Environmental Processes (2021) 8:1047–1072
https://doi.org/10.1007/s40710-021-00526-y

ORIGINAL ARTICLE

Climate Trends in Temperature and Water Variables during Wheat Growing Season and Impact on Yield

Anand Madhukar[1] **· Kavya Dashora**[1] **· Vivek Kumar**[1]

Received: 15 December 2020 / Accepted: 15 June 2021/ Published online: 6 July 2021

Abstract

The paper evaluates varying trends in ten climate variables, i.e., maximum temperature (*Tmx*), mean temperature (*Tmp*), minimum temperature (*Tmn*), diurnal temperature range (*Dtr*), total precipitation (*Pre*), cloud cover (*Cld*), wet day frequency (*Wet*), vapor pressure deficit (*Vpd*), vapor pressure (*Vap*), and potential evapotranspiration (*Pet*), and their impacts on wheat yields during *Rabi* cropping season in India from 1986 to 2015 using regression modeling and correlation analysis. There are three aspects in the present study, i.e., comprehensive coverage of climate variables, use of cropping season over weather classification, and investigation of India as study area because India accounts for ~1/6th of the world population and ~14% of global wheat production. We find that *Tmx, Tmp, Tmn, Vpd*, *Pet* are increasing in eight and *Dtr* and *Cld* in seven Indian states, whereas *Wet* and *Vap* are decreasing in five and *Pre* in four Indian states. Most climate variables in the present study negatively impact wheat yields. The climate trends drive total wheat yield losses up to ~309 kg/ha (~11%) over the study period. The regression models explain up to ~80% of wheat yield variability. The paper provides strong evidence that varying climate trends are negatively impacting wheat yield in India, thus presenting a global concern. Water supply and water demand are important climate variables, essential to be investigated in future studies. Using cropping season over standard weather classification provides more practical insight in the crop yield. This study emphasizes timely attention and intervention in agriculture practices leading to policy formation, amendments and practical execution.

Keywords Climate variability · Food security · Wheat · Correlation analysis · Statistical models · India

Highlights
• Climate trends in temperature and water variables are investigated.
• Climate trends vary per variable per region.
• Wheat is negatively sensitive to varying climate trends.
• Total wheat yield losses are up to ~309 kg/ha (~11%) during 1986–2015.
• Regression models explain up to ~80% of year-to-year variability in wheat yields.

✉ Anand Madhukar
Anmadh11@gmail.com

[1] Indian Institute of Technology Delhi, Hauz Khas, New Delhi 110016, India

1 Introduction

Climate change has a tremendous impact on the environment and socio-economic development on which human lives depend. Understanding climate trends are of considerable importance because of many global challenges such as biodiversity loss (Nunez et al. 2019), water crisis (Schewe et al. 2014), health issues (Hong et al. 2019), and food insecurity (Dahal et al. 2018) are tied to the changing climate. One notable aspect of changing climate is a rise in global temperatures (Pachauri et al. 2014). The rise in temperatures has been even more noticeable in recent years (IPCC-AR4 2007; IPCC-AR5 2014). The rising temperature has also influenced the rainfall patterns and the water cycle of the world (Syed et al. 2010). The global and regional rainfall patterns are changing, and the earth's rain belts are redistributing (Putnam and Broecker 2017). Extreme precipitation frequency has increased with event rareness under global warming (Pendergrass and Hartmann 2014).

Climate variability trends have been studied at different scales across the globe (Lobell and Burke 2010; Tao et al. 2017) and found to be varied by region (Chakraborty et al. 2017). Changing climate is eventually affecting agricultural yields which are recently stagnating (Madhukar et al. 2020). Wheat yields are currently not improving in 69 major wheat-producing Indian districts (Madhukar et al. 2021a). Lobell et al. (2011) pointed out that the temperature and precipitation trends for 1980–2008 had impacted crop yields. Ray et al. (2015) found that changing climate variables explained ~32–39% of the global crop yield variability. Bhatt et al. (2019) explored the impacts of temperature and precipitation on rice yields in India. Among climate variables, temperature and precipitation are the most widely studied. However, a little attention is paid to other water supply and water demand variables. A possible reason for such limited studies might be data unavailability. With recent advances in satellite technology and software programs, climate data is now widely available, so it is possible to deeply investigate and further assess different climate variables such as wet days, cloud cover, vapor pressure deficit, and potential evapotranspiration.

Prior studies (Rao et al. 2015; Sonkar et al. 2019) used few climate variables (mostly temperature and precipitation) as inputs to empirical/statistical models to assess the climate impacts on crop yields, thus lacking to present a comprehensive picture of climate variability impact on crop yields. For example, the earth is currently witnessing a global rise in atmospheric vapor pressure deficit, a trend that is expected to reduce crop yields (López et al. 2021). However, vapor pressure deficit impacts on crop yields have not been typically considered in modeling studies (López et al. 2021). Similarly, the impact of cloud cover, wet days, and potential evapotranspiration on wheat yield remain largely unexplored. It is essential to build a comprehensive understanding of several climate variables simultaneously affecting crop yields to get a practical insight. In the present study, we undertook an analysis of ten climate variables: maximum temperature, mean temperature, minimum temperature, and diurnal temperature range (temperature variables); precipitation, cloud cover, and wet day frequency (water supply variables); and vapor pressure deficit, vapor pressure, and potential evapotranspiration (water demand variables) across a large wheat-producing area in India. This grouping of climate variables into three categories is based on domain knowledge (Cai et al. 2019).

Wheat is among the top three food crops/cereals (wheat, rice, and maize), providing the most calories for the world food supply (Ray et al. 2019). India accounts for ~14% of wheat production globally and is the second-largest producer of wheat after China, with ~99.7 million tonnes production and ~ 29.6 million ha harvested area in 2018 (FAOSTAT 2019). Therefore, an authentic, comprehensive, well-timed, and spatially specific climate variability study on India's wheat yields is crucial for regional and global food security. Wheat is the essential food crop grown during the *Rabi* season in South Asia (India).

Most of the climate variability studies (Arora et al. 2005; Nair and Nayak 2017; Ross et al. 2018) investigate climate trends based on either annual (January to December) or seasonal climate variables using the conventional classification of four weather seasons, i.e., Post-monsoon (October to November), Winter (December to February), Pre-monsoon (March to May), and Monsoon (June to September). In comparison, investigating climate trends per cropping season will provide more practical insight into the impact of climate trends on crop yields. Understanding climate trends during *Rabi* and *Kharif* cropping seasons is essential as most of the crops in South Asia are grown during these two cropping seasons. The major *Rabi* crops include wheat, oats, barley (cereals), gram/chickpea (pulses), mustard, and linseed (oilseeds). Rice, maize, pearl millet, sorghum, ragi/finger millet (cereals), groundnut, soybean (oilseeds), and cotton are the major *Kharif* crops in the region.

Since the weather-based seasonal classification does not exactly overlap with the *Rabi* cropping season in the region, it becomes difficult to link agricultural productivity with climate variables based on four weather seasons. Therefore, we analyze the changes in temperature, water supply, and water demand variables using the wheat growing season (*Rabi*) practiced in India to estimate the impact of climate variability on wheat yields. In contrast to earlier studies, this study analyzes the inter-annual trends in wheat growing season climate variables across major wheat-growing states in India.

There are three aspects of the present study: comprehensive coverage of climate variables, using cropping season over standard weather classification, and investigating India as a study area employing reliable data and rigorous methods. The majority of studies that have focused on temperature and precipitation are not sufficient to comprehensively explain the impact of climate trends on crop production. Water supply and water demand are crucial variables affecting crop yield throughout the world. Typically, precipitation is used as a water supply variable; we have, however, included wet days, cloud cover, and precipitation. There is scarce literature on water demand variables; we have studied vapor pressure deficit, vapor pressure, and potential evapotranspiration as water demand variables. We used cropping season instead of four-season weather classification. Using cropping season helps in impact assessment studies on crop yields.

The manuscript employs 30 years of data (1986–2015) for temperature, water supply, and water demand variables to understand climate variability trends and their impacts on wheat yields in major wheat-producing Indian states. First, we applied climate data analysis to understand climate variability trends over wheat-growing states in India. We then conducted correlation analyses to understand the relationships between different climate variables and wheat yield. Further, we selected the most significant climate variables (across Indian states) as inputs to regression models and performed regression analysis. We aimed to answer the following research questions in this study: (1) How are the different temperature, water supply, and water demand variables (based on wheat growing *Rabi* season) changing in the recent three decades in the study area? (2) How are wheat yields sensitive to these changing climate variables? (3) What is the magnitude of the impact of the most significant climate variables on wheat yields, and how much of the wheat yield variability is explained by these climate variables?

2 Materials and Methods

2.1 Study Area

Major wheat-producing Indian states in descending order are Uttar Pradesh (UP), Punjab (PNB), Haryana (HAR), Madhya Pradesh (MP), Rajasthan (RAJ), Bihar (BIR), Gujarat (GUJ), and Maharashtra (MAH) (Fig. 1). Together, these eight Indian states accounted for ~96% of the total wheat production and ~93% of India's total wheat harvested area over 1986–2015. Therefore, these eight major wheat-producing Indian states were considered in this study. The general description of the study area India is presented in the Supplementary Material (SM) file.

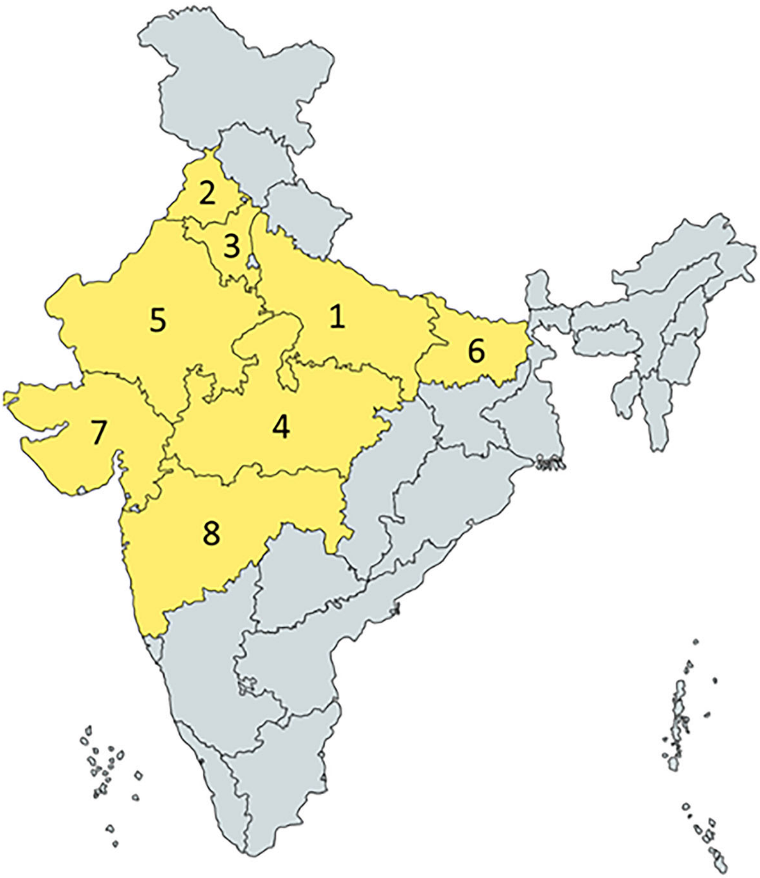

Fig. 1 Major wheat producing Indian states (in descending order): 1. Uttar Pradesh (UP), 2. Punjab (PNB), 3. Haryana (HAR), 4. Madhya Pradesh (MP), 5. Rajasthan (RAJ), 6. Bihar (BIR), 7. Gujarat (GUJ), and 8. Maharashtra (MAH). These eight states together accounted for ~96% of the total wheat production and ~93% of the total wheat harvested area in India during the study period (1986–2015)

2.2 Climate Data

Ten climate variables were used in this study – maximum temperature, mean temperature, minimum temperature, diurnal temperature range, total precipitation, cloud cover, wet day frequency, vapor pressure, potential evapotranspiration, and vapor pressure deficit. We obtained the state-wise monthly datasets for nine climate variables (except vapor pressure deficit) for all the major wheat-producing Indian states (Fig. 1) from the global gridded datasets of Climate Research Unit (CRU), University of East Anglia, UK (http://www.cru.uea.ac.uk/). Each state's climate data was extracted from the CRU data by calculating an average of all grids falling in the state using a shapefile of the respective state. CRU provides high-resolution monthly climate data on a 0.5° latitude by 0.5° longitude grid covering all land surfaces (except Antarctica) from 1901 to 2018 (Harris et al. 2020). Climate data is derived by the interpolation of climate anomalies from the extensive weather station observations using angular distance weighting (ADW). CRU climate data has been widely used in various climate change impact studies (Bapuji Rao et al. 2014; Duncan et al. 2016).

