Science of the Total Environment 905 (2023) 167046

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Climate trends and soybean production since 1970 in Mississippi: Empirical evidence from ARDL model

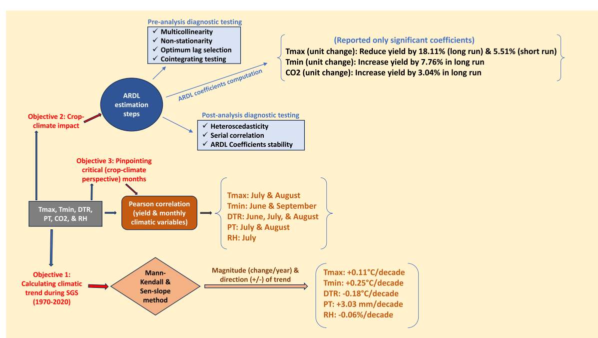
Ramandeep Kumar Sharma [a], Jagmandeep Dhillon [a,*], Pushp Kumar [b], Michael J. Mulvaney [a], Vaughn Reed [a], Raju Bheemanahalli [a], Michael S. Cox [a], Meetpal S. Kukal [c], Krishna N. Reddy [d]

[a] Department of Plant and Soil Sciences, Mississippi State University, MS, USA
[b] School of Humanities, Social Sciences, and Management, Indian Institute of Technology, Odisha, India
[c] Department of Agricultural and Biological Engineering, The Pennsylvania State University, State College, PA, USA
[d] Crop Production Systems Research Unit, USDA-ARS, Stoneville, MS, USA

HIGHLIGHTS

- Newer insights on modeling the climate-change and soybean link in Mississippi
- Mann-Kendall and Sen-slope methods for climatic trends and ARDL model for climate-crop impact were used.
- A positive trend in Tmin (+0.25 °C/decade), and a negative trend in DTR (−0.18 °C/decade) were found.
- Tmax's ongoing trend decreased soybean yield, but Tmin's and CO_2 emissions' trends increased it.
- Altogether, soybeans in MS exhibited variable sensitivity to short- and long-terms climatic changes.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Elena Paoletti

Keywords:
Crop modeling
Climate change
Abiotic stresses
Food security
ARDL model
Crop yield

ABSTRACT

Studying historical response of crops to weather conditions at a finer scale is essential for devising agricultural strategies tailored to expected climate changes. However, determining the relationship between crop and climate in Mississippi (MS) remains elusive. Therefore, this research attempted to i) estimate climate trends between 1970 and 2020 in MS during the soybean growing season (SGS) using the Mann-Kendall and Sen slope method, ii) calculate the impact of climate change on soybean yield using an auto-regressive distributive lag (ARDL) econometric model, and iii) identify the most critical months from a crop-climate perspective by generating a correlation between the detrended yield and the monthly average for each climatic variable. Specific variables considered were maximum temperature (Tmax), minimum temperature (Tmin), diurnal temperature range (DTR), precipitation (PT), carbon dioxide emissions (CO_2), and relative humidity (RH). All required diagnostic-tests *i.e.*, pre-analysis, post-analysis, model-sensitivity, and assessing the models' goodness-of-fit were performed and statistical standards were met. A positive trend in Tmin (+0.25 °C/decade), and a negative trend in DTR (−0.18 °C/decade) was found. Although Tmax, PT, and RH showed non-significant trends, numerical changes were noted as +0.11 °C/decade, +3.03 mm/decade, and −0.06 %/decade, respectively. Furthermore, soybean yield was positively correlated with Tmin (in June and September), PT (in July and August), and RH (in July),

* Corresponding author.
E-mail address: jagman.dhillon@msstate.edu (J. Dhillon).

https://doi.org/10.1016/j.scitotenv.2023.167046
Received 27 July 2023; Received in revised form 7 September 2023; Accepted 11 September 2023
Available online 13 September 2023

but negatively correlated with Tmax (in July and August) and DTR (in June, July, and August). Soybean yield was observed to be significantly reduced by 18.11 % over the long-term and by 5.51 % over the short-term for every 1 °C increase in Tmax. With every unit increase in Tmin and CO_2 emissions, the yield of soybeans increased significantly by 7.76 % and 3.04 %, respectively. Altogether, soybeans in MS exhibited variable sensitivity to short- and long-terms climatic changes. The results highlight the importance of testing climate-resilient agronomic practices and cultivars that encompass asymmetric sensitivities in response to climatic conditions of MS.

1. Introduction

Soybean (*Glycine max* all-oil- Merr.) is the most widely grown crop worldwide (126 million hectares) and the 2nd highest (33.3 million hectares) across the United States (US) (FAOSTAT, 2022). Among top three soybean producers, the US contribution is 34 %, signifying its economic importance to US and global agriculture (Pimentel et al., 2022). Considering its wide array of uses such as human protein, personal care, edible oil, beverages, livestock feed and aquaculture, industrial products, and biofuel, soybean accounts for >10 % of the global trade of agricultural commodities, and its demand is expected to rise in the future *i.e.*, 22 % decade^{-1} (da Silva César et al., 2019). However, like other crops, sustainable production of soybean is continuously challenged by biotic and abiotic stresses caused by the ongoing climate change (Ciscar et al., 2018; Guntukula, 2020: Sharma et al., 2022a; Smith et al., 2019).

The alterations in mean values of temperature, precipitation (PT), and relative humidity (RH) that last for a longer time periods *i.e.*, multiple decades, are referred to as a climate change (Mach et al., 2016). Climate change accelerates the phenological processes diminishing photosynthetic mechanism and shortening the crop growing cycle, which negatively impacts crop productivity (He et al., 2020). Every 1 °C increase in growing season temperature is found to reduce soybean productivity globally by 3 % (Zhao et al., 2017). However, during the growing season, temperature sensitivity varies with crop growth stages (Wang et al., 2023). For example, in soybeans, the reproductive stage, specifically the grain filling and pollination stages, is found to be more sensitive in terms of affecting the yield (Wang et al., 2023). Likewise, it has been observed that drought and extreme variation in the PT pattern can affect physiological processes and, consequently, the yield (Guo et al., 2022a). Moreover, future temperature and PT patterns are predicted to rise further by 2.2 °C and up to 40 % by 2100, faster than historical rates (Pielke Jr et al., 2022; Thackeray et al., 2022 Malla et al., 2022). It is anticipated that these changes, combined with increased ambient CO_2 (e[CO_2]) emissions, will have a greater impact on agricultural productivity than in the past (Lobell et al., 2011). The future mitigation strategies and research priorities are based on past estimates of crop-climate impacts (Rippey, 2015 Sultan et al., 2019). Despite mounting evidence that global climate change negatively impacts crops, some studies reported minimal or no effect (Liu et al., 2010 Sacks and Kucharik, 2011 Liu et al., 2012 Sharma et al., 2022a). Also, some regional-scale studies found a positive correlation between changing climate and yields between 1982 and 1998 (Lobell and Asner, 2003). In other words, crop-climate relationships are complex, and even identical climatic trends can have different impacts on crops, and these impacts differ by region and crop type (Kukal and Irmak, 2018). Therefore, to better understand crop-climate associations, explorations at a finer scale (region or state) are needed, specifically to identify the varied sensitivities of crops to climate change.

There is consensus on the effects of climate change on agriculture on a global and national scale through a vast number of crop simulation and econometric studies (Smith et al., 2000 Tubiello et al., 2000 Tebaldi and Lobell, 2008). Regional perspectives are, however, under-examined (Kunkel et al., 2012 Lychuk et al., 2017) and within the US, Mississippi (MS) is one of those states that experiences severe floods, tropical storms, and droughts that are expected to worsen in the future (EPA, 2016). Mississippi receives 1419.8 mm (55.9 in) of PT per year, making it the third wettest state in the country (NOAA, 2021). Recently, MS experienced its warmest 5-year period from 2016 to 2020 (NOAA, 2021). By 2100 in MS, it is expected that there will be 30 to 60 days per year when temperatures will exceed 35 °C, up from the current 15 days (EPA, 2016). This climate change will have serious implications in MS considering substantial agroeconomic impact, with 4.2 million hectares under agriculture, producing $8.33 billion, and employing 17.4 % of its population in agriculture (MDAC, 2021). Soybean is the most important crop in MS, accounting for 0.91 million hectares, or 2.73 % of the country's cropland, and generating $1.49 billion revenue annually (MDAC, 2021; USDA-NASS, 2022).

Thus far, there are limited studies investigating climate change implications on soybean production in MS (Shammi and Meng, 2021 Sun et al., 2022). The statistical or crop simulation modeling studies has only estimated the direct (short-term) effects of climate change on soybean while ignoring the indirect (long-term) component of crop-climate interactions (Surówka et al., 2020). The present study will employ the auto-regressive distributed lag (ARDL) model, that is an advanced model with robust statistical capabilities to additionally detect the indirect climate-crop impacts by cumulatively distributing the immediate effects over the past years (Warsame et al., 2021). Therefore, this study is the first attempt of using ARDL model in MS (also in the US) to quantify crop-climate impact in soybean. The objectives are i) determining the trends in maximum temperature (Tmax), minimum temperature (Tmin), diurnal temperature range (DTR), precipitation (PT), carbon dioxide emissions (CO_2), and relative humidity (RH) from 1970 to 2020, ii) estimating the impact of these climatic variables on soybean yield, and iii) identifying critical climatic variables for specific months during SGS as they influence soybean production in MS.

2. Materials and methods

2.1. Data

A 50-year (1970–2020) time series dataset for MS (Fig. 1) was used to assess the impact of climate change on soybean yield.

Several studies have documented the use of time series data in crop-climate research (Warsame et al., 2021 Chandio et al., 2022 Gul et al.,

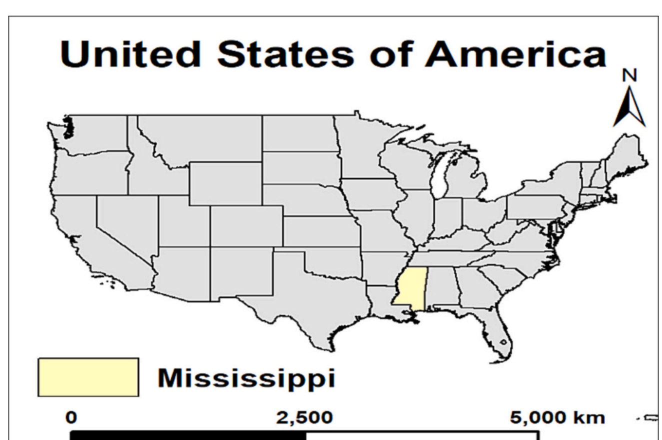


Fig. 1. Map highlighting Mississippi (MS) on the US map.

Table 1
Data description including study variables, units of variables and sources of data used in the study.

