Factors Influencing Climate-Smart Agriculture Practices Adoption and Crop Productivity among Smallholder Farmers in Nyimba District, Zambia

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ABSTRACT: Many smallholder farmers in the developing world live in adverse poverty and rely on agriculture as their primary source of income and household food. This study examines factors influencing the adoption of climate-smart agriculture practices and crop productivity among smallholder farmers in Nyimba District, Zambia. Data were collected from June to July of 2022 from 194 smallholder farmers' households in twelve villages belonging to four agricultural camps of Nyimba District. Four focus group discussions were conducted to supplement data collected from the household interviews. A binary logistic regression model was used to assess the determinants of climate-smart agriculture adoption and crop productivity among smallholder farmers. Propensity score matching was performed to measure the impacts of climate-smart agriculture adoption among adopters and non-adopter farming households. The Logistic regression model showed that the smallholder farmer's level of education, household size, synthetic fertilizer usage, age of household head, gender, farming experience, livestock ownership, annual income, farm size, marital status of household head, and access to climate information, all affect smallholder farmer climate-smart agriculture practices adoption and crop productivity. The propensity score matching the analysis found overall crop yield (for entire crops) was 20.20% higher for climate-smart agriculture practices adopters than for non-adopters. The study also found smallholder farmers' climate-smart agriculture practices adopters maize yield (staple crop) increased by 21.50% higher than non-adopters. The findings from this study have implications for further research and policy design and implementation of climate-smart agricultural practices.

Keywords: Adoption, Agriculture, Climate-smart agriculture, Climate change, Crop productivity.

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INTRODUCTION

Climate changes are already hampering agricultural production growth for both livestock and crop production worldwide (Alfani et al., 2019). Increased climate variability and climate change exacerbate production risks and challenge farmers' coping abilities. These climate changes bring about threats to access nutritious food for urban, peri-urban, and rural communities due to reduced agricultural production and household income (Ivanova et al., 2020; Sharifi, 2021; Mossie, 2022), and increased risks that disrupt food markets. According to the Intergovernmental Panel on Climate Change (IPCC) 2018 report, climate change affects crop production in most parts of the world, with negative effects more common than positive, and developing countries remain extremely susceptible to further negative impacts. Increases in the frequency and intensity of extreme events such as drought, heavy rainfall, flooding, and high maximum temperatures are already occurring and are expected to accelerate in many parts of the world (Murray and Ebi, 2012; IPCC, 2018). Average and seasonal maximum temperatures are projected to continue rising with higher average rainfall overall. These effects will not, however, be evenly distributed and are likely to increase by the end of the 21st century.

Climate change is projected to partake in and contribute to a worldwide reduction in cereal yields (*i.e.*, maize and wheat by 3.8% and 5.5% respectively (Lobell et al., 2011). Smallholder farmers falling in the group of poor producers, the landless, and marginalized ethnic, are all vulnerable to changes in climate (CIAT and World Bank, 2017; Makate, 2019). In addition, climate change extreme events and shocks can be long-lasting, as risk exposure and increased uncertainty affect investment incentives and reduce the likelihood of effective farm innovation while increasing that of low-risk, low-return activities. Climate change will almost certainly have a significant impact on the average yields of Zambia's major crops (maize, wheat, and sorghum), because agronomic conditions for these crops may worsen in large parts of the country

(Molieleng et al., 2021; Chavula, 2022). Climate change extreme events and shocks such as drought and flooding, do have a greater impact on crop production in Zambia and other Sub-Saharan African countries. However, through the intricacy of the agricultural diverse systems in Sub-Saharan African countries and its interrelation between the socio-economic facets of smallholder farmers' households, an integrated approach has been promoted to sustainably increase the productivity of smallholder agricultural landscape to adapt to climate change. These approaches and/or interventions are termed 'climate-smart agriculture (CSA)' farmers (Makate, 2019; Odubote and Ajayi, 2020; Zakaria et al., 2020; Molieleng et al., 2021). Climate-smart agriculture practices (e.g. sustainable agriculture, integrated nutrient management, organic farming, agroforestry technologies, integrated pest management, conservation agriculture, multi-cropping system, among others) are designed to increase household income, improve agricultural production while promoting climate change resilience through sustainable management of arable land and less synthetic fertilizer usage (Newell et al., 2019).

Climate-smart agriculture emerged in the late twentieth century in Zambia, when the country began facing economic, ecological, and/or climate change challenges in line with their agriculture production. The emergency of CSA focused on combating the adverse impacts of climate change on smallholder farming households, the country has embarked on the promotion of CSA practices to reclaim degraded landscapes and enhance households' resilience to climate change (Ngoma et al., 2021). Subsequently, due to the importance of CSA, the country has made climate-smart agriculture practices' promotion (*i.e.*, organic farming, integrated pest management, agroforestry, conservation agriculture, and integrated agriculture practices to mention a few) among the most important components of extension and rural advisory service delivery. These interventions have been conducted in concurrence with national and international research, non-governmental organizations, and development partners (Ngoma et al., 2021). Several studies in Zambia have been conducted to investigate the impact of CSA on smallholder farmers' livelihoods, especially those living in rural areas. Most of these studies have focused on the impacts of CSA practices' adoption on smallholder farmers' household income as a measure of adopters' household livelihood (Kalaba et al., 2010; Kuntashula and Mungatana, 2015; Jama et al., 2019; Nkhuwa et al., 2020). Nkhuwa et al. (2020) and Kuntashula and Mungatana (2015) found that implementing improved fallow and green leaf manure as agroforestry practices considerably boosted smallholder farmers' household income. Jama et al. (2019) observed agroforestry adoption enhanced household income by improving fallow adoption by smallholder cotton growers and Kalaba et al. (2010) revealed that adopting agroforestry practices improved smallholder farmers' household welfare in Southern African nations including Zambia. In Zambia, there appears to be scanty information related to factors influencing climate-smart agricultural practices, adoption, and crop productivity among smallholder farmers in Nyimba district. Hence, this study, unlike earlier empirical studies, examines the factors influencing climate-smart agricultural practices, adoption, and crop production among smallholder farmers in Nyimba district, Zambia.

