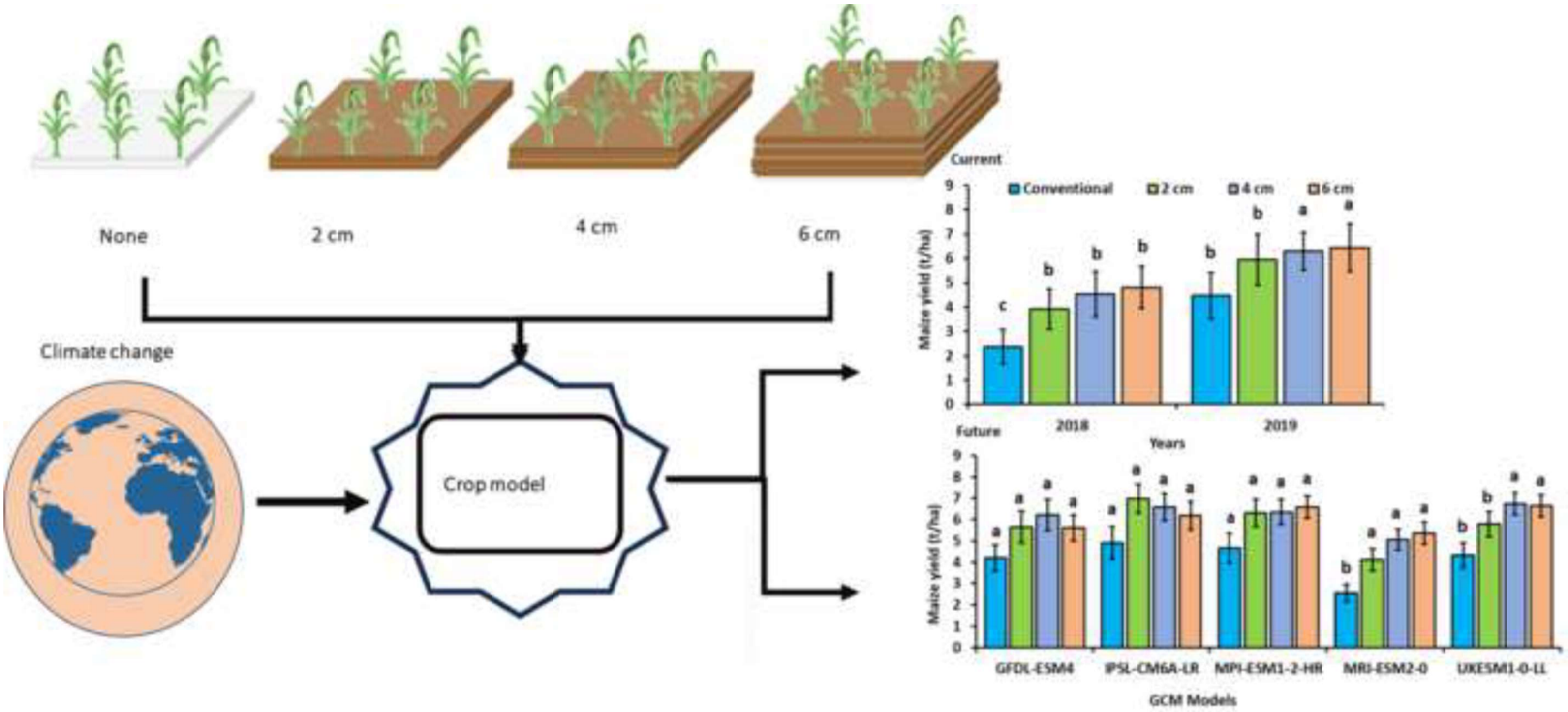
Highlights

- Mulch and crop models guide adaptation in rainfed maize under climate change risks
- Mulching can improve maize yield now, but future impacts are less understood
- AquaCrop model accurately predicted yield, with R^2 values of 0.84 - 0.95
- Mulching boosts yield by up to 40% under current conditions with 4 - 6 cm thickness
- Future yields may increase by 53% with 2 cm mulch under the SSP3-7.0 scenario

Graphical Abstract



Declaration of interests

☒The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Straw Mulching Enhances Rainfed Maize Yield Under Climate Change Scenarios

Alex Zizinga[a d]*, Abel Chemura[b], Alex C. Ruane[c], Britta Tietjen[a]

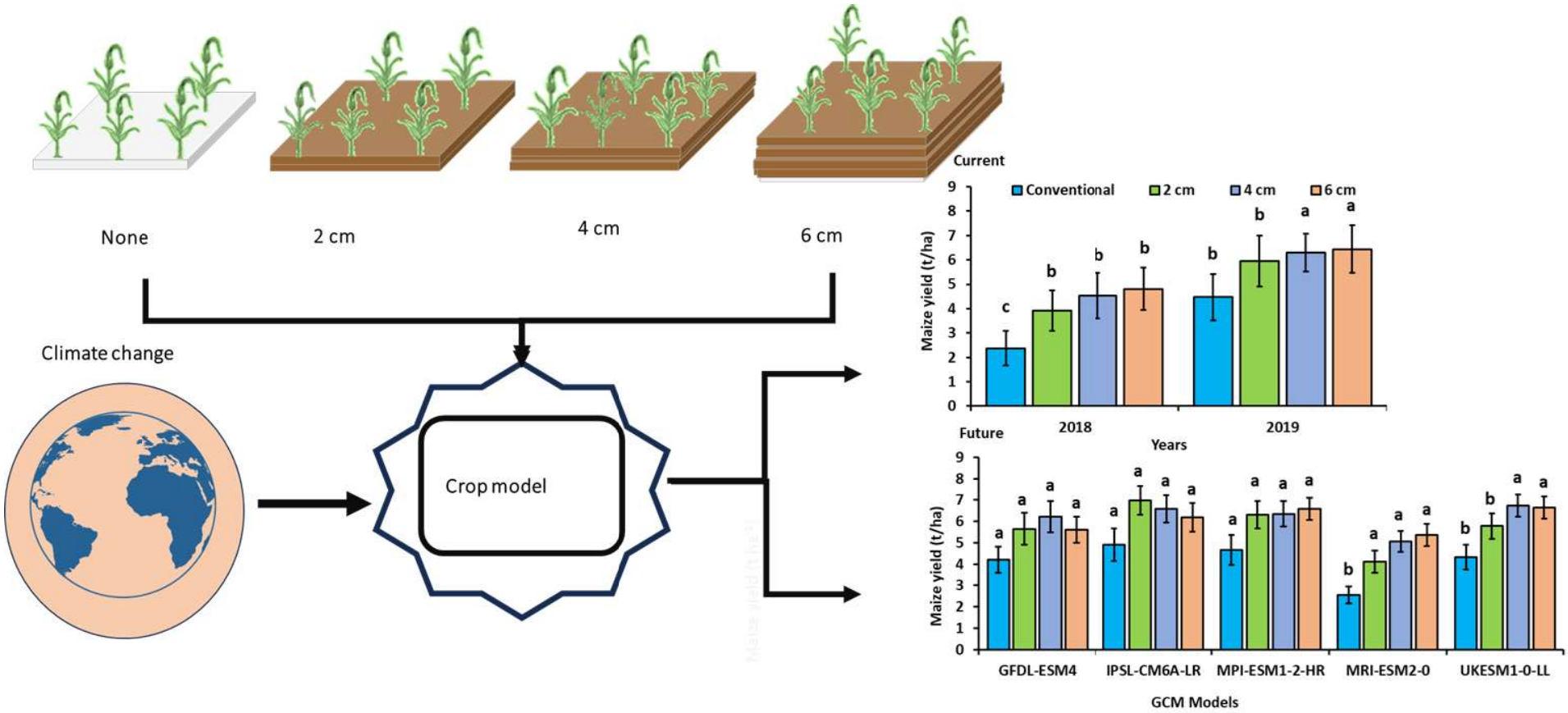
[a]Freie Universität Berlin, Institute of Biology, Theoretical Ecology, Königin-Luise-Str. 2/4, Gartenhaus, D-14195 Berlin, Germany
[b] University of Twente, Enschede, The Netherlands
[c] NASA Goddard Institute for Space Studies (GISS), New York, NY, United States of America
[d] Makerere University, P.O. Box 7062 Kampala, Uganda.
Corresponding author. E-mail address: azizinga@gmail.com

Abstract

Maize cropping systems dominate crop land use in Sub-Saharan Africa (SSA), where rainfed agriculture is highly vulnerable to climate variability, exacerbating hunger and poverty. Effective soil water management practices (SWMPs), such as straw mulching, are known to improve water availability and enhance maize productivity. However, limited research studies have focused on straw mulch thicknesses and depth impact on maize rainfed production systems of SSA. This study evaluates the effects of different straw mulch thicknesses (2 cm, 4 cm, and 6 cm) on maize yield simulated using the AquaCrop model under the low (SSP1-2.6) and the high (SSP3-7.0) emission climate change scenarios from the IPCC's selected CMIP6 climate models. Field experiments with varying straw mulch thicknesses (2 cm, 4 cm, and 6 cm) were used to calibrate the AquaCrop model, which was then applied to simulate maize yields across current (2018 – 2019) and future (2020 – 2099) periods. Results showed that, straw mulch thickness significantly influences maize yields, with 4 cm and 6 cm treatments increasing maize yield by up to 40%. The 2 cm mulch, under the high emission scenario, led to a 53% yield increase, with the 4 cm mulch being identified as the optimal thickness for maximizing yield and water use efficiency (WUE). These findings suggest that straw mulch thickness should be adjusted to regional climatic conditions for optimal effectiveness. This study highlights the importance of integrating SWMPs with climate adaptation strategies to sustain maize productivity and improve food security in the context of climate change.

Keywords: AquaCrop model, soil water management, mulch thickness, maize yield, climate change.

