



# Vulnerability assessment of aerosol and climate variability for rice and maize yield using EO datasets for sustainable agriculture over India

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**Abstract** Human-generated aerosol pollution gradually modifies the atmospheric chemical and physical attributes, resulting in significant changes in weather patterns and detrimental effects on agricultural yields. The current study assesses the loss in agricultural productivity due to weather and anthropogenic aerosol variations for rice and maize crops through the analysis of time series data of India spanning from 1998 to 2019. The average values of meteorological variables like maximum temperature (TMAX), minimum temperature (TMIN), rainfall, and relative humidity, as well as aerosol optical depth (AOD), have also shown an increasing tendency, while the average values of soil moisture and fraction of absorbed photosynthetically active radiation (FAPAR) have followed a decreasing trend over that period. This study's primary finding is that unusual variations in weather variables like maximum and minimum temperature, rainfall, relative humidity, soil moisture, and FAPAR resulted in a reduction in rice and maize yield of approximately (2.55%, 2.92%, 2.778%, 4.84%, 2.90%, and 2.82%) and (5.12%, 6.57%, 6.93%, 6.54%, 4.97%, and 5.84%), respectively. However, the increase in aerosol pollution is also responsible for the reduction of rice and maize yield by 7.9% and 8.8%, respectively. In summary, the study presents

definitive proof of the detrimental effect of weather, FAPAR, and AOD variability on the yield of rice and maize in India during the study period. Meanwhile, a time series analysis of rice and maize yields revealed an increasing trend, with rates of 0.888 million tons/year and 0.561 million tons/year, respectively, due to the adoption of increasingly advanced agricultural techniques, the best fertilizer and irrigation, climate-resilient varieties, and other factors. Looking ahead, the ongoing challenge is to devise effective long-term strategies to combat air pollution caused by aerosols and to address its adverse effects on agricultural production and food security.

**Keywords** AOD · Soil moisture · Rainfall · Temperature · Climate change · Agriculture

## Introduction

India, one of the world's developing nations, has a significant population, representing around 18% of the world's population, and is projected to reach 1.7 billion by 2050, as reported by the United Nations in 2023 (Kasymova, 2024). Food security encompasses the consideration of individuals' dietary requirements and preferences, as well as their physical and economic access to food (Tecu et al., 2020), to ensure a healthy and active lifestyle. It entails ensuring that food is readily available, easily accessible, and nutritionally adequate for all individuals. Food security is

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based on three key elements (Abdullah et al., 2019): consistent food availability, availability of nutritious food, and the utilization of food for basic health and nutrition needs, together with convenient access to sanitary facilities and safe drinking water. The primary barriers to achieving self-sufficiency in emerging nations are food stability and availability. A high level of food production is required without sacrificing its nutritional quality to ensure food security for such a large population of India around 1.44 billion (Devaraj et al., 2024), which is relying on domestic food production. The Asian and African countries are also depending on India's agricultural production for importing wheat and rice grains to ensure their food security (Valera et al., 2024).

Maize crop cultivation covers an area of 150 million hectares in 160 countries, which is responsible for around 36% grain production of the world's total grain production. However, India holds the third position in maize production among the production of their most important crops following rice and wheat (Parihar et al., 2011). It has an average yield of approximately 2.43 tons per hectare and contributes nearly 9% to the overall national food production. Furthermore, maize is a crucial primary resource for a wide range of industrial goods, such as oil, starch, alcoholic drinks, protein, food sweeteners, medicines, cosmetics, films, textiles, gums, and packaging (Iliger Scholar et al., 2022). India has expanded its rice production from 53.6 million tons in the financial year 1980 to 120 million tons in the financial year 2020–2021 and it has become the second largest rice producer and exporter in the whole world (Malabadi et al., 2022). The changes in weather patterns could affect the global food supply due to the shortage of rain in various parts of the globe thereby causing the rice cultivation area to shrink by about 13% during the monsoon season of 2022 in India (Foreign Agricultural Service Global Market Analysis International Production Assessment Division India Rice: Production Down Due to a Decline in Planted Area, 2022). The above discussion shows that rice and maize are very important crops worldwide, which produce large amounts of food grains to ensure global food security (Dixit-Bajpai & K, 2016).

Understanding the intricacies of crop growth and development is essential for maximizing agricultural production and ensuring sufficient food supply in the

face of population rise. Plant development is influenced by a range of elements, such as climate variables, agricultural techniques, nutrient availability, and soil water content. Atmospheric aerosols exert a substantial influence on key climatic variables such as temperature, solar radiation, and precipitation (Mahowald et al., 2011). The evaluation of aerosol interactions with climate variables such as temperature, solar radiation, and precipitation aims to comprehend the impact of aerosols on plant development (Greenwald et al., 2006). This is because particles in the atmosphere have a substantial influence on climate, the water cycle, and human health (Mhawish et al., 2021). Aerosols play a significant role in the Earth's climate by scattering and absorbing solar radiation (Pandolfi et al., 2018). Recognizing the precise impact of aerosols on crop productivity is crucial for evaluating the combined effects of climate change and air quality on agricultural food security. This is especially important in regions with elevated pollution levels, like India (Charles et al., 2014).

Prior research has demonstrated that fluctuations in climate patterns adversely affect Indian agriculture, resulting in a decrease in relative crop yields by a significant percentage (Padakandla, 2016, 2021, 2022; Guntukula, 2020; Guntukula & Goyari, 2020;b; Gupta et al., 2014; Babita Patni and A. S. G. , 2020). The short-lived climate pollutants, such as black carbon and aerosols, as well as the non-long-lived greenhouse gases, including methane, tropospheric ozone, and hydrofluorocarbons, play a crucial role in regional radiative forcing, precipitation, and monsoon patterns, contributing significantly to global warming (Bond et al., 2013; Ramanathan & Carmichael, 2008). The non-long-lived greenhouse gases can remain in the atmosphere for several centuries. However, short-lived climate pollutants are persisted in the atmosphere for shorter lifetimes (from weeks to months). Agricultural productivity is influenced indirectly by short-lived climate pollutants due to their effects on temperature, precipitation, and solar radiation (Menon et al., n.d.). Understanding the specific role of short-lived climate pollutants and aerosols in crop productivity is necessary in high-pollution regions to ensure the food security of any nation, particularly in India. The use of Earth observation datasets is one of the most efficient ways to research the effects of aerosols and climate on agricultural productivity through remote

sensing (Duane Nellis et al., 2009). This technique can be applied to multiple spatial and temporal scales, regardless of geopolitical boundaries (Karthikeyan et al., 2020).

The current manuscript is summarized in the following sections: The “Literature review and motivation” section represents the literature review and motivation of the study. The section ‘Data and methodology’ provides the description and sources of earth observation datasets and agricultural yield data along with the pre processing of these datasets. The section ‘Statistical analysis’ contains the development of the model and its estimations, along with the accuracy checks. Finally, “Results and discussions” and “Conclusions” sections depict the results/discussions and conclusions of the study, respectively.

### Literature review and motivation

The variability in the climate has been attributed to the increment of anthropogenic greenhouse gas (GHG) emissions (like methane (CH<sub>4</sub>), nitrous oxides (N<sub>2</sub>O), and other GHGs) and aerosols from fossil fuel, biofuel, and biomass burning emissions in global atmosphere (Myhre et al., 2013). There are several researchers who have reported the negative impact on plant biophysical activities due to the complicated and uncertain implications of atmospheric aerosols like the extinction of solar radiation, suppression the atmospheric turbulence, modifications in cloud microphysical properties, and influence the boundary layer height (Greenwald et al., 2006; D. K. Gupta et al., 2022; R. Gupta et al., 2017; Sonkar et al., 2019; Zhang et al., 2017; Mittal et al., 2009; Zhang et al., 2021, Nirmalkar & Deb, 2016, Hill et al., 2019; Zhao et al., 2020). The spatial and temporal variation of aerosol loading has been analyzed by various researchers and they found the persistence of thick aerosol layer across India. However, the study of aerosol loading across Indo-Gangetic Plain (IGP) has always been the center of attraction for many researchers (Babu et al., 2013; Mhawish et al., 2021; Mor & Dhankhar, 2022). Moderate AOD loading is responsible for increasing the diffuse radiation, but dense aerosol loadings suppress the plant photosynthesis due to the strong attenuation of total radiation (Yue & Unger, 2018).

