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Effects of future climate on suitability of major crops in Eastern Kansas River Basin

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Highlights
- Projected climate change scenarios reduced the future crop growing suitability in the EKSRB.
- Greater yield loss of maize and soybean was recorded by the end of the century under RCP8.5.
- Growing soybean over maize would be beneficial under future climate in the EKSRB.

Abstract: Climate change significantly threatens food security and the agricultural economy, particularly under rainfed conditions. This study uses the Decision Support System for Agrotechnology Transfer (DSSAT) crop simulation model to evaluate the future suitability of growing maize and soybean in the Eastern Kansas River Basin (EKSRB) under two projected climate scenarios (RCP 4.5 and RCP 8.5) from 2006 to 2099. By comparing the baseline (1990–2019) and future climates, the yield gap percentage method is employed to quantify the discrepancy between actual and potential yields. This innovative approach integrates spatial soil variability and advanced climate projections from 18 global climate model (GCMs), enhancing the accuracy of crop suitability assessments. Results indicate yield losses ranging from 23% to 57% for maize and 20% to 36% for soybean, with maize experiencing a greater yield gap than soybean, highlighting soybean's resilience under future climatic conditions. The study identifies critical regions within the EKSRB where adaptive strategies are most needed and provides insights for policymakers to develop targeted agricultural strategies, facilitate policy planning, and select mitigation strategies for vulnerable areas. This research underscores the necessity for adaptive agricultural practices to ensure food security and sustainability, offering a robust framework that can be adapted to similar regions globally.

Keywords: agriculture, climate change, Decision Support System for Agrotechnology Transfer model, Representative Concentration Pathways, yield gap

INTRODUCTION

Climate change is a global phenomenon marked by increases in the frequency and intensity of extreme events, considerably impacting agricultural production and introducing uncertainty in global food security (Joos *et al*., 2001; Steiner *et al*., 2018). Climate change strongly impacts agriculture, particularly through weather phenomena such as changes in temperature, precipitation levels, and soil moisture availability (Goyal, 2004). Maize and soybeans are the most important crops for U.S. agriculture, with their yields being highly sensitive to environmental conditions (Wang *et al*., 2020). This sensitivity necessitates irrigated agriculture to minimise yield loss, as 60–80% of these crops when grown under rainfed conditions, are vulnerable to unfavourable climatic events (Zhou *et al*., 2021). The Intergovernmental Panel on Climate Change (IPCC) sixth assessment report (AR6) provides evidence that global temperatures are predicted to rise by 3.6–5.7°C by the end of the century, compared to pre-industrial levels (Pörtner *et al*., 2022).

The elevated atmospheric carbon dioxide (CO_2) concentration, increased temperature, and changing precipitation patterns during the growing season directly affect the rainfed crop production system (Nan *et al*., 2016; Qin *et al*., 2023; Onyekwelu and Sharda, 2024b). The climatic variation observed at regional scales (Satta *et al*., 2017) and the sensitivity of rainfed crop production to climate (Yang *et al*., 2017) make it crucial to understand the present and future effects of climate change on U.S. maize and soybean production.

Maize and soybean yields have been subjected to heat stress, and the detrimental impact of high temperatures on yields has been demonstrated in many studies (Prasad, Staggenborg and Ristic, 2008; Schlenker and Roberts, 2009; Lobell and Asseng, 2017). The productivity of these crops has dropped due to the rising growing season temperatures in the U.S. (Ainsworth and Ort, 2010; Kucharik and Serbin, 2008; Onyekwelu and Sharda, 2024b), indicating the sensitivity of maize and soybeans to a changing climate. The sensitivity of U.S. maize and soybean production to drought from 1958 to 2007 has been associated with a 13% yield loss due to extremely hot days during the growing season (Zipper, Qiu and Kucharik, 2016).

Kansas is one of the largest producers of maize and soybean in the U.S. (Sassenrath *et al*., 2023) with the Eastern Kansas River Basin (EKSRB) being a vital agricultural region in the state due to its fertile soils, favourable climate, and abundant water resources, making it ideal for growing crops under rainfed conditions (McVay *et al*., 2006). An increasing number of heat waves and increasing heat wave severity have been observed in Kansas (Feddema *et al*., 2008), significantly impacting the rainfed crop production system. Therefore, it is important to determine the suitability of crops at a regional scale to understand how the cultivation of crops may change over time and to develop a region-specific agricultural strategy to ensure future food security.

The Decision Support System for Agrotechnology Transfer (DSSAT) model is widely used in climate change studies to evaluate the impact of climate change on crop yields and food production (Jones *et al*., 2003; Hoogenboom *et al*., 2019). The DSSAT model simulates crop growth, development, and yield under varying environmental conditions, including changes in temperature, precipitation, and carbon dioxide concentrations (Thorp *et al*., 2008). The DSSAT sub-models – Cropping System Model (CSM)-CERES-Maize (Jones and Kiniry (eds.), 1986) and CROPGRO-Soybean (Wilkerson *et al*., 1983) have been successfully utilised in many studies for a variety of field conditions and management practices worldwide under different climate change scenarios (Bao *et al*., 2017; Liu *et al*., 2019; Richetti *et al*., 2019; Sen, 2023; Onyekwelu and Sharda, 2024b). Several of these studies have focused on the impact of high temperatures and elevated CO_2 levels due to climate change on irrigated or rainfed maize and soybean production, indicating that using DSSAT to examine the impacts of future climate conditions on crop production is a well-accepted approach to understanding future agricultural sustainability.

Crop suitability analysis involves assessing the suitability of growing different crops for a specific location or region under some environmental conditions. There is increasing recognition of the uncertainties in crop production and suitability under future climatic conditions (Biagini *et al*., 2014). The crop simulation models, such as Environmental Policy Integrated Climate (EPIC), Agricultural Production Systems Simulator (APSIM), have been used in addition to DSSAT to analyse crop suitability worldwide (Adejuwon, 2005).

Recent studies (Estes *et al*., 2013; Eitzinger *et al*., 2017) using crop simulation models have shown that DSSAT often outperforms others, such as EPIC and APSIM, in projecting the suitability of maize and other crops in various regions. Estes *et al.* (2013) found DSSAT to provide the most accurate simulations of maize yields in the United States, while Eitzinger *et al.* (2017) reported DSSAT's superior performance in capturing observed yield variability for maize in Europe.

The ability to accurately predict crop suitability under present and future climates is an important tool that could help decide the right crop choice under climate transition to achieve sustainable crop production intensification. Conventional crop suitability assessments are usually based on yield gap analyses (Grassini *et al*., 2015), which compare the actual yield to its potential yield to assess the suitability of the crop growing conditions in response to climatic factors. The yield gap is a crucial idea in crop suitability studies that offers insightful information about the potential productivity of an area for a specific crop. The DSSAT model has been employed in several studies to study the climate change impacts on yield gaps under rainfed or irrigated field conditions (Southworth *et al*., 2000; Basak *et al*., 2010; Shin *et al*., 2020). These studies confirmed that DSSAT is a powerful tool for simulating crop growth and yield under different management scenarios and can help identify areas for potential yield improvements through yield gap analysis. Since most of the past studies for suitability analysis have been done at coarse resolutions/global scales (Metz, Rocchini and Neteler, 2014; Croitoru *et al*., 2020), several gaps remain at local and regional scales, emphasising the need to conduct regional scale suitability analyses to understand the vulnerability associated with climate change at finer spatial scales and provide more site/region-specific solutions.