Graphical abstract



1. Introduction

Climate change is a pressing grand global challenge of the 21st century, affecting the livelihoods and natural resources of the Earth. It poses substantial implications for agriculture in sub-humid tropical regions dominated with rainfed production systems due to increasing water shortages and availability (Ayanlade et al., 2022; Dickerson et al., 2021). In Uganda, a country heavily dependent on rainfed agriculture, climate projections indicate heightened rainfall variability and rising temperatures that directly threaten soil moisture availability and crop productivity (Ayanlade et al., 2018; Harrison et al., 2019; Ongoma et al., 2018; Trambauer et al., 2013). This is a particular concern for high water-use crops like maize, which is widely cultivated and often intercropped to maximize land use efficiency (FOASTAT, 2017). Although maize accounts for nearly 30% of cereal production in Africa (Boote et al., 2015; Shiferaw et al., 2014) and plays a critical role in Uganda's food systems (Kaizzi et al., 2012), yields remain below global averages (< 2 t/ha), largely due to inadequate adaptation to climatic stresses and limited soil water management practices to support optimal growth and productivity. Continuous cultivation without sufficient soil conservation measures has further exacerbated productivity losses affecting ~90% of smallholders (Okoboi, 2010; Kaizzi et al., 2012). Many practices such as half moon pits, contour bunds, Zai pits, cover crops, application of organic amendments such as compost and manure, tied ridges or contour bunds for water retention, among others have been reported in various regions across the sub-humid tropics of Africa (Biazin et al., 2012; Sawadogo et al., 2011).

Among the recommended climate change adaptation strategies, straw mulching has been recognized for its potential to improve soil moisture retention and reduce evapotranspiration under rainfed conditions (Kader et al., 2017; J. Y. Wang et al., 2021; X. Wang et al., 2014). However, the performance of different straw mulch thicknesses under current and future climate conditions remains poorly understood, especially in sub-humid zones characterized by high seasonal rainfall variability. While existing studies have explored soil water conservation technologies through modeling (Araya et al., 2015; Arumugam et al., 2023; Boote et al., 2015; Jägermeyr et al., 2021; Kikoyo and Nobert, 2016; Teshome et al., 2024; Zizinga et al., 2024), few have explicitly examined the long-term effects of straw mulch thicknesses on maize yields using climate projections based on the Coupled Model Intercomparison Project Phase 6 (CMIP6) scenarios. This limits evidence-based guidance on optimal mulch application for smallholder farmers facing increasing climate risks.

To address this knowledge gap, we used the AquaCrop biophysical model to evaluate the effects of varying straw mulch thicknesses (2 cm, 4 cm, and 6 cm) on maize productivity under current and projected climate change scenarios in mid-western Uganda. This region typifies rainfed maize systems in East Africa, where straw mulch is readily available but its application is constrained by insufficient data and localized recommendations.

By calibrating the model with experimental maize yield data collected over two growing seasons, we quantified the potential of straw mulch as a cost-effective, climate-resilient soil water management strategy. This study also informs Uganda's Climate Smart Agriculture strategy, National Adaptation Plans (NAPs), and Nationally Determined Contributions (NDCs), helping to strengthen extension services and guide farmer-level implementation. Additionally, this provides one of the first long-term, process-based assessments of mulch thickness effects on maize yields under climate change conditions in Uganda. It offers actionable insights for improving soil water productivity in rainfed systems and highlights the need for targeted, locally adaptable technologies to build climate resilience in smallholder agriculture. While previous studies such as Zhang et al. (2020) explored similar themes in China, our work uniquely integrates localized SWMPs, CMIP6 datasets, and AquaCrop simulations to assess future impacts on maize yield and water use efficiency under Uganda agro-ecological conditions.

2. Methodology

2.1 Study area

The study was conducted in mid-western Uganda which lies within the western part of the country (Fig.1). This region experiences a sub-humid climate (Uganda Meteorological Authority, 2019), with an average annual precipitation of 1300 mm. Over 80 % of the rainfall occurs during two distinct seasons of March, April, and May while the second rainy season runs from September, October, and November each calendar year. During the maize growing period, the precipitation ranged between 429 mm – 529 mm representative of typical growing conditions and seasonal distribution in the study area.

This area is particularly susceptible to the impacts of climate change due to various factors such as erratic weather patterns, dependence on rain-fed agriculture, and limited economic and institutional capacity to cope with and adapt to climate-related issues, including extended periods of drought (Zizinga et al., 2022).

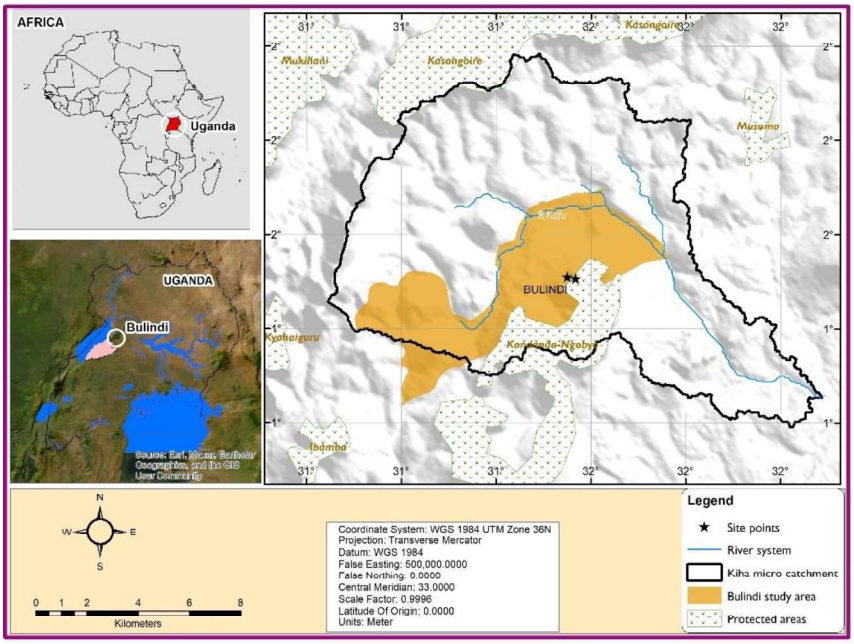


Fig.1. Map showing the location of the study area in Uganda and the insert shows the location of Uganda in Africa.

2.2. Field experiment

A completely randomized block design field experiment was conducted for two years (2018 – 2019). It was replicated four times in plots measuring 5 m × 5 m plots with border widths of 1 m and 2 m between plots, and blocks, respectively. Maize was planted at 5 cm depth at a spacing of 75 cm × 30 cm and thinning was done two weeks after planting to maintain one plant per hill, 111 plants in all the four selected soil water management practices of straw mulch of 2 cm (M2), 4 cm (M4), and 6 cm (M6) thicknesses covered at the soil surface in each treatment plot. Also, the conventional practice or control (C) consisted of land open tilling without any straw mulch. The plants were, 44,444 per hectare for all the four treatments. Seasonal maize biomass was collected by sub-sampling from each plot for the years 2018 – 2019 and the experiment focused on crop parameters for maize biomass in the above described SWMPs as treatments in the entire experiment.

The steps are shown in Fig.2 which have been followed to assess the impacts of selected soil water management practices (SWMPs) in Uganda. The first step was to calibrate the AquaCrop model using data of 2018, and validate with 2019 maize biomass from the observed field experiment.

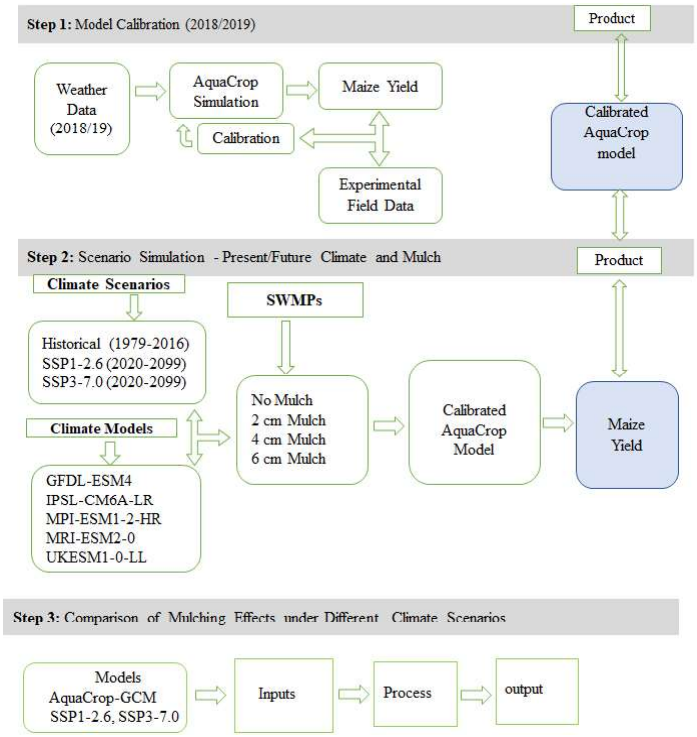


Fig.2. Methodology to assess the impacts of climate change and soil water management practices (SWMPs) on maize yields.