Several studies have been conducted for the examination of rice yield production under air pollution and aerosols (Bond et al., 2013; Ramanathan & Carmichael, 2008; Menon et al., n.d.; Babita Patni, 2020, Zhang et al., 2017; Yue & Unger, 2018). However, limited studies have been carried out for maize crops (Zhao et al., 2020; Hill et al., 2019; Kong et al., 2019; Meng et al., 2020), worldwide. Many studies have also been conducted by several researchers to analyze the air pollution/aerosols impact in association with climate factors on various crops (Kalra et al., 2006; Burney & Ramanathan, 2014; Shuai et al., 2013; Auffhammer et al., 2011; D. K. Gupta et al., 2022; R. Gupta et al., 2017; Sonkar et al., 2019, Zhang et al., 2021). Burney and Ramanathan, 2014 assessed the impact of climate change more specifically temperature and precipitation on wheat and rice production in India. They found that the direct impact of tropospheric ozone and black carbon on crop yields beyond their indirect effects through climate has risen dramatically in India from 1980 to 2010. Gupta et al., 2017 analyzed the impact of temperature, solar radiation, and aerosols on wheat yields in India during 1981–2009. They discovered that there is a 2–4% decrease in wheat production for every 1 °C increase in average daily maximum and lowest temperatures. Nevertheless, a 1% increase in solar radiation has been shown to result in a roughly 1% rise in yields, while a decrease in aerosol optical depth equivalent to one standard deviation is expected to lead to a 4.8% increase in wheat yields. A study conducted by (Auffhammer et al., 2011) found that rice yield in rainfed areas was adversely affected by drought and extreme rainfall between 1966 and 2002. The impact of drought was significantly bigger than that of excessive rainfall. If two further weather adjustments, namely warmer nights and lesser rainfall at the end of the growing season, had not taken place, a 4% increase in rice yield was observed.

Wang et al. (2020) studied the changes in surface solar radiation due to the air pollution effect on rice yield in East China using multi-sensor EO datasets and radiation models for the period 2000–2016. They found aerosol-induced reduction in rice production in about 6.74% and also suggested the impact of aerosols on rice production is non-negligible and the mitigation of aerosols is beneficial for crop production under climate change. Zhou et al., 2018 reported the empirical analysis for estimating the direct and

nonlinear impact of PM<sub>2.5</sub> along with the climate factors on agricultural output for three of the most common crops namely wheat, rice, and corn from 2001 to 2010. This study suggested that the PM<sub>2.5</sub> concentrations have a significant reduction in average yields of wheat and corn similar to the temperature, and precipitation. Additionally, this study also found that aerosols more impacted wheat and corn yield in comparison to rice yield. Mina et al., 2018 conducted an experiment to analyses and monitor the effects of atmospheric particulate matter (PM) deposition under three different treatments, which are low, ambient, and elevated levels of PM deposition ranges of 162–660  $\mu\text{gm}^{-3}$  during rice growing season (August–November) on two basmati rice varieties namely Pusa Basmati-1509 (PB-1509) and Pusa Sugandh-5 (PS-5) at its various growth stages. A 4–7% increment in rice yield has been observed under the low PM deposition treatment, while a 7.5–14% reduction is found in grain yield of rice under elevated PM deposition compared to ambient PM deposition. It also produced a significant effect on the reduction in chlorophyll, leaf water, air pollution tolerance index, enhanced the leaf temperature (1–6%), reduction in photosynthesis, stomatal conductance, and transpiration and carotenoid content were observed in both varieties under elevated PM deposition compared to ambient PM deposition.

The long-term impact of aerosols has been analyzed in our previous study by Gupta et al., 2022 on maize crop yield over the Indian region. The extension of our previous study has been carried out in the present article for the long-term assessment of aerosol impact in association with the weather variables on rice and maize crop yield using earth observation datasets. The particular interest of this article is the study of the aerosol impact in association with the climate variables on rice and maize crop yield over the Indian region because it is the aerosols dominant region worldwide, particularly the Indo-Gangetic Plains (IGP), which is a highly populated region in India and most of the agricultural practices are also performed. According to the above literature studies, most of the researchers have carried out the aerosols/particulate matters impact on crop yield in association with the climate variables particularly for temperature and precipitation. However, very less or no studies have been carried out to analyze the aerosol's impact on crop yield in association with the climate variables

like temperature, precipitation, relative humidity, soil moisture, and fraction of absorbed photosynthetically active radiation (FAPAR). The aerosol's impact on maize crop yield in association with climate variables is also performed in very rare studies in comparison to the rice crop.

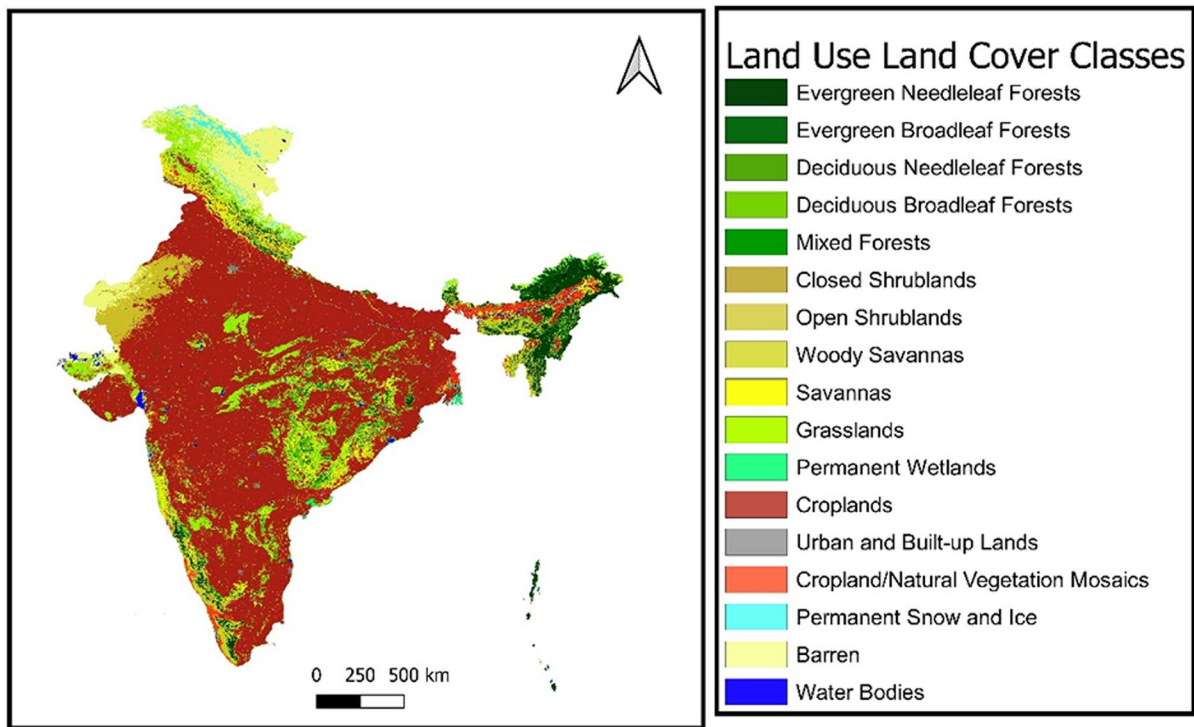
The specific objectives of this study are (1) to investigate the long-term impacts of aerosols, climate factors (particularly temperature and precipitation, humidity), and the fraction of FAPAR and soil moisture on historical rice and maize yields in India using earth observation datasets; (2) to utilizes spatial and temporal variations of earth observation datasets like maximum and minimum temperature, precipitation (RF), relative humidity (RH), FAPAR, soil moisture (SM), and AOD from 1998 to 2019 to construct a statistical model; (3) to analyze their effects on historical rice and maize yields using statistical model output and also assess the impact of temperature, FAPAR, and aerosols on historical rice and maize yields; (4) to evaluate the robustness of the statistical model; and (5) finally discuss the outcomes and limitations of the studies.

## Data and methodology

### Study area

India is a federal union comprised of 28 states and eight union territories. These states and union territories are subdivided into districts, totaling 748 districts according to the 2021 Census records. India, the world's seventh-largest country, spans a vast area of 3,287,263 km<sup>2</sup>. Geographically, it is situated north of the equator, with a latitude range extending from 8°4'N (the mainland) to 37°6'N, and a longitude range from 68°7'E to 97°25'E.

The classification of land use and land cover (LULC) map is one of the most extensively used in remote sensing applications (Sharma et al., 2018). Figure 1 shows the MODIS LULC map based on the International Geosphere-Biosphere Program (IGBP). The procedure of assigning land cover classes to pixels and grouping them into broad categories is commonly referred to as land use and land cover (LULC) classification (Alshari & Gawali, 2021). It is an extremely useful tool for identifying the extent of various land uses and cover types, such as urban, wooded, shrubland,



**Fig. 1** MODIS Land use and land cover (LULC) classification map of India (MODIS data code: MCD12Q1)

agriculture, and so on. In 1987, a worldwide scientific research program namely IGBP (Seitzinger et al., 2015) was established that looked at how Earth’s biological, chemical, and physical processes interact on a regional and global scale, as well as how society affects and is influenced by these processes. The fundamental goal of LULC, which began in 1994 as a main project of IGBP, was to determine how human and biophysical processes affect land/land cover, as well as the environmental and social consequences of these changes. According to this IGBP, the Land cover system can be classified into 17 classes, which consist of the following: (i) Evergreen Needleleaf Forests, (ii) Evergreen Broadleaf Forests, (iii) Deciduous Needleleaf Forests, (iv) Deciduous Broadleaf Forests, (v) Mixed Forests, (vi) Closed Shrublands, (vii) Open Shrublands, (viii) Woody Savannas, (ix) Savannas, (x) Grasslands, (xi) Permanent Wetlands, (xii) Croplands, (xiii) Urban and Built-up Lands, (xiv) Cropland/Natural Vegetation Mosaics, (xv) Permanent Snow and Ice, (xvi) Barren, (xvii) Water Bodies. Out of these seventeen classes, only croplands classified area in India are considered as our study area. Cropland includes those areas,

which are used to produce adapted crops (Hinz et al., 2020). For this purpose, we have further reclassified the LULC map into two categories with the cropland and other classes (the remaining 16 classes) to separate the cropland area over India based on all IGBP classes. The reclassified figure is shown in Fig. 2.

