Impact Evaluation of Shamba Shape Up Weather and Farming News on Smallholder Farmers in Kenya

Calvin Kiprop, Lilian Kirwa, Elias Ngotho, Chris Mwungu, Agnes Wanjau, Felix Otieno, Majambo Gamoyo, Grace Koech, Aniruddha Ghosh

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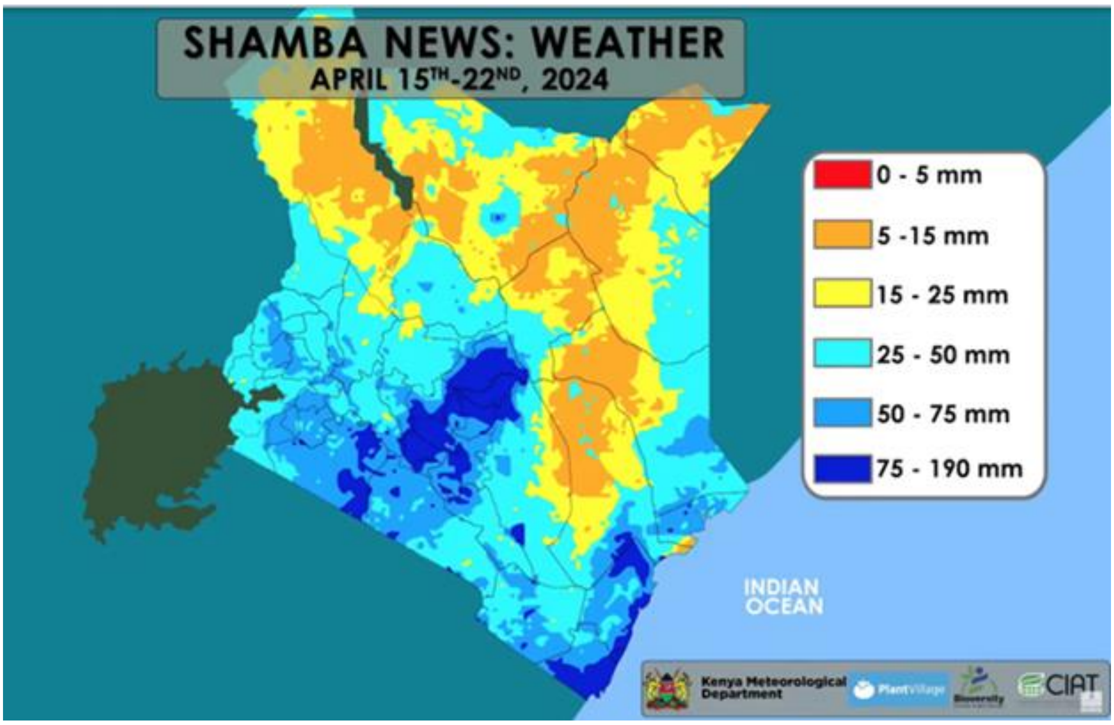

Impact evaluation technical report

Calvin Kiprop, Lilian Kirwa, Elias Ngotho, Chris Mwungu, Agnes Wanjau, Felix Otieno, Majambo Gamoyo, Grace Koech, Aniruddha Ghosh

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About AICCRA Reports
Titles in this series aim to disseminate interim research on the scaling of climate services and climate-smart agriculture in Africa, in order to stimulate feedback from the scientific community.

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Cover photo: © iShamba/Shamba Shape Up

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ABOUT AICCRA

CGIAR | AICCRA Accelerating Impacts of CGIAR Climate Research for Africa

Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA) is a project that helps deliver a climate-smart African future driven by science and innovation in agriculture. It is led by the Alliance of Bioversity International and CIAT and supported by a grant from the International Development Association (IDA) of the World Bank. Explore our work at aiccra.cgiar.org

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EXECUTIVE SUMMARY

Kenya's agricultural sector plays a crucial role, employing over 75% of the rural population and serving as the catalyst for the other sectors. However, despite its significance, the sector's potential and long-term sustainability are hampered by the negative impacts of climate change. A defining characteristic of Kenyan agriculture is the predominance of smallholder farming systems. These smallholder farmers contend with many challenges that limit their ability to adapt to climate change, including inadequate access to resources and information. Additionally, they often face reduced access to modern technologies and economic limitations that hinder investment in climate-resilient practices. In response to these challenges, Climate Information Services (CIS) have emerged as a potential solution, aiming to equip farmers with actionable climate information to enable informed decision-making. Consequently, innovative programs and media segments have been developed to bridge the information gap and support smallholder farmers.

This report presents an impact evaluation of the Shamba Shape Up (SSU) Weather and Farming News segment, focusing on its effectiveness in providing weather-related advisories to smallholder farmers in Kenya to improve farmers' risk mitigation strategies, institutional capacities, and partnerships. The segment has played a vital role in the broader effort to support smallholder farmers in Kenya, providing them with tailored weather advisories to aid in decision-making. The segment has broadcasted for the last 14 years and is part of the Accelerating Impacts of Consultative Group on International Agricultural Research (CGIAR) Climate Research for Africa (AICCRA) and Climate Resilience (ClimBeR) programs in collaboration with Alliance of Bioversity International and International Center for Tropical Agriculture (ABC). This evaluation aims to quantify the program's impact and understand its reach among the local farming communities in Kenya.

The study conducted the evaluation through household surveys across 40 counties in Kenya. The findings revealed that a significant proportion of farmers rely on the SSU Weather News segment for crucial farming decisions, such as when to plant, which crops to plant, where to obtain inputs, seed selection, pest and disease management, soil management and adoption of climate resilient practices. However, the adoption of weather-related risk mitigation measures and sustainable farming practices remains relatively low, indicating the need for increased awareness on such measures to improve resilience among farmers.

The report highlights that, according to the sample from the SSU study, SMS was the preferred platform for smallholder farmers in Kenya to receive weather news and agro-advisories. This could be attributed to the platform being the most commonly used by SSU due to its accessibility and immediate delivery. Timely and accurate weather advisories are crucial for effective decision-making, leading to improved crop yields and reduced losses. Aligning advisories with local knowledge and addressing accuracy disparities across counties were identified as key areas for improvement. The report also found that SSU viewers were more likely to adopt sustainable farming practices and employ risk mitigation strategies, resulting in higher agricultural income compared to non-viewers. This demonstrates the significant impact of SSU viewership on decision-making, adoption of climate-resilient agricultural practices, and improved farm outcomes.

The economic benefits associated with SSU viewership are significant. For instance, maize farmers who watch SSU report an average income of KES 84,605.46 compared to KES 35,083.28 for non-viewers. Similar trends are observed for beans, Irish potatoes, sweet potatoes, and dairy farming, where viewers achieve higher average incomes and return on investment (RoI). For example, Irish potato farmers who follow SSU news achieve an RoI of 3.34, compared to 1.65 for non-viewers. While these results indicate a correlation between SSU viewership and increased income levels, it is crucial to recognize the potential influence of confounding variables such as farm management practices, resource accessibility, and regional climatic conditions. Variations in farmers' income levels are significantly influenced by disparities in access to high-quality inputs such as seeds, fertilizers, irrigation systems, and farm machinery, as well as the adoption of advanced agricultural practices and technologies. Thus, to establish a causal relationship between SSU viewership and income, additional rigorous analysis is necessary to isolate the independent impact of SSU viewership.

Moreover, we used Individual Treatment Effects (ITE) with Causal Forests and Geographically Weighted Regression (GWR) to examine spatial variation, revealing significant differences across counties. Some counties, like Migori, West Pokot, and Makueni, exhibit positive outcomes, while others like Nyandarua and Machakos show negative impacts. Specifically, counties closer to central Kenya (Nyandarua, Nyeri, Murang'a) exhibited lower maximum Individual Treatment Effects (ITEs), whereas Kilifi, Kwale, Migori, West Pokot, Makueni, and Isiolo counties showed higher values, suggesting a potentially greater influence on agricultural revenue in these regions. This underscores the importance of considering location-specific factors when designing interventions. In other words, the unique agricultural, socio-economic, climatic, and cultural factors specific to each geographical location allow sector players to create more effective, targeted, and tailored advisory services. Despite these spatial variations which showed some counties benefiting more from watching SSU weather and farming news, the use of Propensity Score Matching (PSM) showed that, generally, households that watched SSU weather and farming news realized relatively higher incomes. Building on these insights, the evaluation's findings provide valuable guidance for future agricultural development strategies, particularly in the realm of climate advisories.

Overall, the findings of the evaluation provide valuable insights for stakeholders involved in agricultural development and climate resilience initiatives in Kenya and beyond. These findings call for continuous improvement in advisory content and delivery to maximize their benefits and strengthen partnerships with relevant organizations to expand outreach and improve advisory services. In addition, the report highlights the importance of addressing disparities within agricultural communities, particularly regarding gender and education, to design effective and inclusive interventions. The adoption of weather-related risk mitigation measures remains low, indicating a need for increased awareness and content. The integration of local knowledge into weather forecasting has emerged as crucial for enhancing advisories. Therefore, gender-sensitive approaches, youth engagement, and continuous improvement in advisory delivery are essential to maximize the impact of SSU and similar advisories on smallholder farmers' livelihoods in Kenya.

Keywords

Partnerships; agriculture; climate change; food security.

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CONTENTS

ACRONYMS

ABC	Alliance of Bioversity International and CIAT
AEZ	Agro Ecological Zones
AgERA5	Agricultural Meteorology dataset from ERA5
AICCRA	Accelerating Impacts of CGIAR Climate Research for Africa
ASAL	Arid and Semi-Arid Lands
ATE	Average Treatment Effect
BEST	Berkeley Earth Surface Temperature
CARET	Classification and Regression Training
CBA	Cost-Benefit Analysis
CF	Causal Forests
CDF	Cumulative Distribution Function
CHC	Climate Hazards Center
CIAT	International Center for Tropical Agriculture
CGIAR	Consultative Group on International Agricultural Research
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CIS	Climate Information Services
ClimBeR	CGIAR Initiative on Climate Resilience
CRU	TEM4v CRU Temperature Data Set Version 4
CSA	Climate Smart Agriculture
ECMWF	European Centre for Medium-Range Weather Forecasts
ENSO	El Niño Southern Oscillation
FAO	Food and Agriculture Organization of the United Nations
GAP	Good Agricultural Practices
GDP	Gross Domestic Product
GFCS	Global Framework for Climate Services
GoK	Government of the Republic of Kenya
GWR	Geographically Weighted Regression
IE	Impact Evaluation
IFAD	International Fund for Agricultural Development
ITCZ	Inter Tropical Convergence Zone
ITE	Individual Treatment Effects
IV	Instrumental Variable
KALRO	Kenya Agricultural and Livestock Research Organization
KBM	Kernel-Based Matching
KES	Kenyan Shilling
KHCP	Kenya Horticulture Competitiveness Project
KIPPRA	Kenya Institute for Public Policy Research and Analysis
KMD	Kenya Meteorological Department
MAM	March, April, and May
MMO	Munda Makeover
NGOs	Non-Governmental Organizations
NNM	Nearest Neighbor Matching
NOAA	National Oceanic and Atmospheric Administration
OCHA	Office for the Coordination of Humanitarian Affairs
OLS	Ordinary Least Squares
OND	October November December
PSM	Propensity Score Matching
RCMRD	Regional Centre for Mapping of Resources for Development

RFC	Random Forest Classification
RFR	Random Forest Regression
RFE	Recursive Feature Elimination
RM	Radius Matching
ROI	Return on Investment
SDGs	Sustainable Development Goals
SSA	Sub-Saharan Africa
SST	Sea Surface Temperature
SSU	Shamba Shape Up
UNICEF	United Nations International Children's Emergency Fund
UoR	University of Reading
USD	United States Dollar
USGS	United States Geological Survey
WFP	World Food Programme
WHO	World Health Organization
ZMA	Zambia Meteorological Agency
ZNBC	Zambia National Broadcasting Corporation

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1. INTRODUCTION

1.1 Background information

Climate change poses a significant challenge to small-scale farmers, undermining global strides towards achieving Sustainable Development Goals (SDGs) such as good health and well-being, no poverty, zero hunger, and gender equality (Hsieh & Yeh, 2024). It represents a threat to global sustainable development, disproportionately affecting the poorest and most vulnerable communities (Birkmann et al., 2022). The adverse effects on small-scale agriculture are profound and multifaceted, including rising temperatures, unpredictable rainfall patterns, and extreme weather events (Khisa et al., 2014; Mbilinyi et al., 2013; Ochieng et al., 2016). These effects of climatic change impact livestock and crop yields, income generation capacities, and ultimately, overall food security among smallholder farmers.

Globally, there are over 475 million smallholder farmers who are resource-constrained and live under unstable conditions (Fan & Rue, 2020; Harvey et al., 2018). Their reliance on rain-fed agriculture and limited access to resilient farming practices make them particularly vulnerable to climate change (Cohn et al., 2017). Recently, approximately 2.4 billion people, primarily women and rural households, have lacked adequate access to nutritious and sufficient food year-round (FAO et al., 2023). Projections indicate that nearly 670 million people will still be undernourished by 2030 due to climate change impacts (FAO et al., 2020). Addressing these vulnerabilities is crucial for enhancing global food security and resilience.

In Sub-Saharan Africa (SSA), food security has already been adversely affected. Climate change models predict worsening conditions, with increased frequency and intensity of hot days and fewer cold days in West Africa, East Africa, and Southern Africa by the end of the 21st century (Ayanlade et al., 2022). Rainfall projections remain uncertain; however, Southern Africa is likely to experience significant drying, while East Africa may see increased rainfall during the short rainy season (Ongoma et al., 2018). These changes pose significant challenges to water security, hindering agricultural development and food production (Leonard, 2022).

As the urgency of the climate change challenge has risen the political agenda, the need for actionable climate information to inform policy and practice has similarly emerged as a priority. This demand led to the implementation of the Global Framework for Climate Services (GFCS) in 2009, which has since become a prominent mechanism for addressing the identified gap between the societal need for climate information and producer supply (Hewitt et al., 2012). Several studies have shown that many smallholder farmers in developing countries lack access to reliable climate information and the recommended actions to take in response to or in anticipation of climate risks (Antwi, 2024; Ng'ang'a et al., 2021; Zvobgo et al., 2023). Therefore, providing timely and reliable climate information services are critical to farmers and value chain actors in planning and implementing climate adaptation strategies, and in improving productivity, food security and livelihood resilience in rural economies (Brasseur & Gallardo, 2016; Chepkoech et al., 2022; Dinku et al., 2018). By being prepared, farmers can greatly reduce potential losses by taking effective steps to lessen the impact. This not only limits the damage they might face but also strengthens their ability to adapt to changing weather conditions (Funk et al., 2023).

Recognizing the urgent need for provision of Climate Information Services (CIS) to increase farmers' productivity whilst supporting their adoption of sustainable practices in the face of climate change, Shamba Shape Up (SSU), a reality TV show was established by a consortium of research organizations and MediaE (a company specialized in educational productions). The SSU program has been airing over the past 14 years in Kenya, Uganda and recently in Zambia as Munda Makeover (MMO). Each episode is 30 minutes long and split into 5-minute segments covering topics broadly relevant to the stage of the cropping season when the broadcast takes place including seasonal and weather forecasts and good agronomic practices. In Kenya for example, the weather segment usually aired during long rains (March to May) season but given the declaration of El-Nino in 2023, weather segments were also introduced for the 2023 short rains (October to December) season considering that El-Nino was associated to increased wet conditions in Kenya and increased dry conditions in Zambia. Weather and climate information for the weather segments aired on SSU and MMO was obtained from the Kenya Meteorological Agency (KMD) and Zambia Meteorological Agency (ZMA) and translated into relevant information then transferred to the SSU team for production.

In Kenya, each episode is broadcasted twice a week, once in Swahili (on Sunday afternoon) and once in English (on Saturday afternoon) on Citizen TV while in Zambia, MMO is aired every week in English (on Monday), Nyanja (on Friday), Tonga (on Saturday) and in Bemba (on Sunday) on ZNBC TV1 during the cropping season. According to the Africa Enterprise Challenge Fund (AECF) report (each weekly episode consists of a visit to a selected farm where current issues and problems facing a host farmer and household are discussed (AECF, 2014). Solutions and opportunities are identified with the help of experts. Potential changes to the farm enterprises are explored through demonstration and explanation. Additionally, SSU disseminates shorter agronomic advisories and climate forecast videos on social media platforms such as Facebook[1] and YouTube[2], while registered premium farmers receive advisory messages via mobile text and WhatsApp.

Beyond these broadcasts, the Kenyan government and various non-governmental organizations (NGOs) are investing in technologies and systems to provide timely and accurate weather information to farmers (Krell et al., 2021). This includes the development of mobile apps and platforms that deliver real-time climate data and advisories, helping farmers make informed decisions about farming. Alongside SSU, there are several platforms in Kenya where farmers can obtain weather advisory services such as the Kenya Meteorological Department (KMD), the Kenya Agricultural and Livestock Research Institute (KALRO) and Farm Radio (Dhulipala, 2023; Muema et al., 2018; Shilenje & Ogwang, 2015).

This study evaluates the impact of the SSU Weather News segment on agricultural practices and outcomes among Kenyan farmers. The study employs a mixed-

[1] Shamba Shape Up Facebook channel

[2] Shamba Shape YouTube channel

methods approach, combining both empirical and descriptive analyses. The empirical analysis utilizes a three-stage approach to assess the impact of watching SSU weather and farming news on agricultural income among smallholder farmers in Kenya. First, the study identifies key variables influencing income using Recursive Feature Elimination (RFE) and Random Forest Regression (RFR). Second, Causal Forests (CF) estimate Individual Treatment Effects (ITE) to understand the SSU segment's personalized income impact on farmers. This allows for mapping ITEs and to identify areas with positive or negative outcomes, informing targeted advisory and interventions. Additionally, Geographically Weighted Regression (GWR) is employed to assess the spatial heterogeneity in the relationship between agricultural income and watching the SSU weather and farming news segment.

However, impact assessments using observational or non-experimental data face challenges such as self-selection bias, endogeneity, spillover effects, reverse causality, unobserved heterogeneity, and omitted variable bias (Semadeni et al., 2014). For example, participation in groups or social networks facilitates information access for farmers, potentially leading to knowledge sharing and positive spillover effects. However, this ease of access can also introduce selection bias (Wang et al., 2020), as farmers who are more proactive in seeking information may be more likely to watch the SSU weather and farming news segment. While instrumental variables (IV) offer an alternative approach to address selection bias and endogeneity (Guo et al., 2018), identifying suitable instruments can be challenging. Therefore, Propensity Score Matching (PSM) is employed in this study to mitigate these concerns.

PSM addresses self-selection and endogeneity concerns in observational studies by creating a balanced comparison between treated and untreated observations. PSM pairs farmers who watched the SSU weather and farming news segment (treated group) with those who did not (control group) based on similar observable characteristics, such as age, educational level, household size, asset ownership, income level, size of agricultural land owned etc. (Rosenbaum, 2002). This matching process ensures that the two groups are comparable. Using propensity scores to match - the probability of watching SSU weather and farming news segment given the observed covariates - PSM balances the distribution of these covariates between the treated and control groups, reducing bias due to observable confounders. In addressing endogeneity, PSM mitigates a portion of the bias arising from omitted variables by matching on a comprehensive set of observable covariates. This lowers the risk that omitted variables influencing both the treatment and the outcome will bias the results. Caliendo and Kopeinig (2008) argue that PSM achieves comparability between the control and treatment groups, thereby mitigating a portion of the bias from endogenous selection into the treatment group. However, it is important to acknowledge that PSM does not fully address endogeneity caused by unobservable factors, and its effectiveness depends on the assumption that all relevant confounders are observed and included in the matching process (King & Nielsen, 2019).

1.2 Objectives

This study evaluates the impact of the SSU weather and farming news segment on smallholder farmers and related institutions in Kenya. Specifically, the study investigates the SSU weather and farming news segment's effectiveness in delivering timely and site-specific weather information and how farmers utilized these forecasts and localized advisories to inform their decision-making processes related to crop cultivation, harvesting, and management. Furthermore, the study assesses the SSU weather and farming news segment's impact on agricultural productivity, encompassing crop cultivation, harvesting, and management practices. Additionally, the study examines the role of the SSU segment in mitigating weather-related risks for farmers and evaluate how iShamba's[3] initiatives enhance the capacities of institutions to handle agricultural advisories and strengthen institutional partnerships.

1.3 Significance and challenges of agriculture in Kenya

Agriculture is a keystone of Kenya's socio-economic framework, accounting for over one-third of the country's Gross Domestic Product (GDP) (Diao, 2010). It provides employment for over 70% of the rural population and serves as a primary source of foreign exchange, with over 65% of national export revenue generated from agricultural goods (Masłoń-Oracz et al., 2021). This sector directly contributes approximately 26% to GDP, with an additional 27% indirect contribution through linkages with other industries (Osiemo et al., 2021).