In the second step, the AquaCrop model was employed to project maize yields under various climate scenarios, including different SWMPs (Control, 2 cm, 4 cm, and 6 cm mulch thicknesses). The control or conventional treatment was without any SWMPs, and it is a typical farm cultivation practice used in the study area. Also, different time frames or periods are used in the study including the current climate period of 2018 – 2019 and three future periods of 2020 – 2039, 2040 – 2059, 2060 – 2079, 2080 – 2099), with two emission scenarios (SSP1-2.6 and SSP3-7.0). This step also involved a multidimensional comparison of the selected SWMPs under climate change conditions. All simulations were conducted at a spatial resolution of 0.5° x 0.5° (approximately 55 x 55 km²). The impacts of soil water management practices were assessed using integrated assessment models from the General Circulation Models (GCMs) of the sixth phase of the Coupled Model Intercomparison project (CMIP6). This combines and integrates climate change information from CMIP5-modeled RCPs and Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (Jia et al., 2022; Tebaldi et al., 2021). It also introduced new projection scenarios and our study included these in the CMIP6 model intercomparison project (O'Neill et al., 2016; Feng et al., 2025). The study focuses on scenarios SSP1-2.6 and SSP3-7.0 from the IPCC's 6th Assessment Report (IPCC, 2021), which represent a spectrum of potential future socioeconomic and emissions pathways (Arias et al., 2021). The SSP1-2.6 represents a moderate emission scenario requiring global cooperation and policy-driven efforts to mitigate climate change (Jia et al., 2022). It envisions a sustainable future with global warming likely

kept below 2°C, in line with the Paris Agreement goals. In contrast, SSP3-7.0 depicts a high greenhouse gas emissions scenario in future with substantial challenges for mitigation and adaptation due to minimal climate policy interventions (Arumugam et al., 2023). These scenarios integrate radiative forcing and socioeconomic influences, offering a diverse range of future conditions. Although these scenarios have received attention, there are limited studies in Uganda available on their long-term negative effects and potential solutions.

2.3. Climate data, emissions scenarios, and climate indicators

To evaluate the current climate and historical climate changes, this study utilizes the W5E5 dataset (Lange, 2019; Cucchi et al., 2020; Karger et al., 2023). This dataset integrates simulations from global weather models, satellite observations, and weather station data, covering the period from 1979 – 2016 with daily temporal resolution and a global spatial resolution of 0.5° x 0.5° (approximately 55 km x 55 km). The W5E5 dataset supports climate bias adjustment GCMs used in ISIMIP3b (Karger et al., 2023). This study incorporates future climate projections from ISIMIP3b, including bias-adjusted temperature (maximum and minimum), precipitation, and evapotranspiration (ET) simulations from five GCMs using downscaled CMIP6 data for detailed climate impact analysis.

The ISIMIP3b historical simulations span from 1850 – 2014, while future projections extend from 2015 to 2100, all at a daily temporal resolution and a spatial resolution of 0.5° x 0.5°. The analysis uses the period from 1995 – 2014 as a reference and examines four future periods: 2020 – 2039, 2040 – 2059, 2060 – 2079 and 2080 – 2099. The GCMs utilized in the ISIMIP3b project climate conditions with the GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL models (Lange, 2019). These models present varied projections due to inherent uncertainties in climate modeling which may originate from conservative estimates of potential climate changes anticipated with respective individual model results.

2.4. AquaCrop model inputs

In this study, we apply the AquaCrop, a widely used process-based crop model that simulates crop growth and yield as a function of soil-plant-atmosphere and water dynamics model (Doorenbos and Pruitt, 1977; Raes et al., 2006; Steduto et al., 2009). The crop input data in the model (Table 1) consisted of conservative parameters (maize crop phenology and water stress) and non-conservative parameters (plant density, time of sowing, germination period, rooting depth, growing degree days to reach flowering and maturity stages). AquaCrop model also uses daily weather data (air temperature, rainfall, reference evapotranspiration (ETo), and carbondioxide concentration), soil surface, and profile information with detailed crop management characteristics.

Crop yield is influenced by weather and other field inputs such as soil conditions and farmers' agronomic practices. Biophysical crop process-based simulation models like AquaCrop incorporate interactions among soil, water, plant, and atmospheric conditions. Additionally, the model calculates

crop productivity through processes such as canopy development, crop transpiration, biomass accumulation, and final yield. It incorporates input variables related to climate, crop characteristics, soil properties, and agricultural management practices (Raes et al., 2006), generating comprehensive datasets covering crop growth, yield, and soil water dynamics.

Soil properties like soil texture, saturated hydraulic conductivity, bulk density, and other hydraulic parameters were used as inputs for the AquaCrop model to create the soil file (Table 1). Bulk density was determined using the undisturbed soil samples with the core method, and core samples were used to measure saturated hydraulic conductivity (θks) using the constant head method (Eijkelkamp Soil and Water, 2017). The model's initial hydraulic parameters, including field capacity, permanent wilting point, and soil water at saturation, were estimated using the Rosetta pedotransfer functions (Schaap et al., 2001). In this study the capillary rise effects on soil water were not simulated due to the groundwater table being below the rooting zone (Steduto et al., 2012), and other parameters were sourced from a previous study (Zizinga et al., 2022).

Table 1. Soil hydraulic input parameters

Depth (cm)	θ_s (cm³ cm⁻³)	θ_{ks} (cm d⁻¹)	θ_{fc} (cm³ cm⁻³)	BD (g cm⁻³)	θ_{pw} (cm³ cm⁻³)
0–10	0.45	10.6	0.33	1.38	0.21
10–20	0.48	16.8	0.34	1.38	0.21
20–30	0.48	9.3	0.36	1.36	0.24
30–40	0.48	5.4	0.39	1.34	0.26

Note: θs is the saturated soil water content (cm³ cm⁻³); θ_{ks} is the saturated hydraulic conductivity (cm d⁻¹); θ_{fc} is the field capacity (cm³ cm⁻³); θ_{pw} is the permanent wilting point (cm³ cm⁻³); **BD** is the bulk density (g cm⁻³) (Zizinga et al., 2022).

2.5. Model calibration

For this study, we used crop data from 2018 for calibration (Table 2) to simulate maize yields under rainfed conditions in mid-western Uganda specifically for maize biomass yield while for validation, the year of 2019 crop data was used by comparing the field measurements with simulated maize biomass yield. The model best fit was statistically and graphically assessed with illustration using the R statistical tool version 3.6.4 (R Core Team, 2020).

Table 2. Crop parameters of AquaCrop model

	Crop variables	Value, descriptions, and units
Conservative Parameters		
	Base temperature	9 °C
	Upper temperature	34 °C
	Maximum rooting depth	0.45 m
	Canopy growth coefficient (CGC)	0.10988 per day CC increase
	Canopy decline coefficient (CDC)	0.1003 per day CC decrease
Non-Conservative Parameters		

Effect of canopy cover in late season	60 CC effect on soil evaporation
Soil surface covered by an individual seedling	5 CC effect on soil evaporation
Plant population per hectare	44,444 ha^{-1}
Maximum canopy cover (CCx)	0.84 (%) depends on plant spacing
Germination period	5 -6 days
Time of sowing to maximum rooting depth	61 days
Senescence stage	114 days
Maturity time	140 days
Time from sowing to flowering	59 days
Flowering stage duration	8 days

2.6. Soil Water Management (SWM) practices

In this study, we implemented four soil water management practices with mulch at different thicknesses (2 cm, 4 cm, and 6 cm) in the AquaCrop model to assess yield impacts for current and future climate indicated in section 2.3.

First, mulching with straw dry grass is used to increase soil moisture storage in rainfed maize production and insulate the soil surface for soil evaporation (Kaer et al., 2018; El-Beltagi et al., 2019; Demo & Asefa, 2024). In the present study, mulch thicknesses of 2 cm, 4 cm, and 6 cm of straw mulch were used. Studies in southern Africa and the Loes Plateau of Northern China, have conducted studies on the adoption of mulch and its ability to increase water capture and storage, boosted maize yield, and enhance resilience to drought compared to conventional tillage practices (Biazin et al., 2012; Lin et al., 2016; Zhang et al., 2014; Zizinga et al 2022; Lamptey et al., 2020; Lipper et al., 2014; Mhlanga, 2021; Ngetich et al., 2014). Mulch as a soil and water conservation technique for crop production could increase maize yield and improve food security in tropical rainfed-based production systems.

2.7 Simulation of mulch thicknesses in AquaCrop Model

In the AquaCrop model, field management input parameters included the soil moisture collected using the Frequency Domain Reflectometry (FDR) probes (Delta-T Devices Ltd., 2006). Values of 85% for the control treatment and 86% for mulch of 2 cm, 4 cm, and 6 cm thicknesses were obtained from the field experimental plots and included as input in the AquaCrop model.

The application of AquaCrop model version 6.1 (http://www.fao.org/aquacrop/en/) considers alternatives of percentage soil cover like variations in mulch thicknesses (Steduto et al., 2009), and these model features were included in the present study for all the mulch thicknesses. The effect of mulch was simulated in the AquaCrop model with a percentage soil cover based on soil water content of 40%, 90%, and 100% for mulch of 2 cm (M2), 4 cm (M4), and 6 cm (M6) thickness, respectively, and this input was also applied in the calibration process based on recommended ranges for maize growing conditions (Hsiao et al., 2009).

