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Climate change impact assessment of growing degree days and thermal growing period of cotton in north-west India

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ABSTRACT

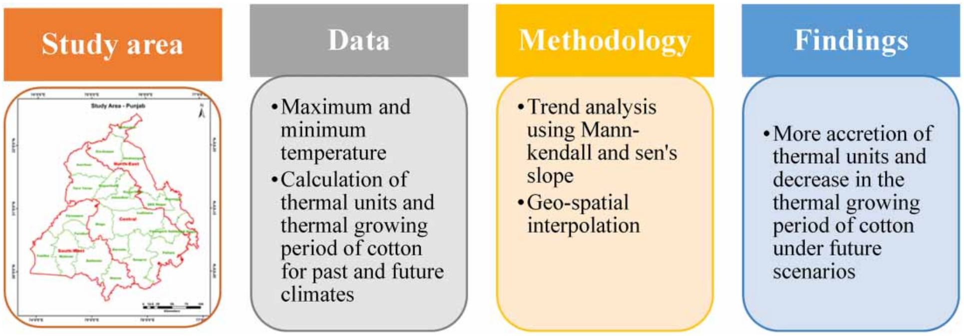
Temperature is an indispensable necessity of plant growth, which explains the 95% variability in plant development. Accumulated temperature, i.e. growing degree day (GDD) is a useful agro-climatic indicator that translates raw climatic data into meaningful decisions. In this study, the GDD concept is used to analyze spatio-temporal variability of accumulated growing degree days (AGDD) and thermal growing period of cotton for the past and future climates in the three different zones (north-east, central and south-west) of Punjab. During the baseline period, higher AGDD were accumulated in the south-western (2,441 °C day), followed by central (2,276.8 °C day) and north-eastern (2,073.8 °C day) zones. During the end of mid-century, AGDD of the central zone was increased by 4–11%, 3–27% for north-eastern, and 3–7% for south-western zones in contrast to the baseline period. This increase in AGDD of cotton might decrease the thermal growing period by 6–14%, 8–25%, and 4–8% for central, north-east and south-western zones, clearly indicating the thermal stress over the cotton crop. This study provides quantitative information for crop breeders and cotton scientists to develop new genetically modified cultivars and improved agronomic practices to mitigate the adverse effect of climate change.

Key words: cotton, climate change, growing degree days, Punjab, spatio-temporal, thermal growing period

HIGHLIGHTS

- This paper analyzes and compares the past and future trends of maximum and minimum temperature over the Indian Punjab region.
- Cotton crop would accumulate more thermal units while thermal growing period of cotton would decrease in the futuristic scenarios.
- The result will help the scientific community to understand the change happening and to plan the agronomic and breeding experiments in north-west India to mitigate it.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Temperature is an indispensable necessity of plant and insect growth, used for phenological predictions in many conceptual models since the middle of the eighteenth century (Felber *et al.* 2018). It is linked both directly and indirectly to the other growth factors like soil temperature, day length and solar radiation. Statistically, it explains the 95% variability in plant development (Russelle *et al.* 1984), when expressed in terms of accumulated temperature. This accumulated temperature can be numerically expressed as growing degree days (GDDs) or sum of effective temperatures or effective degrees or accumulated heat units or thermal units over a specific base temperature (Grigorieva *et al.* 2010). GDD is a useful agro-climatic indicator that translates raw climatic data into meaningful decisions (Pathak & Stoddard 2018). This concept is widely used in agricultural fields to forecast crop and insect phenophases, sowing and harvest timings and pest control applications. In recent times, this concept has also been used as a climate change impact indicator (Mathukumalli *et al.* 2016; King *et al.* 2018; Choudhary *et al.* 2019; Ahmed 2020). Under the changing climatic scenario, a major challenge for the agricultural sciences is to predict the occurrence of biological events (Baker *et al.* 1986). There is a direct effect of the thermal environment on plant development, sowing time, crop phenology and consequently changes in agricultural production.

One common way of obtaining future climatic projections is to use global climatic models (GCMs). Generally, these GCMs are the statistical representation of the physical processes occurring in the atmosphere, hydrosphere and lithosphere. Currently, climatic researchers use these GCMs to understand the nature of the climatic system, retrieve past climatic data and to generate future projections considering different representative concentration pathways (RCPs). Over the years, a large number of GCMs have been developed for projecting global climate. The selection of climatic models is based on the goal of the climate change impact assessment studies. For instance, some studies use the past performance approach, envelop/ensemble approach, selection of only a single climatological variable or multiple climatological variables, etc. (Lutz *et al.* 2016) for selecting appropriate GCM. In the present study, the combination of envelop and past performance approach is used to downscale data from MarkSim GCM, which includes data from 17 climate models that were part of the IPCC's (Intergovernmental Panel on Climate Change) fifth assessment report (Jones & Thornton 2013). For the analysis of climatic data with respect to agriculture or biodiversity, majorly there are three types of approaches used in literature to analyze the climate change impact assessment on agriculture: panel data analyses, cross-sectional analyses and agroeconomic analyses (also called biophysical models). The first two methods use statistical tools to estimate the relationship between climate and agriculture. The major advantages of using statistical approaches are their limited dependency on field calibration data, transparency in model uncertainties, and less data requirement (Blanc & Reilly 2017).

According to IPCC, the global mean surface temperature observed for the decade 2006–2015 was 0.87 °C higher than the average over the late 19th century and it is likely to increase by 1.5 °C between 2030 and 2052 (IPCC 2018). In India, the average rise in temperature during 1901–2018 was 0.7 °C and further it is projected to rise by ~4.4 °C relative to 1976–2005 under the RCP 8.5 scenario (Krishnan *et al.* 2020). In Punjab, over the four decades maximum (−0.03–0.05 °C/year) and minimum (0.02–0.05 °C/year) temperatures showed high variability over the different agro-climatic regions (Kaur *et al.* 2013). Similarly, Kingra *et al.* (2018) also observed that maximum temperature increased from 27–29 to 31–37 °C in the north-eastern and 27–29 °C to 31–33 °C in the central regions of Punjab, whereas minimum temperature increased from 14.0–16.0 to 18.0–20.0 °C in the north-eastern and 14.0–16.0–24.0–26.0 °C in the central regions of Punjab with no significant trends in annual rainfall over the past 40 years. Many studies have analyzed the variations in weather as well as climatic variables over this region but there are very few studies in which spatio-temporal analysis of thermal requirements of crops have been considered using geographic information systems. Therefore, the purpose of the present research is to assess how the rising temperatures are reflected in the temperature accumulation and thermal growing period of cotton in the Indian Punjab.