Conceptual Framework

Climate-smart agriculture is a strategy for changing and reorienting the agricultural landscape to promote food security in light of the emerging climatic realities, variations, and climate change (Chavula, 2021). Climate change disrupts food markets, posing population-wide risks to food production and supply. These risks can be decreased by enhancing farmers' capacity for adaptation as well as enhancing the mitigation and efficiency of agricultural production systems. Smallholder farmers who have received information on climate change and/or perceive it to be real are highly likely to adopt climate-smart agricultural practices to meet its tenets to boost household income and productivity; increase resilience and adaptation; mitigate and reduce greenhouse gas emissions. The adoption of climate-smart agriculture to meet its tenets is affected by institutional, cognitive, and socio-economic factors (Annex 1).

MATERIALS AND METHODS

Study area description

Location

The research was carried out in the Nyimba district of Eastern Province, Zambia. The district is situated 334 kilometers east of Lusaka Zambia's national capital. In the South the district borders with Mozambique, North with Muchinga province, West with Lusaka province, and East with Petauke district. The district lies between latitude (13º30'1019" and 15º55'8146" South) and longitude (30º 48'5047" and 31º48'20252"East) (Figure 1).

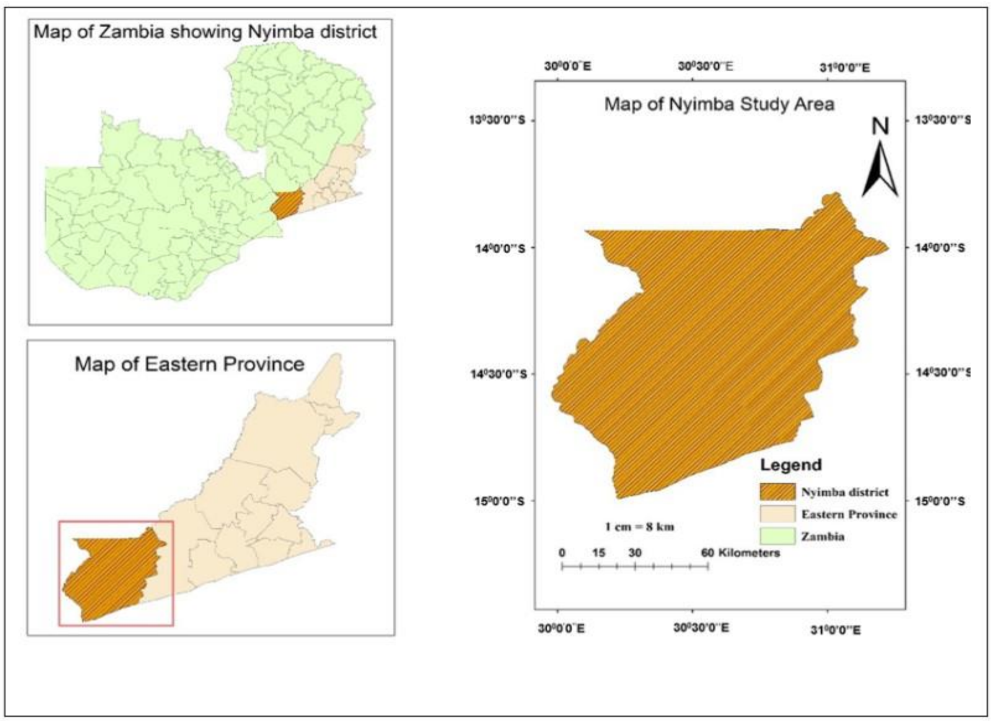

Figure 1. Map of the study area.

Climate, soil, and topography

Zambia as a country is divided into three agro-ecological zones (*i.e.*, Zone I, Zone II (IIa and IIb), and Zone III) of which Nyimba district falls in Zone I. Agro-ecological zone I covers the Zambezi and Luangwa River basins' Southern and Eastern rift valleys. It also stretches to parts of Zambia's Western and Southern provinces in the south (Mtambo et al., 2007). The district's average annual rainfall ranges between 600 to

900 millimeters; the wettest months are December to February, with a distinct dry season from May to November. The annual mean temperature is 24.2°C whereas the daily temperature range is 10.3 °C to 36.5 °C. Topographically, the district is composed of hills and plateaus, soils characterized as Lithosol-Cambisols, whereas in the valleys, soils are classified as Fluvisol-Vertisols. The elevation varies from 450-1000m at the Luangwa River valley bottom and extends to the plateau near Nyimba district center, and even higher on the mountain tops in the district's western part (Halperin et al., 2016).

Vegetation type

The Miombo woodland is the most dominant formation and habitat type in Southern Africa (Gumbo and Dumas-Johansen, 2021; Montfort et al., 2021). Miombo woodland is also the major forest type in Zambia itself, covering approximately 45% of the entire land surface (Kalinda, 2008). Nyimba is located in the middle of the Miombo Ecoregion, a biome with a variety of flora types that is dominated by tree species from the Caesalpinioiae subfamily of leguminous plants (Timberlake and Chidumayo, 2011). Depending on the climate, soil, landscape position, and degree of disturbance, the ecoregion's vegetation varies in composition and structure (Timberlake and Chidumayo, 2011; Halperin et al., 2016). Nyimba is located in the arid ecozone and is characterized by four types of vegetation: Dry miombo woodland (*i.e.*, *Brachystegia spiciformis,* B. boehmii and *Julbernardia globiflora*), Mopane woodland (*i.e.*, *Colophospermum mopan*e), Munga woodland (*i.e.*, Vechellia sp., Senegalia sp., Combretum sp., and trees associated with the Papilionoideae subfamily) and Riparian Forest (*i.e.*, mixed tree species).

