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Impact of future climate from different general circulation models on cotton yield predictions in north Cotton Belt through crop simulation with DSSAT

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ABSTRACT

Context or problem: Future climate scenarios present significant challenges to sustainable cotton production. Developing effective adaptation strategies is crucial to mitigate these threats.
Objective or research question: This study evaluates the impact of climate change on cotton lint yield under different tillage systems and nitrogen application rates to identify potential adaptation strategies.
Methods: A long-term cotton field experiment (39 years) was conducted in Jackson, Tennessee, with two tillage systems (no-tillage and conventional tillage) and four nitrogen (N) application rates (0, 33, 67, and 101 kg ha^{-1}). The DSSAT model, coupled with two representative concentration pathways (RCP4.5 and RCP8.5) and five global circulation models (GCMs), was used to simulate cotton lint yield from 2025 to 2057, encompassing near-term (2025–2035), mid-term (2036–2046), and far-term (2047–2057) future scenarios.
Results: Increasing nitrogen application rates positively influenced cotton lint yield under both tillage systems across all scenarios. However, no-tillage consistently outperformed conventional tillage, particularly under RCP8.5, indicating its potential benefits in a changing climate. Model projections suggest that while initial yield benefits are observed, these may diminish over time as climate impacts intensify. Under RCP4.5, yields increased in the near-term but showed declining trends in the mid-term and far-term. Under RCP8.5, despite initial resilience, all models predicted significant yield declines in the mid-term and far-term, with the most pronounced reductions in the MRI-CGCM3 model.
Conclusions: This study highlights the importance of adaptive strategies such as no-tillage in mitigating negative climate impacts on cotton yields.
Implications or significance: Implementing no-tillage practices combined with optimized nitrogen management may enhance cotton productivity under future climate scenarios, especially under the more severe conditions projected in RCP8.5

1. Introduction

Cotton production has increased threefold worldwide during the last 50 years. The United States is the leader in global exports, supplying more than 35 percent of the world's raw cotton export market (USDA, 2020). Cotton is a dual-purpose crop grown for fiber and oil and is the major world fiber crop (Ali et al., 2019). Under field conditions, various factors such as environmental conditions and agricultural management practices substantially influence cotton growth and productivity (Noor Shah et al., 2022). This study focuses on cotton in Tennessee's North Cotton Belt, a region where cotton is economically crucial and widely grown. Conducting the study here allows us to address specific regional climate challenges, such as variable rainfall and temperature fluctuations, and assess how practices like conservation tillage and optimized nitrogen management can improve yield and soil health (Bange et al., 2016). Conservation tillage and optimal N management are increasingly vital due to concerns over soil health, erosion, and nutrient runoff (Bezboruah et al., 2024). These practices are critical for sustainable production in Tennessee's cotton-growing regions.

Nitrogen is crucial for cotton growth, productivity, and quality, often needing more attention than other nutrients (Khan et al., 2017a). Sustainable cotton production means maintaining and enhancing yield

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levels without harming the land and the environment. However, excessive nitrogen application rates not only lead to stunted growth, prolonged crop maturity, and reduced productivity but also contribute to environmental pollution (Niu et al., 2021; Huang et al., 2022; Kumar et al., 2022; Wang et al., 2022). Previously published reports suggest that providing appropriate nitrogen doses can increase biomass production and improve cotton yield and quality (Chen et al., 2016; Niu et al., 2021). Furthermore, other studies indicate that reducing nitrogen rates through suitable agronomic management practices enhances lint yield and quality (Dong et al., 2012; Luo et al., 2018).

In addition to N fertilization, the tillage system also influences mineralization and later release of nutrients from the soil (Khan et al., 2017b). Among commonly used tillage practices, no-tillage retains more crop residues on soil surface, leading to reduced soil erosion and evaporation and increased nitrogen use efficiency compared to conventional tillage (Lal et al., 2007). Meanwhile, no-tillage resulted in more N uptake by cotton than conventional tillage (Idowa et al., 2020).

Climate change poses significant risks to current global production systems, with evidence indicating that even a slight warming of $+1.5^{\circ}$C could lead to decreased agricultural productivity worldwide, threatening food security (Rosenzweig et al., 2014; Lal et al., 2007). Rising temperatures and unpredictable rainfall patterns negatively affect crop growth, development, and yield (Hogy et al., 2013). Although efforts have been made to gather data and understand crop yield projections, it remains impossible to accurately replicate future ecosystems or atmospheric conditions. Therefore, using models to predict and simulate crop responses to future conditions is justified.

CMIP5 models offer standardized simulations, making them particularly useful for assessing projected changes in temperature, precipitation, and other climatic variables under different greenhouse gas emission scenarios (Miao et al., 2014). The Representative Concentration Pathways (RCPs) are standardized scenarios developed by the Intergovernmental Panel on Climate Change (IPCC) to model future climate trajectories based on various levels of greenhouse gas emissions. By analyzing RCP_S, we capture a range of possible future climates, allowing us to assess the resilience of cotton production under moderate and severe climate stress conditions (Moss et al., 2010; Taylor et al., 2012).

Crop simulation models leverage long-term weather data to account for variability, helping assess the risks of adopting alternative crop management strategies at specific sites (Kephe et al., 2021). These models offer significant advantages, such as minimal reliance on field calibration data and transparent assessment of model uncertainties (Zhao et al., 2015). Studies have demonstrated that yield predictions from regression models based on historical climate data for specific crops are relatively accurate in response to climate variable changes (Isik and Devadoss, 2006; Lobell and Field, 2007).

The Decision Support System for Agrotechnology Transfer (DSSAT) is a widely utilized tool capable of simulating crop growth stage, development, and yield responses to variations in agrometeorological conditions, soil properties, and management practices (Hoogenboom et al., 2012). By employing field experimental data, a well-calibrated DSSAT model can effectively simulate crop responses under various experimental conditions, expediting decision-making processes by reducing the time and resources needed for extensive field experiments. DSSAT-CSM has been employed by numerous researchers for various purposes (Rezzoug et al., 2008; Liu et al., 2011; Hoogenboom et al., 2012; Mauget et al., 2017). For instance, Wajid et al. (2014) utilized the CSM-CROPGRO model to simulate the growth, development, and seed cotton yield of four cotton cultivars under different nitrogen fertilizer rates and planting dates in Pakistan. Their findings showed that the simulated crop phenology, seed cotton yield, and total dry matter aligned reasonably well with the observed data. Similarly, Reddy et al. (2002) employed the cotton simulation model to examine the impact of climate change on cotton production in Stoneville, Mississippi, USA.

This study aimed to assess 1) the impacts of climate changes on cotton production under the RCP4.5, and RCP8.5, 2) cotton yield predictions under key management practices and projected future climate scenarios in three decades, and 3) the effects of long-term N fertilization and tillage on cotton lint yield.

2. Methods

2.1. Study region

The study was conducted at the University of Tennessee Institute of Agriculture's West Tennessee Research and Education Center (UTIA-WTREC) in Jackson, TN, USA with a geographical location of 35°37'N: 88°51'W, altitude 113 m above mean sea level (Fig. 1). The study area is of approximately 0.7 ha and located within the north Cotton Belt in the United States.

The study area is generally flat to gently rolling topography with slopes of less than 2 %. The soil is classified as Aeric Lexington. The texture is silt loam, with moderately well drainage. Soil tests were conducted before planting to assess the physicochemical characteristics of the soil in the study area, which are presented in Table 1.

The climate of the studied area is typically humid subtropical (The Köppen climate classification for this region is Cfa), with an annual average rainfall of 1375 mm and an average temperature of approximately 15.5°C. Fig. 2 shows the maximum rainfall recorded in 1996, totaling 1722.2 mm, while the minimum was in 1988, with 1004.2 mm. Additionally, the highest temperature occurred in 2014, reaching 24.9°C and the lowest was in 2010, at 6.5°C.

