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Can timely planting through the use of climate services mitigate climate risks? An APSIM Model assessment for Kyangwali refugee settlement maize farmers

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APPROVAL SHEET

I undersigned, Prof. Dr. –Ing. John Gathenya, Guest Lecturer at the Pan African University Institute of Water and Energy Sciences, including Climate Change (PAUWES), and permanent lecturer at Jomo Kenyatta University of Agriculture and Technology (JKUAT), Kenya; certify that Mr. Ezira MBALIBULHA conducted his Master Thesis research under my supervision. Certified further, that this master thesis entitled "Can timely planting through use of climate services mitigate climate risks?: An APSIM Model assessment for Kyangwali refugee settlement maize farmers" is an authentic work of Mr. Ezira MBALIBULHA who carried out the research under my guidance.

Signature:

Prof. Dr. –Ing. John Gathenya

Date: 20/03/2025

DEDICATION

I dedicate this report to my dear family for the relentless spiritual, emotional, physical, and financial support offered. Your countless efforts have made this master's dream a possible milestone. Thank you for believing in me; your labor was not in vain.

ORIGINALITY STATEMENT

This is to ratify that the material presented in this thesis report is utterly my work, apart from where specific references have been made to the works of others, and no portion of this work has been submitted for the award of a degree, diploma, or certificate to any university or institution across the globe.

Transitory citations from this study are admissible without special authorization, on condition that accurate acknowledgment of the source is done.

Signature:

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Date: 20/03/2025

BIOGRAPHICAL SKETCH

Ezira MBALIBULHA is an African Union scholar from Uganda who is very passionate at transforming people's lives through research and innovation. He holds a bachelor of science in Agricultural Mechanization and Irrigation Engineering from Busitema University, Tororo, Uganda. Eng Ezira is an ethically prepared professional whose research interests are climate change, crop modeling, climate-smart agriculture, and food security.

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Above all, I give glory to God for life, wisdom and His grace evidenced throughout the course of my study.

ABBREVIATIONS AND ACRONYMS

NARO: National Agricultural ResearchOrganization

NACRRI: National Crops Resources Research Institute

MAAIF: Ministry of Agriculture Animal Industry and Fisheries

NGO: Non-Governmental Organization

USDA: United States Department of Agriculture

IPAD: International Production Assessment Division

FAO: Food and Agricultural Organization

IPCC: Intergovernmental Panel on Climate Change

KARI: Kawanda Research Institute

NAADS: National Agricultural Advisory Services

UBOS: Uganda Bureau of Statistics

MAM: March-April-May season

SOND: September-October-November-December season

CCKP: Climate Change Knowledge Portal

UNFCCC: United Nations Framework Convention on Climate Change

WBG: The World Bank Group

GCMs: Global Circulation Models

RCP: Representative Concentration Pathway

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ABSTRACT

Choosing the right planting date is crucial in adapting to climate variability. This study employs the Agricultural Production Systems Simulator (APSIM) model to quantify the impact of timely maize planting in mitigating climate risks for smallholder refugee maize farmers in Kyangwali Refugee Settlement (KRS), western Uganda. The model simulates maize yield responses to variations in planting windows within the optimal growing season. Three planting windows were determined for model simulation, namely; early planting window (EPW), timely planting window (TPW), and late planting window (LPW). Results indicated that maize planted in the TPW, guided by climate information services (CIS), generated the highest yield potential during both the MAM and SOND seasons, an average of 3,299.7 and 3,535.7 kg/ha respectively. For maize planted during the MAM's TPW, there was a 100% probability of obtaining at least 1,500 kg/ha yield. Additionally, there was a 54.8% chance of obtaining a maximum yield when maize is planted during the TPW of any season as compared to EPW (12.9%) and LPW (32.3%). For both seasons, planting maize during the TPW resulted in low failure rates (29.0% for SOND and 41.9% for MAM) and lower yield variability (23.2% for MAM and 39.9% for SOND) than other planting windows. The findings reveal that sowing maize within the TPW was associated with fewer climate risks, with the potential to significantly boost food security, enhance livelihoods, and contribute to broader development goals within the refugee farming communities. The study highlights the imperativeness of agro-advisory services and access to timely and accurate CIS to support refugee farmers in making informed sowing decisions. The findings underscore the vital role of timely planting in boosting agricultural resilience and contributing to the realization of Uganda's Vision 2040, AU's Agenda 2063, and the UN Agenda 2030.

Keywords: APSIM Model, Climate information services, Climate risks, Planting window, Refugees, Timely planting.

1. INTRODUCTION

1.1 Background

Globally, crop productivity is predicted to be impacted by climate change (CC) and climate variability, both positively and negatively (Ray et al., 2019), depending on the region and the adopted adaptation measures (Morel et al., 2021). It is projected that variations in temperature and precipitation due to a changing climate will strongly alter regional climates causing potential shifts in crop production (De Lima et al., 2021; Hassan et al., 2021; Tripathi et al., 2016). Agriculture, as noted by (Berhane, 2018; Lemi, 2019), is a climate-sensitive sector hugely disrupted by CC and variability, especially the rainfed production system (Moeletsi & Tsubo, 2024). There is much variability in the onset and cessation dates of seasons of each agricultural calendar year, creating difficulty for farmers to make climate-smart decisions on when to sow (Tofa et al., 2020). Climate variability especially increases the frequency of extreme weather conditions such as prolonged dry spells and intense floods (Banerjee et al., 2019), which negatively affects crop productivity, especially in subsistence agriculture. Rainfed crop production is particularly susceptible to fluctuations in precipitation (Fosu-Mensah et al., 2019) and thermal stresses (Waqas et al., 2021), which leads to yield failure (Berhane, 2018). Studies by (Ayanlade et al., 2018; Nidumolu et al., 2015) also report rainfall variability and drought as the two key climate risks that continue to haunt maize production causing global food production fluctuations, especially for low-developing countries like Uganda. Drought stress is particularly becoming a more pronounced abiotic stressor because of its detrimental effects on plant development and yield, which drastically lower plant biomass and yield, exacerbating the world's food insecurity (Markou et al., 2020). Drought stress impedes plant productivity by affecting several metabolic, physiological, and biochemical crop processes (Seleiman et al., 2021).

To manage climate variability, the risks and uncertainties associated with agro-meteorology must be evaluated to aid in devising mitigation and adaptation strategies (Baum et al., 2019; Nidumolu et al., 2015). Farmers employ diverse management techniques such as planting in the right sowing window according to their climatic zone, to maximize corn grain yield (Abendroth et al., 2017). According to (Beah et al., 2021; Santos et al., 2017), choosing the right planting date is crucial to minimizing poor crop establishment and, in the end, avoiding the additional expenses of seed and labor needed for replanting. (Zou et al., 2022) reports that the overall yield of maize per hectare is highly dependent on when sowing was done. Timely planting potentially results in higher yields because the crop will be exposed to ideal growing conditions for longer. Furthermore, planting timing affects how maize varieties respond to different inputs like fertilizer (Beah et al., 2021; Srivastava et al., 2018; Zhiipao et al., 2023). However, (Parker et al., 2017) noted that planting too early could expose the crop to other negative weather factors such as prolonged dry spells. Nevertheless, planting late could also result in reduced overall yield because of a shortened growing season or exposure to bad weather during crucial growth phases (Maresma et al., 2019). Unfortunately, marginalized communities such as refugee settlements have limited access to reliable, affordable, and contextualized climate information services (CIS) which would otherwise be crucial in determining when to plant (Wichern et al., 2019).

The inequality in access to reliable, affordable, actionable, and salient CIS leads to low agricultural production in various communities of many African countries (Moeletsi & Tsubo, 2024). According to (Vaughan et al., 2019), the enhancement of CIS in Africa has the potential to bridge the inequality gap and aid countries in achieving broader sustainability goals such as action to adapt to CC, eradicating hunger, and reducing malnutrition. Moreover, CIS is capable of contributing to improved livelihoods for agricultural communities by boosting productivity and mitigating climate-related losses (Dobardzic et al., 2019). Therefore, to manage climate risks and mitigate vulnerability, it’s imperative that farming refugee communities embrace the integration of CIS into their decision-making (Vincent et al., 2017). However, even though coverage of climate services has improved recently, marginalized communities especially in developing countries still face numerous barriers limiting accessibility and usability (Bremer et al., 2019). For some farming communities, the provided CIS is either irrelevant for users or the forecasts provided are full of uncertainties (Jacobs & Street, 2020). In refugee agricultural communities, there’s an urgent need for CIS to be tailored to a local context. This is because agricultural conditions in most Ugandan refugee settlements are very different from those in citizen communities (Fransen et al., 2024). They are isolated from citizen communities and so, their environmental conditions, such as climate and soil are unique (Ainuddin et al., 2017). There is a greater belief that graduating from general climate services to specialized CIS will improve agricultural production and help feed the world's ever-growing population (Moeletsi & Tsubo, 2024).

According to (FAO, 2024), the global population is increasing exponentially and is estimated to surpass 9.7 billion people by 2050. Yet, crop yields under rainfed agriculture are expected to decrease by over 50% in the next 50 years (Muluneh, 2021), especially in the lower latitudes (Berhane, 2018). In Africa alone, agricultural yields will most likely decline by more than 30% by 2050 (Muluneh, 2021). This will increase the global food demand gap, disproportionately hitting vulnerable populations such as refugees much more severely (El Bilali et al., 2020). Due to a rapidly fluctuating climate, it is noted that the number of refugees in need of support has grown (P. Singh et al., 2023), widening the gap between food resourcing and demand (UNHCR, 2022b). According to UNHCR, there are over 20 million refugees worldwide, and only 4.6 million refugees reside in planned camps. In the past decade, the number of refugees in Eastern Africa has nearly tripled, going from 1.82 million in 2012 to almost 5 million in 2022 (UNHCR, 2022b). With almost 1.6 million refugees and asylum-seekers, Uganda hosts the largest number of refugees in Africa and the third largest in the world (UNHCR, 2022b; van Blerk et al., 2021). From 36,713 refugees in December 2017 to 137,207 in February 2024, Kyangwali Refugee Settlement (KRS) saw a 374% rise in its refugee population (UNHCR, 2024). This influx poses a food security threat to the area in the face of increasing CC.

Maize, which serves as a vital dietary staple for the KRS camp, is increasingly being threatened by erratic rainfall patterns and fluctuating seasonal onsets (van Blerk et al., 2021). KRS particularly experiences averagely lower daily precipitation of 4.55mm/day vis a vis the national daily average of 5.02mm/day (Fransen et al., 2024). This study utilizes the Agricultural Production Systems Simulator (APSIM), a powerful modeling tool, to assess whether timely planting, guided by climate services, can mitigate the climate risks faced by maize farmers in KRS. By exploring this question, potentially transformative strategies for ensuring food security in this climate-sensitive context will be ascertained. APSIM was used for this study because it works well in examining the intricate relationship that exists between crop productivity, management choices, and climate (Fosu-Mensah et al., 2019; Knörzer et al., 2011). Moreover, it offers helpful submodules to simulate the maize crop, evaluated in this study (Chisanga et al., 2022; Tui et al., 2022) as well as effectively modeling the impacts of temperature and precipitation variations on maize phenology and yield (Holzworth et al., 2014; Morel et al., 2021).

In the peer review of crop modeling literature for East Africa, numerous studies have placed much attention on simulating the impact of various CC scenarios on the future productivity of crops. For instance, (Mugo et al., 2023) used the APSIM model to ascertain the effects of CC on green gram production in Kitui County, Kenya. (Dilla et al., 2018) studied the potential of the APSIM model to simulate shading impacts on maize productivity in Ethiopia and Kenya. (Seyoum et al., 2017) characterized production environments for maize in eastern and southern Africa using the APSIM Model. The use of the APSIM model to assess the potential of timely planting as a strategy to mitigate climate risks is very limited in eastern Africa. (Kipkulei et al., 2022) instead used the DSSAT–CERES-Maize Model in Trans Nzoia County-Kenya to assess the yield response to agricultural management strategies. In Uganda, attention has not been placed on the APSIM model to assess the potential of timely maize planting. (Mibulo & Kiggundu, 2018) used the AquaCrop model while (Nimusiima et al., 2018) used the CERES model, to simulate CC impacts on maize yields. In the western Uganda agro-ecological zone, (Babel & Turyatunga, 2015) used the CERES-Maize crop model of DSSAT v4.0.2.0 to evaluate CC impacts and adaptation measures for maize cultivation. In the reviewed literature, only (Luliro et al., 2022) stood out in western Uganda for having employed the APSIM model to simulate Irish potato productivity in the Kigezi highlands. In this context, an assessment of the potential of timely maize planting as a strategy to mitigate climate risks is a novel and original research area as this has not been previously undertaken in Uganda’s refugee settings.

The results of this study will aid in providing evidence for the effectiveness of climate services in mitigating climate risks for marginalized farming communities. By demonstrating the effectiveness of timely planting using climate services, the research will contribute to the development of practical solutions for mitigating climate risks in agricultural production. The findings will inform the development of targeted climate-smart agricultural programs for refugee settlements thereby improving food security and resilience for vulnerable farming communities in KRS and potentially beyond.

1.2 Problem Statement

Kyangwali refugee settlement (KRS) is home to over 135,207 refugees (UNHCR, 2024) whose livelihood mainly depend on local rain-fed agriculture, especially maize for food security (van Blerk et al., 2021). However, CC and especially climate variability pose a major threat to maize production in the area. Increasing temperatures, inconsistent precipitation patterns, shifting seasons, and increased frequency of dry spells are leading to deteriorating maize yields over time and increasing vulnerability within the settlement area. While it is well acknowledged that poorly timed planting has detrimental effects on agriculture (De Lima et al., 2021; Hassan et al., 2021), there is a deficiency of location-specific research to quantify the impact on KRS and its vulnerable population. It is imperative to comprehensively analyze the extent of timely planting in mitigating climate risks so that effective adaptation strategies based on the usage of climate services can be recommended. By applying APSIM to Kyangwali's specific context, valuable corellational insights between timely planting and maize yield will be gained. The results of this study will be very important in developing evidence-based coping and adaptation strategies for maize production in Kyangwali refugee settlement and other areas of a similar context. Ultimately, this research will empower relevant stakeholders with the necessary knowledge to enhance the area’s food security in the face of a changing climate.

1.3 Objectives

1.3.1 Main objective

To assess the potential of timely planting, guided by climate services, as a strategy to mitigate climate risks for maize farmers in Kyangwali refugee settlement, Uganda, using the Agricultural Production Systems Simulator (APSIM) model.

1.3.2 Specific objectives

- To develop scenarios for different planting dates based on climate service information.
- To simulate maize yield under different planting scenarios and climate variability conditions.
- To quantify the potential change in maize yields associated with timely planting and recommend the best climate risk management strategies for KRS maize farmers.

1.4 Hypothesis

1.4.1 Null hypothesis, H_0

There is no significant difference in maize yield between plots planted timely (based on climate service information) and plots planted according to traditional planting practices in KRS.

1.4.2 Alternative hypothesis, H_1

Maize yield in plots planted timely (based on climate service information) is significantly different (higher or lower) compared to plots planted according to traditional planting practices in KRS.

1.5 Research Questions

- Can timely planting based on climate services improve maize yields and reduce climate risks in KRS?
- To what extent will timely planting affect maize yield in KRS?
- How will the research outcomes help to inform interventions for sustainable food security for the KRS population?

1.6 Significance of the Study

The study particularly focuses on Kyangwali refugee community whose population dominantly relies on rain-fed agriculture, especially maize production which is their staple crop for sustenance. In this case, it is crucial to understand how timing the planting window is vital for maize productivity to adopt knowledge-based strategies that guarantee food security for refugees. Secondly, the use of the APSIM model in this study allows for a quantitative and evidence-based assessment of the impact of timely planting on maize yields and thus will generate more informative results as compared to exclusively relying on traditional planting trends. This will support context-specific decision-making on implementing coping and adaptation strategies in KRS. The research findings can be scalable and adopted by other regions facing similar challenges, using the same methodology of the APSIM model. Conclusively, the study will contribute to the promotion of climate-smart agricultural practices that can help refugee settlements and smallholder farmers adapt to changing climate patterns to ensure long-term food security and climate resilience (Sachs et al., 2024).

1.7 Scope of the Study

1.7.1 Geographical scope

The research was limited to Kyangwali Refugee Settlement, Kikuube district, western Uganda, covering an area of 95 km^2.

1.7.2 Content scope

The study focused on assessing the potential of timely planting, guided by climate services, as a strategy to mitigate climate risks for maize farmers in Kyangwali refugee settlement, Uganda, using the Agricultural Production Systems Simulator (APSIM) model.

1.7.3 Time scope

The research was conducted for four months, from December 2024 to March 2025. The yield, biomass, and weather data used were for 31 years, i.e., 1993 - 2023.

1.7.4 Thesis outline

The study is categorized into five (5) chapters as summarized below

Chapter One is the study's introduction, which unveils the research background information, problem statement, objectives, study hypothesis, research questions, significance and scope of the study, and outlines the general structure of the research

Chapter Two involves reviewing relevant literature. It presents a detailed and comprehensive review of the literature related to this study and the research gaps identified that justified the research study at hand.

Chapter Three is the methodology of the study. it describes the materials and methods applied to achieve the objectives of the study

Chapter Four represents the results and discussion. The study findings are chronologically reported therein and their implications are discussed in detail.

Chapter Five presents the conclusion and recommendations to the stakeholders.

2. LITERATURE REVIEW

2.1 Climate Change and Maize Productivity in Uganda

2.1.1 Status of maize production in Uganda

Maize (*Zea mays L.*) crop, of the Poaceae family, belongs to the cereal group, which are the fruits of graminicious plants. It originated in Southern Mexico, South America, and the highlands of Peru, Ecuador, and Bolivia. It was introduced in East Africa in the late 15th century by the Portuguese and is currently the most important cereal after rice and wheat (MAAIF, 2022). In Africa, corn is cultivated on 40.7 Mha of land in over half of the nations, accounting for over 40% of cereal growing (FAO, 2020). Since 2020, its production has been increasing at a rate of 2.2 MMT/annum until 2020 when it hit the 91 MMT mark. Sub-Saharan Africa possesses more than 50% (equivalent to 21.4 Mha) of the total area under maize cultivation in Africa.

In Uganda, maize is a food security crop sustaining the livelihoods of many households (Nimusiima et al., 2018). Although it is planted throughout Uganda, it is most dominant in the eastern (Kapchorwa, Mbale, Kamuli, Jinja, Iganga), central (Masaka, Mubende), and western (Kikuube, Masindi, Hoima, Kamwenge, Kyenjojo, Kasese, Kabarole) regions (MAAIF, 2022). According to the map in Fig. 1, eastern Uganda is the leading corn producer (47%), followed by western (21%) and central regions (19%). The northern part lags, contributing only 13% of the nation's total corn production.

