Regional Environmental Change (2025) 25:62
https://doi.org/10.1007/s10113-025-02403-y

ORIGINAL ARTICLE

Modeling the impact of climate change on maize (*Zea mays* L.) production at the county scale in Kenya

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Received: 19 December 2023 / Accepted: 18 April 2025

Abstract

Global climate change is projected to disproportionately impact cereal crop yields in developing regions, such as Kenya, due to increased vulnerability and limited adaptation capacity of the population. This study examines the current and projected influence of climate change on maize yields in two major maize-producing counties of Kenya. Utilizing the calibrated and evaluated DSSAT-CERES-Maize model (where DSSAT is Decision Support Systems for Agrotechnology Transfer and CERES stands for Crop and Environment REsource Synthesis) for the H614 maize cultivar, we investigated the projected impact of climate change on maize production with reference to a baseline period (1984–2013). Simulations were conducted for the mid-century period (2041–2070) and end-of-century period (2071–2100) using projected climate data from regional climate models (RCMs) under two Representative Concentration Pathways (RCPs; 4.5 and 8.5) scenarios. Our findings indicate a substantial decline in maize yields, ranging from 7 to 20% for the mid-century period and between 22 and 41% for the end-of-century period, with increased temperature during critical growth phases identified as the primary driver. Spatial clustering and hotspot analysis reveal differential climate impacts across the region. In the end-of-century period, both scenarios revealed that the counties will be marked by hotspots and adaptation spots, areas where climate change adaptation should be intensified. The study underscores the urgency for tailored, location-specific adaptation measures such as maize-legume intercropping, drought-resistant crops, soil water conservation and optimum sowing to mitigate future yield losses and adapt maize production to climate change.

Keywords Climate change · Crop modeling · Impact · Maize · Kenya

Introduction

Climate change is a significant threat to global crop production and food security. Its impact is particularly alarming, especially for staple food crops such as maize, wheat and rice, which are critical sources of protein and caloric intake worldwide (Shiferaw et al. 2011; Erenstein et al. 2022). Maize is a dominant crop and a vital source of nutrition and livelihood security in developing regions, particularly in Asia and sub-Saharan Africa (SSA). As the main staple in SSA, maize is extensively cultivated for human consumption (Reynolds et al. 2015). Despite its importance in alleviating food insecurity, maize production remains relatively low compared to other parts of SSA. Maize productivity averages approximately 2 tons per hectare (Leitner et al. 2020), which is five times less than the productivity in developed regions of Europe and North America (Schils et al. 2018; Edgerton 2009). Increasing maize production is therefore critical, given that the population in the country is rising, similar to the larger SSA region (van Ittersum Martin et al. 2016). The challenge of increasing production is complicated by other factors such as climate variability, pests, diseases and poor soils, among other yield constraints (Tittonell and Giller 2013; Mugabe et al. 2024). Furthermore, intense human activities threaten crucial ecosystem services such as pollination for sustainable agricultural production (Rehman et al. 2022).

The effects of climate change on agriculture in the SSA region are well documented in the literature. The region is experiencing rapid global warming, with seasonal temperatures predicted to exceed previously recorded extreme temperatures in the past (Cairns et al. 2013). Kenya, like other

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Extended author information available on the last page of the article nations in the SSA region, is similarly expected to experience adverse effects of climate change. Despite being the largest economy in East Africa and having a highly growing population rate, Kenya is characterized by vast arid and semiarid zones (World Bank 2020). Moreover, its proximity within the equatorial zone and the Indian Ocean and the Intertropical Convergence Zone (ITCZ) influence exposes it to extreme climate risks such as droughts and intense precipitation events (Mamalakis et al. 2021).

Attention to climate change impacts on the production and suitability of various crops has gained traction in Kenya and SSA. Studies have been conducted across the region, albeit at different times and scales. Most of the studies cover regional and national scales, mainly due to the coarse availability of modelling data (Falconnier et al. 2020; Kogo et al. 2019; Chemura et al. 2022). On the other hand, some studies are limited to the field scale, majorly utilizing field and on-farm experiments (Chisanga et al. 2020, 2021; Volk et al. 2021). Studies at small scales provide aggregated findings, which obscure underlying influences of production patterns. On the other hand, experimental studies at the farm or plot level are usually generalized across the region where the experiments were conducted. The assumption is that conditions affecting production are less variable across the region of interest. Detailed assessments that capture production responses to underlying climates at decision-making units are still scarce. Furthermore, analyzing climate change impacts on crop production at spatial explicit levels is necessary for context-specific agronomic planning. At spatial explicit scales, existing research has covered extensively on climate suitability for various crops geospatial techniques and species distribution models (Ojara et al. 2021; Kogo et al. 2019; Chemura et al. 2022).

