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Effectiveness of climate information services on farmer preparedness for climate events in Zambia

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Abstract

Climate change is posing risks to rain-fed agriculture in Zambia, necessitating timely and reliable Climate Information Services (CIS) to enhance farmer preparedness. This study evaluates the effectiveness of CIS use in improving maize productivity among smallholder farmers, using data from 1,356 households across nine districts under the Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA) project. A mixed-methods approach was employed, combining household surveys and focus group discussions. Propensity Score Matching (PSM) was used to evaluate the effects of CIS access and use on yield for maize. Results show that forecasts for rainfall onset and seasonal conditions were the most accessed and used CIS types, leading to early planting and variety selection. However, uptake of advice related to pest outbreaks and extreme events remained low due to financial constraints, late dissemination, and limited trust. The study concludes that CIS use was positively associated with preparedness and adoption of adaptive practices, but wide CIS use was shaped by socio-economic factors. It recommends strengthening CIS delivery through inclusive communication channels, timely dissemination, and integration with extension services and financial support mechanisms to improve uptake and impact.

Keywords: Climate; Information; Preparedness; Adaptation

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1. Introduction

In recent years, climate change has emerged as a major global threat to agricultural systems, with sub-Saharan Africa particularly vulnerable due to its heavy dependence on rain-fed agriculture (Ayanlade et al., 2022; Ng'ombe et al., 2020). The increasing frequency and intensity of extreme climate events have led to declines in both the quality and quantity of crop yields, disproportionately affecting the livelihoods of smallholder farmers (Ayanlade et al., 2022). Despite these challenges, it has been noted that many African farmers, including those in Zambia, were aware of climate change and its associated agricultural risks (Ng'ombe et al., 2020). The awareness has been shaped by socio-demographic characteristics, access to information, and adaptive capacity. Moreover, climate information services have been increasingly recognised as crucial tools for building agricultural resilience, although their effectiveness has varied across countries due to differences in public support, service delivery channels, and policy frameworks (Hansen et al., 2022). Climate-smart agriculture practices, including improved agricultural techniques, land restoration, and weather information services, offered promising adaptation strategies, but their adoption has been heavily dependent on government financial support, policy legislation, and farmers' access to climate information (Ariom et al., 2022).

In Zambia in particular, climate projections indicate declining rainfall and rising temperatures by 2050, with the Southern and Western regions expected to experience the most severe impacts (Ngoma et al., 2021). These climatic shifts are likely to threaten the country's predominantly rain-fed agricultural sector and exacerbate existing cycles of poverty, as they are projected to reduce crop yields, particularly maize production, resulting in lower national Gross Domestic Product (GDP) and declining household welfare (Ayanlade et al., 2022). The persistence of weak policy frameworks and inadequate enabling environments is likely to entrench poverty and climate vulnerability (Rawlins and Kalaba, 2020). Droughts remain the most prevalent climate shock, with 76% of smallholder farmers classified as vulnerable and only 24% as resilient, while female-headed households face disproportionately greater vulnerability (Ngoma et al., 2021).

In the face of such vulnerabilities, Climate Information Services (CIS) has been seen as important tools for enhancing climate adaptation and resilience, particularly within agricultural systems. This is because CIS provide timely, reliable climate information that enables informed decision-making and promotes adaptation to changing climate conditions (Kayusi et al., 2024). According to recent studies, CIS positively impact agricultural yields and economic gains while building resilience, though they also present implementation challenges including capacity development needs and gender imbalances (Kayusi et al., 2024). The effectiveness of CIS depends heavily on understanding contextual dimensions related to information providers, users, and their interactions, requiring flexible service design that can evolve based on local conditions (Guido et al., 2020). Since 2010 there has been growth in CIS studies that seek to provide evidence of their value in increasing yields and supporting decision-making, though challenges remain in forecast interpretation and adoption of anticipatory adaptation techniques (Madhuri, 2025). Successful CIS implementation requires addressing factors such as perceived usefulness, ease of use, social norms, and trust to enhance farmer acceptance and utilisation (Savari et al., 2024).

Current understanding of Climate Information Services (CIS) users, their specific needs and impact remain limited, creating barriers to effective service design, scaling, and responsiveness to changing climatic conditions (Carr et al., 2020). Systematic reviews, however, demonstrate that better-resourced smallholder farmers have higher CIS access and adoption rates, while vulnerable groups including women, elderly, and poorly resourced farmers face greater constraints (Nyoni et al., 2024). Other key barriers include gender inequality, lack of resources, poor infrastructure, and insufficient trust in CIS providers (Warner et al., 2022). Agricultural extension effectiveness depends on regular meetings, technology adoption rates, and Information and Communication Technology (ICT) access, with gender and credit access influencing outcomes (Somanje et

al., 2021). Therefore, strategic investments in infrastructure, capacity development, and targeted interventions are essential for maximising CIS potential across African agricultural systems.

In Zambia, the Accelerating Impacts of Consultative Group on International Agricultural Research (CGIAR) Climate Research for Africa (AICCRA) project supported the development of Climate Information Services (CIS) and promoted Climate-Smart Agriculture (CSA) solutions (AICCRA-CGIAR, 2022). The project was funded by the World Bank and launched in February 2022 (AICCRA-CGIAR, 2022; World Bank, 2020). Its main goal was to strengthen the capacity of CGIAR Climate Change, Agriculture and Food Security (CCAFS) partners and national stakeholders (World Bank, 2020). The project aimed to improve farmers' access to reliable climate information and validated CSA technologies. Through these, farmers were better able to anticipate climate-related events and take preventive actions. AICCRA enhanced the delivery of timely climate advisories and linked them to practical information on adaptive actions. This World Bank-supported programme operated across three key agro-ecological zones in Africa that are highly vulnerable to climate change, namely, the West African and Sahelian drylands, the Eastern African drylands to highlands, and the Southern African drylands. The initial anchor countries included Mali, Ethiopia, Ghana, Senegal, Kenya, and Zambia (World Bank, 2020).

