillage	Crop Rotation	Intercropping	Agroforestry	Drought-Resistant seed variety
Minimum Tillage	1				
Crop Rotation	0.121***	1			
Intercropping	0.040*	0.136***	1		
Agroforestry	0.171***	0.208***	0.242***	1	
Drought-Resistant seed variety	0.017	0.001	0.010	0.038**	1

Note: *, **, and *** reflect the 10%, 5%, and 1% significance levels, respectively.

3.5 The influence of the use of seasonal climate forecast and weather shocks on the adoption of CSA practices

Table 5 shows the parameter estimates obtained by estimating the multivariate probit regression using the maximum-likelihood approach. We found the Wald test [(Wald chi2(155) = 1945.19; Prob > chi2 = 0.0000)] significant by rejecting the null hypothesis that the coefficients belonging to each regression are jointly equal to zero, implying that the model used in our study fits the data well. For robustness checks, we also estimated five separate probit equations for minimum tillage, crop rotation, intercropping, agroforestry, and drought-resistant seed variety along with the multivariate probit to confirm if the parameter estimates are similar to those of the multivariate probit.

Table 16:Determinants of CSA practices

Variables	Multivariate Probit results					Probit results				
	MT	CR	IT	AG	DT	MT	CR	IT	AG	DT
Age	0.0005	-0.0027**	-0.0022*	-0.0019*	0.0010	0.0005	-0.0026**	-0.0023**	-0.0019*	0.0010
	(0.0014)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0014)	(0.0011)	(0.0011)	(0.0011)	(.0012)
Household members	-0.0204	-0.0014	-0.0215*	-0.0080	-0.0043	-0.0207	-0.0016	-0.0210*	-0.0078	-0.0045
	(0.0148)	(0.0111)	(0.0117)	(0.0112)	(0.0117)	(0.0150)	(0.0112)	(0.0115)	(0.0111)	(0.0117)
Prime age (15-59)	0.0050	-0.0149	0.0138	0.0030	0.0181	0.0055	-0.0144	0.0135	0.0036	0.0184
	(0.0198)	(0.0154)	(0.0159)	(0.0153)	(0.0160)	(0.0206)	(0.0154)	(0.0158)	(0.0152)	(0.0160)
Education	-0.0259	-0.0430	-0.0309	-0.0626**	0.0188	-0.0282	-0.0416	-0.0319	-0.0627*	0.0195
	(0.0354)	(0.0269)	(0.0276)	(0.0265)	(0.0277)	(0.0350)	(0.0268)	(0.0276)	(0.0266)	(0.0279)
Married	0.0896	0.0959	0.0838	-0.0026	0.0293	0.0929	0.0969	0.0782	0.0060	0.0310
	(0.0834)	(0.0643)	(0.0689)	(0.0637)	(0.0664)	(0.0840)	(0.0644)	(0.0658)	(0.0641)	(0.0677)
Female head	0.1074	0.0050	0.0483	0.0279	0.0438	0.1064	0.0055	0.0443	0.0378	0.0453
	(0.0836)	(0.0641)	(0.0693)	(0.0635)	(0.0664)	(0.0829)	(0.0644)	(0.0659)	(0.0641)	(0.0677)
Female decision-maker	0.0700	0.0330	-0.0174	0.0005	-0.0199	0.0686	0.0328	-0.0201	-0.0051	-0.0202
	(0.0739)	(0.0578)	(0.0604)	(0.0577)	(0.0607)	(0.0748)	(0.0579)	(0.0596)	(0.0575)	(0.0605)
Farm income	-0.0405**	-0.0409***	-0.0240*	-0.0637***	0.0155	-0.0404**	-0.0416***	-0.0238*	-0.0631***	0.0156
	(0.0170)	(0.0136)	(0.0141)	(0.0136)	(0.0141)	(0.0177)	(0.0135)	(0.0138)	(0.0135)	(0.0143)
Productive assets	0.0250	0.0225*	0.0021	0.0357***	-0.0113	0.0238	0.0225*	0.0026	0.0352***	-0.0114
	(0.0157)	(0.0120)	(0.0125)	(0.0119)	(0.0124)	(0.0158)	(0.0120)	(0.0123)	(0.0119)	(0.0125)
Phone	0.0385	-0.0712*	-0.1371***	-0.0017	-0.0108	0.0384	-0.0715*	-0.1391***	-0.0042	-0.0110
	(0.0514)	(0.0394)	(0.0412)	(0.0392)	(0.0411)	(0.0522)	(0.0393)	(0.0409)	(0.0392)	(0.0410)
Television	0.0422	-0.0010	-0.0017	0.0155	0.0576	0.0439	-0.0039	-0.0023	0.0138	0.0568
	(0.0539)	(0.0409)	(0.0420)	(0.0408)	(0.0422)	(0.0538)	(0.0409)	(0.0423)	(0.0407)	(0.0428)
Radio	-0.0501	-0.0443	-0.0349	0.0090	0.0324	-0.0490	-0.0440	-0.0318	0.0094	0.0324
	(0.0454)	(0.0349)	(0.0363)	(0.0349)	(0.0365)	(0.0462)	(0.0350)	(0.0362)	(0.0348)	(0.0366)
Access to financial credit	0.1650***	0.1355***	0.1423***	0.1481***	-0.0950**	0.1676***	0.1360***	0.1437***	0.1490***	-0.0961**
	(0.0489)	(0.0389)	(0.0413)	(0.0390)	(0.0410)	(0.0486)	(0.0389)	(0.0413)	(0.0388)	(0.0411)
Farm size (Hectares)	0.0029***	0.0043***	-0.0041***	0.0012	-0.0018*	0.0028***	0.0045***	-0.0038***	0.0012	-0.0018*