There is a considerable focus on the impact of climate change on crop production using process-based models in the SSA region, albeit on a regional scale (Stuch et al. 2021; Falconnier et al. 2020; Sultan et al. 2014). Moreover, most of the studies have provided a regional perspective and covered crops such as sorghum and millet, which are increasingly promoted due to their drought-resistant nature and adaptability to climate change effects (Sultan et al. 2013; Alimagham et al. 2024; Adhikari et al. 2015). Process-based crop models have increasingly emerged as useful tools to assess the impact of climate change on crop production due to their strength in capturing plant, atmosphere and soil interactions to mimic crop growth as accurately as possible (Tian et al. 2020; Dokoohaki et al. 2021). These tools offer enormous opportunities for assessing agricultural production under the baseline and future climate scenarios. They are, however, demanding in terms of data requirements to robustly and precisely model climate and production feedback (Silvestro et al. 2017). As simplifications of reality, crop models possess inherent uncertainties that result from the synergistic nature of modelled processes or environmental variabilities (Chapagain et al. 2022). Nonetheless, crop models have demonstrated enormous potential in assessing crop, environmental and management interactions across diverse climatic gradients (Stöckle and Kemanian 2020). Additionally, these models can be applied in other environments with precise accounting of underlying growth, water and nutrient transport processes (Batchelor et al. 2002). Furthermore, the models can robustly integrate mathematical descriptions of the mechanism of plant growth and thus can account for nonlinear and complex processes by simulating them (Pasquel et al. 2022). The application of crop simulation models has seen an exponential rise, especially in documenting production beyond the current climates to develop optimal adaptation options in climate-volatile regions.

This study applies the DSSAT-CERES-Maize model to analyze the future maize productivity across two major maize-growing areas in Kenya. The study also investigates the differential impacts of climate change across the region. The assessment is conducted at a grid-scale using high-resolution climatic and soil data, and spatial analysis was incorporated to assess yield variation across the key production zones/units. The study identifies how various regions within the area will likely respond to future climate change, thus laying the foundation for further analysis of region-specific strategies and interventions for sustaining production under increased warming and variable precipitation.

Materials and methods

Study area description

The study area is situated in the northwestern part of Kenya between latitudes 3° 5′ to 5° 5′ south and longitudes 33° 9′ to 35° 3′ east. The area comprises two counties, Trans Nzoia and Uasin Gishu (Fig. 1), which constitute the major maize-producing zones in Kenya. The region lies in the highland plateaus of the Rift Valley province. Both counties have high agricultural potential within subhumid to humid agro-ecological zones (AEZs) (Sombroek et al. 1982). The region experiences annual precipitation ranging from 1100 to 1800 mm, characterized by a bimodal distribution rainfall pattern. The long rainy season occurs from March to May and is typically more intense and frequent than the short rainy season, which falls between October and December. The study region lies in the highly favourable climatic conditions zone and can have long rainy seasons extending to August (Kwambai et al. 2024).