2.2. Field experiment

The experiment was conducted in 1986–2018 at the UTIA-WTREC in Jackson, Tennessee. The field experiment on the cotton crop was conducted under the combinations of two tillage systems: conventional (CT, chisel plow) and no-tillage (NT); and four N application rates: 0 (N0), 33 (N1), 67 (N2), and 101 (N3) kg ha^{-1}. The field experiment was a randomized complete block with a split-plot design with N rates as the main plots, and tillage systems as the subplots, with four replicates. The crop was sown at a depth of 4 cm. Cotton was uniformly seeded on the plot, targeting about 86,500 plants ha^{-1}. Different cotton cultivars were used over the 40-year study period to reflect regional farming practices and adapt to changing cultivar availability and suitability. This variability allowed the study to maintain relevance across evolving agricultural conditions. The tilled treatments were double-disked to a depth of 10 cm and were harrow-leveled to prepare the seedbed. Irrigation was applied based on the soil water content within the effective root zone depth, measured using soil moisture sensors (tensiometers) at regular intervals throughout the growing season. Irrigation was triggered when soil water content fell below a threshold of 50 % of field capacity, ensuring optimal moisture levels were maintained. The use of irrigation limits the generalizability of these results to systems without irrigation. While these findings are relevant for irrigated fields, caution should be exercised when extrapolating to rain-fed systems. Cotton was harvested mechanically and ginned, and lint yield was recorded in October each year.

2.3. Climate scenarios

The observed daily meteorological data for the baseline (1986–2018) was collected from the Weather Research and Forecasting (WRF) model. The daily maximum and minimum temperature, precipitation, and solar radiation were all adjusted.

The observed daily meteorological data for the baseline period (1986–2018) was collected from the Weather Research and Forecasting (WRF) model, using bias-corrected estimated data to enhance accuracy. Daily maximum and minimum temperatures, precipitation, and solar radiation were adjusted based on historical observational data, focusing

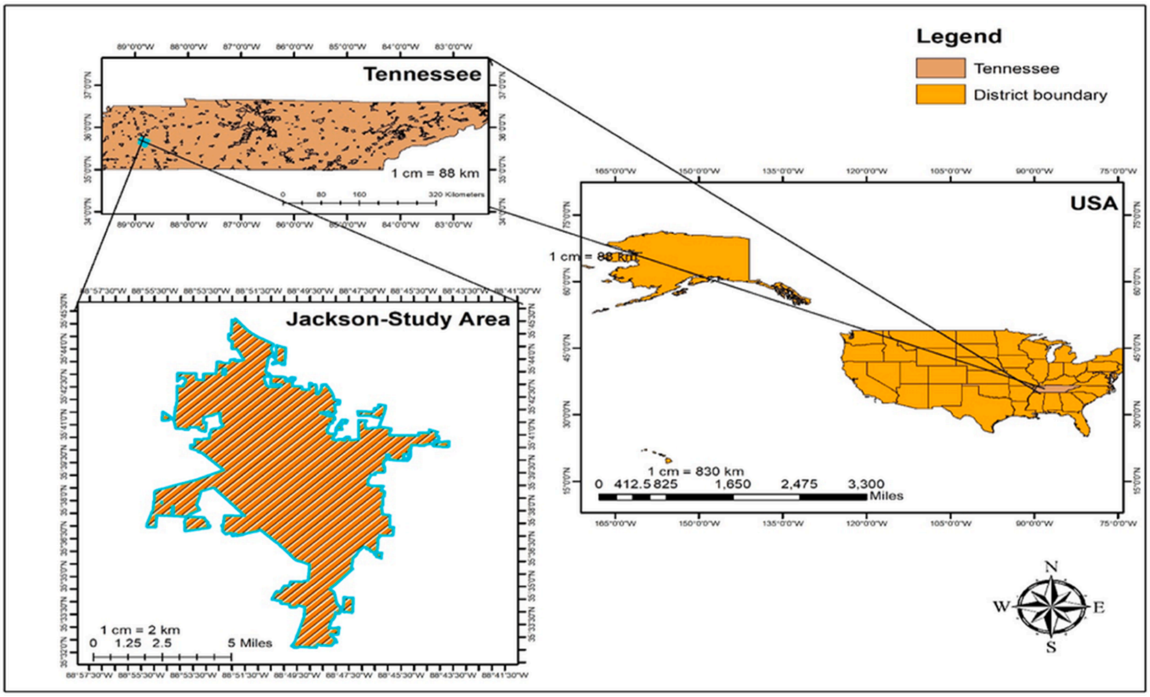

Fig. 1. Map of the study district.

Table 1
Soil physical and chemical properties at 0–15 and 15–30 cm depths in Jackson, TN.

Depth (cm)	Silt (g kg^{-1})	Clay (g kg^{-1})	Sand (g kg^{-1})	Organic C (mg g^{-1})	pH	CEC (cmol kg^{-1})	Total N (mg g^{-1})	Bulk density (g cm^{-3})
0–15	660	165	175	6.1	6.4	20	1.01	1.51
15–30	662	210	128	4.5	6.4	20	1.01	1.52

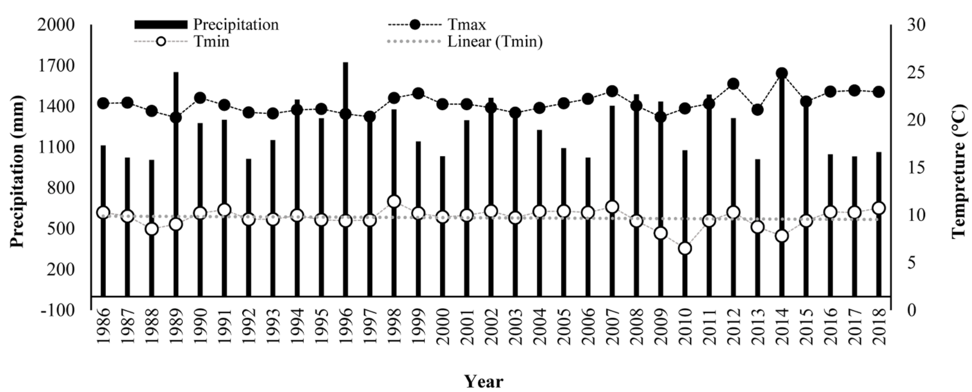

Fig. 2. Annual precipitation and maximum and minimum temperatures during 1986–2018 at Jackson, Tennessee.

on bias-correcting precipitation estimates to align with regional climate trends. This bias correction improves the reliability of model inputs for assessing long-term climate impacts.

General circulation models are the most widely used models to simulate local climate trends relative to the global scale (Sachindra et al., 2014) by producing climate scenarios and time horizons. For this study, future projected climate data of rainfall and temperature for three phases [first decade (2025–2035), second decade (2036–2046), and third decade (2047–2057)] were explored and analyzed from CMIP5 (Coupled Model Inter-comparison Project Phase 5 dataset (Yang and Wang, 2023), from five GCMs under RCP4.5 and RCP8.5 using MarkSim weather generator (Rahman et al., 2021) which has been statistically bias-corrected (Table 2).

2.4. Crop modeling

2.4.1. Crop growth modeling

The DSSAT modeling system consists of crop-specific models for simulating the yield of crops. It is widely used worldwide for climate change impact assessment in field crops. It has different modules to simulate water balance, nutrient dynamics, crop growth, phenology, biomass, and yield based on crop characteristics like phenology, photoperiod, leaf area development, biomass partitioning, etc. The input data required for the calibration and validation in DSSAT includes daily

Table 2
Description of selected five GCMs from Coupled Model Intercomparison Project Phase 5 (CMIP5).

GCMs	Institution	Resolution, Lat. × Long.	Approx. Resolution (km)
FIO-ESM	The First Institute of Oceanography, SOA, China	2.812 × 2.812	~312 × 312
GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory	2.0 × 2.5	~222 × 278
HadGEM2-ES	Met Office Hadley Centre	1.2414 × 1.875	~138 × 208
IPSL-CM5A-MR	Institute Pierre-Simon Laplace	1.2587 × 2.5	~140 × 278
MRI-CGCM3	Meteorological Research Institute	1.125 × 1.125	~125 × 125

weather data, soil data, crop management data, and observed crop data (Hoogenboom et al., 2010). The cropping system model (CSM) in DSSAT consists of different modules for different categories of crops for simulation. In this study, we used the CROPGRO Cotton model.

2.4.2. Model calibration and validation

Twelve cultivar parameters and five ecotype parameters were adjusted until the simulated crop development stages and cotton yields matched reasonably well with measured data (Table 3).