After extracting monthly climate variables, we estimated state-wise seasonal climate variables matching with wheat growing season during 1986–2015. To measure seasonal climate variables, we identified the wheat-growing season in Indian states sourcing the wheat crop data from the Ministry of Agriculture and Farmers' Welfare, Government of India. *Rabi* season (November–March) is the growing period for wheat crop in India, and wheat is commonly sowed from November to December and harvested between March to April in India. Therefore, monthly climate data from November to March were used for the present study.

We averaged monthly climate variables from November to March (except for total precipitation and wet day frequency) to calculate state-wise seasonal maximum temperature (*Tmx*), seasonal mean temperature (*Tmp*), seasonal minimum temperature (*Tmn*), seasonal diurnal temperature range (*Dtr*), seasonal cloud cover (*Cld*), seasonal vapor pressure (*Vap*), and seasonal potential evapotranspiration (*Pet*) for wheat-growing Indian states from 1986 to 2015. Monthly total precipitations and monthly wet day frequencies were added to calculate seasonal total precipitation (*Pre*) and seasonal wet day frequency (*Wet*).

Seasonal vapor pressure deficit (*Vpd*) is computed using the following equations (Cai et al. 2019):

$$Vpd = Svap - Vap \tag{1}$$

$$Svap = 6.108 \cdot e^{\left(\frac{17.27 \times Tmp}{237.3 + Tmp}\right)} \tag{2}$$

where *Svap* is the saturated vapor pressure, *Vap* is the vapor pressure, and *Tmp* is mean temperature. Table 1 shows these ten seasonal climate variables with their units.

Based on the domain knowledge (Cai et al. 2019), ten climate variables were grouped into the following three categories to conduct climate data analysis: (1) Temperature variables (*Tmx*, *Tmp*, *Tmn*, *Dtr*); (2) Water supply variables (*Pre*, *Cld*, *Wet*); and (3) Water demand variables (*Vpd*, *Vap*, *Pet*).

Table 1 Seasonal climate variables during wheat growing *Rabi* season (November to March) used in the study

	Seasonal variable during *Rabi* season	Abbreviation	Units
Temperature variables	Maximum temperature	*Tmx*	°C
	Mean temperature	*Tmp*	°C
	Minimum temperature	*Tmn*	°C
	Diurnal temperature range	*Dtr*	°C
Water supply variables	Total Precipitation	*Pre*	mm
	Cloud cover	*Cld*	%
	Total wet day frequency	*Wet*	days
Water demand variables	Vapor pressure deficit	*Vpd*	hPa
	Vapor pressure	*Vap*	hPa
	Potential evapotranspiration	*Pet*	mm/day

2.3 Wheat Data

We obtained annual wheat yield data of eight major wheat-producing Indian states (Fig. 1) for the recent 30 years (1986–2015) from the Ministry of Agriculture and Farmers' Welfare, Government of India (https://eands.dacnet.nic.in/). Crop statistics on the wheat harvested area and wheat production for major wheat-producing Indian states from 1986 to 2015 were also collected from the Ministry of Agriculture and Farmers' Welfare, Government of India. The quality of the wheat yield data was verified by estimating wheat yields (kg/ha) as the ratio of wheat production (tonnes) and wheat harvested area (ha) in the respective states.

2.4 Statistical Analysis

After the computation of ten seasonal climatic variables for Indian states, we identified the changes and trends in seasonal climate variables in Indian states over 1986–2015 using linear regressions and significance tests. The following linear regression model was fitted for each *Rabi* season climate variable across each Indian state:

$$\text{climate variable} = \alpha_0 + (\alpha_1 \times \text{year}) + \varepsilon \tag{3}$$

Here, α_0, α_1, and ε are intercept, regression coefficient, and the error term, respectively. The sign (negative or positive) and value of the regression coefficient (α_1) determines the nature of the trend and magnitude of change, respectively. The significance test (*p* value) detects the significance level in the trend. Trends were classified as statistically significant for $p < 0.1$. We used state-wise trends because a state is the most important administrative unit under India's federal structure.

After analyzing the climatic trends over wheat-growing Indian areas during the wheat-growing period, we assessed the impact of climate variables on wheat yields. For this, we separated the climate-induced yield from the actual crop yield by linear detrending. The wheat yield data for each Indian state was fitted into the following linear regression model:

$$\text{wheat yield} = \beta_0 + (\beta_1 \times \text{year}) + \varepsilon \tag{4}$$

Here, β_0, β_1, and ε are intercept, regression coefficient, and the error term, respectively. So, climate-induced yields (yield residuals) were calculated by subtracting trend yields from each Indian state's actual yields for each year.

After linear detrending of wheat yield data, we computed Pearson's correlation coefficients between the climate-induced wheat yields and ten seasonal climate variables. These correlations (followed by the significance tests) provided us the nature and strength of association between climate variables and wheat yields across Indian states. Moreover, the calculated correlations also helped identify the most significant climate variable affecting wheat yield in Indian states. So, we selected the climate variables with the maximum absolute correlation with wheat yield in each Indian state. In the next step, we regressed this selected climate variable as the predictor/independent variable with wheat yield as the response/dependent variable using the following linear regression model:

$$\text{wheat yield} = \alpha + (\beta \times \text{selected climate variable}) + \gamma t + \varepsilon \tag{5}$$

Here, α is the constant of the regression, ε is the error term, and t refers to years. β is the regression coefficient (or the regression line's slope) that captures the magnitude of the impact on wheat yield for one unit increase in the predictor climate variable. We developed the above regression model for each major wheat-producing Indian state. We also assessed the accuracy of the regression model in predicting wheat yield by calculating the coefficient of determination (R^2). We used the following equations to calculate the actual impact of changing trend in climate variable on wheat yield over the study period:

$$\text{Impact on wheat yield}\left(\frac{\text{kg}}{\text{ha}}\right) = (\beta) \times (\alpha_1) \times (30) \tag{6}$$

$$\text{Impact on wheat yield }(\%) = \frac{\text{Impact on wheat yield}\left(\frac{\text{kg}}{\text{ha}}\right)}{\text{wheat yield in 1986}} \times 100 \tag{7}$$

Solar radiation is another important variable in the context of crop yields. Therefore, the impact of solar radiation on wheat yield was also investigated in this study. Additionally, we performed multiple regression analysis by employing temperature, water supply, and water demand variables together as explanatory variables in the models. The details of these two aspects, i.e., the impact of solar radiation on wheat yield and multiple regression methods, are presented in the Supplementary Material (SM) file. All computations, including correlation coefficients and setting up regression models, were performed using R v 3.5.1 (R Development Core Team 2018).

3 Results and Discussion

3.1 Changing Climate Variables

3.1.1 Temperature Variables

We considered four temperature variables in this study: *Tmx*, *Tmp*, *Tmn*, and *Dtr*. Figure 2 shows the temporal trends in *Tmx*, *Tmp*, *Tmn*, and *Dtr* for eight major wheat-producing Indian states during 1986–2015. It shows that *Tmx*, *Tmp*, and *Tmn* have increased in all eight Indian states (Fig. 2a–c), whereas *Dtr* has increased in seven Indian states except Maharashtra (Fig.

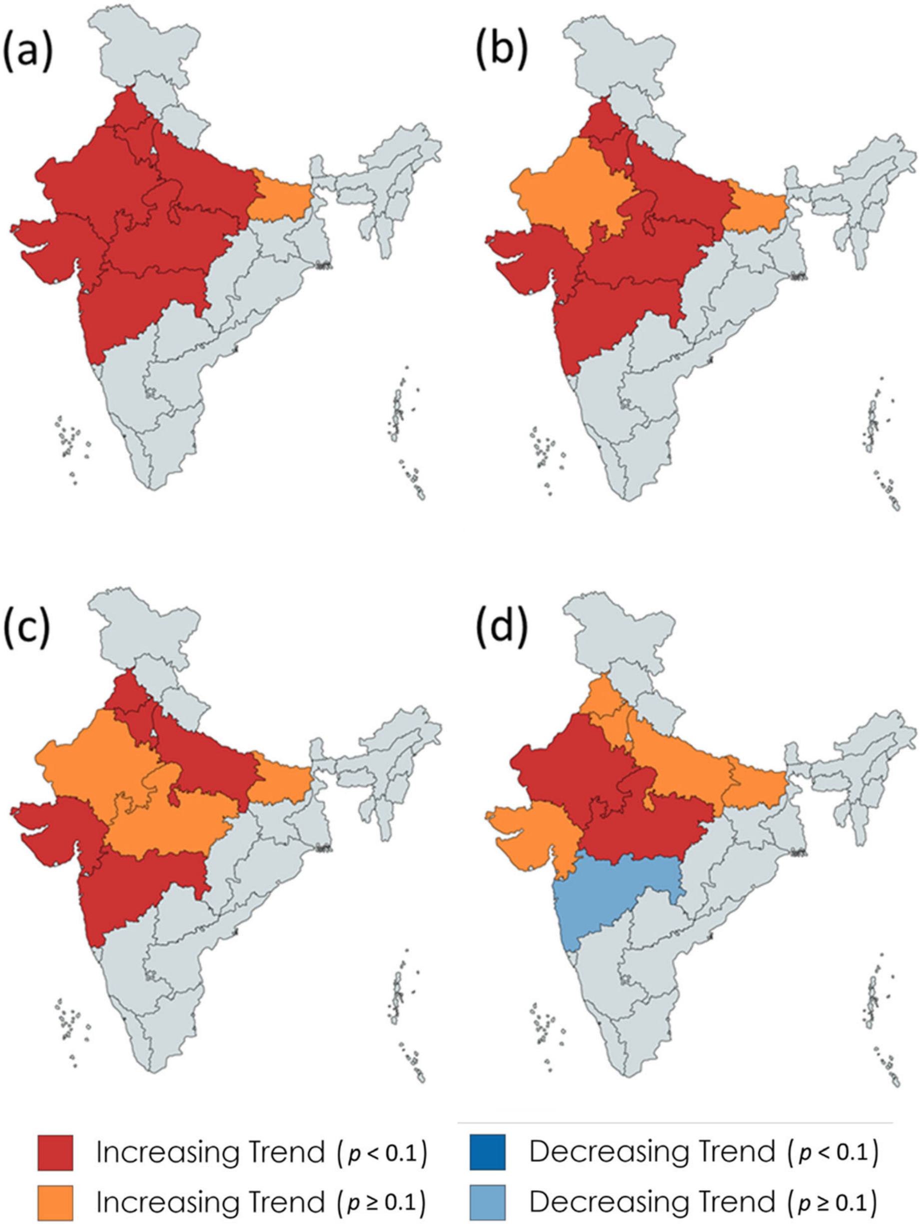

Fig. 2 Trends in temperature related seasonal variables (**a**) maximum temperature, (**b**) mean temperature, (**c**) minimum temperature, and (**d**) diurnal temperature range during *Rabi* season over 1986–2015

2d). Table 2 presents the magnitude of change in temperature variables over 1986–2015 for Indian states.