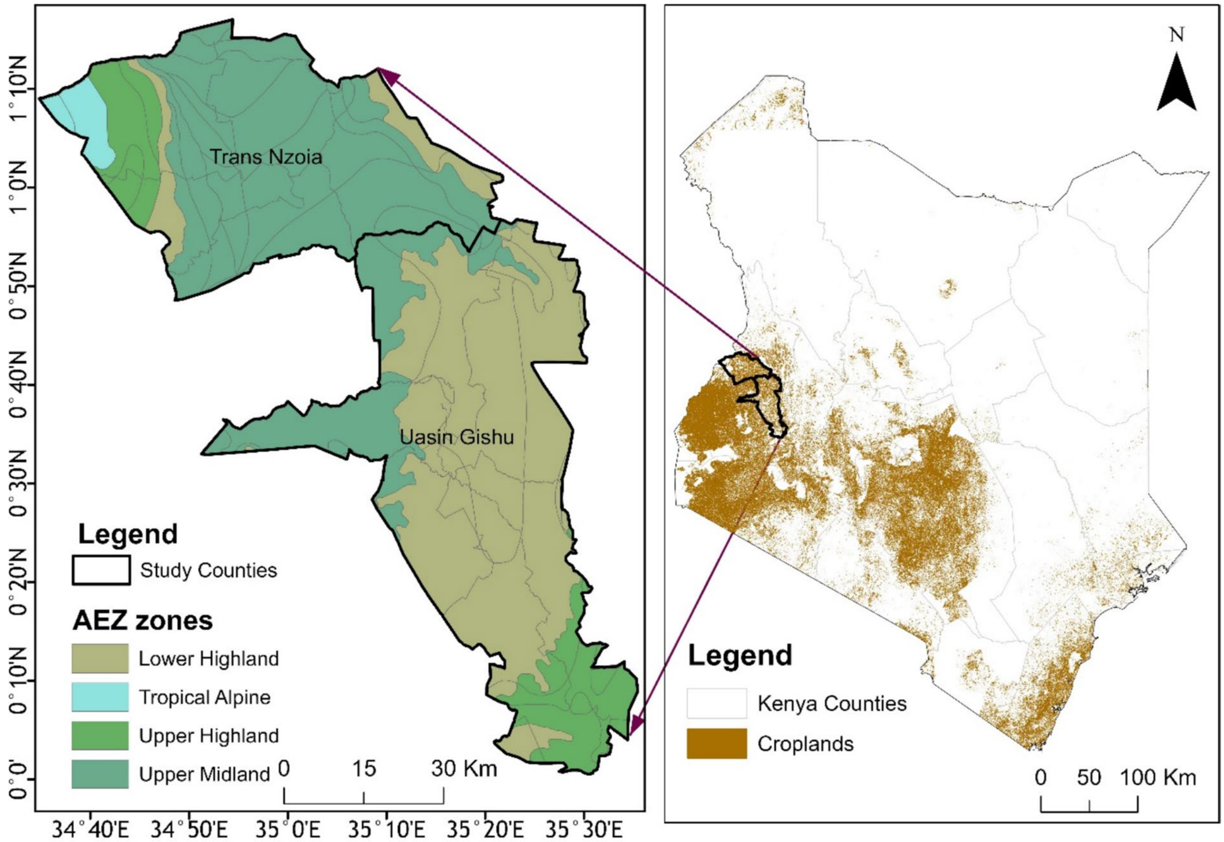

Fig. 1 Map of Trans Nzoia County and Uasin Gishu County and agro-ecological (Baeza et al.) zones characterizing the region (left) and the context of the study area in Kenya. A cropland mask from Digital Earth Africa is superimposed on the Kenyan map

DSSAT-CERES-Maize model and input data

The DSSAT-CERES-Maize model is one of the extensively utilized process-based maize simulation models among crop modelling simulation systems. The model uses various input data, including weather, soil, management and cultivar information, to simulate maize growth and development on a daily temporal scale (Noriega-Navarrete et al. 2023). Daily precipitation, radiation and temperature data from 1984 to 2013 were extracted from various databases to constitute the baseline data. The precipitation data were obtained from Climate Hazard Group Infrared Precipitation with Station version 2 (CHIRPS2) (https://data.chc.ucsb.edu/products/CHIRPS-2.0/). The product has a spatial resolution of approximately 5.5 km and a daily temporal scale, with coverage from 1981 to the present (Funk et al. 2015). On the other hand, the Climate Hazards Center Infrared Temperature with Stations (CHIRTS) data are provided at the same resolutions but with different time coverage (Funk et al. 2019). Both CHIRPS and CHIRTS combine satellite and station-based observations to provide robust estimates that are important in monitoring weather extremes and supporting early warning systems (Funk et al. 2019). Soil physical and chemical variables are also needed as inputs to the model. The variables include soil texture (percentage of clay, sand and silt), bulk density, total nitrogen, total organic carbon, pH and cation exchange capacity). We derived the variables from the global high-resolution soil profile database for crop modelling applications. The database provides global spatial soil profile information at a spatial resolution of approximately $0.1° \times 0.1°$ (~10 km). The global high-resolution soil product was synthesized from the International Soil Reference and Information Centre (ISRIC) and the Africa Soil Information Service (AfSIS) SoilGrids and provides ready DSSAT soil input data (Han et al. 2015).

Other needed information, including sowing depth and density, was specified based on the recommended local practices. The sowing density for each simulation season was approximated to be 50,000 plants per hectare with intra and inter-row spacing at 25 cm and 75 cm, respectively. The DSSAT-CERES-Maize model was configured with sowing dates assessed from a combination of techniques, such as the conventional practices in the region and analysis of time series normalized difference vegetation index (NDVI) profile derived from remote sensing data (Kipkulei et al. 2024b), and conditions for germination under dry sowing and rainfall onset, which considers the soil water balance as specified by Kipkorir et al. (2007). The DSSAT-CERES-Maize model runs on a daily time step and simulates leaf, root and stem growth, phenology, and canopy development (Jones et al. 2003). The model outputs include water and nitrogen balance, leaf area index, biomass and grain yield (Liu et al. 2011). In this study, the model was initiated to run on the first day of each year to provide a steady state of the soil water balance (Volk et al. 2021), and the harvest date in the model was automatically set when the crop reached physiological maturity (Tofa et al. 2020).