AICCRA and its partners in Zambia collaborated with 14 agribusinesses, organised into five innovation bundles targeting key agricultural challenges and value chains (AICCRA-CGIAR, 2022). The solar bundle enabled 5,500 farmers to access off-grid irrigation systems, while the aquaculture bundle trained over 45,000 smallholder fish farmers on integrated agriculture–aquaculture practices for efficient land and water use. Through the seed bundle, 5,200 farmers accessed climate-smart seed varieties and soil-enhancing products. The integrated livestock–legume bundle worked with 55 cooperatives and community leaders to promote organic farming using Gliricidia sepium, benefiting 3,500 farmers. The Gender Empowerment and Social Inclusion (GESI) bundle reached nearly 60,000 individuals, especially women, youth, and vulnerable groups, through mobile-based CIS and CSA training. Collectively, these efforts improved the livelihoods of more than 118,000 farmers (36% women) (AICCRA-CGIAR, 2022)

Despite the growing recognition of Climate Information Services (CIS) as vital tools for climate adaptation, there remains a significant gap in ex-post evaluations that measure their actual effectiveness in improving farmer preparedness and adaptive capacity in Zambia and sub-Saharan Africa at large. Most existing studies have focused on ex-ante analyses, perceptions, or potential benefits of CIS, with limited empirical evidence on how access to, and use of, CIS influence on-farm decisions and productivity outcomes within different socio-economic and gender contexts. This study addresses this gap by conducting an ex-post evaluation within the AICCRA Zambia programme, which integrated CIS delivery with Climate-Smart Agriculture (CSA) innovations. Specifically, the study aims to assess smallholder farmers' access to climate information services, providers, and document observed behavioural and production (Maize) changes resulting from CIS use. The central hypothesis is that farmers who access and use CIS exhibit higher levels of preparedness for climate-related events, adopt more adaptive agricultural practices and have higher yields compared to those without access. The study further hypothesises that gender, education, and resource endowments influenced CIS access and utilisation, thereby shaping differences in adaptive outcomes across farming households.

2. Materials and methods

Data were collected in June 2024 at the end of the 2023/2024 agricultural season as part of the Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA) project. The data were collected from nine (9) districts in Zambia namely Chama, Chibombo, Chisamba, Kasama, Kawambwa, Mansa, Mumbwa, Mungwi, and Nyimba, A total of 1356 farming household heads and/or spouses were interviewed to recall their farming practices over a 12-month period. Well-trained enumerators administered a quantitative questionnaire to collect the data. In addition, two (male only and female only) focus group discussions (FGDs) per district were also

conducted in Kawambwa, Kasama, Mungwi, Chisamba, Mansa, Nyimba and Mumbwa. The distribution of interviews and FGDs across the nine districts is in Table 1.

Table 1. Household interviews and FGDs distribution by district

District	Number of interviews.	Distribution of interviews (%)	Number of Focus Group Discussions (FGDs)
Chama	189	13.9	-
Chibombo	151	11.1	-
Chisamba	153	11.3	2
Kasama	144	10.6	2
Kawambwa	131	9.7	2
Mansa	154	11.4	2
Mumbwa	146	10.8	2
Mungwi	126	9.3	2
Nyimba	162	12.0	2
Total	1356	100.0	14

The study targeted AICCRA-supported districts using a multistage sampling approach. Farm blocks, camps, and villages were randomly selected and households systematically sampled where every third household was selected for interviews. Under AICCRA, some households received climate information services, while others did not, despite district-wide targeting. For FGDs, local traditional leaders purposively identified participants. Each FGD had between 6 and 10 participants, depending on availability of participants in the target village.

2.1. CIS effectiveness estimation

Because households (about 72.7%) self-selected themselves into using CIS during the 2023/2024 agricultural season, treatment assignment was non-random. Because of this, the study applied propensity score matching (PSM) using a logit model to estimate the probability of treatment (use of CIS) conditional on observed covariates. It matched treated and untreated households with similar propensity scores to approximate a counterfactual comparison. The core idea was to estimate the probability of receiving treatment, known as the propensity score, and then match treated and control observations with similar scores to reduce selection bias arising from observable characteristics. PSM is a statistical technique designed to mimic a randomised experiment by balancing the observed covariates between the treated (households using CIS) and control (households not using CIS) groups. Mathematically, the propensity score, the probability of a household using CIS based on observable characteristics, was defined as:

$$e(X) = P(Z = 1|X) \quad (1)$$

where Z is the treatment indicator (1 for treated, 0 for control) and X is the vector of observed covariates which include household head gender and years of education, household size, soil quality, access to irrigation, fertiliser application rate, labour investment, membership in agricultural groups, engagement in off-farm income activities, and household wealth status. These covariates were selected based on agricultural production theory. While most covariates were self-reported by respondents, household wealth status and the outcome (Maize yield) variable were calculated from other survey variables as follows:

- Maize yield (kg/ha): Total maize harvest (kg) divided by the total cultivated area (hectares).

- Household wealth status: A composite asset ownership household indicator calculated from asset ownership dummy variables (Yes = 1, No=0) using Principal Component Analysis (PCA)

Households who did not access CIS were also removed from propensity score matching process. Missing data for continuous variables was replaced with means. For categorical variables, data were filled with the most frequent category. This was done in less than 5% of the cases. Outliers in maize yield above the maximum possible figures were replaces with the normal maximum possible figure from literature. This data cleaning process did not alter distributional structure of the data.