Study variable (units)	Data sources
Soybean yield (Mg ha^{-1})	USDA-NASS https://www.nass.usda.gov/
HA (ha)	
Tmax (°C)	NOAA https://www.noaa.gov/
Tmin (°C)	
DTR (°C)	
PT (mm)	
CO_2 emissions (Mmt)	USEIA https://www.eia.gov/environment/emissions/state/
RH (%)	PRISM https://prism.oregonstate.edu/comparisons/

NOAA represents National Oceanic and Atmospheric Administration, USDA-NASS is United States Department of Agriculture's national agricultural statistics service, USEIA is United States Energy Information Administration, and PRISM is Parameter Elevation Regressions on Independent Slopes Model. Tmax is maximum temperature, Tmin is minimum temperature, DTR is diurnal temperature range, PT is precipitation, CO_2 is carbon emissions, RH is relative humidity, and HA is harvested area for soybean. Mg ha^{-1} denotes megagram per hectare, ha is hectares, °C is degree Celsius, mm is millimeter, and Mmt is million metric tons.

2022). The Tmax, Tmin, DTR, PT, CO_2 emissions, and RH were the independent variables with the harvested area (HA) as a control input variable and soybean yield was the dependent variable in the current study. The area weighted averages of the data (Tmax, Tmin, DTR, PT, and yield) for the counties that produce soybeans were used to represent a single spatial unit for MS for each growing season, creating time series for each variable spanning 51 years. The CO_2 emissions and RH data were available on MS scale which was fed to the model after running pre-analysis diagnostic testing model assumptions. These data compilations were done as guided by previous crop-climate studies (Daly and Bryant, 2013 Sharma et al., 2022a Godwin et al., 2023). The units and sources of the data can be found in Table 1. These data sources use high grid resolutions (4–5 km) to transcode datapoints from monitoring stations to ensure sample coverage on the appropriate geographical scale (Mourtzinis et al., 2017 NOAA, 2021). Daly et al. (2008), EIA (2019), and NOAA (2021), explains the comprehensive algorithms used by these data sources for assembling the data points. The US Department of Agriculture handbook on planting and harvesting calendar suggests May–September as the soybean growing season (SGS) (USDA, 2021). From available monthly data, the Tmax, Tmin, DTR, and RH were averaged, and PT was totaled, over the SGS, following previous relevant studies (Ginbo, 2022 Sharma et al., 2022a). Due to lack of monthly data, CO_2 emissions (atmospheric) values were used as yearly averages instead of SGS averages. The study timeframe included the crucial period of 1983–2012, which has been noted as the warmest 30-year span in the previous 800 years for the Northern Hemisphere (Stocker et al., 2013).

2.2. Methodology for climatic trend detection

The non-parametric Mann-Kendall and Sen slope methods, which the World Meteorological Organization has recommended for use in estimating climate trends, were used in the current study (Mann, 1945; Kendall, 1948; Sen, 1968). These methods have a simplistic computational process and are robust to handle data that contains missing or below-threshold values (Kukal and Irmak, 2016). Also, the data is not necessarily required to be normally distributed for these methods to work. Hence, these are widely used in climatic trend computational studies (Dawood, 2017 Aditya et al., 2021; Karki et al., 2022).

The Mann-Kendall method uses relative ranking by comparing the values from specified time range to calculate Kendall statistics (Aditya et al., 2021). The basic equation guiding Mann-Kendall test is as follow:

$$\text{Kendall statistics (S)} = \sum_{j=1}^{n-1} \sum_{k=j+1}^{n} sgn\left(X_k - X_j\right) \tag{1}$$

In Eq. (1), "sgn" is a mathematical function called signum that can have values +1, 0, or −1 depending if $X_j - X_k$ is >0, =0, or <0. In the time series data used in the study, "X_j" and "X_k" are the consecutive data values for the year "j" and "k" and "n" represents the number of datapoints or years in our case. For $n < 10$, Kendall statistics (S) determines the trend but if $n > 10$ as in the current study, Kendall test standardized value (Z_{MK}) determines the trend that is calculated from S using the Eqs. (2) and (3) (Gujree et al., 2022).

$$\text{Variance(S)} = \frac{n\,(n-1)(2n+1) - \sum_{j=1}^{m} t_j\left(t_j - 1\right)\left(2t_j + 5\right)}{18} \tag{2}$$

In Eq. (2), "m" stands for the taut groups, which indicate data points with common values but not the same rank number position, and "tj" stands for the datapoint numbers in the jth group.

$$Z_{MK} = \frac{S \pm 1}{\sqrt{\text{Variance (S)}}} \tag{3}$$

Eq. (3) uses S-1 if $S > 0$, $S + 1$ if $S < 0$, and $Z_{MK} = 0$ if S is 0. The value of $Z_{MK} > 0$ indicates a positive trend while $Z_{MK} < 0$ implies negative trend.

The Sen slope computes the magnitude (rate of change per year) of trend for each climatic variable (Sen, 1968) following the below mentioned Eq. (4).

$$\beta = median\left[\frac{(X_n - X_m)}{(n - m)}\right] \tag{4}$$

where, X_n and X_m denote the time series of appropriate climatic variable at nth and mth time (in years). For every $m < n$, the magnitude of β denotes the slope of tendency or the rate of change per year of climatic parameters, with the β values greater than zero denoting positive/upward trend and β values less than zero denoting negative/downward trend. For the accurate (unbiased by serial correlation) trend estimation, pre-Whitening procedure was followed prior to feeding the data in Mann-Kendall and Sen slope equations, as suggested in Liu et al. (2020). More detail on step-by-step estimation process for the Mann-Kendall test and Sen slope method is discussed in Kukal and Irmak (2016) and Liu et al. (2020).

2.3. Methodology for calculating impact of climate change on soybean yield

2.3.1. Study model

The ARDL model is also known as the bound test cointegration method, first devised by Pesaran and Shin (1995), and has been used in previous crop-climate studies (Chandio et al., 2020 Nasrullah et al., 2021 Warsame et al., 2021; Ramzan et al., 2022; Agbenyo et al., 2022).

The ARDL model outperforms other econometric models by producing consistent and efficient results even with small sample sizes (Haug, 2002). This model is also robust against endogeneity, which develops when predictor variables in the regression model have a propensity to correlate with the error terms. Endogeneity is common with the crop and climate datasets (Warsame et al., 2021). The ARDL model simultaneously estimates long- and short-term impacts of independent variables on a response variable (Ramzan et al., 2022). The ARDL is a dynamic model, meaning that the changes in regressand (assuming "*y*") generated by the change in regressor (assuming "*x*") do not occur all at once but rather over time (Hassler and Wolters, 2006). This is vital to know in order to comprehend long- and short-term implications. There will only be an immediate (also referred as short-term or direct) effect on "*y*" if "*x*" increases, returns to its initial value, or changes temporarily (Pesaran and Shin, 1995). However, if "*x*" changes permanently (as in the case of climate variables considering a long-term scenario of >30 years), then a smaller proportion of the impact (on "*y*") is visible as direct/immediate/short-term effect, and the remaining impact gets transferred permanently to cumulated immediate effects, which is referred to as a long-term/permanent effect (Pesaran and Shin, 1995 Hassler and Wolters, 2006). It's also known as an indirect impact in relation to climate. The process of transitioning from immediate to permanent effect is represented mathematically by the geometric progression series function with a multiplying factor of less than one (Pesaran and Shin, 1995; Hassler and Wolters, 2006). The ARDL model also estimates the time and rate by which short-term climatic effects translate permanently into long-term effects by incorporating an error correction model (Nasrullah et al., 2021). ARDL models allow researchers to select an ideal lag order for response and explanatory variables for model incorporation (Ramzan et al., 2022). Lag order can be understood by considering agricultural system complexity, where multiple input interactions have the tendency to impact crop output both directly and indirectly (Steffens et al., 2015). For instance, climate change has two dimensional effects on crops: a direct effect on yield due to changes in morphology, physiology, and plant productivity, and an indirect effect due to changes in soil fertility, irrigation availability, pests, heat, and drought that alters resource use efficiency (Steffens et al., 2015 Daloz et al., 2021). Indirect effects are also referred to as residual or rollover effects for instance, how dry fertilizers or cover crops affect following year crop yields (Quemada et al., 2019). The lag order specifies the lag period (usually years) for model regressors against the response variable (yield). It is important to account for indirect effects in order to calculate the total impact on the cropping system (Sultan et al., 2019; Abbas et al., 2022). Statistically, the optimum lag order is the lag number at which the residual sum of squares is minimal, and model's predictive power is greatest as it accounts for the optimal factors that affects response variable (Liew, 2004).

Obviously, other factors besides climate change, including technological advancements, improvements in fertility decision-making, new cultivar adoption, and other crop management practices, have had a significant impact on yield (Oglesby et al., 2023). The literature has described various data-detrending techniques to statistically exclude the contribution of factors (other than climate) to yield change, and the first differencing technique used in the current study is one that has been widely used in similar studies (Ding and Shi, 2022 Mohammadi et al., 2023). According to Lobell and Field (2007), the impact of these unobserved factors on yield can best possibly be eliminated/nullified by differencing the values of previous year from the next throughout the study period. Moreover, other established norms and criteria to apply the ARDL approach were followed as in previous studies (Nasrullah et al., 2021 Abbas et al., 2022 Ramzan et al., 2022).

A natural logarithm form is suggested to adequately deal with issues of multicollinearity and instability, if present, in the data (Sultan et al., 2019). The specific model as adopted from past studies (Warsame et al., 2021; Agbenyo et al., 2022) was as follows:

$$\begin{aligned}\Delta lnY_{it}=&\beta_0+\sum_{i=1}^{n}\beta_1\Delta ln(Y)_{t-i}+\sum_{i=1}^{n}\beta_2\Delta ln(Tmax)_{t-i}+\sum_{i=1}^{n}\beta_3\Delta ln(Tmin)_{t-i}+\\ &\sum_{i=1}^{n}\beta_4\Delta ln(DTR)_{t-i}+\sum_{i=1}^{n}\beta_5\Delta ln(PT)_{t-i}+\sum_{i=1}^{n}\beta_6\Delta ln(CO_2)_{t-i}+\\ &\sum_{i=1}^{n}\beta_7\Delta ln(RH)_{t-i}+\sum_{i=1}^{n}\beta_8\Delta ln(HA)_{t-i}+\sum_{i=1}^{n}\delta_1\Delta ln(Y)_{t-i}+\\ &\sum_{i=1}^{n}\delta_2\Delta ln(Tmax)_{t-i}+\sum_{i=1}^{n}\delta_3\Delta ln(Tmin)_{t-i}+\sum_{i=1}^{n}\delta_4\Delta ln(DTR)_{t-i}+\\ &\sum_{i=1}^{n}\delta_5\Delta ln(PT)_{t-i}+\sum_{i=1}^{n}\delta_6\Delta ln(CO_2)_{t-i}+\sum_{i=1}^{n}\delta_7\Delta ln(RH)_{t-i}+\\ &\sum_{i=1}^{n}\delta_8\Delta ln(HA)_{t-i}+\varnothing(ECT)_{t-i}+\varepsilon_t\end{aligned} \tag{2}$$

where, Y is soybean yield in year t, and Tmax, Tmin, DTR, PT, RH, CO_2, and HA are explanatory variables. β_0 is the intercept, i is the lag order (with "n" is maximum lag length), Δ denotes the first differential, ε_t is the error term, β_1 to β_8 represents coefficients of long-term coefficients for different variables, δ_1 to δ_8 are short term coefficients for different variables, ECT is the error correction term and $\varnothing$ is its coefficient which determines the rate of readjustment of short-term shocks on the long-term equilibrium.