Figure 2a reveals that an increase in *Tmx* is statistically significant at the 10% level ($p < 0.10$) in seven Indian states. The statistically significant ($p < 0.10$) rise in *Tmx* is 0.32 °C per 10-year in Uttar Pradesh ($p = 0.023$), 0.24 °C per 10-year in Punjab ($p = 0.074$),

Table 2 Magnitude of change in temperature, water supply, and water demand variables over 1986–2015 across Indian states

	Climate Variable	Uttar Pradesh	Punjab	Haryana	Madhya Pradesh	Rajasthan	Bihar	Gujarat	Maharashtra
Temperature variables	*Tmx* (°C per 10-year)	0.32**	0.24*	0.31**	0.26**	0.27**	0.20	0.21**	0.22**
	Tmp (°C per 10-year)	0.28**	0.22**	0.24**	0.21*	0.17	0.14	0.21**	0.24**
	Tmn (°C per 10-year)	0.24**	0.21**	0.18*	0.16	0.06	0.09	0.20*	0.25**
	Dtr (°C per 10-year)	0.08	0.04	0.13	0.11*	0.21*	0.11	0.004	−0.03
Water supply variables	*Pre* (mm per 100-year)	−28.3	−46.1	−31.3	3.8	2.0	−24.7	32.5	34.8
	Cld (% per 10-year)	0.58	4.08***	3.69***	0.09	1.16***	−0.51	0.30	0.96**
	Wet (days per 100-year)	−2.76	−3.43	−3.10	1.99	−0.33	−1.83	1.35	2.19
Water demand variables	*Vpd* (hPa per 10-year)	0.71***	0.23**	0.33***	0.58***	0.28**	0.56***	0.31***	0.24**
	Vap (hPa per 10-year)	−0.32***	0.05	−0.01	−0.25***	−0.04	−0.35***	0.05	0.20*
	Pet (mm/day per 10-year)	0.04***	0.002	0.01	0.03**	0.02*	0.03*	0.03**	0.01

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

0.31 °C per 10-year in Haryana ($p = 0.047$), 0.26 °C per 10-year in Madhya Pradesh ($p = 0.034$), 0.27 °C per 10-year in Rajasthan ($p = 0.042$), 0.21 °C per 10-year in Gujarat ($p = 0.046$), and 0.22 °C per 10-year in Maharashtra ($p = 0.019$). The rise in *Tmx* is not statistically significant in Bihar (0.20 °C per 10-year, $p = 0.166$). No Indian state shows a decreasing trend in *Tmx*. Figure 2b shows that increase in *Tmp* is statistically significant at 10% level ($p < 0.10$) in six Indian states – Uttar Pradesh (0.28 °C per 10-year, $p = 0.020$), Punjab (0.22 °C per 10-year, $p = 0.046$), Haryana (0.24 °C per 10-year, $p = 0.045$), Madhya Pradesh (0.21 °C per 10-year, $p = 0.067$), Gujarat (0.21 °C per 10-year, $p = 0.047$), and Maharashtra (0.24 °C per 10-year, $p = 0.020$). The increase in *Tmp* is not statistically significant in Rajasthan (0.17 °C per 10-year, $p = 0.121$) and Bihar (0.14 °C per 10-year, $p = 0.203$). Figure 2c shows that *Tmn* increases significantly at a 10% level ($p < 0.10$) in five Indian states. The magnitude of increase in *Tmn*, statistically significant at 10% level ($p < 0.10$), is 0.24 °C per 10-year in Uttar Pradesh ($p = 0.024$), 0.21 °C per 10-year in Punjab ($p = 0.037$), 0.18 °C per 10-year in Haryana ($p = 0.091$), 0.20 °C per 10-year in Gujarat ($p = 0.063$), and 0.25 °C per 10-year in Maharashtra ($p = 0.027$). The rising *Tmn* trend is not statistically significant in Madhya Pradesh (0.16 °C per 10-year, $p = 0.163$), Rajasthan (0.06 °C per 10-year, $p = 0.562$), and Bihar (0.09 °C per 10-year, $p = 0.360$).

Our findings on temperature variables show a significant rise in *Tmx*, *Tmp*, and *Tmn* for wheat-producing Indian states. These rising trends are comparable with the previous studies in the literature, such as Rao et al. (2015), who also reported an increase in minimum temperature (0.32 °C per 10-year) and maximum temperature (0.28 °C per 10-year) for India overall. The differentiating aspect of the present study (*vs*. Rao et al. 2015) is the reporting of state-wise wheat-growing *Rabi* season *Tmx*, *Tmp*, and *Tmn* trends for Indian states.

Analyzing the magnitude of increase in *Tmx*, *Tmp*, and *Tmn*, some crucial observations are as follows:

- The magnitude of *Tmx* rise is higher than the *Tmp* rise in seven Indian states: Uttar Pradesh (0.04 °C per 10-year), Punjab (0.02 °C per 10-year), Haryana (0.07 °C per 10-year), Madhya Pradesh (0.05 °C per 10-year), Rajasthan (0.10 °C per 10-year), Bihar (0.06 °C per 10-year), and Gujarat (0.001 °C per 10-year); whereas, *Tmx* rise is lower than the *Tmp* rise in only one Indian state, Maharashtra (0.02 °C per 10-year).
- Similarly, the magnitude of increase in *Tmx* is higher than the increase in *Tmn* in Uttar Pradesh (0.08 °C per 10-year), Punjab (0.03 °C per 10-year), Haryana (0.13 °C per 10-year), Madhya Pradesh (0.10 °C per 10-year), Rajasthan (0.21 °C per 10-year), Bihar (0.11 °C per 10-year), and Gujarat (0.01 °C per 10-year); and *Tmx* rise is lower than the increase in *Tmn* in Maharashtra (0.03 °C per 10-year).
- This reveals that *Tmx* rise (daytime warming) is occurring at a faster rate covering major wheat-producing Indian states than *Tmn* rise (nighttime warming).

Diurnal temperature range (*Dtr*) is defined as the temperature difference between the highest and lowest temperature during a day a crop is exposed. Figure 2d shows that *Dtr* has increased significantly (at $p < 0.1$) in two Indian states: Madhya Pradesh (0.11 °C per 10-year, $p = 0.073$) and Rajasthan (0.21 °C per 10-year, $p = 0.056$). Rise in *Dtr* is not statistically significant in Uttar Pradesh (0.08 °C per 10-year, $p = 0.222$), Punjab (0.04 °C per 10-year, $p = 0.631$), Haryana (0.13 °C per 10-year, $p = 0.219$), Bihar (0.11 °C per 10-year, $p = 0.260$), and Gujarat (0.004 °C per 10-year, $p = 0.935$). Maharashtra shows a decreasing but statistically non-significant trend in *Dtr* (−0.03 °C per 10-year, $p = 0.552$).

Overall, our results reveal an increasing trend in *Dtr* for the 1986–2015 period in seven out of eight major wheat-producing Indian states. This is due to a much more rapid increase in *Tmx* than *Tmn* during the *Rabi* period. Earlier, Jaswal et al. (2016) reported uneven changes in India's diurnal temperature range across regions and seasons. Vinnarasi et al. (2017) reported rising but highly local trends in the diurnal temperature range and attributed this to a rise in both minimum and maximum temperatures but a faster rise in maximum temperature than minimum temperature. Our results align with Vinnarasi et al. (2017) and are in contrast with Vose et al. (2005) and Rao et al. (2015), who reported decreasing trends for the diurnal temperature range.

Figure 3 displays the spatial distribution of *Tmx*, *Tmp*, *Tmn*, and *Dtr* averaged over 30 years (1986–2015). The average *Tmx* ranges from 24.2 °C (Punjab) to 32.2 °C (Maharashtra). Average *Tmp* ranges from 17 °C (Punjab) to 24.4 °C (Maharashtra). Average *Tmn* ranges from 9.9 °C (Punjab) to 16.6 °C (Maharashtra). It indicates that temperatures (during the wheat growing season) are relatively higher in Maharashtra and Gujarat. Punjab is the coldest state during the wheat growing season. This spatial pattern has essential consequences for wheat production. As discussed later in section 3.2.1 'Impact of Temperature Variables', the negative impact of rising temperatures is highly significant in Gujarat and Maharashtra, but is not significant in Punjab.

3.1.2 Water Supply Variables

We considered three water supply related climate variables in this study: *Pre*, *Cld*, and *Wet*. Figure 4 shows *Pre*, *Cld*, and *Wet* temporal trends for eight major wheat-producing Indian states during 1986–2015. Table 2 presents the magnitude of change in water supply variables over 1986–2015 for Indian states.

Figure 4a shows that *Pre* trends are not significant in Indian states. *Pre* is decreasing non-significantly in four Indian states and increasing non-significantly in four Indian states. The magnitude of decrease in precipitation is 28.3 mm per 100-year ($p = 0.522$) in Uttar Pradesh, 46.1 mm per 100-year ($p = 0.550$) in Punjab, 31.3 mm per 100-year ($p = 0.508$) in Haryana, and 24.7 mm per 100-year ($p = 0.512$) in Bihar. On the other hand, *Pre* is increasing non-significantly in Madhya Pradesh (3.8 mm per 100-year, $p = 0.953$), Rajasthan (2.0 mm per 100-year, $p = 0.942$), Gujarat (32.5 mm per 100-year, $p = 0.242$), and Maharashtra (34.8 mm per 100-year, $p = 0.573$). Recently, Praveen et al. (2020) have analyzed rainfall trends in India using machine learning approaches. The authors have reported a negative trend for winter rainfall in Bihar, Uttar Pradesh, Haryana, and Punjab. Figure 4b reveals that *Cld* increases significantly in four Indian states and increases non-significantly in three Indian states. The magnitude of increase in *Cld* is statistically significant at 1% level ($p < 0.01$) in Punjab (4.08% per 10-year, $p = 0.000001$), Haryana (3.69% per 10-year, $p = 0.00001$), Rajasthan (1.16% per 10-year, $p = 0.005$), and Maharashtra (0.96% per 10-year, $p = 0.040$). The rising *Cld* trend is statistically not significant in Uttar Pradesh (0.58% per 10-year, $p = 0.127$), Madhya Pradesh (0.09% per 10-year, $p = 0.846$), and Gujrat (0.30% per 10-year, $p = 0.255$). Bihar shows a statistically non-significant decreasing trend in *Cld* (0.51% per 10-year and $p = 0.327$).