2.8. Statistical analysis

The model was evaluated using paired observed (O_i) and simulated (P_i) final maize biomass which were combined to determine the coefficient of determination (R^2) describing the proportion of variance explained by the model with ranges between 0 and 1 as illustrated in (Eq 1), model efficiency (EF) an evaluation index for the EF that determines the relative change in residual variance between O_i and P_i with a range from 0 to 1 (Nash and Sutcliffe, 1970), and this is set in (Eq 2). Additional statistical measures including the root mean square error (RMSE t/ha) measuring the average magnitude of prediction errors computed to measure differences between O_i and P_i values as in (Eq 4) by Loague and Green, (1991),Willmott Index of agreement (d) depicting relative measure of error, ranging from 0 (disagreement) to 1 (agreement) in (Eq 3), and the percentage bias (PBIAS) computed to measure tendencies of larger and smaller O_i and P_i values with a range of 0% indicating a positive bias, while negative values specify under estimation due to model bias (Gupta et al., 1999), and this is shown in the (Eq 5).

$$R^2 = \frac{[\sum_{i=1}^{n}(0_i - \overline{0})\,(P_i - \overline{0})]^2}{\sum_{i=1}^{n}(0_i - \overline{0})^2 \times \sum_{i=1}^{n}(P_i - \overline{P})^2} \quad \text{(Eq 1).}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(P_i - \overline{0})^2}{\sum_{i=1}^{n}(P_i - \overline{0})^2} \quad \text{(Eq 2)}$$

$$d = 1 - \frac{\sum_{i}^{n=1}(|P_i - Oi_|)^1}{\sum_{i}^{n=1}(|P_i| - Oi_|)^1} \quad \text{(Eq 3)}$$

$$RMSE = \frac{\sqrt{\sum_{i}^{n=1}(O_i - P_i)^2}}{n} \quad \text{(Eq 4)}$$

$$PBIAS = 100 \times \frac{\sqrt{\sum_{i}^{n=1}(O_i - P_i)}}{\sum_{i}^{n=1} O_i} \quad \text{(Eq 5)}$$

Where O_i and P_i are the measured and simulated data, O_i and P_i are means for the both measured and simulated number of observations.

The *n* is the number of observations, P_i simulated observation and O_i measured observation. $P_i| = P - M$ and $Oi_| = O_i - \mathrm{M}$ (M is the mean of the observed variable). To analyze the scenarios, we used the AquaCrop model with data from various climate models (GCM-CMIP6) under different climate scenarios (SSP1-2.6 and SSP3-7.0) and applied three mulch thicknesses (2 cm, 4 cm, and 6 cm) with the control. The model was calibrated using historical observed data to ensure accuracy. We assessed the impact of each scenario on maize yield and water use efficiency (WUE) by comparing simulated results with observed data. Statistical metrics like RMSE and R^2 were used to evaluate model

performance. The analysis identified the optimal mulch thickness and its effectiveness under different future climate conditions.

3. Results

3.1. AquaCrop Calibration and Validation

The model veracity was assessed by statistically comparing observed and simulated final maize biomass in response to soil water management practices (Fig.3). This compares predicted and measured biomass (t/ha) for: (a) C, (b) M2, (c) M4, and (d) M6, over the years 2018 and 2019. The coefficient of determination (R^2) values for both years, indicate the goodness of fit. The higher R^2 values signify better predictions.

For instance, C (a), M4 (c), and M6 (d) consistently show high R^2 values for 2018 and 2019, reflecting their strong predictive accuracy. Conversely, M2 (b) has an R^2 of 0.84 in 2018 and 0.95 in 2019, suggesting improvement in performance across years. The grey dotted lines depict the 95% confidence range for the regression lines, demonstrating the reliability of predictions (Fig.3).

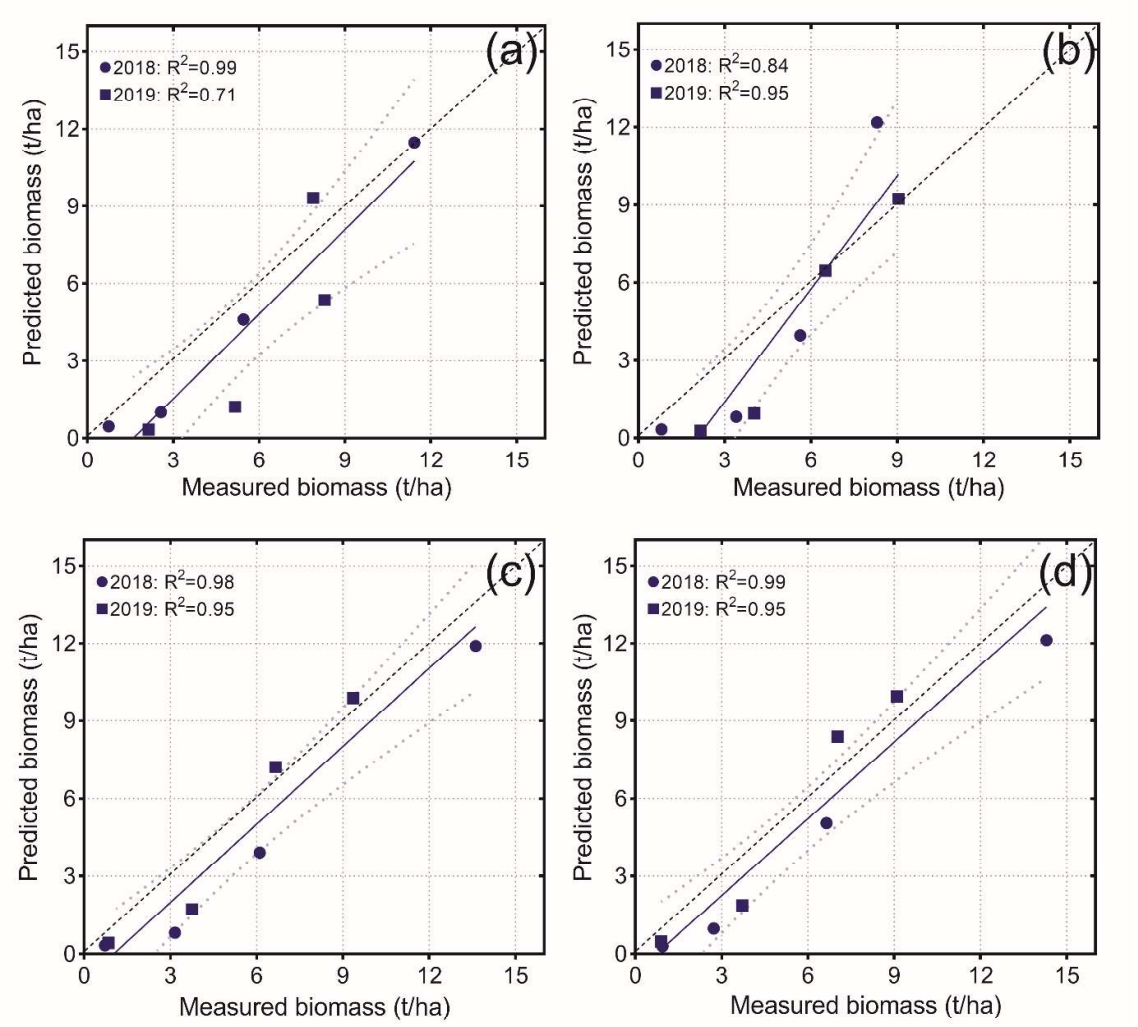


Fig.3. Comparison of observed and simulated maize total biomass: (a) C, (b) M2, (c) M4, and (d) M6.

Overall, the AquaCrop model performance can be observed by the EF values of 0.87 and 0.92 of grain yield (final biomass) under the observed and simulated values from the experimented soil water management practices (SWMPs) which correlated strongly to the final biomass accumulation (Table 3). The Root Mean Squared Error (RMSE) values also provide how well the AquaCrop model predictions matched the actual observed values as illustrated by the respective SWMPs (Table 3). The effect of mulch thickness is illustrated by the validated AquaCrop model and the model accuracy improves with increasing mulch thicknesses compared to the Control (2.56 t/ha), 2 cm (2.06 t/ha), 4 cm (1.38 t/ha), and 6 cm (1.16 t/ha). The 6 cm provides the best fit with even high biomass (14.30 t/ha), showing the smallest prediction error. Overall, higher mulch thickness treatments generally demonstrated better model performance, suggesting the efficiency of mulch to future maize yield increase.

Table 3. Statistical measures for observed vs simulated final biomass for the calibration and validation period at the study sites in mid-western Uganda.

Model evaluation		Statistical Indices								
Validation				**Xobs (CV %)**	**Ysim (CV %)**					
	Treatment	**Xobs (SD)**	**Ysim (SD)**			**RMSE**	**PBias**	**d**	**EF**	**R^2**
	C	11.75 (4.30)	11.19 (4.23)	37.66	41.12	2.56	1.55	0.86	0.48	0.68
	2 cm	9.04 (3.30)	12.19 (4.59)	36.63	39.88	2.06	1.46	0.92	0.68	0.84
	4 cm	13.62(4.92)	11.91(4.48)	36.74	38.83	1.38	0.17	0.96	0.87	0.93
	6 cm	14.30 (5.24)	12.13(4.60)	38.36	40.82	1.16	-0.21	0.98	0.92	0.95
Calibration	C	8.29 (3.21)	8.39 (3.73)	38.51	39.24	2.62	1.63	0.87	0.50	0.70
	2 cm	8.33(3.06)	8.70(3.66)	38.07	39.81	2.50	1.60	0.87	0.54	0.73
	4 cm	8.53(3.19)	8.11(3.25)	36.93	40.26	1.33	0.88	0.96	0.83	0.91
	6 cm	7.87(3.16)	8.84(3.86)	37.20	40.74	1.11	0.13	0.97	0.92	0.94

Notes: C, control or conventional, 2 cm thick, 4 cm thick, and 6 cm thick for straw mulches; Xobs, mean of observed values; Xsim, mean of simulated values; SD, standard deviation; CV, coefficient of variance; RMSE (t/ha), Root Mean Squared Error; R^2, root mean square error; d, Willmot index of agreement; Pbias, Percentage of Bias and EF, modeling efficiency (Moriasi et al., 2007).

3.2. Future climate scenarios

In this study, all models project precipitation decreases under the two scenarios relative to the baseline climate conditions, apart from IPSL-CM6A-LR, MRI-ESM2-0, and UKESM1-0-LL models and in the SSP3-7.0 for the period 2080 – 2099, respectively. Also, the period of 2040 – 2059, and 2060 – 2079 shows an increase in precipitation under the UKESM1-0-LL model projection. Overall, a decrease in precipitation is projected under the SSP1-2.6 climate scenario across all climate models (Table 4).