Despite its importance, the Kenyan agricultural sector faces numerous challenges hindering its productivity and growth. A key obstacle is declining production and efficiency on local farms, often attributed to an aging agricultural workforce and a lack of interest among younger generations in pursuing agriculture as a viable livelihood (Visser, 2024). This is further compounded by the prevalence of food insecurity, posing a significant barrier to progress. Furthermore, the sector's vulnerability to climate variability intensifies food insecurity and poverty (Kogo et al., 2021; Maja & Ayano, 2021). Limited access to modern farming technologies and inadequate infrastructure further constrains the sector's potential (Ogada et al., 2014).

Recognizing these challenges, the Government of the Republic of Kenya (GoK) has implemented various strategies to address them, including prioritizing the expansion of irrigated land, subsidizing agricultural inputs, strengthening agricultural extension services, and undertaking institutional reforms through privatization. However, despite these efforts, public funding allocated to agriculture has consistently remained below 5% for the past decade, which is insufficient to drive significant improvements (FAO, 2017). Essential measures include implementing policies that promote climate-resilient agriculture and enhancing access to loans and markets for farmers.

To complement these efforts, CIS provide farmers with accurate and timely climate information and advisories, crucial for efficient agricultural planning and decision-making. This enables farmers to make informed choices about crop planning, adopting new technologies, and selecting climate-resilient seeds, thereby improving production and adaptation (Ngigi & Muange, 2022). Additionally, CIS help mitigate risks associated with extreme weather events and climate variability,

[3] iShamba is a mobile service that provides customized, up-to-date agricultural information and assistance, facilitating direct communication between farmers and experts. This product is provided by Mediae Company (https://mediae.org/) alongside SSU.

fostering the development of more resilient agricultural systems. Integrating CIS into Kenya's current agricultural policy is essential for increasing agricultural productivity, strengthening system resilience, and reducing greenhouse gas emissions (Akoko & Nduah, 2023).

1.4 Climate profile

Kenya lies within a relatively humid equatorial climate zone, but the topography, prevailing winds and water bodies cause differences in rainfall and temperature patterns across the country. Typically, the rainfall regime is bimodal over much of Kenya, with most of the rain falling in the long rains in March, April, and May (MAM) and less during the short rains in October, November, and December (OND) (Figure 1). Previous work has shown that two rainy seasons are influenced by the Inter Tropical Convergence Zone (ITCZ)[4], and interannual variability is stronger in OND than MAM, but OND rainfall is better understood as it has a strong connection to El Niño Southern Oscillation (ENSO)[5] events which tends to lead to more rainfall during El Niño and less rainfall during La Niña while the Indian Ocean influences rainfall during what is referred to as Indian Ocean Dipole (IOD)[6] events (Funk et al., 2023; Nicholson, 2014; Nicholson et al., 2018).

Kenya has a diverse climate profile where temperatures and rainfall vary (Figure 2). Currently, the mean annual temperatures in the country range between 18 to 28 °C with the coastal areas (eastside) and the shores of Lake Victoria (westside) having a tropical climate, with mean annual temperature between 23°C and 27°C and total annual rainfall of around 1000 to 1500 mm. The highlands (mostly in the central parts of the country) have a temperate climate, with a mean annual temperature of 15°C and total annual rainfall level of around 1000 mm. The northern and eastern parts of Kenya have a much drier climate, with mean annual temperatures of up to 29°C and annual rainfall of around 200 mm.

Between 1981 and 2022, temperatures in Kenya increased while there’s no significant change in rainfall. Temperatures in Kenya have increased by around

[4] The Intertropical Convergence Zone is the region that circles the Earth, near the equator, where the trade winds of the Northern and Southern Hemispheres come together. The intense sun and warm water of the equator heats the air in the ITCZ, raising its humidity and making it buoyant. Aided by the convergence of the trade winds, the buoyant air rises. As the air rises it expands and cools, releasing the accumulated moisture in an almost perpetual series of thunderstorms. Seasonal shifts in the location of the ITCZ drastically affects rainfall in many equatorial nations, resulting in the wet and dry seasons of the tropics rather than the cold and warm seasons of higher latitudes. Longer term changes in the ITCZ can result in severe droughts or flooding in nearby areas.

[5] The El Niño-Southern Oscillation (ENSO) is a recurring climate pattern involving changes in the temperature of waters in the central and eastern tropical Pacific Ocean. El Niño and La Niña are the extreme phases of the ENSO cycle; between these two phases is a third phase called ENSO-neutral.

[6] The Indian Ocean Dipole is a climate pattern affecting the Indian Ocean. During the positive phase of the IOD, heavy rains are experienced while during a negative phase, the country receives less rain.

0.23°C per decade, which translates to an increase of nearly 1°C for the 42-year period based on the AgERA5 dataset (Boogaard et al., 2020) while the long-term trend analysis in seasonal rainfall shows a non-significant change based on CHIRPS data (Funk et al., 2015).

Despite Kenya's naturally moderate climate, increasing climate variability and extremes are intensifying the frequency and severity of extreme weather events.

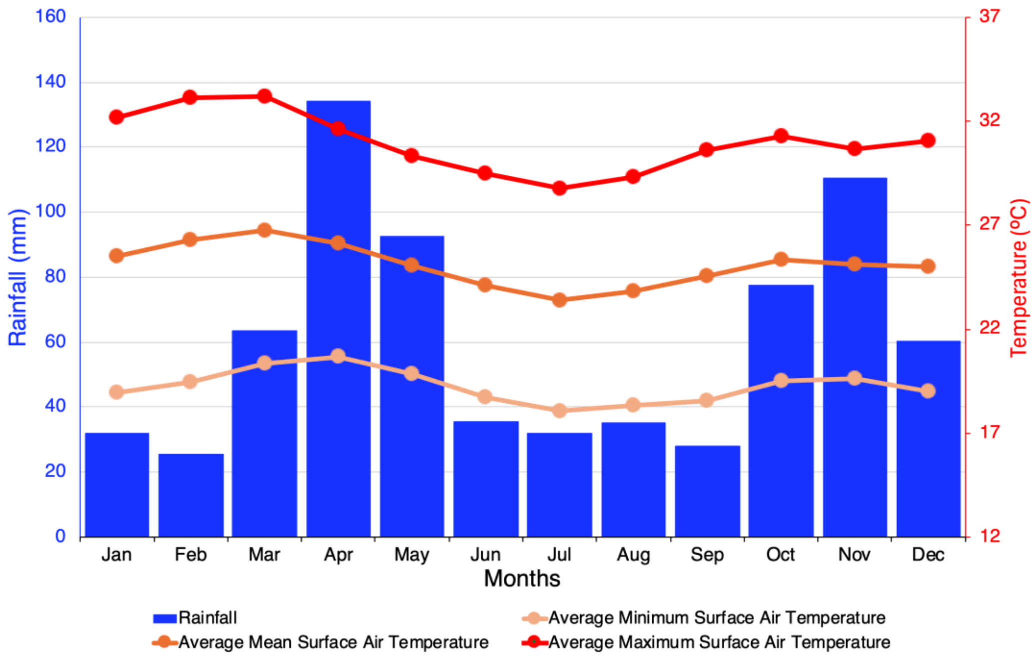

Figure 1. Average monthly rainfall and temperature for Kenya, 1981–2022

In recent decades, erratic rainfall has led to both droughts and floods, causing significant loss of lives and livelihoods. Since 2010, the Kenya Government has declared drought a national disaster thrice: the drought in 2010–2011, the drought in 2016–2017, and the recent drought in 2020–2022 leaving about 4.2 million people in need of humanitarian assistance[7]. The drought adversely affected outputs of the crops and livestock sub-sectors, which in turn reflected in the dismal performance of the economy. The droughts were due to strong La-Niña event. Compared to droughts, more floods have occurred since 2000, mostly severe floods occur during El-Nino years with the recent floods occurring in 2023 during the OND rains. During this period, hundreds of thousands of people were displaced[8].

[7] According to the humanitarian information service provided by the United Nations Office for the Coordination of Humanitarian Affairs (OCHA)

[8] https://www.unocha.org/publications/report/kenya/kenya-heavy-rains-and-floods-impact-and-response-20-december-2023

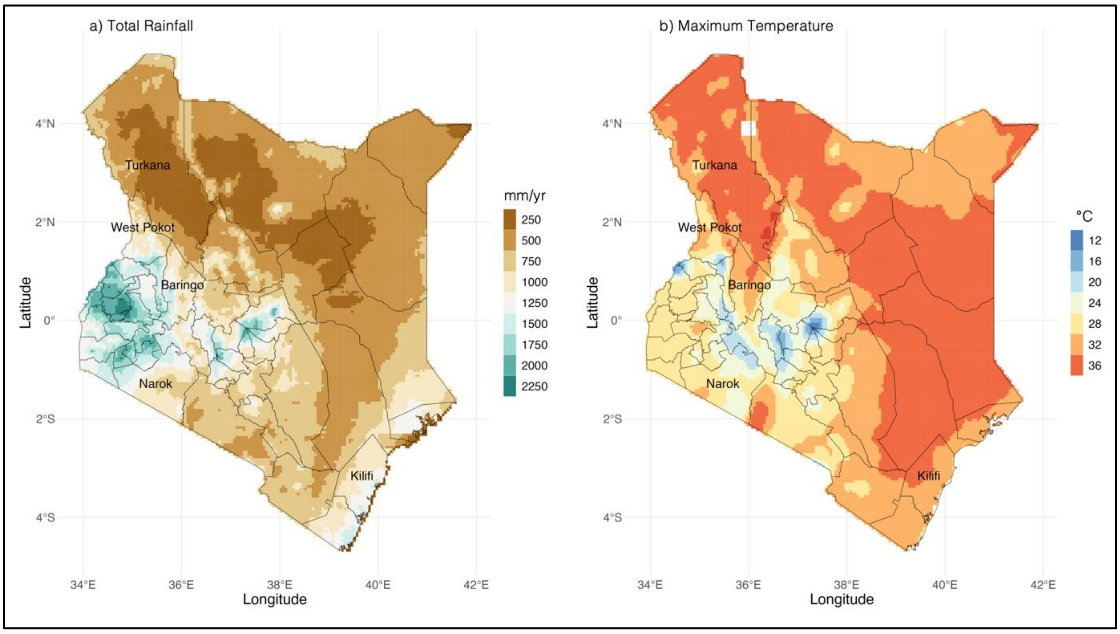

Figure 2. Map of annual total precipitation[9] (left) and annual maximum temperature[10] (right); of Kenya,1981–2020

Beyond the looming threats of droughts and floods, the country is also facing a range of other climate hazards (Figure 3). Notably, Arid and Semi-Arid Lands (ASAL) regions have experienced dry conditions with thermal stress, while the central and parts of the west side of the country are exposed to climate variability leading to droughts. The remaining western part of the country has experienced high climate variability, leading to floods.

[9] Annual total rainfall was calculated from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) data

[10] Annual maximum temperature was calculated from Agricultural ECMWF Re Analysis 5 (AgERA5) data. ECMWF stands for European Centre for Medium-Range Weather Forecasts

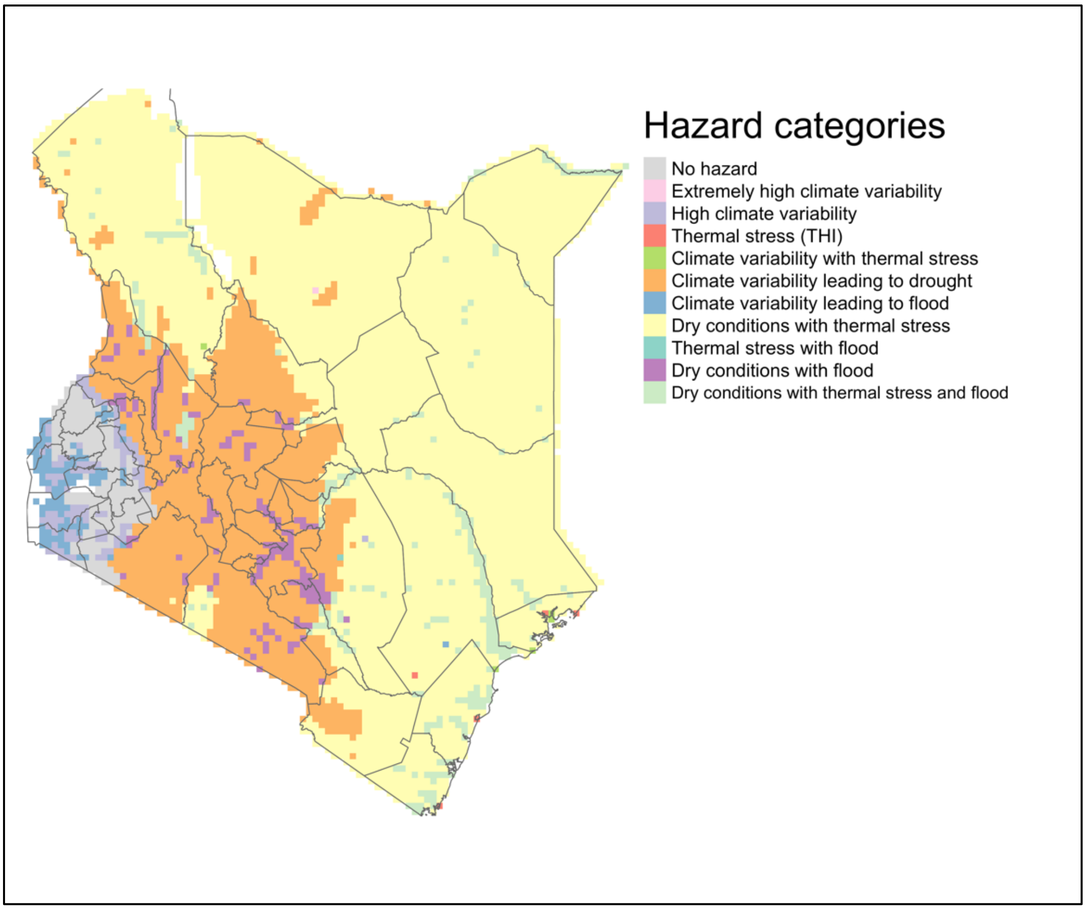

Figure 3. Extreme weather events experienced in Kenya

Prolonged or recurrent exposure to these multifaceted climate hazards carries far-reaching implications. These hazards pose a significant risk to crop yields and livestock production, consequently threatening food security within the counties of interest. As these climatic challenges persist and intensify, the capacity of local communities for sustainable food production and livelihood security becomes increasingly compromised.

2. DATA AND METHODS

2.1 Description of the study area

Data collection for this study occurred in 40 of Kenya's 47 counties, as illustrated in Figure 6. Seven counties were excluded: Garissa, Lamu, Mandera, Wajir, Turkana, Nairobi, and Mombasa. This exclusion was due to two main factors. First, a sufficient number of farmers willing to participate (consenting farmers) were not registered on the iShamba platform in these counties. Second, Nairobi and Mombasa are urban centers with minimal agricultural activity, making them not relevant to the research objectives focused on rural farmers engaged in agriculture. It is also important to note that the distribution of sampled households was skewed within the counties where this study was conducted. For example, as shown in Figure 4, only two and four households were interviewed in Turkana and Nyamira counties, respectively. A detailed breakdown of the sample distribution is provided in Appendix 5. Since this is the initial wave of the planned panel survey by research teams from iShamba and Alliance of Bioversity International and the International Center for Tropical Agriculture (ABC), the number of representative farmers in each county will increase in subsequent surveys.

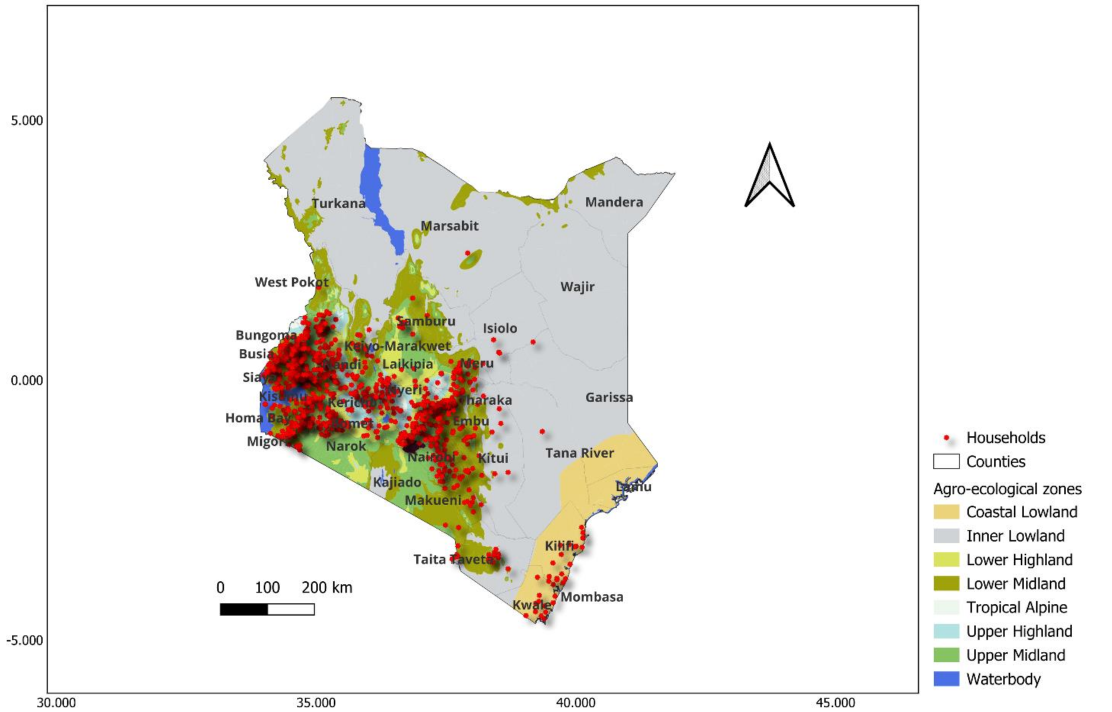

Figure 4. Map showing the distribution of sampled households.

Despite the low representation of the number of households in some counties, the distribution of sampled households reflects a concentration in the agriculturally rich regions of Western, Central, Rift Valley, and Coastal counties. This distribution is likely due to the less favorable conditions for arable agriculture in Northern Kenya, characterized by arid and semi-arid lands (ASALs) with harsh climates, water scarcity, and poor soil fertility (Kirui et al., 2022). However, it is important to note that Northern Kenya is not entirely unproductive. The livestock sector flourishes there, playing a vital role in the local economy and providing primary livelihood for over 10 million Kenyans (Mburu et al., 2022).

Figure 4 further illustrates the distribution of sampled households across Kenya's diverse agro-ecological zones (AEZs) as defined by the Regional Centre for Mapping of Resources for Development (RCMRD)[11]. These zones are categorized based on climate, landform, soils, and land cover, with each zone presenting a unique set of opportunities and limitations for agricultural enterprises. The physical and climatic characteristics of each zone significantly influence the suitability of different crops and livestock.

The agro-ecological zones in Kenya include Tropical Alpine, defined by high altitudes, cool temperatures, and unique vegetation, suitable for specialized crops and livestock adapted to cooler climates. The Coastal Lowland zones, located along the coast, have warm, humid conditions and sandy soils, ideal for crops like coconuts, cashews, and tropical fruits. Inner Lowland areas are generally dry areas constituting the ASALs, suitable for drought-resistant crops and pastoralism. Lower Highland zones, located at mid-elevations with moderate temperatures and rainfall, support various crops including tea, coffee, and maize.

Lower Midland zones have moderate altitudes and temperatures, with diverse agricultural potential including the cultivation of maize, beans, and horticultural crops. Upper Highland zones, characterized by high altitudes and cooler temperatures, are suitable for crops like potatoes, pyrethrum, and dairy farming. Upper Midland zones, found at higher altitudes than the lower midland, have cooler temperatures and higher rainfall, supporting crops such as tea, coffee, and a variety of vegetables. Each of these agro-ecological zones reflects a unique combination of physical and climatic conditions, influencing the agricultural practices and economic activities suitable for the area.

2.2 Sample selection

A sample of 1,000 farmers was chosen using a purposive sampling technique from a pool of 4,262 customers polled in a study connected to weather in 2022. About 3 to 5 survey participants were selected from each of the 47 Kenyan counties' wards for the 2022 survey. Due to their geographic distribution throughout Kenya, this group of farmers—who had previously taken part in a weather-related survey constituted the perfect sampling frame from which we drew our survey subjects. All 4,262 potential respondents received an SMS seeking consent from them to take part in the poll. The questionnaire was then administered using a computer assisted telephone interview to those who gave their consent in a rolling fashion until the target of 1,000 respondents was reached. The iShamba team and ABC worked hand in hand to acquire data from SSU TV subscribers and recorded the data on Google Forms. Phone interviews were conducted between November 2023 and January 2024 to administer the surveys to the participants.