The process of PSM and the eventual estimation of the average treatment effect on the treated (ATT) involved several steps which included estimation of the propensity scores/ probabilities, utilisation of 1:1 Nearest-Neighbor (NN) matching with replacement with a caliper of 0.05, trimming. The caliper was applied to ensure high-quality matches and minimum bias from distant neighbours. The estimation was restricted to the region of common support to ensure that treated households were compared only to control households with similar propensity scores. Observations that fell outside the region of overlap were discarded. The common support condition was assessed graphically using kernel density plots of propensity scores and enforced using the "common" option in matching procedures. Approximately 34% of observations were trimmed due to lack of overlap. Post-matching density plots confirmed a near-perfect overlap between the treated and control groups. While selection bias existed in the raw data, the matched sample effectively eliminated these differences. Moreover, before matching, several covariates exhibited substantial bias (exceeding 20%), but after matching, the standardized mean differences for all covariates fell below the 10% threshold

Additionally, kernel matching which uses weighted averages of multiple control observations, with weights declining with distance in propensity scores was also used for robustness checks. Kernel matching typically reduces variance but may introduce slight bias if bandwidth is large. Mantel-Haenszel bounds were used to assess the sensitivity of the estimates to unobserved confounding factors. The results remained consistent (non-significant) across varying levels of Gamma. This confirmed that the null finding was robust even in the presence of potential hidden bias.

The "teffects psmatch" command was then used to obtain the Average Treatment Effect on the Treated (ATT) with Abadie-Imbens robust standard errors. The ATT was then estimated by comparing the mean maize yields of the matched treated and control groups:

$$ATT = E[Y_1 - Y_0|Z = 1] \quad (2)$$

where Y_1 is the potential outcome (Maize yield) with treatment, Y_0 is the potential outcome (Maize yield) without treatment, and E[·] denotes the expectation.

3. Results

The study results are presented in this section.

3.1. Use of the advice provided with climate information services

Table 2 presents the proportion of households that actually used each CIS type they received across the nine districts. In this study, access and use are not the same thing and the gap between the two varies considerably by CIS type. Generally, there was low usage of advice derived from received CIS in all districts, except for the advice for forecasts for the start of the rains and seasonal forecasts of the weather. These were used by over 50% of households surveyed in most districts, most likely for summer farming planning purposes. One focus group discussion participant said:

We need to know when are the rains likely to start and whether the season is a good season or not so that we plan accordingly.

Female FGD participant, Mumbwa District

This suggests that seasonal and rainfall onset forecasts should be prioritised, and the advice should be actionable. The gap between CIS access and practical application of the provided advice can be attributed to several challenges, notably resource limitations and delays in the timing of information delivery to farmers. Where possible, financial resources should be provided for farmers to act on the recommendations. Generally, across most CIS, Mungwi recorded high usage rates, while Chisamba consistently showed low usage. Daily forecasts were the least used CIS in almost all districts.

Table 2. Use of the advice provided with climate information services

	Chama	Chibombo	Chisamba	Kasama	Kawambwa	Mansa	Mumbwa	Mungwi	Nyimba	All
Forecast of drought, flood, frost, cyclone, or other extreme event										
Access observation (n)	79	50	66	58	53	69	65	66	64	570
Use (%)	24.1	34.0	34.9	36.2	35.9	46.4	41.5	59.1	31.3	38.1
Forecast of pest or disease outbreak										
Access observation (n)	53	35	42	43	47	55	43	39	37	394
Use (%)	30.2	40.0	26.2	46.5	38.3	47.3	46.5	38.5	37.8	39.1
Forecast of the start of the rains										
Access observation (n)	84	64	72	75	68	79	71	67	75	655
Use (%)	52.4	54.7	31.9	54.7	47.1	60.8	60.6	62.7	62.7	54.2
Seasonal forecast of the weather										
Access observation (n)	65	57	57	55	48	61	58	55	66	522
Use (%)	56.9	54.4	35.1	50.9	39.6	45.9	53.5	50.9	56.1	49.6
Forecast of the weather for today, 24 hours and/or next 2-3 days										
Access observation (n)	17	21	28	25	21	25	26	20	26	209
Use (%)	5.9	23.8	10.7	32.0	19.1	32.0	19.2	45.0	30.8	24.4

Note: Use (%) if percentages are based on households with access (n)

The primary sources of climate information services for all the CIS were the same. They were predominantly transmitted through local and national radio stations, neighbours, friends, and other community members. Other sources included television, agricultural extension officers, social media, and family members. CIS providers were Zambia Disaster Management and Mitigation Unit (DMMU), Meteorological Department, NGOs e.g. One Acre fund, World Vision, Faith-based organisations (Churches) and Conservation Farming Unit (CFU). Generally, they were disseminated through both formal and informal networks.

3.2. Farming changes after receiving climate information services

Table 3 presents farming practice changes reported by households that received CIS on forecasts of drought, flood, frost, cyclone, or other extreme events. Out of 570 households who received this CIS type, 189 (33.2%) reported making at least one farming practice change while the remaining 66.8% made no changes. This was attributed to financial constraints, late delivery of information, or scepticism about the accuracy of the provided information. For some households the advice simply arrived after planting had already begun. Of the 189 households that made changes, the majority (42.3%) used CIS on forecasts of drought, flood, frost, cyclone, or other extreme events to select new varieties and plant earlier. The message was timely and practical. One focus group discussion said:

> *Drought forecast led us to start potholing and select appropriate varieties because potholing holds water and right varieties gives us better yields.*
>
> *Female FGD participant, Mumbwa District*

Table 3. Changes from the forecast of drought, flood, frost, cyclone, or other extreme event