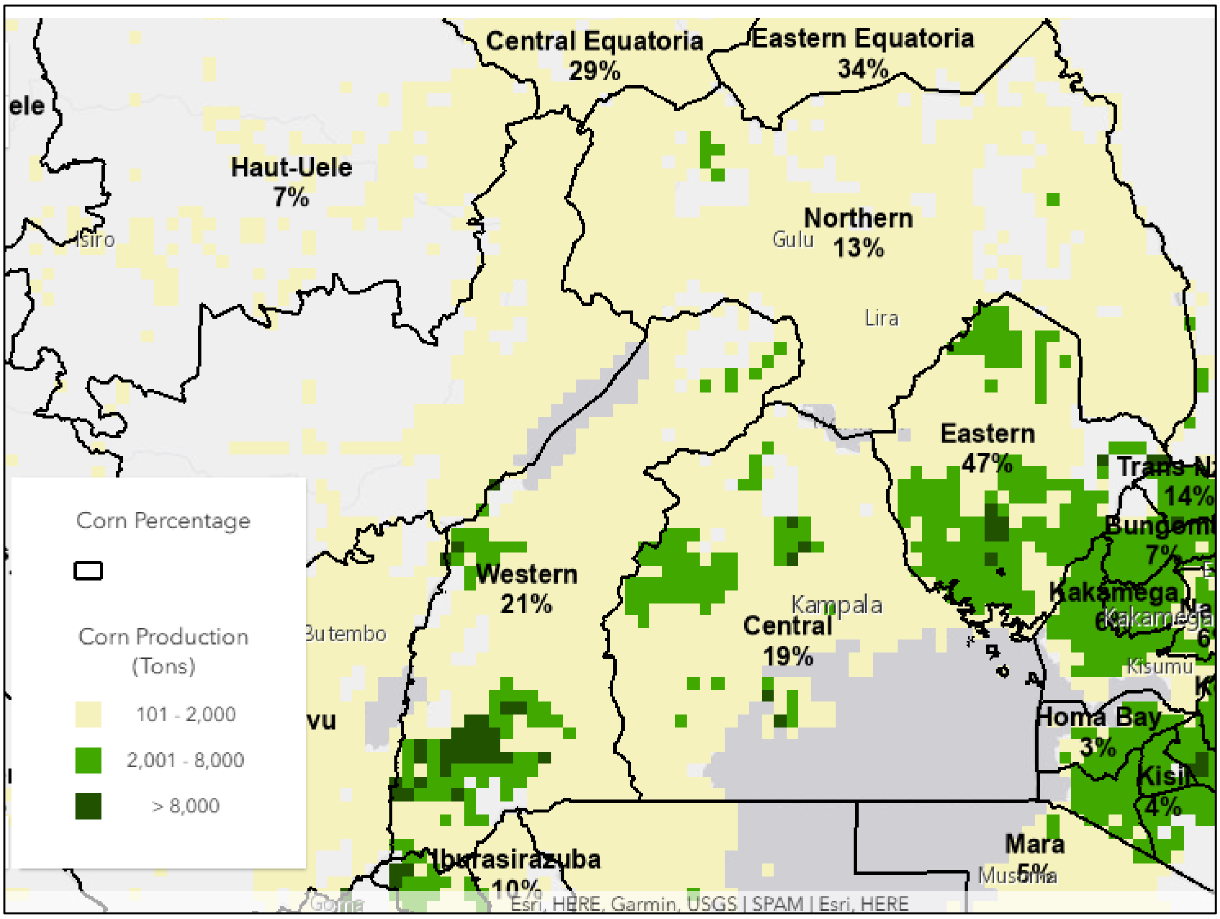


Fig. 1: Map of Uganda showing maize-producing regions (USDA, 2024)

With an annual production of almost 21,000 tons, Masindi, in the western region, is the largest maize producer with Pakanyi Sub County contributing the most of its production (MAAIF, 2022). However, (UBOS, 2022) reports that more than 3 million farmers in Uganda grow maize on less than 0.5 hectares of land. Smallholder farmers produce more than 90% of Uganda's maize, with over 60% of the crop's yearly production being used on the farm, roasted, dried, and turned into flour *(Kawunga, Posho)* for bread and porridge, particularly in urban areas, institutions, and refugee camps (Epule et al., 2017).

In Uganda, maize production occupies more than 23.4% of the land designated for food crops, producing 1,500,000 MT of maize grain annually on average (UBOS, 2022). About 90% of this is used for local and regional human consumption, while 10% is used for animal feed, such as maize bran. Uganda's most widely grown maize varieties include Longe 1, Longe 4, Longe 5, Longe 2H, Longe 6H, 7H, 8H, 9H, 10H, Longe11H, and UH 5051. Since 1961, maize productivity in Uganda has always been below the world average, as depicted in Fig. 2 below. This is partly because about 97% of Uganda’s maize production is rain-fed and maize yields from rain-fed maize farming are only roughly 10–30% of the possible yield, according to (Martínez & Fürst, 2021).

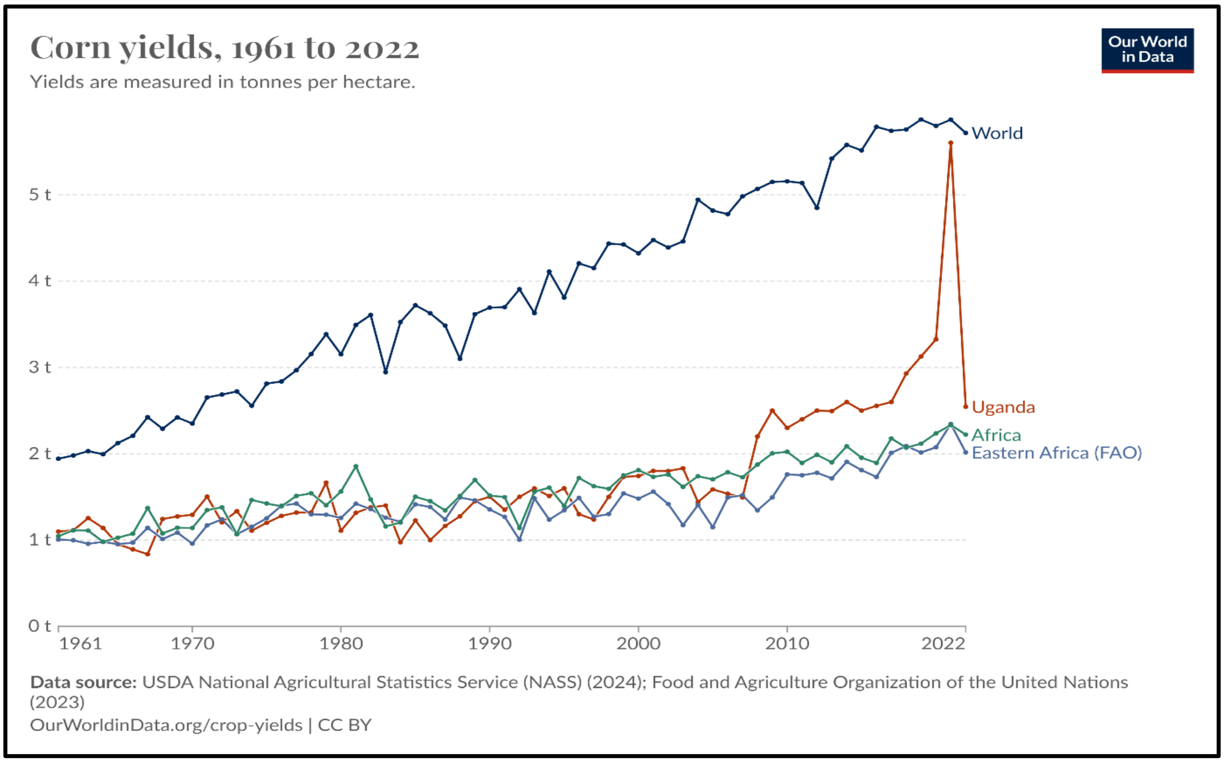


Fig. 2: Corn yields for Uganda rated with East Africa, Africa, and the world average (1961-2022)

As depicted in Fig. 2 above, there's a substantial yield gap between Uganda's corn yields and the global corn productivity. (Nimusiima et al., 2018) report that climate change and climate variability are responsible for about 30% of Uganda's maize yield gap with other factors such as crop management, soil quality and cultivar type contributing to the gap. By mid-century, (Nimusiima et al., 2018) project that climate change will be responsible for over 60% of the maize yield gap. Also, as seen in Fig. 2, Uganda's corn production from 2006-2022 was above the regional (East Africa) and continental (Africa) average. However, a sharp decline has been noted of late (see Fig. 2). This is majorly attributed to the effects of CC aggravating soil moisture availability, shifting seasons, erratic rains and causing favourable conditions for crop pests to thrive (Adunola et al., 2021; Régnier et al., 2023; Tajudeen et al., 2022). The most common pests affecting maize in Uganda include fall armyworm, stem borers, and cutworms, causing diseases such as Maize lethal necrosis disease, maize streak virus (MSV), gray leaf spot (GLS), northern leaf blight (NLB), maize smut, and maize rust. Given that several studies report timely planting as effective in minimizing the impact of pests and diseases on maize yield (Mugiyo et al., 2021; Nyagumbo et al., 2017), this current study is critical.

2.1.2 Ideal growing conditions for optimum maize yields

The performance of the maize crop depends on the previous cropping pattern of the farm, with fallow and virgin land being more productive than overexploited land (Byakagaba et al., 2021). Factors such as the rainfall pattern & amount, agroecological zone (altitude), temperature variations, soil characteristics, and agronomic management practices such as weeding were identified as being crucial determinants in influencing maize yield in Uganda (NAADS, 2024). Maize does well in well-draining soils with an adequate supply of moisture and nutrients (Fang & Su, 2019). Maize cannot tolerate even a small amount of waterlogging since it affects its morphology, physiology, anatomy, and biochemistry (Liang et al., 2020). Additionally, the ideal soil for growing maize should be deep, rich in organic matter (Z. Du et al., 2024), well-aerated, and with a moderate pH of 5.5 to 7.8 (Nwite et al., 2022). All elevations are appropriate for maize growth (Sharma & Kumar Pradhan, 2024), although, for most cultivars, growing degree days (GDD) increases with altitude (Xue-jun et al., 2013). (NAADS, 2024) notes that most Ugandan varieties are better suited for elevations between 0-2,900 masl. Most studies affirm the ideal temperature range for maize to be 25-33°C during the day and 17-23°C at night, and generally 20-22°C for the entire growing season while the optimum precipitation range is 400-800 mm/season (Babyenda et al., 2023; Ban et al., 2022; Lugoi et al., 2022; Ojara et al., 2022; Yin et al., 2022). A report by (MAAIF, 2022) recommends dry planting for mechanized farms to reduce the chances of clogging due to much mud. Precise plant spacing is also encouraged to achieve the desired plant population per acre. In Uganda, about 20,000 kernels or 8-10 kg of quality hybrid seed maize per acre is usually recommended (MAAIF, 2022).

2.1.3 Economic value of maize

Since its domestication, maize (Zea mays L.; corn) has played a diverse and significant role in global agri-food systems. Often referred to as the “queen of cereals”, maize is a staple in many communities worldwide and supplies 19.5% of the world's total caloric intake from all sources (Wattoo et al., 2018). Cultivated on over 200 million hectares globally, maize has an average annual production exceeding 1 billion metric tons (Ortíz-

Islas et al., 2019). As of November 2020, the global maize production was 1,116,185,000 MT whereas the world consumption amounted to 1,132,678,000 MT. The global exports were estimated at 175,124,000 MT vis a vis 175,124,000 MT of imports (USDA, 2024). Currently, the United States, China, Brazil, European Union, and Argentina are the leading corn producers on a global scale, contributing 32%, 24%, 10%, 5%, and 4% of the world production respectively. Global corn-producing regions are depicted in Fig. 3 below.

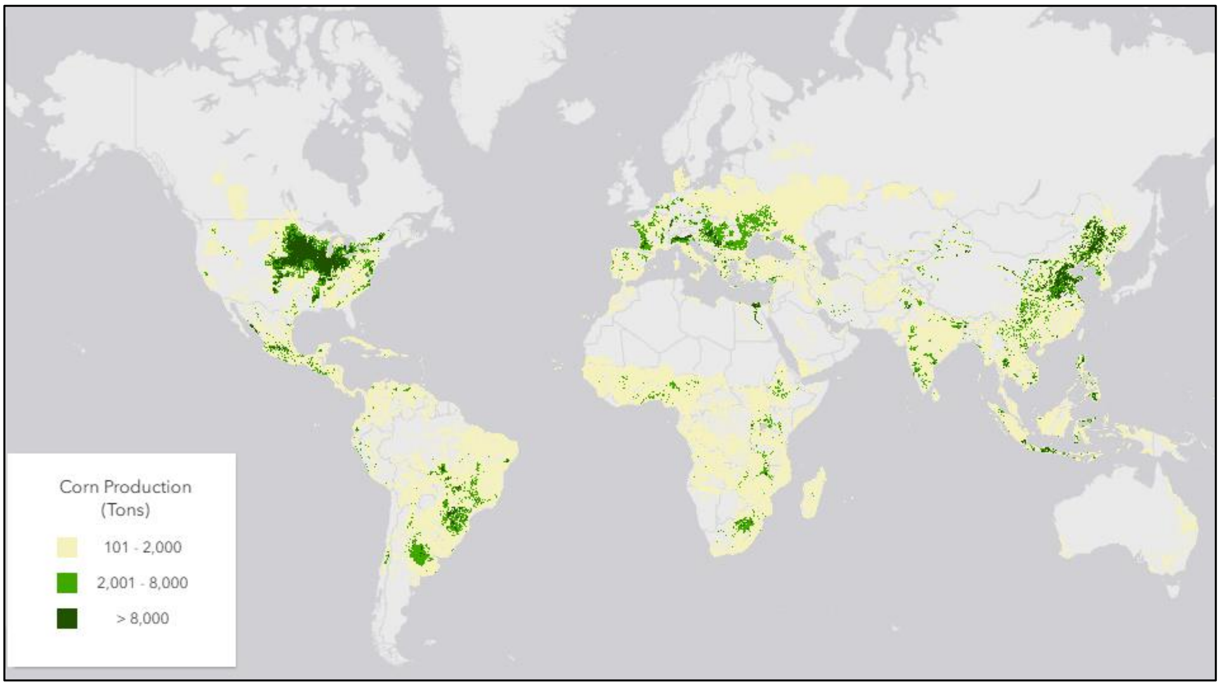


Fig. 3: Global map showing corn-producing areas around the world (USDA, 2024)

Corn is one of the world’s three main food crops (Xu et al., 2021), and the second most important source of calories in Eastern Africa (Daly et al., 2016). In Uganda, it is currently the main staple food, in both rural and urban areas, providing over 40% of the calories (NAADS, 2024), and offering a variety of dietary options to homes, schools, prisons, factories, and other institutions (Mibulo & Kiggundu, 2018). Over 3.8 million Ugandans have their livelihood from the maize value chain, making it a major contributor to the country's foreign exchange revenues, totaling over US$100 million (UBOS, 2022). Over 1,000 traders and over 600 millers gain directly from the maize value chain in the country (NAADS, 2024). In 2020, Uganda earned $121 million in corn export revenue and $99.5 million of this came from Kenya; the remaining amount was earned from South Sudan and the eastern Democratic Republic of the Congo, among other countries (MAAIF, 2022). Uganda’s major maize market is the regional market. Maize also finds its use in numerous industries manufacturing corn-flacks, oil, corn sugar, dextrose, starch, protein, soup, salad, glucose, corn syrup, etc (Alam et al., 2020). According to (Gholami et al., 2014), maize can also be utilized in energy production industries. Nevertheless, CC and variability are endangering the sustainability of this valuable crop (Waqas et al., 2021).

2.1.4 Climate risks affecting maize productivity

According to (Sun et al., 2016), the three main meteorological variables that significantly affect the variation in maize yield are precipitation, temperature, and radiation. Optimum climatic conditions are necessary for the physiological and metabolic processes that take place in maize during the various phenological stages (Yasin et al., 2022). (Schauberger et al., 2017; Waqas et al., 2021) noted that temperature changes deviating away from the optimum, for a prolonged duration, have the potential to negate and ultimately lower maize yield. According to (Roberts et al., 2017), maize yield increases with the rise in temperature to a maximum of 29°C before sharply declining as temperature rises beyond that. But according to (Prueger & Hatfield, 2015), 25°C is the optimum growth temperature for maize. In contrast, (Neild & Newman, 2015) stresses that the maize crop requires a variety of temperatures throughout the whole growing season, and at different times of the day and night to attain maximum growth. His ideal temperature range is 25-33°C during the day and 17-23°C at night, and generally 20-22°C for the entire growing season. According to Waqas et al., 2021, the reproductive stage is the most susceptible to temperature fluctuations away from the optimum. Table 1 below displays the minimum and maximum threshold temperatures for the maize crop at different phenological phases.

Table 1: Minimum and maximum threshold temperatures for maize growth stages

Growth stages	Threshold Tmin (ºC)	Threshold Tmax (ºC)	Symptoms
Sowing to emergence	10 ± 2.2	40 ± 2.1	Inhibited growth rate
Sowing to tasselling	9 ± 2.7	39 ± 0.6	Abnormal growth of tassels
Anthesis	8 ± 0.5	37 ± 1.4	Pollination failure
Grain filling	8 ± 2.0	36 ± 1.4	Gross decrease in starch and sucrose production
Whole maize crop	6 ± 1.1	42 ± 3.3	Crop failure

Source: adopted from (Waqas et al., 2021)

According to (Izaurralde et al., 2011), maize yield can be significantly decreased by 3–13% with just a 1^{o}C shift in mean seasonal temperature outside of the threshold values. A study by (Raza et al., 2019) also denotes that maize yield decreases by 10% for each degree Celsius rising higher than the ideal. Additionally, (Zhao et al., 2017) found that there was a 7.4% decrease in maize yield for every 1°C rise above optimum. Using 17 GCMs in the CERES-Maize model, Saddique et al. (2020) reported a 9% reduction in maize yield for every 1^{o}C temperature rise above the ideal. Another study by (Lobell et al., 2011) reports a 1% decrease in maize production for each degree day spent over 30°C, even in the best rain-fed conditions. Lobell’s study contradicts a study by (Runge, 1968) which notes that temperatures as high as 37.8°C can be beneficial to corn yield, provided that sufficient soil moisture is available. These findings indicate that temperature stress is not the only contributor to maize yield loss but also water/moisture stress. In rain-fed farming such as the case of KRS, precipitation may not always meet the crop water requirement due to its poor distribution and potential variations, especially under a changing climate. It is therefore imperative to optimize the maize planting structure to mitigate the associated climate risks.

2.2 Climate Change Projections

2.2.1 Global perspective

Globally, temperatures have been on an increasing trend above the pre-industrial era. According to (WMO, 2023), the nine warmest years on record have been the last nine, from 2015 to 2023. In October 2023, the average global near-surface temperature was 1.40 ± 0.12 °C higher than the average for the base period 1850-1900. In WMO's 174-year observational record, 2023 has been the warmest year on record, exceeding the two previous joint warmest years; 2020 at 1.27±0.13 °C and 2016 at 1.29 ± 0.12 °C above the 1850–1900 normal. The mean global temperature for 2014–2023 (up to October) was 1.19±0.12°C higher than the average for 1850–1900, making it the warmest 10-year period ever recorded (WMO, 2023). This is evidence that the globe continues to warm up at a faster rate. According to (Xu et al., 2021), the global average surface temperature is expected to surge by 0.3–4.8°C by 2100. With this projection, food security is currently seen as one of the key priority areas on the political agenda (Muluneh, 2021).

In recent years, numerous studies have projected the impact that CC will pose on maize productivity as the future unfolds. In Africa, for example, a study by (Ramirez-villegas, 2015) reported a 12–40% future reduction in maize production due to CC. Under a high emission scenario, RCP8.5, (Deryng et al., 2014) also noted that global maize yield losses would double due to severe heat stress at anthesis. Future maize yields under rain-fed conditions in Mexico are expected to decrease as a result of more frequent and intense heat events, according to projections by (Ureta et al., 2020). According to (Rosenzweig et al., 2014), maize productivity in low-latitude zones is expected to decrease more under RCP8.5. He attributed this finding to the fact that tropical zones were more susceptible to the impacts of CC.