Figure 4c reveals that *Wet* is decreasing non-significantly in five Indian states: Uttar Pradesh (2.8 days per 100-year, $p = 0.404$), Punjab (3.4 days per 100-year, $p = 0.545$), Haryana (3.1 days per 100-year, $p = 0.317$), Rajasthan (0.3 days per 100-year, $p = 0.844$), and Bihar (1.8 days per 100-year, $p = 0.343$). On the other hand, *Wet* is increasing non-significantly in Madhya Pradesh (2 days per 100-year, $p = 0.641$), Gujarat (1.4 days per 100-

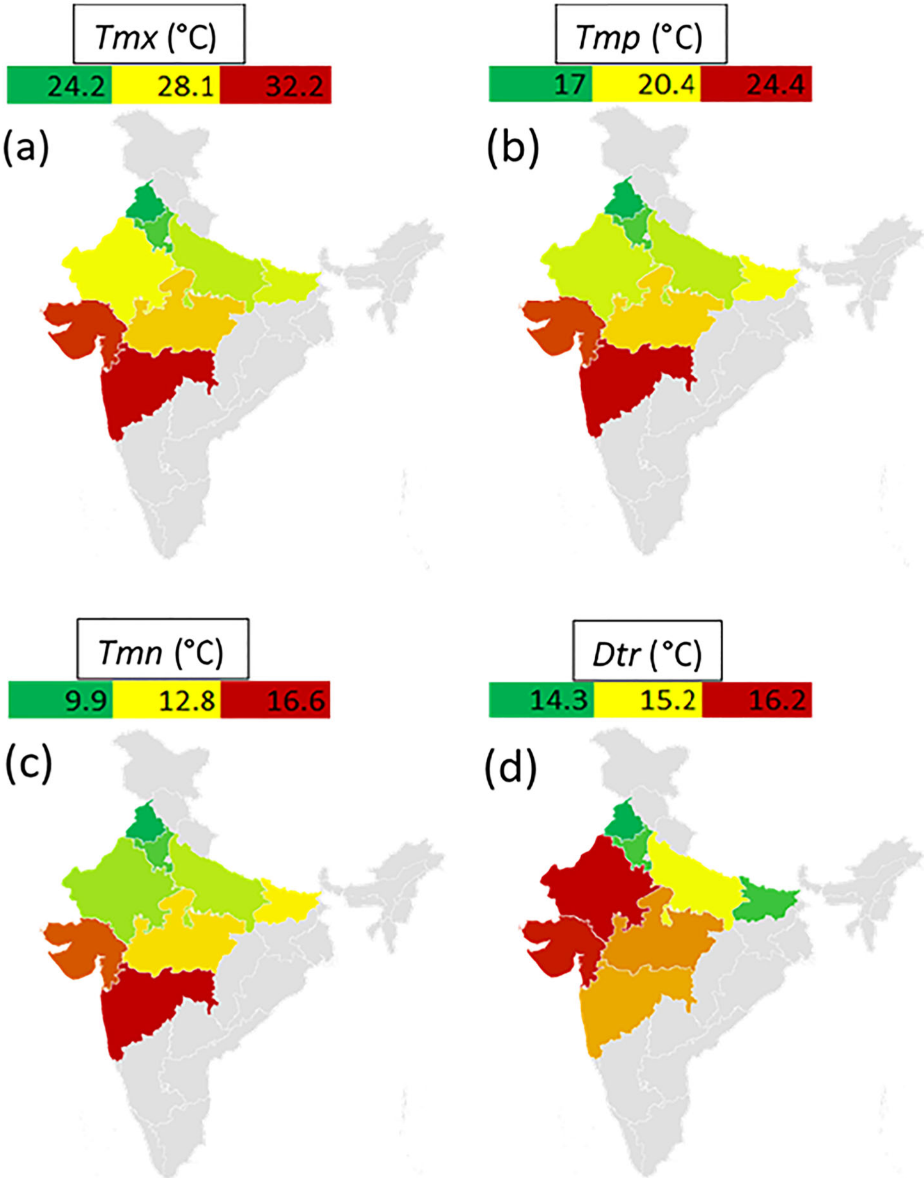

Fig. 3 Spatial distribution of (**a**) maximum temperature, (**b**) mean temperature, (**c**) minimum temperature, and (**d**) diurnal temperature range across eight major wheat producing Indian states. Climate variables *Tmx*, *Tmp*, *Tmn*, and *Dtr* are averaged over the study period 1986–2015

year, $p = 0.260$), and Maharashtra (2.2 days per 100-year, $p = 0.519$). Different sets of temporal and spatial data lead to different findings. Earlier, Kumar and Jain (2011) investigated the trends in annual rainy days (1951–2004) across 22 river basins in India. The authors found increasing trends in four river basins, decreasing trends in 15 river basins, and no trends in three river basins. Similarly, Das et al. (2014) investigated trends in rainy days during the Indian Monsoon (1971–2005) across meteorological subdivisions of India. The

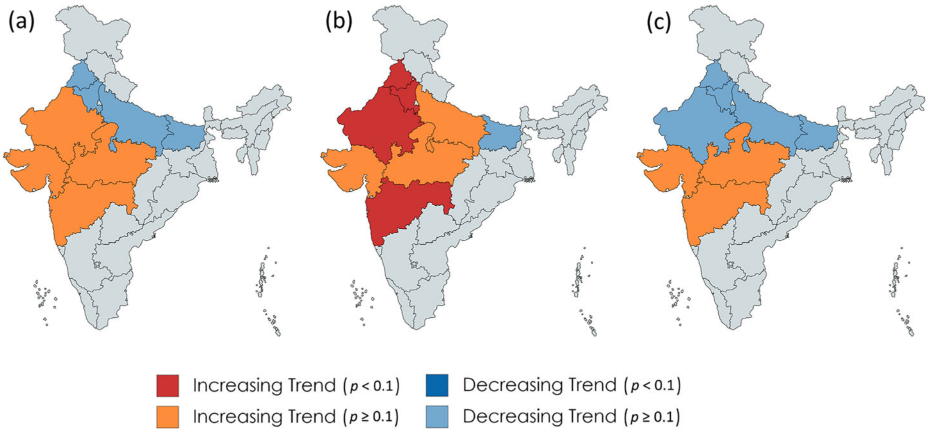

Fig. 4 Trends in water supply related seasonal variables (**a**) precipitation, (**b**) cloud cover, and (**c**) wet day frequency during *Rabi* season over 1986–2015

authors reported a statistically significant increasing trend over the Deccan Plateau, a significantly decreasing trend in the western arid region, and a decreasing trend in India's north and central plains.

Examining trends in *Pre*, *Cld*, and *Wet*, some crucial observations are made: (1) Rajasthan shows a decrease in *Wet* and an increase in *Pre*, indicating more rain on fewer rainy days. This reflects a trend towards heavier and shorter bursts of rainfall. This is not a good sign because heavier rainfalls can dislodge wheat grains from their stalk. (2) There is an increase in *Cld* but a decrease in *Pre* in Uttar Pradesh, Punjab, and Haryana. This indicates an increase in stratus clouds or non-rain-making clouds over Uttar Pradesh, Punjab, and Haryana. Though clouds play a critical role in Indian wheat-growing states climate by warming/cooling the earth's surface and recycling water, their variability remains most uncertain.

Figure 5 shows the spatial distribution of *Pre*, *Cld*, and *Wet* averaged over 30 years (1986–2015). Gujarat and Rajasthan receive the least rainfall during the wheat-growing period. Punjab and Haryana receive comparatively more rainfall due to western disturbances. Average

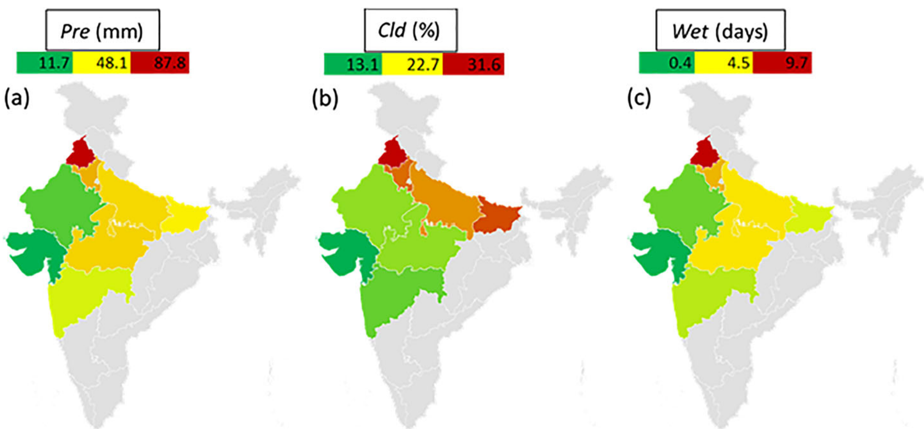

Fig. 5 Spatial distribution of (**a**) precipitation, (**b**) cloud cover, and (**c**) wet day frequency across eight major wheat producing Indian states. Climate variables *Pre*, *Cld*, and *Wet* are averaged over the study period 1986–2015

Pre ranges from 11.7 mm (Gujarat) to 87.8 mm (Punjab). Similarly, cloud cover and wet day frequency (rain days) during the wheat growing season are highest in Punjab and lowest in Gujarat. Average *Cld* ranges from 13.1% (Gujarat) to 31.6% (Punjab). Average *Wet* ranges from 0.4 days (Gujarat) to 9.7 days (Punjab) across major wheat-producing Indian states.

3.1.3 Water Demand Variables

We considered three water demand related climate variables in this study: *Vpd*, *Vap*, and *Pet*. Figure 6 shows the temporal trends in *Vpd*, *Vap*, and *Pet* for eight major wheat-producing Indian states during 1986–2015. Table 2 presents the magnitude of change in water demand variables over 1986–2015 for Indian states.

Figure 6a reveals that *Vpd* has increased significantly at a 10% level ($p < 0.10$) in all studied eight Indian states. The magnitude of rise in *Vpd* is 0.71 hPa per 10-year in Uttar Pradesh ($p = 0.0001$), 0.23 hPa per 10-year in Punjab ($p = 0.012$), 0.33 hPa per 10-year in Haryana ($p = 0.003$), 0.58 hPa per 10-year in Madhya Pradesh ($p = 0.0003$), 0.28 hPa per 10-year in Rajasthan ($p = 0.015$), 0.56 hPa per 10-year in Bihar ($p = 0.004$), 0.31 hPa per 10-year in Gujarat ($p = 0.006$), and 0.24 hPa per 10-year in Maharashtra ($p = 0.01$). Our results are comparable with recent studies on the vapor pressure deficit trends at global or regional scales. For example, Yuan et al. (2019) reported a sharp increase in the global vapor pressure deficit from the late 1990s. The authors also projected a continuous rise in the global vapor pressure deficit throughout the current century. Barkhordarian et al. (2019) reported a recent systematic increasing trend in vapor pressure deficit over tropical South America. Zhang et al. (2017) investigated the spatial and temporal trends in vapor pressure deficit in China and showed that it has increased during the growing period of rice, wheat, maize, and soybean.

Figure 6b shows that *Vap* has decreased in five Indian states over the study period (1986–2015). The decrease in *Vap* is statistically significant at a 10% level ($p < 0.1$) in three Indian states: Uttar Pradesh (0.32 hPa per 10-year, $p = 0.00001$), Madhya Pradesh (0.25 hPa per 10-year, $p = 0.0001$), and Bihar (0.35 hPa per 10-year, $p = 0.00002$). Haryana (0.01 hPa per 10-year, $p = 0.890$) and Rajasthan (0.04 hPa per 10-year, $p = 0.487$) show a statistically non-