The baseline precipitation is 1300 mm. For GFDL-ESM4, a consistent decrease in precipitation is projected under both scenarios until 2080 – 2099, where SSP1-2.6 shows a 16.1% decrease and a 3.9% decrease for SSP3-7.0, indicating potential stabilization. The IPSL-CM6A-LR model predicts generally decreasing precipitation, except for a notable increase of 8.5% in SSP3-7.0 by 2080 – 2099. The MPI-ESM1-2-HR shows significant variability, with early periods indicating decreases and later periods showing smaller reductions or slight increases. MRI-ESM2-0 projects relatively minor changes, with slight increases and decreases across the periods, also indicating less variability. The UKESM1-0-LL model shows increasing precipitation, particularly under SSP3-7.0, with a significant 20.8% increase by 2080 – 2099 (Table 4).

Table 4. Changing in precipitation (mm year $^{-1}$) for the four periods under SSP1-2.6 and SSP3-7.0 climate scenarios.

GCM models	Climate Scenarios		Change		%Change	
GFDL-ESM4	**SSP1-2.6**	**SSP3-7.0**	**SSP1-2.6**	**SSP3-7.0**	**SSP1-2.6**	**SSP3-7.0**
Baseline	1300.0					
2020 - 2039	1051.4	1088.3	-248.6	-211.7	-19.1	-16.3
2040 - 2059	1105.7	1133.4	-194.3	-166.6	-14.9	-12.8
2060 - 2079	1117.2	1123.8	-182.8	-176.2	-14.1	-13.6
2080 - 2099	1090.6	1249.6	-209.4	-50.4	-16.1	-3.9
IPSL-CM6A-LR						
2020 - 2039	1121.0	1137.0	-179.0	-163.0	-13.8	-12.5
2040 - 2059	1169.6	1116.7	-130.4	-183.3	-10.0	-14.1
2060 - 2079	1255.2	1218.9	-44.8	-81.1	-3.4	-6.2
2080 - 2099	1166.2	1410.2	-133.8	110.2	-10.3	8.5
MPI-ESM1-2-HR						
2020 - 2039	1074.7	1213.2	-225.3	-86.8	-17.3	-6.7
2040 - 2059	1174.8	1030.5	-125.2	-269.5	-9.6	-20.7
2060 - 2079	1186.5	1071.2	-113.5	-228.8	-8.7	-17.6
2080 - 2099	1177.0	1246.7	-123.0	-53.3	-9.5	-4.1
MRI-ESM2-0						
2020 - 2039	1264.7	1309.8	-35.3	9.8	-2.7	0.8
2040 - 2059	1194.6	1258.2	-105.4	-41.8	-8.1	-3.2
2060 - 2079	1196.9	1315.2	-103.1	15.2	-7.9	1.2
2080 - 2099	1127.3	1252.4	-172.7	-47.6	-13.3	-3.7
UKESM1-0-LL						
2020 - 2039	1224.6	1241.1	-75.4	-58.9	-5.8	-4.5
2040 - 2059	1215.5	1332.6	-84.5	32.6	-6.5	2.5
2060 - 2079	1248.9	1488.7	-51.1	188.7	-3.9	14.5
2080 - 2099	1247.3	1570.0	-52.7	270.0	-4.1	20.8

Notes: GFDL-ESM4, Geophysical Fluid Dynamics Laboratory – Earth System Model version 4; IPSL-CM6A-LR, Institut Pierre-Simon Laplace – Climate Model version 6A – Low Resolution; MPI-ESM1-2-HR, Max Planck Institute – Earth System Model version 1.2 – High Resolution; MRI-ESM2-0, Meteorological Research Institute – Earth System Model version 2.0; and UKESM1-0-LL, United Kingdom Earth System Model version 1.0 – Low Resolution. SSP1-2.6 and SSP3-7.0 are Shared Socioeconomic Pathways (SSP) with numbers (2.6 and 7.0) referring to radiative forcing levels in watts per square meter (W/m²) reached by 2100 for each SSP, respectively and % is percentage.

3.3. Maximum Temperature

Generally, maximum temperatures in all five GCM models project an increase under SSP1-2.6 and SSP3-7.0 climate scenarios (Table 5). Over the years, the temperature has been increasing with the highest projected in the period 2040 – 2059 and 2060 – 2079 for all the climate scenarios per GCM model (Table 5). Under the MPI-ESM1-2-HR model for periods 2060 – 2079 and 2080 – 2099, the projected maximum temperature will be 32.1°C and 32.4°C, respectively while the UKESM1-0-LL model under similar periods and the climate scenarios projects relatively higher maximum temperatures of 33.6°C and 35.0°C, respectively.

For GFDL-ESM4, maximum temperatures increase consistently, with more substantial rises under SSP3-7.0, reaching 2.6°C above baseline by 2080 – 2099 (8.7%). IPSL-CM6A-LR projects similar patterns, with SSP3-7.0 showing a significant rise of 3.6°C (12.1%) by 2080 – 2099. MPI-ESM1-2-HR indicates moderate increases under SSP1-2.6 up to 2.4°C (7.9%), but less pronounced changes under SSP3-7.0, suggesting potential regional variability. Also, MRI-ESM2-0 displays consistent warming under SSP1-2.6, peaking at 2.9°C (9.6%) by 2080 – 2099, while SSP3-7.0 shows smaller increases, possibly indicating mitigation effects. The UKESM1-0-LL shows the highest temperature increases, particularly under SSP1-2.6, reaching 5.0°C (16.6%) by 2080 – 2099, suggesting a dramatic shift in thermal conditions (Table 5). These projections highlight the significant warming expected, particularly under high-emission climate scenarios, emphasizing the urgent need for robust soil water management strategies.

Table 5. Changing in maximum temperature (°C) for the four periods under SSP1-2.6 and SSP3-7.0 climate scenarios.

GCM models	Climate Scenarios		Change		%Change	
GFDL-ESM4	SSP1-2.6	SSP3-7.0	SSP1-2.6	SSP3-7.0	SSP1-2.6	SSP3-7.0
Baseline	30					
2020 - 2039	31.1	30.7	1.1	0.7	3.7	2.2
2040 - 2059	31.3	31.4	1.3	1.4	4.3	4.5
2060 - 2079	31.4	32.2	1.4	2.2	4.6	7.4
2080 - 2099	31.4	32.6	1.4	2.6	4.5	8.7
IPSL-CM6A-LR						
2020 - 2039	31.2	31.0	1.2	1.0	4.1	3.4
2040 - 2059	31.4	31.8	1.4	1.8	4.6	6.1
2060 - 2079	31.3	32.6	1.3	2.6	4.2	8.8
2080 - 2099	31.2	33.6	1.2	3.6	4.1	12.1
MPI-ESM1-2-HR						
2020 - 2039	30.6	31.0	0.6	1.0	2.1	3.2
2040 - 2059	31.6	30.9	1.6	0.9	5.4	3.1
2060 - 2079	32.1	30.9	2.1	0.9	7.1	3.1
2080 - 2099	32.4	30.8	2.4	0.8	7.9	2.5
MRI-ESM2-0						
2020 - 2039	30.3	30.8	0.3	0.8	0.9	2.6
2040 - 2059	31.3	31.3	1.3	1.3	4.4	4.2
2060 - 2079	32.1	31.5	2.1	1.5	7.1	4.9
2080 - 2099	32.9	31.5	2.9	1.5	9.6	4.9
UKESM1-0-LL						
2020 - 2039	31.7	31.6	1.7	1.6	5.7	5.3
2040 - 2059	32.6	32.3	2.6	2.3	8.8	7.7
2060 - 2079	33.6	32.4	3.6	2.4	12.0	8.1
2080 - 2099	35.0	32.5	5.0	2.5	16.6	8.3

Notes: GFDL-ESM4, Geophysical Fluid Dynamics Laboratory – Earth System Model version 4; IPSL-CM6A-LR, Institut Pierre-Simon Laplace – Climate Model version 6A – Low Resolution; MPI-ESM1-2-HR, Max Planck Institute – Earth System Model version 1.2 – High Resolution; MRI-ESM2-0, Meteorological Research Institute – Earth System Model version 2.0; and UKESM1-0-LL, United Kingdom Earth System Model version 1.0 – Low Resolution. SSP1-2.6 and SSP3-7.0 are Shared Socioeconomic Pathways (SSP) with numbers (2.6 and 7.0) referring to the radiative forcing levels in watts per square meter (W/m^2) reached by 2100 for each SSP, respectively, °C is degrees Celsius and % is percentage.

3.4. Minimum Temperature

Generally, all GCM models project minimum temperature change under the SSP1-2.6 and SSP3-7.0 climate scenarios compared to the baseline minimum temperature conditions. The models show substantial increases from the baseline of 15°C (Table 6). By 2080 – 2099, the minimum temperature rises range from 6.2°C – 8.6°C under SSP1-2.6 and 8.3°C – 10.3°C under SSP3-7.0, indicating significant warming. The highest increase is projected by UKESM1-0-LL, particularly under SSP3-7.0, with a 10.3°C rise, reflecting a 69.0% change from the baseline climate conditions. Such temperature increases could affect agricultural practices, maize yield, and stress tolerance, necessitating adaptive strategies to mitigate negative impacts on food production.

Over the years these temperatures are projected to rise gradually in all periods. From the results illustrated in Table 6, It can be expected that there will be no decrease in minimum temperature as the future period under SSP1-2.6 and SSP3-7.0 climate scenarios project increase. The change in minimum temperature for the period 2080 – 2099 is relatively more significant under MRI-ESM2-0 by 8.5% and UKESM1-0-LL by 7.4% for SSP1-2.6 and 10.3% for SSP3-7.0, respectively. The slightly lowest temperatures are observed in the period 2020 – 2039 under all climate scenarios (Table 6).