2.2.2 The case of Uganda

Uganda's average temperature from 1950 to 2021 has been increasing at a rate of about 0.23°C/decade and this rate has amplified marginally higher, at about 0.25°C/decade, considering only the last thirty-one years (UNMA, 2022). Uganda's National Meteorological Authority (UNMA) notes that the degree of warming in 2021 was approximately 0.68°C higher than the long-term mean value for the 1981-2010 period. This makes it the third warmest year on record since 1950, with 2019 and 2009 respectively leading Uganda's excessive heat charts. The country has had its 20 warmest years on record in just the last two decades and this warming trend is expected to hike (UNMA, 2022). The major droughts in the last two decades posed substantial consequences for Uganda, including hiking food prices in 2006 (Fraser, 2007), disrupted hydro-power generation in 2008-2010, and acutely lowered livestock and food production due to the 2009-2011 droughts (Epule et al., 2017). The 2010-2011 droughts caused damages costing Uganda a deficit of about $1.2 billion (an equivalent of approximately 2.8 trillion Uganda shillings), almost 7% of the nation's GDP (Owani, 2023).

According to a study by (Olaka et al., 2019), by 2085, Uganda's mean annual minimum temperature will have increased significantly, above the pre-industrial era by 1.3–4.5˚C under RCP 4.5 and by up to 4.9˚C under RCP 8.5. Monthly temperature change is predicted to rise by 1.8°C in the 2050s and 3.7°C in the 2090s in a high-emission scenario. Higher temperatures will also affect the duration and intensity of the dry season as well as increased aridity (CCKP, 2021). Temperatures are predicted to rise by 1.5 to 5.4°C by the end of the century, with the highest warming rates occurring during Uganda's coldest season, which runs from June to September (World Bank Group, 2021). By the 2050s, 15–43% of days are predicted to be hot, and by the end of the century, 18–73% of days will be hot (CCKP, 2021). It is anticipated that "hot" nights (>26°C) will rise faster than hot days. It is predicted that over the end of the century, temperature rise will grow under all emission scenarios (Deepa et al., 2024). As seen in Fig. 4, under a high-emission scenario, average temperatures will increase rapidly by mid-century. These high heat days will result in significant implications for human and animal health, agriculture, ecosystems as well as energy generation.

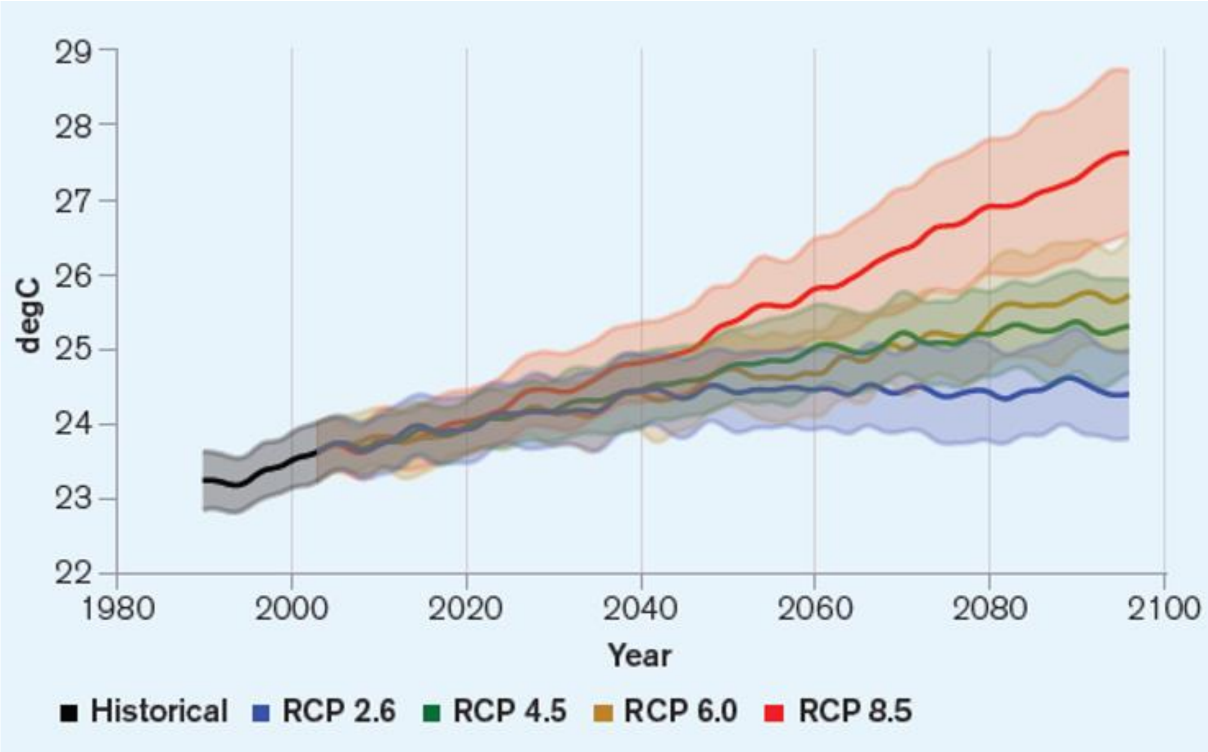


Fig. 4: Historical and projected average temperature for Uganda from 1986 to 2099 (World Bank Group, 2021)

In the western Uganda agroecological zone, where the case study is situated, (Babel & Turyatunga, 2015) projected an increase of about 0.69–2.46 and 0.66–1.78 °C of the annual mean temperature by the 2080s, under SRES scenarios A2 and B2, respectively, relative to the reference period (1961–1990). Additionally, for most months, except November, (Babel & Turyatunga, 2015) reports that the monthly mean temperatures are projected to increase under both scenarios.

Uganda's precipitation patterns are naturally dynamic with high temporal and spatial variability, inducing events such as floods, seasonal shifts, and droughts which often cause significant socio-economic losses to many Ugandans (Hepworth & Goulden, 2008). On average, Uganda loses approximately US$ 113.86 million annually to natural-related disaster damages resulting from floods, droughts, and mudslides, among others (Owani, 2023). Many climate models predict that Uganda's rainfall will rise in the future (Nicholson, 2017). Climate modelling by the World Bank Group using 32 GCMs indicated that both the annual temperature and precipitation increased over different parts of Uganda throughout the century, relative to the 1986-2005 baseline (CCKP, 2021). Likewise, a study by (Sridharan et al., 2019) shows an increase in future annual precipitation in different magnitudes across various regions of Uganda. Contrarily, a study by (Babel & Turyatunga, 2015) projected a 4.7–16.4 and 4.7–11.8% decrease in the annual mean precipitation for western Uganda under SRES scenarios A2 and B2, respectively, by the 2080s. Except for the OND months, the monthly mean precipitation was expected to decrease for most of the months, under both scenarios. This agrees with Uganda's latest NDC updated record of September 2022, as shown in Table 2 below.

Table 2: Uganda's Temperature and Precipitation Projections up to 2100

Variables	2050			2100		
	RCP 2.6	RCP 4.5	RCP 8.5	RCP 2.6	RCP 4.5	RCP 8.5
Temperature anomaly (°C)	0.5-1.0	1.4-2.0	1.8-3.0	1.0-1.5	1.5-2.5	3.0-5.0
Precipitation	-10 mm	-10 mm	-10 mm	-10 mm	-10 mm	-20 mm

Source: (Ministry of Water and Environment, 2022)

Additionally, at higher emission scenarios, the projections indicate that the SOND season will receive more rain than the MAM season. A study by (Omay et al., 2023) also noted that for western Uganda, the MAM season onset will continue to occur earlier than usual whereas the SOND season will continue to come in later than usual. The SOND trend is in agreement with a study by (Haile et al., 2020) whose findings highlighted a delayed onset and early withdrawal of rain around the study area. Due to Uganda's heavy reliance on climate-sensitive economic sectors like agriculture, coupled with its lack of financial and technological capacity to address CC threats, the nation is believed to be among the most vulnerable nations to the effects of CC in the coming future (Gebrechorkos et al., 2023; Nuwagira & Yasin, 2022). Currently, the World Bank ranks Uganda as "highly vulnerable" to CC impacts, only 35.4% resilient; with a vulnerability index of 0.58; and an adaptation readiness index of 0.288 (World Bank, 2022).

2.3 Climate Information Services and Agricultural Resilience

2.3.1 The status of climate services in Uganda.

In Uganda where agriculture generally employs over 73% of the population, accounts to over 48% of export earnings (Epule et al., 2017), and contributes over 28.2% of the nation's GDP (The World Factbook, 2024), CIS is crucial to propel sustainable development. (Owani, 2023) defines climate services as "the value-chain of the production, translation, transfer, and use of climate knowledge and information for climate-informed decision making". UNMA, the Ugandan agency in charge of CIS, disseminates climate products that range from early warnings, short-term weather forecasts to seasonal forecasts (which span a few months ahead) to long-term projects that extend till the end of the century (Mitheu et al., 2022). Uganda's agricultural climate services are majorly a public good, freely disseminated through key stakeholders such as extension workers, radio stations, TV stations, Non-Government Organisations (NGOs), farmer organizations, and individual farmers (Turyasingura & Chavula, 2022). The agency disseminates CIS that's non-excludable and non-rivalrous. However, end users often criticize it for disseminating inaccurate weather and climate-related information. This is majorly attributed to the inadequacy of modern technologies to assist in producing and disseminating precise and reliable real-time information (Dinku et al., 2022).

The adoption of CIS by smallholder farmers and pastoralists (SHFs) in Uganda thus remains low, despite advancements in its distribution in the developing countries courtesy of the internet and telecommunications growth (Nkuba et al., 2021). This is majorly attributed to its low actionability and low public trust, limiting its usability (Moeletsi & Tsubo, 2024). Another reason for the slow adoption is the gross cost hinged on CIS production and dissemination in the face of other competing priorities in the national budget (Owani, 2023). According to (Radeny et al., 2019), the other major CIS downfall in Uganda is poor spatial and temporal resolution, an issue well-addressed by Indigenous knowledge (IK).

Consequentially, using IK in decision-making is a common phenomenon in SHFs. The majority of SHFs have had confidence in IK until recently when climate variability intensified (Spear et al., 2019). They believe that IK predicts seasonal onset at high spatial and temporal scales with a fair degree of accuracy and dependability. It is imperative to note that SHFs are very interested in actionable climate services regarding the onset of rains. Moreover, the IK dissemination in the native languages makes its use prolific in SHF communities (Radeny et al., 2019).

2.3.2 The role of climate services in ensuring agricultural resilience.

(Baffour-Ata et al., 2022) notes that climate information services (CIS) are crucial in building farmers' climate resilience in Africa. (Vogel et al., 2019) reports that it fosters an empowering environment for local, national, and regional decision-makers to more effectively manage climate variability risks. (Naab et al., 2019) also reiterates the imperativeness of mainstreaming CIS in the rural agricultural system and ensuring co-production for a resilient farmer community, especially in Sub-Saharan Africa. According to (Antwi-Agyei & Stringer, 2021), availing CIS on time and making good use of it is a critical first step in enhancing capacity to address climate-related threats. This is because as affirmed by (Hansen et al., 2019), it avails knowledge for successful CC adaptation. WMO reports that enhanced forecasting courtesy of CIS in the agricultural industry is capable of generating an annual revenue of about $300 million through increased productivity in all developing nations. Additionally, it could save up to $2 billion annually through mitigated asset losses and damages (Dobardzic et al., 2019; WMO, 2018). Moreover, (Chemura et al., 2020) assert that CIS plays a vital role in planning for food security, crop growth, and food production stability of an area by driving timely agricultural preparations such as land clearance and tillage, sowing, and harvesting. In general, CIS lowers risks associated with CC and saves lives, property, and livelihoods by guaranteeing access to timely, and contextualized information (Nkiaka et al., 2019). It’s projected that climate and weather information has a great potential for a nation to achieve its climate resilience targets, including supporting the realization of the country’s NDC (Suckall & Soares, 2022), thereby achieving the objectives of the ambitious Paris Agreement.

The key intention for establishing the Global Framework for Climate Services (GFCS) in 2009 was to aid user communities in making climate-smart decisions and ensuring that CIS is effectively disseminated in a manner that more easily leads to practical action (Kijazi et al., 2021). However, much must be done to achieve this in marginalized communities such as refugee settlements. Access to reliable and affordable CIS remains a major challenge in most areas. This limited access further exacerbates the preexisting vulnerabilities (Wichern et al., 2019), making it more difficult to anticipate, plan, and adjust to changing weather patterns, rising temperatures, and other environmental changes.

2.4 Timely Planting and Agricultural Productivity

The date of sowing is a crucial factor in crop productivity. (D. Singh et al., 2023) notes that it aids in making optimum use of light, time, precipitation, temperature, and other factors necessary for plant growth. (Bonelli et al., 2016) affirms planting date as a critical management practice necessary to regulate the timing and incidence of crop phenological stages following environmental settings for crop growth. He further found out that planting date adjustments can affect crop growth rate and crop phenological phase length which consequently affect prospective crop yield. A study by (Sanp & Singh, 2018) also indicated that when a crop is sown either too early or too late, there is a high yield loss tendency due to insect pest infestation. (Alam et al., 2020) notes that early maize planting worries farmers about the plant's poor emergence and growth while late planting makes farmers worry about potential effects on grain moisture and final yield. Delayed sowing results in poor germinability, low productivity, and poor kernel weight at harvest (Zhou et al., 2017). Late maize sowing, according to (Srivastava et al., 2018), also prolongs the grain-filling phase to the end of the crop stage and delays crop flowering.

Numerous researchers have agreed that adjusting maize sowing dates is a great management option to improve yields and mitigate climate risks. For example, using the CSM-CERES-Maize model for planting date evaluation, (Soler et al., 2007) concluded that a delayed maize planting resulted in a 55% yield reduction for all hybrids under rainfed conditions and 21% for the irrigated system. The results from a study by (Joseph Koireng et al., 2018) indicated that delayed maize sowing substantially decreased dry matter yield, green fodder yield, plant height, and crude protein yield respectively. In his study to examine the influence of planting date and nitrogen application rates on grain yield, corn dry matter, and nitrogen use efficiency under rain-fed and irrigated conditions, (Srivastava et al., 2018) affirmed that planting maize on a recommended date with sufficient nitrogen amount substantially increased maize yield and yield components.

On the contrary, (Harrison et al., 2011), while investigating the impacts of temperature changes on maize productivity in Mozambique reported that delaying planting dates and adopting longer-season maize varieties can help farmers to overcome yield losses. Based on APSIM Model simulations, (Traore et al., 2017) found out that even though timely sowing and mineral fertilizer at appropriate rates can buffer the loss in corn yield in southern Mali, they could not completely offset the negative impacts of future CC. Additionally, when studying the impact of CC on crops and adaptation options in Romania, (Cuculeanu et al., 1999) concluded that delaying the sowing date to the last week of April with a sowing density of 5 plants/m^2 can cope with the negative impacts of CC on maize.

2.5 Application of APSIM Model in Climate Change Impact Assessment

Scientists have developed a variety of models that can be applied in CC impact assessments. Some of these models include; APSIM, AquaCrop, EcoCrop, WOFOST, FASSET, HERMES, MONICA, CERES/DSSAT, CROPSYST, COUP, DAISY, EPIC, and STICS. Nonetheless, the model of choice is determined by a number of factors such as; the research objectives, the availability of data, the model's capability, the crop of interest, and the skills of the modeler. The APSIM model was chosen for this particular study. The Agricultural Production Systems Simulator (APSIM) is a modular modeling framework that can simulate biophysical processes in farming systems (Keating et al., 2003), evaluate on-farm management practices, adapt strategies to CC and risk, manage mixed pastures and livestock, simulate nutrient leaching under different conditions, and evaluate gene trait expression, among many other applications (Holzworth et al., 2014). In it, is incorporated various crop models, soil models, and animal models. Since 1990, more external models such as; OZCOT (Hearn, 1994), SWIM (Verburg et al., 1996), AusFARM (Moore et al., 1997), GRASP (Bell et al., 2008), AgPasture (Li et al., 2011), ORYZA (Gaydon et al., 2012) and DYMEX (Whish et al., 2015) have been built into the APSIM environment.

APSIM has been reliably used in research to simulate the impact of various CC scenarios on the future productivity of crops. APSIM was used for this study because of its excellence in examining the intricate relationship between crop productivity, management choices, and climate (Fosu-Mensah et al., 2019; Knörzer et al., 2011). Moreover, it offers helpful submodules to simulate the maize crop, evaluated in this study (Chisanga et al., 2022; Tui et al., 2022) as well as a highly flexible manager module (Holzworth et al., 2014; Morel et al., 2021). APSIM's ability to accurately alter on-farm management interventions using rules without requiring source code modifications is one feature that distinguishes it from the majority of other agricultural models (Moore et al., 2014). Also, upon comparing APSIM crop models with farmer-grown crops, (Carberry et al., 2009) concluded that APSIM was applicable in real-world scenarios as long as the soil parameters were accurately described.

2.6 Climate Change and Refugee Settlements

A study by (Anderson et al., 2021) found out that CC and violent conflict are the two leading vulnerability stressors causing the current and ongoing humanitarian crises in the Horn of Africa. (Bellizzi et al., 2023) and (Thalheimer et al., 2023) reported that an estimated 23 million people were internally displaced in 2021 alone as a result of weather- and climate-related catastrophes, with a large portion of these people living in drylands in Africa.

According to (UNHCR, 2024), a refugee is "someone who is unable or unwilling to return to their country of origin owing to a well-founded fear of being persecuted for reasons of race, religion, nationality, membership of a particular social group, or political opinion". Based on this definition, the accomodation of refugees by the host nation is often considered a temporary phenomenon with a perception that they will voluntarily return to their home country as soon as the circumstances which forced them away end but this seldom materialises (Zaman et al., 2020). This explains why most refugee settlements in Uganda are situated in remote areas with ramshackled housing units, poor-quality land, and harsh climatic conditions (Fransen et al., 2024). As a result, refugee communities are particularly vulnerable to CC impacts. According to (Ainuddin et al., 2017), refugee settlements' vulnerability is a cumulative result of social, physical, economical and institutional factors, while (Zaman et al., 2020) record that these communities have low adaptive capacity due to lack of resources to cope when a climate hazard strikes.

Kyangwali Refugee Settlement (KRS) is not an exception to CC vulnerability. It is located in Kikuube district, western Uganda, well isolated from the neighboring host communities, and was established in 1960 to primarily host refugees from DRC due to its proximity (van Blerk et al., 2021). From 36,713 refugees in December 2017 to 137,207 in February 2024, Kyangwali saw a 374% rise in its refugee population (UNHCR, 2024). 83% of these are women and children, 18% are youth (15-24 years old) and 3% are elderly (UNHCR, 2022a). Refugees in Kyangwali are one of the most vulnerable populations, being disproportionately affected by the effects of a worsening climate crisis exacerbated by more refugee influx *(see Fig. 5)*, politics, and surging food and fuel prices, which intensify as the community is still struggling to recover from two years of socioeconomic COVID-19 fallout (Fransen et al., 2024). A study by (Fransen et al., 2024) indicate worse climatic conditions for KRS as compared to the national average *(see Table 3)* characterised by lower mean daily rains, higher heat wave indicators as well as a higher extreme rainfall indicator.