Model calibration and evaluation and yield simulations

The calibration process involves estimating the cultivar parameters for the simulated cultivar in the region. These cultivar parameters govern the growth and development of maize from germination to physiological maturity (Table S1). Typically, the process approximates the cumulative heat units that the crop requires to transition from one phenological cycle to the other. In addition to the heat units, other parameters, such as the kernel filling rate (mg/day) and the maximum number of kernels, are estimated for a specific cultivar. The model parameters used for calibration are default values reported in Kipkulei et al. (2022). The model was evaluated for performance at the field scale level in a different season. The study documented the satisfactory accuracy of the model in representing the growth and development of the cultivar (Table S2). We adopted the calibrated cultivar coefficients over the entire spatial extent of the study area. The selection of the cultivar was guided by its popularity due to its high resistance to biotic stresses and production stability. The cultivar is also widely grown across the study region, with climatic conditions favouring its growth. We simulated the yield for every grid for 30 years (reference period) and future periods (2041–2070) for the mid-century period and (2071–2100) for the end-of-century period. The reference period was selected as a baseline for assessing the future impacts of climate change on maize production in the mid and end-of-century periods.

Climate models and projection

Future climatic data for the study region were obtained using the Coordinated Regional Climate Downscaling Experiment (CORDEX) Africa simulation data. Six regional climate model (RCM) simulation data (Table S3) were obtained at a spatial resolution of ~50 km (0.44°). Based on this resolution, the entire study area was covered by a 4 × 4 square grid, resulting in 16 derivation grids for climate modelling analysis. The RCMs were developed for the mid-century period (2041–2070) and the end-of-century period (2071–2100) under the Representative Concentration Pathways (RCP4.5 and RCP8.5). GCM downscaling is an effective strategy for obtaining high-resolution future climate simulations on a local scale. Downscaling assumes that weather dynamics at a large scale exert influences at local scales, but disregards reverse local effects. In this study, we used a dynamic downscaling approach with the assumption that the observed predictor and prediction relationships will remain realistic under future climatic forcing conditions. Dynamic downscaling employs a transformation algorithm for adjusting climate model output with the assumption that the correction algorithm and its parametrization for current climate conditions are to be valid for future conditions as well. The climate data was downscaled to merge the resolution of the soil grids used to derive the soil parameters for further yield simulation.

Quality control and evaluation of climate models

The performance of the RCMs for the precipitation and temperature variables was evaluated against the CHIRPS and CHIRTS data (Fig. S1). The accuracy metrics were represented using the Taylor diagram. The diagram provides correlation measures (r), centered root mean square error (RMSE) and standard deviation (SD) measures (Kiprotich et al. 2021). The six RCMs were evaluated for model skill, and the best-performing model was subsequently adopted for bias correction of the precipitation and temperature variables. The Climate Model data for hydrological modelling (CMhyd) (Rathjens et al. 2016) was used to perform the bias correction of the simulated daily precipitation and maximum and minimum temperature datasets for the study area. The bias correction was performed to minimize possible bias for accurate climate projections (Tan et al. 2020). Various bias correction methods have been evaluated and recommended in the literature (Boé et al. 2007; Johnson and Sharma 2011). In this study, we applied local intensity scaling (LOCI) because of its best performance in correcting time-based precipitation indices (Kiprotich et al. 2021). We applied the distribution mapping (DM) technique to correct the temperature variables due to its better performance than other bias correction methods (Zhang et al. 2018). In performing the bias correction, we used the overlapping period of observed data to compute the correction parameters. The patterns and trends of climate projections for the study area are indicated in Figs. S2 and S3 in the supplementary file.