[11] https://opendata.rcmrd.org/search?collection=dataset&q=kenya

2.3 Survey instrument and questions

This study utilized a structured questionnaire to collect both quantitative and qualitative data. The questionnaire combined open-ended and closed-ended questions. The questions addressed various aspects: usage and perceived usefulness of the weather news segment, its impact on crop and livestock production, farmers' coping strategies for agricultural risks, and demographic information. Additionally, the questionnaire assessed farmers' knowledge, awareness, information needs, preferred methods for accessing information, and the relevance of sources for weather forecasts and advisories. Furthermore, we asked questions on the role of weather forecasts and advisories in managing weather-related risks and the impact of iShamba initiatives on enhancing institutional capacities and partnerships within the agricultural sector. The instrument used for data collection, a questionnaire, is included in Appendix 1. Appendix 2 provides a compilation of the indicators assessed by the questionnaire.

2.4 Sources of rainfall and temperature data

To complement and supplement the collected data, we obtained climate and temperature data from multiple sources. Rainfall data was obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)[12], a high-resolution dataset developed by the Climate Hazards Center (CHC) in collaboration with the United States Geological Survey (USGS). CHIRPS offers daily, 5-day, and monthly precipitation estimates from 1981 to present, generated using satellite imagery, in-situ station data, and various climatological sources with a spatial resolution of 0.05 degrees (Funk et al., 2015). For temperature data, we utilized three datasets: Berkeley Earth Surface Temperature[13] (BEST) dataset, National Oceanic and Atmospheric Administration[14] (NOAA) global temperature datasets, and Climatic Research Unit (CRU) Temperature Data Set Version 4[15]. The BEST dataset, developed by the Berkeley Earth project, provides a comprehensive historical temperature record by combining data from weather stations, ocean buoys, and satellite measurements (Rohde & Hausfather, 2020). NOAA's temperature datasets incorporate historical and real-time observations from similar sources, undergoing rigorous processing and quality control to ensure accuracy (Vose et al., 2021). Finally, the CRU dataset, developed and maintained by the Climatic Research Unit at the University of East Anglia, offers gridded monthly temperature data from 1901 to present for global land areas with a resolution of 0.5 degrees latitude by 0.5 degrees longitude (Harris et al., 2020). Similar to NOAA's data, CRU employs processing techniques to create a consistent and quality-controlled product.

[12] https://www.chc.ucsb.edu/data/chirps

[13] https://berkeleyearth.org/data/

[14] https://downloads.psl.noaa.gov/Datasets/udel.airt.precip/

[15] https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.06/cruts.2205201912.v4.06/

2.5 Sources of data on the Cost of Production of Selected Value Chains

To comprehensively assess the economic benefits of consuming weather and farming news, a thorough literature review was conducted to establish production costs[16] for prioritized agricultural value chains: maize (Bii, 2018), common beans (Katungi et al., 2011), Irish potatoes (Bii, 2018), sweet potatoes (Kenya Horticulture Competitiveness Project, 2012), and dairy production (Ndambi et al., 2017). These value chains are fundamental to ensuring national food security and align with the priorities of iShamba.

Maize demand in Kenya exhibits a rising trend, driven by two key factors: population expansion and increased utilization for non-food applications. The 2019 Kenya Maize Flour Market Report estimates a per capita consumption of maize in Kenya at 60 kg annually, translating to approximately 5 kg per person per month (Owino & Waweru, 2023). Common beans also hold significant importance in the Kenyan diet, with estimated annual consumption exceeding national production (755,000 metric tons vs. 600,000 metric tons, respectively) (Obbuyi, 2021). Irish potatoes rank as the second most important food crop following maize, with annual production reaching around 2.3 million metric tons (Muthoni & Nyamongo, 2009; Waaswa et al., 2022). The dairy sector, the largest contributor to Kenya's livestock GDP (approximately 44%), directly employs an estimated 750,000 individuals in the country (Kyule & Nguli, 2020).

Obtaining production cost data was fundamental for calculating the Return on Investment (ROI) for households that watched SSU weather and farming news compared to their counterparts who have never watched. This will provide valuable insights into the economic impact of CIS and inform future policy decisions.

2.6 Empirical models

Assessing the impact of new farming methods and innovations using observational or non-experimental data often faces challenges. This is because some factors, such as individual intrinsic motivation, are hard to measure, and people may adopt new methods, technologies or innovations for personal reasons (Sacha et al., 2021). To address these issues, researchers have used methods like IV regression. However, finding suitable instruments can be difficult. If the instruments aren't closely connected to what is being studied or aren't important, the analysis results may not be accurate. Additionally, IV regression might not solve all the problems related to how varied factors influence each other and spatial relationship between these factors (Ebbes et al., 2022).

This study utilizes a three-stage approach to assess the impact of watching SSU weather and farming news on agricultural income among smallholder farmers in Kenya. First, we identify key income-influencing variables using RFE and RFR. Second, CF estimates ITE to reveal the individual impact of watching SSU weather and farming news on agricultural income. Upon obtaining ITE, we create a layer and add this layer to the Kenyan counties' shapefile. By mapping ITE, we can

[16] Ministry of Agriculture and Livestock Development

identify areas with positive or negative outcomes, informing targeted interventions and advisories. GWR strengthens the ITE analysis by assessing the spatial relationship between watching SSU weather farming news and income changes. Finally, we use PSM to estimate the overall national-level impact of watching SSU weather and farming news, informing policy recommendations at the national level.

2.6.1 Random Forest Regression

The main objective of this study is to assess the effects of the SSU weather and farming news segment on agricultural income among smallholder farmers in Kenya. Additionally, we aim to evaluate the geographical relationship between watching the SSU weather and farming news segment and changes in agricultural income. To achieve this, we first estimate RFR to identify the most critical features influencing agricultural income before analyzing the spatial variation of agricultural income due to watching the SSU weather and farming news segment TV program.

We used RFR as our preferred machine learning algorithm for feature selection due to its ability to capture both linear and non-linear relationships between predictor

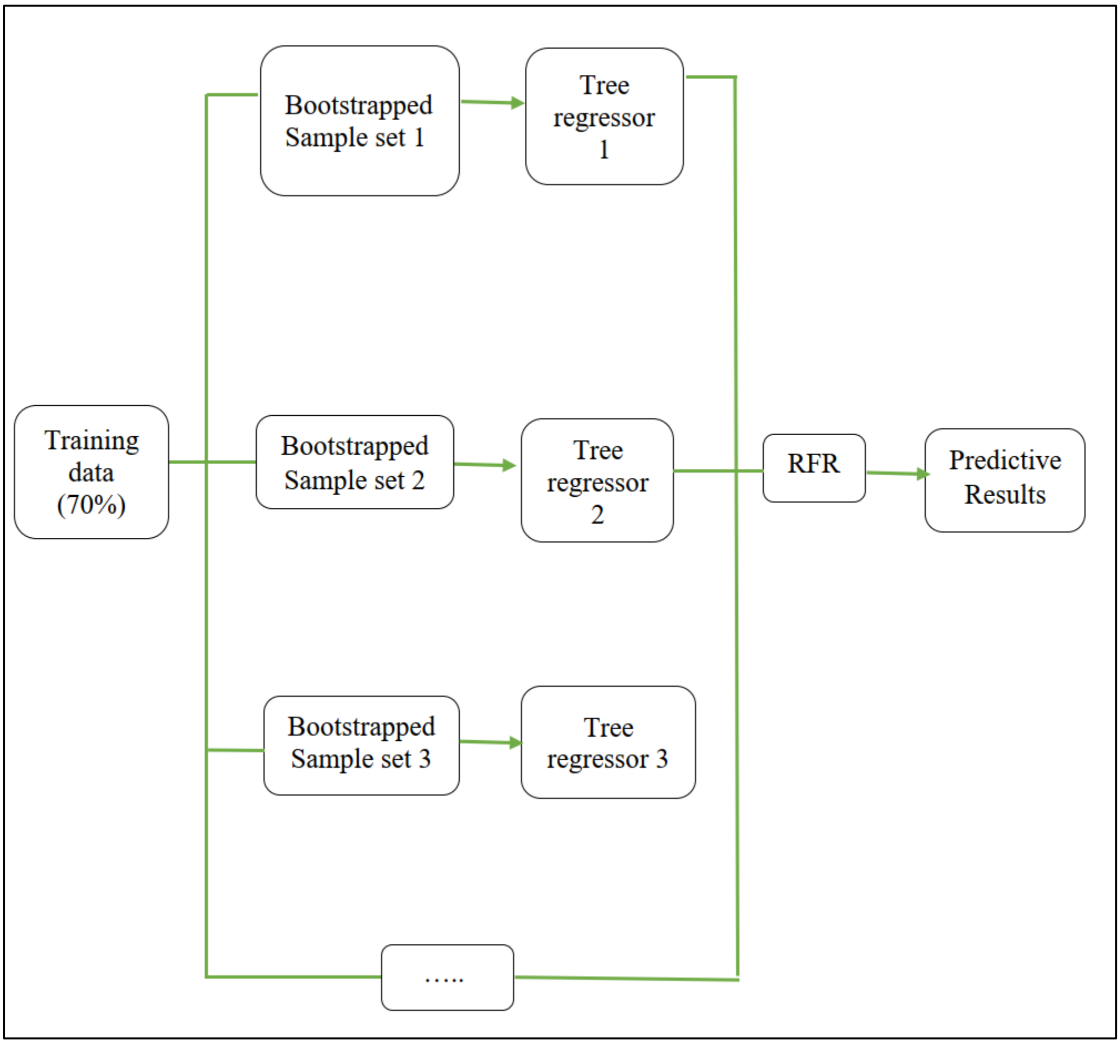

Figure 5. Illustration of the RFR Model training process

and outcome variables (Iranzad & Liu, 2024). Unlike other econometric models, RFR can identify the most important features affecting agricultural income without needing assumptions about the functional relationship between the predictor variables and agricultural income (Breiman, 2001). Additionally, RFR avoids the inherent assumptions of Ordinary Least Squares (OLS) regression and the endogeneity issues that can affect parametric models (Kuhn & Johnson, 2013).

The RFR training process begins with bootstrapping, which involves randomly selecting a subset of data by resampling the original dataset with replacement as shown in Figure 5 below. A decision tree, trained on this subset, predicts the agricultural income of farmers. The tree is constructed by building a series of splitting rules at various nodes (Breiman, 2001). In this study, the maximum depth of the trees was set to three levels using Classification and Regression Training (CARET) R package (Kuhn, 2021). To ensure diversity among the trees, this process is repeated, resulting in a forest of decision trees. Each tree is built using a distinct random subset of the original data and a unique set of predictors at each node. The final prediction is obtained by averaging the predictions from all the trees. This averaging process reduces the variance of individual trees, leading to a more accurate overall model (Ogunleye, 2022).

In our study, the RFR model was trained using a sample of 949 households, 1,000 trees, and 40 predictor variables. We then implemented RFR in Recursive Feature Elimination (RFE) with a cross-validation framework to refine the selection of the most important determinants of agricultural income at the household level. Cross-validation enhances the reliability and robustness of variable importance results obtained through RFE (Darst et al., 2018). The RFE algorithm iteratively removes the least significant variable and retrains the model until only a predetermined set of the most important variables remains. This procedure ensures that the final model is built using the most important factors influencing agricultural income

2.6.2 Individual Treatment Effects using Causal Forests

Obtaining ITE is crucial for informing the targeted delivery CIS and agricultural advisories. This study employs CF to estimate the heterogeneous effects of watching SSU weather and farming news on realized household-level agricultural income. This approach combines the strengths of random forests in capturing complex interactions with the principles of causal inference from classical econometrics (Lechner, 2018).

The procedure begins by splitting the data into training (70%) and test (30%) sets. The test set is used to estimate treatment effects within the leaves of the trees, while the training set is used to grow the trees themselves. For each tree in the forest, a bootstrap sample of the data is drawn as shown in Figure 7. This sample is then recursively partitioned to establish the tree structure. However, unlike standard random forests, the splitting criteria in CF are modified to optimize the heterogeneity of treatment effects within the resulting nodes (Li et al., 2022). This ensures that the differences in treatment effects are effectively captured as the tree grows. Once the trees are grown, the treatment effect of watching SSU weather and farming news for each individual is estimated by averaging the outcomes of individuals with similar characteristics.

Following Bakirov (2023) the ITE for an individual i watching SSU weather and farming news can be expressed as:

$$T(X_i) = \frac{1}{|L_i|} \sum_{j \in L_i} \left(Y_j - \mu\left(X_j\right)\right) \frac{\left(T_j - \hat{e}\left(X_j\right)\right)}{\hat{e}\left(X_j\right)\left(1 - \hat{e}\left(X_j\right)\right)} \quad (1)$$

Where $T(X_i)$ is the estimated treatment effect of watching SSU farming and weather news for individual i, $|L_i|$ is the number of individuals in the same leaf node as i, Y_j is the realized agricultural income for individual j, $\hat{e}\left(X_j\right)$ is the estimated outcome regression, T_j is the treatment indicator for individual j (1 if individual household head i watches SSU weather and farming news and 0 otherwise) ,and $\hat{e}\left(X_j\right)$ is the estimated propensity score. The final estimated of the treatment effect of watching weather and farming news is computed by averaging the estimates across all trees (we use 1000 trees) in the forest:

$$T\,forest\left(X_i\right) = \frac{1}{\beta} \sum_{b=1}^{1000} T^{(b)}\left(X_i\right) \quad (2)$$

Where $T^{b}\left(X_i\right)$ is the treatment effect showing the ITE for watching SSU weather and farming news on agricultural income for each individual household head i.

2.6.3 Geographically Weighted Regression

We employ GWR to account for spatial heterogeneity of treatment effects of watching SSU weather and farming news among smallholder farmers in Kenya. This model estimates spatially varying coefficients in the relationship between watching SSU weather news segments and agricultural income (Wang et al., 2008). Unlike the OLS or global regression model, which assumes a constant relationship between variables across all observations, GWR leverages the spatial nature of the data (Brunsdon et al., 1996). By allowing model parameters to vary geographically, GWR provides a more accurate representation of the potentially shifting relationships between dependent and independent variables across space (Brunsdon et al., 1998). Understanding these spatial variations in the association between watching SSU weather news and agricultural income will facilitate the development of targeted climate information and agricultural advisories.

Building upon the work of Chao et al. (2018), we specify a GWR model to analyze the spatial variations in the relationship between agricultural income and most important income predictors identified using RFR. Household agricultural income serves as the dependent variable in this model. Three independent variables, selected from the previously estimated RFR model, are incorporated into the analysis as illustrated in Equation 3 below.

$$Y\left(\mu\right) = \partial_0\left(\mu\right) + \partial_1(\mu)x_1\left(\mu\right) + \partial_2(\mu)x_2\left(\mu\right) + \partial_3(\mu)x_3\left(\mu\right) + \varepsilon\left(\mu\right) \quad (3)$$

Where $Y\left(\mu\right)$ denotes household agricultural income and x_1 to x_3 represent three independent variables selected from the RFR model. $\varepsilon\left(\mu\right)$ is the Gaussian error term at each spatial location μ. ρ_0 represent the model intercept for each spatial location μ. ∂_1 to ∂_3 are local regression coefficients for independent variables x_1, x_2 and x_3 respectively, at each spatial location μ. The regression coefficients at each spatial location μ are estimated using a weighting function. We compute weights for each spatial location using Gaussian kernel as shown in the equation 4 below:

$$\varpi_{\mu j} = \exp\left(\frac{d_{\mu j}^2}{2b^2}\right) \tag{4}$$

Where $\varpi_{\mu j}$ is the weight assigned to observation j when estimating the parameters at location μ, $d_{\mu j}$ is the Euclidean distance between the location μ and the observation j while b is the adaptive bandwidth parameter that controls the rate at which the weights decay with distance.

Therefore, the local regression coefficients for each household location μ can be estimated using a weighting function, as detailed in Equation 5.

$$\beta(\mu) = \left[X^T W(\mu) X\right]^{-1} X^T W(\mu) Y \tag{5}$$

We denote X and Y as one-dimensional arrays containing the values of variables x and y, respectively. W(u) represents the local weights matrix associated with a specific location μ. This matrix is calculated using a kernel function that assigns higher weights to observations closer (in space) to the calibration location.

2.6.4 Propensity Score Matching

While the methods mentioned above have shown individual and spatial variation in treatment effects, it is also imperative to understand the overall effects of watching SSU weather and farming news. To achieve this, we employ PSM to estimate the causal effect of SSU weather and farming news on farm income. PSM addresses endogeneity by creating comparable treatment and control groups based on propensity scores, reducing bias in estimating treatment effects. PSM accounts for multiple covariates simultaneously. Its robustness ensures reliable estimates even when underlying assumptions are not fully met, making it a valuable tool for causal inference. By reducing selection bias, PSM improves comparability between groups, enabling researchers to draw more accurate conclusions about treatment effects (Carla et al., 2024).

We estimate PSM in a two-stage framework. In the first stage, we estimate a probit model to ascertain the probability of a farmer watching the SSU weather news segment. This allows us to generate propensity scores and match farmers with similar scores in the control and treatment groups. The binary probit model used is represented below.

$$P(T_i = 1 | X_i) = \Phi(X_i \beta) \tag{6}$$

Where T_i is the treatment indicator (1 if the farmer watched SSU, 0 otherwise), X_i is the vector of observed covariates, β is the vector of coefficients, and Φ represents the Cumulative Distribution Function (CDF) of the standard normal distribution.

After estimating propensity scores, we match farmers in the treatment group (those who watched SSU) with control group farmers (those who have never watched the SSU weather news segment). The matching is done based on their propensity scores using three algorithms: nearest neighbor matching (NNM), kernel-based matching (KBM), and radius matching (RM). This way, we were able to match treatment and control groups that are statistically similar on all observed covariates that might influence the decision to watch SSU.

After matching, we conduct covariate balance checks to assess the success of the matching process. This verifies that the treatment and control groups are well-balanced on all observed characteristics besides exposure to the SSU segment. Achieving good balance strengthens the assumption that any observed differences in outcomes between the groups can be attributed to the intervention itself (watching SSU) (Ali et al., 2015). Once balance is established, we estimate the Average Treatment Effect (ATE) by comparing the outcome variables between the matched treatment and control groups. The ATE represents the expected change in the outcome variable for an average farmer due to watching the SSU weather news segment. Finally, we perform a sensitivity analysis to assess the robustness of our findings as recommended by Rosenbaum (2002). This involves exploring how changes in the matching procedure or the presence of unobserved factors might influence the estimated treatment effect as shown below:

$$ATE = \frac{1}{N_T} \sum_{i \in T} (Y_i^T - Y_i^C) \qquad (7)$$

Where N_T is the number of treated units, Y_i^T is the outcome for treated units, and Y_i^C is the outcome for control units. Estimation results are presented in section 3.4.

3. RESULTS

The results section of this report is organized thematically into six key subsections. The first part describes the socioeconomic profile of the farmers who participated in the study. The second subsection provides a descriptive analysis of the impact of SSU Weather and Farming News Segment on smallholder farmers. The third section explores the SSU Weather News and Farmer Advisory segment's ability to provide site-specific and timely weather information to the farmers. The extent to which farmers have made informed decisions based on the weather forecasts received is then explored followed by assessing the impact of the segment. On assessing the impact, the study seeks to understand the impact of the segment on farmers' agricultural practices and economic welfare based on various regions. The fifth subsection investigates the segment's role in mitigating weather-related risks for farmers. Finally, the study examines the SSU's agro-advisory efforts in enhancing institutional capacities and strengthening partnerships with institutions and stakeholders in general.

3.1 Socio-economic profile of the sampled farmers

The socio-economic profile of the sampled farmers reveals several key insights into the demographic characteristics of individuals engaged in agriculture in the SSU target counties. According to Figure 6, most of the farmers who participated in the study were aged 36 years and above, with the productive age group of 36-55 years comprising 55% of the sample. This trend was consistent across both male and female farmers, highlighting that older individuals are relatively more actively involved in agricultural activities compared to their younger counterparts below the age of 35 years (youth). Conversely, youth participation in agriculture was found to be notably low, with individuals aged 18-25 years making up just slightly over 17% of the respondents. This suggests a need for targeted initiatives to encourage young people to engage in agricultural practices.

Gender distribution among the sampled households was relatively balanced across different age groups. Both men and women were equally represented in the age categories, indicating no significant gender disparity in agricultural participation. This gender parity is crucial for developing inclusive agricultural policies and programs that cater to the needs of both male and female farmers. Therefore, the near-equal involvement of men and women in agriculture as seen from this study, underscores the importance of considering gender dynamics when designing interventions aimed at enhancing inclusive agricultural productivity and sustainability.