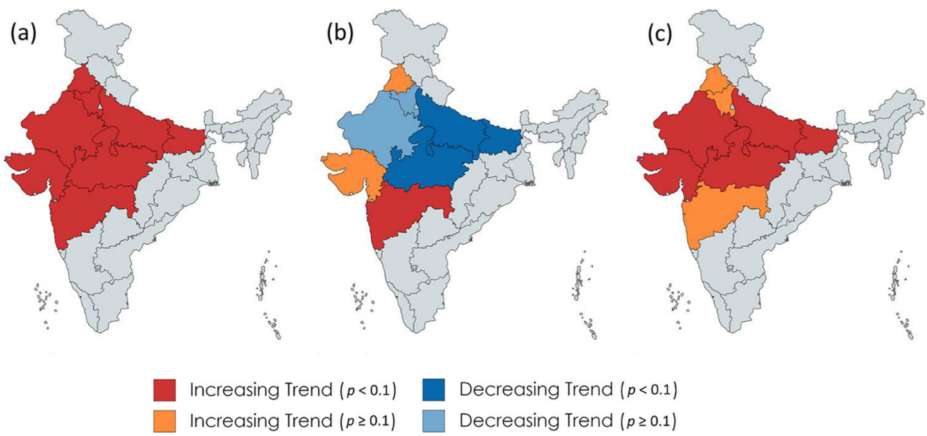

Fig. 6 Trends in water demand related seasonal variables (**a**) vapor pressure deficit, (**b**) vapor pressure, and (c) potential evapotranspiration during *Rabi* season over 1986–2015

significant decrease in *Vap*. On the other hand, an increase in *Vap* is statistically significant at the 10% level ($p < 0.1$) in Maharashtra (0.20 hPa per 10-year, $p = 0.051$). *Vap* increase is statistically on significant in Punjab (0.05 hPa per 10-year, $p = 0.365$) and Gujarat (0.05 hPa per 10-year, $p = 0.526$). Figure 6c reveals that *Pet* is increasing in all the eight Indian states. The magnitude of rise in *Pet* is statistically significant at 10% level ($p < 0.10$) in five Indian states: Uttar Pradesh (0.04 mm/day per 10-year, $p = 0.007$), Madhya Pradesh (0.03 mm/day per 10-year, $p = 0.014$), Rajasthan (0.02 mm/day per 10-year, $p = 0.074$), Bihar (0.03 mm/day per 10-year, $p = 0.066$), and Gujarat (0.03 mm/day per 10-year, $p = 0.018$). The rise in *Pet* is not statistically significant in Punjab (0.002 mm/day per 10-year, $p = 0.885$), Haryana (0.01 mm/day per 10-year, $p = 0.366$), and Maharashtra (0.01 mm/day per 10-year, $p = 0.337$). No Indian state shows a decreasing trend in *Pet*. These increasing trends in potential evapotranspiration in Indian states are consistent with previous literature. Using global climate datasets, Liu et al. (2020) reported that the average potential evapotranspiration has significantly increased across crops' harvested areas (wheat, rice, maize, and soybean) over 1961–2014. Blyth (2019) observed a constant increase in evapotranspiration across Great Britain from 1961 to 2015. An increasing trend for potential evapotranspiration in Northwest China between 2021 and 2100 has already been projected (Qin et al. 2021). Potential evapotranspiration is an important component of the hydrological cycle, and these increasing evapotranspiration trends might impact water availability and agricultural production worldwide.

When analyzing trends in *Vpd*, *Vap*, and *Pet*, some critical observations are: (1) *Vpd* and *Pet* trends are of similar nature (increasing trends) in all states. As the vapor pressure deficit rises, crops tend to draw more water from their roots. So, vapor pressure deficit has a linear relationship with evapotranspiration and other measures of evaporation. (2) The results also show that a rise in temperatures is positively correlated with an increase in *Vpd*. This trend is consistent with Will et al. (2013), who pointed out that temperature rise might lead to increased vapor pressure deficit, further resulting in higher transpiration and water use, thus causing faster mortality in plants during droughts.

Figure 7 shows the spatial distribution of *Vpd*, *Vap*, and *Pet* averaged over 30 years (1986–2015). *Vpd*, *Vap*, and *Pet* values during the wheat-growing season are relatively higher in the Indian states of Maharashtra and Gujarat. Average *Vpd* ranges from 8.1 hPa (Punjab) to

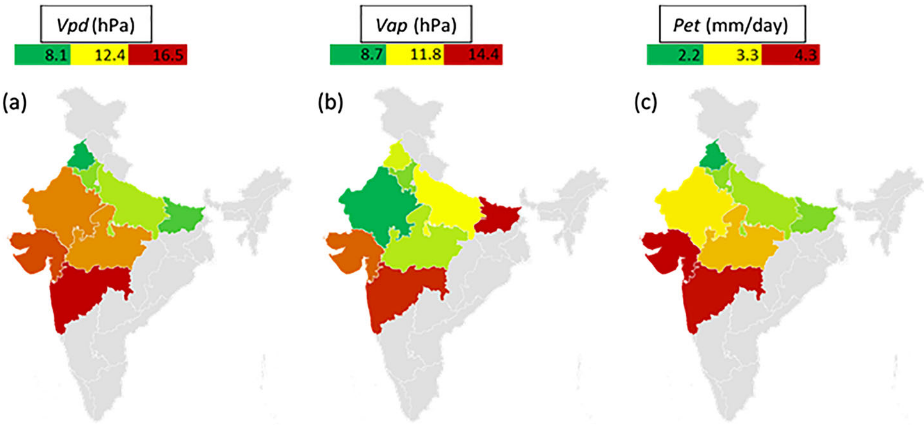

Fig. 7 Spatial distribution of (**a**) vapor pressure deficit, (**b**) vapor pressure, and (**c**) potential evapotranspiration across eight major wheat producing Indian states. Climate variables *Vpd*, *Vap*, and *Pet* are averaged over the study period 1986–2015

16.5 hPa (Maharashtra). Average *Vap* ranges from 8.7 hPa (Rajasthan) to 14.4 hPa (Bihar). Average *Pet* ranges from 2.2 mm/day (Punjab) to 4.3 mm/day (Gujarat) across major wheat-producing Indian states. This spatial pattern has an important impact on wheat yields in these states, as discussed in the next section.

3.2 Impact on Wheat Yields

3.2.1 Impact of Temperature Variables

Indian wheat, due to its significance for global food security, is an ideal crop for investigating climate variability impacts. We detrended the wheat yield datasets to estimate the climate-induced wheat yields (yield residuals) as discussed in the 'Materials and Methods' section. Figure 8 shows the climate-induced wheat yields across Indian states from 1986 to 2015. These climate-induced wheat yields were used for performing correlation analysis with climate variables.

Figure 9 presents the correlations between wheat yields and temperature variables *Tmx*, *Tmp*, *Tmn*, and *Dtr*. It shows that: a rise in *Tmx* and *Tmp* harms wheat yield in seven Indian states (Fig. 9a, b); a rise in *Tmn* harms wheat yield in all eight Indian states (Fig. 9c); whereas a rise in *Dtr* has a negative impact in four Indian states (Fig. 9d). For *Tmp* and *Tmn*, three Indian states - Bihar, Gujarat, and Maharashtra - show statistically significant negative impacts ($p < 0.1$). These three Indian states accounted for ~13.8% of the wheat harvested area (corresponds to ~3.7 million ha) in India during 1986–2015. For *Tmx* (Fig. 9a), one Indian state – Gujarat – shows a statistically significant adverse impact ($p < 0.1$). For *Dtr*, four Indian states show a negative but non-significant impact of rising *Dtr* on wheat yields, three Indian states show a positive but non-significant impact of rising *Dtr* on wheat yields, and Maharashtra shows a statistically significant ($p < 0.1$) positive impact of *Dtr* (Fig. 9d).

Temperature rise reduces crop productivity in warm areas, but it might benefit wheat yields in cool areas (Ye et al. 2021). Our results provide strong evidence for a negative impact of temperature rise on wheat yields over large wheat-producing Indian areas. None of the major wheat-producing Indian states shows a significant positive impact of *Tmx*, *Tmp*, and *Tmn* on wheat yield. Earlier, Asseng et al. (2011) reported that warming accelerates wheat plants' metabolic rate and decelerates photosynthesis. Temperature rise has reduced wheat yields in 145 major wheat-producing Indian districts (Madhukar et al. 2021a). Lobell et al. (2012) mentioned that heat stress causes significant hastening of wheat senescence, early flowering/

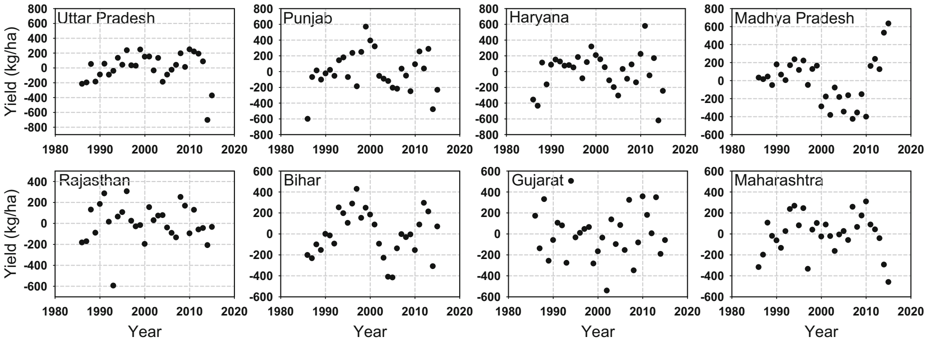

Fig. 8 Climate-induced wheat yields in Indian states from 1986 to 2015

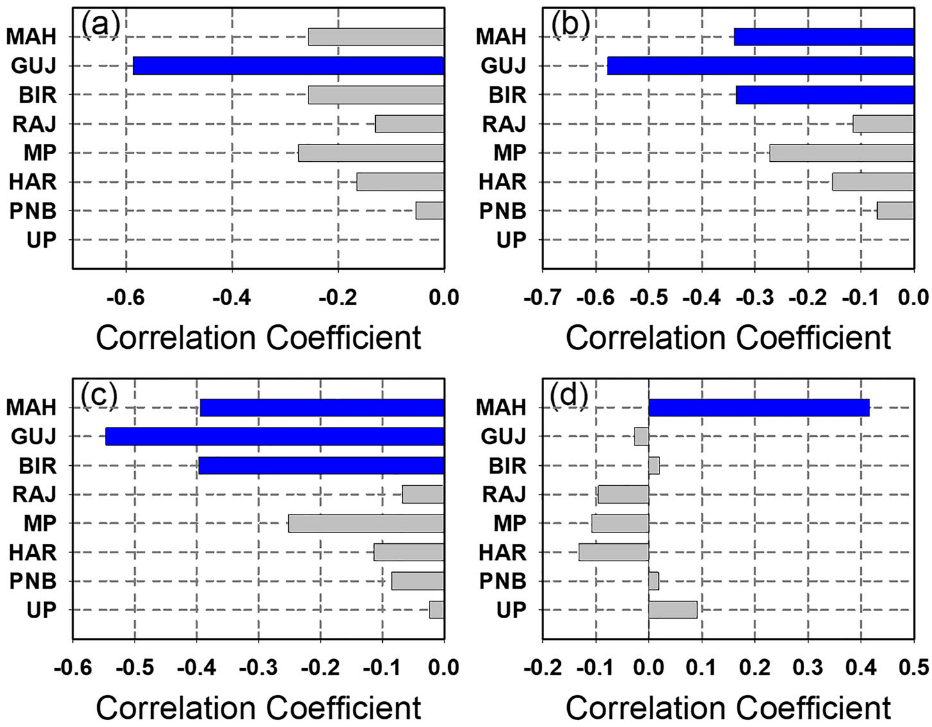

Fig. 9 Correlations between wheat yield and temperature variables (**a**) maximum temperature, (**b**) mean temperature, (**c**) minimum temperature, and (**d**) diurnal temperature range. Bars in blue color show significant correlations at $p < 0.1$

shortening of the grain fill period, thereby it reduces wheat yields. Temperature rise causes various physiological and morphological changes in wheat crops. Temperature rise reduces photosynthetic productivity in wheat plants and hastens leaf senescence (Feng et al. 2014). It changes water relations in wheat crops, reducing wheat crop water-use efficiency (Akter and Islam 2017). Wheat plant relative water content and water potential decrease with a rise in leaf temperature and increased transpiration (Farooq et al. 2009). Increased soil temperature alters soil physical properties adversely and leads to loss of soil moisture. Temperature rise causes oxidative stress in wheat crops, deactivating chloroplast enzymes and reducing the chlorophyll content (Caverzan et al. 2016).