The crop model performance was examined by comparison of observed and simulated values for the crop parameters. Hence, we employed three deviation statistics including determination coefficient (R^2), index of agreement (d), and root means square error (RMSE) to evaluate the CROPGRO-Cotton model, which was calculated using Eqs. (1)-(3), respectively. The R^2 values range between 0 and 1, with 0 indicating "no fit" and 1 indicating "perfect fit" between the simulated and observed values.

$$R^2 = \frac{\left(\sum_{i=1}^{N}(\boldsymbol{Yi}-\overline{\boldsymbol{Y}})(\widehat{Y}-\overline{\boldsymbol{Yi}})\right)^2}{\sum_{i=1}^{N}(\boldsymbol{Yi}-\overline{\boldsymbol{Y}})^2\sum_{i=1}^{N}(\widehat{\boldsymbol{Yi}}-\overline{\boldsymbol{Yi}})^2} \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(\widehat{\mathrm{Y}}-\mathrm{Yi})^2}{\mathrm{N}}} \tag{2}$$

$$d = 1 - \left[\frac{\sum_{i=1}^{N}(\widehat{\mathrm{Yi}}-\overline{\mathrm{Yi}})^2}{\sum_{i=1}^{N}(|\widehat{\mathrm{Yi}}-\overline{\mathrm{Yi}}|+|\mathrm{Yi}-\overline{\mathrm{Yi}}|)^2}\right] \tag{3}$$

where Y_i, observed value, $\widehat{Y}$, simulated value, $\overline{Yi}$, average of simulated value, Y, average of observed value, N, number of observations.

Table 3
Parameters adjusted during the CSM-CROPGRO-Cotton model calibration.

Parameters	Description	Testing range	Calibrated value
Cultivar parameters			
EM-FL	Time between plant emergence and flower appearance (photothermal days)	34–44	39
FL-SH	Time between first flower and first pod (photothermal days)	6–12	8
FL-SD	Time between first flower and first seed (photothermal days)	12–18	15
SD-PM	Time between first seed and physiological maturity (photothermal days)	42–50	40
FL-LF	Time between first flower and end of leaf expansion (photothermal days)	55–75	57
LFMAX	Maximum leaf photosynthesis rate at 30∘C, 350 ppm CO_2, and high light (mg CO_2 m^{-2} s^{-1})	0.7–1.4	1.05
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm^2 g^{-1})	170–175	170
SIZLF	Maximum size of full leaf (three leaflets) (cm^2)	250–320	300
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	0.7–0.9	0.7
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)	22–35	34
PODUR	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)	8–14	14
THRSH	Threshing percentage. The maximum ratio of [seed/ (seed + shell)] at maturity.	68–72	70
Ecotype parameters			
PL-EM	Time between planting and emergence (thermal days)	3–5	4
EM-V1	Time required from emergence to first true leaf, thermal days	3–5	4
RWDTH	Relative width of the ecotype in comparison to the standard width per node	0.8–1.0	1
RHGHT	Relative height of the ecotype in comparison to the standard height per node	0.8–0.95	0.9
FL-VS	Time from first flower to last leaf on main stem (photothermal days)	40–75	57

3. Results

3.1. Effects of temperature and precipitation on cotton yields under NT and CT during 1986–2018

In this experiment, the impact of climate change on cotton yields significantly fluctuated under no-tillage conditions over several decades. The data collected from 1986 to 2018 present a complicated relationship between temperature, precipitation, and cotton yield (Fig. 3).

In 1989, there was a notable decrease in temperature by −9.58 % compared to 1986, coupled with a substantial increase in rainfall by 48.46 %. These changes coincided with a significant reduction in cotton yield, dropping from 1065.40 to 609.84 kg ha^{-1}. The correlation was stronger, with R2 = 0.101 for the relationship between cotton yield and temperature, and R2 = 0.155 for the relationship between yield and precipitation, showing a closer link between climate factors and yield. Despite these severe temperature changes from 1989 to 1993, crop performance remained relatively stable, suggesting a period of adjustment to this altered weather (Fig. 3a, b).

Further significant declines in yield occurred in 1998, 2006, and 2013. Precipitation was up by 23.85 % in 1998, while it fell by −8.11 % and −9.15 % in 2006 and 2013, respectively, from its 1986 level. Temperature trends also showed variability; there was a decrease in temperature of −5.9 % in 1998, but an increase of 6.51 % and 11.03 % in 2006 and 2013, respectively, from the 1986 baseline (Fig. 3a, b).

Peak yield years were recorded in 2015 (1579 kg ha^{-1}), where increases of 48.26 %, were observed, above the 1986 (1065.40 kg ha^{-1}) level. However, starting in 2015, an upward trend in temperature coupled with a reduction in precipitation led to a downward trend in yields, illustrating the ongoing impact of climatic factors on agricultural productivity under no-tillage farming practices (Fig. 3a, b).

Under conventional tillage conditions, significant fluctuations in crop yield were also observed over the years, influenced by changes in both temperature and rainfall (Fig. 4). Significant reductions in yield were observed in the years 1992, 1998, 2006, and 2013, reflecting

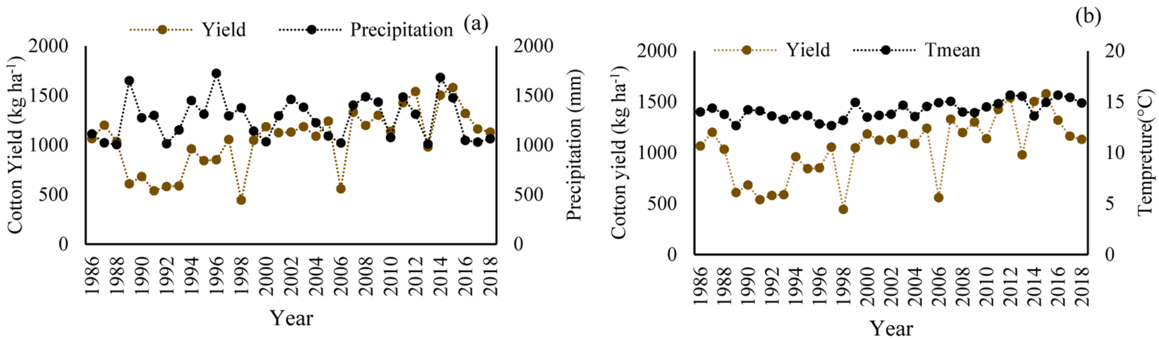

Fig. 3. Correlation between cotton yield and (a) precipitation and (b) mean temperature under no-tillage from 1986 to 2018.

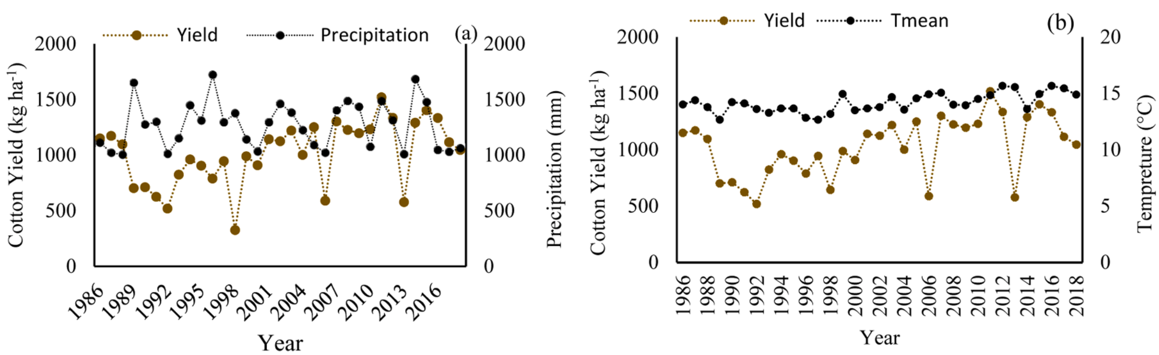

Fig. 4. Correlation between cotton yield and precipitation (a) and mean temperature (b) under conventional -tillage from 1986 to 2018.

similar patterns seen in no-tillage conditions. From 2015 onwards, a trend emerged: declining yields were associated with temperature increases and decreases in precipitation. Notably, the peak yield under conventional tillage was achieved in 2011, showing a 32.13 % increase over the 1986 baseline (Fig. 4).

Regarding extreme weather conditions, the highest temperature and precipitation were recorded in 1996 and 2012, respectively. In these years, yields were notably higher in no-till conditions (1540 and 850.88 kg ha^{-1}) than those under conventional tillage (1334.75 and 789.07 kg ha^{-1}). Conversely, the lowest temperatures and rainfall occurred in 1997 and 1988, respectively. During these years, yields in no-till conditions stood at 1056.21 and 1004.31 kg ha^{-1}, while conventional tillage produced 945.59 and 1095.25 kg ha^{-1}, respectively (Fig. 4).