Simulating climate change impact on maize production

Climate modelling data and soil grids were intersected in a GIS environment to retrieve the desired variables for each grid. Solar radiation data was also retrieved using the soil grid centroid. Solar radiation values for the study region were increased by 10% to account for increased intensity under climate change (Jabeen et al. 2017). The soil grid centroids with unique soil physical and chemical characteristics were further used to extract the climate data using the extract-by-points tool in ArcGIS. The process enabled a unique database for each grid centroid to be created for yield projection in the DSSAT environment. Finally, yield was interpolated, as detailed by Kipkulei et al. (2024a). The potential change in maize productivity under climate change was determined by comparing the baseline simulated yield and the future projected yield. Therefore, the relative yield change was calculated from Eq. 1.

$$\Delta\text{Yield} = \frac{\text{Yield\_future}_{i,j} - \text{Yield\_baseline}_{\text{ref}}}{\text{Yield\_baseline}_{\text{ref}}} \text{x}100 \quad (1)$$

where ΔYield is the relative yield change, $\text{Yield\_future}_{i,j}$ is the future yield for the period i and scenario j and $\text{Yield\_baseline}_{\text{ref}}$ is the reference yield for the baseline period.

Spatial clustering and climate impact spots

Future climates are expected to induce heterogeneous effects of production across locations. Spatial clustering techniques provide powerful visualizations for such analysis. In the present study, we used Moran's I and hotspot analysis to characterize the pattern and distribution of yield values in the baseline and simulated future periods. Therefore, we employed Moran's I to test whether the yield distribution was clustered, randomly distributed or dispersed with a 95% confidence threshold. Moran's I was calculated using Eq. 2.

$$I = \frac{N}{W} \frac{\sum_i \sum_j w_{ij}\left(x_i - \bar{x}\right)(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad (2)$$

where N is the number of observations, x is the variable of interest (yield in our case), $\bar{x}$ is the mean of the variable, w_{ij} represents the spatial weights and W is the sum of the weights. Moran's I ranges between − 1 and + 1. Positive values indicate spatial clusters and negative values depict dissimilar values. A zero value indicates a random distribution.

Once the distribution of data in clusters was established, distance statistics were employed to identify high-impact spots. We utilized function hotspot analysis (Getis-Ord Gi *) based on Gi* spatial statistics (Getis and Ord 1992). The function estimates a Z score and p values to reject or not reject the null hypothesis that the features are structured in complete spatial randomness. The distance statistics analyze the degree of spatial association among neighboring pixels and identify features of pronounced clustering. A high Z score denotes a hotspot, and a low Z score denotes a cold spot. In this study, the analysis was performed based on the yield difference between the future climatic scenarios and the baseline (future yield-baseline yield).

To distinguish climate impacts across the study area, we applied thresholds set in the study of Eitzinger et al. (2017) to classify hotspots, adaptation spots, stable zones and more stable zones. In the study, hotspots were defined as pixels with negative Z values greater than two standard deviations of the mean (95%). These are considered areas with very high deviations between the future yield and the baseline yield and, therefore, significant low-yield zones. In these areas, reduced suitability for maize production might occur due to highly reduced yield. Adaptation spots are areas whose negative Z values of spatial association were equal to or greater than one standard deviation of the mean. These spots show a slight difference between the future yield and the baseline yield. Maize production is expected to decline in these zones. However, appropriate adaptation mechanisms are likely to overcome further yield decline. The stable zones are considered neutral, where average production in the baseline period will likely be maintained. The more stable areas are areas whose positive Z values are greater than one standard deviation of the mean. These regions show a high positive difference between the future yield and the baseline yield. Yield in these areas is likely higher than the average due to the accrued benefits of climatic conditions.

Results

Projections and trends in yield in the mid- and end-of-century periods

The DSSAT-CERES-Maize model characterized maize yield under the RCP scenarios based on the baseline and future climate data (Fig. 2). The model simulated yield decline from the baseline in all future scenarios and across the RCPs. The average modelled yields across the baseline period (1984–2013) ranged from 2.9 to 5.8 t ha^{-1}. This yield range corresponds to the average measured yield reported in the annual government statistics (GOK 2020). The deviation in maize yield from the baseline differed across scenarios and periods. For the mid-century period, the model projected an average decline in yields by 7.9% under the RCP4.5 scenario, whereas the yield decline was approximately 25% under the RCP8.5 scenario. The end-of-century period was even marked with projected higher declines relative to the mid-century period. The yield decline relative to the baseline period is approximately 12% under the RCP4.5 scenario and 36% under the RCP8.5 scenario.

Maize yield was also found to be variable across the different warming levels. The mid-century period depicted high variability in yields in comparison to the end-of-century period, as indicated by the width of the box plots.