2. MATERIALS AND METHODS

2.1. Study area

The Indian Punjab, part of the trans-gangetic plains, situated in the north-west occupies 1.5% geographical area of the country, comprised of three broad agro-climatic zones: north-east, central and south-west regions (Figure 1). The climate of this region varies from semi-humid to semi-arid and annual rainfall varies from 1,000 mm in the north-east to less than 250 mm in the south-west with great seasonal concentration during the monsoon period (Mavi & Tiwana 1993; Humphreys *et al.* 2010). The soil texture varies from sandy to fine silty, with a major share of coarse loamy and fine loamy. Nearly all the

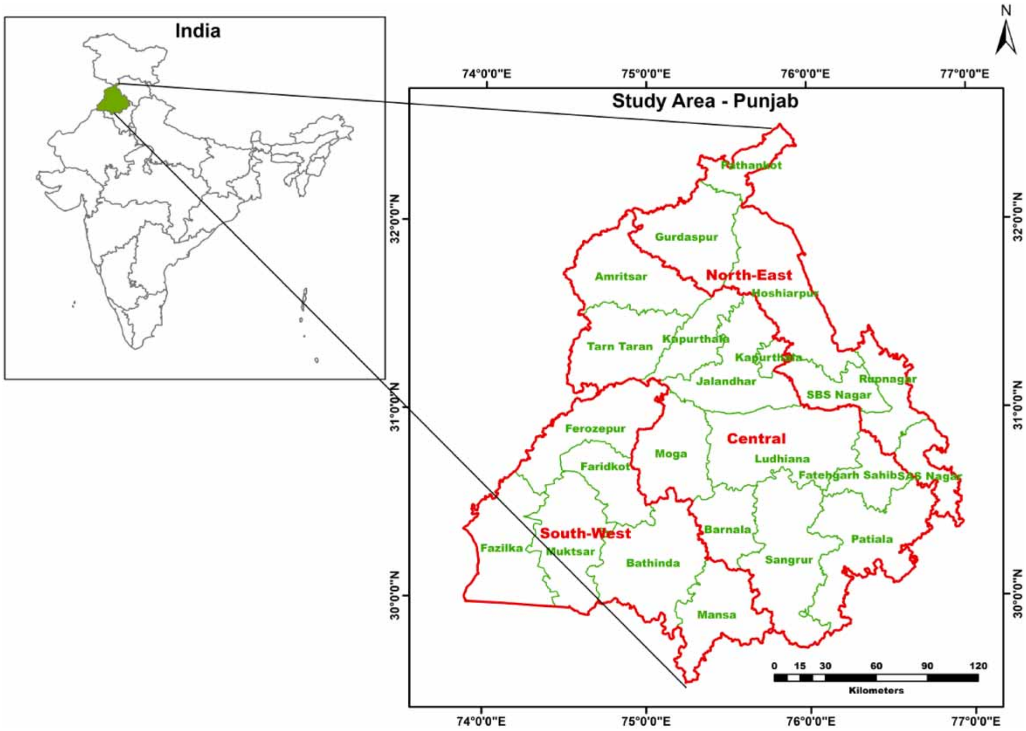


Figure 1 | Study area map showing the Indian Punjab.

soils are low in organic carbon (Sharma *et al.* 2016) and a majority of soils have problems of soil salinity (Ray *et al.* 2005). About 90% of the state is an extensive level tract, facilitating the cultivation of land at a larger scale (Gosal 2004).

The rice–wheat cropping system covers at least 80% of the gross cropped area and cotton is ranked third in the cropping pattern of the state. The state has an excellent network of surface (canal) and groundwater resources that leads to about 99% of the net sown area under irrigation. Since the beginning of the Green Revolution era, the state has made remarkable progress through the use of irrigation facilities, chemical fertilizers, high-yielding varieties, pesticides, mechanization, etc. This type of extensive agriculture practice leads to water table depletion, nutrient deficiency, and insect-pest attacks (Grover *et al.* 2017).

2.2. Field experiment

A field experiment was conducted at Punjab Agricultural University, Regional Research Station, Bathinda (latitude 30°58″N, 74°18″E longitude, altitude 211 m above mean sea level) during the two *kharif* seasons (2020 and 2021) using four sowing dates and two cultivars in factorial randomized complete block design replicated thrice. The experimental site falls under the south-western zone of Punjab having semi-arid climate with an average annual rainfall of about 440 mm. Here, cotton is a major *kharif* crop, staggered from April to October. The mean maturity period and AGDDs obtained from the above experiment were used in the analysis of thermal growing period and growing degree day analysis. This investigation was done with two prospective, i.e. the first one is to analyze the spatio-temporal variation in accumulated GDD using mean maturity period (162 days) from the field experiment and the second is to study the spatio-temporal variation in thermal growing period required to reach the mean AGDD (2,362 °C day) from the above-mentioned field experiment (Table 1) using Equation (1):

$$\mathrm{AGDD} = \frac{\sum_{i=1}^{n} [T_{\max} + T_{\min}]}{2} - T_b \tag{1}$$

Here, n is the phenological duration of the crop from sowing to maturity, $T_{\max}$ and $T_{\min}$ are the daily maximum and minimum temperatures (°C) and T_b is the base temperature (15.5 °C), defined as the temperature below which plant growth stops (Ban *et al.* 2015).

Table 1 | Maturity period and accumulated growing degree days of cotton during both the growing seasons

Cropping season	Statistic	Maturity period	Accumulated growing degree days
2020	Mean	160	2,395
	SD	9	134
2021	Mean	164	2,330
	SD	9	130
Overall mean		**162**	**2,362**

2.3. Data collection

The daily historical climate data (1990–2020) with respect to maximum temperature and minimum temperature, of three broad agro-climatic zones (north-east, central and south-west zones) of Punjab was taken from the Department of Climate Change and Agricultural Meteorology, Punjab Agricultural University, Ludhiana and India Meteorological Department. To assess the future climatic data (2021–2055), ensemble data of 17 available GCMs under MarkSim® DSSAT weather file generator (http://gisweb.ciat.cgiar.org/MarkSimGCM/) was used for four greenhouse gas concentration trajectories: RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5. However, the spatial resolution of these GCMs is too coarse to generate the climatic parameters at a regional scale. Therefore, GCMs are required to apply parameterizations to better produce the regional climatic interactions. For this, the bias correction method is used, given by Hay *et al.* (2000).