3.2. Comparison of Cotton lint yield simulation and observation during 1986–2018

Based on available datasets, Fig. 5 and Fig. 6 showed the observed and simulated cotton lint yields at four nitrogen levels under no-tillage and conventional tillage during calibration (2009–2011) and validation periods (2012–2014). The model accurately predicted lint yield, as evidenced by a strong agreement between observed and simulated yields and favorable model performance statistics.

During the calibration phase, the model performance statistics indicated high levels of accuracy. The coefficient of determination (R^2) and the index of agreement (d) values ranged from 0.8 to 0.9 across both tillage systems for all three years (Table 4). These statistics suggest a strong correlation and agreement between the observed and simulated data, reflecting the model's ability to accurately replicate the actual yield conditions.

The validation phase (2012–2014) further reinforced the model's reliability. The performance statistics for measured and simulated lint yield showed R^2 and d values ranging from 0.8 to 0.9, except for a d value of 0.7 under conventional tillage in 2014 (Table 4). This slight deviation in 2014 under conventional tillage indicates a minor underperformance in one specific scenario but does not significantly detract from the overall model accuracy.

Root Mean Square Error values provided additional insights into the model's predictive accuracy. For conventional tillage, the RMSE values were 152.58 in 2012, 168.23 in 2013, and 254.78 in 2014. Under no-tillage, the RMSE values were 189.53 in 2012, 202.56 in 2013, and 183.47 in 2014 (Table 4). These RMSE values indicate that the discrepancies between observed and simulated yields were relatively low, confirming the model's accuracy in predicting lint yields under varying nitrogen levels and tillage practices.

Overall, the results from both the calibration and validation phases demonstrate that the DSSAT CSM-CROPGRO-Cotton model is highly effective in simulating cotton lint yield. The model's strong performance suggests its suitability for further use in simulating the impacts of different cropping systems on crop yields, providing a reliable tool for agricultural planning and decision-making

3.3. Projected temperature and precipitation in Jackson, Tennessee during 2025–2057

The average temperatures in both RCPs have risen compared to the historical data. In the first, second, and third decades, the temperature increases were 9.48 %, 14.92 %, and 19.45 %, respectively, compared to the historical in RCP 4.5, while the temperature increases in RCP8.5 was 23.76 %, 25.23 %, and 35.43 % respectively. The temperature increase observed in RCP 8.5 exceeded that of RCP 4.5, with the rate of change being 20.22 % higher in RCP8.5 than that in RCP 4.5 in 2057 (Fig. 7a).

Meanwhile, annual precipitation declined in both RCPs compared to the historical records. The precipitation changes in the first, second, and third decades were −0.34 %, −5.84 %, and −17.51 % in RCP 4.5, −29.19 %, −35.29 % and −44.29 % in RCP 8.5, respectively, compared to the historical datum. The decrease in precipitation was more pronounced in RCP 8.5 than in RCP 4.5, with the rate of change being

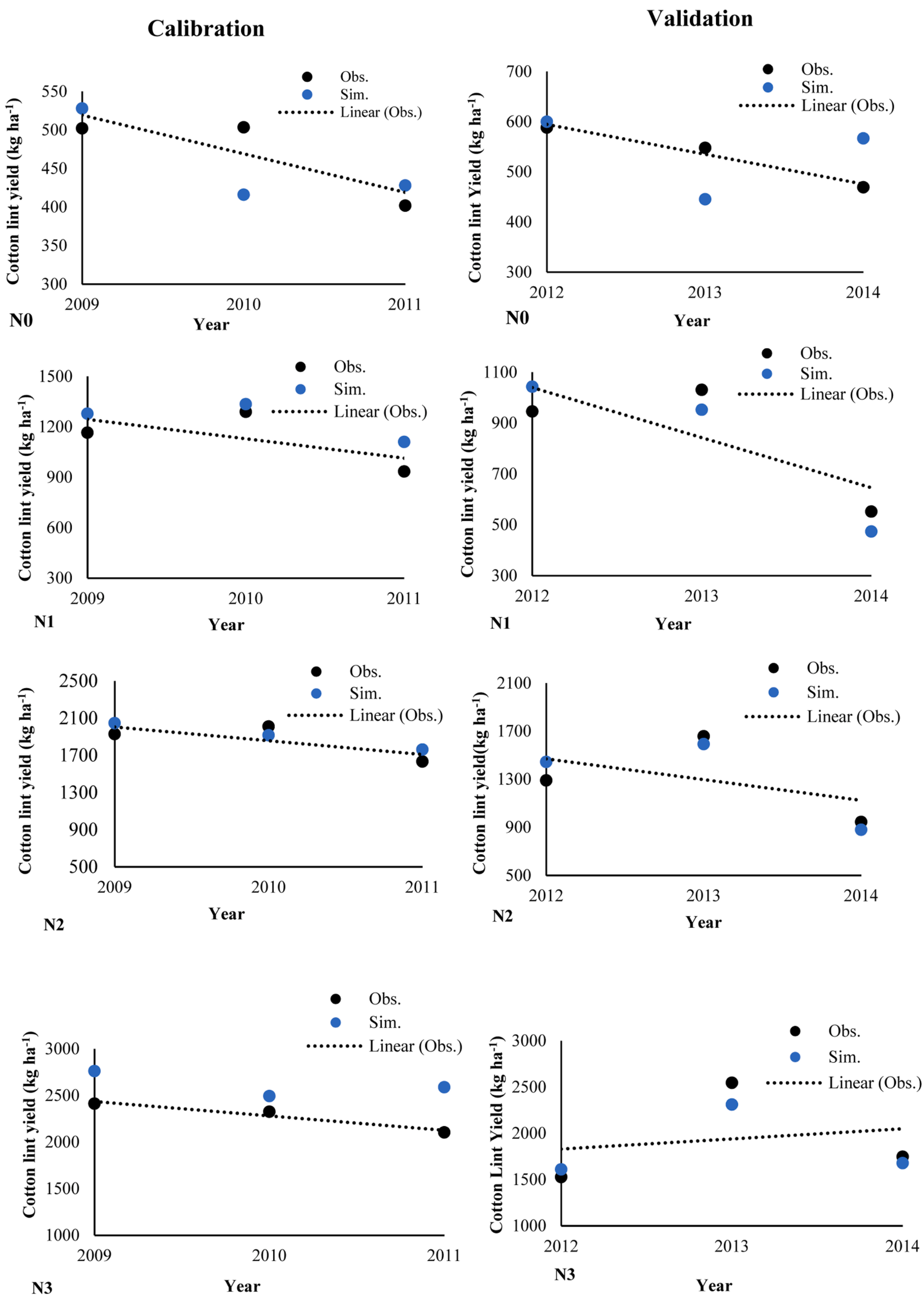

Fig. 5. Comparison between measured and simulated cotton lint yield under no-tillage during 2009–2014.

16.07 % higher RCP 8.5 than in RCP 4.5 in 2057 (Fig. 7b).

3.4. Comparison of changes in cotton lint yields among different nitrogen levels in RCP4.5 and RCP8.5 during 2025–2057

Fig. 8(a,b) represents the changes (%) in cotton lint yield at different nitrogen levels under no-tillage and conventional tillage and their effect