2.3.2. Pre-analysis diagnostic testing

2.3.2.1. Multicollinearity. There is a series of mandatory statistical tests required before running regression using the ARDL model (Warsame et al., 2021). The presence of multiple variables in this study raises the possibility of variable correlation, causing issues such as overfitting, increased variances, and large standard errors (Kim, 2019). It is important to have no multicollinearity or, when not possible, the variables showing multicollinearity should be excluded from the model. To avoid this problem, a variance inflation factor test and a tolerance level test were performed to check multicollinearity (Kim, 2019).

2.3.2.2. Unit roots/non-stationarity. Another key issue with the time series data is the existence of unit root problems (non-stationarity), or non-constant mean, variance, and/or covariance, implying they are either diverging or converging with time (Fingleton, 1999). Non-stationarity causes spurious regression analyses, and as a result, the inferences drawn may inaccurately reflect the relationship. An Augmented Dickey-Fuller (ADF) test and a Phillips Perron (PP) test were performed to check unit root problems (Warsame et al., 2021). The literature suggested detrending or differencing for transforming the data if non-stationarity was found, depending on whether the data showed a stochastic or deterministic trend (Altunkaynak and Nigussie, 2018).

2.3.2.3. Optimum lag selection. The lag component of the ARDL model allows the inclusion of variables from prior years as a regressor against the current year regressand (yield) in the model (Abbas et al., 2022). An optimum lag is number of significant previous years that needs to be included in the model to capture residual effects (of inputs) on current-year crop production (Nasrullah et al., 2021). The optimal lag selection increases model power by lowering endogeneity and residual correlation (Agbenyo et al., 2022). Multiple tests such as likelihood ratio (LR), Final Prediction Error criterion (FPE), Akaike information criterion (AIC), Schwarz Bayesian information criterion (*SIC*), and Hannan-Quinn information criterion (HQ), as suggested in previous studies, were used to select an optimal lag number for the model (Warsame et al., 2021; Agbenyo et al., 2022).

2.3.2.4. Cointegration testing. Prior to computing model coefficients, the Wald F-test is required to determine the existence or absence of a long-term relationship between different regressors and a regressand (soybean yield) (Ramzan et al., 2022). This was tested at 1 %, 5 %, and 10 % significance levels, respectively, and the Wald Fcal (F-calculated) values were compared to the upper bound critical value I (1) and lower bound critical value I (0). If Fcal is more than I (1), a relationship exists between the variables; if Fcal is less than I (0), there is no relationship between the variables (Warsame et al., 2021). However, Fcal values between I (1) and I (0) represent an inconclusive situation. Furthermore, Eq. (1) can be used to calculate the long- and short-term coefficients if long-term cointegration is detected.

2.3.3. Post-analysis diagnostic testing & robustness check of the ARDL model

After estimating the coefficients of the final regression equation of ARDL model, the next step is to test if the error terms are free of serial correlation and heteroscedasticity. Error terms become autocorrelated with their lag values due to serial correlation, and heteroscedasticity produces uneven scattering of residuals (error terms) (Abbas et al., 2022). Both situations cause regression model inferences to be ineffective (Warsame et al., 2021). Therefore, the study employed the Breusch-Godfrey LM test and the Breusch–Pagan–Godfrey test, as described by Ramzan et al. (2022) and Agbenyo et al. (2022), for checking serial correlation (autocorrelation) and heteroscedasticity. Also, the ARDL model regression coefficient stability, accuracy, and goodness of fit were tested to ensure whether the output coefficients of the study model are stable or not throughout the study period to generate inferences (Nasrullah et al., 2021; Li and Shao, 2022; Agbenyo et al., 2022). This was accomplished by running the cumulative sum of recursive residuals (CUSUM) test and cumulative sum of squares of recursive residuals (CUSUMSQR) test. The CUSUMSQ test detects sudden and drastic deviations from the constancy of the model coefficients, whereas the CUSUM test can detect systematic differences (Deng and Perron, 2008). Finally, to validate the robustness and sensitivity of the study's novel ARDL model, the estimations produced by the ARDL model were re-verified using the fully modified ordinary least square (FMOLS) model. Robustness and sensitivity testing were conducted as per previous studies described by Nasrullah et al. (2021) and Li and Shao (2022).

2.4. Methodology for identification of critical months of impact on soybean yield

After examining the impact of climate on soybean yield using SGS averaged values of climate variables, the study extended the methodology to investigate monthly-level controls. Following Eck et al. (2020), critical months were identified using Pearson's correlation coefficient between the first differenced (detrended) yield and monthly values of each climatic variable.

3. Results and discussion

Following the backward elimination method (Halinski and Feldt, 1970 Timm, 2002) for choosing the independent variables for multiple regression analysis, the DTR and RH variables were found to negatively impact the model's overall predictive performance, so they were excluded from the final fitted regression equation for the reduced ARDL model. The remaining variables were included in the ARDL model and were tested in pre- and post-diagnostic tests (Tables 3 and 5), all of which were based on ARDL model assumptions. However, to analyze climatic trends and determine Pearson's correlation between detrended (first differenced) yield and monthly averaged climatic variable values, all variables were taken into consideration (Tables 2 and 4B).

3.1. Climatic trend analysis (1970 to 2020)

The mean Tmin, Tmax, DTR, and PT were found to be 18.94 °C, 31.15 °C, 12.21 °C, and 45.21 mm during SGS over the past five decades in MS (Table 2). Over SGS, the Tmax trend line showed a nonsignificant increase of 0.11 °C every decade; however, the months of June and August exhibited a significant increase in warming with a range of 0.41–0.47 °C per decade (Fig. 2A; Table 2). Sharma et al. (2022b) noted a similar Tmax warming rate (0.11 °C/decade), but a higher Tmin warming rate (0.34 °C/decade) for the southeastern US region. Over SGS, Tmin has shown a significant positive trend with an increase of 0.25 °C each decade (Table 2; Fig. 2B). The most significant contributors to Tmin trend were found to be the months of June, July, and August, with temperatures increases in the range of 0.24–0.35 °C each decade (Table 2). Sen slope comparisons showed that the Tmin warming was 1.27 times Tmax, evidence of an asymmetric (Tmin increase > Tmax increase) warming trend in MS (Table 2). This asymmetrical trend of warming is a significant, and a topic for further explorations to understand climatic impacts on crops. Singh et al. (2021) discovered: the predictability of agricultural output depends more on Tmin when compared to the other eleven climatic parameters considered. The DTR, which refers to the difference between Tmax and Tmin is a critical variable and has gained attention in crop-climate research. The inherent variation of DTR contrasts favorably and is unaffected by fluctuations in the average temperature on decadal time frames (Braganza et al., 2004). While some soybean plant activities, such as photosynthesis, are light-driven, others, such as crop development, have non-linear relationships with temperature that allow Tmax and Tmin to have differing effects on soybean (Dusenge et al., 2019). DTR has proven to be the only index that can concurrently account for both types of plant processes

Table 2
The Mann-Kendall test and Sen slope method for estimating trends in variables, such as maximum temperature (Tmax), minimum temperature (Tmin), diurnal temperature range (DTR), precipitation (PT), and relative humidity (RH) in Mississippi from 1970 to 2020.

Series/test	Tmin (°C)			Tmax (°C)			DTR (°C)			PT (mm)			RH (%)		
	Z_{MK}	*p*-Value	Sen's slope	Z_{MK}	*p*-Value	Sen's slope	Z_{MK}	*p*-Value	Sen's slope	Z_{MK}	*p*-Value	Sen's slope	Z_{MK}	*p*-Value	Sen's slope
May	0.178	0.064	0.022	0.103	0.287	0.012	−0.092	0.340	−0.009	−0.087	0.364	−0.183	0.003	0.981	0.000
June	0.373	**0.000**	0.035	0.051	**0.047**	0.007	−0.261	**0.006**	−0.028	0.095	0.324	0.163	0.125	0.193	0.036
July	0.262	**0.006**	0.024	−0.006	0.956	−0.001	−0.401	**<0.0001**	−0.031	0.119	0.215	0.147	0.068	0.482	0.022
August	0.299	**0.002**	0.027	0.066	**0.041**	0.009	−0.201	**0.037**	−0.019	0.158	0.099	0.269	−0.009	0.931	−0.004
September	0.183	0.057	0.027	0.143	0.136	0.021	0.006	0.956	0.001	−0.063	0.512	−0.112	−0.110	0.253	−0.060
SGS	0.427	**<0.0001**	0.025	0.128	0.182	0.011	−0.276	**0.004**	−0.018	0.062	0.523	0.303	−0.012	0.906	−0.006
Mean	18.94 °C			31.15 °C			12.21 °C			45.21 mm			68.18 %		

Z_{MK} is Kendall test standardized value that ranges from −1 to 1, and its absolute value indicates the strength of the trend. Positive (+) values indicate an upward (increasing) trend, while negative (−) values indicate a downward (decreasing) trend. The strength of the trend increases as Z_{MK} absolute values get closer to 1. The Sen slope value is a measure of the rate of change annually. The annual rate of decrease is indicated by the negative (−) value of the Sen slope, while the annual rate of increase is indicated by the positive (+) value. The significant values are highlighted in bold.

