ABSTRACT

The present study aimed to quantify the impacts of the meteorological drought on the production of maize crops, using district-level observed precipitation and yield data of 21 districts across Punjab, Pakistan from 2001 to 2020. The overall analysis showed that the Standardized Precipitation Index (SPI) effectively reflects the variations in drought characteristics in Punjab on spatiotemporal scales. It also resulted that in south Punjab, the maize yield was negatively affected by the meteorological drought, and yield was sensitive to short-term (1 and 3 months) drought during the critical growth period of the crop. The overall analysis depicted that the meteorological drought was associated with about 27% of overall yield variations. Moreover, all of the southern districts and few districts from Central Punjab were becoming increasingly sensitive to meteorological drought where significant spatial variations in drought effects and sensitivity exist over time. Conclusively, this study showed a spatiotemporal pattern of drought and its impact on maize yield, indicating that the districts where variability in maize production was significantly associated with drought and recommend adoption of the management strategies and mitigation measures.

Key words: agriculture, climate change, drought, SPI, yield

HIGHLIGHTS

- Extreme climate events like drought can cause the greatest impacts especially in agronomic fields.
- Agricultural yield is sensitive to short-term drought during the critical growth period of the crop and is also significantly associated with overall yield variations.
- Management policies that barrier against short-term drought may be most effective at sustaining long-term crop productivity.

INTRODUCTION

The agriculture system is very responsive and sensitive to the fluctuation in rainfall patterns, and due to its dependency on water, it is the extremely affected sector by extreme events like droughts (UNISDR 2009). Droughts are a global phenomenon; however, their effects are more vulnerable in developing countries because of lesser potential to mitigate the impacts of such extreme events. Approximately, two billion people are affected by drought, and seven to eight billion dollars have been spent as a drought-related cost since 1990 (Zipper et al. 2016). Considering the hydrological cycle, drought is classified into different four classes, i.e., meteorological drought, hydrological drought, and agricultural and socio-economic drought (Waseem et al. 2020). Among these different types of droughts, meteorological drought is the most important form of drought as surface water resources, and most importantly, the agriculture of a country is heavily dependent on meteorological information. It is mainly as meteorological drought can cause a significant reduction in agriculture yield especially in the arid region of a country.

Drought influencing factors, e.g., global warming, have caused an increase in the frequency and intensity of meteorological drought in different areas of the world and has produced vulnerable effects on crop production, which ultimately threaten food security both at a global and regional scale (Godfray et al. 2010). For this reason, the important factor affecting the growth and development of crops is changes in rainfall, both spatial and temporal patterns, and its impacts on the crop...
water cycle (Tao et al. 2003; Hanif & Ali 2014). Similarly, a short burst of rising temperature will affect the water cycle and cause soil moisture deficiency, infertility and damage crop yields (McKeown et al. 2005). Recent studies (Janjua et al. 2010; Mahmood et al. 2012; Mendelsohn 2014; Kirby et al. 2016) have also indicated the impacts of climate variations on food production in both Pakistan and globally. These studies recommended detailed accounts of agricultural production and yield variation under extreme events for making sure the sufficient and sustainable food supply (Van Ittersum et al. 2013) to the rapidly growing global population under climate change.

Most of the developing countries are agriculture-based economies and have direct exposure to climate change and extreme events (Mendelsohn 2014). It is also expected that extreme events (e.g., heatwaves, hot extremes, and droughts) could become relatively frequent and intense in the near future (Zaman et al. 2020). Like other countries, Pakistan has also experienced several extreme events especially the droughts, a dramatic shift in the rainfall, and a steady rise in temperature for the past 50 years (Zahid & Rasul 2011; Abbai 2013; Xie et al. 2013; Ali et al. 2015; Khan et al. 2019, 2020; Nawaz et al. 2019). For instance, the 1998–2002 drought, which was one of the worst droughts during the last 50 years, affected 1.2 million people, caused the death of 2 million animals, and major agricultural loss. The southwest region of Pakistan was mainly affected by this 1998–2002 drought and other drought events (e.g., 2004–2005 and 2009), as the annual rainfall of this region mostly fails to meet the annual evaporation. This imbalance is tremendously increasing and causing perpetual drought conditions. In this context, several studies (i.e., Sheikh 2001; Zahid & Rasul 2011; Xie et al. 2013; Ahmed et al. 2018; Muhammad et al. 2018; Khan et al. 2020; Waseem et al. 2020) have been conducted in Pakistan to assess the intensity, duration, and frequency of the low precipitation or drought.