Table. 6. Changing in minimum temperature (°C) for the four periods under SSP1-2.6 and SSP3-7.0 climate scenarios.

GCM models	Climate Scenarios		Change		%Change	
GFDL-ESM4	SSP1-2.6	SSP3-7.0	SSP1-2.6	SSP3-7.0	SSP1-2.6	SSP3-7.0
Baseline	15					
2020 - 2039	21.3	21.5	6.3	6.5	41.9	43.3
2040 - 2059	21.2	22.1	6.2	7.1	41.6	47.3
2060 - 2079	21.3	23.0	6.3	8.0	41.9	53.3
2080 - 2099	21.2	23.6	6.2	8.6	41.5	57.4
IPSL-CM6A-LR						
2020 - 2039	21.0	21.1	6.0	6.1	40.0	40.6
2040 - 2059	21.5	22.4	6.5	7.4	43.1	49.3
2060 - 2079	21.6	23.7	6.6	8.7	43.8	57.7
2080 - 2099	21.5	25.1	6.5	10.1	43.5	67.3
MPI-ESM1-2-HR						
2020 - 2039	21.0	20.8	6.0	5.8	39.8	38.4
2040 - 2059	21.1	22.1	6.1	7.1	40.5	47.1
2060 - 2079	21.1	22.8	6.1	7.8	40.6	52.0
2080 - 2099	20.9	23.3	5.9	8.3	39.4	55.0
MRI-ESM2-0						
2020 - 2039	20.8	20.8	5.8	5.8	38.4	38.4
2040 - 2059	21.7	21.7	6.7	6.7	44.5	44.5
2060 - 2079	22.6	22.6	7.6	7.6	50.9	50.9
2080 - 2099	23.5	23.5	8.5	8.5	56.5	56.5
UKESM1-0-LL						
2020 - 2039	21.4	21.6	6.4	6.6	43.0	44.0
2040 - 2059	22.1	22.6	7.1	7.6	47.6	50.9
2060 - 2079	22.3	23.7	7.3	8.7	48.7	58.3
2080 - 2099	22.4	25.3	7.4	10.3	49.1	69.0

Notes: GFDL-ESM4, Geophysical Fluid Dynamics Laboratory – Earth System Model version 4; IPSL-CM6A-LR, Institut Pierre-Simon Laplace – Climate Model version 6A – Low Resolution; MPI-ESM1-2-HR, Max Planck Institute – Earth System Model version 1.2 – High Resolution; MRI-ESM2-0, Meteorological Research Institute – Earth System Model version 2.0; and UKESM1-0-LL, United Kingdom Earth System Model version 1.0 – Low Resolution. SSP1-2.6 and SSP3-7.0 are Shared Socioeconomic Pathways (SSP) with numbers (2.6 and 7.0) as the radiative forcing levels in watts per square meter (W/m^2) reached by 2100 for each SSP, respectively, °C is degrees Celsius and % is percentage.

3.5. Projected impacts of SWMPs on maize grain yield

Overall, simulations from the GCM climate models (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL) did not show statistical significance ($P > 0.05$) for soil water management practices (SWMPs) and maize grain yield. However, projected increases in maize yield are observed for different time periods (2020 – 2039, 2040 – 2059, 2060 – 2079, and 2080 – 2099) under various climate scenarios (Fig. 4).

The different GCM models exhibit considerable variation in their maize yield projections. For example, the MPI-ESM1-2-HR model frequently predicts decreases in yield (e.g., -15.6% for 2020 – 2039), while other models, such as UKESM1-0-LL, project increases. This variability is not consistent across all scenarios, as some models, like GFDL-ESM4, shift between positive and negative yield projections depending on the climate scenario.

There are significant differences in yield outcomes between the low and high emission scenarios. Under SSP1-2.6, most models predict an increase in maize yield when mulching is applied, although some reductions are observed (e.g., MPI-ESM1-2-HR). Conversely, under the SSP3-7.0 scenario, yield projections tend to be more variable, with GFDL-ESM4 consistently projecting decreases across most treatments.

Mulching thickness plays a crucial role in determining yield outcomes. Thicker mulching layers (4 cm and 6 cm) generally result in higher yields compared to conventional practices or thinner mulching treatments like the 2 cm. The impact of mulching thickness varies slightly across different climate scenarios, but its positive effect is more pronounced under SSP1-2.6. For instance, a 6 cm mulch thickness consistently results in yield increases across most models, except under more extreme conditions like SSP3-7.0, where reductions are seen, particularly with the GFDL-ESM4 model.

Therefore, the interaction between climate models, scenarios, and mulching thickness in Fig. 4 greatly influences maize yield projections, with thicker mulching often providing better yield outcomes, especially in less extreme climate

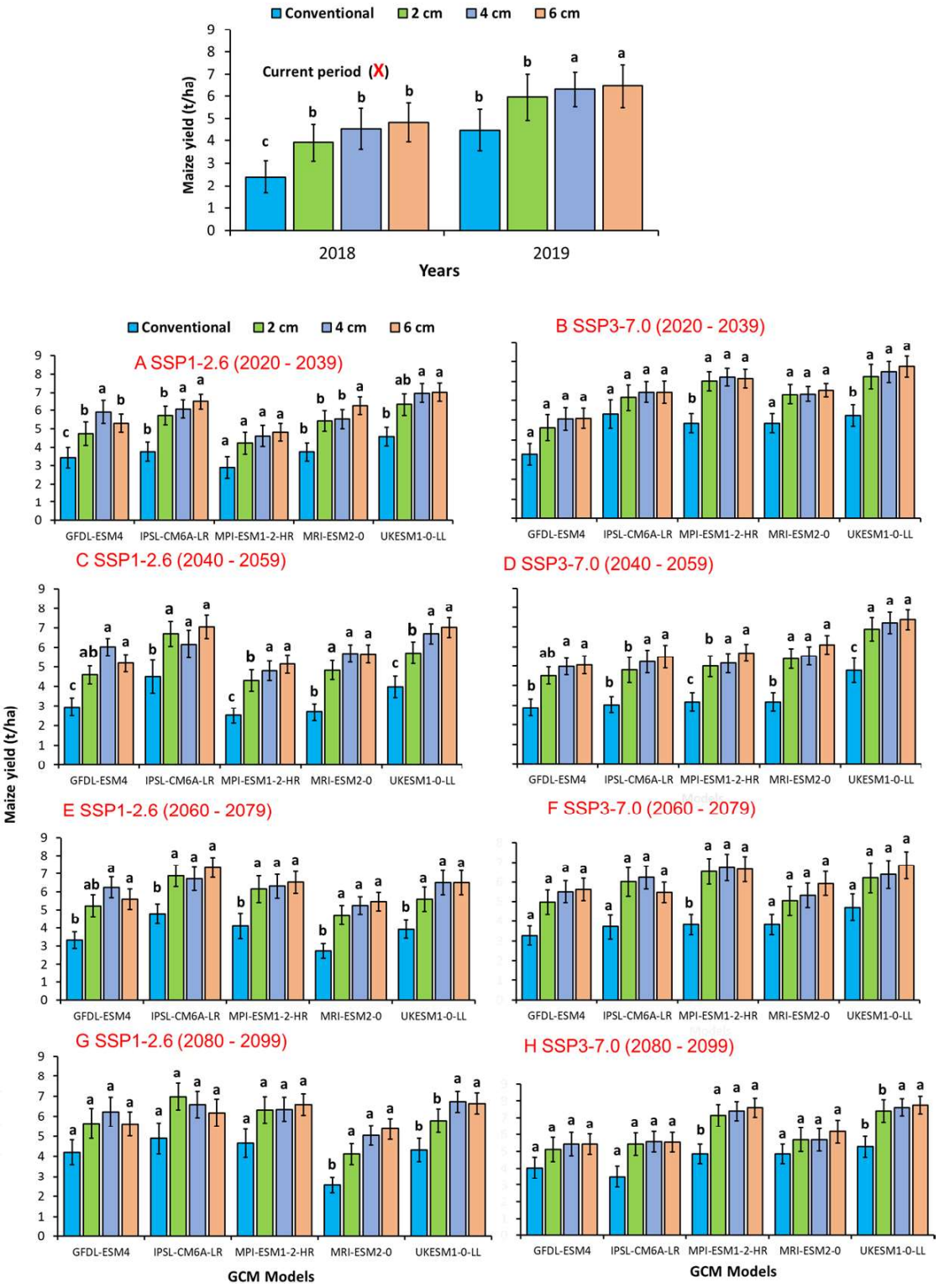


Fig. 4. Maize grain yield with SWMP practices for various time periods and climate scenarios. The graphs A – H present yields for the scenarios SSP1-2.6, and SSP3-7.0. To compare the current period with future effects of selected SWMPs, yield of the current period (2018 – 2019) with the same treatments (C, control or conventional, 2 cm thick, 4 cm thick, and 6 cm thick for straw mulches).

3.6. Projected maize evapotranspiration (ET)

Table 7 illustrates changes in maize ET under different climate models (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL) with respective climate change scenarios (SSP1-2.6 and SSP3-7.0) from 2020 – 2099. The baseline observed ET for the 2018 – 2019 period is given for conventional practice (C) and three mulch thicknesses (2 cm, 4 cm, and 6 cm), showing values between 412 mm and 485 mm. All models generally project significant reductions in ET across both climate change scenarios and all mulch treatments.

The highest reductions in ET are generally observed under conventional practice (C) across most models and scenarios. Mulch treatments (2 cm, 4 cm, and 6 cm) tend to moderate the reductions in ET compared to conventional practice, although reductions are still significant. The SSP1-2.6 shows slightly higher reductions in ET compared to SSP3-7.0 in several instances.

