

Effect of Weather and its Extremes on Soybean and Wheat Yield in Central Parts of India

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by

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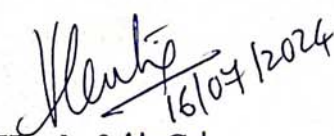
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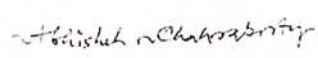
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I hereby declare that, this thesis entitled **“Effect of Weather and its Extremes on Soybean and Wheat Yield in Central Parts of India”** is the result of investigation carried out by me in the Centre for Earth, Ocean and Atmospheric Sciences (School of Physics), University of Hyderabad, India under the direct guidance and supervision of Profs. V. Chakravarthi, and Dr. Abhishek Chakraborty is a bonafide research work and free from plagiarism. I also declare that it has not been submitted previously, in part or in full to this University or any other University or Institute, for the award of any degree or diploma.

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Preface

Agriculture in India is crucial for food security and employment, impacting over 50% of the population and significantly contributing to the nation's GDP. Climate change, with rising temperatures and frequent extreme weather events, poses significant risks to agricultural productivity. Small and marginal farmers (cultivating < 2 hectares land), who make up 85% of India's farming community, are especially vulnerable.

The Intergovernmental Panel on Climate Change (IPCC) 6th Assessment Report indicates that climate change effects vary by region and season. Since 1982, global temperatures have increased by 0.20°C per decade, with further increases projected. In Asia, the temperature rise has been more pronounced, affecting seasonal shifts, rainfall variability, and extreme weather events like heatwaves and droughts. Analysing changes in the amplitude and frequency of these extremes is even more crucial, as their impacts may be irreversible. This study examines the spatio-temporal trends of weather variables such as temperature, rainfall, rainy days, and extremes, alongside crop phenology in various agro-ecological regions of India. Crop phenology, the study of periodic events in the crop growth cycle, is vital for understanding climate impacts on crop yields. Satellite metrics like the Normalized Difference Vegetation Index (NDVI) are used to delineate crop growth patterns, but most studies in India use coarse-resolution data. This study uses moderate resolution MODIS data with a 250-meter resolution to map crop phenology patterns.

Declining major crop yields in India are linked to rising temperatures, water scarcity, and fewer rainy days. For every 1°C increase in temperature, major crop yields are expected to decrease by 3 to 7%. Understanding the relationship between climate variables and yields is crucial, as significant yield declines have been observed in global croplands. Techniques for estimating crop yields include statistical models and machine learning (ML) tools using weather indices. Understanding crop yield sensitivity to each variable and modeling their interactions is essential to maintain food security and economic sustainability.

Study area

The study focuses on the continental mainland of India, spanning from 8°04' to 37°06' North latitude and 68°07' to 97°25' East longitude, encompassing diverse climatic conditions, physiography, soil types, and agricultural practices. To address the significant spatial variability,

the research is conducted at a sub-national scale, specifically across India's 20 Agro-Ecological Regions (AERs). The study examines the spatial patterns of weather data and its impact over crop in two dominant agricultural seasons i.e., *kharif* (monsoon) and *rabi* (winter), pertaining to southwest monsoon and winter season, respectively, from 1981 to 2019. The research specifically evaluates the impact of weather and its extremes on soybean and wheat crops yield in the central Indian states i.e., Maharashtra and Madhya Pradesh, respectively, and are predominantly rainfed. Based on the spatial patterns of rainfall and Plant Available Water Capacity, these states are delineated into homogenous zones, providing insights into the effects of climate variability on crop yields in these respective zones.

Research gap and objectives

Although many studies have analyzed the temporal trends of temperature and rainfall, limited research focuses on weather extremes, specifically for the *kharif* and *rabi* seasons in homogeneous AERs. There is a notable lack of studies addressing the impact of heat events and the combined effects of temperature and moisture extremes on crop phenology at the AER level across the entire country. While several studies have explored climate variables affecting crop yields statistically, both in India and globally, limited research has analyzed the influence of climate extremes on soybean and wheat yields during distinct development stages utilizing machine learning techniques. Only a few studies have examined crop growth-specific Machine Learning models to assess sensitivity in yield estimation. This research aims to fill this gap by providing a comprehensive and fine-scale evaluation of the impact of weather and its extremes on crop phenology and crop yield in India. Based on existing research gap, the research investigates the following objectives:

- To analyse the temporal trends of temperature, its extremes and dryness/wetness using daily gridded temperature and rainfall data
- To study the effect of weather extremes on crop phenology in different agro-ecological regions of India
- To analyse the spatial impact of weather extremes on soybean and wheat crop yield in central part of India

Data and Methodology

The present research utilized various data sources, including meteorological data (daily gridded land surface air temperature data of Climate Prediction Center (CPC) of $0.5^\circ \times 0.5^\circ$ resolution, daily rainfall data from the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) of $0.05^\circ \times 0.05^\circ$ resolution, and 3-months SPEI (SPEI-03) from Global SPEI database of $0.5^\circ \times 0.5^\circ$ resolution); satellite data (MODIS 16-days NDVI composite (MOD13Q1 v006) for period 2001-2019) and other ancillary data such as, Land use/land cover map (1:50,000), soil map (1:50,000), district-level crop yield, administrative boundaries, etc. The Mann-Kendall test and Sen's method were exploited to analyse the direction and magnitude of temporal trends in predictor variables. TIMESAT software was employed to extract phenology metrics, including the start of season (SoS), End of Season (EoS), length of season (LoS), and maximum NDVI ($NDVI_{max}$). The impact of climate extremes, such as SPEI-03 and Heat Wave Magnitude Index daily (HWMId), on crop phenology was assessed using correlation and sensitivity analyses. The relationship between crop yields and climatic variables was examined using Pearson's correlation coefficient. ML models, including Random Forest Regression (RFR) and Neural Network (NN), were developed to predict yields and identify significant climatic factors. Sobol' index, a global sensitivity analysis technique, was utilized to identify the most influential weather variables among multiple factors affecting crop yield.

A brief description of the outcomes of this thesis is given below:

Temporal trends of temperature, its extremes and dryness/wetness

The temporal trends in temperature-based variables, including maximum and minimum temperatures (T_{max} and T_{min}), Growing Degree Days (GDDs), and extreme temperatures (hot and cold days/nights; HWMId) revealed significant increasing trends in northern India and mixed patterns in other regions. The analysis also reveals more frequent hot extremes and fewer cold extremes across India. Trends in rainfall and rainy days during the southwest monsoon season are analyzed, showing an overall increasing trend across India with regional variations. The SPEI-03 index is used to assess drought trends, indicating an increase in drought events in northeastern India despite its high rainfall. The findings suggest that while wet events are increasing across India, certain regions are experiencing significant drying trends. The detailed analysis provides valuable insights into the changing climate patterns and their effects on different AERs in India.

Crop Phenology and Weather Extremes

SPEI-03 and phenology metrics in *kharif* (monsoon) season: Analysis revealed significant spatial and temporal variations in SoS, LoS, and NDVI_{max} across different AERs. Delays in SoS were observed in northern and Deccan plateau regions, while early SoS was found in parts of northern, central, and eastern India. NDVI_{max} showed a decreasing trend in many regions, indicating reduced crop vigor. The relationship between phenology metrics and SPEI-03 highlighted the sensitivity of crop growth to moisture availability. Sensitivity analysis showed varying responses to SPEI-03 across different AERs, with semi-arid regions being more sensitive to moisture changes.

Heat events, SPEI-03 and phenology metrics in *rabi* (winter) season: Early EoS and reduced NDVI_{max} were observed in regions experiencing heat events. The correlation analysis between heat events and phenology metrics revealed significant impacts of heat events on crop maturity and vigour. Positive correlations between SPEI-03 and NDVI_{max} were found, indicating that wet conditions during early monsoon support crop growth. Conversely, dry conditions led to early EoS and reduced LoS. The study highlighted the complex interaction between temperature and moisture extremes, showing that combined hot and dry conditions had severe impacts on crop phenology. The findings highlight significant regional variations in the response of crops to temperature and moisture extremes, emphasizing the importance of localized climate resilience measures.

Impacts of Weather and Extremes on Soybean and Wheat Yield

Impact of weather and extremes on Soybean yield: Negative correlations were found between soybean yield and temperature parameters (Tmax, Tmin, GDD) during the crop establishment phase. Positive correlations were observed with hydro-meteorological parameters (rainfall, rainy days, SPEI) during the crop development stages. In water-scarce regions, rainfall and soil moisture significantly impacted soybean yield.

Impact of weather and extremes on Wheat yield: Temperature parameters (Tmin, GDD) during the reproductive phase showed significant negative correlations with wheat yield. Rainfall parameters had a limited impact, while SPEI showed a positive correlation, indicating its effectiveness in capturing water stress. Hot and cold extremes during critical growth stages (reproductive and grain-filling phases) significantly affected wheat yield.

Sensitivity analysis using Sobol' index revealed that Soybean yield was sensitive to rainy days and Tmax during reproductive stages. Wheat yield was sensitive to temperature extremes (hot days, cold nights) and GDD during reproductive and grain-filling stages. It confirms that temperature and moisture extremes significantly impact crop yields, varying by crop type and region. The findings align with previous studies and suggest adaptation strategies such as altering cropping patterns, adjusting sowing dates, and cultivating heat-tolerant varieties.

6 The research work presented in this thesis is organized into six chapters as detailed below:

Chapter 1 highlights the importance of analysing the dynamics of meteorological parameters in the era of global warming. Temperature and rainfall are identified as critical factors influencing agricultural productivity and variability. Thorough review of literature on the above topics is explored to find the research gap and objectives are presented.

Chapter 2 describes the study area, its 20 AERs, long-term mean temperature (minimum and maximum), annual mean rainfall during southwest monsoon, seasons, soil and landuse. Moreover, it describes the Maharashtra and Madhya Pradesh as the study area to analyse the impact of weather on crop yield.

Chapter 3 explores the spatial patterns of temporal trends in temperature-based variables, including Tmax, Tmin, GDD, and extreme temperatures (hot and cold days/nights, heat events), as well as rainfall-based variables, including rainfall amount, rainy days, and SPEI-03 across 20 AERs of India during the *Kharif* and *Rabi* seasons from 1981 to 2019.

Chapter 4 details the interactions of extremes in temperature and moisture on crop phenological metrics (SoS, EoS, LoS, NDVI_{max}) in different AERs of India in both *kharif* and *rabi* seasons.

Chapter 5 focusses on effect of long-term climatic variations and extreme weather on soybean and wheat yields in central India's rainfed regions. Based on ML-approach of yield prediction coupled with global sensitivity index, crop- and growth stage-specific influencing weather variables on crop yield are identified.

Chapter 6 concludes the overall results from the present work, providing a comprehensive understanding of the findings.

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List of Abbreviations

AER: Agro-Ecological Regions
AR6: 6th Assessment Report
AVHRR: Advanced Very-High-Resolution Radiometer
CHIRPS: Climate Hazards Group InfraRed Precipitations with Stations
CIMMYT: International Maize and Wheat Improvement Center
CPC: Climate Prediction Centre
CRU: Climatic Research Unit
DAS: Days After Sowing
Dem: Digital Elevation Model
DSSAT: Decision Support System for Agro-technological Transfer
EoS: End of Season
EROS: Earth Resources Observation and Science
FAO: Food and Agriculture Organization
HWMId: Heat wave magnitude index daily
ICAR: Indian Council of Agricultural Research
IGP: Indo-Gangetic Plain
IMD: India Meteorological Department
IPCC: Intergovernmental Panel on Climate Change
GDD: Growing Degree Days
GDP: Gross Domestic Product
LAI: Leaf Area Index
LoS: Length of Season
LSP: Land Surface Phenology
LULC: Land Use and Land Cover
MK: Mann–Kendall Test
ML: Machine Learning
MODIS: Moderate-Resolution Imaging Spectroradiometer
MSE: Mean Square Error
NASA: National Aeronautics and Space Administration

NBSSLU&P: National Bureau of Soil Survey & Land Use Planning

NDVI: Normalized Difference Vegetation Index

NDVI_{max}: Maximum Normalized Difference Vegetation Index

NN: Neural Network

NOAA: The National Oceanic and Atmospheric Administration

nRMSE: normalized Root Mean Square Error SPOT-VGT: VEGETATION onboard the NRSC:

National Remote Sensing Centre

Satellite Pour l'Observation de la Terre

OLI: Operational Land Imager

PAWC: Profile Available Water Capacity

PCA: Principal Component Analysis

RCP: Representative Concentration Pathways

RFR: Random Forests Regression

RMSE: Root Mean Square Error

SPEI: Standardized Precipitation Evapotranspiration Index

SPI: Standardized Precipitation Index

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Introduction

1.1 General

Agriculture in India, crucial for food security, is profoundly influenced by prevailing weather patterns, soil conditions, and other environmental factors. It sustains employment for over 50% of the population and is the third most significant contributor to the nation's Gross Domestic Product (GDP), accounting for 18.8% (“Economic Survey of India, 2022”). Observations indicate a significant increase in global mean temperatures and frequent weather extremes, posing risks to agricultural productivity and food security (“Lal, 2011”). In India, approximately 85% of farmers fall into the small and marginal category, with farm holdings of less than 2 hectares. These farmers are particularly vulnerable due to their heavy reliance on climate-sensitive natural resources, despite contributing minimally to climate change (“Gupta and Pathak, 2016”).

1.2 Spatio-temporal trend of climatic/weather variables

The 6th Assessment Report (AR6) of the Intergovernmental Panel on Climate Change highlights that climate change manifests distinctly across different regions, seasons, and variables under analysis (“IPCC, 2021”). Climate change or variabilities in any region are driven by diverse underlying physical mechanisms, with significant spatial variations in warming trends, particularly in Arctic regions during winter and Northern Europe in summer. The AR6 report indicates that the global average temperature has increased by 1.1°C and is projected to surpass 1.5°C by 2040. By the end of the century, temperatures could potentially rise by as much as 3.5°C above the twentieth-century average. The ten warmest years of the century have also been reported within the last decade (2014–2023), whereas the rate of global warming since 1982 has been at 0.20°C decade⁻¹, three times faster than the long-term trend. Furthermore, climate change impacts differ across various weather patterns, causing distinct changes in mean and extreme conditions. While there is a consistent warming trend, precipitation patterns show pronounced regional discrepancies. For instance, southern Europe and northern South America are experiencing drying trends, whereas the Middle East and southern South America are seeing

wetting trends. However, an increase in rainfall extremes has been observed nearly globally. Higher surface temperatures lead to greater evaporation, especially over oceans, causing increased instability and contributing to inter-annual variations in surface temperature and global rainfall. Previous research has investigated the responses of rainfall to temperature fluctuations on an inter-annual timescale utilizing observational data and model simulations (“Ramadan et al. 2012”). Fig 1.1 illustrates the observed changes and future projections of climate and weather extremes under different scenarios, along with the associated levels of confidence, as reported by the “IPCC (2021)”.

Change in Indicator	Observed Changes (since 1950)	Attributed (since 1950)	Projected Changes global warming level		
			+1.5°C	+2°C	+4°C
Warm/hot extremes	↑	✓ Main driver	↑	↑	↑
Cold extremes	↓	✓ Main driver	↓	↓	↓
Heavy rainfall	↑	✓	↑ In most land regions	↑	↑ In most land regions
Agricultural drought	↑ In some regions	✓ In some regions	↑	↑	↑
Compound events: concurrent heatwaves and drought	↑	✓	↑ Frequency and intensity increasing with warming		

Medium confidence
 Likely high confidence
 Very likely
 Virtually certain

Fig 1.1 Summary table on observed changes in extremes and their attribution since 1950 and projected changes at +1.5°C, +2°C, and +4°C (“IPCC 6th Assessment report, 2021”)

In Asia, the temporal trend of temperature rise is more pronounced, with a value of $0.41^{\circ}\text{C decade}^{-1}$ since 1982 compared to the global trend, though it is twice ($+0.18^{\circ}\text{C}$) the longer-term trend (since 1850). AR6 reported increased temperatures with intensified extreme rainfall and drought events in South Asia. In India, part of South Asia, seasonal patterns are changing, and the variability and intensity of rainfall are escalating. Additionally, sea levels are rising, and extreme weather events, including cyclones, heatwaves, heavy rainfall, and droughts, are occurring with greater frequency and severity (“MoEFCC, 2021”). The climatic conditions of India range widely, with extreme continental weather in the north and moderate tropical

conditions in the south. The scattered, region-specific studies will not suffice to represent the temporal trend of climate and weather variables nationally. Moreover, apart from variability in climate, the soil conditions, physiography, and agriculture also vary significantly from region to region within India. To account for these variabilities, India is subdivided into 20 Agro-ecological regions, representing homogenous land units in climate, soil, and physiography (“Subramaniam 1983”). Climate and weather are essential factors in agriculture. Whether in terms of temperature or rainfall, extreme events are defined by daily temperature or rainfall intensities surpassing specific thresholds. Analyzing the location-specific changes in the amplitude and frequency of extremes for prolonged durations is crucial from an agricultural perspective, as their impact may be irreversible even if overall normal conditions are met. Therefore, spatio-temporal trend analysis of climatic data, as well as weather extremes are critical for several reasons, for example, distinguishing climate change from variability (“Hulme et al. 1999”), biogeochemical and hydro-meteorological cycle modeling (“Cramer and Fischer, 1996; Sigalla et al. 2023”), impact assessment due to climate change (“Hulme et al. 1999”), modeling urban heat island (“Badugu et al. 2023”), etc. Several studies have been conducted in India to address the trend at different spatio-temporal scales, and some contrasting results have been reported. One reason could be that most previous studies have been restricted to weather data from limited meteorological stations. In recent decades, however, satellite-based rainfall products, derived from multiple data sources, such as the “Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS)”, have become available on a global scale. These products offer better spatial and temporal resolutions, presenting a viable alternative to traditional meteorological station data (“Dinku et al. 2018”). CHIRPS data are available from 1981 onwards and can be exploited to assess rainfall trends in a timely and repetitive manner, which is mainly helpful in monitoring climate extremes such as drought (“Muthoni et al. 2018”). Similarly, daily gridded “Climate Prediction Centre (CPC)” temperature data at a 50 km resolution is also a high-quality data source to evaluate the spatio-temporal trend of temperature and extremes at a finer resolution (“Ashraf et al. 2022”).

1.3 Impact of climate and extremes on crop phenology

The IPCC reaffirms that climate change significantly impacts agriculture, directly influencing crop phenology, photosynthesis, respiration, and yield, and indirectly affecting irrigation water availability, soil fertility, and erosion. Crop phenology is a crucial indicator of climate

variability's impacts, evident in phenomena such as the premature onset or end of the growing season or the reduction in the crop cycle length due to the early accumulation of required heat units. These changes can lead to decreased photosynthetic activity during peak growing periods and delays in the season's start prompted by late monsoon onset. Crop phenology, defined as the study of the sequential occurrence of periodic events during the crop growth cycle, illustrates the influence of weather dynamics on the initiation of these growth phases. Understanding these changes is vital, as they can affect carbon accumulation, crop yield, duration, disease distribution, and other environmental and social factors ("Richardson et al. 2009"). Variations in crop phenology are recognized as significant indicators for assessing effects of drought on agricultural systems ("Desclaux et al. 2000"), underscoring the importance of phenological studies in climatic and ecological research ("Bhavani et al. 2017; Yang et al. 2021").

Phenological data can be gathered through field observations, bioclimatic models, and remote sensing techniques. Although straightforward, traditional field observations are labor-intensive and need more scalability. In contrast, bioclimatic models, which are crop-specific and data-intensive, require extensive vegetation, climate, and localized calibration data for application over broader areas. Remote sensing offers a comprehensive overview of crop-growing regions, enabling regular crop growth, health, and productivity monitoring. However, due to the coarse spatial resolution of satellite data, remote sensing cannot precisely identify specific crop growth stages or phenological events, often resulting in mixed spectral signals from heterogeneous landscapes. Consequently, more generalized metrics, known as land surface phenology metrics (pheno-metrics), such as the start of season (SoS), length of season (LoS), and Normalized Difference Vegetation Index (NDVI) at the peak stage (also called seasonal peak amplitude), are calculated to reflect changes in seasonality observed in spectral data ("de Beurs and Henebry, 2005"). Figure 1.2 provides a pictorial representation of satellite-based phenological metrics derived from a temporal profile of the vegetation index, illustrating the crop growth profile. Although numerous studies have investigated the temporal patterns of these metrics using satellite-derived NDVI time series, most research focuses on coarse-resolution data over the Indian region ("Chakraborty et al. 2014; Bhavani et al. 2017; Chakraborty et al. 2018"). This approach does not sufficiently capture the variability in agricultural areas and patterns within India's heterogeneous landscape of small landholdings.

Phenological-metrics

- SoS: Start of season
- EoS: End of season
- LoS: Length of season
- PoS: Peak of season
- VI_{max} : Maximum VI amplitude
- VI: Vegetation index

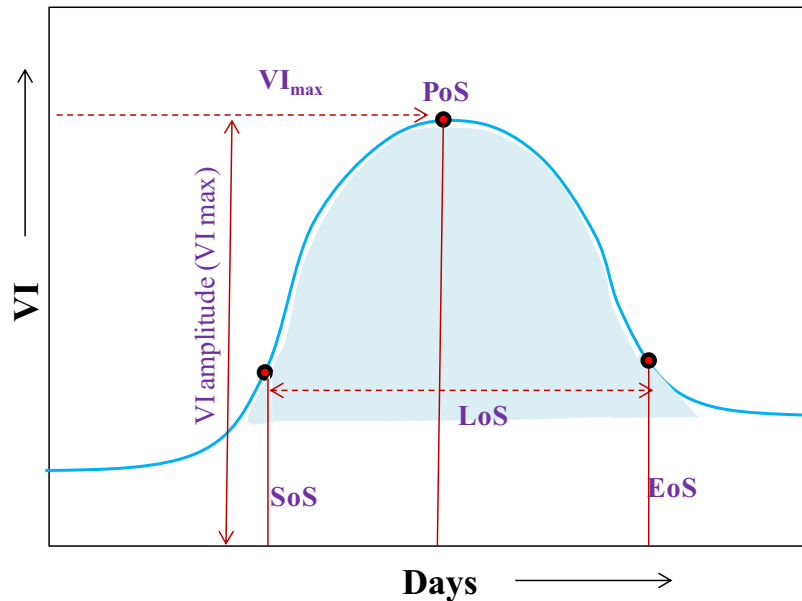


Fig 1.2 Crop growth profile representing different phenological-metrics derived from satellite data

1.4 Impact of climate and extremes on crop yield

It is widely acknowledged that agricultural production must double by 2050 to adequately meet the escalating demands of the expanding global population (“Tilman et al. 2011; FAO, 2012”). However, another study revealed that the current growth rate of crop yield must improve to attain this ambitious target (Ray et al. 2013). Anticipated extreme events are expected to disrupt the crop yield stability, presenting the foremost immediate threat to global food production (“Meehl et al. 2000; Olesen et al. 2007; Urban et al. 2012; Lobell et al. 2013”). Global warming, accompanied by extreme events, can disrupt plant physiology during crop growth; for example, high temperatures above the threshold will cause heat stress and reduced CO_2 assimilation rate and finally limit crop yield (“Bita and Gerats, 2013”). Heat stress disrupts the balance between photosynthesis and respiration rates, affecting metabolic processes and causing stomatal closures, ultimately inhibiting crop growth (“Sicher, 2015”). Additionally, heat stress increases water uptake while reducing the transpiration rate, leading to higher internal temperatures and crop damage (“Lafta and Lorenzen, 1995”). Similarly, crop water stress due to reduced soil moisture availability, called agricultural drought, hampers crop metabolism and reduces yield. The diagrammatic representation of these two stresses, their interconnections, and their impact

on crop yield is shown in Fig 1.3. the impact of excess heat varies with the intensity of high temperature as well as crop type (“Kim and Lee, 2011”), e.g., C4 plants such as sorghum or pearl millets are more adapted to warmer climates as compared to C3 plants such as rice, wheat, soybean, etc. (“Yamori et al. 2014”). The decline in crops yield across India can be attributed to rising temperatures, water scarcity, and a decrease in rainy days. Research indicates that for every 1°C increase in temperature, the crop yield is expected to decrease by 3 to 7% (“Agarwal 2009”). Many cereal and legume crops exhibit more sensitivity to any stress during flowering, resulting in significant reduction in grain or pod formation, likely due to hindered nutrient and water translocation during reproductive development phase (“Young et al. 2004”).

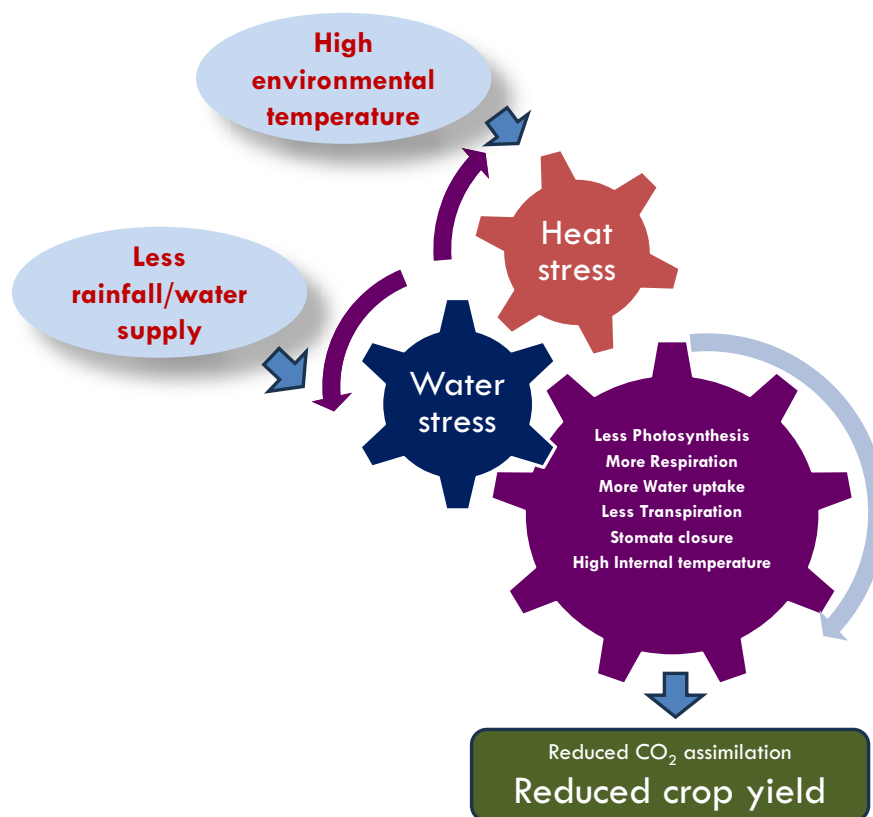


Fig 1.3 Crop stress, its impact on crop physiological processes and crop yield

A natural query arises concerning the measurement of their impacts on crop yield. Since it is established that effect of weather variations is region- and crop-specific, a detail analysis is required to unveil the variations. Climate projections suggest a potential decrease in crop yields

due to climatic changes, ranging from 4.5 to 9.0% (“Naresh Kumar et al. 2020”). By 2040, crop yield losses are anticipated to vary significantly among different crops, with reductions projected to be as high as 18% for maize and at least 9% for wheat under the RCP 4.5 scenario (“Naresh Kumar et al. 2019, 2020”). Understanding the precise relationship between climate variables and crop yield is imperative, given a prior study's findings of significant stagnation and decline in major cereal crops on one-fourth of global croplands (“Ray et al. 2012”). Therefore, analyzing the influence of observed variables at high spatial and temporal resolutions for a specific crop can help to anticipate similar responses under comparable conditions in the future. Various techniques for estimating crop yields are available, including statistical and physical-process-based models. Statistical models and, more recently, machine learning tools have been employed to model crop yield variability using weather indices as inputs. Thus, it is essential to understand the crop yield sensitivity towards each variable and model the complex interplay between climate variables and agricultural productivity to safeguard food security and economic sustainability. This requires a concerted effort in research, technology deployment, and policy-making to equip the farmsector to withstand and adapt to the inevitable risks associated with climate change.

1.5 Review of literature

1.5.1 Temporal trend of temperature and its extreme

Spatio-temporal variations in temperature and its extremes play a pivotal role in agriculture. Several studies have analyzed the temporal trends of air temperature and extremes using data from either single meteorological stations or groups of stations. A snapshot of studies on the temporal trends of temperature and its extremes in India is depicted chronologically in Table 1.1. most of these studies have reported significant increases in global mean temperatures over the last century, with pronounced warming in the past three decades (“Jones et al. 1999; Houghton et al. 2001; Jones and Moberg 2003”). “Dunn et al. (2020)” analyzed the global spatio-temporal variation of temperature and rainfall from 1901 to 2018, reporting increases in hot and rainfall extremes.

A consistent pattern of significant increases in the frequency and magnitude of temperature and hot extremes has been reported across different continents: Africa (“Moron et al. 2016; Perkins-Kirkpatrick and Lewis 2020; Gebrechorkos et al. 2018; Mbokodo et al. 2020”); Australia

(“Alexander and Arblaster 2017; Crimp et al. 2016”); Central and South America (“Dereczynski et al. 2020; Avila-Diaz et al. 2020”); Europe (“Pecina-Argulo et al. 2020; Ruml et al. 2017; Turkes and Erlat, 2018”); North America (“Garcia-Cueto et al. 2019; Vose et al. 2017; Vincent et al. 2018”); and Asia (“Donat et al. 2016; Lu et al. 2016, 2018; Yin et al. 2016 and Dimri et al. 2019”). Despite the global nature of warming, considerable spatial and temporal variability in warming trends has been observed.

In India, “Pramanik and Jagannathan (1954)” analyzed annual mean, maximum, and minimum temperatures using observatory data and found no significant trends. Later studies (“Hingane et al. 1985; Srivastava et al. 1992; Singh and Sontakke, 2002; Arora et al. 2005; Bhutiyani et al. 2007; Pal and Al-Tabbaa, 2010”) identified significant trends both negative and positive, in maximum and minimum temperatures, which also altered the frequency of temperature extreme events. “Kothawale and Rupa Kumar (2005)” examined air temperature trends over India from 1901 to 2003, reporting significant increases in annual mean, maximum, and minimum temperatures by 0.2°C per decade over the last three decades, marking an acceleration of the warming trend compared to the past century. On shorter timescales, significant socio-economic impacts have been observed. “Panda and Sahu et al. (2019)” analyzed long-term and short-term variations in seasonal rainfall and thermal conditions over the Kalahandi, Bolangir, and Koraput districts in Odisha from 1980 to 2017, reported rising trends in annual maximum and minimum temperatures through seasonal maximum and minimum temperatures during the southwest monsoon, which showed a declining trend. They also reported statistically significant increasing trends for yearly and monsoon season rainfall. “Gupta et al. (2021)” assessed spatio-temporal trends in seasonal temperature, rainfall, and potential evapotranspiration (PET) in Jharkhand from 1901 to 2018 using Mann–Kendall and Sen’s slope tests. They found insignificant variations in minimum and maximum temperatures during the pre-monsoon and monsoon seasons, with significantly increasing trends in the post-monsoon and winter seasons. Notably, the study revealed declining trends in monsoon and annual rainfall and significant decreasing trends in PET for both the monsoon season and annually.

Table 1.1 Summary of work carried out to analyse the temporal trend of temperature in India

References	Period of study	Salient findings
“Pramanik and Jagannathan (1954)”	1881-1950	Analyzed annual mean, maximum, and minimum temperature using observatory data; found no significant trends in India.
“Hingane et al. (1985)”	1901-1982	Identified significant trends, both negative and positive, in maximum and minimum temperature.
“Singh and Sontakke (2002)”	1876-1997	Reported significant trends in maximum and minimum temperature.
“Arora et al. (2005)”	1941-1999	Showed significant trends in maximum and minimum temperature.
“Kothawale and Rupa Kumar (2005)”	1901-2003	Annual mean, maximum, and minimum temperature increased significantly by $0.2^{\circ}\text{C decade}^{-1}$, with marked acceleration in the last 03 decades.
“Bhutiya et al. (2007)”	1901–2002	Reported significant trends in maximum and minimum temperature.
“Pal and Al-Tabbaa (2010)”	1901-2003	Observed significant trends in maximum and minimum temperature, impacting frequency of temperature extreme.
“Kothawale et al. (2010)”	1970-2005	Increase in hot days and nights, decrease in cold days and nights; significant increase in heatwave frequency on east and west coasts and peninsular region; decrease in cold events in western Himalayas and west coast; increase in extreme nighttime temperature in several regions in India.
“Dash and Mamgain (2011)”	1969-2005	Reported increase in hot days and nights, decrease in cold days and nights.
“Revadekar et al. (2012)”	1971-2000	Confirmed trends of increasing hot days and nights and decreasing cold days and nights.

Continued...

Continued...

References	Period of study	Salient findings
“Rohini et al. (2016)”	1961-2013	Increase in frequency, total duration, and maximum duration of pre-monsoon heatwaves over central and northwestern parts of India.
“Chakraborty et al. (2017)”	1969-2005	Detected trends in maximum and minimum temperature for pre-monsoon, monsoon, and winter seasons; increase in growing degree days (GDDs) and hot extremes, decrease in cold extremes in India.
“Panda and Sahu et al. (2019)”	1980-2017	Annual maximum and minimum temperature showed rising trends; seasonal maximum and minimum temperature during southwest monsoon months showed declining trends; significant increasing trends in annual and monsoon season rainfall in Koraput district, Odisha.
“Das et al. (2020)”	1979-2017	High frequency and magnitude of heatwaves observed in Rajasthan, Punjab, Haryana, and Madhya Pradesh; lower occurrences in northeast, peninsular, and parts of northern India; increasing trends in heatwaves in several states, no trends in peninsular and northeast regions.
“Gupta et al. (2021)”	1901-2018	Minimum and maximum temperature showed insignificant variation during pre-monsoon and monsoon seasons; significant increasing trends during post-monsoon and winter seasons; declining trends in monsoon and annual rainfall and PET in Jharkhand.

Extreme temperature variations can cause heat or cold waves, which, if persistent, have severe effects due to anomalously high or low surface air temperatures (“Qin et al. 2015; Trenberth et al. 2008”). Analyzing the spatio-temporal patterns of weather extremes, such as heatwaves, is critical due to their impacts on agriculture, society, economics, the environment, and health as a whole (“Coumou et al. 2013; Meehl et al. 2012; Orłowsky and Seneviratne, 2012, 2015; Seneviratne et al. 2014”). Several studies have detected extreme temperature events using arbitrary threshold-based or percentile-based approaches (“Jones et al. 1999; Klein Tank and Konnen, 2003; Plummer et al. 1999; Alexander et al. 2006”). In India, the variation in temperature due to its wide latitudinal range necessitates using a percentile-based approach to compute extreme temperatures (“Pant and Rupa Kumar, 1997; Kothawale, 2005”). “Kothawale et al. (2010)” analyzed data from 121 meteorological observatories for the period 1970-2005 during the pre-monsoon season (March-May) in India using a percentile-based approach, and observed a rise in warm days and nights along with a decline in cool days and nights. They found a significant increase in heatwave frequency on the east- and west-coasts and in peninsular region, whereas reduced cold events in the western Himalayas and west coast. Other studies have reported similar trends (“Dash and Mangain, 2011; Revadekar et al. 2012”). “Rohini et al. (2016)” used gridded daily temperature data (1961 to 2013) to examine pre-monsoon heatwaves in India, reported increase in frequency, total duration, and maximum duration of heatwaves over central and northwestern parts of the country. “Chakraborty et al. (2017)” analyzed daily gridded temperature data (1969 to 2005) to detect temporal trends of maximum and minimum temperatures for pre-monsoon, monsoon, and winter seasons in the context of crop-growing seasons (*kharif*, *rabi*, and *zaid*). They found that the rate of rise in minimum temperature (0.02 to 0.04 °C per year) was greater than that of maximum temperature (0.01 to 0.02 °C per year) during the winter and pre-monsoon periods. However, minimum temperatures decreased over eastern India during monsoon months, while maximum temperatures decreased over northern and eastern parts in winter. Despite these trends, general warming altered the thermal conditions for agricultural cultivation, causing significant increases in growing degree days (GDDs), occurrences of hot extremes and significant decreases in cold extremes. “Das et al. (2020)” used long-term (1979 to 2017) daily gridded “Climate Prediction Centre (CPC)” global daily maximum temperature data to quantify heatwave occurrence during the summer (March to July) in India. They identified heatwave events based on the “India Meteorological Department

(IMD)” criteria, determining various heatwave parameters, including frequency, magnitude, and extent, to compute a combined heat-wave index. High frequency and magnitude of heatwaves were observed in Rajasthan, Punjab, Haryana, and Madhya Pradesh, while lower occurrences were noted in the northeast, peninsular, and parts of northern India. They reported increasing trends in heatwaves over Rajasthan, Haryana, Punjab, East Madhya Pradesh, and Odisha; decreasing trends in Uttar Pradesh, Bihar, Chhattisgarh, Telangana, and Andhra Pradesh; and no trend in the peninsular and northeast regions during the summer season.

1.5.2 Temporal trend of rainfall and its extreme

Monitoring trends in the rainfall time series is necessary to understand rainfall patterns in space and time. Several studies have investigated the rainfall trend at a national, regional or individual station level. A snapshot of studies on the temporal trends of rainfall in India is depicted chronologically in Table 1.2.

In India, early studies have indicated an insignificant trend in mean annual rainfall on a national scale (“Mooley and Parthasarathy, 1984; Sarker and Thapliyal, 1988; Thapliyal and Kulshrestha, 1991; Lal, 2001; Sinha et al. 2003”). However, they did observe significant variability in trends at the regional level during the southwest monsoon season. To identify rainfall trends, these studies have employed various durations and data sources, including point-based meteorological observatory data, gridded data, and data averaged over zones. “Parthasarathy and Dhar (1974)” analyzed annual mean rainfall from 1901 to 1960, revealing an increasing trend in central India and parts of the Indian peninsula, and a decreasing trend in several regions of eastern India. “Rupa Kumar et al. (1992)” identified a significant upward trend in monsoon rainfall along India's west coast, central peninsula, and northwest regions. Conversely, they observed a notable decline in monsoon rainfall over the northeast, northwest peninsula, and northeast India. “Guhathakurta and Rajeevan (2008)” assessed monthly, seasonal, and annual rainfall time series (1901 to 2003) across 36 meteorological subdivisions in India. They concluded that the rainfall trend is decreasing in Jharkhand, Chhattisgarh, and Kerala, while increasing in West Bengal, Uttar Pradesh, Jammu and Kashmir, Konkan and Goa, central Maharashtra, Rayalaseema, Andhra Pradesh, and North Karnataka. Additionally, the contribution of June, July, and September rainfall to the annual total is decreasing, whereas the contribution of August rainfall is increasing. Daily gridded rainfall data spanning from 1951 to 2003 were analyzed by “Ramesh

and Goswami (2007)". Their study identified decreasing trends in early- and late-season monsoon rainfall and the number of rainy days in India. Additionally, they found a negative trend in summer monsoon rainfall across the country, and an positive trend in pre-monsoon and post-monsoon rainfall.

The evaluation of temporal variations in monthly, seasonal, and annual rainfall over Kerala for the period 1871 to 2005, conducted by "Krishnakumar et al. (2009)", unveiled a noteworthy reduction in southwest monsoon rainfall, accompanied by a rise in post-monsoon rainfall. "Pattanaik and Rajeevan (2010)" concluded that extreme rainfall events in India during June, July, August, and September (JJAS) exhibit notable spatial variations across the west coast, central India, and northeast India. Both the average frequency of these extreme events and their contribution to seasonal rainfall show a significant positive trend across the Indian region during the southwest monsoon season. "Pal and Al-Tabbaa (2011)" analyzed precipitation data from 1954 to 2003 and concluded that spring and monsoon precipitation in India showed a declining trend, while autumn and winter precipitation exhibited an increasing trend. "Das et al. (2014)" analyzed daily gridded ($0.5^\circ \times 0.5^\circ$) rainfall data and found increasing rainfall and rainy days over the east coast and Deccan Plateau. In contrast, the west coast, western arid region, and northeastern humid region experienced declining trends. The northern Himalayas showed rising precipitation with a reduction in the number of rainy days, while the north and central plains had fewer rainy days, and the eastern plain had reduced rainfall. "Chandniha et al. (2017)" investigated precipitation patterns within Jharkhand, India, employing the MK test alongside Sen's Slope estimator. Their analysis revealed a noteworthy decreasing trend in annual rainfall from 1901 to 2011. This trend was deemed significant across 65% of the area while remaining statistically insignificant within the remaining 35% of the study area. Similarly, in their study, "Roxy et al. (2017)" observed a decline in the occurrence of moisture-laden depressions forming in the Bay of Bengal, coupled with a reduction in locally available moisture and a weakening monsoon circulation. Despite these unfavorable developments, there was a threefold increase in widespread extreme rainfall across central India from 1950 to 2015. "Jenifer and Jha (2021)" employed station data to analyze the annual rainfall series spanning from 1980 to 2013 in the semi-arid region of Southern India. Their investigation disclosed a noticeable pattern wherein an upward trend in rainfall was observed in the northern segment of South India, contrasted by a declining trend noted in the southern portion of the same study area.

Table 1.2 *Summary of studies on the temporal trend of rainfall over India*

References	Period of study	Salient findings
“Parthasarathy and Dhar (1974)”	1901-1960	Increasing trend of annual rainfall in central India and parts of the Indian peninsula; decreasing trend in eastern India.
“Mooley and Parthasarathy, 1984; Sarker and Thapliyal (1988); Thapliyal and Kulshrestha (1991); Lal (2001); Sinha Ray and De (2003)”	1871-1978 1860-1980 1870-1990 1890-2000	Insignificant trend in mean annual rainfall on a national scale; significant regional variability during the southwest monsoon season.
“Rupa Kumar et al. (1992)”	1871–1984	Upward trend in monsoon rainfall along India's west coast, central peninsula, and northwest regions; decline in monsoon rainfall over northeast, northwest peninsula, and northeast India.
“Guhathakurta and Rajeevan (2007)”	1901-2003	Decreasing rainfall trend in Jharkhand, Chhattisgarh, and Kerala; increasing trend in West Bengal, Uttar Pradesh, Jammu and Kashmir, Konkan and Goa, central Maharashtra, Rayalaseema, Andhra Pradesh, and North Karnataka.
“Ramesh and Goswami (2007)”	1951-2003	Negative trends in early and late monsoon rainfall and in the number of rainy days over India; decreasing summer monsoon rainfall; increasing pre-monsoon and post-monsoon rainfall.
“Krishnakumar et al. (2009)”	1871-2005	Noteworthy reduction in southwest monsoon rainfall; rise in post-monsoon rainfall over Kerala.
“Pattanaik and Rajeevan (2010)”	1951–2005	Notable spatial variations in extreme rainfall events during JJAS; significant positive trend in frequency and contribution to seasonal rainfall.
“Pal and Al-Tabbaa (2011)”	1954-2003	Declining trend in spring and monsoon rainfall; increasing trend in autumn and winter rainfall.

Continued...

Continued...

References	Period of study	Salient findings
“Das et al. (2014)”	1971-2005	Increasing rainfall and rainy days over the east coast and Deccan Plateau, while the west coast, western arid region, and northeastern humid region experienced decreasing trends.
“Chandniha et al. (2017)”	1901-2011	Decreasing trend in annual rainfall in Jharkhand; significant across 65% of the area.
“Roxy et al. (2017)”	1950-2015	Decline in moisture-laden depressions from the Bay of Bengal; reduction in locally available moisture; weakening monsoon circulation; threefold increase in widespread extreme rainfall events across central India.
“Jenifer and Jha (2021)”	1980-2013	Upward trend in rainfall in northern South India; declining trend in southern part of South India.
“Sulugodu and Deka (2019); Prakash (2019); Gupta et al. (2020); Singh et al. (2021); Divya and Shetty (2021); Varghese et al. (2024)”	1983–2012 1998–2015 2007–2016 1981-2020	CHIRPS data provides reliable rainfall estimates comparable to IMD data, especially useful in regions with limited weather station coverage.
“Kumar et al. (2021)”	1981-2020	Rising trend in annual and southwest monsoon rainfall in Punjab, with increases of 5.67% and 6.39%, respectively.
“Pandey et al. (2021)”	1981-2018	Declining trend in SPI during the post-monsoon season in Bundelkhand, indicating increased meteorological drought severity; non-significant declining trend in SPI for winter months.
“Singh et al. (2024)”	1901-2020	Developed a drought atlas for India using high-resolution SPEI data, indicating CHIRPS dataset reliability for long-term precipitation analysis.

In recent years, numerous scientific investigations conducted across diverse regions of India have embraced adopting high spatial resolution ($0.5^\circ \times 0.5^\circ$) satellite-derived CHIRPS data. These studies have recommended using CHIRPS data, particularly in regions with limited weather station coverage, highlighting its potential to yield results comparable to those derived from the IMD. The consensus reached by these studies is that CHIRPS rainfall estimates demonstrate a notable capacity to accurately replicate ground-based monthly rainfall datasets, indicating its potential suitability as a substitute for IMD gridded data (“Sulugodu and Deka, 2019; Prakash, 2019; Gupta et al. 2020; Singh et al. 2021; Divya and Shetty, 2021 and Varghese et al. 2024”). “Kumar et al. (2021)” assessed CHIRPS rainfall data spanning from 1981 to 2020 in Punjab, where non-parametric tests revealed an upward trend in annual and southwest monsoon rainfall, with an increase of 5.67% and 6.39%, respectively. “Pandey et al. (2021)” utilized the CHIRPS-derived “Standardized Precipitation Index (SPI)” to map drought hazard and its trend in the Bundelkhand region of Uttar Pradesh, India, covering the period from 1981 to 2018. They observed a significant declining trend of -0.16 to -0.33 mm month⁻¹ in SPI during the post-monsoon season, indicating a rise in meteorological drought severity. However, a non-significant declining trend was noted in SPI for the winter months. Chupal et al. (2024) developed a drought atlas for India (1901 to 2020) utilizing SPEI data derived from high-resolution (0.05°) and long-term monthly rainfall and temperature datasets. All these findings suggest that the CHIRPS dataset can reliably be used for long-term precipitation analyses with high confidence.

1.5.3 Impact of Climate Extremes on Crop Phenology

Global warming has intensified the frequency and spatial distribution of extreme climatic events, characterized by anomalies in temperature and precipitation compared to average conditions. In this era, phenology serves as a crucial indicator of the impacts of climate and weather extremes. A warming climate influences vegetation phenology by advancing the onset of the “Start of Season (SoS)” and delaying the “End of Season (EoS)”, as observed over the past few decades in various regions worldwide (“Peñuelas and Filella, 2001; Menzel, 2003; Piao et al. 2006, 2011, 2019 and Kang et al. 2018”).

Numerous studies have examined the influence of climate change on crop growth and yield in India, highlighting the varying relationship between crop growth patterns and drought (“Malhi et

al. 2021; Arora, 2019; Kumar and Gautam, 2014; Guntukula, 2020 and Rai et al. 2020”). Phenological metrics are critical indicators of crop growth patterns. Crop phenology can be assessed through field observations, bioclimatic models, and remote sensing techniques. Traditional methods, like field observations, are straightforward but labor-intensive and need more scalability. Bioclimatic models are species-specific and require detailed vegetation and climatic data and local calibration to be effective on larger scales. In contrast, satellite remote sensing provides a unique perspective, enabling regular monitoring of crop-growing regions.

Satellite data has been extensively utilized to address issues related to vegetation dynamics, such as net primary productivity (“Kumar et al. 2018”), chlorophyll databases for phenological variations (“Jeganathan et al. 2010”), and forest cover change dynamics (“Kumar et al. 2014”). Remote sensing has been crucial for assessing vegetation dynamics and retrieving phenology on global and regional scales (“Bórnez et al. 2020; Richardson et al. 2009; Wang et al. 2016; Verger et al. 2016; Atkinson et al. 2012; Delbart et al. 2005”). Phenological metrics have been derived from vegetation indices captured by satellites like the “Advanced Very-High-Resolution Radiometer (AVHRR)”, “Moderate-Resolution Imaging Spectroradiometer (MODIS)”, “VEGETATION onboard the Satellite Pour l’Observation de la Terre (SPOT-VGT)”, “PROBA-V” (“Bórnez et al. 2020; Atkinson et al. 2012; Delbart et al. 2005; Verger et al. 2016; Zhang et al. 2004”), and “Operational Land Imager (OLI)” sensors of Landsat5/7/8 satellites (“Khare et al. 2017; Fassnacht et al. 2019; Thong et al. 2019; Fayech and Tarhouni, 2021”).

Variations in crop phenology are recognized as early indicators of the effects of climate and weather extremes on agricultural systems (“Desclaux et al. 2009”). These variations impact terrestrial ecosystems and social infrastructure by altering carbon accumulation, crop yield, crop duration, and the distribution of diseases (“Richardson et al. 2009”). Consequently, phenological studies have become crucial in climatic and ecological research (“Bhavani et al. 2017; Yang et al. 2021”). Most studies predominantly utilize the NDVI to detect phenological trends (“Julien and Sobrino, 2009; White et al. 2009”), focusing on trends and advancements in the timing of SoS over recent decades. The NDVI, which is ratio of normalized difference in reflectance in red and infrared bands of various earth observation satellites, is a vital indicator of vegetation health and biomass, reflecting the impacts of climate change on vegetation (“Krishnaswamy et al. 2014; Koulgi et al. 2019”). Satellite-derived NDVI monitors crop growth patterns rather than directly indicating crop development stages, which may not always align with agronomic phases

(“Delécolle et al. 1992”). Thus, the term "land surface phenology (LSP)" is used for satellite-derived indicators (“Zhang 2018”). The most critical phenological metrics are the SOS and the EOS, with other metrics like the LoS derived from these. Various methods have been developed to extract these metrics from vegetation index time series, including fixed threshold (“Fischer, 1994; Lloyd, 1990”), moving average (“Duchemin et al. 1999; Reed et al. 1994”), dynamic threshold (“Jonsson and Eklundh, 2002; White et al. 1997”), function fitting (“Beck et al. 2006; Zhang et al. 2003”), maximum-slope (“Sakamoto et al. 2005”), and valley detection (“Atzberger and Eilers, 2011”).

However, most of the studies focus on using coarse resolution time-series data over the Indian region (“Chakraborty et al. 2014; Bhavani et al. 2017; Chakraborty et al. 2018”), which is insufficient to account for the variability in agricultural area and pattern in a heterogeneous landscape with small land holdings in India.

In several parts of the world, a shifting trend in phenology was observed based on vegetation index. Moreover, the impact of abnormal climate/weather conditions on vegetation phenology was also investigated. For example, a delayed SoS was observed in Chile during 2000 to 2013 due to an increase in dry spells by analyzing vegetation index profile (“Stuart-Haëntjens et al. 2018”); a change in vegetation phenology (delayed SoS and advanced senescence) in China due to temperature-induced drought (“Li et al. 2018; Ren et al. 2017; Zhang et al. 2017, Hao et al. 2019; Kang et al. 2018”). Likewise, the trend analysis of vegetation phenology at annual and seasonal scales is assessed through vegetation indices in several other parts, such as the Tibetan Plateau (“Fassnacht et al. 2019”); diverse parts in Asia (“Shrestha et al. 2012”); Africa (“Mbatha and Xulu, 2018”). Some of the phenology-related work is also carried out in India (“Nandy et al. 2021; Parida et al. 2020; Saikia, 2009”). However, most of the earlier studies to analyze the trends of vegetation phenology are either based on the data obtained from coarser-resolution such as 8-km GIMMS NDVI data from NOAA/AVHRR or 500-meter MODIS-based NDVI from Aqua/Terra (“Chen et al. 2019”); or addresses the trend of phenology related to forest or grasslands. Very few studies have evaluated the trend in crop phenology and its relationship to the weather/climate-extremes in crop growing season. “Jeganathan and Nishant, 2014” utilized the GIMMS and MODIS NDVI data to assess the spatio-temporal variations in forest phenology in India. “Ranjan and Gorai, 2022” employed MODIS-derived products such as, land cover, leaf area index (LAI), and gross primary productivity (GPP) for a spatio-temporal analysis of forest

vegetation dynamics in terms of growth and productivity over the Rajmahal Hills, Jharkhand (India) during 2001 to 2019. “Kumar et al. (2022)” utilized Landsat satellite-derived NDVI to analyze the inter-annual vegetation dynamics over the major forest type and forest density classes over the eastern Indian Himalayan. They have accounted the high spatial heterogeneity and fine-scale diversity in vegetation types specific to forest in the Himalayas.

On the other hand, “Parida et al. (2020)” analyzed GIMMS NDVI data from 1981 to 2015 to examine greenness trends in both forests and croplands, along with climatic factors like temperature, rainfall, solar radiation, and soil moisture. They observed a significant greening trend, increasing from 47% to 80% in the northwestern Plain and Central India, especially in dry regions and croplands, driven by moisture-induced greening and cooling temperatures. However, during the *kharif* season, this trend dropped from 84% to 40% in the southern peninsula and west-central regions due to moisture stress from warming temperatures. Croplands accounted for about 88% of the greening trend, while forests contributed around 56% from 1982-2015. In contrast, Northeast India and the Himalayas exhibited a browning trend due to temperature-induced drought stress. These results are consistent with “Chen et al. (2019)”, who found 82% greening from croplands using MODIS LAI data (2001 to 2017), with minor contributions from forests (4.4%) in India, unlike China, which had 32% greening from croplands and 42% from forests. Conversely, “Chakraborty et al. (2018)” reported 67% greening and 12% browning trends in forests using MODIS NDVI data (2001 to 2014). “Chakraborty et al. (2017)” used STAR-Global Vegetation Health Products NDVI and GIMMS-NDVI to study wheat phenology in northern India. They found an earlier SoS in Punjab and Haryana, but a delay in Uttar Pradesh. Despite these variations, the EoS consistently occurred earlier, even in areas with a delayed SoS. The LoS increased in most of Punjab and northern Haryana, while it decreased in Uttar Pradesh.

Fewer studies concentrated on the impact of climate extremes on crop phenology. “Vicente-Serrano et al. (2015)” assessed global land degradation in semiarid regions using NDVI and the “Standardized Precipitation Evapotranspiration Index (SPEI)”. They found that $NDVI_{max}$ values, indicating peak vegetation vigor, increased in most semiarid regions. However, $NDVI_{max}$ was highly correlated with SPEI variability; suggesting that drought trends influenced global $NDVI_{max}$ trends. “Das et al. (2020)” analyzed GIMMS-derived phenology in concurrence with agricultural drought in the *kharif* season to propose a multivariate phenology-based agricultural drought index. Here, it was based on the foundation that agricultural droughts may lead to a

delay in crop sowing, a decrease in cropped area, and a reduction in crop production. “Rezaei et al. (2015)” analyzed the effect of high temperatures on crop phenology in Germany from 1951 to 2009. They demonstrated a strong correlation between the mean temperature and the heading time of winter wheat. They revealed that the early heading time completely compensates for the harmful effect of global warming on crop heat stress.

1.5.4 Impact of weather and Climate on Crop yield

The rising anomalies in crop yields caused by climate variability have become a critical issue in contemporary agricultural research. Efforts to reduce crop yield variability depend on understanding the complex relationship between climatic variables, weather extremes, and crop yield. Therefore, analyzing reduced crop yields at finer spatiotemporal scales and identifying their key climatic drivers is crucial for sustainable food security. Statistical models, physical process-based models, and now machine learning (ML) tools have been used to assess the impact of climate change on crop yield variability. Earlier studies emphasized the importance of seasonal mean temperature and rainfall on crop yields (“Lobell and Field, 2011; Osborne and Wheeler, 2013; Ray et al. 2015”). However, recent studies have highlighted the need to include extreme events in these models, such as the 2010 droughts in Russia and the 2012 drought in the United States (“Otto et al. 2012”).

The impact of climatic variables and extremes on crop yield has been observed across crop types and growth stages, climatic variables under study, and geographical regions (“Irmak and Kukal, 2022”). Many previous studies have reported variable climate change impacts on different crops across the globe using a statistical modeling approach (“Yu et al. 2016; Paymard et al. 2018”). “Novikova et al. (2020)” utilized weather-based regression models of the observations from 1972 to 2017 to identify the climatic factors associated with the variation in soybean productivity under the contrasting eco-geographical conditions of Russia. “Kukal and Irmak (2018)” evaluate climate impacts on maize, sorghum, and soybean yields and the effect of irrigation in the United States by utilizing extensive climate data and yield throughout 1968 to 2013. Approximately one-fourth yield variability of the mean yields was explained by variability in temperature and rainfall. One interesting finding is that though the observed increasing rainfall trend was beneficial for all crops, but observed temperature trend was crop-specific, for example, it was helpful for maize yields, but harmful for sorghum and soybean yields. “Osman et al. (2021)”

examined the impact of historical temperature and rainfall on crop yields in Sudan. Using correlation and multiple linear regression, and found that annual rainfall positively correlated with the yields of sorghum (0.64), sesame (0.58), and sunflower (0.75). They also observed that a more extended rainy season significantly improved crop yield. Temperature and rainfall variables accounted for over 50% of the yield variability in sorghum ($R^2 = 0.70$), sunflower ($R^2 = 0.61$), and millet ($R^2 = 0.54$). Sharma et al. (2022) analyzed future climatic conditions on cotton and soybean in the agroecologically diverse region of the United States from 1980 to 2020 using the fixed-effect model. It was concluded that rainfall does not significantly affect cotton and soybean yields. In contrast, a 20.8% increase in cotton yield and 31.6% in soybean yield was observed by a 1°C increase in minimum temperature (T_{min}). However, a 1°C rise in maximum temperature (T_{max}) decreased both cotton and soybean yield by 10.3% and 25.6%, respectively.

Many recent studies have used the ML approach to assess the impact of weather and climate on crop yield. For example, “Crane-Droesch (2018)” implemented a semiparametric variant of a deep neural network on corn yield from the United States, exhibiting the used technique’s superiority over classical statistical methods and fully nonparametric neural networks in yield estimation. Overall, they also reported significant adverse impacts of climate change on corn yield despite being a C-4 crop, but it was less severe than impacts projected using classical statistical methods. “Vogel et al. (2019)” analyzed the worldwide influence of climate extremes, such as droughts or heat waves, on yield variability of crops such as maize, soybean, rice, and wheat using yield based ML technique. It was observed that climate factors, including both mean climate and climate extremes, describe 20-49% of the crop yield variability compared to 18 to 43% of the yield variability described by climate extremes alone, depending on crop type. Moreover, temperature-extremes show a greater sensitivity towards yield variability than rainfall extremes. “Hoffman et al. (2020)” used Random Forest models to analyze crop yields and climate variables across different development phases, explaining 71 to 86% of yield variability. They found sharp yield decreases for maize and soybean when T_{max} exceeded 29°C and 30°C, respectively. Sorghum showed higher temperature tolerance, with gradual yield decreases above 32.5°C. Additionally, sorghum and soybean positively responded to increases in T_{min} . “Beillouin et al. (2020)” reported that temperature and rainfall extremes result in yield loss. However, impacts vary in different parts of Europe. ML models incorporating historical yield data over 1990 to 2018 could explain up to 65% of historical yield anomalies, though they did

not find any clear upward or downward trend in the frequency of extreme crop yield losses. “Schierhorn et al. (2021)” used the ML approach to analyze the impact of climate and weather on winter wheat yields in Ukraine from 1985 to 2018, focusing on different growth stages. They found that climate and weather variables explained 54% of yield variability. Key factors compromising yields included heat waves, hot nights, frost, and drought, particularly during the reproductive and grain-filling phases.

In India, numerous studies have analyzed the impact of weather extremes on crop yield, concluding that climate change adversely affects yields across all regions. For instance, research indicates significant impacts in Rajasthan (“Singh et al. 2021”) and southern India (“Kumar et al. 2018”), with temperature extremes being more influential than other climatic parameters. Warmer summers and droughts have notably affected agriculture in many parts of India. Despite a steady increase in crop yields, the growth rate is declining, indicating stagnation and growing vulnerability to climate variability (“Rao et al. 2015; Bal et al. 2022”). “Madhukar et al. (2019)” also confirmed yield stagnation in wheat crops due to changing climatic conditions. Empirical modeling revealed that wheat yield is more sensitive to night-time temperature (T_{min}) during the reproductive phase than to day-time temperature (T_{max}). Specifically, a 1°C increase in T_{min} resulted in a 7% decline in mean wheat yield from 1980 to 2011. Furthermore, T_{min} above 12°C for six days and T_{max} above 34°C for seven days during the reproductive phase are particularly detrimental to wheat yield (“Rao et al. 2015”). Future projections suggest that climate change could reduce crop yields by 4.5 to 9.0% (“Naresh Kumar et al. 2020”).

Several studies have employed physical process-based models, such as the “Decision Support System for Agro-technological Transfer (DSSAT)”, at the farm level to predict soybean yield using historical and projected climate scenarios (RCPs at 4.5 and 8.5). The yield response to these climate scenarios varied between 17 to 35% among farms and 10 to 15% across years (“Subash and Ram Mohan 2012”). They reported significant decline in wheat yield due to increased T_{max} than T_{min} under Indian conditions. In another study, “Dubey et al. (2020)” used the InfoCrop simulation model in a field experiment to assess the impact of terminal heat stress on wheat yield. They found 18.1%, 16.1%, and 11.1% yield declines for the present, 2020, and 2050 scenarios, respectively. They recommended adaptation strategies such as tending early sowing, additional nitrogen application, and irrigation during the grain filling stage, which could reduce heat stress impacts by 7.5%, 6.4%, and 9% in the respective scenarios. “Daloze et al.

(2021)” utilized a regional climate model and a crop model to evaluate the impacts of climate change on wheat yields in the Indo-Gangetic plains during the *rabi* season (November-April). They found yield anomalies of 1 to 8% due to changes in temperature and rainfall.

1.6 Statement of Purpose

Based on the review of literature, it is evident that there are a limited number of studies utilizing high-resolution spatial data to analyze the temporal trends of weather and climatic data and their extremes on a national scale. Moreover, there is a notable lack of studies addressing the impact of heat events and the combined effects of temperature and moisture extremes on crop phenology at the AER level across the entire country. Although several studies have utilized linear, nonlinear, and threshold-type methods to examine the relationship between crop yield and weather (“Lobell et al. 2011; Troy et al. 2015”), most have modeled this non-linearity using regression models for mean weather indices without appropriate justification. To the best of our knowledge, no studies have utilized machine learning approaches, which are inherently nonlinear and non-parametric, to investigate the impact of a comprehensive set of weather variables and extremes on crop yield in the Indian context. Although a few global studies have considered the impact of various weather conditions and extremes, such as temperature, rainfall, or their combination, on crop yields, particularly soybean yields, using machine learning techniques, this has yet to be done specifically in the Indian context.

The current study employs daily gridded satellite data to analyze the spatio-temporal trends of a comprehensive set of monthly and seasonal weather variables and crop phenology across different agro-ecological regions in India. Additionally, it accounts for variations in weather extremes, such as droughts and heat extremes, and their concurrent effects on crop phenology, along with a sensitivity analysis at the national scale.

To precisely understand the relationship between weather variables and crop yield, this study conducts a global sensitivity analysis to identify the most influential weather variables among multiple factors. Overall, this study aims to analyze the spatiotemporal impact of weather extremes on crop phenology and the yields of soybean and wheat, two major crops, in central India.

1.7 Objectives

- To analyze the temporal trends of temperature, its extremes and dryness/wetness using daily gridded temperature and rainfall data
- To study the effect of weather extremes on crop phenology in different agro-ecological regions of India
- To analyze the spatial impact of weather extremes on soybean and wheat crop yield in central parts of India

Study Region

2.1 General

The study area encompasses the continental mainland of India, ranging from 8°04' to 37°06' North latitude and 68°07' to 97°25' East longitude. Given India's significant spatial variability in terms of climate, physiography, soils, and agriculture, the study was conducted at a sub-national scale, based explicitly on India's Agro-Ecological Regions (AERs). The current study was conducted in two parts: objectives 1 and 2 at the all-India level, and objective 3 at the state level, specifically in the central region of India.

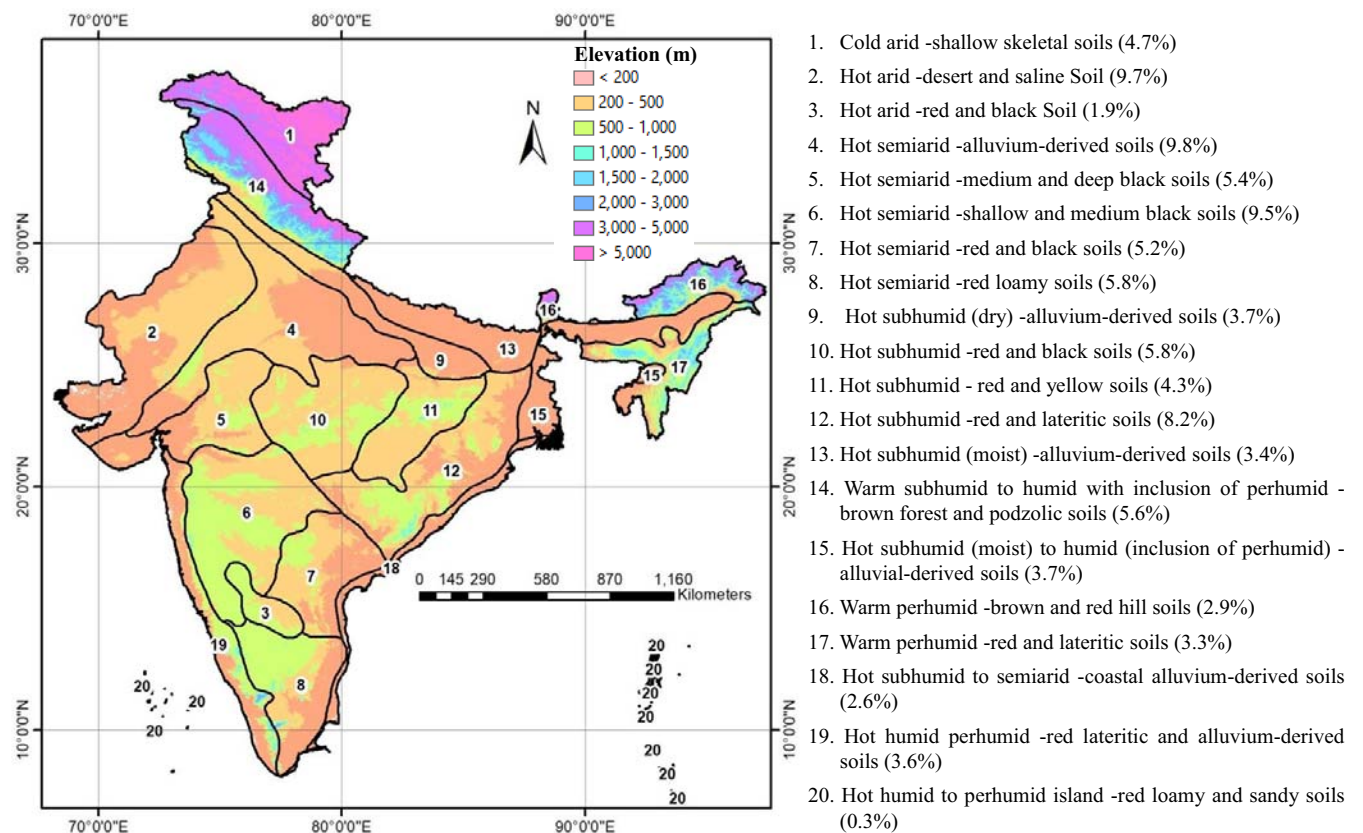


Fig 2.1 Study area showing topography derived from SRTM-DEM overlaid with boundary of different Agro-ecological regions of India

The study was carried out over 20 agro-ecological regions (AERs) of India (Fig 2.1). The AERs have contiguous large agricultural land areas, and each AER is extracted out of a climatic zone,

correlated with landforms, climate, and the length of growing period (Subramaniam 1983). The crop phenology in each AER could easily be identified using time series satellite data. Here, the length of the growing period represents the number of days when moisture is available for crop growth. Each AER is homogenous in terms of physiography, type of climate, length of growing period, and soil types for macro-level agricultural land-use planning. Table 2.1 summarizes the characteristics of different AERs in India.

2.2 Climate

India's climate encompasses variability in weather conditions due to its large geography and diverse topography. India features six broad climatic subtypes (Köppen classification system): Alpine tundra and glaciers in the north (Himalayan region), Arid deserts in the west, and Humid tropical regions with rainforests in the southwest and island territories.

There are four main seasons, as per the IMD: (a) summer (March to May), (b) winter (December to February), (c) monsoon (June to September), and (d) Post-monsoon (October and November)

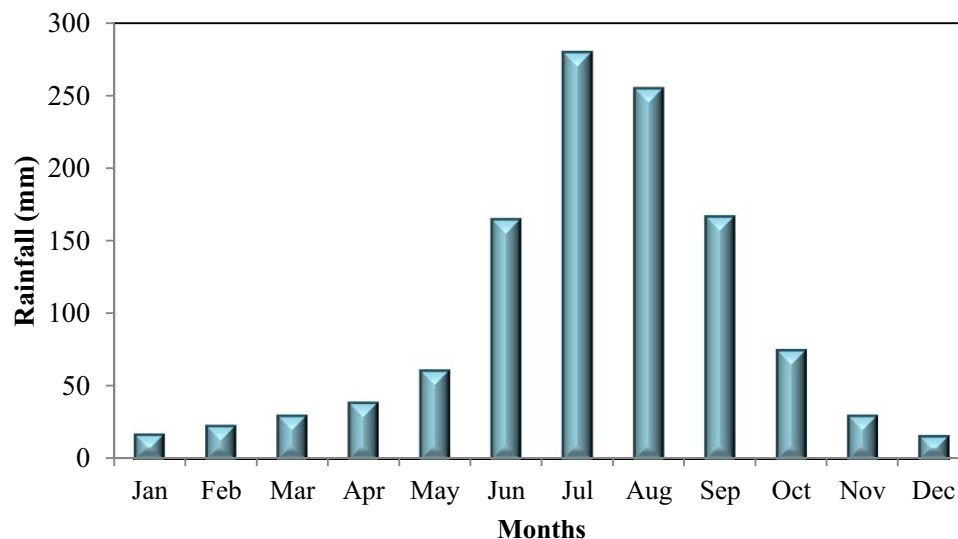


Fig 2.2 Monthly variation of 30-year average total rainfall (mm) in India (IMD, 2018)

Most of the rainfall in India (~75%) occurs during the southwest monsoon in the months of June, July, August, and September (Fig. 2.2). The post-monsoon season, coinciding with the northeast monsoon, contributes an additional 11% of the annual rainfall and is prevalent in southern states such as Tamil Nadu, parts of Kerala, Andhra Pradesh, and Karnataka. The spatial pattern of monsoon-season aggregated average rainfall is exhibited in Fig 2.3. It represents low rainfall in the western part and northern Himalayan regions (<500 mm) in arid zones, moderate to high

rainfall in central regions (500 to 1500 mm) in semi-arid to sub-humid zones, and very high rainfall along the western coast and northeastern regions (>1500 mm) in humid-per humid zones.

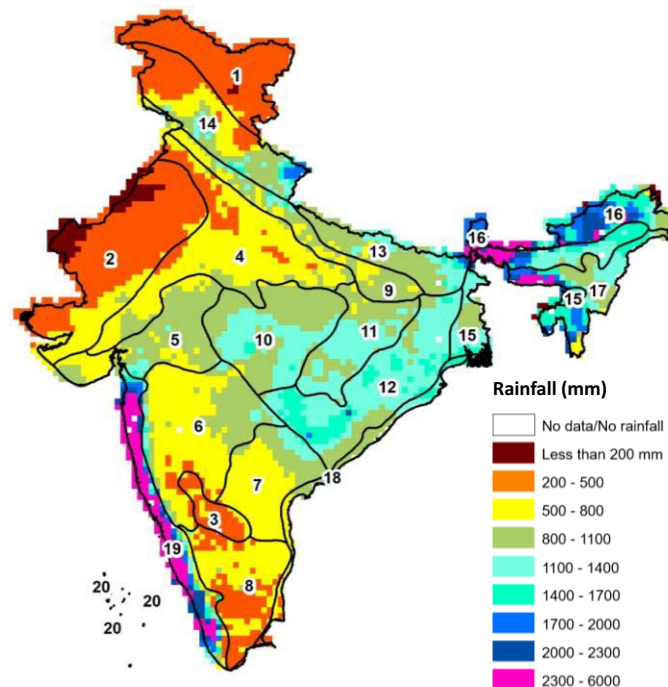


Fig 2.3 Spatial pattern of seasonal (Southwest monsoon) mean Rainfall (1981-2018) in different Agro-ecological regions of India

Fig 2.4 and 2.5 represent the mean monthly maximum (day-time) and minimum (night-time) temperatures, respectively, in different AERs of India. The mean monthly maximum temperature (Tmax) in the winter season varied from 0 to 35°C, with Tmax below 20°C in the northern part of India and above 20°C in the southern part in January. The mean monthly Tmax is even lower than 5°C in the Himalayan region but higher than 25°C in coastal regions. The highest mean monthly Tmax is typically observed in May-June, when central, Indo-Gangetic Plain (IGP), and western parts show temperatures above 40°C (Fig 2.4). The mean monthly minimum temperature (Tmin) generally ranges between 0 to 30°C, with Tmin<10°C in the northern part and Tmin>10°C in the southern part of India during January. The maximum Tmin ranges above 25°C in major central and northern regions of India during April-May-June (Fig 2.5).

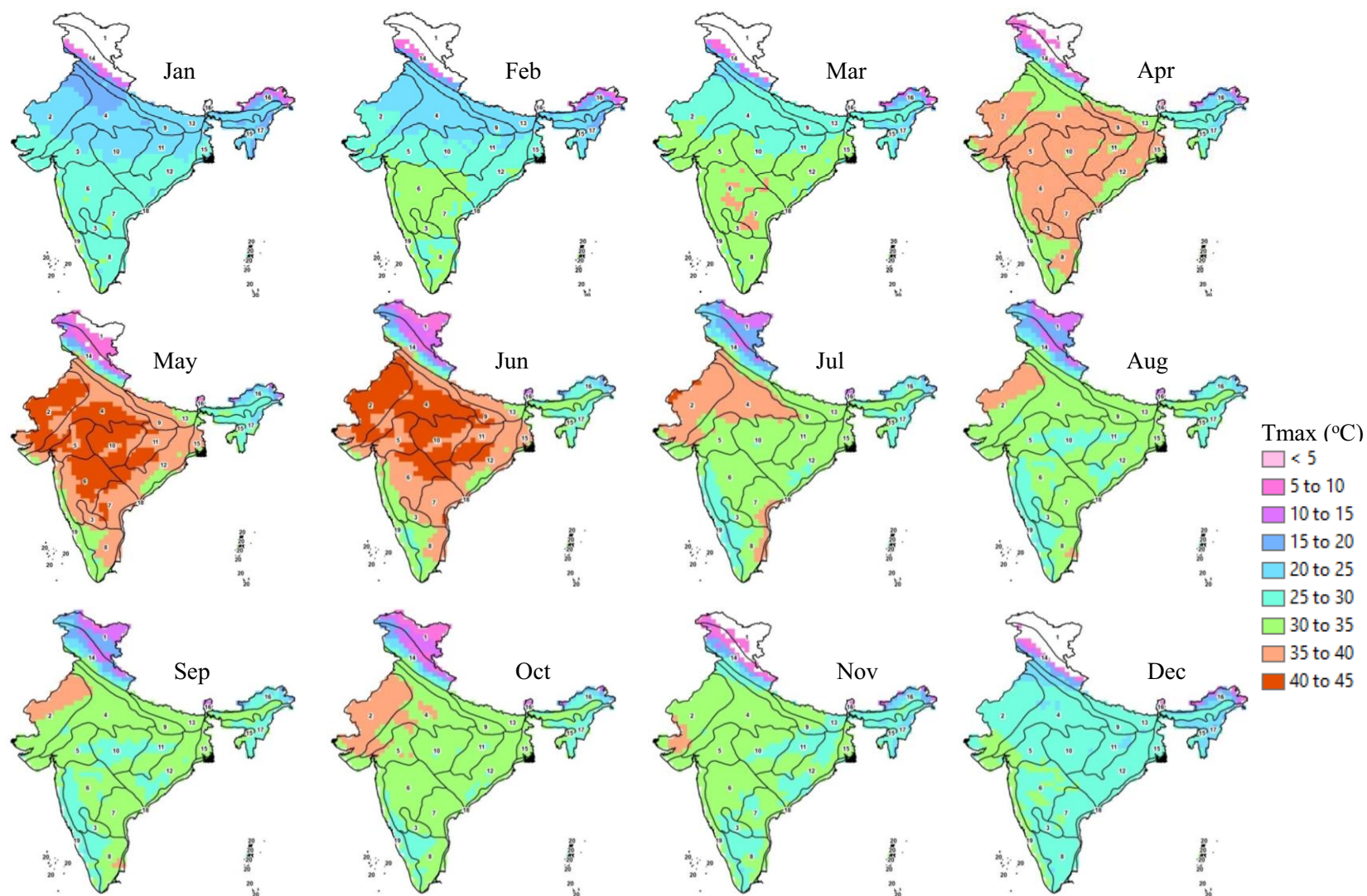


Fig 2.4 Spatial pattern of mean monthly maximum temperature (Tmax) over the period of 1981-2018 in different AERs of India

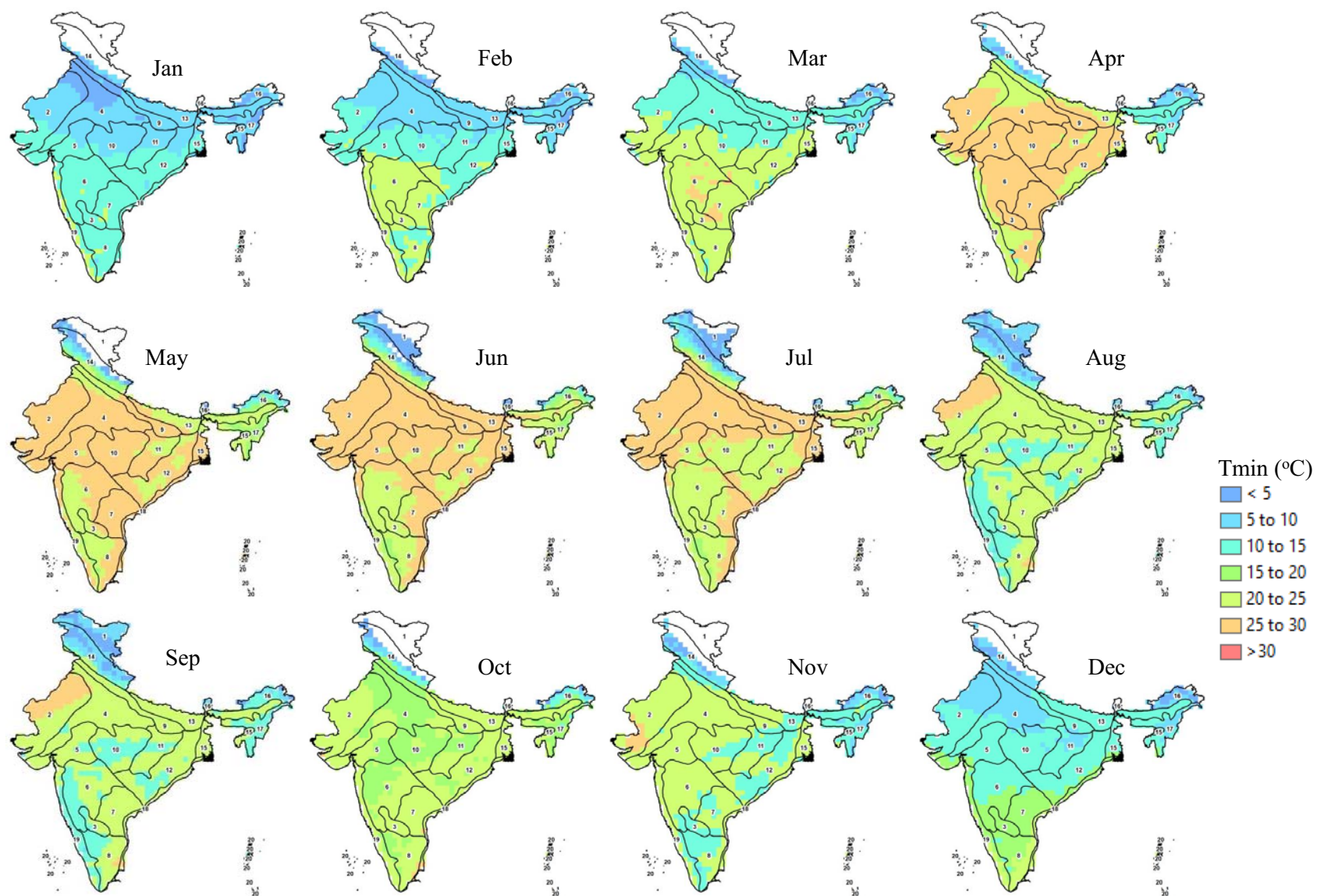


Fig 2.5 Spatial pattern of mean monthly minimum temperature (Tmin) over the period of 1981-2018 in different AERs of India

2.3 Soil and land use

“Indian Council of Agricultural Research (ICAR)” has identified eight soil categories in India as per the USDA soil taxonomy. These categories are Inceptisols (alluvial), Entisols, Alfisols, Vertisols (black cotton soils), Aridisols (desert soils), Ultisols (lateritic), Mollisols (podzolic), and other soil types, with textures ranging from sandy to clay loam. The soil type and depth determine the profile available water capacity (PAWC), which influences the soil's moisture storage capacity and depends on its physico-chemical characteristics, such as structure, organic matter, depth etc. The spatial pattern of PAWC is depicted in Fig 2.6(a).

India ranks second in the world of agricultural production, contributing approximately 18.8 percent to the gross domestic product (GDP) and employing about fifty percent of the population (“Economic Survey of India, 2022”). The cropping intensity in India is 137%, with a net sown area of approximately 140 million hectares (Mha) and a net irrigated area of around 60 Mha. The spatial pattern of agricultural area is displayed in Fig 2.6(b).