Our findings are consistent with these previous studies and further build robust statistical evidence for the negative impact of warming on wheat yield in the Indian region. Moreover, our study reveals a varying negative impact of warming across Indian states as negative impacts are more pronounced in Gujarat and Maharashtra, and less pronounced in Punjab, Haryana and Uttar Pradesh. In earlier section, we discussed that the temperatures (during the wheat growing season) are relatively higher in Maharashtra and Gujarat and relatively lower in Punjab and Haryana. This spatial distribution of temperature is one of the reasons for a heterogeneous temperature impact on wheat. Second, the Indian states of Punjab, Haryana, and Uttar Pradesh have also mitigated the negative impact of warming by adaptation measures such as irrigation (Zaveri and Lobell 2019). Analyzing the relative impacts of *Tmn* and *Tmx*, our study also highlights the varying impacts of *Tmn* and *Tmx* in Indian states. *Tmn* is negatively and significantly impacting three Indian states (more extensive area, ~3.7 million ha), greater than *Tmx* that negatively impacts one Indian state (~0.8 million ha). Therefore, rising *Tmn* (nighttime warming) has a significant negative impact on wheat yields over a larger area than *Tmx* (daytime warming). This indicates a more pronounced role of increased nighttime temperatures (than daytime temperatures) explaining wheat yield reductions in India.

3.2.2 Impact of Water Supply Variables

Figure 10 shows the correlations between wheat yields and water supply variables *Pre*, *Cld*, and *Wet*. For *Pre*, six Indian states, i.e., Uttar Pradesh, Punjab, Haryana, Rajasthan, Bihar and Maharashtra (~74.4% wheat harvested area that corresponds to ~19.8 million ha), show a negative impact on wheat yields, and two Indian states, i.e., Uttar Pradesh and Punjab (~46.5% wheat harvested area that corresponds to ~12.4 million ha), show a statistically significant adverse impact ($p < 0.1$). Two Indian states, i.e., Madhya Pradesh and Gujarat (~18.4% wheat harvested area that corresponds to ~4.9 million ha), show a positive but statistically non-significant impact (Fig. 10a). *Cld* exhibit a negative impact on wheat yields in seven Indian states, i.e., Uttar Pradesh, Punjab, Haryana, Rajasthan, Bihar, Gujarat and Maharashtra (~77.3% wheat harvested area that corresponds to ~20.6 million ha), and of these, two Indian states, i.e., Uttar Pradesh and Punjab (~46.5% wheat harvested area that corresponds to ~12.4 million ha) show a statistically significant adverse impact ($p < 0.1$). The remaining state, i.e., Madhya Pradesh (~15.6% wheat harvested area that corresponds to ~4.2 million ha), exhibits a positive but non-significant impact of *Cld* on wheat yield (Fig. 10b). For *Wet*, two Indian states, i.e., Uttar Pradesh and Punjab (~46.5% wheat harvested area that corresponds to ~12.4 million ha), show a statistically significant negative impact ($p < 0.1$), and the remaining six Indian states, i.e., Haryana, Madhya Pradesh, Rajasthan, Bihar, Gujarat and Maharashtra (~46.4% wheat harvested area that corresponds to ~12.4 million ha), show a negative but non-significant impact (Fig. 10c).

Overall, we found that an increase in *Pre*, *Cld*, and *Wet* during wheat growing *Rabi* season harms wheat yield over large wheat-growing Indian areas. This is because wheat is grown during the non-monsoon season in Indian states, and wheat cultivars being grown are more susceptible/sensitive to an increase in the water supply. The negative response of Indian wheat to growing season precipitation is different from other regional studies. For example, Bekele et al. (2017) showed a moderate positive relationship between wheat yield and wheat growing season rainfall in Ethiopia. Hochman et al. (2017) reported that wheat yield potential in southern Australia has declined due to decreased rainfall. However, on the contrary, our results highlight that a rise in seasonal precipitation during the wheat growing season in India

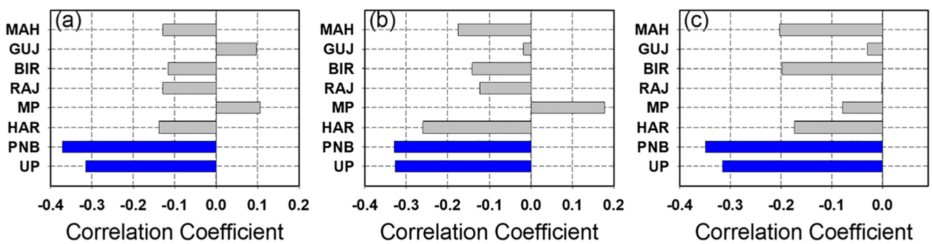

Fig. 10 Correlations between wheat yields and water supply variables (**a**) precipitation, (**b**) cloud cover, and (**c**) wet day frequency. Bars in blue color show significant correlations at $p < 0.1$

harms wheat yield in most of the wheat-producing Indian states. Recently, the impacts of precipitation and wet days on wheat yield have also been analyzed for India (overall) by employing panel-data statistical modeling (Madhukar et al. 2021b). The results had revealed a decrease in wheat yield due to both precipitation and wet days during 1996–2005 (Madhukar et al. 2021b).

Our results show heterogeneity in the negative impacts across Indian states. Though the impacts of *Pre* and *Wet* are primarily negative in all states, they are more pronounced in Punjab and Uttar Pradesh. In north-western India, the rainfall (due to western disturbances) coincides with the post-anthesis and grain filling stage (during February–March) of the wheat plant, thus causes significant yield loss in Punjab and Uttar Pradesh. Higher precipitation during the post-anthesis stage causes insect attacks and a high disease probability for the wheat plant (Tafoughalti et al. 2018). Higher rainy days cause waterlogging making harvesting difficult, and seed sprouting occurs in the field itself (Niwas and Khichar 2016).

Our results also indicate a negative impact of *Cld* on wheat yield in Indian states, particularly in Punjab and Uttar Pradesh, as *Cld* has a negative impact on wheat yield in seven Indian states and a statistically significant negative impact in Punjab and Uttar Pradesh (~12.4 million ha wheat harvested area). There is an increase in stratus clouds and fog during winters in north India, which might harm wheat yields. Though cloud cover (*Cld*) seems to be playing a critical role in Indian wheat-growing states, their understanding remains most uncertain, and there seems to be a need to undertake a comprehensive investigation to understand cloud-wheat yield interaction.

3.2.3 Impact of Water Demand Variables

Figure 11 shows the correlations between wheat yields and water demand variables *Vpd*, *Vap* and *Pet*. It shows that the rise in *Vpd* has a negative impact on wheat yield in seven Indian states: Punjab, Haryana, Madhya Pradesh, Rajasthan, Bihar, Gujarat, and Maharashtra (Fig. 11a). Similarly, *Vap* rise has a negative impact on seven Indian states: Uttar Pradesh, Punjab, Haryana, Rajasthan, Bihar, Gujarat, and Maharashtra (Fig. 11b). *Pet* has a negative impact on six Indian states: Haryana, Madhya Pradesh, Rajasthan, Bihar, Gujarat, and Maharashtra (Fig. 11c). For *Vpd* and *Vap*, two Indian states, i.e., Gujarat and Maharashtra, show a statistically significant adverse impact ($p < 0.1$), accounting for ~6.2% of the wheat harvested area (corresponds to ~1.6 million ha) in India during 1986–2015 (Fig. 11a, b). For *Pet*, two Indian states, i.e., Gujarat and Madhya Pradesh (~18% wheat harvested area that corresponds to ~4.9 million ha), show a statistically significant adverse impact ($p < 0.1$) of rising *Pet* on wheat yields (Fig. 11c).

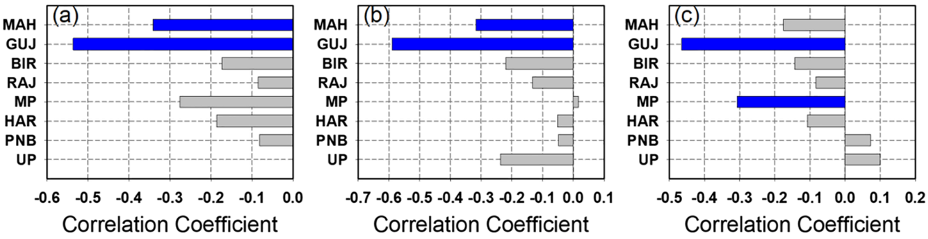

Fig. 11 Correlations between wheat yields and water demand variables (**a**) vapor pressure deficit, (**b**) vapor pressure, and (**c**) potential evapotranspiration. Bars in blue color show significant correlations at $p < 0.1$

Vapor pressure deficit is a critical indicator of atmospheric water demand for plants. It has a major impact on crop yields and is closely related to crop evapotranspiration. Vapor pressure deficit determines plant photosynthesis, and an increase in atmospheric vapor pressure deficit has reduced the vegetation growth globally (Yuan et al. 2019). High vapor pressure deficit leads to a decline in stomatal conductance and an increase in transpiration (up until a given vapor pressure deficit threshold) in most plant species, resulting in reduced growth and photosynthesis and higher risks of hydraulic failure and carbon starvation (Grossiord et al. 2020). Even the short exposure to high vapor pressure deficit might severely impact carbon and nitrogen metabolism in the wheat plant (Fakhet et al. 2021).

Similarly, increasing trends in evapotranspiration could result in decreased groundwater storage and surface water, leading to water availability issues. Earlier, Liu et al. (2020) had found that crop yield elasticities (for wheat, rice, maize, and soybean) were sensitive to potential evapotranspiration across regions. Shah and Paulsen (2003) have suggested that heat stress decreases the wheat plant's water use efficiency. Kirkegaard et al. (2007) reported that temperature rise might lead to evaporation losses (evapotranspiration) and soil moisture loss, leading to significant wheat yield losses due to water shortage and increased water demand. Our results present state-wise empirical evidence of a negative impact of *Vpd*, *Vap*, and *Pet* on wheat yield over a large Indian area.

3.3 Regression Models

The correlation analysis between temperature, water supply, and water demand related variables and wheat yields shows that climate variables are mostly negatively correlated with wheat yield. The correlation analysis also helps select the most crucial climate variable for each Indian state as the predictor/independent variable (input) of regression analysis. So, in the next step, we selected one climate variable (for each Indian state) with the maximum absolute correlation with wheat yield in that state.

We selected *Cld* for Uttar Pradesh because *Cld* has the highest absolute correlation value with wheat yield in Uttar Pradesh. Similarly, we selected *Pre* for Punjab, *Cld* for Haryana, and *Pet* for Madhya Pradesh. For Rajasthan, Bihar, and Gujarat, we selected *Vap*, *Tmn*, and *Vap*, respectively, as they have the highest correlation values with wheat yields in their corresponding state. We observed that Maharashtra is an exception since the correlations contain both significantly negative value (between *Tmn* and wheat yield) and significantly positive value (between *Dtr* and wheat yield). Thus, we selected both *Tmn* and *Dtr* for Maharashtra. We selected the most significant predictor climate variable in each Indian state for performing regression analysis based on the above criteria.

We performed separate linear regressions for eight Indian states with wheat yield as the dependent/response variable and each selected climate variable as an independent/predictor variable to estimate the magnitude of the impact on wheat yield. Table 3 presents the selected predictor variables and coefficients of regression models between wheat yields and predictor variables. It shows that wheat yield declines by 191 kg/ha (in Bihar) and 160 kg/ha (in Maharashtra) with 1 °C rise in *Tmn*. Madhya Pradesh shows a decline in wheat yield by 1442 kg/ha with 1 mm/day rise in *Pet*. Similarly, with 1% increase in *Cld*, wheat yield decreases by 41 kg/ha (Uttar Pradesh) and 28 kg/ha (Haryana). In Gujarat and Rajasthan, wheat yield reduces by 413 kg/ha and 101 kg/ha, respectively, with an increase of 1 hPa in *Vap*. Punjab shows a decline in wheat yield by 3 kg/ha with 1 mm rise in *Pre*.