In terms of education, the study found that most of the respondents had attained at least a secondary education, with secondary education having the highest proportion at approximately 40% for males and 43% for females. This indicates that a significant portion of the farming population was relatively well educated. This revelation shows that farming populations from these areas could positively impact the adoption of new agricultural technologies and practices. Furthermore, access to education appeared equitable across genders, as evidenced by the similar proportions of males and females at various educational levels. A substantial number of respondents had pursued higher education, with 23% of males and 23% of females having completed university education, and 1.9% of males and 0.6% of females attaining postgraduate qualifications. This relatively high level of educational attainment suggested that the farming community had improved

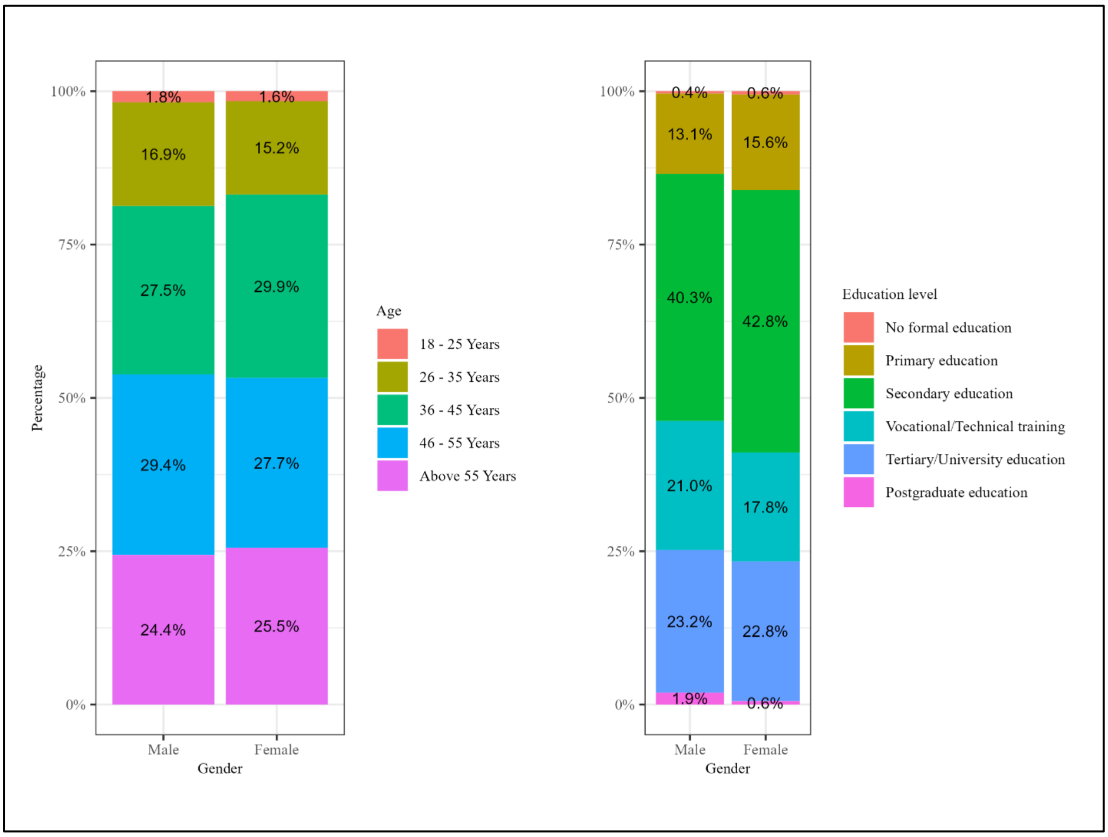

Figure 6. The distribution of the respondents based on gender and age and educational level

knowledge capacity necessary for effective agricultural management. However, there remained a small fraction of respondents with no formal education, highlighting the need for continuous educational outreach and support to ensure that advisories are tailored for diverse farmer profiles. This would ensure that all farmers benefit from advancements in the agricultural sector.

Our findings revealed that the demographic characteristics of the sampled smallholder households showed both similarities and significant differences. Notably, gender representation and educational attainment widely varied. These disparities may affect the success of targeted interventions such as the SSU Weather News and Farming Advisory segment, which aims to reduce risk, boost agricultural productivity, and improve farmers' livelihoods.

3.2 Segment's effectiveness in providing timely and site-specific weather information

The segment's ability to provide site specific information was evaluated based on accessibility of the information to the farmers. This was done by exploring platforms available to the farmers, SSU viewership and comparison of access between the segment's advisory versus other sources of advisory to farmers. To assess the segment's efficiency in providing timely information, the feedback from viewers of the SSU weather segment on the timeliness of the weather forecast advisory to guide their farming practices was taken into consideration. In addition, the study sought to understand the level of access farmers have to SSU weather advisories. Several platforms have been fronted to provide these weather advisories to farmers. While these platforms exist, their level of accessibility to the farmers is always overlooked by the assumption that the information will trickle to them. Accessible weather advisory helps farmers to receive information promptly,

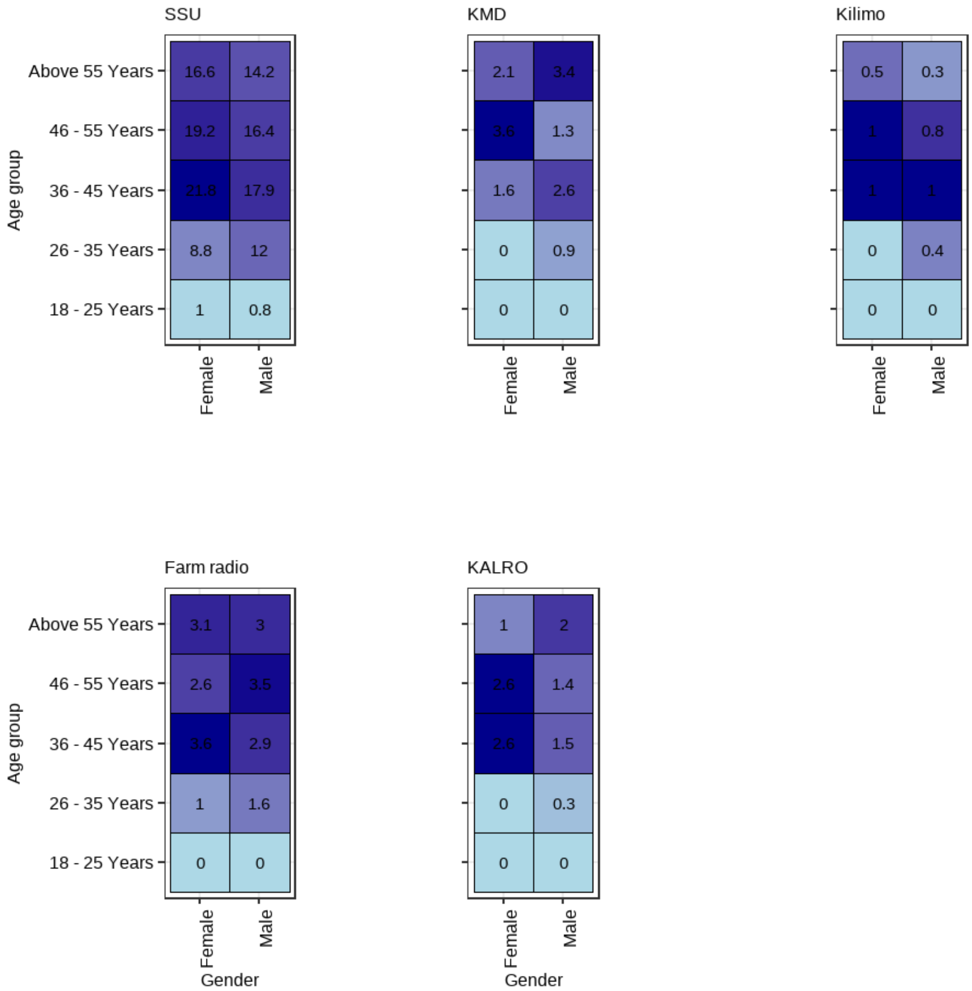

Figure 7. Farmers acknowledged sources of weather advisory

allowing them to make timely decisions regarding their farming activities. These decisions include resource management such as financial planning and adjusting input use for optimized production.

When asked about their sources of weather advisory, most respondents identified the SSU weather segment as their primary source. This was followed by Farm Radio, KMD, KALRO, and Kilimo as shown in Figure 7. To display the distribution of farmers by age, gender, and each advisory source, heat maps were used. These maps visualize age categories in the columns and gender in the rows. The majority of SSU viewers were women aged 36-45 years. Farmers who accessed weather advisories from KMD were majorly female farmers aged 46-55 years and male farmers above 55 years. Kilimo and KALRO had similar distributions, with women aged 46-55 years being the majority in both sources. Male farmers aged 36-45 years made up a significant audience for Kilimo. Farm Radio had a wider listenership among female farmers aged 36-45 years and male farmers aged 46-55 years. Overall, female farmers aged 36-45 years appear to be the largest group of weather advisory consumers.

On the frequency of the respondents interacting with the SSU weather advisory news segment, 58% watched the weather segment often (once every week). This trend was true across all gender and age categories, except among male farmers aged 18 – 25 years, where the majority (about 50%) watched once every two

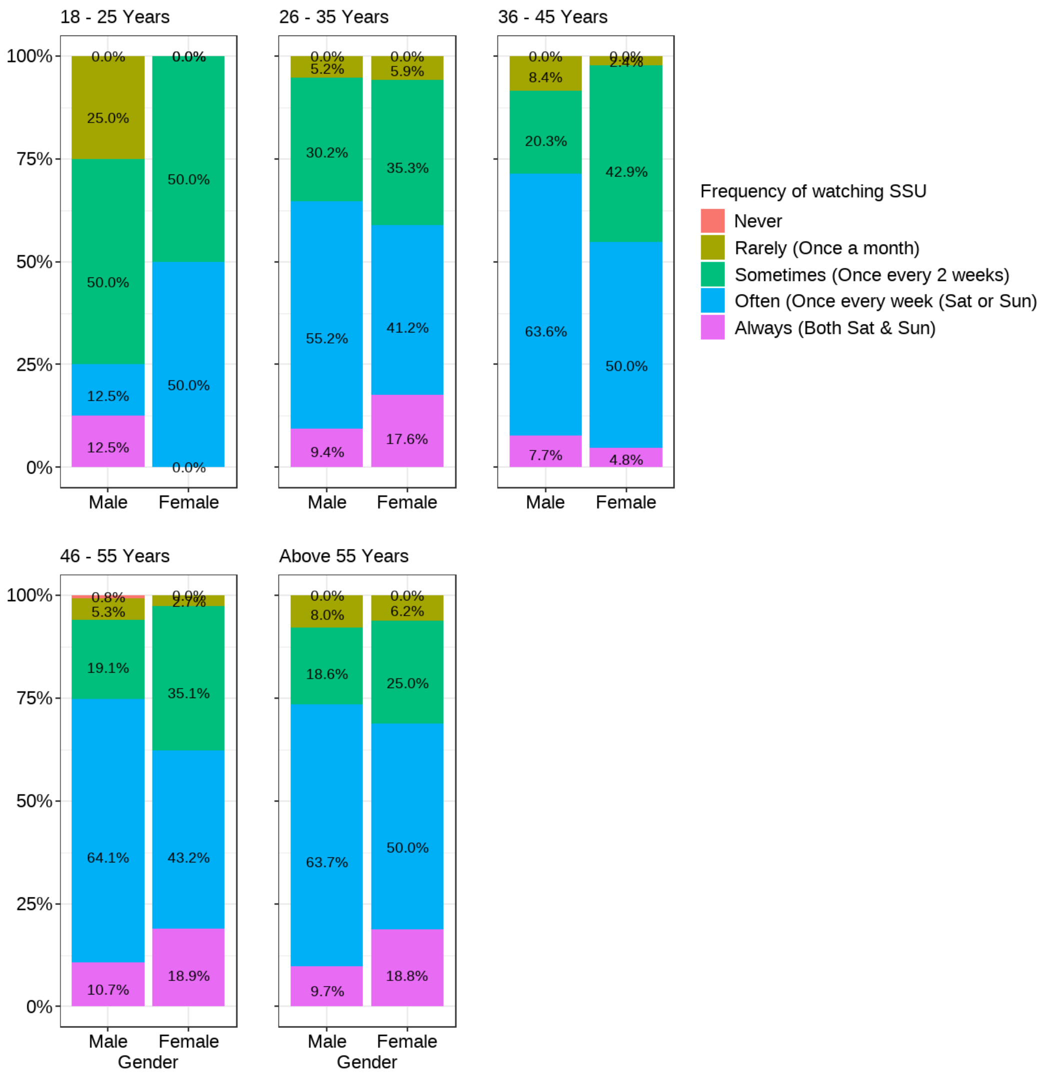

Figure 8. Frequency of SSU News segment viewership

weeks (Figure 9). A quarter of the sampled respondents watched the segment at least once every two weeks. It was also interesting to note an exceptional group of farmers (10%) who watched the program twice per week, (every time it aired on the television). From Figure 8, most of the farmers in this category were female farmers aged 26 – 35 years and above 46 years with proportions approximately equal to 18%. It could be interpreted that over half of the farmers always had an opportunity to follow the advisories regularly, at least once per week.

Access to the SSU weather news segment among farmers was compared to alternative advisory sources and platforms, as shown in Table 1. SMS and television emerged as the most common sources for accessing weather news from SSU, with 81% and 76% of farmers accessing weather information through them, respectively. While a smaller proportion of farmers utilized platforms like YouTube, Facebook, and WhatsApp for weather advisories, over one-third reported accessing information through both television and SMS. Notably, SMS emerged as the preferred method for receiving weather advisories, with 73% of respondents favoring this format. This could be due to the flexibility and conveniences of SMS platforms in the dispatch of weather advisory as compared to other platforms. In addition, SMS platforms are cost-effective, easy to use and accessible even with non-tech-savvy farmers, making it the most preferred platform. While most of the other prevalent platforms could need support of other services such as internet connectivity and related support, SMS can be used with no internet access. It is good to note that the SMSs being referred to here were from iShamba, farmers' mobile information service for Shamba Shape Up. Other platforms gaining traction on preferences for receiving weather advisory amongst the respondents were television (10.3%) and WhatsApp (9.5%).

Table 1. Respondents' sources and channel preferences for receiving weather advisory

SOURCE	ADVISORY SOURCES (%)	MOST PREFERRED (%)
Television	76.1	10.3
YouTube	5.6	2.2
WhatsApp	2.7	9.5
Facebook	4.1	3.2
SMS	80.5	73.2
Google	0.2	0.9
Radio	0.3	0.4
Phone calls	-	0.1
Magazine	-	0.1

Note: 1. Under the first column, farmers are asked to provide a broad list of sources for advisory.
2. Under the most preferred column, farmers chose their primary source of advisory.

Since counties possess varied characteristics such as agroecological properties and weather patterns, it was important to investigate farmers' perceptions of the timeliness of weather advisories within individual counties. A large proportion of respondents reported that weather advisories were timely. This perception was consistent across different counties. However, as shown in Appendix 3, some farmers in counties such as Kilifi (5%), Makueni (4%), Meru (4%), Murang'a (4%), Narok (4%), Uasin Gishu (4%) and Vihiga (13%) registered that weather advisories from SSU were not timely. Overall, 2% of the sampled farmers found the advisories not timely. Since this result is distributed all over the country, it calls for further investigation to understand the reasons behind their feedback on timeliness of weather advisories from SSU.

While timely weather advisory helps farmers majorly in planning purposes for their farming activities, accurate weather advisories help mitigate several pitfalls. For example, accurate weather advisories help farmers to prevent crop losses by anticipating adverse weather conditions such as droughts and taking precautions to minimize losses that could arise from such risks. Timely weather advisories can also help farmers minimize losses by optimizing input use and making decisions on whether to plant or not based on the anticipated implications of the advisory. In line with this, based on their experiences, most farmers indicated that the

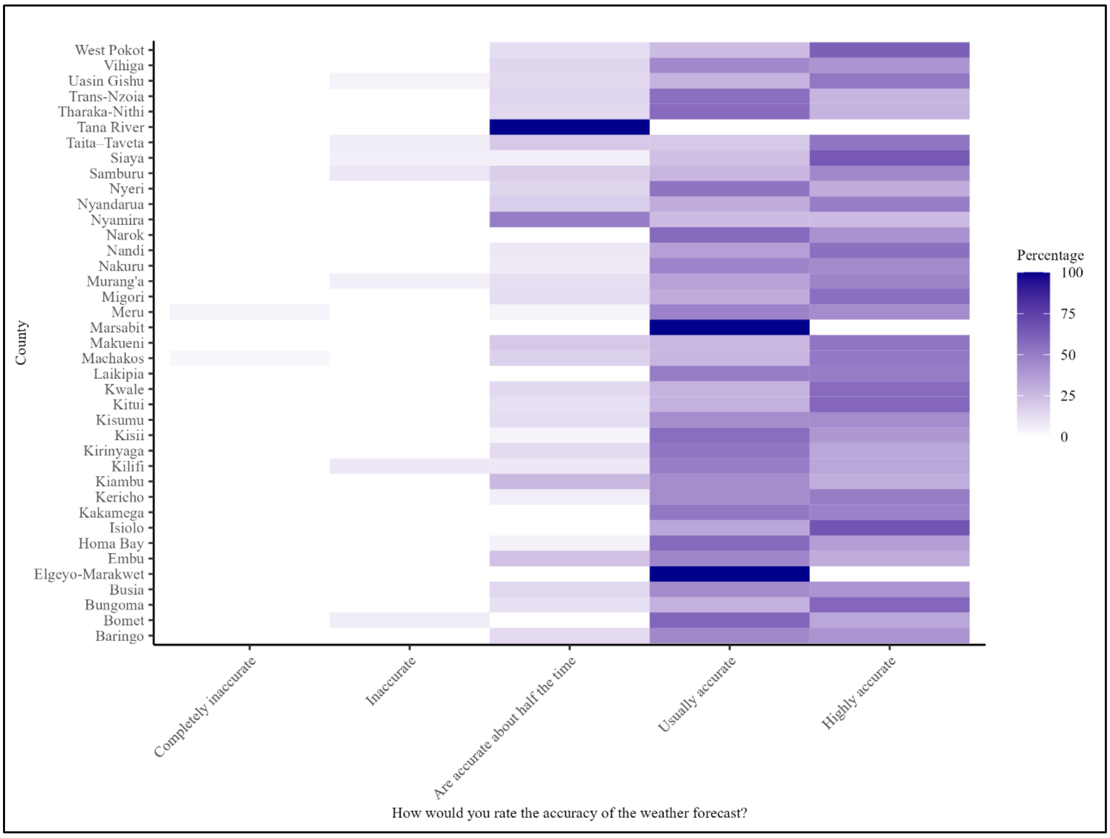

Figure 9. Viewers observation of accuracy levels of weather advisories

weather advisories from SSU were usually accurate or highly accurate as illustrated in Figure 9. The accuracy of the weather advisories is highly dependent on the location of the farmers registered with iShamba. Precision in their locations is crucial for providing tailored, location-specific advisories.

Additionally, as shown in Appendix 4, most of the respondents within the counties registered that the advisories were either “highly accurate" or "usually accurate”. However, 4.8% farmers in Kilifi, 3.6% farmers in Meru, 3.7% farmers in Murang’a, 7.7% farmers in Samburu, 6.5% farmers in Siaya, 5.6% farmers in Taita Taveta and 6.7% farmers in Vihiga counties found the advisories inaccurate. Some of these results were consistent with previous findings on advisory timeliness. For example, Vihiga County had the largest number of farmers reporting that the advisories were not timely and among the counties posing the largest percentage of farmers (6.7%) indicating that the weather advisories from SSU were inaccurate.

More than half of the seven counties presenting that the advisories were inaccurate are considered ASAL counties. This points to the challenging situation in providing advisories to these counties that calls for more thorough methodologies to mitigate highly volatile weather conditions in these counties. On whether the advisory matches their experience and/or knowledge, the majority of farmers indicated

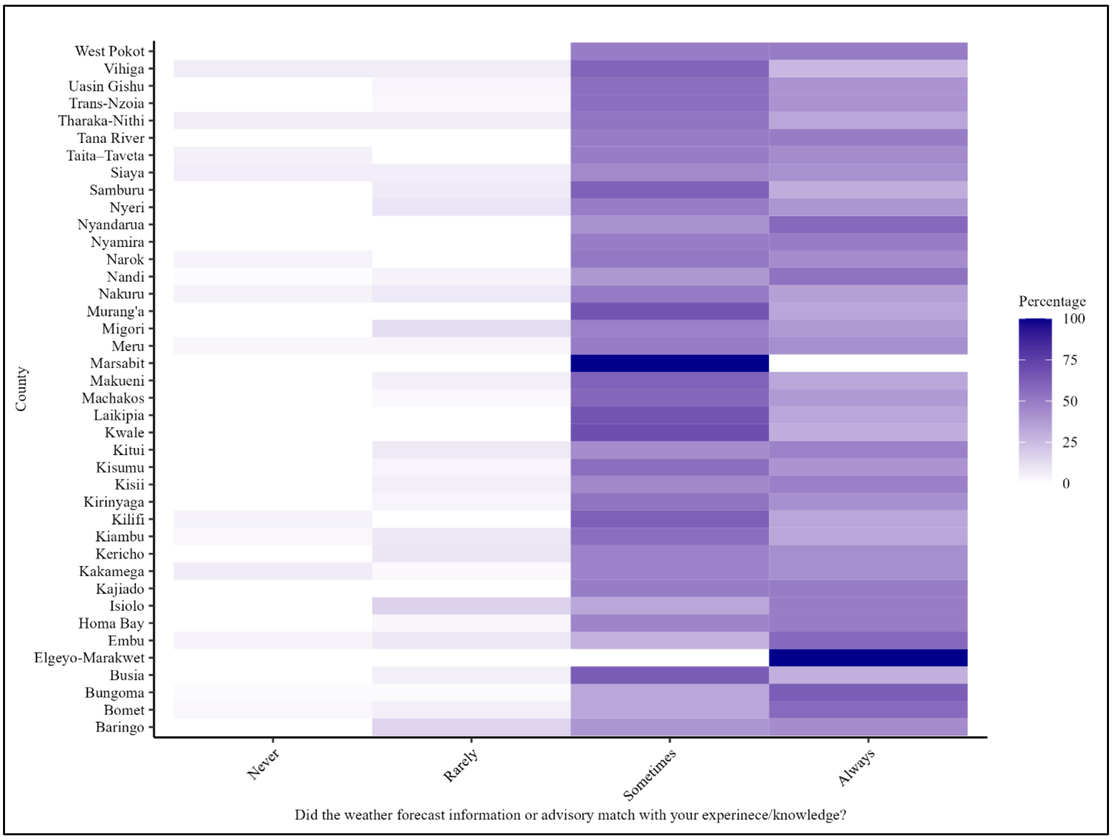

Figure 10. *Weather advisory paired with viewers experiences*

that the weather advisories matched their understanding of the weather conditions in their area, as shown in Figure 10. The figure (Figure 10) illustrates that most farmers across the counties felt that the advisories aligned with their knowledge either sometimes or always. This, therefore, showed that the advisories were accurate based on the farmers' past experiences.