In this study, the DSSAT model was applied in the EKSRB with two specific objectives: (a) to assess the impact of future climate change on maize and soybean yields under two representative concentration pathways, RCP4.5 and RCP8.5 for near-century (2010–2039), mid-century (2040–2069), and end-century (2070–2099); and (b) provide a regional assessment of maize and soybean growing suitability under baseline (1990–2019) and future (2010–2099) climate change scenarios by quantifying the yield gap.

MATERIALS AND METHODS

STUDY AREA

The region of this study is the Eastern Kansas River Basin (EKSRB) – Figure 1, which is the watershed of the Kansas River between the confluence of the Smoky Hill and Republican rivers at Junction City and its terminus is at its confluence with the Missouri River (Onyekwelu and Sharda, 2024b). This region, between 39°N~40°N and 95°W~97°W, is a majority rainfed crop-growing area in Kansas, which consists of seventeen counties, with planted acreage of 1425 and 1659 km^2 for maize and soybean, respectively (CSISS, 2019). The region mainly has a humid climate, with a long-term annual average precipitation of 676 mm (1990–2019) and the maximum and minimum daily air temperatures during the growing season (May–October) of 21.2 and 12.3°C, respectively.

CROP MODEL INPUTS

Climate data

The daily observed weather data, such as daily maximum and minimum temperatures, precipitation, solar radiation, wind speed, and relative humidity for the baseline period of 1990–2019, with a spatial resolution of approximately 4 km, were obtained from the Gridded Surface Meteorological (gridMET) dataset (Abatzoglou and Brown, 2012). The Coupled Model Intercomparison Project Phase 5 (CMIP5) report stated that climate models are used to comprehend the past and quantify the future uncertainty in the climate system (Taylor, Stouffer and Meehl, 2012). CMIP5 Climate models are critical for assessing future climate scenarios and managing uncertainties in projections, which is particularly important for sectors like agriculture (Hawkins and Sutton, 2011). The CMIP5 was chosen for its proven effectiveness in climate impact assessments, as demonstrated by studies like Kumar and Kuttippurath (2024), who successfully projected pest generations in California, and various crop modeling studies that have utilised CMIP5 GCMs (Stella *et al.*, 2023; Yang, Yang and Wang, 2023; Martre *et al.*, 2024; Dahri *et al.*, 2024).

Therefore, to extract the future climate data (2006–2099) from a suite of climate models, the Multivariate Adaptive Constructed Analogs (MACAv2) methodology was used to statistically downscale the output of 18 global circulation models (GCM) of CMIP5 from >200 km native resolution to 4 km (Abatzoglou and Brown, 2012). The MACAv2 is a statistical downscaling technique that combines historical observations with global climate model data to create high-resolution climate projections. It preserves the relationships between multiple climate variables and uses constructed analogs by selecting historically observed days that are similar to the model-projected days, ensuring an accurate representation of climate patterns. The baseline and future climate from each GCM were converted to DSSAT weather file format for the model to assess climate change impact on crop production in the EKSRB. Two representative concentration pathways (RCP4.5 and RCP8.5) were considered to assess the impacts of climate change on crop production in the EKSRB. For predicting future greenhouse gas concentrations with the specified radiative forcing pathways under various scenarios of social, economic, and technological growth, RCPs are frequently utilised (Taylor, Stouffer and Meehl, 2012). Radiative forcing under RCP4.5 is anticipated to rise to about 4.5 $W \cdot m^{-2}$ by 2100, whereas RCP8.5 predicts radiative forcing to be 8.5 $W \cdot m^{-2}$ by 2100. Finally, to compare the changes with the baseline study period (1990–2019); the future study period was divided into three time periods – near-century (2010–2039), mid-century (2040–2069), and end-century (2070–2099).

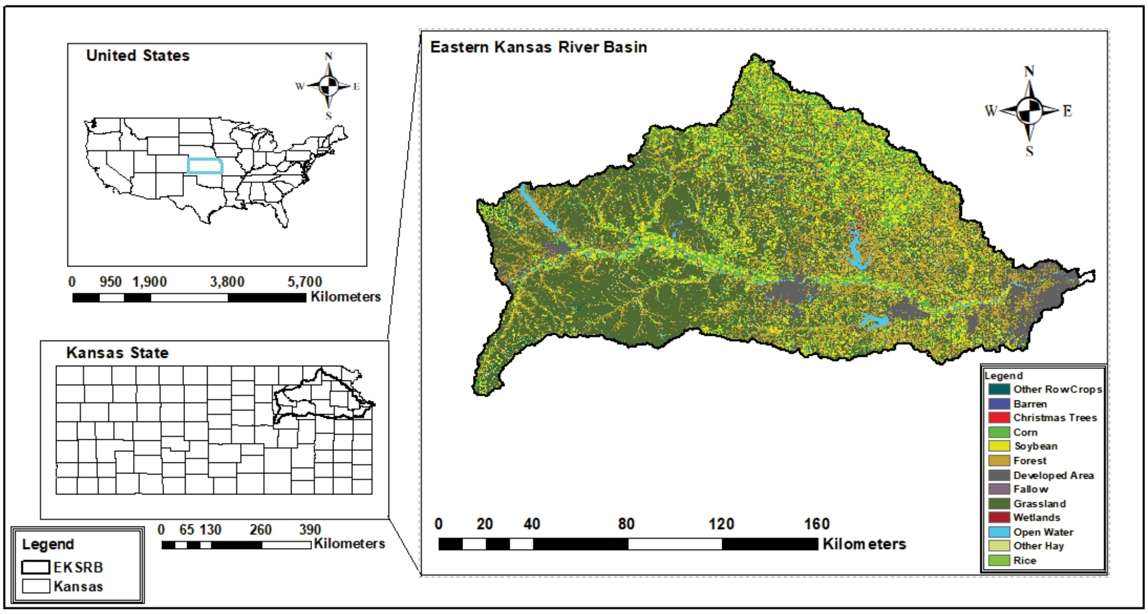

Fig. 1. Location of Eastern Kansas River Basin (EKSRB) in Kansas (with Kansas highlighted in the U.S.) and land use and crop cover (LUCC) map of EKSRB showing the distribution of different crops grown in the basin; source: own elaboration based on: Cropland Data Layer (CSISS (2019))

Soil and crop management data

The DSSAT model requires detailed information on soil properties, including soil layer information – depth and thickness, texture, bulk density, saturated hydraulic conductivity, etc., and soil surface information: albedo, runoff curve number, soil fertility factor, and drainage coefficient (Jones *et al.*, 2003). To account for the spatial soil variability impact in the EKSRB, the Gridded Soil Survey Geographic (gSSURGO) soil dataset (USDA NRCS, 2021) was used. The gSSURGO soil data has a spatial resolution of 30 m and has sampled soil profile properties up to 200 cm in depth. The procedure used for creating DSSAT-compatible soil files is reported in Sen, Zambreski and Sharda (2023).