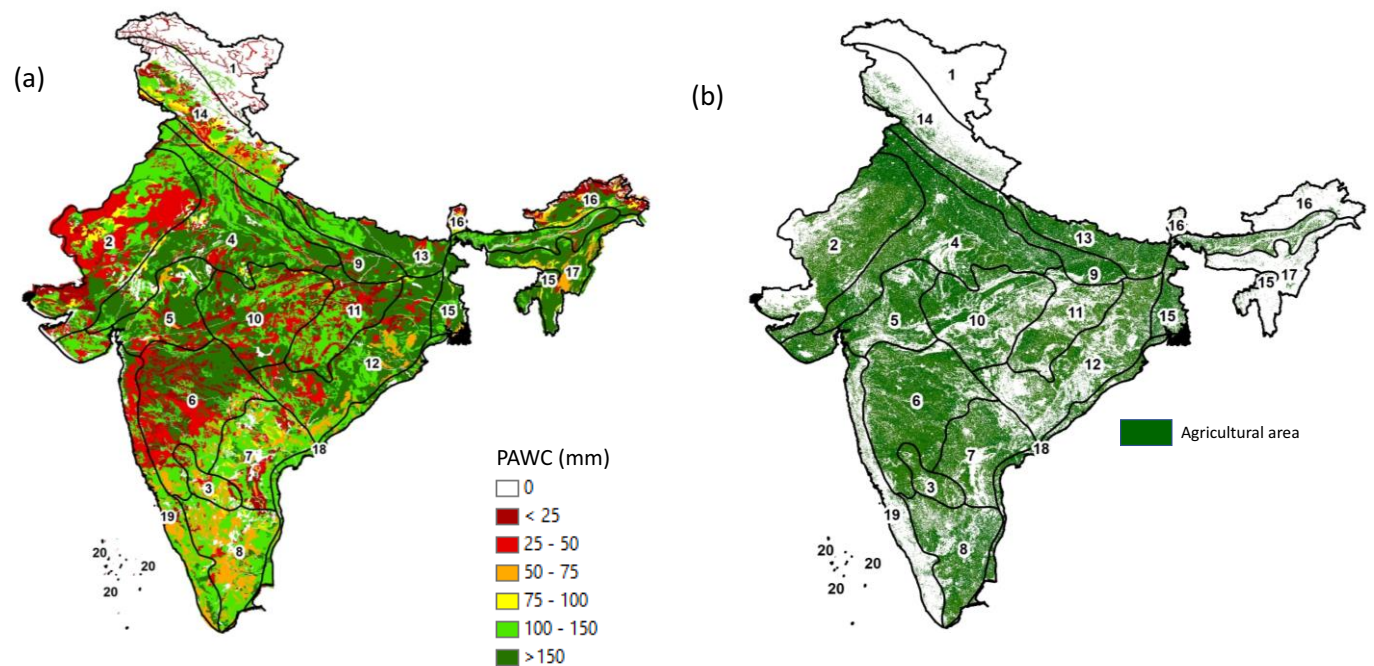


Fig 2.6 Spatial pattern of (a) Profile available water capacity (PAWC) based on National Bureau of Soil Survey & Landuse Planning (NBSSLU&P) and (b) agricultural area based on Landuse/Land cover map of NRSC in different AERs of India

Table 2.1 *Characteristics of various agro-ecological regions of India* (Kumari et al. 2023)

AER	Geographical area (Gross cropped area) (million ha)	Physiography	Precipitation (PET) (mm)	Length of growing period (days)	Major crops growing in AER
AER-01	15.2 (0.07)	Western Himalayas	< 150 (<800)	< 90	Vegetables, millets, wheat, fodder, pulses
AER-02	31.9 (20.85)	Western Plain and part of Kachchh Peninsula	< 300 (1500–2000)	< 90	Millets, fodder, pulses
AER-03	4.9 (4.18)	Deccan Plateau	400–500 (1800–1900)	< 90	Sorghum, cotton, oilseeds, sugarcane
AER-04	32.2 (30.05)	Northern Plain and Central Highlands including parts of Gujarat Plains	500–800 (1400–1900)	90–150	Millets, wheat, pulses, maize, cotton and sugarcane
AER-05	17.6 (11.04)	Central (Malwa) Highlands, Gujarat Plains and Kathiawar Peninsula	500–1000 (1600–2000)	90–150	Millets, wheat, pulses
AER-06	31.0 (25.02)	Deccan Plateau	600–1000 (1600–1800)	90–150	Millets, cotton, pulses, sugarcane
AER-07	16.5 (6.19)	Deccan Plateau (Telangana) and Eastern Ghats	600–1000 (1600–1700)	90–150	Millets, oilseeds, rice, cotton & sugarcane
AER-08	19.1 (6.96)	Eastern Ghats (Tamil Nadu uplands) and Deccan Plateau (Karnataka)	600–1000 (1300–1600)	90–150	Millets, pulses, oilseeds, sugarcane and rice
AER-09	12.1 (11.62)	Northern Plain	1000–1200 (1400–1800)	150–180	Rice, wheat, pigeon pea, sugarcane, mustard, maize
AER-10	22.3 (14.55)	Central Highlands (Malwa and Bundelkhand)	1000–1500 (1300–1500)	150–180	Rice, wheat, sorghum, soybean, pulses
AER-11	11.1 (6.47)	Eastern Plateau (Chhattisgarh Region)	1200–1600 (1400–1500)	150–180	Rice, millets, wheat, pulses

Continued...

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AER	Geographical area (Gross cropped area) (million ha)	Physiography	Precipitation (PET) (mm)	Length of growing period (days)	Major crops growing in AER
AER-12	26.8 (12.09)	Eastern Plateau (Chhotanagpur) and Eastern Ghats	1000–1600 (1400–1700)	150–180	Rice, pulses, millets
AER-13	11.1 (10.95)	Eastern Plains	1400–1600 (1300–1500)	180–210	Rice, wheat, sugarcane
AER-14	18.2 (3.20)	Western Himalayas	1600–2000 (800–1300)	180–210	Wheat, millets, maize, rice
AER-15	12.1 (8.99)	Bengal and Assam Plain	1400–2000 (1000–1400)	> 210	Rice, jute, plantation crops
AER-16	9.6 (1.37)	Eastern Himalayas	2000–4000 (<1000)	> 210	Rice, millets, potato, maize, oilseeds
AER-17	10.6 (1.56)	North-eastern Hills	1600–2600 (1000–1100)	> 210	Rice, millets, potato, plantation crops
AER-18	8.5 (6.12)	Eastern Coastal Plains	900–1600 (1200–1900)	90-210	Rice, coconut, pulses, oilseeds
AER-19	11.1 (5.70)	Western Ghats and Coastal Plains	2000–3200 (1400–1600)	> 210	Rice, tapioca, coconut, spices
AER-20	0.8 (0.05)	Islands of Andaman- Nicobar and Lakshadweep	1600–3000 (1400–1600)	> 210	Rice, coconut, areca nut, oil palm

2.4 Part of Central India

The third objective involved evaluating the impact of weather and its extremes on two crops, soybean and wheat, in the central part of India. Two predominantly rainfed states in India, Maharashtra and Madhya Pradesh, both of which have experienced several drought events in the recent past and are known for cultivating soybean and wheat, were chosen as the study areas (Fig 2.7).

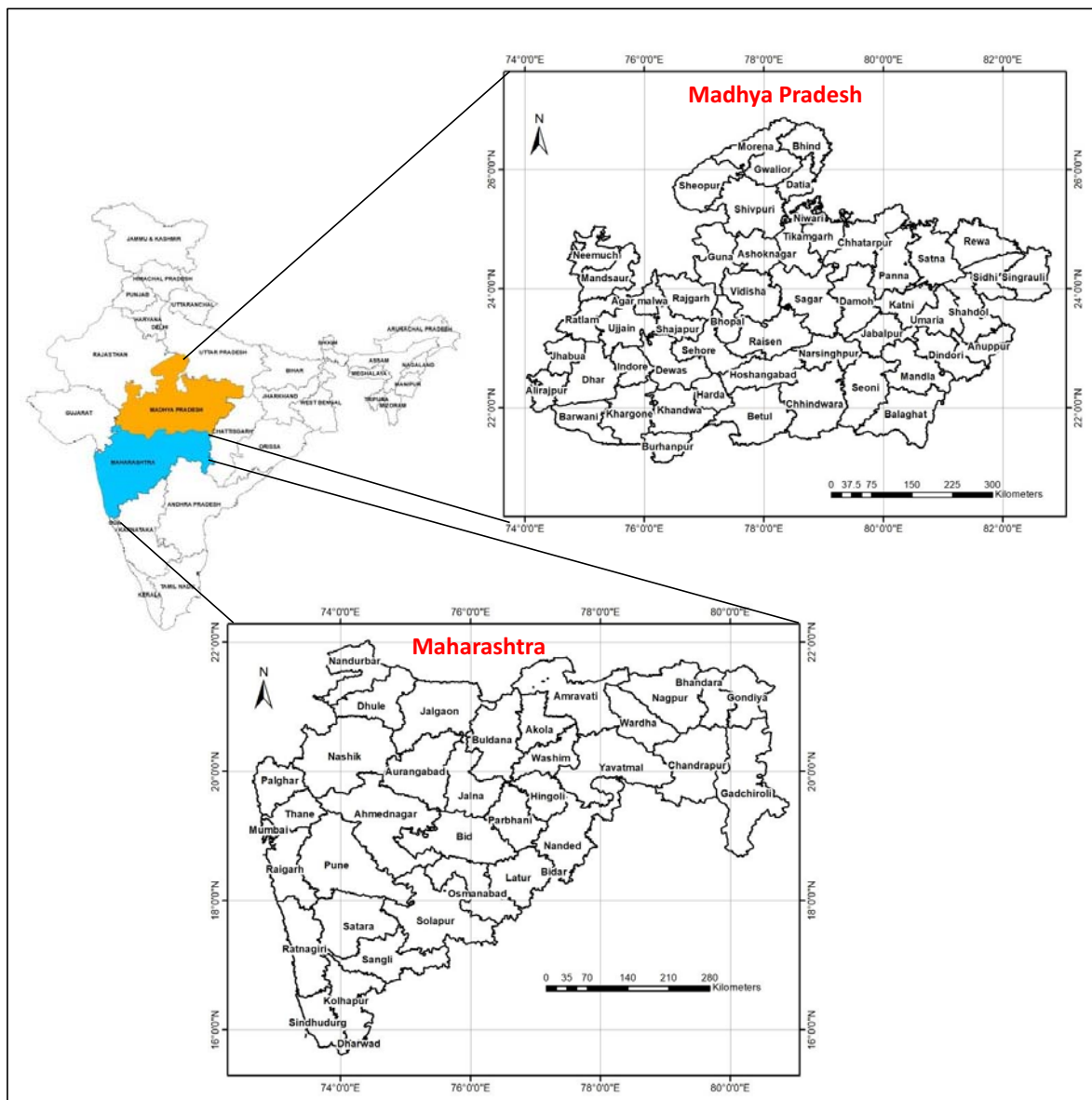


Fig 2.7 Central part of India (Maharashtra and Madhya Pradesh)

Maharashtra, situated in western India, extends from latitudes 15°35' N to 22°02' N and longitudes 72°36' E to 80°54' E, covering an area of 0.31million square kilometers, and divided into 36 districts. In contrast, Madhya Pradesh, the second-largest state in India, encompasses 50 districts that span from latitudes 17°48' N to 26°52' N and longitudes 74°2' E to 84°24' E. Both states experience a monsoon season from June to September, with higher rainfall in the south and southeast compared to the northwest. Approximately 55% of Maharashtra and 50% of Madhya Pradesh's total land area is utilized for cultivation. Soybean and Wheat are the major *kharif* (monsoon) season and *rabi* (winter) season crops in Maharashtra and Madhya Pradesh, respectively. Crop calendars of Soybean and Wheat grown in *kharif* and *rabi* season, respectively are given in Table 2.2.

Table 2.2 Crop calendar of Soybean and Wheat grown in *kharif* and *rabi* seasons, respectively (Kumari et al. 2024)

State	Crops	Initial	Crop development	Reproductive	Maturity	Harvest
Maharashtra	Soybean	Jun-Jul	Jul-Aug	Aug-Sep	Sep-Oct	Oct
Madhya Pradesh	Wheat	Nov-Dec	Dec-Jan	Jan-Feb	Feb-Mar	Mar

Soybean crop growth stages are categorized in following phases:

- Initial Stage corresponds to germination and emergence of seed from soil, focuses on root establishment and the development of cotyledons. Probable dates: 7 to14 days after sowing (DAS) in June to July.
- Crop Development Stage represents vegetative growth by developing leaves, stems, and branches. This stage is crucial for establishing the plant's structure and leaf area. Probable Dates: 15 to 45 DAS in July to August.
- Reproductive Stage shows flowering and pod formation, where successful pollination and pod set are critical for yield potential. Probable Dates: 45 to 75 DAS in August-September.
- Maturity Stage represents pod filling and seed development, determines the final seed size and quality. Probable Dates: 75 to 100 DAS in September to October.

- Harvest Stage corresponds to stage when the seeds reach physiological maturity and the pods begin to dry. Probable Dates: 100 to 120 DAS in October.

Wheat crop growth stages are categorized in following phases:

- Initial Stage involves the germination of seeds and the emergence of seedlings from the soil, with root establishment and initial leaf growth. Probable Dates: 7 to 14 days DAS in November to December.
- Crop Development Stage represents tillering and stem elongation, and this stage is critical for determining the potential number of spikes and overall plant vigour. Probable Dates: 15 to 60 DAS in December to January.
- Reproductive Stage involves booting, heading, and flowering, and this stage determines the potential grain yield. Probable Dates: 60 to 90 DAS in January to February.
- Maturity Stage corresponds to grain filling and ripening, and this stage is critical for grain quality and final yield. Probable Dates: 90 to 120 DAS in February to March
- Harvest Stage arrives when the grains reach physiological maturity and the moisture content is optimal for storage. Probable Dates: 120 to 140 DAS in March

Temporal trends of temperature, its extremes and dryness/wetness

3.1 Introduction

Recent climate variability in the global warming era highlights the urgency of analyzing the spatio-temporal dynamics of meteorological parameters. These parameters, which determine the climate of any region, vary based on an integrated effect of factors such as temperature, rainfall, relative humidity, air pressure, etc. Among these, temperature and precipitation are particularly critical as they significantly influence crop yield (“Praveen et al. 2020, Singh et al. 2013”). Consequently, analyzing spatiotemporal variations is especially vital for countries like India, where agriculture largely depends on rainfall. Understanding long-term spatio-temporal trends of climatic data at national and regional scales and across different time frames, monthly to seasonal, can help mitigate the adverse impacts on agriculture. This understanding is essential for developing effective climate change adaptation and mitigation strategies (“Panda and Sahu, 2019”). Notably, 2015, 2016, and 2019 were the warmest years globally, with mean temperature anomalies approximately $+0.9^{\circ}\text{C}$ above the 1951 to 1980 average. Furthermore, global temperature projections indicate an additional increase of 0.4°C by 2025 (“Hansen et al. 2020”), which could have severe implications for future crop yields. Despite this increasing pattern, the changes in climatic parameters are very much location-specific.

Weather extremes occur when a particular day's meteorological values exceed certain boundary conditions. According to the “IPCC (2020)”, a “climate extreme” or “extreme weather/climate event” is defined as “the occurrence of a value of a weather/climate variable above (or below) a threshold value near the upper (or lower) end of the range of observed values of the variable”. For example, an extreme temperature event involves days with extremely high or low air temperatures and their sequences. Persistent heat events over several days can have significant negative impacts on agriculture.

Two main ways to define the threshold for extreme events are (a) absolute or (b) relative thresholds. Absolute values are hard threshold-based and may not be applicable over a large area with significant variations in climatic condition (“Stephenson, 2008; IPCC, 2012”). Therefore, relative thresholds based on the statistical distribution of meteorological parameters, also known as percentile-based thresholds, are recommended by the “WMO (2009) and IPCC (2012)”. Using relative thresholds has both advantages and disadvantages. The advantage is that it allows for comparisons of results across different climates and seasons. However, the disadvantage is that the derived extreme may not be extreme regarding its impact on the ecosystem (“Zhang et al. 2011; IPCC, 2012”). Additionally, selecting the baseline period to compute the threshold plays an important role. Different studies use different baseline periods, such as 1961-1990 (“Rusticucci et al. 2016; Hoy et al. 2017”), 1971 to 2000 (“Sanderson et al. 2017”), 1981-2010 (“Russo et al. 2015”), and the entire period (“Tomczyk et al. 2018”). The WMO has recommended using the most recent thirty-year time period ending in a year with zero. Therefore, our study uses a baseline period of 1981 to 2020.

Drought is a climatic extreme, with excessive dryness in the prevailing weather (“Wilhite et al. 2007”). Drought can occur under any climatic condition and is categorized into four classes: meteorological, agricultural, hydrological, and socio-economic (“Wilhite and Glantz, 1985”), depending on its impacts. “Wilhite et al. (2006)” defined drought as a severe moisture deficit below expected levels that restricts certain activities. India had 25 primary drought years in India from 1871 to 2015, when the all-India summer monsoon rainfall anomaly was below -10%. These drought years include 1873, 1877, 1899, 1901, 1904, 1905, 1911, 1918, 1920, 1941, 1951, 1965, 1966, 1968, 1972, 1974, 1979, 1982, 1985, 1986, 1987, 2002, 2009, 2014, and 2015 (“Manual for Drought Management, 2016”).

To agricultural drought monitoring along with weather extremes, various bio-meteorological parameters like rainfall, temperature, evapotranspiration, and soil moisture are used to compute the desired composite indices. Since drought events typically begin with a deficiency in precipitation or irregular rainfall patterns, several drought indices have been developed based on rainfall, such as Percent of Normal (“Hayes 2006”), SPI (“McKee et al. 1993”), Deciles (“Gibbs and Maher, 1967”), and Precipitation Condition Index (PCI, “Du et al. 2013”). Along with rainfall, evapotranspiration (ET) is a crucial indicator of agricultural drought, as it characterizes

the atmospheric demand of water. Consequently, several indices have been developed based on ET, including the SPEI (“Vicente-Serrano et al. 2010”), Evaporative Stress Index (ESI, “Anderson et al. 2011”), Evaporative Drought Index (EDI, “Yao et al. 2010”), Evaporative Demand Drought Index (EDDI, “Hobbins, 2016”), and Standardized Evaporative Stress Ratio (SESR, “Christian et al. 2019”). Among these, SPEI is one of the most widely used indices for determining agricultural drought.

A detailed review of the trend of temperature, rainfall, and its extremes over India and the world is presented in Chapter 1.

Trend analysis is essential in climate change research as it identifies and quantifies changes over time, demonstrating their statistical and physical significance. A trend indicates how a specific variable changes over a defined period and can be either linear or nonlinear. Trend analysis of a time series involves identifying the trend, determining its magnitude, and assessing its statistical significance. Various techniques are employed to detect shifts in long-term climatic data, as summarized in Table 3.1. Several studies have analyzed the spatio-temporal trends of rainfall and temperature over India (“Chakraborty et al. 2017; Das et al. 2015”), but limited research was found on the trends of extreme events, whether temperature or rainfall, over homogeneous agro-ecological regions in India. Few studies have focused on areas based on homogeneous temperature zones (“Kothawale et al. 2010”) or agro-climatic zones (“Chakraborty et al. 2018”). A detailed analysis of various agro-ecological regions, accounting for homogeneous climate, soil, and physiography, would provide a comprehensive overview of the changing climate in perspective of cropping system. Furthermore, studies incorporating a vast range of meteorological data, derived indices, and extremes at monthly and seasonal levels, specifically for the *Kharif* (monsoon) and *Rabi* (winter) seasons, are limited. This analysis will offer valuable insights into trend patterns across different agricultural seasons in India, contributing to a better understanding of climate impacts on agriculture.

Table 3.1 Different trend analysis techniques for meteorological data and its salient description

Method	Description	References
Least Squares Linear Regression (LR) Test	Fits a straight line to data points to identify a linear trend. Considers data follows normal distribution. Assumes a linear relationship and is sensitive to outliers.	“Han, 1977”
Mann–Kendall Test (MK)	Non-parametric test that assesses the significance of a trend in a time series. Robust against outliers and does not assume data to be normally distributed. It can also handle missing data.	“Mann, 1945; Kendall, 1978”
Spearman Rank Correlation (SRC) Test	- Measures the strength and direction of the association between two ranked variables. - Non-parametric and assesses monotonic relationships.	“Spearman, 1904”
Sen’s Slope (SS)	- Estimates the slope of the trend line by calculating the median of slopes between all pairs of data points. - Provides a robust measure of trend magnitude. Minimally affected by outliers.	“Sen, 1968”
Trend-Free Pre-Whitening (TFPW) with MK	- Removes serial correlation from a time series before applying the MK test. - Accounts for autocorrelation, making the MK test more reliable.	“Yue and Wang, 2002”
Variance Correction (VC) with MK (MK-CF1)	- Adjusts the MK test for serial correlation using a variance correction method. - Improves the accuracy of trend detection in autocorrelated series.	“Hamed and Rao, 1998”
Variance Correction (VC) with MK (MK-CF2)	- Another method to correct for variance in the presence of autocorrelation, refining previous approaches. - Provides an alternative correction method, refining trend detection.	“Yue and Wang, 2004”
Block Bootstrap (BBS) with MK (BBS-MK)	- Applies block bootstrap method to account for autocorrelation before using the MK test. - Resamples blocks of data to preserve correlation structures.	“Wilks, 1997”
Block Bootstrap (BBS) with Spearman Rank (BBS-SR)	- Uses block bootstrap method with Spearman rank correlation test to handle autocorrelation. - Similar to BBS-MK but uses Spearman's method for trend detection.	“Lahiri, 2003”
Sequential Mann–Kendall Test (SQMK)	- Sequential version of the MK test that detects changes in trend direction over time. - Identifies multiple trend phases within a time series.	“Sneyers, 1990”
Innovative Trend Analysis (ITA) Based on Sen (2012)	- Innovative approach to trend analysis without assumptions about data distribution or linearity. - Offers a flexible and visually intuitive method for detecting trends.	“Şen, 2012”
Fourier Analysis	- Transforms time series data into the frequency domain to identify cycles and periodic trends. - Detects underlying frequencies and periodicities in data.	“Bracewell, 2000”

3.2 Data used

Meteorological data

Temperature data: The global daily land surface air temperature (minimum and maximum) data of the “Climate Prediction Center (CPC)” were downloaded from “<https://psl.noaa.gov/data/gridded/data.cpc.globaltemp.html>” for a period of 1981 to 2019. The CPC air temperature dataset, developed by the “National Oceanic and Atmospheric Administration (NOAA)”, utilizes interpolation of quality-controlled station observation-based data from the Global Telecommunication System network (“Fan and Van den Dool, 2008”).

Rainfall data: In the present study, rainfall data from the “Climate Hazards Group Infrared Precipitation with Station (CHIRPS)” dataset, provided by the “USGS Earth Resources Observation and Science (EROS) Center”, is utilized for the period 1981 to 2019. This daily rainfall data is derived from a combination of satellite imagery and in-situ meteorological observations, producing gridded rainfall time series with a spatial resolution of $0.05^\circ \times 0.05^\circ$ for effective drought monitoring “(<https://data.chc.ucsb.edu/products/CHIRPS-2.0/>)”.

Drought index data: The long- term SPEI data were obtained from the Global SPEI database. The database, available at “http://spei.csic.es/spei_database”, provides SPEI data at a spatial resolution of $0.5^\circ \times 0.5^\circ$ monthly for an extended period. For this particular study, SPEI data at a 3-month time scale (SPEI-03) of version 3.2 “Climatic Research Unit (CRU)” dataset were used for southwest monsoon season months (June, July, August, and September) spanning from 1981 to 2019.

3.3 Methodology

Figure 3.1 illustrates the flowchart of the methodology adopted, involving data download, processing, computation of climatic parameters, and trend analysis.

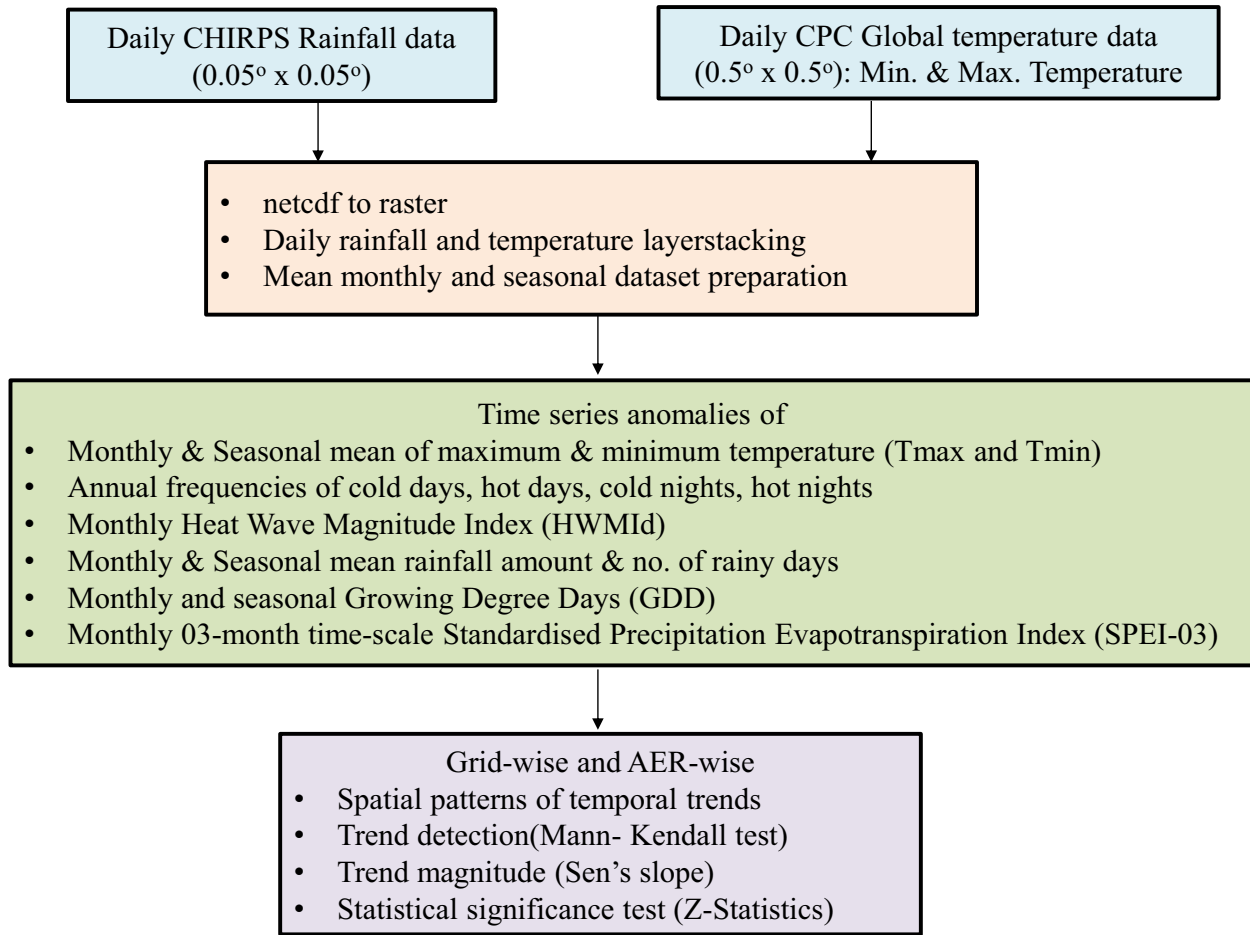


Fig 3.1 Schematic diagram of methodology

A comprehensive set of climatic data is used to compute time series anomalies in temperature, including extremes and Growing Degree Days (GDDs), rainfall, and rainy days, based on the absolute deviation from their respective long-term means. Additionally, to detect the climate extreme, the rainfall-temperature-based Standardized Precipitation Evaporation Index (SPEI) at a 3-month time scale is also utilized in this study. Statistical analyses are conducted to identify significant temporal trends in the following categories of time series anomalies, detailed in the subsections below:

3.3.1 Temperature-based parameters

Maximum Temperature (Tmax): Tmax is the highest temperature recorded at a location over 24 hours. Daily Tmax values are averaged over month and season from 1981 to 2019.

Minimum Temperature (Tmin): Tmin is the lowest temperature recorded at a location over 24 hours. Daily Tmin values are averaged over month and season from 1981 to 2019.

Growing Degree Days (GDDs): GDDs describe the accumulated heat unit necessary for plant growth and development. It is computed by integrating daily average temperatures above a base temperature over a specific period (“Schwartz et al. 2006”), as defined by the following equations 1 and 2:

$$\text{Degree days (DD)} = \frac{(T_{\max} + T_{\min})}{2} - T_b \quad (1)$$

$$\text{GDD} = \int_{i=1}^t DD \quad (2)$$

Where, ‘ T_b ’ is base temperature below which the plant will not having any physiological activities and stop growing (10° C for *kharif* season and 5° C for *rabi* season), ‘ t ’ is the specific period required for growth and development.

Frequency of occurrence of temperature extremes

The frequency distribution of temperature over the baseline period (1981 to 2010 for the present study) forms a bell-shaped normal distribution, as shown in Figure 3.2. The left part of Figure 3.2 depicts that cold extremes occur towards the left tail of the temperature probability distribution, whereas hot extremes occupy the positions towards the right tail. The right part of Figure 3.2 shows the shift in temperature towards higher values, i.e., the frequent occurrence of hot extremes, in the global warming trend. The details of the temperature extremes analyzed in the current study are given below:

Hot Days: Hot days are the frequency of days in a year when $T_{\max}$ exceeds the 90th percentile of the daily $T_{\max}$ probability distribution during the 1981 to 2010 baseline period (Fig 3.2).

Hot Nights: Hot nights are the frequency of days in a year when $T_{\min}$ exceeds the 90th percentile of the daily $T_{\min}$ probability distribution during the 1981 to 2010 baseline period.

Cold Days: Cold days are defined as the frequency of days in a year when $T_{\max}$ is less than the 10th percentile of the daily $T_{\max}$ probability distribution during the 1981 to 2010 baseline period.

Cold Nights: Cold nights are defined as the frequency of days in a year when T_{min} is less than the 10th percentile of the daily T_{min} probability distribution during the 1981 to 2010 baseline period.

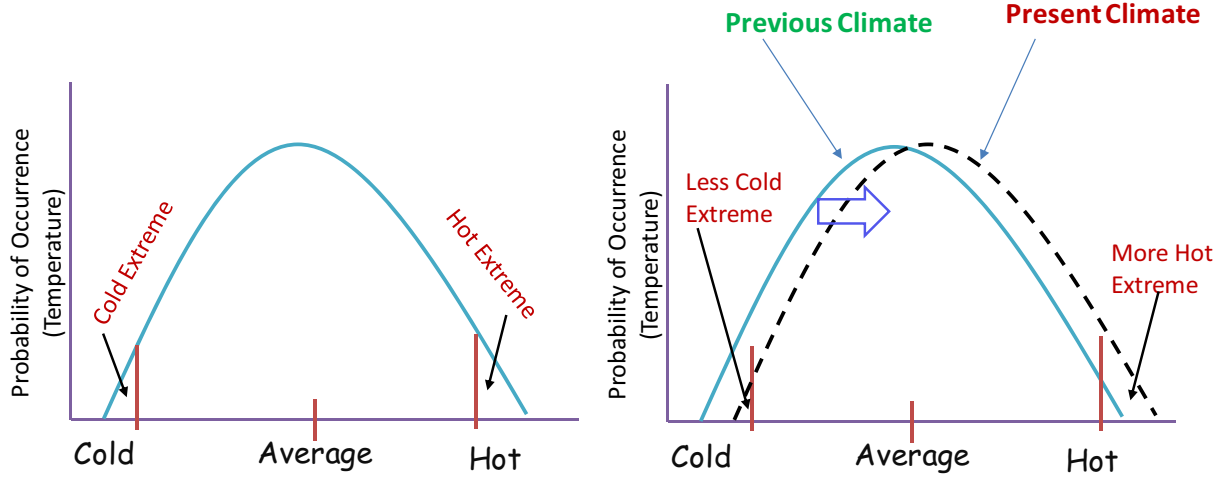


Fig 3.2 Temperature extreme events using percentile of temperature frequency distribution (Chakraborty et al. 2017)

Heat wave magnitude index daily (HWMId)

A Heat Wave Index (HWMId) was computed using equation 3 and equation 4, as described by Russo et al. (2015). This index identifies periods of extreme heat events by combining a percentile-based approach with consistency criteria. An extreme heat event is defined as three consecutive days during which the T_{max} exceeds the daily threshold for the base period of 1981 to 2010. The daily threshold is the 90th percentile of T_{max} , calculated within a centered 31-day time window. Thus, to determine the daily threshold, the 90th percentile of the T_{max} data, ' T_h ,' is given by equation 3.

$$T_h = U_{t=1981}^{2010} U_{i=d-15}^{d+15} T_{t,i} \quad (3)$$

Where, T_h is threshold above which the i^{th} day is detected as the day of the heat event.

To compute the magnitude of a heat event, the Heat Wave Magnitude Index (HWMId) is calculated using equation 4, corresponding to the days of the heat events. HWMId represents the integrated magnitude of successive days of heat events and is defined by equation 4.

$$Md, T_i = \begin{cases} \frac{T_i - T_{30t25p}}{T_{30t75p} - T_{30t25p}} & \text{if } T_i > T_{30t25p} \\ 0 & \text{if } T_i \leq T_{30t25p} \end{cases} \quad (4)$$

Where, T_i is the maximum temperature on the day of the heat event, T_{30t25p} and T_{30t75p} are the 25th and 75th percentile values of the timeseries of 30 years (1981 to 2010).

If a day during a heat wave has a temperature equal to the interquartile range, which is the difference between the 25th and 75th percentiles of the daily maximum temperature, its corresponding magnitude value will be 1. A magnitude of 3 on a particular day indicates that the temperature anomaly is three times the interquartile range. The various classes of HWMId are presented in Table 3.2.

Table 3. 2 Different severity classes based on HWMId range (“Chakraborty et al. 2019”)

Class	HWMId range	Class	HWMId range
Normal	< 2	Very extreme	8 to 16
Moderate	2 to 3	Super extreme	16 to 32
Severe	3 to 4	Ultra-extreme	≥ 32
Extreme	4 to 8		

3.3.2 Rainfall-based parameters

Rainfall magnitude: Firstly, the daily rainfall amount is cumulated at monthly and seasonal (southwest monsoon) scale for the period 1981 to 2019. Rainfall anomalies are computed as an absolute deviation of cumulative rainfall from its respective long-term mean (>30 years) at monthly- and seasonal-time scales.

Rainy days: A day when rainfall exceeds 2.5 mm is considered rainy, as per the criteria given by IMD. Therefore, the daily rainfall amount is converted into rainy days at monthly and seasonal (southwest monsoon) scales for the period 1981 to 2019. Rainy days anomalies are computed as

an absolute deviation of rainy days from their respective long-term mean (>30 years) at monthly- and seasonal-time scales.

Standardized Precipitation Evaporation Index (SPEI): The study utilizes the Standardized Precipitation Evapotranspiration Index (SPEI), a widely adopted multi-scalar drought index, to characterize extremely dry or wet climate conditions across various timescales, ranging from 1 to 48 months (Vicente-Serrano et al. 2010). The SPEI incorporates both precipitation and potential evapotranspiration (PET), capturing increased temperatures' primary impact on water demand. On shorter timescales (1 to 3 months), the SPEI is closely related to soil moisture and can be applied across regions with markedly different climates to assess agricultural drought. It measures observed rainfall/PET as a standardized deviation from a chosen probability distribution function that models the raw rainfall/PET data. Typically, this data is fitted to a gamma or Pearson Type III distribution before being transformed to a normal distribution. SPEI values indicate the number of standard deviations by which the observed anomaly differs from the long-term average. The SPEI can be classified into different wet/dry conditions, as shown in Table 3.3 (Nam et al. 2015).

Table 3.3 Classification of dryness/ wetness condition based on SPEI (“Nam et al. 2015”)

Condition	SPEI class	Condition	SPEI class
Extreme-drought	$\text{SPEI} \leq -2$	Mild-wet	$0.5 < \text{SPEI} \leq 1$
Severe-drought	$-2 < \text{SPEI} \leq -1.5$	Moderate-wet	$1 < \text{SPEI} \leq 1.5$
Moderate-drought	$-1.5 < \text{SPEI} \leq -1$	Severe-wet	$1.5 < \text{SPEI} \leq 2$
Mild-drought	$-1 < \text{SPEI} \leq -0.5$	Extreme-wet	$\text{SPEI} \geq 2$
No-drought	$-0.5 < \text{SPEI} \leq 0.5$		

3.3.3 Trend analysis

In the current study, the Mann-Kendall test (“Mann 1945; Kendall 1975”) and Sen’s method (“Sen, 1968”) are used to detect the trend and to determine the magnitude of trend in the data, respectively.

Mann–Kendall test

It is one of the most widely used non-parametric statistical techniques, which detects the presence of trends in meteorological data over long periods (Mann 1945, Thomas et al. 2014). This method is superior to parametric techniques as it is unaffected by the missing data points in the time-series. Being a non-parametric technique, it is independent of any particular data distribution type and whether time-series is linear or non-linear. Technically, it identifies the trend direction, whether positive or negative, by computing the S statistic. The S statistic is the sum of the difference between the data point values.

$$S = \sum_{a=1}^{n-1} \sum_{b=a+1}^n \text{sign}(x_b - x_a) \quad (5)$$

Where, x_b is observed value at time b, x_a is observed value at time a, b is time after time a; and n is the length of the data set. The sign of the value is defined as

$$\text{sign}(x_b - x_a) = \begin{cases} 1 & \text{if } (x_b - x_a) > 0 \\ 0 & \text{if } (x_b - x_a) = 0 \\ -1 & \text{if } (x_b - x_a) < 0 \end{cases} \quad (6)$$

The direction of the trend is determined by the value of S. A negative value indicates a downward trend, while a positive value signifies an upward trend. According to the Mann–Kendall statistics, if $n \geq 10$, S follows an approximately normal distribution with a specific mean and variance in equation 7 (“Sobrinho and Julien, 2011”).

$$E(S) = 0$$

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{j=1}^q t_j(t_j-1)(2t_j+5)}{18} \quad (7)$$

Here, n represents the number of data points, q denotes the number of tied groups (sets of sample data with identical values), and t indicates the number of data points in the p^{th} group. The statistical significance of S is assessed using the standardized Mann-Kendall Z statistics, which follows a standard normal distribution with a mean of zero and a variance of one.

$$Z = \begin{cases} \frac{s-1}{\sqrt{\text{var}(s)}} & ; S > 0 \\ 0 & ; S = 0 \\ \frac{s+1}{\sqrt{\text{var}(s)}} & ; S < 0 \end{cases} \quad (8)$$

To evaluate the presence of a trend in the time-series data, the null hypothesis (Ho), which suggests that no trend, is tested against the alternative hypothesis (H1), which suggests a significant positive or negative trend. This evaluation is conducted using the two-tailed Z-test statistic. The Z-test statistic is calculated to determine the significance of the observed trend. If the computed Z value is negative, it indicates a decreasing trend, whereas a positive Z value signifies an increasing trend. The statistical significance of these trends is assessed by comparing the Z value to critical values from the standard normal distribution. If the Z value falls beyond the vital thresholds (corresponding to a chosen significance level, 0.1 in this case), the Ho is rejected in favor of the H1, indicating a statistically significant trend in the data.

Sen's method

Sen's slope estimator, a non-parametric method, is widely recognized for its robustness in estimating the magnitude of trends in time series data, particularly for the noisy data (Sen, 1968). This estimator is highly effective in handling datasets that contain outliers, missing values, or other forms of noise, which can significantly distort the results of parametric methods. In contrast to parametric methods, such as ordinary least squares regression, where the trend magnitude is computed by fitting a linear model to the time series data, Sen's slope estimator does not make assumptions about the data distribution. This non-parametric approach calculates the slope for each pair of data points in the time series, thus generating a set of slope estimates. The median of these slopes is then taken as Sen's slope, providing a more reliable estimate of the trend magnitude that is less influenced by extreme values or data anomalies. This method is particularly advantageous for environmental and climatic data analysis, where data irregularities are typical. The mathematical equation involves calculating the slope (Q_i) for all pairs of observations, x_a , and x_b at the time a and b , respectively (where, $b > a$), as illustrated in equation 9.

$$Q_i = \frac{x_b - x_a}{b - a} \quad (9)$$

For n values of the time series of x results, $N = n(n-1)/2$ values of Q_i . Sen's estimator is the median value of Q_i as illustrated in equations 10 and 11:

$$Q = Q_{(\frac{N+1}{2})} \text{ if } N \text{ is odd,} \quad (10)$$

$$Q = \frac{1}{2} (Q_{(\frac{N}{2})} + Q_{(\frac{N+1}{2})}) \text{ if } N \text{ is even} \quad (11)$$

3.4 Results and discussion

3.4.1 Spatial variations of temporal trends of temperature and extremes

This section discusses the spatio-temporal trends in temperature-based variables during the *kharif* and *rabi* seasons from 1981 to 2019. The magnitude of positive and negative trends (slope) was estimated at the grid level using Sen's method and is presented in different colors. The Mann–Kendall test identified grids with significant increasing or decreasing trends at $p < 0.1$. Positive trends indicate an increase in temperature, while negative trends indicate a decrease across different agro-ecological regions.

Temporal trends of maximum and minimum temperature (Tmax and Tmin)

During the *Kharif* season (June to September), a significant positive trend in maximum temperature (Tmax) was observed over parts of northern India (AER 01, AER 02, AER 05, AER 14) with a p -value < 0.1 in June. In contrast, during June, a negative temperature trend was observed over the Deccan Plateau (AER 03, AER 07, and AER 08). A similar pattern of increasing and decreasing Tmax trends was observed in July over AER 14 and AER 08, respectively. A stronger significant increasing trend ($>0.1^\circ\text{C}/\text{year}$) was noted in August in the eastern (AER 12, AER 15, AER 16, AER 17) and northern (AER 14) regions, along with isolated patches in the western part of India (AER 02, AER 05). Conversely, a significant negative trend was observed in southern India (AER 07, AER 08), while a significant positive trend was seen in northeastern India (AER 15, AER 17) during September (Fig 3.2).

In June, the minimum temperature (Tmin) decreased in AER 14, 15, and 16. However, Tmin increased in AER 02, AER 06, AER 12, AER 13, and AER 16 in June and July, with a more considerable area in July. August and September showed mixed patterns of positive and negative

Tmin trends. Areas AER 01, 02, 06, 08, 11, 13, 14, 15, and 17 exhibited an increasing Tmin trend, while AER 09 and 16 showed a negative trend (Fig 3.3).

During the *Rabi* season, November exhibited a significant increasing trend in Tmax ($0.1^{\circ}\text{C}/\text{year}$) over central (AER 04, 05, 06, 10, 12) and northeastern (AER 15, 16, 17) parts of India, with some patches of decreasing trend in AER 08 in southern India. December showed a significant increasing trend ($0.02\text{-}0.05^{\circ}\text{C}/\text{year}$) across the entire eastern part (AER 10, 11, 12, 15, 16, 17) and an increasing trend in the Deccan Plateau (AER 08, 19). A similar positive Tmax trend was observed in January, but a decreasing trend was noted in central and western regions. In February, few grids showed a significant trend, with a positive change in AER 01, 15, and 16 and an adverse change in AER 08 and 13. March showed a mixed pattern, with a significant positive trend in the eastern part and a non-significant negative trend in the Deccan Plateau (Fig 3.4).

During the *Rabi* season, Tmin showed a significant increasing trend ($>0.051^{\circ}\text{C}/\text{year}$) across most of India from November to March, with a consistent trend in the northern, eastern, and western parts and a non-significant decreasing trend in southern India. In March, the entire upper half of India, including AER 2, 5, 6, 9, 10, 11, 14, 15, and 16, showed a significant positive trend in Tmin (Fig 3.5).

In summary, the spatial extent of the increasing Tmin trend is more significant than that of Tmax in northern India compared to southern India, indicating a decreasing difference between daytime and nighttime temperatures. Similar trends have been observed in other studies conducted in India (“Rao et al. 2015”). Moreover, grid-wise significant positive trends were spread over more areas than substantial negative trends. Regions with semi-arid to sub-humid climates surrounded by land masses show significantly increasing trends than those surrounded by water.

Temporal trends of Growing Degree Days (GDD)

In June, the GDD trends for the western coastal region (AER 19) and the eastern coastal region displayed significant but opposite patterns: a decreasing trend on the west coast and an increasing trend on the east coast (Fig 3.6). Additionally, the southern part of India (AER 3, 7, 8) revealed a decreasing trend in GDD for June. In subsequent monsoon months, most of India

exhibited significant positive trends, particularly in the eastern (AER 11, 12, 13, 15, 16, 17), western (AER 02), and northern (AER 01, 04, 14) regions, with non-significant negative trends elsewhere. During the *Rabi* season, central and southern parts of India exhibited significant negative GDD trends, while northern, western, and eastern parts showed non-significant positive trends (Fig 3.7).

Temporal trends of Extreme Temperature

Extreme temperature trends were analyzed using variables such as Tmax extremes (hot days, cold days) and Tmin extremes (hot nights, cold nights) from 1981 to 2019. These extremes represent the frequency of extreme temperature occurrences. The study also used the HWMId based on Tmax to determine consistent hot extremes lasting three or more days. The findings indicate that hot days increase over time as Tmax rises, which is concerning due to the more frequent occurrence of extremely hot temperatures. Except for the Deccan Plateau, the entire country shows an increasing trend in hot days ($> +0.25$ day year⁻¹) and a decreasing trend in cold days (< -0.75 day year⁻¹), signaling an increase in hot extremes and a decrease in cold extremes (Fig 3.8).

Tmin extremes, like hot and cold nights showed a mixed pattern (Fig 3.9). However, there was a clear increasing trend of hot nights ($> +0.5$ day year⁻¹) in the western, eastern, and northern parts of India, while central India showed a non-significant increasing trend for hot nights. In contrast, there was a significant negative trend of cold nights (< -0.5 day year⁻¹), revealing fewer occurrences of cold extremes, especially in the eastern, western, and northern parts of India (AER 01, 02, 14, 15, 16, 17).

The HWMId, which evaluates heat events persisting for ≥ 3 days, was also assessed across different AERs of India from 1981 to 2019 (Fig 3.10). In November, the HWMId showed a significant upward trend in the central part of India (AER 01, 03, 07, 10, 11, 12). In subsequent months, the HWMId exhibited increasing trends in scattered patches across various AERs. However, the northeastern part (AER 15, 16, 17) demonstrated a significant positive trend (HWMId > 1.5 per year) in January, February, and March. The eastern coast (AER 12), northern part (AER 01, 14), and western part (part of AER 02) also showed significant increasing trends of HWMId in February and March.

In summary, India's northern and eastern regions (AER 01, 10, 11, 12, 15, 16, and 17) exhibited a significant upward trend in T_{max} at $p < 0.1$. In contrast the peninsular region showed a significant downward trend in the *kharif* and *rabi* seasons. The magnitude of the trend was higher in the northern region ($\sim 0.05^{\circ}\text{C year}^{-1}$) compared to the eastern region ($\sim 0.02^{\circ}\text{C year}^{-1}$). Regarding T_{min} , the entire country showed an increasing trend, with a higher magnitude ($> 0.05^{\circ}\text{C}$) than T_{max} . However, a non-significant decreasing trend in T_{min} was observed in scattered patches across India in both seasons ($p < 0.1$). The results also indicated an increase in heat events over India, with a distinct spatial pattern. Notably, extreme heat events are significantly increasing in the northeastern region and the Western Ghats, which are biodiversity hotspots, as well as in the northern part of India.

“Ratnam et al. (2016)” identified heat wave regions using IMD criteria from 1982 to 2013 in India's western, eastern, northern, and central parts. In contrast, “Chakraborty et al. (2019)” reported an increase in heatwaves in the western, central, and southern regions from 1980 to 2011, which differs from present findings, though the study periods vary. However, their study showed a low magnitude of heat events in the eastern part of the country. Our results corroborate another study by “Chakraborty et al. (2018)”, which reported an increasing trend of extremely hot day temperatures in the eastern- and western coastal plains and northeastern India. “Chakraborty et al. (2017)” also found a growing trend in T_{min} during the *rabi* season in northern and northeastern India. “Mazdiyasni et al. (2017)” reported an upward trend in heatwaves in non-traditional heatwave zones such as the northeastern, western, and southern regions, with a non-significant downward trend in parts of the IGP, a spatial pattern also observed in our study. It can be concluded that if this positive trend in heatwaves continues in water-limited regions (semi-arid/sub-humid) that rely on rainfed agriculture, it may harm crop production.

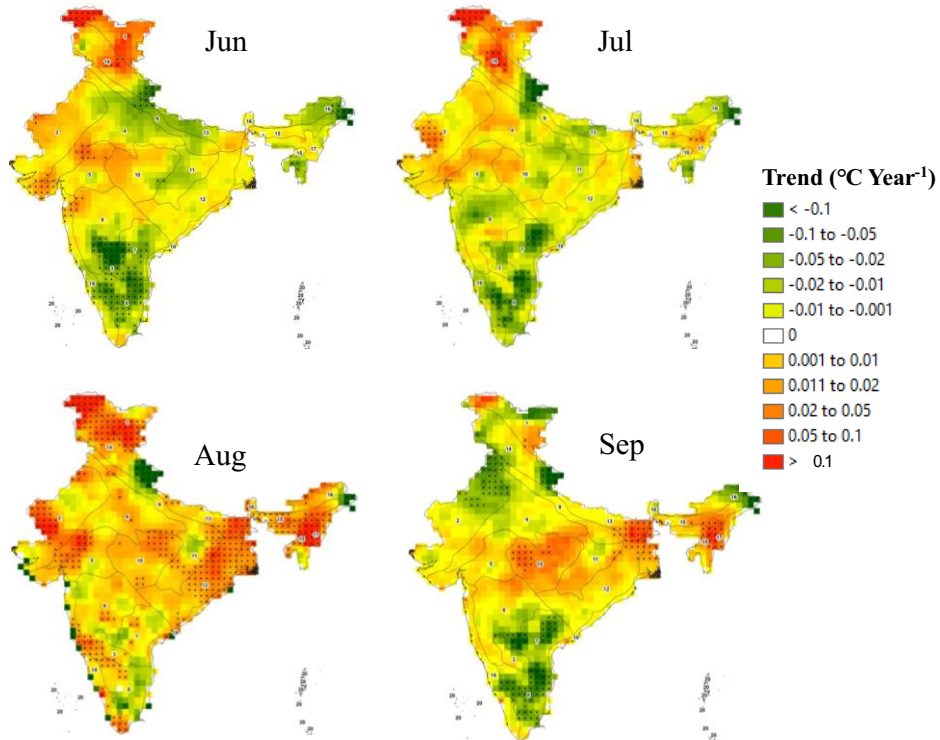


Fig 3.2 Spatial patterns of temporal trends in time-series anomalies (1981-2018) of average monthly maximum temperature (* Significant at $p < 0.1$)

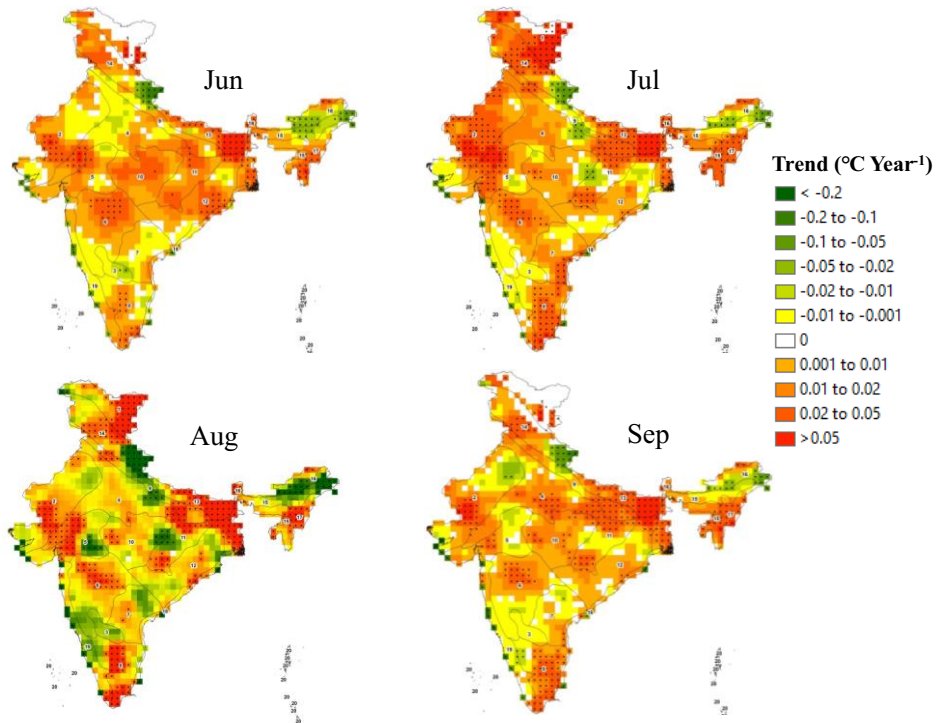


Fig 3.3 Spatial patterns of temporal trends in time-series anomalies (1981-2018) of average monthly minimum temperature (* Significant at $p < 0.1$)

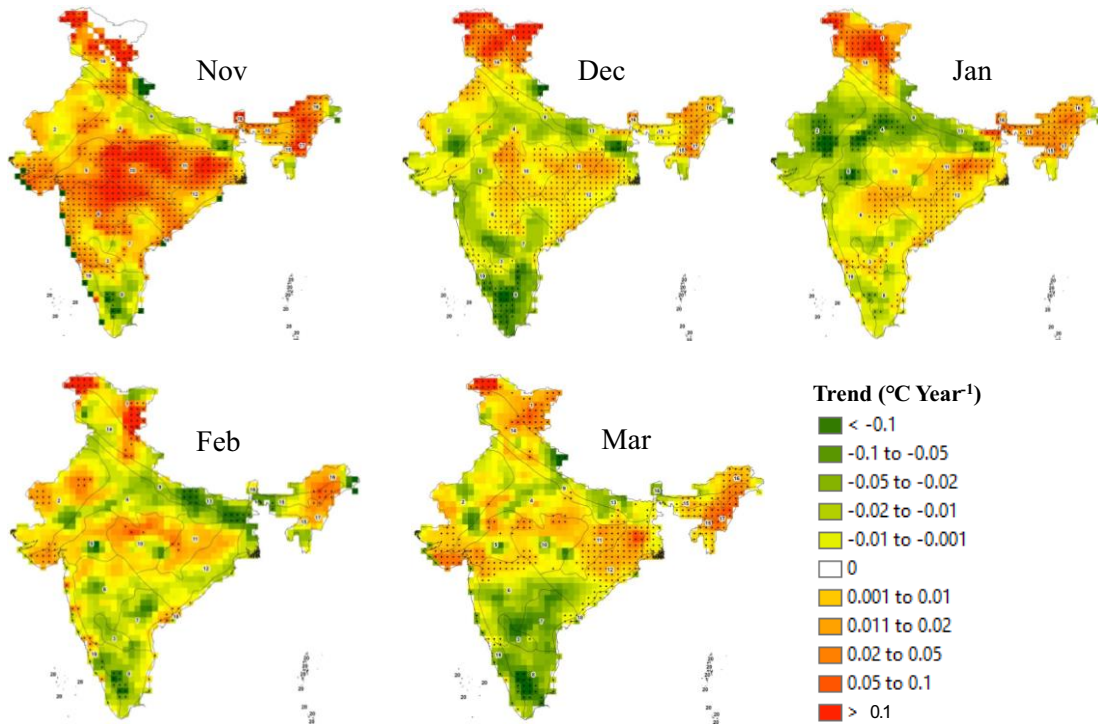


Fig 3.4 Spatial patterns of temporal trends in time-series anomalies (1981-2018) of average monthly maximum temperature (* Significant at $p < 0.1$)

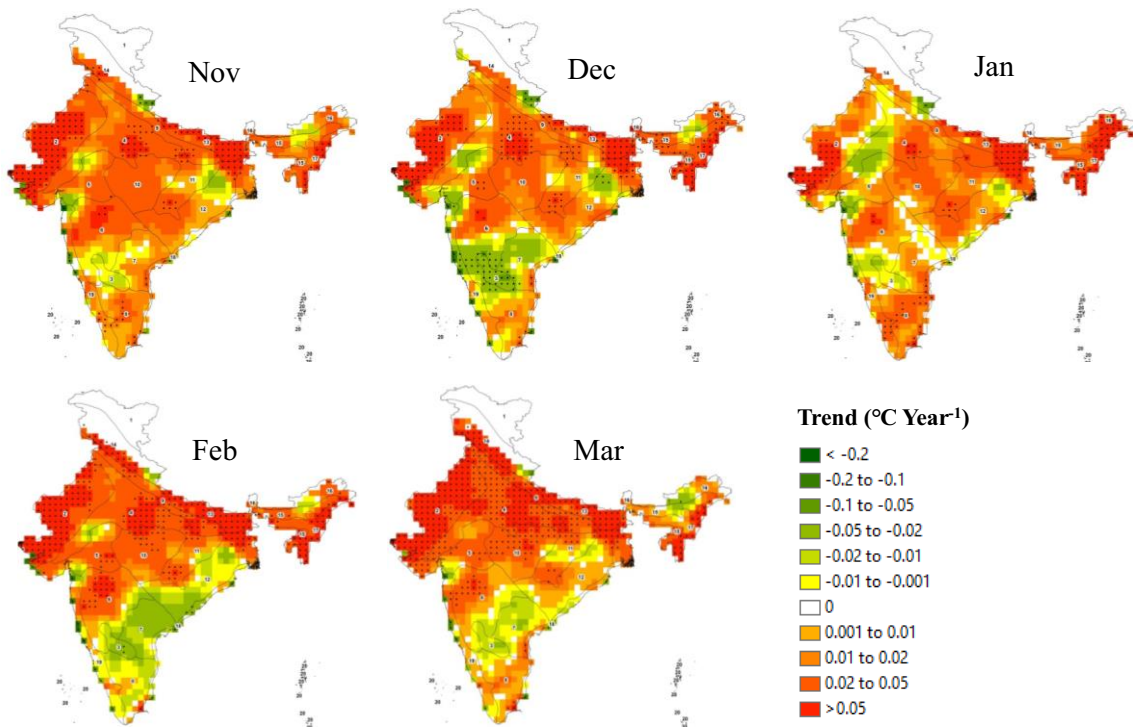


Fig 3.5 Spatial patterns of temporal trends in time-series anomalies (1981-2018) of average monthly minimum temperature (* Significant at $p < 0.1$)

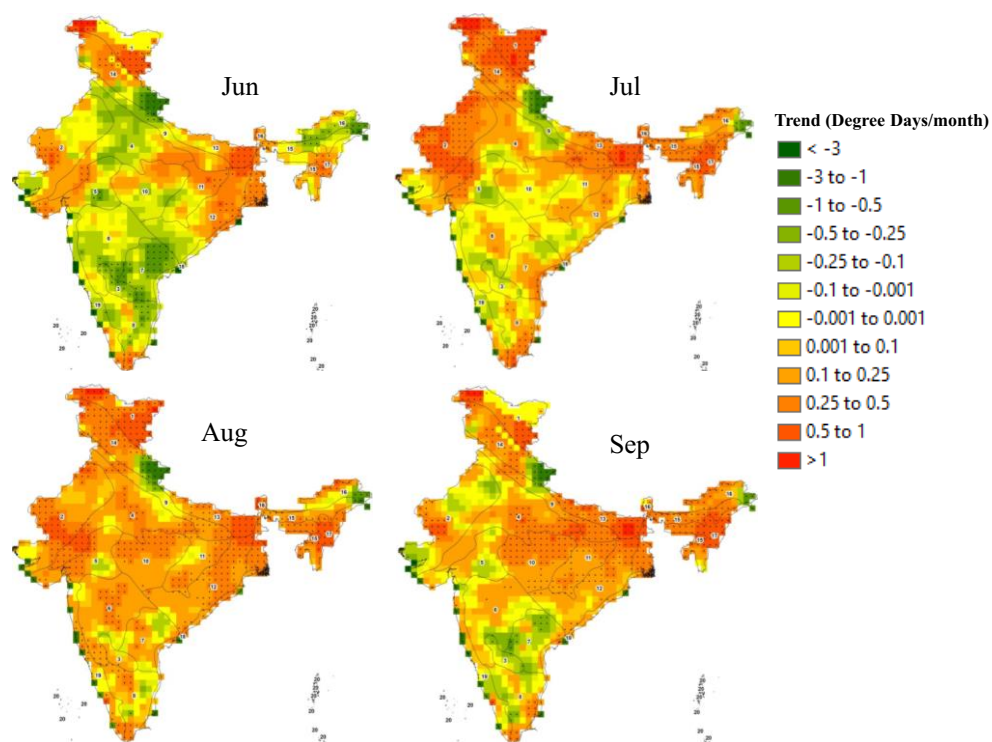


Fig 3.6 Spatial patterns of temporal trends in time-series anomalies of Growing degree days (*kharif* season) over India during 1981-2018 (* Significant at $p < 0.1$)

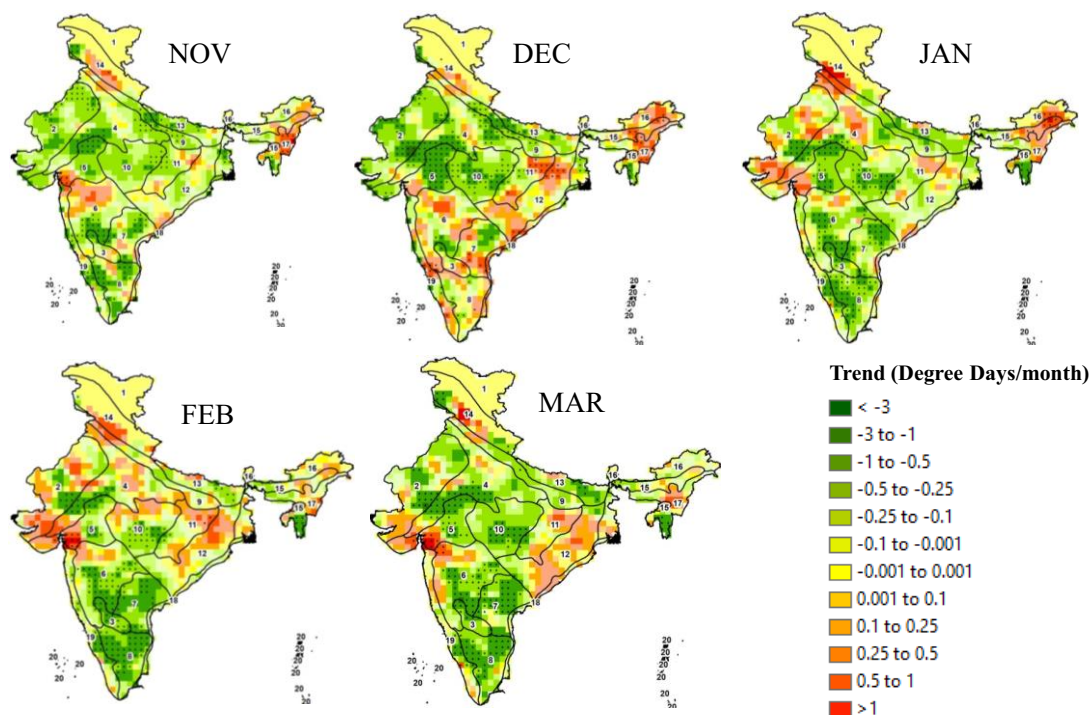


Fig 3.7 Spatial patterns of temporal trends in time-series anomalies of Growing degree days (*Rabi* season) over India during 1981-2018 (* Significant at $p < 0.1$)

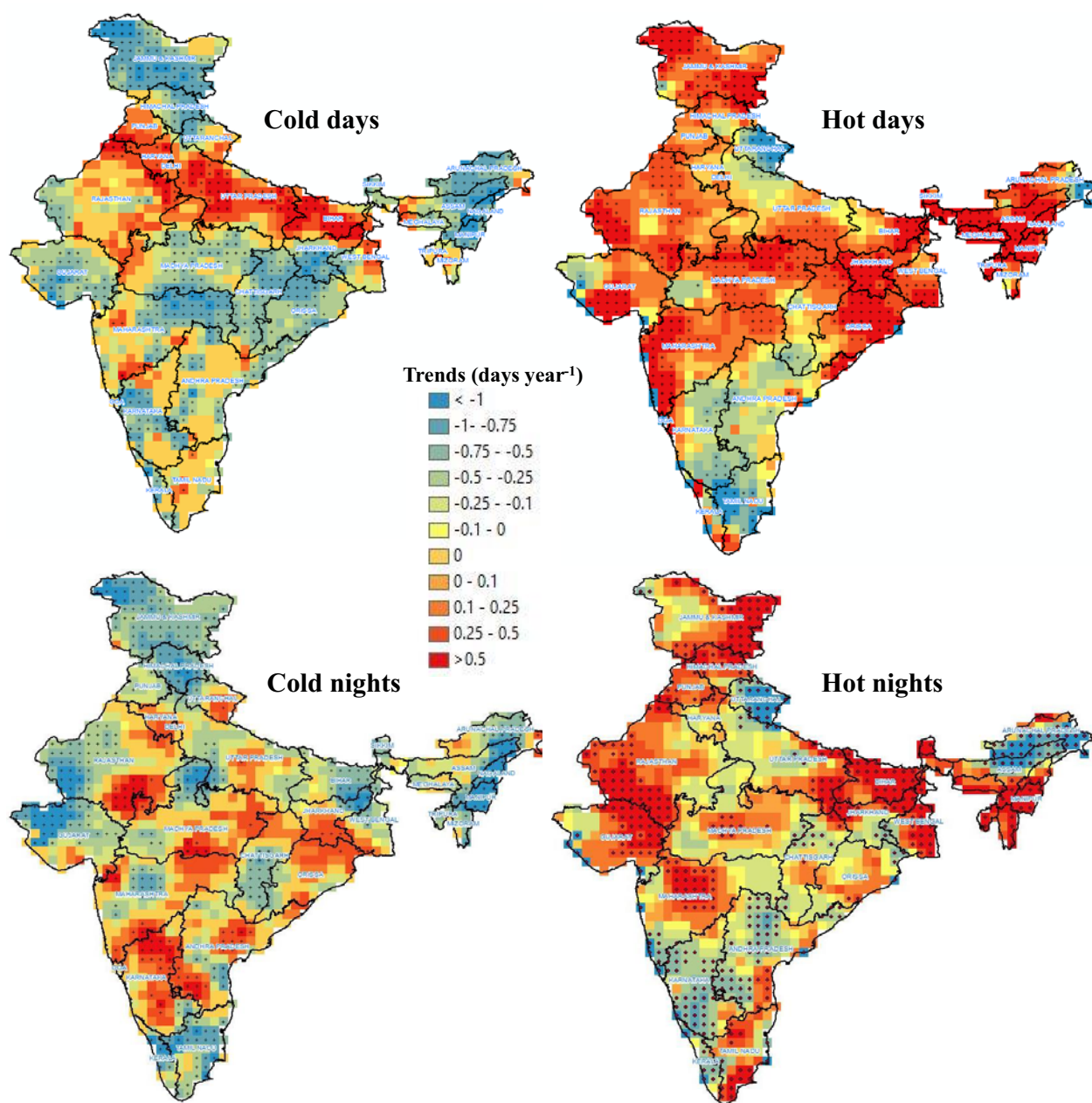


Fig 3.8 Spatial patterns of temporal trend of frequencies of occurrences of temperature extremes over India during 1981-2018 (* Significant at $p < 0.1$)

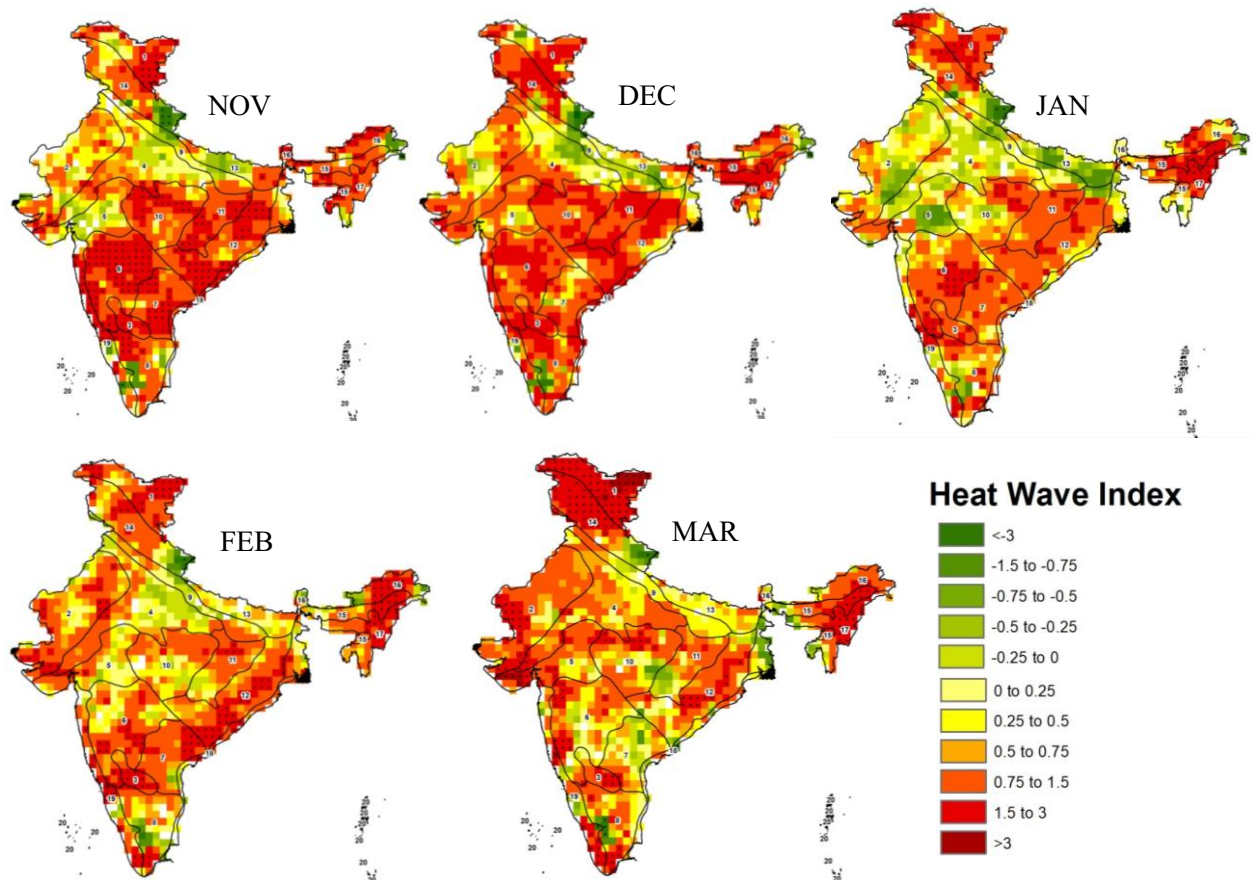


Fig 3.9 Spatial patterns of temporal trend of HWMId in *rabi*-season over India during 1981-2019
 (* Significant at $p < 0.1$)

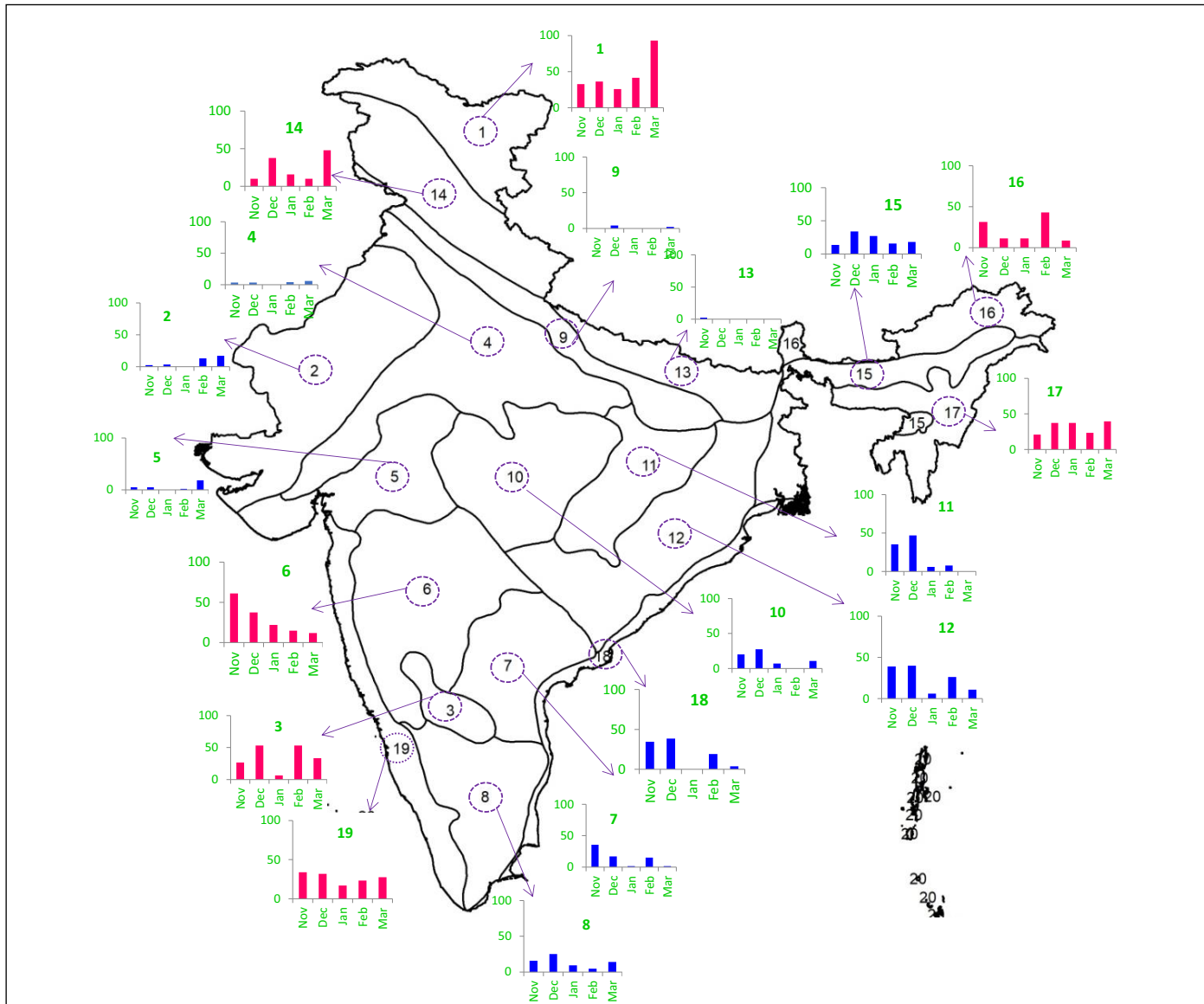


Fig 3.10 AEZ showing % grids of significant (+) trend in Heat wave events (month-wise): Red: large % area experiencing heat event in *rabi*-season; Blue: less/moderate % area experiencing heat event

Table 3.4 AER-wise percentage of grid under positive/ negative trend of of average monthly maximum temperature (Kharif-season) during 1981-2018 along with its mean magnitude. AERs with significant trend (positive/negative) in > 50% of grids are shown as bold italic.

AERs	Jun				Jul				Aug				Sep			
	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend
1	100.0	0.5	0.0	0.0	98.3	0.4	0.0	0.0	91.4	0.1	0.0	0.0	51.7	0.2	41.4	-0.2
2	68.8	0.2	16.0	-0.1	93.6	0.2	0.0	0.0	73.6	0.0	1.6	-0.3	17.6	0.1	58.4	-0.2
3	0.0	0.0	100.0	-0.5	13.3	0.1	53.3	-0.1	60.0	0.0	0.0	0.0	13.3	0.1	66.7	-0.2
4	33.9	0.2	53.7	-0.2	74.4	0.2	14.0	-0.1	84.3	0.0	0.0	0.0	33.1	0.1	41.3	-0.1
5	73.8	0.2	13.1	-0.1	85.2	0.2	4.9	-0.1	80.3	0.0	1.6	-0.2	70.5	0.1	11.5	-0.1
6	34.5	0.1	48.2	-0.3	30.9	0.1	47.3	-0.1	62.7	0.0	1.8	0.0	43.6	0.1	36.4	-0.2
7	5.1	0.1	94.9	-0.3	10.2	0.1	67.8	-0.2	42.4	0.0	10.2	0.0	5.1	0.1	91.5	-0.2
8	4.7	0.1	93.8	-0.4	9.4	0.1	76.6	-0.2	40.6	0.0	20.3	0.0	4.7	0.1	89.1	-0.3
9	18.8	0.1	68.8	-0.3	47.9	0.1	35.4	-0.1	62.5	0.0	10.4	0.0	37.5	0.1	35.4	-0.2
10	64.3	0.2	26.2	-0.2	53.6	0.2	23.8	-0.1	97.6	0.0	0.0	0.0	100.0	0.3	0.0	0.0
11	7.8	0.0	78.4	-0.2	54.9	0.1	25.5	-0.1	76.5	0.0	7.8	0.0	76.5	0.2	11.8	-0.1
12	19.4	0.1	37.9	-0.1	64.1	0.1	4.9	-0.1	96.1	0.0	0.0	0.0	69.9	0.1	7.8	-0.1
13	31.6	0.1	68.4	-0.3	39.5	0.1	36.8	-0.1	92.1	0.0	0.0	0.0	60.5	0.3	0.0	0.0
14	66.7	0.3	29.0	-0.3	72.5	0.4	24.6	-0.3	69.6	0.0	23.2	-0.1	20.3	0.1	63.8	-0.2
15	15.9	0.1	40.9	-0.2	84.1	0.2	4.5	-0.2	95.5	0.0	2.3	0.0	90.9	0.2	4.5	-0.2
16	0.0	0.0	97.1	-0.3	11.4	0.1	57.1	-0.2	77.1	0.0	14.3	0.0	28.6	0.1	60.0	-0.3
17	14.0	0.1	69.8	-0.2	60.5	0.2	23.3	-0.2	86.0	0.0	2.3	-0.1	86.0	0.2	2.3	-0.6
18	19.2	0.1	34.6	-0.2	30.8	0.1	15.4	-0.1	76.9	0.0	15.4	-0.1	19.2	0.1	15.4	-0.1
19	23.4	0.1	51.1	-0.2	12.8	0.1	46.8	-0.1	61.7	0.0	19.1	-0.1	38.3	0.1	21.3	-0.1

Table 3.5 AER-wise percentage of grid under positive/ negative trend of of average monthly maximum temperature (Rabi-season) during 1981-2018 along with its mean magnitude. AERs with significant trend (positive/negative) in > 50% of grids are shown as bold italic.

AERs	Nov				Dec				Jan				Feb				Mar			
	Count(+)		Count(-)		Count(+)		Count(-)		Count(+)		Count(-)		Count(+)		Count(-)		Count(+)		Count(-)	
	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend
1	51.7	0.1	0.0	0.0	100.0	0.7	0.0	0.0	96.6	0.6	0.0	0.0	81.0	0.5	13.8	-0.1	100.0	0.6	0.0	0.0
2	84.0	0.0	1.6	-0.2	88.0	0.2	8.0	-0.2	1.6	0.4	92.8	-0.3	80.8	0.2	8.8	-0.2	89.6	0.3	5.6	-0.1
3	80.0	0.0	0.0	0.0	40.0	0.1	46.7	-0.1	66.7	0.0	20.0	-0.1	6.7	0.1	80.0	-0.1	26.7	0.1	53.3	-0.2
4	77.7	0.0	0.0	0.0	65.3	0.2	16.5	-0.1	10.7	0.4	85.1	-0.3	44.6	0.2	33.9	-0.1	92.6	0.3	3.3	-0.1
5	98.4	0.0	1.6	-0.1	67.2	0.2	6.6	-0.1	0.0	0.3	95.1	-0.3	78.7	0.2	16.4	-0.2	93.4	0.5	3.3	-0.1
6	95.5	0.0	0.0	0.0	70.0	0.2	14.5	-0.1	71.8	0.3	19.1	-0.1	50.0	0.2	26.4	-0.1	71.8	0.2	11.8	-0.1
7	83.1	0.0	1.7	0.0	44.1	0.2	23.7	-0.1	52.5	0.2	32.2	-0.2	27.1	0.1	42.4	-0.2	25.4	0.1	45.8	-0.1
8	15.6	0.0	40.6	0.0	7.8	0.1	84.4	-0.2	35.9	0.0	40.6	-0.2	17.2	0.1	64.1	-0.2	31.3	0.1	48.4	-0.2
9	50.0	0.0	4.2	0.0	77.1	0.2	8.3	-0.1	33.3	0.7	60.4	-0.3	22.9	0.2	60.4	-0.2	91.7	0.3	0.0	0.0
10	100.0	0.1	0.0	0.0	100.0	0.3	0.0	0.0	71.4	0.1	14.3	-0.1	86.9	0.3	6.0	-0.2	94.0	0.4	4.8	-0.1
11	100.0	0.1	0.0	0.0	100.0	0.4	0.0	0.0	90.2	0.3	9.8	-0.1	90.2	0.2	3.9	-0.1	100.0	0.4	0.0	0.0
12	94.2	0.0	2.9	0.0	93.2	0.3	5.8	-0.2	93.2	0.2	2.9	-0.3	67.0	0.2	18.4	-0.1	92.2	0.4	3.9	-0.1
13	15.8	0.0	34.2	0.0	44.7	0.2	36.8	-0.2	15.8	0.2	78.9	-0.3	2.6	0.2	86.8	-0.3	84.2	0.2	10.5	-0.1
14	73.9	0.0	14.5	-0.1	87.0	0.5	10.1	-0.3	84.1	0.9	14.5	-0.3	66.7	0.2	14.5	-0.1	87.0	0.4	8.7	-0.3
15	90.9	0.0	0.0	0.0	88.6	0.3	2.3	-0.1	100.0	0.5	0.0	0.0	36.4	0.3	43.2	-0.2	100.0	0.4	0.0	0.0
16	91.4	0.1	8.6	0.0	91.4	0.4	8.6	-0.1	91.4	0.5	8.6	-0.1	71.4	0.3	22.9	-0.2	94.3	0.4	2.9	-0.1
17	81.4	0.0	7.0	0.0	90.7	0.3	2.3	-0.3	88.4	0.3	2.3	-0.3	67.4	0.3	25.6	-0.2	100.0	0.6	0.0	0.0
18	76.9	0.0	15.4	-0.2	73.1	0.2	3.8	-0.1	76.9	0.2	3.8	-0.1	42.3	0.2	23.1	-0.1	65.4	0.3	3.8	-0.3
19	48.9	0.0	23.4	-0.1	19.1	0.1	53.2	-0.2	19.1	0.4	42.6	-0.1	46.8	0.2	27.7	-0.2	55.3	0.2	19.1	-0.1

Table 3.6 AER-wise percentage of grid under positive/ negative trend of of average monthly minimum temperature (Kharif-season) during 1981-2018 along with its mean magnitude. AERs with significant trend (positive/negative) in > 50% of grids are shown as bold italic.