3.3 Extent to which farmers have made informed decisions based on SSU advisories

The study sought to understand if watching SSU weather and farming news influenced farmers to make changes in their farming practices. Indeed, weather advisories do play an important role in helping farmers make informed decisions by providing timely and accurate information about anticipated future conditions. These advisories would, therefore, enable farmers to plan their activities accordingly, such as land preparation, planting time, choosing the right variety and harvesting to optimize crop yields.

As shown in Figure 11, more SSU weather news segment viewers in crop production (46.8%) compared to those in livestock production (13.9%) made changes to their farming methods after watching the SSU weather advisories. Among the non-viewers of the SSU weather news segment, a similar pattern is noted, with 27.1% in crop production and 5.4% in livestock production making weather-related changes to their farming activities. Overall, a greater proportion of farmers

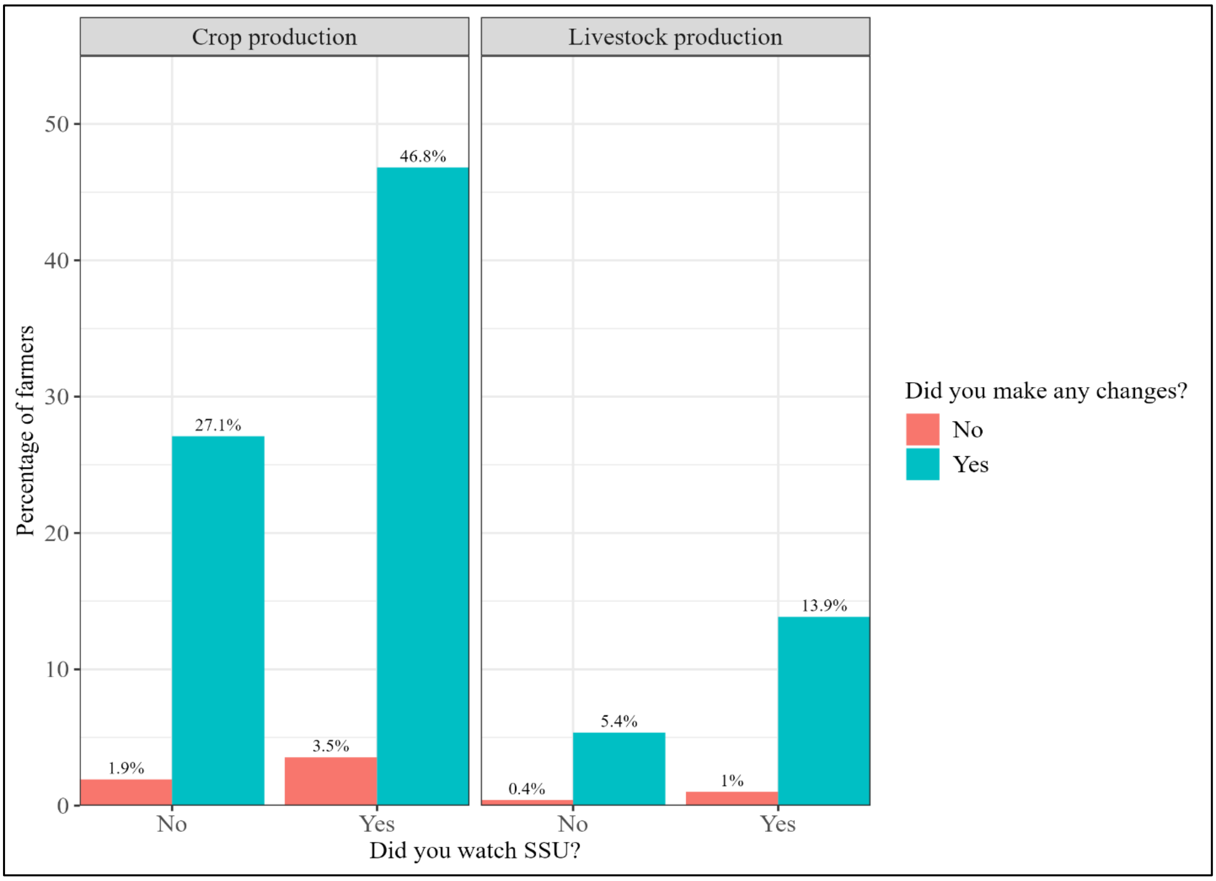

Figure 11. Distribution of farmers by SSU viewership and whether they made changes to their farming practices.

engaged in crop production (46.8%) and animal production (13.9%) who watched SSU made changes to their farming methods, compared to those who did not watch. Specifically, 27.1% of crop producers and 5.4% of livestock producers who did not watch SSU changed farming practices on their farms.

3.3.1 Influence of SSU Weather News segment on farming practices

The study sought to understand if farmers made changes to their farming activities because of interacting with SSU. The study found that among all respondents, certain changes in farming practices were more common, regardless of whether they watched the SSU weather segment. Adjusting planting time was the change that most farmers made, both among those who viewed SSU and those who did not. Among those who viewed SSU, 82% adjusted their planting time, while among those who did not view, 77% did the same, as shown in Figure 12. This was the practice implemented more by the sampled farmers. While non-viewers also changed their planting time, it could be argued that, in the farming communities where the farmers live, they emulate practices from one another. That is why, while most of the viewers were changing planting time due to the SSU advisories, the other farmers could have made the decision to do so based on the common trust they have amongst each other in sharing information communally.

A significant portion of farmers (around 67% of viewers and 56% of non-viewers) also opted for planting different crops. Interestingly, SSU viewership appeared to

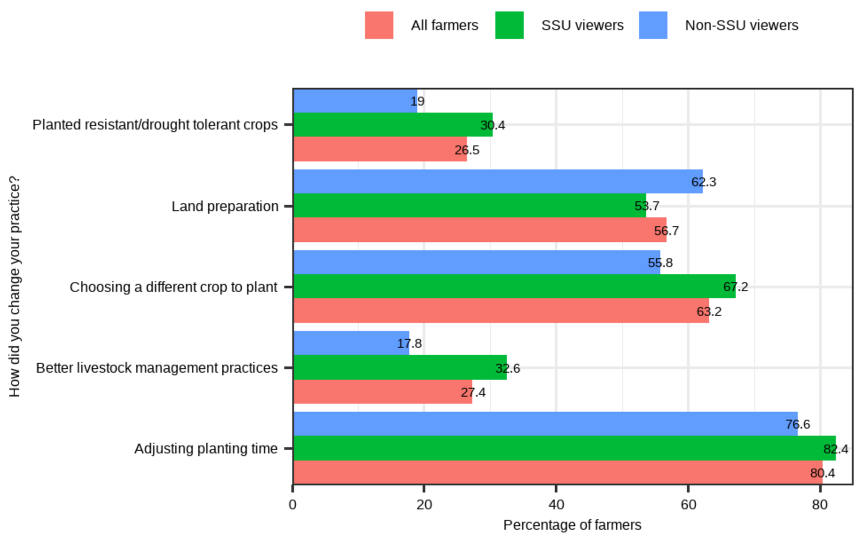

Figure 12. Changes made by farmers on their farming practices

influence the adoption of improved livestock management (33% vs. 18% for non-viewers) and planting resistant/drought tolerant crops (30% vs. 19%). While in

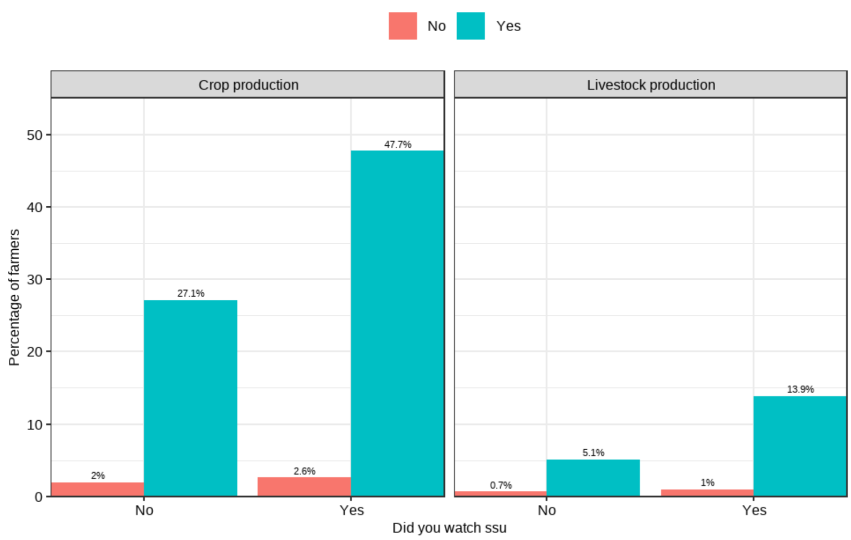

Figure 13. Distribution of farmers by SSU viewership and changes in their activities

most cases SSU viewers predominantly made the largest proportion of changes in their farming practices, changes in land preparation saw farmers who do not view SSU more prevalent (62%) as compared to those who view SSU (54%).

After adjusting their farming practices based on watching the SSU weather news segment, 47.7% of respondents reported noticing changes in their crop production, while 13.9% reported changes in livestock production, as shown in Figure 13. This aligned with the observed trend of adjustments in farming practices, indicating that watching the SSU weather news segment led to changes in both crop and livestock production. This trend was also observed among non-viewers, with 27.1% on crop production and 5.1% on livestock production reporting changes to their farming practices. Nonetheless, the percentage of both crop and livestock farmers who watched the program and observed changes in their farming activities, standing at 47.7% and 13.9% respectively, exceeded those who did not follow the program 27.1% and 5.1% respectively.

3.3.2 Changes on farmers outcomes due to weather advisories

Farmers who adjusted their practices reported experiencing a range of positive outcomes. The most mentioned benefits were increased production, improved produce quality, and reduced crop loss/damage. Interestingly, viewers of the SSU

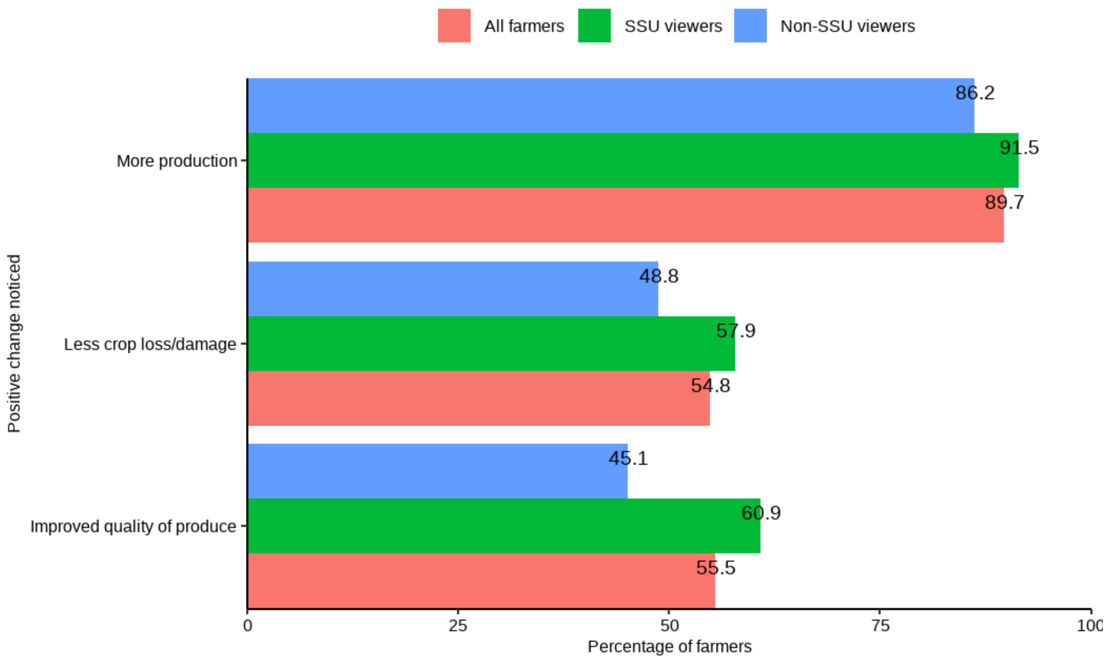

Figure 14. Positive changes noticed by farmers

Weather News segment reported significantly higher percentages of these improvements compared to non-viewers. Figure 14 presents these findings. SSU viewers reported a higher proportion of positive outcomes. Specifically, 91.5% of viewers reported increased production, 60.9% experienced improved produce quality, and 57.9% experienced less crop loss/damage.

On the other hand, non-SSU viewers also observed positive outcomes, even without directly watching the SSU program. Approximately 86.2% reported increased production, 48.8% reported reduced crop loss/damage, and 45.1% reported improved produce quality. This suggested that farmers could have relied on alternative sources for advisory beyond the SSU program. In addition, as noted in the previous section, farmers living in close knit communities share information amongst each other. Therefore, viewers of SSU could have shared the advisories with their neighbors and inadvertently helped improve the outcomes for farmers who do not watch SSU.

The most reported positive change by the farmers interviewed was increased production (89.7%), followed by improved produce quality (55.5%) and reduced crop damage (54.8%). Notably, SSU viewers consistently represented a higher proportion across all three categories when compared to non-viewers and the overall category of farmers. This confirmed that a larger proportion of SSU viewers, compared to non-viewers, were implementing changes in their farming practices informed by the advisories leading to the observed positive outcomes.

3.4 Segment's role in mitigating weather-related risks for farmers

Survey participants were also asked about their commonly used risk mitigation techniques. The results were as displayed in Figure 15, with x-axis showing the proportion of farmers and the y-axis displaying the specific risk mitigation techniques. Each risk mitigation cluster had three bars, corresponding to non-SSU viewers, SSU viewers and all farmers together. Of the 44% (436 respondents) who responded to this survey question, 44.1% said they did not employ any risk mitigation techniques. From the study, 22.4% of the respondents opted to plant a larger area as a way of being risk averse with viewers choosing larger plantations at a rate of 24.3% and non-viewers 18.9%. The results further revealed that the percentage of viewers who did not use any risk mitigation measures was around 43.2%, which was slightly lower than the non-viewer proportion of about 45.9%. Apart from increasing land size, adoption of other risk mitigation strategies like crop/livestock insurance, applying for credit, crop and livestock diversification were comparatively low.

Overall, about 22.4% planted larger areas, 14% increased their livestock size, 11.6% applied for credit, and 10.1% took up alternative non-agricultural activities. Less than half of the farmers did not employ any risk mitigation technique among the three categories of farmers. This could imply that in each category of farmers, more than half of the respondents used at least one risk mitigation technique. However, the portion of farmers (approximately 44%) who never adopted any of the risk mitigation measures should not be overlooked. This could be due to reasons such as a lack of awareness, applicability or resources required to implement the techniques. For techniques such as planting larger areas and increasing the number of animals, a larger percentage of SSU viewers adopted the practice compared to non-SSU viewers. This points to possible effectiveness of the SSU program at promoting these techniques. Farmers applied for credit at the same rate across the three groupings, while more non-viewers than viewers took up alternative non-agricultural activities. The suggestion here is that the SSU program may have improved farmers' resilience and therefore farmers stuck to their agricultural activities.

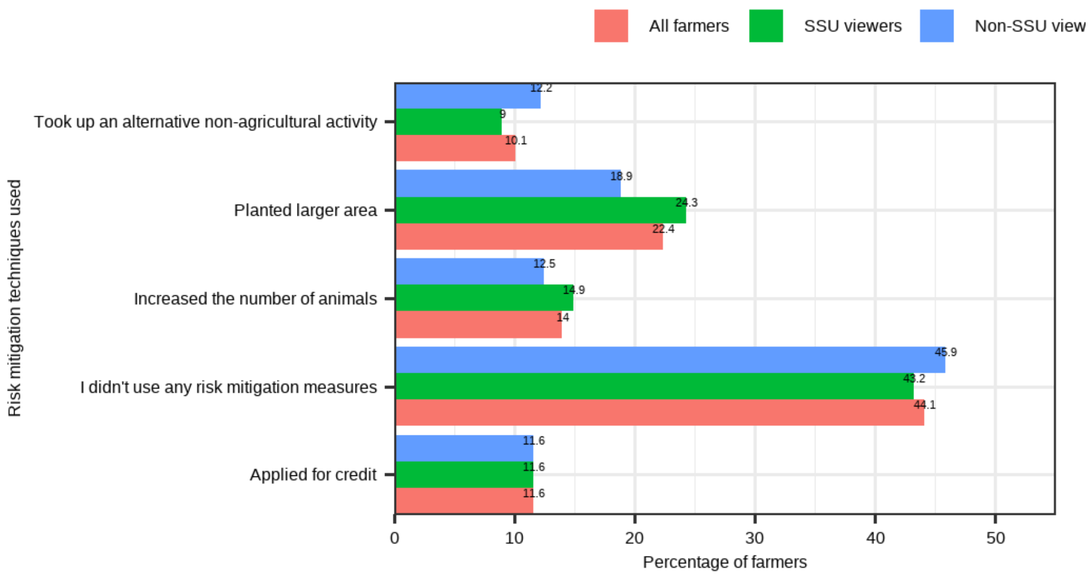

Figure 15. Risk mitigation techniques used by smallholder farmers to address weather-related risks

The data suggests a positive correlation between viewing SSU programs and adoption of risk mitigation techniques. Farmers who watched the SSU program were generally more likely to adopt these techniques than those who did not. However, the significant number of farmers who did not use any of the risk mitigation techniques calls for further efforts to understand the associated reasons and possibly develop additional strategies to encourage wider adoption of the mitigation techniques.

3.5 Impacts of the SSU Weather and Farming News segment

This section investigates the impact of SSU weather segments on farming practices and outcomes. It starts by exploring the economic benefits of SSU viewership. The section also investigates spatial variations in the impacts realized by the sampled farmers. The section concludes with an empirical analysis of the overall effect on agricultural income and the role of the SSU segment in mitigating weather-related risks.

3.5.1 Economic Benefits of Watching SSU Weather and Farming News in Kenya

The study showed a significant disparity in average income between households that regularly viewed SSU news and those who did not, observed across diverse agricultural operations. Table 2 summarizes the economic benefits associated with household viewership of SSU weather and farming news. SSU broadcasts provide valuable agricultural knowledge, potentially influencing farming practices and economic performance across various agricultural value chains. Maize farmers who consistently watched SSU reported an average income of KES 84,605.46, compared to KES 35,083.28 for non-viewers as shown in Table 2. Similar trends were evident for legume farmers, Solanum tuberosum (potato), Ipomoea batatas (sweet potato), and bovine milk production. These income differences underscored the importance of informed decision-making in agriculture, potentially facilitated by SSU broadcasts. The results suggest that watching SSU weather and farming news may empower farmers to enhance agricultural output and generate greater income.

Table 2. Economic benefits of watching SSU Weather and Farming News on agricultural income

CROP	WATCHED SSU	AVERAGE INCOME (KES)	ESTIMATED PRODUCTION COST (KES)	ROI
Maize	No	35083.28	32290	1.09
Maize	Yes	84605.46	32290	2.2
Beans	No	58303.33	50440	1.16
Beans	Yes	89473.88	50440	1.78
Irish potatoes	No	86059.84	52228	1.65
Irish potatoes	Yes	174677.78	52228	3.34
Sweet potatoes	No	36500	63925	0.57
Sweet potatoes	Yes	40000	63925	0.63
Dairy	No	204	40	5.1
Dairy	Yes	388.50	40	9.71

Note: Dairy cost represents the cost obtained per cow per day, while crops refer to average income obtained per acre. It is important to note that cost data presented here are obtained from literature sources. There is a need to collect primary data for a robust analysis of ROI and Cost-Benefit Analysis (CBA).