The DSSAT crop management data, such as plant population, row spacing, and fertiliser application, were collected (Tab. 1) from the Kansas State Research and Extension (Sassenrath, Lingenfelser and Lin, 2023). For the study area, the planting dates for maize and soybean were set to April 20th and May 5th, respectively. To streamline our modelling approach and isolate the impacts of climate change on crop growth and yield, the study employed fixed planting dates and standardised fertiliser applications, which is followed by other climate change studies (Kassie *et al.*, 2016; Mubeen *et al.*, 2020). This methodological simplification, while not capturing the full spectrum of agronomic variability, provided a consistent framework for evaluating the influence of climatic variables.

Table 1. Crop management recommended practices for the Eastern Kansas River Basin

Crop	Plant population (plant per m^2)	Row spacing (m)	Fertiliser (urea) (kg·ha^{-1})	Fertiliser application
Maize	7.6	0.51	170	broadcasted
Soybean	37	0.76	60	broadcasted

Source: own elaboration.

DATA PREPARATION FOR THE DSSAT MODEL RUN

Python (Python 3.8, 2009), a high-level programming language, was used to convert historical and future climate and soil datasets to DSSAT input files format. For the baseline study period, the Python programming code was used to (a) prepare the weather (.WTH) and soil (.SOL) input files for the EKSRB, (b) run the DSSAT model to simulate yields by linking all files, and (c) obtain the output files of the model run (.OSU,. OOV, and warning. OUT) for data analysis. The same process was used in future climate scenario runs where the DSSAT model was run for each soil type of the region and for each of the 18 GCMs for simulating yield, and the ensemble mean yield of 18 GCMs for each soil type was used for further analyses (Fig. 2).

CALIBRATION AND EVALUATION OF CROP MODELS

The DSSAT-CSM CERES-Maize (Jones and Kiniry (eds.), 1986) and CROPGRO-Soybean (Wilkerson *et al.*, 1983) models were calibrated for the study area. The calibration of the CERES-Maize model for this location was meticulously executed following the methodology described by Sen, Zambreski and Sharda (2023).

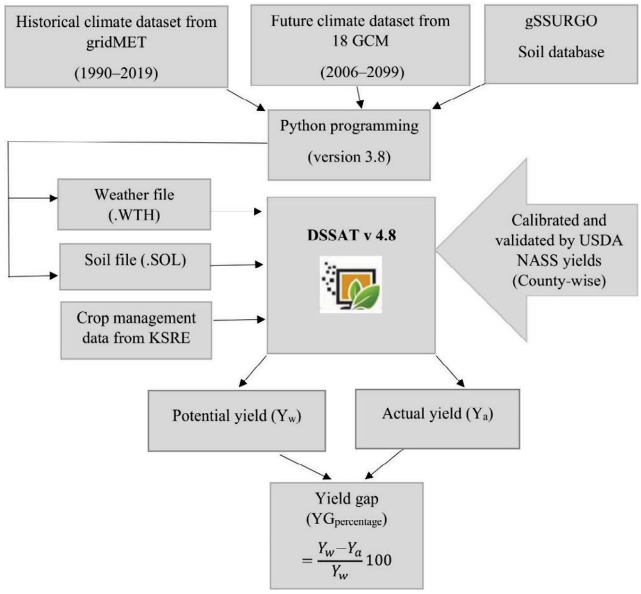

Fig. 2. Flowchart showing yield simulation from the Decision Support System for Agrotechnology Transfer (DSSAT) model; gridMET = Gridded Surface Meteorological; GCM = Global Climate Model; gSSURGO = Gridded Soil Survey Geographic; KSRE = Kansas State Research and Extension, $YG_{percentage}$ = yield gap percentage; source: own elaboration

This process ensured that the chosen maize cultivar (PIO 3489) was accurately represented in the model, leading to a high degree of performance accuracy in simulating growth and yield under various environmental conditions.

The CROPGRO-Soybean model was calibrated systematically for soybeans following the approach reported by Battisti, Sentelhas and Boote (2017). In the CROPGRO-Soybean model, eighteen genetic coefficients determine phenology and yield estimates. Calibration aims to obtain reasonable estimates of these coefficients by sequentially comparing the simulated results with the observed data (Sharda *et al.*, 2021). The 2020 yield trial dataset used for calibration was obtained from six counties in the region: Riley, Republic, Franklin, Shawnee, Saline, and Pottawatomie, made available by Kansas State Research and Extension (Sassenrath, Lingenfelser and Lin, 2023). The genetic coefficients were adjusted using the GENCALC program to initiate a range of cultivar coefficients (Hunt and Pararajasingham, 1993). The GENCALC uses genetic coefficients of the default cultivar in the DSSAT.CUL file and iteratively compares the observed to the simulated data. Since only yield data were available for model calibration, it is essential to note that the GENCALC.RUL file for the CROPGRO-Soybean model was conditioned to iterate for only yield (HWAM). Once a range of cultivar coefficients was obtained from the GENCALC output file, the genetic coefficients of the trial soybean cultivar were manually adjusted until reasonable estimates were achieved. More details can be found in Onyekwelu and Sharda (2024a).

For model evaluation, 2021 variety trial datasets obtained for Riley, Franklin, Shawnee, and Pottawatomie counties in the region were used. Test (*p*-value) and goodness of fit (index of agreement, *d*-statistics (Willmott, 1982), normalise root mean square error (*NRMSE*)) (Araya *et al.*, 2017) were used as indicators to assess model accuracy for the intended application.

The *NRMSE* is the root mean square error (*RMSE*) (Eq. 2) multiplied by 100 and divided by observed mean (Eq. 1).

$$NRMSE = \frac{RMSE}{\bar{O}} 100 \tag{1}$$

where: $\bar{O}$ = observed mean.

$$RMSE = \left(\frac{\Sigma(s_i - o_i)^2}{n}\right)^{0.5} \tag{2}$$

where: n = the number of observations, s_i = the predicted value, and o_i = the measured observation; *NRMSE* values for model evaluation, as described by Soler, Sentelhas and Hoogenboom (2007) are classified as 0–10% excellent, 10–20% – good, 20–30% fair, and >30% – poor. Similarly, *d*-statistic (Eq. (3)) values as 0.7 – poor, 0.7–0.8 – moderate, 0.8–0.9 – good, and 0.9–1.0 – excellent.

$$d = 1 - \frac{\sum_{i=1}^{n} (P_i - O_i)^2}{\sum_{i=1}^{n} \left(|P_i'||O_i'|\right)^2} \tag{3}$$

where: P_i = the predicted value, O_i = the measured observation, $|P_i'| = |P_i - M|$, $|O_i'| = |O_i - M|$, M = the mean of the observed variable (yield).