Table 3 The selected predictor variables and summary statistics of regression models between wheat yields and predictor variables

Indian state	Predictor variable	Regression coefficient	Standard error	T Stat	Lower 95%	Upper 95%
Uttar Pradesh	*Cld*	−40.5*	21.5	−1.881	−84.7	3.7
Punjab	*Pre*	−2.6**	1.3	−2.094	−5.2	−0.1
Haryana	*Cld*	−27.9**	13.5	−2.069	−55.6	−0.2
Madhya Pradesh	*Pet*	−1442.1*	761.9	−1.893	−3005.4	121.2
Rajasthan	*Vap*	−101.4	145.4	−0.697	−399.7	197
Bihar	*Tmn*	−190.7**	83.5	−2.285	−362	−19.4
Gujrat	*Vap*	−412.8***	107.6	−3.836	−633.6	−192
Maharashtra	*Tmn*	−160.0**	64.6	−2.477	−292.6	−27.5
Maharashtra	*Dtr*	330.2**	137.8	2.397	47.5	612.9

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Figure 12 presents the coefficients of determination (R^2) of the linear regression models across Indian states. It shows that ~37–80% of the variability in year-to-year wheat yield changes were explained by the regression models. The remaining ~20–63% of wheat yield variance was unexplained by our models, reflecting the role of variables not included in our analysis. Consideration of the omitted variables from the analysis would likely improve model performance. However, our regression models explained up to ~80% of the wheat yield variance, which signifies that the models provide substantial information and prediction.

We also estimated the wheat yield losses due to the impact of climate trend (in selected predictor variables) over the 30 years study period from 1986 to 2015 (Table 4). The estimated wheat yield losses reflect only the influence of the climate variables included in the regression models. Our findings suggest that total wheat yield losses (computed using Eq. 6) across Indian states range up to ~309 kg/ha. When expressed as a percentage of wheat yields in 1986 (using Eq. 7), the wheat yield losses due to predictor climate variables range up to ~11%.

As referred in the section 'Materials and Methods', we also investigated the impact of solar radiation on wheat yield in India by considering 16 representative districts from 8 states. Additionally, we also performed the multiple regression method analysis. The details of these

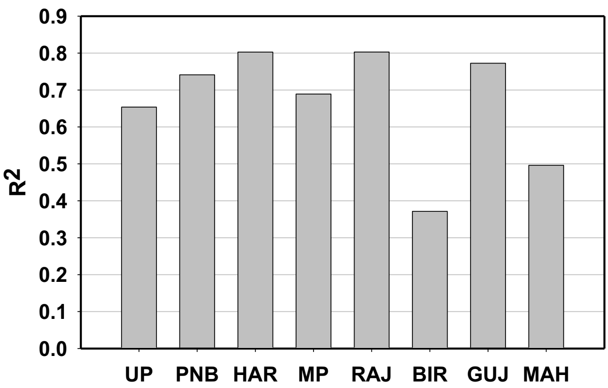

Fig. 12 Coefficient of determination (R^2) for regression models between predictor climate variable and wheat yield across eight Indian states. *Cld*, *Pre*, *Cld*, *Pet*, *Vap*, *Tmn*, *Vap*, and *Tmn* were chosen as predictor climate variables for Uttar Pradesh (UP), Punjab (PNB), Haryana (HAR), Madhya Pradesh (MP), Rajasthan (RAJ), Bihar (BIR), Gujrat (GUJ), and Maharashtra (MAH), respectively

Table 4 Estimated wheat yield losses due to the impact of climate trend (in predictor variable) over the study period (1986–2015)

Indian state	Predictor variable	Yield loss (kg/ha)	Yield loss (%)
Uttar Pradesh	*Cld*	−70.8	−3.6
Punjab	*Pre*	36.2	1.2
Haryana	*Cld*	−309.1	−10.9
Madhya Pradesh	*Pet*	−149.4	−12.1
Rajasthan	*Vap*	10.8	0.6
Bihar	*Tmn*	−51.7	−3.3
Gujrat	*Vap*	−57.7	−2.7
Maharashtra	*Tmn*	−122	−16.7
Maharashtra	*Dtr*	−30.7	−4.2

two studies: (1) Solar Radiation and Yield, and (2) Multiple Regression Methods, are presented in the Supplementary Material (SM) file.

India is a geographically heterogeneous country. Policy formation, amendments and implementation occur at union (federal) and state levels in India. Effective and efficient adaptation strategies require customization and localization. Therefore, state-level insight into climate trends and wheat yield will enable more practical and customized adaptation methods such as innovation in irrigation infrastructure (drip irrigation) and developing new climate-tolerant wheat varieties (Tanaka et al. 2015; Sloat et al. 2020).

4 Conclusions

The manuscript investigates climate variability trends for temperature variables, i.e., maximum temperature (*Tmx*), mean temperature (*Tmp*), minimum temperature (*Tmn*), and diurnal temperature range (*Dtr*); water supply variables, i.e., total precipitation (*Pre*), cloud cover (*Cld*), and wet day frequency (*Wet*); and water demand variables, i.e., vapor pressure deficit (*Vpd*), vapor pressure (*Vap*), and potential evapotranspiration (*Pet*) during *Rabi* season and their impact on wheat yields across eight major wheat-producing Indian states (Uttar Pradesh, Punjab, Haryana, Madhya Pradesh, Rajasthan, Bihar, Gujarat, and Maharashtra) over 1986–2015. These eight states collectively contribute ~96% of wheat production and occupy ~93% of India's wheat harvested area during 1986–2015. Climate trend analysis reveals that temperature, water supply, and water demand related climate variables are changing; however, the nature and magnitude of change varies per region and variable. *Tmx*, *Tmp*, *Tmn*, *Vpd*, and *Pet* are rising in all the eight Indian states. A rise in *Tmn* and *Wet* negatively impacts wheat yields in the eight Indian states (i.e., ~24.7 million ha harvested area). Regression models show that wheat yield declines by 3–1442 kg/ha (across Indian states) with one unit rise in key climate variables explaining up to ~80% of the year-to-year variability in wheat yield. The total wheat yield losses due to the studied climate variables range up to ~309 kg/ha (~11%) over the study period. The results demonstrate a severe challenge of climate variability impacts on wheat yields in India. The approach, studied variables, and findings of the present study shall stimulate further investigation in the field and be relevant for any study area. Also, these findings have the potential to be considered for improving agronomic practices for sustainable wheat production. An insight from this thorough study is bound to guide policymakers and planners. We now aim to develop further insight into various adaptation strategies to manage climate variability impacts on crop yields. Identification and tagging of specific strategies to specific regions will enable a food secure future for the world.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s40710-021-00526-y.

Acknowledgments Anand Madhukar sincerely thank the Indian Institute of Technology Delhi (IIT Delhi) India for providing a research fellowship. Authors declare no conflict of interest or finance.

Author's Contributions Conceptualization, Methodology, Software, Formal analysis and investigation, Data Curation, Writing – Original draft preparation, Writing – review & editing, Visualization: Anand Madhukar; Supervision, Funding acquisition: Kavya Dashora; Validation, Supervision, Funding acquisition: Vivek Kumar.

Funding Anand Madhukar sincerely thank the Indian Institute of Technology Delhi (IIT Delhi) India for providing a research fellowship.

Declarations

Data Availability The authors declare that data supporting the findings of this study are available and were cited within the article.

Conflicts of Interest/Competing Interests Authors declare that they have no conflict of interest or finance.

References

Akter N, Islam MR (2017) Heat stress effects and management in wheat. Rev Agron Sustain Dev 37:37. https://doi.org/10.1007/s13593-017-0443-9

Arora M, Goel NK, Singh P (2005) Evaluation of temperature trends over India/Evaluation de tendances de température en Inde. Hydrol Sci J 50:81–93. https://doi.org/10.1623/hysj.50.1.81.56330

Asseng S, Foster I, Turner NC (2011) The impact of temperature variability on wheat yields. Glob Chang Biol 17:997–1012. https://doi.org/10.1111/j.1365-2486.2010.02262.x

Bapuji Rao B, Santhibhushan Chowdary P, Sandeep VM, Rao VUM, Venkateswarlu B (2014) Rising minimum temperature trends over India in recent decades: implications for agricultural production. Glob Planet Chang 117:1–8. https://doi.org/10.1016/J.GLOPLACHA.2014.03.001

Barkhordarian A, Saatchi SS, Behrangi A, Loikith PC, Mechoso CR (2019) A recent systematic increase in vapor pressure deficit over tropical South America. Sci Rep 9:15331. https://doi.org/10.1038/s41598-019-51857-8

Bekele F, Korecha D, Negatu L (2017) Demonstrating effect of rainfall characteristics on wheat yield: case of Sinana District, south eastern Ethiopia. Agric Sci 08:371–384. https://doi.org/10.4236/as.2017.85028

Bhatt D, Sonkar G, Mall RK (2019) Impact of climate variability on the rice yield in Uttar Pradesh: an agro-climatic zone based study. Environ Process 6:135–153. https://doi.org/10.1007/s40710-019-00360-3

Blyth EM, Torre AM, Robinson EL (2019) Trends in evapotranspiration and its drivers in Great Britain: 1961 to 2015. Prog Phys Geogr: Earth Environ 43(5):666–693. https://doi.org/10.1177/0309133319841891

Cai Y, Guan K, Lobell D, Potgieter AB, Wang S, Peng J, Xu T, Asseng S, Zhang Y, You L, Peng B (2019) Integrating satellite and climate data to predict wheat yield in Australia using machine learning approaches. Agric For Meteorol 274:144–159. https://doi.org/10.1016/j.agrformet.2019.03.010

Caverzan A, Casassola A, Brammer SA (2016) Antioxidant responses of wheat plants under stress. Genet Mol Biol 39:1–6. https://doi.org/10.1590/1678-4685-GMB-2015-0109

Chakraborty D, Saha S, Singh RK, Sethy BK, Kumar A, Saikia US, Das SK, Makdoh B, Borah TR, Chanu AN, Walling I, Anal PSR, Chowdhury S, Daschaudhuri D (2017) Trend analysis and change point detection of