AERs	Jun				Jul				Aug				Sep			
	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend
1	31.0	0.0	1.7	0.0	79.3	0.1	0.0	0.0	89.7	0.4	10.3	-0.1	25.9	0.0	3.4	0.0
2	30.4	0.0	2.4	0.0	68.0	0.0	1.6	-0.1	76.0	0.2	18.4	-0.1	32.0	0.0	18.4	0.0
3	0.0	0.0	53.3	0.0	0.0	0.0	0.0	0.0	6.7	0.2	93.3	-0.1	0.0	0.0	0.0	0.0
4	27.3	0.0	6.6	0.0	56.2	0.0	5.0	0.0	84.3	0.2	13.2	-0.1	60.3	0.0	1.7	0.0
5	31.1	0.0	4.9	0.0	41.0	0.0	6.6	0.0	57.4	0.2	39.3	-0.2	19.7	0.0	13.1	0.0
6	48.2	0.0	0.0	0.0	45.5	0.0	0.0	0.0	79.1	0.2	19.1	-0.1	30.0	0.0	2.7	0.0
7	1.7	0.0	5.1	0.0	37.3	0.0	0.0	0.0	64.4	0.1	33.9	-0.1	5.1	0.0	5.1	0.0
8	34.4	0.0	4.7	0.0	70.3	0.0	0.0	0.0	78.1	0.3	17.2	-0.1	64.1	0.0	6.3	0.0
9	29.2	0.0	8.3	0.0	56.3	0.0	16.7	0.0	60.4	0.3	37.5	-0.2	58.3	0.0	8.3	0.0
10	72.6	0.0	0.0	0.0	28.6	0.0	8.3	0.0	75.0	0.1	20.2	-0.1	51.2	0.0	0.0	0.0
11	74.5	0.0	0.0	0.0	58.8	0.0	17.6	0.0	68.6	0.2	29.4	-0.2	56.9	0.0	2.0	0.0
12	47.6	0.0	1.0	0.0	16.5	0.0	3.9	0.0	68.0	0.2	24.3	-0.1	21.4	0.0	1.0	0.0
13	76.3	0.0	2.6	0.0	84.2	0.1	0.0	0.0	86.8	0.4	10.5	-0.1	92.1	0.0	0.0	0.0
14	42.0	0.0	18.8	-0.1	66.7	0.0	18.8	-0.1	63.8	0.2	34.8	-0.4	33.3	0.0	21.7	-0.1
15	45.5	0.0	29.5	0.0	50.0	0.0	6.8	0.0	61.4	0.3	38.6	-0.2	40.9	0.0	11.4	0.0
16	20.0	0.0	57.1	0.0	31.4	0.0	42.9	0.0	37.1	0.2	60.0	-0.3	20.0	0.0	45.7	0.0
17	44.2	0.0	9.3	0.0	90.7	0.0	2.3	-0.1	93.0	0.2	7.0	-0.3	76.7	0.0	2.3	-0.1
18	38.5	0.0	15.4	0.0	34.6	0.0	15.4	-0.1	61.5	0.2	30.8	-0.2	38.5	0.0	15.4	-0.1
19	14.9	0.0	17.0	-0.1	12.8	0.0	21.3	-0.1	53.2	0.1	44.7	-0.2	10.6	0.0	21.3	-0.1

Table 3.7 AER-wise percentage of grid under positive/ negative trend of of average monthly minimum temperature (Rabi-season) during 1981-2018 along with its mean magnitude. AERs with significant trend (positive/negative) in > 50% of grids are shown as bold italic.

AERs	Nov				Dec				Jan				Feb				Mar			
	Count (+) (%)	Count (-) (%)	trend	trend	Count (+) (%)	Count (-) (%)	trend	trend	Count (+) (%)	Count (-) (%)	trend	trend	Count (+) (%)	Count (-) (%)	trend	trend	Count (+) (%)	Count (-) (%)	trend	trend
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	96.8	0.1	1.6	0.0	88.8	0.1	1.6	-0.1	63.2	0.1	4.8	0.0	98.4	0.1	1.6	-0.1	98.4	0.1	0.0	0.0
3	0.0	0.0	60.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	46.7	0.0	0.0	0.0	93.3	0.0	0.0	0.0	80.0	0.0
4	90.9	0.0	2.5	0.0	79.3	0.0	6.6	0.0	50.4	0.0	19.8	0.0	90.9	0.0	3.3	0.0	98.3	0.0	0.0	0.0
5	67.2	0.0	11.5	0.0	45.9	0.0	26.2	0.0	24.6	0.0	29.5	0.0	70.5	0.0	8.2	0.0	73.8	0.0	1.6	0.0
6	62.7	0.0	4.5	0.0	43.6	0.0	33.6	0.0	40.0	0.0	10.0	0.0	57.3	0.0	16.4	0.0	40.0	0.0	11.8	0.0
7	47.5	0.0	0.0	0.0	3.4	0.0	67.8	0.0	30.5	0.0	0.0	0.0	0.0	0.0	94.9	0.0	8.5	0.0	50.8	0.0
8	62.5	0.0	1.6	0.0	28.1	0.0	15.6	0.0	79.7	0.0	0.0	0.0	6.3	0.0	45.3	0.0	32.8	0.0	3.1	0.0
9	87.5	0.0	0.0	0.0	75.0	0.0	6.3	0.0	62.5	0.0	4.2	0.0	97.9	0.0	0.0	0.0	100.0	0.0	0.0	0.0
10	96.4	0.0	0.0	0.0	89.3	0.0	0.0	0.0	83.3	0.0	0.0	0.0	91.7	0.0	0.0	0.0	90.5	0.0	0.0	0.0
11	56.9	0.0	5.9	0.0	52.9	0.0	7.8	0.0	88.2	0.0	0.0	0.0	74.5	0.0	5.9	0.0	56.9	0.0	5.9	0.0
12	52.4	0.0	10.7	0.0	54.4	0.0	14.6	0.0	55.3	0.0	5.8	0.0	14.6	0.1	47.6	0.0	28.2	0.0	5.8	0.0
13	100.0	0.1	0.0	0.0	97.4	0.1	0.0	0.0	97.4	0.1	0.0	0.0	100.0	0.1	0.0	0.0	100.0	0.1	0.0	0.0
14	27.5	0.0	7.2	-0.1	18.8	0.0	10.1	-0.1	11.6	0.0	8.7	0.0	26.1	0.0	5.8	0.0	39.1	0.1	4.3	0.0
15	75.0	0.0	4.5	0.0	79.5	0.0	4.5	0.0	93.2	0.0	0.0	0.0	84.1	0.0	2.3	0.0	61.4	0.0	13.6	0.0
16	40.0	0.0	11.4	0.0	37.1	0.0	11.4	0.0	42.9	0.0	0.0	0.0	42.9	0.0	8.6	0.0	31.4	0.0	22.9	0.0
17	95.3	0.0	0.0	0.0	100.0	0.1	0.0	0.0	100.0	0.1	0.0	0.0	100.0	0.1	0.0	0.0	81.4	0.1	0.0	0.0
18	30.8	0.0	11.5	-0.1	30.8	0.0	19.2	-0.1	30.8	0.0	15.4	0.0	3.8	0.1	50.0	0.0	34.6	0.0	23.1	0.0
19	36.2	0.0	19.1	-0.1	21.3	0.0	42.6	-0.1	42.6	0.0	21.3	0.0	17.0	0.0	23.4	-0.1	25.5	0.0	21.3	-0.1

Table 3.8 AER-wise percentage of grid under positive/ negative trend of of average growing degree days(Kharif-season)during 1981-2018 along with its mean magnitude. AERs with significant trend (positive/negative) in > 50% of grids are shown as bold italic.

AERs	Jun				Jul				Aug				Sep			
	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend
1	62.1	0.7	0.0	0.0	100.0	0.9	0.0	0.0	98.3	0.7	0.0	0.0	60.3	0.6	0.0	0.0
2	43.2	0.2	31.2	-0.3	88.8	0.4	4.0	-0.9	92.8	0.3	1.6	-2.5	47.2	0.2	35.2	-0.3
3	0.0	0.0	100.0	-0.3	6.7	0.1	53.3	-0.1	66.7	0.1	20.0	-0.1	0.0	0.0	86.7	-0.2
4	38.0	0.2	56.2	-0.2	73.6	0.2	16.5	-0.1	89.3	0.3	0.8	0.0	86.8	0.2	1.7	-0.1
5	45.9	0.2	49.2	-0.3	54.1	0.2	32.8	-0.2	78.7	0.2	13.1	-0.3	49.2	0.1	27.9	-0.2
6	5.5	0.0	68.2	-0.2	33.6	0.1	22.7	-0.1	88.2	0.2	4.5	-0.1	55.5	0.1	20.0	-0.2
7	0.0	0.0	96.6	-0.4	55.9	0.2	27.1	-0.1	57.6	0.2	25.4	-0.1	18.6	0.1	71.2	-0.2
8	20.3	0.2	59.4	-0.2	54.7	0.2	20.3	-0.1	59.4	0.2	18.8	-0.1	43.8	0.2	35.9	-0.2
9	45.8	0.2	37.5	-0.3	66.7	0.3	31.3	-0.3	66.7	0.2	16.7	-0.2	83.3	0.3	10.4	-0.2
10	50.0	0.1	41.7	-0.1	51.2	0.1	10.7	-0.1	100.0	0.2	0.0	0.0	98.8	0.3	0.0	0.0
11	58.8	0.3	27.5	-0.1	72.5	0.2	11.8	-0.1	84.3	0.2	2.0	0.0	100.0	0.3	0.0	0.0
12	58.3	0.3	32.0	-0.2	58.3	0.2	14.6	-0.1	96.1	0.3	0.0	0.0	91.3	0.2	2.9	-0.1
13	78.9	0.4	5.3	-0.1	89.5	0.6	5.3	-0.1	97.4	0.4	0.0	0.0	100.0	0.6	0.0	0.0
14	56.5	0.3	33.3	-0.8	75.4	0.5	21.7	-0.8	72.5	0.4	26.1	-0.8	68.1	0.3	26.1	-0.6
15	54.5	0.3	31.8	-0.2	97.7	0.4	2.3	-0.3	90.9	0.3	4.5	-0.3	97.7	0.4	2.3	-0.1
16	25.7	0.2	65.7	-0.3	74.3	0.2	14.3	-0.6	51.4	0.3	25.7	-0.4	82.9	0.2	14.3	-0.4
17	67.4	0.2	9.3	-0.3	97.7	0.4	2.3	-1.0	97.7	0.4	2.3	-1.2	93.0	0.5	4.7	-0.4
18	38.5	0.3	46.2	-0.9	76.9	0.2	11.5	-1.3	80.8	0.2	11.5	-1.3	80.8	0.2	11.5	-1.5
19	19.1	0.2	59.6	-1.0	27.7	0.2	48.9	-0.5	57.4	0.2	17.0	-1.1	44.7	0.1	40.4	-0.7

Table 3.9 AER-wise percentage of grid under positive/ negative trend of of average growing degree days(Rabi-season)during 1981-2018 along with its mean magnitude. AERs with significant trend (positive/negative) in > 50% of grids are shown as bold italic.

	Nov				Dec				Jan				Feb				Mar			
AERs	Count(+)	Count(-)	Count(+)	Count(-)	Count(+)	Count(-)	Count(+)	Count(-)	Count(+)	Count(-)	Count(+)	Count(-)	Count(+)	Count(-)	Count(+)	Count(-)	Count(+)	Count(-)	Count(+)	Count(-)
	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	49.6	-0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.8	0.1	98.4	-0.7	0.8	0.1	94.4	-0.9	36.8	0.0	100.0	-0.9	41.6	0.4	40.8	-0.7	19.2	0.2	70.4	-0.7
3	20.0	0.1	60.0	-0.7	33.3	0.3	26.7	-0.6	0.0	0.4	56.2	-0.7	0.0	0.0	100.0	-1.1	0.0	0.0	93.3	-1.1
4	0.8	0.3	90.9	-0.5	7.4	0.1	78.5	-0.8	37.2	0.3	65.6	-0.9	43.0	0.3	39.7	-0.7	9.9	0.3	78.5	-0.8
5	6.6	0.3	88.5	-0.8	9.8	0.3	90.2	-1.1	26.2	0.3	77.3	-0.7	34.4	0.5	60.7	-0.6	27.9	0.5	70.5	-0.8
6	31.8	0.3	58.2	-0.6	40.9	0.4	43.6	-0.5	9.1	0.2	89.8	-0.7	13.6	0.3	79.1	-0.8	20.9	0.4	70.9	-0.8
7	10.2	0.3	74.6	-0.7	39.0	0.4	45.8	-0.7	1.7	0.0	93.8	-0.8	0.0	0.0	100.0	-1.0	0.0	0.0	89.8	-1.1
8	10.9	0.2	76.6	-0.9	34.4	0.2	40.6	-0.4	0.0	0.7	75.0	-0.5	0.0	0.0	95.3	-1.1	1.6	0.1	92.2	-0.9
9	14.6	0.3	75.0	-0.6	16.7	0.2	75.0	-0.6	18.8	0.1	96.4	-0.6	27.1	0.4	50.0	-0.3	12.5	0.3	79.2	-0.5
10	0.0	0.0	101.2	-0.6	0.0	0.0	102.4	-0.7	1.2	0.3	60.8	-0.5	27.4	0.2	64.3	-0.5	0.0	0.0	101.2	-0.8
11	13.7	0.3	66.7	-0.5	41.2	0.4	51.0	-0.5	31.4	0.2	69.9	-0.4	47.1	0.3	39.2	-0.4	41.2	0.4	47.1	-0.5
12	14.6	0.2	64.1	-0.3	54.4	0.3	30.1	-0.3	16.5	0.2	94.7	-0.7	36.9	0.3	44.7	-0.3	57.3	0.3	26.2	-0.5
13	2.6	0.1	100.0	-0.6	7.9	0.1	97.4	-0.6	10.5	0.9	13.0	-0.5	18.4	0.3	76.3	-0.5	7.9	0.3	94.7	-0.7
14	26.1	0.4	20.3	-0.5	17.4	0.3	14.5	-0.4	15.9	0.5	45.5	-0.4	23.2	0.5	8.7	-0.4	21.7	0.7	27.5	-1.1
15	29.5	0.3	59.1	-0.5	40.9	0.4	45.5	-0.4	45.5	0.5	17.1	-0.4	36.4	0.2	52.3	-0.2	25.0	0.2	50.0	-0.3
16	20.0	0.2	45.7	-0.3	51.4	0.4	8.6	-0.3	34.3	0.3	58.1	-0.8	14.3	0.2	37.1	-0.4	2.9	0.2	62.9	-0.3
17	51.2	0.5	48.8	-0.5	46.5	0.5	46.5	-0.6	41.9	0.2	50.0	-0.3	30.2	0.3	60.5	-0.9	27.9	0.4	62.8	-0.9
18	15.4	0.3	57.7	-1.3	53.8	0.4	30.8	-0.4	19.2	0.4	72.3	-0.6	7.7	0.2	57.7	-0.4	23.1	0.3	23.1	-0.4
19	14.9	0.4	76.6	-0.9	40.4	0.4	51.1	-0.9	6.4	0.4	49.6	-0.6	8.5	0.4	61.7	-0.6	21.3	0.3	48.9	-0.6

3.4.2 Spatial variations of temporal trends of rainfall, rainy days and SPEI

Temporal trends of rainfall and rainy days

Fig. 3.11 and Table 3.10 represent the spatial patterns and AER-wise percentage of grid under positive/ negative trends of rainfall in *kharif*-season during 1981 to 2018. The monthly and seasonal trends of rainfall amount and rainy days during the southwest monsoon season (June, July, August, and September) were evaluated using the Mann-Kendall method from 2008-2018. The findings are illustrated in Fig. 3.11 and 3.12. AER-wise percentage of grid under positive/ negative trends of rainfall amounts and rainy days are given in in Tables 3.10 and 3.11. An overall increasing trend in monthly rainfall amounts (0.5 to 1.5 mm year⁻¹) was observed across India, with some scattered patches showing a decreasing trend.

In June, a significant increase in rainfall was observed along the eastern coast (AER 18), western coast (AER 19), southern (AER 07, AER 08), and western parts (AER 02) of India. Some parts of AER 11 and AER 12 exhibited a non-significant decreasing trend. In July, rainfall showed a significant increasing trend (> 1 mm year⁻¹) in the central and western parts (AER 04, AER 05, AER 09, AER 10) as well as along the eastern and western coasts (AER 18, AER 19). However, a significant decreasing trend (< -1 mm year⁻¹) was observed in the northern (AER 14) and northeastern (AER 15 and AER 16) parts of India. In August, the Deccan Plateau (AER 03, AER 08, AER 19) and the Indo-Gangetic Plain (IGP; AER 09, AER 13) showed a significant increasing trend, while the central (AER 05, AER 10) and northern parts (AER 14) showed a significant decreasing trend. In September, the increasing trend continued along the western coast (AER 19), but a significant decreasing trend was observed in the IGP (AER 09, AER 13) and the northeastern part (AER 15, 16, 17). A significant positive trend was noted in AER 05, AER 11, and AER 12, while a non-significant negative trend was observed in the southern parts (AER 03, AER 08).

Fig. 3.12 and Table 3.11 represent the spatial patterns and AER-wise percentage of grid under positive/ negative trends of rainy days in *kharif*-season during 1981-2018. Rainy days, with rainfall amounts > 2.5 mm, also increased across India during all southwest monsoon months. Similar to rainfall trends, the number of rainy days significantly increased (> 0.5 days year⁻¹)

over the western and eastern coasts (AER 19 and AER 18) and the southern parts (AER 07 and AER 08) in June. However, no trend in rainy days was observed in the western arid part (AER 02), unlike the significant increasing trend in rainfall amounts observed in June. This pattern indicates that an increase in rainfall amounts without an increase in rainy days suggests an increase in the region's heavy/extreme rainfall events (Samo et al. 2017). In July, the number of rainy days showed a significant increasing trend in the central, western, and coastal regions (AER 04, AER 05, AER 09, AER 10, AER 18, AER 19) and a decreasing trend in the northern part (AER 14), mirroring the rainfall trends. In August, the Deccan Plateau (AER 03, AER 08, AER 19) and the IGP (AER 09, AER 13) showed a significant increasing trend in rainy days, with a significant decreasing trend in the central part (AER 05, AER 10). Unlike the rainfall trend, the northern part (AER 14) showed a significant positive trend on rainy days in August. In September, a trend in rainy days was observed in central and peninsular India, including the Eastern and Western Ghats (AER 05, 06, 07, 08, 10, 13, 18, 19), with an increase of > 1 day year⁻¹. However, a significant decreasing trend was observed in the northern (AER 14) and northeastern parts (AER 16).

The seasonal trends for rainfall amount and rainy days during the southwest monsoon season exhibited a significant upward trend in India's eastern, western, and northern parts (AER 01, 02, 05, 12). Conversely, a significant decreasing trend in rainfall was observed in the Indo-Gangetic Plain (AER 04, 09, 14) and the northeastern parts (AER 14, 15, 16, 17). Additionally, there was a significant increase in the number of rainy days in central (AER 04, 06) and peninsular India (AER 08). Notably, the Himalayan region in the northern part (AER 01 and 14) showed a significantly decreasing trend in the number of rainy days but an increasing trend in rainfall amounts, suggesting a higher probability of heavy rainfall events in this region (Fig. 3.13). This specific spatial pattern of trends in rainfall and rainy days in these AERs was also observed by Das et al. (2014).

Temporal trends of SPEI-03

Fig. 3.14 and Table 3.13 represent the spatial patterns and AER-wise percentage of grid under positive/negative trends of SPEI-03 in *kharif*-season during 1981 to 2018. In July, a significant positive trend in SPEI-03 was observed in the central and southern parts of India (AER 03, AER

05, AER 10, AER 12, and AER 18), while a significant decreasing trend was found in the north-eastern part (AER 15 and AER 17). The trend analysis of August revealed scattered patches of increasing trends in AER05, AER 06, AER 08, and AER 11, as well as decreasing trends in AER 15 and AER 17 across India. In September, the entire north-eastern part of India exhibited a negative trend in SPEI-03 indicating an increase in drought events in this region (AER 15, AER 17), despite being a high rainfall zone. Some areas of central and peninsular India showed an increasing trend in September SPEI-03 (AER 03, AER 05, AER 06, AER 08 and AER11). Overall, the trend analysis results indicated that northeast India (a high rainfall zone) experienced the most significant increase in drought events over the past 38 years. In contrast, central India had the lowest increase (Fig 3.14). In general, wet events have significantly increased across India. This information is valuable for understanding the impact of changing rainfall and temperature patterns on different areas and can be utilized to develop strategies for mitigating climate-related impacts on agriculture in these regions.

Table 3.13 presents the AER-wise percentage of grids exhibiting positive/negative trends in SPEI-03 during 1981-2018, along with the mean magnitude of these trends during the monsoon months. AERs with a significantly high trend ($> 0.5 \text{ year}^{-1}$) over more than 50% of the grid are marked in bold italics. It is evident from Table 3.13 that AER 3, 7, 14, and 18 displayed a positive trend over a large area with a magnitude of $0.5\text{-}1.14 \text{ year}^{-1}$ during June. Similarly, during July, a positive trend of $0.56\text{-}0.73 \text{ year}^{-1}$ was observed over a significantly large area in AER 3, 5, 10, 12, and 18. AER 8 showed a high positive trend ($0.52\text{-}0.57 \text{ year}^{-1}$) over most of the grid in August. In September, AER 3, 5, and 8 also exhibited a high positive trend in the lion's share of the grid. A significantly high negative trend ($0.5\text{-}0.8 \text{ year}^{-1}$) is observed over large contiguous AER 15 and 17 areas from July to September. The present findings are in the agreement with the findings of “Das *et al.* (2014) and Das *et al.* (2020)”.

During the *rabi* season, a significant upward trend in the Standardized Precipitation-Evapotranspiration Index (SPEI-03) was observed in the eastern and western parts of India (AER 02, AER 05, AER 06, AER 11, AER 12) in November, while a downward trend was noted in the northern part (AER 01). In December, a significant positive trend was observed in the western part (AER 06). Conversely, the trend analysis for January and February revealed increasing trends in the eastern India (AER 09, AER 11, AER 12), with scattered patches of significant declining trends in the northern and central parts (Fig 3.15 and Table 3.14).

In summary, most regions of India show an upward trend in rainfall and the number of rainy days. Panda and Sahu (2019) also reported a significant increasing trend in monsoon season rainfall at a rate of approximately 4 mm/year in parts of Odisha, which aligns with our findings in AER 12. Jenifer and Jha identified both positive and negative trends in rainfall in the southern part. Similarly, Halдар et al. (2023) investigated rainfall data from 1970 to 2019 and revealed a decreasing trend in rainfall in parts of Assam (AER 15), consistent with our results. “Chauhan et al. (2022)” found a non-significant declining trend for monsoon season rainfall in Haryana state (AER 04); this pattern was observed for July only, while other monsoon months showed a non-significant increasing trend. “Das et al. (2014)” observed a significant positive trend in both rainfall and rainy days during the southwest monsoon season over the eastern coast and southern parts and a significant negative trend in the western coast, western arid region, and northeastern humid region, which aligns with our findings. The Indian peninsula, particularly the eastern and upper-western coastal regions, exhibited a significant trend of increasing wetness during the *kharif* season.

Conversely, the northeastern region, known for its high rainfall levels and biodiversity hotspots, demonstrated a significant drying trend. Notably, a substantial portion of the uppercentral part of India, the Indo-Gangetic Plain, often referred to as the country's food basket, displayed a drying trend. However, it did not reach statistical significance at the $p < 0.1$ level during the *kharif* season. A similar spatial pattern of decreasing SPEI-03 trends was also observed during the *rabi* season.

Table 3.15 presents the consolidated data of different AERs, illustrating significant positive or negative trends for each meteorological variable.

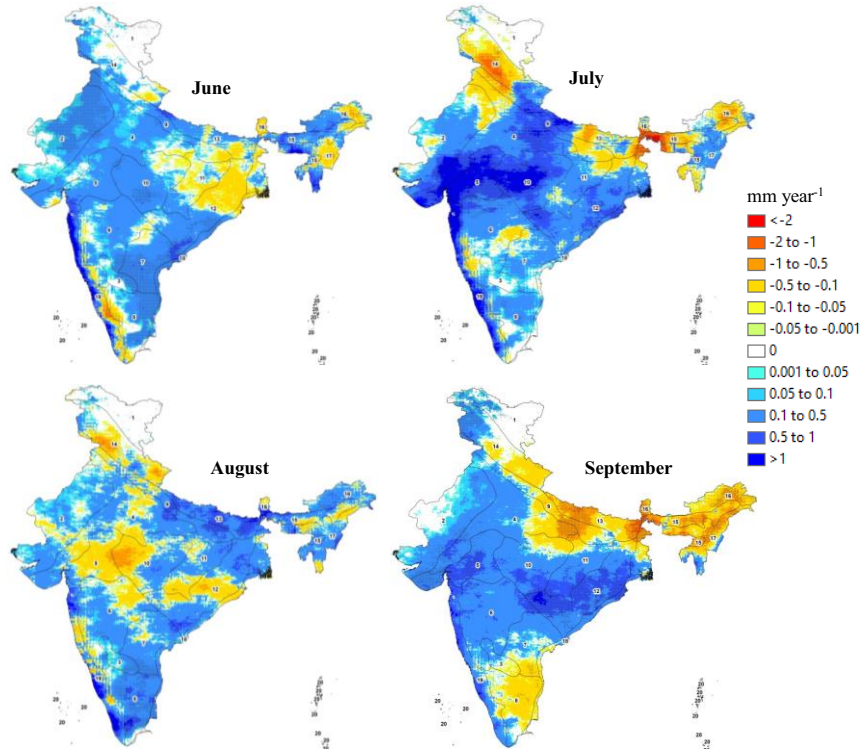


Fig 3.11 Spatial patterns of temporal trends in time-series anomalies (1981-2018) of average monthly rainfall amount during SW monsoon; significant grids at $p < 0.1$ are shown as '+'.

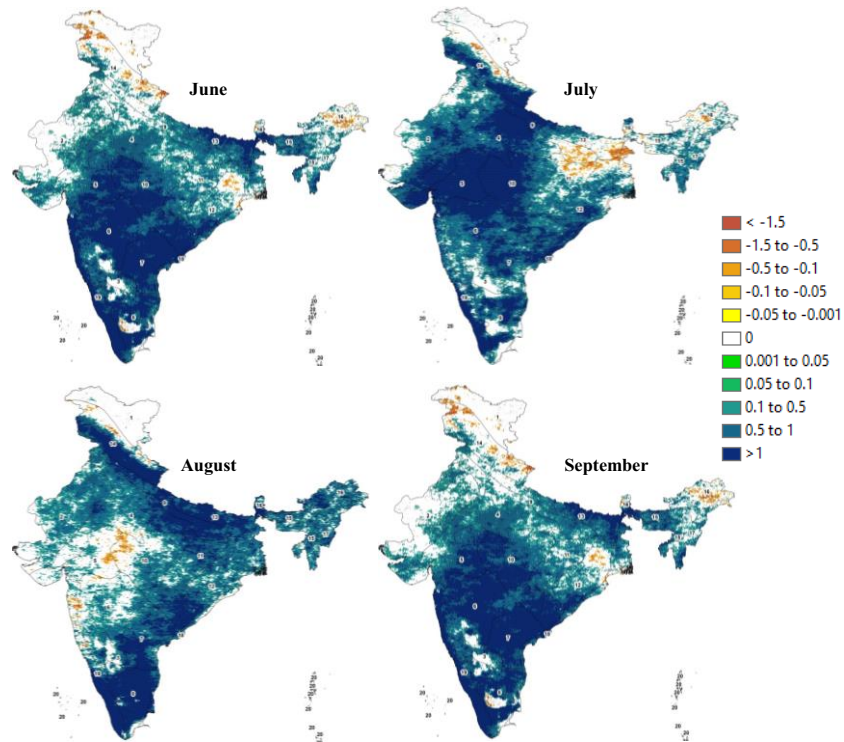


Fig 3.12 Spatial patterns of temporal trends in time-series anomalies (1981-2018) of average monthly rainy days during SW monsoon; significant grids at $p < 0.1$ are shown as '+'.

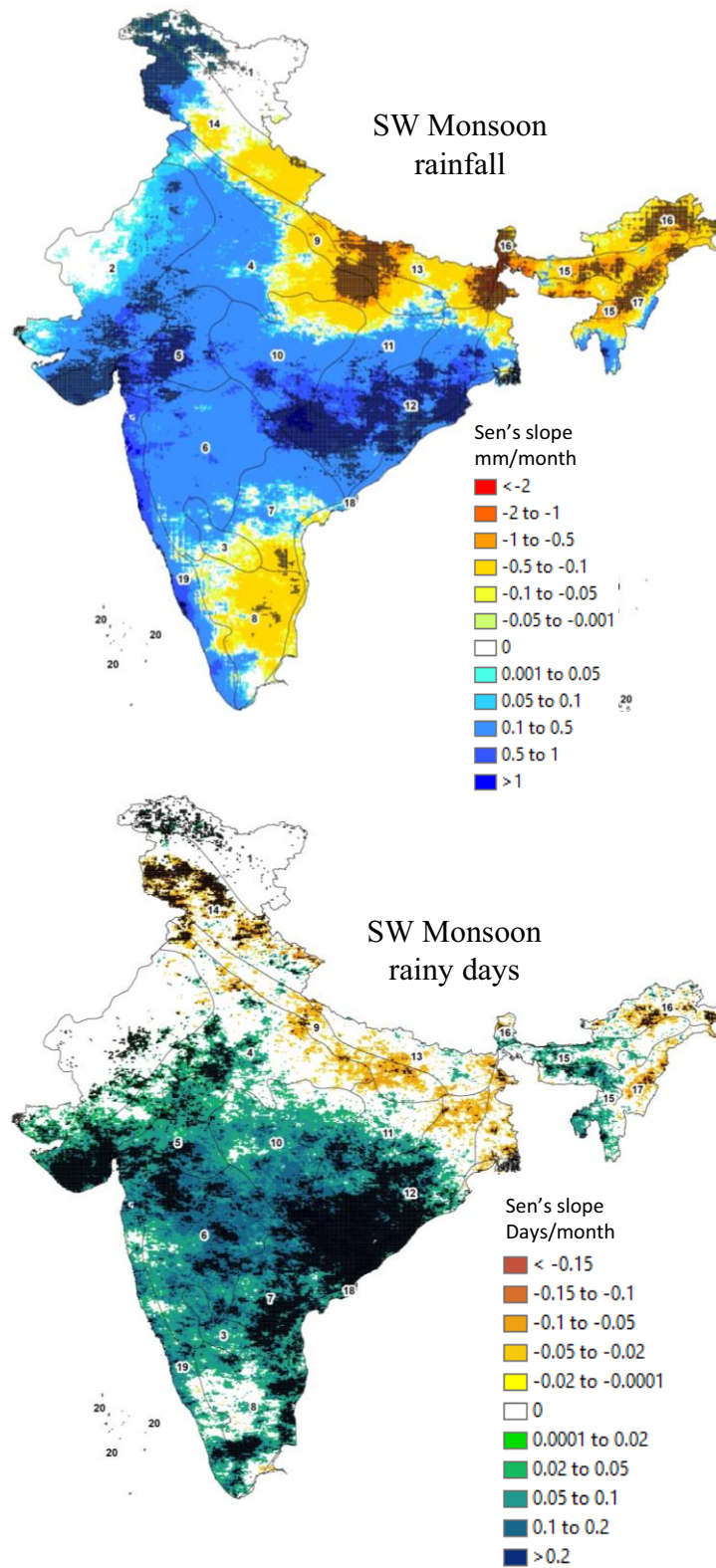


Fig 3.13 Spatial patterns of temporal trends in time-series anomalies (1981-2018) of SW monsoon rainfall and rainy days (seasonal); significant grids at $p < 0.1$ are shown as '+'.

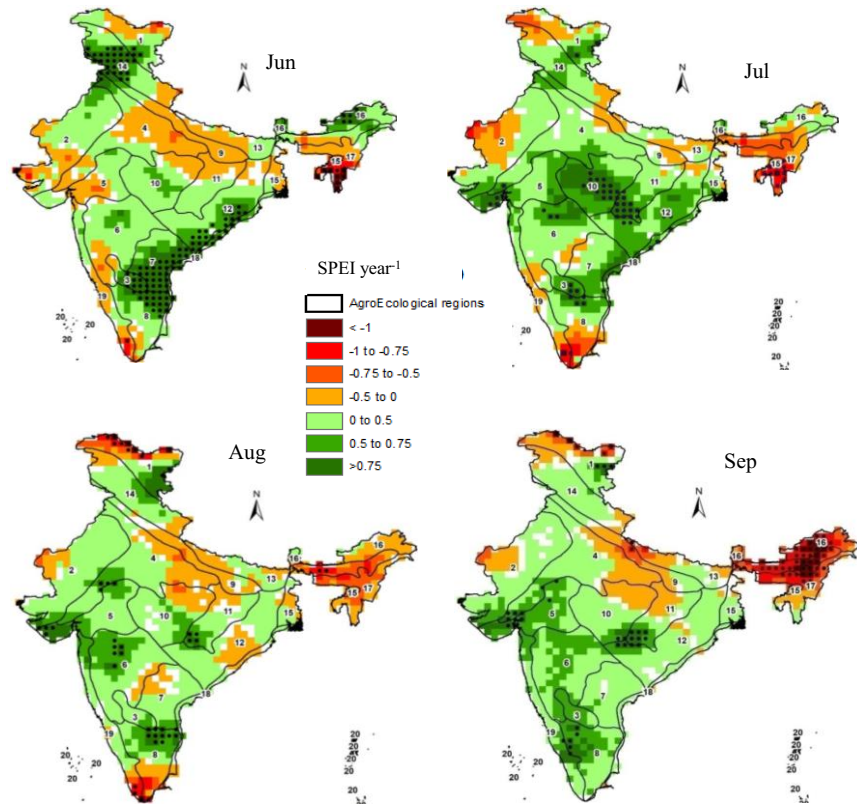


Fig 3.14 Spatial patterns of temporal trends of SPEI-03 in *kharif*-season during 1981-2018. Grids with significant trend (positive/negative) at $p < 0.1$ are represented with black dots (Kumari et al. 2023).

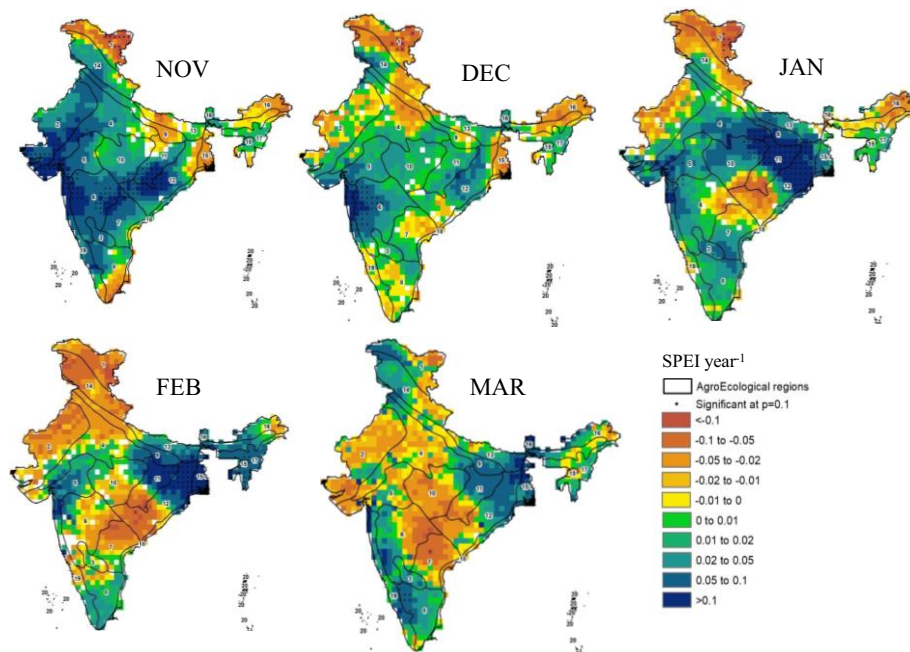


Fig 3. 15 Spatial patterns of temporal trends of SPEI-03 in *rabi* season during 1981-2019. Grids with significant trend (positive/negative) at $p < 0.1$ are represented with black dots.

Table 3.10 AER-wise percentage of grid under positive/ negative trend of rainfall amount during 1981-2018 along with its mean magnitude over the monsoon months. AERs with significant trend (positive/negative) in > 50% of grids are shown as bold italic.

AERs	Jun				Jul				Aug				Sep			
	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend
1	8.8	0.1	0.5	0.0	5.5	0.1	4.1	-0.5	5.1	0.1	0.5	-0.5	20.6	0.1	1.0	0.0
2	88.5	0.1	0.9	0.0	68.1	0.3	0.0	-0.3	73.2	0.1	0.2	-0.4	75.5	0.2	0.0	0.0
3	69.8	0.1	0.0	0.0	40.6	0.1	0.0	0.0	89.0	0.1	0.0	0.0	46.7	0.1	32.3	-0.1
4	87.2	0.1	11.2	0.0	83.6	0.6	0.0	0.0	57.3	0.2	0.2	-0.4	73.7	0.2	20.9	-0.3
5	91.9	0.2	0.0	0.0	100.0	1.0	0.0	-0.4	34.9	0.2	0.0	0.0	100.0	0.5	0.0	0.0
6	78.9	0.2	0.0	0.0	73.6	0.3	0.0	0.0	60.6	0.1	0.0	0.0	97.2	0.3	0.5	-0.1
7	90.5	0.3	0.0	0.0	77.3	0.1	0.0	0.0	85.1	0.2	0.0	-0.3	66.3	0.2	18.4	-0.1
8	65.6	0.2	0.7	0.0	73.7	0.2	1.3	-0.5	91.0	0.4	0.2	-0.4	11.7	0.1	69.1	-0.2
9	61.1	0.2	38.7	-0.1	47.3	0.6	0.3	-0.4	72.7	0.4	11.4	-0.4	25.3	0.1	58.0	-0.3
10	76.7	0.2	0.2	0.0	99.7	0.8	0.0	0.0	47.2	0.2	0.0	0.0	76.1	0.4	16.9	-0.2
11	37.2	0.1	3.7	0.0	77.3	0.3	0.1	-0.4	59.0	0.2	8.8	-0.4	84.8	0.4	10.6	-0.3
12	48.9	0.3	8.3	-0.1	90.3	0.4	2.5	-0.4	63.9	0.3	2.2	-0.4	94.4	0.6	4.0	-0.2
13	65.3	0.2	20.2	0.0	42.5	0.5	0.0	-0.2	99.9	0.6	9.7	-0.5	1.2	0.1	95.1	-0.5
14	42.3	0.1	38.5	-0.1	22.6	0.3	16.1	-0.6	22.2	0.1	4.2	-0.6	34.3	0.2	42.0	-0.2
15	58.8	0.3	19.2	-0.1	42.0	0.3	3.2	-0.5	73.1	0.3	8.5	-0.5	18.2	0.3	77.1	-0.5
16	57.5	0.3	27.3	-0.1	21.2	0.2	13.1	-0.5	83.4	0.3	8.7	-0.5	0.9	0.1	95.0	-0.4
17	54.5	0.5	16.2	-0.1	54.6	0.2	0.8	-0.4	68.5	0.3	0.7	-0.4	17.5	0.2	77.1	-0.4
18	72.7	0.3	4.2	0.0	75.1	0.3	2.1	-0.4	72.5	0.2	0.6	-0.4	61.3	0.4	29.4	-0.1
19	70.6	0.9	0.2	0.0	90.5	1.1	0.2	-0.7	75.3	0.6	0.2	-0.5	87.5	0.5	5.3	-0.1

Table 3.11 AER-wise percentage of grid under positive/ negative trend of rainy days amount during 1981-2018 along with its mean magnitude over the monsoon months. AERs with significant trend (positive/negative) in > 50% of grids are shown as bold italic.

AERs	Jun				Jul				Aug				Sep			
	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend
1	0.0	0.0	0.0	0.0	1.0	0.4	5.8	-0.1	1.8	0.4	0.9	-0.1	20.6	0.1	1.0	0.0
2	43.2	0.5	0.0	0.0	76.0	0.8	14.3	-0.1	72.0	0.6	7.3	-0.1	75.5	0.2	0.0	0.0
3	54.2	0.8	0.0	0.0	30.3	0.5	2.2	0.0	70.5	0.8	0.0	0.0	46.7	0.1	32.3	-0.1
4	73.6	0.6	2.5	-0.1	93.7	1.1	12.6	-0.2	76.3	0.8	26.0	-0.1	73.7	0.2	20.9	-0.3
5	90.6	0.9	2.1	-0.1	100.0	1.4	0.0	0.0	21.2	0.4	56.2	-0.2	100.0	0.5	0.0	0.0
6	97.9	1.2	6.9	-0.1	94.1	1.0	13.6	-0.2	54.9	0.5	22.4	-0.1	97.2	0.3	0.5	-0.1
7	100.0	1.5	2.6	-0.1	94.5	0.9	5.3	-0.1	98.9	1.1	5.0	-0.1	66.3	0.2	18.4	-0.1
8	83.4	1.1	15.8	-0.2	77.4	0.9	3.6	-0.1	93.0	1.6	1.4	-0.1	11.7	0.1	69.1	-0.2
9	65.2	0.6	16.4	-0.1	59.5	1.1	46.2	-0.3	99.8	1.2	17.3	-0.2	25.3	0.1	58.0	-0.3
10	95.5	1.0	9.6	-0.1	99.0	1.3	0.1	-0.1	55.4	0.6	41.4	-0.3	76.1	0.4	16.9	-0.2
11	80.9	0.6	38.9	-0.1	51.9	0.5	13.3	-0.2	92.0	0.8	28.9	-0.2	84.8	0.4	10.6	-0.3
12	76.1	0.9	41.7	-0.2	85.9	0.8	7.1	-0.2	93.8	0.8	27.9	-0.2	94.4	0.6	4.0	-0.2
13	98.7	1.0	21.3	-0.1	49.2	0.8	47.4	-0.4	99.9	1.2	0.0	-0.1	1.2	0.1	95.1	-0.5
14	19.5	0.5	8.5	-0.1	63.2	1.0	58.8	-0.4	67.3	1.3	44.2	-0.3	34.3	0.2	42.0	-0.2
15	72.3	0.7	26.3	-0.1	42.3	0.5	51.5	-0.7	89.5	0.7	17.8	-0.2	18.2	0.3	77.1	-0.5
16	26.7	0.6	36.0	-0.2	22.8	0.5	54.3	-0.4	89.7	0.8	6.3	-0.1	0.9	0.1	95.0	-0.4
17	71.3	0.7	36.3	-0.2	70.6	0.6	35.2	-0.3	86.7	0.7	22.0	-0.2	17.5	0.2	77.1	-0.4
18	76.3	0.9	19.8	-0.2	74.9	0.8	1.8	-0.1	74.6	0.8	18.3	-0.2	61.3	0.4	29.4	-0.1
19	98.7	1.7	24.9	-0.3	91.9	1.2	5.3	-0.2	67.0	1.5	18.3	-0.2	87.5	0.5	5.3	-0.1

Table 3.12 AER-wise percentage of grid under positive/ negative trend of seasonal rainfall amount and rainy day during 1981-2018 along with its mean magnitude over the monsoon months. AERs with significant trend (positive/negative) in > 50% of grids are shown as bold italic.

AERs	Seasonal Rainfall				Seasonal Rainy days			
	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend
1	20.63	0.10	1.04	-0.04	4.44	0.05	0.47	-0.05
2	75.53	0.16	0.00	0.00	23.49	0.05	0.90	-0.04
3	46.72	0.15	32.33	-0.08	96.12	0.08	0.00	0.00
4	73.72	0.23	20.95	-0.31	34.53	0.06	11.24	-0.05
5	99.95	0.47	0.00	0.00	97.67	0.09	0.00	0.00
6	97.19	0.34	0.53	-0.05	96.71	0.11	0.00	0.00
7	66.34	0.19	18.35	-0.14	99.24	0.11	0.00	0.00
8	11.66	0.11	69.07	-0.18	62.97	0.08	0.65	-0.04
9	25.34	0.13	57.95	-0.33	2.41	0.05	38.69	-0.05
10	76.13	0.38	16.93	-0.18	78.08	0.08	0.20	-0.03
11	84.79	0.41	10.61	-0.31	66.26	0.10	3.70	-0.05
12	94.41	0.57	3.99	-0.25	75.74	0.14	8.28	-0.05
13	1.22	0.09	95.11	-0.52	4.99	0.05	20.24	-0.05
14	34.30	0.20	42.02	-0.17	4.70	0.05	38.53	-0.07
15	18.17	0.28	77.12	-0.50	18.93	0.05	19.18	-0.05
16	0.87	0.08	94.96	-0.36	11.75	0.05	27.28	-0.06
17	17.54	0.23	77.09	-0.43	34.36	0.07	16.20	-0.06
18	61.33	0.36	29.38	-0.10	78.31	0.10	4.19	-0.05
19	87.47	0.49	5.28	-0.10	78.82	0.08	0.23	-0.04

Table 3.13 AER-wise percentage of grid under positive/ negative trend of SPEI-03 during 1981-2018 along with its mean magnitude over the monsoon months. AERs with significant trend (positive/negative) in > 50% of grids are shown as bold italic. (Kumari et al. 2023)

AERs	Jun				Jul				Aug				Sep			
	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend	Count (%)	(+) trend	Count (%)	(-) trend
2	44.1	0.27	23.5	-0.05	52.9	0.26	39.2	-0.29	55.9	0.31	14.7	0.02	38.2	0.30	16.7	-0.13
3	56.3	1.14	37.5	-0.31	82.1	0.62	0.0	0.00	93.8	0.47	0.0	0.00	91.0	0.57	0.0	0.00
4	36.7	0.18	42.9	-0.26	88.8	0.36	3.1	-0.19	75.5	0.27	13.3	-0.26	72.4	0.24	15.3	-0.33
5	28.3	0.28	47.2	-0.12	90.2	0.56	0.0	0.00	88.7	0.46	0.0	0.00	88.7	0.56	0.0	0.00
6	68.8	0.29	12.9	-0.04	82.8	0.41	10.8	-0.13	83.9	0.39	0.0	0.00	93.5	0.49	0.0	0.00
7	56.5	0.76	0.0	0.00	89.1	0.49	5.5	-0.15	49.1	0.33	18.2	-0.02	92.7	0.25	0.0	0.00
8	57.9	0.63	26.3	-0.18	56.1	0.47	38.6	-0.49	63.2	0.56	29.8	-0.36	98.2	0.52	0.0	0.00
9	15.8	0.37	71.1	-0.24	44.7	0.24	36.8	-0.14	2.6	0.08	60.5	-0.21	15.8	0.18	65.8	-0.25
10	80.3	0.35	9.9	-0.15	89.3	0.73	0.0	0.00	66.2	0.30	15.5	-0.19	70.4	0.33	19.7	-0.21
11	53.3	0.25	33.3	-0.18	91.1	0.46	2.2	-0.04	55.6	0.37	20.0	0.01	46.7	0.48	40.0	-0.05
12	80.7	0.48	3.6	-0.02	91.6	0.57	4.8	-0.07	63.9	0.21	13.3	-0.14	77.1	0.32	2.4	0.15
13	15.6	0.21	68.8	-0.02	40.6	0.16	40.6	-0.08	25.0	0.08	59.4	-0.08	28.1	0.07	46.9	-0.32
14	68.4	0.50	7.0	-0.27	64.9	0.40	28.1	-0.22	52.6	0.33	14.0	-0.13	54.4	0.24	8.8	-0.15
15	45.9	0.17	24.3	-0.21	32.4	0.26	56.8	-0.52	24.3	0.05	56.8	-0.54	24.3	0.29	56.8	-0.86
17	11.4	0.45	54.3	-0.41	5.7	0.20	80.0	-0.63	0.0	0.00	68.6	-0.48	0.0	0.00	68.6	-0.63
18	64.7	0.76	0.0	0.00	64.7	0.64	11.8	-0.31	35.3	0.20	29.4	-0.24	52.9	0.24	0.0	0.00
19	0.0	0.00	7.3	0.05	48.8	0.33	39.0	-0.50	4.9	0.39	7.3	-0.14	14.6	0.59	0.0	0.00

Table 3.14 AER-wise percentage of grid under positive/ negative trend of SPEI-03 during 1981-2018 along with its mean magnitude in rabi season. AERs with significant trend (positive/negative) in > 50% of grids are shown as bold italic.

AERs	Nov				Dec				Jan				Feb				Mar			
	Count (+)	Count (-)	Count (+)	Count (-)	Count (+)	Count (-)	Count (+)	Count (-)	Count (+)	Count (-)	Count (+)	Count (-)	Count (+)	Count (-)	Count (+)	Count (-)	Count (+)	Count (-)	Count (+)	Count (-)
	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend	(%)	trend
1	6.9	0.6	89.7	-2.5	3.4	0.4	93.1	-2.1	0.0	0.0	96.6	-2.3	0.0	0.0	96.6	-2.1	51.7	1.6	43.1	-1.2
2	93.6	2.6	0.0	0.0	40.0	0.7	48.8	-0.7	36.0	1.1	52.0	-1.0	4.8	0.9	81.6	-1.5	10.4	0.8	79.2	-1.1
3	106.7	2.3	0.0	0.0	100.0	0.8	0.0	0.0	100	1.9	0.0	0.0	40.0	0.6	53.3	-0.6	100.0	1.2	0.0	0.0
4	90.9	2.1	5.8	-0.4	66.1	0.8	32.2	-1.0	93.4	2.0	2.5	-0.4	43.8	1.2	50.4	-1.0	28.9	1.0	63.6	-0.7
5	93.4	2.6	0.0	0.0	93.4	1.5	0.0	0.0	91.8	1.9	1.6	-0.4	78.7	1.7	13.1	-0.6	27.9	0.9	60.7	-0.8
6	99.1	3.1	0.0	0.0	96.4	1.9	1.8	-0.3	76.4	1.2	18.2	-0.8	27.3	1.3	60.9	-0.9	49.1	1.4	47.3	-1.6
7	91.5	2.1	0.0	0.0	44.1	0.6	42.4	-0.5	57.6	1.4	30.5	-0.6	15.3	0.4	74.6	-1.8	8.5	0.4	81.4	-1.8
8	57.8	1.6	34.4	-1.2	45.3	0.7	46.9	-0.4	93.8	1.1	1.6	-0.2	73.4	1.0	20.3	-0.7	90.6	1.5	3.1	-0.2
9	47.9	1.4	35.4	-1.1	39.6	0.9	45.8	-0.8	68.8	2.4	14.6	-0.7	39.6	2.8	50.0	-1.3	58.3	1.8	27.1	-0.3
10	86.9	1.2	4.8	-0.3	90.5	0.9	1.2	-0.1	86.9	2.3	10.7	-1.1	47.6	1.1	40.5	-0.8	16.7	1.1	81.0	-1.4
11	80.4	2.7	13.7	-0.5	98.0	1.0	2.0	-0.1	74.5	4.3	27.5	-2.2	64.7	3.6	35.3	-2.4	64.7	2.4	37.3	-1.5
12	77.7	2.6	11.7	-0.8	70.9	1.4	14.6	-0.7	52.4	3.6	37.9	-1.5	43.7	3.5	47.6	-2.3	52.4	2.0	35.9	-1.3
13	34.2	0.4	55.3	-0.9	68.4	0.8	23.7	-0.7	84.2	1.8	7.9	-0.6	92.1	2.0	10.5	-0.4	81.6	1.9	15.8	-0.4
14	81.2	1.3	21.7	-0.7	37.7	1.3	65.2	-1.2	18.8	0.8	84.1	-1.3	0.0	0.0	94.3	-2.1	65.2	1.5	33.3	-0.7
15	22.7	1.0	77.3	-1.0	22.7	0.6	79.5	-1.3	45.5	1.7	54.5	-0.8	97.7	3.2	4.5	-0.7	77.3	2.2	20.5	-0.4
16	14.3	0.8	71.4	-1.2	14.3	1.1	74.3	-1.4	14.3	0.9	71.4	-1.4	60.0	1.4	25.7	-0.7	62.9	1.9	20.0	-0.8
17	69.8	0.5	23.3	-0.7	58.1	0.8	32.6	-0.6	65.1	0.6	27.9	-0.4	97.7	2.6	2.3	-0.6	65.1	0.9	25.6	-0.4
18	50.0	1.0	61.5	-1.2	42.3	0.9	65.4	-0.7	88.5	1.9	26.9	-0.4	73.1	2.0	42.3	-1.1	65.4	1.3	46.2	-1.0
19	85.1	2.9	8.5	-1.0	51.1	2.8	40.4	-0.4	70.2	1.7	19.1	-0.4	61.7	1.9	21.3	-1.0	74.5	1.7	2.1	-0.6

Table 3.15 Summary table displaying the AERs with significant positive (+) or negative (-) trend of meteorological variables

Variables	Trend	Kharif-season					Rabi-season			
		Jun	Jul	Aug	Sep	Nov	Dec	Jan	Feb	Mar
Tmin	+	-	-	AER-01, 02, 04, 05, 06, 08, 09, 11, 13, 14, 15, 17, 18	-	-	AER-01, 10, 11, 12, 14, 15, 16	AER-01, 06, 14, 15, 16, 17	AER-01, 15, 16, 17	AER-01, 02, 05, 10, 11, 12, 14, 15, 16
	-	-	-	AER-16	-	-	AER-08	-	AER-01, 13	-
Tmax	+	AER-02, 05, 14	AER-01, 02, 04, 05, 14, 15, 17	-	AER-01, 10, 13, 15, 17	-	AER-01, 10, 11, 12, 14, 15, 16	AER-01, 06, 14, 15, 16, 17	AER-01, 15, 16, 17	AER-01, 02, 05, 10, 11, 12, 14, 15, 16
	-	AER-03, 08	-	-	AER-08, 16	-	AER-08	-	AER-01, 13	-
GDD	+	AER-01, 13	AER-01, 02, 13, 14, 15, 17	AER-01, 13, 14, 17	AER-01, 13, 15, 17	AER-17	AER-02, 04	-	-	-
	-	AER-03, 07, 19	-	-	-	AER-02 to 11 13, 15, 18, 19	-	AER-4, 5, 6, 7, 12	AER-03 to 08, 10, 13, 17	AER-02 TO 10, 13, 17
HWMld	+	-	-	-	-	AER-01, 03, 06, 07, 11, 12, 16, 18	AER-01, 03, 06, 100, 11, 12, 14, 15, 17, 18, 19	-	AER-01, 03, 07, 16, 17, 18, 19	AER-01, 03, 05, 14, 17, 19
	-	-	-	-	-	-	-	-	-	-
Rainfall	+	AER-07, 15, 16, 17, 18	AER-04, 05, 10, 11, 12, 18, 19	AER-09, 19	AER-05, 06, 10, 11, 12, 18, 19	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-
Rainy days	+	AER-03 to 19	AER-02, 04 to 10, 12, 14, 17-19	AER- 06 to 19	AER-05, 10, 11, 12, 19	-	-	-	-	-
	-	-	-	-	AER-13, 15, 16, 17	-	-	-	-	-
SPEI	+	AER-03, 14, 18	AER-03, 05, 10, 12, 18	AER-08	AER-03, 05, 08	AER-02 to 07, 10, 11, 14, 18, 19	AER-05, 06, 11, 12, 19	AER-03 to 13, 18, 19	AER-05, 08, 10, 11, 13, 15 to 19	AER-01, 03, 08, 11 to 19
	-	-	AER-15, 17	AER-15	AER-15, 17	AER-01, 15, 16, 18	AER-01, 14 to 16	AER-01, 12, 14, 16	AER-01, 02, 07, 14	AER-02, 07, 10

Crop phenology and weather extremes

4.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) sixth assessment report (“IPCC 2021”) has reported a significant increase in global mean air temperature, leading to intensified heat waves, extreme rainfall, and drought events in South Asia. Global warming has altered the timing of crop seasonal events. Several studies have been carried out to analyze the temporal trend of temperature and rainfall on vegetation seasonality (“Liu et al. 2016; Zhang et al. 2017a”); however, only some studies are available in case of extremes (“Hatfield and Prueger 2015”). Moreover, understanding the impact of weather extremes on the physiology of crops is even more critical to avoid yield losses. Extremes in moisture or temperature can affect crop physiology, and if they coincide with sensitive growth stages, they may cause severe crop damage. The additional sign to identify the effect of high temperature and its extremes is accelerating the crop growth rate leading to advanced flowering time and early senescence. Climatic extremes such as agricultural drought are crucial for monsoon season (*kharif*) crops, for which soil moisture plays an important role. Likewise, extreme weather events especially heat stress is more influential for winter season (*rabi*) crop where temperature plays an important role. In India, the *kharif* season starts in June with the onset of the monsoon and ends in October-November after the withdrawal of the monsoon. Therefore, the late onset of monsoons or break in monsoons either affects the late start of the agricultural season or causes poor crop vigor. Similarly, *rabi* season mostly starts in November-December and is harvested during early summer, i.e., April. So, the heat-sensitive growth stage corresponds to late February-March, which may accelerate the onset of each growth stage (“Rao et al. 2015”). Remote sensing could provide valuable information, such as long-term changes in crop seasonality at a regional scale. Crop phenology is the expression of the seasonal cycles of plant processes and their responses to climate change, which could be linked to assessing the impact of extreme temperature or dryness/wetness. Based on long-term land surface phenology data, numerous studies have focused on the detecting temporal trends at the start and end of the growing season, and the length of the growing season during the last several decades. However, limited studies are

available on analyzing the impact weather and climate extremes over crop phenology, especially in a country like India. Therefore, the aims of the present study were multifold: (a) to analyze the impacts of monthly and seasonal agricultural drought on *kharif* crop phenology across different Agro-Ecological Regions (AERs) in India, and (b) to investigate the impacts of monthly and seasonal hot and dry extremes on *rabi* crop phenology in the country.

“Chakraborty et al. (2017)” have reported a significant warming trend and an increase in the extreme hot events over India. These changes impact society and ecosystems differently, varying across regions based on their vulnerabilities (“Parsons et al. 2019”). Among the different types of droughts, agricultural drought is one of the complex hazards where soil moisture is limited to support crop growth (“Dalezios et al. 2014; Wilhite and Buchanan-Smith 2005”). The agricultural drought has a pronounced effect on rainfed regions, which is prevalent in India, occupying nearly two-thirds of agricultural land (“Rao et al. 2015; Sathyan et al. 2018”). Agricultural productivity in these areas is heavily influenced by climatic factors, viz., rainfall and evapotranspiration (“Mall et al. 2006”). Previous studies have primarily focused on the effect of temperature or rainfall on crop growth rather than the impact of drought on crops (“Hatfield and Prueger 2015”). Drought indices, such as SP, Palmer Drought Severity Index (PDSI), and SPEI, are valuable indicators for analyzing and interpreting drought severity (“McKee et al. 1993; Palmer 1965; Vicente-serrano et al. 2010”). However, these indices have certain limitations. For example, PDSI requires comprehensive water balance components, making it data-intensive and restricted use (“Zhai et al. 2010; Li et al. 2015”). Based on long-term rainfall data, SPI needs more consistency, especially in arid regions with high evaporation demands (“Pramudya and Onishi 2018; Mishra and Singh 2011”). In contrast, SPEI overcomes these limitations by incorporating rainfall and evapotranspiration data, making it a valuable indicator for monitoring wet and dry events (“Tirivarombo et al. 2018; Chen and Sun 2017”). SPEI is sensitive to changes in climatic demand of evaporation (“Beguería et al. 2014”) and can act as a proxy for soil moisture (“Ahmad et al. 2018; Das et al. 2021”). Very recent studies have used SPEI as an essential indicator to analyze the compound effect of the impact of hot and dry extremes on agriculture (“Mishra et al. 2020; Lesk et al. 2022”). “Klein Tank et al. (2006)” have shown that hot extremes are increasing sharply over central and southern Asia, including India. Extreme

temperatures affect physiological processes in plants by closing stomata, reducing transpiration rates, and decreasing photosynthesis (“Ayeneh et al. 2002”). These effects are particularly severe during the reproductive phase, causing early maturity (“Duncan et al. 2015”) and yield loss. Various criteria have been used worldwide to designate a hot day. Some studies have used a percentile-based threshold approach on daily maximum temperature, while others have used an absolute threshold-based approach to detect heatwaves. This study employs the Heat Wave Magnitude Index daily (HWMId), a widely used index, to assess the spatio-temporal distribution of hot extremes.

Recent studies revealed that croplands are the major contributor to greening in India, while forests have a minor contribution (“Parida et al. 2020; Chen et al. 2019”). While previous studies have examined vegetation dynamics in India, they focus on forests at the national and regional levels (“Ranjan and Gorai 2022; Jeganathan et al. 2010; Kumar et al. 2022; Chakraborty et al. 2018a”), neglecting explicit analysis of croplands. Crop phenology, which expresses the seasonal events of plant processes, is a crucial indicator of crop growth pattern changes in response to climate change. Understanding crop phenology is vital as changes in crop phenology can impact carbon accumulation, crop yield, crop duration and distribution of diseases, and other environmental and social aspects (“Richardson et al. 2009”). Remote sensing provides a synoptic overview of crop-growing regions, enabling regular crop growth, health, and productivity monitoring. Remote sensing cannot directly identify a particular crop growth stage or phenological events due to the coarse spatial resolution of satellite data, resulting in mixed spectra, particularly from heterogeneous grids. Therefore, a more generalized phenology, i.e., “land surface phenology” metrics (pheno-metrics) are computed (“deBeurs and Henebry 2005”), which indicates the seasonality change in spectral observation and depicted as SoS, LoS, NDVI at peak stage, etc. Previous research has examined the influence of climate change on crop growth and crop yield in India, demonstrating the varying relationship between crop growth patterns and drought (“Malhi et al. 2021; Arora 2019; Kumar and Gautam 2014; Guntukula 2020; Rai and Apoorva 2020”). Several studies are carried out to explore the temporal pattern of phenology metrics using satellite data derived NDVI time series in wetlands (“Shen et al. 2023”), forests (“Friedl et al. 2014; Liu et al. 2020; Wang et al. 2020”), croplands (“Anwar et al. 2015; Ishtiaq et al. 2022; Ge et al. 2021; Javed et al. 2021; Yang et al. 2021”) and grasslands (“Shen et al. 2022”) in different parts of world. However, sparse studies are available analyzing the impact

of dry/wet events on crop phenology, especially in a country like India. Limited research (“Chakraborty et al. 2014; Chakraborty et al. 2018b; Das et al. 2020”) utilized 8-km GIMMS NDVI3g data to analyze the trend in phenology and its association with rainfall. These studies have exploited meteorological unit-level or state-administrative boundaries to represent the findings that do not capture the variability in agricultural area and patterns within an India’s heterogeneous landscape characterized by small land holdings. While a few studies have addressed the cropland phenology using high-resolution MODIS or Landsat, they have been limited to specific areas and focused on production or vegetation condition anomaly (“Kumar et al. 2022; Bhavani et al. 2017; Singh and Sanatan, 2021”).

Several studies have analyzed the impact of climate change on vegetation phenological metrics in forest ecosystems, identifying anomalies such as the start of the season advancing to 20 days more than usual (“Liu and Zhang, 2020”). Additionally, some research has observed pre-occurrence at the beginning of the season by approximately one day per year due to rising temperatures (“Zhang et al. 2017b”). It has also been found that significant trends in phenological shifts are more pronounced in colder regions (“Zhang et al, 2014”). Furthermore, land surface phenology spatial patterns primarily change with altitude and land cover type. “Garonna et al. (2016)” analyzed NDVI-based global land surface phenology from 1982 to 2012. They found spatial heterogeneity in the increasing trend of the length of the season, ranging from 0.22 to 0.34 days per year. They also reported that cold environmental zones are hotspots for phenological shifts, accounting for 30% of these trends.

Some studies have reported the absence of a direct link between phenology and temperature or rainfall, concluding that shifts were more likely due to soil moisture associated with high temperatures (“Liu et al. 2016”). The effect is even more uncertain in agro-ecosystems, where human intervention in agricultural management plays a significant role (“Wang et al. 2018”). “Rauschkolb et al. (2024)” analyzed spatial variability in the phenology of herbaceous plants, linking it to variability in environmental variables using ground networks and confirming the importance of temperature alongside photoperiod.

Few studies have attempted to analyze the interaction of hot (cold) and dry (wet) extremes on significant crop yields, confirming that the co-occurrence of these extremes negatively affects crop yield (“Heino et al. 2023”). However, the impact of extremes on crop phenology remains

understudied. “Hatfield and Prueger (2015)” confirmed the effect of weather extreme temperatures on the enhanced crop growth rate in controlled environments. They emphasized the need to understand the combined effects of temperature and moisture on crop growth. Combined extremes have been associated with crop yield losses of up to 30% in India, though in some cases, combinations of crop stresses might generate compensatory effects (“Leske et al. 2022”). Similarly, “Mishra et al. (2020)” identified that the six times India produced below normal crop production between 1951 and 2016, all coincided with hot ($>0.5^{\circ}\text{C}$ above mean temperature) and dry (<100 mm below mean rainfall) extremes. Using knowledge of the effect of warm temperatures on phenology, “Le Roux et al. (2024)” adjusted phenological stages to avoid periods of heat stress and moisture deficit in wheat cultivation.

Notably, more studies need to address the impact of the combined effects of temperature and moisture extremes on crop phenology at the AER level across the entire country. AER represents a homogeneous land unit in terms of climate, soil, and physiography, accounting for agriculture heterogeneity. This study aims to fill this gap by providing a comprehensive and fine-scale evaluation of the impact of dry and wet events on crop phenology at the AER level.

Present study analyzes the impact of climate warming-induced dry and hot extremes on vegetation phenology in various agro-ecological regions of India during the *kharif* and *rabi* seasons from 2001 to 2019. This analysis was performed using the SPEI with a 3-month timescale (SPEI-03) during *kharif* season, whereas both SPEI-03 and the HWMId during *rabi* season, along with phenological metrics. This study aims to analyze the effect of the spatio-temporal patterns of SPEI-03 and HWMId on phenological metrics across India. By examining this objective, the study aims to provide valuable insights into the impact of climate change-induced drought on vegetation and agricultural systems in India.

4.2 Data used and Methodology

The flowchart of the methodology followed in the current study is shown in Fig. 1.

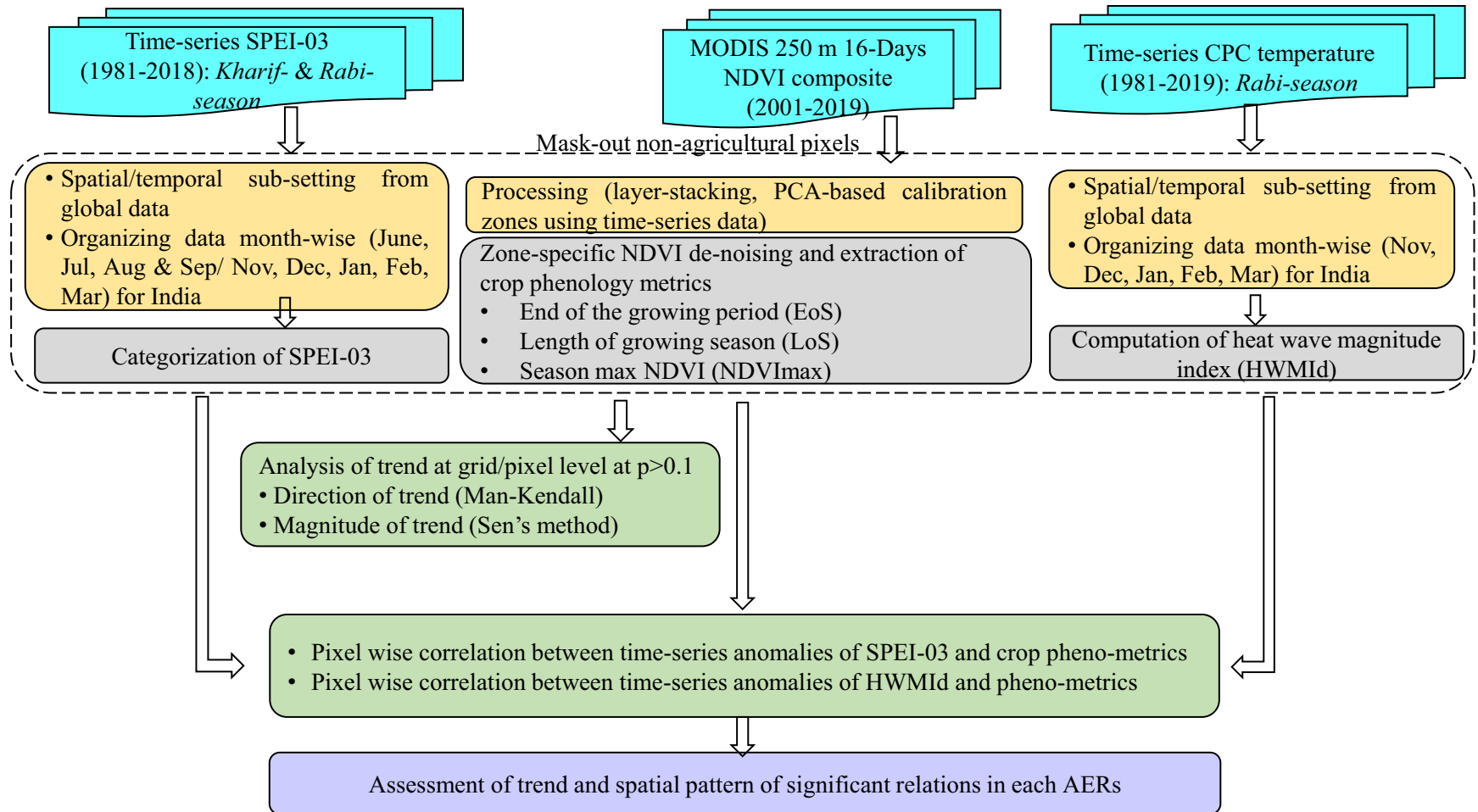


Fig 4.1 Schematic diagram of the methodology followed in the present study

4.2.1 Data

The details of data used in the study are given in table 4.1.

Table 4.1 *Datasets used for study over India.*

S No.	Data	Spatial resolution	Duration	Months	Source
1.	MODIS 16-days NDVI composite (MOD13Q1 v006)	250m × 250m	2001-2019	November-March	"https://modis.gsfc.nasa.gov/data/dataproduct/mod13.php"
2.	SPEI data at a 3-month time scale (SPEI-03) of version 3.2 Climatic Research Unit (CRU)	0.5° × 0.5°	1981-2019	• June-September • November-March	"http://spei.csic.es/spei/database"
3.	CPC Global daily maximum and minimum temperature data	0.5° × 0.5°	1981-2019	November-March	"https://psl.noaa.gov/data/gridded/data.cpc.globtemp.html"

4.2.2 Processing of MODIS NDVI time series

This study analyzed 250 m spatial resolution Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI product (MOD13Q1 v006) from 2001 to 2019 to analyze the spatio-temporal variations of agricultural croplands. The 16-day maximum value composite approach reduced cloud cover, allowing for capturing local crop phenology variations.

The study utilized TIMESAT tool to extract crop phenology metrics (pheno-metrics) from the NDVI timeseries ("Jonsson and Eklundh, 2004; Eklundh and Jönsson, 2017"). Agricultural practices in the Indian subcontinent differ significantly in terms of crop type, sowing time window, cropping pattern, intensity, irrigation potential, fertilization, etc. Thus, a single equation to fit the NDVI temporal curve may not be considered suitable for India, owing to the large variability among agricultural practices. Therefore, a data-driven approach is adopted by dividing India into different calibration zones. To determine the appropriate smoothing techniques and associated zone-specific parameter settings in TIMESAT, Principal Component

Analysis (PCA) was employed on the time-series NDVI data (“Heumann et al. 2007”). PCA is a statistical technique used to reduce the dimensionality of data. This study used multiple-year land use land cover maps (“NRSC 2014”) to extract potential agricultural areas in India.

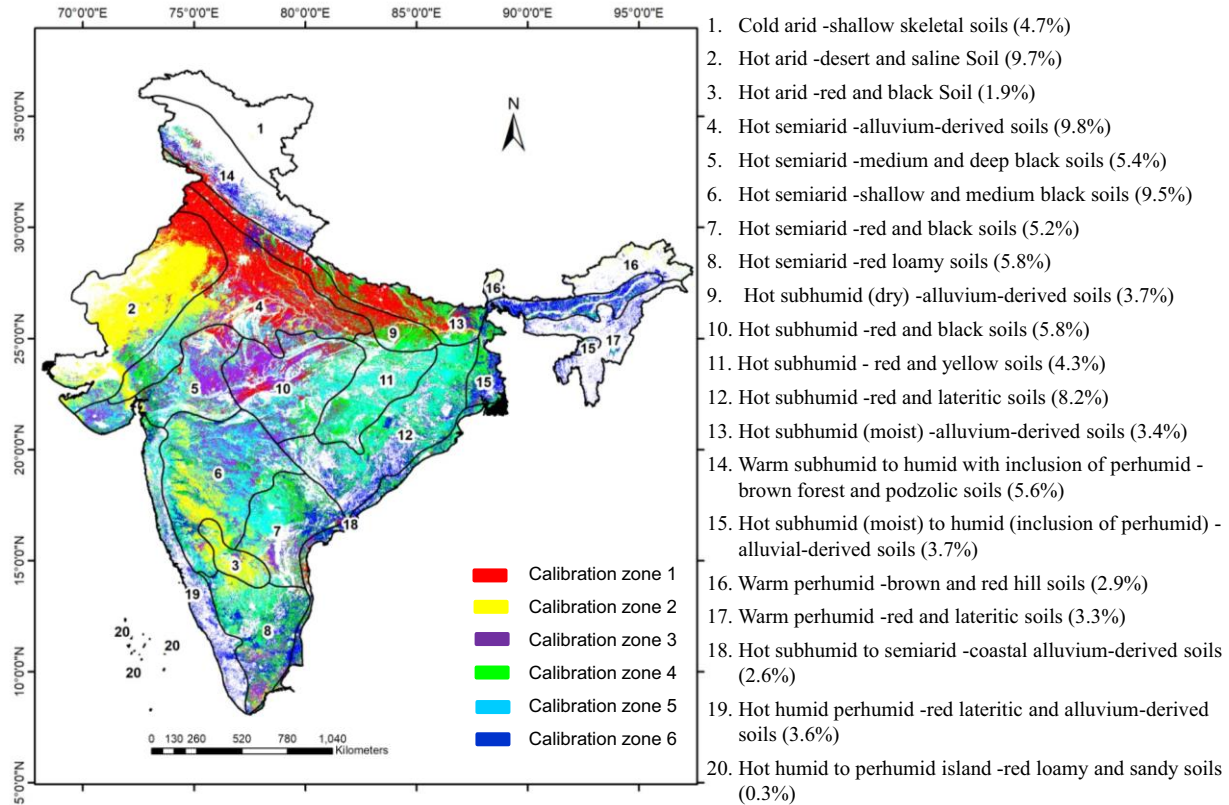


Fig 4.2 Study area encompassing agro-ecological regions (AERs) of India representing dominant climate and soil types along with 06 calibration zones; (values inside brackets depict percentage of geographical area falling in each AER) (“Kumari et al. 2023”)

To implement PCA, NDVI images were selected for each month’s first fortnight (i.e., the first 15 days) in 2006, 2013, and 2017. These years were considered “normal” years and were representative of typical crop growth periods. The data clustering technique used the first four principal components to extract six calibration zones (Fig 4.2). The fact that these four PCs explain over 95% of the variance in the data indicates that they capture a significant portion of the critical information in the NDVI images. The Savitsky–Golay filter (“Chen et al. 2004”) and double logistic function (“Tan et al. 2010”) were applied with various parameter settings (seasonality, envelope adaptation strengths, and window sizes) to denoise the NDVI profiles within each calibration zone. Please be informed that the calibration zone was delineated to

capture areas with similar patterns of temporal NDVI profiles for implementing zone-specific settings of the fitted equation.

4.2.3 Extraction of crop phenology metrics

The method described by Jönsson and Eklundh (2004) extracts phenology metrics in this study. The reflectance signals in optical wavelength regions in satellite data are often contaminated by poor atmospheric conditions such as aerosols, clouds, etc. (“Hadjimitsis et al. 2010”). Therefore, the satellite-derived time-series NDVI data contains residual noise, which should be reduced to improve its quality for further application. We have subdued this residual noise by filtering the time-series NDVI data using TIMESAT software to get a smooth NDVI profile. Three methods were used to filter the NDVI profile specific to the calibration zone: Savitzky Golay and Double logistic methods. In the current study, the other calibration-zone- specific parameters used for denoising the NDVI profile in TIMESAT software are:

- (a) Seasonal parameter = 0 (2 cropping seasons per year).
- (b) Number of envelope iterations = 2 to 3,
- (c) Adaptation strength = 4 to 5
- (d) Force minimum value = 0,
- (e) Start of season method = Seasonal amplitude
- (f) Season start and end value = 0.2.

The TIMESAT software is employed to fit a curve to the NDVI timeseries and extract the following pheno-metrics:

- (a) Start of the season (SoS): The time point when the NDVI value of the fitted curve first exceeds the 0.2 times value of the distance between the minimum and maximum NDVI values on the rising side. It signifies the onset of crop growth during the monsoon season;
- (b) End of the season (EoS): The time point when the NDVI value of the fitted curve falls below the 0.2 times value of the distance between the minimum and maximum NDVI values on the falling side of the curve.
- (c) Season maximum NDVI amplitude ($NDVI_{max}$): The difference between the maximum NDVI and the base NDVI values. $NDVI_{max}$ represents the magnitude of the NDVI increase during the growing season;

- (d) Length of the growing season (LoS): The duration between the SoS and the EoS. LoS indicates the length of time the crop experiences active growth.

4.2.4 Calculation of temporal trends of crop phenology metrics

In this study, anomalies of the crop phenology metrics (SoS, LoS, and NDVI_{max}) are computed by subtracting the long-term mean from each year's value at both the pixel and AER levels. The anomalies show the deviation of pheno-metrics from their typical values over time. Mann–Kendall test (“Mann 1945; Kendall 1976”), a widely used non-parametric statistical test for trend detection in environmental time-series data, was used for trend analysis. The Mann-Kendall test compares the ranks of each observation with those of all other observations to assess whether there is a significant increasing or decreasing trend over time. In addition to detecting significant trends, Sen's method (Sen 1968) was used to estimate the magnitude of the trend. Sen's non-parametric method calculates the median slope between all pairs of observations, providing a robust estimate of the trend magnitude. Pixel-wise Mann-Kendal test ($p > 0.1$) for the time series anomalies of SoS, LoS, and NDVI_{max} was performed for the null hypothesis of no trend against the alternative hypothesis of decreasing/increasing trend. On a similar line, trend analysis was carried out for time-series SPEI-03 data for June, July, August, and September.

4.2.5 Relating climatic extremes and crop phenology metrics

Pearson's correlation analysis was used to investigate the temporal relationships with monthly SPEI-03 of four monsoon months and phenological metrics. Generally, crop phenological events in an area are primarily determined by the climatic conditions preceding the events (“Shen et al. 2014; Güsewell et al. 2017”). The anomalies of time series SPEI-03 and crop phenology metrics were brought to 50 km spatial resolution for 2001 to 2018.

This study analyzed the spatial patterns of significant correlations ($p > 0.1$) to gain insight into how changes in rainfall affect crop phenology (SoS, LoS, and NDVI_{max}). Sensitivity analysis was performed between the phenology metrics and SPEI-03 of individual months in the monsoon season. The sensitivity analysis was conducted across the twenty different AERs of India. The sensitivity of each AER was defined as the change in phenology metrics per unit change in SPEI-03, i.e., the slope of the regression model between phenology metrics and SPEI-03 over 2001 to 2018.

4.3 Results and discussion

4.3.1 SPEI-03 and Pheno-metrics in *Kharif* season

4.3.1.1 Zone-wise temporal characteristics of SPEI-03

The average SPEI-03 for the entire country of India during the period 1981 to 2018 is presented in Fig. 4.3. Wet events ($\text{SPEI} \geq 0.5$) and dry events ($\text{SPEI} \leq -0.5$) were calculated for each monsoon month (June to September) during the same period for each AER and are summarized in Table 4.3. Additionally, the entire time series (1981 to 2018) was divided into four decades to compute the percentages of occurrence of dry, wet, and normal ($-0.5 < \text{SPEI} < 0.5$) events for each specific month, as shown in Fig. 4.4.

Fig. 4.3 shows that wet and dry events based on SPEI-03 are well distributed across the time series (1981 to 2018). Notably, the severity of the dry events is found to be more pronounced in the later part of the time series, particularly during the initial part of the 21st century. Conversely, the frequency and intensity of wet events were observed to be higher towards the end of the time series (2006-2018).

Based on the monthly frequency of occurrence of wet ($\text{SPEI} > 0.5$) and dry ($\text{SPEI} < -0.5$) events, the AERs were classified into three categories: wetting, drying, and mixed (Table 4.2). AER 2, 3, 4, and 14 exhibited a higher occurrence of wet events compared to dry events during the period 1981 to 2018 and are classified as "Wetting" regions (Table 4.2). These AERs predominantly cover the hot/warm, arid regions of India. Conversely, AERs 10, 11, 13, 15, and 17 displayed a "Drying" pattern with more dry events than wet events. These AERs are primarily located in hot sub-humid regions of India. The remaining AERs showed mixed results.

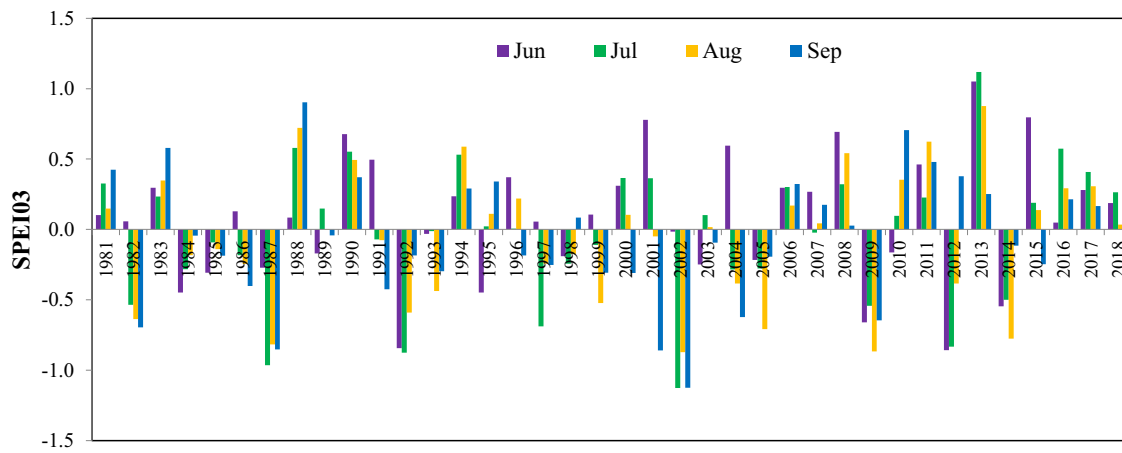


Fig 4.3 Temporal variation of SPEI-03 over India during 1981-2018 (“Kumari et al. 2023”)

Table 4.2 Distribution of dry ($SPEI-03 \leq 0.5$) and wet ($SPEI-03 \geq 0.5$) month counts in each AER over the monsoon months (June - September) during 1981-2018 (“Kumari et al. 2023”)

			June		July		August		September		
			AER	Wet	Dry	Wet	Dry	Wet	Dry	Wet	Dry
Wetting	2	13	10	9	8	11	7	9	8		
	3	17	10	13	11	13	11	12	15		
	7	12	12	12	9	11	7	13	10		
	14	20	2	21	7	17	11	9	9		
Mixed	4	15	6	12	11	8	10	7	12		
	5	9	9	9	11	13	9	13	11		
	6	8	8	8	12	11	11	12	14		
	9	15	7	11	12	6	15	5	17		
	8	7	13	11	9	11	11	12	10		
	19	9	11	9	8	10	11	12	9		
Drying	10	10	13	10	16	5	15	7	16		
	11	9	12	9	16	5	17	4	21		
	13	8	10	8	14	4	20	7	16		
	15	10	15	5	11	8	18	10	13		
	17	11	17	7	13	6	17	9	15		

The decade-wise analysis of the monthly occurrence of wet, dry, and normal events, as depicted in Fig. 4.4, reveals that drought events (dry) were evenly distributed in the first decade (1981 to 1990). However, there was a shift in the distribution of dry events in the subsequent decades. Notably, the frequency of late-season drought was high during 2001 to 2010, whereas early-season drought was more prevalent in the last decade (2011 to 18).