Change	Chama	Chibombo	Chisamba	Kasama	Kawambwa	Mansa	Mumbwa	Mungwi	Nyimba	All
Total observation (N)	79	50	66	58	53	69	65	66	64	570
Households that observed changes (n)	**21**	**15**	**18**	**16**	**19**	**23**	**24**	**33**	**20**	**189**
Adopted CSA (%)	28.6	6.7	22.2	10.5	0.0	8.7	12.5	0.0	35.0	13.2
Selected appropriate varieties (%)	38.1	53.3	55.6	42.1	25.0	47.8	54.2	33.3	35.0	42.3
Planted early (%)	42.9	26.7	22.2	31.6	50.0	26.1	29.2	42.4	30.0	33.9
Planted trees (%)	0.0	0.0	0.0	0.0	6.3	13.0	8.3	3.0	0.0	3.7
Removed weeds (%)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0	0.5
Applied less fertiliser and chemicals (%)	4.8	0.0	5.6	5.3	0.0	0.0	0.0	6.1	0.0	2.6
Reduced cultivated land (%)	0.0	0.0	5.6	0.0	0.0	0.0	0.0	3.0	0.0	1.1
Diversified to gardening or livestock (%)	4.8	0.0	0.0	5.3	12.5	8.7	0.0	0.0	0.0	3.2
Other (%)	0.0	13.3	5.6	10.5	6.3	8.7	8.3	3.0	5.0	6.3
Households that did not observe changes (%)	**73.4**	**70.0**	**72.7**	**67.2**	**69.8**	**66.7**	**63.1**	**50.0**	**68.8**	**66.8**

Note: Multiple responses were allowed among households that reported changes and percentages therefore do not sum to 100.

Mungwi had the highest proportion of farmers (50%) who changed their farming practices. Chama had the lowest (26.6%). But information alone might not be enough. CIS interventions targeting extreme event forecasts has to be tied to seed access and input supply since farmers cannot act on advice without the resources to do so.

3.3. Forecast of pest or disease outbreak

Changes in farming practices following CIS on the forecasts of pest or disease outbreaks are shown in Table 4. Of the 394 households who received this CIS type, 111 (28.2%) reported making at least one change while 71.8% made no change. Farmers noted that they could not afford the recommended chemicals, some doubted the accuracy of the forecast, and others simply saw no pests in their fields. Among the 111 households that did change their farming practices, the majority (64%) used the CIS on the forecasts of pest or disease outbreaks to treat their crops and livestock using modern methods, particularly in Chisamba (90%), Mansa (75%) and Mumbwa (80%).

Table 4. Changes from the forecast of pest or disease outbreak

Changes	Chama	Chibombo	Chisamba	Kasama	Kawambwa	Mansa	Mumbwa	Mungwi	Nyimba	All
Total observation (N)	53	35	42	43	47	55	43	39	37	394
Households that observed changes (n)	**13**	**12**	**10**	**12**	**15**	**12**	**15**	**10**	**12**	**111**
Used traditional methods to treat crops and livestock (%)	7.7	16.7	10.0	25.0	0.0	8.3	6.7	0.0	33.3	11.7
Selected appropriate varieties (%)	0.0	25.0	10.0	33.3	6.7	8.3	6.7	0.0	0.0	9.9
Planted early (%)	30.8	0.0	0.0	0.0	20.0	0.0	0.0	0.0	0.0	6.3
Checked pests on the farm (%)	0.0	0.0	0.0	8.3	6.7	8.3	13.3	0.0	8.3	5.4
Used modern methods to treat crops and livestock (%)	61.5	58.3	90.0	41.7	40.0	75.0	80.0	70.0	66.7	64.0
Other (%)	7.7	16.7	10.0	8.3	33.3	8.3	0.0	20.0	8.3	12.6
Households that did not observe changes (%)	**75.5**	**65.7**	**76.2**	**72.1**	**68.1**	**78.2**	**65.1**	**74.4**	**67.6**	**71.8**

Note: Multiple responses were allowed among households that reported changes and percentages therefore do not sum to 100.

Mumbwa had the highest proportion of farmers (34.9%) who changed their farming practices while Mansa had the lowest at 21.8%. However, changes in response to this CIS only work when agrochemicals are available and affordable. This CIS type should be linked to input credit facilities or subsidised chemical supply programmes.

3.4. Forecast of the start of the rains

Table 5 presents farming practice changes among households that received CIS on forecasts of the start of the rains. Of the 655 households who received this CIS type, 341 (52.1%) reported making at least one change. The remaining 47.9% made no change, particularly farmers in Chisamba (69.4%). Among the 341 households that did change their farming practices, the majority (63.6%) used the CIS on the forecasts of the start of the rains

to plant early, particularly in Mungwi (82.9%), Kawambwa (79.3%) and Chama (72.7%). One focus group discussion participant said:

> *When it comes to crop production, if the rains come early, we do plant early through the information we received, when it comes to livestock, we do build new houses, fish farming we close the inlet and open the outlet of the fish pond.*
>
> *Female FGD participant, Kawambwa District*

Table 5. Changes from forecast of the start of the rains

Change	Chama	Chibombo	Chisamba	Kasama	Kawambwa	Mansa	Mumbwa	Mungwi	Nyimba	All
Total observation (N)	84	64	72	75	68	79	71	67	75	655
Households that observed changes (n)	**44**	**35**	**22**	**39**	**29**	**43**	**42**	**41**	**46**	**341**
Adopted CSA (%)	0.0	0.0	4.5	0.0	3.4	2.3	7.1	0.0	6.5	2.6
Selected appropriate varieties (%)	15.9	45.7	22.7	12.8	3.4	25.6	35.7	7.3	17.4	20.8
Planted early (%)	72.7	37.1	50.0	66.7	79.3	60.5	50.0	82.9	67.4	63.6
Prepared land early (%)	18.2	17.1	27.3	17.9	24.1	23.3	19.0	0.0	8.7	16.4
Other (%)	6.8	14.3	9.1	10.3	10.3	7.0	11.9	14.6	10.9	10.6
Households that did not observe changes (%)	**47.6**	**45.3**	**69.4**	**48.0**	**57.4**	**45.6**	**40.8**	**38.8**	**38.7**	**47.9**

Note: Multiple responses were allowed among households that reported changes and percentages therefore do not sum to 100.