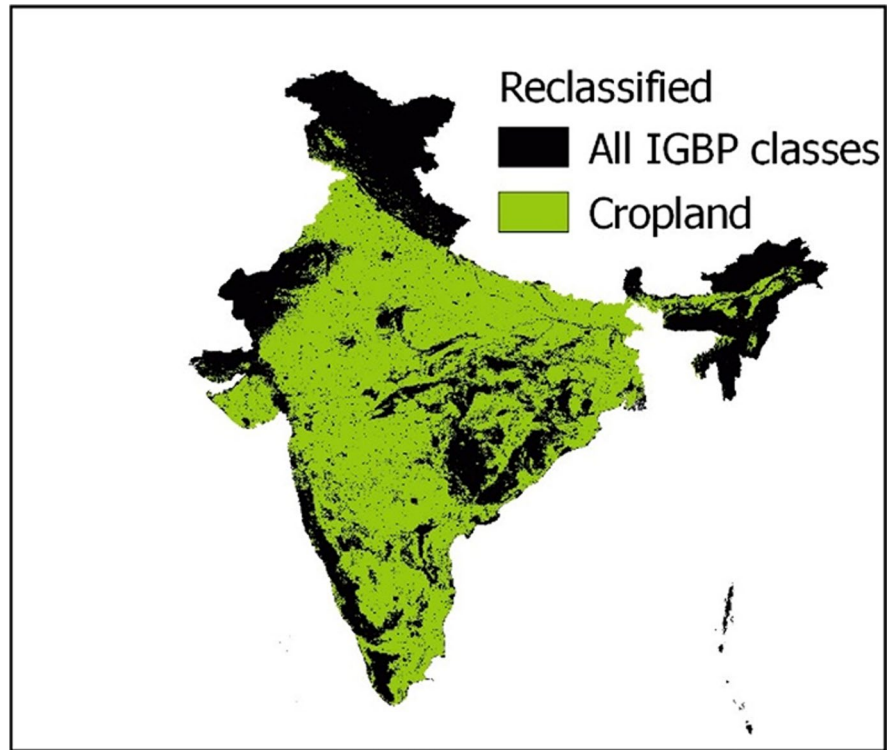
Data processing

*Agricultural data*

The Ministry of Agriculture’s Directorate of Economics and Statistics has recorded the ninefold land classification, irrigated area (source-wise and crop-wise), and total area under crops at the district level in India. The Special Data Dissemination Standard Division, Directorate of Economics & Statistics, Ministry of Agriculture and Farmers Welfare, Govt. of India, New Delhi has published this data on web-based land use and statistics information systems from the years 1998–2019 for various crops (<https://aps.dac.gov.in>).

The yield per hectare, cultivation area, and production of the kharif season crops (rice and maize crops)

**Fig. 2** MODIS LULC reclassification map of India on the basis of croplands vs all other IGBP classes (MODIS data code: MCD12Q1)



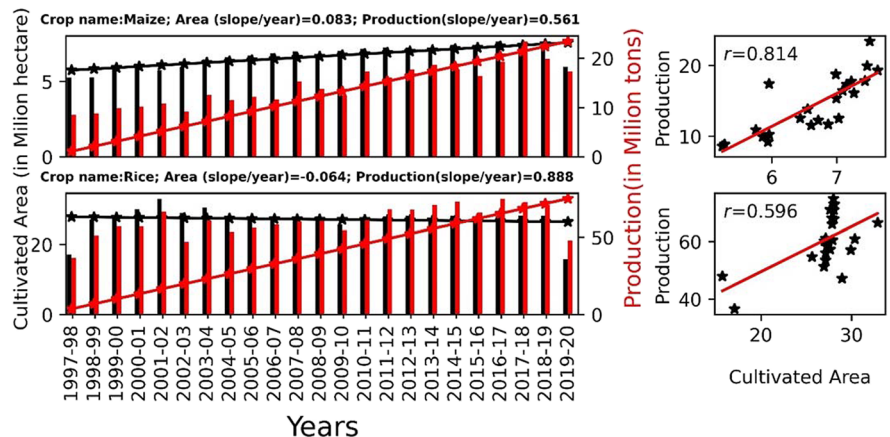
have been downloaded for each district during the years 1998 to 2019. The average crop yield per hectare, cultivation area, and production have been taken at a yearly scale over India. Figure 3 shows the bar plot of cultivation area and production of rice and maize crops with the scatter plot between them. The linear regression analysis was also carried out between the cultivation area vs years and production vs years to evaluate the temporal changes in cultivation area and respective

production of rice and maize crops. The linear regression analysis is also carried out between the cultivation area and production to analyze the linkage of the cultivation area with the production of crops.

#### *Climate and aerosol optical depth data*

The daily gridded data ( $1^\circ \times 1^\circ$ ) for maximum and minimum temperatures over India from 1998 to 2019

**Fig. 3** Bar and scatter plots for annual cultivation area and production of rice and maize crops in India (Ministry of Agriculture and Farmers Welfare, Govt. of India)



were obtained from the official website of the Indian Meteorological Department (<https://mausam.imd.gov.in/>). Rainfall is the primary need for any kharif crop like rice and maize (Singh et al., 2017). The daily gridded ( $0.25^\circ \times 0.25^\circ$ ) rainfall data of India for the duration of 1998 to 2019 is also downloaded from the official website of IMD. The fraction of absorbed photosynthetically active radiation (FAPAR) is the energy source for crop growth, which is used in the photosynthesis process. The daily gridded FAPAR data is downloaded from the official website of NCEI-NOAA (National Centers for Environmental Information, National Oceanic and Atmospheric Administration) at a spatial resolution of  $0.05^\circ \times 0.05^\circ$  from 1998 to 2019. This FAPAR data is developed using the Advanced Very High-Resolution Radiometer (AVHRR) sensor observations onboard the NOAA 19 platform. Relative Humidity (RH) is another important weather parameter, which is the indication of the water vapor content of air. Daily relative humidity data for the period 1998 to 2019 is taken from the official website of the Physical Sciences Laboratory with a spatial resolution of  $2.5^\circ$ . On the other hand, the moisture content in the soil is also an important parameter for plant growth, which helps to regulate the plant temperature and help in the nutrients taken from the soil. It is also one of the essential parameters for rice and maize crop growth (Gines et al., 2018). The daily gridded ( $0.25^\circ \times 0.25^\circ$ ) soil moisture data is obtained from Climate Change Initiative's (CCI) official website (<https://esa-soilmoisture-cci.org/>) for the years 1998 to 2019.

Aerosols in the atmosphere consist of a mixture of solid and liquid particles that vary in size (ranging from 0.1 to 20  $\mu\text{m}$ ), shape, and content (Colbeck & Lazaridis, 2010). Smoke, dust, sulfate, organic carbon, and sea salt spray make up these particles, which can come from either natural or man-made sources. Through their ability to reflect, absorb, and scatter radiation, these aerosol particles have a significant impact on the climate system as well as agriculture (Mahowald et al., 2011). The aerosol optical depth (AOD) is the parameter, which is used to measure the haziness of the atmosphere. The monthly gridded (spatial resolution of  $1^\circ \times 1^\circ$ ) aerosol optical depth (AOD) data at 550 nm is taken from GIOVANNI (Goddard Earth Sciences Data and Information Services Centre) with two different sensors namely Moderate Resolution Imaging Spectroradiometer

(MODIS) onboard Terra Satellite from 2000-02-01 to 2019-12-31 and Sea-Viewing Wide Field-of-View Sensor (SeaWiFS) onboard OrbView-2 platform from 1998-01-01 to 2000-01-31. The two-sensor AOD data is used due to the unavailability of data from one sensor for the duration of 1998 to 2019. The AOD data parameters are the same for both datasets in terms of wavelength, temporal, and spatial resolution.