Most extreme drought events occurred between 2001 and 2010, consisting of 10%, 20%, 30%, and 40% for June, July, August, and September, respectively. No drought was observed during September 1991 to 2000 and 2011 to 2018, while the other months experienced dry spells in all decades. In the decade of 2001 to 2010, almost all the months of SW monsoon exhibited drought incidences (early, mid, and late-season). However, the frequency of dry spells mostly coincided with crops’ reproductive/maturity growth stage due to the onset of late-season drought. Early-season drought was found to be more prevalent in the decade 2011 to 2018.

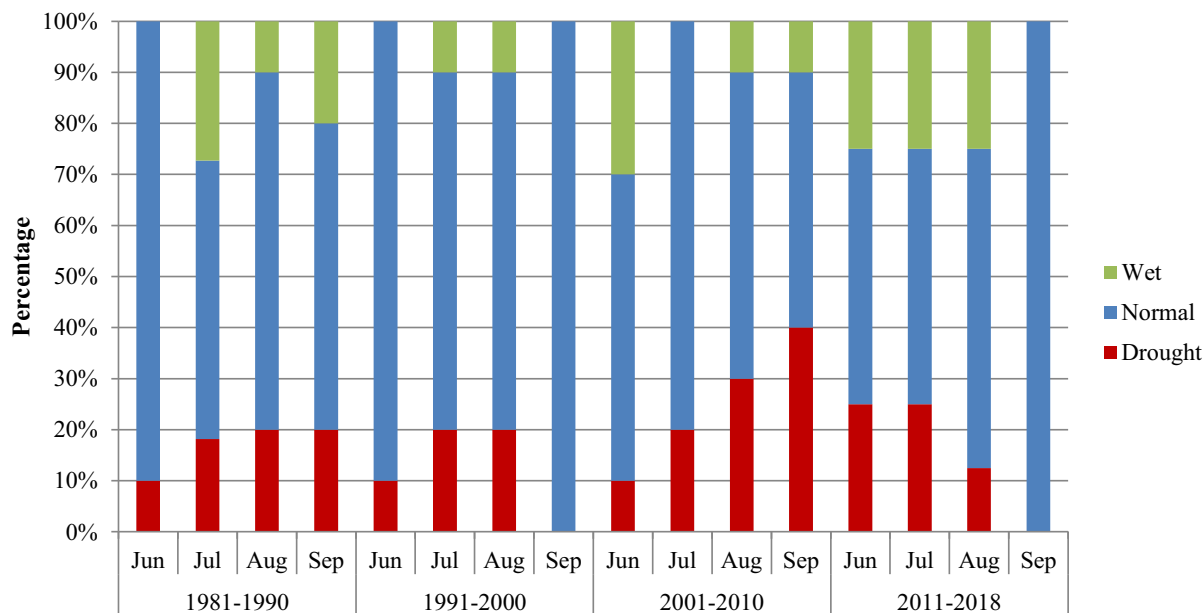


Fig 4.4 Frequency (%) of occurrence of wet, normal, drought events during different decades from 1981 to 2018 based on SPEI-03 (“Kumari et al. 2023”)

4.3.1.2 Spatial patterns of temporal trend of crop phenology metrics over India

The spatial distribution of the temporal trends in crop phenology metrics (SoS, NDVI_{max}, LoS) during the southwest monsoon season was analyzed at 250-m spatial resolution using time-series NDVI data from 2001 to 2018, employing the Mann-Kendal method. The analysis excluded AER 01, 16, and 20, due to negligible agricultural activity. The resulting spatial patterns of temporal trends of the phenology metrics are presented in Fig. 4.5.

An increasing trend ($>1 \text{ day year}^{-1}$) in SoS, indicating a delay in sowing activities during the monsoon season, was observed across large parts of the country, including north, northwest, and Deccan plateau regions (AER 04, AER 02, AER 08, AER 09 and AER 13). Conversely, a pre-occurrence of sowing activities or a decreasing trend ($< -1 \text{ day year}^{-1}$) in SoS was found in certain parts of northern, central, and eastern India (AER 14, AER 12, and AER 10). Previous research studies examining spatio-temporal trends in phenology across India (“Chakraborty et al. 2014; Das et al. 2020”) or specific regions like the Indo-Gangetic Plain (“Sehgal et al. 2011; Chakraborty et al. 2018b”) have reported divergent findings. These discrepancies arise from variations in the period considered, the spatial resolution of the data, choice of fitting function and pheno-metrics retrieval algorithms, and the aggregation of the results based on administrative or agro-climatic boundaries. However, the majority of these studies have reached

a consensus that the SoS trend is increasing significantly in many parts of India. The present study found that approximately 59 % of agricultural areas exhibited an increasing trend in SoS, while 21% showed a decreasing trend. It is apt to mention that the highest proportion of AER 04 (64%) experienced a delay in the SoS, whereas a pre-occurrence of SoS was noted in nearly 31.7% of the area in AER 09.

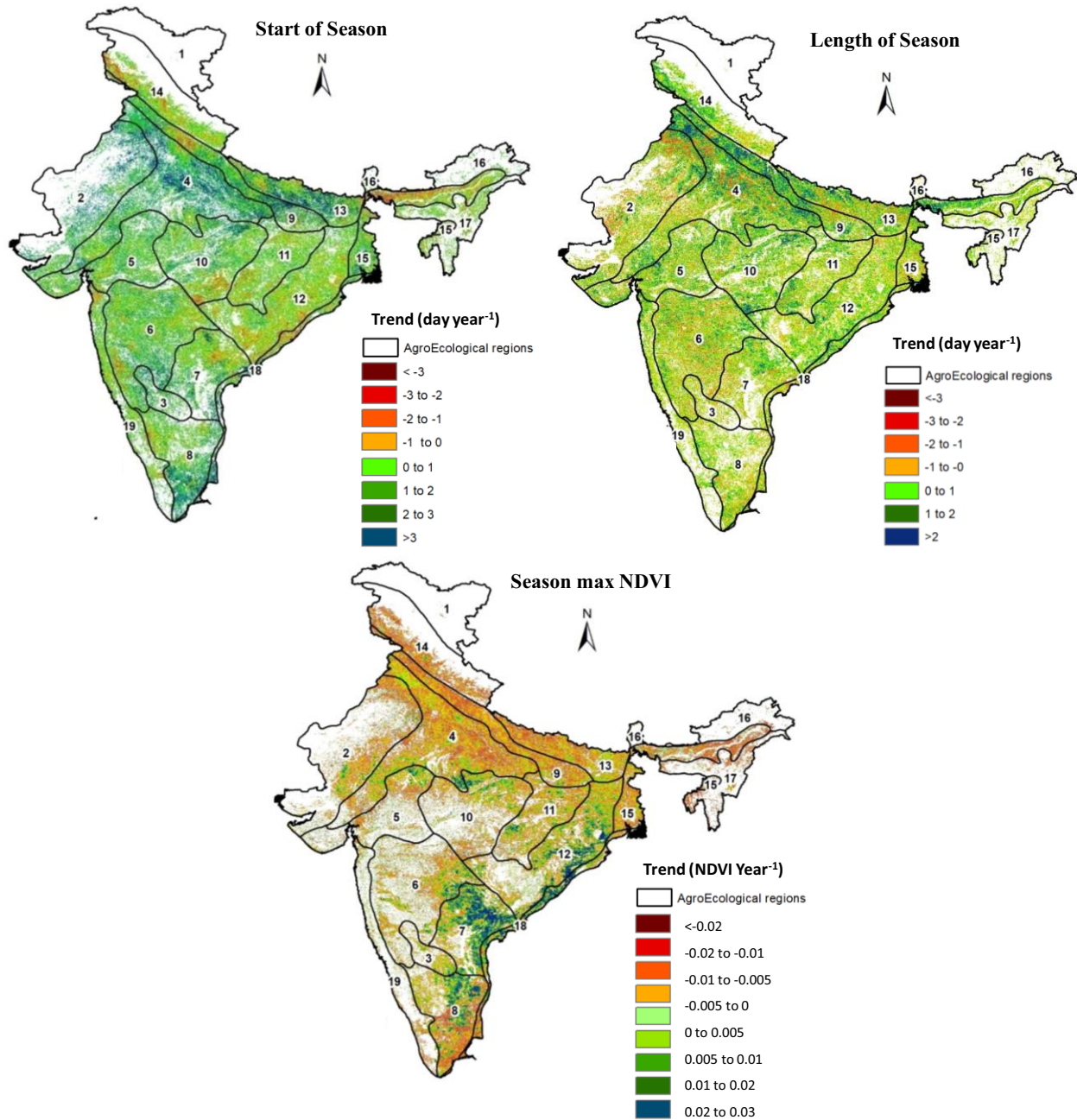


Fig 4.5 Spatial patterns of temporal trends of crop phenology metrics (SoS, LoS, NDVI_{max}) in different AERs during *kharif* season, 2001-2018 (“Kumari et al. 2023”)

The spatial patterns of temporal trends of NDVI_{max} (crop vigor) during the monsoon season (Fig. 4.5) revealed a decreasing trend over large contiguous areas in the north, east, central, west, and south of India (AER 14, AER 04, AER 09, AER 13, AER 15, AER 08, and AER 02). Conversely, an increasing trend of NDVI_{max} was observed in India's central and southern regions (AER 07, AER 12, AER 18, AER 08 and AER 10). The central part of India, characterized by vertisols or black soil with high water holding capacity, might be experiencing changes in NDVI_{max} trend due to improved crop management practices (irrigation, fertilization, plant protection, etc.) or the introduction of new crops in the region. Approximately 23.3% of the agricultural area exhibited a positive trend in NDVI_{max}, while only 5.17% displayed a decreasing trend. The region with the highest percentage of areas experiencing increasing trends in NDVI_{max} was AER 07 (33.1%), while AER 09 had the highest proportion of areas with decreasing trends (24.25%). The spatial analysis of temporal trends in LoS (shown in Fig. 6) revealed increasing trends ($> 1\text{ day year}^{-1}$) in a significant portion of the northern, eastern, and some parts of central regions of India. In contrast, decreasing trends ($< -1\text{ day year}^{-1}$) were observed in some western, central, and southern areas. Approximately 61% of the agricultural area exhibited an increasing trend in LoS, while 28% displayed a decreasing trend. The regions with the highest percentage of area under increasing and decreasing trend in LoS were AER 09 (73.1%) and AER 02 (38.12%), respectively.

4.3.1.3 Influence of drought and wet years on crop phenology metrics

AER-wise mean phenology metrics (i.e., SoS, LoS, and NDVI_{max}) based on 250-m MODIS NDVI data of 2001 to 2018 are given in Fig. 4.6. Results revealed substantial variation in phenology metrics among the different AERs. No consistent relationship was found between AER-wise mean pheno-metrics. For instance, early SoS coincided with long-duration LoS in AER 09, whereas short-duration LoS was associated with late SoS in AER 08. The mean NDVI_{max} also exhibited extensive divergence among different AERs, with higher values observed in AER 10-17 and lower in AER 2, 8, 9, and 19.

To assess the sensitivity of the pheno-metrics to SPEI-03, two contrasting years, namely 2012 and 2013, were selected based on overall dryness/wetness conditions. The year 2012 was characterized by dry conditions, while 2013 experienced wet conditions, according to the India Meteorological Department (IMD) and National Agricultural Drought Assessment and

Monitoring System ([“https://www.ncfc.gov.in/nadams”](https://www.ncfc.gov.in/nadams)). Spatial maps of monthly SPEI-03 during 2012 and 2013 in Fig. 4.7 clearly illustrate the contrasting wetness conditions with moderate to severe drought prevailing in most areas of India from June to August 2012 and moderate to severe wetness dominating during the monsoon months of 2013.

These dry and wet conditions during the monsoon months may have influenced crop phenology by altering the crop-growing environment. AER-wise mean crop phenology metrics (SoS, LoS, and NDVI_{max}) during drought and wet years demonstrated the impact of climatic extremes on crop phenology across different AERs. In dry conditions, SoS exhibited delays in sowing activities and emergence, LoS showed a decrease in the length of the crop growing period, and NDVI_{max} displayed reduced seasonal amplitude. These effects may be attributed to the selection of short-duration crops or failed sowing due to inadequate soil moisture availability. The temporal pattern of AER-wise phenology metrics is graphically represented in Fig. 4.8, and the spatio-temporal pattern is depicted in Fig. 4.9. These comparisons revealed that climatic variations significantly affect crop phenology. In 2013, there was generally an advancement of SoS ($\Delta\text{SoS} = -25 \pm 28$ days), while a slight delay of SoS was observed during 2012 ($\Delta\text{SoS} = 44 \pm 23$ days). NDVI_{max} also exhibited reduced amplitude during drought years compared to wet years. The AERs showed minimum changes in pheno-metrics between 2012 and 2013 are climatic resilient. This may be due to high irrigation potential, water holding capacity of the soil, or prevailing cropping pattern.

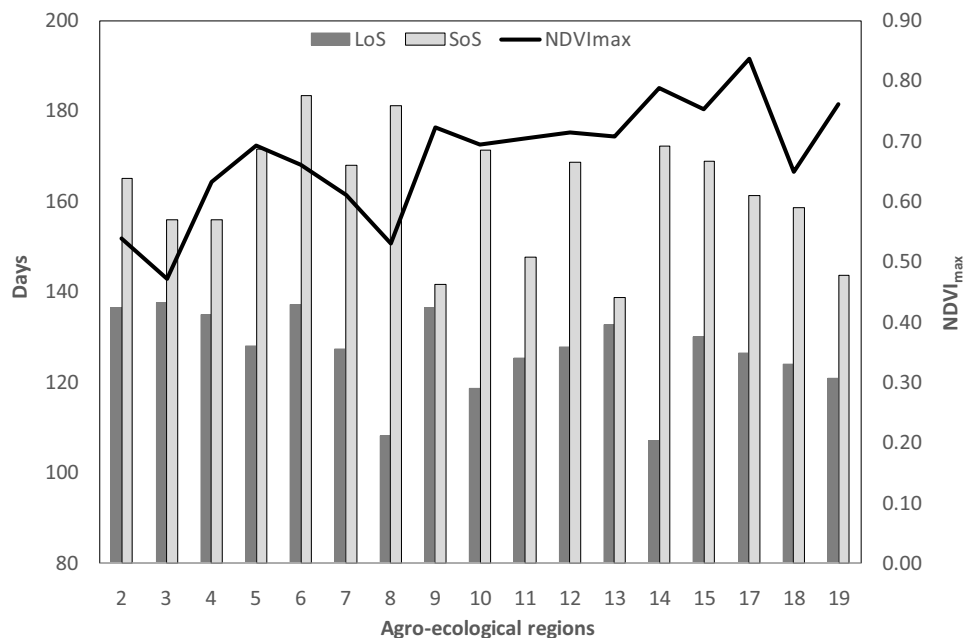


Fig 4.6 AER-wise mean SoS (Julian day), LoS (Number of days) and NDVImax over 2001-2018 (“Kumari et al. 2023”)

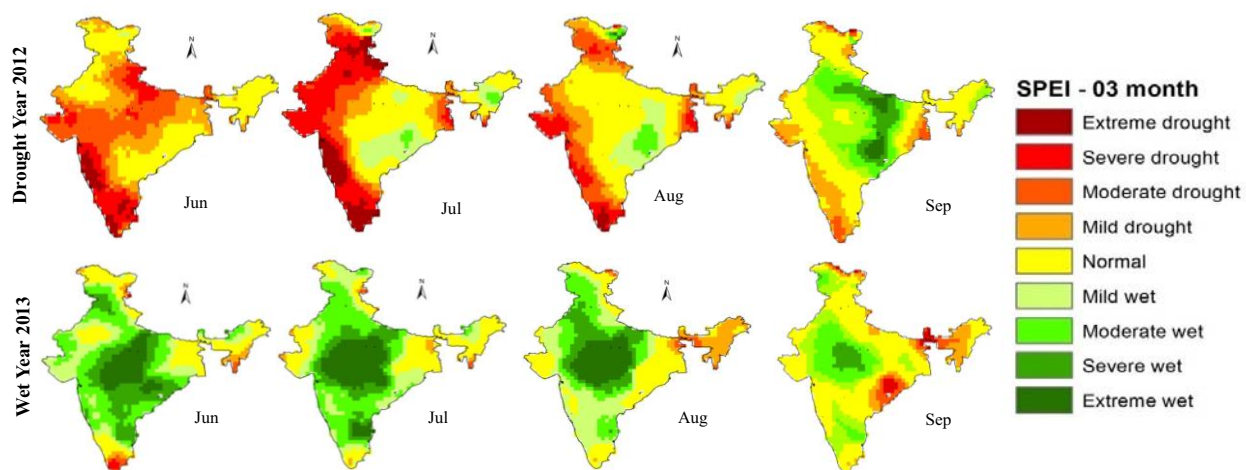


Fig 4.7 Spatial pattern of SPEI-03 of monsoon months during a drought (2012) and wet (2013) years (“Kumari et al. 2023”)

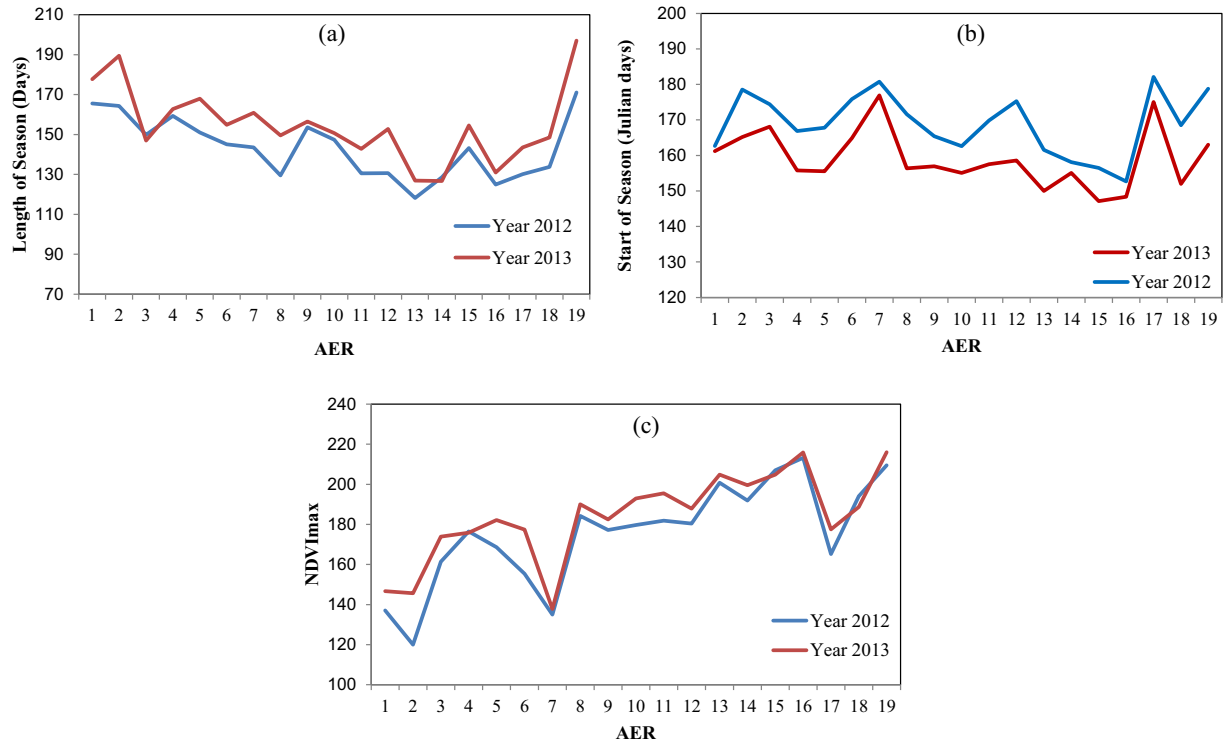


Fig 4.8 Temporal pattern of pheno-metrics in wet and dry year for each AER (a) LoS, (b) SoS, and (c) NDVImax (“Kumari et al. 2023”)

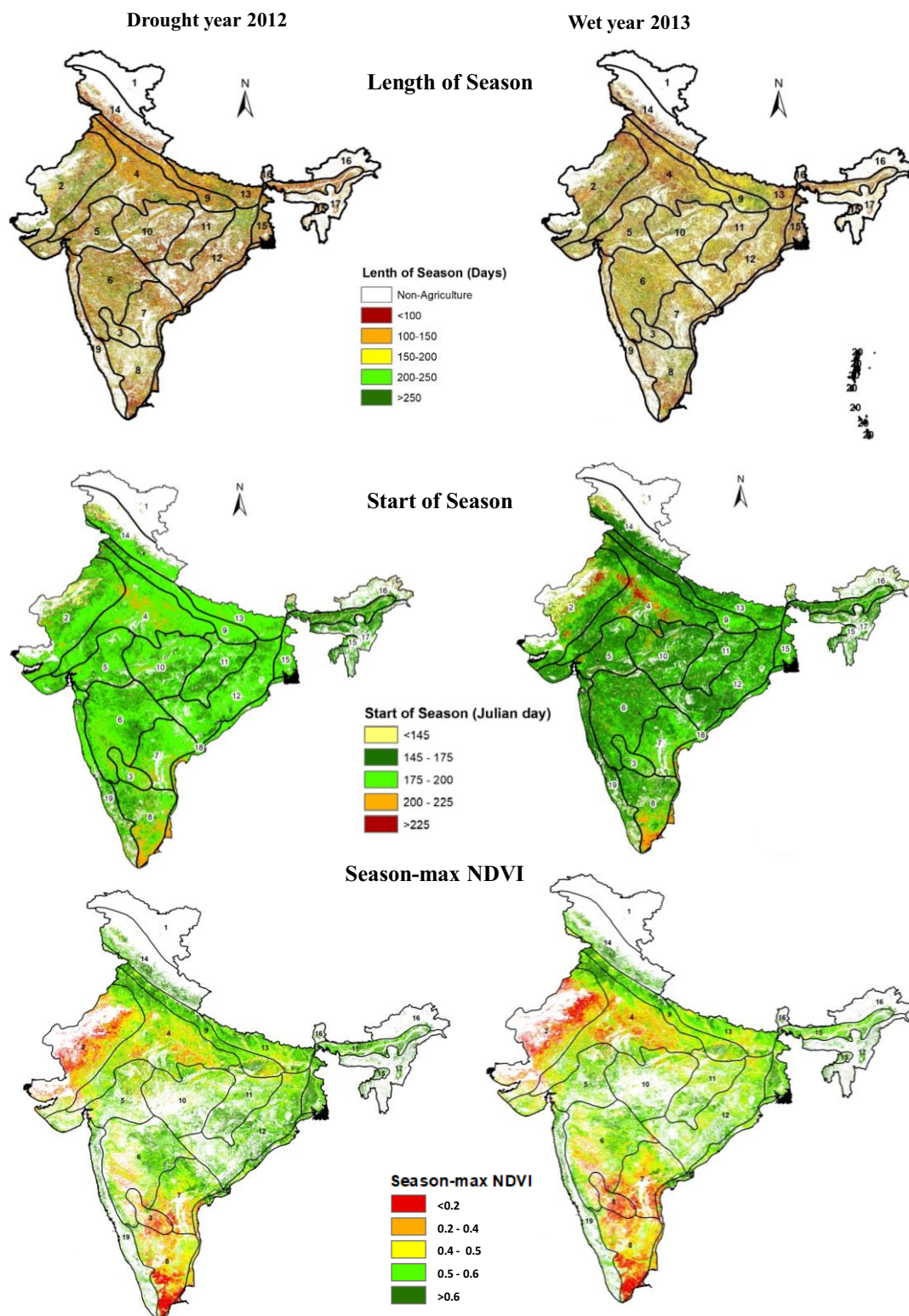


Fig 4.9 Spatial pattern of pheno-metrics (LoS, SoS and NDVImax) in dry (2012) and wet (2013) years in each AERs (“Kumari et al. 2023”)

4.3.1.4 Relationship between SPEI-03 and crop phenology metrics

Correlations between SPEI-03 and agricultural activities

The Pearson correlation coefficient (at $p < 0.1$) was calculated to assess the influence of wet and dry conditions on crop phenology metrics by analyzing the relationship between SPEI-03 and crop pheno-metrics. Fig. 4.10 presents pixel-wise correlation between monthly SPEI-03 and the pheno-metrics. Several factors, such as the introduction of new crop types or crop varieties, irrigation, and crop management practices, may contribute to changes in crop phenology metrics, and climate variations across different AERs. Around two-thirds of India's agricultural land is under rainfed, making southwest monsoon rainfall a crucial factor in agricultural productivity. The spatio-temporal distribution of rainfall and the climatic water demand govern crop growth and development, making SPEI-03 a potentially attributing factor to crop phenology during the monsoon season.

The start of the crop growing season is determined by crop sowing activities, influenced by soil moisture availability during the early part of the season, mainly determined by the onset of rainfall. In India, the southwest monsoon typically begins in June, and the timely onset of the monsoon significantly impacts crop sowing operations, especially under rainfed conditions. A delayed onset or insufficient rainfall during the early monsoon season can delay crop sowing operations. Consequently, negative SPEI-03 during the early monsoon season results in positive anomalies at the start of the season, indicating a delay in SoS and vice-versa. A significant negative correlation between SoS and June rainfall was observed in large areas of India, highlighting the critical role of June rainfall in the timely onset of the crop season (Fig. 4.10). However, this relationship diminishes as the monsoon progresses into July and August. The LoS is also dependent on the timely start of the crop season. Therefore, June month's SPEI-03 also positively correlates with LoS over large areas of India. The SPEI-03 and SoS correlation analysis revealed a significant negative correlation in June and July, primarily concentrated in Central and Northern India (AER 10, AER 11 and AER 14).

The $NDVI_{max}$, which represents crop vigor, may be subject to change due to variations in crop type/varieties within the study area. An increase in SPEI-03 (indicating wetter conditions) correlated positively with $NDVI_{max}$, with a correlation coefficient greater than 0.5. Monsoon crops generally reach their peak vegetation phase in August-September. Timely sowing followed

by well-distributed rainfall becomes critical for achieving high crop vigor ($NDVI_{max}$). Accordingly, June's SPEI-03, crucial for SoS, showed a positive correlation with $NDVI_{max}$ over large areas of India. Similarly, August SPEI-03 strongly correlated with $NDVI_{max}$ across India. The analysis revealed that the majority of AERs exhibited the maximum NDVI values in August to September, with the largest area (23%) showing a significant positive correlation with August's SPEI-03 (Fig. 4.10). For the relationship between SPEI-03 and pheno-metrics, we combined statistically significant pixels ($p < 0.1$) in June, July, and August across the study area (Fig. 4.11). The results indicate a uniform spread of significant correlation (positive/negative) between SPEI-03 and SoS/LoS throughout India. However, areas exhibiting a substantial correlation between SPEI-03 and $NDVI_{max}$ are predominantly concentrated in AER 2 and AER 5, highlighting the crucial impact of wetness/dryness on agriculture in these regions of India. Previous studies have primarily focused on analyzing the spatio-temporal variation of either rainfall or temperature on vegetation phenology ("Fu et al. 2018; Kang et al. 2018; Chakraborty et al. 2014"). Furthermore, the findings from other studies have demonstrated that croplands are particularly sensitive to climatic variability ("Javed et al. 2021; Felton et al. 2019"). Consequently, the current study investigated the impact of dry and wet climatic variability on crop phenology. The significant aspect of this study lies in exploring the effects of drought and wetness, specifically during the months of the crop growing season. In contrast to most previous studies ("Potopová et al. 2015; Liu et al. 2018"), this study focuses on examining the relationship between drought and pheno-metrics during the cropping season rather than considering the entire annual calendar.

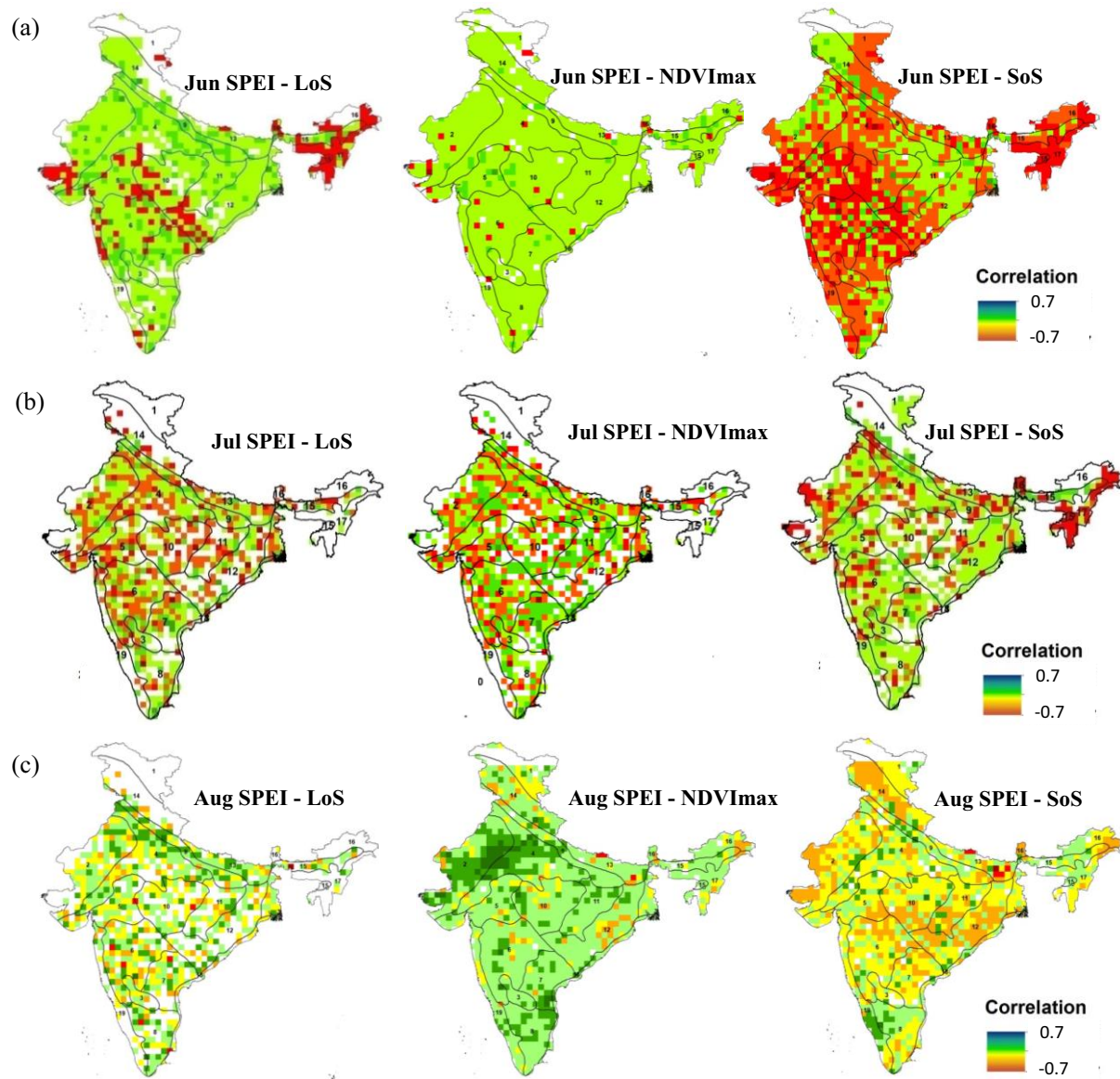


Fig 4.10 Correlation between SPEI-03 vs phenology metrics (LoS, NDVImax and SoS) (a) June, (b) July, and (c) August months (“Kumari et al. 2023”)

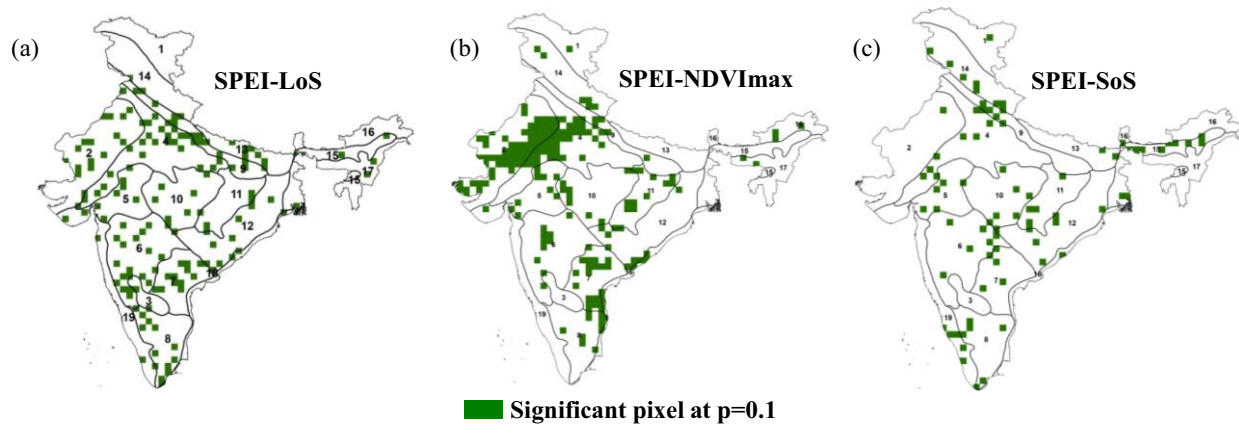


Fig 4.11 Statistically significant pixels ($p < 0.1$) in any of Jun, July and August months for SPEI-03 vs crop phenological metrics relation; (a) SPEI-03 and LoS, (b) SPEI-03 and NDVI_{max}, and (c) SPEI-03 and SoS

4.3.1.5 Sensitivity of pheno-metrics with SPEI-03

Table 4.3 provides the sensitivity of the phenology metrics to monthly SPEI-03 across different AERs. The slope in the table represents the change in the magnitude of pheno-metrics (expressed in "days" for SoS and LoS) per unit change in SPEI-03. Our observations indicate that a one-unit increase in SPEI-03, i.e., indicating higher wetness, leads to an early SoS of 01 to 18 days, depending on the AERs. Almost all the AERs exhibit a pre-occurrence of SoS with increasing wetness (Table 4.3). The pre-occurrences of SoS were particularly noticeable in semi-arid regions with black soils (AER 03, 04, 05, 06, 07) due to their high moisture holding capacity, as well as in humid/sub-humid AERs such as 13, 14, 15, 17. Conversely, semi-arid climates with red lateritic soils (AER 08, 09, 11, 12), characterized by poor water holding capacity, showed little or no change in SoS.

Similarly, increased moisture availability resulted in an extended length of the crop-growing period. Abundant soil moisture availability may trigger the farmers to select water-demanding crops for a longer duration. The sensitivity of LoS to wetness varied across different climatic regions. Humid/sub-humid climates showed negative or no sensitivity of LoS to an increase in wetness, while semi-arid AERs exhibited a rise in LoS with greater SPEI-03. LoS sensitivity increased from arid to semi-arid regions (AER 02 to AER 08) and decreased from semi-humid to humid areas (AER 10 to AER 19). In July and August, NDVI_{max} also displayed positive sensitivity to increased wetness, indicating high crop vigor in response to greater soil moisture availability across most AERs. We noted that the effect of dryness/wetness on SoS is more pronounced than LoS, consistent with the findings of “Ge et al. 2021”.

Table 4.3 Sensitivity of SoS (Julian day SPEI-03⁻¹), LoS (Day SPEI-03⁻¹) and NDVI_{max} (NDVI value SPEI-03⁻¹) with SPEI-03 over different AERs

AER	SoS			LoS			NDVI _{max}		
	Jun	Jul	Aug	Jun	Jul	Aug	Jun	Jul	Aug
2	-4.47	-7.17	-10.64	4.06	2.87	3.96	0.002	0.058	0.106
3	-6.57	0.04	-0.09	1.71	5.57	-0.34	-0.008	0.015	0.062
4	-5.07	-2.64	-2.14	0.44	0.22	3.50	-0.004	0.030	0.052
5	-12.01	0.60	-3.40	0.38	-1.66	0.77	-0.033	0.006	-0.003
6	-9.54	-2.26	-6.23	2.13	2.67	-1.46	-0.003	0.029	0.029
7	-6.72	-0.64	-8.17	4.77	7.38	3.08	0.024	0.052	0.064
8	-2.36	-0.87	2.92	2.53	5.22	4.73	0.015	0.020	0.049
9	0.59	-1.03	-2.39	4.33	2.61	2.87	0.005	0.019	0.024
10	-5.25	-0.50	-5.79	-2.68	-1.33	0.25	-0.018	0.008	0.002
11	1.38	-2.26	-8.54	-1.06	-0.31	-0.58	0.018	0.038	0.033
12	-0.69	0.78	-11.26	-1.18	0.19	2.67	0.018	0.025	0.023
13	-6.37	-9.19	-11.71	2.85	4.10	6.07	-0.001	0.001	-0.004
14	5.63	-5.36	-10.94	-1.97	-2.29	-0.36	-0.010	0.006	0.008
15	-2.76	-1.27	-1.84	-3.82	0.44	-0.71	-0.012	-0.006	0.000
17	-18.25	-16.23	-3.02	-3.13	2.80	1.74	0.003	0.002	-0.003
18	-3.15	-0.66	-4.89	1.44	2.27	-8.45	-0.007	-0.003	-0.002
19	-8.36	-0.79	3.72	-2.27	0.98	0.86	0.027	0.038	0.040

The sensitivity analysis revealed a rapid increase in sensitivity from arid to semi-arid regions, followed by a decline from semi-humid to humid areas (“Piao 2011; Javed et al. 2021”). Furthermore, we found that extreme wet or dry years resulted in relatively less change in NDVI_{max} than in the SoS. This finding aligns with the results of other studies (“Jiang et al. 2018; Javed et al. 2021”). Previous research (“Glade et al. 2016; Hao et al. 2019; Stocker 2014”) has reported that excessive rainfall can lead to cloudy conditions, obstructing incoming solar radiation and reducing vegetation photosynthesis and plant growth. Therefore, the effect of the extremely wet conditions on the NDVI_{max} during the peak growth stage is not considerable since crops require ample solar radiation for photosynthesis during this phase (“Hao et al. 2019”). Pheno-metrics in semi-arid regions exhibited more wetness and dryness sensitivity than in the arid regions. This contrasts with the notion that arid regions, characterized by limited water availability, are more sensitive to climatic variations (“Delgado et al. 2018”). This discrepancy may be due to the apparent plant acclimatization and resilience to drought conditions due to physiological adaptations (“Ma et al. 2015”).

4.3.2 HWMId and Pheno-metrics in *rabi* season

4.3.2.1 Zone-wise temporal characteristics of HWMId

The area under frequent hot extremes in March during the period 1981 to 2019 for India is presented in Fig. 4.12. It is evident that areas under extreme heat events have increased over the years, especially in the 21st century. The year 2004 found to have highest area coverage (>90% area) all across the country under extreme heat events in March, followed by 2010 and 2009 with 79% and 61% coverage, respectively. Most extreme heat events occurred between 2001 and 2019, comprising more than 20% of the area during March.

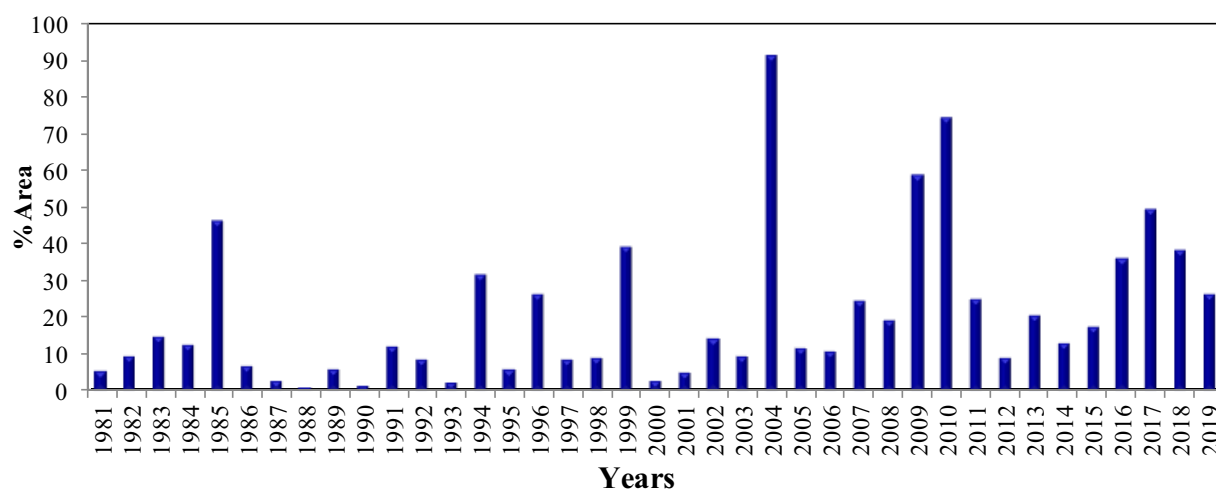


Fig 4.12 Graph showing percent area under extreme heat during March spanning from 1981 to 2019

Fig 4.13(a) shows the frequency of HWMId over the period 1981 to 2019 for November, December, January, February, and March. In contrast, Fig 4.13(b) shows the frequency of high magnitude of hot-extremes (HWMId >8) over the same period. Though the spatio-temporal variability of extreme heat events is high and well distributed across India, some regions show frequent occurrence over a period of 39 years with a low magnitude of HWMId and vice-versa. More than 12 out of 39 years are observed in AER 11 during November, in AER 11 and AER 12 during December, in AER 12 during February, and AER 2, AER 05, AER 15, and AER 17 during March. There is a similar spatial pattern of more frequent heat events with high magnitude HWMId in March over India's western (part of AER 02, AER 05) and eastern part and eastern coast (AER 15, AER 16). Additionally, more frequent heat events with high magnitude HWMId are increasing in November in the central part of India (AER 06), during December in AER 03, AER 06, AER 10, AER 11, AER 12, and during January in AER 04.

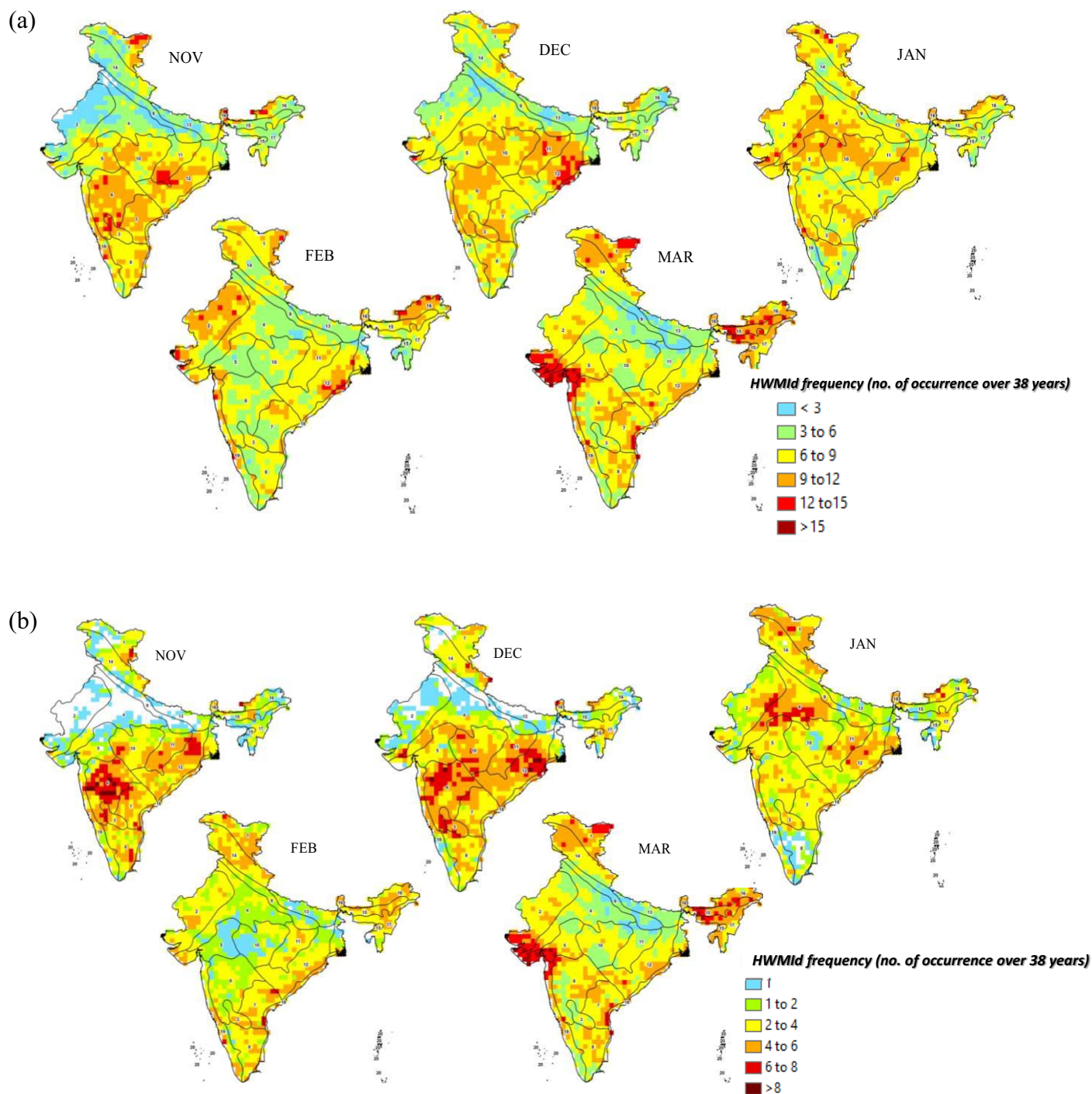


Fig 4.13 Spatial pattern of frequency of occurrence of extreme heat events over period of 1981-2019 (a) frequency of HWMIId (b) frequency of HWMIId (>8)

4.3.2.2 Spatial patterns of the temporal trend of crop phenology metrics in the *rabi* season

The spatial distribution of temporal trends in crop phenology metrics (EoS, NDVI_{max}, and LoS) during the *rabi* season are presented in Fig 4.14.

A decreasing trend ($<-1\text{day year}^{-1}$) in EoS, indicating earlier senescence during the *rabi* season, was observed in the northern and Deccan plateau regions (AER 04, AER 06, AER 08, and AER 15). Conversely, a delay in maturity or an increasing trend ($>-1\text{day year}^{-1}$) in EoS was found in parts of central and western India (AER 02, AER 04, AER 05, AER 10, AER 11, and AER 14). Approximately 37% of agricultural areas exhibited an increasing trend in EoS, while 32% showed a decreasing trend. Notably, the highest proportion of AER 04 (24.28%) experienced a delay in EoS, whereas early EoS occurred in nearly 11.7% of AER 08.

The spatial patterns of temporal trends in NDVI_{max} (crop vigor) during the *rabi* season (Fig 4.14) revealed an increasing trend over large contiguous areas in central India (AER 02, AER 04, AER 05, AER 06, AER 07, AER 09, AER 10, AER 11, AER 13). Similar to the *kharif* season phenology trend, this could be due to improved crop management practices or the introduction of crops with higher NDVI_{max} in the region. Conversely, a decreasing trend of NDVI_{max} was observed in the Indo-Gangetic Plain (IGP) and southern regions of India (AER 08 and AER 19). Approximately 53% of the agricultural area exhibited a positive trend in NDVI_{max}, while only 20.8% displayed a decreasing trend. AER 04 had the highest percentage of areas experiencing increasing trends in NDVI_{max} (22.7%), while AER 08 had the highest rate of areas with decreasing trends (16.47%).

The spatial analysis of temporal trends in LoS (Fig 4.14) revealed increasing trends ($>1\text{day year}^{-1}$) across India, particularly in AER 02, AER 03, AER 04, AER 05, AER 08, AER 09, AER 12, AER 13. In contrast, decreasing trends ($<-1\text{day year}^{-1}$) were observed in some regions of the western and central parts. Approximately 45% of the agricultural area exhibited an increasing trend in LoS, while 21% displayed a decreasing trend. AER 04 had the highest percentage of area under increasing trends in LoS (29%), while AER 11 had the highest area under decreasing trends (10.7%).

In a study by Das et al. (2020) using 8-km GIMMS NDVI data, a significant portion of India experienced a decreasing trend in LoS. However, “Chakraborty et al. (2018b)”, using 4-km STAR-global vegetation health products-NDVI, found an increasing trend in LoS. Using 250-m MODIS data, the current study also revealed a rising trend in LoS across a significant part of India. It is important to note that these studies differed in the spatial resolution of satellite data

and the time series considered. Despite some discrepancies, the current study's findings align with those of other reported studies conducted in various regions of India.

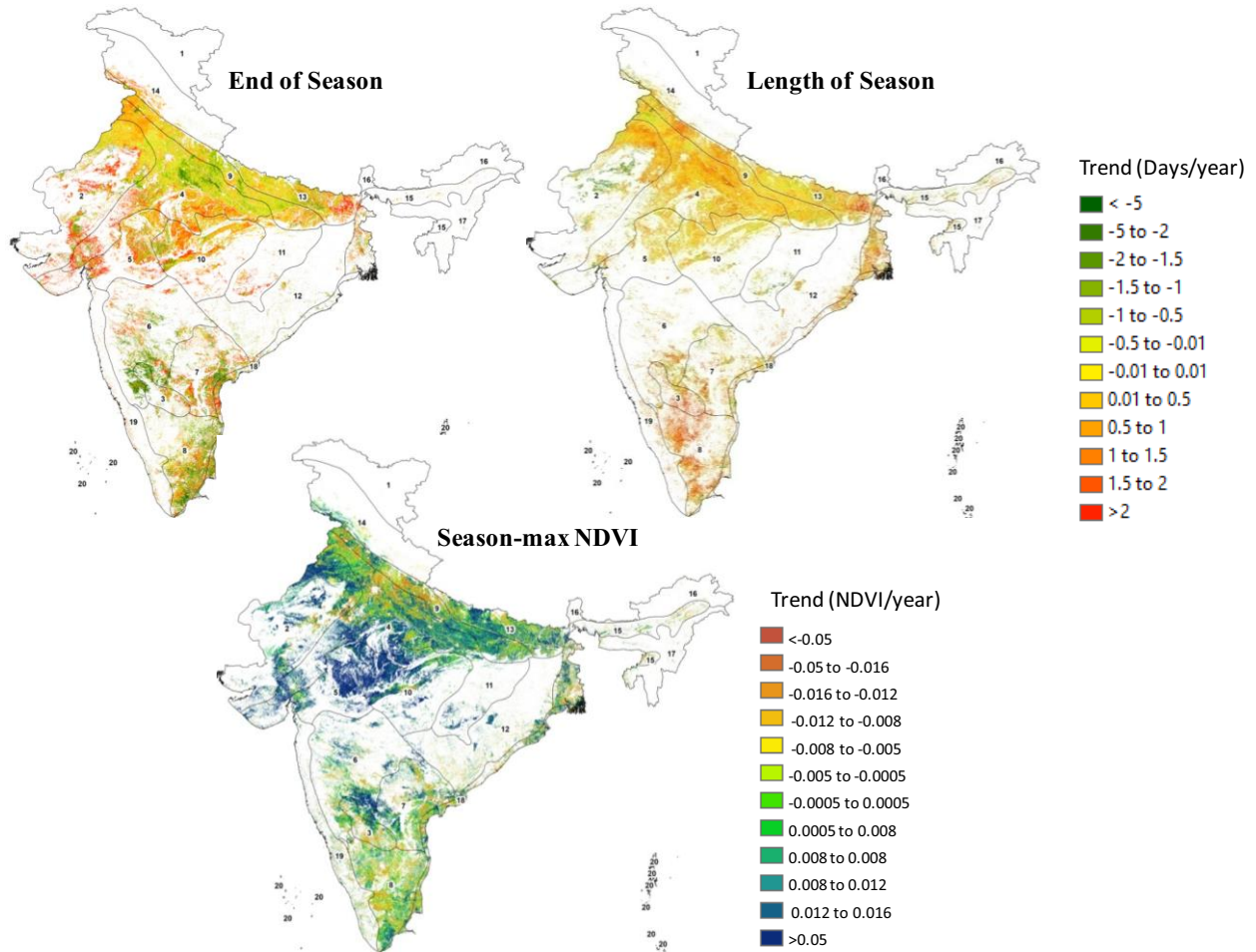


Fig 4.14 Spatial patterns of temporal trends of crop phenology metrics (SoS, LoS, NDVI_{max}) in different AERs during Rabi season (2001-2019) (Kumari et al. 2023)

4.3.2.3 Relationship between SPEI-03 and crop phenology metrics

Relationship between HWMId and Phenology

The pixel-wise correlation between monthly HWMId and crop pheno-metrics was analyzed using the Pearson correlation coefficient (at $p < 0.1$) across India during the *rabi* season (Fig. 4.15 and 4.16). As discussed, changes in plant physiological processes are evident through alterations in phenology. Various environmental conditions and human interventions, such as agricultural management practices, including irrigation, fertilizer, and pesticide application, may contribute to temporal changes in crop phenology, aside from existing weather conditions. This

effect could be more specific during the *rabi* season due to its higher dependency on irrigation and lesser reliance on rainfall, in contrast to the *kharif* season, where the monsoon plays a significant role. Therefore, extreme temperatures are crucial in governing crop growth and water demand during the *rabi* season.

The end of the crop growing season is determined by crop senescence, which is influenced by air temperature throughout the season, particularly towards the end. The types of crops grown in the study area also affect the season's end. Insufficient rainfall during the season or a scarcity of irrigation facilities forces farmers to cultivate short-duration crops, resulting in an early EoS. Moreover, heat stress during the growing season can lead to premature crop maturity. Consequently, a high HWMId value during the crop season results in negative anomalies in EoS, indicating an earlier EoS, and vice versa.

A significant negative correlation between EoS and HWMId for February and March was observed across large areas of India, highlighting the critical role of hot extremes in the early cessation of the crop season. Hot extremes during the post-anthesis (reproductive) phase accelerate crop growth, reducing crop yield (“Rao et al. 2015”). In corroboration to previous studies, the current analysis of the impact of monthly and seasonal hot extremes on crop phenology exhibited an advancement in EoS with an increase in HWMId in January, February, and March, particularly in the IGP of India (Fig. 4.15). However, this relationship is not predominant during the early part of the season, i.e., in November and December. Overall, a non-significant positive correlation was observed across the country, still, a significant negative correlation was found in specific AERs, namely, AER 02, AER 04, AER 09, and AER 13 in the IGP, between EoS and HWMId.

Similarly, the LoS also depends on hot extremes during the crop-growing season. Both negative and positive relationships were observed across the country, but a significant negative correlation was found in northeastern India during February and March (Fig. 4.15). AER 15, AER 16, and AER 17, located in this region, exhibited a clear response by shortening the LoS, indicating these regions as hotspots in India. Additionally, parts of AER 04, AER 06, and AER 09 in the IGP and central India showed a significant negative correlation with HWMId.

The NDVI_{max}, which indicates crop vigor, is also associated with HWMId on both monthly and seasonal scales (Fig. 4.16). Variations in NDVI_{max} can result from differences in crop types or

varieties within the study area. An increase in HWMId, indicating hot extremes, negatively correlated with $NDVI_{max}$ with a correlation coefficient less than 0.4. Winter-season crops typically reach their peak vegetation phase in January-February. Hot extremes during this period are critical and reduce crop vigor. Consequently, the HWMId for January and February negatively correlated with $NDVI_{max}$ across large areas of India. Significant negative correlations were observed in AER 04, AER 05, AER 09, and AER 10 (central part and IGP) in January; in AER 05, AER 09, AER 10, and AER 13 (central part and IGP) in February, and AER 02 (western part) in December. The analysis revealed that HWMId for almost all months showed a significant negative correlation with $NDVI_{max}$ despite variations in the timing of these events. This observation could be attributed to the cascading effects of hot extremes from the previous month, which harm crop growth and result in a lower $NDVI_{max}$ for the season.

Correlations between SPEI-03 and Phenology

The pixel-wise correlation between monthly SPEI-03 and crop pheno-metrics was analyzed using the Pearson correlation coefficient (at $p < 0.1$) across India during the *rabi* season (Fig. 4.17 and 4.18). In India, insufficient rainfall during the monsoon season significantly impacts crop-sowing operations in the forthcoming *rabi* season, especially in rainfed conditions. Insufficient rainfall or scarcity of irrigation compels the farmers to cultivate short-duration crops at an early end of the season (EoS). Therefore, SPEI-03, during the early part of the season, provides crucial information for the timeliness of crop sowing operations and crop selection based on duration (short or long).

A positive SPEI-03 during the early monsoon season, indicating a wet and cool climate, results in positive anomalies at the EoS. Moreover, moisture and heat stress during the growing season can lead to forced crop maturity. A significant positive correlation was observed between EoS and SPEI-03 for November, February, and March across the IGP of India (Fig. 4.17). The availability of soil moisture during the early part of the season is crucial, as reflected by the positive correlation in November in the upper part of AER 02 and AER 04 in the IGP. However, the exact locations showed a significant negative correlation in February, possibly due to the non-requirement of excess moisture during the reproductive phase. In February, AER 04, AER 09, AER 10, and AER 13 showed a positive correlation with SPEI-03, corresponding to crop

growth entering the reproductive phase. March also showed a similar association with SPEI-03 in the IGP and central parts of India (AER 02, AER 04, AER 09, AER 10, and AER 13).

Similarly, the LoS also depends on soil moisture availability during the growing season. Fig. 4.17 shows a prevailing significant positive correlation across the IGP in November (AER 02, AER 04, AER 09, and AER 13), in the north-eastern part of India in December (AER 15 and AER 16), in AER 09 in January, and along the western coast in February (AER 19). No significant correlation was found using SPEI-03 for March and LoS.

NDVI_{max} is mostly positively associated with SPEI-03 across all months (Fig. 4.18). A change in SPEI-03 was found to correlate with NDVI_{max} positively. Low values of SPEI-03, representing hot and dry extremes, are critical and reduce crop vigor throughout the growing season across the country. Consequently, SPEI-03 showed a positive correlation with NDVI_{max} in the central part (AER 05, AER 10, AER 11), Deccan Plateau (AER 03, AER 08), and IGP (AER 04, AER 09, AER 13) during November, December, and January. The correlation in the Deccan Plateau (AER 08) turned negative in February and March, though statistically insignificant. This could be attributed to excess moisture availability, as high SPEI-03 is associated with low NDVI_{max} during the senescence phase (“Benso et al. 2024”).

To analyze the relationship between extremes (HWMId or SPEI-03) and phenometrics, pixels with a significant correlation ($p < 0.1$) in any month from November to March across the study area were combined (Fig. 4.19). The results indicate a uniform distribution of significant correlations (both positive and negative) between HWMId and EoS, as well as SPEI-03 and NDVI_{max}, throughout India. These findings suggest that hot extremes predominantly affect the EoS, while hot and dry extremes (SPEI-03) primarily influence crop vigor. The impact of HWMId and SPEI-03 is region-specific within the country. For example, HWMId shows a significant correlation with the length of season (LoS) in the north-eastern part of India, whereas SPEI-03 shows a significant correlation with LoS in the IGP, highlighting the crucial impact of wetness/dryness on agriculture in these regions. This study investigated the effects of climatic variability, including hot, cold, dry, and wet extremes, on crop phenology during the critical months of the crop growing season.

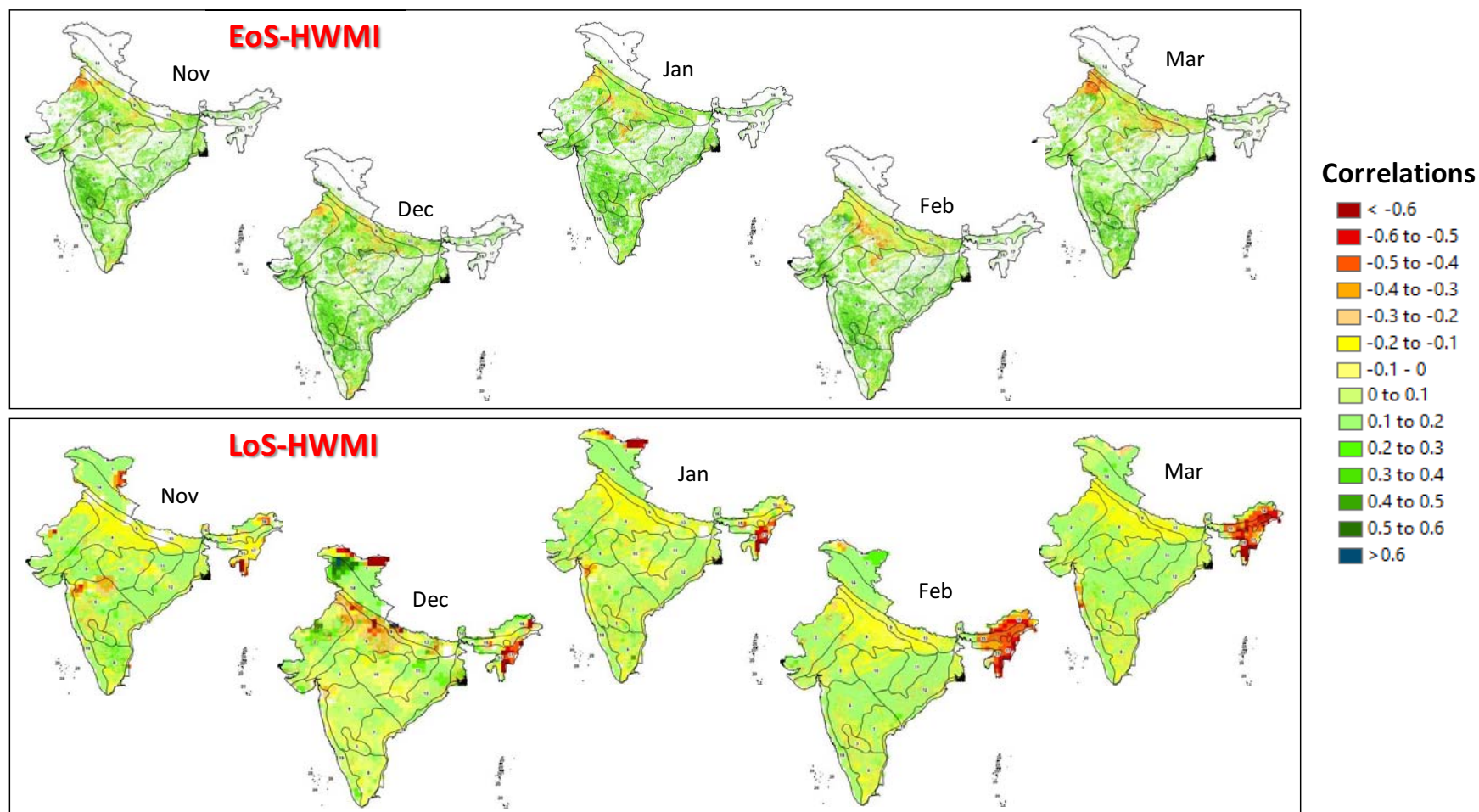


Fig 4.15 Correlation between HWMI and phenology metrics (EoS and LoS) in November, December, January, February and March

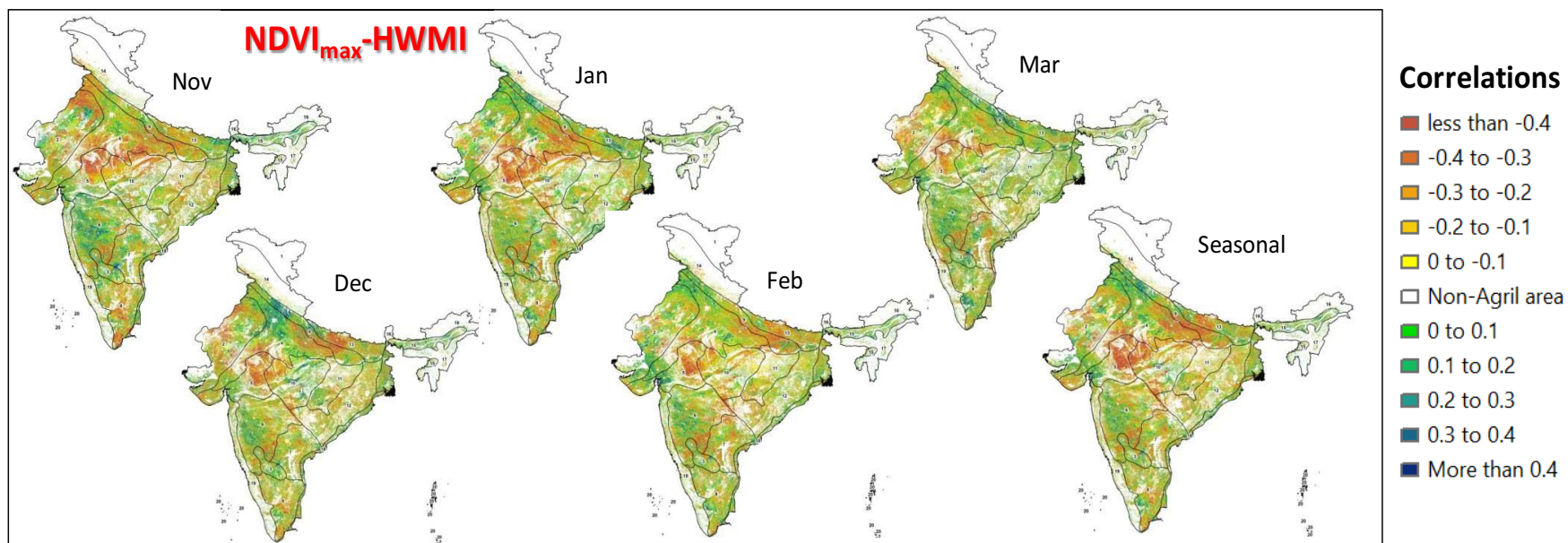


Fig 4.16 Correlation between HWMId and phenology metrics (NDVI_{max}) in November, December, January, February and March

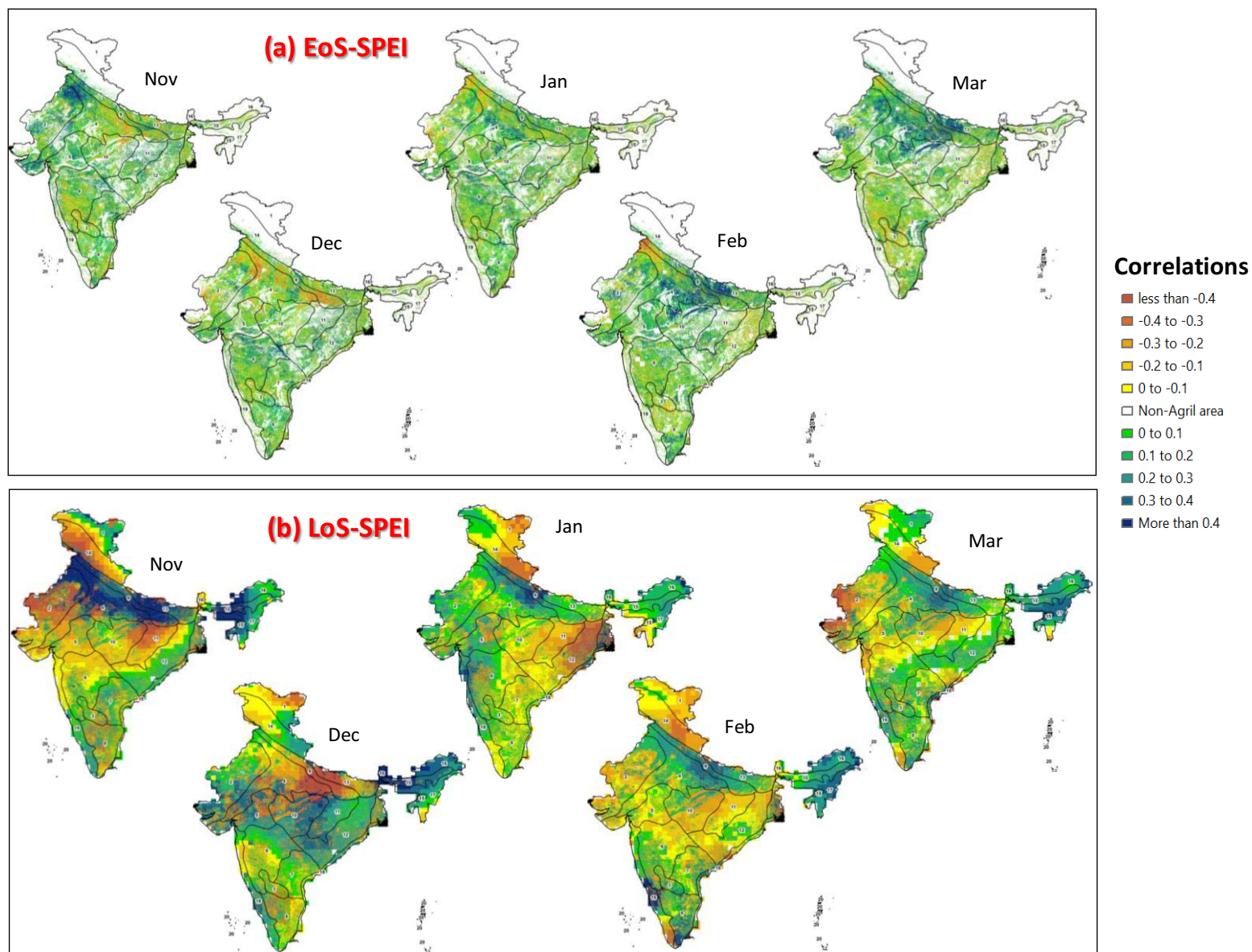


Fig 4.17 Correlation between SPEI-03 and phenology metrics (EoS and LoS) in November, December, January, February and March

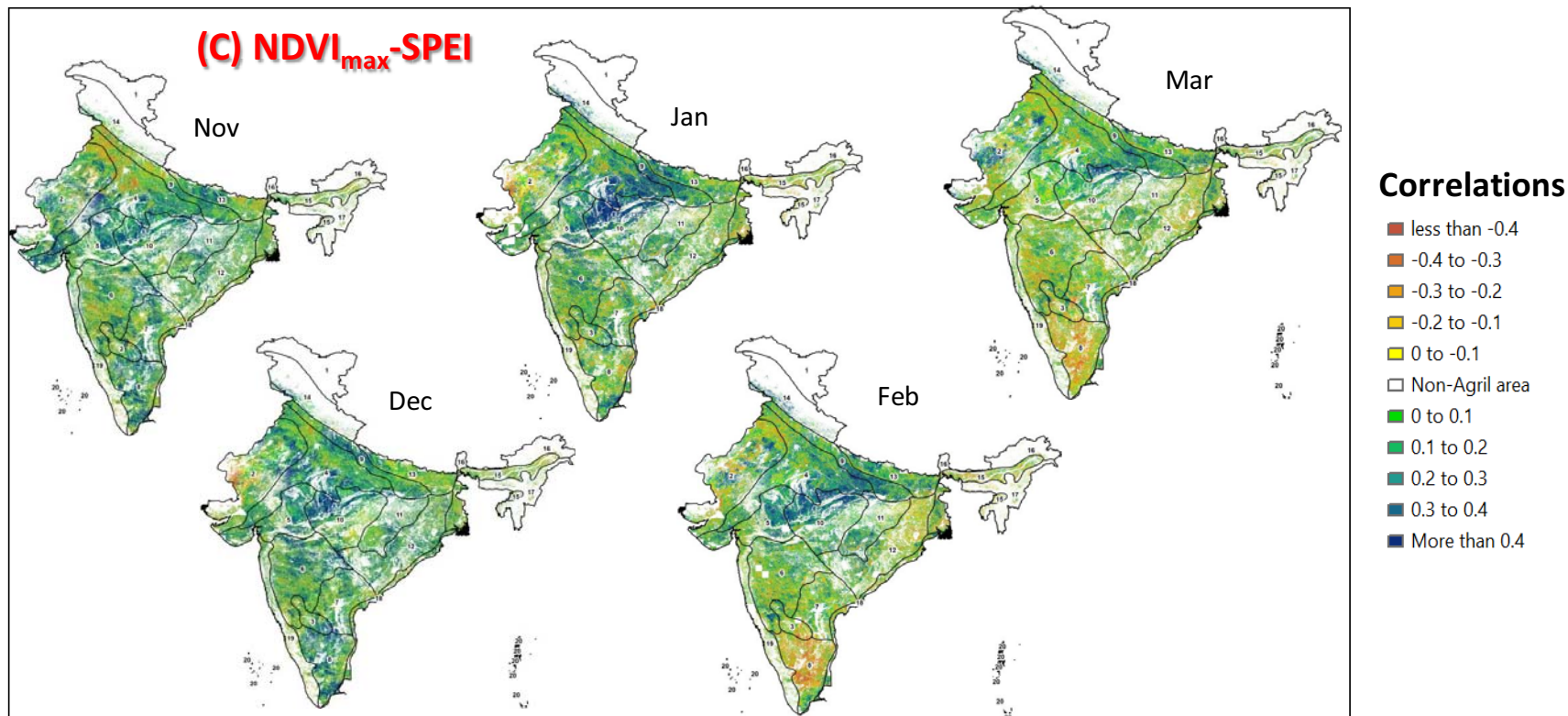


Fig 4.18 Correlation between SPEI-03 and phenology metrics (NDVI_{max}) in November, December, January, February and March

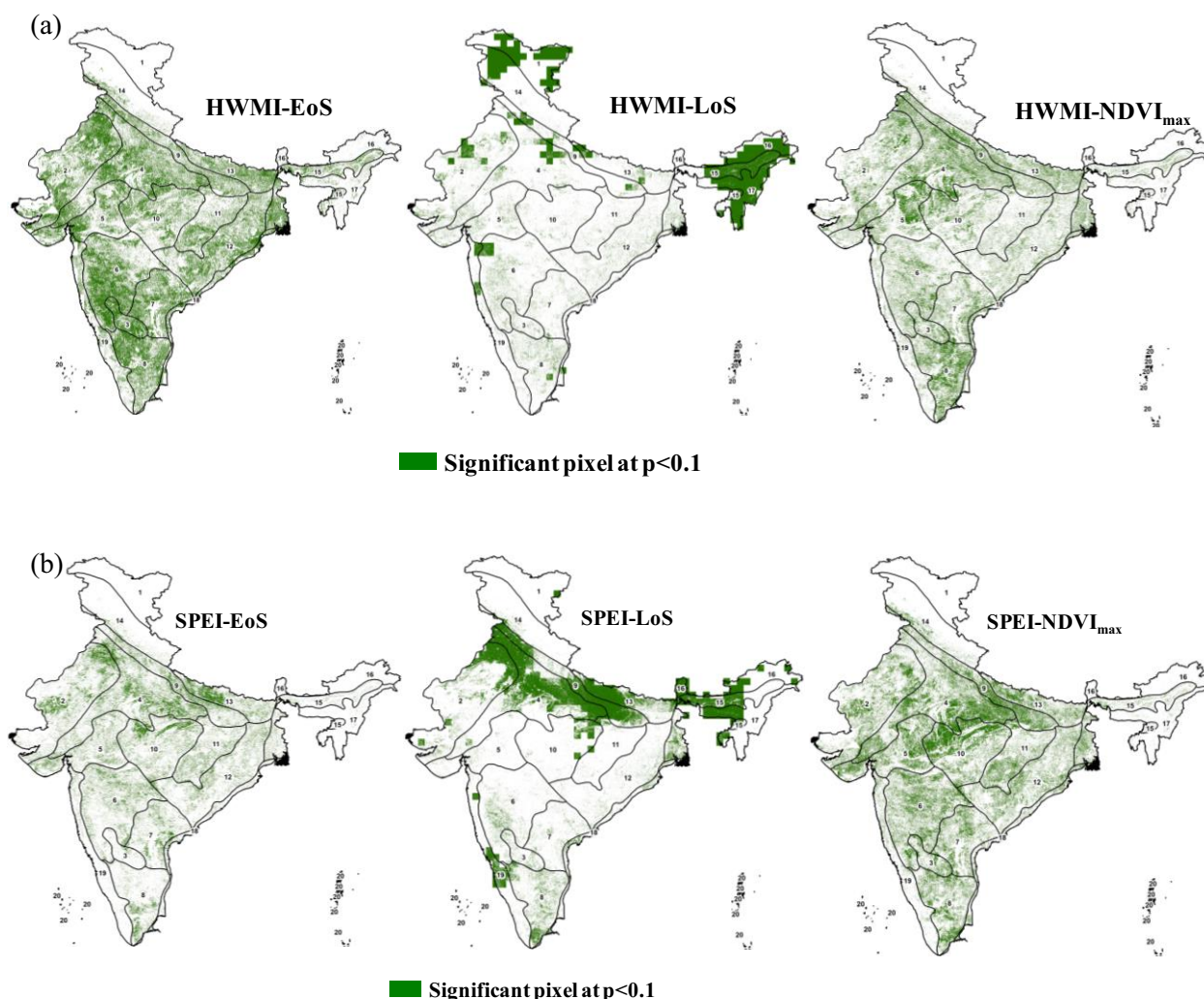


Fig 4.19 Pixels with significant correlation ($p < 0.1$) between pheno-metrics vs (a) HWMI and (b) SPEI-03 in any of month of *rabi* season (November – March)

4.4 Concurrent effect of SPEI and hot-extremes on pheno-metrics

The interaction and inter-dependence of temperature and moisture in the environment lead to compound extremes, such as hot and dry conditions. Hot extremes often result from clear skies, direct solar radiation, and warm winds, reducing rainfall. Furthermore, strong heating leads to soil drying and reduced soil moisture availability for evaporative fluxes (“Berg et al. 2016, Miralles et al. 2014, Seneviratne et al. 2010”). This situation causes hot extremes and the SPEI to be often negatively correlated, increasing the probability of co-occurring hot and dry conditions. This occurrence is more prevalent in transitional zones such as semi-humid to semi-arid regions (“Zscheischler and Seneviratne, 2017”).

As temperature increases, the atmospheric water-holding capacity and demand also increase non-linearly (“Fowler et al. 2021; Grossiord et al. 2020”). Plants respond to higher temperatures by closing their stomata to reduce transpiration and avoid moisture stress, increasing canopy temperature and exacerbating heat stress. Stomatal closure has been reported to increase canopy temperature by as much as 7 to 10°C (“Luan and Vico, 2021; Siebert et al. 2014”). Therefore, segregating the impact of these two stresses on crops is complex, despite their distinct effects, and is less addressed in the literature. Additionally, the response of crops to these extremes is also influenced by management practices adopted by farmers, such as the application of irrigation, which can counterbalance the effects of hot and dry extremes (“Siebert et al. 2017; Schaubberger et al. 2017”).

Indeed, the dynamics of temperature and moisture extremes and their impact on crops are frequently governed by interacting stresses and physiological responses, making them intrinsically compound in nature. Fig 4.20, Fig 4.21, and Fig 4.22 show the distribution of the standardized anomaly of NDVI_{max}, EoS, and LoS, respectively, in response to the corresponding period SPEI-3 and HWMId. It was observed that the point distribution forms a triangular pattern with three axes: wet + cool (high SPEI-03 and low HWMId), dry + cool (low SPEI-03 and low HWMId), and dry + hot (high HWMId and low SPEI-03). As expected, very few or no points lie on the fourth axis with wet and hot extremes. It was observed that positive anomalies in NDVI_{max}, representing good crop vigor, lie on the wet + cool axis. In contrast, NDVI_{max} with negative anomalies lies on the dry + cool and dry + hot axes. This physiological response was predominant in January and February, corresponding to the peak crop growth stage, i.e., the period of season-max NDVI.

A similar pattern was shown by the standardized anomaly of EoS and LoS; however, a distinct response was visible in February and March for EoS, whereas all *rabi*-season months showed an equal response for LoS. Nevertheless, a distinct negative deviation was observed across all pheno-metrics when monthly hot extremes (HWMId > 7) coincided with negative SPEI-03 values. Understanding the impact of concurrent extremes on crops is crucial. Although a 10% increase in monsoon intensity is projected, rising temperatures and increased rainfall variability will lead to severe extremes in India, altering crop physiology, shifting phenology, and reducing yields.