2.4. Bias correction

The bias in the MarkSim output was removed by the delta method (Hay *et al.* 2000) on a daily basis using the observed and modeled data of 2010–2015. In this method, the daily difference between modeled data and observed data of weather parameters was averaged and taken as 'daily correction factors'. After that, these correction factors were subtracted from the model uncorrected data to get the model corrected data (Equation (2)). Then its suitability was validated for the period of 2016–2020.

$$X_{\text{modelcorr}} = X_{\text{modeluncorr}} - (X_{\text{modeluncorr}} - X_{\text{obs}}) \tag{2}$$

Here, $X_{\text{modelcorr}}$ is the daily corrected modeled value, $X_{\text{modeluncorr}}$ is the daily uncorrected modeled value and $X_{\text{modeluncorr}} - X_{\text{obs}}$ is the deviation of the daily observed value from modeled value averaged over 6 years (2010–2015) as correction factors.

2.5. Trend analysis

The historical and future climatic data (April–October) were analyzed by using statistical techniques like mean, standard deviation, Mann–Kendall test for the significance of the trend and Sen's slope estimator for finding the slope of the trend. The null hypothesis (H_0) stated by the Mann–Kendall test is that a sample has no trend, i.e. the observations (x_i) are randomly ordered in time, against the alternative hypothesis (H_1), where there is an increasing or decreasing monotonic trend. The Mann–Kendall test statistics S is calculated using the Equation (3):

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn\ (x_j - x_k) \tag{3}$$

where x_j and x_k are the annual values in years j and k, $j > k$, respectively, and

$$sgn(x_j - x_k) = \begin{cases} +1 & \text{if} \quad (x_j - x_k) > 0 \\ 0 & \text{if} \quad (x_j - x_k) = 0 \\ -1 & \text{if} \quad (x_j - x_k) < 0 \end{cases} \tag{4}$$

$$\text{Var}(S) = \frac{[n(n-1)(2n+5) - \sum_t t(t-1)(2t+5)]}{18} \tag{5}$$

Here, t is the extent of a given tie, and $\sum t$ represents the summation over all ties (it is the set of sample data having the same value). In cases where the sample size (n) is >10, the standard normal variable Z is calculated using Equation (6):

$$Z = \begin{cases} \frac{S-1}{\sqrt{\mathrm{Var}(S)}} & \text{if} \quad S > 0 \\ 0 & \text{if} \quad S = 0 \\ \frac{S+1}{\sqrt{\mathrm{Var}(S)}} & \text{if} \quad S < 0 \end{cases} \tag{6}$$

Increasing trends are presented by positive values of Z, while decreasing trends are represented by negative values. In order to find the increasing or decreasing monotonic trends at the α significance level, the null hypothesis was rejected when the absolute value of Z greater than $Z_{1-\alpha/2}$ was detected, where $Z_{1-\alpha/2}$ was obtained from the standard normal cumulative distribution tables. The analysis of any increasing or decreasing trends in this study was represented at four levels of significance (0.1, 1, 5 and 10%).

After investigating the trend, a non-parametric method is used to compute the magnitude of the slope. The Theil-Sen's method can be used in cases where the trend can be assumed to be linear (Equation (7)):

$$f(t) = Qt + B \tag{7}$$

where Q represents the slope and B represents a constant. To find the value of Q, first calculate the slopes of all the data pairs using Equation (8):

$$Q_i = \frac{x_j - x_k}{j - k}, \ \text{where } j > k \tag{8}$$

If there are n values x_j in the time series we found as many as $N = n(n-1)/2$ slope estimates Q_i. The Sen's estimator of slope is the median of these N values of Q_i (Salmi *et al.* 2002).

2.6. Spatial data interpolation

The spatial interpolation of the thermal requirement of cotton was carried out by using the inverse distance weighted (IDW) method which works well with uniformly distributed and high-density data, available in the ArcGIS environment (Wu *et al.* 2021). IDW is a deterministic interpolation method where weights are given to point estimates using a mathematical equation with a principle that point estimates lying in closer vicinity to the prediction location will be more influential than the ones farthest away. The algorithm followed by the IDW interpolation method to determine the value of the variable of interest at an unknown location ($Z(S_0)$) by using Equation (9):

$$Z(S_0) = \sum_{i=1}^{N} \lambda_i \mathrm{Z}(\mathrm{S_i}) \tag{9}$$

where S_0 represents the location at which the value is to be predicted and $Z(S_0)$ represents value for the prediction location $S_{0,}$ S_i is the ith location and $Z(S_i)$ is the known value at the ith location, λ_i is an unknown weight for the known value at ith location (Equation (10)).

$$\lambda_i = \frac{d_j^{-p}}{\sum_{i=1}^{N} d_j^{-p}} d \tag{10}$$

where N represents the total number of known points to be used for interpolation, d is the distance of the unknown value location from the known value location, p is a power parameter whose magnitude governs the assignment of weights.

3. RESULTS

3.1. Bias removal

The annual average five-year (2016–20) observed, modeled and bias-corrected data over three broad climatic regions are presented in Table 2. In case of maximum temperature, the mean difference between observed and modelled value was 2.9°C for central, 2.1°C for south-west and 3.4°C for north-east regions, which was reduced to 0.1 (29.7°C), 0.4 (31.0°C) and 0.3°C (28.7°C) after bias removal for respective regions. Similarly for minimum temperature, the mean difference was reduced to 0.0 (16.9 °C), 0.4 (17.5 °C) and −0.3 °C (15.8 °C) from 1.1, 0.7 and 2.0 °C for central, south-western and north-eastern zones of Punjab after bias correction.

3.2. Spatio-temporal variability in maximum and minimum temperatures

Significant variations were observed in future (2021–2055) maximum temperature projected by ensemble output in comparison to the baseline (1990–2020) period for all the three agro-climatic zones of Punjab (Table 3). The highest mean maximum temperature was observed for the south-western zone (35.9 °C), followed by the central zone (34.6 °C) and north-eastern zone (33.3 °C) during the historical period without any significant increasing or decreasing trend. For the future scenarios (2020–2055), all the agro-climatic regions showed a significant increasing trend under RCP 2.6 (0.01 °C/year), RCP 4.5 (0.02 °C/year), RCP 6.0 (0.02 °C/year) and RCP 8.5 (0.05–0.06 °C/year).