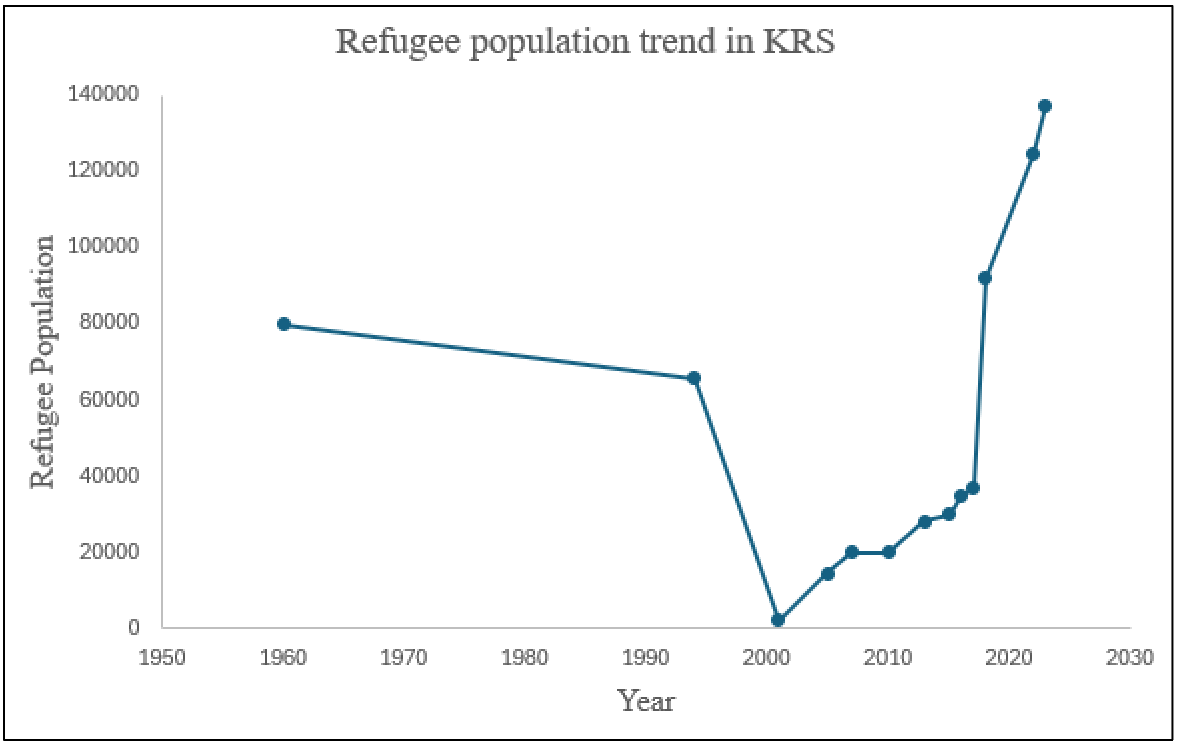


Fig. 5: Population trends in KRS since the year 1960, adopted from (Nandala, 2023)

2.7 Knowledge Gaps and Rationale for the Study

While it is well acknowledged that CC and variability have detrimental effects on agriculture (De Lima et al., 2021; Hassan et al., 2021), there is a lack of location-specific research particularly to quantify the impact on KRS and its vulnerable population. It is imperative to comprehensively understand the effect of timely planting on Kyangwali's primary agricultural output (maize) to best develop effective coping and adaptation strategies. Moreover, the use of the APSIM model for climate change-crop productivity analysis is still very limited in Uganda. (Mibulo & Kiggundu, 2018) used the AquaCrop model while (Nimusiima et al., 2018) used the CERES model, to simulate maize yields in Uganda. In Western Uganda, only (Luliro et al., 2022) stand out for employing the APSIM model to simulate Irish potato productivity in Kigezi highlands. This study aims to employ the APSIM model to investigate the potential of timely planting on maize yield in KRS, Kikuube district, Western Uganda. By applying APSIM to Kyangwali's specific context, valuable correlational insights between timely planting and maize yield will be gained. The results of this study will be vital in developing evidence-based coping and adaptation strategies for maize production in Kyangwali refugee settlement and other areas of a similar context. Ultimately, this research will empower relevant stakeholders with the necessary knowledge to enhance the area’s food security in the face of a changing climate.

3. MATERIALS AND METHODS

3.1 Study Area

Kyangwali refugee settlement (KRS), with an area of about 95km^2 (van Blerk et al., 2021) is located in Kikuube district, western Uganda *(see Fig. 6).* It's within altitude ranges of 1,100-1,250 masl. KRS is bordered by Lake Albert to the west and Bugoma Central Forest Reserve to the east.

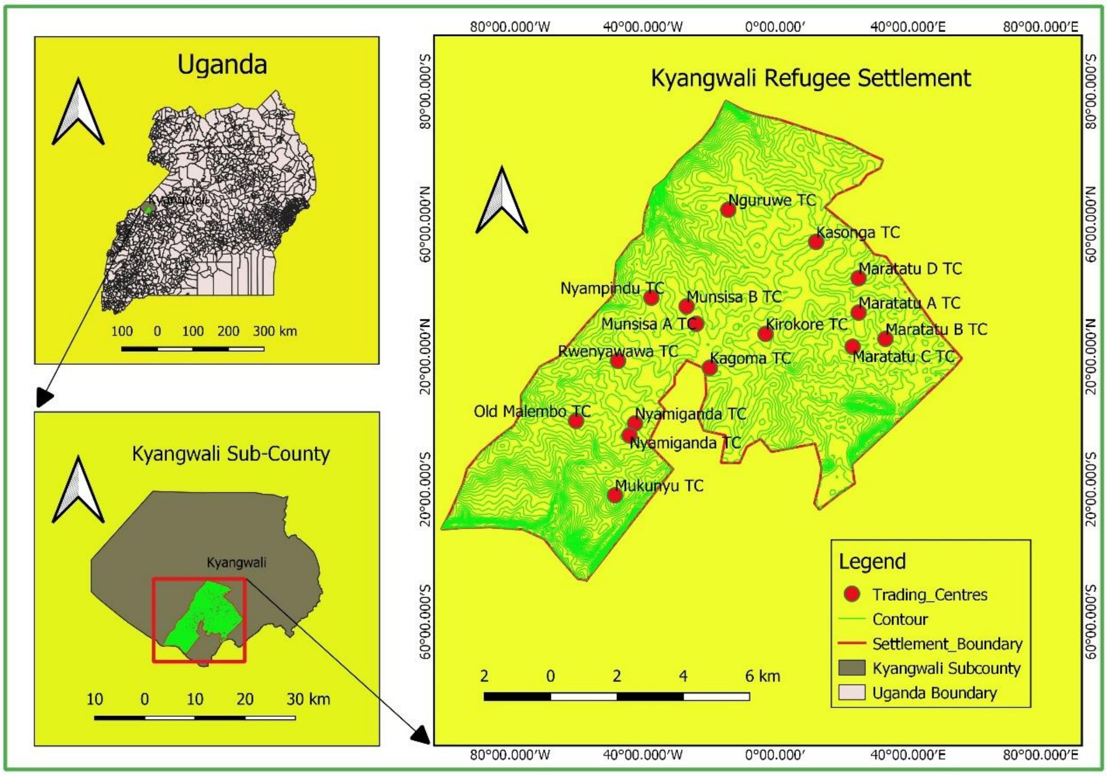


Fig. 6: Map showing location of Kyangwali Refugee Settlement

The area experiences two rainy seasons in a year *(see Fig. 7)* from March to May (MAM) and September to December (SOND), and averagely experiences 63 dry days in any given year (van Blerk et al., 2021). Located in the tropical savannah climate zone, in the western clay loam farmland agroecological zone, KRS experiences annual mean daily minimum and maximum temperatures of 19.9^{o}C and 29.3^{o}C respectively. For 1982-2022, the area received MAM rains in the 283-475mm range and SON rainfall ranges of 279-547 mm, indicating seasonal means of 347mm and 371mm respectively. Maize is the staple crop grown in this area. The open-pollinated variety (OPV), Longe 4 (L4) is the most dominant maize cultivar in the study area (NAADS, 2024). Other major crops grown around KRS include rice (upland varieties), beans (NABE series), coffee (Arabica), and bananas. Farmers in this area depend on rainfed agriculture for livelihood. Given that the crop water requirement of maize L4 is ~335 mm/season (Abirdew et al., 2018; Bhat et al., 2017; Haruna et al., 2022; Parmar et al., 2023; Suryadi et al., 2019), the rainfall received in the area is mostly sufficient for as long as the planting is timely.

Table 3: Key average climatological stats for KRS since 1981

Parameter	**Time Range**	**KRS average**	**National Average**	**Difference**
Mean daily temperature (^{o}c)	1981-2020	23.56	21.49	2.07
Mean daily rainfall (mm)	1981-2020	4.55	5.02	-0.47
Heatwave indicator (SNR)	1981-2018	0.94	0.85	0.09
Coldwave indicator (SNR)	1981-2018	0.20	0.08	0.12
Extreme rainfall indicator (SNR)	1981-2018	0.20	0.08	0.12

Adopted from (Fransen et al., 2024)

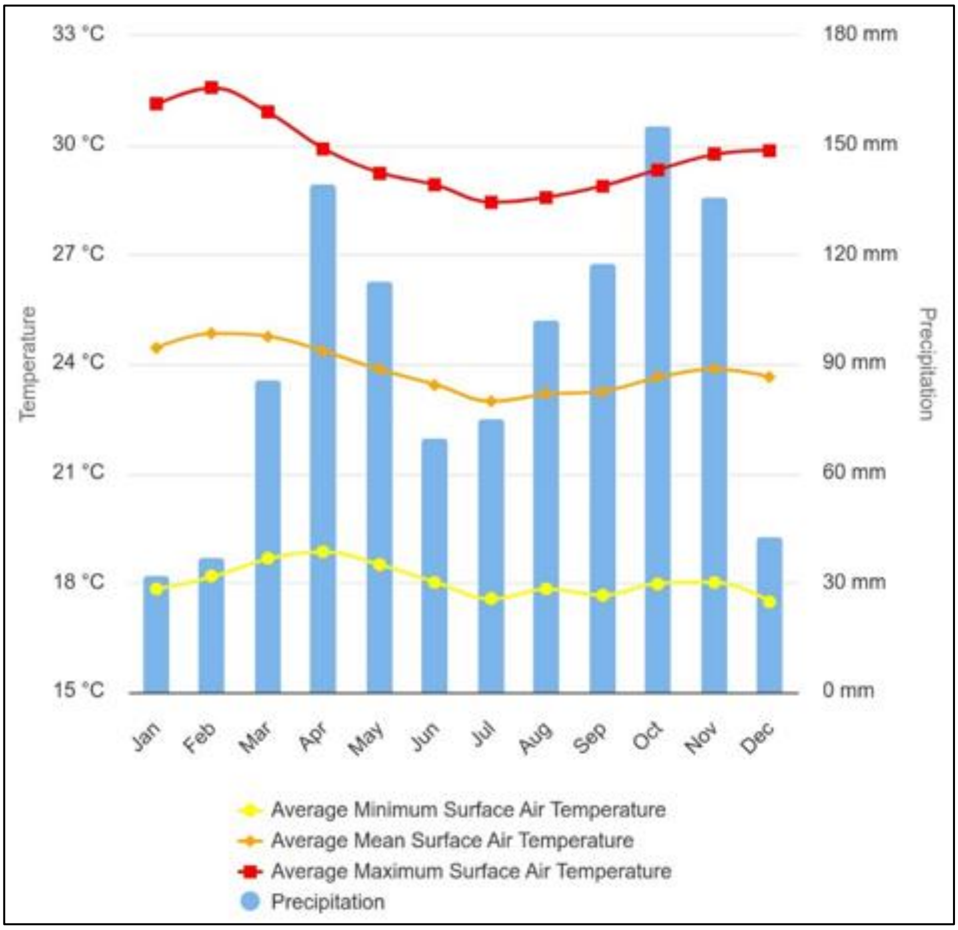


Fig. 7: A graph showing the monthly climatology around KRS, (1991-2020)

3.2 Methodological framework

Fig. 8 below is a representation of the methodological outline utilized to achieve the objectives of the study.

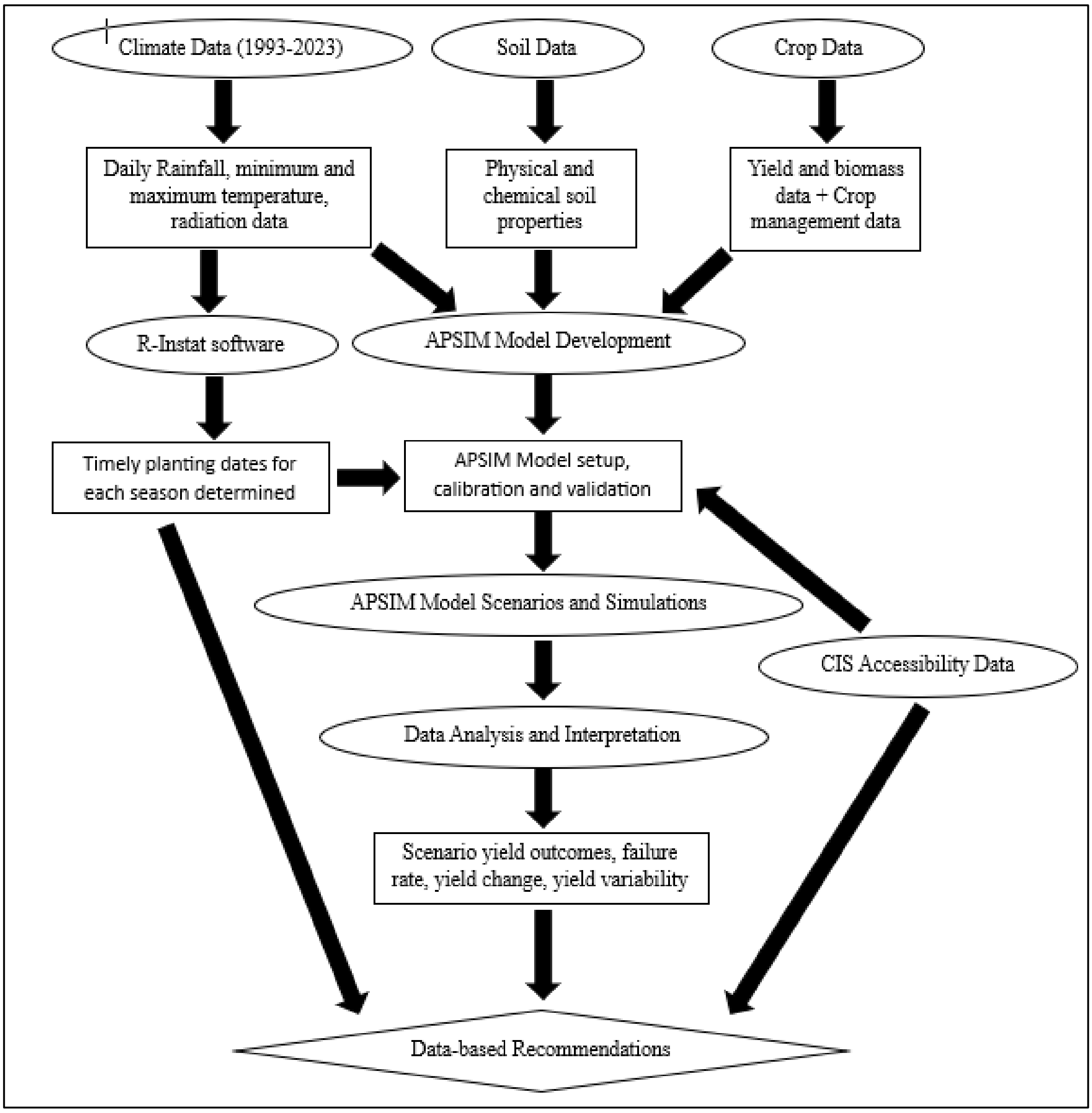


Fig. 8: Showing the methodological framework employed for the study

3.3 Data Collection:

3.3.1 Obtaining climate data

This study used daily gauge-based station data for historical daily weather data on average precipitation (rain in mm), maximum (maxt) and minimum (mint) temperatures (°C), and solar radiation (radn in MJ/m^2) for the period 1993-2023. It was obtained from Masindi station (1.68ºN, 31.78ºE), an established meteorological station nearest KRS, as guided by the Uganda National Meteorological Authority (UNMA). Masindi meteorological station is at an altitude of 1,147 m.a.s.l and approximately 110 km from the study area.

3.3.2 Accessing soil data

This was obtained from the NARO's National Agricultural Research Laboratories (NARL) at Kawanda Research Institute (KARI). A clay-loam texture characterizes the soil in the KRS study area. The soils are alluvial and slightly acidic with pH ranges (5.8-7.0). The soil's physical and chemical properties used for APSIM soil parameterization, calibration, and evaluation are shown in Table 4 below.

Table 4: Physical and chemical properties of soils around KRS

Soil depth (cm)	Air Dry (mm/mm)	LL15 (mm/mm)	DUL (mm/mm)	SAT (mm/mm)	BD (g cm^{-3})	OC (%)	Sand (%)	Silt (%)	Clay (%)	pH (1:5$H_2$0)	NO_3 (kg/ha)	NH_4 (kg/ha)
0-20	0.12	0.29	0.39	0.45	1.66	3.52	30.93	39.00	30.07	6.90	15.60	35.64
20-50	0.08	0.16	0.29	0.47	1.58	2.75	25.75	42.00	32.25	6.25	30.26	30.75
50-85	0.06	0.12	0.27	0.42	1.56	3.29	25.75	42.00	32.25	6.12	28.83	32.84
85-130	0.06	0.12	0.26	0.42	1.53	1.95	23.50	41.00	35.50	5.85	25.75	30.79
130-180	0.08	0.15	0.28	0.41	1.52	0.98	21.93	38.00	40.07	5.80	12.50	28.74

LL15 = lower limit at 15 barometric pressure; DUL = drained upper limit; SAT = volumetric water content at saturation; BD = Bulk density; OC = organic carbon content; NO_3 = nitrate content and NH_4 = ammonium content.

3.3.3 Crop data acquisition

Consultations with agricultural extension service providers helped collect information on the maize varieties most cultivated in KRS. The open-pollinated variety (OPV) Longe 4 as introduced by NARO's NACRRI was identified as the dominantly cultivated variety in the study area and was thus considered for the study. Longe 4 is an early maturing variety that takes 100-105 days to physiological maturity. It is drought-tolerant and resistant to Maize Streak Virus (MSV), Gray Leaf Spot (GLS), and Northern Leaf Blight (NLB). It performs well in all tropical areas except highlands, with a high yield potential. Since Longe 4 was introduced in Uganda for commercial production in the early 2000s, the cultivar's phenology and yield data were only available for 2003–2023.

3.3.4 Obtaining data on CIS accessibility

The study purposed to understand the level of accessibility of smallholder maize farmers to CIS. A sample of 16 respondents corresponding to the number of maize farming zones in KRS were interviewed using a Google form questionnaire, contextually designed (Link: https://forms.gle/STstQmvCUjCvbqN38). The interviewees were purposively selected depending on their knowledge and experiences in CIS and maize farming. Informed consent was obtained before interviewing each of them. Appendix 1 shows the consent form template that was used. Quantitative data analysis was done by exporting the collected data to a Google spreadsheet (Tuheirwe-Mukasa et al., 2019), for filtering, sorting, and aggregating in pivot tables before graphs and charts could be generated. Qualitative data was analysed by content analysis (Mugagga et al., 2020; Twinomuhangi et al., 2021).

3.4 Data quality control (QC) diagnostics

To ensure the reliability of our findings, a rigorous data QC was conducted on both yield, biomass, and climate datasets. The datasets were examined for consistency, completeness, and accuracy before model simulation. Outliers were detected using box plots, missing value analysis was done using the R Software, and homogeneity was determined using the RH tests. These methods were chosen because they are user-friendly and free. As reported by (J. Du et al., 2020), the RH test can detect and correct several change points in a time series based on the penalized maximal t (PMT) or F test (PMF). This study utilized the PMF method to determine the homogeneity of the climate dataset since it can be utilized in isolation, in the absence of neighbouring stations for comparison.