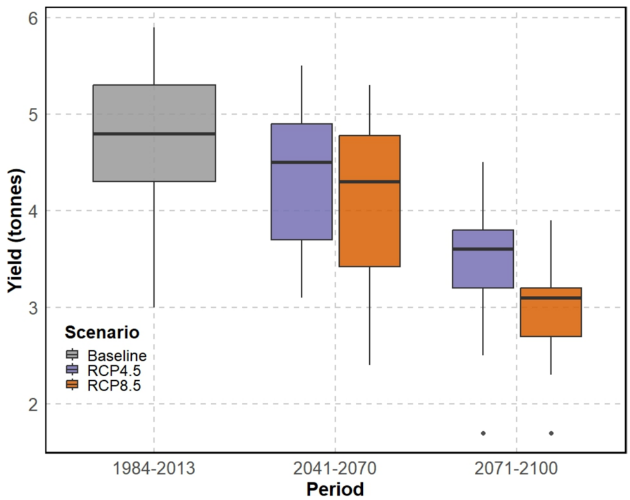

Fig. 2 Mean yields and distribution of the H614 cultivar for the baseline (1984–2013), the future projections, mid-century period (2041–2070) and end-of-century period (2071–2100) under RCP4.5 and RCP8.5 scenarios

Despite the significant decline, the yield under the RCP4.5 scenario will likely become higher than the yield under the RCP8.5 scenario. The results indicate that the yield will range between 2.50 and 4.50 t ha^{-1} across the years under RCP4.5. However, under RCP8.5, the minimum yield will remain the same, whereas the maximum yield will decrease to approximately 3.90 t ha^{-1}.

Spatial clustering and climate impact spots

Moran's *I* indices for future-baseline yield ranged between 0.42 and 0.77, indicating positive spatial clustering of yield differences in the region. The analysis of impact spots arising from climate change effects revealed various patterns across the study area (Fig. 3). Hotspots under RCP4.5 and 8.5 covered fewer areas in the mid-century period but increased in the end-of-century period. However, adaptation spots covered substantial parts of the study area under the two climatic scenarios and periods. Adaptation spots under RCP4.5 were located mostly in the southern regions of Uasin Gishu County. Similarly, some eastern parts of Trans Nzoia County revealed decreased yields in the mid-century period. The RCP8.5 scenario, however, revealed a slight difference in the representation of adaptation spots in Trans Nzoia County. Some northern parts of the county were mapped as adaptation locations. Both scenarios showed agreement in representing adaptation spots in Uasin Gishu County, where southern parts of the region revealed low yields from the baseline period. Stable areas in the mid-century period cover western parts of Trans Nzoia and northern and southern parts of Uasin Gishu County. More stable zones were found in Trans Nzoia County and northern parts of Uasin Gishu County.

In the end-of-century period, both scenarios (RCP4.5 and RCP8.5) revealed that the counties will likely be marked by hotspots and adaptation spots. These zones significantly increased in the end-of-century period, which also reflects the yield distribution in the period. Hotspot zones are likely to increase during this period for both climate scenarios. The zones are concentrated in the southern parts of Uasin Gishu County and central western Trans Nzoia County. Stable zones were significantly reduced in the projected end-of-century period. The zones are mapped in the western parts of Trans Nzoia County under RCP4.5. Similarly, more stable zones might be further reduced and are projected as small pockets in both counties under the two climatic scenarios. Surprisingly, the end-of-century period was marked by decreased hotspots under the RCP8.5 relative to the RCP 4.5 scenario. The possible reason for the finding could be attributed to the increased precipitation under the RCP 8.5 scenario. It is projected that most parts of the East Africa region will record increased precipitation, which could enhance crop growth in some parts of the region. Therefore, yield decline as a result of increased warming could be compensated by rainfall increase in the high emission scenario (Cook and Vizy 2013; Choi et al. 2023).

Discussion

Projections and trends in yield under future climate scenarios

The DSSAT-CERES model was used to quantify future production based on the projected climate of the study area. Crop models are powerful tools for quantifying future climate impacts. With the DSSAT-CERES-Maize model, the present study assessed the impact of future climates on maize production in key maize-growing regions in Kenya. The results show that the projected period will likely face varied magnitudes of maize yield decline in the study area. The study found a decline between −7 and −20% in the mid-century period and from −22 to −41% in the end-of-century period. These ranges align with other studies in the East African region using various modelling platforms (Bwambale and Mourad 2021; Volk et al. 2021; Babel and Turyatunga 2015). Similarly, other studies in the larger Eastern Africa region experienced yield declines of magnitudes relative to that observed in the study (Abera et al. 2018; Chekole and Mohammed Ahmed 2023). A possible reason for the projected yield is the increase in temperature and highly varying precipitation in the future. For instance, the climate models projected suppressed precipitation during the region's main sowing window (March–May). The