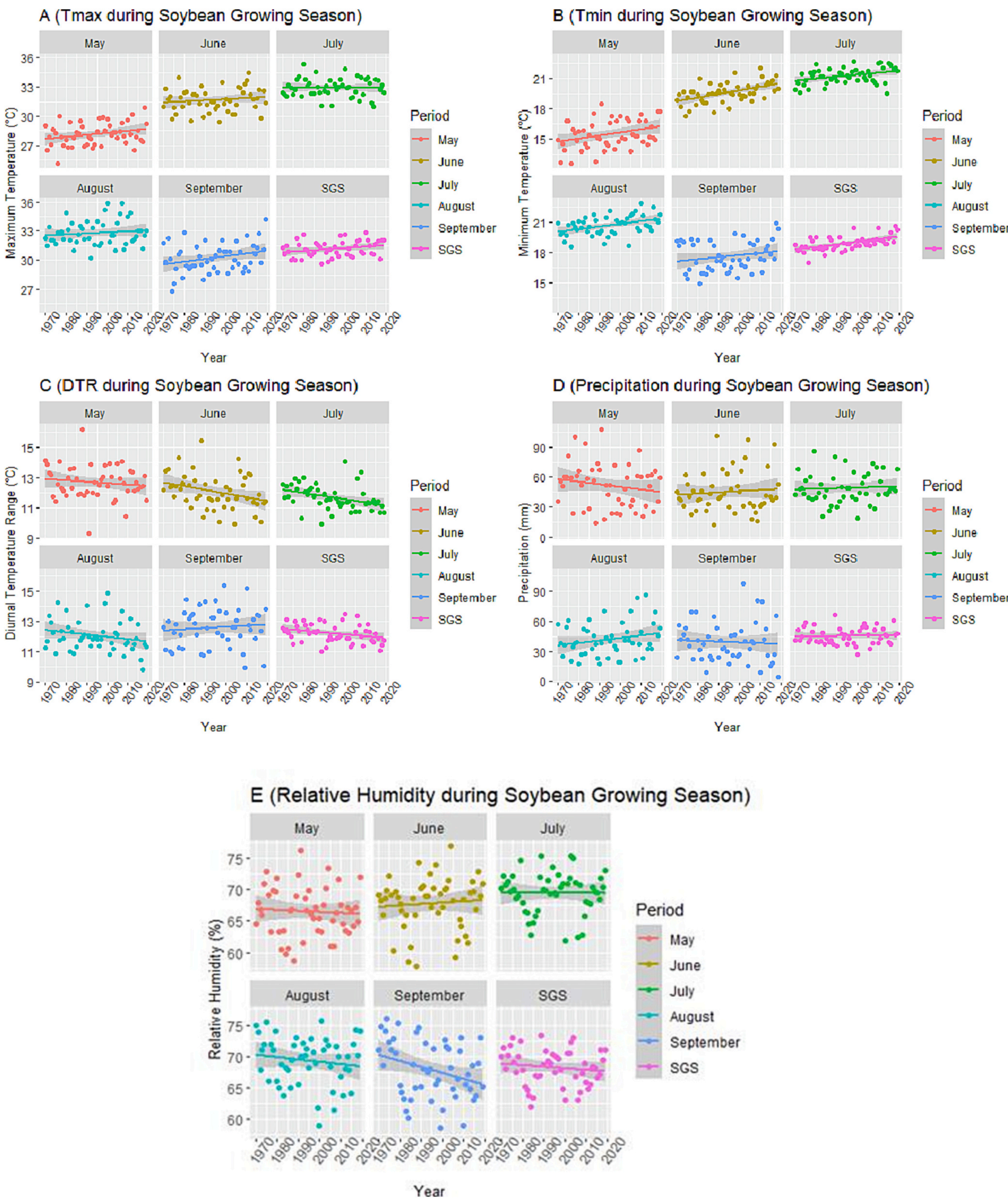


Fig. 2. Trend lines showing the direction (upward or downward) of trend for maximum temperature (A), minimum temperature (B), diurnal temperature range (C), precipitation (D), and relative humidity (E) for SGS, from 1970 to 2020 in Mississippi (MS). Each figure is categorized by the months from May to September and the SGS average of all the months.

(Lobell, 2007). The DTR trend was noted to be significantly negative for SGS, specifically during June, July, and August (Fig. 2C), with an asymmetricity (Tmax-Tmin) of warming continuously decreasing at the rate of 0.18 °C/decade (over SGS), and in the range of 0.19–0.31 °C/decade (in June–August) (Table 2). This decreased DTR trend is attributable to the increased cloud cover resulting in reduction of incoming short radiation rate during the day (Doan et al., 2022). Furthermore, PT and RH exhibited no significant trend over SGS (Fig. 2D, E). These climatic rates are essential to determine the speed at which ecosystems need to readapt and return to equilibrium (Smith et al., 2015).

3.2. Pre-analysis diagnostic test results

3.2.1. Unit root testing results

The study variables were found to be stationary at level I (0) or first difference I (1) at the $p < 0.01$ level of significance (Table 3A). This verified that the means, variances, and covariances were not time dependent, enabling the regression coefficients to accurately reflect the actual relationship between variables (Baumohl and Lyocsa, 2009) and thereby fulfilling the assumptions of the ARDL model (Agbenyo et al., 2022).

Table 3
Pre-analysis diagnostic test results.

(A) Results of unit root tests using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests of variables involving maximum temperature (Tmax), minimum temperature (Tmin), CO_2 emission (CO_2), harvested area (HA), precipitation (PT), and soybean grain yield (Y)

Variables	ADF		PP	
	Level	First difference	Level	First difference
Tmax (°C)	−6.978***		−7.571***	
Tmin (°C)	−8.111***		−9.019***	
CO_2 (Mt)	−2.256	−8.400***	−2.264	−8.357***
HA (ha)	−1.975	−6.919***	−1.970	−6.922***
PT (mm)	−6.485***		−7.013***	
Y (Mg ha^{-1})	−5.724***		−5.780***	

(B) Results of the multicollinearity testing using the variance inflation factor (VIF) and tolerance value (TOV) tests for variables such as the maximum temperature (Tmax), the minimum temperature (Tmin), the carbon dioxide emission (CO_2), the harvested area (HA), and the precipitation (PT)

Variable	Variance inflation factor (VIF)	Tolerance level
Tmax (°C)	8.06	0.124
Tmin (°C)	4.87	0.205
CO_2 (Mt)	2.52	0.397
PT (mm)	4.16	0.240
HA (ha)	2.1	0.477
Mean value	4.34	0.288

(C) Model's ideal lag determination criteria employing the sequential modified statistics test (SMLR), final prediction error (FPE) test, Akaike information criterion (AIC) technique, Schwarz information criterion (*SIC*) method, and Hannan-Quinn information criterion (HQ) method

Lag	SMLR	FPE	AIC	SC	HQ
0	NA	1.27e-13	−12.665	−12.427	−12.576
1	186.956*	5.11e-15*	−15.894*	−14.224*	−15.268*
2	34.683	9.27e-15	−15.379	−12.279	−14.218
3	47.865	9.38e-15	−15.587	−11.055	−13.889
4	28.476	1.85e-14	−15.378	−9.4153	−13.144

(D) Results of the ARDL bounds cointegration test

Test statistic	Value	Significance (%)	I (0)	I (1)
F-statistic	7.150	10 %	2.08	3
		5 %	2.39	3.38
		1 %	3.06	4.15

*** Indicates significance at $p < 0.01$.
* Indicates lag order selected by the criterion, SMLR: sequential modified LR test statistic, FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion, and each test at 5 % level of significance.

3.2.2. Multicollinearity test results

The multicollinearity results are provided in Table 3B. The average variance inflation factor (VIF) and tolerance values were 4.34 and 0.288, staying within the permissible limits. VIF values smaller than 10 and tolerance values larger than 0.1 confirms the data were free from significant multicollinearity issues (Miles, 2014).

3.2.3. Optimum lag selection test results

The results of five different tests used in selecting the optimum lag length, are shown in Table 3C. All tests suggested the lag length to be 1, indicating that model response variables depended only on one previous year of the explanatory variables within the model.

3.2.4. ARDL Bounds Cointegration test results

The estimated Wald F-test value (7.150) exceeded the upper threshold values of 3, 3.38, and 4.14 at 10 %, 5 %, and 1 % levels of significance, indicating the existence of long term cointegration or a relationship between the explanatory variables and the response variable (Table 3D).

3.3. Impact of climate change on soybean

The relationship between climatic variables and soybean yield over the long- and short-term are presented in Table 4A. At the 1 % and 5 % levels of significance, the Tmax coefficient of ARDL was determined to be negative for both short- and long-term, indicating that the Tmax trend had significantly reduced soybean yield in MS (Table 4A). This is in line with the findings of Goldblum (2009), Mourtzinis et al. (2015), and Sharma et al. (2022b). Specifically, every 1 °C rise in Tmax, was noted to significantly reduce long-term soybean yield by 18.11 % and

Table 4
Impact of climate change on soybean from 1970 to 2020.

(A) Estimates derived from the ARDL model for short- and long-term effects of Tmax, Tmin, CO_2, HA, and PT on soybean yield (dependent variable)

Variable	Coefficient	Std. error	t-Statistic	*P*-value
ARDL model long-term effects				
Tmax (°C)	−18.115	5.734	−3.159***	0.004
Tmin (°C)	7.760	2.695	2.880***	0.008
CO_2 (Mt)	3.048	0.673	4.526***	0.000
HA (ha)	0.517	0.265	1.949	0.061
PT (mm)	−0.977	0.737	−1.325	0.196
ARDL model short-term effects				
Tmax (°C)	−5.515	2.607	−2.115**	0.041
Tmin (°C)	1.274	1.462	0.871	0.389
CO_2 (Mt)	0.926	0.533	1.737	0.090
HA (ha)	0.109	0.209	0.526	0.602
PT (mm)	−0.105	0.282	−0.374	0.710
C	15.782	12.620	1.251	0.221
Error correction model	−0.435	0.056	−7.796	0.000
R Square	0.848			
Adjusted R Square	0.799			

(B) Pearson's correlation matrix between the first differenced (detrended) yield and climatic variables (Tmax, Tmin, DTR, PT, RH) determined for every month of SGS.

Growing season months	Climatic variables				
	Tmax	Tmin	DTR	PT	RH
May	0.117	0.163	−0.085	−0.153	−0.012
June	0.007	0.442**	−0.376**	0.269	0.238
July	−0.264**	0.273	−0.548***	−0.296*	0.308*
August	−0.184**	0.272	−0.464***	−0.448***	0.233
September	0.135	0.315*	−0.204	−0.013	0.08

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

5.51 % in the short-term (Table 4A). These findings were corroborated by Tao et al. (2008), Kucharik and Serbin (2008), and Guo et al. (2022b), all documented soybean yield reduction in the range of 3.57 % to 22.70 % with every 1 °C rise in Tmax. According to studies by Jones et al. (2003), Boote et al. (2011), and Ramirez-Villegas et al. (2013), the maximum cardinal temperature for soybeans is 30 °C; above this, reproductive growth, and consequently yield, are negatively impacted. With every 0.8 °C rise above 30 °C, especially at post-anthesis growth stage, yield is reduced by 2.4 % (Hatfield et al., 2011). However, the SGS in MS witnessed a Tmax average of 31.15 °C throughout the 1970–2020 timespan (Table 2). The elevated Tmax (>30 °C) reduces crop water use efficiency (WUE) up to 60 %, triggers leaf senescence (Egli and Bruening, 2004; Hatfield and Dold, 2019), reduces transpiration and photosynthetic rates (up to 12.7 %), and subsequently reduces yield (Tao et al., 2006 Djanaguiraman and Prasad, 2010). Additionally, the interaction between higher Tmax and vapor pressure deficit (VPD) further complicates gas exchange mechanisms, decreasing photosynthesis and consequently yield (Alsajri et al., 2022). A study by Shammi and Meng (2021) determined the daytime temperature in MS exceeds the ideal growing range for soybean. In addition, current study discovered the July and August to be the most consequential months for the negative effect of Tmax on soybean yield (Table 4B). This is due to the occurrence of flowering and grain-filling during these months (Teixeira et al., 2013). Altered, temperature-sensitive morpho-physiology and pollen viability during these stages severely lowers the yield (Cohen et al., 2021). It has been shown that increased temperatures can decrease pod number plant^{-1}, pod set, seed number, and seed size by 10–30 %, 11 %, 11–35 %, and 5–14 %, respectively, all of which can decrease seed yield by 16–40 % (Allen Jr et al., 2018).