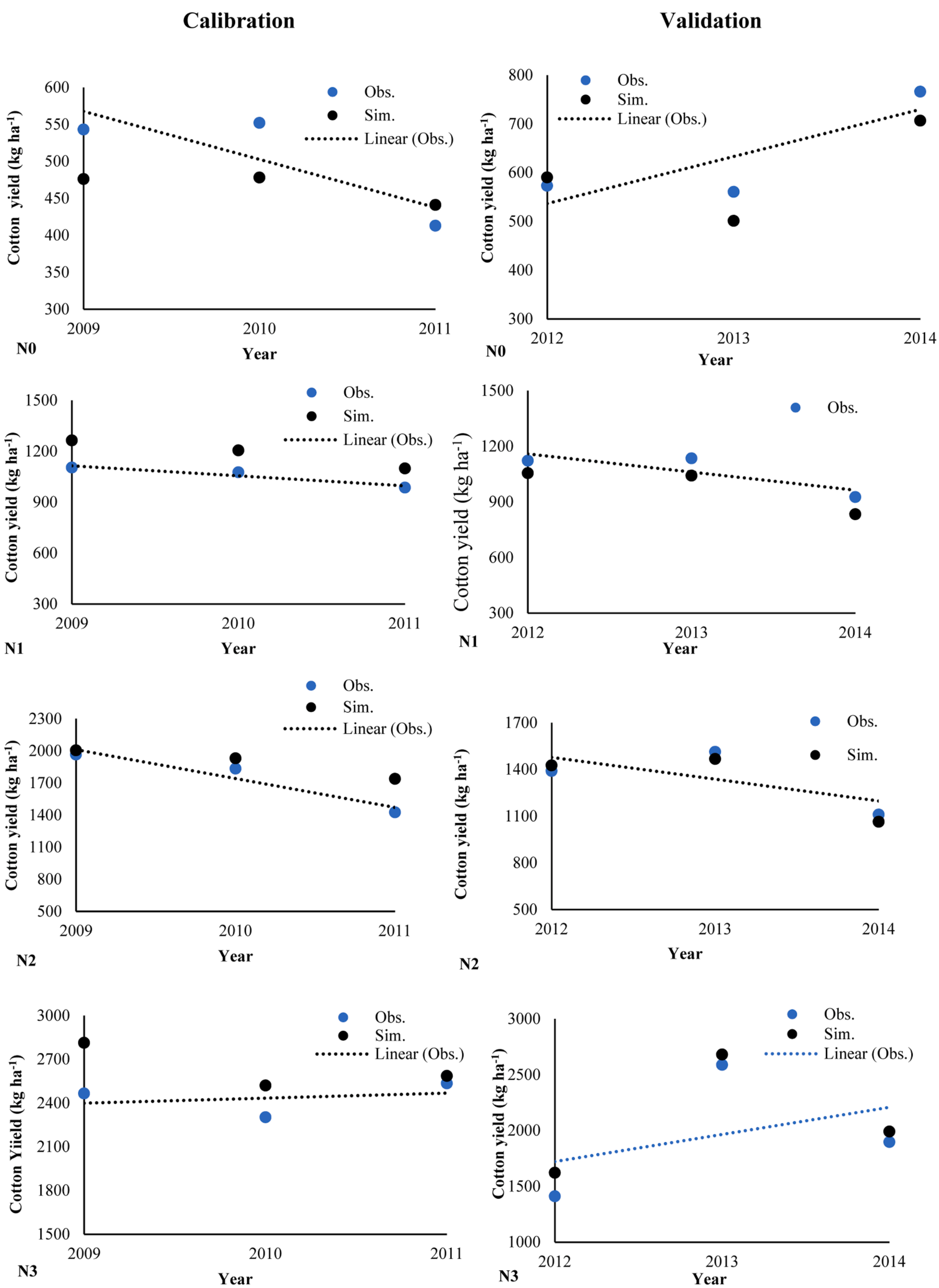

Fig. 6. Comparison between measured and simulated cotton lint yield under conventional tillage during 2009–2014.

in historical and future periods.

For the first, second, and third decades under no-tillage conditions in the RCP4.5 scenario, increasing nitrogen rate led to positive yield changes of 13.34 %, 22.89 %, and 3.91 % respectively at the N2 level, and 8.38 %, 6.03 %, and 14.33 % respectively at the N3 level, relative to their base yields. In contrast, under the RCP8.5 scenario, positive yield changes were observed only in the second and third decades, with changes of 8.89 % and 9.50 % at the N2 level, and 8.92 % and 9.21 % at the N3 level. Nitrogen-free conditions resulted in negative yield changes across all three decades under both scenarios and tillage practices compared with its base yields (Fig. 8a).

Under conventional tillage, the RCP4.5 scenario showed more

Table 4
Comparison statistics between observed and simulated cotton lint yield during model calibration in 2009, 2010, and 2011 and validation in 2012, 2013, and 2014.

Tillage	Year	RMSE (kg ha^{-1})	d-statistic	R^2
Calibration				
	2009	139.51	0.90	0.97
Conventional tillage	2010	184.22	0.98	0.95
	2011	233.00	0.87	0.84
	2009	249.71	0.89	0.91
No-tillage	2010	219.59	0.80	0.80
	2011	223.98	0.90	0.92
Validation				
	2012	152.58	0.96	0.96
Conventional tillage	2013	168.23	0.97	0.91
	2014	254.78	0.72	0.83
	2012	189.53	0.93	0.90
No-tillage	2013	202.56	0.84	0.86
	2014	183.47	0.91	0.98

positive yield changes compared to the base yield, with changes of 16.60 %, 10.78 %, and 24.38 % at the N2 level, and 19.73 %, 8.04 %, and 16.15 % at the N3 level for the first, second, and third decades, respectively. In the RCP8.5 scenario, conventional tillage at the N3 level resulted in yield changes of 5.99 %, 8.04 %, and 8.66 % for the first, second, and third decades, respectively (Fig. 8b).

The findings indicate that RCP4.5 generally exhibited more positive performance changes in cotton yield across all decades compared to RCP8.5, highlighting the lower stress conditions under moderate emissions scenarios. Conventional tillage consistently led to more positive yield changes than no-tillage at both N2 and N3 nitrogen levels. However, under more extreme conditions in RCP8.5, the benefits of conventional tillage were less pronounced, underscoring the need for additional adaptive measures to cope with severe climatic stresses. This study suggests that conventional tillage in the future under moderate emission scenarios performs better than itself at the base period.

3.5. Comparison of cotton lint yields between no-tillage and conventional tillage in RCP4.5 and RCP8.5 at different nitrogen levels

Increasing nitrogen application resulted in enhanced cotton yields under both conventional tillage and no-tillage practices in RCP4.5 and 8.5 scenarios (Fig. 9a,b).

Under RCP4.5, during the first decade, cotton yields under no-tillage surpassed those under conventional tillage across all nitrogen levels. Specifically, at nitrogen levels N2 and N3, cotton yields under conventional tillage were 2734 kg ha^{-1} and 2963.32 kg ha^{-1}, respectively, while yields under no-tillage were 2856 kg ha^{-1} and 3276.51 kg ha^{-1}, respectively (Fig. 9a). In the second decade, no significant differences in cotton yields were observed between the two tillage systems at the N0 level. However, at nitrogen levels N1, N2, and N3, no-tillage consistently outperformed conventional tillage. At the N3 level, during the second decade, yields under conventional tillage and no-tillage were 2756 kg ha^{-1} and 2999.08 kg ha^{-1}, respectively, and in the third decade, they were 2578.45 kg ha^{-1} and 2615.87 kg ha^{-1}, respectively (Fig. 9a).

While under RCP8.5, at the N0 level, conventional tillage yielded higher cotton outputs compared to no-tillage during the first and second decades, with no significant differences observed in the third decade. At the N1 level, no-tillage produced higher yields than conventional tillage across all three decades. For the N2 level, in the first, second and third decades, no-tillage yields (2594.86, 2412.32 and 2245.36 kg ha^{-1}, respectively) exceeded those of conventional tillage (2278.16, 2081.88 and 1909.12 kg ha^{-1}, respectively). At the N3 level, a significant difference was observed in the first decade, with yields under conventional tillage at 2467.32 kg ha^{-1} and under no-tillage at 2900.76 kg ha^{-1}. This difference diminished in the second and third decades, with yields in the second decade being 2256.06 kg ha^{-1} under conventional tillage and 2778 kg ha^{-1} under no-tillage, and in the third decade, 2073.23 kg ha^{-1} and 2586.54 kg ha^{-1}, respectively (Fig. 9b). These results suggest that no-tillage performs better than conventional tillage, particularly at higher nitrogen levels and under RCP8.5.

3.6. Responses of cotton lint yield to N rates and tillage systems under different general circulation models during 2025–2057

Fig. 10 (a) illustrates the changes in cotton yield under conventional tillage conditions for the RCP 4.5 and RCP8.5 scenario across three decades, based on five different models. In the first decade, all five models indicated an increase in cotton yield. The FIO-ESM and MRI-CGCM3 models showed the highest increases, with yields improving by 7.6 % and 7.91 %, respectively, compared to the baseline performance. In the second decade, the FIO-ESM model shows a decrease in yield by 4.1 % relative to the baseline, while the other models maintain positive performance changes. By the third decade, only the HADGEM2-ES model shows a positive yield change, increasing 4.32 %. The other models display decreasing trends, with the GFDL-ESM2M model experiencing the largest decrease of 10.8 %. This trend suggests that the initial benefits observed may not be sustainable over the long term, as more pronounced climate impacts take effect.