Under SSP1-2.6, all models show substantial reductions in ET across all treatments (Table 7). The GFDL-ESM4 model shows significant ET reductions of -81.3% for conventional practice and -64.4% for 6 cm mulch thickness. Similarly, SSP3-7.0 also shows considerable ET reductions under selected SWMPs practices. The MRI-ESM2-0 model reduces ET by -66.9% for conventional practice and -74.0% for 6 cm mulch thickness. This indicates that, without significant mitigation efforts, climate change will still lead to substantial decreases in ET, potentially impacting maize yield.

Table 7. Changing in maize ET (mm) SSP1-2.6 and SSP3-7.0 climate scenarios.

GCM models	Observed ET (2018 – 2019)	Climate Scenarios (2018 – 2099)		Change in ET		% Change in ET	
GFDL-ESM4	Baseline	SSP1-2.6	SSP3-7.0	SSP1-2.6	SSP3-7.0	SSP1-2.6	SSP3-7.0
C	485.0	90.6	152.5	-394.4	-332.5	-81.3	-68.6
2 cm	468.0	102.0	217.7	-366.0	-250.3	-78.2	-53.5
4 cm	417.0	123.7	92.1	-293.3	-324.9	-70.3	-77.9
6 cm	412.0	146.7	101.0	-265.3	-311.0	-64.4	-75.5
IPSL-CM6A-LR							
C	485.0	101.2	197.2	-383.8	-287.8	-79.1	-59.3
2 cm	468.0	119.1	114.9	-348.9	-353.1	-74.6	-75.4
4 cm	417.0	164.3	98.3	-252.7	-318.7	-60.6	-76.4
6 cm	412.0	150.0	112.0	-262.0	-300.0	-63.6	-72.8
MPI-ESM1-2-HR							
C	485.0	91.2	168.9	-393.8	-316.1	-81.2	-65.2
2 cm	468.0	100.6	97.3	-367.4	-370.7	-78.5	-79.2
4 cm	417.0	133.1	105.5	-283.9	-311.5	-68.1	-74.7
6 cm	412.0	154.1	104.4	-257.9	-307.6	-62.6	-74.7
MRI-ESM2-0							
C	485.0	80.3	160.7	-404.7	-324.3	-83.4	-66.9
2 cm	468.0	94.0	95.3	-374.0	-372.7	-79.9	-79.6
4 cm	417.0	126.3	105.9	-290.7	-311.1	-69.7	-74.6
6 cm	412.0	146.6	107.3	-265.4	-304.7	-64.4	-74.0
UKESM1-0-LL							
C	485.0	121.0	192.6	-364.0	-292.4	-75.1	-60.3
2 cm	468.0	137.7	137.2	-330.3	-330.8	-70.6	-70.7
4 cm	417.0	152.0	134.5	-265.0	-282.5	-63.5	-67.7
6 cm	412.0	184.6	149.7	-227.4	-262.3	-55.2	-63.7

Notes: GFDL-ESM4, Geophysical Fluid Dynamics Laboratory – Earth System Model version 4; IPSL-CM6A-LR, Institut Pierre-Simon Laplace – Climate Model version 6A – Low Resolution; MPI-ESM1-2-HR, Max Planck Institute – Earth System Model version 1.2 – High Resolution; MRI-ESM2-0, Meteorological Research Institute – Earth System Model version 2.0; and UKESM1-0-LL, United Kingdom Earth System Model version 1.0 – Low Resolution. SSP1-2.6 and SSP3-7.0 are Shared Socioeconomic Pathways (SSP), numbers (2.6 and 7.0) refer to the radiative forcing levels in watts per square meter (W/m^2) reached by 2100 for each SSP, respectively and % is percentage. C, control or conventional, 2 cm thick, 4 cm thick, 6 cm thick for straw mulches and ET, Evapotranspiration.

3.7. Water Use Efficiency

Across all GCMs and SWMPs, there is a substantial increase in maize water use efficiency (WUE) under both climate scenarios of SSP1-2.6 and SSP3-7.0 (Table 8). This indicates that, despite the challenges posed by climate change, maize can potentially become more water-efficient. The baseline WUE values, observed from 2018 – 2019, serve as a reference point for assessing future changes for two climate scenarios. Under both climate scenarios, there is a substantial increase in WUE across all GCMs and SWMPs, indicating that maize could potentially become more water-efficient despite the challenges posed by climate change. For example, the GFDL-ESM4 model projects an increase in WUE of 260% for conventional practices under SSP1-2.6 and 454% for 6 cm mulch thickness. Similar trends are observed with IPSL-CM6A-LR, where the 4 cm mulch thickness shows an increase of 670% for SSP1-2.6 and 761% under SSP3-7.0.

The MPI-ESM1-2-HR model indicates a WUE increase of 239.5% for conventional practice under SSP1-2.6 and 302.5% for SSP3-7.0, with the highest increase noted for the 4 cm mulch thickness, which rises by 690.5% under SSP1-2.6 and 805% with SSP3-7.0. The MRI-ESM2-0 model shows significant WUE increases across all practices, with the 4 cm mulch thickness experiencing a rise of 680% under SSP1-2.6 and 769% under SSP3-7.0, while the 6 cm mulch also shows substantial improvements. The UKESM1-0-LL model projects notable WUE increases across all SWMPs, with the 4 cm mulch thickness showing the highest increase of 805.5% under SSP1-2.6 and 877.5% for SSP3-7.0, respectively marking the strongest potential for water efficiency improvements among the models.

Table 8. Changing in WUE (kg m^{-3}) under SSP1-2.6 and SSP3-7.0 climate scenarios.

GCM models	Observed biomass (2018 – 2019)	Climate Scenarios (2018 – 2099)		Change in WUE		% Change WUE	
GFDL-ESM4	Baseline	SSP1-2.6	SSP3-7.0	SSP1-2.6	SSP3-7.0	SSP1-2.6	SSP3-7.0
C	0.20	0.72	0.72	0.52	0.52	260.0	258.0
2 cm	0.30	1.26	1.18	0.96	0.88	318.3	294.0
4 cm	0.20	1.72	1.56	1.52	1.36	760.0	677.5
6 cm	0.30	1.66	1.66	1.36	1.36	454.0	454.7
IPSL-CM6A-LR							
C	0.20	0.77	0.72	0.57	0.52	286.0	260.0
2 cm	0.30	1.64	1.35	1.34	1.05	446.0	351.0
4 cm	0.20	1.54	1.72	1.34	1.52	670.0	761.0
6 cm	0.30	2.08	1.79	1.78	1.49	593.3	495.0
MPI-ESM1-2-HR							
C	0.20	0.68	0.81	0.48	0.61	239.5	302.5
2 cm	0.30	1.22	1.47	0.92	1.17	307.7	390.3
4 cm	0.20	1.58	1.81	1.38	1.61	690.5	805.0
6 cm	0.30	1.79	1.92	1.49	1.62	496.7	539.0
MRI-ESM2-0							
C	0.20	0.60	0.81	0.40	0.61	199.0	302.5
2 cm	0.30	1.20	1.43	0.90	1.13	298.7	375.7
4 cm	0.20	1.56	1.74	1.36	1.54	680.0	769.0
6 cm	0.30	1.71	1.89	1.41	1.59	470.3	530.7
UKESM1-0-LL							
C	0.20	0.90	1.07	0.70	0.87	350.0	435.5
2 cm	0.30	1.41	1.66	1.11	1.36	370.0	453.0
4 cm	0.20	1.81	1.96	1.61	1.76	805.5	877.5
6 cm	0.30	1.90	2.06	1.60	1.76	533.0	587.0

Notes: GFDL-ESM4, Geophysical Fluid Dynamics Laboratory – Earth System Model version 4; IPSL-CM6A-LR, Institut Pierre-Simon Laplace – Climate Model version 6A – Low Resolution; MPI-ESM1-2-HR, Max Planck Institute – Earth System Model version 1.2 – High Resolution; MRI-ESM2-0, Meteorological Research Institute – Earth System Model version 2.0; and UKESM1-0-LL, United Kingdom Earth System Model version 1.0 – Low Resolution. SSP1-2.6 and SSP3-7.0 are Shared Socioeconomic Pathways (SSP), numbers (2.6 and 7.0) refer to the radiative forcing levels in watts per square meter (W/m^2) reached by 2100 for each SSP, respectively and %, percentage. C, control or conventional, 2 cm thick, 4 cm thick, 6 cm thick for straw mulches and WUE, Water Use Efficiency in kilograms per cubic meter expressed as WUE (kg m^{-3}).

4. Discussion

4.1. Model performance

The evaluation of the AquaCrop model using different soil water management practices (SWMPs) in mid-western Uganda revealed significant insights into the model's accuracy and the effectiveness of mulch thickness in improving maize yield predictions. This observation is consistent with findings from other studies (Ding et al., 2018; Keesstra et al., 2019; Li et al., 2018; Quan et al., 2024), which similarly report increased maize yields with straw mulch. Similar trends of improved accuracy with thicker mulching have been noted in studies using AquaCrop and other models, suggesting that mulch thickness enhances soil moisture retention, leading to better yield outcomes. The calibration and validation phases of this study showed that AquaCrop model effectively simulates final maize biomass, with high modeling efficiency (EF) values of 0.87 and 0.92, indicating a strong correlation between observed and simulated values.

The RMSE values further validated model's accuracy decreasing with increasing mulch thickness: were 2.56, 2.06, 1.38, and 1.16 t/ha for the control, 2 cm, 4 cm, and 6 cm mulch thicknesses, respectively. The 6 cm mulch treatment showed the lowest RMSE, indicating the smallest average prediction error and the best model fit. This trend underscores how thicker mulch significantly enhances the model's predictive accuracy by reducing soil water evaporation. Similar observations have been made in the past studies such as studies of Jia et al.(2021), which highlighted the insulating effect of mulch in reducing soil water evaporation rates, particularly under maize production systems. Also, the PBias analysis further confirmed that higher mulch thickness improves model accuracy, with progressively smaller PBias values indicating minimal over or under-prediction. This suggests that thicker mulch applications lead to more reliable model predictions and greater accuracy.