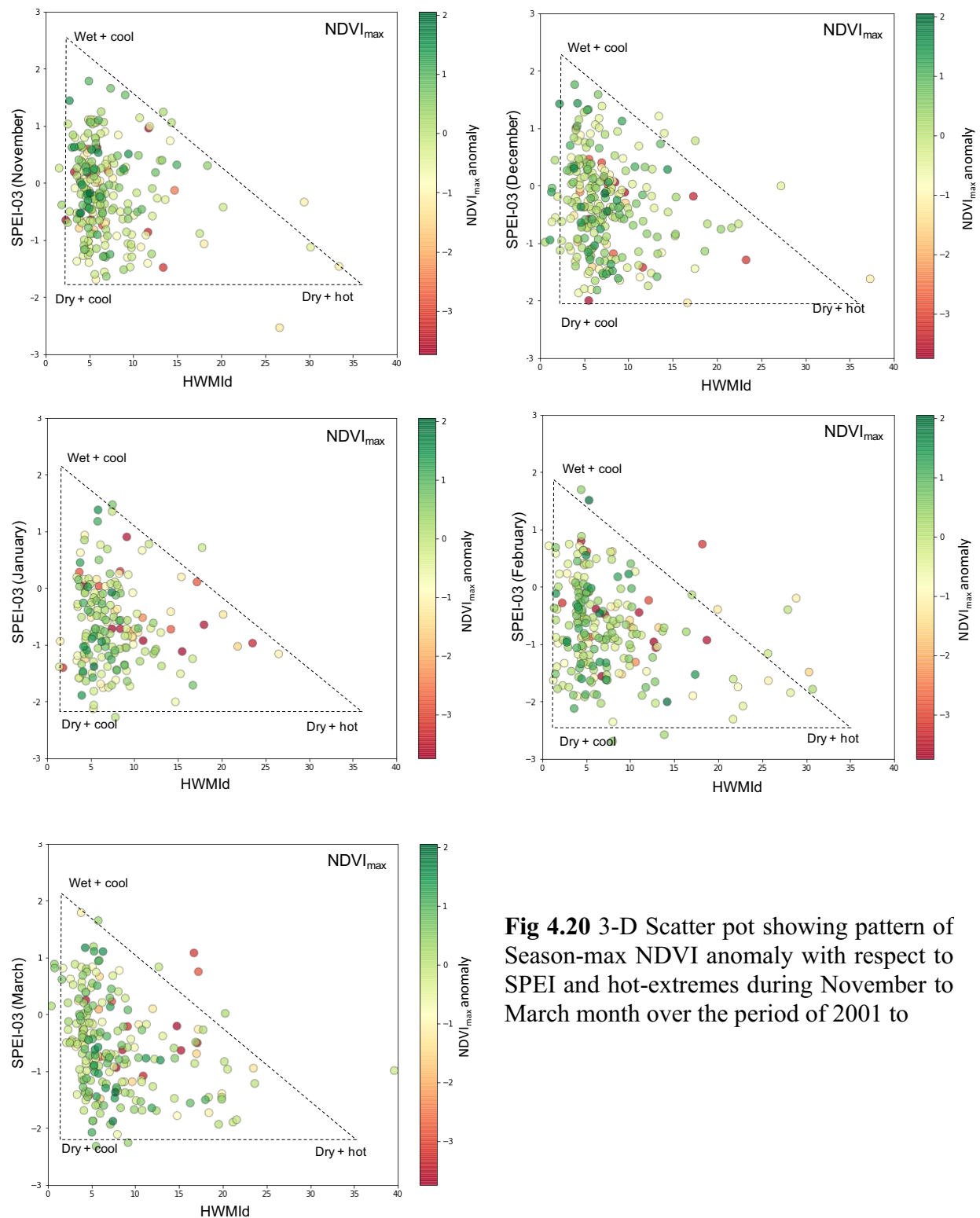


Fig 4.20 3-D Scatter plot showing pattern of Season-max NDVI anomaly with respect to SPEI and hot-extremes during November to March month over the period of 2001 to

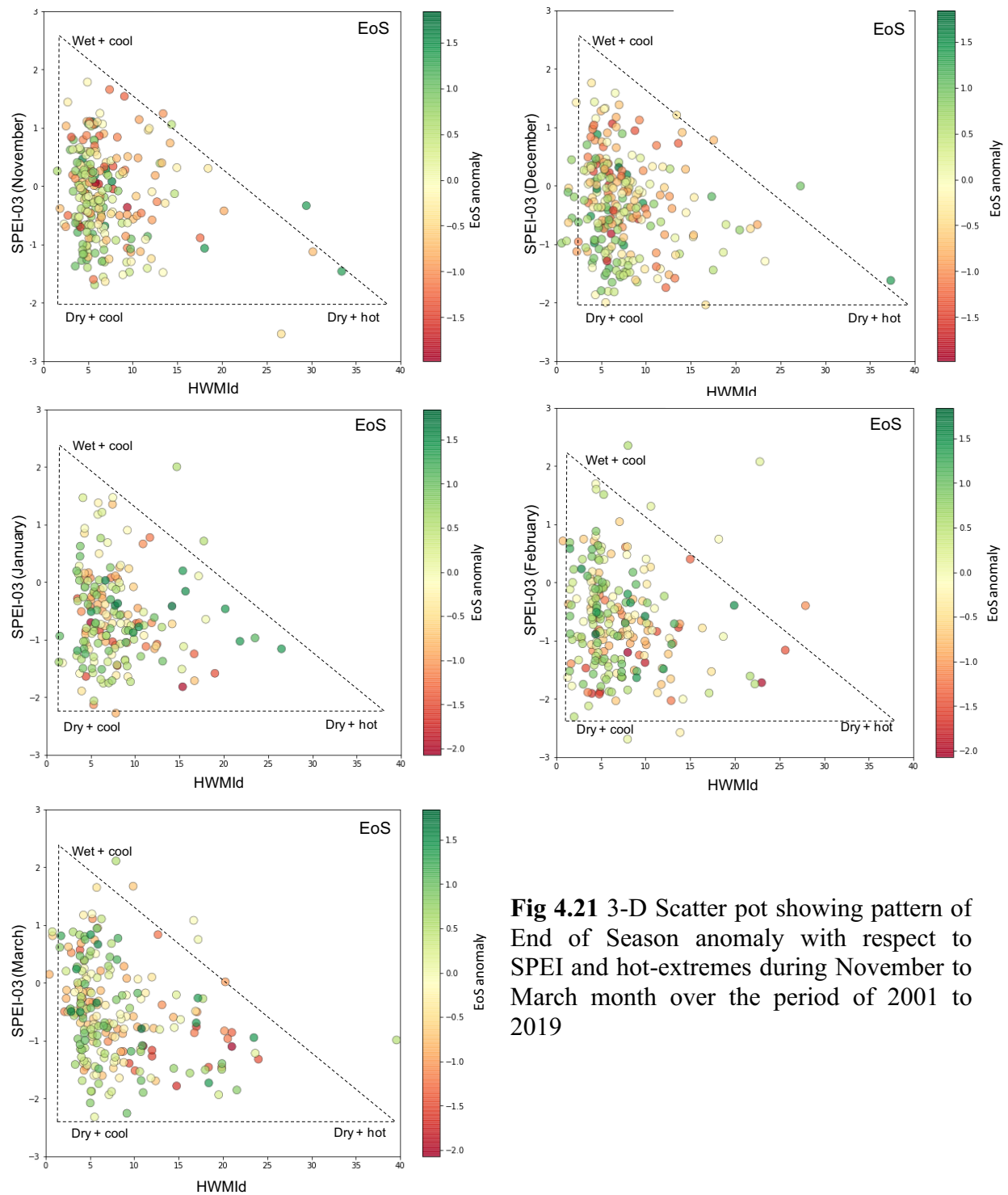


Fig 4.21 3-D Scatter plot showing pattern of End of Season anomaly with respect to SPEI and hot-extremes during November to March month over the period of 2001 to 2019

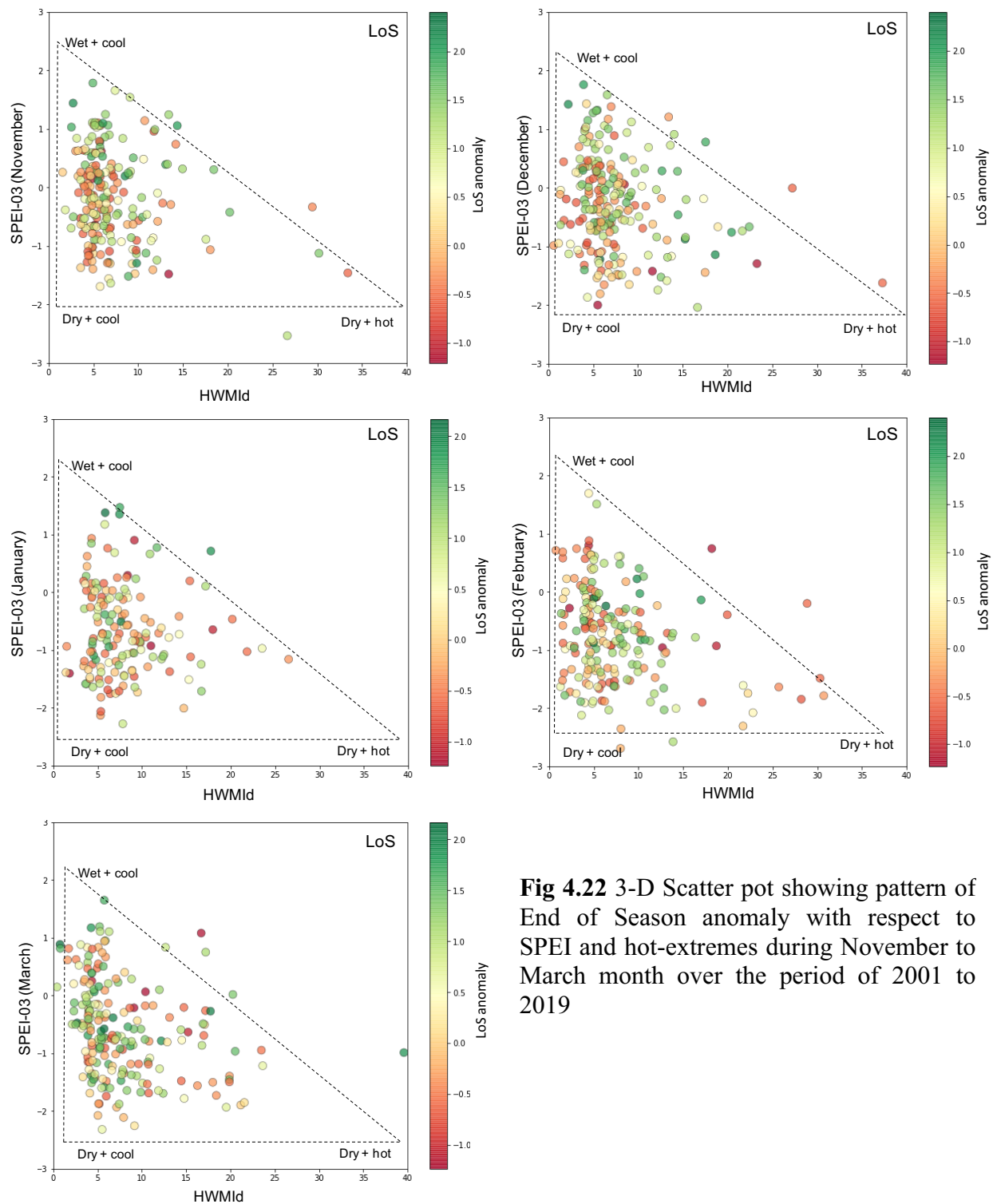


Fig 4.22 3-D Scatter pot showing pattern of End of Season anomaly with respect to SPEI and hot-extremes during November to March month over the period of 2001 to 2019

4.5 Limitations and Challenges

Analyzing the impact of dry and wet events on crop phenology is crucial for comprehending its relationship with climate change. Satellite data can effectively monitor crop phenology over large areas; however, several limitations and challenges exist in phenology retrieval. Cloud and cloud shadows often contaminate satellite data during the monsoon season, introducing uncertainty. Extricating the noise from the growth profile and preserving the relevant information proves exceedingly tricky. Although various smoothing techniques are available to mitigate noise, selecting the most suitable method that accounts for crop variability over large heterogeneous areas remains a challenge. A recent study by “Meroni et al. (2021)” explored using high-resolution Sentinel-1 data in the microwave region and Sentinel-2 data in the optical region to map the phenology in Europe using TIMESAT. Future research should focus on joint analysis of multi-source data to study the pheno-metrics while avoiding cloud/noise contamination. Additionally, combining data from optical and microwave sources can be a valuable tool for understanding underlying physiological processes, such as changes in biomass with phenology. Apart from this, the accuracy of outputs is influenced by the pheno-metrics detection method and trend analysis techniques employed. The current detection methods rely on mathematical theories rather than physiological foundations, limiting understanding and accuracy. Nonetheless, several emerging techniques and sensors offer promising options for future research in exploring the effect of drought events on agriculture.

Impact of Climate and Weather Extremes on Soybean and Wheat Yield

5.1 Introduction

This Chapter evaluates the effects of long-term climatic variations and extreme weather conditions on soybean and wheat yields in the rainfed regions of central India. Analyzing these effects at specific crop growth stages and under particular meteorological conditions is essential for formulating robust adaptation and mitigation strategies in response to climate emergencies.

As noted in the initial chapter, the AR6 by the IPCC underscores ongoing challenges related to climatic variables across South Asia (“IPCC, 2021”). These challenges include rising temperatures, unpredictable rainfall, and an increasing occurrence of extreme weather events. Notably, this region is predominantly inhabited by small-scale farmers, who account for over 70% of the farming population and are especially susceptible to these climatic extremes (“Harvey et al. 2018”). The variable impact of climate change on crop yields adds another layer of complexity to the food security concerns in the area (“Praveen et al. 2017”). The report stresses the critical need for mitigation and adaptation strategies to manage the effects of climate change on crop yields and to promote sustainable agricultural practices, highlighting the importance of a thorough understanding of how climatic extreme events interact with agrarian productivity (“Webber et al. 2018”).

Long-term climatic factors are pivotal in determining the potential for regional crop growth; however, extreme weather events significantly control their impact on actual yields. Such extremes cause significant yield reductions, sometimes even under optimal weather conditions (“Tigchelaar et al. 2018”). Process-based and statistical approaches are utilized to quantify crop yield losses due to climate change. A substantial body of research confirms these methods’ effectiveness of in identifying the critical impacts of climate and weather extremes on crop productivity and guiding agricultural decision-making (“Lobell and Asseng, 2017”).

Process-based models, which simulate crop growth and development, struggle with reproducing historical yield anomalies and often require extensive, challenging-to-source input data, which can lead to inaccuracies if omitted (“De Wit, 1965; Van Oort et al. 2011; Lu et al. 2017; Robert et al. 2017”). In contrast, statistical models consider the historical data to encapsulate the impacts of climate and weather extremes on crop yields through both linear/non-linear parametric and non-parametric (machine learning, ML) approaches. These models are adept at forecasting yields under varied climatic conditions, including changes in temperature, rainfall, and drought levels. Recent advancements in ML, such as the use of random forests and neural networks, have further enhanced the precision of impact assessments and yield predictions (“Crane-Droesch, 2018; Vogel et al. 2019; Konduri et al. 2020; Schierhorn et al. 2021”). It has been suggested that statistical models, particularly those utilizing ML, require fewer resources than process-based models and are better equipped to handle spatial heterogeneities in yield, climate, and soil conditions (“Lu et al. 2017”).

Wheat (a dominant cereal crop) and soybean (a legume and an oilseed crop) play an essential role in food and nutritional security. However, both crops have faced considerable impacts from recent climatic fluctuations. Recent studies have reported substantial global climate change effects on these crops (“Yu et al. 2013; Paymard et al. 2018”). However, such studies are found to be limited in India. “Mohanty et al. (2017)” examined the impact of future climatic scenarios, including CO₂ fertilization, temperature, and rainfall, on soybean yield using a process-based crop model, concluding that reduced precipitation and increased temperatures significantly reduced soybean yield. “Birthal et al. (2014)” observed that rising maximum temperature harms crops such as pigeon peas, rice, chickpeas, and wheat, while the increase in minimum temperature was found to have some positive effects but cannot surpass the damage caused by the rise in maximum temperature. Rainfall generally benefited most crops but couldn't counterbalance the adverse effects of the temperature rise. “Mohapatra et al. (2022)” investigated multiple climatic parameters and found that an increase in temperature had the most pronounced impact on grain yield in eastern India. “Gupta et al. (2022)” assessed the adverse effects of temperature and rainfall anomalies on crop yields. “Madhukar et al. (2021)” explored historical climatic impacts on wheat yield in India using statistical modeling. These studies highlight that rainfall and wet days had a limited effect on wheat yield. Most Indian studies have predominantly focused on temperature and rainfall as vital climatic factors, often overlooking the

influence of extreme weather events. Few studies have specifically investigated the effects of extreme weather events on crop yields, and some have been limited to single-year analyses. These studies have yet to address various climatic factors and their associated extremes comprehensively. Therefore, understanding the sensitivity of soybean and wheat yields to climatic variability and identifying the critical climate variables affecting these crop yields in India is imperative.

Wheat constitutes 36% of global food grain production, with Central India being a major contributor in South Asia as per CIMMYT, Mexico (“Braun et al. 1997”). The crop is susceptible to high temperatures (“Wheeler et al. 2000”), which affects photosynthesis, growth & development, and grain yield (“Mukherjee et al. 2018”). Wheat crops exposed to temperatures beyond 34°C experience significant yield reduction due to accelerated senescence (“Lobell et al. 2012”). Furthermore, the temperature requirements are growth stage-dependent, ranging from 22°C for the vegetative stage to 21°C for the reproductive stage and 35°C being the maximum limit for the grain-filling stage (‘Porter and Gawith 1999”). “Powell and Reinhard (2016)” reported that the effects of extreme weather events on field-scale wheat yield are time-specific and depend on event occurrence.

Soybean is one of the significant oilseeds in India and globally, accounting for about 25% of global edible oil production and two-thirds of the world's protein concentrate for livestock feed. Comprising approximately 20% vegetable seed oil and 40% protein, it offers high nutritional and health benefits. Soybean yields decline with increasing temperature deviations from the optimum range (“MacCarthy et al. 2022”). The availability of moisture from flowering to pod formation is critical to yield. The ideal rainfall range for soybean cultivation is between 500 to 1000 mm. Precipitation is a significant factor in soybean yield models and has been reported to have a negative effect due to insufficient precipitation. Soybean thrives in warm and moist climates and is resistant to both low and high temperatures. However, growth rates decline above 35°C and below 18°C, with an optimum temperature range of 26°C to 30°C. Temperatures below 21°C and above 32°C can reduce flowering and pod set. Soybean can grow and yield with as little as 180 mm of rain in the season, but this can result in a 40 to 60 percent yield reduction compared to optimal conditions. Given the sensitivity of crop growth stages to temperature and rainfall, including monthly mean climatic data, in conjunction with seasonal data, is a valuable addition to the analysis.

The critical role of wheat and soybean crops in ensuring India's food security emphasizes the necessity of thoroughly comprehending the spatial and temporal dimensions of climate change impacts on these crops at the regional level. Though several studies have explored climate variables affecting crop yields statistically, both in India and globally (“Novikova 2020; Chakraborty et al. 2019; Zampieri et al. 2017; Matiu et al. 2017”), limited research has analyzed the influence of climate and its extremes (Beillouin et al. 2020) on soybean and wheat yields during distinct development stages (“Peichl et al. 2018”) utilizing machine learning techniques (“Schierhorn et al. 2021”). Only a few studies have examined crop growth-specific Machine-Learning models to assess sensitivity in yield estimation (“Hoffman et al. 2020; Beillouin et al. 2020”). This study utilized ML models (random forest and neural network) to discern vital climatic factors (monthly and seasonal) linked to yield anomalies in soybean and wheat.

5.2 Methodology

The schematic diagram of the methodology is presented in Figure 5.1.

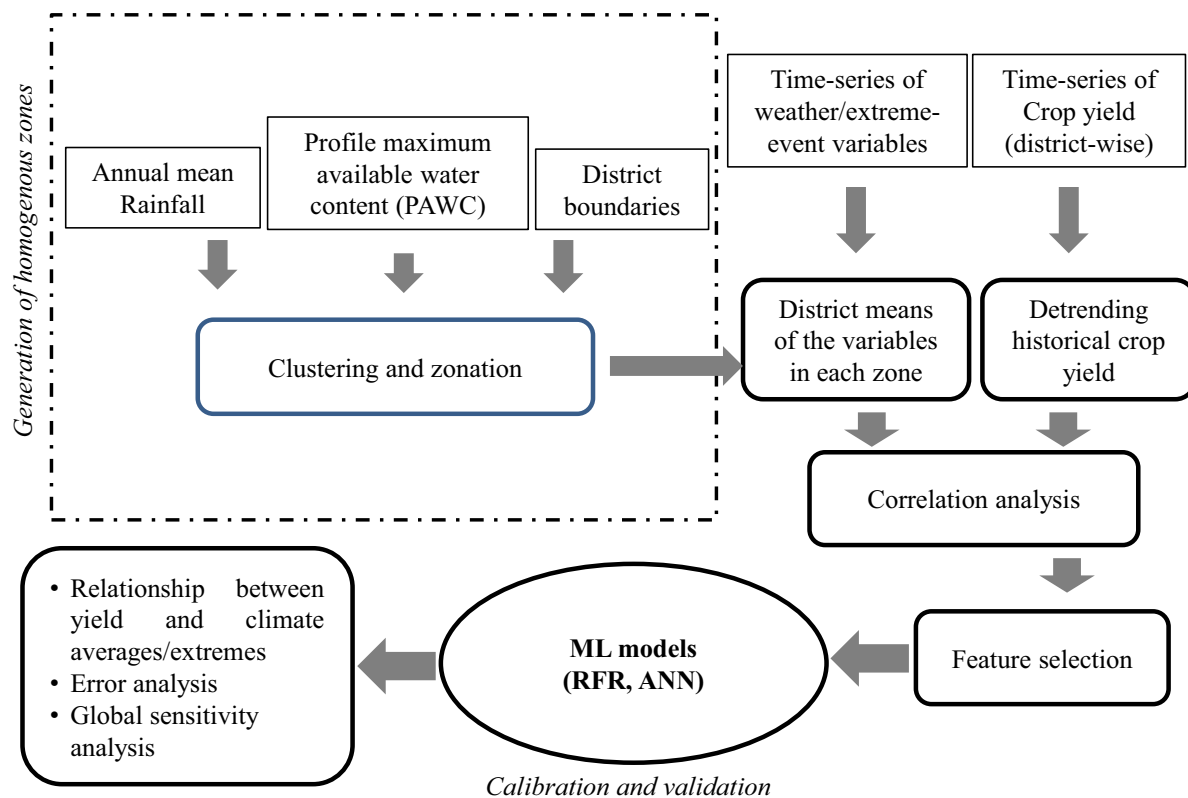


Fig 5.1 Schematic diagram of the methodology (“Kumari et al. 2024”)

5.1.1 Clustering of the Study Area into Homogeneous Zones

Both Maharashtra and Madhya Pradesh exhibit significant spatial variability in climate and soil types. Consequently, agricultural practices in these states vary considerably across different regions, as evident in the spatial distribution of crop types and crop calendars. This study examined the impact of climatic and weather extremes on wheat and soybean yields by delineating the selected states into homogeneous zones (Figure 5.2). This division was based on rainfall patterns and the Profile of Available Water Capacity (PAWC) of soil using a rule-based approach. PAWC refers to the capacity of the soil to store water in the soil profile as available soil moisture. It comprises water retained between field capacity and the wilting point of soil. Factors influencing PAWC include soil texture, organic matter content, and depth. Rainfall and PAWC are critical factors in crop production, as the former affects water supply while the latter determines water availability for crop growth. Annual mean rainfall data of CHIRPS (5 km × 5 km) and PAWC data derived from soil map of “National Bureau of Soil Survey & Land Use Planning (NBSS&LUP)” at 1:50,000 scales were employed to divide Maharashtra and Madhya Pradesh into homogeneous zones.

Initially, rainfall and PAWC were categorized into three classes for each parameter across the study area, as mentioned in Fig. 5.2. Subsequently, combining the classes from each parameter generated a total of nine classes, forming a 3x3 matrix. The majority rule was applied to assign a single class to each district (Fig 5.2). As a result, each state was delineated into three homogeneous zones, grouping districts with similar characteristics. These three zones in each state serve as fundamental ecosystem units strongly influenced by natural conditions and human activities. Salient characteristics of the homogeneous zones of Maharashtra and Madhya Pradesh were taken from the respective agro-ecological zone are presented in Table 5.1 (“Subramaniam 1983”).

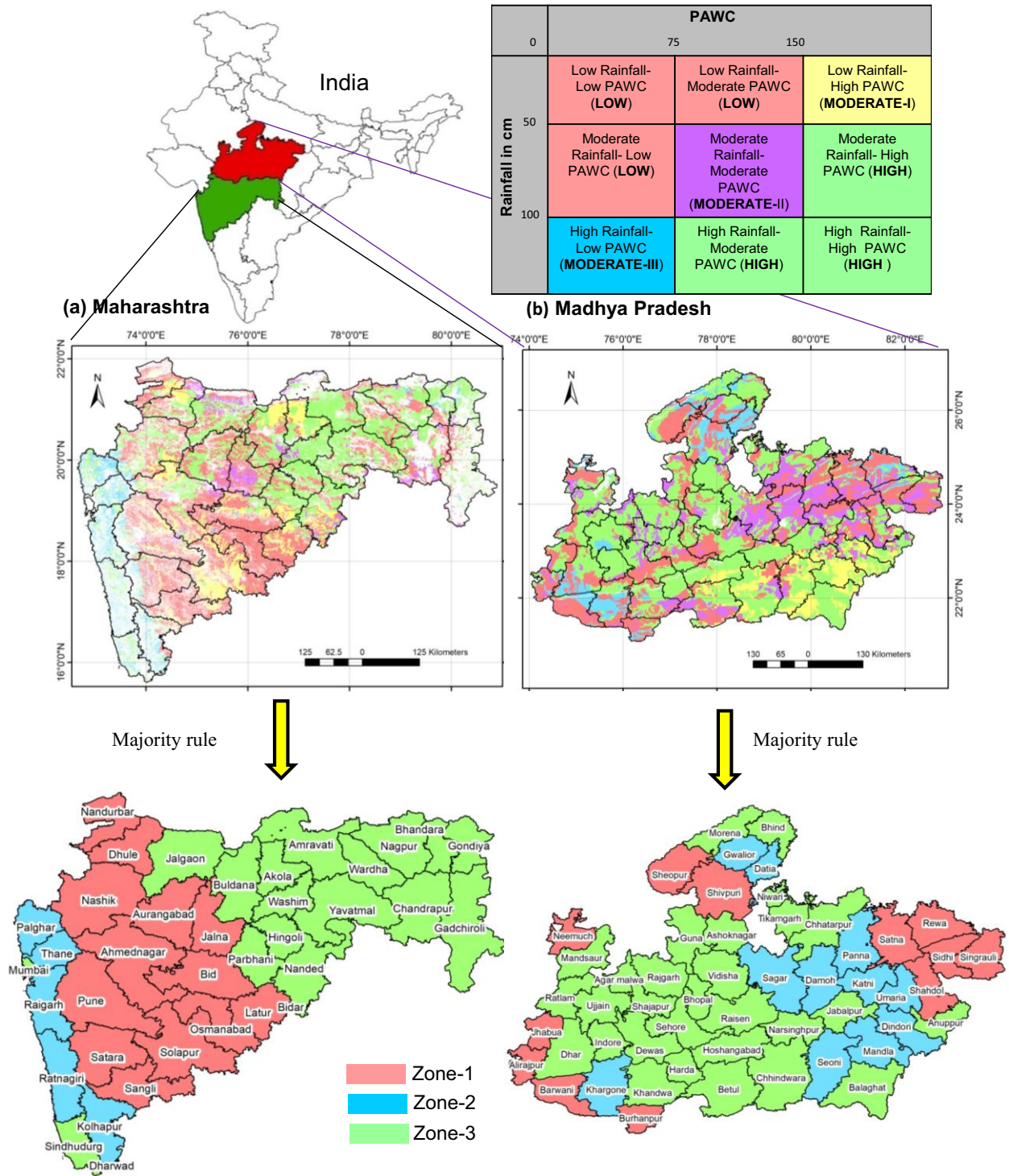


Fig 5.2 Homogenous zone delineation in the study area (Kumari et al. 2024)

Table 5.1 Characteristics of various delineated zones in study area (Kumari et al. 2024)

State	Zones	% Area	Climate	Soil	LGP (days)
Maharashtra (Soybean)	Zone-1: Rainfall ($\leq 100\text{cm}$)/ PAWC ($\leq 150\text{cm}$): both are limiting	48.87	Hot semi-arid	Shallow/medium/deep black soil	90-150
	Zone-2: Either rainfall $< 100\text{cm}$ or PAWC $< 150\text{cm}$: One of these is limiting	20.5	Hot humid/Per-humid	Red-lateritic and alluvium soil	> 210
	Zone-3: Rainfall ($> 100\text{cm}$)/ PAWC ($> 150\text{cm}$): both are sufficient	38.05	Hot sub-humid	Red and black soil	150-180
Madhya Pradesh (Wheat)	Zone-1: Rainfall ($\leq 100\text{cm}$)/ PAWC ($\leq 150\text{cm}$): both are limiting	22.6	Hot semi-arid	Alluvium-derived soils	90-150
	Zone-2: Either rainfall $< 100\text{cm}$ or PAWC $< 150\text{cm}$: One of these is limiting	23.3	Hot semi-arid	medium/deep black soil	90-150
	Zone-3: Rainfall ($> 100\text{cm}$)/ PAWC ($> 150\text{cm}$): both are sufficient	55.1	Hot sub-humid	Red and black soil	150-180

5.2.2 Predictor variables employed in the analysis

In this study, a range of predictor variables were obtained, systematically organized, and used to compute climatic parameters and weather extremes from 1999 to 2019, as outlined in Table 5.2.

During the *kharif* season, predictor variables for four consecutive months (June, July, August, and September) were employed to conduct an impact analysis of soybean cultivation in Maharashtra. Similarly, during the *rabi* season, predictor variables spanning five months (November, December, January, February, and March) were utilized to evaluate their impact on wheat cultivation in Madhya Pradesh. In total, 43 variables were computed using daily data for soybean crop analysis, while 53 variables were calculated for wheat crop analysis. Soybean and wheat crop yield data were obtained from the “Ministry of Agriculture” website

(“<https://data.desagri.gov.in/website/crops-apy-report-web>”) for the Maharashtra and Madhya Pradesh regions, respectively. A linear regression detrending approach was applied for crop yield data pre-processing to remove inherent trends in the data.

Table 5. 2 Predictor variables used (1999-2019) for studying the impact of mean and extreme weather on crop yield (Kumari et al. 2024)

Predictor variables	Definition	Source
Tmax, Tmin (monthly)	Monthly Mean of maximum temperature and minimum temperature during the growing season	CPC temperature (0.5°×0.5°): https://www.esrl.noaa.gov/psd/data/gridded/data.cpc.globaltemp.html
Rainfall and Rainy days (monthly/seasonal)	Sum of monthly rainfall during the growing season, no. of days in season when Rainfall >2.5mm	CHIRPS (0.05°×0.05°): https://data.chc.ucsb.edu/products/CHIRPS-2.0/
Growing Degree Days (GDD): monthly and seasonal	Sum of difference of daily mean temperature and reference temperature (10°C for Soybean/ 5°C for Wheat) in growing season	CPC temperature (0.5°×0.5°): https://www.esrl.noaa.gov/psd/data/gridded/data.cpc.globaltemp.html
Standardized Precipitation Evapotranspiration index (SPEI): monthly	Time-series of the climatic water balance (P-PET) fitted to log-logistic and then Gaussian distribution to get SPEI. Here, SPEI at 3-months time-interval during growing season are used	CRU (0.5°×0.5°): https://spei.csic.es/database.html
Maximum Temperature (Tmax) extremes (Hot day, Cold day): monthly	No. of days during the growing season with daily Tmax > 90 th percentile (Hot day); with daily Tmax < 10 th percentile (Cold day)	CPC temperature (0.5°×0.5°): https://www.esrl.noaa.gov/psd/data/gridded/data.cpc.globaltemp.html
Tmin extremes (Hot night, cold night)	No. of days during the growing season with daily Tmin > 90 th percentile (Hot night); with daily Tmin < 10 th percentile (Cold night)	CPC temperature (0.5°×0.5°): https://www.esrl.noaa.gov/psd/data/gridded/data.cpc.globaltemp.html

5.2.3 Correlation between yield and climatic parameters/ extremes

Pearson’s correlation coefficient was calculated to examine the relationship between crop yields, weather and climatic variables. This provides insight into how climatic and weather extremes affect crop yields. The correlation study was carried out on a seasonal and monthly basis to understand the specific impact of weather extremes on crop yield during different growth stages. It is important to note that correlation does not imply causation; a more detailed data analysis follows the study. The formula to compute the correlation coefficient (r) is given below:

$$r = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^N (y_i - \bar{y})^2}} \quad (1)$$

Where, x_i is the crop yield in time-series data in a point i for a particular district, y_i is the weather/climatic variables in time-series data in a point i for a specific district, $\bar{x}$ and $\bar{y}$ is district

mean yield and weather/climatic variables in time-series, respectively. N is the total number of data points.

5.2.4 Development of models

For the present study, two ML models, viz., Random Forest regression (RFR) and Neural network (NN) are developed for each zone and each crop.

Table 5.3 Hyperparameters range and the optimal values for each ML model for yield modeling

	Model description	Parameters	Zones			
			Parameters range with step size	Zone-01	Zone-02	Zone-03
				Optimized parameters	Optimized parameters	Optimized parameters
Soybean	RFR Loss function: RMSE Maximum no. of feature: Sqrt	Number of trees	10 to 500 @ 1	274	219	351
		Minumum sample split	2 to 8 @ 1	2	2	3
		Minimum sample leaf	1 to 6 @ 1	1	1	2
	NN Learning function: Leaky ReLU Learning algorithm: SGD Loss function: RMSE	Learning rate	0.001 to 1 @ 0.01	0.01	0.01	0.02
		momentum	0.1 to 1 @ 0.1	0.8	0.9	0.8
		Batch size	10 to 100 @ 10	30	30	30
		training epochs	50 to 300 @10	120	190	150
Wheat	RFR Loss function: RMSE Maximum no. of feature: Sqrt	Number of trees	10 to 500 @ 1	318	252	290
		Minumum sample split	2 to 8 @ 1	2	2	3
		Minimum sample	1 to 6 @ 1	1	2	2
	NN Learning function: ReLU Learning algorithm: Adam Loss function: RMSE	Learning rate	0.001 to 1 @ 0.01	0.02	0.01	0.02
		momentum	0.1 to 1 @ 0.1	0.5	0.6	0.8
		Batch size	16 to 256 @ 10	20	20	20
		training epochs	10 to 300 @10	200	210	200

Approximately 70% of data was utilized for model training, and the remaining 30% was used to test the model. A grid-search and 10-fold cross-validation technique was used for each model to select the optimum hyper parameters to tune the machine learning models. Then, for each grid location, the performance of each model was evaluated using statistical measures of error

between the predicted and observed values, i.e., Root Mean Squared Error (RMSE). A well-trained statistical model generates small RMSE values. The optimum values of hyper-parameters producing maximum accuracy for each ML model are given in Table 5.3. District-level seasonal and month-wise climatic and weather extreme variables are predictor variables in this analysis, while the crop yields (soybean and wheat) are the response variable in each zone.

Random Forest Regression (RFR) model

Random Forest Regression is an ensemble machine learning algorithm (Brieman 2001) used for regression (or classification) tasks, able to handle a large volume of input data and simultaneously reduce overfitting. RFR is comprises multiple decision trees (DT), and the final prediction aggregates the predictions made by these individual trees. The accuracy of the random forest algorithm relies mainly on the strength of the individual tree classifiers and the dependency between the classifiers (“Amit and Geman 1997”). Including several trees increases the probability of deriving an effective prediction model (“Breiman 2001; Strobl et al. 2008”). The key components and steps involved in RFR with input features (x) and corresponding target values (y) are given below:

- RFR consists of an ensemble of DT. Each tree is trained independently on a subset of the data using bootstrapped sampling (randomly selecting samples with replacement) as per “Liaw and Wiener 2002”.
- Consider a dataset of size $P \times Q$, where P is the number of data points, and Q is the number of features.

Let $P1$ data points be present at some node d . RFR selects K random features out of Q ($K < Q$), and a net reduction in variance is computed for each feature. The feature for which net reduction in variance is maximum is selected for decision- making.

The criteria for nodal feature selection can be expressed as follows:

$$f_{selected\ feature} = argmax_i(\Delta V_d^{f_i}) \quad (2)$$

$$\Delta V_d^{f_i} = V_d - (\alpha_1 V_{S1}^{f_i} + \alpha_2 V_{S2}^{f_i}) \quad (3)$$

$$\alpha_1 = \frac{Number\ of\ data\ points\ in\ S1}{P1} \quad (4)$$

$$\alpha_2 = P1 - \alpha_1 \quad (5)$$

Where:

V_d is the variance at node d,

ΔV_d^{fi} represents the reduction in the variance at node d when fi is selected for decision-making,

$V_{S_1}^{fi}$ is the variance present in the S_1 subset when the feature fi is selected for decision making ($i \in (1, K)$), and

$V_{S_2}^{fi}$ is the variance present in the S_2 subset when the feature fi is selected for decision - making ($i \in (1, K)$).

- Each of the trees is grown till maximum depth to reduce bias. Finally, the RFR aggregates the predictions from all the individual decision trees by averaging, which reduces the overall variance of the model (Brieman 2001).

Mathematically, the prediction made by an RFR for regression can be represented as follows:

Given a new data point with new feature values x_{new} , and RFR with N decision trees, the prediction (y_{pred}) is:

$$y_{pred} = \frac{\sum_{i=1}^N (tree_i(x_{new}))}{N} \quad (6)$$

The $tree_i(x_{new})$ represents the prediction of the i^{th} decision tree for the latest data point x_{new} .

Neural network (NN) model

A neural network model with two hidden layers (input-8-4-1) was constructed to predict the zone-wise yield of soybean and wheat using Python programming language and PyTorch library ("Paszke et al. 2019"). Several hyperparameters (number of hidden layers, number of neurons per layer, learning rate, and batch size) that affect the performance of an ANN are tuned using grid-search optimization and a 10-fold cross -validation technique (Table 5.3). Here, data was used in 70:30 ratios to train and test the model. The leaky Rectified Linear Unit (ReLU) activation function was used in each layer with a decay coefficient 0.01. The model was optimized using a momentum-based Stochastic Gradient Descent (SGD) optimizer algorithm. Momentum-based SGD is a variation of the traditional SGD optimization algorithm incorporating momentum to accelerate convergence. The momentum term allows the optimizer to build up velocity in directions where gradients consistently point, accelerating convergence

and escapes local minima. The Mean Square Error (MSE) was used as loss function to evaluate the model. The steps involved in NN training are as follows:

1. Initialize Model parameters (weights and biases) with Xavier initialization (“Glorot and Bengio 2010”).
2. Define Leaky ReLU as an activation function as follows:

$$\text{Leaky ReLU}(x) = \begin{cases} x, & \text{if } x > 0 \\ \alpha * x, & \text{if } x \leq 0 \end{cases} \quad (7)$$

3. Define a list of learning rate, batch size and momentum parameters to be tested for model performance.
4. For each combination in step 3, train the NN model, update model parameters via SGD with momentum (equations 8 and 9), and evaluate model performance on the validation dataset.

$$W_{t+1} = W_t + V_{t+1} \quad (8)$$

$$V_{t+1} = \mu \times V_t - \alpha \times \nabla L_t \quad (9)$$

Where W_t is the weight at t^{th} epoch,

V_t is the velocity at t^{th} epoch,

μ is the decaying factor accounts the number of iterations of previous gradients into the current update; $\mu \in (0,1)$

α is learning rate,

∇L_t is gradient of loss function at t^{th} epoch.

5. Compute the loss for each model-parameter combination in step 3 and select the model parameter corresponding to the minimum MSE.

5.2.5 Evaluation of modeling performance

Three statistical criteria, including coefficient of determination (R^2), root mean square error (RMSE), and normalized root mean square error (nRMSE), are used to evaluate the performance of the ML models. Equations to compute RMSE and nRMSE are given below:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N (y_i - \hat{y})^2}{N}} \quad (10)$$

$$\text{nRMSE} = \frac{\sqrt{\frac{\sum_{i=1}^N (y_i - \hat{y})^2}{N}}}{\bar{y}} \quad (11)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y})^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (12)$$

Where, y_i is the actual crop yield in time-series data in a point i for a particular district, $\hat{y}$ is estimated yield using model in same district, N is the total number of data points, $\bar{y}$ is district mean yield in time-series.

5.2.6 Impact analysis of predictive variables in crop yield estimation

The impact of various predictor variables on crop yield estimation was analyzed through sensitivity analysis under different presumed scenarios. We assumed the accuracy to be highest with the least RMSE, with all predictor variables. Therefore, we systematically removed individual predictor variables to evaluate their influence on crop yield estimation using different machine-learning approaches. This analysis aims to quantify the significance of predictor variables in predicting crop yield based on historical data. Combinations of predictor variables under different scenarios were analyzed for soybean and wheat crops during their respective growing seasons. The following is a summary of the scenarios:

- Scenario 1 (S1): All predictor variables were retained in each machine learning model for soybean and wheat crops.
- Scenario 2 (S2): Monthly temperature extremes are excluded from the input data.
- Scenario 3 (S3): Monthly minimum temperatures, maximum temperatures, and temperature extremes are excluded from the input data.
- Scenario 4 (S4): Both monthly and seasonal Growing Degree Days (GDD), as well as minimum temperatures, maximum temperatures, and temperature extremes are excluded from the input data.
- Scenario 5 (S5): Monthly and seasonal rainfall, rainy days, GDD, minimum temperatures, maximum temperatures, and temperature extremes are excluded from the input data.
- Scenario 6 (S6): Monthly SPEI, GDD, minimum temperatures, maximum temperatures, and temperature extremes are excluded from the input data, retaining monthly and seasonal rainfall and rainy days.

5.2.7 Global sensitivity analysis

The current study uses a global sensitivity index, often called the first-order Sobol's index (“Sobol 2001”). It measures the first-order effect of an input variable on the output of a model. It quantifies the portion of the total output variance attributed to the variation in a single input variable while keeping all other input variables fixed. Mathematically, the first-order Sobol's index for an input variable x_i is defined as follows:

Let y be the model's output, and let x_i be the i^{th} input variable. Then, the first-order Sobol's index S_i is calculated as:

$$S_i = \frac{V[E(y|x_i)]}{V(y)} \quad (13)$$

Where, S_i is the first-order Sobol's index for input variable x_i , $E(y|x_i)$ is the expected value (mean) of the output, and y is conditioned on the value of input variable x_i . In other words, it's the average value of the output when x_i varies while all other inputs are fixed. V represents the variance of a random variable. $V(y)$ is the variance of the total output y , considering all input variables.

The first-order Sobol's index provides insight into how much the variation in an individual input variable contributes to the overall variability of the model output. A high first-order Sobol's index suggests that the variable significantly influences the output, while a low index indicates that the variable's effect is relatively small.

5.3 Results

5.3.1 Correlation between crop yield and different predictor variables

Different hydro-meteorological (rainfall, rainy days, SPEI) and thermo-meteorological (T_{max} , T_{min} , GDD) parameters over a monthly/seasonal scale along with the temperature extremes (hot days, hot nights, cold days, cold nights) are linearly correlated with the district level crop yield throughout 1999 to 2019. The zone-wise correlation matrix for soybean and wheat yield is presented in Tables 5.4 and 5.5 respectively. As detailed in Table 2, in zone 1, rainfall and Plant Available Water Capacity (PAWC) are limiting factors. In zone 2, either rainfall or PAWC is limiting, while in zone 3, neither rainfall nor PAWC imposes limitations.

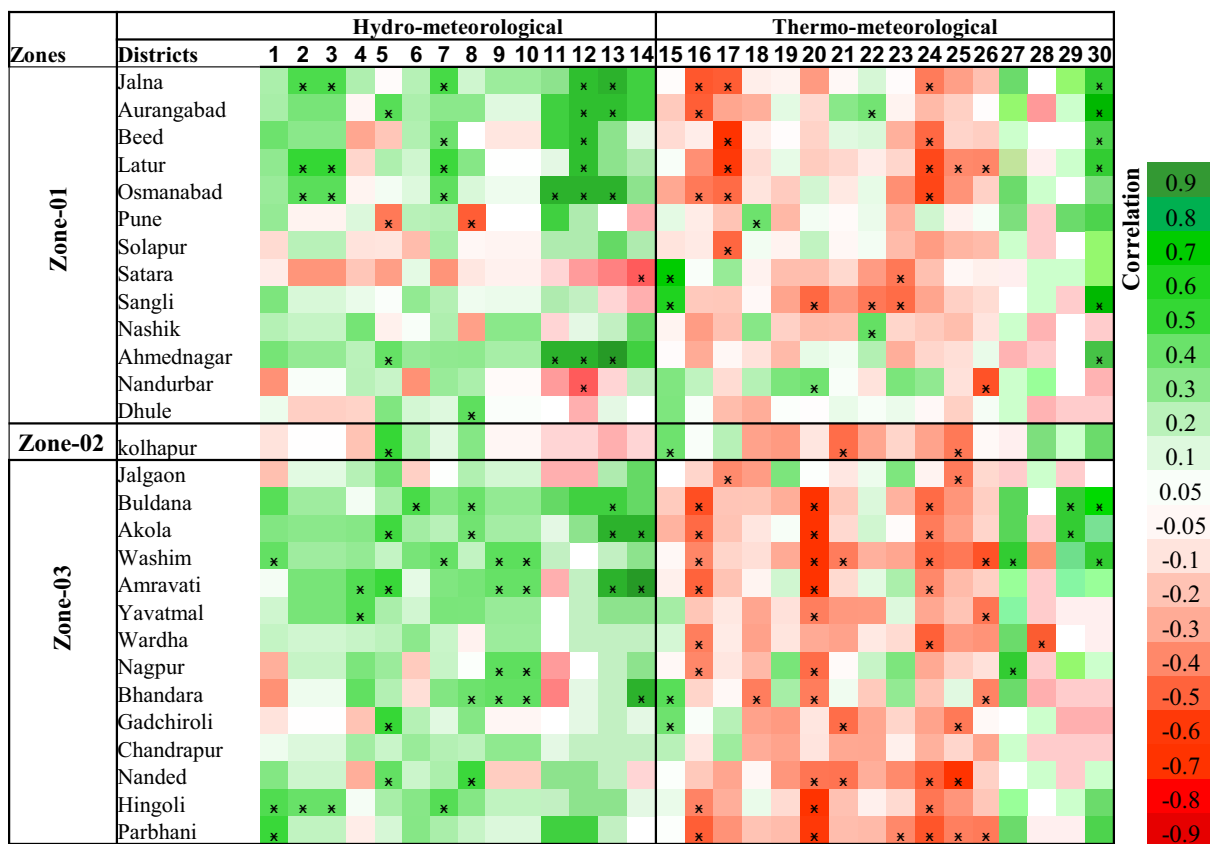
In general, across the zones, thermo-meteorological parameters were found to be negatively correlated with soybean yield, whereas a positive correlation was observed with hydro-meteorological parameters (Table 5.4). The area under soybean cultivation in zone 2 is tiny; therefore, it should be discussed further. In zone 1, a significant negative correlation was observed between the Tmax of July and August months and soybean yield across most districts. A similar trend was also observed for the GDD of July month. However, no consistent statistically significant result was found for the Tmin across the months of the soybean crop season. Additionally, temperature extremes showed no significant correlation with soybean yield, except for hot nights, which exhibited a positive correlation. In contrast, across zone 3, both the Tmax and Tmin of July were significantly negatively correlated with soybean yield across most districts. Similarly, the GDD of July, August, and September exhibited a significant negative correlation with soybean yield. However, temperature extremes did not show any significant correlation. Soybean is likely cultivated in the warm and humid climate of the *kharif* season in central India. “Chakraborty et al. (2017)” reported a substantial increase in temperature, particularly Tmin, in these areas due to climate change. This rise in temperature has a cascading effect on the *kharif* season GDD, making it significantly higher and negatively impacting soybean yield. The present study also revealed a significant negative correlation between temperature (particularly Tmax, Tmin, and GDD) during the crop establishment phase and soybean yield.

As most soybean crops are rainfed, hydro-meteorological parameters generally correlate positively with soybean yield. Specifically, rainfall in July and August, rainy days in July, and the SPEI in July and August were significantly positively correlated with soybean yield across most districts in zone 1. In zone 3, seasonal rainfall, rainfall in September, seasonal rainy days, rainy days in August and September, and SPEI in August and September showed significant positive correlations with soybean yield.

In zone 1, low rainfall during the crop establishment and development phases may negatively affect yield, especially if the soil's water-holding capacity is insufficient to meet the crop's requirements. However, in zone 3, significant yield reductions were observed only during critical growth stages, such as flowering and pod filling, when water demand is high and rainfall is scarce. Therefore, rainfall and its distribution have a positive effect on soybean yield.

Additionally, SPEI, which reflects the ecosystem's overall moisture surplus or deficit condition, exhibits a positive correlation with soybean yield.

Table 5.4 Correlation coefficient between Soybean yield and climate/weather extremes over different zones of Maharashtra (Kumari et al. 2024)



* Statistically significant at $p < 0.1$

Hydro-meteorological variables: (1: RF_Jun, 2: RF_Jul, 3: RF_Aug, 4: RF_Sep, 5: RF_Seasonal, 6: RD_Jun, 7: RD_Jul, 8: RD_Aug, 9: RD_Sep, 10: RD_Seasonal, 11: SPEI_Jun, 12: SPEI_Jul, 13: SPEI_Aug, 14: SPEI_Sep)

Thermo-meteorological variables: (15: Tmax_Jun, 16: Tmax_Jul, 17: Tmax_Aug, 18: Tmax_Sep, 19: Tmin_Jun, 20: Tmin_Jul, 21: Tmin_Aug, 22: Tmin_Sep, 23: GDD_Jun, 24: GDD_Jul, 25: GDD_Aug, 26: GDD_Sep, 27: Cold days, 28: Cold nights, 29: Hot days, 30: Hot nights)

RF: Rainfall; RD: Rainy days; GDD: Growing Degree Days, SPEI: Standardized Precipitation Evaporation Index

In India, wheat (a long-day plant) is cultivated during winter to cope with rising temperatures during its crucial ripening and reproductive growth phases. Table 5.5 represents the correlations between climatic variables and their extremes with district-level wheat yield in three zones. As nearly half of the crop's water requirements are typically met by rainfall, a significant correlation

was observed only some districts in Madhya Pradesh, indicating the complexity of the relationship between rainfall patterns and wheat yield.

The SPEI of November, January, March, and Rainy days over the season and November month showed a significant positive correlation with wheat yield over Zone 1. Similarly, SPEI of February and March were found to have a considerable positive correlation with wheat yield over zone 2. The monthly SPEI of December to March and Rainfall of December showed similar results over zone 3. In a nutshell, rainfall and moisture surplus conditions as depicted by SPEI, have a significant positive effect on wheat yield as it is grown under limited irrigation conditions in Madhya Pradesh.

The effect of thermo-meteorological parameters on the wheat yield was significant. Tmin of November, December, March; GDD of November, December, March, and the whole season were found to have significant negative correlations with wheat yield over widespread districts of Zone 1. Similarly, Tmin of November, December, January, and March; GDD of November, December, March, and the whole season showed a significant negative correlation with wheat yield over the majority of the districts of Zone 2. Tmin of December, January, March; GDD of November, December, January, March and the whole season significantly negatively correlated with wheat yield over Zone 3. Tmax did not show any consistent results across the zones. It is important to note that Tmin and its coupled parameter GDD during the latter part of the wheat season (ripening stage) plays a significant role in the wheat yield. Any increase in the thermal environment, particularly in the later part of the wheat crop season, has a substantial adverse effect on the yield. It is apt to mention that such scenarios of terminal heat stress on wheat crops are frequent in India in climate change scenarios. Hence, the result of the present study could further assist in avoiding/ mitigating such stress towards sustainable wheat yield.

Table 5.5 Correlation coefficient between Wheat yield and climate /weather extremes over different zones in Madhya Pradesh (Kumari et al. 2024)

* Statistically significant at $p<0.1$

RF: Rainfall; RD: Rainy days; GDD: Growing Degree Days, SPEI: Standardized Precipitation Evaporation Index

Overall, in a region facing water scarcity, such as Zone-01, wheat yield exhibits a significant positive correlation with seasonal and November rainy days. The SPEI at a 3-month time scale, which captures the integrated response of rainfall and temperature, displays a significant positive correlation across all zones, especially during the reproductive growth stage. Additionally, temperature-related parameters, including climatic extremes, show substantial correlations. Specifically, increasing minimum temperature adversely affects wheat yield in all zones. GDD, whether calculated seasonally or monthly, is inversely related to wheat yield.

Moreover, the study identifies weather extremes, such as a rise in the frequency of cold days and nights (indicating a decrease in maximum and minimum temperatures, respectively), positively affecting yield. Conversely, an increase in hot days and hot nights during the ripening phase negatively impacts wheat yield, aligning with previous studies (“Rao et al. 2015; Dubey et al. 2020; Farhad et al. 2023”). The observed yield reduction due to increased temperature may be related to increased crop water demand in heat-induced limited water conditions (“Zhao et al. 2017; Zaveri and Lobel 2019”). Furthermore, the study reveals a distinct effect of climate and its extremes varying with crop growth stages. In wheat, crown root initiation, which usually occurs after 21 days of sowing, is one of the most critical stages for water stress. Therefore, an increase in temperature (T_{max}) or a decrease in water availability (RD or SPEI) in November negatively affects crop yield. Other critical growth stages, such as flowering, jointing, and milking stages corresponding to January, February, and March, respectively, also exhibit sensitivity towards temperature-related parameters (T_{max} , frequency of hot days, cold days, and cold nights). Wheat yields in Madhya Pradesh exhibited a weak correlation with rainfall parameters across all zones. However, the SPEI displayed a reasonably positive relationship with wheat yields. This suggests that SPEI serves as a better indicator of water availability for crops than rainfall, as it effectively captures water stress (“Tirivarombo et al. 2018; Ortiz-Bobea et al. 2019”).

4.2 Influence of predictive variables in crop yield estimation

4.2.1 Sensitivity analysis based on RMSE

Towards developing the impact of climate parameters on crop yield, the sensitivity of causative parameters was assessed by systematically removing individual predictor variables in machine learning models. Six sets of scenarios were created, as mentioned in section 5.2.6, and in the case of soybean, Scenario 1 (where all parameters were employed for prediction) exhibited the lowest

RMSE in both RFR and NN models (0.3 t/ha and 0.34 t/ha in Zone-01; 0.35 t/ha and 0.39 t/ha in Zone-02; and 0.27 t/ha and 0.29 t/ha in Zone-03), as given in Figure 6.3. To account for zone-wise variations in absolute yield, nRMSE was calculated, reflecting the residual variance in models and relating RMSE to the observed range of variables. Models employing all parameters also yielded the lowest normalized RMSE (nRMSE) values of 19% and 21% in Zone-01; 22.2% and 24.32% in Zone-02; and 15.2% and 16.2% in Zone-03 for RFR and NN models, respectively. Subsequent removal of individual parameters led to increases in both RMSE and nRMSE. Similarly, the R^2 for both models in Scenario 1, encompassing all climatic variables and temperature extremes, could explain the variability in soybean yield to the extent of 65-66% in Zone-01, 56 to 59% in Zone-02, and 53 to 55% in Zone-03 (Figure 5.3). Interestingly, the stepwise removals of thermal parameters such as temperature extremes, Tmax, Tmin, and GDD, as mentioned in Scenarios 2, 3, and 4, did not significantly impact the uncertainty estimates, suggesting that these parameters are intertwined in affecting the crop yield. Temperature extremes had already captured a considerable portion of the influence of other temperature parameters on yields. For instance, an increase in the frequency of hot days inherently raises the monthly average Tmax, Tmin, and heat accumulation (via GDD) during grain formation stages (“Vogel et al. 2019”). This intricate relationship indicates that segregating the effect of temperature and its extremes on crop yield is challenging as these are often collinear. The maximum reduction (6 to 7%) in the model’s explanatory power was observed after the exclusion of hydro-meteorological parameters in Zone-01, whereas a decrease of 2 to 4% in explanatory power occurred after removing thermo-meteorological parameters in Zone-03. Notably, using only the rainfall parameter or SPEI parameter in RFR and NN models (RMSE 0.36 t/ha and 0.45 t/ha) increased the soybean yield estimation error by 18% and 32%, respectively, compared to when all parameters were utilized.

Similarly, all predictor variables (Scenario 1) could able to estimate wheat yield and explain the variability with RMSE (and R^2) values of 0.54 t/ha (0.67) and 0.58 t/ha (0.65) in Zone-01; 0.57 t/ha (0.60) and 0.42 t/ha (0.64) in Zone-02; and 0.59 t/ha (0.59) and 0.51 t/ha (0.57) in Zone-03 using RFR and NN, respectively (Figure 5.4). RFR and NN models utilizing all parameters exhibited nRMSE values of 21.7% and 23.5% (Zone-01); 25.5% and 18.8% (Zone-02); and 20% and 17% (Zone-03), respectively. The stepwise removal of predictor variables increased both RMSE and nRMSE. In Zone-01, models incorporating only hydro-meteorological parameters

and excluding thermal parameters (Scenario 4) resulted in a 20% increase in RMSE and a 10% reduction in model explanatory capability. Conversely, models working with either RF/RD or SPEI (Scenarios 5 or 6) showed increased RMSE (and decreased R^2) accounting for the less variability in crop yield, underscoring their significant role in wheat yield in Zone-01 with low rainfall. While increases in RMSE were observed in Zone-03, the extent was not as high as in water-limited Zone-01 and Zone-02, indicating that thermal parameters explained most of the variability. It is worth noting to note that both state-of-the-art ML models captured the similar pattern in all scenarios despite of different extent of RMSE values.

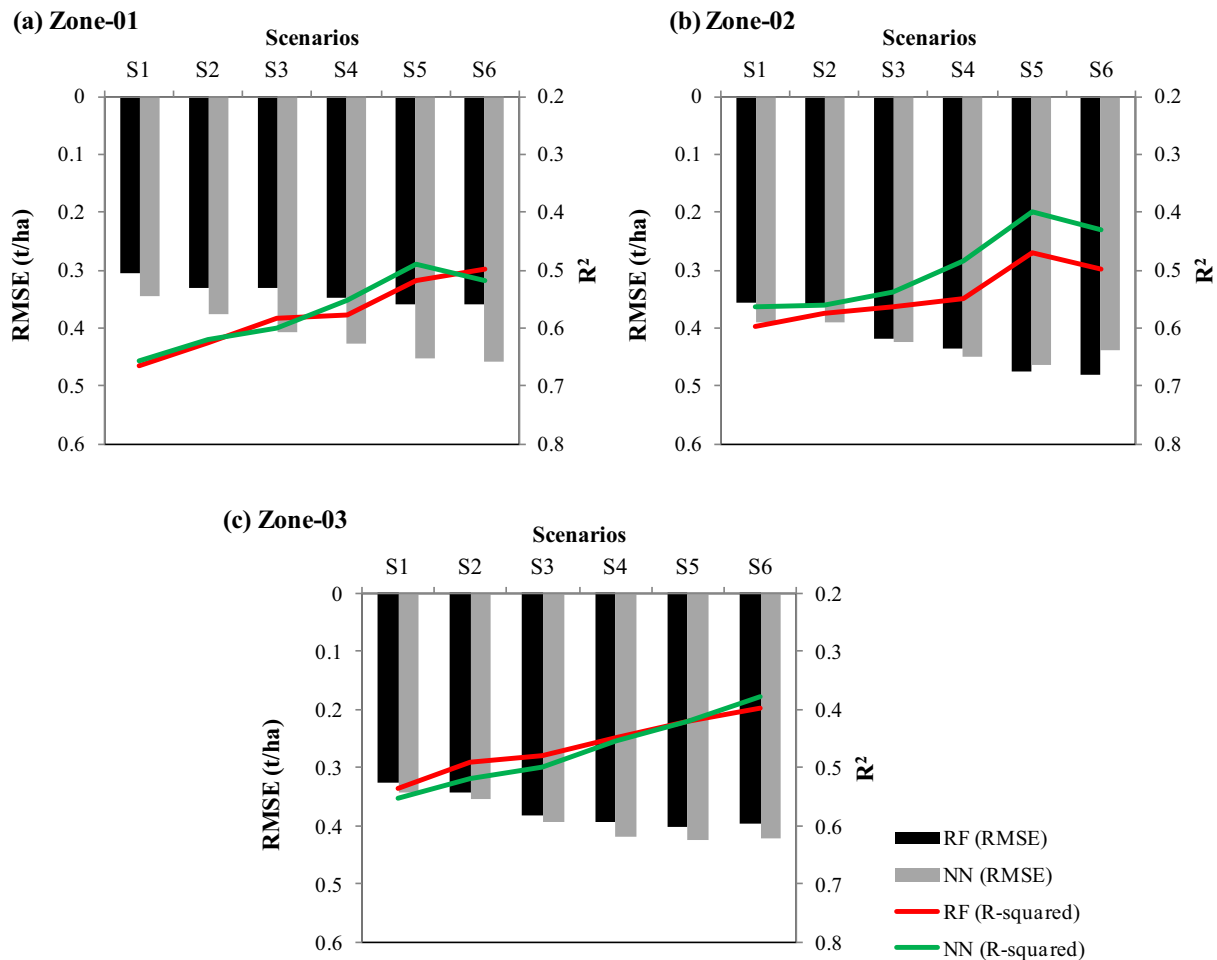


Fig 5.3 Error (RMSE) estimation and explained variance (R^2) using various combinations of predictor variables for Soybean yield across different zones

S1: Scenario 1, **S2:** Scenario 2, **S3:** Scenario 3, **S4:** Scenario, **S5:** Scenario 5, **S6:** Scenario 6

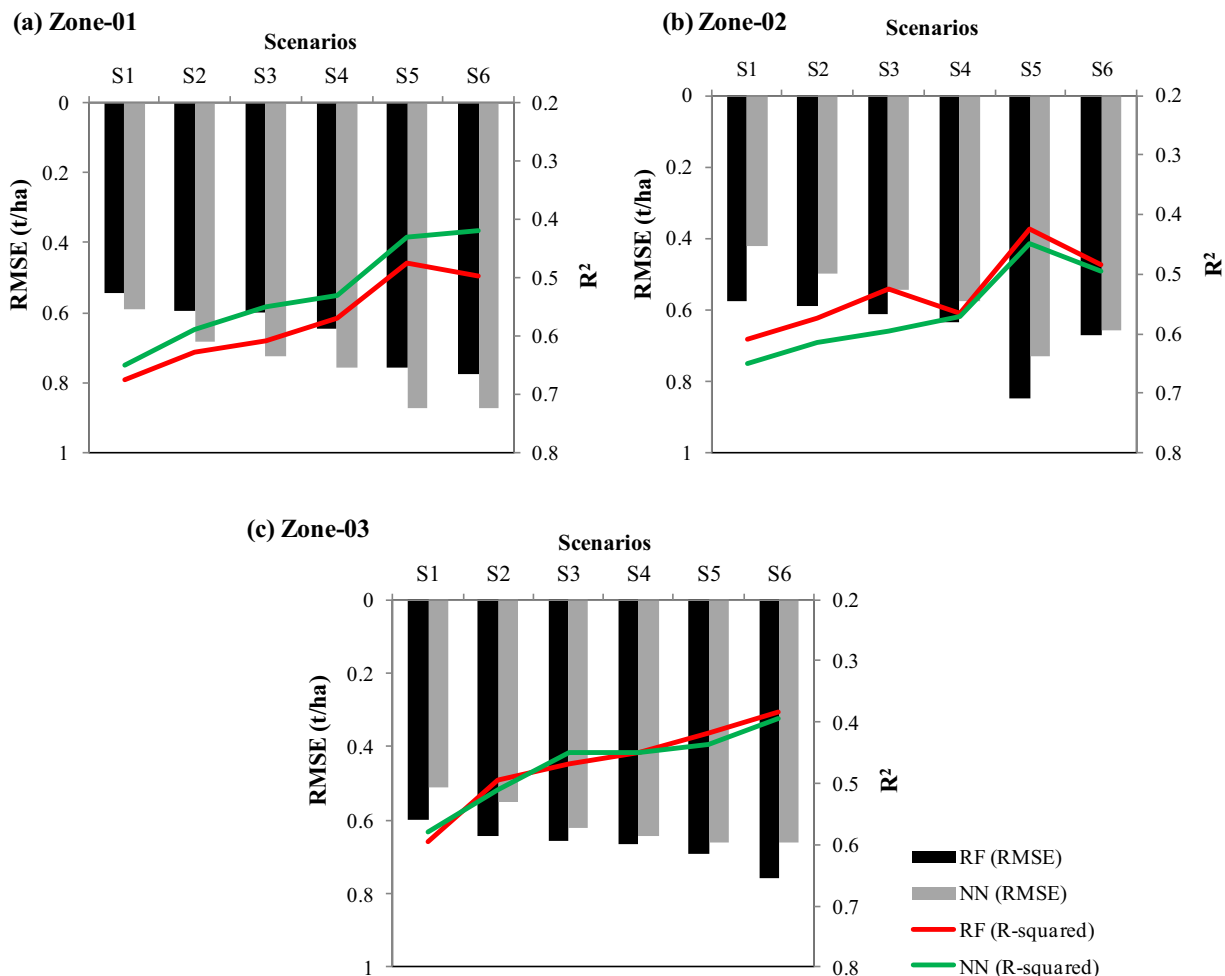


Fig 5.4 Error (RMSE) estimation and explained variance (R^2) using various combinations of predictor variables for Wheat yield across different zones

S1: Scenario 1, S2: Scenario 2, S3: Scenario 3, S4: Scenario, S5: Scenario 5, S6: Scenario 6

4.2.2 Sensitivity analysis of different predictor variables using Sobol's index

Sobol sensitivity analysis is commonly employed for complex system models to decompose output variance concerning input parameters quantitatively. In this study, a first-order Sobol's index was utilized to assess the individual impact of input parameters on the model while keeping all other parameters fixed. The first-order Sobol's index always provides positive values (directionless), and the sum of all individual parameters should equal 1. Parameters more than 5% of the sensitivity indices are deemed significant ("Zhang et al. 2015").

For soybean yield, the study revealed sensitivity to seasonal RD (>20%), followed by RD in July and August in Zone-01 (Fig 5.5). This underscores water stress as a limiting factor for yield

during the crop development stages (from leaf and stem development to flowering) in regions facing water scarcity. In Zone-02, characterized by high rainfall but poor soil water retention, T_{max} significantly influences soybean yield variability in both RFR and NN models. T_{max} accelerates leaf senescence and restricts photosynthetic activity, affecting soybean pod filling. In Zone-03, temperature and rainfall during soybean's reproductive growth stages (flowering to pod filling) are critical factors influencing yield.

In the case of wheat crops, the study found sensitivity to spells of cold nights (i.e., frequency of T_{min} lower than the 10th percentile) during the reproductive phase in both Zone-01 and Zone-02. Other parameters influencing wheat yield include thermal factors such as GDD, T_{max} , cold days, and hot days. In Zone-03, temperature extremes like spells of hot days and chilly nights in March emerged as crucial factors affecting wheat yield (Fig 5.6). It is well-known that wheat exposure to extreme heat events during the reproductive phase leads to sterile flowers, damaged pollen tube growth, and fertilization issues, resulting in reduced wheat yield (“Shenoda et al. 2021; Ullah et al. 2022”). Wheat yields in the central part of India appear unresponsive to hydro-meteorological parameters (<5% Sobol’ index) across all growth stages in all zones, aligning with findings from similar studies conducted elsewhere (“Birthal et al. 2014; Peterson et al. 2019; Schierhorn et al. 2021”). An agreement exists between RFR and NN models regarding the relative importance of climatic factors affecting soybean and wheat crop yield despite differences in Sobel's index magnitude.

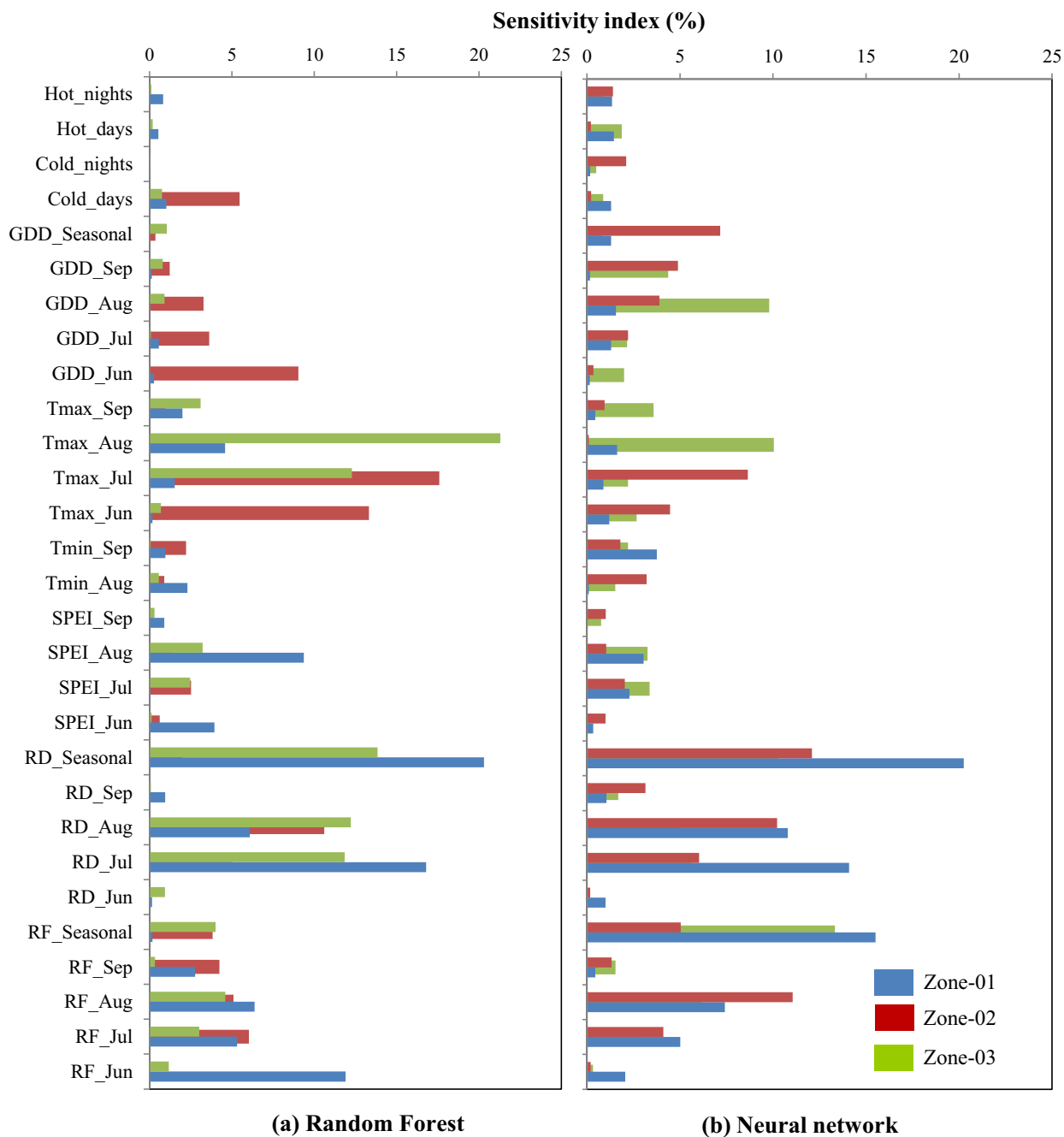


Fig 5.5 Sobol's sensitivity index of different predictor variables of Soybean yield over different zones

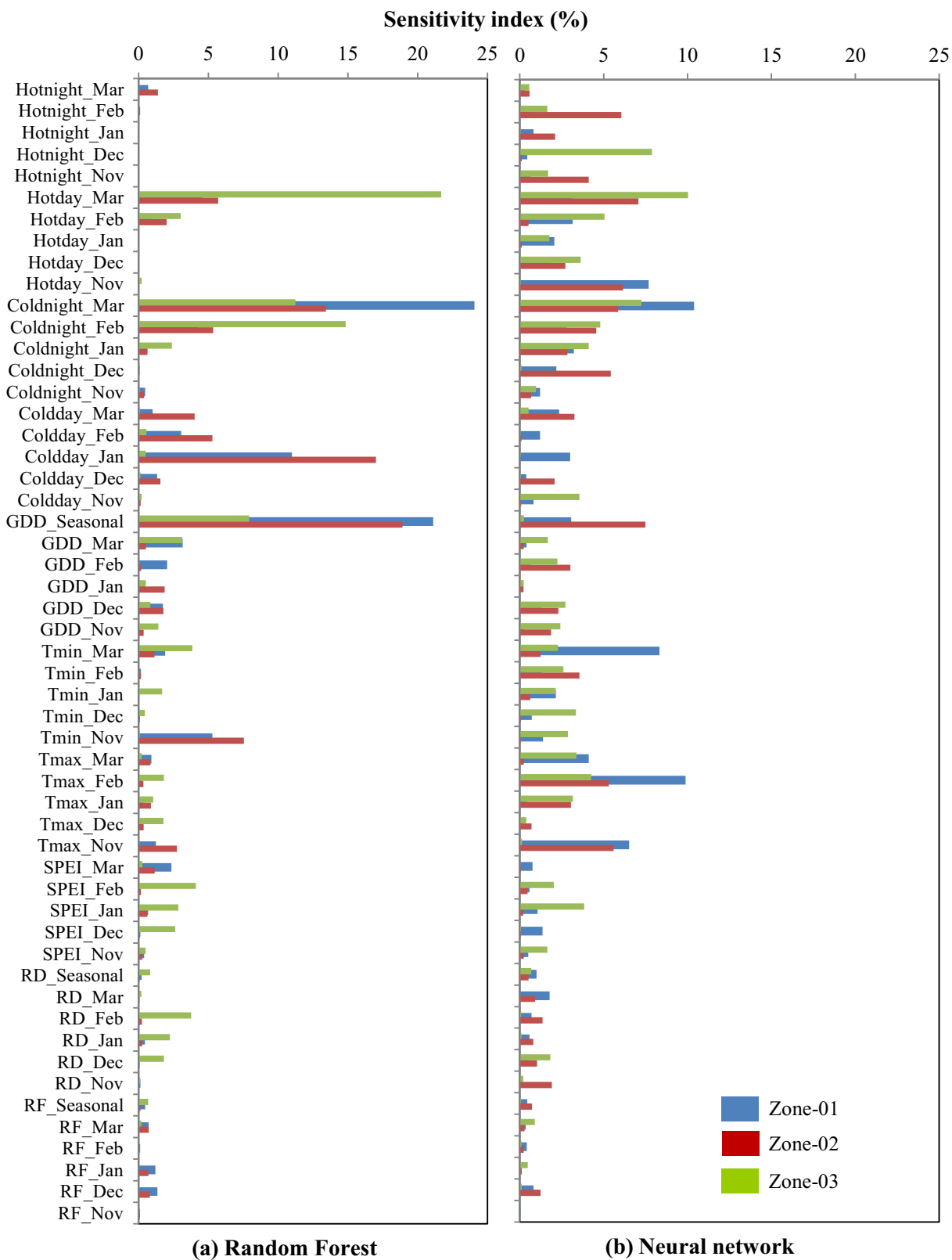


Fig 5.6 Sobol's sensitivity index of different predictor variables of Wheat yield over different zones

5.2 Discussion

While previous studies have examined the influence of in-season climatic variables on crop yield (“Harkness et al. 2020”), there has been relatively little research linking these variables to specific crop development phases and their contribution to understanding the relationship between weather and crop yield using ML techniques (“Hoffman et al. 2020; Beillouin et al. 2020; Schierhorn et al. 2021”). Assuming zone-wise consistent soil conditions, we focus on climate variability as the primary determinant of soybean and wheat crop yield in each zone. Our results indicate that climatic variables can explain a significant proportion of yield variability, ranging from 66% to 42% in zone-01 and 59% to 37% in zone-03, regardless of crop type. Additionally, weather extremes play a crucial role during specific crop growth stages, although their impact is less pronounced than to climatic variables, as “Schierhorn et al. (2021)” observed. These climate-driven impacts vary with crop types such as soybean or wheat and the region’s prevailing climate and soil characteristics (“Kukul and Irmak 2018”). In our study, we found that the effects of heat and water stress vary significantly among different crop types and regions. “Vicente-Serrano et al. (2013)” noted reduced vegetation sensitivity to water stress in regions with climatological water excess, which is consistent with our findings. For instance, hydro-meteorological parameters were not found to be sensitive in Zone-03, which does not lack rainfall. Moreover, even as an irrigated crop, wheat did not exhibit sensitivity to hydro-meteorological parameters, which led to a decline in yield.

“Murari et al. (2018)” emphasized the significance of temperature extremes on crop yield, particularly in southern India. “Hoffman et al. (2020)” also found a positive response of soybeans to increases in cool minimum temperatures using RF models. This study found no significant association between cold nights (minimum temperature extremes) and soybean yield in Indian conditions. However, soybean yield decreased with high maximum temperatures (Tmax) during the pod-filling stage, consistent with findings for soybean yield sensitivity to August Tmax in Zone-03. “Sharma et al. (2022)” reported a 25.6% decline in soybean yield with a 1°C rise in Tmax. In wheat crops, extreme heat during the grain-filling phase, particularly in Zone-03, reduced yield, as heat stress accelerates grain filling, reducing both duration and grain yield (“Barlow et al. 2015”). Hot nights during February negatively affected wheat yields during the anthesis phase, reducing photosynthesis and increasing respiration, leading to yield loss (“Sadok and Jagadish, 2020”). “Rao et al. (2015)” found a significant negative relation between

wheat yield and increased Tmax and Tmin in January and February in India, with Tmin exhibiting a more pronounced impact. Various studies have reported different degrees of yield decline under temperature effects, depending on the location of the study. For instance, “Rao et al. (2015)” documented a 7% yield loss with a 1°C rise in Tmin in India, while “You et al. (2009)” reported a 3-10% range in China. “Lobell et al. (2005)” also observed a 10% decline in Mexico, among others. It was observed that Tmin exceeding 12°C and Tmax exceeding 34°C were identified as critical during the post-anthesis period (“Rao et al. 2015”). Our study indicates that in zones with limited moisture and soil water-holding capacity, Tmin extremes and seasonal GDD are determining factors for wheat yield. However, in Zone-03 (without limitations), extreme Tmax in March, representing the grain filling and ripening period, emerges as a sensitive parameter for wheat yield. Additionally, cold nights (Tmin extremes) during the reproductive phase of wheat were identified as one of the most sensitive parameters, along with seasonal GDD, using global sensitivity analysis.

The outcome of the present study may align with several adaptation strategies helpful to mitigate the impact of climate and weather extremes on wheat and soybean crop yield, including altering cropping patterns, practicing minimum tillage (“Biswas et al. 2008”), adjusting sowing dates, cultivating heat-tolerant varieties, and implementing additional fertilizer and irrigation (“Dubey et al. 2020”).

5.3 Limitations and Future Scope

The present study emphasizes that utilizing intra-seasonal climatic variables for distinct crop developmental stages enhances understanding of the relationship between weather and yield during these critical periods, aligning with previous research findings (“Schierhorn et al. 2021”). A more profound comprehension of intra-seasonal climate effects on yields can provide valuable insights for decision-making processes among farmers and policymakers. However, it is noteworthy that the current study has yet to utilize the explicit consideration of phenology. Instead, it employs monthly weather and climatic parameters as representatives of the dominant growth stage occurring in that respective month. As a future scope of work, we propose a more distinct approach by integrating satellite-derived crop growth stages, encompassing key phases like the start of the season, peak growth stage, reproductive stage, and senescence, which will

enhance the precision of the analysis. Moreover, the current study has utilized district-level yield data, which sometimes nullifies the impact of spatial variability of soil and rainfall on crop yield. Therefore, the utilization of sub-district level yield data holds promises for providing more granular insights to capture the localized effects of weather and climate dynamics more effectively. To comprehensively enrich the model, it is imperative to extend its scope by incorporating additional meteorological parameters, specifically addressing extreme events such as rainfall extremes, hailstorms, and floods. This inclusion will undoubtedly contribute to a more holistic and robust analysis, equipping farmers and policymakers with more informed decision-making tools to face the climate vagaries.

Conclusions

The study assessed the spatio-temporal trends of meteorological variables and their extremes, examining the impact of extreme temperatures and dryness/wetness conditions on crop phenology across various agro-ecological zones in India. Furthermore, it evaluated the influence of these meteorological variables on soybean and wheat yield over central India.

The key findings of first objective are summarized below:

The thermo-meteorological variables were analyzed during the *kharif* and *rabi* seasons. In June-July of the *kharif* season, T_{max} showed a positive trend in northern India and a negative trend in southern peninsular India. In August, a stronger increasing trend of T_{max} ($>0.1^{\circ}\text{C year}^{-1}$) with a larger spatial extent ($>60\%$) was observed in the eastern and northern regions. Similar patterns were seen for T_{min} during *kharif* season months. During the *rabi* season, T_{max} was found to have significant positive trend in November ($0.1^{\circ}\text{C year}^{-1}$) over central and northeast India. December-January exhibited a significant increase in T_{min} ($0.02\text{-}0.05^{\circ}\text{C year}^{-1}$) across the eastern parts. In March, T_{max} revealed a significant positive trend in the east and northeast, with the sub-humid region ($>70\%$ spatial extent) exhibiting a higher magnitude increase ($0.2\text{-}0.4^{\circ}\text{C year}^{-1}$). Overall, magnitude of positive trend of T_{max} was observed more in the *rabi* season ($\sim 0.2^{\circ}\text{C year}^{-1}$) than in the *kharif* season ($\sim 0.1^{\circ}\text{C year}^{-1}$). T_{min} in the *rabi* season showed a significant increasing trend ($>0.051^{\circ}\text{C year}^{-1}$) across most of India from November to March, with consistent increases in the north, east, and west. Extreme temperature trends indicated more hot days across India, especially in the northeast and Western Ghats, with mixed patterns for hot nights. India showed a decreasing trend in cold extremes across major regions. The HWMId, a T_{max} extreme, showed increasing trends in central India in November and in northeastern India from January to March.

Hydro-meteorological trends from 1981 to 2018 during the southwest monsoon season indicate an overall increase in monthly rainfall ($0.5\text{-}1.5\text{ mm year}^{-1}$) and rainy days ($\sim 0.5\text{ day year}^{-1}$) across India, signifying more wet events with notable spatio-temporal variations. Early in the

monsoon season, significant rainfall increases ($>1 \text{ mm year}^{-1}$) were observed along the eastern and western coasts, and in central and western parts, but decreased significantly ($<-1 \text{ mm year}^{-1}$) in northern and northeastern India. Rainy days also showed an increasing trend, mirroring the rainfall patterns. However, the western arid region showed no trend in rainy days despite increased rainfall in June. Similarly, the Himalayan region showed a decreasing trend in seasonal rainy days but an increasing trend in seasonal rainfall, indicating a higher likelihood of heavy rainfall events. In September, both rainfall and rainy days decreased in northern and northeastern regions, suggesting a trend towards dryness in these areas. The SPEI-03, which combines both rainfall and temperature, indicates that hot sub-humid regions are more prone to dryness than semi-arid regions, with increasing dryness in northeastern India despite being a high rainfall zone. The Indian peninsula and upper western coastal regions exhibit significant wetness during the *kharif* season, while the Indo-Gangetic Plain and northeastern regions display drying trends. During the *rabi* season, increasing SPEI-03 trends were observed in eastern and western India, with mixed trends elsewhere. The major highlights are given below:

- In both the *kharif* and *rabi* seasons, both Tmax and Tmin are significantly increasing in the northern and north-eastern parts of India, while the peninsular region shows downward trends. Tmin showed a larger spatial extent with a higher rate of positive trends, indicating a decreasing difference between daytime and night-time temperatures.
- Regions with semi-arid to sub-humid climates surrounded by land masses show significantly increasing trends compared to those surrounded by water.
- Rising extreme heat events, particularly in biodiversity hotspots (Western Ghats and north-eastern regions), are a major concern. Observations indicate that the significant positive trends in Tmax and its extremes could threaten rainfed agriculture in semi-arid and sub-humid regions, potentially impacting crop production in water-limited areas.
- An overall increase in monthly rainfall and rainy days was observed across India; however, both rainfall and rainy days decreased in northern and north-eastern regions, suggesting a trend towards dryness in these areas. Moreover, the western arid region and the Himalayan region showed a higher probability of heavy/extreme rainfall events.
- The SPEI-03 revealed a more pronounced drying trend in hot sub-humid regions and increasing dryness in north-eastern India.

The key findings of the second objective are outlined below:

Wet events ($\text{SPEI} \geq 0.5$) and dry events ($\text{SPEI} \leq -0.5$) for each monsoon month (June to September) revealed that dry events are more pronounced in the early 21st century. Hot sub-humid regions exhibited a "drying" pattern with more dry events. Late-season droughts were frequent during 2001-2010, while early-season droughts were more prevalent in 2011-2018.

Spatio-temporal trend of pheno-metrics:

- SoS: During *kharif* season, 59% of agricultural areas showed an increasing trend ($>1 \text{ day year}^{-1}$) indicating delayed sowing in the north, northwest, and Deccan Plateau, while a decreasing trend ($<-1 \text{ day year}^{-1}$) indicating earlier sowing was found in northern, central, and eastern India.
- NDVI_{max} (Crop Vigor): During *kharif* season, a decreasing trend was observed in the north, east, central, west, and south, with an increasing trend in central and southern regions. During *rabi*, 53% of agricultural areas showed an increasing trend in central India, while 20.8% showed a decreasing trend in the IGP and southern regions.
- LoS: During *kharif* season, 61% of agricultural areas showed increasing trends ($>1 \text{ day year}^{-1}$) in the north, east, and some central regions, while 28% showed decreasing trends ($<-1 \text{ day/year}$) in the west, central, and south. During *rabi* season, 45% of agricultural areas showed increasing trends ($>1 \text{ day/year}$) across India, with 21% showing decreasing trends ($<-1 \text{ day year}^{-1}$) in certain western and central regions.
- EoS: During *rabi* season, 32% of agricultural areas showed a decreasing trend ($<-1 \text{ day year}^{-1}$) indicating earlier senescence in the north and Deccan Plateau, while a delay in maturity ($>1 \text{ day year}^{-1}$) was found in central and western India.

