



# Evaluating agricultural activity dynamics over the Uttar Pradesh state of India using satellite-based datasets

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## Abstract

Climate change and anthropogenic activities (changes in rainfall and temperature pattern) activities have significantly affected agricultural activity and crop production. So, studying cropland greenness and crop yield trends is essential to understand their impacts and to ensure food security. The present study attempted to depict the cropland greenness and wheat yield trends in Uttar Pradesh (UP) state, India, during 2001–2019. The Moderate Resolution Imaging Spectroradiometer (MODIS) based Normalised Difference Vegetation Index (NDVI) dataset was used to decipher the cropland greenness trends through the Mann-Kendall (MK) test. Furthermore, the wheat yield dataset from Baghel and Sharma (2022) was used to depict the wheat yield trends using the Thiel-Sen slope test from 2001 to 2019. The study's results showed that ~37.3% (82,041 km<sup>2</sup>) area of the total agricultural land was with positive cropland greenness (NDVI) trend, and 1.67% (3673 km<sup>2</sup>) area was under a negative cropland greenness trend. On the other hand, ~8463 km<sup>2</sup> (at 99% significance level) and 160,557 km<sup>2</sup> (90% significance level) area corresponding to the ~4% and 73%, respectively, of the total agricultural land has shown positive (increasing) wheat yield trends during 2001–2019. In conclusion, the findings of this study emphasize the need for ongoing monitoring and a comprehensive understanding of cropland greenness and wheat yield trends over different agroclimatic zones. By gaining insights into these trends, policymakers and stakeholders can develop and implement effective mitigation and adaptation strategies to minimize the adverse effects of climate change and anthropogenic activities on agricultural systems.

**Keywords** Climate change · Mann-Kendall test · NDVI · Satellite data · Sens's slope · Yield trends

## Introduction

Assessing cropland greenness trends is essential, both temporally and spatially, to identify the growth or reduction in agricultural span in a particular geographical context. It is also crucial to generate and evaluate the crop yield trends to ensure a balance in demand and supply relationships (Parida and Ranjan 2019a; Ladli et al. 2020), considering the population explosion in the countries like India and the rest of the world as well. Agricultural activities and yields depend on complex and interrelated climatic processes and interactions (Chang 2017; Ranjan and Parida 2021). The climatic conditions are changing across time and space (Swain et al. 2019, 2022a, e), changing the agricultural dynamics. The major climatic parameters affecting agricultural yields are

temperature and precipitation (Hatfield et al. 2011; Parida and Ranjan 2019b). The temperature has always been a limiting factor for crop yields when it approaches the higher ends of the range (Ottman et al. 2012; Zhao et al. 2017). Precipitation provides the impetus to higher crop yields, as obtained in the results of the studies (Kukul et al. 2018, Zachariah et al. 2020). Extreme climatic conditions such as drought need proper assessments, and some impactful efforts have been made for different regions by (Swain et al. 2021, 2022c, d, e). Food security, climate change, and anthropogenic activities are interlinked globally and coexist among the most critical challenges of the 21st century (Lal et al. 2005, Wheeler et al. 2013). The essential requirement to protect food security is to ensure yearly increasing agricultural yields in the appropriate proportion of the population growth. In this direction, the anthropogenic usage of machinery and other energy inputs results in higher yields as suggested by Singh (2006) in his study. In addition to managing anthropogenic activities, the important challenge to fulfilling this requirement is to evaluate and accurately

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identify the climatic change impacts on crop yields (Schmidhuber and Tubiello 2007). So, it becomes imperative to study and assess the impacts of climate change and anthropogenic interventions on agricultural activities and yield. In this direction, numerous studies and efforts have been made to look for solutions in different regions of the world (Guntukula et al. 2020, Singh et al. 2021).

Assessing climatic impacts and trends on agriculture and crop yield requires vast spatial and temporal data (Ramirez-Villegas et al. 2012). Traditional data acquisition methods, such as manual surveys, field surveys, report analyses, etc., cannot quickly serve these data demand. The other problems in this mode include unreliability, human errors, high cost, and above all, temporal data cannot be gathered due to its unavailability by stakeholders (Balaselvakumar and Saravanan 2006). Remote sensing data is an effective option used in many applications, including but not limited to agriculture, hydrology, and climatology (Guptha et al. 2021; Swain et al. 2022e). In the context of cropland greenness and yields also, the remote sensing-based long-term satellite data archive is crucial in generating and analyzing cropland greenness and yield trends in temporal and spatial contexts. The most accepted solution to these problems (e.g., crop monitoring, mapping, and management) have been provided by satellite-based remote sensing and their derived data products (Huang et al. 2018). The most used remote sensing data products for crop/vegetation monitoring, mapping, and management are satellite-derived vegetation indices (e.g., normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), leaf area index (LAI), etc.). The satellite-derived vegetation indices are used as proxies for crop/vegetation health, vigor, growth, and yield (Ranjan and Parida 2020; Ranjan and Gorai 2022; Parida et al. 2022). These vegetation indices are widely used solely/combinedly as a key input in various statistical models (regression) for crop/vegetation health, growth, and productivity estimation. Kern et al. (2018) have used multiple linear regression models to predict the crop yield of different crops using climatic data and vegetation indices (NDVI and EVI) for central Europe regions at different levels of spatial administrative units. Maize and Soybean yield was forecasted with remotely sensed EVI, NDVI, and Normalized difference water index (NDWI) by Bolton and Friedl (2013) for central United States agricultural counties. Banti et al. (2019) analyzed vegetation using annual and seasonal NDVI data and the least square line fitting method during 2000–2017 for various land-use environments. Results highlighted the dominating vegetation greening throughout the country during all seasons except for a few sporadic spots with fire events and urban development. Barbosa et al. (2015) investigated the spatial patterns of NDVI and rainfall variability in South America and their relationships based on analyses of the Standardized Difference Vegetation Index (SDVI) and

the Standardized Precipitation Index (SPI) using the linear least square method for the period April 1998–March 2012. The vegetation degradation in 8% area is attributed to a significant decrease in rainfall as opposed to an increase in vegetation greenness across 18% area coupled to an increase in rainfall. Vegetation trends could not be linked to rainfall changes over 46% area, indicating human impact or the influence of other climatic factors.

In the Indian context, one such work by Parida et al. (2020) uses 3rd generation Normalised difference vegetation index (NDVI3g) from Global Inventory Modelling and Mapping Studies (GIMMS) records based on NOAA AVHRR sensor for assessing the greenness trends over forest and cropland in India. The temporal period spans from 1981 to 2015, whereas the spatial context spans throughout India. The vegetation trends were identified by the Mann Kendal (MK) test.

In the general context of yield trends based on data other than vegetation indices, Chen et al. (2017) have used parsimonious regression models of increasing order to analyze the rice, wheat, and soybean crop yield trends in the Japan archipelago from 1958 to 2016. Dynamic linear models (DLMs) were used by Schauburger et al. (2018) to assess the crop yield trends in France from 1900 to 2016. DLMs facilitate the adjustment of trends temporally and govern annual growth rates while not making robust assumptions regarding functional form of yield trends.