Land use and farming systems

Nyimba district's total land area is about 10,500 square kilometers according to the population and housing census of 2010 (Central Statistical Office, 2011). Therefore, 82% of the district population is agrarian and three-quarters are impoverished, living in rural areas, and earning less than the international poverty threshold of $2.15 a day. These households are farmers who are into mixed agriculture practices dominating the district. Under this agricultural system, crops are grown in mounds or ridges, in most cases maize. The major crops grown include banana (Musa sp.), maize (*Zea mays*), finger millet (*Eleusine coracana*), groundnuts (*Arachis hypogaea*), haricot bean *(Phaseolus vulgaris)*, cowpeas (*Vigna unguiculata* spp.) and soybean (*Glycine max*). Multiple cropping systems are common where the cultivated land is on gently and moderately steep slopes. The topography of the land in the district makes the agricultural cultivation pattern different from other areas. Therein, the cropping system is alongside livestock production such as cattle, goats, chickens, ducks, and doves. Besides agricultural activities, farmers are engaged in charcoal production, timber, firewood supply, and non-timber forest products (NTFPs) from the miombo woodland for household economic gain (Gumbo et al., 2016).

Site selection

The selection of the study area was based on non-governmental organizations implementing CSA projects in Nyimba district. Non-governmental organizations for over 15 years and currently work with 80 community cooperatives providing relevant farmer support services to more than 69,000 farmers' households. These organizations are well embedded with local communities and have long experience working on CSA intensification through networks of peer-selected lead farmers to maximize outreach and knowledge sharing. This existing system enabled the study to conduct a reconnaissance to gather basic information about the study area before data collection. Information gathered included; distance between villages, number of farming households per village, contact details for lead farmers, CSA practices of adopters' households, and the location of croplands, and identifying central meeting points for focus group discussion (FGD).

Data sources

This research employs both quantitative and qualitative data collection techniques and both primary and secondary sources as data sources. The primary data sources for this study were obtained through a structured questionnaire and crucial oral interviews with sample households and key respondents. The Agricultural Office, extension officers, lead farmers, project reports and paperwork, further research papers, demographic and socioeconomic profiles, and published materials such as books and journals were used as secondary sources for this study.

Sampling technique

This research used a multistage random sampling technique to select participants to be part of the study. This study drew smallholder farmers from agricultural camps. An agricultural camp is a delineation made by the Republic of Zambia Ministry of Agriculture containing a certain number of smallholder farmers' households in a district across villages for easy access by agriculture extension officers. From the eight agricultural camps in Nyimba District, four agricultural camps were randomly selected (*i.e.*, Ndake, Central camp, Lwende, and Ofumaya). The total number of farmers in the selected four agricultural camps in Nyimba District is 10,700. The study used Slovin's formula for sample size calculation. Furthermore, the study randomly selected three villages from each camp (*i.e.*, Sikwenda, Sichipale, Mawanda, Elina, Katumbila, Sichalika, Malalo, Mwenecisango, Mulivi, Lengwe, Mofu and Yona). The study first used a margin of error of 0.05 and obtained a sample size of 386 participants. However, as this sample size required more time and resources, to reduce the sample size, the study then used a margin of error of 0.1 and obtained a size of 99, as shown below.

Sample size formula: Slovin's (1960) formula:

$$n = \frac{N}{1 + Ne^2}$$

$$n = 10700/(1 + 10700(0.1^2)$$

$$n = 10700/27.75 \qquad n = 99.07$$

The study therefore settled for a sample size of 194 participants, which is between the sample size of 99 (0.1 margin of error) and 386 (0.05 margin of error). Through the aid of agricultural camp officers, farmer registers for each village were used to randomly select participants in an Excel spreadsheet.

Focus group discussion

Focused group discussions (FGD) were conducted to collect in-depth data about smallholder farmers' factors affecting climate-smart agriculture practices (CSAP) adoption, and crop productivity. This was attained through means of a developed open-ended FGD study tool. The FGDs are regarded to be better than individual interviews as sensitive issues come out during the implementation. A total of four (FGDs were carried out in the study area comprising village headmen, women, men, and youths. The FGD meetings were held at central places for easy access by individual farmers.

Household interviews

A household survey was utilized to obtain quantitative and qualitative data from the sampled smallholder farmers in the study area. To obtain data, a semi-structured questionnaire comprising open-ended and closed questions was employed. However, data on the socioeconomic, institutional, and demographic characteristics of the sampled homes were attained from smallholder farmers' households. Before beginning the data collection activity, the questionnaires were pretested multiple times for suitability (e.g., clarity, adequacy, and question sequence), correctness, and coherence of the survey questions, and the findings were used to make changes. The questionnaire was pretested on 23 randomly selected households that were not part of the survey's sampled group. The researcher trained enumerators after pretesting and before presenting questionnaires to smallholder farmers on the final interview schedule. Finally, the enumerators gathered information under the supervision of researchers and supervisors. Collected data was verified and amended after each fieldwork day and backed to CSPRO Cloud.

Data quality control

Before performing data analysis, the household survey data was scrutinized on six dimensions: (1) correctness, (2) completeness, (3) consistency, (4) timeliness, (5) validity, and (6) originality. As a result, duplicated data, incomplete data, inconsistent data, poorly organized data, and inadequate data were eliminated.

Data analysis

Data from the household survey was analyzed with STATA 15MP for descriptive statistics such as mean, frequency, standard deviation, and percentage to describe household characteristics and socio-economic dynamics among CSA practices, adopters, and non-adopters smallholder households.