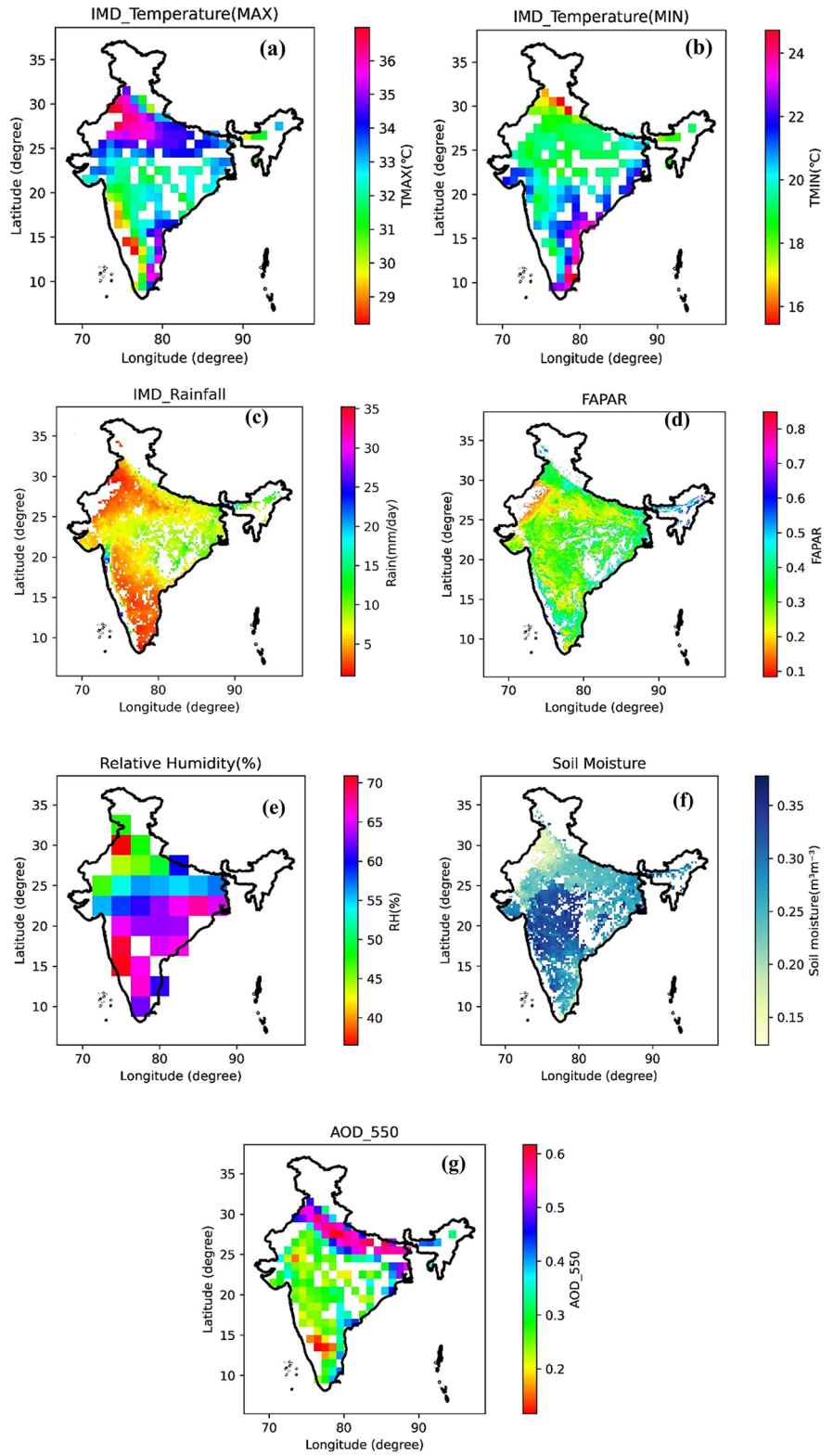
The study area for this study is the whole Indian region. The Indian region has various land cover like agriculture/cropland, forest, and water bodies. This study is conducted for agricultural land only in the Indian region. So, all the datasets are converted at the India level (over only cropland) spatial scale by taking the spatial average of daily and monthly datasets to remove the spatial resolution effect. The daily and monthly datasets were converted into annual datasets by taking time-series averages of the maximum and minimum temperature, relative humidity, FAPAR, soil moisture, and AOD. The annual conversion of rainfall datasets is carried out by taking the time series summation. Figure 4a, b shows the spatial variation of the time-series averages of the maximum and minimum temperature over the cropland of India during the years 1998 to 2019. Figure 5a, b shows the variation of average maximum and minimum temperatures at a monthly scale over cropland of India throughout the years 1998 to 2019. Figures 4c and 5c show the spatial variation of time-series averages of rainfall over the cropland of India during the years 1998 to 2019 and the total monthly rainfall over the cropland of India throughout the years 1998 to 2019. Figure 4d–g shows the spatial variation of the time series average of FAPAR, relative humidity, soil moisture, and AOD over the cropland of India during the years 1998 to 2019. Figure 5d–g shows the variation of average FAPAR, relative humidity, soil moisture, and AOD at a monthly scale over the cropland of India throughout the years 1998 to 2019.

#### Statistical analysis

##### *Association among climate and aerosol variables*

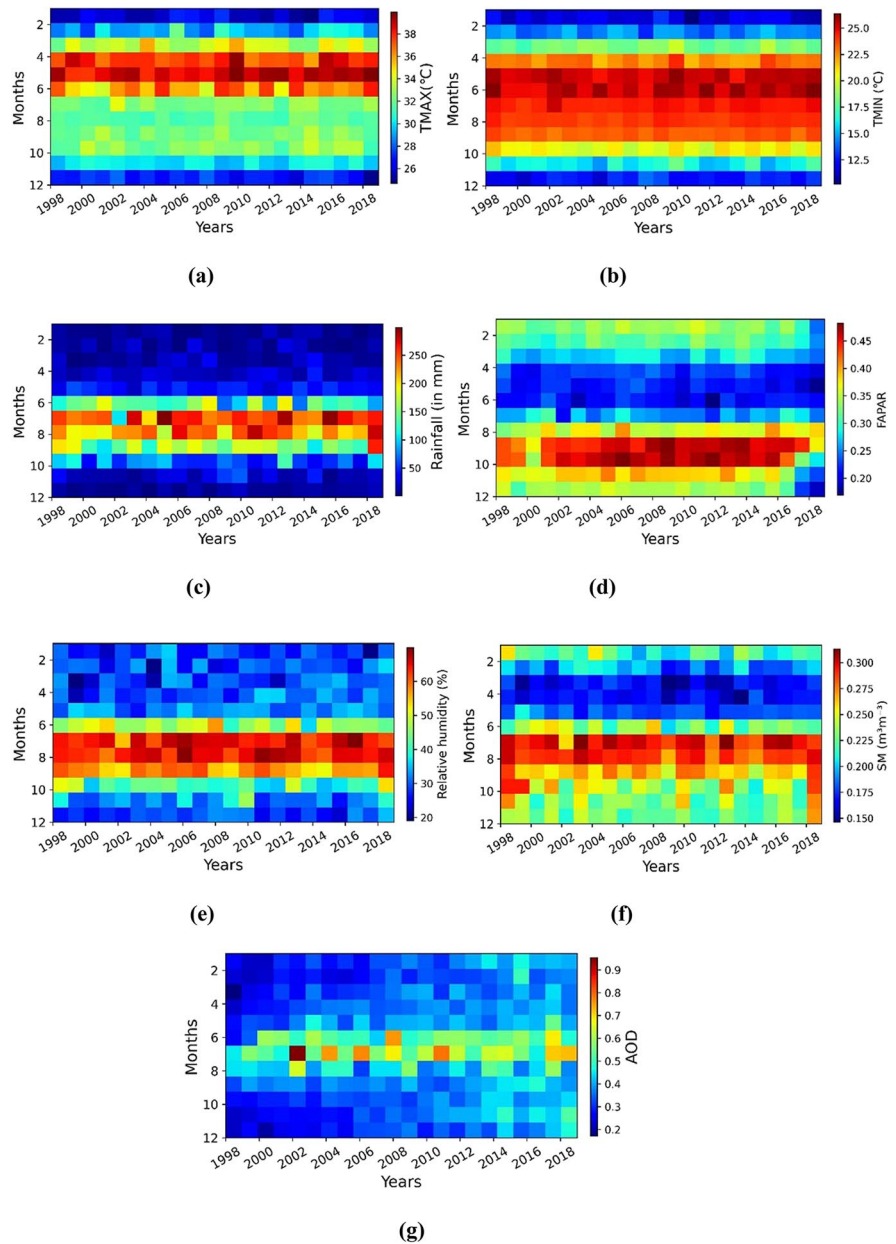
The multicollinearity and autocorrelation tests are applied among the climate and aerosol variables to evaluate the association between these variables for the development of the significant linear model. Pearson's correlation test (Bewick et al., 2003) was

**Fig. 4 a–g** Spatial plot for the time-series average of climate variables/AOD/ FAPAR from 1998 to 2019 during the growing season **a** maximum temperature, **b** minimum temperature, **c** precipitation or rainfall, **d** FAPAR, **e** relative humidity, **f** soil moisture, and **g** AOD