It is quite important how the climatic variables drive cropland greenness and wheat yield trends. The spatial data of cropland greenness is crucial to achieving this goal. At the same time, there are real difficulties in obtaining such data from the field at a desirable scale, and it may also not be feasible to get this data by using traditional ways. The satellites can act as an important alternative data source in this scenario. NDVI is referred to as a representative of greenness due to its linear relationship with green plant cover (Purevdorj et al. 1998; Calera et al. 2001). So, satellite-derived NDVI is a good option to get greenness cover and its trends. Uttar Pradesh (UP) is the most populous (census (2011) state of India. The state's land use is dominated by agriculture and India's highest wheat-producing state (Ramadas et al. 2019). The available literature does not report any such study that has presented the cropland greenness and wheat yield trends specifically for India's Uttar Pradesh (UP) state. So, this study aims to assess the cropland greenness and wheat yield trends for the UP state of India using satellite/gridded data from 2001 to 2019. Thus, the broad objectives of the present study are:

- (1) To assess cropland greenness trends and wheat yields over the UP state using MK and Sens's slope tests, respectively.

- (2) To analyse how the climatic drivers correlate with the NDVI and wheat yield trends.

## Materials and methods

### Study area

The Uttar Pradesh state (UP) of India is selected for the study. The study area extended over 23° 52' N and 30° 40' N latitudes and 77° 3' E and 84° 63' E longitudes. This study covers the 73 districts (excluding Banda and Chitrakoot districts with district ID's 40 and 41, respectively) of Uttar Pradesh (UP) state of India, consisting of about 14% of cropped area in the country. Agricultural land is 80.7% of the state's total area, 6.4% of the area is a forest area, and more than 5% of the total land cover contains rural and urban development and mining area. The Terai-Bhabar region in the north, the alluvial Gangetic plains constituting the central portion, and the southern plateau region are the three main topographical regions of the state (Gupta et al. 2021). The major rivers flow through the study area are Ganga, Yamuna, Ramganga, Gomati, and Ghaghra. Kharif, from June or July to October, and rabi, from November to April,

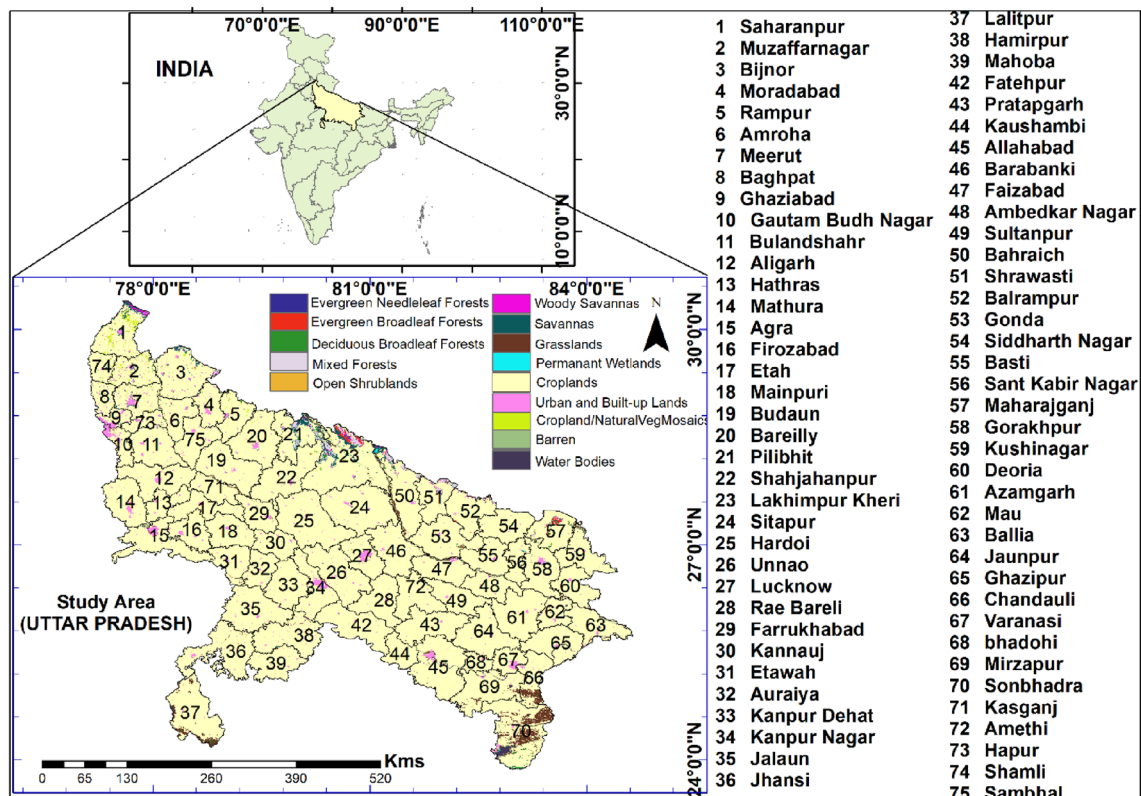
are two dominant crop-growing seasons. The state's major crops are winter wheat, rice, mustard, sugarcane, maize, and pulses. The state is defined to be a tropical monsoon-type climatic region with three main seasons summer (March–May), monsoon (June–October), and winter (November–February). The region has a mean annual rainfall of about 800 mm, most (> 80%) of which occurs during the monsoon season (Guhathakurta et al. 2020). The average temperature ranges between 30 and 35 °C, with heat waves (> 45 °C) arriving during the peak of the summer season (Baghel and Sharma 2022) Fig. 1.

### Data used

The details of data used in the present study, including product name, resolution, duration, and source, are summarised in Table 1.

### MODIS NDVI datasets

MODIS Terra (product name MOD13A1) and Aqua (product name MYD13A1) satellites provide Normalised difference vegetation index (NDVI) at 500-m resolution with 16-day revisit frequency. The present study



**Fig. 1** Map showing Uttar Pradesh state of India with district boundaries overlaid with LULC features. The LULC classes are shown based on the MODIS MCD12Q1 product for 2010

**Table 1** Data used in the present study

Data Product	Spatial/Temporal resolution	Duration	Data source
MODIS NDVI (MOD13A1)	500 m/16 days	1st Jan to 31st March every year	USGS earth explorer
MODIS land cover (MCD12Q1)	500 m/Annual	2010	USGS earth explorer
Temperature (TerraClimate)	4 km/Monthly	1st Jan to 31st March every year	Abatzoglou et al. (2018)
Precipitation (TerraClimate)	4 km/Monthly	1st Jan to 31st March every year	Abatzoglou et al. (2018)
Soil Moisture (TerraClimate)	4 km/Monthly	1st Jan to 31st March every year	Abatzoglou et al. (2018)
Downward Radiation (TerraClimate)	4 km/Monthly	1st Jan to 31st March every year	Abatzoglou et al. (2018)
Spatial wheat yield maps	500 m/Yearly	2001–2019	Baghel and Sharma (2022)
Fertilizer consumption	Yearly	2001–2017	ICRISAT

used MODIS Terra NDVI data from 1st January to 31st March 2001–2019 as a substitute for vegetation over the study area. The vegetation/crop characteristics such as leaf area index (LAI) (Tan et al. 2020), biomass (Zhu and Liu 2015), vegetation trends (Tenreiro et al. 2021) and many others are often measured using a satellite-based proxy, namely Normalised difference vegetation index (NDVI). The primary reason for using NDVI as a proxy of these characteristics is its linear relationships with vegetation/crop growth and productivity (Lopresti et al. 2015). NDVI is defined as the normalized ratio of NIR and red bands as given in Eq. 1:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \quad (1)$$

NIR is the near-infrared, and R is the red band. The value of NDVI ranges between  $-1$  and  $1$ , wherein for crop/vegetation, NDVI values generally range from  $0.2$  to  $0.6$  (depending upon season and stages of crops).