mean air temperature: a spatio-temporal perspective of north-eastern India. Environ Process 4:937–957. https://doi.org/10.1007/s40710-017-0263-6
Dahal V, Gautam S, Bhattarai R (2018) Analysis of long-term temperature trend in Illinois and its implication on the cropping system. Environ Process 5:451–464. https://doi.org/10.1007/s40710-018-0306-7
Das PK, Chakraborty A, Seshasai MVR (2014) Spatial analysis of temporal trend of rainfall and rainy days during the Indian summer monsoon season using daily gridded (0.5° × 0.5°) rainfall data for the period of 1971–2005. Meteorol Appl 21:481–493. https://doi.org/10.1002/met.1361
Duncan JMA, Saikia SD, Gupta N, Biggs EM (2016) Observing climate impacts on tea yield in Assam, India. Appl Geogr 77:64–71. https://doi.org/10.1016/j.apgeog.2016.10.004
Fakhet D, Morales F, Jauregu I, Erice G, Aparicio-Tejo PM, González-Murua C, Aroca R, Irigoyen JJ, Aranjuelo I (2021) Short-term exposure to high atmospheric vapor pressure deficit (VPD) severely impacts durum wheat carbon and nitrogen metabolism in the absence of edaphic water stress. Plants 10:120. https://doi.org/10.3390/plants10010120
FAOSTAT (2019). FAOSTAT Agricultural data, 2019 http://wwwfaoorg/faostat/en/. Accessed 2 Dec 2019
Farooq M, Wahid A, Kobayashi N, Fujita D, Basra SMA (2009) Plant drought stress: effects, mechanisms and management. Agron Sustain Dev 29:185–212. https://doi.org/10.1051/agro:2008021
Feng B, Liu P, Li G, Dong ST, Wang FH, Kong LA, Zhang JW (2014) Effect of heat stress on the photosynthetic characteristics in flag leaves at the grain-filling stage of different heat-resistant winter wheat varieties. J Agron Crop Sci 200:143–155. https://doi.org/10.1111/jac.12045
Grossiord C, Buckley TN, Cernusak LA, Novick KA, Poulter B, Siegwolf RTW, Sperry JS, McDowell NG (2020) Plant responses to rising vapor pressure deficit. New Phytol 226(6):1550–1566. https://doi.org/10.1111/nph.16485
Harris I, Osborn TJ, Jones P, Lister D (2020) Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. Sci Data 7:109. https://doi.org/10.1038/s41597-020-0453-3
Hochman Z, Gobbett DL, Horan H (2017) Climate trends account for stalled wheat yields in Australia since 1990. Glob Chang Biol 23:2071–2081. https://doi.org/10.1111/gcb.13604
Hong C, Zhang Q, Zhang Y, Davis SJ, Tong D, Zheng Y, Liu Z, Guan D, He K, Schellnhuber HJ (2019) Impacts of climate change on future air quality and human health in China. Proc Natl Acad Sci 116(35):17193–17200. https://doi.org/10.1073/pnas.1812881116
IPCC-AR4 (2007) IPCC-AR4, 2007, climate change 2007, the scientific basis, contribution of working group-I to the fourth assessment report of intergovernmental panel on climate change (IPCC). Cambridge University Press, Cambridge
IPCC-AR5 (2014) IPCC-AR5, 2014, climate change 2014, the scientific basis, contribution of working group-I to the fourth assessment report of intergovernmental panel on climate change (IPCC). Cambridge University Press, Cambridge
Jaswal AK, Kore PA, Singh V (2016) Trends in diurnal temperature range over India (1961–2010) and their relationship with low cloud cover and rainy days. J Clim Chang 2:35–55. https://doi.org/10.3233/jcc-160016
Kirkegaard JA, Lilley JM, Howe GN, Graham JM (2007) Impact of subsoil water use on wheat yield. Aust J Agric Res 58:303. https://doi.org/10.1071/ar06285
Kumar V, Jain SK (2011) Trends in rainfall amount and number of rainy days in river basins of India (1951–2004). Hydrol Res 42(4):290–306. https://doi.org/10.2166/nh.2011.067
Liu D, Mishra AK, Ray DK (2020) Sensitivity of global major crop yields to climate variables: a non-parametric elasticity analysis. Sci Total Environ 748:141431. https://doi.org/10.1016/j.scitotenv.2020.141431
Lobell DB, Burke MB (2010) On the use of statistical models to predict crop yield responses to climate change. Agric For Meteorol 150:1443–1452. https://doi.org/10.1016/j.agrformet.2010.07.008
Lobell DB, Schlenker W, Costa-Roberts J (2011) Climate trends and global crop production since 1980. Science 333:616–620. https://doi.org/10.1126/science.1204531
Lobell DB, Sibley A, Ivan Ortiz-Monasterio J (2012) Extreme heat effects on wheat senescence in India. Nat Clim Chang 2:186–189. https://doi.org/10.1038/nclimate1356
López J, Way DA, Sadok W (2021) Systemic effects of rising atmospheric vapor pressure deficit on plant physiology and productivity. Glob Chang Biol 27(9):1704–1720. https://doi.org/10.1111/gcb.15548
Madhukar A, Kumar V, Dashora K (2020) Spatial and temporal trends in the yields of three major crops: wheat, rice and maize in India. Int J Plant Prod 14:187–207. https://doi.org/10.1007/s42106-019-00078-0
Madhukar A, Dashora K, Kumar V (2021a) Spatial analysis of yield trends and impact of temperature for wheat crop across Indian districts. Int J Plant Prod 15:325–335. https://doi.org/10.1007/s42106-021-00140-w
Madhukar A, Dashora K, Kumar V (2021b) Investigating historical climatic impacts on wheat yield in India using a statistical modeling approach. Model Earth Syst Environ 7:1019–1027. https://doi.org/10.1007/s40808-020-00932-5
Nair MR, Nayak S (2017) Observed climate variability and change over the Indian region. Springer, Singapore
Niwas R, Khichar ML (2016) Managing impact of climatic vagaries on the productivity of wheat and mustard in India. Mausam 67:205–222
Nunez S, Arets E, Alkemade R, Verwer C, Leemans R (2019) Assessing the impacts of climate change on biodiversity: is below 2 °C enough? Clim Chang 154:351–365. https://doi.org/10.1007/s10584-019-02420-x

Pachauri RK, Allen MR, Barros VR, Broome J, Cramer W, Christ R, Church JA, Clarke L, Dahe Q, Dasgupta P, Dubash NK, Edenhofer O, Elgizouli I, Field CB, Forster P, Friedlingstein P, Fuglestvedt J, Gomez-Echeverri L, Hallegatte S, Hegerl G, Howden M, Jiang K, Jimenez Cisneroz B, Kattsov V, Lee H, Mach KJ, Marotzke J, Mastrandrea MD, Meyer L, Minx J, Mulugetta Y, O'Brien K, Oppenheimer M, Pereira JJ, Pichs-Madruga R, Plattner GK, Pörtner HO, Power SB, Preston B, Ravindranath NH, Reisinger A, Riahi K, Rusticucci M, Scholes R, Seyboth K, Sokona Y, Stavins R, Stocker TF, Tschakert P, van Vuuren D, van Ypserle JP (2014) Climate change 2014: synthesis report. Contribution of working groups I, II and III to the fifth assessment report of the intergovernmental panel on climate change (IPCC 2014). 10013/epic.45156

Pendergrass AG, Hartmann DL (2014) Changes in the distribution of rain frequency and intensity in response to global warming. J Clim 27:8372–8383. https://doi.org/10.1175/JCLI-D-14-00183.1

Praveen B, Talukdar S, Shahfahad MS, Mondal J, Sharma P, Islam ARMT, Rahman A (2020) Analyzing trend and forecasting of rainfall changes in India using non-parametrical and machine learning approaches. Sci Rep 10:10342. https://doi.org/10.1038/s41598-020-67228-7

Putnam AE, Broecker WS (2017) Human-induced changes in the distribution of rainfall. Sci Adv 3(5):e1600871. https://doi.org/10.1126/sciadv.1600871

Qin J, Su B, Tao H, Wang Y, Huang J, Li Z, Jiang T (2021) Spatio-temporal variations of dryness/wetness over Northwest China under different SSPs-RCPs. Atmos Res 259:105672. https://doi.org/10.1016/j.atmosres.2021.105672

R Development Core Team (2018) R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna URL http://www.R-project.org/. https://www.r-project.org/. Accessed 20 May 2021

Rao BB, Chowdary PS, Sandeep VM, Pramod VP, Rao VUM (2015) Spatial analysis of the sensitivity of wheat yields to temperature in India. Agric For Meteorol 200:192–202. https://doi.org/10.1016/j.agrformet.2014.09.023

Ray DK, Gerber JS, Macdonald GK, West PC (2015) Climate variation explains a third of global crop yield variability. Nat Commun 6:1–9. https://doi.org/10.1038/ncomms6989

Ray DK, West PC, Clark M, Gerber JS, Prishchepov AV, Chatterjee S (2019) Climate change has likely already affected global food production. PLoS One 14:e0217148. https://doi.org/10.1371/journal.pone.0217148

Ross RS, Krishnamurti TN, Pattnaik S, Pai DS (2018) Decadal surface temperature trends in India based on a new high-resolution data set. Sci Rep 8:7452. https://doi.org/10.1038/s41598-018-25347-2

Schewe J, Heinke J, Gerten D, Haddeland I, Arnell NW, Clark DB, Dankers R, Eisner S, Fekete BM, Colón-González FJ, Gosling SN, Kim H, Liu X, Masaki Y, Portmann FT, Satoh Y, Stacke T, Tang Q, Wada Y, Wisser D, Albrecht T, Frieler K, Piontek F, Warszawski L, Kabat P (2014) Multimodel assessment of water scarcity under climate change. Proc Natl Acad Sci 111(9):3245–3250. https://doi.org/10.1073/pnas.1222460110

Shah NH, Paulsen GM (2003) Interaction of drought and high temperature on photosynthesis and grain-filling of wheat. Plant Soil 257:219–226. https://doi.org/10.1023/A:1026237816578

Sloat LL, Davis SJ, Gerber JS, Moore FC, Ray DK, West PC, Mueller ND (2020) Climate adaptation by crop migration. Nat Commun 11:1243. https://doi.org/10.1038/s41467-020-15076-4

Sonkar G, Mall RK, Banerjee T, Singh N, Kumar TVL, Chand R (2019) Vulnerability of Indian wheat against rising temperature and aerosols. Environ Pollut 254:112946. https://doi.org/10.1016/j.envpol.2019.07.114

Syed TH, Famiglietti JS, Chambers DP, Willis JK, Hilburn K (2010) Satellite-based global-ocean mass balance estimates of interannual variability and emerging trends in continental freshwater discharge. Proc Natl Acad Sci 107(42):17916–17921. https://doi.org/10.1073/pnas.1003292107

Tafoughalti K, el Faleh EM, Moujahid Y, Ouargaga F (2018) Climate change impact on rainfall: how will threaten wheat yield? E3S Web Conf 37:03001. https://doi.org/10.1051/e3sconf/20183703001

Tanaka A, Takahashi K, Masutomi Y, Hanasaki N, Hijioka Y, Shiogama H, Yamanaka Y (2015) Adaptation pathways of global wheat production: importance of strategic adaptation to climate change. Sci Rep 5:14312. https://doi.org/10.1038/srep14312

Tao F, Xiao D, Zhang S, Zhang Z, Rötter RP (2017) Wheat yield benefited from increases in minimum temperature in the Huang-Huai-Hai Plain of China in the past three decades. Agric For Meteorol 239:1–14. https://doi.org/10.1016/j.agrformet.2017.02.033

Vinnarasi R, Dhanya CT, Chakravorty A, Aghakouchak A (2017) Unravelling diurnal asymmetry of surface temperature in different climate zones. Sci Rep 7:7350. https://doi.org/10.1038/s41598-017-07627-5

Vose RS, Easterling DR, Gleason B (2005) Maximum and minimum temperature trends for the globe: an update through 2004. Geophys Res Lett 32:1–5. https://doi.org/10.1029/2005GL024379

Will RE, Wilson SM, Zou CB, Hennessey TC (2013) Increased vapor pressure deficit due to higher temperature leads to greater transpiration and faster mortality during drought for tree seedlings common to the forest–grassland ecotone. New Phytol 200:366–374. https://doi.org/10.1111/nph.12321

Ye J, Gao Z, Wu X, Lu Z, Li C, Wang X, Chen L, Cui G, Yu M, Yan G, Liu H, Zhang H, Wang Z, Shi X, Li Y (2021) Impact of increased temperature on spring wheat yield in northern China. Food Energy Secur 10(2): 368–378. https://doi.org/10.1002/fes3.283

Yuan W, Zheng Y, Piao S, Ciais P, Lombardozzi D, Wang Y, Ryu Y, Chen G, Dong W, Hu Z, Jain AK, Jiang C, Kato E, Li S, Lienert S, Liu S, Nabel JEMS, Qin Z, Quine T, Sitch S, Smith WK, Wang F, Wu C, Xiao Z, Yang S (2019) Increased atmospheric vapor pressure deficit reduces global vegetation growth. Sci Adv 5:8. https://doi.org/10.1126/sciadv.aax1396

Zaveri E, Lobell DB (2019) The role of irrigation in changing wheat yields and heat sensitivity in India. Nat Commun 10:4144. https://doi.org/10.1038/s41467-019-12183-9

Zhang S, Tao F, Zhang Z (2017) Spatial and temporal changes in vapor pressure deficit and their impacts on crop yields in China during 1980–2008. J Meteorol Res 31:800–808. https://doi.org/10.1007/s13351-017-6137-z