Variables specification

Outcome variables

The outcome variable for this study is the impact of CSA practice adoption among smallholder farmers' households' crop productivity.

Dependent variables

Smallholder farmers' household decision to adopt CSAPs

The dependent variable was the smallholder farmers' household to adopt CSAPs taking a value of one (1) and zero (0) if the smallholder farmers' household does not adopt. The main reason was to identify factors that influence the adoption of CSAP among smallholder farmers' households in the Nyimba district, Zambia.

Propensity score matching

Propensity score matching (PSM) method was used in this study to determine the effect of CSAP on crop productivity among adopters and non-adopters. Propensity score matching is a way of correcting treatment effect estimates by adjusting for confounding variables across a sampled population. According to Caliendo and Kopeinig (2008), there are steps in implementing PSM for a study. These are estimation of the propensity scores using a binary model, choosing a matching algorithm, checking against a common support condition, and testing the matching quality of the treatment and/or participants (Caliendo and Kopeinig, 2008).

Step 1: Model Specification

The Logit model in this research can be preferred due to the consistency of parameter estimation associated with the assumption that the error term in the equation has a logistic distribution (Baker, 2000; Ravallion, 2001). Therefore, the Logit model was used to estimate the probability of smallholder farmers' adoption of CSAPs allotted to socio-economic, agroecological, and institutional characteristics. Therein, a dependent variable is considered a value of 1 for CSAP adoption and 0 for non-CSAP adopters.

$$P_i = P(Y = 1|X) \qquad (1)$$

In line with Pindyck and Rubinfeld (1981), the cumulative logistic probability function is specified as follows;

$$P_i = F(Z_i) = F[a + \sum_{i=1}^{m} \beta_i X_i] = \left[\frac{1}{1+e^{-(a+\sum \beta_i X_i}}\right] \qquad (2)$$

where e represents the base of natural logs, X_i represents the ith explanatory variable, P_i is the probability that a household adopts CSAPs, and α\, and β_i are the parameters to be estimated.

Interpretation of coefficients is made easier if the logistic model can be written in terms of the odds and log of odds (Gujarati, 1995). The odds ratio implies the ratio of the probability that an individual will be a participant (P_i) to the probability that he/she will not be a participant ($1-P_i$). The probability that he/she will not be a participant is defined by:

$$(1 - P_i) = \frac{1}{1+ e^{zi}} \qquad (3)$$

$$\left(\frac{P_i}{1+ P_i}\right) = \left[\frac{1+e^{zi}}{1+ e^{-zi}}\right] = e^{zi} \qquad (4)$$

Alternatively,

$$\left(\frac{P_i}{1+ P_i}\right) = \left[\frac{1+e^{zi}}{1+e^{-zi}}\right] = e^{[a+ \sum B_i X_i]} \qquad (5)$$

Taking the natural logarithms of equation (3.5) will give the logit model as indicated below.

$$Z_i = ln\left(\frac{P_i}{1-P_i}\right) = a + B_1X_{1i} + B_2X_{2i} + \cdots B_mX_{mi} \tag{6}$$

If consider a disturbance term, μ_i, the logit model becomes

$$Z_i = a + \sum_{t=1}^{m} B_tX_{ti} + \mu_i$$

So the binary logit will become:

$$Pr(pp) = f(X) \tag{7}$$

Where *pp* is CSAPs adoption, *f(X)* is the dependent variable project adoption, and *X* is a vector of observable covariates of the households. The dependent variable will take a value of 1 for CSAP adoption and 0 for non-adopters.

In addition to the estimated coefficients, the marginal effects of the change in the explanatory variables on the probability of CSAP adoption are also estimated. The interpretation of these marginal values will be dependent on the unit of measurement for the explanatory variables. However, when the explanatory variable is dummy, the marginal effects generally produce a reasonable approximation to the change in the probability that *Y* = 1 at a point such as the regressors' average.

Step 2: Defining the Region of Common Support and Balancing Tests

The region of common support needs to be defined where distributions of the propensity score for treatment and comparison groups overlap. Sampling bias may still occur, however, if the dropped CSAP's non-adopters observations are systematically different in terms of observed characteristics from the retained non-adopters; these differences should be monitored carefully to help interpret the treatment effect. Balancing tests can also be conducted to check whether, within each quantile of the distribution of propensity scores, the average propensity score and mean of *X* are the same. For PSM to work, the comparison and treatment groups must be balanced in that similar propensity scores are based on similar observed *X*. The distributions of the treated group and the comparator must be similar, which is what the balance implies. Formally, one needs to check if $\hat{}\mathrm{P}(X|T=1) = \hat{}\mathrm{P}(X|T=0)$.

Step 3: Matching Adopters to Non-adopters

The third step is to choose an algorithm for data matching available. Matching is a common method for deciding on control subjects who are matched to the treated subjects based on context covariates that the investigator believes need to be monitored. Different ones may employ matching standards. to assign adopters to non-adopters based on the propensity score. The most common matching algorithms are nearest neighbor matching (NN), radius matching (RM), and kernel-based matching (KBM).

Step 4: Matching Quality

In the fourth step, matching quality tests could be done. Checking for matching regardless of quality, the matching methods can balance the distribution of various variables or not. If differences exist, there may be an indication of incomplete matching, and remedial actions are suggested (Caliendo and Kopeinig, 2008). The following step is to check whether the treatment introduced a distinction in the indicators of impact. The average treatment effect of the treated (ATT) is given by the distinction within the mean outcome of matched adopters and nonadopters that have common support conditional on the propensity score.