### MODIS cropland mask

The MODIS combined land cover data (MCD12Q1, v06) for the year 2010 was used in this study over the study region. The International Geosphere-Biosphere Programme (IGBP) classification scheme of MCD12Q1 governs 17 land cover classes. The cropland pixels were only included in the analyses, while 16 other classes were masked. The supervised classification method is used to derive the product from MODIS reflectance data with a classification accuracy of  $>75\%$  (Friedl et al. 2010). The year 2010 for mask data is chosen as it lies in the middle of the study period and hence can work best for little variations in the extent of the croplands. Subsequently, the cropland map was used to extract only the NDVI, temperature, precipitation, soil moisture, and downward radiation data for the cropland areas.

### Yearly long-term (2001–2019) wheat yield datasets of Uttar Pradesh state

The annual wheat yield at satellite pixel level (500 m) resolution from 2001 to 2019 was taken from Baghel and Sharma (2022). These datasets were generated by yearly regression models, which employed the NDVI, temperature, precipitation, evapotranspiration, and Directorate of Economics and Statistics (DES) based on mean wheat yields of the corresponding years. The developed models have shown moderate to strong correlation coefficients between  $0.5$  and  $0.7$ . Comparatively, the  $R^2$  values for 2013, 2015, 2017, and 2018 were marginally lower than other years. Notably, all the developed models were significant at  $p < 0.01$ . The accuracy of generated datasets at the satellite footprint scale was maintained as the  $R^2$  values of all year's datasets ranged between  $0.3$  and  $0.76$ , and the mean absolute error was about  $0.2$  t/ha except few odd outliers. This study uses these simulated yearly wheat yield datasets to assess the yield trends.

### Climatic datasets

Different climatological and hydrological parameters, namely, temperature, precipitation, soil moisture, and downward shortwave radiation, were used to analyze these parameters' influence on agricultural activity and wheat yield trends. Numerous studies suggest that temperature and solar radiation are key climatic factors in crop growth and yield (Holzman et al. 2018; Zhu et al. 2018). Like temperature, precipitation, and soil moisture also have greater control over crop growth and productivity, and these parameters are typically found to be well correlated with crop yields (Prasanna et al. 2014). Thus, the current study used TerraClimate monthly maximum temperature, downward radiation, precipitation, and soil moisture with a native resolution of  $4$  km. The NDVI and spatial wheat yield maps are resampled to  $4$  km resolution using the bilinear resampling

method while making their correlation with temperature, precipitation, downward radiation, and soil moisture.

### Fertilizer datasets

The study utilized fertilizer consumption data from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) website (<http://data.icrisat.org/dld/src/inputs.html>). This dataset covers the period from 2001 to 2017 but is limited to a few districts. To explore the relationship between mean yield and mean fertilizer applied in the district, the study randomly selected four districts: Agra, Hamirpur, Mirzapur, and Gorakhpur. The datasets used in the study specifically focused on the rabi season of each year throughout the study period.

## Methods

### Mann-Kendall (MK) test

The Mann–Kendall trend test (Mann 1945; Kendall 1975) is used to analyse time-series data to identify the increasing or decreasing trends of the parameter of interest. This study analyses the cropland greenness trends across UP state, India, by analyzing the NDVI time-series data using the MK test for 2001–2019. One of the merits of the MK test is that it works better than other statistical methods (e.g., linear regression), even if the size of the datasets is small or the datasets contain outliers. Thus, the MK test has been widely used in various applications related to climatology, hydrology, ecology, and agriculture (Parida et al. 2020; Ranjan et al. 2022a, b). Three parameters of interest, i.e., statistic  $S$ ,  $\text{var}(S)$ , and  $Z$  values, are calculated as given below:

For time series  $\{X_i, i = 1, 2, \dots, n\}$ , the test statistic  $S$  can be computed by:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(X_j - X_i) \quad (2)$$

$$\text{sgn}(X_j - X_i) = \begin{cases} +1, & \text{if } (X_j - X_i) > 0 \\ 0, & \text{if } (X_j - X_i) = 0 \\ -1, & \text{if } (X_j - X_i) < 0 \end{cases} \quad (3)$$

where  $n$  is the size of time-series,  $X_i$  and  $X_j$  are values for sequence  $i = 1, 2, \dots, n-1$  and  $i + 1, \dots, n$ . If  $n > 8$ , statistic  $S$  approximates to normal distribution. The mean of  $S$  is 0, and the variance of  $S$  can be computed as:

$$\text{var}(S) = \frac{n(n-1)(2n+5)}{18} \quad (4)$$

The  $Z$  value is computed by:

$$Z = \begin{cases} \frac{(S-1)}{\sqrt{\text{var}(S)}}, & \text{if } S > 0 \\ 0, & \text{if } S = 0 \\ \frac{(S+1)}{\sqrt{\text{var}(S)}}, & \text{if } S < 0 \end{cases} \quad (5)$$

for a given confidence level  $c$ , sequential data trend is meant to be statistically significant if  $|z| > z(1-c/2)$ , where  $z(1-c/2)$  represents the value corresponding to  $p = c/2$  under the standard normal distribution. The vegetation trend's proxy, i.e., NDVI, is associated with  $Z$  value.

### Theil-Sens's slope test

In this study, a non-parametric method proposed by Theil (1950) and later modified by Sen (1968) was used to calculate the magnitude of the wheat yield trend. The merit of the Thiel-Sen slope is that the estimator can be computed efficiently and is insensitive to outliers. It is more accurate for skewed and heteroskedastic data than simple regression. It outperforms simple regression even in normal data distribution scenarios. Thus, the Thiel-Sen slope test has been widely used in various applications related to climatology, hydrology, ecology, and agriculture (Parida et al. 2020; Ranjan et al. 2023). The magnitude is calculated by Eq. 6:

$$\alpha = \text{Median} \left( \frac{X_j - X_i}{j - i} \right), j > i \quad (6)$$

$\alpha > 0$  states increasing trend and  $\alpha < 0$  states decreasing trend while  $\alpha = 0$  specifies no trend.

### Pearson's correlation analysis

Pearson's correlations of climatic variables of temperature, precipitation, downward radiation, and soil moisture with NDVI and wheat yield trends are established. Pearson's correlations are obtained on district-wise zonal means of all years of the whole study period. The total samples generated were 1387, with 73 district's zonal mean for 19 years of study periods. The Pearson correlation is given by the following Eq. 7 given below:

$$r = \frac{\sum (x_i - x_m)(y_i - y_m)}{\sqrt{\sum (x_i - x_m)^2 (y_i - y_m)^2}} \quad (7)$$

Where  $r$  is Pearson's correlation coefficient and  $x_i, y_i$  are NDVI and chosen climatic variables. The  $x_m, y_m$  variables represent the means of observed NDVI and chosen observed variables.