ROI further strengthens the economic benefits of watching SSU weather and farming news. Maize farmers who followed SSU news achieved an ROI of 2.62. This translated to KES 2.62 in income (KES 84,605.46) for every KES 1.00 invested in production costs (KES 32,290). Notably, Irish potato cultivation and dairy farming demonstrated exceptionally high ROI for households that watched SSU, suggesting efficient resource allocation and potentially increased profitability. It is important to acknowledge that the data employed in this analysis originates from secondary sources, which may have inherent limitations. The results presented in Table 2 do not imply a causal interpretation of the impact of watching SSU weather and farming news on agricultural income. Additionally, unobserved variables may explain the differences in income between adopters and non-adopters. Accounting for these unobserved variables is necessary to identify the causal effects of watching SSU weather and farming news on agricultural income. Results accounting for endogeneity are presented in section 3.4.3.

3.5.2 Spatial variation in impacts of Watching SSU Weather and Farming News

Significant spatial heterogeneity exists in the impacts of watching SSU weather and farming news. Figure 16 presents the results from the Causal Forest analysis. The figure depicts the spatial variation of maximum, median, and minimum ITE across counties. Additionally, individual ITE values are plotted without calculating summary statistics. Counties with no data points represent areas where fewer than five households were included in this analysis. The median ITE plot shows variation between positive and negative effects across counties. Households in Nyandarua and Machakos counties experience negative impacts, while those in Migori, West Pokot, and Makueni exhibit positive outcomes. This suggests a location-dependent influence of SSU weather and farming news.

The maximum ITE plot provides further evidence. While most counties displayed positive maximum ITE values, the magnitude varied. Counties closer to central Kenya (Nyandarua, Nyeri, Murang'a) exhibited lower maximum ITEs, whereas Kilifi, Kwale, Migori, West Pokot, Makueni, and Isiolo counties showed higher values, suggesting a potentially greater influence on agricultural revenue in these regions. Interestingly, all counties exhibited negative minimum ITE values, indicating a varied distribution of impacts. Notably, Nyandarua, Machakos, and Makueni counties consistently demonstrated lower benefits. Plotting individual ITE values without summary statistics revealed similar patterns, although the coefficients were relatively small. This suggested potential effects, but further investigation is warranted to confirm their significance.

However, watching SSU news is potentially endogenous. To address this, the coefficient of variation of temperature and rainfall from the preceding five years was employed as instrumental variables. However, weak instrument tests were not conducted to validate this choice. The rationale lies in the assumption that farmers experiencing greater fluctuations in temperature and rainfall are more likely to rely on weather advisories. This analysis of spatial ITE using Causal Forests yielded valuable insights into the geographically diverse effects of watching SSU weather and farming news. While both positive and negative consequences exist, the overall outcomes varied significantly across counties. The results emphasized the importance of considering spatial variation when designing policies and interventions.

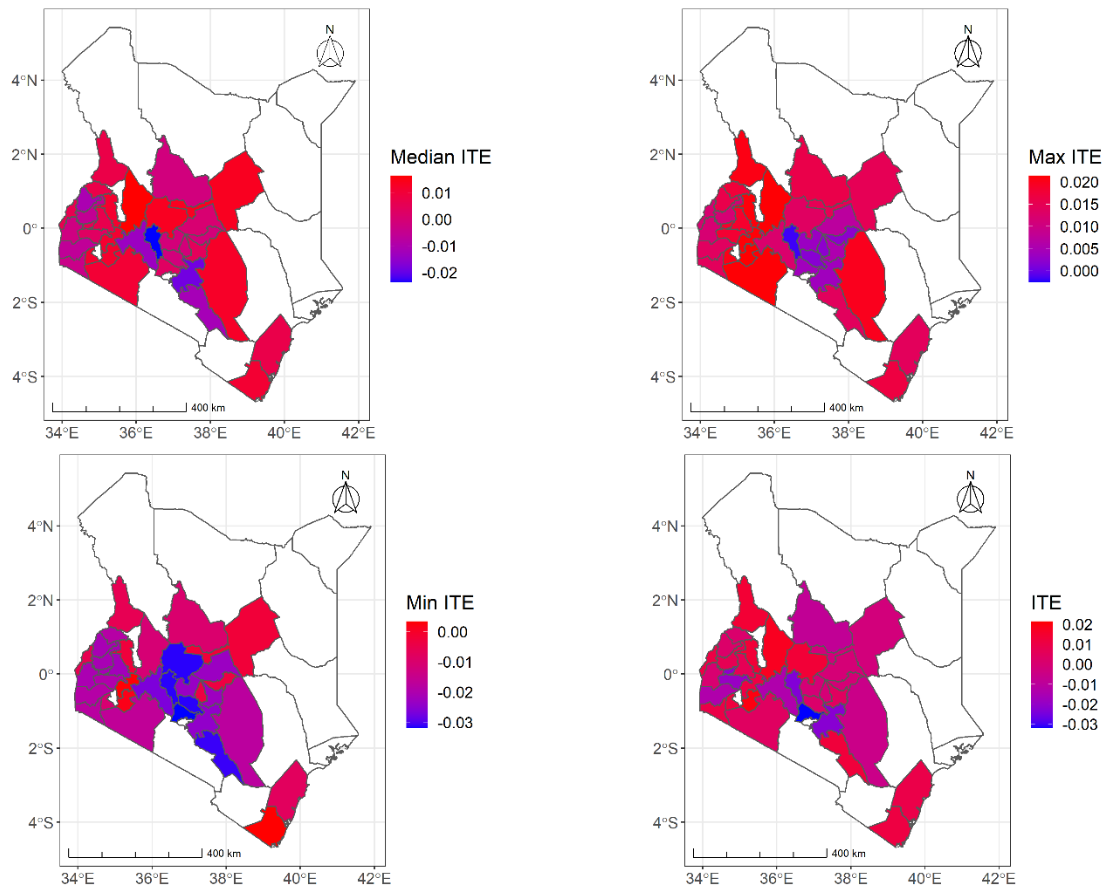

Figure 16. Spatial variation in impacts of Watching SSU Weather and Farming News.

To strengthen the robustness of our findings, we incorporated the viewing duration of SSU by each household using GWR. While the overall results demonstrated consistent effects of SSU viewership across the majority of the counties, a closer examination in Appendix 7 reveals spatial heterogeneity. Counties like Homa Bay, Kisumu, and Siaya displayed a stronger program impact compared to Busia, Kakamega, Vihiga, and Bungoma. The remaining counties exhibited impacts of relatively similar magnitude. These findings suggest a geographically varying influence of the SSU program. Prior to employing GWR, we conducted spatial autocorrelation and non-stationarity tests to ensure model validity.

3.5.3 Overall effect of SSU Weather News Segment on smallholder farmers income

The study employed PSM to evaluate the causal impact of watching SSU weather news segments. The study utilized similar control variables used in the initial probit regression model for both the treatment and control groups. To ensure successful matching, a balancing test was conducted to verify that the distribution of these covariates was comparable across both groups. Table 3 shows a summary of the mean and median values of the observable variables for the treatment and control groups before and after matching. A significant reduction in both mean and median biases is observed, suggesting the effectiveness of our matching strategy. Additionally, the low pseudo-R^2 value after matching indicates minimal systematic differences between farmers who watch and those who do not watch SSU weather news segments in terms of the included covariates (changes in their agricultural income). This finding, along with

Table 3. Balancing test of observable variables in propensity score matching (PSM)

SAMPLE	PS R^2	LR CHI^2	P> CHI^2	MEAN BIAS	MEDIAN BIAS
Unmatched	0.090	19.98	0.006	10.7	8.6
Matched	0.030	10.75	0.550	7.8	5.7

the reduced bias and statistically non-significant likelihood ratio test p-values, further supported the validity of using PSM for this analysis.

Table 4. Average Treatment Effect of Watching SSU Weather News Segment on crop net income among maize farmers in Kenya

ALGORITHMS	ATT	S. E	T-VALUES
NNM	96769.8222	30775.7742	3.144
KBM	96769.8222	30967.519	3.125
RM	96769.8222	30765.768	3.145

Following the matching procedure, most respondents used to estimate the average treatment effect are in this common support region. From Table 4, the estimated Average Treatment Effects (ATT) on per capita net crop revenue among maize farmers, obtained using different PSM algorithms. All three algorithms yielded statistically significant results, indicating that maize farmers who have watched the SSU weather news segment in the last four years had higher income on average than those who did not watch.

A Rosenbaum bounds sensitivity analysis was conducted to evaluate the robustness of estimated Average Treatment Effects (ATT). This analysis assessed the potential impact of unobserved confounders on the treatment effect estimates. It revealed that even when the strength of association (gamma) between unobserved confounders and the treatment assignment was tripled, the statistical significance of the findings remained unchanged. This suggested that the results were relatively insensitive to potential biases arising from unmeasured factors, strengthening confidence in the conclusions. Based on the analysis on maize respondents above, it indicated that viewers of the SSU weather news segment reported more yields and income as compared to non-viewers.

Table 5. Results of the sensitivity analysis

GAMMA	SIG+	SIG-
1	0.4668	0.4668
1.25	1.5578	0.0554
1.5	2.4597	0.0043
1.75	2.8526	0.0000
2	2.9679	0.0000
2.25	2.9940	0.0000
2.5	2.9990	0.0000
2.75	2.9999	0.0000
3	3.0000	0.000

4. DISCUSSION

The impact of climate change and variability on smallholder farmers is a pressing concern for many countries. Building climate readiness and resilience among these farmers has become a priority for many governments, development practitioners, and policymakers. This study assesses the impact of the SSU Weather and Farming News segment on smallholder farmers in Kenya, specifically investigating the efficacy of the SSU Weather News segment in delivering weather advisories to farmers. Additionally, the study evaluates the segment's influence on farming practices, risk mitigation strategies, and agricultural outcomes among smallholder farmers in Kenya.

The objectives of this study are derived from the activities of iShamba, which collaborates with partners to deliver impactful agricultural advisory services. According to 60_decibels (2020), iShamba services have a transformative effect on farmers, with over 90% of respondents reporting significant improvements in farming practices, production, and overall quality of life. Farmers who used iShamba information for over 25 months experienced even deeper impacts: 65% saw a significant improvement in quality of life, 67% witnessed a substantial increase in farm production, and 74% reported enhanced productivity on the same land. Serving over half a million subscribers, primarily smallholder farmers across Kenya, iShamba provides customized agricultural advice, localized weather information, and up-to-date market prices to enhance farm productivity (Etchells, 2019; Gonzalez Bujedo, 2023).

While there is evidence on the transformative benefits of SSU, limited studies have been conducted regarding the benefits of SSU scientifically. This study builds on the existing knowledge gaps and focuses on the effects of the weather and farming news segment part of the SSU program.

Our results revealed a balanced age distribution across genders, indicating no significant gender disparity in agricultural participation. However, a clear trend emerged: individuals older than 35 were more actively involved in agricultural activities compared to younger respondents. This finding aligns with Chipfupa and Tagwi (2021), who reported that factors such as farming experience, skills, land, financial support, markets, and institutions hinder youth from actively participating in agriculture. Therefore, there is a need for targeted weather information and agro advisories to increase the participation of both young and older farmers in agricultural activities. Such programs could address the challenges of engaging younger individuals in agriculture and ultimately attract and retain youth involvement in the sector.

Additionally, results show equitable access to education across genders, with similar proportions of males and females in different educational categories. Research suggests that CIS effectiveness hinges on users' ability to understand and utilize the provided information (Ofoegbu & New, 2022). Higher educational attainment is often linked to a greater capacity for interpreting complex climate information and integrating it into decision-making for agricultural practices (Ngigi & Muange, 2022). However, a small portion of the study population lacked formal education. This highlights the need for continuous educational outreach programs and support services. Tailoring advisories to diverse farmer profiles based on educational background is crucial to ensure the accessibility and relevance of agricultural information and interventions. Ensuring that all farmers, regardless of their educational background, have access to understandable and actionable climate information is essential for maximizing the impact of CIS (Okoro et al., 2016). Given that educational attainment enhances the ability to interpret and utilize complex climate information, continuous efforts are needed to bridge any educational gaps among the farming population. This involves not only providing tailored advisories but also leveraging accessible platforms to disseminate information effectively.

Prompt access to information is important for farmers for effective decision-making in farming activities. The study found that most respondents identified the SSU weather segment as their primary source of agri-advisory, highlighting its widespread adoption among farmers. Other sources like Farm Radio, KMD, and KALRO also contributed, albeit to a lesser extent. Similarly, the SSU viewership revealed that a considerable proportion of farmers engaged with the weather segment regularly, with 57.9% watching it weekly. Moreover, SMS and television emerged as the most prevalent platforms for receiving advisory among farmers, with SMS being the most preferred. The reason farmers could have preferred SMS was supposedly due to its flexibility/portability and cost-effectiveness. The literature review supports these findings, indicating that SMS is the most common channel for delivering CIS to smallholder farmers in developing countries (Nepal et al., 2024; Yegbemey & Egah, 2021). This preference for SMS highlights the crucial role of timely and accurate weather advisories in agricultural decision-making.

Timely and accurate weather advisories are key for farmers' agricultural activities to enable them to plan and adapt their agricultural practices well. They enable timely actions, such as planting, harvesting, etc., while minimizing losses due to weather-related risks. Almost all the respondents revealed that the SSU weather advisories were timely, facilitating effective planning and resource management. However, certain counties, particularly those with varied agroecological properties, reported lower levels of timeliness. This calls for targeted interventions to ensure universal access and timely delivery of advisories. On the other hand, accurate forecasts ensure resource optimization, leading to increased productivity and food security. Similarly, almost all the respondents perceived SSU advisories to be accurate. The report also connected the advisories to local knowledge of the farmers. Local knowledge is an important aspect of weather forecasting since it enhances weather advisories by incorporating indigenous wisdom and community-specific insights. While 43% of respondents affirmed a match between advisory and experience, 50% indicated occasional alignment, suggesting opportunities for further refinement in advisory content. Aligning the SSU advisories with local indigenous knowledge will add depth to forecasts and advisories, considering local climate patterns, ecological distinctions, and traditional farming practices. This will also foster trust, improve accuracy, and create a sense of ownership among the farmers, which will, in turn, ensure farmers have a sense of belonging with the advisories. County-level analysis revealed disparities in accuracy perceptions, particularly in ASAL regions, highlighting the need for tailored approaches to address unique agroecological contexts, especially in the arid regions of Kenya, to maximize the impact of advisory interventions on farmers’ livelihoods.

Furthermore, the effectiveness of these advisories can be observed in the changes made by farmers in their agricultural practices. Consequently, the report, while analyzing how the farmers made informed decisions from the advisories, found that a higher proportion of SSU weather segment viewers, particularly in crop production (46.8%), compared to livestock production (13.9%), made changes to their farming methods after watching the advisories. A relatively lower percentage of non-viewers of the SSU weather segment doing crop production (27.1%) made weather-related adjustments to their farming activities, cementing the influence of SSU on the agricultural practices done by farmers. This result align with findings in literature. For instance, Ngigi and Muange (2022) demonstrates that access to CIS improves the adoption of climate-smart agriculture (CSA) practices such as multiple cropping, water management, crop rotation, soil conservation, change in animal breeds, diversified livestock, and the use of pest-resistant crops.

Across all respondents, certain changes in farming practices emerged as more prevalent, including adjusting planting time, choosing different crops, and improving land preparation. SSU viewers exhibited a slightly higher adoption rate of these practices compared to non-viewers, suggesting that SSU weather advisory viewership enhances awareness and adoption of weather-related farming practices. Notably, it was found that adjusting planting time emerged as the most adopted practice among both SSU viewers and non-viewers, while planting resistant/drought-tolerant crops had the lowest adoption rate. The data also indicated that a larger proportion of SSU viewers adopted sustainable farming practices compared to non-viewers, except for land preparation, which saw higher adoption among non-viewers. Consequently, due to changes in farming activities, a significant percentage of respondents in both crop production and livestock production reported observed changes, particularly among SSU weather segment viewers. These decisions made by farmers to their farming practices were found to have led to positive changes in farming practices among farmers, with notable improvements in production, quality of produce, and reduced crop loss/damage. This impact was lower on non-viewers, indicating the influential role of SSU weather advisories in prompting adjustments to farming practices and subsequent changes in crop and livestock production. Closely related, adoption of risk mitigation techniques suggested that SSU viewers were more likely to employ strategies such as planting larger areas. While SSU viewership correlated with the adoption of these techniques, a significant proportion of farmers did not employ any risk mitigation measures, highlighting the need for further efforts to promote resilience in farming practices.

In agreement, the ROI for households that watched SSU is higher for all iShamba priority crops. For example, the ROI for maize farmers who watched SSU was 2.2, while for those who didn't watch, it was 1.09. This aligns with the findings of Clarkson et al. (2018), who reported that SSU viewers obtained significantly higher yields, leading to greater income and ROI compared to their counterparts. However, ROI calculations often generalize results without accounting for spatial variation. Besides, climate information must be locally relevant to be useful in guiding decisions at the local level (Reyes-García et al., 2016). We used ITE and GWR and found interesting spatial variations in the impacts of watching SSU. For example, counties like Nyandarua, Nyeri, and Murang'a benefit less from watching SSU weather and farming news, whereas Kilifi, Kwale, Migori, West Pokot, Makueni, and Isiolo counties benefit more. This agrees with Thornton et al. (2009), who suggest that the benefits of CIS may vary spatially based on factors like local climate, crop types, and farming practices. Overall, spatial variations enhance policy formulation because different regions experience varying climate patterns, including temperature, precipitation, and extreme weather events. Policies must account for these variations to provide localized, accurate and relevant climate information that can help farmers adapt their practices to local conditions.

To further understand the impact, the report employed PSM to predict outcomes and identify causality among the variables to evaluate the effect of watching SSU weather news segments on agricultural income. The model revealed that the farmers who watched the SSU weather news segment realized relatively higher income on average compared to those who were non-watchers. This could have been witnessed since the farmers who watched SSU weather news segments likely benefited from timely and tailored agricultural advice, enabling them to make informed decisions regarding planting and crop management. This may have led to improved yields, reduced losses due to adverse weather events, and enhanced resilience to climate risks. Additionally, access to accurate weather forecasts could have facilitated efficient resource allocation and risk mitigation strategies, contributing to higher agricultural income among SSU viewers compared to non-viewers.

While this study has provided valuable insights into the impact of SSU on farming practices, several limitations should be considered. These limitations not only present the scope of our findings but also show the areas where further research is needed. These limitations will help gain a clearer perspective on the study, enabling a more informed interpretation of its results.

- Sampling bias. The study's reliance on self-reported data from farmers during the interviews could introduce sampling bias. Respondents might be inclined towards reporting favorable outcomes or exaggerated impacts due to their awareness of participating in the study. Moreover, the sample was predominantly male, which may not accurately represent the broader farming population's gender distribution and perspectives across the entire population.
- Temporal constraints. The study was based on cross-sectional data, capturing experiences of the farmers at a single point in time. This limits the ability to draw conclusions about causality or the long-term impacts of the SSU Weather and Farming News segment on farming practices and outcomes.
- Geographical and contextual variability. The study involved diverse counties with varying agroecological conditions. The study notes significant variations in the sources and accuracy of weather advisories across different counties. For example, 100% of farmers in Kajiado rely on Farm Radio, and there are discrepancies in perceived advisory accuracy in the ASALs. This geographic variability limits the ability to make uniform conclusions applicable to all regions. While efforts were made to account for these differences, the unique characteristics of each region could have influenced the results. Therefore, the findings might not be uniformly applicable across all regions.
- Unmeasured confounding variables. Despite efforts to control for observable variables in the PSM, there remains the potential for unmeasured confounding factors that could influence the observed outcomes. For example, factors such as local climate knowledge, community support systems, and individual farmer's risk tolerance were not measured but could affect the use and effectiveness of the SSU.

5. CONCLUSION AND RECOMMENDATIONS

The report found that the SSU Weather News Segment significantly influences smallholder farmers' farming practices, risk mitigation strategies, and institutional capacities. The report additionally stresses the heterogeneity within agricultural communities, particularly concerning gender representation and educational attainment. Addressing these disparities is essential for designing effective and inclusive interventions such as SSU weather news, aimed at enhancing resilience, productivity, and livelihoods among farmers. By recognizing and accounting for the diverse socio-economic profiles of agricultural communities, stakeholders such as SSU can better tailor interventions to meet their specific needs and priorities, ultimately contributing to more sustainable and equitable agricultural development.