**Fig. 5 a–g** The matrix plot for the monthly average of climate variables/AOD/FAPAR (the accumulated rainfall is computed in case of rainfall data) from 1998 to 2019 during the growing season **a** maximum temperature, **b** minimum temperature, **c** precipitation or rainfall, **d** FAPAR, **e** relative humidity, **f** soil moisture, and **g** AOD



used to assess the collinearity between different climate and aerosol variables. The climate and aerosol datasets on an annual scale in the cropland of India, including  $T_{max}$ ,  $T_{min}$ , RF, FAPAR, RH, SM, and AOD, were utilized to assess the presence of multicollinearity among these variables. The values of Pearson correlation coefficients among the climate and aerosol datasets have been tabulated in Table 1. The Pearson correlation coefficients have a range of

possible values from  $-1$  to  $+1$  (Schober & Schwarte, 2018). A positive value of the coefficient signifies a positive correlation, while a negative value signifies a negative correlation. A value less than 0.2 signifies a weak correlation and greater than 0.8 signifies a strong correlation (Ratner, 2009). Any one variable has been selected as a predictor variable for the further regression analysis in case of strong correlation

**Table 1** Pearson correlation coefficients among various weather variables and AOD

↓→	$T_{MAX}$	$T_{MIN}$	$FAPAR$	$RF$	$RH$	$SM$	$AOD$
$T_{MAX}$	1.000	0.585	-0.028	-0.544	-0.215	-0.608	0.458
$T_{MIN}$	0.585	1.000	-0.135	0.002	0.320	-0.026	0.157
$FAPAR$	-0.028	-0.135	1.000	-0.007	-0.205	-0.264	-0.242
$RF$	-0.544	0.002	-0.007	1.000	0.786	0.577	-0.204
$RH$	-0.215	0.320	-0.205	0.786	1.000	0.564	-0.058
$SM$	-0.608	-0.026	-0.264	0.577	0.564	1.000	-0.513
$AOD$	0.458	0.157	-0.242	-0.204	-0.058	-0.513	1.000

(Pearson correlation coefficients > 0.8) is observed between any two variables.

Another multicollinearity test namely variance inflation factor (VIF) is also applied among climate and aerosol variables at an annual scale for determining VIF factors (Hong et al., 2020). The variance inflation factor is employed to quantify the extent to which the variance of the predicted regression coefficient is inflated when there is a correlation among the independent variables. In general, VIF values equal to 1 refer to no multicollinearity, less than 10 refer to moderate multicollinearity, and greater than 10 refer to harmful multicollinearity between any two predictors (O’Brien, 2007; Kim, 2019). All the computed VIF values are found less than 10 and are presented in Table 2. The autocorrelation among climate and aerosol variables is analyzed using the Durbin-Watson (D-W) statistics (Sonkar et al., 2019). The D-W statistics of the linear model for rice and maize crops are found near about 1.53. However, the value of D-W statistics ranging from 1.5 to 2.5 refers to no autocorrelation.

*Statistical model*

The results of the multicollinearity and autocorrelation test indicate that the independent variables (maximum temperature, minimum temperature, FAPAR, relative humidity, rainfall, soil moisture, and AOD) may be suitable for developing the linear model using multiple regression analysis. In order to ascertain the relationship between one dependent variable and two

or more independent variables, multiple regression analysis is employed (Piekutowska et al., 2021). Multiple linear regression analysis is conducted to assess the influence of various factors, including maximum and minimum temperature, FAPAR, relative humidity, rainfall, soil moisture, and AOD, on the yield of rice and maize crops (D. K. Gupta et al., 2022). The dependent variable in our model is the crop yield, while the independent variables or predictors are the maximum temperature, minimum temperature, FAPAR, relative humidity, rainfall or precipitation, soil moisture, and AOD as follows:

$$\begin{aligned}
 Yield_{at} = & \beta_0 + (\beta_1 \times Year) + (\beta_2 \times T_{max_{ga}}) + (\beta_3 \times T_{min_{ga}}) \\
 & + (\beta_4 \times RF_{gs}) + (\beta_5 \times RH_{ga}) + (\beta_6 \times SM_{ga}) \\
 & + (\beta_7 \times FAPAR_{ga}) + (\beta_8 \times AOD_{ga}) + \epsilon
 \end{aligned}
 \tag{1}$$

where,  $T_{max}$ ,  $T_{min}$ , RF, RH, SM, FAPAR, and AOD stand for maximum temperature, minimum temperature, rainfall, relative humidity, soil moisture, a fraction of absorbed photosynthetically active radiation, and aerosol optical depth respectively. The terms  $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7,$  and  $\beta_8$  represent the regression coefficients.  $\beta_0$  represents the y-intercept, while  $\epsilon$  represents the residual error term. In Eq. (1), the subscript “at” represents the yearly total, “ga” represents the average during the growing season, and “gs” represents the sum during the growing season. The growing season for rice and maize output is from July to October.

**Table 2** VIF factors of all predictors

Weather variables	$T_{MAX}$	$T_{MIN}$	$FAPAR$	$RF$	$RH$	$SM$	$AOD$
VIF	8.084	5.572	1.256	5.081	6.999	3.166	1.486

## Results and discussions

### Assessment of crop yield, weather variables, and aerosol optical depth

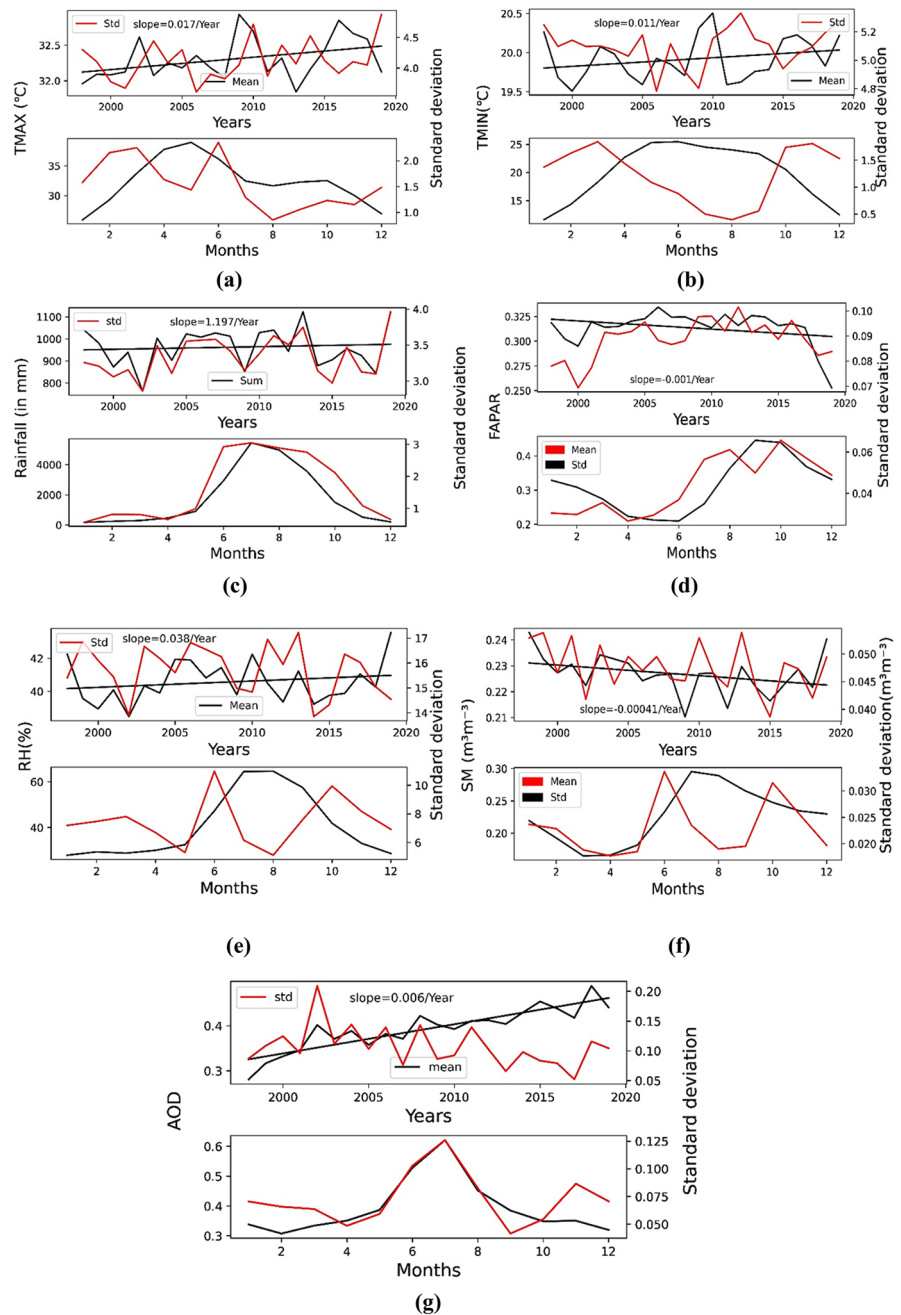
The district-wise rice and maize yield (tons per hectare), production (in million tons), and cultivation area (in million hectares) data were converted into the India-level data by taking the spatial average of the districts lies in the cropland (MODIS LULC map) for the years 1998 to 2019. The yearly bar plots of area cultivation and production of rice and maize crops are shown in Fig. 3. Figure 3 also shows the scatter plot between the cultivation area and production of crops. The regression lines are also drawn between the cultivated area vs year of observation (black color) and production vs year of observation (red color) to evaluate the rate of change of cultivation area and production of rice and maize crops. It is observed that the cultivated area and production of maize crops have increased yearly by 0.083 (in million hectares) and 0.561 (in million tons). However, the total cultivated area of rice crops has yearly decreased by 0.064 (in million hectares) and yearly rice production has increased by 0.888 (in million tons). The value of the positive correlation coefficient is found 0.814 and 0.595 between the annual production and cultivation area of rice and maize crops, respectively. It indicates the dependency of production on the total cultivated area is more for maize yield than for rice yield.