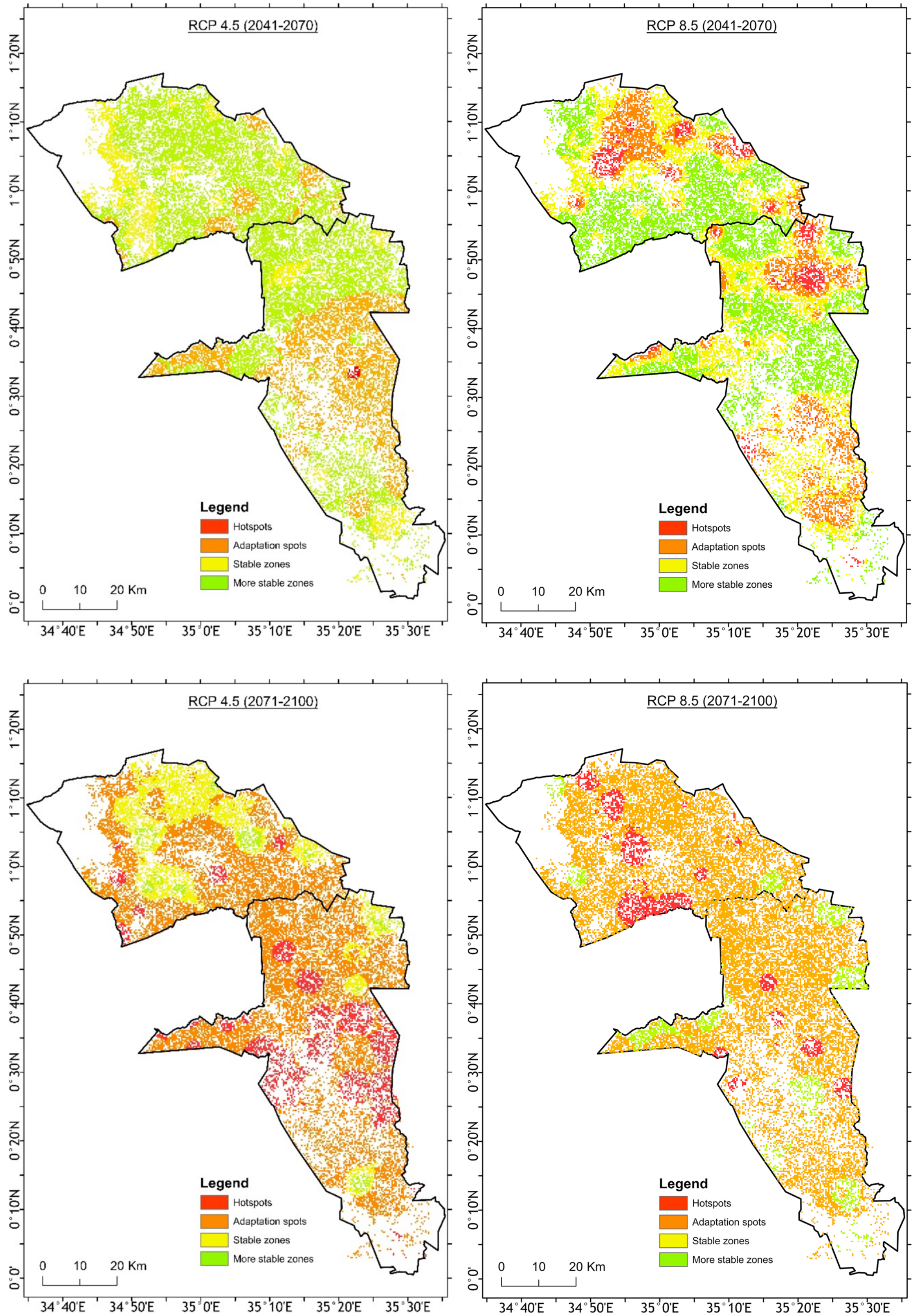

Fig. 3 Characterization of impact spots and stable maize yield zones for the mid-century period (2041–2070) and end-of-century period (2071–2100) under **a** RCP 4.5 and **b** RCP 8.5

literature suggests that water deficit at sowing significantly affects maize growth and development (Song et al. 2019). Additionally, suppressed precipitation and elevated temperature levels reduce crop growing seasonal length and affect maize organ development. Furthermore, important crop phase durations, such as flowering and maturity, are shortened under future climate changes, leading to yield decline (Lin et al. 2015; Hatfield 2016). The study reveals that the projected maximum rise in minimum and maximum temperatures will likely coincide with the sowing and reproductive stages. These stages are sensitive to heat stress and critical in maize development, as they determine the plant population and kernel formation (Wang et al. 2021).