Over the past 4 years the segment has continued to gain traction as one of the captors of SSU viewers with about 68% of the respondents reporting watching the segment every weekend, either Saturday, Sunday or on both days. Consequently, due to this success, approximately 43% of the respondents were found to be keen on weather advisory and their experiences at farm level. Hence, these groups can be used as model farmers to improve reach and peer education on implementing weather advisories within the farming communities.

Findings show that the adoption of weather-related risk mitigation is preferably low. There is a need for increasing content and more awareness on adoption of weather-related risks mitigating measures in subsequent segments. Also, there is a need for future relativity on aspects of the impact of the segment related to increase in income levels and yields needs to be explored for more weather-related products and tailored initiatives.

Local knowledge emerged as an important aspect in weather forecasting, enhancing advisories by incorporating indigenous knowledge and community-specific insights. Aligning the SSU advisories with local indigenous knowledge can add depth to forecasts and advisories, fostering trust, improving accuracy, and creating a sense of ownership among farmers.

Therefore, gender-sensitive approaches, youth engagement, timely and accurate advisory delivery, and continuous improvement in agricultural interventions should be emphasized in related activities. By addressing these key areas, stakeholders such as SSU can maximize the impact of weather advisories on smallholder farmers' livelihoods and contribute to sustainable agricultural development in Kenya.

Future research should expand on this study's findings and address its limitations through various approaches. Longitudinal studies will track changes over time, revealing sustained impacts of SSU advisories on farming practices and livelihoods. Incorporating unobserved variables like local climate knowledge and social networks can enrich understanding of the study outputs, while experimental designs such as randomized controlled trials will provide robust evaluation of the effectiveness of SSU. These approaches will therefore enhance the evaluation of SSU, and related weather advisory services adapted to the needs of agricultural communities from diverse regions.

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APPENDICES

Appendix 1: Questionnaire

Section 0: Pre-survey administration

Note to enumerator: Read aloud.

Good morning/afternoon, my name is ……………………………from iShamba. Thank you for the opportunity to speak with you. I am part of the research team working for Shamba Shape Up. Shamba Shape Up assists farmers in improving their farms and achieving better yields by providing tailored weather-related advisories. Additionally, we have agricultural experts who can help with your farming needs. We have also been airing our program, Shamba Shape Up, for the last 14 years. To deliver these services, we work in collaboration with other organizations, including the International Center for Tropical Agriculture (CIAT). CIAT focuses on scientific research and development aimed at increasing agricultural productivity, improving key crops, reducing environmental impact, and building climate resilience in tropical regions.

Currently, we are conducting a study to understand the practicality of the program to farmers' needs and areas for improvement. In this survey, iShamba, in partnership with CIAT, is conducting a survey to gather your views on the Shamba Shape-Up Weather News Segment. This survey is part of the project Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA), which aims to deliver a climate-smart African future driven by science and innovation in agriculture. Led by CIAT and supported by a grant from the International Development Association (IDA) of the World Bank, AICCRA has participating partners from six countries: Ethiopia, Kenya, Zambia, Ghana, Mali, and Senegal.

The study population is farming households residing in the 45 counties in Kenya, that is excluding Mombasa and Nairobi counties. The study will target households in these counties who have been receiving advisories from iShamba.

Your participation is completely voluntary. The researchers will make every effort to protect your confidentiality. However, if you are uncomfortable answering any of these questions, you may skip them and you can let us know if you do not want to answer any specific question, we ask you. In addition, you can withdraw from the survey at any point and there will be no penalty or loss of benefits if you withdraw.

As a selected participant in this study, you will be invited to participate in a one-on-one interview. The interviews should take 15-20 minutes to complete. We will ask you questions about the Weather News Segment, use and usefulness of the information as well as the impact on crops/livestock production. We will also ask you for some information about coping strategies to various agricultural risks.

The responses and information you provide during the interview will be treated with utmost discretion and while the data will be used for research purposes only, it will not be presented in any way that may allow the identification of the respondents. To guarantee confidentiality, data collected will be transferred securely to servers where only the project research team can access. The data may be transmitted to other computers for further analyses. In this case, the data will be stripped of any personal identifiable information (PII) such as names, phone numbers and any other data that can link the respondent to the data. iShamba will store PIIs separately and securely from the rest of the data. In addition, your responses will be pooled with those of other respondents from other areas and research results will only be presented as aggregate and not identifiable by individual respondents. Only anonymized data will be available to researchers and project partners.

Your participation may not benefit you directly, but your contribution may benefit other farmers like you as your responses will help in improving the Shamba Shape-Up Weather News Segment for tailored weather information to benefit all farmers. There are no anticipated risks and/or discomfort in taking part in the survey. The risks associated with participating in this study are negligible. One risk is that we will know your personal information. However, we will not reveal any of this personal information about you or your household to any other person.

We will not pay you directly for participating in the study. However, to appreciation your time participating in the interview, we will offer a token airtime of KES 150.

The findings from this study will be summarized in a report and help to inform the design of iShamba activities and similar programs in the future. The information collected will be used for research purposes, specifically developing a technical report, blogs, and journal articles. The output may also be used by the government and other stakeholders to design policies that may benefit farmers like you.

If you have questions or are interested in the outcome of this survey, please contact iShamba via email at ishamba@mediae.org, call us on **0711 082 606** or SMS to **21606**.

You will receive an SMS requesting your consent from iShamba. If you are willing to voluntarily take part in the survey, kindly reply with **YES**. If you do not wish to take part, kindly reply with **NO**.

Thank you.

N	Question	Answer set	Instructions/hint
001	Is now a convenient time for you?	1=Yes, let's talk now. 2=I'd prefer to talk later. 3=Not interested	If the farmer responds with "Yes, let's talk now," please proceed with the interview. If the farmer chooses "Not interested," please halt the interview and find a replacement as directed by your supervisor. If the farmer selects "I'd prefer to talk later," please schedule an appointment.
002	Name of the enumerator.	List	Select one.
003	Date of interview	State	dd/mm/yyyy

Section O: Farmers' characteristics (Demographics: Profile and Details).

In this section, we aim to gather information about the characteristics and demographics of the farmers participating in our survey. Your responses will provide us with valuable insights into the diverse backgrounds and profiles of farmers, which can help us tailor agricultural services and support to better meet your specific needs.

N	Question	Answer set	Instructions

O1	Respondent ID		[Surveyor: Fill in the respondent unique ID]
O2	Gender	1. Male 2. Female 3. Prefer not to say	Open ended (Text)
O3	Which county do you reside in?	Select	(Please refer to the county list provided)
O4	How old are you?	1. Below 18 Years 2. 18 - 25 Years 3. 26 - 35 Years 4. 36 - 45 Years 5. 46 - 55 Years 6. Above 55 Years 98. Don't know/prefer not to answer	Select one.
O5	What is the highest level of formal education you have completed?	No formal education Primary education Secondary education Vocational/Technical training Tertiary/University education Postgraduate education 98. Don't know/prefer not to answer	Select one.
O6	Including yourself, how many adults and children, live in your household? The individuals who have been residing in your household	State	Open-ended (Number)

	continuously for the past six months		

Section A: Assessment of knowledge and impact of the SSU weather segment

In this section, our discussion will focus on your knowledge, awareness, information needs, preferred methods of accessing information, the relevance of sources for weather forecast information and advisory, as well as the benefits of weather forecast or agro-advisory information.

N	Question	Answer set	Instructions/hint
A1	Have you watched or received any weather forecast or agro-advisory in the past 12 months?	1=Yes 2=No	Skip to A7 if A1=1 Ask A2 to A6 if A1=2.
A2.1	Are you interested in receiving weather forecasts or agro-advisory?	1=Yes 2=No	If A2.1 is 2=No > =A6
A2.2	What kind of advisory would you want to receive?	1=Rainfall forecast 2=Localized seasonal weather outlooks 3=Probability of dry spells or early end to rains 4= Early warnings for extreme events 5= Drought and water availability 6= Weather-responsive farming practices 77=Other (specify)	Select multiple
A3	What is your preferred channel for receiving weather forecasts or agro-advisory information?	1=TV 2=YouTube 3=WhatsApp 4=Facebook/Twitter/Instagram	Select one.

		77=Other (please specify)	
A4	What is the main purpose for which you require weather information?	1=To plan day to day farm work 2=For longer term farm planning 3=To increase the economic return from farming 4=General information 77=Other (specify)	Select one.
A5	What is the MOST important element of the weather forecast that you would like to receive?	1=Start of rain 2=Likelihood of rain 3=Amount of rainfall 4=Flood 5=Temperature 6=Drought 7=Storm 8=Frost 77=Other (specify)	Select one.
A6	What is the primary reason for not being interested in receiving weather forecasts or agro-advisory?	1=Not relevant to my needs. 2=Lack of time to use such information. 3=Data accuracy concerns. 77=Other (specify)	Select one. If A2.1=2
A7	What are the sources of weather forecasts or agro-advisories you have received in the past 12 months?	1=KMD 2=KALRO 3=Farm Radio 4=Shamba shape-up weather news segment.	Select multiple. Skip to A11 if Option 4 is not selected, either individually or in combination with other options.

		5=Kilimo 77=Other (specify)	Ask questions A8 to A10 if Option 4 is selected, either individually or in combination with other options.
A8	How long have you been watching the Shamba Shape Up Weather News Segment? Please remind the farmer that this is the segment when a map of Kenya is displayed with weather information during the shamba shape up program.	1=0-6 months 2=6-12 months 3=1-1.5 years 4=1.5-2 years 5=2-2.5 years 6=2.5-3 years 7=3-3.5 years 8=3.5-4 years 9=Not sure	Select one.
A9.1	Who do you usually watch the Shamba Shape-Up news segment with?	1=I usually watch it alone. 2=I usually watch it with others.	
A9.2	On average, how many members of your household do you watch the Shamba Shape Up weather news segment with?	Text	If A9.1=2
A10	On a scale of 1 to 5, with 5 being 'always', how often do you watch the Shamba Shape-Up weather news segment?	1=Never. 2=Rarely (Once a month). 3=Sometimes (Once every 2 weeks). 4=Often (Once every week (Sat or Sun). 5=Always (Both Sat & Sun).	Select one

A11	On which platform(s) do you watch or receive weather forecast information or advisory?	1=TV 2=YouTube 3=WhatsApp 4=Facebook/Twitter/Instagram 77=Other (specify)	Select multiple
A12	From the above platforms, which is your **MOST** preferred way to watch or receive weather forecast information or advisory?	1=TV 2=YouTube 3=WhatsApp 4=Facebook/Twitter/Instagram 77=Other (specify)	Select one.
A13	What is your **MOST** important element of the weather forecast to you?	1=Start of rain 2=Likelihood of rain 3=Amount of rainfall 4=Flood 5=Temperature 6=Drought 7=Storm 8=Frost 77=Other (specify)	Select one.
A14	Was the weather forecast information/advisory timely to guide your farming activities?	1=Yes 2=No	Select one.
A15	How would you rate the accuracy of the weather forecast?	1=Highly accurate. 2=Usually accurate.	Select one.

		3=Are accurate about half the time. 4=Inaccurate. 5=Completely inaccurate.	
A16	Have you changed your practices/decisions following the advice you received?	1=Yes 2=No	Ask A17 to A19.2 if A16=1 Skip to A20 if A16=2
A17	How did you change your practice/decision?	1=Land preparation. 2=Adjusting planting time 3=Choosing a different crop to plant 4=Making irrigation decisions 5=Weeding/mulching 6=Bought/sold livestock. 7=Better livestock management practices. 8=Preservation of fodder e.g., silage/hay. 9=Planted resistant/drought tolerant crops. 10=Adopted good post-harvest handling techniques. 77=Other (specify)	Select multiple.
A18.1	Did you notice any change in your farming activities after making changes in your farming practice following the forecast/advisory?	1=Yes 2=No	If A18.1=1, ask A18.2 to A19
A18.2	What kind of positive change did you notice?	1=More production. 2=Less crop loss/damage.	Select multiple.

		3=Less expenses. 4=Better labor use. 5=More peace of mind. 6=Less animal losses. 7=Improved quality of produce 77=Other (specify).	
A19.1	Have you noticed negative effects after making changes in your farming practice following the forecast/advisory?	1=Yes 2=No	If A19.1=1, ask 19.2 If A19.1=2, skip to A21
A19.2	Please specify the kind of negative effects.	Text	Open ended
A20	What are the main reasons why you did not make any changes, despite receiving the advisory?	1=I was already making the correct decisions. 2= It was not timely. 3=I was not sure what to do. 4=I don't trust the information. 5=I did not have money to make decisions. 6=It was too late. 7=I was happy with my farm output. 77=Other (specify).	If A16=2 Select multiple.
A21	Did the weather forecast information or advisory match with your experience/knowledge?	1=Never 2=Rarely 3=Sometimes 4=Always	Select one.

A22	What are your suggestions to improve weather forecasts or agro-advisory services?	Text	Open ended

Section B: Impact of SSU Weather segment on Crop productivity and Livestock Production

In this section, we want to know how the weather information and farming tips from Shamba Shape Up weather news segment and other weather forecast advisories have affected your crops and animals on your farm. Your answers will show us how this information has changed the way you farm and what results you have seen. Your thoughts are very important and will help us understand how SSU and other sources of weather forecast, and agricultural advice are assisting farmers like you. In case you do not receive any weather advisories, we would still like to learn more about your farming practices and farm production.

N	Question	Answer set	Instructions
B1	What is your main farming activity in 2022?	1=Crop production. 2=Livestock production.	Select one.
B2	What is the name of the MAIN crop you produce?	CROPCODES	If B1=1
B3	What is the size of your agriculture in acres?	Integer	
B4	What area of land does B2 occupy in acres?	Integer	If B1=1
B5	Who mainly decided how to cultivate B2?	1= Male HHD 2=Female HHD 3=Joint 77=Other (specify)	Select one
B6	In the normal main cropping season, how much B2 do you harvest?	Integer	If B1=1

B7	Unit	CROPPRODUCTUNITS	Select one
B8	During the main cropping season 2022, how much B2 did you harvest?	Integer	If B1=1
B9	Unit	CROPPRODUCTUNITS	Select one
B10	What was the prevailing market price per unit for B2?	Text	
B11	Who mainly made the decision on how to dispose of B2?	1= Male HHD 2=Female HHD 3=Joint 77=Other (specify)	Select one
B12	Which livestock did you mainly raise in 2022?	LIVESTOCK CODES	If B1=2
B13	What was the size of B12?	Text	Integer
B14	Who mainly decided how to keep B12?	1= Male HHD 2=Female HHD 3=Joint 77=Other (specify)	Select one
B15	What was the main product of B12?	Text	
B16	In a normal year, how much of B15 do you get?	Text	
B17	Unit	LIVESTPRODUCTUNITS	Select one
B18	How much of B15 did you get in 2022?	Text	

B19	Unit	LIVESTPRODUCTUNITS	Select one
B20	What was the unit price?	Text	
B21	Who mainly made the decision on how to use B15?	1= Male HHD 2=Female HHD 3=Joint 77=Other (specify)	Select one

Codes for livestock: 1=Dairy Cow 2=Beef Cattle 3=Dairy Goats 4=Meat goats 5=Sheep 6=Chickens 7=Pigs 8=Rabbits 9=Bees 10=Ducks 11=Gees 12=Turkeys 13=Camels 77=Other (specify)

Unit codes for crop: 1=90kg bag 2=70 kg bag 3=50kg bag 4=10kg bag 5=Gorogoro (2kg tin) 6=Count 7=Headloads 8=Wheelbarrows 9=bunches 10=bales 11=crates 12=other (specify)

Codes for livestock products: 1=liters 2=count 3=kilogram 4=trays 5=jars 6=bales 7=cups 77=other (specify)

Section C: Role of the Shamba Shape Up News Segment in Weather-Related Risk Mitigation

In this section, we aim to understand the role of weather forecasts or agro-advisory in helping farmers like you manage weather-related risks on your farm. Your insights will provide valuable information on how weather forecast/advisory assists in mitigating the impact of weather uncertainties on your agricultural activities. In case you don't receive any weather advisories, we would still like to learn how you manage risks on your farm.

N	Question	Answer set	Instructions
C1	After receiving a weather forecast/advisory, which of these risk mitigation techniques did you start using?	1=Got insurance for my crops. 2=Got insurance for my livestock. 3=Applied for credit. 4=Planted a smaller area. 5=Planted larger area. 6=Did not plant/did not establish a crop on the farm.	Multiple choices Please ask if A1=1 Then move to Section D

		7=Increased the number of animals. 8=Reduced number of livestock. 9=Did not keep animals. 10=Took up an alternative non-agricultural activity. 11=I didn't use any risk mitigation measures. 77=Other (specify)	
C2.1	Are you currently using any risk mitigation strategies on your farm?	1=Yes 2=No	If A1=2
C2.2	Which of the following risk mitigation strategies are you currently using?	1=Got insurance for my crops. 2=Got insurance for my livestock. 3=Applied for credit. 4=Planted a smaller area. 5=Planted larger area. 6=Did not plant/did not establish a crop on the farm. 7=Increased the number of animals. 8=Reduced number of livestock. 9=Did not keep animals. 10=Took up an alternative non-agricultural activity. 11=I do not use any risk mitigation measures. 77=Other (specify)	If A1=2 **AND** C2.1=1

Section D: Impact of the 'Shamba Shape Up' News Segment on Institutional Capacities for Agro Advisories and Strengthening Partnerships

In this section, we aim to understand how iShamba helps make organizations better at giving agricultural advice and forming partnerships. Your thoughts will tell us how iShamba helps build stronger institutions and collaborative relationships in the agricultural sector.			
N	Question	Answer set	Instructions
D1	Have you heard about the Shamba Shape Up program from iShamba?	1=Yes 2=No	Please ask if A1=2 **AND** if Option 4 is not selected for question A7, either alone or with other options.
D2	How long have you been associated with iShamba?	State	Please ask the rest of the questions in this section if D1=1
D3	Are you aware of other organizations or sources of weather advisories apart from the Shamba Shape Up Weather News Segment?	1=Yes (please specify) 2=No	Select one.
D4	Are you aware of any organizations that partner with iShamba?	1=Yes (please specify) 2=No	Select one.
D5	Are there any partner organizations that you would like to see collaborate with iShamba?	1=Yes (please specify) 2=No	Select one.
D6	Would you recommend the 'Shamba Shape Up' news segment to other farmers as a reliable source of information on weather-related risk mitigation?	1=Strongly recommend it. 2=Recommend. 3=Neutral / Not sure. 4=Probably not recommended. 5=Definitely not recommended.	Select one.

D7	What are your suggestions to improve the quality of weather forecasts or agro-advisory services provided by iShamba in the Shamba Shape Up weather news segment?	Text	Open ended

Appendix 2: Indicators

1. Evaluate the segment's effectiveness in providing timely and site-specific weather information.

Timeliness of information: Percentage of farmers who received the weather information before the start of their farming activities. [A14]

- Accuracy of weather predictions: Proportion of farmers who found the weather information specific to their location. [A15]
- Accessibility of information. [A10, A11, A12]
- Farmers interpretation and understanding. [A15 & A21]
- Utilization of information received [A16, A17]
- Change in farming behavior [A16, A17 supported by A18.1 to A19.2]

2. Measure the extent to which farmers have made informed decisions based on the weather forecasts and localized advisories.

- Number and percentage of farmers who made changes to their farming practices after receiving weather advisories. [A16]
- Types of decisions made based on the weather information (e.g., planting time, type of crop planted, irrigation decisions). [A17]]
- Risk management strategies. Assess whether farmers implement specific risk management strategies (e.g., diversification of crops, adjusting planting/harvesting times) in response to weather forecasts to mitigate potential risks [C1, C2.1, C2.2]
- Resource Allocation: Determine if there are changes in resource allocation (e.g., labor, water, fertilizers) based on the weather forecasts provided by Shamba Shape-Up.
- Quantitative Changes in Productivity: Measure any quantifiable changes in productivity, such as increased yield or reduced crop or livestock losses, that can be attributed to informed decision-making influenced by the weather forecasts and advisories. [Relevant here but will be answered in the third objective. We can find a way to answer this by use of such variables as A18.2]
- Comparison of Practices: Compare the practices of farmers who actively use the weather information from Shamba Shape-Up against those who do not, to assess differences in decision-making and resulting outcomes.

3. Assess the impact of the segment on agricultural productivity, including crop cultivation, harvesting, and management.

- Crop/livestock productivity: Measure changes in crop yield or livestock production attributed to the implementation of practices influenced by Shamba Shape-Up's advisories. In our case we will use normal versus actual. Percentage increase or decrease in crop/ livestock yield in areas where farmers rely on the segment. [Series of variables in Section B]
- Changes in the frequency of crop loss due to weather conditions. [A18.2=2]
- Improved management practices (e.g., soil management, pest control) due to the segment's advice. [A17]
- Enterprise Diversity: Assess if there is an increase in crop/livestock diversity as a result of the advisories provided by iShamba. [A17]
- Quality of Produce: Evaluate changes in the quality of agricultural produce, such as improved size, appearance of produce, because of implementing recommended practices. [A18.2=7]

- Resource Use Efficiency: Assess the efficiency of resource use (e.g., water, fertilizers, pesticides) in relation to productivity. Determine if advised practices lead to better resource management and increased productivity. [A18=,1,2,3,4]
- Comparative Analysis: Compare the productivity of farmers who have benefited from Shamba Shape-Up news segment against those who haven't, to gauge the differences in agricultural output.