ARDL regression coefficients for Tmin were positive in both the long- and short-term, but only the long-term was significant at the 1 % level, indicating that Tmin had a positive impact on soybean yield in MS over longer period (Table 4A). Further examination revealed that the soybean yield increased significantly by 7.76 % for every 1 °C Tmin rise in long-term (Table 4A). These results are in line with the findings of Cabas et al. (2010), Ferreira and Rao (2011), and Zhang et al. (2022). Also in the present study, Tmin during June and September were found to be strongly correlated with increased yields (Table 4B), which agrees with the findings of Egli and Wardlaw (1980) and Seddigh and Jolliff (1984). Shammi and Meng (2021) conducted a study in MS with data from 1980 to 2019 and found a positive relationship between Tmin and soybean yield, with a 6.38 % increase in yield for every 1 °C rise in Tmin. According to Tao et al. (2008), an increase in soybean yield caused by 1 °C Tmin rise was in the range of 3–19.7 %. Zheng et al. (2009) noted a 17–31 % increase in soybean yield with each 1 °C rise in Tmin. Until now, a clear agreement has not been established on physiological impact of Tmin on soybean but, literature on grass species contains evidence that higher Tmin stimulates nocturnal respiration, leading to losses in carbohydrates (Guo et al., 2019 Shu, 2021). This carbon-starvation boosts the photosynthetic rate the following day to more than make up for the losses caused by the increased nocturnal respiration, improving the plant's overall productivity (Wan et al., 2009). Contrarily, Jumrani et al. (2017), Alsajri et al. (2019), Lin et al. (2021), and Zhang et al. (2016) demonstrated negative effect of Tmin rise on soybean yield. Furthermore, Guo et al. (2022b) claimed that the Tmin negative effect on soybean would not be noticeable if it stays below 22 °C during SGS. The average Tmin for the study period was found to be 18.94 °C (Table 2), well below this level, and in such cases, yield continues to increase as Tmin approaches 22 °C (Baker and Allen, 1993). The current findings are consistent with those of Boote et al. (2005) and Gibson and Mullen (1996), who determined that the optimal Tavg range for soybeans is 27–29 °C, and that if Tavg is below this range, a further rise in Tmin brings the Tavg closer to its optimal range. This causes an increase in yield until Tavg is moved out of the optimal range. Similar was the case with the current study, where Tavg was recorded as 25.05 °C and Tmin was never high enough to push the SGS Tavg above the optimal range (Table 2). Moreover, we should note that in the studies that describe the detrimental effects of Tmin on soybean production, either Tmin or Tavg were found to be above their optimum temperatures, 22 °C and 27 °C–29 °C or both (Jumrani et al., 2017 Alsajri et al., 2019 Lin et al., 2021 Zhang et al., 2016). These researchers evaluated response of soybean at increased temperatures anticipated by 2050 or 2100 by running models at higher Tmin or Tavg than that prevailed in the current study (Feng et al., 2014 Brown and Caldeira, 2017).

The CO_2 model coefficient was positive and significant at $p < 0.001$, indicating rise in CO_2 emissions between 1970 and 2020 have increased soybean yields in the long-term (Table 4A). Specifically, one unit increase in CO_2 emissions was found to significantly increase soybean yield by 3.04 %. Research by Jancic et al. (2015), Fodor et al. (2017), Ejemeyovwi et al. (2018), Sun et al. (2022), and Ntiamoah et al. (2022) supported similar conclusions. Bhattarai et al. (2017) quantified a 2–20 % yield increase by every one unit rise in CO_2 emissions. This is because elevated CO_2 is documented to enhance the stomata functionality, which controls evapotranspiration, canopy energy reserves, photosynthetic rate, growth parameters, soybean pod traits, and thus yield (Allen Jr et al., 1987; Gray et al., 2016 Lenka et al., 2017).

The ARDL coefficient for PT in the current study was found to be non-significant, indicating that the overall PT shifts in MS during SGS over the study period had no impact on soybean yield (Table 4A). However, when the analysis was scaled down to monthly basis, it was revealed that July and August PT were strongly correlated with soybean yield (Table 4B), a finding corroborated by Zipper et al. (2016). The correlation of PT (in July and August) with reduced yield can possibly be caused by the often poorly drained soils, high annual PT (1544.44 mm) in MS, extended wet and anoxic conditions which altogether could result in stand loss or higher disease pressure (MPR, 2022). In addition, the inability to use ground equipment for crop protection product application may cause a delay in pest applications (Kozdrój and van Elsas, 2000). Yield losses of up to 10 % under such circumstances has been recorded as per previous research (Rosenzweig et al., 2002). The change in HA on soybean yield was non-significant during the study period in MS (Table 4A). June, July, and August DTR had significantly negative, and July humidity had significantly positive association with soybean yield (Table 4B). These results were consistent with the findings of McFadden and Miranowski (2016) and were attributable to the fact that the asymmetric warming (Tmin rise > Tmax rise) poses comparatively more harsh effect on flowering and grain filling stages of soybean as they coincide with these months.

Although research efforts testing various soybean cultivars for drought tolerance have already been progressing in MS (Poudel et al., 2023a,b), current research findings call for the research to be expanded to develop and test the soybean cultivars in excess moisture and anoxic conditions. Shammi and Meng (2021) and the current study initiated the research on separating the effects of Tmax and Tmin on soybean in MS, but additional research in a controlled environment is recommended to validate the results of the current study by examining the soybean's response to Tmin prevailing rates (18.94 °C).

3.4. Post analysis diagnostics for sensitivity and robustness of the ARDL model

The results of diagnostic analyses on coefficient stability and residual error terms (heteroskedasticity and serial correlation) of the final regression equation derived from the ARDL model, which represents the relationship between soybean yield and study variables, are shown in Table 5A. The results confirmed the absence of serial correlation among the error terms (residuals) of the model. Also, there was no significant heteroskedasticity, meaning the residuals were evenly scattered (Table 5A). The CUSUM and CUSUM square (Fig. 3) plot lines were well specified and stayed within the critical boundaries at 5 % level of significance. This confirmed the goodness of fit, accuracy, and stability of short- and long-term coefficients of the ARDL model.

Table 5
Post analysis diagnostic testing results.

(A) Results of diagnostic tests used to evaluate the stability/robustness of model coefficients and recursive residuals, including the Breusch-Pagan-Godfrey test, Breusch-Godfrey LM test, cumulative sum (CUSUM), and cumulative sum of squares (CUSUMSQ).

Test	Statistics	Probability
BPG test for heteroskedasticity	0.543	0.905
BG LM test for serial correlation	0.053	0.948
CUSUM and CUSUM of squares	Stable (Fig. 3)	–

(B) Results of the fully modified ordinary least squares (FMOLS) model, used to revalidate model robustness.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Tmax (°C)	−10.456	4.255	−2.457	0.018
Tmin (°C)	6.351	2.357	2.694	0.010
CO_2 (Mt)	1.702	0.400	4.252	0.000
HA (ha)	0.234	0.193	1.212	0.232
PT (mm)	−0.344	0.442	−0.779	0.440
C	9.841	11.164	0.881	0.383
R Square	0.687			
Adjusted R Square	0.651			

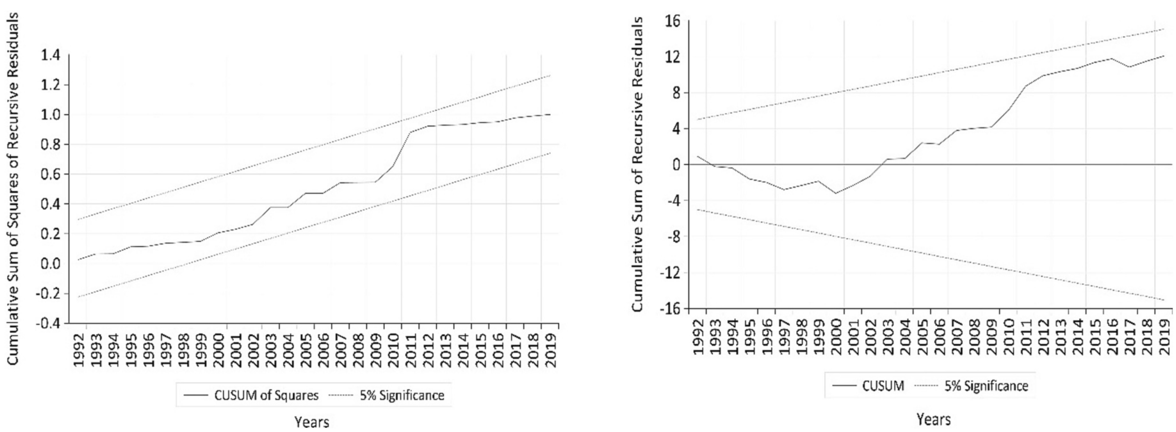


Fig. 3. Cumulative sum (CUSUM) and CUSUM of squares of recursive residuals of the model displaying stability of model coefficients.

The robust estimator obtained from the FMOLS model, as shown in Table 5B, indicated that the coefficients for Tmax, Tmin, CO_2, and PT were found to have same sign as of the coefficients generated by the ARDL model. This supports the robustness of the study model by providing results similar to those of the ARDL model.

3.5. Study limitations

Every study has a unique set of limitations, which leaves possibilities for future research advancements. The current studies limitations are listed below:

1. Even though the current study used more variables than usual (Tavg and PT), other yield-impacting factors like fertilizer, pesticides, sunshine hours/solar radiation, vapor pressure deficit, irrigation, evaporative demand, crop evapotranspiration, wind velocity, as well as trends in technological advancement, could result in more accurate and practically useful results for the crop stakeholders (Kukal and Irmak, 2018 Sharma et al., 2023). The current study was limited to the study factors used due to a lack of consistently available (minimum 30 years is required) data, precluding the use of additional variables.
2. The data used in this study were based on monthly averages. However, if daily or hourly data were available for at least 30 years, it would allow for a more precise understanding of the relationship between crops and climate.
3. Being an econometric model, the ARDL model calculated the impact of regressors at the *ceteris paribus* (Warsame et al., 2021). The interaction between numerous climatic variables, however, might produce additional and more nuanced information for growers and other agricultural stakeholders (Elias et al., 2019).