3.5 APSIM Model Setup, Calibration and Validation

3.5.1 Model selection and justification

The APSIM crop growth model version 7.10, build number r4221, was used for this study. It is a dynamic model that consists of four modules, namely; crop module, weather module, soil module, and field management module. Its utility in this study was attributed to its excellence in examining the intricate relationship between crop productivity and management choices under various climate scenarios (Fosu-Mensah et al., 2019; Knörzer et al., 2011). In a daily time step, the APSIM model simulates well the growth of a maize crop (Wang et al., 2020). Moreover, it offers helpful submodules to simulate the maize crop, evaluated in this study (Chisanga et al., 2022; Moot et al., 2015) as well as ascertaining the impacts of temperature and precipitation variations on maize phenology and yield (Morel et al., 2021). With its one-dimensional modular environment, APSIM's modeling platform perfectly replicates plant growth by simulating its mechanistic interactions with the atmosphere and soil. It is especially appropriate for evaluating long-term crop performance since it focuses on modeling the dynamics of soil resources (Gaydon et al., 2017).

3.5.2 APSIM model setup

First, a met file was prepared as follows; An Excel file with climate data (1993-2023) organized in columns; year, day of year, maxt, mint, rain, and radn was saved as a **.prn** file and then converted to **.met** file using the Tav_Amp FORTRAN software. The generated **.met** file was then imported into the APSIM met module. APSIM's crop module aided in simulating the cultivar's physiological processes. The APSIM maize crop module particularly contains numerous cultivars. The Longe 4 cultivar used for this study was not in APSIM. The cultivar-specific parameters were estimated by iteration of the APSIM model against the data obtained from NARO. Growing degree days from sowing to emergence, emergence to tasselling phase, tasselling to anthesis, anthesis to grain filling, and grain filling to whole maize crop, were appropriately determined to mimic Longe 4 phenological characteristics. All the other parameters were not changed.

The cultivar was sowed at a depth of 10 mm, the sowing density set at 5 plants/m^2, and the row spacing at 500 mm. At planting, the initial soil nitrate nitrogen and ammonium contents were fixed at 5 kg/ha and 1 kg/ha, respectively. All model simulations were conducted as a succession of independent growing seasons so that soil initial conditions are reset at the start of each simulation. Not a single other parameter was altered.

APSIM's heavy soil module was also edited to mimic the soil characteristics typical of KRS soils. Table 4 shows the physical and chemical soil parameters used as input in the APSIM soil module. The maximum available water content of the soil at sowing was adjusted to 90% and evenly distributed across the soil profile. The soil water module belongs to APSIM's soil module and is a daily water balance model specifying soil water characteristics in terms of the LL15, DUL, and SAT (http://www.apsim.info/). Since the farming system at KRS predominantly rainfed, the irrigation module was not included in the simulation. Also, the fertilizer module was not considered for the study since soil nutrients were assumed sufficient to meet the maize's nutritional requirements. Furthermore, factors such as pests, and infrastructural and technological advancements were not taken into account before and during the growing season (Wang et al., 2020; Wu & Wilhite, 2004).

3.5.3 Calibration and validation

The APSIM model was calibrated and validated using maize grain yield and biomass data. The 2004-2013 data aided in model calibration while data from 2014-2023 was used to validate the model. Details on how the APSIM model is calibrated can be found in (Deihimfard et al., 2015) and (Deihimfard et al., 2018).

The performance of the APSIM model in KRS was evaluated using root mean square error (RMSE, Equation (1)) and normalized root mean square error (nRMSE, Equation (2)). These aided in determining the relative difference between the measured and simulated values of the model (Wang et al., 2020); lower error values denote a lower residual variance. If the nRMSE value falls below 10%, the simulation is deemed exceptional; if it falls between 10% and 20%, the model is rated good; and if it falls between 20% and 30%, it's rated fair (Deihimfard et al., 2018). The consistency between the measured and simulated values was evaluated using the coefficient of determination (R^2), Equation (3). The closer it is to one, the higher the consistency.

$$\mathbf{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(B_i - S_i)^2}{N}} \qquad \textbf{Equation 1}$$

$$\mathbf{nRMSE} = \frac{\boldsymbol{RMSE}}{\boldsymbol{B}} \qquad \textbf{Equation 2}$$

$$\boldsymbol{R^2} = \left(\frac{\sum(\boldsymbol{B_i}-\boldsymbol{B})(\boldsymbol{S_i}-\boldsymbol{S})}{\sqrt{\sum(\boldsymbol{B_i}-\boldsymbol{B})^2\sum(\boldsymbol{S_i}-\boldsymbol{S})^2}}\right)^{\mathbf{2}} \qquad \textbf{Equation 3}$$

Where S_i represents the simulated values; B_i is the measured value; B represents the mean of the measured values; S is the mean of simulated values; and N is the number of samples.

3.5.4 APSIM model sensitivity analysis

Before implementing the APSIM model, it is crucial to evaluate its behavior and sensitivity to input parameters. According to (Dokoohaki et al., 2022; Swamila et al., 2022; Tadiello et al., 2023; Yan & Du, 2023), sensitivity analysis aids in identifying model inputs that significantly increase output uncertainty as well as those that have little impact. When input parameters have little effect on the model's predictions, it can be said that input data has little influence on the model outcomes and can thus be fixed. To determine the sensitivity of the APSIM model used in this study, the nominal input data values for each input parameter were used to generate fundamental outputs. One input was varied while maintaining the others at their baseline. Having noted the outputs, the variable was returned to its nominal value, and the process was repeated for each of the other inputs in successive iterations of the model. The model outputs and the basic outputs were compared using the following relationship after the input parameter values were changed (Kikoyo & Nobert, 2016).

$$\boldsymbol{S_c} = \frac{\Delta\boldsymbol{W}}{\overline{\boldsymbol{W}}} / \frac{\Delta\boldsymbol{P}}{\overline{\boldsymbol{P}}} \qquad \textbf{Equation 4}$$

Where Sc is the sensitivity coefficient, ΔW is the output difference before and after changing the input, $\overline{W}$ is the mean of outputs, ΔP is the input difference and $\bar{P}$ is the mean of inputs.

The inputs used in the APSIM model sensitivity analysis were; soil initial water, soil nitrate (NO_3) content, soil ammonium (NH_4) content, maize sowing density, and row spacing. Percentage change in input selection depended on the sensitivity of the model to various parameters, the limits of the input parameters, and their convergence rate. The variation of the inputs was chosen to range from -25% to +25% off the median value. The sensitivity of the parameters was divided into three categories based on their relative impact on the simulated maize yield, (namely; high, moderate, and low). A high *Sc* indicates that the input has a great impact on maize yield outcomes. It also identifies input parameters with higher uncertainty (Chisanga et al., 2020).

3.6 Determining the Timely Planting Window (TPW) Around KRS

Timely planting of maize refers to sowing maize seeds within the optimal period, considering factors like climate, soil conditions, and cultivar characteristics such as days to maturity and growth habits (Srivastava et al., 2018).

To determine the TPW, the onset and cessation dates for the MAM and SOND seasons for the study period (1993-2023) were computed by R-Instat software. A .csv file of the R-Instat input climate data was prepared, containing five columns (year, day of year, maximum temperature, minimum temperature, and precipitation). The prepared file was imported into R-Instat and while in R-Instat, the “prepare” tab was used to check, reshape, and organize the data. The “climatic” tab was then used to prepare climatic summaries and determine the start of the rains, the end of the rains, and the length of the two seasons/year. The condition to determine the onset of the rainy season was set to three consecutive days with a total PR ≥20 mm and no nine consecutive dry days in the first twenty-one days thereafter. Contrarily, the end of the season was determined as the last day in the season to receive PR>10 mm. As depicted in Appendix 2, start and end dates were determined for each of the MAM and SOND seasons. The TPW was taken as the range between the earliest and latest seasonal onset.

3.7 Scenarios Development

To develop the scenarios to help in model simulations, the TPW for the MAM and SOND seasons for the study period (1993-2023) was first determined as in the preceding section. Two other planting windows were determined for model simulation, namely; the early planting window (EPW) and late planting window (LPW) as shown in Fig. 9 below. EPW was considered as the month earlier than the TPW whereas LPW was taken as the month later than the TPW.

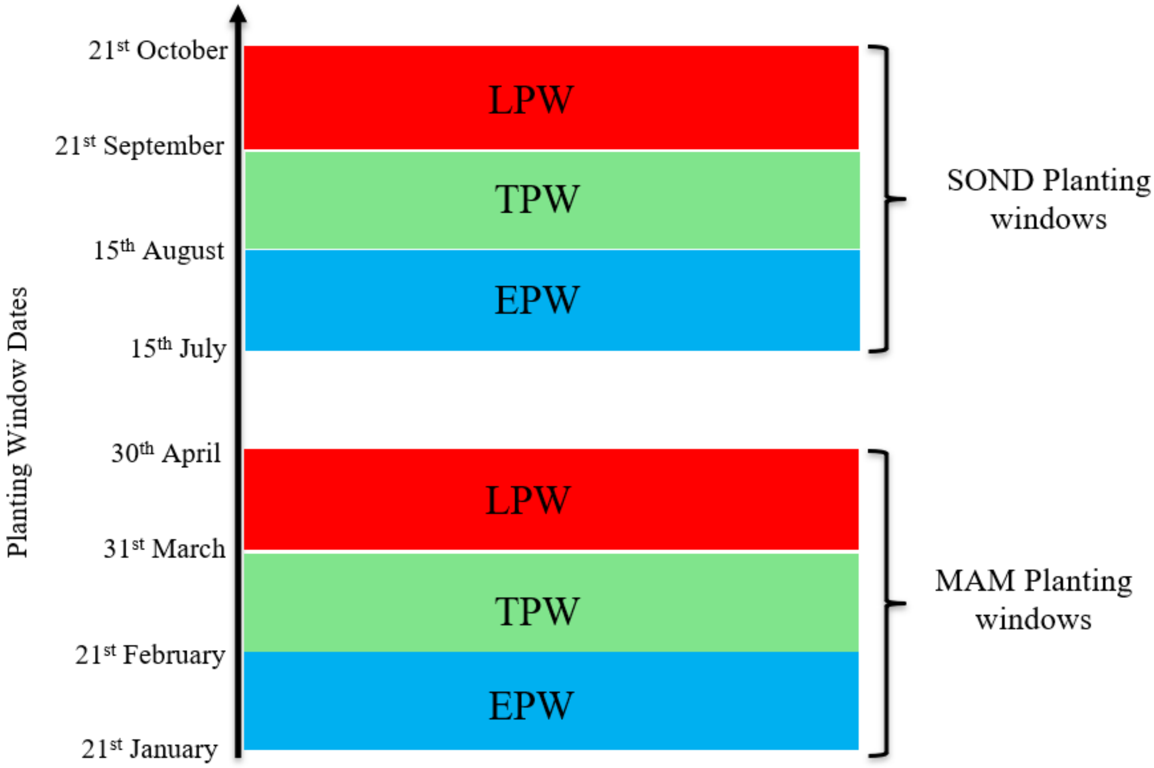


Fig. 9: Determined dates for planting window scenarios used for simulation

3.8 Model Simulations and Analysis:

The simulations will be performed using the APSIM-Maize module, which may be found at *www.apsim.info*, and as described by (Keating et al., 2003). This module operates on a daily time step in response to daily inputs of meteorological data, soil properties, and crop management practices. It replicates several fundamental physiological processes (Seyoum et al., 2017). Using this validated maize module, the effects of changing planting dates on maize grain yield, during the MAM and SOND seasons were examined for the years; 1993 to 2023.

APSIM output results were imported and analyzed with R-Instat 0.7.16.50. The maize production response was determined using two indicators: yield change and yield variability.

Yield change, δ_y (%) will be computed as;

$$\boldsymbol{\delta_y = \frac{(m_y - b_y)}{b_y}} \qquad \textbf{Equation 5}$$

Where m_y is the median yield of a given maize variety for a given planting date scenario and site, and b_y is the reference yield of the given maize variety, and will be computed as;

$$\boldsymbol{b_y = \frac{\sum_1^n r_n}{n}} \qquad \textbf{Equation 6}$$

Where r_n is the median yield of a given maize variety under the baseline scenario, for the nth location.

Yield variability, v_y (%) was computed as the ratio of the standard deviation, σ_y and the mean, μ_y of the yields for a given crop-location-planting date scenario combination;

$$\boldsymbol{v_y = \frac{\sigma_y}{\mu_y}} \qquad \textbf{Equation 7}$$

Based on simulated grain yields in APSIM, criteria for classifying a given planting window as a failure was established. If the window yield is less than the average yield of TPW for that season, the planting window is considered a failure. The proportion of failures was used to calculate the risk of planting window failure. A year was considered good if it possessed at least one successful planting window for each season of that same year, otherwise, it would be considered bad.

The resulting maize yield metrics were analyzed using the t-test (one-tailed and two-tailed). Conversely, Excel software was used to examine the magnitude of the trend. A significance level, p-value of 0.05 was used to assess if a trend is statistically significant, for a 95% confidence. For the t-test, the null hypothesis is rejected for a p-value<0.05 and the reverse is true. Additionally, if the absolute value of the “t statistic” is greater than the “t critical” value, the null hypothesis is rejected and the reverse is true. Because the t-test method can reliably work with non-normality, seasonality, hypothesis testing, missing data, and outliers in a time series, it was chosen for trend analysis. The t-test has been utilized and trusted in various research such as (Koskei et al., 2020; Nkosi et al., 2023; Sanaullah et al., 2020; Tiwari et al., 2021).

4. RESULTS AND DISCUSSION

4.1 Analyzing Access to CIS in KRS

The proceeding results are the analysis of data obtained from 16 respondents, all of whom were maize farmers, and 9 were female. Their average household size was 4.6. Results indicated that 93.7% of the respondents were entirely under the rain-fed farming system and only 6.3% in both rain-fed and micro-irrigation farming. Furthermore, 50% of the interviewees were above 50 years and only 6.3% were younger than 24 years. All the respondents said they needed weather and climate information for their farming activities. This is because all respondents reported having noted seasonal unpredictability in recent years. In Fig. 10 below, 56.3% of the respondents reported having no access to any form of scientific forecasts while 37.5% only accessed seasonal forecasts. None of the respondents had access to early warnings and alerts, 7-14-day forecasts, monthly forecasts, and bi-seasonal forecasts. Only one respondent confessed to receiving 24-hour forecasts.

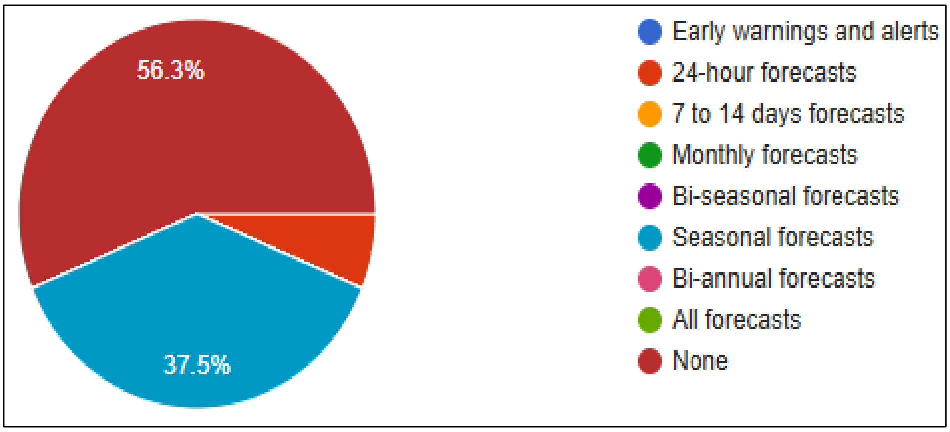


Fig. 10: Smallholder farmers' level of CIS accessibility around KRS

All those who reported inaccessibility pointed to the fact that CIS was not readily available to them. This spells the need for more CIS accessibility and adoption to mitigate climate risks and ignite sustainable development in KRS. A number of factors contributed to this CIS gap. 44.4% of them highlighted the language of dissemination as a barrier while only one respondent reported that the provided CIS was not relevant. The language of CIS dissemination is an issue in KRS since the refugee farmers come from various countries, majorly the DRC and South Sudan, with no unifying dialect. Neither are their languages compatible with those of the host communities.

The respondents who received none of the scientific forecasts were either using previous weather patterns (66.7%), traditional knowledge (55.6%), and/or the agricultural calendar

(33.3%) to determine the onset of seasons. However, the reliability of their options was average (53.4%). Of the 7 respondents who reported access to some form of CIS, the majority (71.4%) accessed it via radio. Data analysis also revealed that radios majorly disseminated seasonal forecasts only, while the only 24-hour forecast recipient reported receiving it via a smartphone. These findings indicate that CIS inaccessibility is partly due to the refugee's incapacity to acquire dissemination tools such as smartphones, TVs, and radios. A study by (Balgobin & Dubus, 2022) reported that about 32% of Ugandans owned no mobile phone, around 21% owned a basic mobile phone, and only 7% had a smartphone. These stats could be even worse for refugee settings such as KRS. As shown in Fig.11(a), no respondent reported accessing CIS via TV and extension workers. One respondent reported receiving CIS via an NGO project whose availability diminished after the expiry of the project. Recipients who reported accessing CIS through friends/fellow farmers were all female maize farmers. This could be attributed to the fact that women farmer groups are more prevalent than their male counterparts (Theeuwen et al., 2021), facilitating information exchange between them.

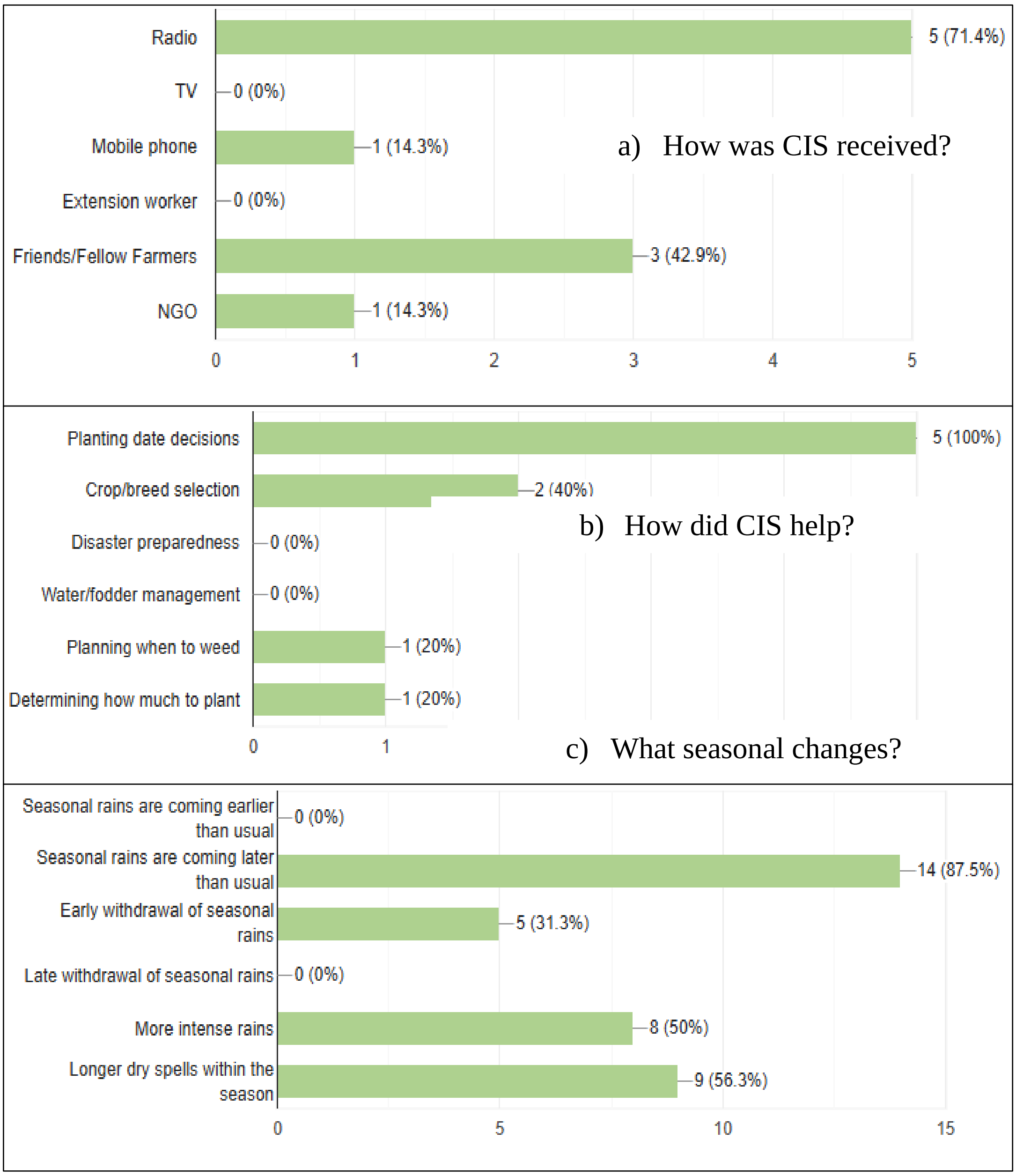


Fig. 11: (a) Means of CIS access, (b) value of CIS, (c) noted seasonal changes around KRS

71.4% of the CIS recipients said it was sometimes useful for their farming activities while the rest reported that the received CIS didn't help them. All recipients that confessed usefulness pointed out that CIS helped them in making planting date decisions. As shown in Fig. 11(b), only 40% of them reported that CIS helped them in crop/breed selection. Planning when to weed and determining how much to plant were the other benefits cited. The respondents who reported that the received CIS didn't help them pointed out its inconsistent availability, low actionability and accuracy as the major downfalls. The other cited issue was the language barrier, given that the forecasts are disseminated in Ugandan local languages which the refugees do not readily comprehend since they originate from other countries. Studies by (Guadagno & Matthews, 2022; Kletečka-Pulker et al., 2019) noted language barrier as a gross socio-cultural barrier limiting refugee access to valuable information necessary for sustainable development. Women refugees were particularly more vulnerable to this challenge, according to (Kainat et al., 2022).