Figures 4 and 5 display the spatial distribution (average for the period 1998–2019) and temporal changes (monthly average) of climatic and aerosol variables. In Figs. 4a and 5a, the spatial and temporal plots of maximum temperature show the variation from 33 to 36 °C in the northern region of India and from 29 to 32 °C in the southern region of India (Mondal et al., 2015). The maximum values of maximum temperature reached in Delhi, Punjab, and Rajasthan states with higher values above 36 °C in April, May, and June. On the other hand, the average minimum temperature (Figs. 4b and 5b) in general varies from 18 to 20 °C in the northern region of India and from 20 to 22 °C in the southern region of India. Maximum values of minimum temperature belong to Delhi, Punjab and some parts of Tamil Nadu states and cross its higher value above 23 °C in May, June, July, and August. The spatial and temporal average value of rainfall (Figs. 4c and 5c) indicates

that in general, coastal regions like West Bengal, Odisha, Gujrat, etc. are suffering comparatively higher rainfall than non-coastal regions in the months from July to September, which is monsoon season of India. The average values of FAPAR during the years 1998–2019 lay between 0.3 and 0.4 in most parts of India (Fig. 4d). The maximum values of FAPAR are found in the months of August, September, and October (Fig. 5d). Generally, the months of August, September, and October come under the monsoon season and frequent rainfall events occur during this tenure, which is responsible for the settle down of aerosols present in the atmosphere. Central India suffers an average relative humidity of 60% and the maximum relative humidity is found in the months of July, August, and September (Figs. 4e and 5e). The spatial and temporal variation of soil moisture concluded that the west and central regions of India including Madhya Pradesh and Maharashtra have comparatively higher values of soil moisture and the maximum value of soil moisture arises in the months of July, August, and September (Figs. 4f and 5f). Figures 4g and 5g show the spatial (mean for the duration 1998–2019) and temporal (monthly mean) variation of aerosols indicating that the Punjab, Haryana, Delhi, and some parts of Uttar Pradesh suffer from a higher amount (near AOD 0.75) of aerosol (Mor & Dhankhar, 2022).

Figure 6a–g shows the time series plots of the annual mean (sum for rainfall only) and standard deviation of weather parameters like maximum temperature, minimum temperature, FAPAR, relative humidity, soil moisture, and AOD. From Fig. 6a, b, it is observed that the maximum and minimum temperatures have risen by 0.017 °C and 0.014 °C per year, respectively, from 1998 to 2019. It simply means that the annual average of daily mean temperature has also risen by a significant amount in India for this period. It is the indication of heat stress that may occur in Indian agricultural crops, due to which it is suggested that a new variety of crops should be developed that can tolerate such warming conditions. A detailed study already proved that temperatures in India have risen by 0.7 °C between 1901 and 2010 (Bhatla et al., 2020; Sanjay et al., 2020). This increment of temperature during this long period signifies climate change in India (Sanjay et al., 2020). During this period (1998–2019), total annual rainfall has also increased at the rate of 1.197 mm per year

**Fig. 6** Time series plot of **a** maximum temperature, **b** minimum temperature, **c** precipitation or rainfall, **d** FAPAR, **e** relative humidity, **f** soil moisture, and **g** AOD with standard deviation during the years 1998 to 2019



(Fig. 6c) and the annual average value of FAPAR has decreased at a rate of 0.001 per year (Fig. 6d). The decrement of FAPAR suggests an idea that aerosol has increased during this period which reconciles the time series plot of aerosol. The annual average of relative humidity has also increased at a rate of 0.038% per year (Fig. 6e) whereas, the annual average of soil moisture has decreased at a rate of  $0.00041 \text{ m}^3 \text{ m}^{-3}$

per year (Fig. 6f). Figure 6g shows the annual average value of AOD (i.e., aerosol) has also increased at a rate of 0.006 per year during this period. It indicates that the sources of anthropogenic aerosol have also increased day by day due to an increase in the number of industries, factories, etc. (Babu et al., 2013).

One thing is noticeable here is that the annual average of rice and maize yield (tons per hectare)

has increased during the period of 1998 to 2019 although the climate variables (like aerosol, temperature, rainfall, relative humidity, and FAPAR) have had their negative impact (Padakandla, 2016, 2021). The reason behind this discrepancy is that rice and maize yield depends on not only climatic factors and edaphic factors (like soil moisture) (Nkurunziza et al., 2020), but also biotic factors (like pests and fertilizers), which may have a more positive impact on rice and maize yields than the negative impact of climate and aerosol variables.

Assessment of crop yield statistical model

The annual data of weather variables (maximum temperature, minimum temperature, precipitation or rainfall, relative humidity, FAPAR, soil moisture) and aerosols have been prepared for the development of a yield model by taking the growing seasonal average except rainfall (taking sum) for the years 1998 to 2019. The multiple linear regression analysis is conducted using independent variables (climate variables and aerosols) and dependent variables (rice or maize yield) with the least square fitting algorithm of Eq. 1. The values of the regression coefficients are tabulated in Table 3.

Figure 7a, b shows the scatter plot between the estimated and observed rice and maize yield, respectively. The assessment of the developed model is performed based on the values of performance indices

namely coefficients of determination or R-squared ( $R^2$ ), root mean squared error (RMSE), and bias. The  $R^2$  or regression score or coefficient of determination, is a statistical metric that quantifies the degree to which the data points align with the regression line. (Bewick et al., 2003). The  $R^2$  value indicates that the model’s prediction accuracy is approximately 95.8% for rice crop yields and 94.5% for maize crop yields. The RMSE value between estimated and observed yield values are found 0.486 (tons/hectare) and 0.515 (tons/hectare) for rice and maize crops, respectively (Chai & Draxler, 2014). The bias value between estimated and observed yield values is found nearly 0.0 (tons/hectare) for rice and maize crops. The performance of the yield model is found very good with the comparison of these performance indices values.

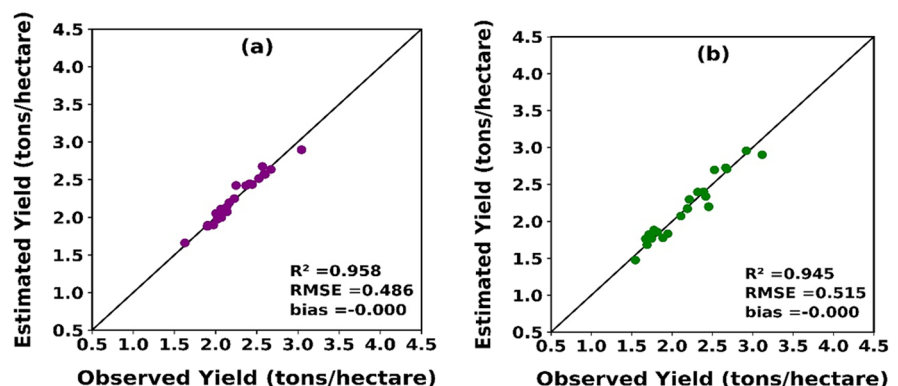
Impact assessment of climate variables on rice and maize yield

The statistical model (Eq. 1) was utilized to assess the impact of weather variables (including maximum and minimum temperature, precipitation, relative humidity, surface soil moisture, and FAPAR) on rice and maize crops throughout their respective growing seasons. To estimate the effect of weather variables on the yields of rice and maize, the percentage difference between the predictions from the historical level and a hypothetical scenario with the mean value of the respective weather variable is