	(0.0011)	(0.0014)	(0.0012)	(0.0011)	(0.0010)	(0.0010)	(0.0012)	(.0012)	(0.0009)	(0.0011)
Agriculture extension	0.1580***	0.2776***	0.1690***	0.1619***	0.0784*	0.1609***	0.2749***	0.1694***	0.1595***	0.0781*
	(0.0614)	(0.0447)	(0.0444)	(0.0438)	(0.0457)	(0.0622)	(0.0446)	(0.0440)	(0.0437)	(0.0461)
Farmer group	-0.0095	0.0894***	0.0800**	0.0613*	-0.0356	-0.0089	0.0897***	0.0791**	0.0618*	-0.0356
	(0.0426)	(0.0325)	(0.0335)	(0.0324)	(0.0338)	(0.0426)	(0.0325)	(0.0336)	(0.0322)	(0.0338)
Savings group	0.0589	0.0904**	0.1902***	0.0205	0.0424	0.0559	0.0945**	0.1938***	0.0295	0.0423
	(0.0596)	(0.0460)	(0.0488)	(0.0459)	(0.0483)	(0.0597)	(0.0460)	(0.0490)	(0.0460)	(0.0483)
Kinship	0.0223	0.1030***	0.0954***	0.0501	-0.0352	0.0209	0.1035***	0.0903	0.0462	-0.0350
	(0.0402)	(0.0310)	(0.0319)	(0.0308)	(0.0323)	(0.0408)	(0.0309)	(0.0320)	(0.0307)	(0.0323)
Distance to Boma (Km)	-0.0002	-0.0017***	0.0011*	0.0014**	0.00002	-0.0003	-0.0017***	0.0011*	0.0013**	0.00001
	(0.0008)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0008)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Distance to markets (Km)	0.00009	-0.0003	0.0011	-0.0019***	0.0009	0.0001	-0.0003	0.0011	-0.0018***	0.0009
	(0.0009)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0009)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Distance to agricultural camp (Km)	0.0007	0.0010	-0.0012	-0.0000	0.0021***	0.0007	0.0010	-0.0012	-0.00003	0.0021***
	(0.0010)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0010)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Agroecological zone (AEZ)	-0.1980***	0.0642***	0.0175	-0.0334	0.1100***	-0.1957***	0.0611**	0.0209	-0.0356	0.1092***
	(0.0305)	(0.0245)	(0.0255)	(0.0245)	(0.0253)	(0.0325)	(0.0249)	(0.0251)	(0.0245)	(0.0259)
Use of weather forecast	-0.0062	0.0107	0.1412***	0.0739**	0.0502	-0.0070	0.0135	0.1427***	0.0776**	0.0500
	(0.0443)	(0.0338)	(0.0355)	(0.0337)	(0.0352)	(0.0441)	(0.0338)	(0.0352)	(0.0336)	(0.0352)
Rainfall variability	-0.2433***	-0.2479***	0.3190***	0.0603	-0.2884***	-0.2419***	-0.2516***	0.3177***	0.0450	-0.2890***
	(0.0846)	(0.0660)	(0.0690)	(0.0658)	(0.0724)	(0.0910)	(0.0686)	(0.0690)	(0.0669)	(0.0709)
Drought risk$_t$	-0.1514***	-0.0514	-0.0966***	-0.2299***	-0.7482***	-0.1548***	-0.0494	-0.0988***	-0.2244***	-0.7475***
	(0.0491)	(0.0362)	(0.0372)	(0.0361)	(0.0378)	(0.0491)	(0.0365)	(0.0375)	(0.0361)	(0.0380)
Flood risk$_t$	0.0370	-0.0283	-0.2050****	-0.2491***	0.1320***	0.0429	-0.0279	-0.2131***	-0.2429***	0.1324***
	(0.0566)	(0.0448)	(0.0472)	(0.0446)	(0.0454)	(0.0571)	(0.0447)	(0.0460)	(0.0443)	(0.0446)
Flood risk$_{t-1}$	0.4043	-0.0148	-0.3427*	-0.0820	0.2416	0.4209	-0.0198	-0.3274	-0.0859	0.2455
	(0.2678)	(0.1772)	(0.2050)	(0.1805)	(0.1923)	(0.2618)	(0.1823)	(0.2092)	(0.1821)	(0.1873)
Drought risk$_{t-2}$	-0.2745	-0.3943*	-0.1536	0.1846	-0.2474	-0.2567	-0.3924	-0.1469	0.1790	-0.2474
	(0.2994)	(0.2336)	(0.2338)	(0.2370)	(0.2405)	(0.3020)	(0.2420)	(0.2380)	(0.2383)	(0.2328)
Flood risk$_{t-2}$	-0.0442	0.1717	0.2468	0.0003	-0.3027	-0.0566	0.1822	0.2310	0.0162	-0.3054
	(0.2686)	(0.1774)	(0.2052)	(0.1808)	(0.1927)	(0.2627)	(0.1826)	(0.2094)	(0.1823)	(0.1875)
Flood risk$_{t-3}$	0.2040***	-0.0782*	0.1605***	0.0527	0.2796***	0.2038***	-0.0710*	0.1638***	0.0571	0.2795***
	(0.0591)	(0.0476)	(0.0479)	(0.0468)	(0.0497)	(0.0598)	(0.0475)	(0.0477)	(0.0470)	(0.0493)
Drought risk$_{t-3}$	0.0881*	-0.0499	0.6473***	0.0889**	0.3781***	0.0842*	-0.0495	0.6487***	0.0921***	0.3788***
	(0.0473)	(0.0360)	(0.0387)	(0.0360)	(0.0370)	(0.0481)	(0.0361)	(0.0383)	(0.0359)	(0.0367)
Constant	-1.0772***	-0.0847	0.2249	0.3747**	-0.4137**	-1.0780***	-0.0810	0.2248	0.3653**	-.4160**
	(0.2162)	(0.1677)	(0.1746)	(0.1675)	(0.1734)	(0.2215)	(0.1686)	(0.1725)	(0.1673)	(0.1772)