Step 5: Sensitivity Analysis

Finally, a sensitivity analysis will be carried out to check the conditional independence assumption strength. Sensitivity analysis also will be utilized to look at whether an unmeasured variable's effect on the choice process is strong enough to jeopardize the matching approach (Ali and Abdulai, 2010). The Rosenbaum bound sensitivity test will be used to carry out the sensitivity analysis (r-bounded test).

RESULTS

Characteristics of the participant smallholder farmers

The household survey comprised 194 smallholder farmer participants from the research area, who were chosen at random. The smallholder farmers were interviewed about crop production and their applications of various CSA practices. The study presents the household survey's findings, starting with the demographic characteristics of the participants, crop production and productivity, adoption of CSA, constraints on the adoption of CSA practices, effects of CSA practices on crop productivity, and factors affecting crop productivity. The study obtained a total of 339 field plots of various crops from 194 farmer participants.

From the results in Table 1, the study obtained that the mean age of the respondents was 46 years of age, with a standard deviation of 14.59. A majority (62.18%) were male-headed households, and 69.43% were married. The mean year of formal education was found to be 5.49 years, with a standard deviation of 3.5. The mean year of farming was found to be 26.22, with a standard deviation of 15.55. Concerning the years of living in the area, the mean was 30.92, and the standard deviation was 18.68. The average family size was 5.42, with a standard deviation of 2.14. The average total annual income was revealed to be K 5472.68 (USD 331.68) (K 16.5 per 1 USD), and 57.51% reported participating in any off-farm activities. Improved seed varieties were used by 78.76% of the smallholder farmer participants. The average farm size (landholding) was 3.396 ha, with a standard deviation of 3.363. The land tenure system was all customary land (100%). The mean cultivated land was 1.83 ha and 1.45 standard deviation. The average number of crops grown by smallholder farmers was 2, with a standard deviation of 0.930.

Table 1. Characteristics of the participant smallholder farmers.

Variable	Mean	Std. Deviation
HH Head Age	46.181	14.593
HH Head Sex	Male: 62.18% (120)	
Marital Status	Married: 69.43% (134)	
Years of formal education	5.487	3.499
Years of farming	26.218	15.545
Years of living in the area	30.917	18.680
Household size	5.420	2.137
Total Annual Income (in Kwacha)	5472.689	7626.52
Participation in any off-farm activity	Yes: 57.51% (111)	
Used Improved Maize Seed	Yes: 78.76% (152)	
Farm Size (ha)	3.396	3.363
Land tenure system (Customary)	100% (194)	
Cultivated land (2021/2022), ha	1.828	1.448
Number of Crops (2021/2022)	2	0.930

HH - household

Crops grown by smallholder farmers

Concerning the crops grown by the farmers, the study found that maize ranked first, reported in 194 crop plots, followed by groundnuts, reported in 99 plots, sunflower in 69 plots, and soya beans in 16 plots (Table 2). Other crops; Cowpea, Bambara nuts, Cotton, Millet, and Sweet Potatoes were reported to have been grown in a few plots.

Table 2. Crops grown by smallholder farmers.

Crops Grown	Frequency	Percent	Cumulative
Maize	194	50.13	50.13
Soybeans	16	4.13	54.26
Groundnuts	99	25.58	79.84
Cowpea	2	0.52	80.36
Bambara nuts	2	0.52	80.88
Sunflower	69	17.83	98.71
Cotton	1	0.26	98.97
Sweet potatoes	3	0.78	99.74
Millet	1	0.26	100
Total	**387**	**100**	

Climate-smart agriculture practices adopted by smallholder farmers

From the results obtained, pot-holing (basin) was implemented in 61 field plots (17.99%), multi-cropping in 50 plots (14.75%), minimum tillage in 34 plots (10.03%), ripping in 32 plots (9.44%), crop rotation in 18 plots (5.31%), and manure in 11 plots (3.24%) as well as alley cropping in 9 plots (2.65%) (Table 3). The other CSA practices were implemented in a few plots less than ten.

Table 3. Climate-smart agriculture practices adopted by smallholder farmers.

CSA Practices	Frequency	Percent
Ripping	32	9.44
Basin	61	17.99
Crop rotation	18	5.31
Crop residue	2	0.59
Alley cropping	9	2.65
Multi cropping	50	14.75
Contour ploughing	6	1.77
Compost	5	1.47
Manure field	11	3.24
Zero tillage	34	10.03
Bunding	2	0.59

Number of climate-smart agriculture practices adopted by smallholder farmers

Concerning the number of CSA practices adopted, no single CSA practice was implemented in 167 plots (49.26%), one CSA practice was implemented in 123 plots (36.28%), two CSA practices were implemented in 43 plots (12.68%), 4 plots had three different CSA practices implemented, and only 1 plot had four CSA practices implemented and another plot with five CSA practices implemented (Table 4). Based on these results, farmers' implementation of many CSA practices in a single plot was found to be very low.

Table 4. Number of climate-smart agriculture practices adopted by smallholder farmers.

No._CSA_Adopted/Plot	Freq.	Percent	Cum.
0	167	49.26	49.26
1	123	36.28	85.55
2	43	12.68	98.23
3	4	1.18	99.41
4	1	0.29	99.71
5	1	0.29	100
Total	**339**	**100**	

Quantities harvested for various crops (kg)

Maize, groundnuts, sunflower, and soya beans were the most grown crops by the farmers (Table 5). The mean quantity of harvest for all crops was 1223.51 kg with a standard deviation of 1442.82. The mean quantity of maize harvested for maize was 1766.57 kg with a standard deviation of 1594.23, while the mean quantity of groundnuts harvested was 511.08 kg with a standard deviation of 605.07, the mean quantity of 609.67 kg with a standard deviation of 513.02 for sunflower, while for soya beans the mean quantity harvested was 1007.5 kg with standard deviation of 1835.615.