To enhance regional model calibration and evaluation accuracy and possibly reduce model uncertainty and to assess how well the model simulated the variability in the observed end-of-season yield, the coefficient of variation (*CV*) was also calculated. The *CV* match of simulated and observed data was checked alongside other test and fitness statistics. The closer the simulated *CV* is to the observed *CV*, the better and more confident the calibrated and evaluated regional model (Onyekwelu and Sharda, 2024a).

SUITABILITY ANALYSIS

To assess crop suitability in the EKSRB region, the yield gap percentage ($YG_{\text{percentage}}$) was calculated as shown in equation in Figure 2.

$YG_{\text{percentage}}$ is calculated as the percentage difference between the potential and actual yield and divided by the potential yield. Both yields were simulated by the DSSAT model where potential yield is the yield achievable with optimal water and nutrient levels, i.e the crop experiences no nitrogen or water stress. Potential and actual yield (i.e., rainfed yield considering water and nitrogen-limited conditions) was simulated for maize and soybean using DSSAT-CSM CERES-Maize and CROPGRO-Soybean models, respectively under baseline and future climate change scenarios.

The national average yield gap percentage (*NAYG*) quantifies the disparity between potential and actual crop yields at a national level, serving as a benchmark for evaluating agricultural productivity. In the present study, the classification of crop suitability in the EKSRB was based on the *NAYG* for maize and soybean. The *NAYG* values for rainfed maize (26%) and rainfed soybean (22%) (Wart van *et al.*, 2013; Grassini *et al.*, 2015) were used as thresholds to determine suitability. Areas with yield gap percentages less than the national average were considered highly suitable for growing the respective crops, while those with greater percentages were deemed unsuitable. The study categorised suitability into highly suitable, moderately suitable, and unsuitable based on these NAYG thresholds.

Highly suitable: highly suitable areas were identified where the yield gap percentage was below or equal to the *NAYG*. These areas exhibited climatic conditions conducive to supporting greater yields of maize and soybean.

Moderately suitable: several studies showed that a 25% increase in the *NAYG* would be expected under extreme future climate change scenarios, and a proper adaptive plan could mitigate the negative impacts of climate change (Schmidhuber and Tubiello, 2007; Pörtner *et al.*, 2022). Hence, this study classifies the moderately suitable area as having yield gap percentages greater than the *NAYG* but less than a 25% increase in *NAYG*. Therefore, the upper limit of yield gap percentage for the moderately suitable area of maize and soybean would be 32.5 and 27.5%, respectively.

Unsuitable: unsuitable areas were considered when the yield gap percentage was greater than 25% increase in *NAYG*.

RESULTS AND DISCUSSION

CALIBRATION AND EVALUATION OF DSSAT MODELS

The genotype coefficients adjusted for an ASGROW maturity group III soybean cultivar during the CROPGRO-Soybean model calibration for the EKSRB region are presented in Table 2.

The adjustment of 18 CROPGRO-Soybean coefficients (Tab. 2) related to phenology and crop development resulted in a close agreement between simulated and observed yield values. Model performance was highly satisfactory during calibration with *NRSME* = 8% (334 $kg \cdot ha^{-1}$), *p*-value = 0.62, *d*-statistics = 0.88, and observed and simulated *CV* of 12% each. The mean observed

Table 2. Genotype coefficients adjusted during CROPGRO-Soybean regional model calibration

Coefficient	Definition	Calibrated value
CSDL	critical short-day length below which reproductive development progresses with no day length effect (for short-day plants) (h)	14.14
PPSEN	slope of the relative response of development to photoperiod with time (positive for short-day plants) ($1 \cdot h^{-1}$)	0.340
EM-FL	time between plant emergence and flower appearance (R1) (photothermal days)	22.50
FL-SH	time between first flower and first pod (R3) (photothermal days)	9.00
FL-SD	time between first flower and first seed (R5) (photothermal days)	10.00
SD-PM	time between the first seed (R5) and physiological maturity (R7) (photothermal days)	38.60
FL-LF	time between first flower (R1) and end of leaf expansion (photothermal days)	27.0
LFMAX	maximum leaf photosynthesis rate at 30 C, 350 ppm CO_2, and high light ((mg CO_2)$\cdot m^{-2} \cdot s^{-1}$)	1.35
SLAVR	specific leaf area of cultivar under standard growth conditions ($cm^2 \cdot g^{-1}$)	375.00

cont. Tab. 2

Coefficient	Definition	Calibrated value
SIZLF	maximum size of the full leaf (three leaflets) (cm^2)	180.00
XFRT	maximum fraction of daily growth that is partitioned to seed + shell	1.00
WTPSD	maximum weight per seed (g)	0.195
SFDUR	seed filling duration for pod cohort at standard growth conditions (photothermal days)	29.90
SDPDV	average seed per pod under standard growing conditions (pcs.·pod^{-1})	2.20
PODUR	time required for cultivar to reach final pod load under optimal conditions (photothermal days)	13.00
THRSH	threshing percentage; the maximum ratio of (seed:(seed + shell)) at maturity; causes seeds to stop growing as their dry weight increases until shells are filled in a cohort	79.00
SDPRO	fraction protein in seeds expressed in gram of protein per gram of seed	0.405
SDLIP	fraction oil in seeds expressed in gram of oil per gram of seed	0.205

Source: own study.

and simulated yield during calibration were 3,999 and 4,158 kg·ha^{-1}, respectively. Yield overestimation in this study may have resulted from an underestimation of water stress. According to Kothari *et al.* (2019), the overestimation of dryland wheat yield in Texas High Plains using the CERES-Wheat model resulted from an underestimation of water stress. Model structure simplification could be another factor accounting for the overestimation. However, model performance based on yield calibration ranges from good to excellent following the recommendations of Soler, Sentelhas and Hoogenboom (2007), thus confirming the fitness of our model for the intended use.

During the model validation, observed and simulated yields matched closely (Fig. 3) as indicated by *NRMSE* = 11% (*RMSE* = 480 kg·ha^{-1}), *p*-value = 0.78, *d*-statistic = 0.75, and observed and simulated *CV* of 14% and 9%, respectively. Simulated and observed yield values during model validation were 4,308 and 4,432 kg·ha^{-1}, respectively. Overall, the variety of trial datasets employed in this study for model calibration and validation proved very satisfactory and should be recommended in the absence of detailed in-season data.