Relationships between pheno-metrics and weather extremes:

- In both *kharif* and *rabi* seasons, early-season dryness delayed the SoS, reduced NDVI_{max}, and shortened the LoS. SoS was sensitive to drought during June-July in almost all AERs, and NDVI_{max} was sensitive to SPEI-03 in August.
- During the *rabi* season, correlations between HWMId, SPEI-03, and crop pheno-metrics reveal that extreme temperatures and moisture availability significantly influence crop growth. High HWMId values correlate with earlier EoS and reduced crop vigor, especially in the IGP.

Significant negative correlations for LoS were found in northeastern and central India. SPEI-03 correlates positively with LoS and NDVI_{max}. Hot extremes (high HWMId) predominantly affect EoS, while hot and dry conditions (low SPEI-03) affect crop vigour.

- Significant negative deviations in pheno-metrics occur when high HWMId coincides with negative SPEI-03, highlighting the critical impact of concurrent hot and dry extremes.

The major outcomes of the third objective are presented below:

- The impact of climatic variables and extremes on crop yield varied according to the region's biophysical characteristics. RF models predicted soybean and wheat yields with RMSE values of 0.28-0.38 tons ha⁻¹ and 0.45-0.6 tons ha⁻¹, respectively. NN models showed similar accuracy, with RMSE values of 0.27-0.39 tons ha⁻¹ for soybean and 0.4-0.58 tons ha⁻¹ for wheat. These results underscore the models' precision in capturing the complex interplay between climate variables and crop yield.
- Rainfall and its derivatives significantly influence soybean yield during the monsoon season, particularly in regions with limited water supply. In contrast, temperature and its extremes dictate wheat yield during the winter season. These effects vary across zones within each season. For soybean, parameters like rainfall and rainy-days in July-August are crucial during flowering and pod-filling stages. Conversely, in well-irrigated areas, temperature-related factors play a key role. Cold nights and hot days during reproductive growth stages show sensitivity, positively and negatively impacting wheat yield, respectively.

Implications of Current Work for Decision Making

Given the anticipated increase in climatic extremes in the future, a deeper understanding of the intricate relationship between climate and crop yield variability is crucial. Understanding bio-climate data is essential for developing enhanced adaptation strategies to mitigate potential yield losses and ensure sustainable agricultural practices. In India, common adaptive measures to combat climate change focus on adjusting the crop calendar and sowing times, considering factors such as rainfall amounts, prevailing temperatures, soil moisture availability, and the occurrence of extreme events. These methods include selecting short-duration crops or varieties to avoid heat stress during the reproductive phase of *rabi* crops, practicing minimum or zero-

tillage for early sowing, adjusting sowing times, changing cropping systems according to site suitability, and choosing heat- and drought-resistant crop cultivars.

Another approach to mitigating the impact of climate variability on crop yield is through crop insurance, a financial mechanism designed to protect farmers against climatic risks. Crop insurance relies on long-term bio-climate data to identify areas exposed to significant climatic risks, such as extreme events and drought, and their links to sowing delays or failures, crop damage, and yield reductions. This information is crucial for assessing basis risk and calculating premium rates. By integrating these strategies, farmers can better withstand the challenges posed by climate variability.

Spatial maps generated from current studies will help identify AERs sensitive to rainfall and temperature variations, which are essential for implementing adaptation measures and developing local crop insurance solutions. Furthermore, analyzing spatio-temporal trends in phenometrics will aid in pinpointing the most vulnerable AERs, facilitating improved management strategies. Understanding the zones where soybean and wheat crop yields are sensitive to specific meteorological variables will guide the selection of appropriate agronomic practices in response to current climatic variability.

Future research will focus on evaluating the sensitivity of resilient crop varieties to climate variability, using finer-resolution temperature data to evaluate the concurrent effects of heat and moisture extremes on crop yields, integrating satellite-derived crop phenology with yield assessments, and employing multi-sensor data (including optical, thermal, and microwave) for enhanced agricultural outcomes.

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References

- Agarwal B (2010) Rethinking agricultural production collectivities. *Economic and Political Weekly*. 27:64-78.
- Ahmad FM, Shen R, Zaheer AB, Ahmad MN, Zhang Y (2018) Study capability of Standardized Precipitation Evapotranspiration Index to represent soil moisture variability during winter season over Pakistan for the period 1951–2010. *Meteorol Atmos Phys* 130(6):689–699.
- Alexander LV, Arblaster JM (2017) Historical and projected trends in temperature and precipitation extremes in Australia in observations and CMIP5. *Weather and climate extremes*. 15:34-56.
- Alexander LV, Zhang X, Peterson TC, Caesar J, Gleason B, Klein Tank AM, Haylock M, Collins D, Trewin B, Rahimzadeh F, Tagipour A (2006) Global observed changes in daily climate extremes of temperature and precipitation. *Journal of Geophysical Research: Atmospheres*. 111(D5).
- Amit Y, Geman D (1997) Shape quantization and recognition with randomized trees. *Neural computation* 9(7):1545-88
- Anderson MC, Hain C, Wardlow B, Pimstein A, Mecikalski JR, Kustas WP (2011). Evaluation of drought indices based on thermal remote sensing of evapotranspiration over the continental United States. *Journal of Climate*. 24(8):2025-44.
- Anwar MR, Li Liu D, Farquharson R, Macadam I, Abadi A, Finlayson J, Wang B & Ramilan T (2015) Climate change impacts on phenology and yields of five broadacre crops at four climatologically distinct locations in Australia. *Agricultural Systems*, 132:133-144.
- Arora M, Goel NK, Singh P (2005) Evaluation of temperature trends over India. *Hydrological Sciences Journal*. 50:81–93.
- Arora NK (2019) Impact of climate change on agriculture production and its sustainable solutions. *Environmental sustainability*. 2(2):95-6.

- Ashraf M, Ullah K, Adnan S (2022) Satellite based impact assessment of temperature and rainfall variability on drought indices in Southern Pakistan. *International Journal of Applied Earth Observation and Geoinformation*. 108:102726.
- Atkinson PM, Jeganathan C, Dash J, Atzberger C (2012) Inter-comparison of four models for smoothing satellite sensor time-series data to estimate vegetation phenology. *Remote sensing of environment*. 123:400-17.
- Atzberger C, Eilers PH (2011) A time series for monitoring vegetation activity and phenology at 10-daily time steps covering large parts of South America. *International Journal of Digital Earth*. 4(5):365-86.
- Avila-Diaz A, Justino F, Lindemann DS, Rodrigues JM, Ferreira GR (2020) Climatological aspects and changes in temperature and precipitation extremes in Viçosa-Minas Gerais. *Anais da Academia Brasileira de Ciências*. 92:e20190388.
- Ayeneh A, Van Ginkel M, Reynolds MP, Ammar K (2002) Comparison of leaf, spike, peduncle and canopy temperature depression in wheat under heat stress. *Field Crops Research*. 79(2-3):173-84.
- Badugu A, Arunab KS, Mathew A, Sarwesh P (2023) Spatial and temporal analysis of urban heat island effect over Tiruchirappalli city using geospatial techniques. *Geodesy and Geodynamics*. 14(3):275-91.
- Bal SK, Sandeep VM, Kumar PV, Rao AS, Pramod VP, Manikandan N, Rao CS, Singh NP, Bhaskar S (2022) Assessing impact of dry spells on the principal rainfed crops in major dryland regions of India. *Agricultural and Forest Meteorology*. 313:108768.
- Barlow KM, Christy BP, O’Leary GJ, Riffkin PA, Nuttall JG (2015) Simulating the impact of extreme heat and frost events on wheat crop production: A review. *Field crops research*. 171:109-19.
- Beck PS, Atzberger C, Høgda KA, Johansen B, Skidmore AK (2006) Improved monitoring of vegetation dynamics at very high latitudes: A new method using MODIS NDVI. *Remote sensing of Environment*. 100(3):321-34.

- Beguería S, Vicente-Serrano SM, Reig F, Latorre B (2014) Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. *International journal of climatology*. 34(10):3001-23.
- Beillouin D, Schauburger B, Bastos A, Ciais P, Makowski D (2020) Impact of extreme weather conditions on European crop production in 2018. *Philos Trans R Soc B: Biol Sci* 375:20190510
- Benso MR, Silva RF, Chiquito GG, Saraiva AM, Delbem AC, Marques PA, Mendiondo EM (2024) A data-driven framework for assessing climatic impact-drivers in the context of food security. *EGUsphere*. 2024:1-32.
- Berg A, Findell K, Lintner B, Giannini A, Seneviratne SI, Van Den Hurk B, Lorenz R, Pitman A, Hagemann S, Meier A, Cheruy F (2016) Land–atmosphere feedbacks amplify aridity increase over land under global warming. *Nature Climate Change*. 6(9):869-74.
- Bhavani P, Chakravarthi V, Roy PS, Joshi PK, Chandrasekar K (2017) Long-term agricultural performance and climate variability for drought assessment: a regional study from Telangana and Andhra Pradesh states, India. *Natural Hazards and Risk*. 8(2):822-40.
- Bhutiyani MR, Kale VS, Pawar NJ (2007) Long-term trends in maximum, minimum and mean annual air temperatures across the northwestern Himalaya during the twentieth century. *Climate Change*. 85:159–177.
- Birthal PS, Khan T, Negi DS, Agarwal S (2014) Impact of climate change on yields of major food crops in India: Implications for food security. *Agricultural Economics Research Review* 27(2):145-55
- Biswas DK, Xu H, Li YG, Liu MZ, Chen YH, Sun JZ, Jiang GM (2008) Assessing the genetic relatedness of higher ozone sensitivity of modern wheat to its wild and cultivated progenitors/relatives. *Journal of Experimental Botany*. 59(4):951-63.
- Bitá CE, Gerats T (2013) Plant tolerance to high temperature in a changing environment: scientific fundamentals and production of heat stress-tolerant crops. *Frontiers in plant science*. 4:273.

- Bórnez K, Richardson AD, Verger A, Descals A, Peñuelas J (2020) Evaluation of vegetation and phenology using phenocam and eddy covariance data. *Remote Sensing*. 12(18):3077.
- Bracewell RN (2000) *The Fourier Transform and Its Applications*. 3rd Edition, McGraw-Hill, New York.
- Braun HJ, Rajaram S, Ginkel M. CIMMYT's approach to breeding for wide adaptation. In *Adaptation in Plant Breeding: Selected Papers from the XIV EUCARPIA Congress on Adaptation in Plant Breeding held at Jyväskylä, Sweden from July 31 to August 4, 1995* (pp. 197-205). Springer Netherlands.
- Breiman L (2001) Random forests. *Mach Learn* 45:5–32
- Chakraborty A, Seshasai MV R, Reddy CS, & Dadhwal VK (2018a) Persistent negative changes in seasonal greenness over different forest types of India using MODIS time series NDVI data (2001–2014). *Ecological Indicators*, 85:887-903.
- Chakraborty A, Seshasai MV, Dadhwal VK (2014) Geo-spatial analysis of the temporal trends of *kharif* crop phenology metrics over India and its relationships with rainfall parameters. *Environmental monitoring and assessment*. 186:4531-42.
- Chakraborty A, Seshasai MV, Rao SK, Dadhwal VK (2017) Geo-spatial analysis of temporal trends of temperature and its extremes over India using daily gridded (1×1) temperature data of 1969–2005. *Theoretical and Applied Climatology*. 130:133-49.
- Chakraborty D, Sehgal VK, Dhakar R, Das DK, Sahoo RN (2018) Trends and change-point in satellite derived phenology parameters in major wheat growing regions of North India during the last three decades. *Journal of the Indian Society of Remote Sensing*. 46:59-68.
- Chakraborty D, Sehgal VK, Dhakar R, Ray M, Das DK (2019) Spatio-temporal trend in heat waves over India and its impact assessment on wheat crop. *Theoretical and Applied Climatology*. 138:1925-37.
- Chakraborty D, Sehgal VK, Dhakar R, Ray M, Das DK (2019) Spatio-temporal trend in heat waves over India and its impact assessment on wheat crop. *Theoretical and Applied Climatology* 138:1925-37

- Chandniha SK, Meshram SG, Adamowski JF, Meshram C (2017) Trend analysis of precipitation in Jharkhand State, India: investigating precipitation variability in Jharkhand State. *Theoretical and Applied Climatology*. 130:261-74.
- Chauhan AS, Maurya RK, Rani A, Malik A, Kisi O, Danodia A (2022) Rainfall dynamics observed over India during last century (1901–2020) using innovative trend methodology. *Water Supply*. 22(8):6909-44.
- Chen C, Park T, Wang X, Piao S, Xu B, Chaturvedi RK, Fuchs R, Brovkin V, Ciais P, Fensholt R & Myneni RB (2019) China and India lead in greening of the world through land-use management, *Nat. Sustain.*, 2:122–129.
- Chen H, Sun J (2017) Characterizing present and future drought changes over eastern China. *International Journal of Climatology*. 37:138-56.
- Chen J, Jönsson P, Tamura M, Gu Z, Matsushita B, Eklundh L (2004) A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky–Golay filter. *Remote sensing of Environment*. 91(3-4):332-44.
- Chen L, Huang JG, Ma Q, Hänninen H, Tremblay F, Bergeron Y (2019) Long-term changes in the impacts of global warming on leaf phenology of four temperate tree species. *Global change biology*. 25(3):997-1004.
- Christian JI, Basara JB, Otkin JA, Hunt ED (2019) Regional characteristics of flash droughts across the United States. *Environmental Research Communications*. 1(12):125004.
- Chuphal DS, Kushwaha AP, Aadhar S, Mishra V (2024) Drought atlas of India, 1901–2020. *Scientific Data*. 11(1):7.
- Coumou D, Robinson A, Rahmstorf S (2013) Global increase in record-breaking monthly-mean temperatures. *Climatic Change*. 118(3):771-82.
- Cramer W, Fischer A (1996) Data requirement for global terrestrial ecosystem modeling. In: Walker B, Steffen W (eds) *In global change and terrestrial ecosystems*. Cambridge University Press, Cambridge. 530–565.

- Crane-Droesch A (2018) Machine learning methods for crop yield prediction and climate change impact assessment in agriculture. *Environmental Research Letters*. 13(11):114003.
- Crimp SJ, Gobbett D, Kokic P, Nidumolu U, Howden M, Nicholls N (2016) Recent seasonal and long-term changes in southern Australian frost occurrence. *Climatic Change*. 139:115-28.
- Dalezios NR, Blanta A, Spyropoulos NV, Tarquis AM (2014) Risk identification of agricultural drought for sustainable agroecosystems. *Natural Hazards and Earth System Sciences*. 14(9):2435-48.
- Daloz AS, Rydsaa JH, Hodnebrog Ø, Sillmann J, van Oort B, Mohr CW, Agrawal M, Emberson L, Stordal F, Zhang T (2021) Direct and indirect impacts of climate change on wheat yield in the Indo-Gangetic plain in India. *Journal of Agriculture and Food Research*. 4:100132.
- Das PK, Chakraborty A, Seshasai MV (2014) Spatial analysis of temporal trend of rainfall and rainy days during the Indian Summer Monsoon season using daily gridded (0.5×0.5) rainfall data for the period of 1971–2005. *Meteorological Applications*. 21(3):481-93.
- Das PK, Das R, Das DK, Midya SK, Bandyopadhyay S, Raj U (2020) Quantification of agricultural drought over Indian region: a multivariate phenology-based approach. *Natural Hazards*. 101:255-74.
- Das PK, Mohinuddin SK, Midya SK., Das DK., Sharma R, & Bandyopadhyay S (2021) Can multiscalar meteorological drought indices detect soil moisture droughts? A study of Indian regions. *Hydrological Sciences Journal*, 66(9);1475-1487.
- Dash SK, Mangain A (2011) Changes in the frequency of different categories of temperature extremes in India. *Journal of Applied Meteorology and Climatology*. 50(9):1842-58.
- Data C. Guidelines on analysis of extremes in a changing climate in support of informed decisions for adaptation (2009) World Meteorological Organization;1500:72.
- De Beurs KM, & Henebry GM (2005) Land surface phenology and temperature variation in the International Geosphere–Biosphere Program high-latitude transects. *Global Change Biology*, 11(5):779-790.
- De Wit CT (1965) Photosynthesis of leaf canopies. Pudoc; 1965.

- Delbart N, Kergoat L, Le Toan T, Lhermitte J, Picard G (2005) Determination of phenological dates in boreal regions using normalized difference water index. *Remote Sensing of Environment*. 97(1):26-38.
- Delécolle R, Maas SJ, Guerif M, Baret F (1992) Remote sensing and crop production models: present trends. *ISPRS Journal of Photogrammetry and Remote Sensing*. 47(2-3):145-61.
- Delgado M, Hidalgo M, Puerta P, Sánchez-Leal R, Rueda L, Sobrino I (2018) Concurrent changes in spatial distribution of the demersal community in response to climate variations in the southern Iberian coastal Large Marine Ecosystem *Marine Ecology Progress Series*. 607:19-36.
- Dereczynski C, Chou SC, Lyra A, Sondermann M, Regoto P, Tavares P, Chagas D, Gomes JL, Rodrigues DC, de los Milagros Skansi M (2020) Downscaling of climate extremes over South America–Part I: Model evaluation in the reference climate. *Weather and Climate Extremes*. 29:100273.
- Desclaux D, Chiffolleau Y, Nolot JM (2009) Pluralité des agricultures biologiques: Enjeux pour la construction des marchés, le choix des variétés et les schémas d'amélioration des plantes. *Innovations agronomiques*. 4:297-306.
- Desclaux D, Huynh TT, Roumet P (2000) Identification of soybean plant characteristics that indicate the timing of drought stress. *Crop science*. 40(3):716-22.
- Dimri AP (2019) Comparison of regional and seasonal changes and trends in daily surface temperature extremes over India and its subregions. *Theoretical and Applied Climatology*. 136:265-86.
- Dinku T, Funk C, Peterson P, Maidment R, Tadesse T, Gadain H, Ceccato P (2018) Validation of the CHIRPS satellite rainfall estimates over eastern Africa. *Quarterly Journal of the Royal Meteorological Society*. 144:292-312.
- Divya P, Shetty A (2021) Evaluation of CHIRPS satellite rainfall datasets over Kerala, India. *Trends in Civil Engineering and Challenges for Sustainability: Select Proceedings of CTCS 2019*. 655-64.

- Donat MG, Alexander LV, Herold N, Dittus AJ (2016) Temperature and precipitation extremes in century-long gridded observations, reanalyses, and atmospheric model simulations. *Journal of Geophysical Research: Atmospheres*. 121(19):11-74.
- Du L, Tian Q, Yu T, Meng Q, Jancso T, Udvardy P, Huang Y (2013). A comprehensive drought monitoring method integrating MODIS and TRMM data. *International Journal of Applied Earth Observation and Geoinformation*. 23:245-53.
- Dubey R, Pathak H, Chakrabarti B, Singh S, Gupta DK, Harit RC (2020) Impact of terminal heat stress on wheat yield in India and options for adaptation. *Agricultural Systems* 181:102826
- Duchemin B, Goubier J, Courrier G (1999) Monitoring phenological key stages and cycle duration of temperate deciduous forest ecosystems with NOAA/AVHRR data. *Remote Sensing of Environment*. 67(1):68-82.
- Duncan JM, Dash J, Atkinson PM (2015) Elucidating the impact of temperature variability and extremes on cereal croplands through remote sensing. *Global change biology*. 21(4):1541-51.
- Dunn RJ, Alexander LV, Donat MG, Zhang X, Bador M, Herold N, Lippmann T, Allan R, Aguilar E, Barry AA, Brunet M (2020) Development of an updated global land in situ-based data set of temperature and precipitation extremes: HadEX3. *Journal of Geophysical Research: Atmospheres*. 125(16):e2019JD032263.
- Economic Survey of India 2021-22. (2022) Available: https://www.indiabudget.gov.in/economicsurvey/ebook_es2022/index.html. 01 March, 2023.
- Eklundh L and Jönsson P (2017) Timesat 3.3 Software Manual, Lund and Malmö University, Sweden.
- Fan Y, Van den Dool H (2008) A global monthly land surface air temperature analysis for 1948–present. *Journal of Geophysical Research: Atmospheres*. 113 (D1).
- FAO, IFAD & WFP (2012) The State of Food Insecurity in the World 2012. Economic growth is necessary but not sufficient to accelerate reduction of hunger and malnutrition. Rome. FAO.

- Farhad M, Kumar U, Tomar V, Hossain A (2023) Heat stress in wheat: a global challenge to feed billions in the current era of the changing climate. *Frontiers in Sustainable Food Systems* 7:1203721.
- Fassnacht FE, Schiller C, Kattenborn T, Zhao X, Qu J (2019) A Landsat-based vegetation trend product of the Tibetan Plateau for the time-period 1990–2018. *Scientific data*. 6(1):78.
- Fayech D, Tarhouni J (2021) Climate variability and its effect on normalized difference vegetation index (NDVI) using remote sensing in semi-arid area. *Modelling Earth Systems and Environment*. 7:1667-82.
- Felton AJ, Zavislan-Pullaro S, Smith MD (2019) Semi-arid ecosystem sensitivity to precipitation extremes: weak evidence for vegetation constraints. *Ecology* 100:e02572.
- Fischer A (1994) A model for the seasonal variations of vegetation indices in coarse resolution data and its inversion to extract crop parameters. *Remote Sensing of Environment*. 48(2):220-30.
- Fowler HJ, Lenderink G, Prein AF, Westra S, Allan RP, Ban N, Barbero R, Berg P, Blenkinsop S, Do HX, Guerreiro S (2021) Anthropogenic intensification of short-duration rainfall extremes. *Nature Reviews Earth & Environment*. 2(2):107-22.
- Friedl MA, Gray JM, Melaas EK, Richardson, AD, Hufkens K, Keenan TF, Bailey A & O’Keefe J (2014) A tale of two springs: using recent climate anomalies to characterize the sensitivity of temperate forest phenology to climate change. *Environmental Research Letters*, 9(5):054006.
- Fu YH, Piao S, Delpierre N, Hao F, Hänninen H, Liu Y, Sun W, Janssens IA, Campioli M (2018) Larger temperature response of autumn leaf senescence than spring leaf-out phenology. *Glob Chang Biol* 24: 2159–2168.
- García-Cueto OR, Santillán-Soto N, López-Velázquez E, Reyes-López J, Cruz-Sotelo S, Ojeda-Benítez S (2019) Trends of climate change indices in some Mexican cities from 1980 to 2010. *Theoretical and Applied Climatology*. 137:775-90.

- Garonna I, de Jong R, Schaepman ME (2016) Variability and evolution of global land surface phenology over the past three decades (1982–2012). *Global change biology*. 22(4):1456-68.
- Ge W, Han J, Zhang D, Wang F (2021) Divergent impacts of droughts on vegetation phenology and productivity in the Yungui Plateau, southwest China. *Ecological Indicators*. 127:107743.
- Gebrechorkos SH, Hülsmann S, Bernhofer C (2018) Evaluation of multiple climate data sources for managing environmental resources in East Africa. *Hydrology and Earth System Sciences*. 22(8):4547-64.
- Gibbs, W. J., & Maher, J. V. (1967). Rainfall deciles drought indicators. Bureau of Meteorology Bulletin No. 48, Melbourne: Bureau of Meteorology.
- Glade FE, Miranda MD, Meza FJ, van Leeuwen WJ (2016) Productivity and phenological responses of natural vegetation to present and future inter-annual climate variability across semi-arid river basins in Chile. *Environ Monit Assess* 188:676.
- Glorot X, Bengio Y (2010) Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics* 31 (pp. 249-256). *JMLR Workshop and Conference Proceedings*
- Grossiord C, Buckley TN, Cernusak LA, Novick KA, Poulter B, Siegwolf RT, Sperry JS, McDowell NG (2020) Plant responses to rising vapor pressure deficit. *New phytologist*. 226(6):1550-66.
- Guhathakurta P, Rajeevan M (2008) Trends in the rainfall pattern over India. *International Journal of Climatology* 28: 1453–1469.
- Guntukula R (2020) Assessing the impact of climate change on Indian agriculture: evidence from major crop yields. *Journal of Public Affairs*. 20(1):e2040.
- Guntukula R, Goyari P (2020) Climate change effects on the crop yield and its variability in Telangana, India. *Studies in Microeconomics*. 8(1):119-48.

- Gupta S, Bhandari L, Jakhu R, Sharma M (2022) Climate Change, Weather Anomalies, and Agriculture: Impact on Output of Major Crops in India (CSEP Working Paper 46). New Delhi: Centre for Social and Economic Progress.
- Gupta S, Tiwari YK, Revadekar JV, Burman PK, Chakraborty S, Gnanamoorthy P (2021) An intensification of atmospheric CO₂ concentrations due to the surface temperature extremes in India. *Meteorology and Atmospheric Physics*.133:1647-59.
- Gupta V, Jain MK, Singh PK, Singh V (2020) An assessment of global satellite-based precipitation datasets in capturing precipitation extremes: A comparison with observed precipitation dataset in India. *International Journal of Climatology*. 40(8):3667-88.
- Güsewell S, Furrer R, Gehrig R, Pietragalla B (2017) Changes in temperature sensitivity of spring phenology with recent climate warming in Switzerland are related to shifts of the preseason. *Glob. Change Biol*. 23 (12), 5189–5202.
- Haan CT (1977) *Statistical Methods in Hydrology*. The Iowa State University Press, Ames, Iowa, 378.
- Hadjimitsis DG, Papadavid G, Agapiou A, Themistocleous K, Hadjimitsis MG, Retalis A, Michaelides S, Chrysoulakis N, Toullos L, Clayton CR (2010) Atmospheric correction for satellite remotely sensed data intended for agricultural applications: impact on vegetation indices. *Natural Hazards and Earth System Sciences*. 10(1):89-95.
- Haldar S, Choudhury M, Choudhury S, Samanta P (2023) Trend analysis of long-term meteorological data of a growing metropolitan city in the era of global climate change. *Total Environment Research Themes*. 7:100056.
- Hamed KH, Rao AR (1998) A modified Mann-Kendall trend test for autocorrelated data. *Journal of hydrology*. 204(1-4):182-96.
- Hansen J, Sato M, Ruedy R, Schmidt GA, Lo K, Hendrickson M. (2020) Global Temperature in 2019. Earth Institute, Columbia University: New York.1-5.

- Hao H, Li Y, Zhang H, Zhai R, Liu H (2019) Spatiotemporal variations of vegetation and its determinants in the National Key Ecological Function Area on Loess Plateau between 2000 and 2015. *Ecology and evolution*. 9(10):5810-20.
- Hao Z, Di S, Wu M, Zheng J (2019) Does El Niño play an early signal role for the south-flood north-drought pattern over eastern China? *Theoretical and Applied Climatology*. 137:217–227.
- Harkness C, Semenov MA, Areal F, Senapati N, Trnka M, Balek J, Bishop J (2020) Adverse weather conditions for UK wheat production under climate change. *Agricultural and Forest Meteorology*. 282:107862
- Harvey C (2018) Scientists can now blame individual natural disasters on climate change extreme event attribution is one of the most rapidly expanding areas of climate science. *Scientific American*.
- Hatfield JL, Prueger JH (2015) Temperature extremes: Effect on plant growth and development. *Weather and climate extremes*. 10:4-10.
- Hayes, M. J., Svoboda, M. D., Wardlow, B. D., Anderson, M. C., & Kogan, F. (2012). Drought monitoring: Historical and current perspectives. Drought Mitigation Center Faculty Publications: 94.
- Heino M, Kinnunen P, Anderson W, Ray DK, Puma MJ, Varis O, Siebert S, Kummu M (2023) Increased probability of hot and dry weather extremes during the growing season threatens global crop yields. *Scientific reports*. 13(1):3583.
- Heumann BW, Seaquist JW, Eklundh L, Jönsson P (2007) AVHRR derived phenological change in the Sahel and Soudan, Africa, 1982–2005. *Remote sensing of environment*. 29;108(4):385-92.
- Hingane LS, Rupa Kumar K, Murty VR (1985) Long-term trends of surface air temperature in India. *International Journal of Climatology* 5:521–528.
- Hobbins MT, Wood A, McEvoy DJ, Huntington JL, Morton C, Anderson M, Hain C (2016) The evaporative demand drought index. Part I: Linking drought evolution to variations in evaporative demand. *Journal of Hydrometeorology*. (6):1745-61.

- Hofman A, Kemanian A, Forest C (2020) The response of maize, sorghum, and soybean yield to growing phase climate revealed with machine learning. *Environ Res Lett* 15:094013
- Houghton JT, Ding, YDJG and Griggs DJ (2001) *Climate change 2001: the scientific basis* (Vol. 881, No. 9). Cambridge: Cambridge university press.
- Hoy A, Hänsel S, Maugeri M (2020) An endless summer: 2018 heat episodes in Europe in the context of secular temperature variability and change. *International Journal of Climatology* :1-22
- Hulme M, Mitchell J, Ingram W, Lowe J, Johns T, New M, Viner D (1999). *Climate change scenarios for global impacts studies*. *Global Environmental Change*. 9:S3-19.
- IPCC, 2021. Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, Caud N, Chen Y, Goldfarb L, Gomis MI, Huang M. *Climate change 2021: the physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change*.
- IPCC, 2021. Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, Caud N, Chen Y, Goldfarb L, Gomis MI, Huang M (2021) *Climate change 2021: the physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change*. 2021 Jun;2.
- IPCC, 2021. Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, Caud N, Chen Y, Goldfarb L, Gomis MI, Huang M. *Climate change 2021: the physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change 2021*.
- Irmak S, Sandhu R, Kukal MS (2022) Multi-model projections of trade-offs between irrigated and rainfed maize yields under changing climate and future emission scenarios. *Agricultural Water Management*. 261:107344.
- Ishtiaq M, Maqbool M, Muzamil M, Casini R, Alataway A, Dewidar AZ, El-Sabroun AM & Elansary HO (2022) Impact of Climate Change on Phenology of Two Heat-Resistant Wheat Varieties and Future Adaptations. *Plants*, 11(9):1180.

- Javed T, Li Y, Feng K, Ayantobo OO, Ahmad S, Chen X, Rashid S, Suon S (2021) Monitoring responses of vegetation phenology and productivity to extreme climatic conditions using remote sensing across different sub-regions of China. *Environmental Science and Pollution Research*. 28(3):3644-59.
- Jeganathan C, Dash J, & Atkinson PM (2010) Mapping the phenology of natural vegetation in India using a remote sensing-derived chlorophyll index. *International Journal of Remote Sensing*, 31(22):5777-5796.
- Jeganathan C, Ganguly S, Dash J, Friedl M, Atkinson PM (2010) Terrestrial vegetation phenology from MODIS and MERIS. In 2010 IEEE International Geoscience and Remote Sensing Symposium. 2699-2702.
- Jeganathan C, Nishant N (2014) Scrutinising MODIS and GIMMS vegetation indices for extracting growth rhythm of natural vegetation in India. *Journal of the Indian Society of Remote Sensing*. 42:397-408.
- Jenifer MA, Jha MK (2021) Assessment of precipitation trends and its implications in the semi-arid region of Southern India. *Environmental challenges*. 5:100269.
- Jiang Y, Wang R, Peng Q, Wu X, Ning H, Cheng L (2018) The relationship between drought activity and vegetation cover in Northwest China from 1982 to 2013. *Nat Hazards*. 92(1):145-63.
- Jones PD, Horton EB, Folland CK, Hulme M, Parker DE, Basnett TA (1999) The use of indices to identify changes in climatic extremes. *Climatic Change*. 42:131-49.
- Jones PD, Moberg A (2003) Hemispheric and large-scale surface air temperature variations: An extensive revision and an update to 2001. *Journal of climate*. 16(2):206-23.
- Jones PD, New M, Parker DE, Martin S, Rigor IG (1999) Surface air temperature and its changes over the past 150 years. *Reviews of Geophysics*. 37(2):173-99.
- Jonsson P, Eklundh L (2002) Seasonality extraction by function fitting to time-series of satellite sensor data. *IEEE transactions on Geoscience and Remote Sensing*. 40(8):1824-32.
- Jönsson P, Eklundh L. (2004) TIMESAT—a program for analyzing time-series of satellite sensor data. *Computers and geosciences*. 30(8):833-45.

- Julien Y, Sobrino JA (2009) Global land surface phenology trends from GIMMS database. *International Journal of Remote Sensing*. 30(13):3495-513.
- Kang W, Wang T, Liu S (2018) The response of vegetation phenology and productivity to drought in semi-arid regions of Northern China. *Remote Sensing*. 10(5):727.
- Kang W, Wang T, Liu S (2018) The response of vegetation phenology and productivity to drought in semi-arid regions of Northern China. *Remote Sensing*. 10:727.
- Kendall M (1976) Rank correlation methods, 4th edn. Griffin, London
- Khare S, Ghosh SK, Latifi H, Vijay S, Dahms T (2017) Seasonal-based analysis of vegetation response to environmental variables in the mountainous forests of Western Himalaya using Landsat 8 data. *International journal of remote sensing*. 38(15):4418-42.
- Kim J, Shon J, Lee CK, Yang W, Yoon Y, Yang WH, Kim YG, Lee BW (2011) Relationship between grain filling duration and leaf senescence of temperate rice under high temperature. *Field Crops Research*. 122(3):207-13.
- Klein Tank AM (2004) Changing temperature and precipitation extremes in Europe's Climate of the 20th century. Utrecht University.
- Klein Tank AM, Peterson TC, Quadir DA, Dorji S, Zou X, Tang H, Santhosh K, Joshi UR, Jaswal AK, Kolli RK, Sikder AB (2006) Changes in daily temperature and precipitation extremes in central and south Asia. *Journal of Geophysical Research: Atmospheres*. 111(D16).
- Konduri VS, Vandal TJ, Ganguly S, Ganguly AR (2020) Data science for weather impacts on crop yield. *Frontiers in Sustainable Food Systems* 19;4:52
- Kothawale DR, Revadekar JV, Rupa Kumar K (2010b) Recent trends in pre-monsoon daily temperature extremes over Indian Journal of Earth System Science. 119:51–65.
- Kothawale DR, Rupa Kumar K (2005) On the recent changes in surface temperature trends over India. *Geophys Res Lett* 32:L18714. doi:10.1029/2005GL023528.
- Koulgi PS, Clinton N, Karanth KK (2019) Extensive vegetation browning and drying in forests of India's Tiger Reserves. *Scientific Reports*. 9(1):14976.

- Krishnakumar KN, Rao GSLHVP, Gopakumar CS. 2009. Rainfall trends in twentieth century over Kerala, India. *Atmos. Environ.* 43:1940–1944.
- Krishnaswamy J, John R, Joseph S (2014) Consistent response of vegetation dynamics to recent climate change in tropical mountain regions. *Global change biology*. 20(1):203-15.
- Kukul MS, Irmak S (2018) Climate-driven crop yield and yield variability and climate change impacts on the US Great Plains agricultural production. *Scientific reports* 22;8(1):1-8
- Kukul MS, Irmak S (2018) Climate-driven crop yield and yield variability and climate change impacts on the US Great Plains agricultural production. *Scientific reports* 22;8(1):1-8
- Kumar A, Giri RK, Taloor AK, Singh AK (2021) Rainfall trend, variability and changes over the state of Punjab, India 1981–2020: A geospatial approach. *Remote Sensing Applications: Society and Environment*. 23:100595.
- Kumar M, Phukon SN, Paygude AC, Tyagi K, Singh H (2022) Mapping phenological functional types (PhFT) in the Indian Eastern Himalayas using machine learning algorithm in Google Earth Engine. *Computers & Geosciences*. 158:104982.
- Kumar P, Tokas J, Kumar N, Lal M, Singal HR (2018) Climate change consequences and its impact on agriculture and food security. *International Journal of chemical studies*. 6(6):124-33.
- Kumar R, Gautam HR (2014) Climate change and its impact on agricultural productivity in *Indian Journal of Climatology & Weather Forecasting*. 2(1):1-3.
- Kumar R, Gautam HR. (2014) Climate change and its impact on agricultural productivity in *Indian Journal of Climatology and Weather Forecasting*.
- Kumar R, Nandy S, Agarwal R, Kushwaha SP (2014) Forest cover dynamics analysis and prediction modeling using logistic regression model. *Ecological indicators*. 45:444-55.
- Kumar R, Nath AJ, Nath A, Sahu N, & Pandey R (2022) Landsat-based multi-decadal spatio-temporal assessment of the vegetation greening and browning trend in the Eastern Indian Himalayan Region. *Remote Sensing Applications: Society and Environment*, 25:100695.
- Kumari M, Chakraborty A, Chakravarathi V, Pandey V, Roy PS (2024) Impact of climate and weather extremes on soybean and wheat yield using machine learning approach. *Stochastic*

Environmental Research and Risk Assessment. [https:// doi.org/ 10.1007/s00477-024-02759-3](https://doi.org/10.1007/s00477-024-02759-3).

Kumari M, Chakraborty A, Chakravarathi V, Roy PS (2023) Spatio-temporal trend of crop phenology, SPEI, and their interactions over different agro-ecological regions of India. *Theoretical and Applied Climatology*. 154(1):291-309.

Lafta AM, Lorenzen JH (1995) Effect of high temperature on plant growth and carbohydrate metabolism in potato. *Plant physiology*. 109(2):637-43.

Lahiri P (2003) On the impact of bootstrap in survey sampling and small-area estimation. *Statistical Science*. 18(2):199-210.

Lal M (2001) Climatic change–implications for India’s water resources. *Journal of Indian Water Resource*. 21: 101–119.

Lal M (2011) Implications of climate change in sustained agricultural productivity in South Asia. *Regional environmental change*. 11(Suppl 1):79-94.

Le Roux R, Furusho-Percot C, Deswarte JC, Bancal MO, Chenu K, de Noblet-Ducoudré N, de Cortázar-Atauri IG, Durand A, Bulut B, Maury O, Décome J (2024) Mapping the race between crop phenology and climate risks for wheat in France under climate change. *Scientific Reports*. 14(1):8184.

Lesk C, Anderson W, Rigden A, Coast O, Jägermeyr J, McDermid S, Davis KF, Konar M (2022) Compound heat and moisture extreme impacts on global crop yields under climate change. *Nature Reviews Earth & Environment*. 3(12):872-89.

Li Y, Piao S, Li LZ, Chen A, Wang X, Ciais P, Huang L, Lian X, Peng S, Zeng Z, Wang K (2018) Divergent hydrological response to large-scale afforestation and vegetation greening in China. *Science Advances*. 4(5): 4182.

Li Z, Lyu S, Ao Y, Wen L, Zhao L, Wang S (2015) Long-term energy flux and radiation balance observations over Lake Ngoring, Tibetan Plateau. *Atmospheric Research*. 155:13-25.

Liaw A, Wiener M (2002) Classification and regression by random Forest. *R news*. 3;2(3):18-22

- Liu H, Jiao F, Yin J, Li T, Gong H, Wang Z, & Lin Z (2020) Nonlinear relationship of vegetation greening with nature and human factors and its forecast—a case study of Southwest China. *Ecological Indicators*, 111:106009.
- Liu L, Zhang X (2020) Effects of temperature variability and extremes on spring phenology across the contiguous United States from 1982 to 2016. *Scientific Reports*. 21;10(1):17952.
- Liu Q, Fu YH, Zeng Z, Huang M, Li X, Piao S (2016) Temperature, precipitation, and insolation effects on autumn vegetation phenology in temperate China. *Global change biology*. 22(2):644-55.
- Liu X, Pan Y, Zhu X, Yang T, Bai J, Sun Z (2018) Drought evolution and its impact on the crop yield in the North China Plain. *Journal of hydrology*. 564:984-96.
- Lloyd D (1990) A phenological classification of terrestrial vegetation cover using shortwave vegetation index imagery. *Remote Sensing*. 11(12):2269-79.
- Lobell DB (2013) The use of satellite data for crop yield gap analysis. *Field crops research*. 143:56-64.
- Lobell DB, Asseng S (2017) Comparing estimates of climate change impacts from process-based and statistical crop models. *Environmental Research Letters* 4;12(1):015001
- Lobell DB, Field CB (2011) California perennial crops in a changing climate. *Climatic Change*. 109:317-33.
- Lobell DB, Ortiz-Monasterio JI, Asner GP, Matson PA, Naylor RL, Falcon WP (2005) Analysis of wheat yield and climatic trends in Mexico. *Field crops research*. 94(2-3):250-6.
- Lobell DB, Sibley A, Ivan Ortiz-Monasterio J (2012) Extreme heat effects on wheat senescence in India. *Nature Climate Change* 2(3):186-9
- Lu C, Sun Y, Wan H, Zhang X, Yin H (2016) Anthropogenic influence on the frequency of extreme temperatures in China. *Geophysical Research Letters*. 43(12):6511-8.
- Lu J, Carbone GJ, Gao P (2017) Detrending crop yield data for spatial visualization of drought impacts in the United States, 1895–2014. *Agricultural and forest meteorology* 1;237:196-208

- Lu M, Yang S, Li Z, He B, He S, Wang Z (2018) Possible effect of the Tibetan Plateau on the “upstream” climate over west Asia, North Africa, south Europe and the North Atlantic. *Climate Dynamics*. 51:1485-98.
- Luan X, Vico G (2021) Canopy temperature and heat stress are increased by compound high air temperature and water stress and reduced by irrigation—a modeling analysis. *Hydrology and Earth System Sciences*. 25(3):1411-23.
- Ma X, Huete A, Moran S, Ponce-Campos G, Eamus D (2015) Abrupt shifts in phenology and vegetation productivity under climate extremes. *J Geophys Res Biogeosci*. 120:2036–2052.
- MacCarthy DS, Traore PS, Freduah BS, Adiku SG, Dodor DE, Kumahor SK (2022) Productivity of Soybean under Projected Climate Change in a Semi-Arid Region of West Africa: Sensitivity of Current Production System. *Agronomy* 24;12(11):2614
- Madhukar A, Dashora K, Kumar V (2021) Climate trends in temperature and water variables during wheat growing season and impact on yield. *Environmental Processes* 8:1047-72.
- Mahesh KM, Aithal PS, Sharma KR (2023) Impact of Aatmanirbharta (Self-reliance) Agriculture and Sustainable Farming for the 21st Century to Achieve Sustainable Growth. *International Journal of Applied Engineering and Management Letters*. 7(2):175-90.
- Malhi GS, Kaur M, Kaushik P (2021) Impact of climate change on agriculture and its mitigation strategies: A review. *Sustainability*. 13(3):1318.
- Malhi RK, Kiran GS, Shah MN, Mistry NV, Bhavsar VH, Singh CP, Bhattacharya BK, Townsend PA, Mohan S (2021) Applicability of Smoothing Techniques in Generation of Phenological Metrics of *Tectona grandis* L. Using NDVI Time Series Data. *Remote Sensing*. 13, 3343.
- Mall RK, Singh R, Gupta A, Srinivasan G, Rathore LS (2006) Impact of climate change on Indian agriculture: a review. *Climatic change*. 78(2):445-78.
- Mann HB (1945) Nonparametric tests against trend. *Econometrica: Journal of the econometric society*. 1:245-59.

- Matiu et al. 2017 Matiu M, Ankerst DP, Menzel A. 2017. Interactions between temperature and drought in global and regional crop yield variability during 1961-2014. *PloS one*. 26;12(5):e0178339
- Mazdiyasni O, AghaKouchak A, Davis SJ, Madadgar S, Mehran A, Ragno E, Sadegh M, Sengupta A, Ghosh S, Dhanya CT, Niknejad M (2017) Increasing probability of mortality during Indian heat waves. *Science advances*. 3(6):e1700066.
- Mbatha N, Xulu S (2018) Time series analysis of MODIS-Derived NDVI for the Hluhluwe-Imfolozi Park, South Africa: Impact of recent intense drought. *Climate*.6(4):95.
- Mbokodo I, Bopape MJ, Chikoore H, Engelbrecht F, Nethengwe N (2020) Heatwaves in the future warmer climate of South Africa. *Atmosphere*. 11(7):712.
- McKee TB, Doesken NJ, Kleist J (1993) The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology*. 17(22):179-183.
- Meehl GA, Hu A, Tebaldi C, Arblaster JM, Washington WM, Teng H, Sanderson BM, Ault T, Strand WG, White III JB (2012) Relative outcomes of climate change mitigation related to global temperature versus sea-level rise. *Nature Climate Change*. 2(8):576-80.
- Meehl GA, Zwiers F, Evans J, Knutson T, Mearns L, Whetton P (2000) Trends in extreme weather and climate events: issues related to modelling extremes in projections of future climate change. *Bulletin of the American Meteorological Society*. 81(3):427-36.
- Menzel A (2003) Plant phenological anomalies in Germany and their relation to air temperature and NAO. *Climatic change*. 57(3):243-63.
- Meroni M, d'Andrimont R, Vrieling A, Fasbender D, Lemoine G, Rembold F, Seguni L & Verhegghen A (2021) Comparing land surface phenology of major European crops as derived from SAR and multispectral data of Sentinel-1 and-2. *Remote sensing of environment*, 253:112232.
- Miralles DG, Teuling AJ, Van Heerwaarden CC, Vilà-Guerau de Arellano J (2014) Mega-heatwave temperatures due to combined soil desiccation and atmospheric heat accumulation. *Nature geoscience*. 7(5):345-9.

- Mishra AK, Singh VP (2011) Drought modeling—A review. *Journal of Hydrology*. 403(1-2):157-75.
- Mishra V, Thirumalai K, Singh D, Aadhar S (2020) Future exacerbation of hot and dry summer monsoon extremes in India. *Npj Climate and Atmospheric Science*. 23;3(1):10.
- MoEFCC (2021) India: third biennial update report to the United Nations Framework Convention on Climate Change. Ministry of Environment, Forest and Climate Change, Government of India.1-501.
- Mohanty M, Sinha NK, McDermid SP, Chaudhary RS, Reddy KS, Hati KM, Somasundaram J, Lenka S, Patidar RK, Prabhakar M, Cherukumalli SR (2017) Climate change impacts vis-a-vis productivity of soybean in vertisol of Madhya Pradesh. *Journal of Agrometeorology* 1;19(1):10-6
- Mohapatra S, Mohapatra S, Han H, Ariza-Montes A, López-Martín MD (2022) Climate change and vulnerability of agribusiness: Assessment of climate change impact on agricultural productivity. *Frontiers in Psychology* 26;13:955622
- Mooley DA, Parthasarathy B (1984) Fluctuations in all India summer monsoon rainfall during 1871–1978. *Climate Change* 6: 287–301.
- Moron V, Oueslati B, Pohl B, Rome S, Janicot S (2016) Trends of mean temperatures and warm extremes in northern tropical Africa (1961–2014) from observed and PPCA-reconstructed time series. *Journal of Geophysical Research: Atmospheres*. 121(10):5298-319.
- Mukherjee A, Huda AK (2018) Assessment of climate variability and trend on wheat productivity in West Bengal, India: crop growth simulation approach. *Climatic change* 147(1-2):235-52
- Murari KK, Mahato S, Jayaraman T, Swaminathan M (2018) Extreme temperatures and crop yields in Karnataka, India. *Review of Agrarian Studies*. 8(2)
- Murray V, Ebi KL (2012) IPCC special report on managing the risks of extreme events and disasters to advance climate change adaptation (SREX). *Journal of Epidemiology Community Health*. 66(9):759-60.

- Muthoni FK, Odongo VO, Ochieng J, Mugalavai EM, Mourice SK, Hoesche-Zeledon I, Mwila M, Bekunda M (2019) Long-term spatial-temporal trends and variability of rainfall over Eastern and Southern Africa. *Theoretical and Applied Climatology*. 137:1869-82.
- Nam WH, Hayes MJ, Svoboda MD, Tadesse T, & Wilhite DA (2015) Drought hazard assessment in the context of climate change for South Korea. *Agricultural Water Management*, 160:106-117.
- Nandy S, Ghosh S, Singh S (2021) Assessment of Sal (*Shorea robusta*) forest phenology and its response to climatic variables in India. *Environmental Monitoring and Assessment*. 193(9):616.
- Novikova LY, Bulakh PP, Nekrasov AY, Seferova IV (2020) Soybean response to weather and climate conditions in the Krasnodar and Primorye territories of Russia over the past decades. *Agronomy*10(9):1278
- NRSC (2014) Land Use/Land Cover Database on 1:50,000 Scale. Natural Resources Census Project. Hyderabad: LUCMD, LRUMG, RSAA, National Remote Sensing Centre, ISRO.
- Olesen JE, Carter TR, Diaz-Ambrona CH, Fronzek S, Heidmann T, Hickler T, Holt T, Minguez MI, Morales P, Palutikof JP, Quemada M (2007) Uncertainties in projected impacts of climate change on European agriculture and terrestrial ecosystems based on scenarios from regional climate models. *Climatic Change*. 81:123-43.
- Orlowsky B, Seneviratne SI (2012) Global changes in extreme events: regional and seasonal dimension. *Climatic change*. 110:669-96.
- Ortiz-Bobea A, Wang H, Carrillo CM, Ault TR (2019) Unpacking the climatic drivers of US agricultural yields. *Environ Res Lett* 14:064003
- Osborne TM, Wheeler TR (2013) Evidence for a climate signal in trends of global crop yield variability over the past 50 years. *Environmental Research Letters*. 8(2):024001.
- Osman MA, Onono JO, Olaka LA, Elhag MM, Abdel-Rahman EM (2021) Climate variability and change affect crops yield under rainfed conditions: A case study in Gedaref State, Sudan. *Agronomy*. 11(9):1680.

- Otto FE, Massey N, van Oldenborgh GJ, Jones RG, Allen MR (2012) Reconciling two approaches to attribution of the 2010 Russian heat wave. *Geophysical Research Letters*. 39(4).
- Pal I, Al-Tabbaa A (2010) Long-term changes and variability of monthly extreme temperatures in India. *Theoretical and Applied Climatology*. 100:45–56.
- Pal I, Al-Tabbaa A (2011) Assessing seasonal precipitation trends in India using parametric and non-parametric statistical techniques. *Theoretical and Applied Climatology*. 103:1-1.
- Palmer WC. Meteorological drought. US Department of Commerce, Weather Bureau; 1965.
- Panda A, Sahu N (2019) Trend analysis of seasonal rainfall and temperature pattern in Kalahandi, Bolangir and Koraput districts of Odisha, India. *Atmospheric Science Letters*. 20(10):e932.
- Pandey V, Srivastava PK, Singh SK, Petropoulos GP, Mall RK (2021) Drought identification and trend analysis using long-term CHIRPS satellite precipitation product in Bundelkhand, India. *Sustainability*. 13(3):1042.
- Pant GB, Rupa Kumar K (1997) *Climates of south Asia*. Chichester: John Wiley & Sons.
- Parida BR, Pandey AC, Patel NR (2020) Greening and browning trends of vegetation in India and their responses to climatic and non-climatic drivers. *Climate*. 8(8):92.
- Parsons DJ, Rey D, Tanguy M, Holman IP (2019) Regional variations in the link between drought indices and reported agricultural impacts of drought. *Agricultural systems*. 173:119-29.
- Parthasarathy B, Dhar ON (1974) Secular variations of regional rainfall over India. *Q. J. R. Meteorol. Soc.* 100: 245–257.
- Paszke A, Gross S, Massa F, Lerer A, Bradbury J, Chanan G, Killeen T, Lin Z, Gimelshein N, Antiga L, Desmaison A (2019) Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems* 32
- Pattanaik DR, Rajeevan M (2010) Variability of extreme rainfall events over India during southwest monsoon season. *Meteorological Applications: A journal of forecasting, practical applications, training techniques and modelling*. 17(1):88-104.

- Paymard P, Bannayan M, Haghighi RS (2018) Analysis of the climate change effect on wheat production systems and investigate the potential of management strategies. *Natural Hazards*. 91:1237-55.
- Peichl M, Thober S, Meyer V, Samaniego L (2018) The effect of soil moisture anomalies on maize yield in Germany. *Natural Hazards Earth System Science* 18:889–906
- Peñuelas J, Filella I (2001) Responses to a warming world. *Science*. 294(5543):793-5.
- Perkins-Kirkpatrick SE, Lewis SC (2020). Increasing trends in regional heatwaves. *Nature communications*. 11(1):3357.
- Petersen LK (2019) Impact of climate change on twenty-first century crop yields in the U.S. *Climate* 7:40.
- Piao S, Liu Q, Chen A, Janssens IA, Fu Y, Dai J, Liu L, Lian XU, Shen M, Zhu X (2019) Plant phenology and global climate change: Current progresses and challenges. *Global change biology*. 25(6):1922-40.
- Piao S, Wang X, Ciais P, Zhu B, Wang T, Liu J (2011) Changes in satellite-derived vegetation growth trend in temperate and boreal Eurasia from 1982 to 2006. *Glob Chang Biol* 17:3228–3239.
- Piao S, Fang J, Zhou L, Ciais P, Zhu B (2006) Variations in satellite-derived phenology in China's temperate vegetation. *Global change biology*. 12(4):672-85.
- Plummer N, Salinger MJ, Nicholls N, Suppiah R, Hennessy KJ, Leighton RM, Trewin B, Page CM, Lough JM (1999) Changes in climate extremes over the Australian region and New Zealand during the twentieth century. *Weather and climate extremes: Changes, variations and a perspective from the insurance industry*. 183-202.
- Porter JR, Gawith M (1999) Temperatures and the growth and development of wheat: a review. *European journal of agronomy*. 10(1):23-36
- Potopová V, Štěpánek P, Možný M, Türkott L, Soukup J (2015) Performance of the standardised precipitation evapotranspiration index at various lags for agricultural drought risk assessment in the Czech Republic. *Agricultural and Forest Meteorology*. 202:26-38.

- Powell JP, Reinhard S (2016) Measuring the effects of extreme weather events on yields. *Weather and Climate extremes* 1(12):69-79
- Prakash S (2019) Performance assessment of CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA precipitation products across Indian Journal of hydrology. 571:50-9.
- Pramanik SK, Jagannathan P (1954) Climatic changes in India rainfall. *Indian Journal of Meteorology Geophysics*. 4:291–309.
- Pramudya Y, Onishi T (2018) Assessment of the standardized precipitation index (SPI) in Tegal City, Central Java, Indonesia. *INOP conference series: earth and environmental science* 129(1):012019.
- Sathyan A, Funk C, Aenis T, Breuer L (2018) Climate Vulnerability in Rainfed Farming: Analysis from Indian Watersheds.
- Praveen B, Sharma P (2020) Climate variability and its impacts on agriculture production and future prediction using autoregressive integrated moving average method (ARIMA). *Journal of Public Affairs*. 20(2):e2016.
- Praveen D, Palanivelu K (2017) Spatiotemporal analysis of projected impacts of climate change on the major C3 and C4 crop yield under representative concentration pathway 4.5: Insight from the coasts of Tamil Nadu, South India. *PloS one* 12(7):e0180706
- Qin N, Wang J, Yang G, Chen X, Liang H, Zhang J (2015) Spatial and temporal variations of extreme precipitation and temperature events for the Southwest China in 1960–2009. *Geoenvironmental Disasters*. 2:1-4.
- Rai A, Sharma V, Heitholt J (2020) Dry bean [*Phaseolus vulgaris* L.] growth and yield response to variable irrigation in the arid to semi-arid climate. *Sustainability*. 12(9):3851.
- Rai SK and Apoorva SPR (2020) Climate Change, Pandemic and its Impact on Indian Agriculture. *Agriculture & Food: e-Newsletter*, 2(10).
- Ramadan HH, Ramamurthy AS, Beighley RE (2012) Inter-annual temperature and precipitation variations over the Litani Basin in response to atmospheric circulation patterns. *Theoretical and applied climatology*. 108:563-77.
- Ramesh KV, Goswami P (2007) The shrinking Indian summer monsoon. Research Report RR CM 0709, CSIR Centre for Mathematical Modelling and Computer Simulation: Bangalore.

- Ranjan AK, & Gorai AK (2022) Evaluating phenological trends of different vegetation types in response to climate change over the Rajmahal Hills in India during 2001-2019. *Remote Sensing Letters*, 13(9):898-911.
- Rao BB, Chowdary PS, Sandeep VM, Pramod VP, Rao VU (2015) Spatial analysis of the sensitivity of wheat yields to temperature in India. *Agricultural and Forest Meteorology* 15;200:192-202
- Rao CS, Lal R, Prasad JV, Gopinath KA, Singh R, Jakkula VS, Sahrawat KL, Venkateswarlu B, Sikka AK, Virmani SM (2015) Potential and challenges of rainfed farming in India. *Advances in agronomy*. 133:113-81.
- Ratnam JV, Behera SK, Ratna SB, Rajeevan M, Yamagata T (2016). Anatomy of Indian heatwaves. *Scientific Reports*. 6(1):1-1.
- Rauschkolb R, Bucher SF, Hensen I, Ahrends A, Fernández-Pascual E, Heubach K, Jakubka D, Jiménez-Alfaro B, König A, Koubek T, Kehl A (2024) Spatial variability in herbaceous plant phenology is mostly explained by variability in temperature but also by photoperiod and functional traits. *International Journal of Biometeorology*. 68(4):761-75.
- Ray DK, Gerber JS, MacDonald GK, West PC (2015) Climate variation explains a third of global crop yield variability. *Nature communications*. 6(1):5989.
- Ray DK, Mueller ND, West PC, Foley JA (2013) Yield trends are insufficient to double global crop production by 2050. *PloS one*. 8(6):e66428.
- Ray DK, Ramankutty N, Mueller ND, West PC, Foley JA (2012) Recent patterns of crop yield growth and stagnation. *Nature communications*. 3(1):1293.
- Reed BC, Brown JF, VanderZee D, Loveland TR, Merchant JW, Ohlen DO (1994) Measuring phenological variability from satellite imagery. *Journal of vegetation science*. 5(5):703-14.
- Ren S, Yi S, Peichl M, Wang X (2017) Diverse responses of vegetation phenology to climate change in different grasslands in Inner Mongolia during 2000–2016. *Remote Sensing*. 10(1):17.

- Revadekar JV, Kothawale DR, Patwardhan SK, Pant GB, Rupa Kumar K (2012) About the observed and future changes in temperature extremes over India. *Natural hazards*. 60:1133-55.
- Rezaei EE, Siebert S, Ewert F (2015) Intensity of heat stress in winter wheat—phenology compensates for the adverse effect of global warming. *Environmental Research Letters*. 10(2):024012.
- Richardson AD, Keenan TF, Migliavacca M, Ryu Y, Sonnentag O, Toomey M (2013) Climate change, phenology, and phenological control of vegetation feedbacks to the climate system. *Agricultural and Forest Meteorology*. 169:156-73.
- Richardson AD, Braswell BH, Hollinger DY, Jenkins JP, Ollinger SV (2009) Near-surface remote sensing of spatial and temporal variation in canopy phenology. *Ecological Applications*. 19(6):1417-28.
- Richardson AD, Hollinger DY, Dail DB, Lee JT, Munger JW, O’keefe J (2009) Influence of spring phenology on seasonal and annual carbon balance in two contrasting New England forests. *Tree physiology*. 29(3):321-31.
- Robert M, Thomas A, Sekhar M, Badiger S, Ruiz L, Raynal H, Bergez JE (2017) Adaptive and dynamic decision-making processes: A conceptual model of production systems on Indian farms. *Agricultural systems* 1;157:279-91
- Rohini P, Rajeevan M, Srivastava AK (2016) On the variability and increasing trends of heat waves over India. *Scientific reports*.6(1):1-9.
- Roxy MK, Ghosh S, Pathak A, Athulya R, Mujumdar M, Murtugudde R, Terray P, Rajeevan M (2017) A threefold rise in widespread extreme rain events over central India. *Nature communications*. 8(1):1-1.
- Ruml M, Gregorić E, Vujadinović M, Radovanović S, Matović G, Vuković A, Počuča V, Stojičić D (2017) Observed changes of temperature extremes in Serbia over the period 1961– 2010. *Atmospheric Research*. 183:26-41.

- Rupa Kumar K, Pant GB, Parthasarathy B, Sontakke NA (1992) Spatial and sub-seasonal patterns of the long term trends of Indian summer monsoon rainfall. *International Journal of Climatology* 12: 257–268.
- Russo S, Sillmann J, Fischer EM (2015). Top ten European heatwaves since 1950 and their occurrence in the coming decades. *Environmental Research Letters*. 10(12):124003.
- Rusticucci M, Kysely J, Almeida G, Lhotka O (2016) Long-term variability of heat waves in Argentina and recurrence probability of the severe 2008 heat wave in Buenos Aires. *Theoretical and Applied Climatology*. 124:679-89.
- Sadok W, Jagadish SK (2020) The hidden costs of night time warming on yields. *Trends in Plant Science*. 25(7):644-51.
- Saikia B, Banerjee SA, Sarkar SS (2009) Crop weather relationship in *Brassica campestris* var. yellow Sarson grown in Gangetic West Bengal. *Journal of Agrometeorology*. 11:67-9.
- Sakamoto T, Yokozawa M, Toritani H, Shibayama M, Ishitsuka N, Ohno H (2005) A crop phenology detection method using time-series MODIS data. *Remote sensing of environment*. 96(3-4):366-74.
- Sanderson BM, Xu Y, Tebaldi C, Wehner M, O'Neill B, Jahn A, Pendergrass AG, Lehner F, Strand WG, Lin L, Knutti R (2017). Community climate simulations to assess avoided impacts in 1.5 and 2 C futures. *Earth System Dynamics*. 8(3):827-47.
- Sarker RP, Thapliyal V (1988) Climate change and variability. *Mausam* 39: 127–138.
- Sathyan AR, Funk C, Aenis T, & Breuer L (2018) Climate vulnerability in rainfed farming: analysis from Indian watersheds. *Sustainability*, 10(9):3357.
- Schauberger B, Archontoulis S, Arneth A, Balkovic J, Ciais P, Deryng D, Elliott J, Folberth C, Khabarov N, Müller C, Pugh TA (2017) Consistent negative response of US crops to high temperatures in observations and crop models. *Nature communications*. 8(1):13931.
- Schierhorn F, Hofmann M, Gagalyuk T, Ostapchuk I, Müller D (2021) Machine learning reveals complex effects of climatic means and weather extremes on wheat yields during different plant developmental stages. *Climatic Change* 169(3-4):39

- Sehgal VK, Jain S, Aggarwal PK, & Jha S (2011) Deriving crop phenology metrics and their trends using times series NOAA-AVHRR NDVI data. *Journal of the Indian Society of Remote Sensing*, 39:373-381.
- Şen Z (2012) Innovative trend analysis methodology. *Journal of Hydrologic Engineering*. 17(9):1042-6.
- Sen PK (1968) Estimates of the regression coefficient based on Kendall's tau. *Journal of the American statistical association*. 63(324):1379-89.
- Seneviratne SI, Corti T, Davin EL, Hirschi M, Jaeger EB, Lehner I, Orlowsky B, Teuling AJ (2010) Investigating soil moisture–climate interactions in a changing climate: A review. *Earth-Science Reviews*. 99(3-4):125-61.
- Seneviratne SI, Xuebin Z, Muhammad A,,Wafae B,, Claudine DA, Di L, Ghosh S, Iskandar I, Kossin J, Lewis S, Otto F (2021) Weather and climate extreme events in a changing climate. 1513-1766.
- Sharma RK, Kumar S, Vatta K, Dhillon J, Reddy KN (2022) Impact of recent climate change on cotton and soybean yields in the southeastern United States. *Journal of Agriculture and Food Research*. 9:100348.
- Shen M, Tang Y, Chen J, Yang X, Wang C, Cui X, Yang Y, Han L, Li L, Du J, Zhang G (2014) Earlier-season vegetation has greater temperature sensitivity of spring phenology in Northern Hemisphere. *PloS one*. 5;9(2):e88178.
- Shen X, Jiang M, & Lu X (2023) Diverse impacts of day and night temperature on spring phenology in freshwater marshes of the Tibetan Plateau. *Limnology and Oceanography Letters*, 8(2):323-329.
- Shen X, Liu B, Henderson M, Wang L, Jiang M, & Lu X (2022) Vegetation greening, extended growing seasons, and temperature feedbacks in warming temperate grasslands of China. *Journal of Climate*, 35(15):5103-5117.

- Shenoda JE, Sanad MN, Rizkalla AA, El-Assal S, Ali RT, Hussein MH (2001) Effect of long-term heat stress on grain yield, pollen grain viability and germinability in bread wheat (*Triticum aestivum* L.) under field conditions. *Heliyon* 1;7(6)
- Shrestha UB, Gautam S, Bawa KS (2012) Widespread climate change in the Himalayas and associated changes in local ecosystems. *PloS one*. 7(5):e36741.
- Sicher RC (2015) Temperature shift experiments suggest that metabolic impairment and enhanced rates of photorespiration decrease organic acid levels in soybean leaflets exposed to supra-optimal growth temperatures. *Metabolites*. 5(3):443-54.
- Siebert S, Ewert F, Rezaei EE, Kage H, Graß R (2014) Impact of heat stress on crop yield—on the importance of considering canopy temperature. *Environmental Research Letters*. 9(4):044012.
- Sigalla OZ, Valimba P, Selemani JR, Kashaigili JJ, Tumbo M (2023) Analysis of spatial and temporal trend of hydro-climatic parameters in the Kilombero River Catchment, Tanzania. *Scientific Reports*. 13(1):7864.
- Singh N, Sontakke NA (2002) On climatic fluctuations and environmental changes of the Indo-Gangetic plains, India. *Climate Change* 52(3): 287–313.
- Singh RN, Sah S, Das B, Potekar S, Chaudhary A, Pathak H (2021) Innovative trend analysis of spatio-temporal variations of rainfall in India during 1901–2019. *Theoretical and Applied Climatology*. 145(1):821-38.
- Singh S & Sanatan N (2021) Assessment of climate change impact on wheat yield in western dry region: A district level analysis. *Climate Change*, 6(21):25-34.
- Singh SD, Chakrabarti B, Muralikrishna KS, Chaturvedi AK, Kumar V, Mishra S, Harit R (2013) Yield response of important field crops to elevated air temperature and CO. *Indian Journal of Agricultural Sciences*. 83(10):1009-2.
- Sinha Ray KC, De US (2003) Climate change in India as evidenced from instrumental records. *WMO Bull*. 52: 53–59.

- Sneyers R (1997) Climate chaotic instability: statistical determination and theoretical background. *Environmetrics: The official journal of the International Environmetrics Society*. 8(5):517-32.
- Sobol IM (2001) Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Mathematics and computers in simulation* 55(1-3):271-80
- Soora NK, Aggarwal PK, Saxena R, Rani S, Jain S, Chauhan N (2013). An assessment of regional vulnerability of rice to climate change in India. *Climatic change*. 118:683-99.
- Spearman C (1904) The Proof and Measurement of Association between Two Things. *America Journal of Psychology*, 15, 72-101.
- Srivastava HN, Dewan BN, Dikshit SK, Rao PGS, Singh SS, Rao KR (1992) Decadal trends in climate over India. *Mausam* 43:7–20.
- Stephenson DB, Diaz HF, Murnane RJ (2008) Definition, diagnosis, and origin of extreme weather and climate events. *Climate extremes and society*. 340:11-23.
- Stocker T (2014) Climate change 2013: The physical science basis: Working Group I contribution to the Fifth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press.
- Strobl C, Boulesteix AL, Kneib T, Augustin T, Zeileis A (2008) Conditional variable importance for random forests. *BMC bioinformatics* 9:1-1
- Stuart-Haëntjens E, De Boeck HJ, Lemoine NP, Mänd P, Kröel-Dulay G, Schmidt IK, Jentsch A, Stampfli A, Anderegg WR, Bahn M, Kreyling J (2018) Mean annual precipitation predicts primary production resistance and resilience to extreme drought. *Science of the Total Environment*. 636:360-6.
- Subash N, Mohan HR (2012) Evaluation of the impact of climatic trends and variability in rice–wheat system productivity using Cropping System Model DSSAT over the Indo-Gangetic Plains of India. *Agricultural and Forest Meteorology*. 164:71-81.
- Subramaniam AR (1983) Agro-ecological zones of India. *Archives for meteorology, geophysics, and bioclimatology, Series B*. 32(2):329-33

- Sulugodu B, Deka PC (2019) Evaluating the performance of CHIRPS satellite rainfall data for streamflow forecasting. *Water Resources Management*. 33:3913-27.
- Tan B, Morisette JT, Wolfe RE, Gao F, Ederer GA, Nightingale J, Pedelty JA (2010) An enhanced TIMESAT algorithm for estimating vegetation phenology metrics from MODIS data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. 4(2):361-71.
- Thapliyal V, Kulshrestha SM (1991) Climate changes and trends over India. *Mausam* 42: 333–338.
- Thomas JL, Waugh DW, Gnanadesikan A (2015) Southern Hemisphere extratropical circulation: Recent trends and natural variability. *Geophysical Research Letters*. 42(13):5508-15.
- Thong P, Sahoo UK, Pebam R, Thangjam U (2019) Spatial and temporal dynamics of shifting cultivation in Manipur, Northeast India based on time-series satellite data. *Remote Sensing Applications: Society and Environment*. 14:126-37.
- Tigchelaar M, Battisti DS, Naylor RL, Ray DK (2018) Future warming increases probability of globally synchronized maize production shocks. *Proceedings of the National Academy of Sciences* 26;115(26):6644-9
- Tilman D, Balzer C, Hill J, Befort BL (2011) Global food demand and the sustainable intensification of agriculture. *Proceedings of the national academy of sciences*. 108(50):20260-4.
- Tirivarombo S, Osupile D, Eliasson P (2018) Drought monitoring and analysis: standardised precipitation evapotranspiration index (SPEI) and standardised precipitation index (SPI). *Physics and Chemistry of the Earth, Parts A/B/C* 1;106:1-0.
- Tomczyk AM, Bednorz E (2020). The extreme year analysis of thermal conditions in Poland in 2018. *Theoretical and Applied Climatology*. 139(1):251-60.
- Trenberth KE (2008) Climate change and extreme weather events. In *Proceedings of the Catastrophe Modeling Forum: Changing Climatic Dynamic and Catast*; Epstein, P., Ed 22.
- Troy TJ, Kipgen C, Pal I (2015) The impact of climate extremes and irrigation on US crop yields. *Environmental Research Letters*. 10(5):054013.

- Türkeş M, Erlat E (2018) Variability and trends in record air temperature events of Turkey and their associations with atmospheric oscillations and anomalous circulation patterns. *International Journal of Climatology*. 38(14):5182-204.
- Ullah A, Nadeem F, Nawaz A, Siddique KH, Farooq M (2022) Heat stress effects on the reproductive physiology and yield of wheat. *Journal of Agronomy and Crop Science* 208(1):1-7
- Urban D, Roberts MJ, Schlenker W, Lobell DB (2012) Projected temperature changes indicate significant increase in interannual variability of US maize yields: A Letter. *Climatic change*. 112:525-33.
- Van Oort PA, Zhang T, De Vries ME, Heinemann AB, Meinke H (2011) Correlation between temperature and phenology prediction error in rice (*Oryza sativa* L.). *Agricultural and Forest Meteorology* 15;151(12):1545-55
- Varghese SJ, Surendran S, Rajendran K, Ghosh S, Kitoh A, Ashok K (2024) Precipitation Scaling in Extreme Rainfall Events and the Implications for Future Indian Monsoon: Analysis of High-Resolution Global Climate Model Simulations. *Geophysical Research Letters*. 51(1):e2023GL105680.
- Verger A, Filella I, Baret F, Peñuelas J (2016) Vegetation baseline phenology from kilometeric global LAI satellite products. *Remote sensing of environment*. 178:1-4.
- Vicente-Serrano SM, Cabello D, Tomás-Burguera M, Martín-Hernández N, Beguería S, Azorín-Molina C, El Kenawy A (2015) Drought variability and land degradation in semiarid regions: Assessment using remote sensing data and drought indices (1982–2011). *Remote Sensing*. 7(4):4391-423.
- Vicente-Serrano SM, Gouveia C, Camarero JJ, Beguería S, Trigo R, López-Moreno JI, Azorín-Molina C, Pasho E, Lorenzo-Lacruz J, Revuelto J, Morán-Tejeda E (2013) Response of vegetation to drought time-scales across global land biomes. *Proceedings of the National Academy of Sciences*. 110(1):52-7
- Vicente-Serrano SM, Beguería S, López-Moreno JI (2010) A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *Journal of climate*. 23(7):1696-718.

- Vincent LA, Zhang X, Mekis É, Wan H, Bush EJ. Changes in Canada's climate: Trends in indices based on daily temperature and precipitation data (2018) *Atmosphere-Ocean*.56(5):332-49.
- Vogel E, Donat MG, Alexander LV, Meinshausen M, Ray DK, Karoly D, Meinshausen N, Frieler K. (2019) The effects of climate extremes on global agricultural yields. *Environ Res Lett* 14:054010
- Vose RS, Easterling DR, Kunkel KE, LeGrande AN, Wehner MF (2017) Temperature changes in the United States. Climate science special report: Fourth national climate assessment. 1(GSFC-E-DAA-TN49028).
- Wang H, Wu C, Ciais P, Peñuelas J, Dai J, Fu Y, & Ge Q (2020) Overestimation of the effect of climatic warming on spring phenology due to misrepresentation of chilling. *Nature Communications*, 11(1):4945.
- Wang J, Zhou T, Peng P (2018) Phenology response to climatic dynamic across China's grasslands from 1985 to 2010. *ISPRS International Journal of Geo-Information*. 7(8):290.
- Wang S, Yang B, Yang Q, Lu L, Wang X, Peng Y (2016) Temporal trends and spatial variability of vegetation phenology over the Northern Hemisphere during 1982-2012. *PloS one*. 11(6):e0157134.
- Webber H, Ewert F, Olesen JE, Müller C, Fronzek S, Ruane AC, Bourgault M, Martre P, Ababaei B, Bindi M, Ferrise R, Finger R, Fodor N, Gabaldón-Leal C, Gaiser T, Jabloun M, Kersebaum K-C, Lizaso JJ, Lorite IJ, Manceau L, Moriondo M, Nendel C, Rodríguez A, Ruiz-Ramos M, Semenov MA, Siebert S, Stella T, Stratonovitch P, Trombi G, Wallach D (2018) Diverging importance of drought stress for maize and winter wheat in Europe. *Nature Communication*. 9:4249
- Wheeler TR, Craufurd PQ, Ellis RH, Porter JR, Prasad PV (2000) Temperature variability and the yield of annual crops. *Agriculture, Ecosystems & Environment* 82(1-3):159-67.
- White MA, de Beurs KM, Didan K, Inouye DW, Richardson AD, Jensen OP, O'keefe J, Zhang G, Nemani RR, van Leeuwen WJ, Brown JF (2009) Intercomparison, interpretation, and

- assessment of spring phenology in North America estimated from remote sensing for 1982–2006. *Global change biology*. 15(10):2335-59.
- White MA, Thornton PE, Running SW (1997) A continental phenology model for monitoring vegetation responses to interannual climatic variability. *Global biogeochemical cycles*. 11(2):217-34.
- Wilhite DA (2007) *Drought International Perspectives on Natural Disasters: Occurrence, Mitigation, and Consequences*. Dordrecht: Springer Netherlands:147-162.
- Wilhite DA, Svoboda MD, Hayes MJ (2007). Understanding the complex impacts of drought: A key to enhancing drought mitigation and preparedness. *Water resources management*. 21:763-74.
- Wilhite DA, Buchanan-Smith M (2005) Drought as hazard: understanding the natural and social context. *Drought and water crises: Science, technology, and management issues*. 22:3-29.
- Wilhite DA, Glantz MH (1985) Understanding the drought phenomenon: the role of definitions. *Water international*. 10(3):111-20.
- Wilks DS (1997) Resampling hypothesis tests for autocorrelated fields. *Journal of Climate*. 10(1):65-82.
- Yamori W, Hikosaka K, Way DA (2014) Temperature response of photosynthesis in C3, C4, and CAM plants: temperature acclimation and temperature adaptation. *Photosynthesis research*. 119:101-17.
- Yang J, Zhou M, Ren Z, Li M, Wang B, Liu DL, Ou CQ, Yin P, Sun J, Tong S, Wang H (2021) Projecting heat-related excess mortality under climate change scenarios in China. *Nature communications*. 12(1):1039.
- Yang Y, Tao B, Liang L, Huang Y, Matocha C, Lee CD, Sama M, Masri BE, Ren W (2021) Detecting Recent Crop Phenology Dynamics in Corn and Soybean Cropping Systems of Kentucky. *Remote Sensing*. 13(9):1615.

- Yao X, Zhang H, Lemckert C, Brook A, Schouten P (2010). Evaporation reduction by suspended and floating covers: overview, modelling and efficiency. Urban water security research alliance technical report. 28:1-3.
- Yin Y, Ma D, Wu S (2018) Climate change risk to forests in China associated with warming. *Scientific reports*. 8(1):493.
- Young LW, Wilen RW, Bonham-Smith PC (2004) High temperature stress of *Brassica napus* during flowering reduces micro-and megagametophyte fertility, induces fruit abortion, and disrupts seed production. *Journal of experimental botany*. 55(396):485-95.
- Yu Y, Huang Y, Zhang W (2013) Projected changes in soil organic carbon stocks of China's croplands under different agricultural managements, 2011–2050. *Agriculture, ecosystems & environment* 15;178:109-20
- Yu Y, Stomph TJ, Makowski D, Zhang L, Van Der Werf W (2016). A meta-analysis of relative crop yields in cereal/legume mixtures suggests options for management. *Field Crops Research*. 198:269-79.
- Yue S, Hashino M (2003) Temperature trends in Japan: 1900–1996. *Theoretical and Applied Climatology*. 75:15-27.
- Yue S, Wang CY (2002) Regional streamflow trend detection with consideration of both temporal and spatial correlation. *International journal of climatology*. 22(8):933-46.
- Zampieri M, Ceglar A, Dentener F, Toreti A (2017) Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. *Environ Res Lett* 12:064008
- Zaveri E, Lobell D (2019) The role of irrigation in changing wheat yields and heat sensitivity in India. *Nature. Communications* 10 (1), 9
- Zhai L, Feng Q, Li Y (2010) Calculation of actual evapotranspiration based on Morton CRAE in Northwest China. *Journal of Irrigation and Drainage*. 29 (5):33-38.
- Zhang Q, Kong D, Shi P, Singh VP, Sun P (2018) Vegetation phenology on the Qinghai-Tibetan Plateau and its response to climate change (1982–2013). *Agricultural and forest meteorology*. 248:408-17.

- Zhang X, Zwiers FW, Li G, Wan H, Cannon AJ (2017a) Complexity in estimating past and future extreme short-duration rainfall. *Nature Geoscience*. 10(4):255-9.
- Zhang Y, Li L, Wang H, Zhang Y, Wang N, Chen J (2017b) Land surface phenology of Northeast China during 2000–2015: temporal changes and relationships with climate changes. *Environmental monitoring and assessment*. 189:1-3.
- Zhang Y, Song C, Band LE, Sun G, Li J (2017) Reanalysis of global terrestrial vegetation trends from MODIS products: Browning or greening?. *Remote Sensing of Environment*. 191:145-55.
- Zhang Y, Song C, Band LE, Sun G, Li J (2017) Reanalysis of global terrestrial vegetation trends from MODIS products: Browning or greening?. *Remote Sensing of Environment*. 191:145-55.
- Zhang XY, Trame MN, Lesko LJ, Schmidt S (2015) Sobol sensitivity analysis: a tool to guide the development and evaluation of systems pharmacology models. *CPT: pharmacometrics & systems pharmacology* 4(2):69-79.
- Zhang X, Tan B, Yu Y (2014) Interannual variations and trends in global land surface phenology derived from enhanced vegetation index during 1982–2010. *International journal of biometeorology*. 58:547-64.
- Zhang H, Zhai P (2011) Temporal and spatial characteristics of extreme hourly precipitation over eastern China in the warm season. *Advances in Atmospheric Sciences*:1177-83.
- Zhang X, Friedl MA, Schaaf CB (2004) Strahler AH, Schneider A. The footprint of urban climates on vegetation phenology. *Geophysical research letters*. 31(12).
- Zhang X, Friedl MA, Schaaf CB, Strahler AH, Hodges JC, Gao F, Reed BC, Huete A (2003) Monitoring vegetation phenology using MODIS. *Remote sensing of environment*. 84(3):471-5.
- Zhao C, Liu B, Piao S, Wang X, Lobell DB, Huang, Y, Huang M, Yao Y, Bassu S, Ciais P, Durand JL, Elliott J, Ewert F, Janssens IA, Li T, Lin E, Liu Q, Martre P, Müller C, Peng S, Peñuelas J, Ruane AC, Wallach D, Wang T, Wu D, Liu Z, Zhu Y, Zhu Z, Asseng S

(2017) Temperature increase reduces global yields of major crops in four independent estimates. *Proc. Natl. Acad. Sci.* 114 (35), 9326–9331

Zscheischler J, Seneviratne SI (2017) Dependence of drivers affects risks associated with compound events. *Science advances.* 3(6):e1700263.



Spatio-temporal trend of crop phenology, SPEI, and their interactions over different agro-ecological regions of India

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Abstract

The study focuses on analyzing the impact of dryness/wetness, derived from Standardized Precipitation Evapotranspiration Index (SPEI), on vegetation phenology in different agro-ecological zones (AERs) of India during 2001–2018. Long-term CRU TS3 SPEI datasets at a 3-month time scale were used to characterize the drought events, while Normalized Difference Vegetation Index (NDVI) data from MODIS at a 250 m scale was used to extract crop phenology metrics. The results revealed that the dryness was prevalent in the hot sub-humid regions since the new millennium. Non-parametric trend analysis showed that northeast India experienced the highest increase in drought events over the past 38 years. In terms of phenology metrics, approximately 59, 23, and 61% of agricultural areas displayed an increasing trend of the start of season (SoS), seasonal NDVI amplitude (NDVI_{max}), and length of season (LoS). However, 21% of agricultural area showed a decreasing trend in SoS, 5.17% in NDVI_{max}, and 28% in LoS. The impact of climate extremes varied across different AERs, that too in dry and wet years. During drought years, most AERs exhibited a delayed SoS, reduced NDVI_{max}, and decreased LoS. The sensitivity of LoS to dryness is higher in semi-arid and sub-humid regions compared to arid and humid regions. Under the projected increase in extreme events, understanding resilient crop growth in response to dryness/wetness is crucial for adaptation and mitigation strategies. The findings of this study help in identifying areas that are particularly vulnerable to drought events and can contribute in informed decision-making.

1 Introduction

A significant increase in global mean air temperature has recently been reported by the Intergovernmental Panel on Climate Change (IPCC) sixth assessment report (IPCC 2021), leading to intensified extreme rainfall and drought events in south Asia. Chakraborty et al. (2017) have reported a significant warming trend and an increase in the extreme hot events over India. These changes have diverse impacts on society and ecosystems, varying across different regions based on their vulnerabilities (Parsons et al. 2019).