Likewise, mean minimum temperature was 22.3 °C during the baseline period for the central region, which would be increased up to 0.7 °C (23.0 °C) under RCP 2.6, 1.0 °C (23.3 °C) under RCP 4.5, 0.7 °C (23.0 °C) under RCP 6.0 and 1.7 °C (24.0 °C) under RCP 8.0 at the end of mid-century (Table 4). Furthermore, for the south-western zone mean minimum temperature was 23.0 °C during the historical period, which would be increased by 0.02–0.05 °C (24.0–24.6 °C) for the futuristic scenarios (2021–55). For the north-western zone, minimum temperature might increase up to 0.6–3.5 °C (21.6–24.5 °C) under various RCP scenarios from the baseline period (21.0 °C). All three agro-climatic zones showed a significant increasing

Table 2 | Statistical parameters of annual observed, model uncorrected and model corrected maximum and minimum temperatures

	Maximum temperature (°C)			Minimum temperature (°C)		
Location/Parameter	**Observed**	**Model uncorrected**	**Model corrected**	**Observed**	**Model uncorrected**	**Model corrected**
Amritsar	29.9 ± 7.2	31.8 ± 8.2	30.2 ± 7.4	17.0 ± 8.0	17.3 ± 9.6	16.6 ± 8.2
Fatehgarh Sahib	28.1 ± 6.1	32.5 ± 7.8	28.2 ± 6.1	16.1 ± 7.0	18.5 ± 9.0	16.2 ± 7.0
Jalandhar	28.9 ± 6.5	32.3 ± 8.0	29.1 ± 6.5	16.4 ± 7.3	18.0 ± 9.3	16.5 ± 7.4
Kapurthala	29.7 ± 6.9	32.1 ± 7.7	29.4 ± 6.6	16.0 ± 7.4	17.7 ± 9.0	15.7 ± 7.3
Ludhiana	29.7 ± 7.1	32.8 ± 7.9	30.0 ± 7.2	17.8 ± 7.9	18.2 ± 9.4	17.9 ± 7.9
Moga	30.0 ± 6.7	32.6 ± 8.1	30.1 ± 6.7	16.8 ± 7.7	17.8 ± 9.5	16.9 ± 7.7
Patiala	30.7 ± 6.9	32.6 ± 7.6	30.7 ± 7.0	18.6 ± 7.6	18.6 ± 8.9	18.6 ± 7.6
Sangrur	29.8 ± 6.6	33.0 ± 7.8	29.9 ± 6.6	16.8 ± 7.6	18.2 ± 9.3	16.9 ± 7.6
Central zone	**29.6 ± 6.8**	**32.5 ± 7.9**	**29.7 ± 6.8**	**16.9 ± 7.6**	**18.0 ± 9.3**	**16.9 ± 7.6**
Bathinda	30.8 ± 7.4	33.2 ± 8.0	30.9 ± 7.7	16.9 ± 8.0	18.0 ± 9.7	17.7 ± 8.2
Faridkot	30.1 ± 7.3	32.6 ± 8.1	30.9 ± 7.2	17.5 ± 8.4	17.9 ± 9.6	17.6 ± 8.0
Ferozepur	31.4 ± 6.8	31.4 ± 7.6	32.4 ± 8.1	17.2 ± 7.7	17.3 ± 8.2	17.9 ± 9.4
Mansa	30.4 ± 6.6	33.3 ± 7.8	30.4 ± 6.6	17.2 ± 7.7	18.1 ± 9.5	17.3 ± 7.7
Muktsar	30.3 ± 6.8	32.9 ± 8.0	30.4 ± 6.8	17.0 ± 7.8	17.9 ± 9.6	17.1 ± 7.8
South-western zone	**30.6 ± 7.0**	**32.7 ± 7.9**	**31.0 ± 7.3**	**17.1 ± 7.9**	**17.8 ± 9.3**	**17.5 ± 8.2**
Gurdaspur	28.7 ± 7.1	31.7 ± 8.0	28.0 ± 6.9	16.6 ± 7.2	18.1 ± 9.0	15.1 ± 7.3
Hoshiarpur	28.1 ± 6.4	31.8 ± 7.9	28.2 ± 6.4	15.7 ± 7.2	18.2 ± 8.9	15.8 ± 7.1
Rupnagar	27.4 ± 6.1	31.5 ± 5.9	28.0 ± 6.2	15.4 ± 6.9	17.7 ± 6.8	15.5 ± 7.2
SBS Nagar	29.5 ± 6.6	32.4 ± 7.7	30.5 ± 6.5	16.8 ± 7.2	18.5 ± 9.0	16.7 ± 7.4
North-eastern zone	**28.4 ± 6.5**	**31.8 ± 7.4**	**28.7 ± 6.5**	**16.1 ± 7.1**	**18.1 ± 8.4**	**15.8 ± 7.3**

Table 3 | Spatio-temporal variability in maximum temperature during past (1990–2020) and future period (2021–2055)