Droughts in Pakistan have seriously affected the economy, agricultural system, cropping pattern, and annual productivity in most parts of the country, and this situation could be worse in the future (Akmal et al. 2014; Khan et al. 2020). Hence, the agricultural sector of Pakistan is under serious threat under this kind of climate variation (Janjua et al. 2010). These facts highlight the dire need to understand the resilience of agricultural systems to drought so that effective plans and policies can be made to mitigate the impacts of drought in the near future (Zipper et al. 2016).

Punjab, the province of Pakistan, is considered as the food basket of Pakistan but climate-induced changes have placed a greater risk to its agricultural systems. So, the present study focuses to assess the impacts of drought on the yield of one of the major food crops (i.e., maize) grown in Punjab province. Maize is one of the food and cash crops of the Punjab agricultural sector and serves as feed and silage as well. It is a high-yield cereal crop globally and, in Pakistan, it is the third main cereal crop after wheat and rice. It is sown in two seasons, i.e., spring (locally called Rabi) and autumn (locally called Kharif). In spring, it is sown from February till March and the crop completes its tasseling and silking stages in April–early May. Till the end of May, it reaches its grain filling and maturity stage and is harvested in June. While the autumn maize crop is sown from July to August and harvested between September and December. The life cycle of the maize crop depends upon the availability of water, and drought stress at the reproductive or maturity stage can damage the grain yield of the maize crop. Water deficiency during pre-flowering, flowering, and post-flowering stages can cause yield reduction by 25, 50, and 21%, respectively (Sah et al. 2020). According to an estimation, climate change has caused a decline in global maize production by 3.8% between 1980 and 2010 (Lobell et al. 2011).

In view of this, it would be essential to understand the spatiotemporal variation of drought impacts on maize crop yield so that the negative consequences of future drought can be minimized. Particularly, the timing (i.e., time of the year drought occurs) and timescale (i.e., drought duration) at which the strongest impacts of drought on crop yield need to be quantified, and this information will help the government organizations and stakeholders for designing the drought mitigation strategies. Furthermore, understanding the spatial pattern of drought sensitivity for crops and variations in their patterns over time can help stakeholders plan for regional shifts in actual and realized crop production under the stress of future climate change (Zipper et al. 2016). Hence, in the current study, to find the impact of meteorological drought at the local scale, the following research questions are framed: (1) to what extent does the meteorological drought exert influence on maize yield, and how does the spatial pattern of this relationship vary and (2) what timescale and timing of the drought put the strongest influence on the maize yield?