While higher mulch thickness treatments generally improved the accuracy of the AquaCrop model in simulating maize yield, not all observed effects were statistically significant ($P > 0.05$). This may be attributed to limited inter-annual climatic variability during the study period and the inherent uncertainties associated with future climate projections. Additionally, the relatively short time frame and limited range of conditions may have constrained the robustness of the results. Future studies involving longer-term simulations and field experiments across diverse climatic conditions and management scenarios would help enhance statistical power and reduce variability in evaluating the impacts of mulch application.

4.2. Climate trends, and maize yields

The variations among GCM models underscore the importance of considering a range of scenarios and models to capture the breadth of potential future conditions on maize productivity, corroborating previous studies (Chemura et al., 2022b; Ruane et al., 2013; Tesfaye et al., 2017). Changes in maximum and minimum temperatures will have profound implications for ecosystems, agriculture, water resources, and human health, necessitating comprehensive adaptation and mitigation plans. Such temperature increases could affect agricultural practices, maize yield, and stress tolerance, necessitating adaptive strategies to mitigate negative impacts on food production.

In mid-western Uganda, annual precipitation sums are projected to change, with the magnitude and direction of change depending on the emissions scenario and climate model. The majority of models indicate an increase in future precipitation, potentially substantial under the high emissions scenario, though variability exists between models (Chemura et al., 2019; Jägermeyr et al., 2021). Some models in this study show increases in precipitation with higher intensity and frequency in the future compared to current and historical scenarios.

The GFDL-ESM4 model projected consistent decreases in precipitation under both scenarios until 2080 – 2099, with potential stabilization indicated by a smaller decrease under SSP3-7.0. Conversely, the UKESM1-0-LL model projected significant increases in precipitation, particularly under SSP1-7.0, suggesting regional variability and the influence of different emission scenarios.

Under the SSP1-2.6 scenario, which represents a sustainable pathway with significant mitigation efforts, results show varying changes in precipitation, with some models projecting increases and others decreases, reflecting inherent uncertainties in climate projections. The SSP3-7.0 scenario, indicative of a high-emission future with minimal climate policy interventions, generally shows more pronounced changes in precipitation patterns, suggesting greater volatility and variability, which could have significant implications for agricultural planning and water resource management. Climate models project mixed signals of both wet and dry conditions in mid-western Uganda over the 21st century, affecting soil water management practices and maize yield.

Maximum and minimum temperatures are projected to increase across all GCMs and scenarios. Projected increases in maximum temperature range from 0.8°C to 3.6°C under SSP1-2.6 and up to 8.7°C under SSP3-7.0. These significant temperature increases highlight potential stress on maize crops and the need for adaptive strategies. Similarly, minimum temperatures are projected to rise, with increases ranging from 6.2°C to 10.3°C by 2080 – 2099, indicating a substantial warming trend that could impact crop growth and stress tolerance.

4.3. Soil water management practices and maize productivity

The findings of this study emphasize the significant impacts of climate change on soil water management practices (SWMPs) and their subsequent influence on maize productivity under rainfed conditions. Our projections highlight that climate change alters precipitation patterns, which can substantially affect soil water availability and, consequently, maize yield. These changes necessitate adaptive strategies to mitigate potential adverse effects and enhance food security and environmental sustainability.

A key finding is the consistent improvement in water use efficiency (WUE) with the application of different SWMPs, particularly a 6 cm mulch thickness. This increase in WUE across various climate models suggests that mulching can play a crucial role in enhancing maize productivity and resilience to climate change. By improving soil moisture retention and reducing evaporation, mulching helps maize plants better withstand climatic stresses, thereby contributing to more sustainable agricultural practices. These results align with other research conducted in Uganda and similar environments like (Kassam et al., 2014; Siatwiinda et al., 2021), reported that effective soil water management is vital for coping with climate variability and improving maize yields. Our study builds on this by demonstrating the effectiveness of specific SWMPs in maintaining and improving maize productivity. Furthermore, the findings are consistent with past studies by Bu et al., (2013) and Zhang et al., (2020), which have shown that, various SWMPs, such as mulching, improve water retention and crop resilience across different regions and crops. For instance (Bu et al., 2013; Mupangwa et al., 2013; Okunade et al., 2020; Kader et al., 2019; Ullah et al., 2019; Zhang et al., 2020), highlights the effectiveness of mulching in diverse agricultural settings, showing that it can mitigate the impacts of climate change on crop yields by enhancing soil moisture and reducing temperature fluctuations. This supports our findings that mulching is a valuable practice for improving water use efficiency and crop productivity.

The discrepancy between the 6 cm mulch thickness for being optimal for maize grain yield and the 4 cm mulch thickness achieving the highest water use efficiency may be reflecting complementary relationship between productivity and efficiency under projected climate change. The 4 cm mulch thickness improves WUE across the GCMs, this may be due to a favourable balance of transpiration and evaporation, the 6 cm mulch thickness more consistently enhanced grain yield, particularly under the SSP1-2.6 scenario. This may be attributed to better soil moisture retention, moderated soil temperature, and improved root-zone conditions as corroborated by studies of Liu et al.(2017), Maharjan et al. (2018), Tian et al.(2022), Wang et al., (202), Wang et al., (2019), and Zhao et al. (2022). The slightly lower WUE at 6 cm mulch is not indicative of inefficiency but results from increased total water uptake associated with higher biomass production. Thus, rather than being contradictory, these findings highlight a trade-off like, the 4 cm mulch optimizes per unit water efficiency, while the 6 cm mulch maximizes overall yield, making it the more effective choice for integrated soil and water management. Therefore, under changing climates, 6 cm straw mulch provides

a balanced strategy to enhance productivity while maintaining sustainable water use (Ullah et al., 2022; Zhang et al., 2017), supporting resilient agroecosystem development.

Also, the observed reductions in evapotranspiration (ET) across all climate models and mulch treatments (Table 7) align strongly with the substantial improvements in water use efficiency (WUE) reported in Table 8. This relationship highlights the role of reduced ET as a direct contributor to enhancing the WUE under future climate change scenarios, and this has been reported in previous studies (Huang et al., 2015; Zhao et al., 2022). Specifically, mulch reduces water losses which are non-productive to crops like evaporation and more water is directed in transpiration, hence a physiologically productive component of ET (Wang et al., 2021). In the present study, the 4 cm and 6 cm straw mulches consistently reduce ET compared to the baseline, with the 4 cm mulch achieving the highest WUE in most GCMs and climate change scenarios. For instance, under the GFDL-ESM4 model with SSP1-2.6, there is a 70.3% ET reduction and a 760% increase in WUE for the 4 cm mulch thickness, which indicates a strong inverse relationship. Notably, while 6 cm mulch results in slightly less WUE than 4 cm, it maintains greater yield due to higher overall water retention and improved microclimatic conditions similar to previous studies (Liu et al., 2014; Rahman et al., 2017). Therefore, these findings support the hypothesis that WUE gains stem from a more favourable partitioning of water fluxes, where mulching reduces total ET by significantly reducing and suppressing soil evaporation, thereby improving transpiration efficiency (El-Beltagi et al., 2022; Farzi et al., 2017; Y. Liu et al., 2017). Thus, application of mulching techniques in the progressive projected climate change should consider the scale of ET reduction and contribute to yield driven WUE gains.

However, the practical adoption of mulching faces several challenges. While the benefits of mulching are evident, its implementation involves labour and costs that can be prohibitive, particularly for farmers with large fields or limited resources. The availability of mulching materials to optimize the thickness and the additional labour required for application may be significant barriers. Farmers may be hesitant to adopt these practices due to these constraints, despite the potential yield improvements. Addressing these barriers is crucial for broader adoption and research into the cost-benefit ratios of mulching and other adaptation strategies is necessary to determine if the increased yield justifies the investment. Evaluating the economic viability and providing support for accessing materials and labour could enhance the adoption of effective SWMPs. The effectiveness of mulching as a SWMP for enhancing maize productivity in the face of climate change, practical considerations regarding its implementation must be addressed for future increased adoption. Future research should also focus on detailed cost-benefit analyses and strategies to overcome barriers to adoption, ensuring that the benefits of these adaptive practices can be realized in real-world agricultural settings.

5. Conclusion

The results indicate that climate change, as projected by different GCMs and scenarios is expected to significantly impact maize productivity and, consequently, maize yield. While mulch thickness help mitigate some of these impacts by reducing evapotranspiration, there is need for additional adaptive measures in agriculture to sustain productivity in the face of climate change.

Also, the AquaCrop model demonstrated robust performance in simulating maize biomass under different soil water management practices, with higher mulch thickness treatments significantly improving model accuracy. The findings emphasize the importance of mulch application in reducing soil water evaporation and enhancing maize yield predictions. The model's ability to accurately simulate biomass with different mulch thicknesses suggests its utility in optimizing soil water management strategies for improved agricultural productivity.

Future climate projections indicate significant challenges for maize production due to expected decreases in precipitation and substantial increases in maximum and minimum temperatures. These changes underscore the urgency for adaptive strategies to mitigate the negative impacts on maize yields. The variability among GCM projections also highlights the need for region-specific climate adaptation plans.

In conclusion, the combination of effective soil water management practices, as evidenced by the AquaCrop model simulations, and proactive soil water management practices will be crucial for sustaining maize production in the face of future climate challenges. Further research should focus on refining model predictions and precision under varying climatic conditions and exploring additional soil and crop management practices to enhance resilience and productivity in maize farming systems.

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Declaration of Competing Interest

The authors declare that they have no competing financial interests

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