Location	Test	Past	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
Amritsar	Mean ± SE	35.3 ± 0.10	35.9 ± 0.02	36.4 ± 0.06	36.1 ± 0.04	36.5 ± 0.09
	Sen-slope	0.00	0.01	0.04	0.02	0.05
Fatehgarh Sahib	Mean ± SE	33.3 ± 0.06	33.0 ± 0.02	33.2 ± 0.05	32.9 ± 0.03	33.5 ± 0.08
	Sen-slope	0.00	0.01	0.03	0.02	0.05
Jalandhar	Mean ± SE	34.1 ± 0.11	34.1 ± 0.03	34.6 ± 0.06	34.3 ± 0.04	34.7 ± 0.09
	Sen-slope	−0.03	0.01	0.03	0.02	0.05
Kapurthala	Mean ± SE	34.4 ± 0.09	34.7 ± 0.03	35.1 ± 0.06	34.7 ± 0.05	38.7 ± 0.08
	Sen-slope	0.00	0.01	0.03	0.02	0.05
Ludhiana	Mean ± SE	34.8 ± 0.11	35.4 ± 0.02	35.8 ± 0.06	35.4 ± 0.04	35.9 ± 0.09
	Sen-slope	0.02	0.01	0.03	0.02	0.05
Moga	Mean ± SE	35.3 ± 0.12	35.5 ± 0.02	35.8 ± 0.05	35.4 ± 0.04	36.0 ± 0.09
	Sen-slope	−0.03	0.01	0.03	0.02	0.05
Patiala	Mean ± SE	34.3 ± 0.21	35.9 ± 0.03	36.2 ± 0.05	35.8 ± 0.04	36.4 ± 0.08
	Sen-slope	0.10	0.01	0.03	0.02	0.05
Sangrur	Mean ± SE	35.1 ± 0.13	35.2 ± 0.03	35.5 ± 0.05	35.1 ± 0.03	35.6 ± 0.08
	Sen-slope	−0.03	0.01	0.03	0.02	0.05
Central zone	**Mean ± SE**	**34.6 ± 0.46**	**35.0 ± 0.14**	**35.3 ± 0.32**	**35.0 ± 0.22**	**35.9 ± 0.5**
	Sen-slope	**0.00**	**0.01**	**0.03**	**0.02**	**0.05**
Bathinda	Mean ± SE	36.0 ± 0.09	36.7 ± 0.03	37.1 ± 0.06	36.6 ± 0.03	37.3 ± 0.09
	Sen-slope	0.02	0.01	0.03	0.02	0.05
Faridkot	Mean ± SE	35.9 ± 0.11	36.5 ± 0.04	36.8 ± 0.06	36.3 ± 0.03	36.9 ± 0.09
	Sen-slope	−0.01	0.01	0.03	0.02	0.05
Ferozepur	Mean ± SE	36.1 ± 0.10	38.4 ± 0.03	38.8 ± 0.06	38.5 ± 0.04	39.1 ± 0.09
	Sen-slope	0.03	0.01	0.03	0.02	0.05
Mansa	Mean ± SE	35.6 ± 0.12	35.6 ± 0.04	36.0 ± 0.05	35.5 ± 0.03	36.2 ± 0.08
	Sen-slope	−0.03	0.01	0.03	0.01	0.05
Muktsar	Mean ± SE	35.7 ± 0.12	35.8 ± 0.03	36.2 ± 0.06	35.7 ± 0.04	36.4 ± 0.09
	Sen-slope	−0.03	0.01	0.03	0.02	0.05
South-west zone	**Mean ± SE**	**35.9 ± 0.51**	**36.6 ± 0.16**	**37 ± 0.33**	**36.5 ± 0.20**	**37.2 ± 0.52**
	Sen-slope	**– 0.01**	**0.01**	**0.03**	**0.02**	**0.05**
Gurdaspur	Mean ± SE	33.1 ± 0.23	33.3 ± 0.02	33.8 ± 0.06	33.5 ± 0.04	33.9 ± 0.09
	Sen-slope	0.04	0.01	0.03	0.03	0.05
Hoshiarpur	Mean ± SE	33.2 ± 0.11	33.2 ± 0.03	33.8 ± 0.06	33.4 ± 0.04	33.8 ± 0.09
	Sen-slope	−0.03	0.01	0.03	0.02	0.05
SBS nagar	Mean ± SE	34.5 ± 0.13	35.3 ± 0.02	35.8 ± 0.06	35.5 ± 0.04	35.9 ± 0.09
	Sen-slope	0.03	0.01	0.03	0.02	0.05
Rupnagar	Mean ± SE	32.3 ± 0.10	32.4 ± 0.03	32.7 ± 0.05	32.4 ± 0.04	41.9 ± 0.66
	Sen-slope	−0.03	0.02	0.03	0.02	0.06
North-east zone	**Mean ± SE**	**33.3 ± 0.56**	**33.6 ± 0.13**	**34 ± 0.34**	**33.7 ± 0.24**	**36.4 ± 1.20**
	Sen-slope	**0.00**	**0.01**	**0.03**	**0.02**	**0.06**

trend (0.03 °C/year) during the baseline period for minimum temperature but no such significant trend was found for maximum temperature for the same period.

3.3. Spatio-temporal variability in accumulated GDDs

In the first perspective of this study, the mean thermal growing period required to complete crop maturity, i.e. 162 days, is used as a standard value over the seasons, four sowing dates and two cultivars (Table 1). The spatio-temporal variations in thermal units accumulated during the mean maturity period for the present and future environments are depicted in Figure 2

Table 4 | Spatio-temporal variability in minimum temperature during past (1990–2020) and future period (2021–55)