4. Conclusions

The warming trend in MS was primarily explained by Tmin, which contributed 69 % while Tmax contributed 30 % to the overall climate warming in MS. Consequently, these results (Tmin increase-Tmax increase) led the DTR to exhibit a significant downward trend from 1970 to 2020. A significant positive trend was observed for CO_2 emissions while Tmax, PT, and RH changes were non-significant for the 50-yr period. Rates of change for Tmin (+0.25 °C/decade), Tmax (+0.11 °C/decade), PT (+3.03 mm/decade), DTR (−0.18 °C/decade), CO_2 (5.4 Mt/decade), and RH (−0.06 %/decade) were found in this study. The crop-climate ARDL model captured 79.9 % of total soybean yield variability caused by climate change over the 50-yr period from 1970 to 2020. Tmax was found to reduce soybean yield by 18.11 % over the long-term and 5.51 % over the short-term for every 1 °C increase. Unit increases in Tmin (°C) and CO_2 (Mt) were found to increase soybean yield over the long-term by 7.76 % and 3.04 %, respectively. Soybean yield was positively correlated with Tmin in June and September, PT (in July and August), and RH (in July), but negatively with Tmax (in July and August) and DTR (in June, July, and August).

Overall, in MS, soybean yield showed unequal elasticity to long- and short-term climatic variations, which should inform research priorities on best management practices and new variety breeding and testing, considering the asymmetric sensitivities of long- and short-term crop-climate relationships.

CRediT authorship contribution statement

Ramandeep Kumar Sharma: Conceptualization, Methodology, Writing – original draft, Visualization. Jagmandeep Dhillon: Conceptualization, Investigation, Writing – review & editing, Supervision, Project administration, Funding acquisition. Pushp Kumar: Data analysis. Michael J. Mulvaney: Writing – review & editing. Vaughn Reed: Writing – review & editing. Raju Bheemanahalli: Writing – review & editing. Michael S. Cox: Writing – review & editing. Meetpal S. Kukal: Writing – review & editing. Krishna N. Reddy: Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors of this manuscript have no conflict interests to disclose.

Data availability

The online link for the data sources are shared in the section “Data” of the manuscript.

Acknowledgement

The Northern Gulf Institute at Mississippi State University's Dr. Yen-Heng Lin helped with gathering the relative humidity data, which the authors gratefully thank. This publication is a contribution of the Mississippi Agricultural and Forestry Experiment Station. This work is jointly funded by USDA ARS, under cooperative Agreement Number 58-6066-020.

References

Abbas, S., Kousar, S., Khan, M.S., 2022. The role of climate change in food security; empirical evidence over Punjab regions, Pakistan. Environ. Sci. Pollut. Res. 1–19.
Aditya, F., Gusmayanti, E., Sudrajat, J., 2021. Rainfall trend analysis using Mann-Kendall and Sen’s slope estimator test in West Kalimantan. In: Proceedings of the IOP Conference Series: Earth and Environmental Science, Surakarta, Indonesia, 24–25 August 2021, p. 012006.
Agbenyo, W., Jiang, Y., Ding, Z., Titriku, J.K., Ntim-Amo, G., 2022. Impact of climate change on cocoa production in Africa: an approach of cross-sectional ARDL. Int. J. Environ. Res. 16 (5), 1–12.
Allen Jr., L.H., Boote, K.J., Jones, J.W., Jones, P.H., Valle, R.R., Acock, B., Rogers, H.H., Dahlman, R.C., 1987. Response of vegetation to rising carbon dioxide: photosynthesis, biomass, and seed yield of soybean. Glob. Biogeochem. Cycles 1 (1), 1–14.
Allen Jr., L.H., Zhang, L., Boote, K.J., Hauser, B.A., 2018. Elevated temperature intensity, timing, and duration of exposure affect soybean internode elongation, mainstem node number, and pod number per plant. Crop J. 6 (2), 148–161.
Alsajri, F.A., Singh, B., Wijewardana, C., Irby, J.T., Gao, W., Reddy, K.R., 2019. Evaluating soybean cultivars for low-and high-temperature tolerance during the seedling growth stage. Agronomy 9 (1), 13.
Alsajri, F.A., Wijewardana, C., Bheemanahalli, R., Irby, J.T., Krutz, J., Golden, B., Reddy, V.R., Reddy, K.R., 2022. Morpho-physiological, yield, and transgenerational seed germination responses of soybean to temperature. Front. Plant Sci. 13, 839270.
Altunkaynak, A., Nigussie, T.A., 2018. Monthly water demand prediction using wavelet transform, first-order differencing and linear detrending techniques based on multilayer perceptron models. Urban Water J. 15 (2), 177–181.
Baker, J.T., Allen, L.H., 1993. Contrasting crop species responses to CO_2 and temperature: rice, soybean and citrus. Vegetatio 104 (1), 239–260.
Baumohl, E., Lyocsa, S., 2009. Stationarity of Time Series and the Problem of Spurious Regression (Available at SSRN 1480682).
Bhattarai, M.D., Secchi, S., Schoof, J., 2017. Projecting corn and soybeans yields under climate change in a Corn Belt watershed. Agr. Syst. 152, 90–99.
Boote, K.J., Allen, L.H., Prasad, P.V., Baker, J.T., Gesch, R.W., Snyder, A.M., Pan, D., Thomas, J.M., 2005. Elevated temperature and CO_2 impacts on pollination, reproductive growth, and yield of several globally important crops. J. Agric. Meteorol. 60 (5), 469–474.
Boote, K.J., Allen, L.H., Vara Prasad, P.V., Jones, J.W., 2011. Testing effects of climate change in crop models. In: Hillel, D., Rosenzweig, C. (Eds.), Handbook of Climate Change and Agroecosystems Impacts, Adaptation and Mitigation.
Braganza, K., Karoly, D.J., Arblaster, J.M., 2004. Diurnal temperature range as an index of global climate change during the twentieth century. Geophys. Res. Lett. 31 (13).
Brown, P.T., Caldeira, K., 2017. Greater future global warming inferred from Earth’s recent energy budget. Nature 552 (7683), 45–50.
Cabas, J., Weersink, A., Olale, E., 2010. Crop yield response to economic, site and climatic variables. Clim. Chang. 101 (3), 599–616.
Chandio, A.A., Jiang, Y., Rauf, A., Ahmad, F., Amin, W., Shehzad, K., 2020. Assessment of formal credit and climate change impact on agricultural production in Pakistan: a time series ARDL modeling approach. Sustainability 12 (13), 5241.
Chandio, A.A., Jiang, Y., Fatima, T., Ahmad, F., Ahmad, M., Li, J., 2022. Assessing the impacts of climate change on cereal production in Bangladesh: evidence from ARDL modeling approach. Int. J. Clim. Chang. Strat. Manag. 14 (2), 125–147.
Ciscar, J.C., Fisher-Vanden, K., Lobell, D.B., 2018. Synthesis and review: an inter-method comparison of climate change impacts on agriculture. Environ. Res. Lett. 13 (7), 070401.
Cohen, I., Zandalinas, S.I., Huck, C., Fritschi, F.B., Mittler, R., 2021. Meta-analysis of drought and heat stress combination impact on crop yield and yield components. Physiol. Plant. 171 (1), 66–76.
da Silva César, A., Conejero, M.A., Ribeiro, E.C.B., Batalha, M.O., 2019. Competitiveness analysis of “social soybeans” in biodiesel production in Brazil. Renew. Energy 133, 1147–1157.
Daloz, A.S., Rydsaa, J.H., Hodnebrog, Ø., Sillmann, J., van Oort, B., Mohr, C.W., Agrawal, M., Emberson, L., Stordal, F., Zhang, T., 2021. Direct and indirect impacts of climate change on wheat yield in the Indo-Gangetic plain in India. J. Agric. Food Res. 4, 100132.
Daly, C., Bryant, K., 2013. The PRISM Climate and Weather System—An Introduction. PRISM Climate Group, Corvallis, OR, p. 2.
Daly, C., Halbleib, M., Smith, J.I., Gibson, W.P., Doggett, M.K., Taylor, G.H., Curtis, J., Pasteris, P.P., 2008. Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. Int. J. Climatol. 28 (15), 2031–2064.
Dawood, M., 2017. Spatio-statistical analysis of temperature fluctuation using Mann–Kendall and Sen’s slope approach. Clim. Dyn. 48 (3), 783–797.
Deng, A., Perron, P., 2008. A non-local perspective on the power properties of the CUSUM and CUSUM of squares tests for structural change. J. Econ. 142 (1), 212–240.
Ding, R., Shi, W., 2022. Contributions of climate change to cereal yields in Tibet, 1993–2017. J. Geogr. Sci. 32 (1), 101–116.
Djanaguiraman, M., Prasad, P.V., 2010. Ethylene production under high temperature stress causes premature leaf senescence in soybean. Funct. Plant Biol. 37 (11), 1071–1084.
Doan, Q.V., Chen, F., Asano, Y., Gu, Y., Nishi, A., Kusaka, H., Niyogi, D., 2022. Causes for asymmetric warming of sub-diurnal temperature responding to global warming. Geophys. Res. Lett. 49 (20), e2022GL100029.
Dusenge, M.E., Duarte, A.G., Way, D.A., 2019. Plant carbon metabolism and climate change: elevated CO_2 and temperature impacts on photosynthesis, photorespiration and respiration. New Phytol. 221 (1), 32–49.
Eck, M.A., Murray, A.R., Ward, A.R., Konrad, C.E., 2020. Influence of growing season temperature and precipitation anomalies on crop yield in the southeastern United States. Agric. For. Meteorol. 291, 108053.
Egli, D.B., Bruening, W.P., 2004. Water stress, photosynthesis, seed sucrose levels and seed growth in soybean. J. Agric. Sci. 142 (1), 1–8.
Egli, D.B., Wardlaw, I.F., 1980. Temperature response of seed growth characteristics of soybeans 1. Agron. J. 72 (3), 560–564.
EIA, U., 2019. US States: State Profiles and Energy Estimates. United States Energy Information Administration, Washington DC. https://www.eia.gov/state/seds/data.php.
Ejemeyovwi, J., Obindah, G., Doyah, T., 2018. Carbon dioxide emissions and crop production: finding a sustainable balance. Int. J. Energy Econ. Policy 8 (4), 303 (Sensitivity analysis).
Elias, E.H., Flynn, R., Idowu, O.J., Reyes, J., Sanogo, S., Schutte, B.J., Smith, R., Steele, C., Sutherland, C., 2019. Crop vulnerability to weather and climate risk: analysis of interacting systems and adaptation efficacy for sustainable crop production. Sustainability 11 (23), 6619.
EPA, 2016. United States Environmental Protection Agency. https://www.epa.gov/sites/default/files/2016-08/documents/climate_indicators_2016.pdf (Accessed on 28 December 2022).
FAOSTAT, 2022. Available online: https://www.fao.org/faostat/en/#data/QCL (accessed on 28 December 2022).
Feng, S., Hu, Q., Huang, W., Ho, C.H., Li, R., Tang, Z., 2014. Projected climate regime shift under future global warming from multi-model, multi-scenario CMIP5 simulations. Glob. Planet. Chang. 112, 41–52.
Ferreira, D.B., Rao, V.B., 2011. Recent climate variability and its impacts on soybean yields in Southern Brazil. Theor. Appl. Climatol. 105 (1), 83–97.
Fingleton, B., 1999. Spurious spatial regression: some Monte Carlo results with a spatial unit root and spatial cointegration. J. Reg. Sci. 39 (1), 1–19.
Fodor, N., Challinor, A., Droutsas, I., Ramirez-Villegas, J., Zabel, F., Koehler, A.K., Foyer, C.H., 2017. Integrating plant science and crop modeling: assessment of the impact of climate change on soybean and maize production. Plant Cell Physiol. 58 (11), 1833–1847.
Gibson, L.R., Mullen, R.E., 1996. Influence of day and night temperature on soybean seed yield. Crop. Sci. 36 (1), 98–104.