## Results

### Cropland greenness trends in UP state during 2001–2019

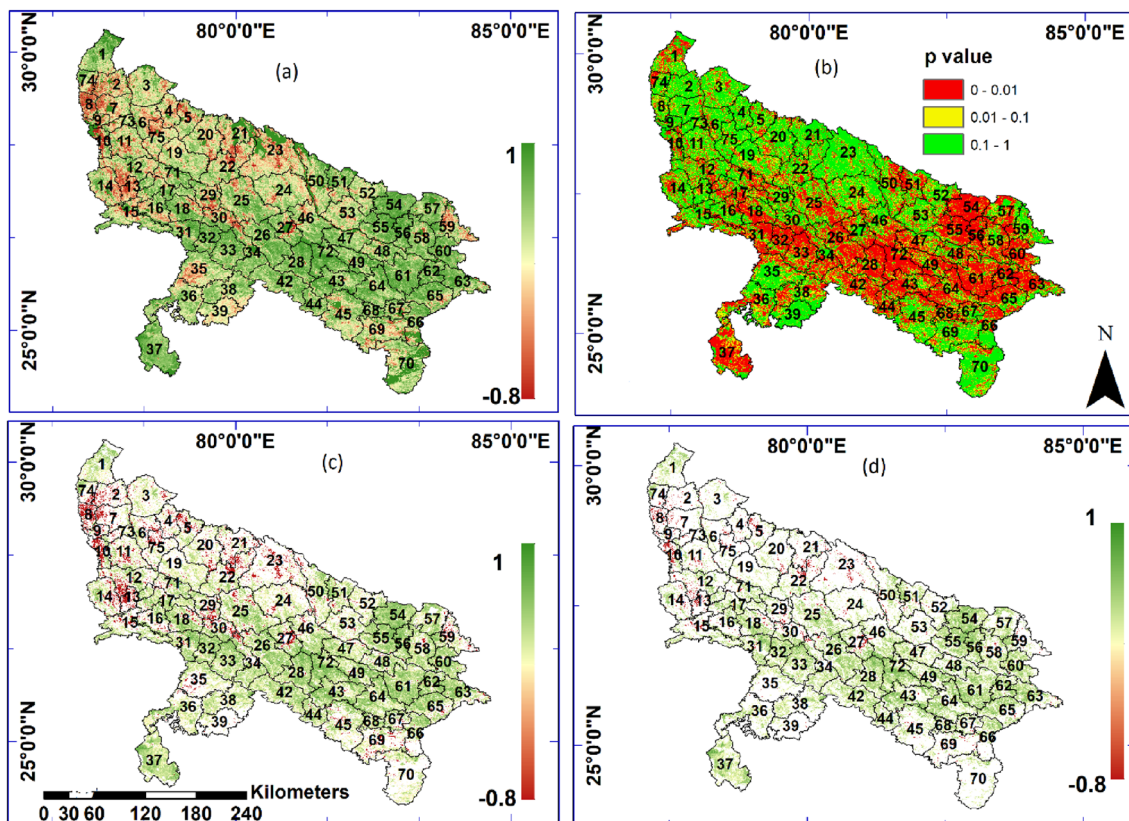
The cropland greenness trends across the study area for 2001–2019 are shown in Fig. 2. A total of 17.67% (38,881 km<sup>2</sup>) area of the total cropland area showed a negative greenness trend. In comparison, 82.33% (181,095 km<sup>2</sup>) of the cropland area exhibited a positive greenness trend out of the 219,976 km<sup>2</sup> cropland area in Mann-Kendall results

**Table 2** Positive and negative cropland greenness trends over cropland in UP state, India, during 2001–2019

Significance	Area with positive cropland greenness trends	Area with negative cropland greenness trends
No significance consideration	82.33% (181,095 km <sup>2</sup> )	17.67% (38,881 km <sup>2</sup> )
90% significance	56.87% (125,102 km <sup>2</sup> )	4.82% (10,609 km <sup>2</sup> )
99% significance	37.30% (82,041 km <sup>2</sup> )	1.67% (3673 km <sup>2</sup> )

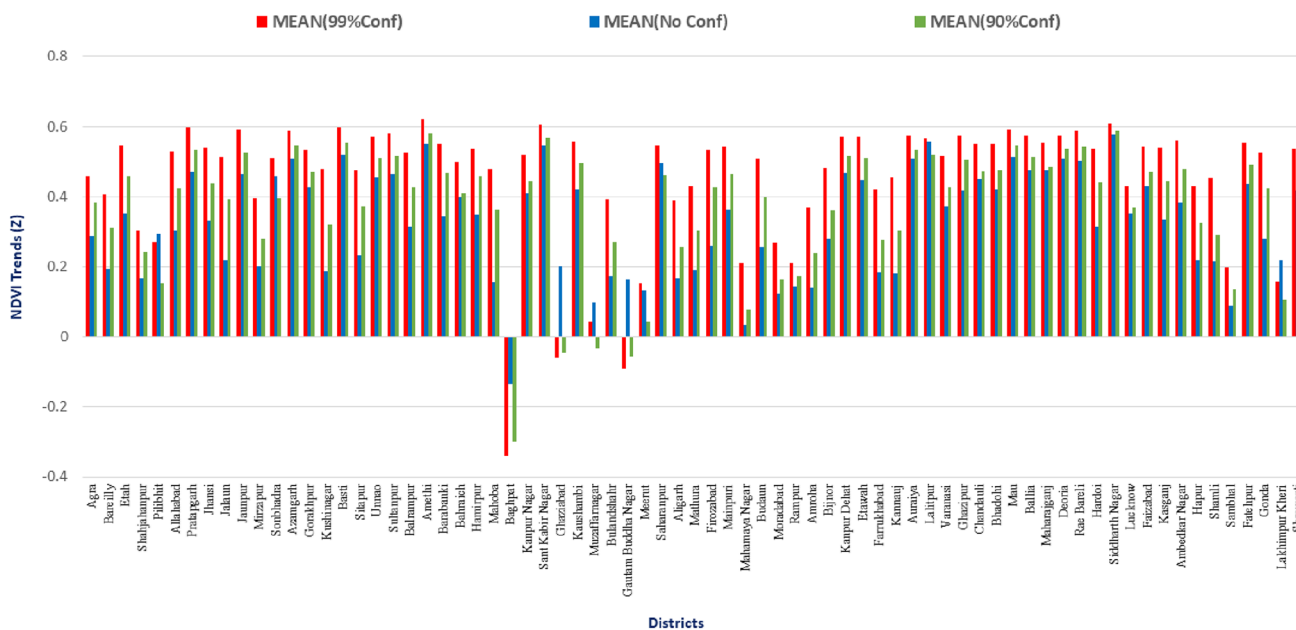
without considering any imposing condition of significance. The significance level criterion of 90% suggests that districts with unique ID values 2,7,8,9,10,11,12,13,21,23,29,30,69 and 75 have shown negative agricultural growth, and all other districts have either partial or complete extent agriculture growth (spatial). Overall, in quantitative terms, 56.87% (125,102 km<sup>2</sup>) area was observed with positive greenness trends, and 4.82% (10,609 km<sup>2</sup>) area fell under negative greenness trends (at a 90% significance level). Spatially, more or less, similar observations are found at a 99% significance level, but in quantitative terms, 37.3% (82,041 km<sup>2</sup>) area was observed with positive greenness trends, and 1.67% (3673 km<sup>2</sup>) area was estimated under negative greenness trends. In the case of no significance level, the positive greenness trend was observed over 82.33% of areas of total agricultural land, wherein ~17.67% were found under a negative greenness trend (Table 2).