Location	Test	Past	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
Amritsar	Mean ± SE	22.3 ± 0.11	23.1 ± 0.03	23.5 ± 0.06	23.2 ± 0.04	23.6 ± 0.09
	Sen-slope	0.03	0.02	0.03	0.03	0.05
Fatehgarh Sahib	Mean ± SE	21.5 ± 0.07	21.8 ± 0.03	22.2 ± 0.06	21.9 ± 0.04	22.4 ± 0.09
	Sen-slope	0.01	0.02	0.03	0.02	0.05
Jalandhar	Mean ± SE	22.0 ± 0.07	22.3 ± 0.04	22.7 ± 0.06	22.4 ± 0.04	22.9 ± 0.09
	Sen-slope	0.01	0.01	0.03	0.02	0.05
Kapurthala	Mean ± SE	21.6 ± 0.10	21.7 ± 0.04	22.1 ± 0.06	21.7 ± 0.05	25.6 ± 0.09
	Sen-slope	−0.02	0.02	0.03	0.02	0.05
Ludhiana	Mean ± SE	23.2 ± 0.10	24.2 ± 0.03	24.5 ± 0.06	24.2 ± 0.04	24.7 ± 0.09
	Sen-slope	0.04	0.01	0.03	0.02	0.05
Moga	Mean ± SE	22.7 ± 0.07	23.1 ± 0.03	23.4 ± 0.06	23.1 ± 0.04	23.6 ± 0.09
	Sen-slope	0.01	0.01	0.03	0.02	0.05
Patiala	Mean ± SE	22.6 ± 0.24	24.7 ± 0.04	24.9 ± 0.06	24.7 ± 0.05	25.2 ± 0.09
	Sen-slope	0.13	0.02	0.03	0.03	0.05
Sangrur	Mean ± SE	22.6 ± 0.07	22.8 ± 0.17	23.3 ± 0.14	23.1 ± 0.05	23.7 ± 0.11
	Sen-slope	0.01	0.02	0.03	0.02	0.05
Central zone	**Mean ± SE**	**22.3 ± 0.45**	**23.0 ± 0.21**	**23.3 ± 0.35**	**23.0 ± 0.26**	**24.0 ± 0.51**
	Sen-slope	**0.03**	**0.02**	**0.03**	**0.02**	**0.05**
Bathinda	Mean ± SE	23.0 ± 0.10	24.2 ± 0.03	24.5 ± 0.06	24.2 ± 0.04	24.7 ± 0.09
	Sen-slope	0.04	0.02	0.03	0.02	0.05
Faridkot	Mean ± SE	23.0 ± 0.11	23.9 ± 0.04	24.3 ± 0.06	23.9 ± 0.04	24.5 ± 0.09
	Sen-slope	0.04	0.01	0.03	0.02	0.05
Ferozepur	Mean ± SE	22.8 ± 0.08	25.2 ± 0.03	25.6 ± 0.06	25.3 ± 0.04	25.9 ± 0.09
	Sen-slope	0.02	0.01	0.03	0.03	0.05
Mansa	Mean ± SE	23.1 ± 0.07	23.3 ± 0.04	23.8 ± 0.06	23.5 ± 0.04	24.0 ± 0.09
	Sen-slope	0.01	0.02	0.03	0.02	0.05
Muktsar	Mean ± SE	23.0 ± 0.08	23.4 ± 0.03	23.7 ± 0.06	23.4 ± 0.04	23.9 ± 0.09
	Sen-slope	0.02	0.01	0.03	0.02	0.05
South-west zone	**Mean ± SE**	**23.0 ± 0.46**	**24.0 ± 0.17**	**24.4 ± 0.33**	**24.0 ± 0.25**	**24.6 ± 0.53**
	Sen-slope	**0.03**	**0.02**	**0.03**	**0.02**	**0.05**
Gurdaspur	Mean ± SE	20.6 ± 0.26	20.9 ± 0.03	21.3 ± 0.06	21.0 ± 0.05	21.5 ± 0.09
	Sen-slope	0.06	0.01	0.03	0.03	0.05
Hoshiarpur	Mean ± SE	21.2 ± 0.06	21.6 ± 0.03	22.0 ± 0.06	21.7 ± 0.05	22.2 ± 0.09
	Sen-slope	0.01	0.02	0.03	0.03	0.05
SBS nagar	Mean ± SE	21.7 ± 0.09	22.6 ± 0.03	22.9 ± 0.06	22.6 ± 0.04	23.2 ± 0.09
	Sen-slope	0.04	0.01	0.03	0.03	0.05
Rupnagar	Mean ± SE	20.7 ± 0.06	21.2 ± 0.03	21.5 ± 0.06	21.2 ± 0.05	31.1 ± 0.67
	Sen-slope	0.01	0.02	0.03	0.03	0.06
North-east zone	**Mean ± SE**	**21.0 ± 0.54**	**21.6 ± 0.16**	**21.9 ± 0.34**	**21.6 ± 0.28**	**24.5 ± 1.26**
	Sen-slope	**0.03**	**0.02**	**0.03**	**0.03**	**0.07**

(Supplementary material, Table S1). Among the different agro-climatic regions, higher AGDD were accumulated in the south-western zone (2,441 °C day) where most of the cotton crop is concentrated, followed by central (2,276.8 °C day) and north-eastern zone (2,073.8 °C day) during the baseline period within a maturity period of 162 days. However, the highest increasing trend of AGDD was observed in the central zone (1.65 °C day/year), followed by north-east (1.59 °C day/year) and south-western (0.77 °C day/year) zones. Both the north-eastern and central zones accumulated less AGDD than the mean AGDD (2,362 °C day) in our field experiment, which means cotton cultivation is not possible in these zones.

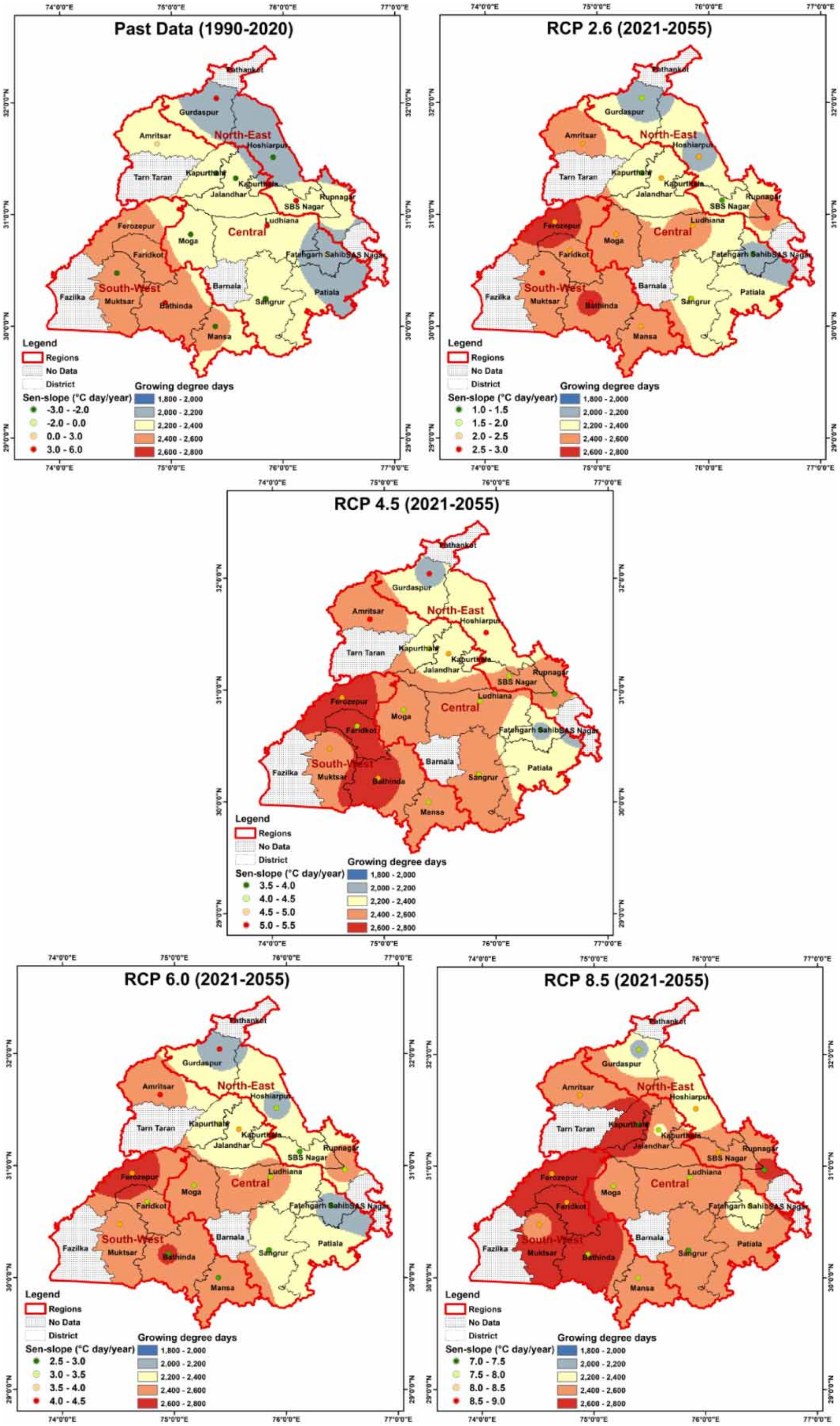


Figure 2 | Spatio-temporal distribution of accumulated growing degree days of cotton over past and future scenarios.