Nyimba (61.3%) had the highest proportion of farmers who changed their farming practices. Chisamba had the lowest (30.6%). The rainfall onset forecasts were the most actioned CIS. Farmers paid attention to this CIS type and used the information.

3.5. Seasonal forecast of the weather

Results from Table 6 show farming practices that changed after farming households received seasonal weather forecast CIS. The results indicate that the majority of farmers (56.1%) did not make any farming changes after receiving seasonal weather forecasts, especially in Chisamba (71.9%), Kawambwa (64.6%) and Mansa (70.5%). Of the 522 households who received this CIS type, 229 (43.9%) reported making at least one change, and most (48.9%) were able to select appropriate varieties, in particular, in Chibombo (60.0%) and Mumbwa (62.1%).

Table 6. Changes from seasonal forecast of the weather

Change	Chama	Chibombo	Chisamba	Kasama	Kawambwa	Mansa	Mumbwa	Mungwi	Nyimba	All
Total observation (N)	65	57	57	55	48	61	58	55	66	522
Households that observed changes (n)	**34**	**30**	**16**	**22**	**17**	**18**	**29**	**26**	**37**	**229**
Adopted CSA (%)	20.6	6.7	0.0	9.1	0.0	0.0	6.9	0.0	10.8	7.4
Selected appropriate varieties (%)	38.2	60.0	43.8	54.5	35.3	44.4	62.1	46.2	48.6	48.9
Planted early (%)	44.1	36.7	62.5	31.8	52.9	33.3	48.3	42.3	43.2	43.2
Prepared land early (%)	17.6	23.3	25.0	0.0	5.9	16.7	13.8	0.0	13.5	13.1
Other (%)	11.8	6.7	6.3	13.6	11.8	27.8	3.4	19.2	8.1	11.4
Households that did not observe changes (%)	**47.7**	**47.4**	**71.9**	**60.0**	**64.6**	**70.5**	**50.0**	**52.7**	**43.9**	**56.1**

Note: Multiple responses were allowed among households that reported changes and percentages therefore do not sum to 100.

Nyimba (56.1%) had the highest proportion of farmers who changed their farming practices. Chisamba had the lowest (28.1%). This was one of the most actioned CIS, as farmers used the information to make decisions about which crops to plant in the coming season. Seasonal forecasts usually should be delivered early enough in the pre-season period to allow farmers to source appropriate seed varieties before the planting windows close.

3.6. Forecast of the weather for today, 24 hours and/or next 2-3 days

As shown in Table 7 most households (91%) did not change their farming practices after receiving the daily or 2-3 days forecast of weather. Of the 209 households that received this CIS type, only 19 (9%) households did change their farming practice. Of these about 78.9% used the daily or 2-3 days forecast of weather to decide when to apply fertiliser. This CIS type helped them to avoid fertiliser application during dry spells or on dry soil.

Table 7. Changes from forecast of the weather for today, 24 hours and/or next 2-3 days

Change	Chama	Chibombo	Chisamba	Kasama	Kawambwa	Mansa	Mumbwa	Mungwi	Nyimba	All
Total observation (N)	17	21	28	25	21	25	26	20	26	209
Households that observed changes (n)	**0**	**2**	**2**	**1**	**3**	**3**	**4**	**4**	**0**	**19**
Adopted CSA (%)	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Selected appropriate varieties (%)	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Planted early (%)	0	0.0	0.0	0.0	0.0	0.0	0.0	25.0	0.0	5.3
Applied fertiliser (%)	0	50.0	100.0	100.0	100.0	100.0	75.0	50.0	0.0	78.9
Other (%)	0	0.0	0.0	0.0	0.0	0.0	0.0	25.0	0.0	5.3
Households that did not observe changes (%)	**100.0**	**90.5**	**92.9**	**96.0**	**85.7**	**88.0**	**84.6**	**80.0**	**100.0**	**91**

Note: Multiple responses were allowed among households that reported changes and percentages therefore do not sum to 100

Very few farmers (19) made changes after receiving this CIS. This is because daily forecasts have limited decision space for farmers to make changes, unlike seasonal or rain onset forecasts which provides farmers with time to make planting and crop variety choice decisions. Daily forecasts are actionable only for time-sensitive input applications such as the timing of fertiliser application.

3.7. Impact of access to climate information services on maize yield

This section presents the analysis results before and after matching treated households to control households. It further assesses the effect of household use of climate information services on maize yield. It also reports diagnostic procedures that were conducted to verify the robustness and validity of the findings.

3.7.1. Descriptive statistics (before matching)

Table 8 presents the descriptive statistics of the variables used in the PSM analysis. Most of the key variables were statistically and significantly different between treated and control households. This indicated that a simple comparison of the two groups without matching was likely to produce biased estimates of the treatment effect. Treated households had better access to irrigation (43.4% vs 32.0%) and more favourable soil types (58.8% vs 49.3%), both of which independently influenced maize yield. Similarly, treated household heads were better educated (8.0 vs 7.4 years) and belonged to more agricultural groups (2.2 vs 1.6). This suggested that CIS users had better social, human and environmental capital when compared to non-users. These pre-matching differences painted a clear picture that households that used CIS were systematically better-off, better-connected, and better-resourced than those that did not.