Table 5. Quantities harvested for various crops (kg).

Variable	Obs	Mean	Std. Dev.	Min	Max
All Crops	339	1223.51	1442.82	50	9450
Maize	173	1766.57	1594.23	165	9450
Groundnuts	85	511.08	605.07	50	3450
Sunflower	61	609.6721	513.0212	50	2800
Soya beans	14	1007.5	1835.615	200	7245

Productivity of various crops (Yield (Kg) per hectare)

Concerning the productivity of various crops, the overall yield per hectare of all crops was 1316.60 kg. The yield per hectare for maize was found to be at 1682.52 kg per hectare, and for groundnuts,

Sunflower, and soybean the mean yield per hectare was found to be 822.90 kg, 962.79 kg and 808.40 respectively.

Impact of climate-smart practices on crop productivity among smallholder farmers

The study investigated how climate-smart agriculture techniques affected smallholder farmers' crop yield. The study found that crop yield for CSA adopters was 20.20% higher than the CSA non-adopters (Table 6). The results were statistically significant at 0.027 p-value ($p<0.05$). This entails that adopting CSA practices increases crop yield.

Table 6. Impact of climate-smart practices on crop productivity among smallholder farmers.

Treatment-effects estimation					Number of Obs = 194	
Estimator: propensity-score matching					Matches: requested = 1	
Outcome model: matching					min = 1	
Treatment model: logit					max = 2	
log_yield	Coef.	AI Robust Std. Err.	Z	P>z	[95% Conf.	Interval]
ATE CSA_Practice (Adopters vs Non_Adopters)	.2019652	.0911943	2.21	0.027**	.0232276	.3807028

***<1%, **<5% and *<10%

Impact of climate-smart practices on maize productivity among smallholder farmers

The study conducted a propensity score matching analysis to specifically determine how CSA affects maize productivity (Table 7). The research showed that implementing CSA increases maize yield for adopters by 21.50% higher than non-adopters. This shows that adopting CSA practices significantly increases maize yield. The results were statistically significant at 0.035 p-value ($p<0.05$).

Table 7. Impact of climate-smart practices on maize productivity among smallholder farmers.

Treatment-effects estimation					Number of Obs = 194	
Estimator: propensity-score matching					Matches: requested = 1	
Outcome model: matching					min = 1	
Treatment model: logit					max = 1	
log_yield	Coef.	AI Robust Std. Err.	Z	P>z	[95% Conf.	Interval]
ATE CSA_Practice (Adopters vs Non_Adopters)	0.215012	0.101795	2.11	0.035**	0.015496	0.414527

***<1%, **<5% and *<10%

Factors affecting smallholder farmers' adoption of climate-smart agricultural

The study conducted a logistic regression analysis to determine factors affecting the adoption of CSA practices. Age has a favorable impact on the adoption of CSA practices, the higher the age, the more likely a farmer will adopt CSA practice, statistically significant (p<0.001). The study recorded the age category of 40-55 years and > 55 years to have adopted more CSAP in the study area.

Adopting CSA practices is influenced by farming experience, the more years a farmer spends in farming, the less likely a farmer will use CSA practices, statistically significant at 0.0000 p-value (p<0.001). Income was found to have a statistically positive effect on the adoption of CSA practices, the greater a farmer's income level, a farmer is more likely to adopt CSA practice, statistically significant at 0.0640 p-value (p<0.1) (Table 8). On the other hand, the size of the farm, the distance between the farmers' homes and the farm sites, the location, and the rise in temperature all harmed the farmers' intention of technology adoption. Gender was found to have statistically significant effect at 0.0660 p-value (p<0.1). Farm size was also found to have a negative significant effect on climate-smart agricultural practices adoption at 0.0050 (p<0.01). Livestock quantity was also found to have a significant effect on CSA adoption at 0.0180 p-value (p<0.1), while access to climate information had a negative influence on climate-smart agriculture adoption p-value

0.0060 (p<0.01). On the other hand; marital status, education, fertilizer, credit access, and access to extension services were found not to have a significant effect on the adoption of CSA practices.

Table 8. Factors affecting smallholder farmers' adoption of climate-smart agricultural practices.

Logistic regression					Number of Obs = 194	
					Wald chi2(10) = 27.34	
					Prob > chi2 = 0.0112	
Log pSeudolikelihood = -204.0124					Pseudo R2 = 0.0965	
CSA_Practice	Coef.	Robust Std. Err.	z	P>z	[95% Conf.	Interval]
Age	0.085697***	0.0222	3.8600	0.0000	0.0422	0.1292
Gender	0.017260*	0.4056	0.4400	0.0660	0.7776	0.8122
Marital_status	-0.178756	0.1399	-1.2800	0.2010	-0.4530	0.0955
Education	-0.051048	0.0387	-1.3200	0.1870	-0.1270	0.0249
Farming_experience	0.087116***	0.0200	-4.3600	0.0000	-0.1263	-0.0480
Household_size	-0.027906	0.0658	-0.4200	0.6720	-0.1569	0.1011
Income	0.000035*	0.0000	1.8500	0.0640	0.0000	0.0001
Fertilizer	0.000727	0.0007	1.1200	0.2630	-0.0005	0.0020
Farm_size	-0.02006**	0.0449	-0.4500	0.0050	-0.1082	0.0680
Livestockqt	0.006734*	0.0083	0.8100	0.0180	-0.0230	0.0095
Credit_access	-0.150782	0.2405	-0.6300	0.5310	-0.6221	0.3205
Access_to_climate_inform	-0.44108**	0.5920	-0.7500	0.0060	-1.6014	0.7192
Extension_services	-0.018090	0.2964	-0.0600	0.9510	-0.5989	0.5628
_cons	-0.416121	1.0016	-0.4200	0.6780	-2.3792	1.5470