The district-wise zonal mean cropland greenness trends of districts at specified significance levels are plotted in Fig. 3 to show how agricultural trends varied across the districts. The mean trend dynamics, which falls from -0.4 to 0.6 of Z values at 90% significance level, shows negative growths for Baghpat, Ghaziabad, Muzaffarnagar, and Gautambudhnagar



**Fig. 2** Cropland greenness trends of Uttar Pradesh state of India for the period of 2001–2019. Cropland greenness trends in **a** Greenness trends without considering significance level, **b** Shows p-value

classes for Fig. (2a), **c** Greenness trends with  $p < 0.1$  (90%), and **d** Greenness trends with  $p < 0.01$  (99%)



**Fig. 3** Cropland greenness trends of Uttar Pradesh state of India based on the zonal mean (district-wise) from 2001 to 2019. Cropland greenness trends are shown without considering the significance level

(blue colour bar), at 90% (green colour bar) and 99% significance levels (red colour bar) (color figure online)

districts. Similarly, the gloomy ( $0 < Z < 0.2$ ) trend was found for Meerut, Mahamayanagar (now Hathras), Pilibhit, Moradabad and Rampur, Sambhal, and Lakhimpur Kheri districts. The high mean positive growth was observed in Pratapgarh, Jaunpur, Azamgarh, Basti, Unnao, Sultanpur, Amethi, Sant Kabir Nagar, Kaushambi, Kanpur Dehat, Etawah, Auraiya, Lalitpur, Ghazipur, Mau, Ballia, Deoria, Rae Bareilly, Siddharth Nagar, and Fatehpur districts.

**Wheat yield trends over UP state during 2001–2019**

Wheat yield trends are shown in Fig. 4. The yield trend map predominantly showed a positive trend across the study area without considering the significance level. The magnitude of the trend ranges from  $-0.04$  t/ha to  $0.17$  t/ha. At a 90% significance level, the districts with unique IDs 26, 28, 31, 32, 33, 34, 37, 42, 44, 54, 55, 63, 66, 69, and 70 have shown more than  $0.1$  t/ha yield growth, whereas other districts have either a low positive yield trend or a negative yield trend. Notably, at a 99% significance level, districts with unique ids 10, 11, 12, 13, 14, 15, 17, 18, 29, 31, 32, 71, and 75 have shown less than  $0.1$  t/ha positive growth to a partial spatial extent. Districts with unique ids 37, 45, 69 and 70 exhibited more than  $0.1$  t/ha positive growth. The other districts have shown no trends at a 99% significance level. Overall, more specific quantitative information on trends at different significance levels is presented in Table 3.

The zonal statistics operations were performed on yield trend (Sen’s slope) raster generated at no consideration of

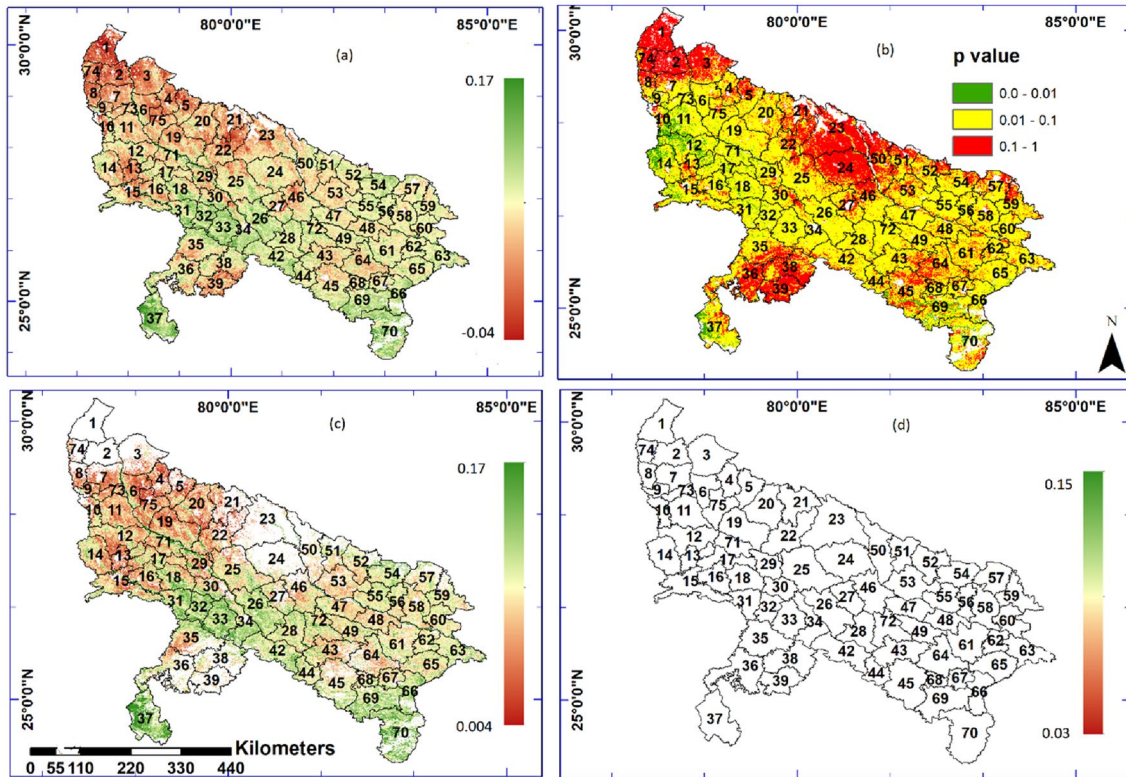
**Table 3** Positive and negative yield trends

Significance	Area under positive wheat yield trend	Area under negative wheat yield trend
No significance consideration	99.99% (219,897 km <sup>2</sup> )	0.00035% (79 km <sup>2</sup> )
90% significance	72.98.% (160,557 km <sup>2</sup> )	0% (0 km <sup>2</sup> )
99% significance	3.85% (8463 km <sup>2</sup> )	0 (0 km <sup>2</sup> )

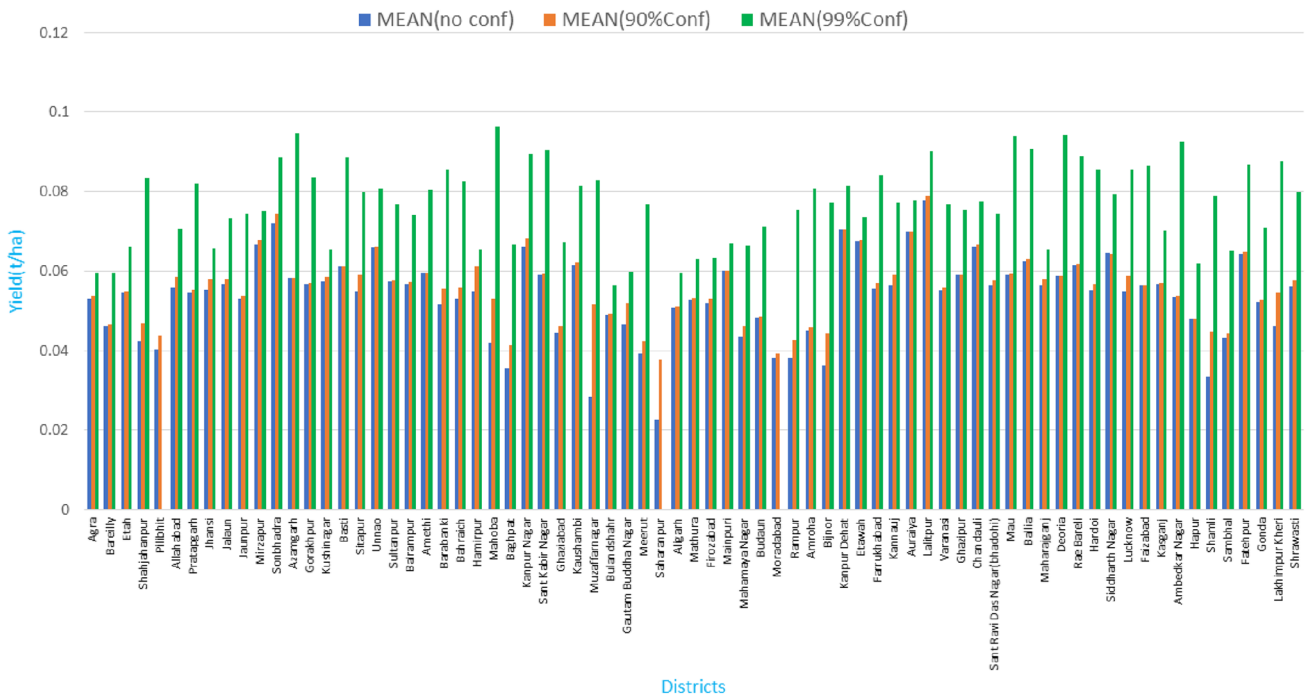
significance, 90% significance, and 99% significance level. The mean (MEAN) Sen’s slope values of districts are plotted in Fig. 5 to show how long-term yield varied across the districts. The Sen’s slope mean value at 90% significance level was  $0.03$  to  $0.08$  t/ha. Saharanpur, Baghpat, Pilibhit, and Mordabad were among the lowest positive yield trend districts, while Mirzapur, Sonbhadra, Unnao, Hamirpur, Kanpur Nagar, Kaushambi, Kanpur Dehat, Etawah, Auraiya, Lalitpur, Chandauli, Siddhartnagar, and Fatehpur have shown the high positive yield trends.