In future, AGDD of the central region was increased by 4% (2,371.9 °C days) under RCP 2.6, by 7% (2,430.4 °C day) under RCP 4.5, by 5% (2,379.4 °C day) under RCP 6.0 and by 11% (2,532.2 °C day) under RCP 8.5 climatic scenario than the baseline period. It means that future agro-climate becomes favorable for cotton cultivation under all the climatic scenarios. Likewise, AGDD of the north-eastern zone was increased by 3% (2,142.7 °C day), by 7% (2,209.7 °C day), by 4% (2,157.6 °C day) and by 27% (2,643.4 °C day) under RCP 2.6, 4.5, 6.0 and 8.5 scenarios. In this region, cotton cultivation can only be possible under the RCP 8.5 scenario as other scenarios couldn't overcome the mean AGDD (2,362 °C day). AGDD of the south-western zone would be increased by 3 to 7% among all the scenarios at the end of the mid-century in contrast to the baseline period.

3.4. Spatio-temporal variability in thermal growing period of cotton

In the second perspective of this study, the mean accumulated GDDs required to complete crop maturity, i.e. 2,362 °C day is used as a standard value over the seasons, four sowing dates and two cultivars (Table 1). The spatio-temporal variability in the thermal growing period required to accumulate mean GDD for the past and future scenarios is depicted in Figure 3 (Supplementary material, Table S2). For the baseline period, the number of days required to accumulate mean AGDD (2,362 °C day) varied from 155.1 (south-western zone) to 201.7 (north-eastern zone) days among different agro-climatic zones. Over the years (1990–2020), the thermal growing period of cotton showed a decreasing trend. This decrease was more for the north-eastern zone (0.49 day/year), followed by central (0.22 day/year) and south-western (0.04 day/year) zones.

Among all the agro-climatic zones, the highest decrease in the thermal growing period was observed under the worst climatic scenario, i.e. RCP 8.5 at the end of the mid-century. For the central zone, future thermal growing period might decrease up to 6–14% (162.4–150.1 days). Likewise, for south-western zone decrease in thermal growing period up to 4–8% (148.4–142.3 days) and up to 8–25% (185.4–151.9 days) for the north-eastern zone under all the future RCP scenarios. In future, the shortening of the growing season will clearly indicate the thermal stress over cotton crops for upcoming decades.

4. DISCUSSION

Past AGDD trend analysis showed that there is an increasing trend all over the Punjab state, indicating the changing agro-climatic conditions (Figure 2). The changing AGDD requirements could be due to the variability in the maximum and minimum temperatures (Table 3). These results are in confirmation with Kaur *et al.* (2013), who also observed the variability in maximum temperature (−0.03–0.05 °C/year) and minimum temperature (0.02–0.05 °C/year) over the four decades in Punjab region. The maximum and minimum temperatures varied considerably from region to region, but the magnitude of variations was higher for the north-east zone than the other two zones (Tables 3 and 4). During the baseline period, both temperatures showed an increasing trend but the trend was only significant for minimum temperature. Kingra *et al.* (2018) also found that over the past 40 years (1974–2014) maximum temperature increased from 27–29 to 31–37 °C in north-eastern and 27–29–31–33 °C in central regions whereas minimum temperature increased from 14.0–16.0 to 18.0–20.0 °C in north-eastern and 14.0–16.0 °C to 24.0–26.0 °C in central regions of Punjab. As a result of this warming, there was an increase in thermal unit accretion of cotton crops especially in the north-west and central zones. This means that Punjab state is already witnessing the effects of global warming, which can have deleterious effects on crops and allied activities of humans.

In future, these conditions will be further aggravated by the increasing temperatures under all four scenarios. These future changes in temperature have the potential to manipulate the crop phenology, decrease in thermal growing period and more accretion of thermal units. These fluctuations exhorted the agricultural researchers to improve their understanding of site-specific changes in phenology and thermal time requirements. At the end of the mid-century, the projected increase in AGDD would be 3–27% among the climatic scenarios that may decrease the length of thermal growing period by 4–25% in contrast to baseline or historical periods under different agro-climatic zones of Punjab (Figures 2 and 3). The results are consistent with the findings of Ahmed (2020) who also observed the projected rise in GDDs by 9 and 35% for winter wheat and sorghum at the end of the mid-century. This means that cotton crops will grow earlier and have to be harvested prior to the normal. Grigorieva *et al.* (2010) analyzed GDD using four threshold values *viz.* GDD was calculated using base temperatures 0 °C (GDD_0), 5 °C (GDD_5), 10 °C (GDD_{10}) and 15 °C (GDD_{15}) and found a significant positive trend for GDD_0 (depicting the increase in the duration of the warm season) while there was little change for GDD_{15}. Ruosteenoja *et al.* (2016) also analyzed the future projections of growing season length and GDDs and confirmed the prolongation by 1.5–2.0 months and GDD above 5 °C was increased by 60–100% in the late 21st century under RCP 8.5 and a similar response was observed for RCP 4.5 but with lower magnitude. The findings of the present study are in line with the findings of Castillo & Ospina