**METHODOLOGY**

**Study area**

Punjab province (Figure 1) is the food basket of Pakistan with fairly flat alluvial land and fertile soil for agricultural activities. It is irrigated by five rivers (i.e., Jehlum, Ravi, Sutlej, Chenab, and Indus) and is considered as the lifeline of Pakistan. The total
area of Punjab is 205,344 km² (79,284 sq mi). Climatically, there are four seasons in Punjab, i.e., hot weather (April to June), cold weather/mild weather (October to March), and rainy season (July to September). Average rainfall varies from 460 to 960 mm and temperature ranges from -2 to 45 °C, but in some regions of Punjab, temperature exceeds 50 °C. The topography of Punjab also includes several mountainous ranges, such as the Suleiman range in Southwest Punjab, Margalla Hills in North and Salt range (Pothohar Plateau), and deserts including Rajasthan in Southern Punjab and parts of Thal and Cholistan also lie in the south of Punjab. Punjab’s agricultural sector comprises major crops including maize, rice, cotton, wheat, and sugarcane and minor crops such as onion, potato, chilies, mash, mung, and masoor with two cropping seasons, i.e., Autumn (Kharif) and Spring (Rabi) seasons are observed (Amjad et al. 2008). In the current study, 36 districts of Punjab were divided into the southwestern region (Dera Ghazi Khan), southeastern region (Bahawalpur, Bahawalnagar), south Punjab (Multan), and north region of Punjab/Pothohar region (Jehlum, Chakwal, Rawalpindi, and Khushab). Moreover, this study is based on secondary data covering the period from 2001 to 2020. Monthly precipitation data were only available from 21 weather stations, established in 21 districts out of 36 total districts, so in the current study, only these gauging stations were considered for further analysis. The meteorological data were collected from the Pakistan Meteorological Department (https://www.pmd.gov.pk/en/). District-wise yearly maize yield and area data were collected from the Crop Reporting Service Government of Punjab (http://www.crs.agripunjab.gov.pk/) for the same districts and the years for which precipitation data were available.

Calculation of drought severity
The Standardized Precipitation Index (SPI) was developed by McKee (1995) for meteorological drought monitoring and to assess the changes in climatic conditions at different timescales (Liu et al. 2021). It is a widely used drought index (Tigkas et al. 2015) and has also been applied in studies related to the quantification of drought effects (Yildirak & Selcuk-Kestel 2015; Bautista-Capetillo et al. 2016). In the current study, SPI was used at 1-, 3-, 6-month, and annual timescales. SPI is used for the identification of meteorological drought. In general, for estimation of SPI, long-term rainfall data are first transformed into a most fitted probability distribution (e.g., Gamma distribution) and then further converted into a normal
distribution, such that the mean SPI is zero (Edwards 1997).

$$\text{SPI} = \frac{X_i - \bar{X}}{\sigma} \quad (1)$$

where $X$ is the precipitation observation, $\bar{X}$ is the long-term mean, and $\sigma$ is the standard deviation.

The SPI value ranges from $-3$ to $3$, where the positive value of SPI indicates wet condition while the negative value represents the drought condition. A region is said to be in a drought condition if the index value of SPI is constantly negative. That drought event finishes when the value of SPI converts to positive. Therefore, each drought occurrence has a period determined by its start and end, and the severity for each month.

The SPI can be estimated at different timescales, e.g., 1-, 3-, 6- and 12-month reference duration. Moreover, the cumulative sums of precipitation for 3-, 6-, 9-, and 12-month timescales were used to calculate SPI-3, SPI-6, SPI-9, and SPI-12, respectively. For example, the cumulative sum for October while calculating SPI-3 was obtained by adding previous 2-month (i.e., August and September) data to the October data. Similarly, for November, September, and October data were added. For SPI-6, the cumulative sum was obtained by adding 6 months from May to October. Moreover, the time series were fitted to the Gamma probability distribution, and the cumulative probability distribution of the series data was transformed into the normal distribution.

**Agricultural yield data processing**

District-wise maize yield data were obtained from the Cropping Reporting Service Government of Punjab from 2001 to 2020. The length of the crop yield record was the same for all the selected districts. In addition, the districts were categorized by keeping in view the crop growing seasons (i.e., Kharif and Rabi crop). It was observed that only five districts have only Kharif maize crop, whereas the rest of the districts have both season’s maize crop. This division helped to calculate the impacts of drought stress and shift in drought sensitivity for a particular month of the crop cycle. Before further analysis, the crop yield data were also auto-scaled using linear regression for the elimination of the gradual trend due to non-climatic factors, e.g., agronomic and genetic improvements (Potop et al. 2010). The auto-scaled analysis was carried out due to the reason that in some districts an increase in yield area was observed, whereas in some others yield area was decreased over time and a few districts have shown exceptional behavior. Moreover, crop yield variability with respect to time is measured by a coefficient of variation (CV). The CV is a statistical measure of the relative spread of data points around the mean ($\mu$) in a data series.

$$\text{CV} = \frac{\sigma}{\mu} \quad (2)$$

where $\sigma$ represents the standard deviation.