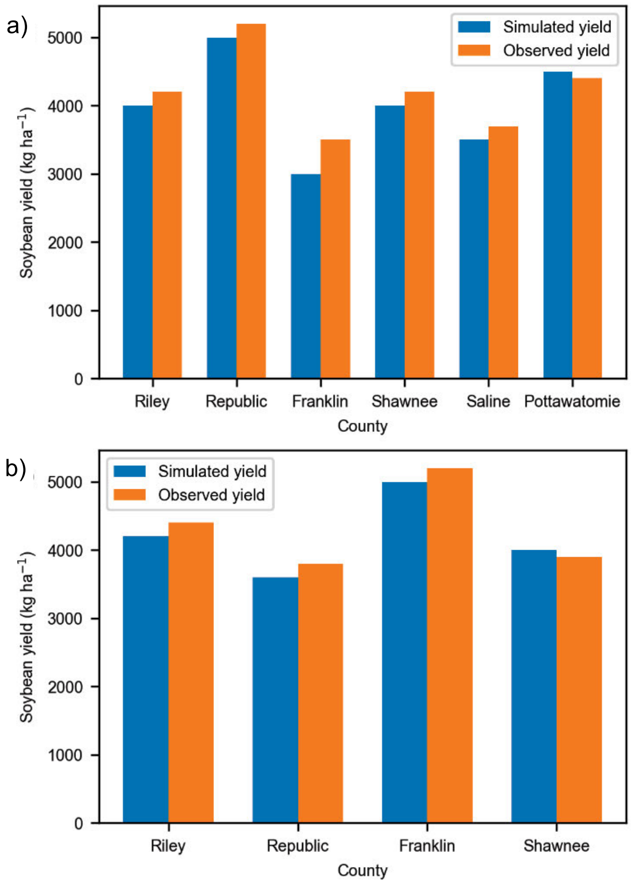

Fig. 3. Decision Support System for Agrotechnology Transfer CROP-GRO-Soybean model for selected counties in Eastern Kansas River Basin: a) calibration – 2020 experiment, b) validation – 2021 experiment; source: own study

IMPACTS OF CLIMATE CHANGE ON YIELD VARIABILITY IN THE EASTERN KANSAS RIVER BASIN

The changes in the mean crop yields and inter-annual variability (*CV*) for maize and soybean were calculated for the two long-term climate change emission scenarios (RCP4.5 and RCP8.5) – Figure 4. Maize yield loss was observed under both RCPs with an increasing *CV*. Under the baseline study period (1990–2019), the mean yield for the entire EKSRB was 8978 kg·ha^{-1} with a *CV* of 35%. Under RCP4.5 and RCP8.5, the mean yield for near, mid, and end-century was 7,995 kg·ha^{-1} (*CV* = 36%), 6,532 kg·ha^{-1} (*CV* = 39%), 5,092 kg·ha^{-1} (*CV* = 37%), and 6,874 kg·ha^{-1} (37%), 5,665 kg·ha^{-1} (37%), 3,834 kg·ha^{-1} (36%), respectively (Fig. 4a). Similarly, under the baseline study period for soybeans, the mean yield was 3,712 kg·ha^{-1} with a *CV* of 32%. Unlike maize, soybean yield under RCP4.5 (near-century) was 3,917 kg·ha^{-1} (*CV* = 34%), 6% greater than the baseline yield. This increase can be attributed to soybean's resilience to high temperatures and elevated CO_2 levels, which are conditions expected under RCP4.5 near-century scenarios. However, under RCP4.5, the projected mean yield for mid-century and end-century was 3,248 kg·ha^{-1} (*CV* = 38%) and 2,504 kg·ha^{-1} (34%), respectively (Fig. 4b).

The projected soybean yield declined under RCP8.5; the mean yield for the near, mid, and end centuries was 3,002 kg·ha^{-1}, 2,044 kg·ha^{-1}, and 1,831 kg·ha^{-1}, with a *CV* of 35%, 36%, and 34%, respectively. This decline under RCP8.5 aligns with findings by Jin *et al.* (2018), who noted that while elevated CO_2 enhances soybean growth, this benefit is diminished by increased drought stress. Projections indicate that rising drought frequency in the U.S. Midwest will significantly undermine these positive effects by 2050. The results showed that changes in average climate conditions cause alterations in crop yield levels and variability. This study strongly reinforces the conclusions drawn by Sen, Zambreski and Sharda (2023), which highlighted a concerning trend of rising mean air temperatures and declining precipitation levels in northeastern Kansas. These trends, particularly pronounced towards the end of the century under RCP4.5 and RCP8.5

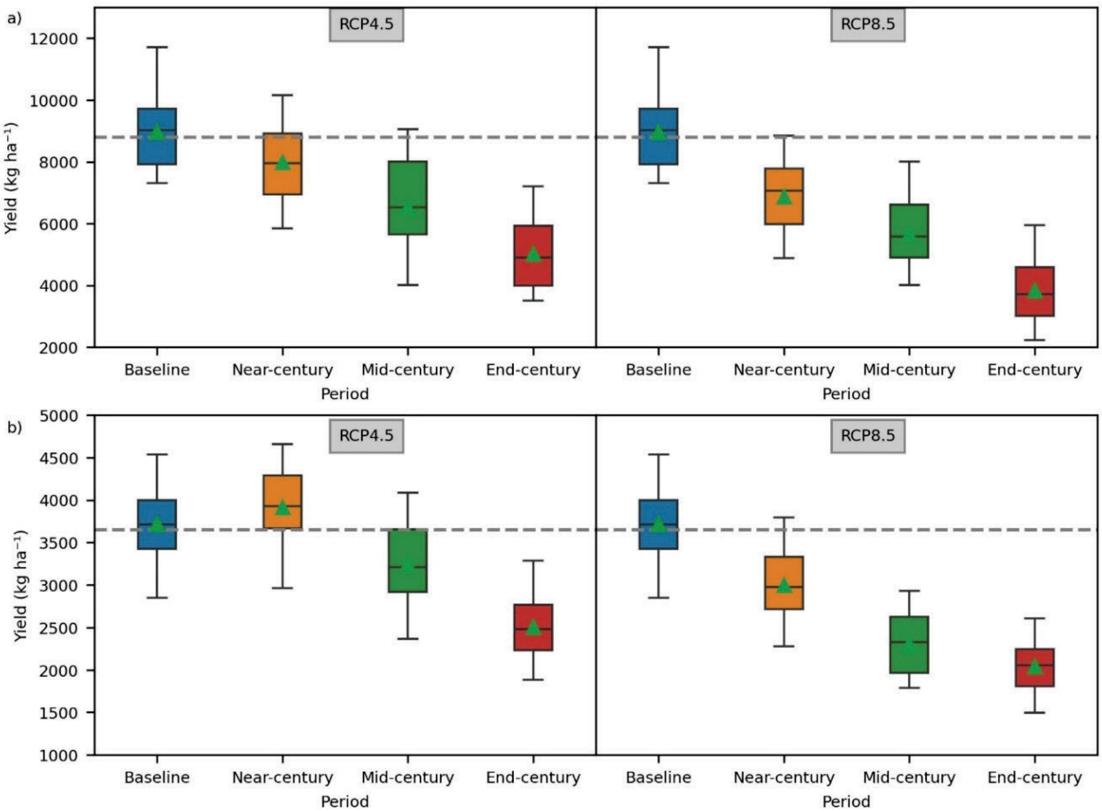

Fig. 4. Comparison of two crops yield variation under present and future climate change scenarios under RCP4.5 and RCP8.5: a) maize, b) soybean; study periods: baseline = 1990–2019, near-century = 2010–2039, mid-century = 2040–2069, and end-century = 2070–2099; the coloured boxes indicate the interquartile range of simulated yields, while the whiskers indicate the 95% confidence limit; horizontal dashed lines show the average yield in the Eastern Kansas River Basin under the baseline study period; source: own study

scenarios, significantly and negatively impacted maize yields in the region. Several studies found that the sensitivity of growing crops under future climate change scenarios reduced the maize and soybean yields in the Midwestern U.S. (Cai, Wang and Laurent, 2009; Lobell and Asseng, 2017; Zhou *et al*., 2021) due to increased CO_2 concentration induced heat extremes, and the changing precipitation patterns. Greater maize yield loss was observed as compared to soybean in the study area under both RCP scenarios, which could be attributed to the fact that maize production is more sensitive to extremely high temperatures than soybean due to the growth behaviour (Deryng *et al*., 2014; Mera, Lizana and Calderini, 2015; Petersen, 2019). Those studies found increased inter-annual yield variability under future climate change scenarios due to climatic variability, which supported this study's outcome of increased maize and soybean yield loss along with increased inter-annual variability in yield in the EKSRB region.