Furthermore, all the interviewees confessed having noticed changes in the timing of the seasons in recent years with 87.5% reporting that the seasonal rains were coming later than usual. 56.3% of the respondents reported experiencing longer dry spells within the season (see Fig. 11(c)). Other noted changes were the early withdrawal of the seasonal rains and the occurrence of more intense rains. These findings agree with a study by (Ocen et al., 2021), which reported the probability that a given location in Uganda experienced a false start of a season as falling between 0-53%. Findings by (Gudoshava et al., 2022) also point to great rainfall variability over East Africa, affecting seasonal predictability and causing huge implications for agriculture-led economies such as Uganda (Babyenda et al., 2023). Contrarily, (Omay et al., 2023) reported that the seasonal rains were coming earlier than usual over western and southwestern Uganda. The most highlighted adaptation/coping strategies the respondents were employing to manage the seasonal changes included diversification of crop types, opting for early maturing and drought-resistant crop varieties, and reducing crop acreage to opt for livestock. Only one respondent was practicing some form of irrigation and none had given up on cropping. This is especially true given that less than 3% of smallholder farmers in Uganda are involved in irrigated agricultural production, according to (Sridharan et al., 2019). Only 8,716 hectares of agrarian land are irrigated out of the total potential 9.2 million hectares (Happy et al., 2024).

4.2 Seasonal Variability Around KRS

Results from the R-Instat analysis indicated a trend of the MAM season around KRS onsetting earlier than usual and receding later than usual (see Fig. 12(a)). Contrarily, the SOND season continued to onset and recede later than usual as depicted in Fig. 12(b). Consequently, the length of the MAM season displays a positive trend whereas the SOND season continued to shorten during the study period (see Fig. 12(c)).

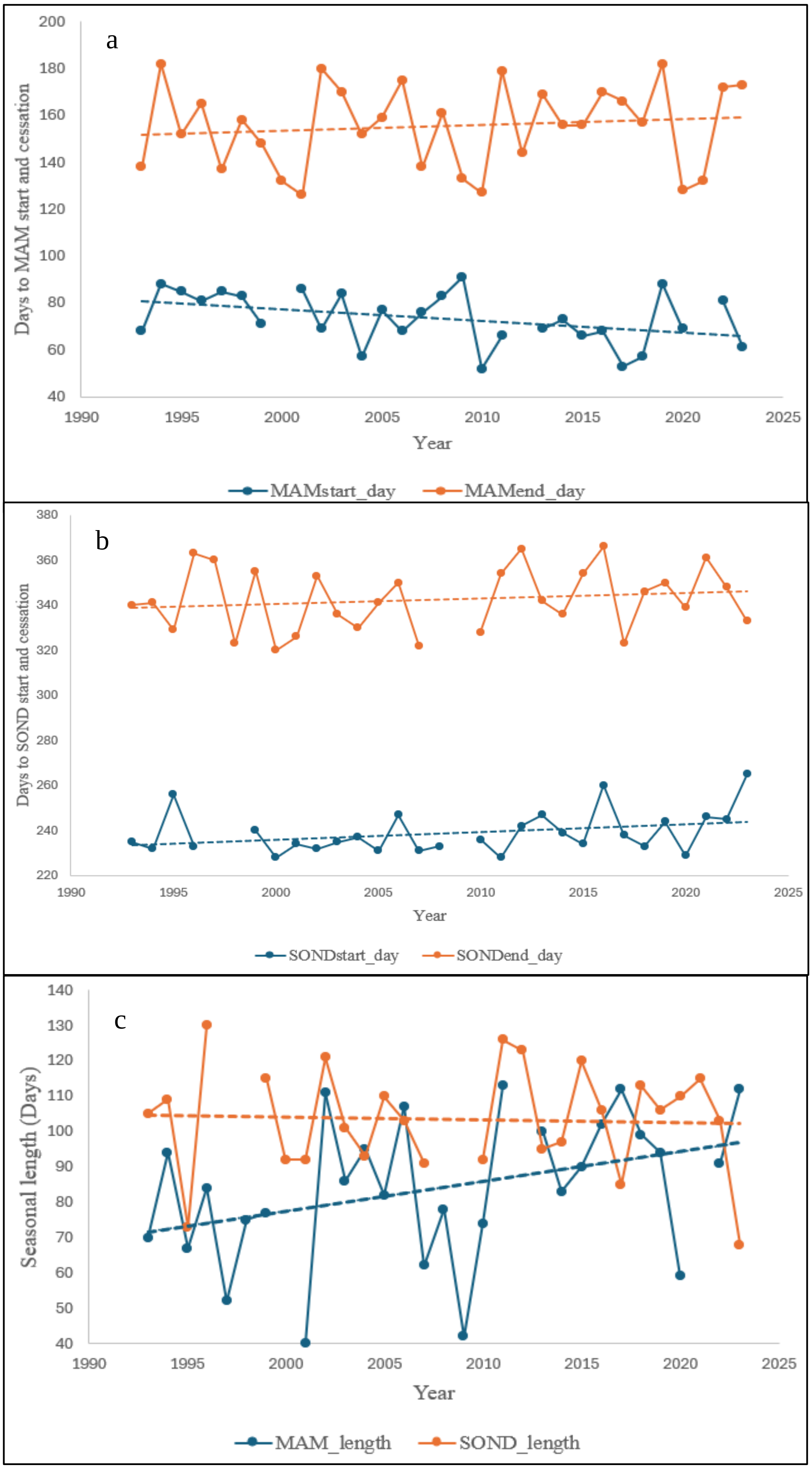


Fig. 12: Start and cessation days for (a) MAM and (b) SOND, and (c) seasonal length

These findings are consistent with research conducted by Omay et al. (2023) that focused on the Intergovernmental Authority for Development (IGAD) region of East Africa and observed a comparable trend around western Uganda. Moreover, the SOND trend corresponds to the findings of Haile et al. (2020), which highlighted a deferred onset and early retreat of rain around most regions of East Africa during this season. Early MAM seasonal onset is an agricultural advantage for the area since it extends the length of the growing season, but the shortening trend of the SOND season could interfere with the crop phenological stages, lowering yield.

This annual unpredictability of seasonal onsets and cessations makes it difficult for smallholder farmers to time when to plant (D. Singh et al., 2023), leading to increased susceptibility to crop yield failure and food insecurity. Omay et al. (2023) asserted that although rainfall commencement and end dates and the seasonal extent are important for crop productivity and food security, they are not well documented and highlight the importance for more precise data. According to Chemura et al. (2020), understanding the spatial-temporal characteristics of seasonal lengths, onsets, and cessations in an area is imperative in planning for increased crop production, thus advancing food security. Improving CISs around KRS would be crucial to achieving climate-resilient agricultural productivity (Partey et al., 2018), and contributing to sustainable development (Tumushabe, 2017).

From 1933–2023, the length of the MAM season fluctuated more than the SOND season, with ranges between 40–113 days and 68–130 days, respectively (see Fig. 12(c)). The increasing MAM seasonal variability poses a risk for climatic hazards like flash floods (Ainuddin et al., 2017), which severely impact agricultural operations, livelihoods, and food security. These consequently impede sustainable development around the refugee settlement.

4.3 APSIM Model Calibration and Validation

The APSIM model was calibrated and validated using maize grain yield data. The 2004-2013 data aided in model calibration while data from 2014-2023 was used to validate the model. Fig. 11(a) and (b) indicate graphs of simulated yield and biomass against their measured counterparts during calibration and validation respectively.

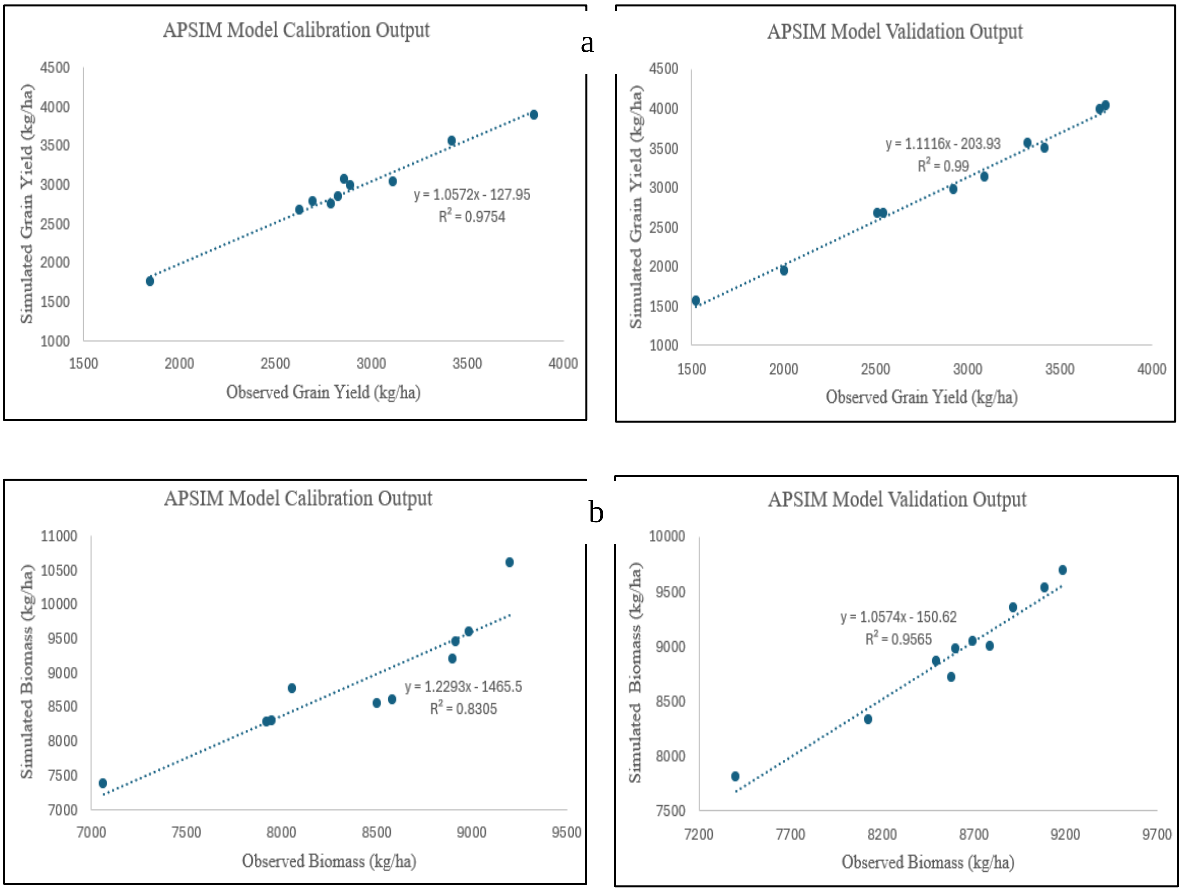


Fig. 13: Graphs of simulated versus observed (a) yield and (b) biomass during calibration and validation respectively.

Table 5 below shows the results of how effective the APSIM model simulated the maize grain yield.

Table 5: Shows APSIM's model calibration and validation results for various metrics

	Calibration		Validation	
Metric	Yield	Biomass	Yield	Biomass
RMSE	95.535	594.511	161.097	360.447
nRMSE	0.033 (3.3%)	0.071 (7.1%)	0.056 (5.6%)	0.042 (4.2%)
R	0.988	0.911	0.995	0.978
R^2	0.975	0.831	0.990	0.957

The performance of the APSIM model in KRS was deemed exceptional in simulating both the yield and biomass since the nRMSE values were below 10% during both calibration and validation. This indicates a lower residual variance between the simulated and measured yield and biomass values. Additionally, the coefficient of determination (R^2) for yield was closer to one in both calibration (0.9754) and validation (0.990) cases, indicating a higher consistency between the measured and simulated yield values. However, though satisfactory, the consistency was lower for biomass simulation. Generally, the APSIM maize model was more excellent in simulating grain yield than biomass. Additionally, the APSIM model generally overestimated the grain yield and biomass compared to the observed values during most of the maize growing seasons from 1993 to 2023 (see Fig. 14). This could be partly attributed to APSIM not accounting for pests' and diseases' impact on maize crop growth (Richetti et al., 2024). Overall, the model was trusted for the study and approved for future crop modelling studies.

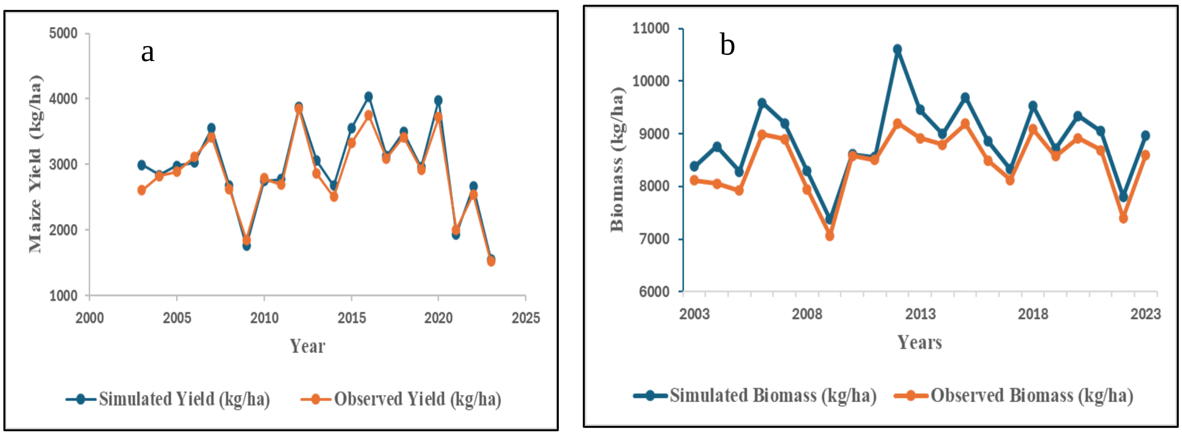


Fig. 14: Simulated and observed (a) yield and (b) biomass trends in KRS (2003-2023)

4.4 APSIM Model Sensitivity Analysis

During model calibration and validation, APSIM model sensitivity to various input parameters was ascertained. Table 6 shows the results of the sensitivity analysis. The sensitivity coefficient was evaluated according to Equation 4 in section 3 above.

Table 6: Shows sensitivity analysis results for five selected input parameters

Input parameter	S_c (-25%)	S_c (+25%)	Magnitude	Sensitivity level
Soil initial water	0.340	0.412	0.072	Moderate
Soil NO_3 content	0.124	0.087	0.037	Moderate
Soil NH_4 content	0.021	0.025	0.004	Low
Maize sowing density	0.035	1.818	1.783	High
Row spacing	0.136	0.006	0.130	High

Results indicate that maize sowing density is the most sensitive input parameter especially if it is overestimated during model calibration. Conversely, soil NH_4 content portrayed the lowest sensitivity, with minimal impact on maize yield when adjusted ±25% away from its median value. Maize yield was more sensitive to underestimating row spacing and soil NO_3 content than overestimating them. The NO_3 and NH_4 sensitivity results are consistent with those by (Chisanga et al., 2020), who noted a similar trend in their study.

Conclusively, two input parameters, namely; sowing density and row spacing exhibited higher uncertainty than the others. This means these two inputs are the most critical factors influencing the model's performance. Row spacing and sowing density are important agronomic techniques that have a direct effect on crop yield, growth, and resource utilization (Tobiasz-Salach et al., 2023). Higher densities can increase competition for resources such as water, light, and nutrients, potentially lowering yield. Contrarily, lower densities result in underutilization of resources, reducing overall yield (Z. Du et al., 2024; Xu et al., 2021). Moreover, as much as wider rows can increase air circulation and light penetration, they lead to increased water evaporation. Conversely, narrower rows reduce water infiltration and intensify competition for resources (Tobiasz-Salach et al., 2023). Maximum attention was paid to these input parameters during model calibration since small alterations could lead to significant discrepancies in the model's output.

However, it’s imperative to note that the model may still experience uncertainties, even after addressing the sensitivity of these two parameters. Factors such as soil infertility, pests and diseases, and weather variability may significantly influence model predictions (Hao et al., 2024). Furthermore, there’s need for site-specific recommendations considering factors such as crop variety, soil type, and climate.

4.5 Scenario Analysis of Maize Yields

4.5.1 Simulated maize yields under various planting windows

Detailed simulations of maize yields (in kg/ha) under various planting windows were generated as shown in Fig. 15 below. Appendix 3 displays these results in a tabular form.