Table 8. Descriptive statistics (before matching)

Variable	Treated (n = 512)	Control (n = 724)	t-test/χ^2
Household characteristics			
Gender of household head (1=male %)	84	75	***
Education level of household head (years)	8.0(3.0)	7.4(3.0)	***
Household size (mean)	5.9(2.7)	5.5(2.6)	***
Soil type (1=good %)	58.8	49.3	***
Access to irrigation (1=yes %)	43.4	32.0	***
No. of agricultural groups membership (mean)	2.2(2)	1.6(1.7)	***
Off-farm income (1=yes %)	67.4	63	+
Wealth group			
Poor-resourced (1=yes%)	21.3	35.5	***
Average-resourced (1=yes%)	34.8	34.1	+
Well-resourced (1=yes%)	43.9	27.3	***

Notes: Standard deviation in parentheses

*Significance level: *** p < 0.01, ** p ≤ 0.05, * p < 0.1, + > 0.05*

t-test/χ^2 - Statistical significance of differences between treated and control groups were assessed using two-sample t-tests for continuous variables and Pearson chi-squared (χ^2) tests for binary and categorical variables.

3.7.2. Propensity score estimation

Table 9 presents the results of the logit model used to estimate the probability of household participation in the treatment. The model is statistically significant overall (LR chi^2 = 94.54, p < 0.001). These results indicate that the explanatory variables jointly explain a significant proportion of the variation in treatment participation. Specifically, access to irrigation, soil type, and the number of agricultural group memberships were statistically significant predictors of treatment participation. Even so, households classified as poorly-resourced and average-resourced were less likely to participate in the treatment relative to well-resourced households. These findings suggested that relatively better-resourced households were more likely to be selected into the treatment group. The presence of this systematic selection bias necessitated the application of propensity score matching.

Table 9. Logit results for propensity scores before matching

Variables	Coef.
Household size (mean)	0.0226 (0.0235)
Gender of household head (1=male %)	0.192 (0.163)
Education level of household head (years)	0.0290 (0.0214)
Access to irrigation (1=yes %)	0.254** (0.127)
Soil type (1=good %)	0.340*** (0.121)
No. of agricultural groups membership (mean)	0.134*** (0.0331)
Off-farm income (1=yes %)	0.0143 (0.130)
Poor-resourced (1=yes%)	-0.813*** (0.162)
Average-resourced (1=yes%)	-0.365** (0.144)
Constant	-1.027*** (0.297)
Observations	1,236
LR chi2(9)	94.54
Prob > chi2	0.0000
Log likelihood	-791.18825
Pseudo R^2	0.0564

Standard errors in parentheses

*Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1*

3.7.3. Overlap / common support

Figure 1 presents the distribution of propensity scores estimated from the logit model before matching.

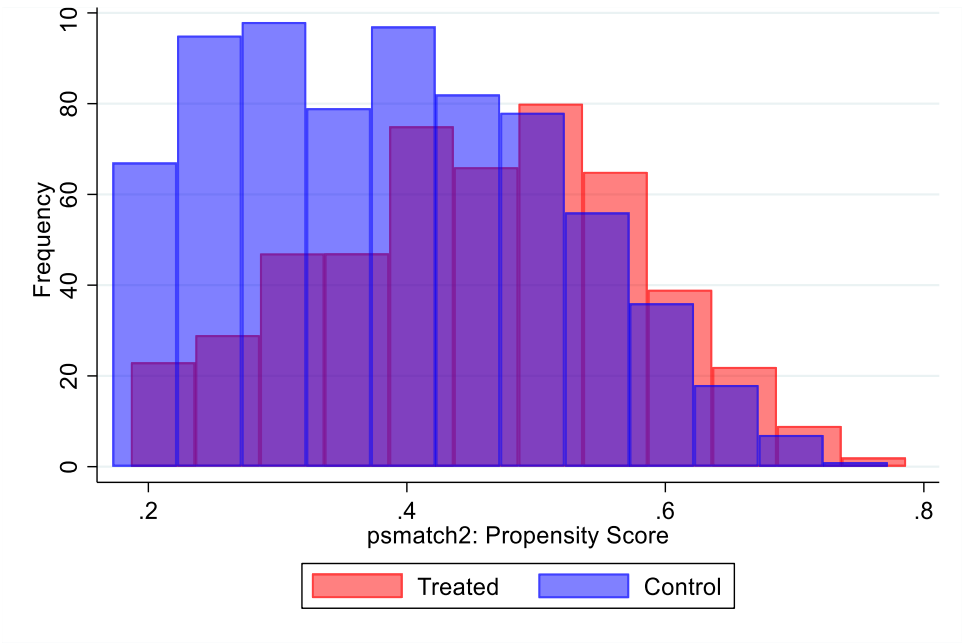


Figure 1. Overlap / common support (Propensity score distribution)

The overlap between the treated and control groups indicates the presence of a common support region. This region is where treated households have comparable control households with similar predicted probabilities of participation in the treatment. This confirms that the sample possesses adequate distributional overlap to facilitate the construction of a well-matched control group for the treated households through the propensity score matching procedure. The observations falling outside the common support region were trimmed through imposing the common support condition during the matching process.

3.7.4. Balance diagnostics

Following the matching procedure, the standardised mean bias was substantially reduced across all covariates as shown in Figure 2. Before matching, several variables including irrigation access, household education, and household size exhibited biases exceeding 20%. After matching, all covariates fell below the 10% threshold. This indicated that the matching procedure successfully balanced observable characteristics between treated and control households. Based on this, estimated treatment effects could be measured using the matched sample.