LR test for independent equations: ρ21 = ρ31 = ρ41 = ρ51 = ρ32 = ρ42 = ρ52 = ρ43 = ρ53 = ρ54 = 0;
chi2 (10) = 435.641 Prob > chi2 = 0.0000
Wald chi2 (155) = 1945.19; Prob > chi2 = 0.0000

Note: The 10% (p<0.1), 5% (p<0.05), and 1% (p<0.01) significance levels are indexed by *, **, and ***, respectively. ρ=rho; ZMK=Zambian Kwacha currency; $1=ZMK13.24 exchange rate.

The results in Table 5 show that the household head's age had a negative and significant influence on crop rotation, intercropping, and agroforestry adoption in Zambia. This could be because crop rotation and intercropping are relatively traditional methods, and farmers are turning to newer agricultural innovations and technologies because their mindset is adaptive and not difficult to change. This result aligns with those of Hong et al. (2020) and Kassie et al. (2013), who find that younger farmers are less likely to adopt intercropping because they are risk-averse and willing to embrace improved and profitable innovations. In addition, younger farmers can provide the necessary labor to enhance productivity using improved technologies. This result contradicts the findings of Tufa et al. (2023), who found that farmer age influenced the likelihood of adopting intercropping crop rotation in Zambia, Zimbabwe, and Malawi. They noted a significant positive association between farmer's age and crop rotation in Zimbabwe and Malawi, while age and intercropping showed a significant and positive relationship in Malawi and Zambia. This is because crop rotation and intercropping are considered old practices that are part of conventional farming. For agroforestry, the high cost and the time taken to receive dividends from adopting the practices are long, and this is crucial in the farmer's decision-making regarding its adoption. However, Bandi et al. (2022) observed that farmers whose age ranges between 51-60 years more likely to adopt agroforestry in the Democratic Republic of Congo (DRC) because they were more committed to other aspects of agroforestry such as apiforestry, entomoforestry and sylvopasture which do not require drudgery.