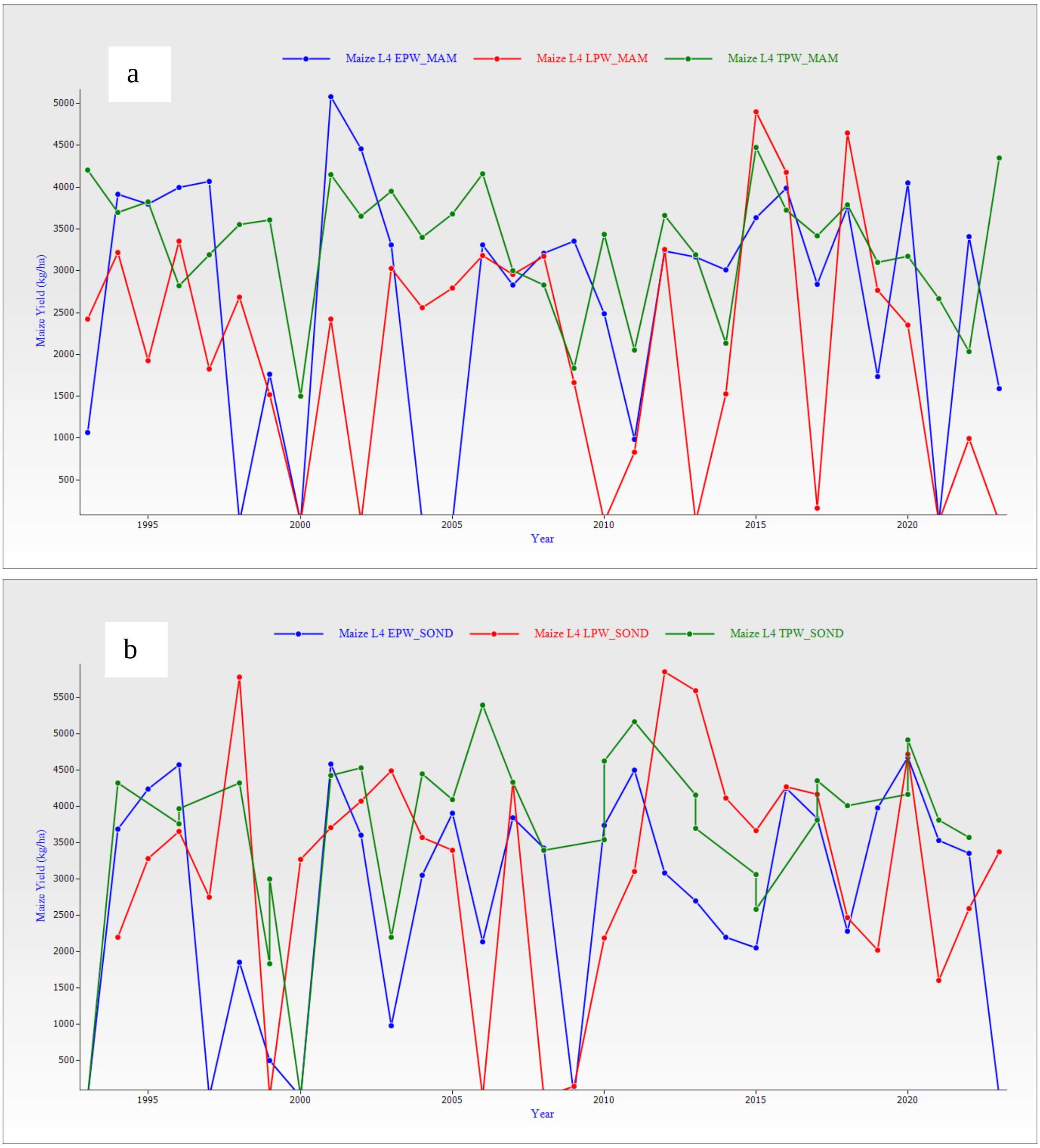


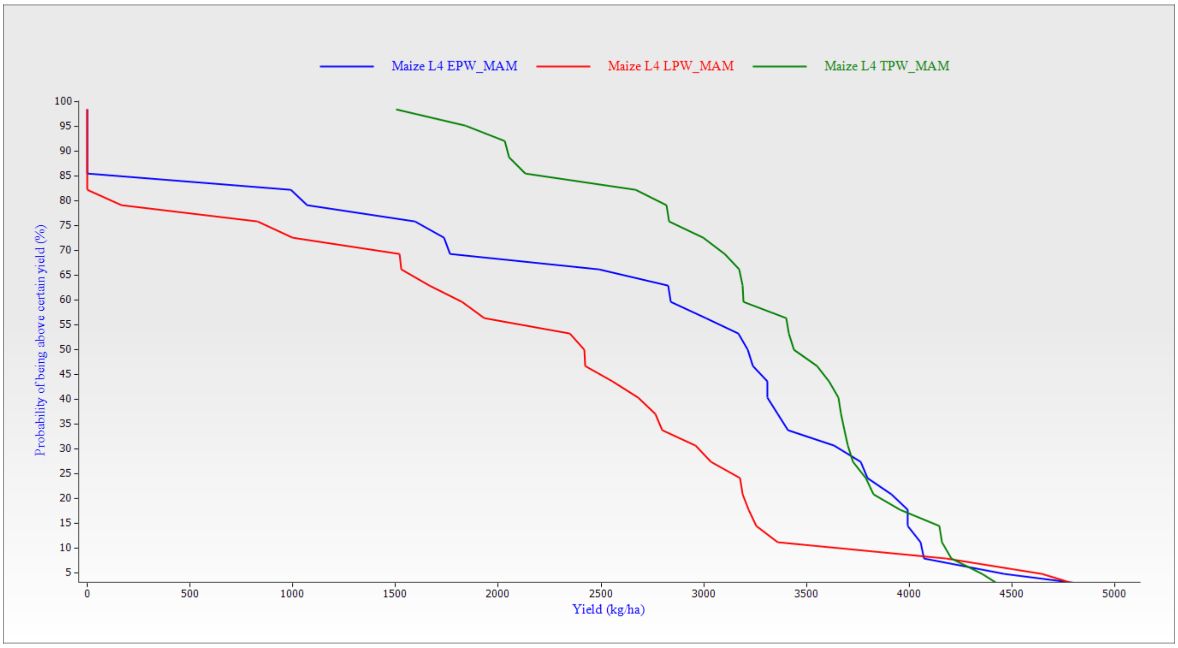
Fig. 15: Maize yield for the (a) MAM and (b) SOND planting windows at KRS

Simulated results indicated that maize farmers around KRS obtain an average yield of 2,889.5 kg/ha per season. Maize yield analysis for the MAM season from 1993-2023 indicated the best-performing windows as TPW>EPW>LPW with corresponding average yields of 3,299.7, 2,648.3, and 2076.7 kg/ha respectively. Contrarily, the best-performing SOND windows were TPW>LPW>EPW with average yields; 3,535.7, 3,046.7, and 2,730.2 kg/ha respectively. It can be witnessed that in both seasons, TPW is a generally more productive window than other windows. This implies that during this window, variables such as temperature, soil moisture, and rainfall patterns are most conducive to crop development (Srivastava et al., 2018). These findings agree with studies by (Baum et al., 2019; Beah et al., 2021; Mugiyo et al., 2021; Srivastava et al., 2018; Tofa et al., 2020) in which timely planting was associated with higher yields.

Additionally, findings indicated that SOND windows were more productive than their MAM counterparts. This might be attributed to factors like better rainfall distribution (Kisakye et al., 2018), improved soil moisture retention throughout the SOND season (Vennam et al., 2023), or pests and disease pressure (Nurhasan et al., 2022; Pawar & Varma, 2014). The fact that the SOND seasonal length around KRS is less variable as compared to MAM's could be another contibuting factor to SOND's advantaged productivity. Planting maize in MAM's late window was the riskiest, yielding the least output. This implies augmented vulnerability to late-season stresses such as increased pest and disease prevalence (Tofa et al., 2020), or drought (Babyenda et al., 2023), since the MAM season is always shorter (Ayugi et al., 2021; Omondi & Lin, 2023).

4.5.2 Probability of exceedance

Fig. 16 (a) and (b) are graphs showing the likelihood of planting windows to surpass certain maize yield values.



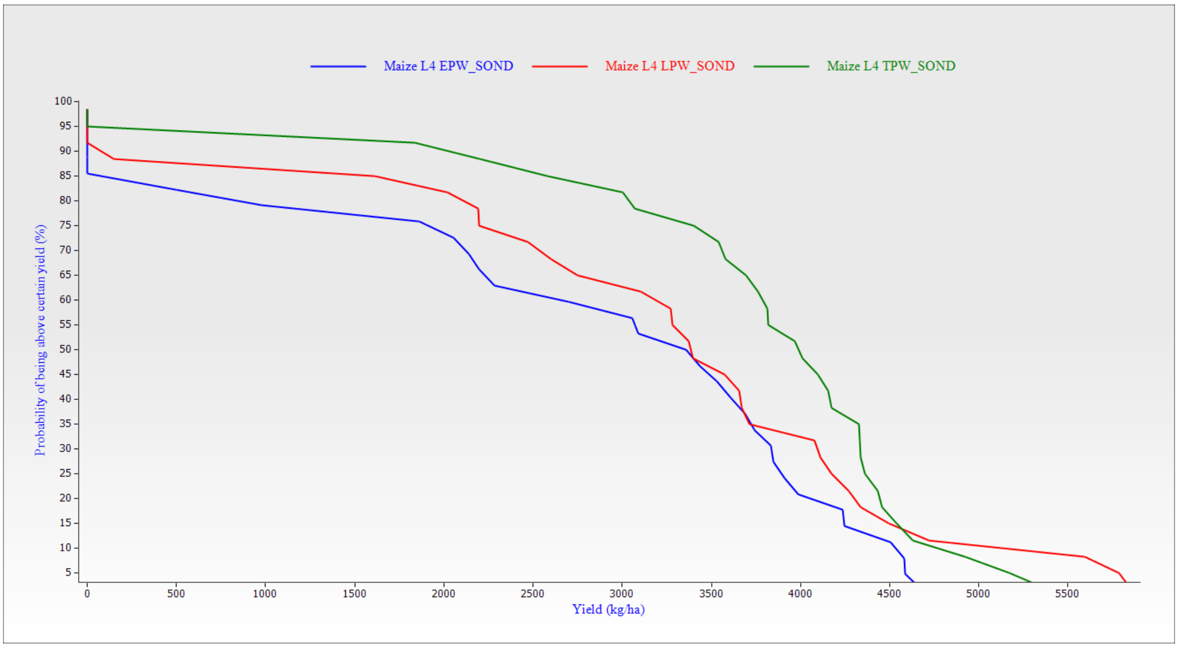


Fig. 16: Probability of exceedance for (a) MAM and (b) SOND windows (1993-2023)

For the MAM season, results indicated that when maize was planted during the TPW, the probability of obtaining yields of at least 1,500 kg/ha was ~100%. However, planting during this window could not generate yields >4,500 kg/ha. For maize planted in the EPW and LPW, there was a 15 and 18% respective chance of obtaining no yield at all. For the 1993-2023 MAM seasons, the ranges of yield possibility were; 0≤EPW≤5,100 and 0≤LPW≤4,900 kg/ha.

For the SOND season, 1993-2023 study period findings indicated a 5% chance for TPW, 8% for LPW, and 15% for EPW, of obtaining zero yield during the entire season. Furthermore, when planting was done in the TPW, there was an 80% chance of yielding at least 3,500 kg/ha. It was rather a 50% chance of obtaining the same maize yield if planted during the EPW or LPW. The probability of obtaining yield >4,700 (for EPW), >5,300 (for TPW), and >5,800 kg/ha (for LPW) were respectively zero.

These results indicate that TPW offers high yield certainty and the lowest risk of total crop failure during both seasons. These findings are in agreement with studies by (Alam et al., 2020; Xu et al., 2021) who noted a lower crop failure risk when corn is planted on time.

4.5.3 Frequencies of planting windows that recorded the highest yield per year

Table 7 below shows the number of times a planting window registers the highest yield in a given year.

Table 7: Frequency of a planting window to record the highest yield in a given year

	MAM Season	SOND Season	Total	Percentage
EPW	1	3	4	12.9
TPW	3	14	17	54.8
LPW	2	8	10	32.3
Total	6	25	**31**	
Percentage	19.4	80.6		**100**

Results indicated that for any given year from 1993 to 2023, there was a 54.8% chance of obtaining a maximum yield if maize is planted during the TPW of any season as compared to EPW and LPW with 12.9% and 32.3% respectively. The findings above further depict that planting late is generally better than early planting if a farmer is targeting maximum yield possibilities for a given year. Moreover, there was a greater (80.6%) chance of obtaining a maximum yield when maize is planted during the SOND season than during the MAM season (19.4%) of any given year. During the study period, planting maize during MAM's EPW produced the least expectations (3.2%) of generating a maximum possible yield whereas planting maize during SOND's TPW generated the greatest possibility (45.2%) of achieving the maximum yield.

These findings imply that farmers around KRS ought to prioritize planting maize during the TPW, especially within the SOND season, to maximize the possibility of achieving maximum yields. During the MAM season, farmers should consider mitigation strategies such as crop insurance, crop diversification, and/or capitalizing on early warning systems to lower the risks of poor yields.

4.6 Assessment of the Mitigation Potential of Timely Planting

To determine the effectiveness of timely sowing in mitigating climate risks, I assessed the maize yield failure rate for each planting window and categorized study years into "bad" or "good". After that, a yield variability assessment for each window was determined. Consequently, a comparison of predicted yields under timely planting informed by climate services versus early and late planting practices was conducted and a t-test was performed. This aided in evaluating the effectiveness of timely planting in mitigating climate risks and supporting our alternative hypothesis.

4.6.1 Determination of planting window yield failure rate.

Table 8 below shows the yield failure rate of each planting window during the study period. A planting window was considered a failure (F) if the window yield was less than the average yield of TPW for that season, otherwise, it was a success (S). A year was considered good if it possessed at least one successful planting window for each season of that same year, otherwise, it would be considered bad (see detailed table in Appendix 6).

Table 8: Summary of yield failure rate for MAM and SOND season planting windows

	MAM Season			SOND Season			Remarks
	EPW	TPW	LPW	EPW	TPW	LPW	
Failures	17	13	27	18	9	17	11 bad years
Rate (%)	54.8	41.9	87.1	58.1	29.0	54.8	35.5

Results indicated that MAM's LPW and SOND's EPW had the highest failure rates of 87.1% and 58.1% respectively. For both seasons, planting maize during the TPW resulted in low failure rates (29.0% for SOND and 41.9% for MAM). This implies that maize planted during the TPW exhibited greater resilience to various risks. However, findings indicate that it is generally riskier to plant maize in the MAM season than in the SOND season. This suggests that SOND offers more favorable and reliable conditions for maize growth than the MAM. Furthermore, there were more good than bad years for the period studied, with only 11 bad years out of 31. The years; 2000 and 2008 were the worst years for maize farming, registering no successful planting window highlighting the significant impact of climate variability on maize production. Contrarily, 2016 was the best year for planting maize during any window, with all planting windows registering success. Moreover, the years; 1996, 2001, and 2002 were also favourable years for maize production, with only one failing window each year.

These yield variations between planting windows and seasons indicate the significant impact of climate variability on maize production in KRS. A study by (Fransen et al., 2024) reveals that refugee farmers are more vulnerable to climate variability and extreme weather events. Increased seasonal failure rates impede the food security hopes of any community and hinder economic growth, directly compromising livelihoods (Mekonen & Berlie, 2021). The consequence is a failed effort to achieve Uganda's vision 2040, AU's Agenda 2063, and the UN Agenda 2030 of the SDGs.

4.6.2 Yield variability

Table 9 below shows the variability of maize yields for each of the planting windows of the MAM and SOND seasons in KRS for the study period 1993-2023

Table 9: Yield variability of each planting window for the MAM and SOND seasons.

	MAM			SOND		
	EPW	TPW	LPW	EPW	TPW	LPW
μ_y (kg/ha)	2648.3	3299.7	2076.7	2730.2	3535.7	3046.7
σ_y (kg/ha)	1506.8	765.6	1443.5	1588.1	1412.4	1692.7
$\boldsymbol{v_y}$ (%)	56.9	23.2	69.5	58.2	39.9	55.6

Results showed that MAM's LPW and SOND's EPW had the greatest yield variability of 69.5% and 58.2% respectively. This indicates greater yield uncertainty and potential for significant crop failure any year. For both seasons, the TPW was characterized by lower yield variability (23.2% for MAM and 39.9% for SOND). This indicates that growing maize during the TPW of any season is less risky compared to the other windows, signifying more consistent and predictable outcomes with a higher degree of stability for farmers. A study by (Ocen et al., 2021) reveals that farmers are more motivated to capitalize on investing in seasonal windows that ensure more predictable outcomes. Consistent productivity bolsters food security and economically empowers smallholder farmers, improving their livelihoods (Lolaso et al., 2024). This consequently contributes to sustainable development both at a local and national level.

4.6.3 Assessing the validity of the alternative hypothesis

Table 10 below shows the yield change when other planting windows are compared with the TPW. The t-test outputs are also presented in the table.

Table 10: Yield change (TPW vs other windows) and t-test results

Season	MAM		SOND	
	TPW vs EPW	TPW vs LPW	TPW vs EPW	TPW vs LPW
Yield Change, $\boldsymbol{\delta_y}$ (%)	24.6	58.9	29.5	16.0
Degrees of freedom, df	45	46	59	58
t statistic	-2.15	-4.17	-2.11	-1.23
P(T<=t) one-tail	0.0187	0.000067	0.0195	0.1109
t Critical one-tail	1.68	1.68	1.67	1.67
P(T<=t) two-tail	0.0373	0.00013	0.0391	0.2218
t Critical two-tail	2.01	2.01	2.00	2.00
Interpretation	H_0 Rejected	H_0 Rejected	H_0 Rejected	H_0 Accepted

On comparing the TPW yield with the yield for other windows, it was identified that planting maize in the MAM's TPW yielded 58.9% more yield than planting the same in the LPW. It also yielded 24.6% more than the EPW's yield. For the SOND season, timely planting of maize yielded 29.5% more yield than EPW's yield and 16% more yield than LPW's yield. SOND season window yield comparisons were characterized by higher degrees of freedom compared to MAM's case. Moreover, the t statistic was greater for MAM window comparisons than for SOND. The t statistic aided in determining how far the yield mean of other planting windows deviated from the TPW yield mean, relative to the standard error. Comparisons of the SOND's TPW with LPW yielded a p-value>0.05 and the absolute value of the "t statistic" less than the "t critical" value. This implies that whether planting is done in the SOND's TPW or LPW, the climate risk and yield possibilities are the same. However, for the rest of the seasonal planting window comparisons, sowing during the TPW yielded the most maize productivity and the least climate risks.

The TPW yield superiority, exhibiting substantial yield gains than other sowing windows highlights the imperativeness of timely sowing for maximizing maize yields. Moreover, the yield advantage of TPW is more pronounced in the MAM season, with greater yield variances compared to EPW and LPW. The higher degrees of freedom in SOND comparisons suggest greater variability in yield data, suggesting the MAM's TPW to be more robust, consistent, and reliable than the SOND's. In a nutshell, these findings can be utilized to advise farmers about the expected yield discrepancies across sowing windows and inform their planting decisions.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The current study utilized the APSIM crop model to quantify the impact of timely maize planting in mitigating climate risks for smallholder refugee farmers in KRS. R-Instat software was applied in the analysis. The findings reveal that sowing maize within the timely planting window (TPW) was associated with less climate risks, with the potential to significantly boost food security, enhance livelihoods, and contribute to broader development goals within the refugee farming communities. The model simulations demonstrated that timely planting resulted in lower crop failure rates and significantly higher and consistent maize yields compared to early or late sowing. This yield intensification directly translates to reduced dependence of refugees on external food aid and enhances their nutritional status, contributing to general health outcomes for refugee communities. Additionally, surplus sales from higher maize harvests can help refugee households make more money, lowering poverty rates and enabling refugees to become more independent.

However, various challenges still exist. For timely planting to be successfully implemented, it is essential to have access to timely, accurate, actionable, and affordable meteorological information, quality seeds, and the right agricultural inputs. Furthermore, the successful implementation of timely planting methods depends on enhancing the capacity of refugee farmers through training programs, agricultural extension services, and access to pertinent data and technologies. Conclusively, this study demonstrates that by promoting timely sowing practices and addressing the related challenges, policymakers and humanitarian organizations can effectually support refugee livelihoods, improve food security, and contribute to sustainable development.