***<1%, **<5% and *<10%

Factors affecting smallholder farmers' crop productivity

The study carried out Cobb Douglas production analysis to determine factors affecting the productivity of crops (Table 9). Study results showed that income has a positive significant impact on crop productivity, productivity improves by 0.002%, with the outcome of increase in income level, which statistically significant at 0.0040 p-value (p<0.01). Fertilizer was found to have a significant positive impact on crop productivity. A unit increase in fertilizer use was associated with a 0.12% increase in crop yield, statistically significant at 0.0000 p-value (p<0.001). Farm size was found to harm crop productivity, the bigger the farm size, the lower the crop productivity by 6.52%. Livestock quantity was found to have a positive significant influence on crop productivity, the higher the number of livestock a farmer has, the higher the yield of crops by 0.86%, statistically significant at 0.0001 p-value (p<0.001). Adopting CSA practices was found to have a profoundly favourable effect on crop productivity, if one more farmer adopts CSA practice, the average yield for the farmers improves by 13.49%, statistically significant at 0.0720 p values (p<0.1). The other factors were found not to have a significant impact on crop yield. Marital status influenced crop productivity by 0.07% while the education level of the household head had a 0.098% influence on contribution to crop productivity among smallholder farmers. Household size also contributed 0.2% to smallholder farmer crop productivity.

Table 9. Factors affecting smallholder farmers' crop productivity.

Linear regression				Number of Obs = 194		
				F(9, 179)	= 11.05	
				Prob > F	= 0.0000	
				R-squared	= 0.6441	
				Root MSE	= 0.74495	
log_yield	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
Age	-0.00192	0.0051	-0.3700	0.7090	-0.0120	0.0082
Gender	0.03854	0.1126	0.3400	0.7320	-0.1830	0.2601
Marital_status	0.00755*	0.0379	0.8410	0.0220	-0.0821	0.0670
Education	0.00980*	0.0122	0.8000	0.0420	-0.0338	0.0142
Farming_experie~e	0.00434	0.0049	0.8800	0.3770	-0.0053	0.0140
Household_size	0.02308**	0.0181	1.2800	0.0012	-0.0586	0.0124
Income	0.00002**	0.0000	2.9400	0.0040	0.0000	0.0000
Fertilizer	0.00123***	0.0002	8.1300	0.0000	0.0009	0.0015
Farm_size	-0.06518***	0.0145	-4.4900	0.0000	-0.0938	-0.0366
Livestockqt	0.00863***	0.0018	4.7900	0.0000	0.0051	0.0122
CSA_Practice	0.13490*	0.0747	1.8100	0.0720	-0.0120	0.2818
Credit_access	-0.11707	0.0741	-1.5800	0.1150	-0.2629	0.0287
Access_to_climate Inform	-0.15234	0.1974	-0.7700	0.4410	-0.5408	0.2361
Extension_services	0.04293	0.0846	0.5100	0.6120	-0.1236	0.2094
__cons	7.19355	0.3095	23.2400	0.0000	6.5845	7.8026

***<1%, **<5% and *<10%

DISCUSSION

The impact of CSA practice adoption on crop productivity among smallholder farmers and factors affecting adoption of smart climate-smart agricultural ppractices among smallholder farmers in Nyimba district were determined in this study. Among the factors affecting smallholder farmers' adoption of climate-smart agricultural practices, age, gender, farming experience, income, fertilizer use and livestock quantity were found to have a positive effect on CSA adoption while farm size and access to climate information had a negative influence on CSA adoption. The age category of 40-55 years and > 55 years to have adopted more CSAP in the study area. This indicates that most participants have long years of experience in the area which is helpful for farmers in climate change adaptation options including CSA. A study by Saha et al. (2019) and Zakaria et al. (2020) the level of agricultural experience is one of the factors for farmers choice of adaptation techniques for climate. Kurgat et al. (2020) showed that female ownership of farm assets, farm location, and household resources were major determinants of climate-smart agricultural adoption in Tanzania. A study by Aryal et al. (2018) concluded that factors such as household characteristics, market access, and main climate hazards are found to affect the probability and level of implementing different climate-smart practices of climate-smart agricultural adoption by smallholder farmers.

Concerning the factors affecting smallholder farmers' crop productivity, the results in this study showed that income, fertilizer and livestock quality are among the factors that have a positive significant impact on crop productivity. Livestock provides farming households with manure and animal draught power to produce crops and the investment of income from livestock into technologies that benefit crop production. In addition to the effects of manure and draught on crop output; money from livestock is frequently invested in terms that improve crop production. Mujeyi et al. (2021) found similar results on the adoption of climate-smart agriculture to significantly contribute to the crop yield of smallholder farmers in an integrated crop-livestock system. Marital status, education level of the household head and household size contribute to crop productivity by 0.07%, 0.098% and 0.2% respectively. In a study by Serote et al. (2021) household demographics characteristics influenced the adoption of climate-smart agriculture and crop productivity. Smallholder farmers' crop yields of CSAP adopters were 20.20% higher than for non-adopters. This study revealed that implementing CSAP increases maize yield for smallholder farmer adopters by 21.50% higher than non-adopters. Furthermore, including climate-smart agriculture practices in smallholder farmers' farming systems initiatives is critical for establishing resilient and sustainable farming communities. Prior research findings support our results; CSA practices can help resource-poor farmers become more resilient to climate change by increasing crop yields. Aa study by Abegunde et al. (2022) on the effect of climate-smart agriculture on household food security, also revealed that CSA practice adoption significantly and favorably affects household food security. The findings also indicated that agricultural revenue and income from non-farm sources had a significant impact on household food security (Abegunde et al., 2022).