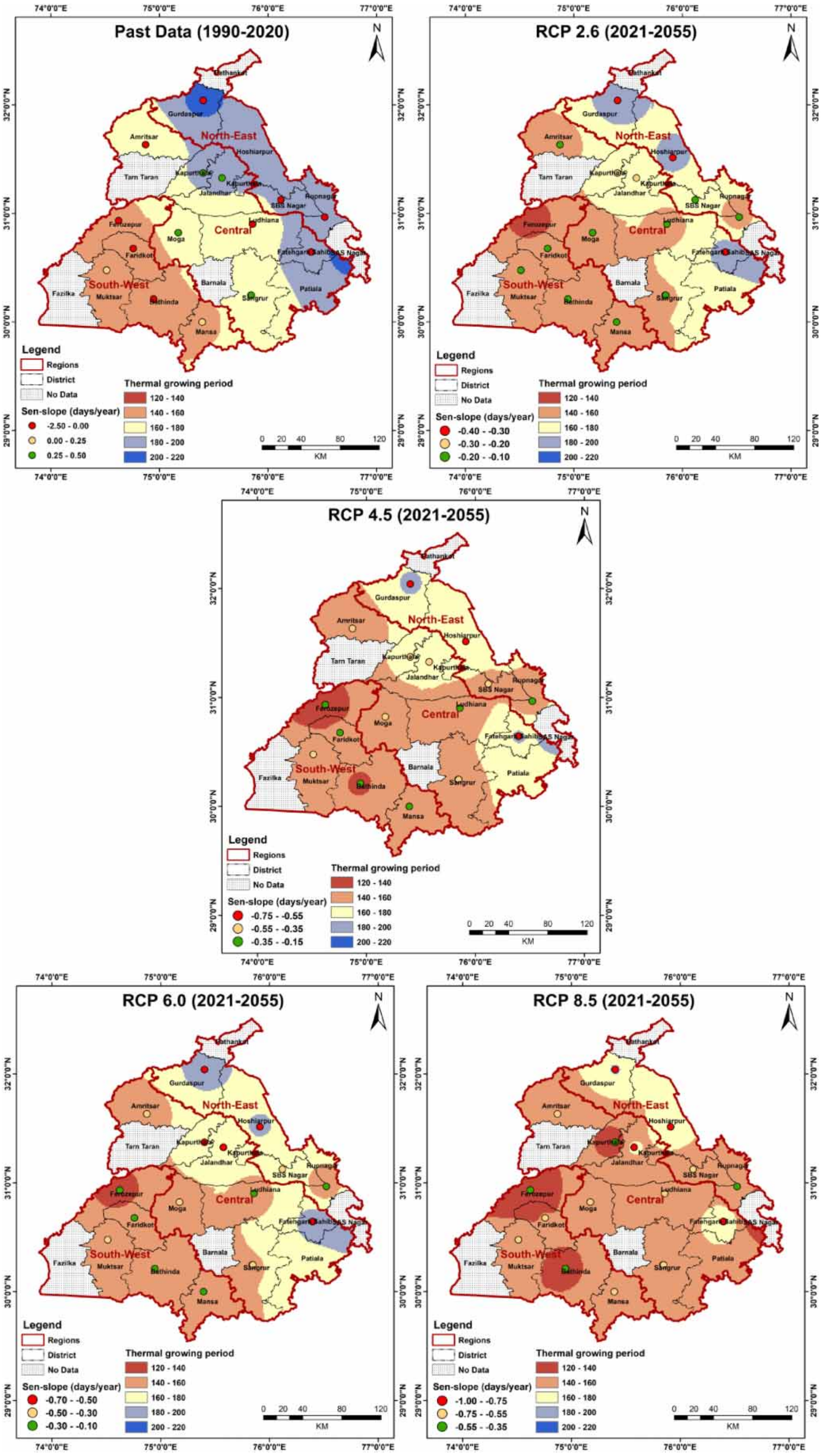


Figure 3 | Spatio-temporal distribution of thermal growing period of cotton over past and future scenarios.

(2016) who also observed that a projected rise in temperature would shorten the growing period and increase the thermal stress in winter wheat. The shortening of the growing season might be due to the higher ambient temperature that advances the crop phenology (Paparrizos & Matzarakis 2016). Further, this advancement is also enhanced by extreme weather events like heat waves, drought, etc. Scientific experiments on cotton plants have also shown that growth stages occurred much earlier with elevated temperature. In this regard, Luo *et al.* (2013) studied the effect of future climate (2020–2039) on cotton phenology using a growing degree day concept and found that the time of first square, first flower and first open boll would be advanced by 4–13, 5–14 and 8–16 days and time of last effective square, last effective flower and last harvestable boll, would be delayed by 7–12, 6–9 and 3–9 days in comparison to the baseline period of 1980–1999. Further, this decrease in the number of days between the growth stages will reduce seed cotton yield as well as fiber quality (Sharma *et al.* 2021). Yin *et al.* (2017) also found that the start of the growing period was advanced by 4.9–6.7 days, the end of the growing period was delayed by 4.3–6.2 days and the overall lengthening of the growing season by 10.8–11.0 days. Further, this led to increased GDD by 218.9–339.4 °C over the period of 52 years with a more alarming trend of GDD with lower base temperature. Future climate not only shortened the thermal growing period of cotton but also resulted in the expansion of growing degree day classes, i.e. more area under warmer classes at the end of the mid-century. The expansion of these classes was from south-west to north-east (Figure 2). King *et al.* (2018) used GDD for studying the global northward shift of agro-climatic zones. Paparrizos & Matzarakis (2016) also examined the expansion of GDD units as well as their respective area and earlier crop maturity in Greek for the past and future scenarios.

The continuous adoption of new cotton cultivars with higher thermal requirements can help to mitigate climatic warming. Some agronomic practices such as early sowing may be adopted to avoid the negative impacts of future increases in temperature (Chen *et al.* 2019; Sharma *et al.* 2021). The outcomes of the present study totally depend on temperatures whereas other practical factors such as rainfall, elevated CO_2, advances in technology, cultivars, agricultural disasters, solar radiation and soil conditions should be considered under projected climate change scenarios. The present studies were conducted considering the increase in temperature alone due to the scarcity of available information although other factors also influence the same. This study can provide quantitative information for crop breeders and cotton researchers to develop new genetically modified cultivars and improved agronomic practices that can mitigate the adverse effects of climate in time and space.

5. CONCLUSIONS

Overall, this study concluded that future climate induced more accretion of GDDs and shortening of the thermal growing period of cotton in the Indian Punjab leading to thermal stress over cotton plants. There was a significant increase in minimum temperature over the region but no such significant trend was observed for maximum temperature. The highest increasing trend of AGDD was observed in the central zone followed by the north-east and south-west zones. Likewise, the highest decreasing trend of the thermal growing period was observed in the north-east followed by central and south-west zones. This warming showed the expansion of area under respective GDD classes, which was from south-west to north-east. In comparison to other zones, the north-eastern zone showed more warming especially under the RCP 8.5 scenario at the end of the mid-century. In future, Punjab state is going to face challenges to sustain cotton productivity as well as having to reconsider its present sowing windows and other agronomic practices.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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