Under the RCP8.5 scenario, a more severe climate change projection, the trends are markedly different. In the first decade, the FIO-ESM (3.61 %), MPI-ESM (3.94 %), and HADGEM2-ES (4.81 %) models show positive yield changes. This indicates some initial resilience to more extreme climate conditions. However, in the second and third decades, all five models exhibited negative changes in yield compared to the baseline. The most significant declines occur in the MRI-CGCM3 model, with reductions of 29.41 % in the second decade and 33.83 % in the third decade (Fig. 10)

Under no-tillage conditions in the RCP4.5 scenario, all models displayed positive performance changes in the first decade. The IPSL-

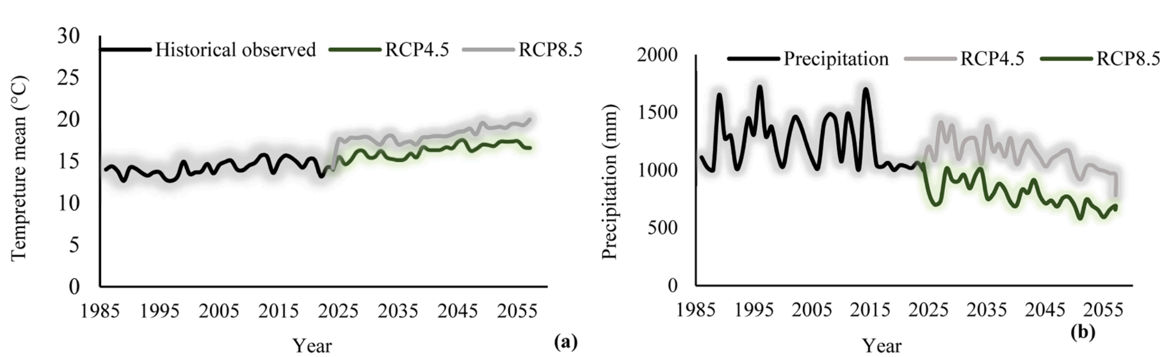

Fig. 7. Annual mean temperature (a) and precipitation (b) changes for the historical reference period (1986– 2018), and future periods (2019–2057) are projected under scenarios RCP4.5 and RCP8.5.

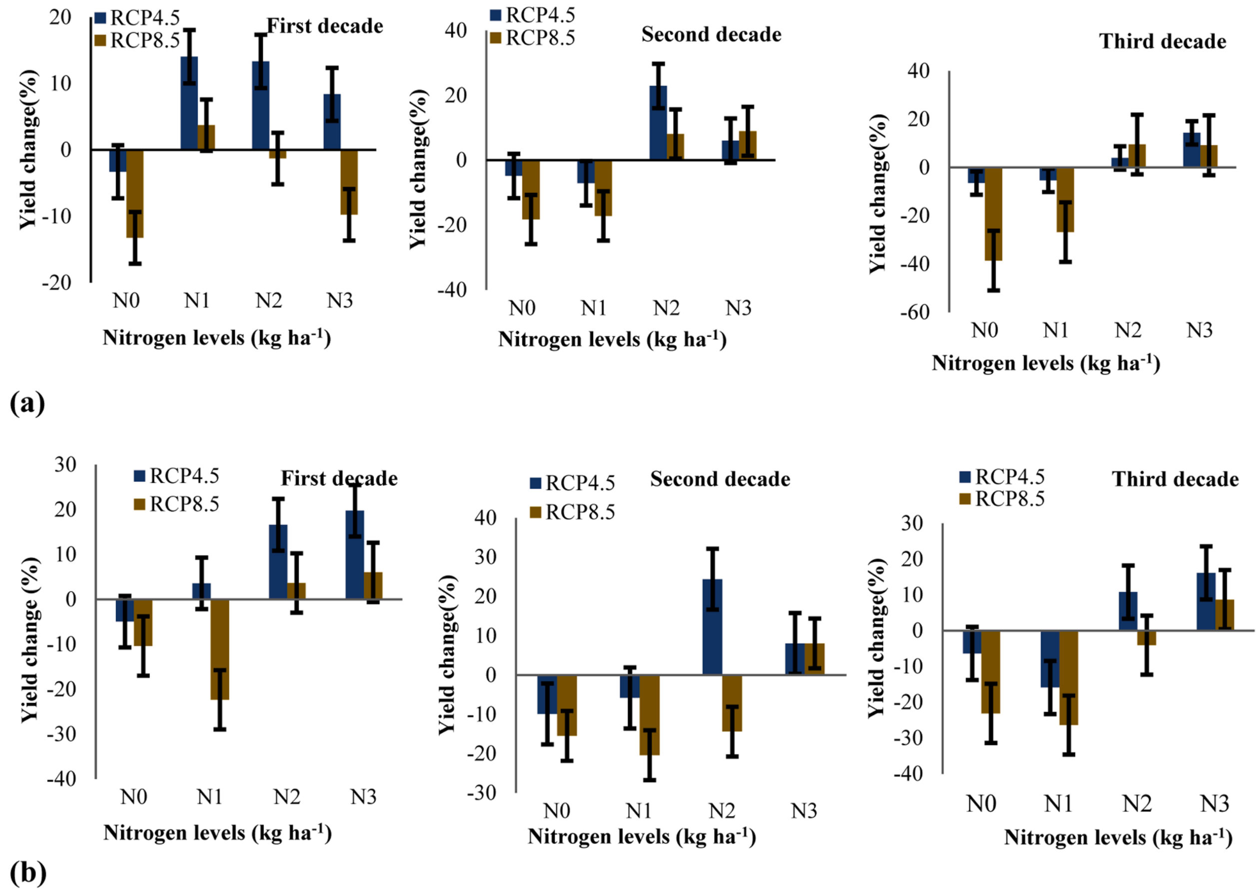

Fig. 8. Change (%) in cotton lint yield with recommended different nitrogen fertilizer levels (N0: control, N1: 33, N2:67, N3: 101 kg N ha^{-1}) under no-tillage (a) and conventional tillage (b) for two RCPs (4.5 and 8.5) under three time slice periods: first decade (2025–2035), second decade (2036–2046), and third decade (2047–2057).

CM5A-MR model exhibited the highest yield increase at 5.02 %. However, in the second decade, the IPSL-CM5A-MR model showed a slight decrease of 1.80 %, and the MRI-CGCM3 model saw a decrease of 3.56 %. By the third decade, all five models demonstrated a decline in performance compared to the baseline, with the GFDL-ESM2M model experiencing the largest decrease at 13 % (Fig. 10b).

In the RCP 8.5 scenario, only the IPSL-CM5A-MR model showed a yield increase of 1.73 % in the first decade, while the other models exhibited negative changes. In the second and third decades, all models indicated a trend of decreasing performance. The MRI-CGCM3 model, in particular, showed the most significant declines, with decreases of 26.36 % in the second decade and 29.77 % in the third decade (Fig. 10b).

4. Discussion

Using crop growth models to analyze crop growth and yield variations across diverse nitrogen levels and tillage systems proves valuable across various weather conditions. These models assist researchers in comprehending optimal strategies for both short- and long-term agricultural planning (Aurbacher et al., 2013; Mubeen et al., 2019).

The CROPGRO Cotton model simulated crop yield very well with satisfactory mean percent difference values during the process of calibration and validation (Figs. 5 and 6). For cotton lint yield attributes, the CROPGRO Cotton model predicted a lesser mean percent difference between simulated and observed cotton yield with RMSE values (139.51–249.71), higher *d*-index (0.8 and 0.9), along with fair R^2 (0.8 and 0.9), respectively (Table 4). Similar results were reported by Mishra et al. (2021) and Mubeen et al. (2019) that the CROPGRO Cotton model simulated cotton yield very well with less difference between simulated and observed values under a semi-arid environment. The CROPGRO Cotton model could be used under different climates for simulation studies and mounting crop management activities (White et al., 2011). These results are similar to Adhikari et al. (2017) and Khatua et al. (2023), which reported that the CROPGRO Cotton model can predict cotton yield very closely under different environments.