Another study on the impact of climate-smart agriculture technology on productivity in southern Ethiopia showed that implementing CSA practice (row planting), had a significant impact on wheat yield among smallholder farmers' adopters (Mossie, 2022). Tadesse et al. (2021) conducted a study on the impact of climate-smart agriculture on soil carbon, crop productivity, and fertility in Ethiopia and revealed that climate-smart agriculture experimental fields showed yields 30–45% higher under CSA practice than the control ($p<0.05$).

Kichamu-Wachira et al. (2021), revealed similar results on the effect of CSAP to significantly increase crop yields among smallholder farmers in Africa. The study further concluded that CSAPs are an alternative advanced agricultural technology compared to conventional farming typologies due to their enhancement of food production through climate mitigation and improving soil quality. Furthermore, Amadu et al. (2020) found that 53% of CSAP adopters had increased yields of maize in the drought year of 2016 in southern Malawi. Fentie and Beyene's (2019) research findings from the PSM model revealed that the adoption of CSAPs had a significant impact on crop yield per hectare. Therefore, scaling up CSA will significantly contribute to farmers' resilience to the adverse effects of climate change and climate variation by enhancing crop productivity and contributing to food security among farming households. Beedy et al. (2010) showed the significant and positive influence of *Gliricidia sepium* alley cropping on soil organic matter influence on the compiled single field of maize. Alley cropping had impacts on soil physicochemical properties in turn enhanced maize yields and increased soil nutrients over the mid-and-long term.

CONCLUSION

The findings of this study support previous empirical studies' notion that the implementation of climate-smart agriculture improves crop productivity among adopter farmers. However, the adoption of CSA practices, despite its benefits, is not automatic among smallholder farmers, hence evaluating factors influencing CSA adoption and crop productivity in smallholder farming typologies is also important. This study found influencing factors such as farmer's level of education, household size, synthetic fertilizer usage, age of household head, gender, farming experience, livestock ownership, annual income, farm size, marital status of household head, and access to climate information, are significant determinants of CSA practice adoption and crop productivity.

The results of this study are crucial to the governmental and non-governmental organizations in Zambia especially those housed in Nyimba district with an interest in agriculture and working with smallholder farmers. This study provides a direction for policymakers to strengthen farmers' ability to climate-smart agricultural practices adoption through information sharing and policy reform around the agricultural sphere.

It is recommended that scholars undertake further similar research on the factors influencing CSA adoption and crop productivity in other parts of the country, but with more detailed inquiry, incorporating other indicators or variables not considered in this study and with a more holistic approach focussing on an independent CSA practice for a given farming typology.

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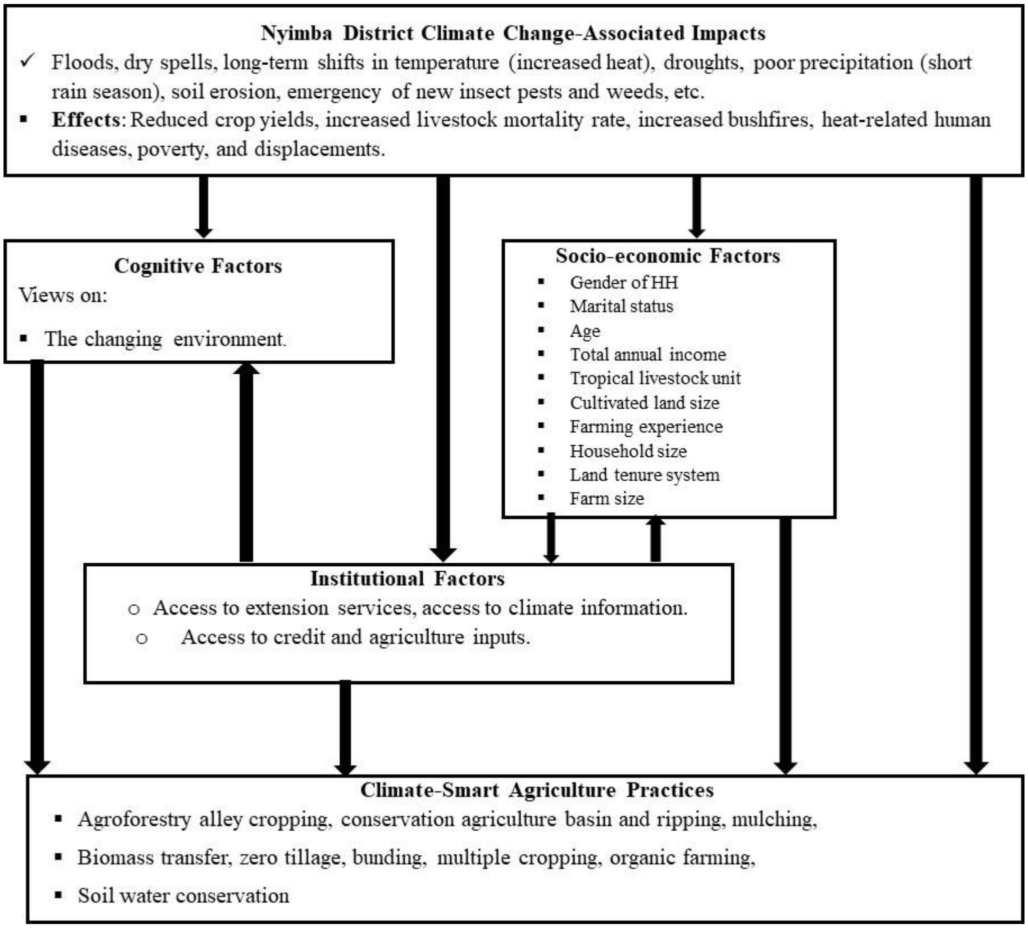
Annex 1. Conceptual framework based on adoption.



Source: Adopted and modified from Serrat (2008).