Ginbo, T., 2022. Heterogeneous impacts of climate change on crop yields across altitudes in Ethiopia. Clim. Chang. 170 (1), 1–21.
Godwin, A., McGill, C., Ward, A., Sofkova-Bobcheva, S., Pieralli, S., 2023. Phenological phase affects carrot seed production sensitivity to climate change–a panel data analysis. Sci. Total Environ. 164502.
Goldblum, D., 2009. Sensitivity of corn and soybean yield in Illinois to air temperature and precipitation: the potential impact of future climate change. Phys. Geogr. 30 (1), 27–42.
Gray, S.B., Dermody, O., Klein, S.P., Locke, A.M., McGrath, J.M., Paul, R.E., Rosenthal, D. M., Ruiz-Vera, U.M., Siebers, M.H., Strellner, R., Ainsworth, E.A., Bernacchi, C.J., Long, S.P., Ort, D.R., Leakey, A.D.B., 2016. Intensifying drought eliminates the expected benefits of elevated carbon dioxide for soybean. Nat. Plants 2, 16132.
Gujree, I., Ahmad, I., Zhang, F., Arshad, A., 2022. Innovative trend analysis of high-altitude climatology of Kashmir valley, North-West Himalayas. Atmosphere 13 (5), 764.
Gul, A., Xiumin, W., Chandio, A.A., Rehman, A., Siyal, S.A., Asare, I., 2022. Tracking the effect of climatic and non-climatic elements on rice production in Pakistan using the ARDL approach. Environ. Sci. Pollut. Res. 29 (21), 31886–31900.
Guntukula, R., 2020. Assessing the impact of climate change on Indian agriculture: evidence from major crop yields. J. Public Aff. 20 (1), e2040.
Guo, H., Li, S., Kang, S., Du, T., Tong, L., Ding, R., 2019. Annual ecosystem respiration of maize was primarily driven by crop growth and soil water conditions. Agric. Ecosyst. Environ. 272, 254–265.
Guo, S., Guo, E., Zhang, Z., Dong, M., Wang, X., Fu, Z., et al., 2022a. Impacts of mean climate and extreme climate indices on soybean yield and yield components in Northeast China. Sci. Total Environ. 838, 156284.
Guo, S., Zhang, Z., Guo, E., Fu, Z., Gong, J., Yang, X., 2022b. Historical and projected impacts of climate change and technology on soybean yield in China. Agric. Syst. 203, 103522.
Halinski, R.S., Feldt, L.S., 1970. The selection of variables in multiple regression analysis. J. Educ. Meas. 7 (3), 151–157.
Hassler, U., Wolters, J., 2006. Autoregressive Distributed Lag Models and Cointegration. Springer, Berlin Heidelberg, pp. 57–72.
Hatfield, J.L., Dold, C., 2019. Water-use efficiency: advances and challenges in a changing climate. Front. Plant Sci. 10, 103.
Hatfield, J.L., Boote, K.J., Kimball, B.A., Ziska, L.H., Izaurralde, R.C., Ort, D., Thomson, A.M., Wolfe, D., 2011. Climate impacts on agriculture: implications for crop production. Agron. J. 103 (2), 351–370.
Haug, A.A., 2002. Temporal aggregation and the power of cointegration tests: a Monte Carlo study. Oxf. Bull. Econ. Stat. 64 (4), 399–412.
He, L., Jin, N., Yu, Q., 2020. Impacts of climate change and crop management practices on soybean phenology changes in China. Sci. Total Environ. 707, 135638.
Jancic, M., Lalic, B., Mihailovic, D.T., Jacimovic, G., 2015. Impact of climate change and carbon dioxide fertilization effect on irrigation water demand and yield of soybean in Serbia. J. Agric. Sci. 153 (8), 1365–1379.
Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. Eur. J. Agron. 18 (3–4), 235–265.
Jumrani, K., Bhatia, V.S., Pandey, G.P., 2017. Impact of elevated temperatures on specific leaf weight, stomatal density, photosynthesis and chlorophyll fluorescence in soybean. Photosynth. Res. 131 (3), 333–350.
Karki, J.R., Kumar, P., Baniya, B., 2022. Climate change and mountain environment in context of sustainable development goals in Nepal. Appl. Ecol. Environ. Sci. 10 (9), 588–594.
Kendall, Maurice G., 1948. Rank Correlation Methods. Charles Griffin and Company, London.
Kim, J.H., 2019. Multicollinearity and misleading statistical results. Korean J. Anesthesiol. 72 (6), 558–569.
Kozdrój, J., van Elsas, J.D., 2000. Response of the bacterial community to root exudates in soil polluted with heavy metals assessed by molecular and cultural approaches. Soil Biol. Biochem. 32 (10), 1405–1417.
Kucharik, C.J., Serbin, S.P., 2008. Impacts of recent climate change on Wisconsin corn and soybean yield trends. Environ. Res. Lett. 3 (3), 034003.
Kukal, M., Irmak, S., 2016. Long-term patterns of air temperatures, daily temperature range, precipitation, grass-reference evapotranspiration and aridity index in the USA Great Plains: part II. Temporal trends. J. Hydrol. 542, 978–1001.
Kukal, M.S., Irmak, S., 2018. Climate-driven crop yield and yield variability and climate change impacts on the US Great Plains agricultural production. Sci. Rep. 8 (1), 1–18.
Kunkel, K.E., Easterling, D.R., Kristovich, D.A., Gleason, B., Stoecker, L., Smith, R., 2012. Meteorological causes of the secular variations in observed extreme precipitation events for the conterminous United States. J. Hydrometeorol. 13 (3), 1131–1141.
Lenka, N.K., Lenka, S., Thakur, J.K., Elanchezhian, R., Aher, S.B., Simaiya, V., Yashona, D.S., Biswas, A.K., Agrawal, P.K., Patra, A.K., 2017. Interactive effect of elevated carbon dioxide and elevated temperature on growth and yield of soybean. Curr. Sc. 2305–2310.
Li, S., Shao, Q., 2022. Greening the finance for climate mitigation: an ARDL–ECM approach. Renew. Energy 199, 1469–1481.
Liew, V.K.S., 2004. Which lag length selection criteria should we employ? Econ. Bull. 3 (33), 1–9.
Lin, T., Okamoto, Y., Nagasaki, Y., Shiraiwa, T., 2021. The influence of high night temperature on yield and physiological attributes of soybean cv. fukuyutaka. Plant Prod. Sci. 24 (3), 267–278.
Liu, Y., Wang, E., Yang, X., Wang, J., 2010. Contributions of climatic and crop varietal changes to crop production in the North China Plain, since 1980s. Glob. Chang. Biol. 16 (8), 2287–2299.
Liu, L., Wang, E., Zhu, Y., Tang, L., 2012. Contrasting effects of warming and autonomous breeding on single-rice productivity in China. Agric. Ecosyst. Environ. 149, 20–29.
Liu, D., Mishra, A.K., Ray, D.K., 2020. Sensitivity of global major crop yields to climate variables: a non-parametric elasticity analysis. Sci. Total Environ. 748, 141431.
Lobell, D.B., 2007. Changes in diurnal temperature range and national cereal yields. Agric. For. Meteorol. 145 (3–4), 229–238.
Lobell, D.B., Asner, G.P., 2003. Climate and management contributions to recent trends in US agricultural yields. Science 299 (5609), 1032.
Lobell, D.B., Field, C.B., 2007. Global scale climate–crop yield relationships and the impacts of recent warming. Environ. Res. Lett. 2 (1), 014002.
Lobell, D.B., Schlenker, W., Costa-Roberts, J., 2011. Climate trends and global crop production since 1980. Science 333 (6042), 616–620.
Lychuk, T.E., Hill, R.L., Izaurralde, R.C., Momen, B., Thomson, A.M., 2017. Evaluation of climate change impacts and effectiveness of adaptation options on crop yield in the Southeastern United States. Field Crop. Res. 214, 228–238.
Mach, K.J., Mastrandrea, M.D., Bilir, T.E., Field, C.B., 2016. Understanding and responding to danger from climate change: the role of key risks in the IPCC AR5. Clim. Chang. 136 (3), 427–444.
Malla, F.A., Mushtaq, A., Bandh, S.A., Qayoom, I., Hoang, A.T., 2022. Understanding climate change: scientific opinion and public perspective. In: Climate Change. Springer, Cham, pp. 1–20.
Mann, H.B., 1945. Nonparametric tests against trend. Econ. J. Econ. Soc. 245–259.
McFadden, J.R., Miranowski, J.A., 2016. Climate change: challenge and opportunity to maintain sustainable productivity growth and environment in a corn-soybean bioeconomy. AgBioForum 19 (2), 92–111.
MDAC, 2021. Mississippi Department of Agriculture and Commerce. https://www.mdac.ms.gov/agency-info/mississippi-agriculture-snapshot/ (Accessed on 29 December 2022).
Miles, J., 2014. Tolerance and variance inflation factor. In: Wiley Statsref: Statistics Reference Online.
Mohammadi, S., Rydgren, K., Bakkestuen, V., Gillespie, M.A., 2023. Impacts of recent climate change on crop yield can depend on local conditions in climatically diverse regions of Norway. Sci. Rep. 13 (1), 3633.
Mourtzinis, S., Specht, J.E., Lindsey, L.E., Wiebold, W.J., Ross, J., Nafziger, E.D., Kandel, H.J., Mueller, N., Devillez, P.L., Arriaga, F.L., Conley, S.P., 2015. Climate-induced reduction in US-wide soybean yields underpinned by region-and in-season-specific responses. Nat. Plants 1 (2), 1–4.
Mourtzinis, S., Edreira, J.I.R., Conley, S.P., Grassini, P., 2017. From grid to field: assessing quality of gridded weather data for agricultural applications. Eur. J. Agron. 82, 163–172.
MPR, 2022. http://coolweather.net/staterainfall/mississippi.htm (Accessed on 20 May 2023).
Nasrullah, M., Rizwanullah, M., Yu, X., Jo, H., Sohail, M.T., Liang, L., 2021. Autoregressive distributed lag (ARDL) approach to study the impact of climate change and other factors on rice production in South Korea. J. Water Clim. Chang. 12 (6), 2256–2270.
NOAA. National Oceanic and Atmospheric Administration, 2021. https://www.ncei.noaa.gov/pub/data/cirs/climdiv/ (Accessed 29 November 2022).
Ntiamoah, E.B., Li, D., Appiah-Otoo, I., Twumasi, M.A., Yeboah, E.N., 2022. Towards a sustainable food production: modelling the impacts of climate change on maize and soybean production in Ghana. Environ. Sci. Pollut. Res. 1–20.
Oglesby, C., Dhillon, J., Fox, A., Singh, G., Ferguson, C., Li, X., Kumar, R., Dew, J., Varco, J., 2023. Discrepancy between the crop yield goal rate and the optimum nitrogen rates for maize production in Mississippi. Agron. J. 115 (1), 340–350.
Pesaran, M.H., Shin, Y., 1995. An autoregressive distributed lag modelling approach to cointegration analysis. In: Strom, S. (Ed.), Econometrics and Economic Theory: The Ragnar Frisch Centennial Symposium. Cambridge University Press, Cambridge.
Pielke Jr., R., Burgess, M.G., Ritchie, J., 2022. Plausible 2005–2050 emissions scenarios project between 2 °C and 3 °C of warming by 2100. Environ. Res. Lett. 17 (2), 024027.
Pimentel, M.F., Srour, A.Y., Warner, A.J., Bond, J.P., Bradley, C.A., Rupe, J., Chilvers, M. I., Rojas, J.A., Jacobs, J.L., Little, C.R., Roberson, A.E., Giesler, L.J., Malvick, D., Wise, K., Tenuta, A., Fakhoury, A.M., 2022. Ecology and diversity of culturable fungal species associated with soybean seedling diseases in the Midwestern United States. J. Appl. Microbiol. 132 (5), 3797–3811.
Poudel, S., Adhikari, B., Dhillon, J., Reddy, K.R., Stetina, S.R., Bheemanahalli, R., 2023a. Quantifying the physiological, yield, and quality plasticity of Southern USA soybeans under heat stress. Plant Stress 100195.
Poudel, S., Vennam, R.R., Shrestha, A., Reddy, K.R., Wijewardane, N.K., Reddy, K.N., Bheemanahalli, R., 2023b. Resilience of soybean cultivars to drought stress during flowering and early-seed setting stages. Sci. Rep. 13 (1), 1277.
Quemada, M., Alonso-Ayuso, M., Castellano-Hinojosa, A., Bedmar, E.J., Gabriel, J.L., González, I.G., Valentin, F., Calvo, M., 2019. Residual effect of synthetic nitrogen fertilizers and impact on Soil Nitrifiers. Eur. J. Agron. 109, 125917.
Ramirez-Villegas, J., Challinor, A.J., Thornton, P.K., Jarvis, A., 2013. Implications of regional improvement in global climate models for agricultural impact research. Environ. Res. Lett. 8 (2), 024018.
Ramzan, M., Iqbal, H.A., Usman, M., Ozturk, I., 2022. Environmental pollution and agricultural productivity in Pakistan: new insights from ARDL and wavelet coherence approaches. Environ. Sci. Pollut. Res. 29 (19), 28749–28768.
Rippey, B.R., 2015. The US drought of 2012. Weather Clim. Extreme 10, 57–64.
Rosenzweig, C., Tubiello, F.N., Goldberg, R., Mills, E., Bloomfield, J., 2002. Increased crop damage in the US from excess precipitation under climate change. Glob. Environ. Chang. 12 (3), 197–202.