**Relationship between long-term NDVI, wheat yield, and climatic factors**

This section emphasizes the relationship between NDVI and wheat yield relationships with climatic parameters: temperature, precipitation, soil moisture, and downward radiation. The graphs in Fig. 6 show how NDVI relates to various climatic factors: temperature, precipitation, soil moisture,

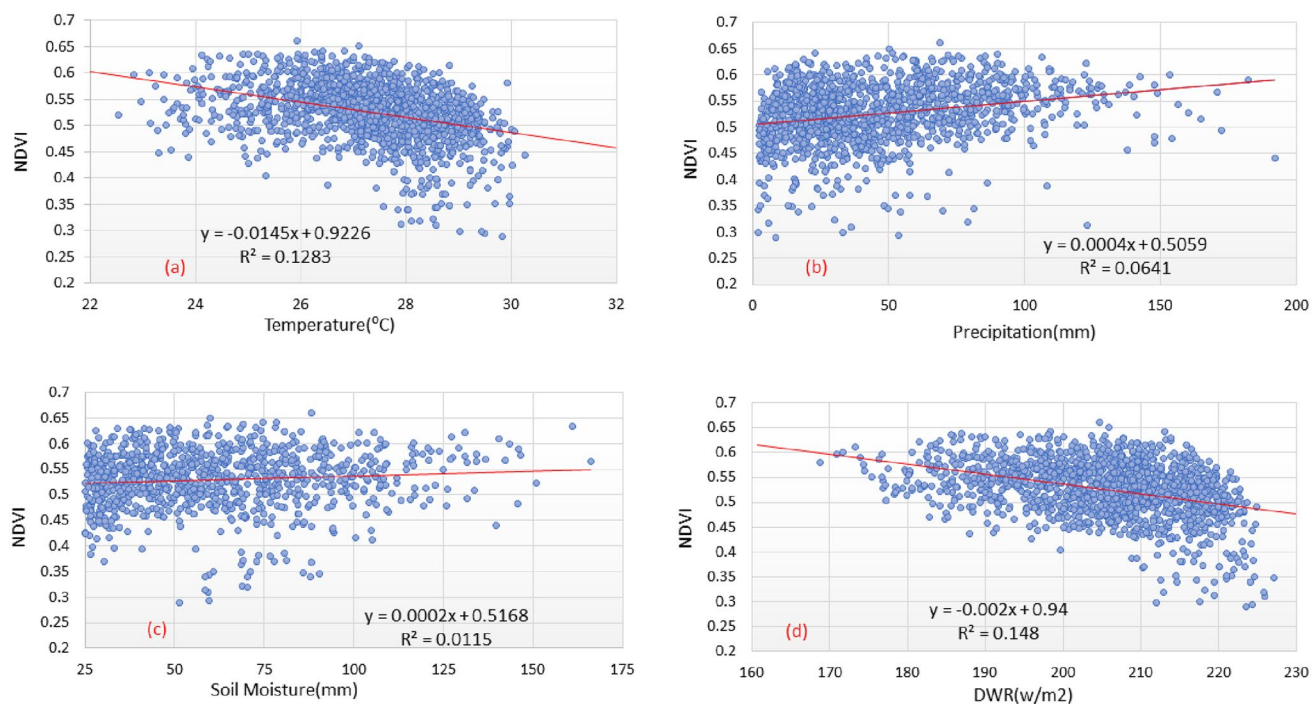


**Fig. 4** Wheat yield trends (t/ha) of Uttar Pradesh state of India for the period of 2001–2019. Yield trends in **a** without significance level, **b** shows p-value classes for Fig. (2a), **c** yield trends with  $p < 0.1$  (90%), and **d** yield trends with  $p < 0.01$  (99%)



**Fig. 5** Wheat yield trends of Uttar Pradesh state of India based on zonal statistics of yield (Sen's slope) for 2001–2019. Yield slopes are without considering significance level, at 90% significance level and at 99% significance level





**Fig. 6** Scatter plot showing the relationship between NDVI and **a** Temperature, **b** Precipitation, **c** Soil Moisture, and **d** Downward Radiation.

and downward radiation. The temperature was negatively correlated with NDVI, indicating a negative R-value of 0.36. A weak and positive correlation was found between precipitation and NDVI, as an r-value of 0.25 is not so strong. Notably, soil moisture has not shown any correlation with NDVI. This may be due to winter season effects, as a significant correlation is typically observed between NDVI and soil moisture or precipitation for the kharif season (June–September) in many studies, e.g., Bhimala et al. (2020). The downward radiation and NDVI possess a significant negative correlation.