Amid the different types of droughts, agricultural drought is one of the complex hazards where soil moisture is limited to support crop growth (Dalezios et al. 2014; Wilhite and Buchanan-Smith 2005). The agricultural drought has pronounced effect on rainfed regions, which is prevalent in India occupying nearly two-thirds of agricultural land (Rao et al. 2015; Sathyan et al. 2018). Agricultural productivity in these areas is heavily influenced by climatic factors, viz., rainfall and evapotranspiration (Mall et al. 2006). Previous studies have primarily focused on the effect of temperature or rainfall on crop growth, rather than the impact of drought on crops (Hatfield and Prueger 2015). Drought indices, such as Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), and Standardized Precipitation Evapotranspiration Index (SPEI), are valuable indicators for analyzing and interpreting drought severity (McKee et al. 1993; Palmer 1965; Vicente-serrano et al. 2010). However, these indices have certain limitations. For example, PDSI requires comprehensive water balance components, making it data-intensive and restricted in use (Zhai et al. 2010; Li et al. 2015). SPI, based on long-term rainfall data, can lack consistency, especially in arid regions with

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high evaporation demands (Pramudya and Onishi 2018; Mishra and Singh 2011). In contrast, SPEI overcomes these limitations by incorporating rainfall and evapotranspiration data, making it useful indicator for monitoring wet and dry events (Tirivarambo et al. 2018; Chen and Sun 2017). SPEI is sensitive to changes in climatic demand of evaporation (Beguería et al. 2014) and can act as a proxy for soil moisture (Ahmad et al. 2018; Das et al. 2021).

Recent studies revealed that the croplands are the major contributor to greening in India, while forests have a minor contribution (Parida et al. 2020; Chen et al. 2019). While previous studies have examined vegetation dynamics in India, they focus on forests at the national and regional levels (Ranjan and Gorai 2022; Jeganathan et al. 2010; Kumar et al. 2022; Chakraborty et al. 2018a), neglecting explicit analysis of croplands. Crop phenology, which expresses the seasonal events of plant processes, is a crucial indicator of crop growth pattern changes in response to climate change. Understanding crop phenology is crucial as changes in crop phenology can impact carbon accumulation, crop yield, crop duration and distribution of diseases, and other environmental and social aspects (Richardson et al. 2009). Remote sensing provides a synoptic overview of crop-growing regions, enabling regular monitoring of crop growth, health, and productivity. Remote sensing cannot directly identify a particular crop growth stage or phenological events due to coarse spatial resolution of satellite data, resulting into mixed spectra, particularly from heterogeneous grid. Therefore, a more generalized phenology, i.e., “land surface phenology” metrics (pheno-metrics), is computed (de Beurs and Henebry 2005) which indicates the seasonality change in spectral observation and depicted as SoS, LoS, and NDVI at peak stage, etc. Previous research have examined the influence of climate change on crop growth and crop yield in India, demonstrating the varying relationship between crop growth patterns and drought (Malhi et al. 2021; Arora 2019; Kumar and Gautam 2014; Guntukula 2020; Rai and Apoorva 2020). Several studies are carried out to explore the temporal pattern of phenology metrics using satellite data derived Normalized Difference Vegetation Index (NDVI) time series in wetlands (Shen et al. 2023), forests (Friedl et al. 2014; Liu et al. 2020; Wang et al. 2020), croplands (Anwar et al. 2015; Ishtiaq et al. 2022; Ge et al. 2021; Javed et al. 2021; Yang et al. 2021), and grasslands (Shen et al. 2022) in different parts of the world. However, sparse studies are available analyzing the impact of dry/wet events on crop phenology, especially in a country like India. Limited researches (Chakraborty et al. 2014; Chakraborty et al. 2018b; Das et al. 2020) utilized 8-km GIMMS NDVI3g data to analyze the trend in phenology and its association with rainfall. These studies have exploited meteorological unit-level boundary or state-administrative boundary to represent the findings that do not capture the variability in agricultural

area and patterns within an India’s heterogeneous landscape characterized by small land holdings.

While a few studies have addressed the cropland phenology using high-resolution MODIS or Landsat, they have been limited to specific areas; and focused on production or vegetation condition anomaly (Kumar et al. 2022; Bhavani et al. 2017, Singh and Sanatan 2021). Notably, there is lack of studies that address impact of dryness/wetness on crop phenology at the agro-ecological region (AER) level for the entire country. AER represents homogenous land unit in terms of climatic, soil, and physiography which accounts the heterogeneity in agriculture. This study aims to fill this gap by comprehensive and fine scale evaluation of the impact of dry/wet events on crop phenology at AER level.

In a nutshell, the study involves analysis of the impact of climate warming-induced drought on vegetation phenology in various agro-ecological regions of India from 2001 to 2018. This analysis was performed using SPEI with a 3-month time scale (SPEI-03) along with phenological metrics. The objectives of this study are to (1) analyze the spatio-temporal pattern of SPEI-03 and phenological metrics across India, (2) quantify the impacts of dry and wet events on crop phenology in the study area, and (3) explore the relationship between SPEI-03 and phenology metrics during the study period in the Indian region. By examining these objectives, the study aims to provide valuable insights into the effects of climate change-induced drought on vegetation and agricultural systems in India.

2 Study area

The study was carried out over 20 AERs of India (Fig. 1). The AERs have continuously large agricultural land areas and each AER is extracted out of a climatic zone, correlated with landforms, climate, and the length of growing period (Subramaniam 1983). The crop phenology in each AER could easily be identified using time series satellite data. Here, the length of growing period represents the number of days when moisture is available for crop growth. Each AER is homogenous in terms of physiography, type of climate, length of growing period, and soil types for macro-level agricultural land-use planning. Table 1 summarizes the characteristics of different AERs in India.

3 Data used and methodology

The schematic diagram of the methodology followed in the present study is shown in Fig. 2.

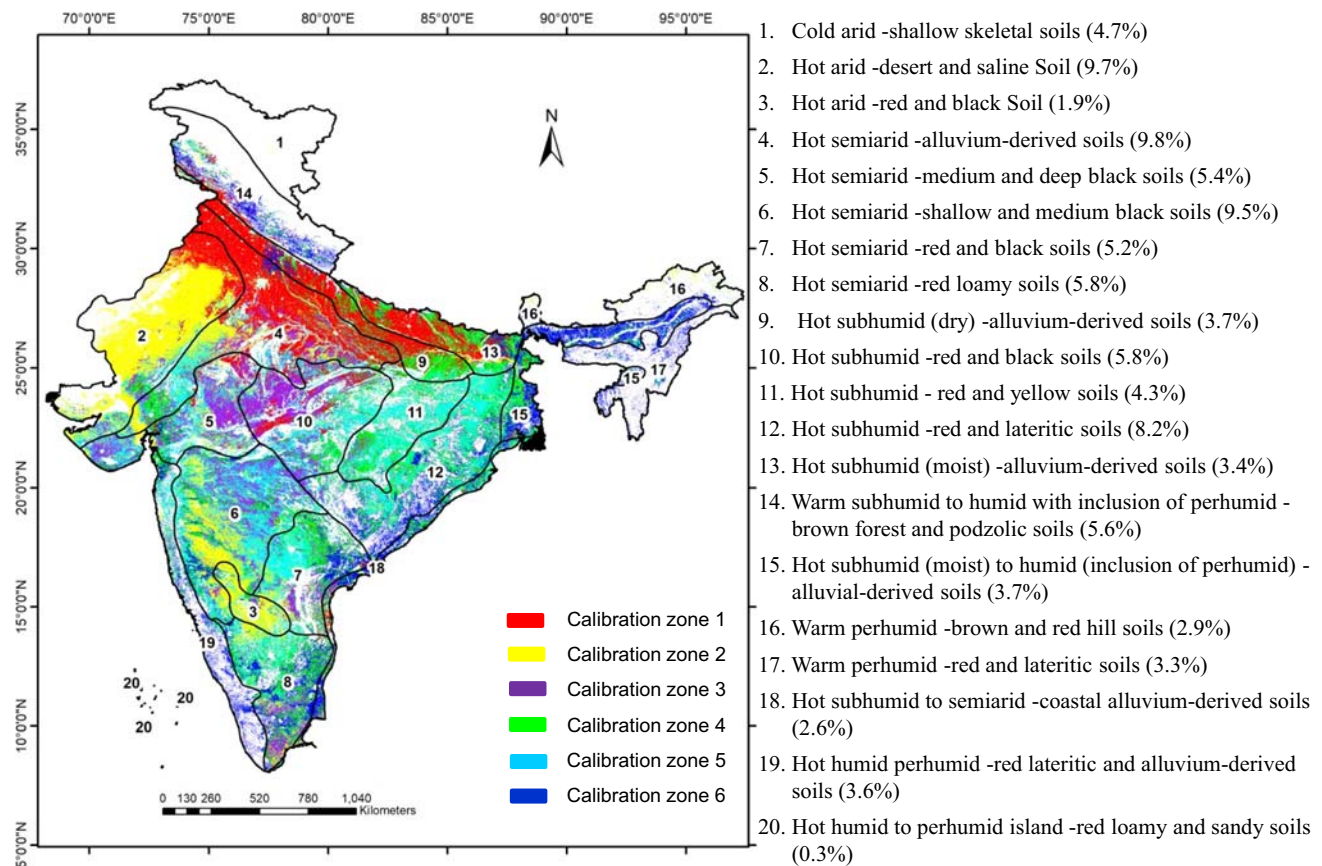


Fig. 1 Study area encompassing agro-ecological regions (AERs) of India representing dominant climate and soil types along with 06 calibration zones (values inside brackets depict percentage of geographical area falling in each AER)

3.1 Meteorological data

The long-term SPEI data were obtained from the Global SPEI database. The database, available at http://spei.csic.es/spei_database, provides SPEI data at a spatial resolution of $0.5^\circ \times 0.5^\circ$ on monthly basis for an extended period of time. For this particular study, SPEI data at a 3-month time scale (SPEI-03) of version 3.2 Climatic Research Unit (CRU) dataset were used for southwest monsoon season months (June, July, August, and September) spanning from 1981 to 2018. The SPEI can be classified into different wet/dry conditions, as shown in Table 2 (Nam et al. 2015).

3.2 Processing of MODIS NDVI time series

This study analyzed 250 m spatial resolution Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI product (MOD13Q1 v006) from 2001 to 2018. The 16-day maximum value composite approach reduced cloud cover, allowing for capturing local crop phenology variations.

The study utilized TIMESAT software to extract crop phenology metrics (pheno-metrics) from the NDVI time

series (Jonsson and Eklundh 2004; Eklundh and Jönsson 2017). Due to significant variability in agricultural practices across the Indian subcontinent, a data-driven approach is adopted by dividing India into different calibration zones. To determine the appropriate smoothing techniques and associated zone-specific parameter settings in TIMESAT, principal component analysis (PCA) was employed on the time series NDVI data (Heumann et al. 2007). PCA is a statistical technique used to reduce the dimensionality of data. Multiple-year land use land cover maps (NRSC 2014) were used to extract potential agricultural areas in India.

To implement PCA, NDVI images for the first fortnight (i.e., first 15 days) of each month in 2006, 2013, and 2017 were selected. These years were considered as “normal” years and were representative of typical crop growth periods. The first four principal components were used to extract six calibration zones (Fig. 1) using ISODATA clustering technique. The fact that these four PCs explain over 95% of the variance in the data indicates that they capture a significant portion of the important information in the NDVI images. The Savitsky–Golay filter (Chen et al. 2004) and double logistic function (Tan et al. 2010) were applied with

Table 1 Characteristics of various agro-ecological regions of India

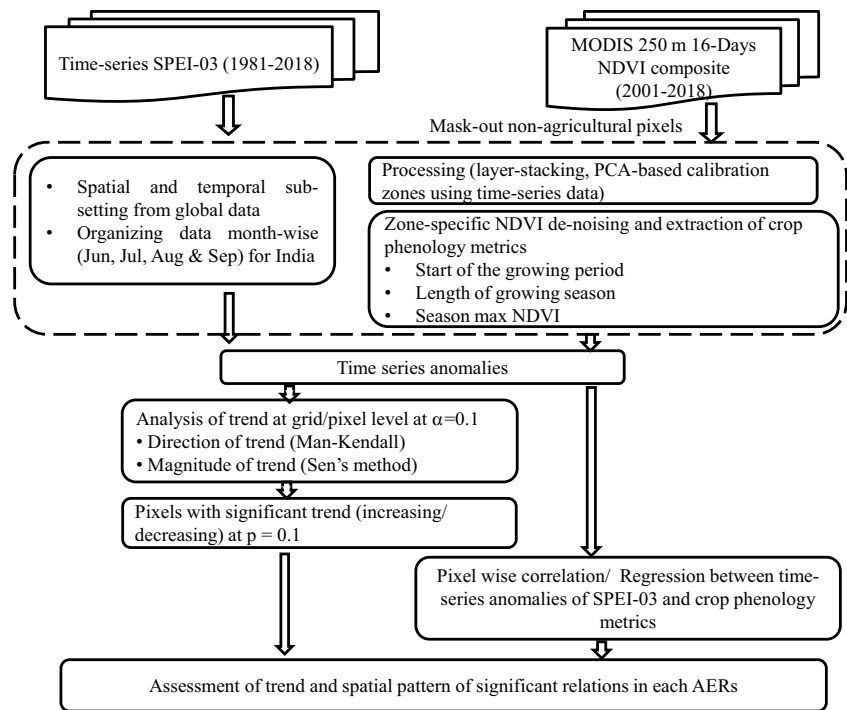
AER	Geographical area (gross cropped area) (million ha)	Physiography	Precipitation (PET) (mm)	Length of growing period (days)	Major crops growing in AER
AER-01	15.2 (0.07)	Western Himalayas	< 150 (<800)	< 90	Vegetables, millets, wheat, fodder, pulses
AER-02	31.9 (20.85)	Western Plain and part of Kachchh Peninsula	< 300 (1500–2000)	< 90	Millets, fodder, pulses
AER-03	4.9 (4.18)	Deccan Plateau	400–500 (1800–1900)	< 90	Sorghum, cotton, oilseeds, sugarcane
AER-04	32.2 (30.05)	Northern Plain and Central Highlands including parts of Gujarat Plains	500–800 (1400–1900)	90–150	Millets, wheat, pulses, maize, cotton, and sugarcane
AER-05	17.6 (11.04)	Central (Malwa) Highlands, Gujarat Plains, and Kathiawar Peninsula	500–1000 (1600–2000)	90–150	Millets, wheat, pulses
AER-06	31.0 (25.02)	Deccan Plateau	600–1000 (1600–1800)	90–150	Millets, cotton, pulses, sugarcane
AER-07	16.5 (6.19)	Deccan Plateau (Telangana) and Eastern Ghats	600–1000 (1600–1700)	90–150	Millets, oilseeds, rice, cotton, & sugarcane
AER-08	19.1 (6.96)	Eastern Ghats (Tamil Nadu uplands) and Deccan Plateau (Karnataka)	600–1000 (1300–1600)	90–150	Millets, pulses, oilseeds, sugarcane, and rice
AER-09	12.1 (11.62)	Northern Plain	1000–1200 (1400–1800)	150–180	Rice, wheat, pigeon pea, sugarcane, mustard, maize
AER-10	22.3 (14.55)	Central Highlands (Malwa and Bundelkhand)	1000–1500 (1300–1500)	150–180	Rice, wheat, sorghum, soybean, pulses
AER-11	11.1 (6.47)	Eastern Plateau (Chhattisgarh Region)	1200–1600 (1400–1500)	150–180	Rice, millets, wheat, pulses
AER-12	26.8 (12.09)	Eastern Plateau (Chhotanagpur) and Eastern Ghats	1000–1600 (1400–1700)	150–180	Rice, pulses, millets
AER-13	11.1 (10.95)	Eastern Plains	1400–1600 (1300–1500)	180–210	Rice, wheat, sugarcane
AER-14	18.2 (3.20)	Western Himalayas	1600–2000 (800–1300)	180–210	Wheat, millets, maize, rice
AER-15	12.1 (8.99)	Bengal and Assam Plain	1400–2000 (1000–1400)	> 210	Rice, jute, plantation crops
AER-16	9.6 (1.37)	Eastern Himalayas	2000–4000 (<1000)	> 210	Rice, millets, potato, maize, oilseeds
AER-17	10.6 (1.56)	North-eastern Hills	1600–2600 (1000–1100)	> 210	Rice, millets, potato, plantation crops
AER-18	8.5 (6.12)	Eastern Coastal Plains	900–1600 (1200–1900)	90–210	Rice, coconut, pulses, oilseeds
AER-19	11.1 (5.70)	Western Ghats and Coastal Plains	2000–3200 (1400–1600)	> 210	Rice, tapioca, coconut, spices
AER-20	0.8 (0.05)	Islands of Andaman-Nicobar and Lakshadweep	1600–3000 (1400–1600)	> 210	Rice, coconut, areca nut, oil palm

various parameter settings (seasonality, envelope adaptation strengths, and window sizes) to denoise the NDVI profiles within each calibration zones. Please be informed that the calibration zone was delineated to capture areas with similar pattern of temporal NDVI profiles for implementing zone-specific setting of the fitted equation.

3.3 Extraction of crop phenology metrics

The method described by Jönsson and Eklundh (2004) is used to extract phenology metrics in this study. Specifically,

TIMESAT software is employed to fit a curve to the NDVI time series and extract the following pheno-metrics: (a) start of season (SoS): The time point when the NDVI value of the fitted curve first exceeds the 0.2 times value of distance between the minimum and maximum NDVI values on the rising side. It signifies the onset of crop growth during the monsoon season; (b) season maximum NDVI amplitude ($NDVI_{max}$): The difference between the maximum NDVI and the base NDVI values. $NDVI_{max}$ represents the magnitude of the NDVI increase during the growing season; (c) length of growing season (LoS): The duration between the SoS

Fig. 2 Schematic diagram of the methodology followed in the present study**Table 2** Classification of dryness/wetness condition based on SPEI (Nam et al. 2015)

Condition	SPEI class	Condition	SPEI class
Extreme drought	$\text{SPEI} \leq -2$	Mild wet	$0.5 < \text{SPEI} \leq 1$
Severe drought	$-2 < \text{SPEI} \leq -1.5$	Moderate wet	$1 < \text{SPEI} \leq 1.5$
Moderate drought	$-1.5 < \text{SPEI} \leq -1$	Severe wet	$1.5 < \text{SPEI} \leq 2$
Mild drought	$-1 < \text{SPEI} \leq -0.5$	Extreme wet	$\text{SPEI} \geq 2$
No drought	$-0.5 < \text{SPEI} \leq 0.5$		

and the end of the season, which is the point in time when the NDVI value falls below the 0.2 times value of distance between the minimum and maximum NDVI values on the falling side of curve. LoS indicates the length of time the crop experience active growth.

3.4 Calculation of temporal trends of SPEI-03 and crop phenology metrics

In this study, anomalies of the crop phenology metrics (SoS, LoS, and NDVI_{max}) are computed by subtracting the long-term mean from each year's value at both the pixel and AER level. The anomalies show the deviation of pheno-metrics from their typical values over time. Mann–Kendall test (Mann 1945; Kendall 1976), a widely used non-parametric statistical test for trend detection in environmental time

series data, was used for trend analysis. The Mann–Kendall test compares the ranks of each observation with those of all other observations to assess whether there is a significant increasing or decreasing trend over time. In addition to detecting significant trends, Sen's method (Sen 1968) was used to estimate the magnitude of the trend. Sen's method is a non-parametric technique that calculates the median slope between all pairs of observations, providing a robust estimate of the trend magnitude. Pixel-wise Mann–Kendall test ($p = 0.1$) for the time series anomalies of SoS, LoS, and NDVI_{max} was performed for the null hypothesis of no trend against the alternative hypothesis of decreasing/increasing trend. On a similar line, trend analysis was carried out for time series SPEI-03 data for June, July, August, and September.

3.5 Relating SPEI-03 and crop phenology metrics

Pearson's correlation analysis was used to investigate the temporal relationships with monthly SPEI-03 of four monsoon months and phenological metrics. Generally, crop phenological events in an area are primarily determined by the climatic conditions preceding the events (Shen et al. 2014; Güsewell et al. 2017). The anomalies of time series SPEI-03 and crop phenology metrics were brought to 50 km spatial resolution for 2001–2018.

This study analyzed the spatial patterns of significant correlations ($p = 0.1$) to gain the insight into how changes in rainfall affect crop phenology (SoS, LoS, and NDVI_{max}). Sensitivity analysis was performed between the phenology

metrics and SPEI-03 of individual months in the monsoon season. The sensitivity analysis was performed across the twenty different AERs of India. The sensitivity of each AER was defined as the change in phenology metrics per unit change in SPEI-03, i.e., slope of the regression model between phenology metrics and SPEI-03 over 2001–2018.

4 Results and discussion

4.1 Zone-wise temporal characteristics of SPEI-03

The average SPEI-03 for the entire country of India during the period 1981–2018 is presented in Fig. 3. Wet events ($\text{SPEI} \geq 0.5$) and dry events ($\text{SPEI} \leq -0.5$) were calculated for each monsoon months (June to September) during the same period for each AER and are summarized in Table 3. Additionally, the entire time series (1981–2018) was divided into four decades to compute the percentages of occurrence

of dry, wet, and normal ($-0.5 < \text{SPEI} < 0.5$) events for each specific month, as shown in Fig. 4.

Figure 3 clearly shows that wet and dry events based on SPEI-03 are well distributed across the time series (1981–2018). Notably, the severity of the dry events are found to be more pronounced in the later part of the time series, particularly during the initial part of the twenty-first century. Conversely, the frequency and intensity of wet events were observed to be higher towards the end of the time series (2006–2018).

Based on the monthly frequency of occurrence of wet ($\text{SPEI} > 0.5$) and dry ($\text{SPEI} < 0.5$) events, the AERs were classified into three categories: wetting, drying, and mixed. AERs 2, 3, 4, and 14 exhibited a higher occurrence of wet events compared to dry events during the period 1981–2018 and are classified as “Wetting” regions. These AERs predominantly cover the hot/warm, arid regions of India. Conversely, AERs 10, 11, 13, 15, and 17 displayed a “Drying” pattern with more dry events than wet events. These AERs

Fig. 3 Temporal variation of SPEI-03 (year 1981–2018) of India

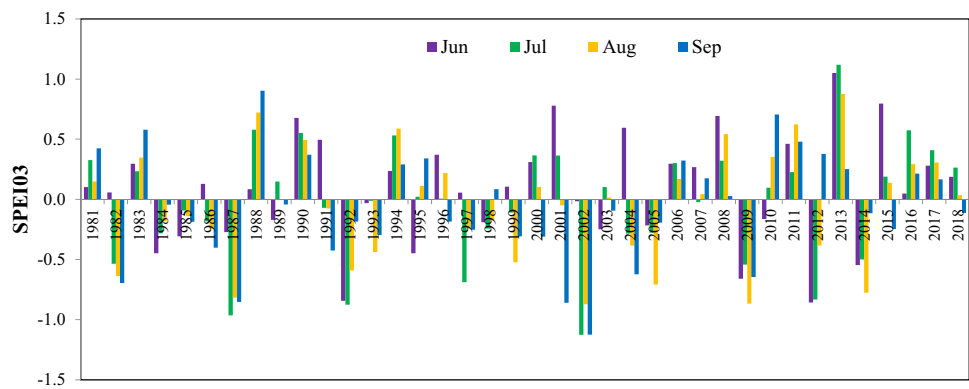
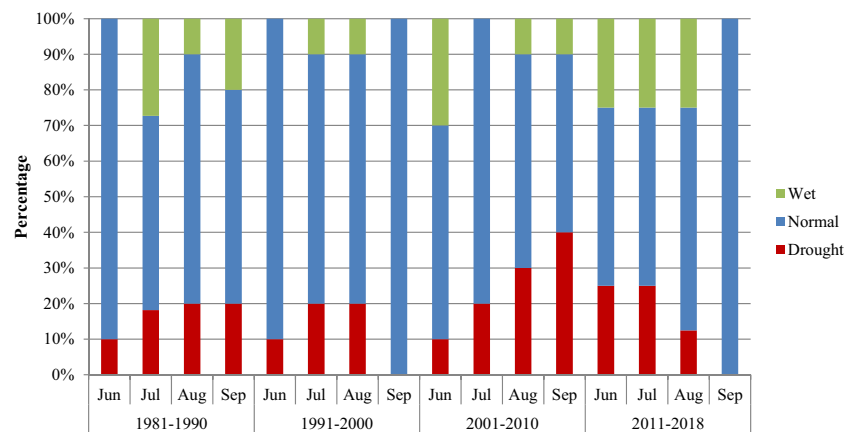


Table 3 Distribution of dry ($\text{SPEI-03} \leq 0.5$) and wet ($\text{SPEI-03} \geq 0.5$) month counts in each AER over the monsoon months (June–September) during 1981–2018

	AER	June		July		August		September	
		Wet	Dry	Wet	Dry	Wet	Dry	Wet	Dry
Wetting	2	13	10	9	8	11	7	9	8
	3	17	10	13	11	13	11	12	15
	7	12	12	12	9	11	7	13	10
	14	20	2	21	7	17	11	9	9
Mixed	4	15	6	12	11	8	10	7	12
	5	9	9	9	11	13	9	13	11
	6	8	8	8	12	11	11	12	14
	9	15	7	11	12	6	15	5	17
Drying	8	7	13	11	9	11	11	12	10
	19	9	11	9	8	10	11	12	9
	10	10	13	10	16	5	15	7	16
	11	9	12	9	16	5	17	4	21
	13	8	10	8	14	4	20	7	16
	15	10	15	5	11	8	18	10	13
	17	11	17	7	13	6	17	9	15

Fig. 4 Frequency (%) of occurrence of wet, normal, and drought events during different decades from 1981 to 2018 based on SPEI-03



are primarily located in hot sub-humid regions of India. The remaining AERs showed mixed results.

The decade-wise analysis of monthly occurrence of wet, dry, and normal events, as depicted in Fig. 4, reveals that drought events (dry) were evenly distributed in the first decade (1981–1990). However, there was a shift in the distribution of dry events in the subsequent decades. Notably, the frequency of late-season drought was high during 2001–2010, whereas early-season drought was more prevalent in the last decade (2011–2018).

In general, the majority of the extreme drought events occurred between 2001 and 2010, consisting 10%, 20%, 30%, and 40% for the months of June, July, August, and September, respectively. No drought was observed during September of 1991–2000 and 2011–2018, while the other months experienced dry spell in all decades. In the decade of 2001–2010, almost all the months of SW monsoon exhibited drought incidences (early, mid, and late seasons). However, the frequency of dry spells mostly coincided with the reproductive/maturity growth stage of crops due to the onset of late-season drought. Early-season drought was found to be more prevalent in the decade 2011–2018.

4.2 Spatial variations of temporal trends of SPEI-03

The spatial distribution of the temporal trends of SPEI-03 during SW monsoon months is illustrated in Fig. 5. Pixel-wise trend was estimated using Mann–Kendall statistics. Further, Sen's method was used to estimate the magnitude of the trend (positive/negative) at pixel level. Pixels having statistically significant trend at $p = 0.1$ were marked as “*” as shown in Fig. 5. Positive trends indicate an increase in wet events, while negative trends indicate an increase in drought events.

In June, a significant positive trend in SPEI-03 (at $p = 0.01$) was observed in parts of northern India, the eastern coastal parts of central and southern India, and isolated patches in the north-eastern part of India (AER 03, AER

07, AER 14, and AER 18). On the contrary, a significant negative trend was observed in the lower parts of the north-eastern India (AER 15) during June. In July, a significant positive trend in SPEI-03 was observed in the central and southern parts of India (AER 03, AER 05, AER 10, AER 12, and AER 18), while a significant decreasing trend was found in the north-eastern part (AER 15 and AER 17). The trend analysis of August month revealed scattered patches of increasing trends in AER 05, AER 06, AER 08, and AER 11, and decreasing trends in AER 15 and AER 17 across India. In September, the entire north-eastern part of India exhibited a negative trend in SPEI-03 indicating an increase in drought events in this region (AER 15, AER 17), despite being a high rainfall zone. Some areas of central and peninsular India showed an increasing trend in September SPEI-03 (AER 03, AER 05, AER 06, AER 08, and AER 11). Overall, the trend analysis results indicated that northeast India (a high rainfall zone) experienced the greatest increase in drought events over the past 38 years, whereas central India had the lowest increase (Fig. 5). In general, wet events have significantly increased across India. This information is valuable for understanding the impact of changing rainfall and temperature patterns on different areas and can be utilized to develop strategies for mitigating climate-related impacts on agriculture in these regions.

Table 4 presents the AER-wise percentage of grids exhibiting positive/negative trends in SPEI-03 during 1981–2018, along with the mean magnitude of these trends during the monsoon months. AERs with a significantly high trend ($> 0.5 \text{ years}^{-1}$) over more than 50% of the grid are marked in bold italics. It is evident from Table 3 that AERs 3, 7, 14, and 18 displayed a positive trend over a large area with a magnitude of $0.5\text{--}1.14 \text{ year}^{-1}$ during the month of June. Similarly, during July, a positive trend of $0.56\text{--}0.73 \text{ year}^{-1}$ was observed over a significantly large area in AERs 3, 5, 10, 12, and 18. AER 8 showed a high positive trend ($0.52\text{--}0.57 \text{ year}^{-1}$) over the majority of the grid in August. In September, AERs 3, 5, and 8 also exhibited a high

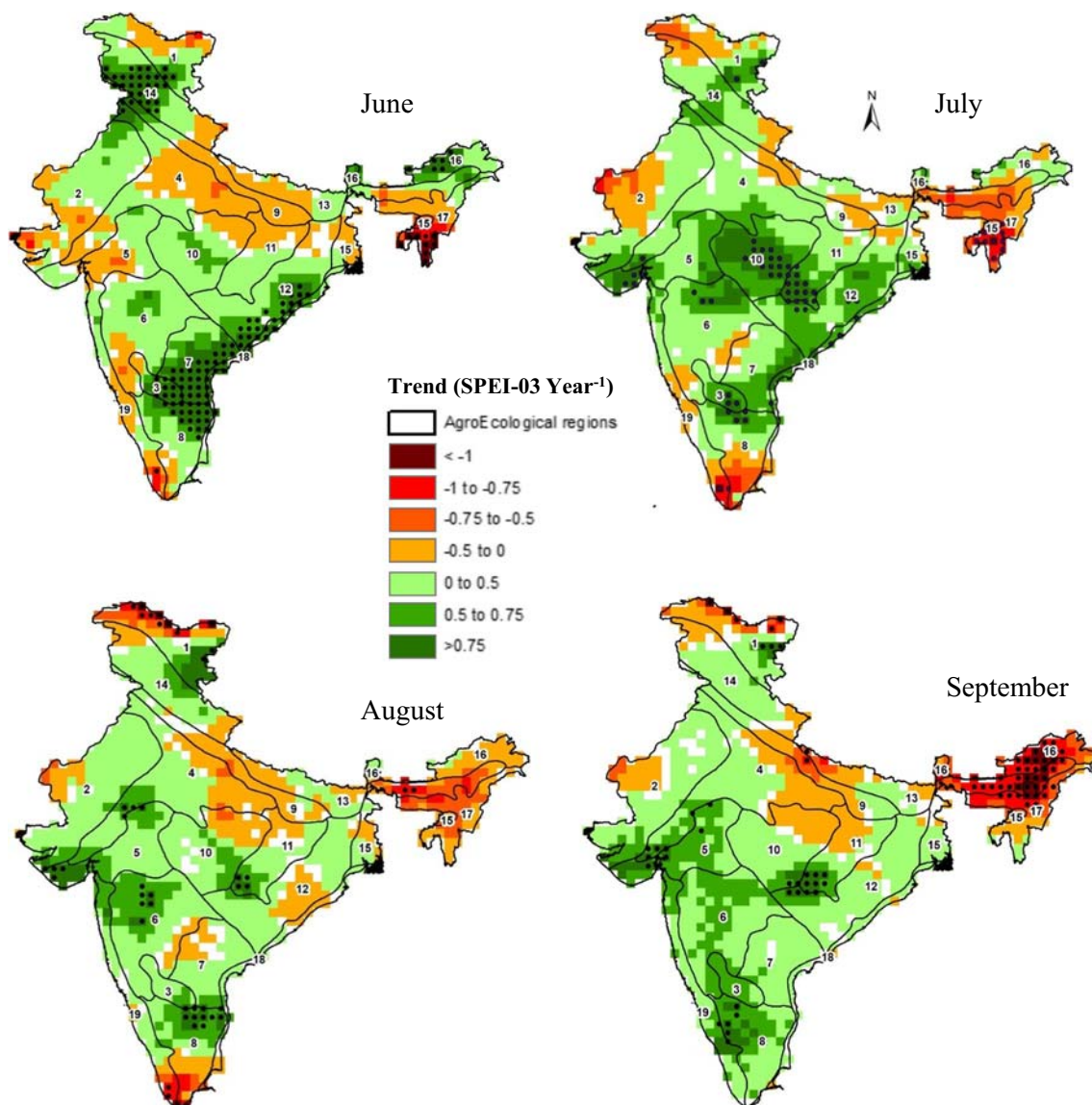


Fig. 5 Spatial patterns of temporal trends of SPEI-03 across the monsoon months (June, July, August, and September) during 1981–2018. Grids with significant trend (positive/negative) at $p = 0.1$ are represented with black dots

positive trend in the lion's share of the grid. A significantly high negative trend ($0.5\text{--}0.8\text{ year}^{-1}$) is observed over large contiguous areas of AERs 15 and 17 during July–September. The present findings are in agreement with the findings of Das et al. (2014) and Das et al. (2020).

In summary, the Indian peninsula, specifically the eastern coastal region and the upper western coastal region, exhibited a significant trend of increasing wetness. Conversely, the north-eastern region, known for its high rainfall levels and biodiversity hotspots, demonstrated a significant drying trend. It is noteworthy that a substantial portion of the upper-central part of India, the Indo-Gangetic plain, often referred to as the country's food basket, displayed a drying trend, although it did not reach statistical significance at the $p = 0.1$ level.

4.3 Spatial patterns of temporal trend of crop phenology metrics over India

The spatial distribution of the temporal trends in crop phenology metrics (SoS, NDVI_{max} , LoS) during the southwest monsoon season was analyzed at 250-m spatial resolution using time series NDVI data from 2001 to 2018, employing the Mann–Kendall method. The analysis excluded AERs 01, 16, and 20 due to negligible agricultural activity. The resulting spatial patterns of temporal trends of the phenology metrics are presented in Fig. 6.

An increasing trend ($>1\text{ day/year}$) in SoS, indicating a delay in sowing activities during the monsoon season, was observed across large parts of the country, including

Table 4 AER-wise percentage of grid under positive/negative trend of SPEI-03 during 1981–2018 along with its mean magnitude over the monsoon months.

AERs	Jun			Jul			Aug			Sep		
	Positive		Negative	Positive		Negative	Positive		Negative	Positive		Negative
	Grid (%)	Mean trend		Grid (%)	Mean trend		Grid (%)	Mean trend		Grid (%)	Mean trend	
2	44.1	0.27	23.5	-0.05	0.26	39.2	-0.29	0.31	14.7	0.02	38.2	0.30
3	56.3	1.14	37.5	-0.31	0.62	0.0	0.00	0.47	0.0	0.00	91.0	0.57
4	36.7	0.18	42.9	-0.26	0.36	3.1	-0.19	0.27	13.3	-0.26	72.4	0.24
5	28.3	0.28	47.2	-0.12	0.56	0.0	0.00	0.46	0.0	0.00	88.7	0.56
6	68.8	0.29	12.9	-0.04	0.41	10.8	-0.13	0.39	0.0	0.00	93.5	0.49
7	56.5	0.76	0.0	0.00	0.49	5.5	-0.15	0.33	18.2	-0.02	92.7	0.25
8	57.9	0.63	26.3	-0.18	0.47	38.6	-0.49	0.56	29.8	-0.36	98.2	0.52
9	15.8	0.37	71.1	-0.24	0.24	36.8	-0.14	0.08	60.5	-0.21	15.8	0.18
10	80.3	0.35	9.9	-0.15	0.73	0.0	0.00	0.30	15.5	-0.19	70.4	0.33
11	53.3	0.25	33.3	-0.18	0.46	2.2	-0.04	0.37	20.0	0.01	46.7	0.48
12	80.7	0.48	3.6	-0.02	0.57	4.8	-0.07	0.21	13.3	-0.14	77.1	0.32
13	15.6	0.21	68.8	-0.02	0.16	40.6	-0.08	0.08	59.4	-0.08	28.1	0.07
14	68.4	0.50	7.0	-0.27	0.40	28.1	-0.22	0.33	14.0	-0.13	54.4	0.24
15	45.9	0.17	24.3	-0.21	0.26	56.8	-0.52	0.05	56.8	-0.54	24.3	0.29
17	11.4	0.45	54.3	-0.41	0.20	80.0	-0.63	0.00	68.6	-0.48	0.0	0.00
18	64.7	0.76	0.0	0.00	0.64	11.8	-0.31	0.20	29.4	-0.24	52.9	0.24
19	0.0	0.00	7.3	0.05	0.33	39.0	-0.50	0.39	7.3	-0.14	14.6	0.59

AERs with significant trend (positive/negative) in > 50% of grids are shown as bold italic

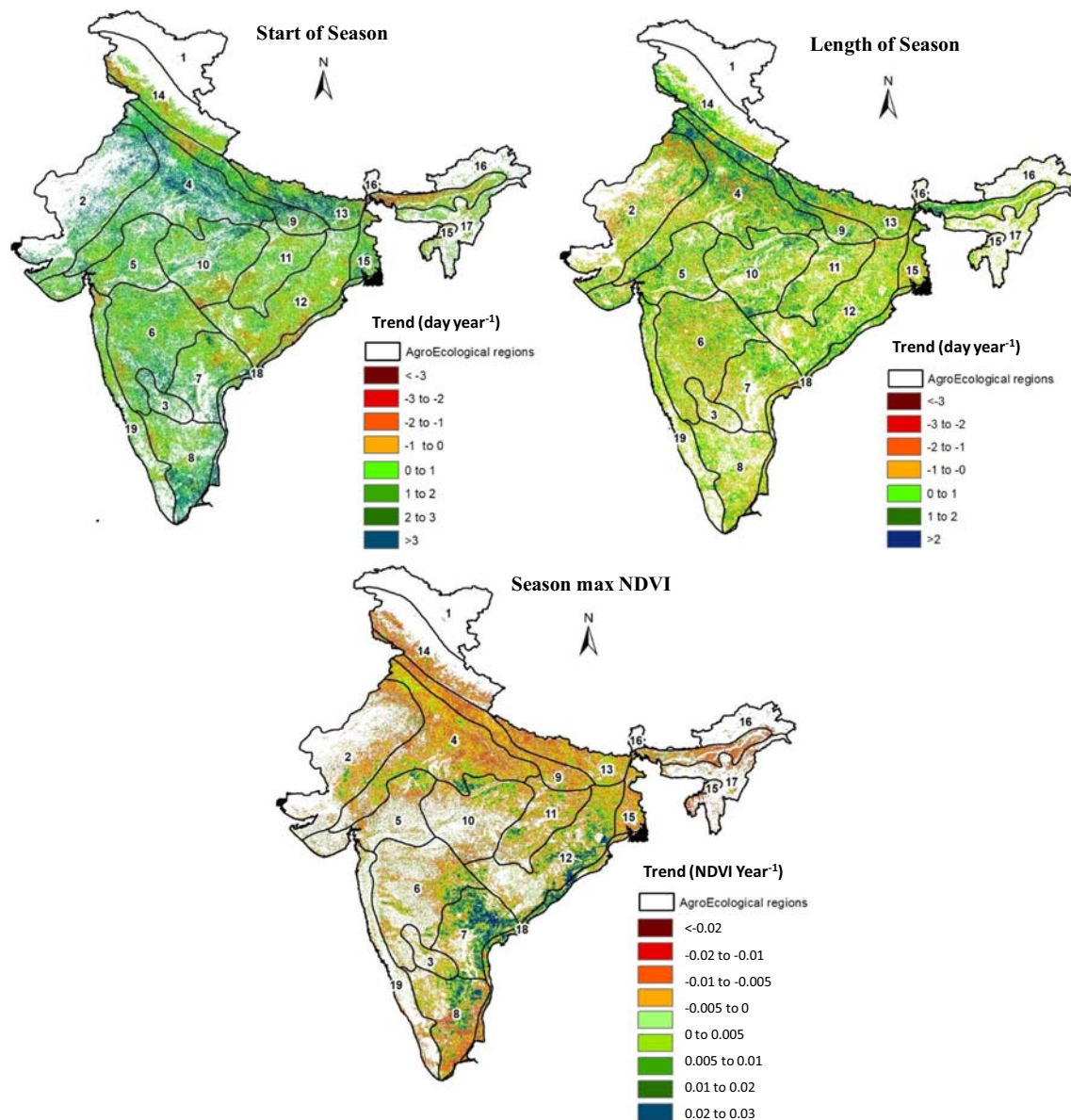


Fig. 6 Spatial patterns of temporal trends of crop phenology metrics (SoS, LoS, $NDVI_{max}$) in different AERs during 2001–2018

north, northwest, and Deccan plateau regions (AER 04, AER 02, AER 08, AER 09, and AER 13). Conversely, a pre-occurrence of sowing activities or a decreasing trend (<-1 day/year) in SoS was found in certain parts of the northern, central, and eastern India (AER 14, AER 12, and AER 10). Previous research studies examining spatio-temporal trends in phenology across India (Chakraborty et al. 2014; Das et al. 2020) or specific regions like the Indo-Gangetic plain (Sehgal et al. 2011; Chakraborty et al. 2018b) have reported divergent findings. These discrepancies arise from variations in the time period considered, spatial resolution of the data, choice of fitting function and pheno-metrics retrieval algorithms, and the aggregation of

the results based on administrative or climatic boundaries. However, majority of these studies have reached a consensus that SoS trend is increasing significantly in many parts of India. In the present study, it was found that approximately 59% of agricultural areas exhibited an increasing trend in SoS while 21% showed a decreasing trend. It is apt to mention here that the highest proportion of AER 04 (64%) experienced a delay in the SoS, whereas a pre-occurrence of SoS was noted in nearly 31.7% of the area in AER 09.

The spatial patterns of temporal trends of $NDVI_{max}$ (crop vigor) during the monsoon season (as shown in Fig. 6) revealed a decreasing trend over large contiguous areas in

the north, east, central, west, and south of India (AER 14, AER 04, AER 09, AER 13, AER 15, AER 08, and AER 02). Conversely, an increasing trend of $NDVI_{max}$ was observed in the central and southern regions of India (AER 07, AER 12, AER 18, AER 08, and AER 10). The central part of India, characterized by vertisols or black soil with high water holding capacity, might be experiencing changes in $NDVI_{max}$ trend due to improved crop management practices (irrigation, fertilization, plant protection, etc.) or the introduction of new crops in the region. Approximately 23.3% of the agricultural area exhibited a positive trend in $NDVI_{max}$, while only 5.17% displayed a decreasing trend. The region with the highest percentage of area experiencing increasing trends in $NDVI_{max}$ was AER 07 (33.1%), while AER 09 had the highest percentage of area with decreasing trends (24.25%). The spatial analysis of temporal trends in LoS (shown in Fig. 6) revealed increasing trends (>1 day/year) in a significant portion of the northern, eastern, and some parts of central regions of India. In contrast, decreasing trends (<-1 day/year) were observed in certain areas of the western, central, and southern parts. Approximately 61% of the agricultural area exhibited an increasing trend in LoS, while 28% displayed a decreasing trend. The regions with the highest percentage of area under increasing and decreasing trend in LoS were AER 09 (73.1%) and AER 02 (38.12%), respectively.

In a study conducted by Das et al. (2020), utilizing 8-km GIMMS NDVI data, it was concluded that a significant portion of India experienced a decreasing trend in LoS. However, Chakraborty et al. (2018b), using 4-km STAR-global vegetation health products-NDVI, found an increasing trend in LoS. In the current study, the analysis of 250-m MODIS data also revealed an increasing trend of LoS across a major part of India. It is important to note that these studies differed not only in spatial resolution of satellite data but also

in the time series considered. Despite some scattered discrepancies, the findings of the current study align with other reported studies conducted in various regions of India.

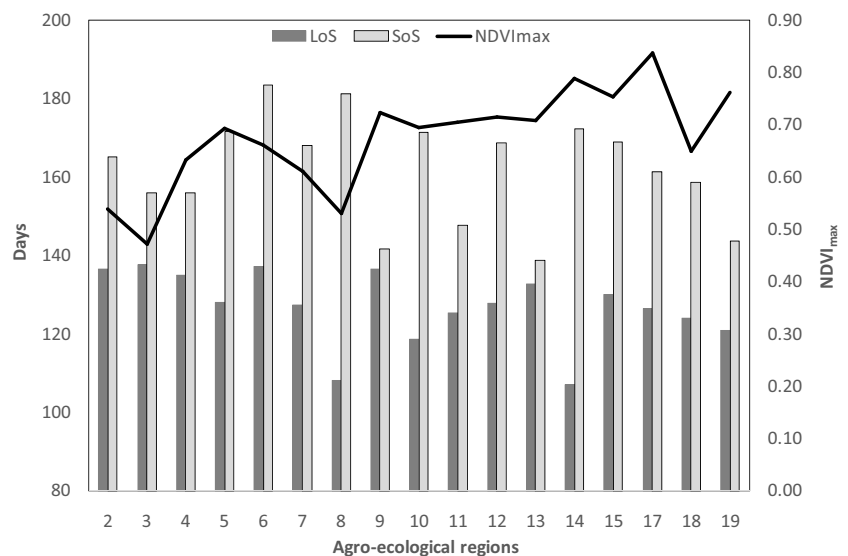
4.4 Influence of drought and wet years on crop phenology metrics

AER-wise mean phenology metrics (i.e., SoS, LoS, and $NDVI_{max}$) based on 250-m MODIS NDVI data of 2011–2018 are given in Fig. 7. Results revealed substantial variation in phenology metrics among the different AERs. There was no consistent relationship found between AER-wise mean pheno-metrics. For instance, early SoS coincided with long-duration LoS in AER 09, whereas short-duration LoS was associated with late SoS in AER 08. The mean $NDVI_{max}$ also exhibited extensive divergence among different AERs, with higher values observed in AERs 10–17 and lower values in AERs 2, 8, 9, and 19.

To assess the sensitivity of the pheno-metrics to SPEI-03, two contrasting years, namely 2012 and 2013, were selected based on overall dryness/wetness conditions. The year 2012 was characterized by dry conditions, while 2013 experienced wet conditions according to India Meteorological Department (IMD) and National Agricultural Drought Assessment and Monitoring System (<https://www.ncfc.gov.in/nadams>). Spatial maps of monthly SPEI-03 during 2012 and 2013 in Fig. 8 clearly illustrate the contrasting wetness conditions with moderate to severe drought prevailing in most areas of India during June to August 2012 and moderate to severe wetness dominating during the monsoon months of 2013.

These dry and wet conditions during the monsoon months may have influenced crop phenology by altering the crop-growing environment. AER-wise mean crop phenology

Fig. 7 AER-wise mean SoS (Julian day), LoS (number of days), and $NDVI_{max}$ over 2001–2018



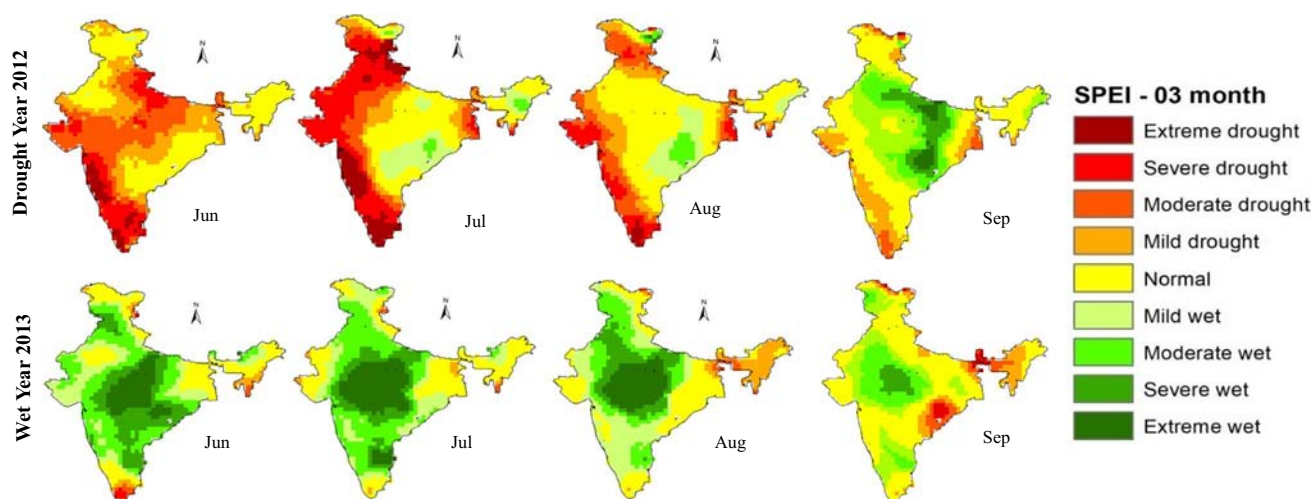


Fig. 8 Spatial pattern of SPEI-03 of monsoon months during drought (2012) and wet (2013) years

metrics (SoS, LoS, and $NDVI_{max}$) during drought and wet years demonstrated the impact of climatic extremes on crop phenology across different AERs. In dry conditions, SoS exhibited delays in sowing activities and emergence, LoS showed a decrease in the length of the crop-growing period, and $NDVI_{max}$ displayed reduced seasonal amplitude. These effects may be attributed to the selection of short-duration crops or failed sowing due to inadequate soil moisture availability. The temporal pattern of AER-wise phenology metrics is graphically represented in Fig. 9, and the spatio-temporal pattern is depicted in Fig. 10. These comparisons revealed that climatic variations significantly affect crop phenology. In 2013, there was generally an advancement of SoS ($\Delta SoS = -25 \pm 28$ days), while a slight delay of SoS was observed during 2012 ($\Delta SoS = 44 \pm 23$ days). $NDVI_{max}$ also exhibited reduced amplitude during drought year compared to wet year. The AERs, which showed minimum changes in phenometrics between 2012 and 2013, are climatic resilient. This may be due to high irrigation potential, water holding capacity of the soil, or prevailing cropping pattern.

4.5 Relationship between SPEI-03 and crop phenology metrics

4.5.1 Correlations between SPEI-03 and agricultural activities

The Pearson correlation coefficient (at $p = 0.1$) was calculated to assess the influence of wet and dry conditions on crop phenology metrics by analyzing the relationship between SPEI-03 and crop phenometrics. Figure 11 presents pixel-wise correlation between monthly SPEI-03 and the phenometrics. Several factors, such as the introduction of new crop type or crop variety, irrigation, and crop

management practices, may contribute to changes in crop phenology metrics, in addition to climate variations across different AERs. Around two-thirds of the country's agricultural land in India is under rainfed, making southwest monsoon rainfall crucial factor in agricultural productivity. The spatio-temporal distribution of rainfall and the climatic water demand govern crop growth and development, making SPEI-03 a potentially attributing factor to crop phenology during the monsoon season.

The start of the crop-growing season is determined by crop sowing activities, which is influenced by soil moisture availability during the early part of the season, mainly determined by the onset of rainfall. In India, the southwest monsoon typically begins in June, and the timely onset of monsoon significantly impacts crop sowing operation, especially under rainfed conditions. Delayed onset or insufficient rainfall during the early monsoon season leads to delay in crop sowing operations. Consequently, negative SPEI-03 during the early monsoon season results in positive anomalies in the start of season, indicating a delay in SoS, and vice-versa. A significant negative correlation between SoS and June rainfall was observed in large areas of India, highlighting the critical role of June rainfall in the timely onset of the crop season (Fig. 11). However, this relationship diminishes as the monsoon progresses into July and August. The LoS is also dependent on the timely start of the crop season. Therefore, June month's SPEI-03 also positively correlates with LoS over large areas of India. Correlation analysis between the SPEI-03 and SoS revealed a significant negative correlation in June and July, primarily concentrated in the central and northern parts of India (AER 10, AER 11, and AER 14).

The $NDVI_{max}$, which represents crop vigor, may be subject to change due to variations in crop type/varieties

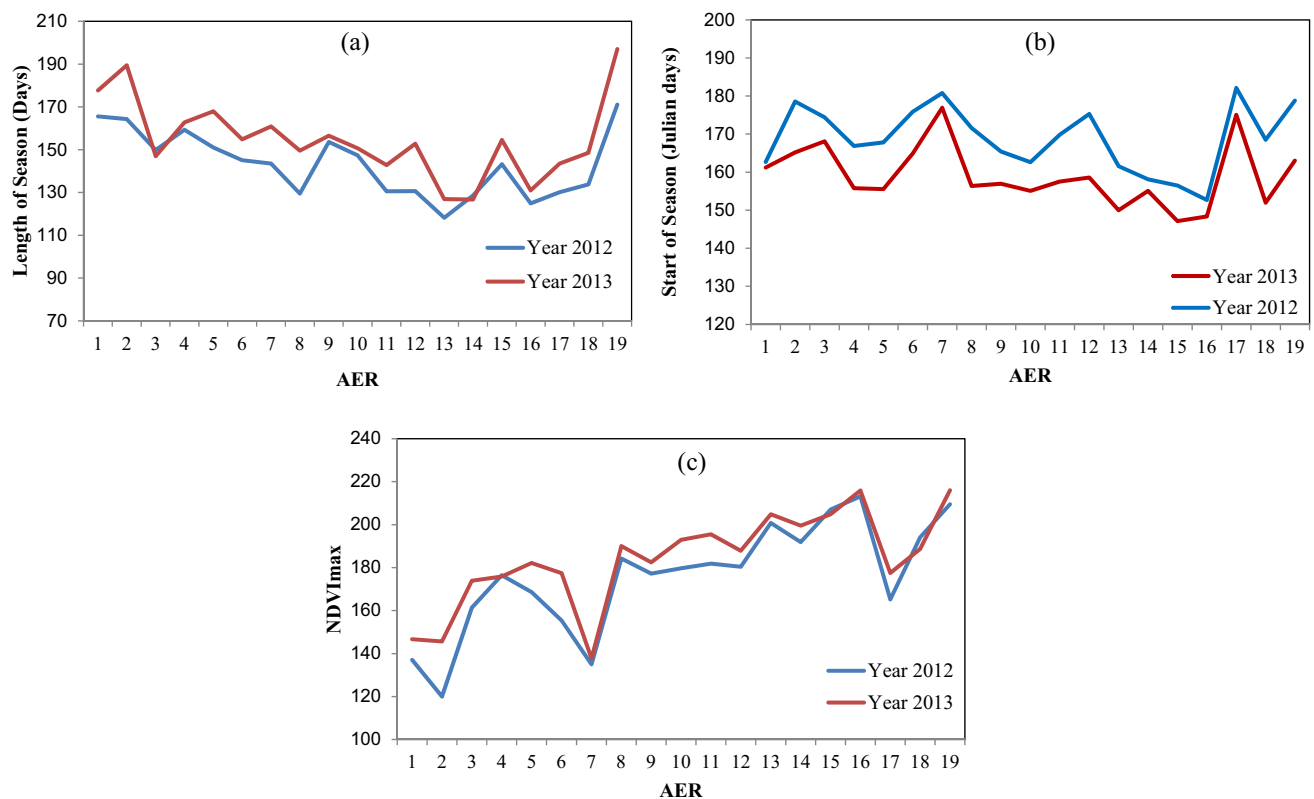


Fig. 9 Temporal pattern of pheno-metrics in wet and dry years for each AER: **a** LoS, **b** SoS, and **c** NDVI_{max}

within the study area. An increase in SPEI-03 (indicating wetter conditions) was found to correlate positively with NDVI_{max}, with a correlation coefficient greater than 0.5. Monsoon crops generally reach their peak vegetation phase in August–September. Timely sowing followed by well-distributed rainfall becomes critical for achieving high crop vigor (NDVI_{max}). Accordingly, June month's SPEI-03, which is crucial for SoS, showed a positive correlation with NDVI_{max} over large areas of India. Similarly, August month's SPEI-03 demonstrated a strong correlation with NDVI_{max} across India. The analysis revealed that the majority of AERs exhibited the maximum NDVI values in August–September, with the largest area (23%) showing a significant positive correlation with August month's SPEI-03 (Fig. 11). For the relationship between SPEI-03 and pheno-metrics, we combined statistically significant pixels ($p = 0.1$) in June, July, and August across the study area (Fig. 12). The results indicate a uniform spread of significant correlation (positive/negative) between SPEI-03 and SoS/LoS throughout India. However, areas exhibiting a significant correlation between SPEI-03 and NDVI_{max} are predominantly concentrated in AER 2 and AER 5, highlighting the crucial impact of wetness/dryness on the agriculture in these regions of India. Previous studies have primarily focused on analyzing the spatio-temporal variation of either rainfall or

temperature on vegetation phenology (Fu et al. 2018; Kang et al. 2018; Chakraborty et al. 2014). Furthermore, the findings from other studies have demonstrated that croplands are particularly sensitive to climatic variability (Javed et al. 2021; Felton et al. 2019). Consequently, the current study investigated the impact of dry and wet climatic variability on crop phenology. The significant aspect of this study lies in exploring the effects of drought and wetness specifically during the months of the crop-growing season. In contrast to most previous studies (Potopová et al. 2015; Liu et al. 2018), this study focuses on examining the relationship between drought and pheno-metrics during the actual cropping season, rather than considering the entire annual calendar.

4.5.2 Sensitivity of pheno-metrics with SPEI-03

Table 5 provides the sensitivity of the phenology metrics to monthly SPEI-03 across different AERs. The slope in the table represents the change in the magnitude of pheno-metrics (expressed in “days” for SoS and LoS) per unit change in SPEI-03. Our observations indicate that a one-unit increase in SPEI-03, i.e., indicating greater wetness, leads to an early SoS of 01 to 18 days depending on the AERs. Almost all the AERs exhibit a pre-occurrence of SoS with increasing wetness (Table 5). The pre-occurrences of SoS was particularly

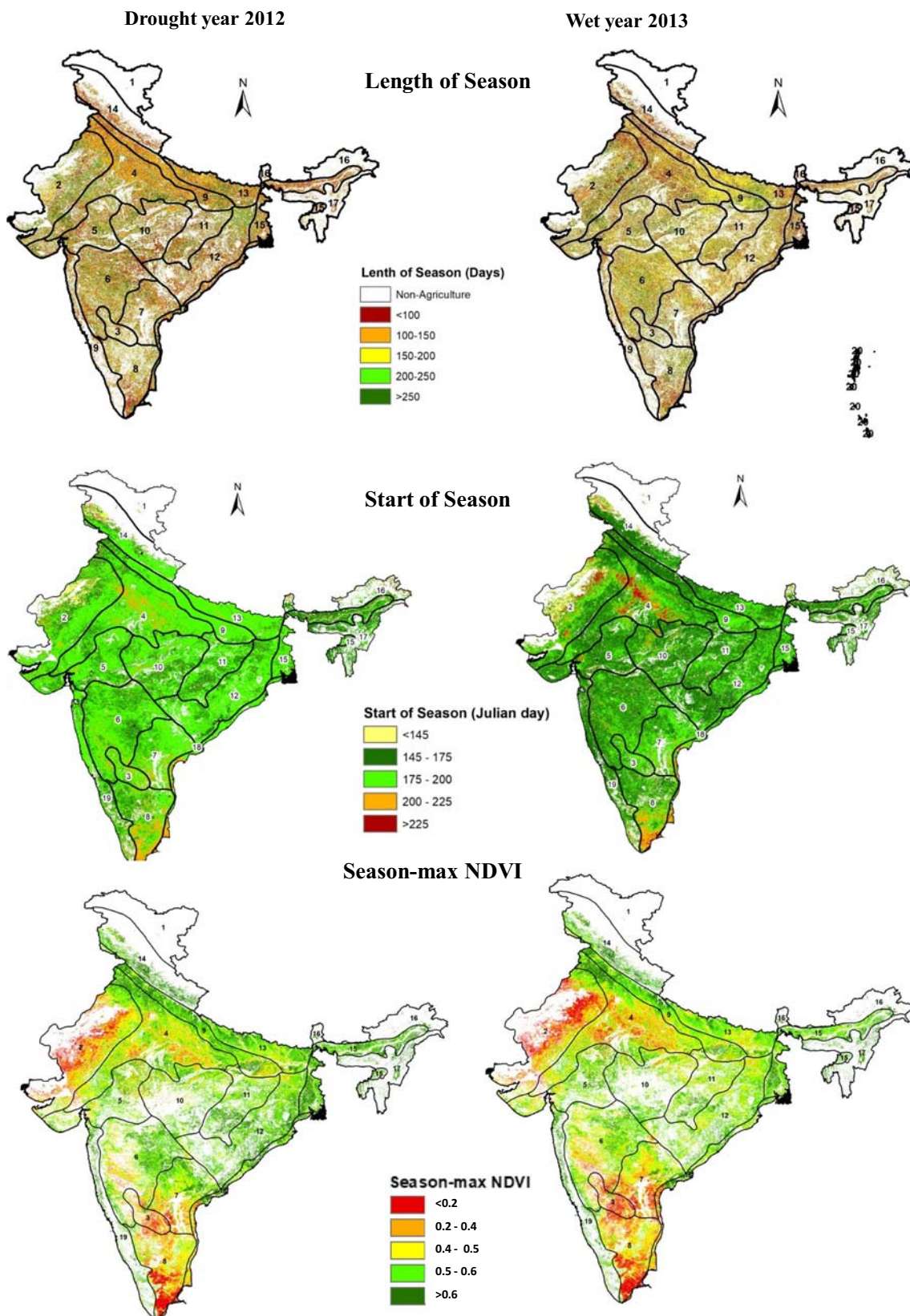


Fig. 10 Spatial pattern of pheno-metrics (LoS, SoS, and $NDVI_{max}$) in dry (2012) and wet (2013) years in each AER

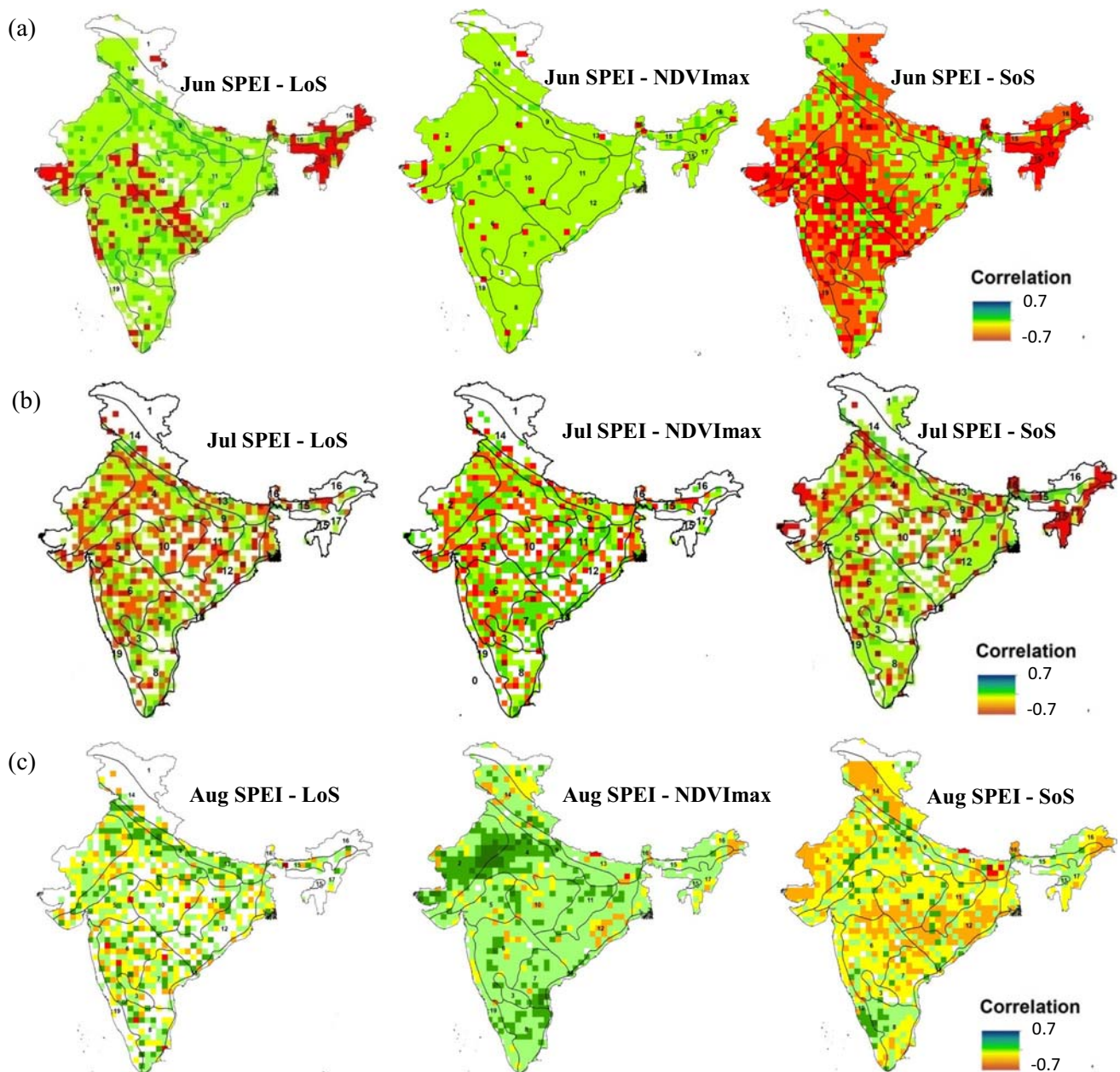


Fig. 11 Correlation between SPEI-03 vs phenology metrics (LoS, $NDVI_{max}$, and SoS): **a** June, **b** July, and **c** August months

noticeable in semi-arid regions with black soils (AERs 03, 04, 05, 06, 07) due to their high moisture holding capacity, as well as in humid/sub-humid AERs such as 13, 14, 15, and 17. Conversely, semi-arid climates with red lateritic soils (AERs 08, 09, 11, 12), characterized by poor water holding capacity, showed little or no change in SoS.

Similarly, increased moisture availability resulted in an extended length of the crop-growing period. Abundant soil moisture availability may trigger the farmers to select water-demanding crops with longer duration. The sensitivity of LoS to wetness varied across different climatic regions.

Humid/sub-humid climates showed negative or no sensitivity of LoS to increase in wetness, while semi-arid AERs exhibited an increase in LoS with greater SPEI-03. LoS sensitivity increased from arid to semi-arid regions (AER 02 to AER 08) and decreased from semi-humid to humid regions (AER 10 to AER 19). In July and August, $NDVI_{max}$ also displayed positive sensitivity to increase wetness, indicating high crop vigor in response to greater soil moisture availability across most of the AERs. We noted that the effect of dryness/wetness on SoS is more pronounced than LoS, consistent with the findings of Ge et al. (2021).

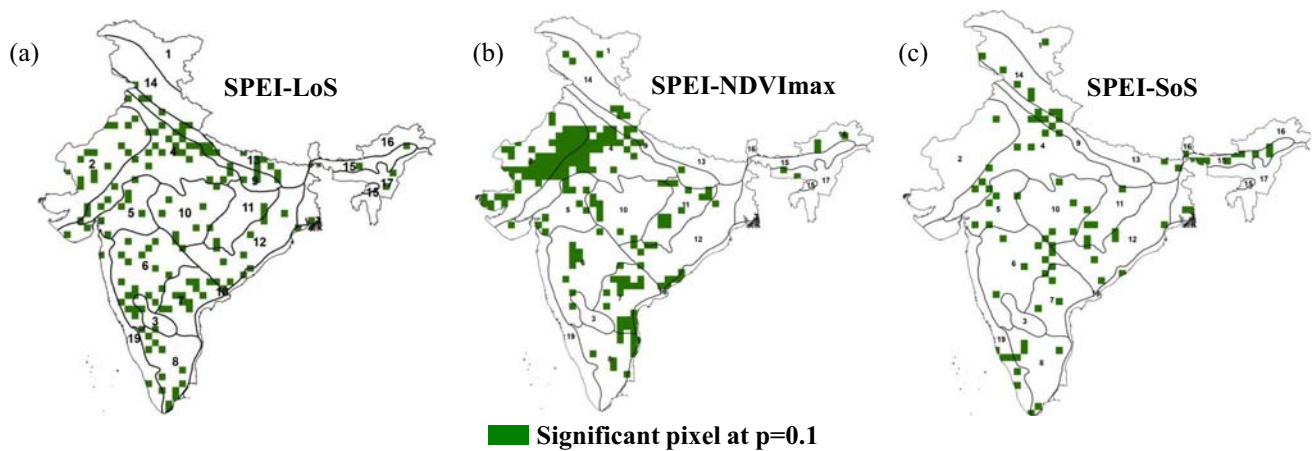


Fig. 12 Combined statistically significant pixels ($p = 0.1$) in June, July, and August months over study area for SPEI-03 and phenological metrics relation: **a** SPEI-03 and LoS, **b** SPEI-03 and NDVI_{max}, and **c** SPEI-03 and SoS

Table 5 Sensitivity of SoS, LoS, and NDVI_{max} with SPEI-03 over different AERs

AER	SoS			LoS			NDVI _{max}		
	Jun	Jul	Aug	Jun	Jul	Aug	Jun	Jul	Aug
2	-4.47	-7.17	-10.64	4.06	2.87	3.96	0.002	0.058	0.106
3	-6.57	0.04	-0.09	1.71	5.57	-0.34	-0.008	0.015	0.062
4	-5.07	-2.64	-2.14	0.44	0.22	3.50	-0.004	0.030	0.052
5	-12.01	0.60	-3.40	0.38	-1.66	0.77	-0.033	0.006	-0.003
6	-9.54	-2.26	-6.23	2.13	2.67	-1.46	-0.003	0.029	0.029
7	-6.72	-0.64	-8.17	4.77	7.38	3.08	0.024	0.052	0.064
8	-2.36	-0.87	2.92	2.53	5.22	4.73	0.015	0.020	0.049
9	0.59	-1.03	-2.39	4.33	2.61	2.87	0.005	0.019	0.024
10	-5.25	-0.50	-5.79	-2.68	-1.33	0.25	-0.018	0.008	0.002
11	1.38	-2.26	-8.54	-1.06	-0.31	-0.58	0.018	0.038	0.033
12	-0.69	0.78	-11.26	-1.18	0.19	2.67	0.018	0.025	0.023
13	-6.37	-9.19	-11.71	2.85	4.10	6.07	-0.001	0.001	-0.004
14	5.63	-5.36	-10.94	-1.97	-2.29	-0.36	-0.010	0.006	0.008
15	-2.76	-1.27	-1.84	-3.82	0.44	-0.71	-0.012	-0.006	0.000
17	-18.25	-16.23	-3.02	-3.13	2.80	1.74	0.003	0.002	-0.003
18	-3.15	-0.66	-4.89	1.44	2.27	-8.45	-0.007	-0.003	-0.002
19	-8.36	-0.79	3.72	-2.27	0.98	0.86	0.027	0.038	0.040

The sensitivity analysis revealed a rapid increase in sensitivity from arid to semi-arid regions, followed by a decline from semi-humid to humid regions (Piao 2011; Javed et al. 2021). Furthermore, we found that extreme wet or dry years resulted in relatively less change in NDVI_{max} compared to change in the SoS. This finding aligns with the results of other studies (Jiang et al. 2018; Javed et al. 2021). Previous research (Glade et al. 2016; Hao et al. 2019; Stocker 2014) has reported that excessive rainfall can lead to cloudy conditions, thereby obstructing incoming solar radiation and reducing vegetation photosynthesis and plant growth. Therefore, the

effect of the extreme wet conditions on the NDVI_{max} during the peak growth stage is not considerable since crops require ample solar radiation for photosynthesis during this phase (Hao et al. 2019). Pheno-metrics in semi-arid regions exhibited greater sensitivity to wetness and dryness compared to arid regions. This is in contrast with the notion that arid regions, characterized by limited water availability, are more sensitive to climatic variations (Delgado et al. 2018). The reason for this discrepancy may be attributed to the apparent plant acclimatization and resilience to drought conditions due to physiological adaptations (Ma et al. 2015).

4.6 Limitations and challenges

Analyzing the impact of dry and wet events on crop phenology is crucial for comprehending its relationship with climate change. Satellite data can effectively monitor the crop phenology over large areas; however, several limitations and challenges exist in phenology retrieval. Satellite data in monsoon season is often contaminated by cloud and cloud shadows, which introduces uncertainty. Extricating the noise from growth profile and preserving the relevant information proves to be exceedingly difficult. Although various smoothing techniques are available to mitigate noise, selecting the most suitable method that accounts for crop variability over large heterogeneous areas remains a challenge. A recent study by Meroni et al. (2021) explored the use of high-resolution Sentinel-1 data in microwave region and Sentinel-2 data in optical region to map the phenology in Europe using TIMESAT. Future research should focus on joint analysis of multi-source data to study the pheno-metrics while avoiding cloud/noise contamination. Additionally, combining data from optical and microwave sources can be a valuable tool for understanding underlying physiological processes, such as changes in biomass with phenology. Apart from this, the accuracy of outputs is influenced by the pheno-metrics detection method and trend analysis techniques employed. The current detection methods rely on mathematical theories rather than physiological foundations, limiting both understanding and accuracy. Nonetheless, several emerging techniques and sensors offer promising options for future research in exploring the effect of drought events on agriculture.

5 Conclusions

Given the importance of assessing impact of the dryness/wetness condition on crop phenology in the context of climate change, the present study analyzed the spatial patterns and temporal trend of phenological metrics vis-à-vis SPEI-03 as per the prevailing soil and climate resilience. The study has further examined the sensitivity of SPEI-03 derived dryness/wetness patterns to the satellite-derived phenological metrics in agro-ecological zones over India. The SPEI-03 revealed that the hot sub-humid regions were more prone to dryness than semi-arid regions. An increasing trend in dryness was observed in the north-eastern part of India comprising AERs 15, 16, and 17. The SPEI-03 in dry and wet years also revealed an abrupt change in the phenological metrics such as SoS, LoS, and NDVI_{max} in most AERs. As expected, dryness during the early monsoon period delayed SoS, reduced NDVI_{max}, and decreased LoS in most of the AERs. The NDVI_{max} in July and August also showed positive sensitivity towards an increase in wetness. Most of the agricultural area (>50%) showed an increasing trend of SoS and LoS. Drought

resistance to agriculture is more robust in the northwest part of India than in the central and northeast parts. Moreover, SoS exhibited a stronger correlation with SPEI-03 than LoS. The sensitivity of each phenological metric revealed that SoS is sensitive to drought during the monsoon period in almost all AERs. In contrast, NDVI_{max} exhibited much sensitivity towards SPEI-03 in August month. Our results will be helpful in understanding the agricultural crop resilience to drought, decision-making for crop management, and crop insurance in future course of time.

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Author contribution M.K.: conceptualization, methodology, data curation, investigation, formal analysis, writing original draft paper, editing. A.C.: conceptualization, methodology, resources, supervision, writing, review, editing. V.C.: supervision, resources, writing—review, editing. P.S.R.: supervision, writing—review, editing.

Data availability Data are available upon request on the corresponding author.

Declarations

Conflict of interest The authors declare no competing interests.