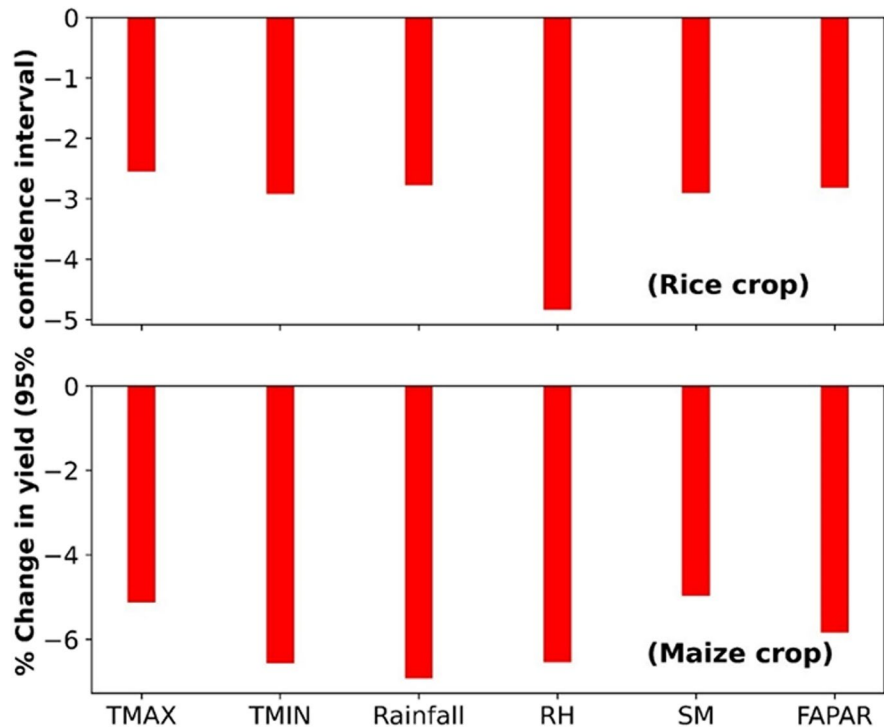
**Table 3** Regression coefficients (RC) values of our model for rice and maize crop

RC →	$\beta_0$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	$\beta_5$	$\beta_6$	$\beta_7$	$\beta_8$
Rice	-90.227	0.053	-0.079	-0.255	0.002	-0.066	-0.627	-1.734	-2.024
Maize	-161.807	0.086	-0.354	0.179	-0.002	-0.024	15.259	-5.846	-2.790

**Fig. 7** Scatter plots between estimated yield and observed yield value. **a** For rice, **b** for maize



**Fig. 8** Percent change (mean in 95% CI) in rice and maize yield against weather variables during the years 1998–2019



utilized. From 1998 to 2019, the percentage change in rice and maize yield attributable to meteorological variables is depicted in Fig. 8. The rice and maize harvests are adversely impacted by every meteorological variable. The yield changes due to the maximum and minimum temperature are found for rice crops ( $-2.548\%$  and  $-2.920\%$ ) and for maize crops ( $-5.123\%$  and  $-6.570\%$ ), respectively. The negative impacts of rainfall, relative humidity, and soil moisture are found on rice ( $-2.773\%$ ,  $-4.840\%$ , and  $-2.906\%$ ) and maize ( $-6.926\%$ ,  $-6.546\%$ , and  $-4.972\%$ ) yields, respectively. The rice and maize yield changes due to the FAPAR are found  $-2.822\%$  and  $-5.840\%$ , respectively. The changes in yield due to the impact of weather variables are computed with the mean value from the 95% confidence intervals (CI) of annual percentage changes of those specified periods. The change in yield given the estimated sensitivity of rice and maize crop is observed from  $-2\%$  to  $-5\%$  and  $-4\%$  to  $-7\%$ , respectively. It indicated that the maize yield is more sensitive to weather conditions than rice crop yield, which is consistent with another study by Vogel et al. (2019). The increase in relative humidity showed a higher negative impact on the rice yield, while the increase in rainfall also

showed a higher negative impact on the maize yield. The FAPAR is found slightly higher impact on the reduction of rice and maize yield than the maximum temperature. The Indian farming industry adopts an irrigated cropping system that is tailored to meet the specific water needs of each crop. According to (Schlenker & Roberts, 2009), irrigation has been discovered to safeguard maize crops against reduced yields caused by high temperatures.

#### Impact assessment of aerosols on rice and maize yield

Aerosol particles can impact agriculture indirectly by shading the leaf surface (Shu et al., 2022) because dust loading on the leaf surface (leaf shadowing) has the potential to lower the net photosynthetic rate in plants. Aerosols on the leaf surface can absorb solar radiation, leading to an increase in leaf temperature (Zhou et al., 2018). This can have a significant impact on agriculture. Aerosol pollution reduces the solar radiation that reaches the ground, indicating a potential impact on the fraction of solar radiation, known as FAPAR utilized by plants in their photosynthetic activities. So, the estimation of aerosols'

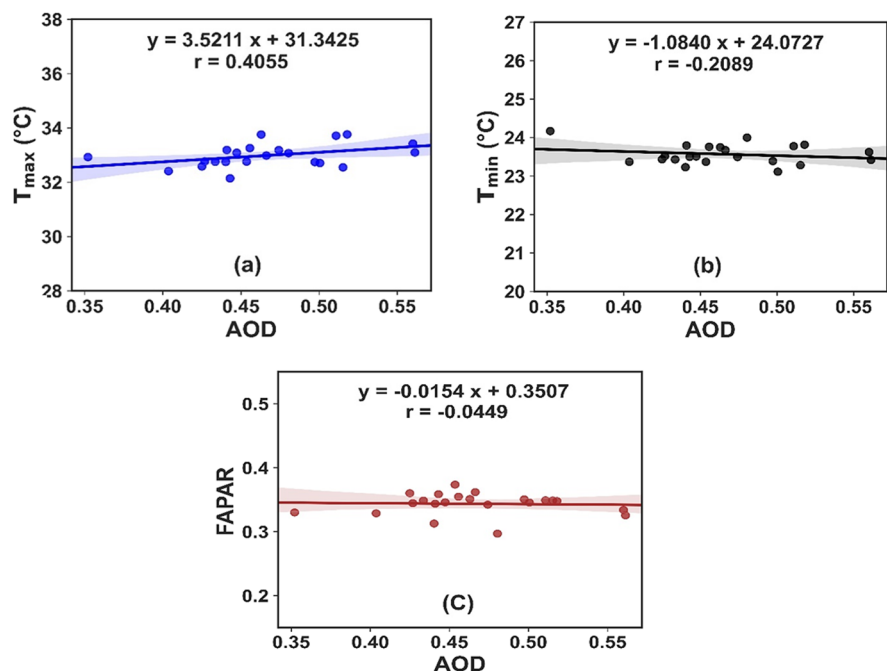
impacts on crop growth and its yield is very tedious, and no direct method is available. The solar radiation absorbed or scattered by the atmospheric aerosols has an indirect impact on agriculture (Ren-Jian et al., 2012) and which is indirectly acting as cloud condensation nuclei (Sarangi et al., 2018). The weather variables are directly affected by the absorption and scattering of solar radiation by atmospheric aerosols.

A regression analysis is conducted to evaluate the influence of aerosol pollution on agricultural yields by examining the relationship between AOD, weather factors, and crop yields. The individual effects of meteorological factors on crop yields and the influence of AOD on these weather variables are assessed individually. These estimates are then combined to calculate the overall impact of aerosol pollutants on the reduction of rice and maize yields. A linear regression analysis is conducted between historical AOD and weather variables to compute the aerosol’s impact on the weather variables. Figure 9a–c captures the scatter plots between maximum temperature vs AOD, minimum temperature vs AOD, and FAPAR vs AOD with results of linear regression analysis maintaining the 95% confidence interval, respectively. Figure 10a–c shows the scatter plots between rice yield and maximum temperature, rice yield and minimum temperature, rice yield, and FAPAR with results of