Sacks, W.J., Kucharik, C.J., 2011. Crop management and phenology trends in the U.S. Corn Belt: impacts on yields, evapotranspiration and energy balance. Agric. For. Meteorol. 151, 882–894.
Seddigh, M., Jolliff, G.D., 1984. Night temperature effects on morphology, phenology, yield and yield components of indeterminate field-grown soybean 1. Agron. J. 76 (5), 824–828.
Sen, P.K., 1968. Estimates of the regression coefficient based on Kendall's tau. J. Am. Stat. Assoc. 63 (324), 1379–1389.
Shammi, S.A., Meng, Q., 2021. Modeling the impact of climate changes on crop yield: irrigated vs. non-irrigated zones in Mississippi. Remote Sens. 13 (12), 2249.
Sharma, R.K., Kumar, S., Vatta, K., Bheemanahalli, R., Dhillon, J., Reddy, K.N., 2022a. Impact of recent climate change on corn, rice, and wheat in southeastern USA. Sci. Rep. 12 (1), 1–14.
Sharma, R.K., Kumar, S., Vatta, K., Dhillon, J., Reddy, K.N., 2022b. Impact of recent climate change on cotton and soybean yields in the southeastern United States. J. Agric. Food Res. 9, 100348.
Sharma, R.K., Dhillon, J., Kumar, S., Vatta, K., Reddy, K.N., 2023. Crop-climate link in the southeastern USA: a case study on oats and Sorghum. J. Agric. Food Res. 100626.
Shu, T., 2021. Soybean Phenotypic Variation Under High Night Temperature Stress. Auburn State University (Master).
Singh, A., Kukal, M.S., Shapiro, C.A., Snow, D.D., Irmak, S., Iqbal, J., 2021. Growth phase-specific evaporative demand and nighttime temperatures determine Maize (Zea Mays L.) yield deviations as revealed from a long-term field experiment. Agric. For. Meteorol. 308, 108543.
Smith, P., Powlson, D.S., Smith, J.U., Falloon, P., Coleman, K., 2000. Meeting Europe's climate change commitments: quantitative estimates of the potential for carbon mitigation by agriculture. Glob. Chang. Biol. 6 (5), 525–539.
Smith, S.J., Edmonds, J., Hartin, C.A., Mundra, A., Calvin, K., 2015. Near-term acceleration in the rate of temperature change. Nat. Clim. Chang. 5 (4), 333–336.
Smith, J.R., Gillen, A.M., Nelson, R.L., Bruns, A., Mengistu, A., Li, S., Bellaloui, N., 2019. Registration of high-yielding exotically derived soybean germplasm line LG03-4561-14. J. Plant Reg. 13 (2), 237–244.
Steffens, K., Jarvis, N., Lewan, E., Lindström, B., Kreuger, J., Kjellström, E., Moeys, J., 2015. Direct and indirect effects of climate change on herbicide leaching—a regional scale assessment in Sweden. Sci. Total Environ. 514, 239–249.
Stocker, T., Qin, D., Platner, G.K., 2013. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Edited by: Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.
Sultan, B., Defrance, D., Izumi, T., 2019. Evidence of crop production losses in West Africa due to historical global warming in two crop models. Sci. Rep. 9 (1), 1–15.
Sun, W., Fleisher, D., Timlin, D., Li, S., Wang, Z., Beegum, S., Reddy, V., 2022. Evaluation of models for simulating soybean growth and climate sensitivity in the US Mississippi Delta. Eur. J. Agron. 140, 126610.
Surówka, E., Rapacz, M., Janowiak, F., 2020. Climate change influences the interactive effects of simultaneous impact of abiotic and biotic stresses on plants. In: Plant Ecophysiology and Adaptation Under Climate Change: Mechanisms and Perspectives I. Springer, Singapore, pp. 1–50.
Tao, F., Yokozawa, M., Xu, Y., Hayashi, Y., Zhang, Z., 2006. Climate changes and trends in phenology and yields of field crops in China, 1981–2000. Agric. For. Meteorol. 138 (1–4), 82–92.
Tao, F., Yokozawa, M., Liu, J., Zhang, Z., 2008. Climate–crop yield relationships at provincial scales in China and the impacts of recent climate trends. Clim. Res. 38 (1), 83–94.
Tebaldi, C., Lobell, D.B., 2008. Towards probabilistic projections of climate change impacts on global crop yields. Geophys. Res. Lett. 35 (8).
Teixeira, E.I., Fischer, G., Van Velthuizen, H., Walter, C., Ewert, F., 2013. Global hot-spots of heat stress on agricultural crops due to climate change. Agric. For. Meteorol. 170, 206–215.
Thackeray, C.W., Hall, A., Norris, J., Chen, D., 2022. Constraining the increased frequency of global precipitation extremes under warming. Nat. Clim. Chang. 12 (5), 441–448.
Timm, N.H. (Ed.), 2002. Applied Multivariate Analysis. Springer New York, New York, NY.
Tubiello, F.N., Donatelli, M., Rosenzweig, C., Stockle, C.O., 2000. Effects of climate change and elevated CO_2 on cropping systems: model predictions at two Italian locations. Eur. J. Agron. 13 (2–3), 179–189.
USDA, 2021. USDA-national Agricultural Statistics Service. https://www.nass.usda.gov/Publications/Todays_Reports/reports/fcdate10.pdf.
USDA-NASS, 2022. USDA-National Agricultural Statistics Service. https://quickstats.nass.usda.gov/.
Wan, S., Xia, J., Liu, W., Niu, S., 2009. Photosynthetic overcompensation under nocturnal warming enhances grassland carbon sequestration. Ecology 90 (10), 2700–2710.
Wang, X., Luo, N., Zhu, Y., Yan, Y., Wang, H., Xie, H., Wang, P., Meng, Q., 2023. Water replenishment to maize under heat stress improves canopy temperature and grain filling traits during the reproductive stage. Agric. For. Meteorol. 340, 109627.
Warsame, A.A., Sheik-Ali, I.A., Ali, A.O., Sarkodie, S.A., 2021. Climate change and crop production nexus in Somalia: empirical evidence from ARDL technique. Environ. Sci. Pollut. Res. 28 (16), 19838–19850.
Zhang, L., Zhu, L., Yu, M., Zhong, M., 2016. Warming decreases photosynthates and yield of soybean [*Glycine max* (L.) Merrill] in the North China Plain. Crop J. 4 (2), 139–146.
Zhang, J., Liu, Y., Dai, L., 2022. Agricultural practice contributed more to changes in soybean yield than climate change from 1981 to 2010 in northeast China. J. Sci. Food Agric. 102 (6), 2387–2395.
Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D.B., Huang, Y., Huang, M., Asseng, S., 2017. Temperature increase reduces global yields of major crops in four independent estimates. Proc. Natl. Acad. Sci. 114 (35), 9326–9331.
Zheng, H.F., Chen, L.D., Han, X.Z., 2009. The effects of global warming on soybean yields in a long-term fertilization experiment in Northeast China. J. Agric. Sci. 147 (5), 569–580.
Zipper, S.C., Qiu, J., Kucharik, C.J., 2016. Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes. Environ. Res. Lett. 11 (9), 094021.