CONSEQUENCES OF CLIMATE CHANGE ON THE COUNTY LEVEL MAIZE AND SOYBEAN YIELDS

The results of change in yield, expressed as percent difference for the seventeen counties of EKSRB calculated by comparing the future projected maize and soybean yields to the baseline yields, are shown in Figure 5.

The maize yield loss under RCP4.5 and RCP8.5 in the near-century, mid-century, and end-century ranged between 4–11%, 11–22%, and 23–34%, and 12–20%, 22–38%, and 36–57%, respectively. Soybean yield increased under RCP4.5 in the near-century by 6%, whereas in the mid and end-century, the yield loss ranged from 11–22% and 20–25%, respectively. Under RCP8.5, in the near-century, mid-century, and end-century, the soybean yield loss was recorded as 3–8%, 16–22%, and 24–36%, respectively. The three counties of the northeastern part of EKSRB (Atchison, Brown, and Nemaha) exhibited less yield loss than other counties in the study region under all climate change scenarios. On the other hand, five counties of the southwestern part of EKSRB, such as Geary, Wabaunsee, Riley, Pottawatomie, and Shawnee counties, were considered hot spots of greater yield loss under all climate change scenarios.

It must be noted that the maize yield loss was greater than soybean under all climate change scenarios explored. This study's findings are similar to those of some of the other studies that have focused on the climate change impact on maize and soybean yields (Kucharik and Serbin, 2008; Deryng *et al*., 2014; McGrath *et al*., 2015). Since maize is more sensitive to water and nutrients to support its growth, particularly during the reproductive stages; therefore, the shortage of precipitation and extremely high temperatures could cause a greater reduction in maize yields than soybean (Wang *et al*., 2020).

YIELD GAP TREND UNDER CHANGING CLIMATE

The long-term yield gap analysis for maize and soybean under baseline and future climate change scenarios (RCP4.5 and RCP8.5) was conducted, and an increasing yield gap trend was observed in both crops (Fig. 6).

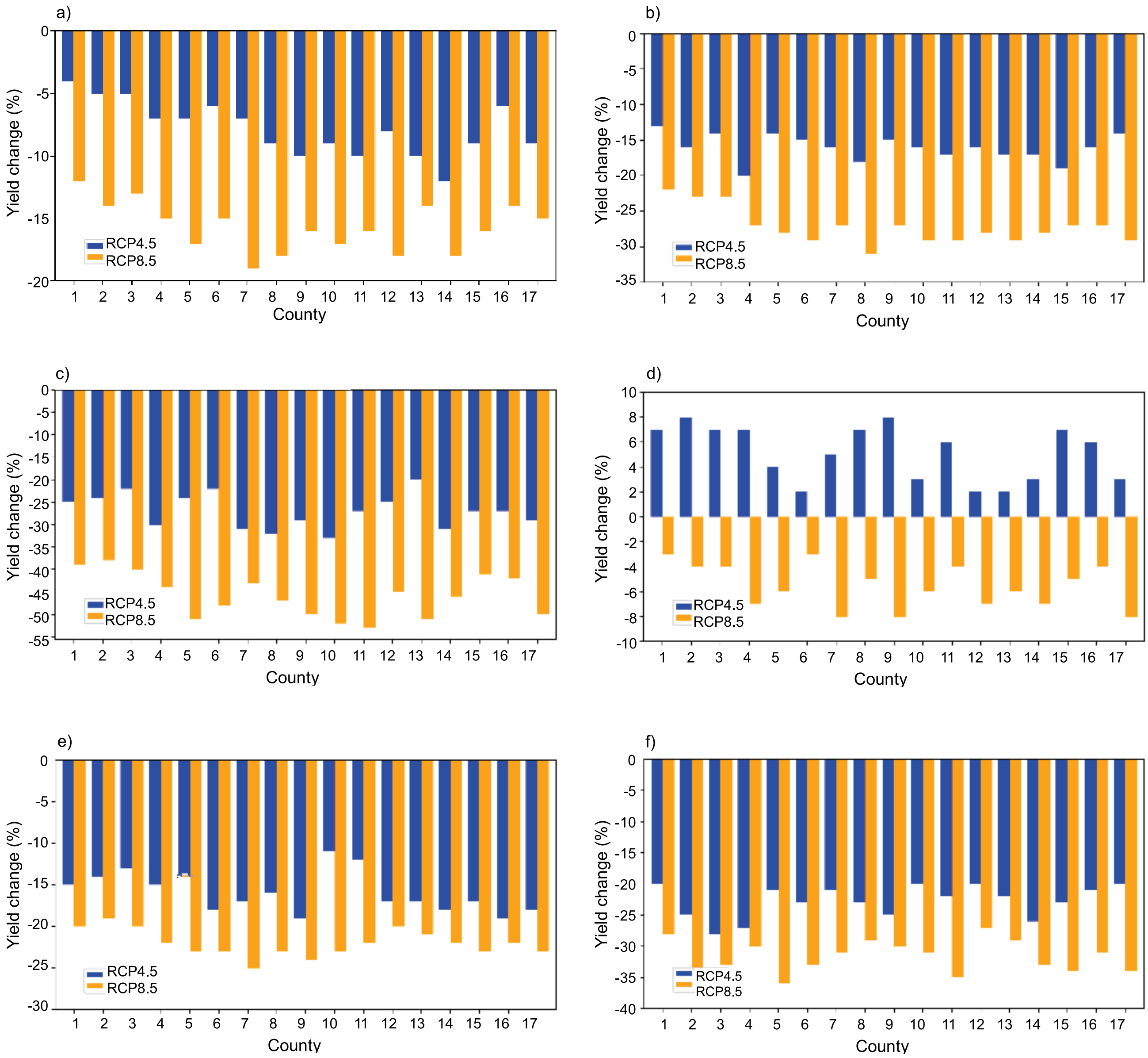

Fig. 5. Projected yield change (a), b) and c) for maize and d), e) and f) for soybean) for seventeen counties of the Eastern Kansas River Basin under RCP4.5 and RCP8.5 compared to the baseline study period; 1 = Atchison, 2 = Brown, 3 = Nemaha, 4 = Douglas, 5 = Geary, 6 = Jackson, 7 = Jefferson, 8 = Johnson, 9 = Leavenworth, 10 = Marshall, 11 = Morris, 12 = Osage, 13 = Pottawatomie, 14 = Riley, 15 = Shawnee, 16 = Wabaunsee, and 17 = Wyandotte; source: own study