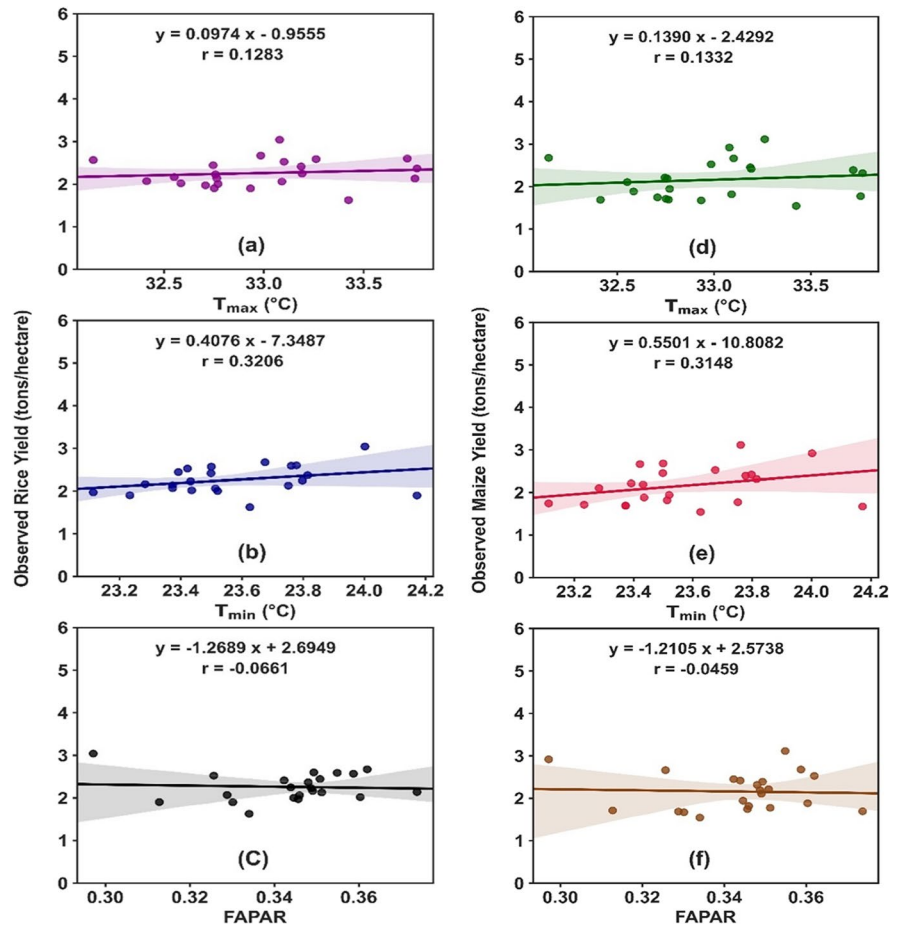
linear regression analysis maintaining the 95% confidence interval, respectively. On the other hand, the scatter plots between maize yield and maximum temperature, minimum temperature, and FAPAR, respectively, in Fig. 10d–f display the results of the linear regression within a 95% confidence interval. The plots (Figs. 9 and 10) with the shaded area indicate the estimate’s confidence interval (which maintains a 95% confidence level) (Bewick et al., 2003). However, linear regression analysis is also used to determine how meteorological variables affect crop yield for the crops of rice and maize. The rate of change of weather variables with respect to AOD has been evaluated to examine the impact of AOD on weather variables, i.e.,  $\left(\frac{\partial T_{MAX}}{\partial AOD}\right)$ ,  $\left(\frac{\partial T_{MIN}}{\partial AOD}\right)$ , and  $\left(\frac{\partial FAPAR}{\partial AOD}\right)$ . However, the meteorological variables’ impact on crop yield is considered the rate of change of crop yield with respect to meteorological variables, i.e.,  $\left(\frac{\partial Yield}{\partial T_{MIN}}\right)$ , and  $\left(\frac{\partial Yield}{\partial T_{MAX}}\right)$ .

The net effect of aerosol pollution on rice and maize yields is calculated by combining the estimated effects of weather variables on yield and the estimated effects of aerosol pollution on weather variables. The datasets of AOD, meteorological factors, and yield exhibit significant annual variation, enabling accurate identification of the influence of weather and

**Fig. 9** Scatter plots between AOD\_550 vs a maximum temperature ( $T_{max}$ ), b minimum temperature ( $T_{min}$ ), and c FAPAR (indicating 95% confidence interval)



**Fig. 10** Scatter plots between yield and maximum temperature ( $T_{max}$ ), minimum temperature ( $T_{min}$ ), and FAPAR. **a–c** For rice crop, **d–f** for maize crop (indicating 95% confidence interval)



pollution on crop output. The effect of aerosols on crop yields is calculated using the following Eq. (2).

$$\frac{\partial \text{Yield}}{\partial \text{AOD}} = \frac{\partial T_{MAX}}{\partial \text{AOD}} \frac{\partial \text{Yield}}{\partial T_{MAX}} + \frac{\partial T_{MIN}}{\partial \text{AOD}} \frac{\partial \text{Yield}}{\partial T_{MIN}} + \frac{\partial \text{FAPAR}}{\partial \text{AOD}} \frac{\partial \text{Yield}}{\partial \text{FAPAR}} \quad (2)$$

The impact of aerosol loading on rice and maize yield ( $\frac{\partial \text{Yield}}{\partial \text{AOD}}$ ) is estimated at  $-0.079$  ( $-7.9\%$ ) and  $-0.088$  ( $-8.8\%$ ), respectively over India during the time period from 1998 to 2019. Due to the increase in atmospheric aerosol contaminants, the total yield of rice and maize in India decreased by 7.9% and 8.8%, respectively, over the past 22 years, from 1998 to 2019. A reduction in aerosol pollution would result in an increase in solar radiation, which appears to have a substantial and positive direct impact on crop yields. An increase in the quantity of solar radiation that reaches the Earth's surface

during the day would correspondingly lead to a rise in maximum temperature, resulting in a decreased yield in the response of reduction in aerosol pollution. Huang et al., (2014) reported that the nighttime temperature increases by  $0.7$  °C, while the daytime temperature decreases by  $-0.7$  °C on the basis of a model simulation in East Asia due to aerosols. It has been noted that the elevated levels of cloudiness caused by aerosols may indirectly contribute to an increase in minimum temperature. The precision and confidence in predicting the extent of crop production decline rely on the model's capability to accurately replicate the properties of aerosols and incorporate the feedback mechanisms (R. Gupta et al., 2017). Currently, there is no climate model available that accurately represents the dispersion of aerosols over India in a realistic manner (Sanap et al., 2015). Hence, there is a potential for uncertainty in estimating the impact of AOD on



maximum temperature, minimum temperature, and solar radiation as predicted by climate models. This uncertainty may be substantial.

## Conclusions

The rice and maize yields have shown a consistent upward trend, with an annual increase of 0.888 million tons/year and 0.561 million tons/year, respectively, from 1998 to 2019. However, the cultivation area is found decreasing trend with a rate of 0.064 million hectares/year for rice crops and the increasing trend of cultivation area is found for maize crops with a rate of 0.083 million hectares/year. The maize yield depends on the cultivated area more than the rice yield by comparing the value of correlation coefficients between the production and cultivation area for both crops. The increase in rice output surpasses that of maize yield due to the implementation of advanced agricultural techniques, optimal utilization of fertilizers and irrigation, and the cultivation of climate-resistant cultivars.

The key discoveries of this research reveal a decrease in rice and maize yields by approximately (2.55%, 2.92%, 2.778%, 4.84%, 2.90%, 2.82%) and (5.12%, 6.57%, 6.93%, 6.54%, 4.97%, and 5.84%), respectively, attributed to unwanted fluctuations in weather variables, specifically maximum and minimum temperatures, rainfall, relative humidity, soil moisture, and FAPAR, spanning from 1998 to 2019. Additionally, the study highlights a notable reduction in rice and maize yields by 7.9% and 8.8%, respectively, as a result of increased aerosol pollution. Notably, the annual averages of weather variables (TMAX, TMIN, rainfall, and relative humidity) and AOD demonstrate an upward trend, while surface soil moisture and FAPAR exhibit a declining trend during the same time frame from 1998 to 2019. The decrement in the average value of surface soil moisture is an indication that agricultural drought happened due to the unequal distribution of rainfall causing a reduction in food-grain production in India. The increase in the average temperature, rainfall, and relative humidity also has a negative impact on rice and maize yield. Extreme rainfall is responsible for the flood and damages the crop growth in the affected area. Anthropogenic aerosol sources have grown rapidly during this

time as the expansion of industries and urbanization is responsible for the increment in atmospheric aerosols or aerosol optical depth (AOD). Actually, India emits the third-highest amount of greenhouse gases globally, and coal is the biggest contributor. Extreme weather variations occur due to the increment in aerosol pollution over India such as a decrease in solar radiation, and a warmer climate, which impacts agriculture, human health, and other factors. As a result, India faces a significant problem in the years to come in producing high-quality crop production for a feeding population with nutritious food. The separate impact of weather variables and AOD is also estimated for rice and maize yield during the time period of 1998 to 2019 over India.

This is restricted to the specification and hypothesis of the model, and it requires enhancement in terms of utilizing larger datasets, technology advancements, genetic enhancements, improved irrigation methods, and incorporating the effects of regional heterogeneity in the model across India. Developing a more advanced decision support system will enhance its ability to respond to climate change. The assessment of the developed model needs to be evaluated under different environmental conditions, adaption, and mitigation measures to cope with climate change and aerosol pollution variability. The crop yield model will need nonlinear terms of aerosols associated with the climate variables for the accurate estimation of aerosols/climate impact on the crop yield. The results are statistically significant and show that the aerosol impact on yields is much higher than the climate factors. The results of the study indicate that increasing atmospheric pollution may produce an adversely negative impact on crop productivity in the future.

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**Author contribution** Dileep Kumar Gupta (conceptualization, methodology, algorithm formulation, investigation, original draft preparation, visualization and editing, and validation), Subhajit Pramanick (formal analysis, original draft preparation, algorithm formulation, reviewing, editing, visualization and editing and revision), and Abhay Kumar Singh (supervision, conceptualization, methodology, investigation, reviewing, editing, and validation). All the authors (Dileep Kumar Gupta, Subhajit Pramanick, and Abhay Kumar Singh) declare their contributions.

**Data Availability** The open source data and material have been used in this study provided by various agencies IMD, NASA, NOAA, CCI, Physical Sciences Laboratory, Directorate of Economics and Statistics, Ministry of Agriculture, Cooperation and Farmers Welfare, Government of India. The web link to the data has also been provided.

## Declarations

**Competing interests** The authors declare no competing interests.

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