Household size, which proxies for labor availability, negatively influences intercropping adoption, denoting that smallholder households with more family members are less likely to practice intercropping. A plausible explanation for this low adoption could be that countries like Zambia, with vast land coupled with lower population density, limit labor availability — a stand-in for high labor prices — affecting the probability of adopting CA practices, including intercropping (Ngoma et al., 2021). In addition, it could suggest that household members engage in off-farm employment or have high opportunity costs (Ngoma et al., 2016). However, Ng'ombe et al. (2017) found a positive correlation between CA and household size. They concluded that having more family members in their productive age was pivotal in carrying out CA practices that were drudgery in nature. In Zimbabwe, a similar study by Pedzisa et al. (2015) found no relationship and called for improved methods of measuring family labor. Another study that reported inconclusive results was that by Jaleta et al. (2016) in Ethiopia.

Furthermore, being an educated head of the household reduced the chances of using agroforestry. With higher levels of education, farmers can understand the concepts of various agricultural innovations and make informed decisions to embrace and use technology. This result is not in line with Bandi et al. (2022) and Nyamweya and Moronge (2019), who found that the education level of the household head positively and significantly influences the adoption of agroforestry. However, the authors further noted that formal education alone was not a necessary and sufficient condition to increase agroforestry adoption, but that providing adequate farmer training on the practice would bolster its adoption.

Table 5 displays that income negatively and significantly influences the adoption of minimum tillage, crop rotation, intercropping, and agroforestry among rural smallholder farmers. The reasonable explanation could be that smallholder farmers may perceive these options as low-level strategies and, therefore, may prefer to invest in other livelihood strategies that cushion climate-induced risks. Also, farmers may encounter other non-monetary issues affecting their cash outlays. These results are incoherent with those of Uddin et al. (2016), who finds farm income to have a positive and significant association with conservation agriculture, like minimum tillage in Bangladesh. In Zambia, Lungu (2019) observed a similar influence on crop rotation, suggesting that wealthier households adopted crop rotation. Also, Chichongue et al. (2020) and Nyamweya and Moronge (2019) revealed that better off-farm income earning households went for intercropping and agroforestry, respectively, because having more household income translated to more disposable incomes, which could be used for investments in agroforestry, including intercropping. Also, the authors added that farmers with higher earnings could purchase different agroforestry innovations and use them to diversify their livelihoods further.

As expected, we found significant positive effects of productive assets on crop rotations and agroforestry. This result departs from that of Zulu-Mbata et al. (2016), who found that households' productive assets negatively influenced the adoption of conservation agriculture. We also find that farmers with financial incentives are more likely to use CSAs. Credit access allows cash-strapped smallholder farmers to acquire farming equipment and inputs such as fertilizer and seeds. Zulu-Mbata et al. (2016) noted that both dis(non)-adoption of CSAs was largely due to farmers' liquidity challenges. Therefore, fostering loan access is crucial to scale up CSA adoption. These findings are consistent with (Ng'ombe et al., 2014; Zulu-Mbata et al., 2016). However, we observed that farmers with access to credit encountered immediate concerns rather than investing more in drought-tolerant seed varieties.

Household farm size positively and significantly influenced the adoption of minimum tillage and crop rotation. However, it reduces the likelihood of adopting intercropping and drought-tolerant seeds among smallholder farmers. Ngoma et al. (2021) and Tufa et al. (2023) observed that farm size had an indeterminate effect on CSA adoption, depending on the type of agricultural innovation. In addition, it might enable smallholder farmers with large farms to practice minimum tillage and crop rotation while maintaining or reducing the use of intercropping or drought-tolerant seeds to spread the risk of crop failure.