5.2 Recommendations

Based on the study findings, the following recommendations were deemed crucial to mitigate climate-related agricutural risks and ensuring sustainable development in refugee contexts;

1) There's a need to provide tailored and actionable climate information dissemination. Integrating CIS within local refugee agricultural extension services to access contextualized information on weather forecasts, pest and disease outbreaks, and best management practices would be crucial in determining the right time to plant. Based on the study findings, refugee farmers should be encouraged to adhere to the recommended planting windows, based on the CIS provided before that season. Prioritizing the TPW within each season was the safest option to maximize the prospect of realizing maximum yields.
2) The government, humanitarian, and private organizations need to intensify the dissemination of agricultural extension services to provide targeted recommendations to refugee farmers on optimal planting dates and practices. Embracing the public-private partnership approach in delivering extension services adds more efficiency in the dissemination.
3) Early warning systems ought to be developed and disseminated to alert refugee farmers on potential agricultural risks such as drought and pest outbreaks based on weather forecasts. This would aid in mitigating the associated yield losses that can curtail economic growth in the already marginalized environment.
4) Crop insurance programs and safety nets should be introduced and implemented within the settlement to support refugee farmers during years/seasons of unprecedented low yields.
5) Refugee smallholder farmers should be encouraged to diversify agricultural enterprises to mitigate risks associated with any single enterprise. This will aid in absorbing the shock that often leads smallholder farmers into frustration and withdrawal. Moreover, exploring alternative off-farm livelihoods such as trading can be an effective resilience strategy for the farmers
6) Refugee farmers should be encouraged to promote the adoption of climate-resilient maize varieties and improved agronomic practices to improve yield potential and reduce the associated risk. This is a suitable long-term strategy for refugee farmers to adapt to changing climate conditions

7) Refugee farmers in KRS should be advised to adopt climate-smart agricultural practices such as implementing appropriate soil and water management practices, optimizing irrigation, improving soil fertility, and agroforestry, embracing integrated pest management, and implementing water conservation measures to boost their climate adaptive capacity. Farmers should also consider early maturing maize varieties, especially during the LPW and short seasons, to minimize exposure to late-season stresses.

Conclusively, more refined probabilistic models need to be developed to improve yield predictions and risk assessment. This would help to investigate specific contributing factors to yield variability and risk across planting windows. Overall, the study aided in understanding the probabilities of achieving maximum yields across seasons and planting windows in KRS, empowering farmers to make more informed decisions to enhance production, manage risk, and strengthen their resilience to climate variability and climate change.

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APPENDICES

Appendix 1: Consent form template used for CIS accessibility data collection

Introduction and consent form

Study title:

Can timely planting through use of climate services mitigate climate risks? An APSIM Model assessment for Kyangwali refugee settlement maize farmers.

Principal Investigator:

Mbalibulha Ezira/Pan African University of Water & Energy Sciences, Including Climate Change

Introduction and purpose of the study

Dear Respondent, you're invited to participate in a research study to ascertain the accessibility to climate information services (CIS) for maize farmers in the Kyangwali Refugee Settlement. This study aims to;

- Assess the level of awareness and use of CIS among maize farmers
- Identify the barriers to accessing and using CIS
- Gather feedback on the usefulness and relevance of CIS

If you agree to participate in this study, kindly feel free to answer a short questionnaire which will take approximately 15-20 minutes.

Risks and benefits

There are no risks anticipated in undertaking this study. your participation will contribute to a better understanding of maize farmers' need for CIS. Consequently, it will lead to improvements in the design and delivery of CIS to farmers in refugee settings.

Confidentiality

The information you provide will be used exclusively for the research study and not for any commercial gains. It will remain confidential to the extent permitted by law. The data collected will be anonymized and aggregated for analysis.

Voluntary participation

Your participation in this study is entirely voluntary and you have a right to withdraw from the study at any time without penalty.

Please consent:

I, ____, grant permission to use my information for this study's analysis.

Signature/thumbprint: ________________________ Date: ___________________________________

Mobile: ______________________ KRS Farming zone: ____________________________________

Enumerators Name: _____________________________________ Signature: __________________

Appendix 2: The onset and cessation dates for each season (1993-2023)

	MAM Season		SOND Season	
Year	Onset	Cessation	Onset	Cessation
1993	1993-03-08	1993-05-17	1993-08-22	1993-12-05
1994	1994-03-28	1994-06-30	1994-08-19	1994-12-06
1995	1995-03-25	1995-05-31	1995-09-12	1995-11-24
1996	1996-03-21	1996-06-13	1996-08-20	1996-12-28
1997	1997-03-25	1997-05-16	NA	1997-12-25
1998	1998-03-23	1998-06-06	NA	1998-11-18
1999	1999-03-11	1999-05-27	1999-08-27	1999-12-20
2000	NA	2000-05-11	2000-08-15	2000-11-15
2001	2001-03-26	2001-05-05	2001-08-21	2001-11-21
2002	2002-03-09	2002-06-28	2002-08-19	2002-12-18
2003	2003-03-24	2003-06-18	2003-08-22	2003-12-01
2004	2004-02-26	2004-05-31	2004-08-24	2004-11-25
2005	2005-03-17	2005-06-07	2005-08-18	2005-12-06
2006	2006-03-08	2006-06-23	2006-09-03	2006-12-15
2007	2007-03-16	2007-05-17	2007-08-18	2007-11-17

2008	2008-03-23	2008-06-09	2008-08-20	NA
2009	2009-03-31	2009-05-12	NA	NA
2010	2010-02-21	2010-05-06	2010-08-23	2010-11-23
2011	2011-03-06	2011-06-27	2011-08-15	2011-12-19
2012	NA	2012-05-23	2012-08-29	2012-12-30
2013	2013-03-09	2013-06-17	2013-09-03	2013-12-07
2014	2014-03-13	2014-06-04	2014-08-26	2014-12-01
2015	2015-03-06	2015-06-04	2015-08-21	2015-12-19
2016	2016-03-08	2016-06-18	2016-09-16	2016-12-31
2017	2017-02-22	2017-06-14	2017-08-25	2017-11-18
2018	2018-02-26	2018-06-05	2018-08-20	2018-12-11
2019	2019-03-28	2019-06-30	2019-08-31	2019-12-15
2020	2020-03-09	2020-05-07	2020-08-16	2020-12-04
2021	NA	2021-05-11	2021-09-02	2021-12-26
2022	2022-03-21	2022-06-20	2022-09-01	2022-12-13
2023	2023-03-01	2023-06-21	2023-09-21	2023-11-28

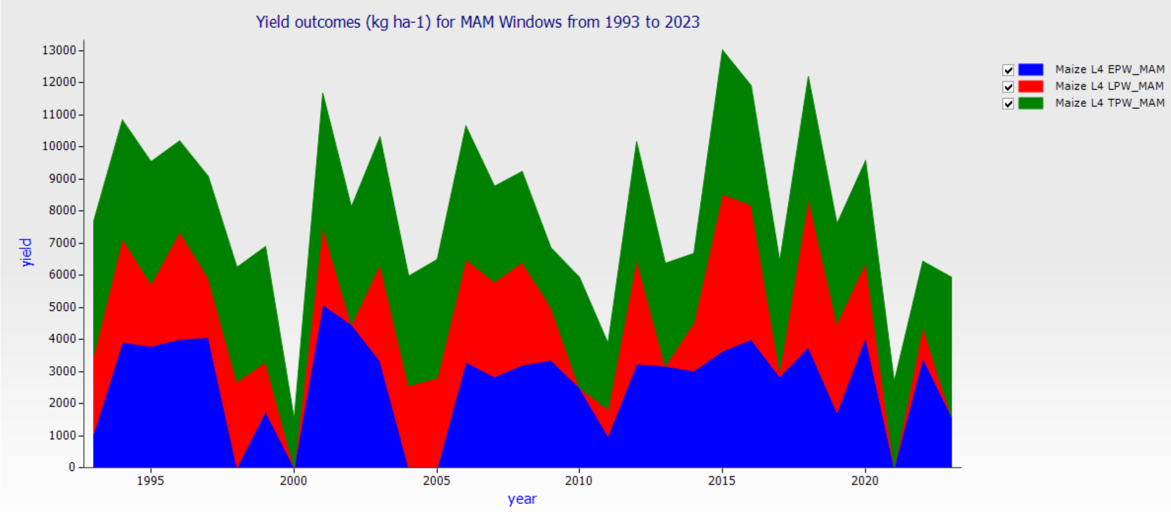
N/A = No date fitting the conditions set for the onset/cessation of the season

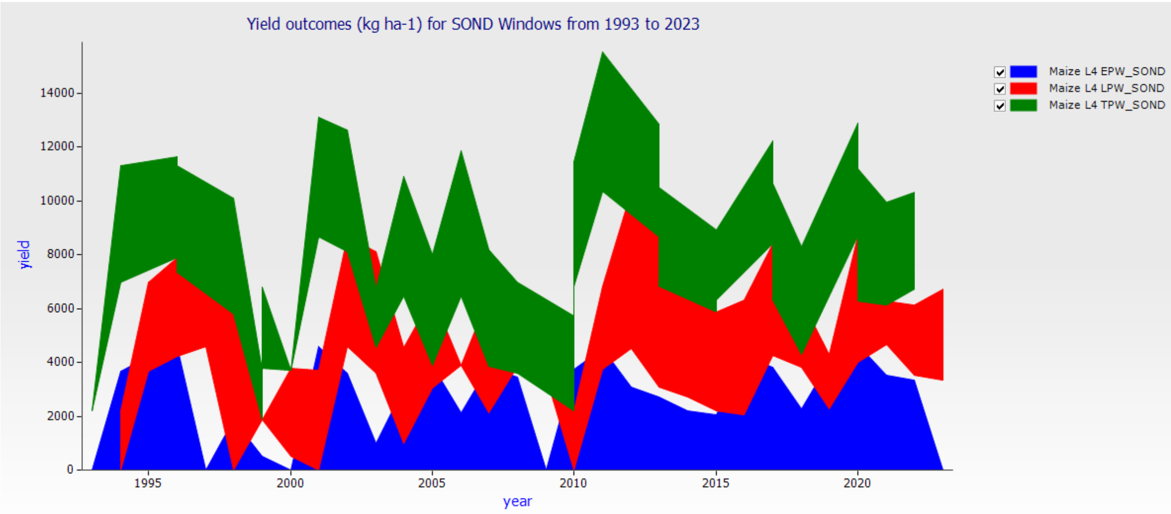
Appendix 3: Simulated maize yield per planting window of each season

	Simulated Maize Yield (kg/ha)							
	MAM Season			SOND Season			Annual Total	Annual Average
Year	EPW	TPW	LPW	EPW	TPW	LPW		
1993	1071.7	4203.6	2422.5	0	0	0	7697.8	1283.0
1994	3913.4	3699.9	3219.2	3688.9	4329.6	2199.5	21050.5	3508.4
1995	3795.1	3825.5	1929.6	4237.5	3760.9	3283.7	20832.3	3472.1
1996	3994.3	2819.1	3359	4579.9	3967.2	3654.2	22373.7	3729.0
1997	4072.2	3191	1823.1	0	4330	2750.9	16167.2	2694.5
1998	0	3552.3	2682.5	1860.4	1835.7	5785.9	15716.8	2619.5
1999	1766.1	3608.7	1517.8	501	3002	0	10395.6	1732.6
2000	0	1504.2	0	0	0	3272.7	4776.9	796.2
2001	5083.1	4147.5	2420	4586.1	4432.6	3714.3	24383.6	4063.9
2002	4462.8	3655.6	0	3607.5	4538.8	4078.3	20343	3390.5
2003	3309.1	3955.2	3033.3	977.3	2203.8	4492.9	17971.6	2995.3
2004	0	3400.8	2557.1	3057.4	4455.7	3574.2	17045.2	2840.9
2005	0.1	3684.6	2798.5	3909.8	4094.8	3396.3	17884.1	2980.7
2006	3308.4	4158.7	3188.1	2139.1	5399	0	18193.3	3032.2
2007	2828.4	2999.2	2958.8	3848	4335.3	4338.1	21307.8	3551.3
2008	3213.9	2829.6	3178.3	3434	3401.7	0	16057.5	2676.3
2009	3359.5	1838.2	1666.3	0	3540.1	148.8	10552.9	1758.8
2010	2487.7	3438	0	3740	4628.2	2190.6	16484.5	2747.4

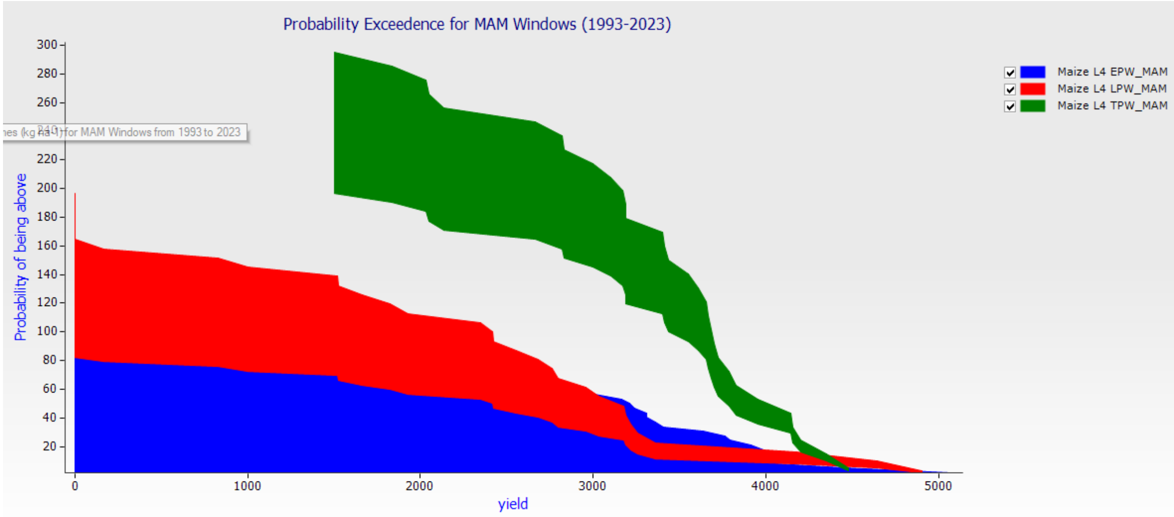
2011	989.5	2052.2	828.8	4504.5	5170.1	3103.2	16648.3	2774.7
2012	3238.7	3667.2	3257.4	3089.6	4154.7	5857.7	23265.3	3877.6
2013	3166.8	3190.6	0	2700.9	3695	5593.6	18346.9	3057.8
2014	3010.8	2133	1526.9	2198.9	3068.7	4112.1	16050.4	2675.1
2015	3636	4480	4902.6	2052.9	2582.5	3668.6	21322.6	3553.8
2016	3992.2	3725.6	4179.8	4248	3816	4269.1	24230.7	4038.5
2017	2840.8	3415.3	165.9	3831.3	4359.4	4171.5	18784.2	3130.7
2018	3762.2	3788.6	4647.5	2284.7	4010	2469.1	20962.1	3493.7
2019	1737.8	3101	2763.8	3985.2	4173.8	2018.4	17780	2963.3
2020	4054.7	3171.7	2348.9	4681.6	4924.1	4722.3	23903.3	3983.9
2021	0	2667.7	2	3532.4	3819	1610	11631.1	1938.5
2022	3407.6	2031.3	999.2	3358.7	3576.8	2598.6	15972.2	2662.0
2023	1595.9	4354	0	0	0	3372.8	9322.7	1553.8
Total	82098.8	102289.9	64376.9	84635.6	109605.5	94447.4	**537,454.1**	
Average	2648.3	3299.7	2076.7	2730.2	3535.7	3046.7		**2,889.5**

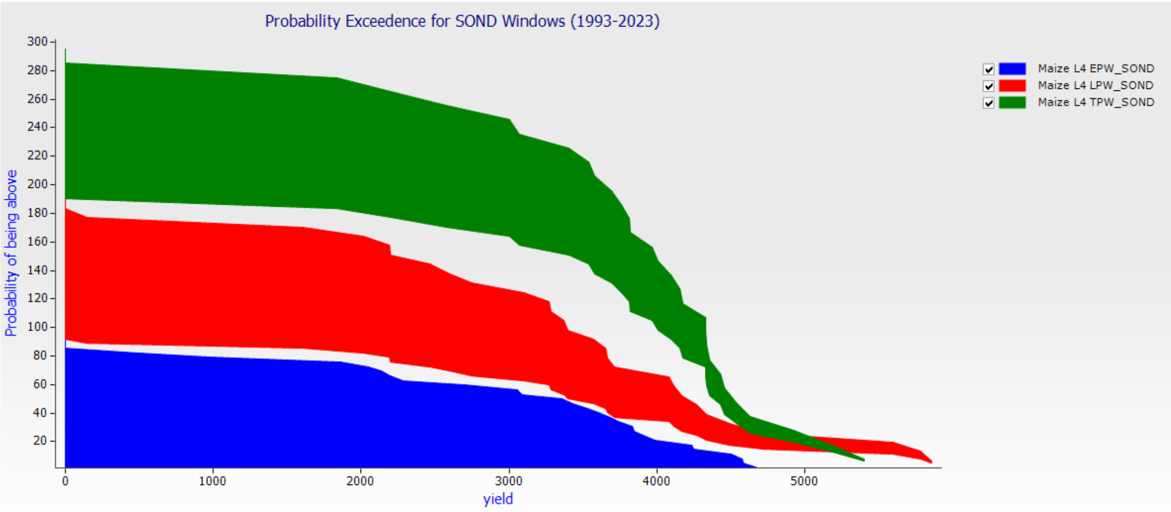
Appendix 4: Stacked diagram for MAM and SOND planting window yield outcomes





Appendix 5: Probability of exceedance for MAM and SOND planting window yields





Appendix 6: Yield failure rate of each planting window of the MAM and SOND seasons

	MAM Season			SOND Season			Failure rate (%)	Remarks (good or bad)
Year	EPW	TPW	LPW	EPW	TPW	LPW		
1993	F	S	F	F	F	F	83.3	Bad
1994	S	S	F	S	S	F	33.3	Good
1995	S	S	F	S	S	F	33.3	Good
1996	S	F	S	S	S	S	16.7	Good
1997	S	F	F	F	S	F	66.7	Good
1998	F	S	F	F	F	S	66.7	Good
1999	F	S	F	F	F	F	83.3	Bad
2000	F	F	F	F	F	F	100.0	Bad
2001	S	S	F	S	S	S	16.7	Good
2002	S	S	F	S	S	S	16.7	Good
2003	S	S	F	F	F	S	50.0	Good
2004	F	S	F	F	S	S	50.0	Good
2005	F	S	F	S	S	F	50.0	Good
2006	S	S	F	F	S	F	50.0	Good

2007	F	F	F	S	S	S	50.0	Bad
2008	F	F	F	F	F	F	100.0	Bad
2009	S	F	F	F	S	F	66.7	Good
2010	F	S	F	S	S	F	50.0	Good
2011	F	F	F	S	S	F	66.7	Bad
2012	F	S	F	F	S	S	50.0	Good
2013	F	F	F	F	S	S	66.7	Bad
2014	F	F	F	F	F	S	83.3	Bad
2015	S	S	S	F	F	S	33.3	Good
2016	S	S	S	S	S	S	0.0	Good
2017	F	S	F	S	S	S	33.3	Good
2018	S	S	S	F	S	F	33.3	Good
2019	F	F	F	S	S	F	66.7	Bad
2020	S	F	F	S	S	S	33.3	Good
2021	F	F	F	F	S	F	83.3	Bad
2022	S	F	F	F	S	F	66.7	Good

2023	F	S	F	F	F	F	83.3	Bad
Failures	17	13	27	18	9	17		11 bad years
Rate (%)	54.8	41.9	87.1	58.1	29.0	54.8		35.5