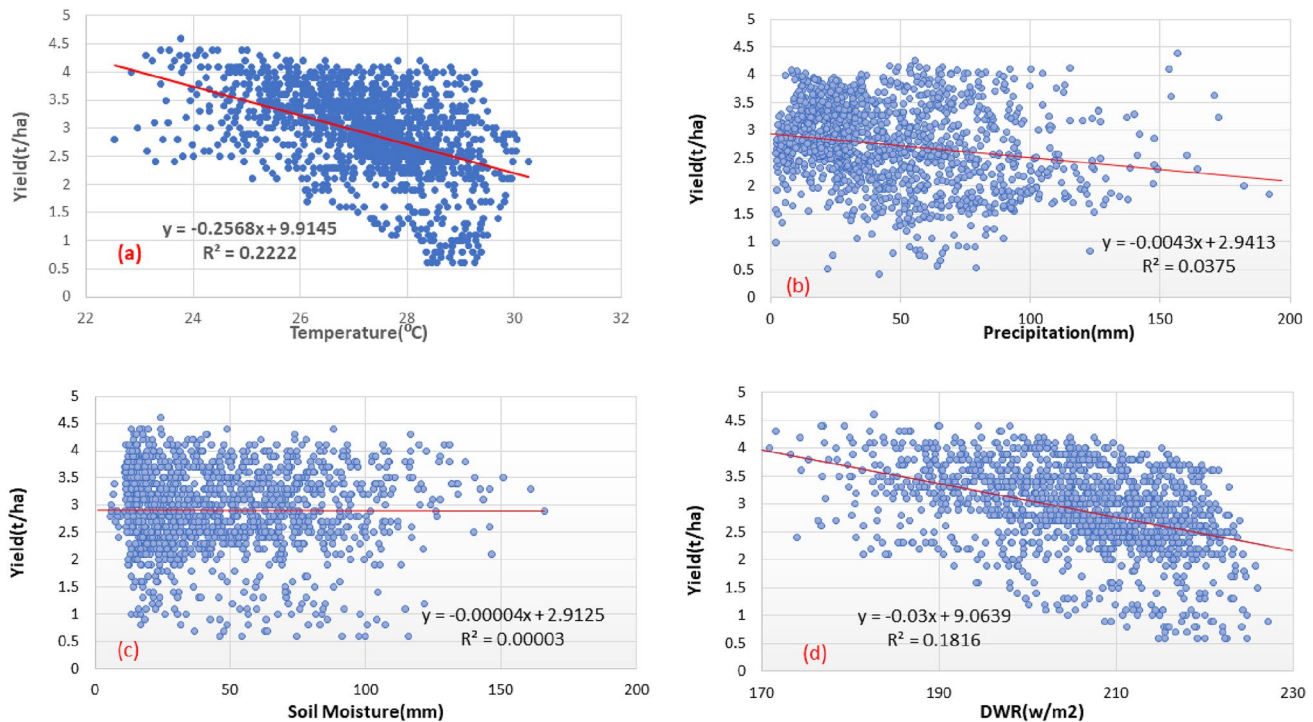
The crop yield depends on multiple factors and complex process dynamics. Figure 7 shows the graph of wheat yield and its correlation to climatic factors. The wheat yield exhibited a significant negative correlation with temperature and downward radiation, while it showed a weakly positive correlation with precipitation and no correlation with soil moisture.

## Discussion

In the present study, the MK trend and Sen’s slope analysis were performed on long-term NDVI and wheat yield datasets for analysing cropland greenness and wheat yield trends over the UP state of India from 2001 to 2019. Furthermore, the influence of climatic parameters on long-term NDVI and wheat yield was also analysed. The trends

exhibited that the western (except Saharanpur and Bijnor districts) and mid-upper northern region has shown negative cropland greenness trends. In contrast, UP’s lower half to the mid-eastern part has demonstrated a positive cropland greenness trends. These trend results are mostly in harmony with results produced by Kushwaha et al. (2020) in their study using ancillary datasets; however, the cropland area values differ by about 4%. The area spanning through the south dry zone, Bundelkhand region, and mid-western planes have shown positive trends. All other areas exhibited negative cropland greenness trends, which is remarkably similar to the results of this study. One small reason for negative cropland greenness trends in the western and mid-upper northern regions may be the rapid growth in settlement areas. Similar thoughts on the conversion of croplands into settlement areas have been expressed by Pandey et al. (2015). In this context, Fazal et al. (2022) have also emphasized that the growth rate of different categories of land use has witnessed declining trends, except the area under nonagricultural land use due to anthropogenic interventions (e.g., settlement encroachment, construction works, etc.).

On the other hand, the long-term wheat yield trend was also found to be negative (very close to 0) in the major part of western UP but a mix of high and low positive starting from lower central UP to eastern UP. Notably, the least wheat yield in the southern and southeast regions and lower to moderate yield in the lower-middle to the lower right portion of the state have been observed during the study years,



**Fig. 7** Scatter plot showing the relationship between yield and **a** Temperature, **b** Precipitation, **c** Soil Moisture, and **d** Downward Radiation.

as indicated by Baghel and Sharma (2022). However, the positive aspect indicated by the current study is the positive long-term yield trend in these regions. We could not produce a comparison or critique of this outcome to another similar study as no such study exists to the best of our knowledge.

The analysis of the influence of climatic parameters on NDVI trends and wheat yield trends has not shown much significant and remarkable correlation in our study. The temperature and downward radiation negatively correlated with NDVI trends with  $R^2$  0.13 and 0.15 ( $R$ -value 0.36 and 0.38), respectively. The precipitation and soil moisture have a positive but negligible or no correlation with NDVI. Nevertheless, in some cases, other researchers found that climatic parameters significantly correlate with NDVI. For instance, Parida et al. (2020) found that NDVI is positively correlated with soil moisture/precipitation, with an  $R$ -value ranging from 0.72 to 0.83. The negative correlation between NDVI and temperature/solar radiation ranged from  $r$ -value 0.71 to 0.82. The correlation between NDVI and temperature/downward radiation in our study agrees with Parida et al. (2020) to some extent; however, the range of the  $R$ -value was relatively low.

The yield also negatively correlates with temperature and downward radiation with  $R^2$  0.22 and 0.18 ( $r$ -value 0.47 and 0.42). Kuriachen et al. (2022) have also concluded that the relationship between wheat yield and growing and terminal stage temperatures was negative and non-linear; however, terminal stage temperature affects more negatively in

comparison to growing stage temperature. This study found a minor negative or no correlation between yield with precipitation and soil moisture. Typically, annual precipitation plays a positive role in higher wheat yields. However, the seasonal and, specifically, March month higher precipitation has a negative impact on rabi season wheat yield in the study region, as confirmed by the findings of Madhukar et al. (2022). Since this study used the composite image datasets of January, February, and March, the negligible negative impacts may be the March month effect in the correlation of yield and precipitation outliers.

This study finds the marginal impacts of climatic parameters on NDVI and yield. However, this observation is found when each of the climatic parameters is considered in isolation from other parameters. The combined or interaction-based impact produced a greater correlation than the isolated impact of the climatic variable on NDVI and Yield. A total of 11 possible sets of parameters correlation is studied, indicating that the highest correlation (for NDVI multiple  $R = 0.41$  and  $R^2 = 0.16$ , for Yield multiple  $R = 0.52$  and  $R^2 = 0.27$ ) was found when all four parameters: Temperature, Precipitation, Soil moisture, and Downward radiation were taken together. The correlation of all remaining sets of parameters is shown in Table 4. The commonly and well-understood fact that the climate parameters have a confounding effect in the yield and climatic variables modeling is very well addressed by these results. Moreover, combining climatic parameters has found suitable support from the