**Statistical modeling of drought and agricultural yield**

The statistical modeling between meteorological drought and agriculture yield has been investigated using regression analysis. Regression analysis is a statistical tool used to estimate the level of effect of any independent time series (hereafter meteorological drought index) on any dependent time series (hereafter agriculture yield). Regression analysis is generally performed to understand the relationships between independent time series and dependent time series. The mathematical expression of regression between any independent time series and any dependent time series is as follows:

$$Y = \beta_0 + \alpha X + \varepsilon \quad (3)$$

where $Y$ is the dependent time series, $\alpha$ is the regression coefficient (slope), $X$ is the independent time series, $\beta_0$ is the intercept, and $\varepsilon$ is an error term.

Drought sensitivity could be defined as the slope of linear regression ($\alpha$) between detrended crop yield anomalies and SPI (Vicente-Serrano et al. 2013). A positive value of slope will indicate the low yield in case of severe drought and vice versa, as a more negative value of SPI shows more severe drought. Furthermore, to assess the temporal shifts in drought sensitivity, a linear regression was employed using monthly, 3-, 6-month, and annual timescales for SPI to the first 10 years (i.e., 2001–2010) and the last 10 years (2011–2020) of data, and significant differences of slope between these two spans were observed.
Districts were labeled as no change where slopes did not show a significant difference ($p < 0.05$) in either period. In this way, the behavior of other slopes was observed to find if they shifted toward the steeper slopes, i.e., higher value (negative to positive) or shallow slopes, i.e., the lower value (positive to negative). A positive slope indicates lower yield during meteorological drought and a negative slope indicates higher yield during meteorological drought. Moreover, for each district, a separate linear relationship was developed between maize yield and SPI at different timescales, i.e., monthly, 3-, 6-month, and annual timescales. For each relationship, $R^2$, slope, and $p$-value were calculated using the two-tailed $t$-test, and $R^2$ was used to indicate the best relationship between crop yield and SPI (Vicente-Serrano et al. 2013; Zipper et al. 2016). The $R^2$ formula is calculated by dividing the sum of the first errors by the sum of the second errors and subtracting the derivation from (1). Here is what the $R^2$ equation looks like:

$$R^2 = 1 - \frac{R_{SS}}{T_{SS}}$$

where $R^2$ represents the coefficient of determination, $T_{SS}$ is the total sum of squares, and $R_{SS}$ is the sum of squares of residuals.

**RESULTS**

**Spatiotemporal variation of maize yield**

During the past two decades (2001–2020), Punjab's annual maize yield has gradually increased over time with the rising trend (mean trends of 0.8140 tonnes acre$^{-1}$ year$^{-1}$), accompanied by an increasing trend in the range of spatial variability (Figure 2(a)). Furthermore, crop yield variability with respect to time is measured by a CV. The analysis showed that CV has a lower value in the districts with higher productivity and increasing yielding trends, and a higher value of CV in the districts having low yield with mild increasing yield trends. The overall analyses resulted in the strongest increasing yield trend and the lowest yield variability in Sahiwal, Okara, Jhang, Toba Tak Singh, and Faisalabad (1.841, 1.476, 1.460, 1.188, and 1.057 tonnes acre$^{-1}$ year$^{-1}$, respectively), whereas the weakest increasing trend (0.020 tonnes acre$^{-1}$ year$^{-1}$) and higher yield variability were observed in districts of South Punjab. These variations are mainly due to climatic factors, fertility, and other soil properties. Figure 2(b) and 2(c) shows the spatial pattern of maize production and long-term trend in Punjab.