The assessment of the variance ratios further confirmed the robustness of the matching process. Prior to matching, the variance ratio for the number of agricultural group memberships deviated outside the acceptable range of [0.84; 1.19], recording a value of 1.34, indicating meaningful distributional differences between treated and control households on this variable. Following matching, all variance ratios fell within the acceptable bounds, with the number of agricultural group memberships reducing to 0.90, household size marginally adjusting to 1.12, and household head education remaining close to unity at 1.04. For binary variables, variance ratios were not applicable and were therefore not reported. The convergence of all variance ratios within the acceptable threshold after matching confirms that the matched sample achieves distributional balance not only in means but also in the spread of covariates across treated and control groups, thereby satisfying a more stringent criterion of covariate balance than mean bias reduction alone.

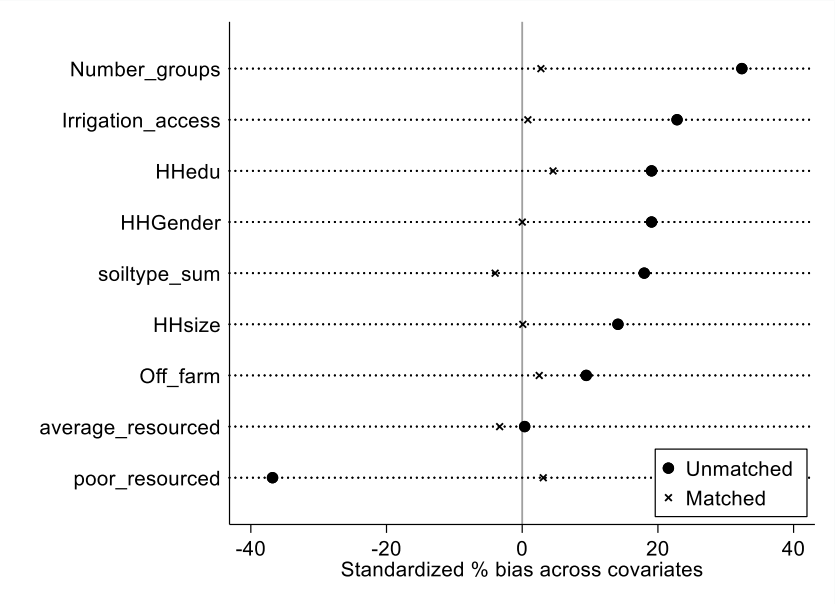


Figure 2. Standardised mean differences

3.7.5. Balance plot

Figure 3 shows the distribution of propensity scores before and after matching. The treated group generally had higher propensity scores than the control group. This indicated an initial imbalance between the two groups. After matching the distributions overlapped much more closely. This showed that the matching procedure was successful. The improvement in overlap meant that treated and control households became more comparable.

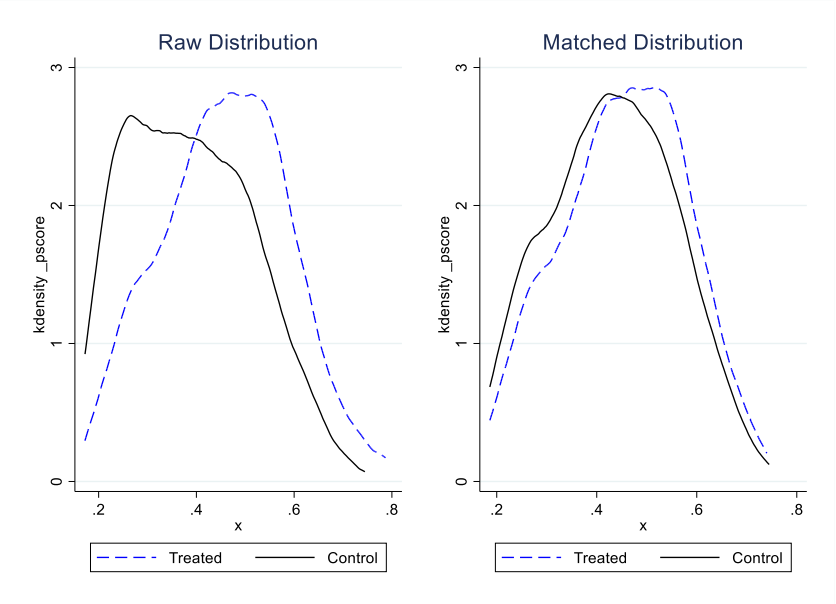


Figure 3. Distribution of propensity scores before and after matching

3.7.6. Estimation of treatment effects (main results)

Smallholder farmers who used climate information services (CIS) were significantly associated with higher maize yields than comparable households without access. The results in Table 10 show that CIS users

harvested on average 39.2 kg/ha more maize than matched non-users. This association was statistically significant at the 5% level with a t-statistic of 2.13. The consistency of the ATT estimates across both nearest-neighbour and kernel matching algorithms provided evidence that the finding was robust and not sensitive to the choice of matching method. These results suggested that CIS use may contribute to improved maize productivity among smallholder farmers. This is because the farmers who received and used climate information were more likely to adopt adaptive practices such as timely planting and appropriate variety selection which could partly explain the observed yield differences. These findings provide suggestive evidence that investing in CIS delivery may support smallholder productivity and contribute to food security among farming households in similar contexts.

Table 10. Average treatment effect of CIS use

Matching method	Outcome		ATT	t-statistics	Std. Err	Treated (n)	Control (n)
Nearest-neighbour	Maize yield (kg/ha)		39.2	2.13	18.40	504	303
Kernel matching	Maize yield (kg/ha)		39.2	2.13	18.403	504	303

3.7.7. Sensitivity analysis

The Rosenbaum bounds sensitivity analysis presented in Table 11 was conducted to assess the extent to which the estimated treatment effect was sensitive to unobserved confounding factors. Gamma equal to 1 represents the assumption of no hidden bias and serves as the baseline scenario for the sensitivity analysis, where treatment assignment depends only on observed characteristics. As Gamma increases to 2 and 3 the p-value for the overestimation scenario (p_mh+) remains at 0.514 which is well above the conventional 5% significance threshold. This indicates that if unobserved factors were to increase the odds of treatment assignment by up to three times, the estimated treatment effect would no longer remain statistically significant under the overestimation assumption. Therefore, the estimated impact of CIS use on maize yield may be sensitive to hidden bias arising from unobserved factors. This suggests that the estimated positive effect of CIS access on maize yield should be interpreted with caution, as the results may be sensitive to unobserved heterogeneity and potential selection bias arising from unobservable characteristics.