The positive influence of increased nitrogen levels on cotton yield, particularly under RCP4.5, is well-documented. Nitrogen is a critical nutrient that enhances plant growth and resilience, enabling crops to withstand climatic stresses better. Wu et al. (2023) demonstrated similar trends, showing that appropriate nitrogen management significantly boosts cotton productivity under changing climate conditions. However, the diminishing returns of nitrogen application under RCP8.5 highlight a critical challenge. As climate conditions become more severe, the capacity of nitrogen to offset the negative impacts on yield, necessitates additional adaptive measures. This observation is consistent with the findings of Zhao et al. (2017), who noted that the efficacy of nitrogen fertilization diminishes under higher temperatures and drought stress conditions.

These results suggest that no-tillage and appropriate nitrogen management can significantly enhance cotton yield under moderate climate change scenarios, aligning with the findings of Singh et al. (2022), who demonstrated similar trends using the DSSAT cotton model. In contrast, under the RCP8.5 scenario, positive performance changes were limited to the second and third decades (Fig. 8a, b). The reduced effectiveness in the first decade highlights the heightened vulnerability of cotton yield to extreme climate conditions. These findings resonate with the work of Powlson et al. (2014), who noted that the benefits of no-tillage practices

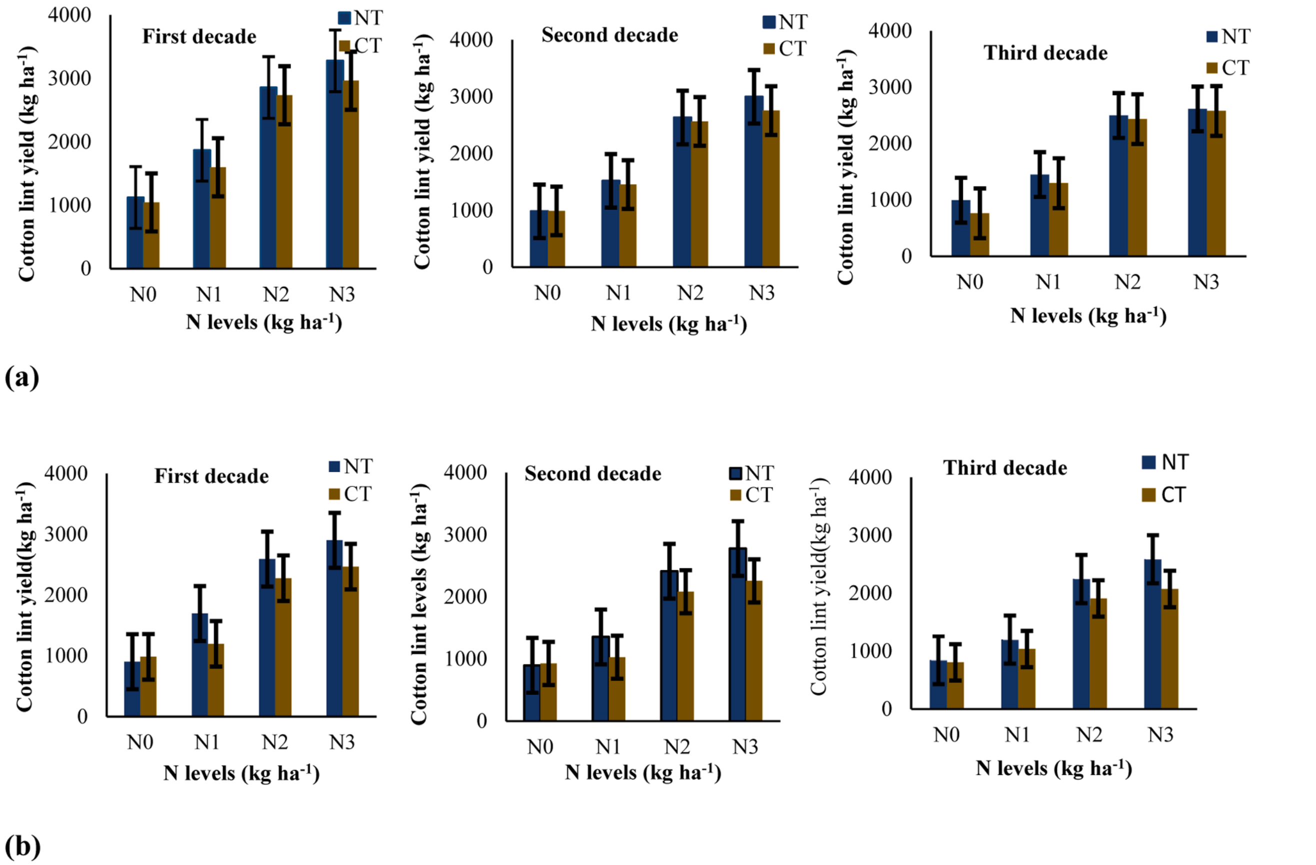

Fig. 9. Comparison cotton lint yield between no-tillage (NT) and conventional tillage (CT) under different nitrogen (N0: control, N1: 33, N2:67, N3: 101 kg N ha^{-1}) for RCP4.5 (a) RCP8.5 (b) under three-time slice periods: first decade (2025–2035), second decade (2036–2046), and third decade (2047–2057).

diminish under more severe climate scenarios.

Under RCP4.5, all models across the three decades demonstrated fewer negative changes in cotton yield with conventional tillage than no-tillage relative to their base yields, respectively. This suggests that conventional tillage is an effective strategy for mitigating the adverse impacts of moderate climate change. Conventional tillage likely helps to maintain soil moisture, reducing erosion, and enhancing soil structure, thereby buffering the cotton crops against climatic stresses (Haddaway et al., 2017). In contrast, under RCP8.5, the benefits of conventional tillage diminish in the second and third decades. The percentage changes in cotton yield under conventional tillage compared to no-tillage became more negative. This indicates that under more extreme climate scenarios, the protective effects of conventional tillage are insufficient to counteract the severe climatic stresses (Pittelkow et al., 2015; Powlson et al., 2014).

The reduced effectiveness of conventional tillage under RCP8.5 is a concerning trend. Extreme climate conditions, characterized by higher temperatures and more frequent droughts, can overwhelm the benefits provided by conventional tillage (Fig. 8a, b). Powlson et al. (2014) and Pittelkow et al. (2015) highlighted similar limitations, noting that while conventional tillage is beneficial under moderate stress, its advantages are less pronounced under severe climatic conditions. This suggests that conventional tillage alone may not be sufficient to mitigate the impacts of extreme climate change and should be integrated with other adaptive strategies. Rosenzweig et al. (2014) emphasized the necessity of a multifaceted approach to climate adaptation in agriculture, advocating for the combination of various practices to bolster crop resilience.

In RCP 8.5, the cotton lint yield across all three decades was consistently lower than in RCP4.5, regardless of nitrogen level (Fig. 8a, b). The decrease in crop yield in RCP8.5 compared to RCP4.5 could be attributed to various factors such as higher greenhouse gas emissions, more severe climate conditions, and/or reduced availability of resources like water or nutrients (Zhao, et al., 2017; Habib-ur-Rahman et al., 2022). The RCP8.5 represents a scenario of higher greenhouse gas emissions and less effective mitigation efforts compared to RCP4.5, leading to more adverse environmental conditions that can negatively impact crop growth, development, and yield (Van Vuuren et al., 2011).

In both RCPs, the yield was higher in the first decade than in the third decade (Fig. 8a,b). Higher temperatures can have varied effects depending on the region. For instance, they might result in either an extended growing season with increased rainfall or reduced rainfall and a shorter growing period. The impact of higher temperatures can differ across regions. Conversely, elevated temperatures in cotton-producing areas and those already experiencing high temperatures may lead to adverse outcomes such as increased shedding of flower buds (Sharma et al., 2022).

Consistent with findings by Devkota et al. (2013), no-tillage practices often outperform conventional tillage, especially at higher nitrogen levels and over extended periods. Under RCP4.5, no-tillage resulted in higher yields across all nitrogen levels during the first decade and maintained superiority at higher nitrogen levels (N1 to N3) in subsequent decades (Fig. 10a). Similarly, under RCP 8.5, no-tillage produced higher yields than conventional tillage at nitrogen levels N2 and N3 across all decades (Fig. 10b). These results reinforce the benefits of no-tillage systems combined with optimal nitrogen management, aligning with the work of Watts et al. (2017), suggesting no-tillage as a sustainable practice to enhance cotton productivity in changing climate conditions.