**Spatial variability of drought impact**

The variability analysis of drought indicated significant spatial variations in the relationship between meteorological drought and maize yield. The strength of the relationship between SPI-1, SPI-3, SPI-12, and maize yield helped to figure out the districts that were more sensitive to drought. The $R^2$ value for the fitted relationship ranged from 0 to 37% for Rabi maize and 0 to 41% for Kharif maize (Figure 3). Southwestern region (Dera Ghazi Khan), southeastern region (Bahawalpur and Bahawalnagar), south Punjab (Multan), and north region of Punjab (Jehlum, Chakwal, Rawalpindi, and Khushab) were identified as the drought-sensitive region with the moderate to strong correlation between SPI-1, SPI-3, and maize yield (i.e., severe drought was associated with a large negative yield, indicating the increase in drought sensitivity), whereas the weak or even negative correlation with negative or very low slope values was observed in Northeastern and Central Punjab (Gujranwala, Gujrat, Sialkot, Lahore, Mandi Bahauddin, Toba Tak Singh, Jhang, Sahiwal, and Okara), indicating reduced drought sensitivity or high yield during the drought period as shown in Figure 3, except Faisalabad, where the moderate correlation was found during the growing season of Kharif and Rabi crop.

Slopes of the relationship between detrended Maize yield and SPI-1, SPI-3, and SPI-12 are shown in Figure 4. It will be noteworthy to mention that a positive slope reveals yield losses during drought and a negative slope shows yield gain in response to drought conditions. Moreover, 15 districts out of 21 districts of this study are fully or partially irrigated areas except for Pothohar Plateau. Hence, results reveal that irrigation reduces the negative effects of weather unevenness on maize yield, particularly in the Northeastern and Central regions of Punjab, and therefore eliminates the yield sensitivity to meteorological drought. Maize yield data reveal that about 88–97% of potential agriculture is reported from irrigated zones, and only 3–12% of maize production comes from the non-irrigated zones of these districts. In other words, irrigation decouples the yield from inter-annual drought. But, despite having an irrigation system, some districts in south Punjab (e.g., Dera Ghazi Khan and Bahawalpur) and north Punjab (Jehlum) had shown a significant positive correlation between drought and maize yield during the growing season of Kharif and Rabi maize crops.
As maize is sown in two seasons, namely, spring and autumn, all districts bearing diverse topography and water resources availability and, hence, give separate responses to the meteorological drought timescale during different stages of Kharif and Rabi maize crop cycles (Figure 5). The analysis showed that maize yield is sensitive to the drought occurring at the

![Figure 2](https://example.com/figure2.png)

**Figure 2** | (a) Annual distribution of yield in Punjab Pakistan; (b) CV of maize yield over the study period of 2001–2020; and (c) long-term trend in maize yield (Tonnes/acre).

**Timescale and timings of drought impact on maize yield**

As maize is sown in two seasons, namely, spring and autumn, all districts bearing diverse topography and water resources availability and, hence, give separate responses to the meteorological drought timescale during different stages of Kharif and Rabi maize crop cycles (Figure 5). The analysis showed that maize yield is sensitive to the drought occurring at the
growing stage. The spring maize is sown in February–March and completes its tasseling and silking stages in April–early May. Toward the end of May, the crop reaches its grain filling and maturity stage, and after passing through the grain formation stage, it is harvested in early June. Spring maize is generally grown in Jhelum (North Punjab) and Central Punjab. Maize yield in Jhelum (North Punjab) was more sensitive to a 1-month drought occurring in February, which corresponds to the sowing stage of the crop, whereas yield from the districts of South Punjab (Bahawalpur, Bahawalnagar, Multan, and Rahim Yar Khan), and Central Punjab (Faisalabad, Toba Tak Singh, and Sialkot) are more sensitive to a 2-month drought (i.e., April and May), which are the growing season of spring maize crop.

Moreover, autumn maize is grown in all districts of Punjab and is more susceptible to meteorological drought as compared to spring maize. Autumn maize is sown in July–August and harvested between September till December. September, October, and November are probably the growing stage of the autumn maize depending upon the early or late sowing of the crop. The districts lying in the North and South Punjab exhibit more sensitivity for a growing stage of maize crop at a 2–3-month timescale (i.e., September to November) of drought, with the moderate to strong correlation between SPI and maize yield. Dera Ghazi Khan, Bahawalpur, and Multan (Southern Punjab) are identified as more drought-stressed districts for autumn maize and are strongly correlated with the 1-month SPI of October and November.