Extension services reflect the number of times a smallholder farmer is in contact with extension agents, and this variable is expected to have a positive influence on adoption (Manda et al., 2015). This study found that farmers' access to extension services influences CSA adoption. Thus, the farmer's frequency of contact with extension agents had a positive and significant influence on adopting all practices of interest. This suggests that farmers are exposed to information on CSA practices, input delivery, and credit access, resulting in increased adoption. These findings conform to (Anik et al., 2021; Aryal et al., 2018; Danso-Abbeam, 2022; Igberi et al., 2022; Obeng, E., A. Weber, 2014), who reported the positive influence of extension services on minimum tillage, crop rotation, intercropping, agroforestry, and drought-tolerant varieties across different countries. On the other hand, Tufa et al. (2023) found that extension services did not have a significant relationship with minimum tillage, and they attributed it to poor delivery services from extension agents and farmers' lack of confidence in their skills.

The results in Table 5 also illustrate that adopters of crop rotation, intercropping, and agroforestry were members of the farmers' associations. Those with savings group membership and kinship ties practiced crop rotations. Thus, being a member of these social groups increases their probability of using these portfolios. It is imperative to note that the coefficient of the savings group had the highest effect under intercropping because the farmers were more coordinated and had a revolving fund, making it easier to access credit to buy inputs and hire labor. As suggested by Negi et al. (2020), social networks are important enablers for delivering information related to improved technological innovations required for agricultural growth. This finding corroborates Mulimbi et al. (2019), who reported that group membership influenced CSA uptake among poor smallholder farmers and concluded that not only do these groups bring social capital, but they also serve as a basic foundation for learning, discussions, and sharing information in communities with low extension services.

Some households living in places distant from district centers and markets were less likely to adopt crop rotation and agroforestry, respectively, as this could be a result of the high transaction costs and limited access to markets that act as a source of inputs or technological innovation. For households that observed a positive and significant association between distance (i.e., distance to district centers and extension service) and the CSA practice under consideration, a plausible explanation could be that the smallholder farmers were staying closer to the district centers and extension offices and possibly could access the markets and learn from their neighbors through peer influence. This result was consistent with (Tufa et al., 2023).

Zambia's agroecological zones (AEZ) affect smallholder farmers' uptake of minimum tillage, crop rotation, and drought-tolerant seed varieties. Belonging to a particular agroecological zone other than zone one (AEZ 1) reduced the household's likelihood of using minimum tillage. At the same time, there are existing positive influences on the adoption of crop rotation and drought-tolerant varieties. Unlike crop rotation and drought-tolerant varieties, the low minimum tillage uptake indicates that the households were situated in AEZ III, which receives rainfall above 1000 mm. Minimum tillage is used cautiously in high-rainfall regions, as this practice is more suitable in stress-related conditions (World Bank, 2019). Ng'ombe et al. (2014) suggested that conservation farming (i.e., minimum tillage and crop rotation) is suitable for AEZ I and II, as these regions are associated with inadequate rainfall and frequent droughts in Zambia. In contrast, the World Bank (2019) showed that drought-tolerant seed varieties can adapt to different environments, such as dry or wet conditions, suggesting that they perform better across different agroecological zones.

Furthermore, seasonal climate forecasts potentially influence the adoption of intercropping and agroforestry. Households that used climate information were more likely to adopt these practices as their adaptation strategies because intercropping and agroforestry are important for soil health, producing diversified foods, and increasing crop yields, which are needed for sustainable agricultural growth and climate risk mitigation. The study results agree with those of Mulwa et al. (2017), who noted that households accessing climate-related information were expected to use different adaption strategies, as they underscored the importance of making climate information available to smallholder farmers. Djido et al. (2021) found similar results in Ghana. However, the findings of McKune et al. (2018) were inconclusive.

The study reported that high rainfall variability decreased the probability of adopting minimum tillage, crop rotation, and drought-tolerant varieties, except for intercropping, denoting that adopting these practices is site-specific, as variations in rainfall differ across regions in Zambia. As Ngoma et al. (2021) asserted, rainfall variability exposes households to weather shocks, such as drought and flood extremes. Therefore, conservation agriculture is a potential enabler for managing climate risks (Michler et al., 2019).

Furthermore, weather shocks, particularly droughts experienced in the 2018/2019 agricultural season, reduced the likelihood of farmers practicing minimum tillage, intercropping, agroforestry, and drought-tolerant varieties. This could be attributed to the farmers' past experiences and anxieties about climate effects, making them adopt newer innovations to reduce climate risk. In addition, it could result from the site specificity of these practices, suggesting that CSA adoption is not a one-size-fits-all phenomenon. This result does not agree with the findings of Thierfelder et al. (2015), who observed that the components of conservation agriculture and drought-tolerant varieties performed better under stress conditions. Furthermore, the results revealed that households experiencing floods in different parts of the country during the 2018/2019 farming seasons were least likely to embrace intercropping and agroforestry, except for drought-tolerant seed varieties. The World Bank (2019) supported these results, confirming that drought-tolerant seed varieties produce better results under flood-risk conditions.