The climate models projected increased precipitation in September and a subsequent short rainy season in the study area. Considering the current standard agronomic practices in the study area, precipitation variability might necessitate adjustment in future agronomic planning by farmers (Shiferaw et al. 2011). Other related studies have also found projected favorable climates beyond the standard growing periods (Dunning et al. 2018; Palmer et al. 2023) in the East African region, which might trigger the adjustment of agronomic practices to meet future crop climatic demands. Furthermore, the findings of this study indicate that crop yields will likely be severely affected under both emission scenario pathways. Under future climates, CO_2 concentration levels and temperatures are expected to rise, and these variables are projected to influence maize yields (Zhai et al. 2021). The mid-century period is characterized by lower precipitation declines than in the end-of-century period. Nonetheless, the study reveals that the yield for both periods will be impacted by climate change.

Therefore, the combined precipitation and temperature dynamics will affect the evapotranspiration demand and soil water content, posing risks to maize growth and development. This finding is especially true in the study area where maize production is dominantly rainfed, leading to higher production risks. Therefore, changes in climatic patterns will necessitate the adjustment of agronomic practices, especially in hotspot zones, to alleviate the decline in future production. Agronomic, vegetative and soil and water management measures are among the feasible strategies that can be employed to bridge the yield gaps and curb yield declines, as indicated by studies in the region (Rotich et al. 2024; Oduor et al. 2021).

Implications of the study for future maize production

This article contributes to the knowledge of the impact of climate change on future maize production in two maize-producing counties in Kenya. The study has demonstrated the usefulness of crop modelling and spatial analysis techniques for understanding the heterogeneous impacts of climate change. The combined approach allowed the understanding of complex relations of productivity-climate dynamics interactions and provided insights into future production patterns and trends that enable the visualization of the differential impacts of climate change in the study region. In this way, the varied yield response has been classified to depict areas of possible high-yield decline (hotspots), below-average yield (adaptation spots), maintained production (stable zones) and possible yield increase (more stable zones). The mapped environments provide meaningful information regarding tailoring strategies that can overcome the decline in maize productivity in the study region. Some useful initiatives for enhancing productivity include:

i. Supporting efforts and projects that are aimed at creating farmers' awareness and supporting climate-smart initiatives should be enhanced, especially in hotspots and adaptation zones;
ii. Emphasizing the identification of context-specific targeted adaptation strategies, for example, maize-legume intercropping, soil water conservation practices, drought-resistant varieties and optimum sowing for possible up- and out-scaling;
iii. Optimizing agronomic practices, for example, sowing practices, nutrient management in low-yield zones and the selection of resilient maize cultivars to help farmers better cope with climate change impacts and
iv. Enhancing early warning systems to mitigate the anticipated production declines.

Conclusions

This study is aimed at assessing the impact of climate change on maize yield at the county scale in Kenya using the DSSAT-CERES-Maize model. The study revealed possible yield declines under future climates, which also demonstrated varied patterns across the region. The study revealed a projected yield decline of up to -41% in some parts of the area based on future climate dynamics. Furthermore, the study found that hotspots and adaptation zones will expand in the future, compromising food demand in a substantial part of the study area. However, few areas were flagged as stable zones and more stable zones. These findings highlight the need for region-specific adaptation and mitigation strategies such as maize-legume intercropping, soil water conservation practices, drought-resistant varieties and optimum sowing, particularly in hotspots and adaptation regions.

The implications of this research extend to agronomists and policy-makers at the county and national levels, informing agricultural planning and climate adaptation efforts. By enabling the scaling up of targeted adaptation strategies and enhancing early warning systems, the study contributes to mitigating the anticipated production declines. Moreover, the potential reduction in maize suitability indicated by the expanded adaptation locations suggests the urgency for addressing food security in Kenya's key food-producing regions.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10113-025-02403-y.

Funding Open Access funding enabled and organized by Projekt DEAL. The German Academic Exchange Service (DAAD) supported the first author through the joint Kenya-German Postgraduate Training Programme (Ref. No 91770355).

Data availability The climatic data for the baseline and projection analysis are available on the websites. CHIRPS and CHIRTS data can be accessed through the Climate Hazards Centre website. The CORDEX data can be downloaded freely using various access methods: https://cordex.org/. The global high-resolution soil profile dataset can be derived from the Harvard University dataverse website (https://dataverse.harvard.edu/dataset.xhtml?persistentId=https://doi.org/10.7910/DVN/1PEEY0).

Declarations

Conflict of interest The authors declare no competing interests.

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