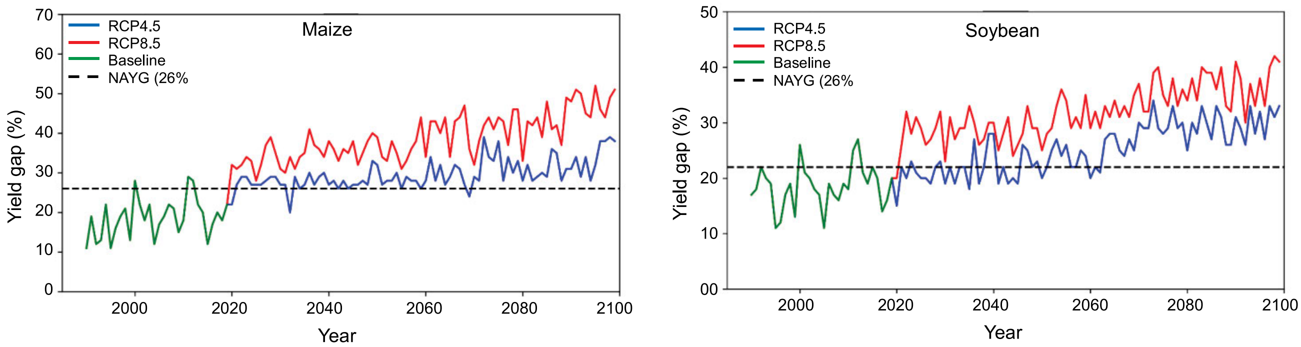

Fig. 6. Temporal evaluation of average yield gap percentage trend for maize and soybean in the Eastern Kansas River Basin under climate change scenarios (RCP4.5 and RCP8.5); source: own study

In particular, a greater yield gap percentage trend was observed under RCP8.5 as compared to RCP4.5. During the baseline period, the highest yield gap for maize was 30%, while for the future projection under RCP4.5 and RCP8.5, it was 43 and 52%, respectively, by the end of the century. Similarly, the highest yield gap in soybean was observed at 27% under the baseline study period; however, under RCP4.5 and RCP8.5 scenarios, the yield gap increased to 29 and 36%, respectively.

The increase in yield gap under future climate change scenarios indicated several factors that limited crop growth and reduced yields, including changes in temperature, rainfall patterns, extreme weather events, soil moisture availability, and pest and disease pressures (Challinor *et al*., 2014; Lobell and Asseng, 2017). Since the study was conducted under rainfed conditions, the greater greenhouse gas emissions scenario under RCP8.5 leads to more severe climate change impacts, like high-temperature days, and exacerbates the factors that contribute to the yield gap, resulting in a greater increase in the yield gap compared to RCP4.5.

CROP AREA SUITABILITY FOR MAIZE AND SOYBEAN UNDER FUTURE CLIMATE

The shifting pattern of the areas suitable for growing maize under climate change scenarios in the EKSRB is given in Figure 7.

Similarly, under the RCP8.5, near-century, the area suitable for growing maize was mainly concentrated in the northeastern EKSRB, and the suitable area decreased in the near-century, mid-century, and end-century to 69, 39, and 10%, respectively, of the original maize planted acreage of the EKSRB. The comparison between the RCP scenarios showed a lesser maize-suitable growing area with a greater yield gap percentage under RCP8.5 as compared to RCP4.5 scenarios.

In the case of soybean, the suitable area under the baseline study period was 91% (Fig. 8). Most counties were found suitable for growing soybean except for three southwest counties (Wabaunsee, Geary, and Riley).

The soybean-suitable growing area under RCP4.5 in the near, mid, and end centuries was 92, 82, and 60% of the original soybean planted acreage of the EKSRB. Similarly, under RCP8.5, the suitable soybean-growing area was concentrated on the northeast side of the EKSRB and was found to be 58%, 51%, and 38% in the near, mid, and end centuries, respectively.

Several studies have shown a significant decline in crop suitability recorded at the end of the century under RCP8.5 scenarios due to abrupt climate change issues (Chhogyel, Kumar and Bajgai, 2020; Lyon *et al*., 2022). A study conducted by Rosenzweig *et al*. (2013) to determine the suitability of major crops on a global scale showed that the basic patterns of rainfed crops depend on climatic conditions, regional temperatures, precipitation patterns, atmospheric carbon dioxide concentrations (CO_2), and latitudes. This is similar to our study, which found that greater warming and less precipitation under future