4. Determine the segment's role in mitigating weather-related risks for farmers.

- Number of farmers who adopted new farming techniques or crop varieties to mitigate weather risks. [A17 AND Section C]
- Reduction in losses. Reduction in reported losses (e.g., crops, livestock) due to extreme weather events among the viewers of the segment. [A18.2 AND Section C]
- The proportion of farmers who took up insurance or other risk mitigation strategies due to the segment's advice. [Section C]
- Resilience Indicators: Determine indicators of resilience, such as the ability to bounce back from weather-related setbacks, changes in coping strategies, and recovery rates post adverse weather events. [Section C]
- Comparative Analysis: Compare the resilience and risk mitigation strategies of farmers who engage with iShamba advisories against those who do not.

Appendix 3: Contingency table for SSU weather advisory timeliness by gender and county

GENDER	COUNTY	RESPONSE	PERCENTAGE
Female	Baringo	Yes	20
Male	Baringo	Yes	80
Female	Baringo	No	0
Male	Baringo	No	0
Female	Bomet	Yes	18
Male	Bomet	Yes	82
Female	Bomet	No	0
Male	Bomet	No	0
Female	Bungoma	Yes	20
Male	Bungoma	Yes	78
Female	Bungoma	No	0
Male	Bungoma	No	2
Female	Busia	Yes	12
Male	Busia	Yes	85
Female	Busia	No	0
Male	Busia	No	3
Female	Elgeyo-Marakwet	Yes	0
Male	Elgeyo-Marakwet	Yes	100
Female	Elgeyo-Marakwet	No	0
Male	Elgeyo-Marakwet	No	0
Female	Embu	Yes	21
Male	Embu	Yes	75
Female	Embu	No	4
Male	Embu	No	0
Female	Homa Bay	Yes	25
Male	Homa Bay	Yes	75
Female	Homa Bay	No	0
Male	Homa Bay	No	0
Female	Isiolo	Yes	33
Male	Isiolo	Yes	67
Female	Isiolo	No	0
Male	Isiolo	No	0
Female	Kajiado	Yes	0
Male	Kajiado	Yes	100
Female	Kajiado	No	0
Male	Kajiado	No	0
Female	Kakamega	Yes	20
Male	Kakamega	Yes	78
Female	Kakamega	No	0
Male	Kakamega	No	3
Female	Kericho	Yes	10
Male	Kericho	Yes	90
Female	Kericho	No	0

Male	Kericho	No	0
Female	Kiambu	Yes	17
Male	Kiambu	Yes	83
Female	Kiambu	No	0
Male	Kiambu	No	0
Female	Kilifi	Yes	14
Male	Kilifi	Yes	81
Female	Kilifi	No	0
Male	Kilifi	No	5
Female	Kirinyaga	Yes	4
Male	Kirinyaga	Yes	96
Female	Kirinyaga	No	0
Male	Kirinyaga	No	0
Female	Kisii	Yes	9
Male	Kisii	Yes	89
Female	Kisii	No	0
Male	Kisii	No	3
Female	Kisumu	Yes	7
Male	Kisumu	Yes	93
Female	Kisumu	No	0
Male	Kisumu	No	0
Female	Kitui	Yes	32
Male	Kitui	Yes	68
Female	Kitui	No	0
Male	Kitui	No	0
Female	Kwale	Yes	0
Male	Kwale	Yes	100
Female	Kwale	No	0
Male	Kwale	No	0
Female	Laikipia	Yes	17
Male	Laikipia	Yes	83
Female	Laikipia	No	0
Male	Laikipia	No	0
Female	Machakos	Yes	31
Male	Machakos	Yes	67
Female	Machakos	No	3
Male	Machakos	No	0
Female	Makueni	Yes	27
Male	Makueni	Yes	70
Female	Makueni	No	0
Male	Makueni	No	3
Female	Marsabit	Yes	0
Male	Marsabit	Yes	100
Female	Marsabit	No	0
Male	Marsabit	No	0
Female	Meru	Yes	18
Male	Meru	Yes	79

Female	Meru	No	0
Male	Meru	No	4
Female	Migori	Yes	6
Male	Migori	Yes	94
Female	Migori	No	0
Male	Migori	No	0
Female	Murang'a	Yes	33
Male	Murang'a	Yes	63
Female	Murang'a	No	0
Male	Murang'a	No	4
Female	Nakuru	Yes	18
Male	Nakuru	Yes	80
Female	Nakuru	No	0
Male	Nakuru	No	2
Female	Nandi	Yes	15
Male	Nandi	Yes	85
Female	Nandi	No	0
Male	Nandi	No	0
Female	Narok	Yes	22
Male	Narok	Yes	74
Female	Narok	No	0
Male	Narok	No	4
Female	Nyamira	Yes	50
Male	Nyamira	Yes	50
Female	Nyamira	No	0
Male	Nyamira	No	0
Female	Nyandarua	Yes	29
Male	Nyandarua	Yes	71
Female	Nyandarua	No	0
Male	Nyandarua	No	0
Female	Nyeri	Yes	25
Male	Nyeri	Yes	75
Female	Nyeri	No	0
Male	Nyeri	No	0
Female	Samburu	Yes	23
Male	Samburu	Yes	77
Female	Samburu	No	0
Male	Samburu	No	0
Female	Siaya	Yes	13
Male	Siaya	Yes	84
Female	Siaya	No	0
Male	Siaya	No	3
Female	Taita–Taveta	Yes	22
Male	Taita–Taveta	Yes	78
Female	Taita–Taveta	No	0
Male	Taita–Taveta	No	0
Female	Tana River	Yes	0

Male	Tana River	Yes	50
Female	Tana River	No	50
Male	Tana River	No	0
Female	Tharaka-Nithi	Yes	27
Male	Tharaka-Nithi	Yes	73
Female	Tharaka-Nithi	No	0
Male	Tharaka-Nithi	No	0
Female	Trans-Nzoia	Yes	24
Male	Trans-Nzoia	Yes	74
Female	Trans-Nzoia	No	0
Male	Trans-Nzoia	No	3
Female	Uasin Gishu	Yes	26
Male	Uasin Gishu	Yes	70
Female	Uasin Gishu	No	0
Male	Uasin Gishu	No	4
Female	Vihiga	Yes	20
Male	Vihiga	Yes	67
Female	Vihiga	No	3
Male	Vihiga	No	10
Female	West Pokot	Yes	30
Male	West Pokot	Yes	70
Female	West Pokot	No	0
Male	West Pokot	No	0

Appendix 4: Perceived levels of accuracy for SSU weather advisory by county

County	CATEGORY	PERCENTAGE (%)
Baringo	Are accurate about half the time	16
Baringo	Completely inaccurate	0
Baringo	Highly accurate	40
Baringo	Inaccurate	0
Baringo	Usually, accurate	44
Bomet	Are accurate about half the time	0
Bomet	Completely inaccurate	0
Bomet	Highly accurate	54.6
Bomet	Inaccurate	3.0
Bomet	Usually, accurate	42.4
Bungoma	Are accurate about half the time	7.8
Bungoma	Completely inaccurate	0
Bungoma	Highly accurate	60.8
Bungoma	Inaccurate	0
Bungoma	Usually, accurate	31.4
Busia	Are accurate about half the time	12.1
Busia	Completely inaccurate	0
Busia	Highly accurate	45.5
Busia	Inaccurate	0
Busia	Usually, accurate	42.4
Elgeyo-Marakwet	Are accurate about half the time	0
Elgeyo-Marakwet	Completely inaccurate	0
Elgeyo-Marakwet	Highly accurate	50
Elgeyo-Marakwet	Inaccurate	0
Elgeyo-Marakwet	Usually, accurate	50
Embu	Are accurate about half the time	20.8
Embu	Completely inaccurate	0
Embu	Highly accurate	37.5
Embu	Inaccurate	0
Embu	Usually, accurate	41.7
Homa Bay	Are accurate about half the time	9.4
Homa Bay	Completely inaccurate	0
Homa Bay	Highly accurate	40.6
Homa Bay	Inaccurate	0
Homa Bay	Usually, accurate	50
Isiolo	Are accurate about half the time	0
Isiolo	Completely inaccurate	0
Isiolo	Highly accurate	66.7
Isiolo	Inaccurate	0
Isiolo	Usually, accurate	33.3
Kajiado	Are accurate about half the time	50
Kajiado	Completely inaccurate	0
Kajiado	Highly accurate	0

Kajiado	Inaccurate	0
Kajiado	Usually, accurate	50
Kakamega	Are accurate about half the time	10
Kakamega	Completely inaccurate	0
Kakamega	Highly accurate	50
Kakamega	Inaccurate	0
Kakamega	Usually, accurate	40
Kericho	Are accurate about half the time	4.8
Kericho	Completely inaccurate	0
Kericho	Highly accurate	47.6
Kericho	Inaccurate	0
Kericho	Usually, accurate	47.6
Kiambu	Are accurate about half the time	22.2
Kiambu	Completely inaccurate	0
Kiambu	Highly accurate	25
Kiambu	Inaccurate	0
Kiambu	Usually, accurate	52.8
Kilifi	Are accurate about half the time	14.3
Kilifi	Completely inaccurate	0
Kilifi	Highly accurate	33.3
Kilifi	Inaccurate	4.8
Kilifi	Usually, accurate	47.6
Kirinyaga	Are accurate about half the time	7.7
Kirinyaga	Completely inaccurate	0
Kirinyaga	Highly accurate	42.3
Kirinyaga	Inaccurate	0
Kirinyaga	Usually, accurate	50
Kisii	Are accurate about half the time	2.9
Kisii	Completely inaccurate	0
Kisii	Highly accurate	42.9
Kisii	Inaccurate	0
Kisii	Usually, accurate	54.2
Kisumu	Are accurate about half the time	7.4
Kisumu	Completely inaccurate	0
Kisumu	Highly accurate	48.1
Kisumu	Inaccurate	0
Kisumu	Usually, accurate	44.4
Kitui	Are accurate about half the time	12
Kitui	Completely inaccurate	0
Kitui	Highly accurate	60
Kitui	Inaccurate	0
Kitui	Usually, accurate	28
Kwale	Are accurate about half the time	7.7
Kwale	Completely inaccurate	0
Kwale	Highly accurate	46.2
Kwale	Inaccurate	0
Kwale	Usually, accurate	46.2

Laikipia	Are accurate about half the time	0
Laikipia	Completely inaccurate	0
Laikipia	Highly accurate	66.7
Laikipia	Inaccurate	0
Laikipia	Usually, accurate	33.3
Machakos	Are accurate about half the time	17.9
Machakos	Completely inaccurate	2.6
Machakos	Highly accurate	46.2
Machakos	Inaccurate	0
Machakos	Usually, accurate	33.3
Makueni	Are accurate about half the time	21.2
Makueni	Completely inaccurate	0
Makueni	Highly accurate	51.5
Makueni	Inaccurate	0
Makueni	Usually, accurate	27.3
Marsabit	Are accurate about half the time	0
Marsabit	Completely inaccurate	0
Marsabit	Highly accurate	0
Marsabit	Inaccurate	0
Marsabit	Usually, accurate	100
Meru	Are accurate about half the time	10.7
Meru	Completely inaccurate	3.6
Meru	Highly accurate	35.7
Meru	Inaccurate	0
Meru	Usually, accurate	50
Migori	Are accurate about half the time	9.7
Migori	Completely inaccurate	0
Migori	Highly accurate	61.3
Migori	Inaccurate	0
Migori	Usually, accurate	29
Murang'a	Are accurate about half the time	14.8
Murang'a	Completely inaccurate	0
Murang'a	Highly accurate	40.7
Murang'a	Inaccurate	3.7
Murang'a	Usually, accurate	40.7
Nakuru	Are accurate about half the time	6.6
Nakuru	Completely inaccurate	1.6
Nakuru	Highly accurate	42.6
Nakuru	Inaccurate	0
Nakuru	Usually, accurate	49.2
Nandi	Are accurate about half the time	8.2
Nandi	Completely inaccurate	0
Nandi	Highly accurate	52.5
Nandi	Inaccurate	0
Nandi	Usually, accurate	39.3
Narok	Are accurate about half the time	4.3
Narok	Completely inaccurate	0

Narok	Highly accurate	47.8
Narok	Inaccurate	0
Narok	Usually, accurate	47.8
Nyamira	Are accurate about half the time	50
Nyamira	Completely inaccurate	0
Nyamira	Highly accurate	25
Nyamira	Inaccurate	0
Nyamira	Usually, accurate	25
Nyandarua	Are accurate about half the time	12.5
Nyandarua	Completely inaccurate	0
Nyandarua	Highly accurate	45.8
Nyandarua	Inaccurate	0
Nyandarua	Usually, accurate	41.7
Nyeri	Are accurate about half the time	30
Nyeri	Completely inaccurate	0
Nyeri	Highly accurate	25
Nyeri	Inaccurate	0
Nyeri	Usually, accurate	45
Samburu	Are accurate about half the time	15.4
Samburu	Completely inaccurate	0
Samburu	Highly accurate	46.2
Samburu	Inaccurate	7.7
Samburu	Usually, accurate	30.8
Siaya	Are accurate about half the time	6.5
Siaya	Completely inaccurate	0
Siaya	Highly accurate	64.4
Siaya	Inaccurate	6.5
Siaya	Usually, accurate	22.6
Taita–Taveta	Are accurate about half the time	22.2
Taita–Taveta	Completely inaccurate	0
Taita–Taveta	Highly accurate	44.4
Taita–Taveta	Inaccurate	5.6
Taita–Taveta	Usually, accurate	27.8
Tana River	Are accurate about half the time	50
Tana River	Completely inaccurate	0
Tana River	Highly accurate	50
Tana River	Inaccurate	0
Tana River	Usually, accurate	0
Tharaka-Nithi	Are accurate about half the time	13.3
Tharaka-Nithi	Completely inaccurate	0
Tharaka-Nithi	Highly accurate	40
Tharaka-Nithi	Inaccurate	0
Tharaka-Nithi	Usually, accurate	46.7
Trans-Nzoia	Are accurate about half the time	14.7
Trans-Nzoia	Completely inaccurate	0
Trans-Nzoia	Highly accurate	29.4
Trans-Nzoia	Inaccurate	0

Trans-Nzoia	Usually, accurate	55.9
Uasin Gishu	Are accurate about half the time	18.5
Uasin Gishu	Completely inaccurate	0
Uasin Gishu	Highly accurate	48.1
Uasin Gishu	Inaccurate	3.7
Uasin Gishu	Usually, accurate	29.6
Vihiga	Are accurate about half the time	20
Vihiga	Completely inaccurate	0
Vihiga	Highly accurate	40
Vihiga	Inaccurate	6.7
Vihiga	Usually, accurate	33.3
West Pokot	Are accurate about half the time	10
West Pokot	Completely inaccurate	0
West Pokot	Highly accurate	70
West Pokot	Inaccurate	0
West Pokot	Usually, accurate	20

Appendix 5: Sample distribution of respondent across the counties

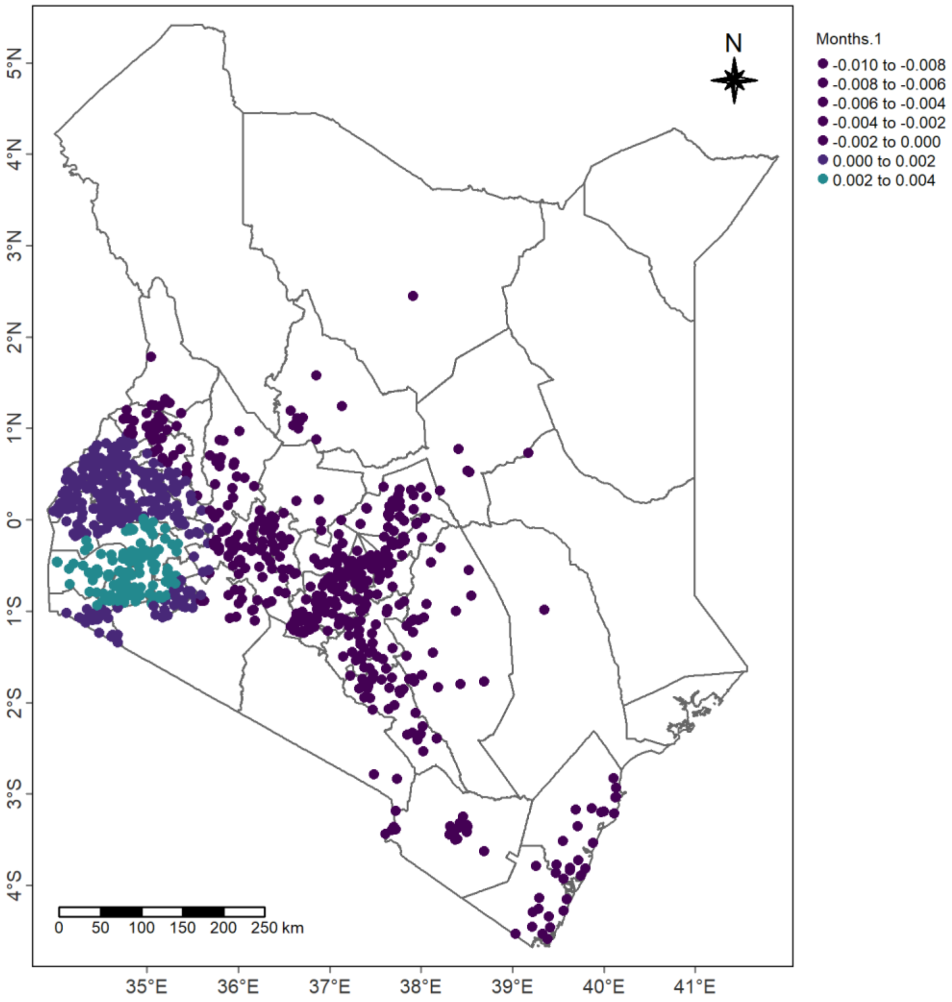
COUNTY	% OF SAMPLE			COUNTY	% OF SAMPLE	% OF SAMPLE		COUNTY	% OF SAMPLE	% OF SAMPLE		COUNTY	% OF SAMPLE	% OF SAMPLE
1	Baringo	2.5%		11	Kericho	2.1%		21	Makueni	3.3%		31	Nyeri	2.0%
2	Bomet	3.3%		12	Kiambu	3.6%		22	Marsabit	0.1%		32	Samburu	1.3%
3	Bungoma	5.1%		13	Kilifi	2.1%		23	Meru	2.8%		33	Siaya	3.1%
4	Busia	3.3%		14	Kirinyaga	2.6%		24	Migori	3.1%		34	Taita–Taveta	1.8%
5	Elgeyo-Marakwet	0.2%		15	Kisii	3.5%		25	Murang'a	2.7%		35	Tana River	0.2%
6	Embu	2.4%		16	Kisumu	2.7%		26	Nakuru	6.1%		36	Tharaka-Nithi	1.5%
7	Homa Bay	3.2%		17	Kitui	2.5%		27	Nandi	6.1%		37	Trans-Nzoia	3.4%
8	Isiolo	0.6%		18	Kwale	1.3%		28	Narok	2.3%		38	Uasin Gishu	2.7%
9	Kajiado	0.2%		19	Laikipia	0.6%		29	Nyamira	0.4%		39	Vihiga	3.0%
10	Kakamega	4.2%		20	Machakos	3.9%		30	Nyandarua	2.4%		40	West Pokot	1.0%

Appendix 6: Top Four Predictors of Crop Income and Watching of SSU Weather and Farming News using RFE algorithm

PREDICTORS	CROP INCOME	WATCHING SSU WEATHER SEGMENT	NUMBER OF MONTHS WATCHING SSU
Size of owned Agricultural land	100	-	-
Main enterprise	51.37	-	-
Average temperature last 5 years	24.51	-	100
Rainfall coefficient of variation past 5 years	0	-	80.58
Average rainfall last 5 years	-	-	91.56
County dummies	-	-	80.80
Obtain weather information from KALRO	-	1000	-
Number of months since started watching SSU	-	23.54	-
Aware of SSU	-	17.58	-
Number of household members watching SSU together	-	16.09	-

Note: This table presents importance scores for the predictors generated using the RFE algorithm with 50 predictors in the decorrelated dataset. The symbol "-" denotes predictors that were not selected for the outcome variable. We use RFR to estimate predictors of crop income and the number of months watching SSU. For the dummy variable "Watching SSU Weather Segment," we use random forest classification (RFC).

Appendix 7: Spatial variation in impacts of Watching SSU Weather and Farming News using GWR



Note: In this figure, we use GWR to assess the spatial variation in the impacts of watching SSU Weather and Farming News. It is also important to note that, in this figure, we use the number of months as a proxy for SSU intervention, rather than the yes/no indicator variable used in Figure 16.

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