Table 11. Sensitivity analysis

Gamma	Q_mh+	Q_mh-	p_mh+	p_mh-
1	.	.	.	.
2	-.036347	.	.514497	.
3	-.036347	-.036347	.514497	.514497

Notes:

Gamma: odds of differential assignment due to unobserved factors
Q_mh+: Mantel-Haenszel statistic (assumption: overestimation of treatment effect)
Q_mh-: Mantel-Haenszel statistic (assumption: underestimation of treatment effect)
p_mh+: significance level (assumption: overestimation of treatment effect)
p_mh-: significance level (assumption: underestimation of treatment effect)

4. Discussion

The study examined the impact of access to climate information services on maize yield across nine districts under the AICCRA project. The findings align with broader literature that highlight both the potential and limitations of CIS in enhancing farmer decision-making. Consistent with Kayusi et al. (2024), the study finds that CIS particularly seasonal forecasts and rainfall onset predictions were widely accessed by the majority of farmers, but only a modest proportion adaptive farming decision (Kayusi et al., 2024). However, access and use of CIS, the low uptake of advice related to pest/disease forecasts and extreme weather events reflected persistent implementation challenges noted by Madhuri (2025) and Guido et al. (2020), including late delivery, financial constraints, and limited trust in forecast accuracy. Nyoni et al. (2024) and Warner et al. (2022) noted that women and other vulnerable groups face systemic barriers to CIS access due to socio-cultural norms and resource limitations.

Moreover, the observed limited behavioural change among farmers after receiving CIS, echoed concerns raised by Carr et al. (2020) and Savari et al. (2024) about the gap between information provision and actionable adaptation. While some farmers adopted climate-smart practices such as early planting and selection of appropriate varieties, behavioural changes were not uniform across districts. This is because farmers were often constrained by financial capacity after receiving CIS, reinforcing the argument by Somanje et al. (2021) that effective CIS must be coupled with infrastructure, credit access, and extension support. The AICCRA programme's bundled approach, integrating CIS with CSA innovations and gender-inclusive outreach, represented a promising model for addressing these gaps. However, the findings suggest that further investment in capacity building, timely dissemination, and trust-building mechanisms was essential to fully realise the adaptive potential of CIS in Zambia's smallholder farming systems.

Despite the highlighted challenges, the empirical results indicate that adaptive farm management decisions among CIS users were associated with higher maize productivity. The magnitude of this gain was robust across different matching algorithms; nearest-neighbour matching and kernel matching. The use of CIS was statistically and significantly associated with maize yield increase by 39.2 kg per hectare. These findings are consistent with the view that CIS use is positively associated with better smallholder maize productivity. This is consistent with findings from Kayusi et al. (2024). Within the broader context of rain-fed agriculture, increasingly threatened by climate variability these findings provide suggestive evidence that CIS delivery may support smallholder resilience. This is reflected in the greater likelihood of CIS users adopting adaptive practices such as adjusting planting dates and selecting appropriate crop varieties, behaviours that may partly explain the observed yield differences between matched treated and control households.

5. Limitations

This study has limitations that are important to consider when interpreting the findings. PSM reduces selection bias arising from observed characteristics. It cannot rule out bias from unobserved factors that simultaneously influence both CIS access and maize yield. In this study such unobserved factors may include farmer motivation and innate managerial ability. They may also include informal social networks and access to non-surveyed extension contacts. These factors were not captured in the survey instrument. Therefore, the estimated association between CIS access and maize yield may still partly reflect the influence of these unobservable factors.

What PSM can rule out is that the observed yield difference between CIS users and non-users is driven by the observable characteristics included in the matching model. These include wealth status, irrigation access, soil type, education and agricultural group membership. After matching these characteristics were balanced between the two groups. The yield difference therefore cannot be attributed to these factors. What PSM cannot

rule out is that farmers who accessed CIS were already more motivated or better connected than those who did not. These unobserved traits may independently contribute to higher yields. The Rosenbaum bounds test showed the findings were robust to moderate levels of hidden bias. However, this test does not eliminate the possibility of unobserved confounding entirely. Future studies using randomised designs or panel data would provide a stronger basis for drawing causal conclusions about the effect of CIS on maize productivity in Zambia.

6. Conclusion and recommendations

This study provides evidence consistent with the view that access to Climate Information Services (CIS) is associated with greater farmer preparedness and adaptive agricultural practices in Zambia, particularly in relation to early planting and crop variety selection for maize. While the majority of farmers received forecasts on rainfall onset and seasonal conditions, actual behavioural change remained limited, with financial constraints, late information delivery, and trust issues cited as key barriers. The findings are consistent with the central hypothesis that farmers who use CIS were more likely to adopt adaptive actions to climate-related events and were associated with higher maize productivity levels than those without access or using the CIS they received. Furthermore, disparities in CIS utilisation across resource endowments were consistent with the secondary hypothesis, suggesting that better-resourced farmers and those with access to irrigation favourable soils and agricultural group membership were more likely to access and utilise CIS. These insights highlight the need for inclusive, timely, and context-sensitive CIS delivery models to enhance climate resilience across diverse farming households.

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Data availability statement

Data used in this research are available upon request.

Conflicts of interest

The authors declare no conflicts of interest.

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