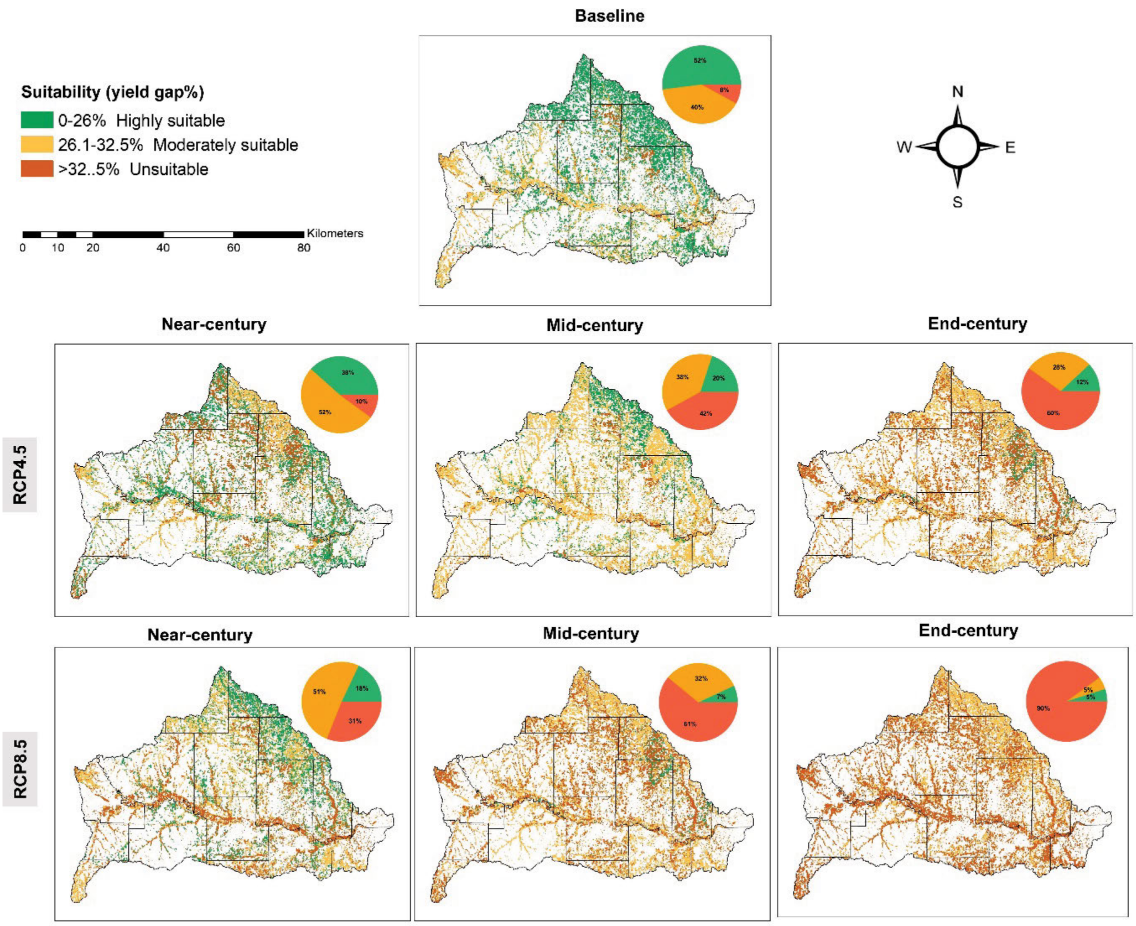

Fig. 7. Area suitable for growing maize in the Eastern Kansas River Basin under baseline (1990–2019), near-century (2010–2039), mid-century (2040–2069), and end-century (2070–2099) under the two representative concentration pathway scenarios (RCP4.5 and RCP8.5); source: own study

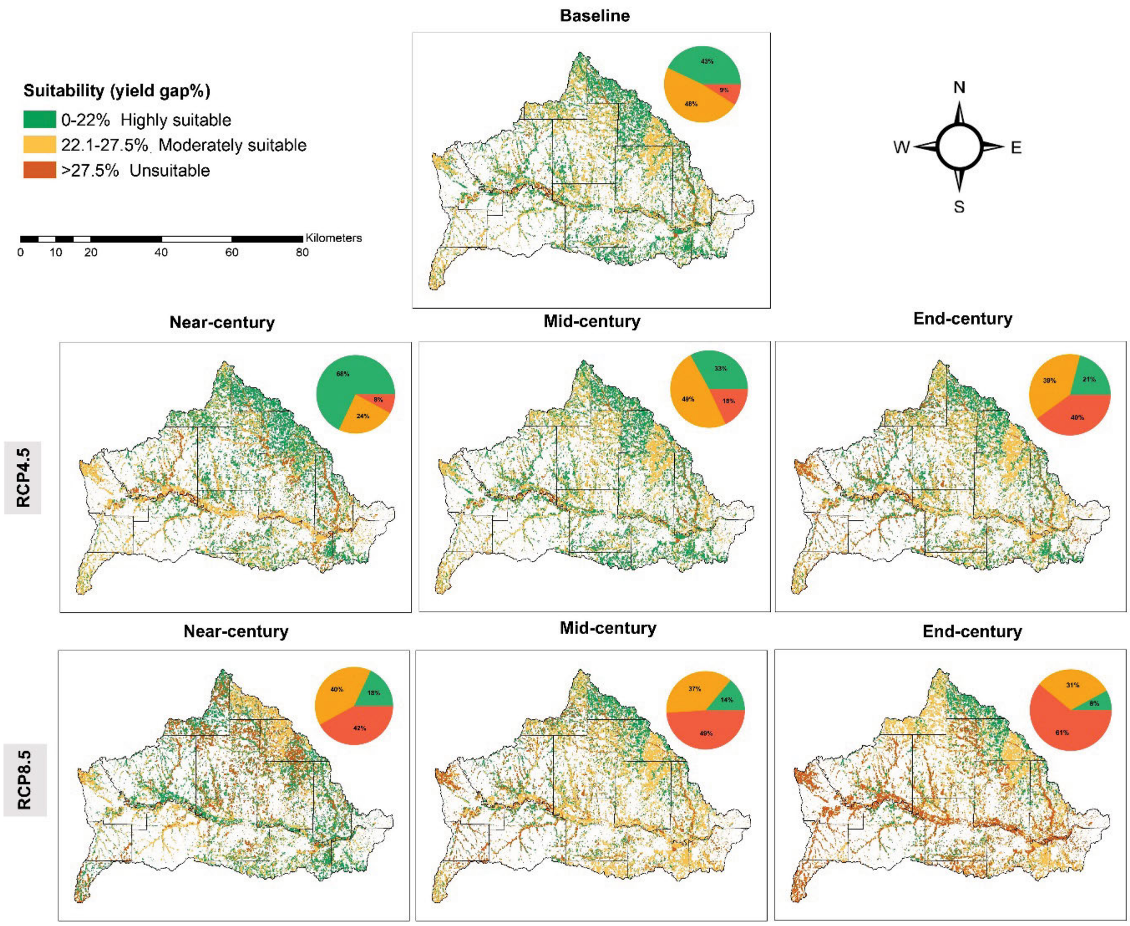

Fig. 8. Area suitable for growing soybean in the Eastern Kansas River Basin under baseline (1990–2019), near-century (2010–2039), mid-century (2040–2069), and end-century (2070–2099) under the two representative concentration pathway scenarios (RCP4.5 and RCP8.5); source: own study

climate change scenarios for a rainfed agricultural system resulted in fewer suitable areas for growing maize and soybeans. The outcome from two climate change scenarios showed that fewer suitable areas existed for soybeans at the end of the century under the RCP4.5 and RCP8.5 compared to the baseline study period. However, based on the overall suitability analysis of the two crops, it can be concluded that relatively more areas would be suitable for growing soybean than maize in the EKSRB under future climate scenarios studied.

CONCLUSIONS

This study calibrated and validated Decision Support System for Agrotechnology Transfer (DSSAT) CERES-Maize and CROP-GRO-Soybean models in seventeen rainfed maize-producing counties in the Eastern Kansas River Basin (EKSRB). The seasonal analysis feature of DSSAT was used to simulate maize and soybean yields for the 30-year baseline study period and for future climate scenarios using forecasted climate from 18 GCMs and under two CO_2 emission scenarios, RCP4.5 and RCP8.5. The suitability of growing maize and soybean in the EKSRB under future climate change scenarios was assessed by determining the yield gap percentage using DSSAT simulated historical and future yields. Key findings indicate substantial yield losses for both maize and soybean, particularly by the end of the century under RCP8.5, with maize showing a higher yield gap and greater sensitivity to climate changes. The suitability analysis revealed a consistent shift in crop growing areas, with soybeans demonstrating higher suitability percentages, suggesting it is a more resilient crop choice. Regional variability in yield losses underscores the need for region-specific adaptation strategies.

Policymakers can use these insights to develop targeted agricultural strategies, transitioning to more climate-resilient crops like soybean, and help to facilitate agricultural policy planning and the selection of mitigation strategies for vulnerable regions. Future research should enhance model calibration with detailed in-season data, explore drought-resistant varieties, diverse irrigation and nutrient management practices, and integrate socio-economic variables to develop holistic approaches to agricultural planning. This study underscores the urgent need for adaptive agricultural practices to enhance food security and sustainability in the EKSRB and similar regions.

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CONFLICTS OF INTEREST

All authors declare that they have no conflict of interest.

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