Substantial differences were observed in the quantity of the simulated yield changes among the different GCMs and RCP combinations, contributing to uncertainty in yield projection under climate change. However, one consensus was that the yield change trends were negative

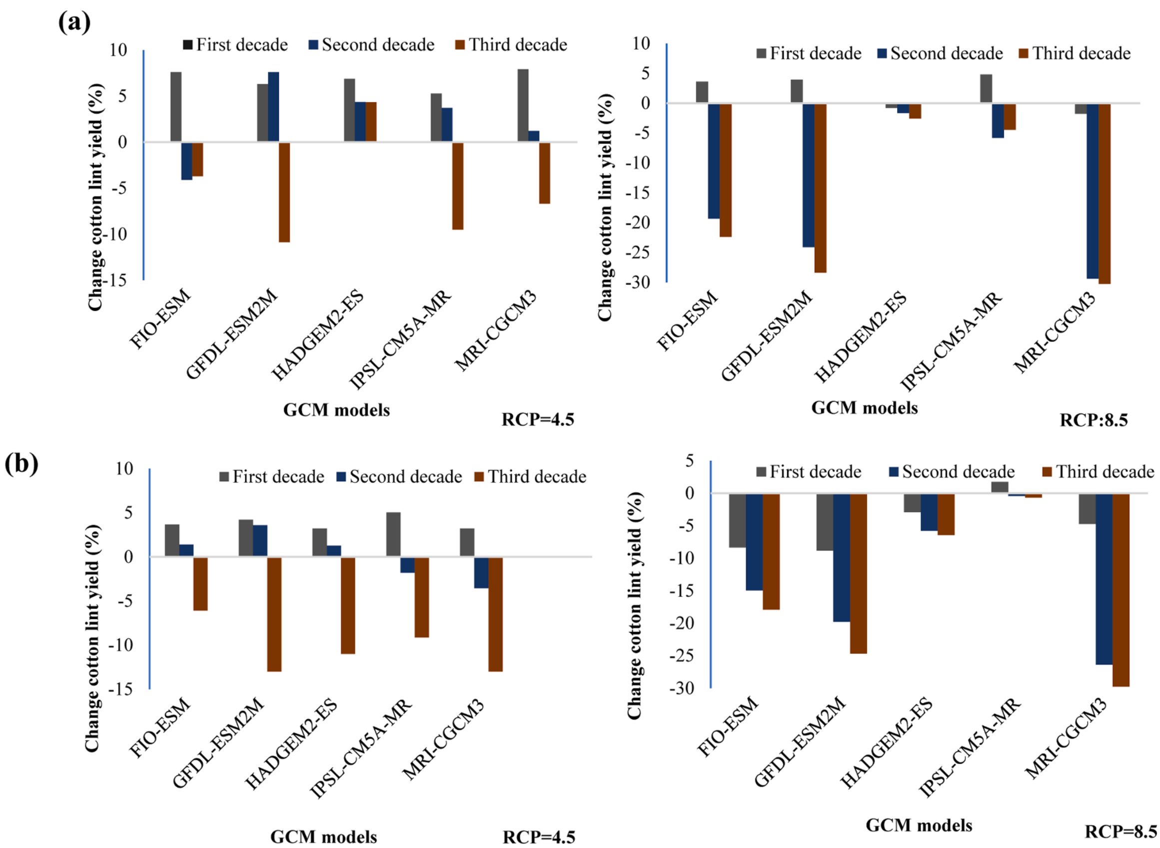

Fig. 10. Relative changes in the mean cotton lint yield under five GCMs models (FIO-ESM, GFDL-ESM2M, HADGEM2-ES, IPSL-CM5A-MR, MRI-CGCM3) to historical cotton yield with conventional tillage (a) and no tillage (b) under RCP4.5 and RCP8.5.

for different GCMs and RCPs. The strong agreement among the different GCMs and RCPs in projecting yield changes revealed some confidence that climate change might decrease future yields compared with historical climate data. These results are close to the findings in different regions of Jans et al. (2021), Arshad et al. (2021), and Chen et al. (2019).

The adverse impacts of climate change on productivity vary with events during different plant growth stages (Doherty, et al., 2003). Several studies have examined the impact of climate change on crop yields. For instance, Deryng et al. (2014) projected that global cotton yields could decrease by 20 % under high-emission scenarios due to increased temperature and water stress. Similarly, Zhao et al. (2017) reported that cotton yields will likely decline in many regions due to climate change, with significant variations depending on local conditions and adaptation measures.

The findings of this study align with these broader trends, showing initial increases in yield followed by declines as climate impacts intensify. Specifically, under the RCP4.5 scenario, all models indicate positive yield changes in the first decade under both conventional tillage and no-tillage conditions. However, the sustainability of these gains diminishes in subsequent decades, particularly under the more severe RCP 8.5 scenario, where negative yield changes become predominant.

The consistent decline in cotton yields over time, particularly under the RCP8.5 scenario, highlights the need for robust adaptation strategies (Fig. 10). The findings indicate that performance changes in cotton yield under the RCP8.5 scenario were more negative compared to the RCP4.5 scenario across all decades. This aligns with expectations, as RCP8.5 represents a high greenhouse gas emissions trajectory leading to more severe climate impacts. In contrast, RCP4.5 represents a more moderate emissions scenario with less severe climate impacts (Challinor et al., 2014). The consistent trend of more negative changes in RCP8.5 underscores the increased vulnerability of cotton yields to higher greenhouse gas concentrations and associated climatic changes.

Cotton yield in the third decade decreased more than in the first decade across all models. This suggests a worsening trend over time, highlighting the cumulative adverse effects of climate change on cotton productivity (Li et al., 2020). As climate conditions progressively worsen, it is evident that cotton yields are increasingly compromised, which could have severe implications for agricultural sustainability and food security in the long term (Wang et al., 2018).

These results highlight the importance of considering both climate scenarios and agricultural practices when planning for future agricultural resilience in cotton production in the north Cotton Belt.

5. Conclusion

In this experiment, the effects of climate change over three decades (2025–2035, 2036–2046, and 2047–2057) based on 5 GCMs under two RCPs on cotton lint yield were analyzed in a humid subtropical region of the north Cotton Belt through the aid of a well-calibrated and validated CROPGRO Cotton model. Projected future climate change showed increased temperature and decreased precipitation under both RCP4.5 and RCP8.5 in all three decades.

This study demonstrates a consistent improvement in cotton yield with increasing nitrogen levels from 0 up to 101 kg N ha^{-1} under both RCP4.5 and RCP8.5 scenarios over the next three decades. Cotton yield peaked in the first decade but declined across all nitrogen levels thereafter. The comparison of RCP4.5 and RCP8.5 reveals varying impacts on cotton productivity, with RCP4.5 generally outperforming RCP8.5 across the four nitrogen levels and three decades.

The study demonstrates that increasing nitrogen application significantly enhances cotton yields under both conventional tillage and no-tillage systems in RCP4.5 and RCP8.5 scenarios and the magnitude of yield increase was lower under RCP8.5 than RCP4.5. Notably, no-tillage practices frequently result in higher yields than conventional tillage, especially at higher nitrogen levels and over extended periods. These findings suggest that adopting no-tillage practices with optimized nitrogen management could be a viable strategy for improving cotton productivity under changing climate conditions.

Cotton yields under all five GCMs experienced consistent negative changes from the first decade to the third decade regardless of the tillage system and RCP. Overall, the magnitude of yield reduction was more pronounced under RCP8.5 than under RCP4.5. The five GCMs predicted varying impacts of future climate change on cotton yield regardless of RCP and decade, contributing to uncertainty in yield projection under climate change. The GFDL-ESM2M under conventional tillage and HADGEM2-ES under no-tillage predicted lower yield than the other GCMs under RCP4.5 and MRI-CGCM3 forecasted lower yield than the other GCMs under RCP8.5 for both tillage systems. However, a consensus lay in that the yield change trends were negative from the first decade to the third decade for all GCM and RCP combinations, which revealed confidence that climate changes decrease cotton yield in the north Cotton Belt from 2025 to 2057. Hence, the findings of this study will help not only understand the future climate change in the region but also see the adoption of climate-smart adaptation options in the future.

CRediT authorship contribution statement

Joshua S. Fu: Writing – review & editing. **Cheng-En Yang:** Writing – review & editing. **Xinhua Yin:** Supervision. **Pourebrahimi Foumani Mohil:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Formal analysis. **Regina Adotey:** Writing – review & editing.

Declaration of Competing Interest

The authors declare no conflict of interest.

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Data availability

The authors do not have permission to share data.

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