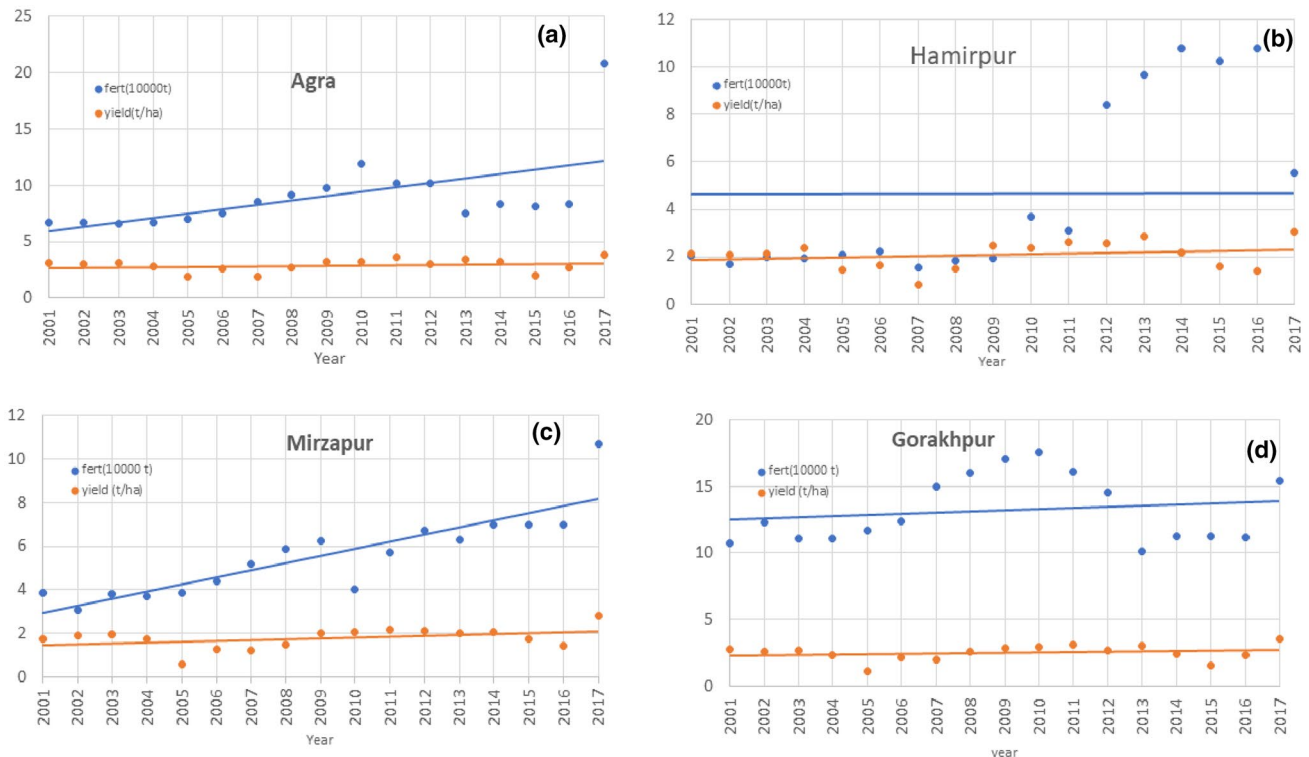
**Table 4** Parameters combination sets and their correlation with NDVI and Yield

S.No.	Parameter set	NDVI		Yield	
		Multiple R	R <sup>2</sup>	Multiple R	R <sup>2</sup>
1	Temperature, Precipitation	0.37	0.13	0.51	0.26
2	Temperature, Soil moisture	0.36	0.13	0.30	0.09
3	Temperature, Downward radiation	0.39	0.15	0.32	0.10
4	Precipitation, Soil moisture	0.26	0.07	0.20	0.04
5	Precipitation, Downward radiation	0.38	0.15	0.42	0.18
6	Soil moisture, Downward radiation	0.40	0.16	0.17	0.03
7	Temperature, Precipitation, Soil moisture	0.37	0.14	0.51	0.26
8	Temperature, Precipitation, Downward radiation	0.40	0.15	0.51	0.26
9	Temperature, Soil moisture, Downward radiation	0.40	0.16	0.32	0.10
10	Precipitation, Soil moisture, Downward radiation	0.40	0.16	0.44	0.22
11	Temperature, Precipitation, Soil moisture, Downward radiation	0.41	0.16	0.52	0.27

studies of (Mera et al. 2006; Gray et al. 2011; Volenec and Belovsky 2018; Yin et al. 2022).

The observed trends of NDVI and wheat yield may be due to anthropogenic activities such as land use management, irrigation, fertilizer application, and use of machinery (Kumar et al. 2021; Schröter et al. 2021). Schröter et al. (2021) found fertilizer application as the highest impacting anthropogenic variable among all studied variables. We evaluated this fact in

this study by observing trend lines for yield and available fertilizer application data for overlapping periods with the study period. These findings are shown in Fig. 8. Hamirpur, Gorakhpur, and Mirzapur districts were randomly chosen for this observation (based on the data availability). The trendlines suggested that the yield is growing marginal with fertilizer application. On the other hand, urbanization and land use applications other than agricultural activities have been the

**Fig. 8** Scatter plot showing the trend of fertilizer application and yield trend for **a** Agra, **b** Hamirpur, **c** Mirzapur, and **d** Gorakhpur districts, respectively

reasons for the decrease in vegetation area and yield (Nath et al. 2021; Fazal et al. 2022).

Of late, the policies and practices during COVID-19 have thrown a light on the impacts on vegetation in a new and remarkably interesting dimension. In this context, Ranjan et al. (2022a, b) have concluded a noteworthy increase in vegetation and productivity based on satellite datasets of the lockdown period in India. Based on these observations, it is quite clear that no single factor is outrightly affecting the vegetation and yield. It may be the mixed and interaction-based effect of numerous factors, i.e., anthropogenic, climatic, etc., and this probability may be the subject of future studies in this domain.

So, it can be inferred from the above discussion that the climatic parameters have a reasonable impact on cropland greenness trends and yield trends. However, our study found the marginal effect of climatic factors on agricultural and yield trends. In addition to the anthropogenic factors discussed above, this contradiction may be because of seasonal differences. Our study data belongs to only the rabi season, and the study portrays wheat yield only. The methods (MK and Sen's slope) used in this study have limitations, such as the assumption of normal data distribution, problems due to autocorrelation, and ties in the data considering the study's time span. These limitations can be resolved by Modified Mann-Kendall (MMK) test and Innovative Trend Analysis (ITA) (Hamid and Rao 1998; Sahoo et al. 2021; Swain et al. 2022e). Another limitation of the study is the exclusion of anthropogenic factors in cropland greenness and yield trends. In contrast, anthropogenic factors such as government policies, irrigation systems, availability of machinery, improved high-yield seeds etc., are major factors affecting cropland greenness, agricultural activities, and yields (Acemoglu and Restrepo 2018; Liliame and Charles 2020). Future studies may focus on finding trends and critically analyzing the impacts of anthropogenic and climatic factors on the various crop yield trends using MMK, ITA, and other more appropriate methods.

Nevertheless, the present study efficiently portrayed the cropland greenness trends and, more importantly, the wheat yield trends. This study is possibly the first to generate and assess the wheat yield trends for the study area at the satellite footprint scale. We foresee that it can be utilized to manage food security measures at the regional to national scales.

## Conclusions

In conclusion, the study conducted an assessment of long-term cropland greenness and wheat yield trends in Uttar Pradesh (UP), India, from 2001 to 2019 using satellite/gridded datasets. The study has resulted in the following conclusions:

1. NDVI trends portrayed that the western UP (except Saharanpur and Bijnor districts) and mid-upper northern region has shown negative cropland greenness trends. In contrast, UP's lower half to the mid-eastern part has shown positive cropland greenness trends.
2. The wheat yield trend was lowly negative in a major part of western UP but a mix of high and low positive starting from lower central UP to eastern UP.
3. While precipitation and soil moisture did not significantly impact the observed cropland greenness (NDVI) and wheat yield trends in Uttar Pradesh, India, temperature and downward radiation showed a weak negative correlation with these trends. This implies that changes in temperature and radiation levels can potentially influence cropland greenness and wheat productivity in the region.
4. The study suggests that while the MODIS-based datasets were utilized in this analysis, it has limitations due to their coarse spatial resolution. Therefore, alternative moderate to finer resolution data sources, such as Landsat and Sentinel-based products, could be considered for future research to improve the accuracy of assessments.

Overall, these findings contribute to our understanding of the spatial and temporal variations in cropland greenness and wheat yield trends in the UP state of India, providing valuable insights for policymakers and stakeholders in implementing targeted interventions and strategies to enhance agricultural productivity and mitigate the potential impacts of climate change on food security in the region.

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**Data availability** Not Applicable

## Declarations

**Conflict of interest** The authors declare no potential conflict of interest.

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