Drought sensitivity shift quantification over time
The results indicated a substantial spatial pattern in drought sensitivity across Punjab for maize yield between period 1 (2001–2010) and period 2 (2011–2020) as shown in Figure 6. It was observed that some districts of Central and Northeastern Punjab (such as Gujranwala, Sialkot, Sargodha, Faisalabad, and Okara) exhibit the shifts toward increased drought sensitivity (which can be defined as a higher slope of the relationship between SPI and maize yield) for the 1-month SPI during the growing season of the Kharif maize crop. During the 3-month SPI (October–December and January–March), reduced drought sensitivity has been prevalent in South Punjab including districts of Dera Ghazi Khan, Bahawalpur, and Rahim Yar Khan, whereas...
increased sensitivity was common in some districts of Central Punjab (Gujranwala, Gujrat, Sialkot, Sargodha, and Okara). During the 3-month SPI (April–June), which is the growing season for the Rabi maize crop, a scatter pattern of a shift in drought sensitivity is observed across Punjab. On the other hand, the 12-month SPI shows increased drought sensitivity for Gujranwala, Sargodha (Central Punjab), and Bakhar (Southwestern Punjab). In Figure 6, the legend ‘No change’ indicates no significant changes among the two periods, shallower represents the slope of the relationship was lower in the second period as compared to the first period, and ‘Pos. To Neg.’ shows the shift of slope from a positive value to a negative value. ‘Steeper’ signposts the increase in slope. ‘Neg. To Pos.’ shows the shift of slope from negative to positive, and the ‘missing data’ indicates the districts with missing data.

DISCUSSIONS

Considering the food, energy, and water nexus, one of the major challenges is to ensure food security at the global level for a rapidly increasing population while conserving water and land resources. For achieving this goal, it is essentially required to improve the food productivity, manage existing agricultural land, and other strategies, e.g., minimize the agricultural inputs and food waste (McLaughlin & Kinzelbach 2015). To make the agricultural system better adaptive to climate variation, it is important to recognize the impacts of climate extremes events (e.g., drought) on the agricultural system (Chen et al. 2014). Hence, this study attempted to quantify the spatiotemporal variations of drought sensitivity of maize yield for the identification of both when and where the meteorological drought is strongly associated with the variations in maize yield.
Figure 5 | Graph showing the number of best-fit relationships at the different timescales of drought (red color indicating the significant relations with $p > 0.05$). Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/wcc.2021.244.

Figure 6 | Shift in maize yield in response to drought between (2001–2010) and (2011–2020).
The results showed large spatial variations in drought sensitivity and its impacts on maize yield. It was hypothesized that district-level variability in drought sensitivity and impacts could be controlled by local physical characteristics such as the availability of groundwater or soil water retention ability, as the SPI does not consider the soil moisture or groundwater storage (Ma et al. 2014). For instance, the districts of southern Punjab have sandy soil, which may be the cause of an increase in drought sensitivity for this region due to the poor water retention capacity. The results also reveal the negative drought sensitivity in the districts of Central Punjab, where supplemental water sources in the form of shallow groundwater or irrigation are available for the crops and could help in the mitigation of drought, however, ignored in the SPI calculation. In other words, poorly drained soils and the shallow water table provide a buffer from drought. Previous studies also showed that crops could receive groundwater as a subsidy (Zipper et al. 2015), mainly in a drought period; hence, an increase in yield could possibly be due to the availability of groundwater. Another extensive supportive source of water for crops is irrigation (Hain et al. 2015). The results of $R^2$ in the case of the districts in Central Punjab such as Gujranwala, Gujrat, Sahiwal, Okara, Mandi Bahaudin, Lahore, and Jhang indicate that irrigation might have decoupled the drought effects on crop yield. These findings agree with the preceding research studies (e.g., Troy et al. 2015; Araujo et al. 2016), which describe that irrigation acts as a mitigation tool in reducing crop yield sensitivity to dry spells. Although irrigation might be an effective source for decreasing drought sensitivity, at the same time, groundwater abstraction already goes beyond the sustainable yield in various aquifers in numerous areas of the world, including Pakistan (Iqbal et al. 2016). Therefore, a careful approach and practices in addition to the irrigation as a mitigation tool for reducing the drought impacts are required, such as genetics for more drought-resistant crops, and advances in plant breeding may also reduce the drought sensitivity in the future (Manavalan et al. 2009).