Following El Niño weather conditions during the 2015/2016 farming season in Zambia, smallholder farming households adopted minimum tillage, intercropping, agroforestry, and drought-tolerant seed varieties. Affected households were most likely to use these practices. Our results indicated a positive and significant correlation between droughts experienced in the 2015/2016 season and CSA adoption (i.e., minimum tillage, intercropping, agroforestry, and drought-resistant seed variety). On the other hand, households experiencing floods during the same period (i.e., the 2015/2016 agricultural season) went for minimum tillage, crop rotation, intercropping, and drought-tolerant seed varieties. Unlike crop rotation, we showed a positive relationship between flood risk and other practices such as minimum tillage, intercropping, and drought-tolerant seed varieties. Adopting the CSA technologies considered in our study suggests that smallholder farmers were aware of them and their role in attenuating the impacts of the changing climate, which could affect food security. These findings are supported by Gjengedal (2016), who reported that smallholder farmers' awareness of changes in weather conditions leads them to embrace CA practices. In addition, the FAO (2017) revealed that adopting CSA innovations in light of climate change can bolster productivity and reduce vulnerability. These findings disagree with those of Chichongue et al. (2020), who found negative and significant effects of the changing climate on minimum tillage and intercropping. In contrast, the opposite was true for the crop rotation. Their study attributed this negative relationship to farmers' lack of awareness of changing weather patterns and climate change.

4.0 Conclusion and Recommendations

This study explored the determinants of climate smart practices using a nationally representative survey and rainfall data. Using kappa statistics, we found poor agreement between self-reported household data and weather shocks, suggesting that smallholder farmers should be trained to identify and report climate-related shocks more effectively through standard reporting techniques to enhance the reliability of self-reported data. This study further rejects the null hypothesis of independence between farming practice choice decisions. Therefore, we adopted an alternative hypothesis and employed a multivariate probit model. We found that CSA practices were complementary, implying that farmers should adopt at least one farming strategy in their activities. This paints a realistic picture of smallholder farmers' thought processes in making farm decisions, which is crucial for policy direction. Hence, policymakers should devise action-oriented strategies that encourage farmers to adopt complementary packages to optimize their utility in response to climate stressors.

The overall understanding of agricultural resilience and sustainability under the face of climate change often draws attention and varying opinions. The study establishes concrete evidence in relation to the adoption and use of climate smart agricultural innovations among rural smallholder farmers in Zambia. Key socioeconomic factors such as age and marital status of the household head, income, access to credit, education level, social capital, access to agricultural extension services, agroecological factors, seasonal climate forecasts and weather shocks impact the adoption behaviour of smallholder farmers in relation to CSA innovations.

The government and relevant stakeholders should invest in strengthening financial inclusion in rural areas to foster access to credit for smallholder farmers, enabling them to have more access to the farm inputs, technology, and equipment necessary to improve their uptake of these practices. Farmer education and training on various technologies are still needed while emphasizing their potential benefits regarding productivity and climate change. In addition, these training programs should be tailored to target different groups of smallholder farmers depending on their education levels. The government and other organizations should put concerted efforts into forming and empowering savings groups in rural areas, farmer associations, marketing groups, and other relevant social network groups, because developing such platforms is necessary to support increased access to credit, asset stocks, sharing information, and collective action, which is vital for enhanced adoption.

The study findings should be interpreted with caution because of the cross-sectional nature of the data used in the analysis. Therefore, we recommend longitudinal studies to capture farmers' choice adoption behavior over time. Further, future studies should use different climate-smart practices using more recent country-level data to gain a broader understanding of farmers' choices towards other practices.

Author contribution statement

Patrick Lupiya: Conceived and designed the study, conducted the analysis and interpreted the findings, drafted the paper, revised it critically for intellectual content and final version to be published.

Raphael Gitau: Conceived and designed the study, conducted the analysis and interpreted the findings, drafted the paper, revised it critically for intellectual content and final version to be published

Hillary K. Bett: Conceived and designed the study, conducted the analysis and interpreted the findings, drafted the paper, revised it critically for intellectual content and final version to be published.

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