The analysis also indicated that short-term drought (i.e., 1–3 months) events during the growing season (i.e., April–May for Rabi maize crop and September–October for Kharif maize crop) tend to be a dominant factor for maize yield variability in the south region of Punjab. Short-term drought is more important for the study of annual crop yield responses because crop growth and yield are more responsive to the fluctuation in short-term weather events that could extensively and rapidly change the soil moisture conditions (Wu & Wilhite 2004).

Moreover, spatial shifts in drought sensitivity were observed across Punjab and resulted in more drought sensitivity in Central Punjab especially during the flowering and post-flowering maize season of the Kharif crop. The present study also indicates that the regions, such as South Punjab and some districts of Potohar Plateau (North Punjab), might also be at high risk from droughts, particularly when drought comes about at the flowering stage of maize development. Moreover, it will be noteworthy here to mention that as SPI does not take into account the soil moisture conditions and, hence, may not explain the actual soil moisture regime experienced by crops, hence, some soil moisture based methods for drought quantification (Carrão et al. 2016) could enhance impact assessment analysis, which was lacking in the current study due to limited availability of observed soil moisture data.

Overall, this study highlights the challenge of sustainable food supply amidst the meteorological drought. These results contribute to understanding the climate-induced yield variability by quantifying the variability in drought sensitivity both at spatial and temporal scales across Punjab for one of the major cereal crops, i.e., maize. Such spatiotemporal understanding helps us to find both, i.e., when and where meteorological droughts have strong impacts on maize yield, and how yield sensitivity to drought has changed over time, which can guide management, stakeholders, and farmer’s drought responses and mitigation at district and regional levels.

**CONCLUSION**

Conclusively, this study resulted that meteorological drought has been associated with Punjab maize yield variability with an average of 27% over the past two decades (2001–2020), and short-term droughts (i.e., 1 and 3 months) during the critical growth stage of the crop cycle were more correlated with yield variations having a higher value of $R^2$. Moreover, substantial spatial variations in drought effects with respect to the magnitude might be due to the local physical characteristics (e.g., topography, soil texture, and water table) and agricultural management such as surface or groundwater irrigation. The results also illustrated that maize yield from South Punjab was more sensitive (having a higher slope) to droughts as compared to Central Punjab, where there is the availability of an extensive irrigation network. In addition to the above, drought shift analysis revealed that Central Punjab might also be severely affected by drought shift, particularly during the growing season of the
Kharif maize crop. These results emphasize the need to examine the resilience and sustainability of the current irrigation system in order to mitigate the drought impacts in the future.

Furthermore, the adoption of multi-pronged approaches, e.g., the growing of more drought-resistant crops, and the adoption of agronomic mitigation practices (irrigation) are required to cope with future drought challenges. This study presents a detailed spatiotemporal analysis of drought impacts on the maize yield of the Punjab province and describes the need for research, management, and policy changes to buffer future maize production from anticipated variations in the future drought intensity, frequency, and duration. As Punjab maize yield contributes significantly to national maize production, and therefore, this study has considerable implications for national agricultural output and, hence, food security. At the same time, efforts would be needed to introduce measures (structural and nonstructural including bio-engineering measures) to protect natural resources from climate-related hazards that are expected to increase due to climate change and may well outpace the positive impacts of these climate changes.

**DATA AVAILABILITY STATEMENT**

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

**REFERENCES**


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