References

- Ahmad FM, Shen R, Zaheer AB, Ahmad MN, Zhang Y (2018) Study capability of Standardized Precipitation Evapotranspiration Index to represent soil moisture variability during winter season over Pakistan for the period 1951–2010. *Meteorol Atmos Phys* 130(6):689–699
- Anwar MR, Li Liu D, Farquharson R, Macadam I, Abadi A, Finlayson J, Wang B, Ramilan T (2015) Climate change impacts on phenology and yields of five broadacre crops at four climatologically distinct locations in Australia. *Agric Syst* 132:133–144
- Arora NK (2019) Impact of climate change on agriculture production and its sustainable solutions. *Environ Sustain* 2(2):95–96
- Beguéría S, Vicente-Serrano SM, Reig F, Latorre B (2014) Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. *Int J Climatol* 34(10):3001–3023
- Bhavani P, Chakravarthi V, Roy PS, Joshi P K, Chandrasekar K (2017) Long-term agricultural performance and climate variability for drought assessment: a regional study from Telangana and Andhra Pradesh states, India. *Geomat Nat Hazards Risk* 8(2):822–840. <https://doi.org/10.1080/19475705.2016.1271831>
- Chakraborty A, Seshasai MV, Dadhwal VK (2014) Geo-spatial analysis of the temporal trends of kharif crop phenology metrics over India and its relationships with rainfall parameters. *Environ Monit Assess* 186(7):4531–4542

- Chakraborty A, Seshasai MV, Rao SV, Dadhwal VK (2017) Geo-spatial analysis of temporal trends of temperature and its extremes over India using daily gridded ($1^\circ \times 1^\circ$) temperature data of 1969–2005. *Theor Appl Climatol* 130(1):133–149
- Chakraborty A, Seshasai MVR, Reddy CS, Dadhwal VK (2018a) Persistent negative changes in seasonal greenness over different forest types of India using MODIS time series NDVI data (2001–2014). *Ecol Indic* 85:887–903
- Chakraborty D, Sehgal VK, Dhakar R, Das DK, Sahoo RN (2018b) Trends and change-point in satellite derived phenology parameters in major wheat growing regions of north India during the last three decades. *J Indian Soc Remote Sens* 46(1):59–68
- Chen H, Sun J (2017) Characterizing present and future drought changes over eastern China. *Int J Climatol* 37:138–156
- Chen J, Jönsson P, Tamura M, Gu Z, Matsushita B, Eklundh L (2004) A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky–Golay filter. *Remote Sens Environ* 91(3–4):332–344
- Chen C, Park T, Wang X, Piao S, Xu B, Chaturvedi RK, Fuchs R, Brovkin V, Ciais P, Fensholt R, Myneni RB (2019) China and India lead in greening of the world through land-use management. *Nat Sustain* 2:122–129
- Dalezios NR, Blanta A, Spyropoulos NV, Tarquis AM (2014) Risk identification of agricultural drought for sustainable agroecosystems. *Nat Hazards Earth Syst Sci* 14(9):2435–2448
- Das PK, Chakraborty A, Seshasai MV (2014) Spatial analysis of temporal trend of rainfall and rainy days during the Indian Summer Monsoon season using daily gridded ($0.5^\circ \times 0.5^\circ$) rainfall data for the period of 1971–2005. *Meteorol Appl* 21(3):481–493
- Das PK, Das R, Das DK, Midya SK, Bandyopadhyay S, Raj U (2020) Quantification of agricultural drought over Indian region: a multivariate phenology-based approach. *Nat Hazards* 101(1):255–274
- Das PK, Mohinuddin SK, Midya SK, Das DK, Sharma R, Bandyopadhyay S (2021) Can multiscale meteorological drought indices detect soil moisture droughts? A study of Indian regions. *Hydrol Sci J* 66(9):1475–1487
- De Beurs KM, Henebry GM (2005) Land surface phenology and temperature variation in the International Geosphere–Biosphere Program high-latitude transects. *Glob Chang Biol* 11(5):779–790
- Delgado M, Hidalgo M, Puerta P, Sánchez-Leal R, Rueda L, Sobrino I (2018) Concurrent changes in spatial distribution of the demersal community in response to climate variations in the southern Iberian coastal Large Marine Ecosystem. *Mar Ecol Prog Ser* 607:19–36
- Eklundh L, Jönsson P (2017) TIMESAT 3.3 Software Manual. Lund and Malmö University, Sweden
- Felton AJ, Zavislan-Pullaro S, Smith MD (2019) Semi-arid ecosystem sensitivity to precipitation extremes: weak evidence for vegetation constraints. *Ecol* 100:e02572
- Friedl MA, Gray JM, Melaas EK, Richardson AD, Hufkens K, Keenan TF, Bailey A, O’Keefe J (2014) A tale of two springs: using recent climate anomalies to characterize the sensitivity of temperate forest phenology to climate change. *Environ Res Lett* 9(5):054006
- Fu YH, Piao S, Delpierre N, Hao F, Hänninen H, Liu Y, Sun W, Janssens IA, Campioli M (2018) Larger temperature response of autumn leaf senescence than spring leaf-out phenology. *Glob Chang Biol* 24:2159–2168
- Ge W, Han J, Zhang D, Wang F (2021) Divergent impacts of droughts on vegetation phenology and productivity in the Yungui Plateau, southwest China. *Ecol Indic* 127:107743
- Glade FE, Miranda MD, Meza FJ, van Leeuwen WJ (2016) Productivity and phenological responses of natural vegetation to present and future inter-annual climate variability across semi-arid river basins in Chile. *Environ Monit Assess* 188:676
- Guntukula R (2020) Assessing the impact of climate change on Indian agriculture: evidence from major crop yields. *J Public Aff* 20(1):e2040
- Güsewell S, Furrer R, Gehrige R, Pietragalla B (2017) Changes in temperature sensitivity of spring phenology with recent climate warming in Switzerland are related to shifts of the pre-season. *Glob Chang Biol* 23(12):5189–5202
- Hao Z, Di S, Wu M, Zheng J (2019) Does El Niño play an early signal role for the south-flood north-drought pattern over eastern China? *Theor Appl Climatol* 137:217–227
- Hatfield JL, Prueger JH (2015) Temperature extremes: effect on plant growth and development. *Weather Clim Extrem* 10:4–10
- Heumann BW, Seaquist JW, Eklundh L, Jönsson P (2007) AVHRR derived phenological change in the Sahel and Soudan, Africa, 1982–2005. *Remote Sens Environ* 108(4):385–392
- IPCC, 2021. Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, Caud N, Chen Y, Goldfarb L, Gomis MI, Huang M. Climate change 2021: the physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change. 2021 Jun;2.
- Ishtiaq M, Maqbool M, Muzamil M, Casini R, Alataway A, Dewidar AZ, El-Sabrou AM, Elansary HO (2022) Impact of climate change on phenology of two heat-resistant wheat varieties and future adaptations. *Plants* 11(9):1180
- Javed T, Li Y, Feng K, Ayantobo OO, Ahmad S, Chen X, Rashid S, Suon S (2021) Monitoring responses of vegetation phenology and productivity to extreme climatic conditions using remote sensing across different sub-regions of China. *Environ Sci Pollut Res* 28(3):3644–3659
- Jeganathan C, Dash J, Atkinson PM (2010) Mapping the phenology of natural vegetation in India using a remote sensing-derived chlorophyll index. *Int J Remote Sens* 31(22):5777–5796
- Jiang Y, Wang R, Peng Q, Wu X, Ning H, Cheng L (2018) The relationship between drought activity and vegetation cover in Northwest China from 1982 to 2013. *Nat Hazards* 92(1):145–163
- Jönsson P, Eklundh L (2004) TIMESAT—a program for analyzing time-series of satellite sensor data. *Comput Geosci* 30(8):833–845
- Kang W, Wang T, Liu S (2018) The response of vegetation phenology and productivity to drought in semi-arid regions of Northern China. *Remote Sens* 10:727
- Kendall M (1976) Rank correlation methods, 4th edn. Griffin, London
- Kumar R, Gautam HR (2014) Climate change and its impact on agricultural productivity in India. *J Climatol Weather Forecast* 2(1):1–3
- Kumar R, Nath AJ, Nath A, Sahu N, Pandey R (2022) Landsat-based multi-decadal spatio-temporal assessment of the vegetation greening and browning trend in the Eastern Indian Himalayan Region. *Remote Sens Appl: Soc Environ* 25:100695
- Li Z, Lyu S, Ao Y, Wen L, Zhao L, Wang S (2015) Long-term energy flux and radiation balance observations over Lake Ngoring, Tibetan Plateau. *Atmos Res* 155:13–25
- Liu X, Pan Y, Zhu X, Yang T, Bai J, Sun Z (2018) Drought evolution and its impact on the crop yield in the North China Plain. *J Hydrol* 564:984–996
- Liu H, Jiao F, Yin J, Li T, Gong H, Wang Z, Lin Z (2020) Nonlinear relationship of vegetation greening with nature and human factors and its forecast—a case study of Southwest China. *Ecol Indic* 111:106009
- Ma X, Huete A, Moran S, Ponce-Campos G, Eamus D (2015) Abrupt shifts in phenology and vegetation productivity under climate extremes. *J Geophys Res Biogeosci* 120:2036–2052
- Malhi GS, Kaur M, Kaushik P (2021) Impact of climate change on agriculture and its mitigation strategies: a review. *Sustain* 13(3):1318
- Mall RK, Singh R, Gupta A, Srinivasan G, Rathore LS (2006) Impact of climate change on Indian agriculture: a review. *Clim Chang* 78(2):445–478. <https://doi.org/10.1007/s10584-005-9042-x>

- Mann HB (1945) Nonparametric tests against trend. *Econometrica: J Econom Soc* 1:245–259
- McKee TB, Doesken NJ, Kleist J (1993) The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology*. 17(22):179–183.
- Meroni M, d'Andrimont R, Vrieling A, Fasbender D, Lemoine G, Rembold F, Seguíni L, Verhegghen A (2021) Comparing land surface phenology of major European crops as derived from SAR and multispectral data of Sentinel-1 and-2. *Remote Sens Environ* 253:112232
- Mishra AK, Singh VP (2011) Drought modeling—a review. *J Hydrol* 403(1–2):157–175
- Nam WH, Hayes MJ, Svoboda MD, Tadesse T, Wilhite DA (2015) Drought hazard assessment in the context of climate change for South Korea. *Agric Water Manag* 160:106–117
- NRSC (2014) Land Use/Land Cover Database on 1:50,000 Scale. In: *Natural Resources Census Project*. LUCMD, LRUMG, RSAA, National Remote Sensing Centre, ISRO, Hyderabad
- Palmer WC (1965) Meteorological drought. US Department of Commerce, Weather Bureau
- Parida BR, Pandey AC, Patel NR (2020) Greening and browning trends of vegetation in India and their responses to climatic and non-climatic drivers. *Clim* 8(8):92
- Parsons DJ, Rey D, Tanguy M, Holman IP (2019) Regional variations in the link between drought indices and reported agricultural impacts of drought. *Agric Syst* 173:119–129
- Piao S, Wang X, Ciais P, Zhu B, Wang T, Liu J (2011) Changes in satellite-derived vegetation growth trend in temperate and boreal Eurasia from 1982 to 2006. *Glob Chang Biol* 17:3228–3239
- Potopová V, Štěpánek P, Možný M, Türkott L, Soukup J (2015) Performance of the standardised precipitation evapotranspiration index at various lags for agricultural drought risk assessment in the Czech Republic. *Agric For Meteorol* 202:26–38
- Pramudya Y, Onishi T (2018) Assessment of the standardized precipitation index (SPI) in Tegal City, Central Java, Indonesia. *IOP Conf Ser: Earth Environ Sci* 129(1):012019
- Rai SK, Apoorva SPR (2020) Climate change, pandemic and its impact on Indian agriculture. *Agric Food* 2(10):284–287
- Ranjan AK, Gorai AK (2022) Evaluating phenological trends of different vegetation types in response to climate change over the Rajmahal Hills in India during 2001–2019. *Remote Sens Lett* 13(9):898–911
- Rao CS, Lal R, Prasad JV, Gopinath KA, Singh R, Jakkula VS, Sahrawat KL, Venkateswarlu B, Sikka AK, Virmani SM (2015) Potential and challenges of rainfed farming in India. *Adv Agron* 133:113–181
- Richardson AD, Hollinger DY, Dail DB, Lee JT, Munger JW, O'keefe J (2009) Influence of spring phenology on seasonal and annual carbon balance in two contrasting New England forests. *Tree Physiol* 29(3):321–331
- Sathyan A, Funk C, Aenis T, Breuer L (2018) Climate Vulnerability in Rainfed Farming: Analysis from Indian Watersheds. *Sustain* 10(9):3357
- Sehgal VK, Jain S, Aggarwal PK, Jha S (2011) Deriving crop phenology metrics and their trends using times series NOAA-AVHRR NDVI data. *J Indian Soc Remote Sens* 39:373–381
- Sen PK (1968) Estimates of the regression coefficient based on Kendall's tau. *J Am Stat Assoc* 63(324):1379–1389
- Shen M, Tang Y, Chen J, Yang X, Wang C, Cui X, Yang Y, Han L, Li L, Du J, Zhang G (2014) Earlier-season vegetation has greater temperature sensitivity of spring phenology in Northern Hemisphere. *PLoS One* 9(2):e88178
- Shen X, Liu B, Henderson M, Wang L, Jiang M, Lu X (2022) Vegetation greening, extended growing seasons, and temperature feedbacks in warming temperate grasslands of China. *J Clim* 35(15):5103–5117
- Shen X, Jiang M, Lu X (2023) Diverse impacts of day and night temperature on spring phenology in freshwater marshes of the Tibetan Plateau. *Limnol Oceanogr Lett* 8(2):323–329
- Singh S, Sanatan N (2021) Assessment of climate change impact on wheat yield in western dry region: a district level analysis. *Clim Change* 6(21):25–34
- Stocker T (2014) Climate change 2013: the physical science basis: Working Group I contribution to the fifth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press
- Subramaniam AR (1983) Agro-ecological zones of India. *Theor Appl Climatol* 32(2):329–333
- Tan B, Morissette JT, Wolfe RE, Gao F, Ederer GA, Nightingale J, Pedely JA (2010) An enhanced TIMESAT algorithm for estimating vegetation phenology metrics from MODIS data. *IEEE J Sel Top Appl Earth Obs Remote Sens* 4(2):361–371
- Tirivivarombo S, Osupile D, Eliasson P (2018) Drought monitoring and analysis: standardised precipitation evapotranspiration index (SPEI) and standardised precipitation index (SPI). *Phys Chem Earth* 106:1–10
- Vicente-Serrano SM, Beguería S, López-Moreno JI (2010) A multiscale drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *J Clim* 23(7):1696–1718
- Wang H, Wu C, Ciais P, Peñuelas J, Dai J, Fu Y, Ge Q (2020) Overestimation of the effect of climatic warming on spring phenology due to misrepresentation of chilling. *Nat Commun* 11(1):4945
- Wilhite DA, Buchanan-Smith M (2005) Drought as hazard: understanding the natural and social context. *Drought and water crises* 22:3–29
- Yang Y, Tao B, Liang L, Huang Y, Matocha C, Lee CD, Sama M, Masri BE, Ren W (2021) Detecting recent crop phenology dynamics in corn and soybean cropping systems of Kentucky. *Remote Sens* 13(9):1615
- Zhai L, Feng Q, Li Y (2010) Calculation of actual evapotranspiration based on Morton CRAE in Northwest China. *J Irrig Drain* 29(5):33–38

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Impact of climate and weather extremes on soybean and wheat yield using machine learning approach

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Abstract

The escalating climate instability and extreme weather events significantly jeopardize food security. The study assessed the impact of long-term climatic variables and extreme weather events on soybean and wheat yields in rainfed central India. To address inherent spatial variability, the study area was divided into homogeneous zones based on rainfall and soil parameters. Crop yields were correlated with a comprehensive set of driving variables at seasonal and monthly scales within each zone. Machine learning algorithms, including Random Forest Regression (RFR) and Neural Networks (NN), were employed to analyze crop yield anomalies caused by climate and weather extremes. The Sobol' index was utilized for global sensitivity analysis to identify key parameters. Results showed significant negative correlations between thermo-meteorological parameters and yields of both monsoon soybean and winter wheat across multiple districts. Soybean yield exhibited a notable positive correlation with hydro-meteorological parameters, while wheat yield displayed a significant positive correlation with cold temperature extremes. RFR and NN demonstrated similar performance, with Root Mean Square Error (RMSE) values ranging from 0.27 to 0.39 t/ha for soybean and 0.4 to 0.6 t/ha for wheat. The Sobol' index highlighted the high sensitivity of soybean yield to rainfall and rainy days during July and August, corresponding to the crop development and flowering stages. In contrast, wheat yield was primarily influenced by temperature extremes, particularly cold nights and hot days during the reproductive-maturity stage. These crop- and growth-stage-specific analyses of meteorological parameters are essential for devising effective strategies to adapt and mitigate climate emergencies.

Keywords Crop yield · Central India · Random forest · Neural network · Sobol' index

1 Introduction

The Intergovernmental Panel on Climate Change's (IPCC) Sixth Assessment Report (2021) emphasizes persistent challenges in climatic variables, including rising temperatures, erratic rainfall patterns, and an increasing frequency of extreme weather events across South Asia. Significantly,

this region is inhabited by over 70% of small farmholders, who are notably susceptible to the effects of extreme weather events (Harvey 2018). Furthermore, the impacts of climate change on crop yield demonstrate spatiotemporal variations, intensifying concerns regarding food security (Praveen and Palanivelu 2017). Overall, the IPCC report highlights the paramount importance of mitigation and adaptation strategies in addressing the influence of climate change on crop yields and sustainable agriculture. This necessitates comprehensive understanding of the interaction between climatic variables/weather extremes and crop yields (Webber et al. 2018).

While long-term climatic variables determine the regional crop growth potential, their impact on crop yields varies significantly by the influence of weather extremes. Weather extremes can result in yield reduction below region-specific potential, persisting even when crops are exposed to optimal weather conditions (Tigchelaar et al. 2018). In general, process-based and statistical approaches

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are being employed to assess and quantify climate change-induced crop yield losses. Several studies have described the efficacy of both approaches in discerning the criticality of climate and weather extremes influencing crop yields and decision-making (Lobell and Asseng 2017). Process-based crop models (De Wit 1965) simulate crop growth and development but are incapable of generating historical crop yield anomalies. Additionally, these models necessitate extensive and often hard-to-obtain input parameters (Van Oort et al. 2011; Lu et al. 2017), which are frequently omitted from the modeling process, thus compromising accuracy (Robert et al. 2017). In contrast, statistical modeling encompasses the effects of climate and weather extremes on crop yield by utilizing historical data (Moore et al. 2017; Kukul and Irmak 2018) through two approaches: linear/non-linear parametric and non-linear non-parametric (or machine learning) statistical models. These models can predict crop yield under varying weather conditions, including rainfall, temperature, drought indices, etc. Recently, machine learning (ML) techniques such as random forest and neural networks have been employed for impact assessment and yield estimation (Crane-Droesch 2018; Vogel et al. 2019; Konduri et al. 2020; Schierhorn et al. 2021). Lu et al. (2017) suggested that statistical models require fewer resources compared to process-based models. Furthermore, these can account for spatial heterogeneities in yield, climate, and soil conditions, making ML models the preferred choice for performance.

Wheat, a dominant cereal crop, and soybean, a legume-oilseed crop, play crucial roles in ensuring food and nutritional security, but are significantly affected by recent climatic fluctuations. Wheat constitutes 36% of global food grain production, with Central India being a major contributor as per CIMMYT, Mexico (Braun et al. 1997). It is highly sensitive to temperature increase, with yield declining significantly above 34 °C due to accelerated senescence (Lobell et al. 2012). Temperature requirements vary across growth stages, such as 22 °C for the vegetative stage, 21 °C for the reproductive stage, and 35 °C as the maximum limit for the grain-filling stage (Porter and Gawith 1999), making the effects of extreme weather events time-specific (Powell and Reinhard 2016). Soybean contributes to 25% of global edible oil production and is crucial for livestock feed. Yield declines of soybean occurs outside the optimal temperature range of 26 °C to 30 °C, with adverse effects on flowering and pod setting. Insufficient precipitation negatively impacts soybean yield, with an ideal rainfall range of 500–1000 mm (MacCarthy et al. 2022). Though soybean can grow with as little as 180 mm of rain in a season, it results in a 40 to 60% yield reduction compared to optimal conditions. Considering the sensitivity of crop growth stages to temperature and rainfall, the inclusion of monthly mean climatic data,

in conjunction with seasonal data, is a valuable addition to the analysis.

The influence of climatic variables and weather extremes on crop productivity is intricate, influenced by various factors such as geographical location, crop type, and prevailing agricultural practices. For instance, Kang et al. (2009) noted that regions characterized by high soil water holding capacity exhibit resilience to climate variability impacts while sustaining crop yields. Recent research has endeavored to assess the influence of weather and climate on crop yield; however, much of it has relied on regression models to establish relationships between climatic variables such as temperature and rainfall and crop yield (Novikova et al. 2020; Paymard et al. 2018; Zampieri et al. 2017; Matiu et al. 2017; Yu et al. 2013). However, there is a growing recognition of the need to explore further into this relationship by considering additional factors such as weather extremes during crop-specific developmental phases in different agro-ecological conditions. While a few studies have employed machine learning (ML) techniques to capture the complex nonlinear associations between yield and climatic variables, the incorporation of weather extremes remains limited. For instance, Peichl et al. (2018) and Hofman et al. (2020) explored crop-yield dependencies on crop-specific development phases using ML models but did not include extreme weather events or conduct agro-ecological area-specific evaluations. Beillouin et al. (2020) examined the impact of diverse extreme weather and climatic conditions on historical yield anomalies in European crop production using ML techniques but did not consider crop development phases. Similarly, Schierhorn et al. (2021) investigated the contribution of climate and weather extremes to wheat yield across various growth stages but did not account for agro-ecological conditions.

In the Indian context, studies analyzing the impact of climate and weather extremes on crop yield using ML techniques and considering different development phases are scarce. While some research, such as that by Mohanty et al. (2017) and BIRTHAL et al. (2014), has explored the impact of climatic scenarios on soybean and other crop yields, these studies often focus on temperature and rainfall, neglecting the influence of extreme weather events. Mohapatra et al. (2022) found that increasing temperatures significantly affected grain yield in eastern India, while Gupta et al. (2022) and Madhukar et al. (2021) highlighted adverse effects of temperature and rainfall anomalies on crop yields, with limited attention to extreme weather events. Few investigations have focused on explaining the impact of heat waves on wheat yield, often confined to single-year analyses (Chakraborty et al. 2019) or employing linear regression approaches (Rao et al. 2015). None of these studies have comprehensively addressed the full range of climatic

factors and their associated extremes. Furthermore, the Sobol' index, a widely utilized global sensitivity analysis method, is employed in the present study to identify sensitive parameters by simultaneously varying them across the entire parameter space (Sobol 1993). Therefore, understanding the sensitivity of soybean and wheat yields to climatic variability and identifying the critical climate variables affecting these crop yields in India is imperative for effective agricultural management strategies. This study utilized ML models to discern vital climatic factors (monthly and seasonal) linked to yield anomalies in soybean and wheat in homogenous zones. Our findings contribute to existing knowledge by identifying the climatic variables specific to each growth stage that had the most significant impact on soybean and wheat yield losses in India, based on long-term historical data.

2 Study area

Two predominantly rainfed states in India, Maharashtra and Madhya Pradesh, both of which have experienced several drought events in recent past and are known for cultivating soybean and wheat, were chosen as the study areas (Fig. 2).

Maharashtra, situated in western India, extends from latitudes 15°35' N to 22°02' N and longitudes 72°36' E to 80°54' E, covering an area of 3.08 lakh square kilometers, and divided into 36 districts. In contrast, Madhya Pradesh, the second-largest state in India, encompasses 50 districts which spans from latitudes 17°48' N to 26°52' N and longitudes 74°2' E to 84°24' E. Both states experience a monsoon season from June to September, with higher rainfall in the south and southeast compared to the northwest. Approximately 55% of Maharashtra and 50% of Madhya Pradesh's total land area is utilized for cultivation. Soybean and Wheat are the major *kharif* (monsoon) season and *rabi* (winter) season crop in Maharashtra and Madhya Pradesh, respectively. The crop calendar of Soybean and Wheat crops, in respective study area, is given in Table 1.

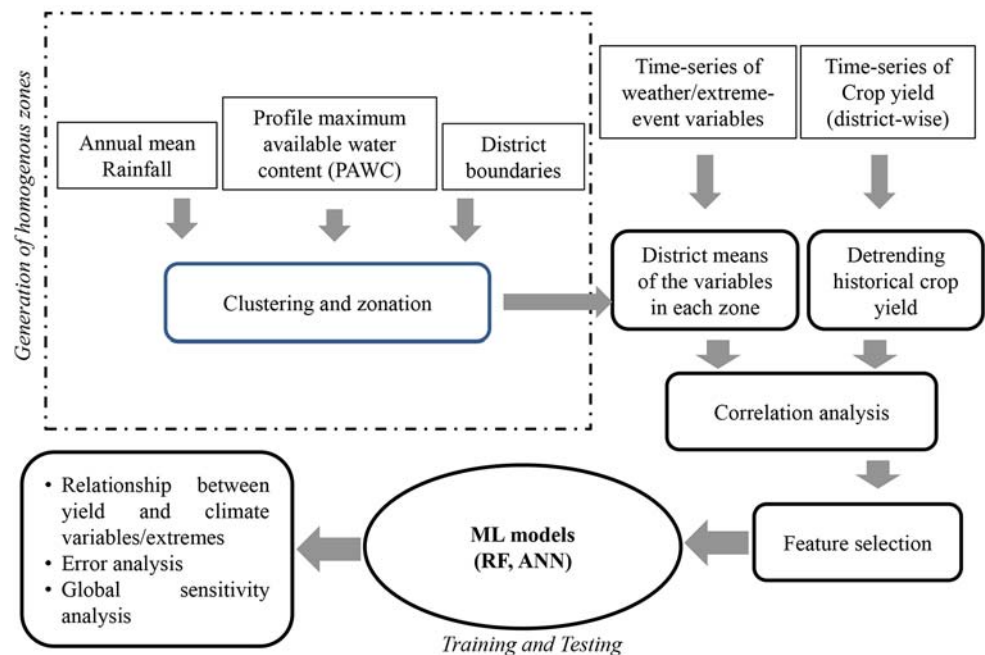
3 Data used and methodology

The schematic diagram of methodology is presented in Fig. 1.

Table 1 Crop calendar of Soybean and Wheat grown in *kharif* and *rabi* season, respectively

State	Crops	Initial	Crop development	Reproductive	Maturity	Harvest
Maharashtra	Soybean	Jun-Jul	Jul-Aug	Aug-Sep	Sep-Oct	Oct
Madhya Pradesh	Wheat	Nov-Dec	Dec-Jan	Jan-Feb	Feb-Mar	Mar

Fig. 1 Schematic diagram of methodology



3.1 Clustering of the study area into homogeneous zones

Both Maharashtra and Madhya Pradesh exhibit significant spatial variability in terms of climate and soil types. Consequently, agricultural practices in these states vary considerably across different regions, which is evident in the spatial distribution of crop types and crop calendars. In this study, the impact of climatic and weather extremes on wheat and soybean yields was studied by delineating the study states

into homogeneous zones (Fig. 2). This division was based on rainfall patterns and Profile Available Water Capacity (PAWC) of soil using a rule-based approach. PAWC refers to the capacity of the soil to store water in the soil profile as available soil moisture. It comprises water retained between field capacity and permanent wilting point of soil. Factors influencing PAWC include soil texture, organic matter content and depth. Both rainfall and PAWC are critical factors in crop production, as the former affects water supply while the latter determines water availability for crop growth.

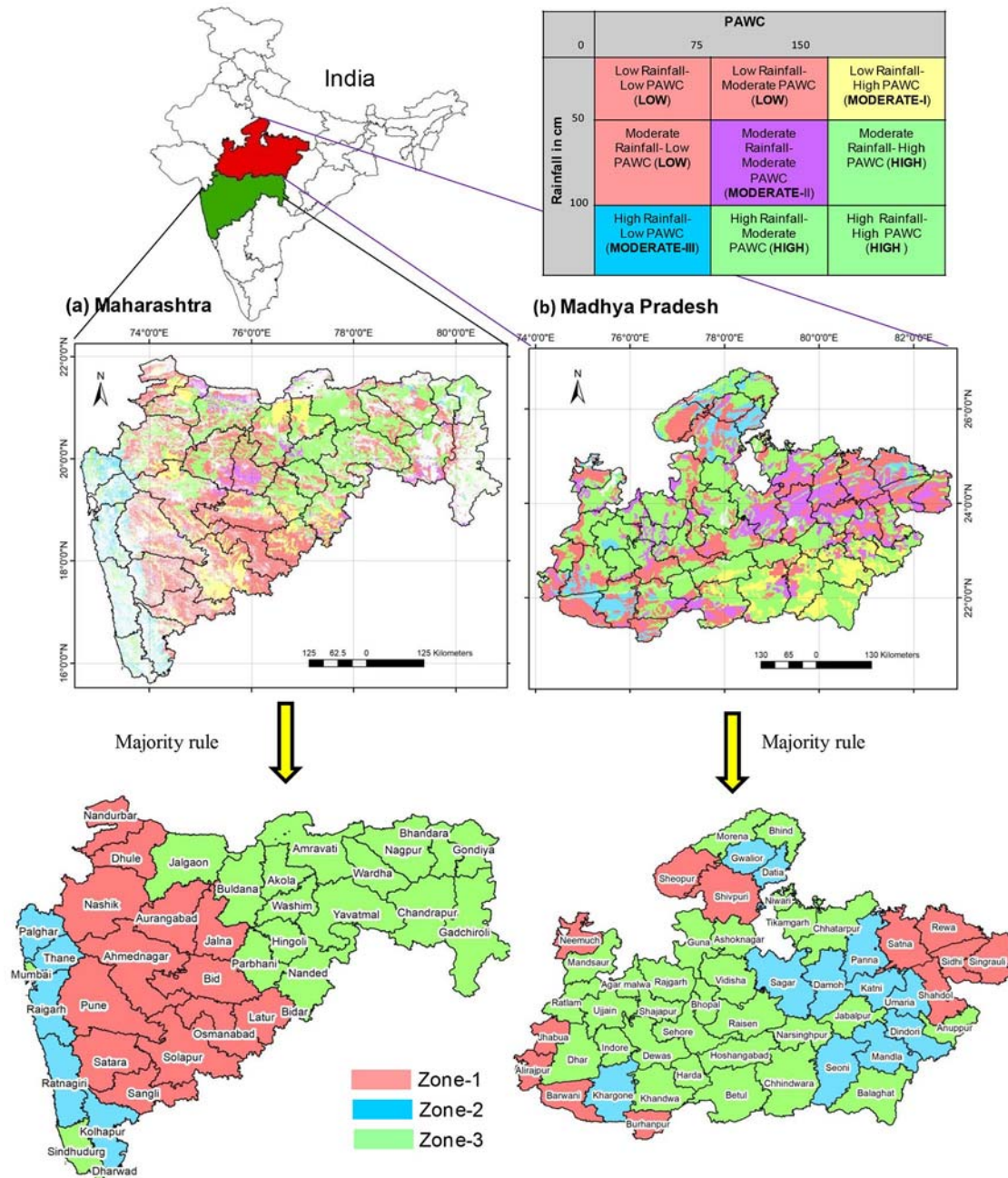


Fig. 2 Homogenous zones delineation in study area using rainfall and PAWC

Table 2 Characteristics of various delineated zones in study area

State	Zones	% Area	Climate	Soil	LGP (days)
Maharashtra (Soybean)	Zone-1: Rainfall (≤ 100 cm)/PAWC (≤ 150 cm): both are limiting	48.87	Hot semi-arid	Shallow/medium/deep black soil	90–150
	Zone-2: Either rainfall < 100 cm or PAWC < 150 cm: One of these is limiting	20.5	Hot humid/Per-humid	Red-lateritic and alluvium soil	> 210
	Zone-3: Rainfall (> 100 cm)/PAWC (> 150 cm): both are sufficient	38.05	Hot sub-humid	Red and black soil	150–180
Madhya Pradesh (Wheat)	Zone-1: Rainfall (≤ 100 cm)/PAWC (≤ 150 cm): both are limiting	22.6	Hot semi-arid	Alluvium-derived soils	90–150
	Zone-2: Either rainfall < 100 cm or PAWC < 150 cm: One of these is limiting	23.3	Hot semi-arid	medium/deep black soil	90–150
	Zone-3: Rainfall (> 100 cm)/PAWC (> 150 cm): both are sufficient	55.1	Hot sub-humid	Red and black soil	150–180

Annual mean rainfall data of CHIRPS ($5 \text{ km} \times 5 \text{ km}$) and PAWC derived from soil map of National Bureau of Soil Survey & Land Use Planning (NBSS&LUP) at 1:50,000 scales was employed to divide Maharashtra and Madhya Pradesh into homogeneous zones.

Initially, rainfall and PAWC were categorized into three classes for each parameter across the study area, as mentioned in Fig. 2. Subsequently, by combining the classes from each parameter, a total of nine classes were generated, forming a 3×3 matrix. Majority rule was applied to assign a single class to each district (Fig. 2). As a result, each state was delineated into three homogeneous zones, grouping together districts with almost similar characteristics. Salient characteristics of the homogenous zones of Maharashtra and Madhya Pradesh were taken from the respective agro-ecological zones and are presented in Table 2 (Subramaniam 1983).

3.2 Predictor variables employed in the analysis

In this study, a range of predictor variables were obtained, systematically organized, and used to compute climatic parameters and weather extremes spanning the period from 1999 to 2019, as outlined in Table 3. During the *kharif* season, predictor variables for four consecutive months (June, July, August, and September) were employed to conduct an impact analysis of soybean cultivation in Maharashtra. Similarly, during the *rabi* season, predictor variables spanning five months (November, December, January, February, and March) were utilized to evaluate their impact on

Table 3 Predictor variables used (1999–2019) for studying the impact of mean and extreme weather on crop yield

Predictor variables	Definition	Source
Tmax, Tmin (monthly)	Monthly Mean of maximum temperature and minimum temperature during the growing season	CPC temperature ($0.5^\circ \times 0.5^\circ$): https://www.esrl.noaa.gov/psd/data/gridded/data.cpc.globaltemp.html
Rainfall and Rainy days (monthly/seasonal)	Sum of monthly rainfall during the growing season, no. of days in season when Rainfall > 2.5 mm	CHIRPS ($0.05^\circ \times 0.05^\circ$): https://data.chc.ucsb.edu/products/CHIRPS-2.0/
Growing Degree Days (GDD): monthly and seasonal	Sum of difference of daily mean temperature and reference temperature (10°C for Soybean/ 5°C for Wheat) in growing season	CPC temperature ($0.5^\circ \times 0.5^\circ$): https://www.esrl.noaa.gov/psd/data/gridded/data.cpc.globaltemp.html
Standardized Precipitation Evapotranspiration index (SPEI): monthly	Time-series of the climatic water balance (P-PET) fitted to log-logistic and then Gaussian distribution to get SPEI. Here, SPEI at 3-months time-interval during growing season are used	CRU ($0.5^\circ \times 0.5^\circ$): https://spei.csic.es/database.html
Maximum Temperature (Tmax) extremes (Hot day, Cold day): monthly	No. of days during the growing season with daily Tmax $> 90^{\text{th}}$ percentile (Hot day); with daily Tmax $< 10^{\text{th}}$ percentile (Cold day)	CPC temperature ($0.5^\circ \times 0.5^\circ$): https://www.esrl.noaa.gov/psd/data/gridded/data.cpc.globaltemp.html
Tmin extremes (Hot night, cold night)	No. of days during the growing season with daily Tmin $> 90^{\text{th}}$ percentile (Hot night); with daily Tmin $< 10^{\text{th}}$ percentile (Cold night)	CPC temperature ($0.5^\circ \times 0.5^\circ$): https://www.esrl.noaa.gov/psd/data/gridded/data.cpc.globaltemp.html

wheat cultivation in Madhya Pradesh. In total, 43 variables were computed using daily data for soybean crop analysis, while 53 variables were computed for wheat crop analysis. Soybean and wheat crop yield data were obtained from the Ministry of Agriculture website (<https://data.desagri.gov.in/website/crops-apy-report-web>) for the Maharashtra and Madhya Pradesh regions, respectively. To remove inherent trends in the data, a linear regression detrending approach was applied for crop yield data preprocessing.

3.3 Correlation between yield and climatic parameters/ extremes

A Pearson's correlation coefficient was calculated to examine the relationship between crop yields and the various weather and climatic variables. This provides insight into how climatic and weather extremes affect crop yields. The correlation study was carried out on seasonal and monthly basis to understand the specific impact of weather extremes on crop yield during different growth stages. It is important to note that correlation does not imply causation, so the study was followed by more detailed analysis of the data. The formula to compute the correlation coefficient (r) is given below:

$$r = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^N (y_i - \bar{y})^2}} \quad (1)$$

Where, x_i is the crop yield in time-series data in a point i for a particular district, y_i is the weather/climatic variables in time-series data in a point i for a particular district, $\bar{x}$ and $\bar{y}$ is district mean yield and weather/climatic variables in time-series, respectively, and N is total number of data points.

3.4 Development of models

For the present study, two ML models viz., Random Forest regression (RFR) and Neural network (NN) are developed for each zone and each crop. Approximately, 70% of data were used for model training and remaining 30% were used for model testing. For each model, a grid-search and 10-fold cross validation technique was used to select the optimum hyperparameters to tune the machine learning models. Then, for each grid location, performance of each model was evaluated using statistical measures of error between the predicted and observed values i.e., Root Mean Squared Error (RMSE). A well-trained statistical model generates small RMSE values. The optimum values of hyper-parameters producing maximum accuracy for each ML model are given in Table 4. District-level seasonal and month-wise

climatic, weather extreme variables are predictor variables in this analysis, while the crop yields (soybean and wheat) as response variable in each zone.

3.4.1 Random forest regression (RFR) model

Random Forest Regression is an ensemble machine learning algorithm (Breiman 2001) used for regression (or classification) tasks, able to handle a large volume of input data and simultaneously can reduce overfit. RFR is composed of multiple decision trees (DT), and the final prediction is an aggregation of the predictions made by these individual trees. The accuracy of the random forest algorithm relies mainly on the strength of the individual tree classifiers and the dependency between the classifiers (Amit and Geman 1997). The inclusion of several trees increases the probability of deriving an effective prediction model (Breiman 2001; Strobl et al. 2008). The key components and steps involved in RFR with input features (x) and corresponding target values (y) are given below:

- RFR consists of an ensemble of DT. Each tree is trained independently on a subset of the data using a process called bootstrapped sampling (randomly selecting samples with replacement) as per Liaw and Wiener (2002).
- Consider a dataset of size $P \times Q$, where P is the number of data points and Q is the number of features.

Let $P1$ data points be present at some node d . RFR selects K random features out of Q ($K < Q$); and for each feature net reduction in variance is computed. The feature for which net reduction in variance is maximum is selected for decision making.

The criteria for nodal feature selection can be expressed as follows:

$$f_{\text{selected feature}} = \operatorname{argmax}_i (\Delta V_d^{fi}) \quad (2)$$

$$\Delta V_d^{fi} = V_d - (\alpha_1 V_{S1}^{fi} + \alpha_2 V_{S2}^{fi}) \quad (3)$$

$$\alpha_1 = \frac{\text{Number of data points in } S1}{P1} \quad (4)$$

$$\alpha_2 = P1 - \alpha_1 \quad (5)$$

Where:

V_d is the variance at node d ,

ΔV_d^{fi} represents the reduction in the variance at node d when fi is selected for decision making,

V_{S1}^{fi} is the variance present in $S1$ subset when feature fi is selected for decision making ($i \in (1, K)$), and

Table 4 Hyperparameters range and the optimal values for each ML model for yield modeling

	Model description	Parameters	Zones			
			Parameters range with step size	Zone-01	Zone-02	Zone-03
				Optimized parameters	Optimized parameters	Optimized parameters
Soybean	RFR	Number of trees	10 to 500 @ 1	274	219	351
	Loss function: RMSE	Minimum sample split	2 to 8 @ 1	2	2	3
	Maximum no. of feature: Sqrt	Minimum sample leaf	1 to 6 @ 1	1	1	2
	NN	Learning rate	0.001 to 1 @ 0.01	0.01	0.01	0.02
	Learning function: Leaky ReLU	momentum	0.1 to 1 @ 0.1	0.8	0.9	0.8
	Learning algorithm: SGD	Batch size	10 to 100 @ 10	30	30	30
	Loss function: RMSE	training epochs	50 to 300 @10	120	190	150
	RFR	Number of trees	10 to 500 @ 1	318	252	290
	Loss function: RMSE	Minimum sample split	2 to 8 @ 1	2	2	3
	Maximum no. of feature: Sqrt	Minimum sample	1 to 6 @ 1	1	2	2
Wheat	NN	Learning rate	0.001 to 1 @ 0.01	0.02	0.01	0.02
	Learning function: ReLU	momentum	0.1 to 1 @ 0.1	0.5	0.6	0.8
	Learning algorithm: Adam	Batch size	16 to 256 @ 10	20	20	20
	Loss function: RMSE	training epochs	10 to 300 @10	200	210	200

$V_{S_2}^{fi}$ is the variance present in S_2 subset when feature fi is selected for decision making ($i \in (1, K)$).

- Each of the trees is grown till maximum depth to reduce bias. Finally, the RFR aggregates the predictions from all the individual decision trees by averaging, which reduces the overall variance of model (Breiman 2001).

Mathematically, the prediction made by a RFR for regression can be represented as follows:

Given a new data point with feature values x_{new} , and a RFR with N decision trees, the prediction (y_{pred}) is:

$$y_{pred} = \frac{\sum_{n=1}^N (\text{tree}_i(x_{new}))}{N} \quad (6)$$

Where, $\text{tree}_i(x_{new})$ represents the prediction of the i^{th} decision tree for the new data point x_{new} .

3.4.2 Neural network (NN) model

A neural network model with 2 hidden layers (input-8-4-1) was constructed to predict the zone-wise yield of soybean and wheat using Python programming language and PyTorch library (Paszke et al. 2019). Several hyperparameters (number of hidden layers, number of neurons per layer, learning rate, and batch size) which affect the performance of an ANN are tuned using grid-search optimization and 10-fold cross validation technique (Table 4). Here, data was used in a 70:30 ratios to train and test the model. The leaky Rectified Linear Unit (ReLU) activation function was used in each layer with decay coefficient of 0.01. The model was optimized using momentum-based Stochastic Gradient Descent (SGD) optimizer algorithm. Momentum-based SGD is a variation of the traditional SGD optimization algorithm that incorporates momentum to accelerate convergence. The momentum term allows the optimizer to build up velocity in directions where gradients consistently point, which accelerates convergence and escape local minima. The Mean Square Error (MSE)

was used as loss function to evaluate the model. The steps involved in NN training are as follows:

1. Initialize model parameters (weights and biases) with Xavier initialization (Glorot and Bengio 2010)
2. Define Leaky ReLU as activation function as follows

$$\text{Leaky ReLU}(x) = \begin{cases} x, & \text{if } x > 0 \\ \alpha^* x, & \text{if } x \leq 0 \end{cases} \quad (7)$$

3. Define a list of learning rate, batch size and momentum parameters to be tested for model performance.
4. For each combination in step 3, train the NN model and update model parameters via SGD with momentum (Eqs. 8 and 9) and evaluate model performance on validation dataset.

$$W_{t+1} = W_t + V_{t+1} \quad (8)$$

$$V_{t+1} = \mu \times V_t - \alpha \times \nabla L_t \quad (9)$$

Where W_t is weight at t^{th} epoch,

V_t is velocity at t^{th} epoch,

μ is decaying factor accounts the number of iterations of previous gradients into the current update; $\mu \in (0, 1)$.

α is learning rate,

∇L_t is gradient of loss function at t^{th} epoch.

5. Compute loss for each of the model-parameter combination in step 3 and select the model parameter with corresponding to minimum MSE.

3.5 Evaluation of modeling performance

Three statistical criteria, including coefficient of determination (R^2), root mean square error (RMSE), and normalized root mean square error (nRMSE), are used to evaluate the performance of the ML models. Equations to compute RMSE and nRMSE are given below:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N (y_i - \hat{y})^2}{N}} \quad (10)$$

$$\text{nRMSE} = \frac{\sqrt{\frac{\sum_{i=1}^N (y_i - \hat{y})^2}{N}}}{\bar{y}} \quad (11)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y})^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (12)$$

Where, y_i is the actual crop yield in time-series data in a point i for a particular district, $\hat{y}$ is estimated yield using model in same district, N is total number of data points, $\bar{y}$ is district mean yield in time-series.

3.6 Impact analysis of predictive variables in crop yield estimation

Impact of various predictor variables on crop yield estimation was analyzed through sensitivity analysis under different presumed scenarios. We assumed the accuracy to be highest with least RMSE, with all predictor variables. Therefore, we systematically removed individual predictor variables to evaluate their influence on crop yield estimation using different machine learning approaches. This analysis aims to quantify the significance of predictor variables in predicting crop yield based on historical data. Combinations of predictor variables under different scenarios were analyzed for soybean and wheat crops during their respective growing seasons. The following is a summary of the scenarios:

- Scenario 1 (S1): All predictor variables were retained in each machine learning model for both soybean and wheat crops.
- Scenario 2 (S2): Monthly temperature extremes are excluded from the input data.
- Scenario 3 (S3): Monthly minimum temperatures, maximum temperatures, and temperature extremes are excluded from the input data.
- Scenario 4 (S4): Both monthly and seasonal Growing Degree Days (GDD), as well as minimum temperatures, maximum temperatures, and temperature extremes are excluded from the input data.
- Scenario 5 (S5): Monthly and seasonal rainfall, rainy days, GDD, minimum temperatures, maximum temperatures, and temperature extremes are excluded from the input data.
- Scenario 6 (S6): Monthly SPEI, GDD, minimum temperatures, maximum temperatures, and temperature extremes are excluded from the input data; retaining monthly and seasonal rainfall and rainy days.

3.7 Global sensitivity analysis

In the current study, a global sensitivity index, often referred to as the first-order Sobol' index is used (Sobol 2001). It measures the first-order effect of an input variable on the output of a model and quantifies the portion of the total output variance that can be attributed to the variation in a single input variable while keeping all other input variables fixed.

Mathematically, the first-order Sobol' index for an input variable x_i is defined as follows:

Let y be the output of the model, and let x_i be the i^{th} input variable. Then, the first-order Sobol' index S_i is calculated as:

$$S_i = \frac{V[E(y|x_i)]}{V(y)} \quad (13)$$

Where, S_i is the first-order Sobol' index for input variable x_i , $E(y|x_i)$ is the expected value (mean) of the output, y conditioned on the value of input variable x_i . In other words, it's the average value of the output when x_i varies while all other inputs are fixed. V represents the variance of a random variable. $V(y)$ is the variance of the total output y , considering all input variables.

The first-order Sobol' index provides insight into how much the variation in an individual input variable contributes to the overall variability of the model output. A high

first-order Sobol' index suggests that the variable has a significant influence on the output, while a low index suggests that the variable's effect is relatively small.

4 Results

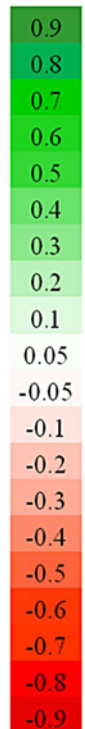
4.1 Correlation between crop yield and different predictor variables

Different hydro-meteorological (rainfall, rainy days, SPEI) and thermo-meteorological (Tmax, Tmin, GDD) parameters over monthly/ seasonal scale along with the temperature extremes (hot days, hot nights, cold days, cold nights) are linearly correlated with the district level crop yield over the time period of 1999–2019. Zone-wise correlation matrix for soybean and wheat yield is presented in Tables 5 and 6 respectively. As detailed in Table 2, in zone 1, both rainfall and Plant Available Water Capacity (PAWC) are limiting

Table 5 Correlation coefficient between Soybean yield and climate/weather extremes over different zones of Maharashtra

Zones	Districts	Hydro-meteorological														Thermo-meteorological															
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Zone-01	Jalna		x	x				x					x	x		x	x							x							x
	Aurangabad					x							x	x		x						x									x
	Beed							x					x				x							x							x
	Latur		x	x				x					x				x							x	x	x					x
	Osmanabad		x	x				x					x	x		x	x							x							x
	Pune					x			x									x													
	Solapur																x														
	Satara														x									x							
	Sangli															x					x		x	x							x
	Nashik																						x								
	Ahmednagar						x						x	x	x																x
	Nandurbar												x																		
	Dhule								x													x						x			
Zone-02	Kolhapur					x										x						x				x					
Zone-03	Jalgaon																x							x							
	Buldana							x									x							x							x
	Akola					x											x							x							x
	Washim	x						x									x							x			x				x
	Amravati				x												x							x				x			
	Yavatmal				x												x														
	Wardha																x							x							
	Nagpur																x														
	Bhandara																x														
	Gadchiroli					x											x														
	Chandrapur																														
	Nanded					x																									
	Hingoli	x	x	x				x									x														
	Parbhani	x															x														

Correlation

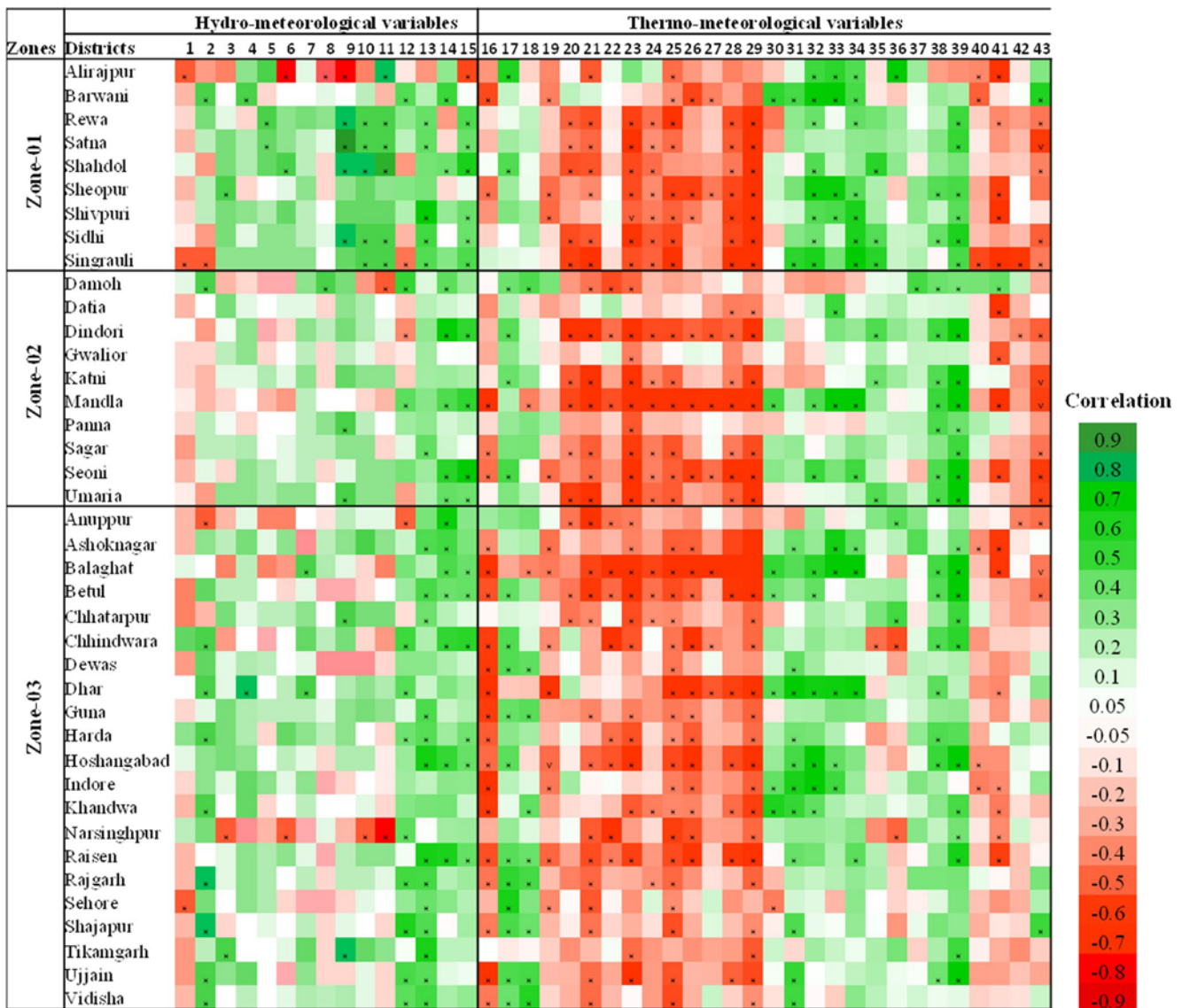


* Statistically significant at $p < 0.1$

Hydro-meteorological variables: (1: RF_Jun, 2: RF_Jul, 3: RF_Aug, 4: RF_Sep, 5: RF_Seasonal, 6: RD_Jun, 7: RD_Jul, 8: RD_Aug, 9: RD_Sep, 10: RD_Seasonal, 11: SPEI_Jun, 12: SPEI_Jul, 13: SPEI_Aug, 14: SPEI_Sep)

Thermo-meteorological variables: (15: Tmax_Jun, 16: Tmax_Jul, 17: Tmax_Aug, 18: Tmax_Sep, 19: Tmin_Jun, 20: Tmin_Jul, 21: Tmin_Aug, 22: Tmin_Sep, 23: GDD_Jun, 24: GDD_Jul, 25: GDD_Aug, 26: GDD_Sep, 27: Cold days, 28: Cold nights, 29: Hot days, 30: Hot nights)

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* Statistically significant at $p < 0.1$.

Hydro-meteorological variables: (1: RF_Nov, 2: RF_Dec, 3: RF_Jan, 4: RF_Feb, 5: RF_Mar, 6: RF_Seasonal, 7: RD_Dec, 8: RD_Jan, 9: RD_Feb, 10: RD_Seasonal, 11: SPEI_Nov, 12: SPEI_Dec, 13: SPEI_Jan, 14: SPEI_Feb, 15: SPEI_Mar)

Thermo-meteorological variables: (16: Tmax_Nov, 17: Tmax_Dec, 18: Tmax_Feb, 19: Tmax_Mar, 20: Tmin_Nov, 21: Tmin_Dec, 22: Tmin_Jan, 23: Tmin_Mar, 24: GDD_Nov, 25: GDD_Dec, 26: GDD_Jan, 27: GDD_Feb, 28: GDD_Mar, 29: GDD_Seasonal, 30: Coldday_Nov, 31: Coldday_Dec, 32: Coldday_Jan, 33: Coldday_Feb, 34: Coldday_Mar, 35: Coldnight_Nov, 36: Coldnight_Dec, 37: Coldnight_Jan, 38: Coldnight_Feb, 39: Coldnight_Mar, 40: Hotday_Feb, 41: Hotday_Mar, 42: Hotnight_Nov, 43: Hotnight_Mar)

factors. In zone 2, either rainfall or PAWC is limiting, while in zone 3, neither rainfall nor PAWC imposes limitations.

In general, across the zones, thermo-meteorological parameters were found to be negatively correlated with soybean yield, whereas, positive correlation was observed with hydro-meteorological parameters (Table 5). The area under soybean cultivation in zone 2 is very small; therefore, it is not discussed further. In zone 1, there was a significant negative correlation observed between the Tmax of July and August months and

soybean yield across the majority of districts. A similar trend was also observed for the GDD of July month. However, there was no consistent statistically significant result found for the Tmin across the months of the soybean crop season. Additionally, temperature extremes showed no significant correlation with soybean yield, except for hot nights, which exhibited a positive correlation. In contrast, across zone 3, both the Tmax and Tmin of July were found to be significantly negatively correlated with soybean yield across the majority of districts.

Similarly, the GDD of July, August, and September exhibited a significant negative correlation with soybean yield. However, temperature extremes did not show any significant correlation. It is apt to mention that soybean is cultivated in the warm and humid climate of the *kharif* season in central India. Chakraborty et al. (2017) reported a significant increase in temperature, particularly T_{min} , in these areas due to climate change. This rise in temperature has a cascading effect on the *kharif* season GDD, making it significantly higher, and consequently, negatively impacting soybean yield. The present study also revealed a significant negative correlation between temperature (particularly T_{max} , T_{min} , and GDD) during the crop establishment phase and soybean yield.

As the majority of soybean crops are rainfed, hydro-meteorological parameters generally exhibit a positive correlation with soybean yield. Specifically, rainfall in July and August, rainy days in July, and the SPEI in July and August were significantly positively correlated with soybean yield across most districts in zone 1. In zone 3, seasonal rainfall, rainfall in September, seasonal rainy days, rainy days in August and September, and SPEI in August and September showed significant positive correlations with soybean yield.

In zone 1, low rainfall during the crop establishment and development phases may negatively affect yield, especially if the soil's water-holding capacity is insufficient to meet the crop's requirements. However, in zone 3, significant yield reductions were observed only during critical growth stages, such as flowering and pod filling, when water demand is high and rainfall is scarce. Therefore, rainfall and its distribution have a positive effect on soybean yield. Additionally, SPEI, which reflects the overall moisture surplus or deficit condition of the ecosystem, also exhibits a positive correlation with soybean yield.

In India, wheat (a long-day plant) is cultivated during the winter season to cope with rising temperatures during its crucial ripening and reproductive growth phases. Table 5 represents the correlations between climatic variables and their extremes with district-level wheat yield in three zones. As nearly half of the crop's water requirements are typically met by rainfall, a significant correlation was not observed in most districts in Madhya Pradesh, indicating the complexity of the relationship between rainfall patterns and wheat yield.

The SPEI of November, January, March, Rainy days over the season and November month showed significant positive correlation with wheat yield over Zone (1) Similarly, SPEI of February and March were found to have significant positive correlation with wheat yield over zone (2) Monthly SPEI of December to March and Rainfall of December showed similar result over zone (3) In nutshell, rainfall and moisture surplus condition as depicted by SPEI has significant positive effect on

wheat yield as it is grown under limited irrigation condition in Madhya Pradesh.

Effect of thermo-meteorological parameters over the wheat yield was significant. T_{min} of November, December, March; GDD of November, December, March and the whole season were found to have significant negative correlation with wheat yield over wide spread districts of Zone (1) Similarly, T_{min} of November, December, January, March; GDD of November, December, March and the whole season showed significant negative correlation with wheat yield over majority of the districts of Zone (2) T_{min} of December, January, March; GDD of November, December, January, March and the whole season showed significant negative correlation with wheat yield over Zone (3) T_{max} did not show any consistent result across the zones. Important to note that T_{min} and its coupled parameter GDD during the latter part of the wheat season (ripening stage) plays a significant role in the wheat yield. Any increase in the thermal environment particularly in the later part of the wheat crop season has significant negative effect on the yield. It is apt to mention here that such scenarios of terminal heat stress on wheat crop are frequent over India in climate change scenarios. Hence, result of the present study could further assist in avoiding/ mitigating such stress towards sustainable wheat yield.

Overall, a region facing water scarcity such as Zone-01, wheat yield exhibits significant positive correlation with both seasonal and November month rainy days. The SPEI at a 3-month time scale, which captures the integrated response of rainfall and temperature, displays a significant positive correlation across all zones, especially during reproductive growth stage. Additionally, temperature-related parameters, including climatic extremes, show significant correlations. Specifically, an increase in minimum temperature adversely affects wheat yield in all zones. GDD, whether calculated seasonally or monthly, are inversely related to wheat yield.

Moreover, the study identifies weather extremes such as a rise in the frequency of cold days and cold nights (indicating a decrease in maximum and minimum temperatures, respectively), positively affecting yield. Conversely, an increase in the occurrence of hot days and hot nights during the ripening phase negatively impacts wheat yield, aligning with previous studies (Rao et al. 2015; Dubey et al. 2020; Farhad et al. 2023). The observed yield reduction due to an increase in temperature may be related to increased crop water demand in heat-induced limited water conditions (Zhao et al. 2017; Zaveri and Lobell 2019). Furthermore, the study reveals a distinct effect of climate and its extremes varying with crop growth stages. In wheat, crown root initiation, which usually occurs after 21 days of sowing, is one of the most critical stages for water stress. Therefore, an increase

in temperature (Tmax) or a decrease in water availability (RD or SPEI) in November shows a negative association with crop yield. Other critical growth stages such as flowering, jointing, and milking stages corresponding to January, February, and March, respectively, also exhibit sensitivity towards temperature-related parameters (Tmax, frequency of hot days, cold days, and cold nights). Wheat yields in Madhya Pradesh exhibited a weak correlation with rainfall parameters across all zones. However, the Standardized Precipitation Evapotranspiration Index (SPEI) displayed a reasonable positive relationship with wheat yields. This suggests that SPEI serves as a better indicator of water availability for crops compared to rainfall, as it captures water stress effectively (Tirivarambo et al. 2018; Ortiz-Bohea et al. 2019).

4.2 Influence of predictive variables in crop yield estimation

4.2.1 Sensitivity analysis based on RMSE

Towards developing the impact of climate parameters on crop yield, sensitivity of causative parameters was assessed by systematically removing individual predictor variables in machine learning models. Six sets of scenarios were created as mentioned in Sect. 3.6. In the case of soybean, Scenario 1 (where all parameters were employed for prediction) exhibited the lowest RMSE in both RFR and NN models (0.3 t/ha and 0.34 t/ha in Zone-01; 0.35 t/ha and 0.39 t/ha in Zone-02; and 0.27 t/ha and 0.29 t/ha in Zone-03), as given in Fig. 3. To account for zone-wise variations in absolute yield, nRMSE was calculated, reflecting the residual variance in models and relating RMSE to the observed range of variables. Models employing all parameters also

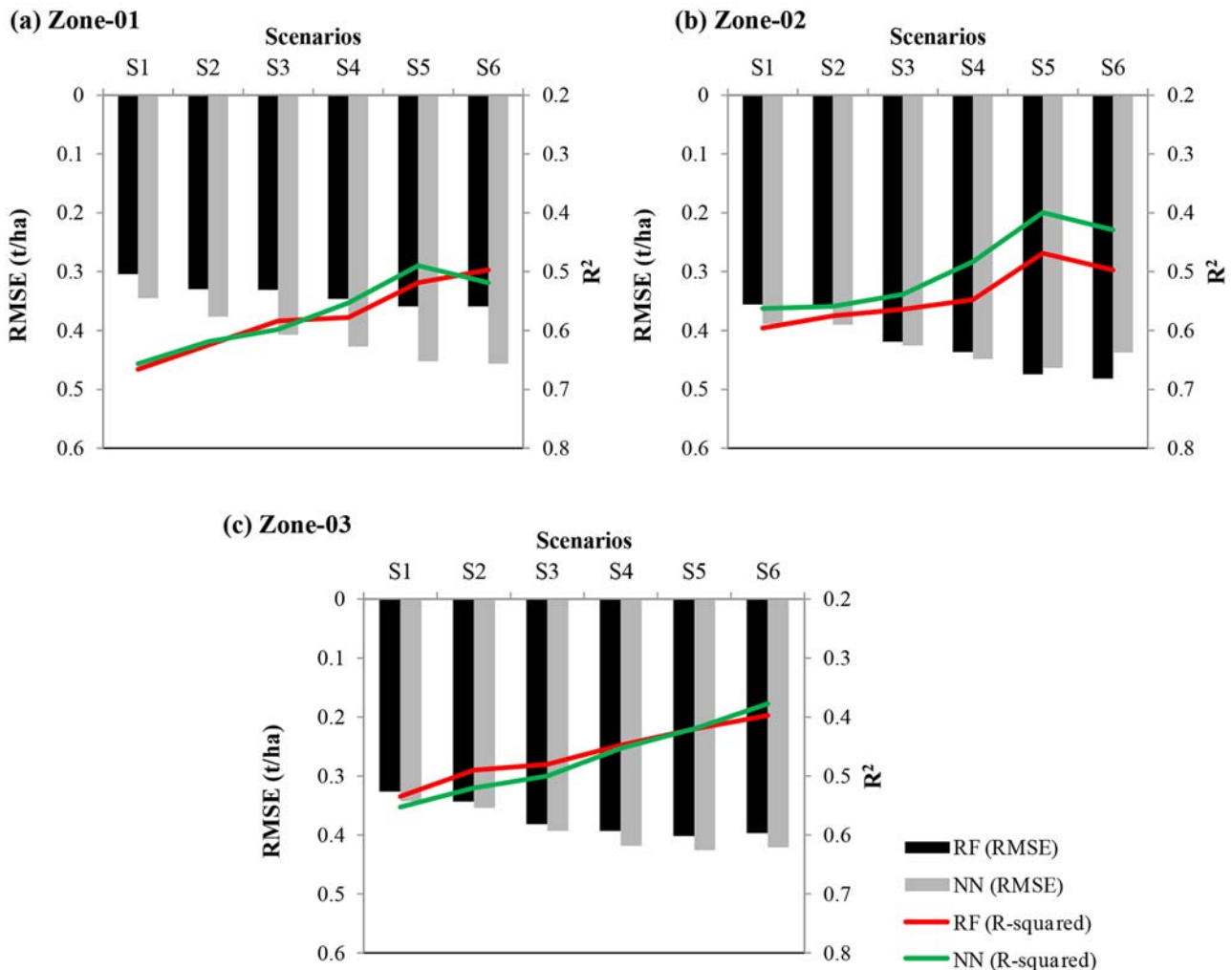


Fig. 3 Error (RMSE) estimation and explained variance (R^2) using various combinations of predictor variables for Soybean yield across different zones. *S1*: Scenario 1, *S2*: Scenario 2, *S3*: Scenario 3, *S4*: Scenario, *S5*: Scenario 5, *S6*: Scenario 6

yielded lowest normalized RMSE (nRMSE) values of 19% and 21% in Zone-01; 22.2% and 24.32% in Zone-02; and 15.2% and 16.2% in Zone-03 for RFR and NN models, respectively. Subsequent removal of individual parameters led to increases in both RMSE and nRMSE. Similarly, the R^2 for both models in Scenario 1, encompassing all climatic variables and temperature extremes, could explain the variability in soybean yield to the extent of 65–66% in Zone-01, 56–59% in Zone-02, and 53–55% in Zone-03 (Fig. 3). Interestingly, the step-wise removals of thermal parameters such as temperature extremes, T_{max} , T_{min} , and GDD as mentioned in Scenarios 2, 3, and 4 did not significantly impact the uncertainty estimates, suggesting that these parameters are intertwined in affecting the crop yield. A considerable portion of the influence of other temperature parameters on yields had already been captured by temperature extremes. For instance, an increase in the frequency of hot days inherently raises the monthly average T_{max} , T_{min} , and heat accumulation (via GDD) during grain formation stages (Vogel et al. 2019). This intricate relationship indicates that

segregating the effect of temperature and its extremes on crop yield is challenging as these are often collinear. The maximum reduction (6–7%) in the explanatory power of the model was observed after the exclusion of hydro-meteorological parameters in Zone-01, whereas a decrease of 2–4% in explanatory power occurred after removing thermo-meteorological parameters in Zone-03. Notably, using only the rainfall parameter or SPEI parameter in RFR and NN models (RMSE 0.36 t/ha and 0.45 t/ha) increased the soybean yield estimation error by 18% and 32%, respectively, compared to when all parameters were utilized.

Similarly, all predictor variables (Scenario 1) could able to estimate wheat yield and explain the variability with RMSE (and R^2) values of 0.54 t/ha (0.67) and 0.58 t/ha (0.65) in Zone-01; 0.57 t/ha (0.60) and 0.42 t/ha (0.64) in Zone-02; and 0.59 t/ha (0.59) and 0.51 t/ha (0.57) in Zone-03 using RFR and NN, respectively (Fig. 4). RFR and NN models utilizing all parameters exhibited nRMSE values of 21.7% and 23.5% (Zone-01); 25.5% and 18.8% (Zone-02); and 20% and 17% (Zone-03), respectively. The stepwise

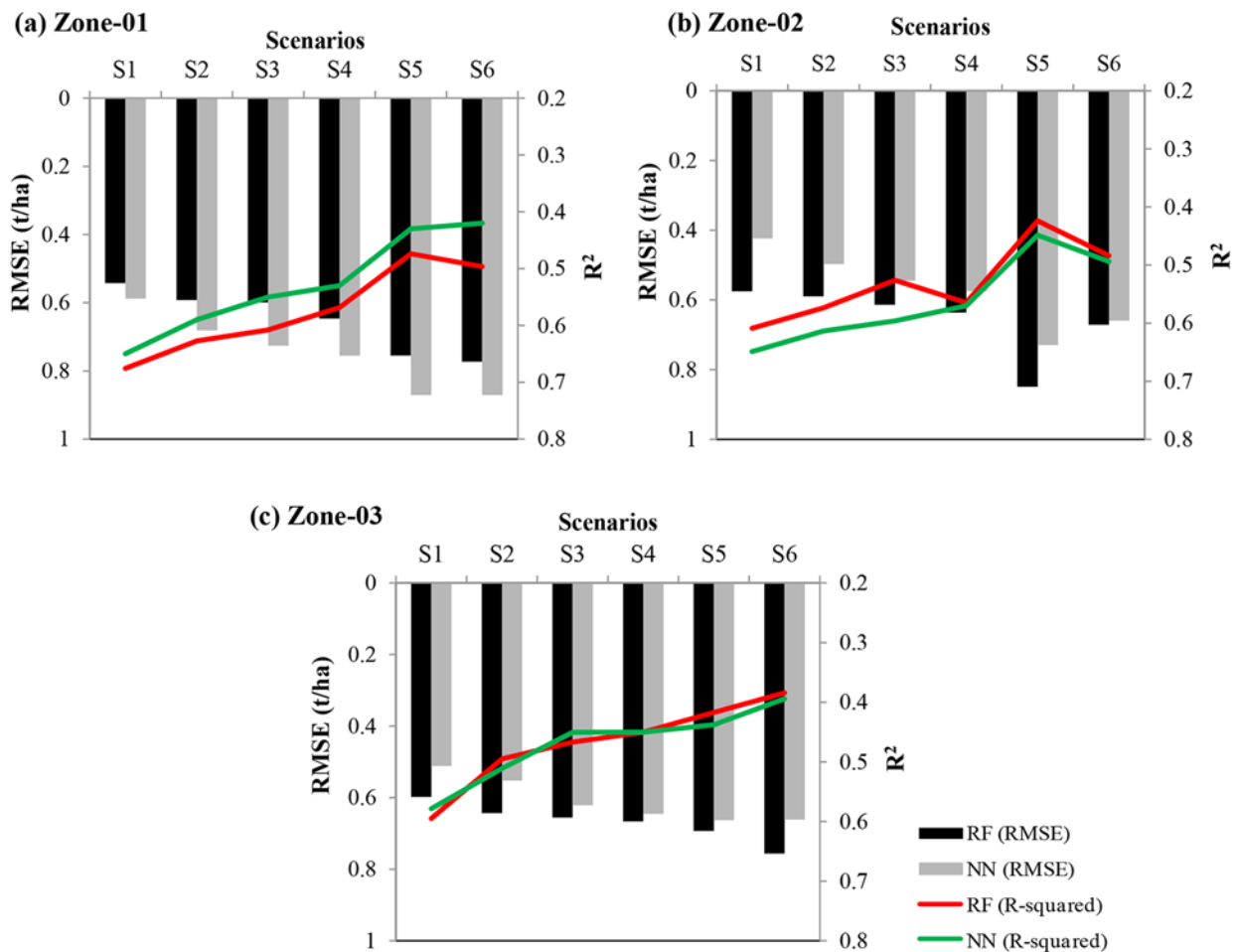
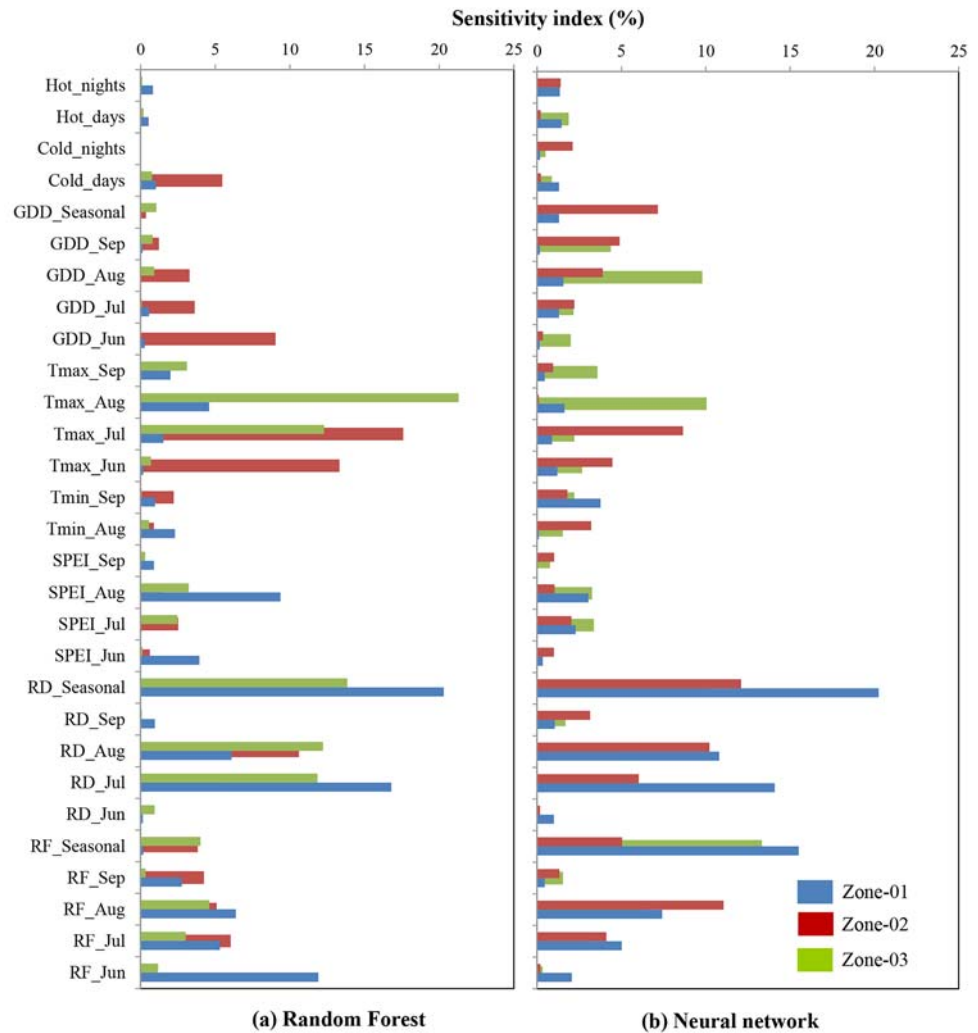


Fig. 4 Error (RMSE) estimation and explained variance (R^2) using various combinations of predictor variables for Wheat yield across different zones. **S1**: Scenario 1, **S2**: Scenario 2, **S3**: Scenario 3, **S4**: Scenario, **S5**: Scenario 5, **S6**: Scenario 6

Fig. 5 Sobols' sensitivity index of different predictor variables of Soybean yield over different zones



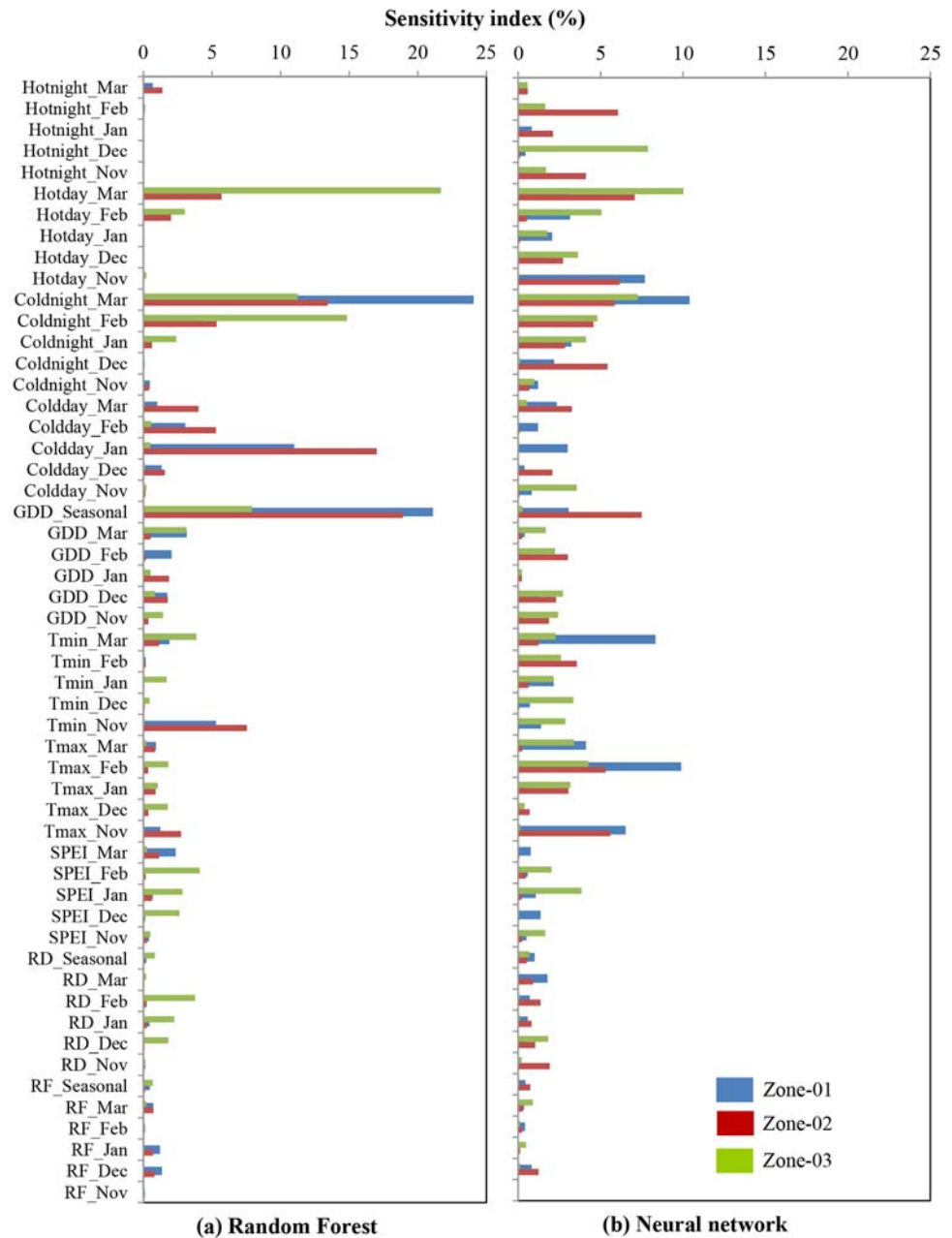
removal of predictor variables increased both RMSE and nRMSE. In Zone-01, models incorporating only hydro-meteorological parameters and excluding thermal parameters (Scenario 4) resulted in a 20% increase in RMSE and 10% reduction in model explanatory capability. Conversely, models working with either RF/RD or SPEI (Scenarios 5 or 6) showed increased RMSE (and decreased R^2) and therefore, accounted the less variability in crop yield, underscoring their significant role in wheat yield in Zone-01 with low rainfall. While increases in RMSE were observed in Zone-03, the extent was not as high as water limited Zone-01 and Zone-02, indicating that thermal parameters explained most of the variability. It is worth to note that both state-of-the-art ML models captured the similar pattern in all scenarios despite of different extent of RMSE values.

4.2.2 Sensitivity analysis of different predictor variables using Sobol' index

Sobol sensitivity analysis is commonly employed for complex system models to quantitatively decompose output variance concerning input parameters. In this study, a first-order Sobol' index was utilized to assess the individual impact of input parameters on the model while keeping all other parameters fixed. The first-order Sobol' index always yields positive values (direction-less), and the sum of all individual parameters should be equal to 1. Parameters with sensitivity indices greater than 5% are deemed significant (Zhang et al. 2015).

For soybean yield, the study revealed sensitivity to seasonal RD (>20%), followed by RD in July and August in Zone-01 (Fig. 5). This underscores water stress as a limiting factor for yield during the crop development stages (from leaf and stem development to flowering) in regions facing water scarcity. In Zone-02, characterized by high rainfall but poor soil water retention, Tmax plays a major role in

Fig. 6 Sobols' sensitivity index of different predictor variables of Wheat yield over different zones



soybean yield variability in both Random Forest (RFR) and Neural Network (NN) models. Tmax accelerates leaf senescence and restricts photosynthetic activity, consequently affecting soybean pod filling. In Zone-03, both temperature and rainfall during soybean's reproductive growth stages (flowering to pod filling) are critical factors influencing yield.

In the case of wheat crops, the study found sensitivity to spells of cold nights (i.e., frequency of Tmin lower than the 10th percentile) during the reproductive phase in both Zone-01 and Zone-02. Other parameters influencing wheat yield include thermal factors such as GDD, Tmax, cold days, and

hot days. In Zone-03, temperature extremes like spells of hot days and cold nights in March emerged as crucial factors affecting wheat yield (Fig. 6). It is a well-known fact that exposure of wheat to extreme heat events during the reproductive phase leads to sterile flowers, damaged pollen tube growth, and fertilization issues, resulting in reduced wheat yield (Shenoda et al. 2001; Ullah et al. 2022). Wheat yields in the central part of India appear unresponsive to hydro-meteorological parameters (<5% Sobol' index) across all growth stages in all zones, aligning with findings from similar studies conducted elsewhere (BIRTHAL et al. 2014; Petersen 2019; Schierhorn et al. 2021). Notably, an agreement exists

between RFR and NN models in terms of the relative importance of climatic factors affecting soybean and wheat crop yield, despite differences in Sobol' index magnitude.

5 Discussion

While previous studies have examined the influence of in-season climatic variables on crop yield (Harkness et al. 2020), there has been relatively little research linking these variables to specific crop development phases and their contribution to understanding the relationship between weather and crop yield using machine learning (ML) techniques (Hofman et al. 2020; Beillouin et al. 2020; Schierhorn et al. 2021). Assuming zone-wise consistent soil conditions, we focus on climate variability as the primary determinant of soybean and wheat crop yield in each zone. Our results indicate that climatic variables can explain a significant proportion of yield variability, ranging from 66 to 42% in zone-01 and 59–37% in zone-03, regardless of crop type. Additionally, weather extremes play a crucial role during specific crop growth stages, although their impact is less pronounced compared to climatic variables, as observed by Schierhorn et al. (2021). These climate-driven impacts vary not only with crop types such as soybean or wheat but also with the prevailing climate and soil characteristics of the region (Kukul and Irmak 2018). In our study, we found that the effects of heat and water stress vary significantly among different crop types and regions. Vicente-Serrano et al. (2013) noted reduced vegetation sensitivity to water stress in regions with climatological water excess, consistent with our findings. For instance, hydro-meteorological parameters were not found to be sensitive in Zone-03, which does not lack rainfall. Moreover, wheat, even as an irrigated crop, did not exhibit sensitivity to hydro-meteorological parameters leading to yield decline.

Murari et al. (2018) emphasized the significance of temperature extremes on crop yield, particularly in the southern part of India. Hofman et al. (2020) also found a positive response of soybean to increases in cool minimum temperatures using random forest (RF) models. In our study, we did not find a significant association between cold nights (minimum temperature extremes) and soybean yield in Indian conditions. However, a decrease in soybean yield was observed with high maximum temperatures (Tmax) during the pod filling stage, consistent with findings for soybean yield sensitivity to August Tmax in Zone-03. Sharma et al. (2022) reported a 25.6% decline in soybean yield with a 1 °C rise in Tmax. In wheat crops, extreme heat during the grain-filling phase, particularly in Zone-03, reduced yield, as heat stress accelerates grain filling, reducing both duration and ultimately grain yield (Barlow et al. 2015). Hot

nights during February negatively affected wheat yields during the anthesis phase, reducing photosynthesis and increasing respiration, leading to yield loss (Sadok and Jagadish 2020). Rao et al. (2015) found a significant negative relation between wheat yield and increased Tmax and Tmin in January and February in India, with Tmin exhibiting a more pronounced impact. Various studies have reported different degrees of yield decline under temperature effects, depending on the location of the study. For instance, Rao et al. (2015) documented a 7% yield loss with a 1 °C rise in Tmin in India, while You et al. (2009) reported a range of 3–10% in China. Additionally, Lobell et al. (2005) observed a 10% decline in Mexico, among others. It was observed that Tmin exceeding 12 °C and Tmax exceeding 34 °C were identified as critical during the post-anthesis period (Rao et al. 2015). Our study indicates that in zones with limited moisture and soil water-holding capacity, Tmin extremes and seasonal GDD are determining factors for wheat yield. However, in Zone-03 (without limitations), extreme Tmax in March, representing the grain filling and ripening period, emerges as a sensitive parameter for wheat yield. Additionally, cold nights (Tmin extremes) during the reproductive phase of wheat were identified as one of the most sensitive parameters, along with seasonal GDD, using global sensitivity analysis.

The outcome of present study may align to several adaptation strategies useful to mitigate the impact of climate and weather extremes on wheat and soybean crop yield, including altering cropping patterns, practicing minimum tillage (Biswas et al. 2008), adjusting sowing dates, cultivating heat-tolerant varieties, and implementing additional fertilizer and irrigation (Dubey et al. 2020).

6 Limitations and future scope

Our study emphasizes that utilizing intra-seasonal climatic variables for distinct crop developmental stages enhances the understanding of the relationship between weather and yield during these critical periods, aligning with previous research findings (Schierhorn et al. 2021). A deeper comprehension of intra-seasonal climate effects on yields can provide valuable insights for decision-making processes among farmers and policymakers. However, it is noteworthy that the current study has not utilized the explicit consideration of phenology. Instead, it employs monthly weather and climatic parameters as representatives of the dominant growth stage occurring in that respective month. As a future scope of work, we propose for a more distinct approach by integrating satellite-derived crop growth stages, encompassing key phases like the start of the season, peak growth stage, reproductive stage, and senescence, which will enhance the

precision of the analysis. Moreover, the current study has utilized district-level yield data, which sometimes nullifies the impact of spatial variability of soil and rainfall on crop yield. Therefore, the utilization of sub-district level yield data holds promises for providing more granular insights to capture the localized effects of weather and climate dynamics more effectively. To comprehensively enrich the model, it is imperative to extend its scope by incorporating additional meteorological parameters, specifically addressing extreme events such as rainfall extremes, hailstorms, floods, among others. This inclusion will undoubtedly contribute to a more holistic and robust analysis, equipping farmers and policymakers with more informed decision-making tools to face the climate vagaries.

7 Conclusions

Climate variability significantly influences crop yield during both the monsoon and winter seasons, as demonstrated by studies on soybean and wheat crops. The impact of climatic variables and extremes varies in intensity and extent based on the biophysical characteristics of the region. To explore this phenomenon, the present study was conducted across homogenous zones categorized by rainfall patterns and soil parameters. Monthly and seasonal climatic variables and extremes were evaluated to assess their impact on the critical growth stages of the crops. Machine Learning (ML) techniques such as, RFR and NN were employed to understand the complex relationship between climate/weather extremes vis-a vis crop yield. RF successfully predicted soybean and wheat yields with RMSE values of 0.28–0.38 t/ha and 0.45–0.6 t/ha, respectively. Similarly, NN predicted yields with RMSE values of 0.27–0.39 t/ha and 0.4–0.58 t/ha for soybean and wheat, respectively. These findings highlight the accuracy of the models in capturing the intricate relationship between climate variables and crop yield.

The study revealed that rainfall and its derivatives significantly influence soybean crop yield during the monsoon season. In contrast, temperature and its extremes dictate wheat crop yield in the winter season. However, these effects exhibit variations across different zones within a season. In regions with limited water supply, parameters such as rainfall and rainy-days in July–August play a pivotal role in determining soybean crop yield, corresponding to the flowering and pod-filling stages. Conversely, in well-irrigated regions, temperature-related parameters exert control over crop yield. Cold nights and hot days during reproductive growth stages demonstrated sensitivity concerning wheat yield, with positive and negative relationships, respectively. Considering the anticipated increase in climatic extremes in the future, gaining a deeper understanding of the intricate

relationship between climate and yield variability is imperative. This knowledge will pave the way for enhanced adaptation strategies, mitigating potential yield losses and ensuring sustainable agricultural practices.

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References

- Amit Y, Geman D (1997) Shape quantization and recognition with randomized trees. *Neural Comput* 10(7):1545–1588
- Barlow KM, Christy BP, O’Leary GJ, Riffkin PA, Nuttall JG (2015) Simulating the impact of extreme heat and frost events on wheat crop production: a review. *Field Crops Res* 171:109–119
- Beillouin D, Schauburger B, Bastos A, Ciais P, Makowski D (2020) Impact of extreme weather conditions on European crop production in 2018. *Philos Trans R Soc B: Biol Sci* 375:20190510
- Birthal PS, Khan T, Negi DS, Agarwal S (2014) Impact of climate change on yields of major food crops in India: implications for food security. *Agricultural Econ Res Rev* 27(2):145–155
- Biswas DK, Xu H, Li YG, Liu MZ, Chen YH, Sun JZ, Jiang GM (2008) Assessing the genetic relatedness of higher ozone sensitivity of modern wheat to its wild and cultivated progenitors/relatives. *J Exp Bot* 59(4):951–963
- Braun HJ, Rajaram S, Ginkel M (1997) CIMMYT’s approach to breeding for wide adaptation. In: *Adaptation in plant breeding: selected papers from the XIV EUCARPIA Congress on Adaptation in Plant breeding held at Jyväskylä, Sweden from July 31 to August 4, 1995* (pp. 197–205). Springer Netherlands
- Breiman L (2001) Random forests. *Mach Learn* 45:5–32
- Chakraborty A, Seshasai MV, Rao SK, Dadhwal VK (2017) Geo-spatial analysis of temporal trends of temperature and its extremes over India using daily gridded (1° × 1°) temperature data of 1969–2005. *Theoretical Appl Climatol* 130:133–149
- Chakraborty D, Sehgal VK, Dhakar R, Ray M, Das DK (2019) Spatio-temporal trend in heat waves over India and its impact assessment on wheat crop. *Theoret Appl Climatol* 138:1925–1937

- Crane-Droesch A (2018) Machine learning methods for crop yield prediction and climate change impact assessment in agriculture. *Environ Res Lett* 13(11):114003
- de Wit CT (1965) Photosynthesis of leaf canopies. *Pudoc*; 1965
- Dubey R, Pathak H, Chakrabarti B, Singh S, Gupta DK, Harit RC (2020) Impact of terminal heat stress on wheat yield in India and options for adaptation. *Agric Syst* 181:102826
- Farhad M, Kumar U, Tomar V, Hossain A (2023) Heat stress in wheat: a global challenge to feed billions in the current era of the changing climate. *Front Sustainable Food Syst* 7:1203721
- Glorot X, Bengio Y (2010) Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics* 31 (pp. 249–256). *JMLR Workshop and Conference Proceedings*
- Gupta S, Bhandari L, Jakhu R, Sharma M (2022) Climate change, weather anomalies, and agriculture: impact on output of major crops in India (CSEP Working Paper 46). New Delhi: Centre for Social and Economic Progress
- Harkness C, Semenov MA, Areal F, Senapati N, Trnka M, Balek J, Bishop J (2020) Adverse weather conditions for UK wheat production under climate change. *Agric for Meteorol* 282:107862
- Harvey C (2018) Scientists can now blame individual natural disasters on climate change extreme event attribution is one of the most rapidly expanding areas of climate science. *Scientific American*
- Hofman A, Kemanian A, Forest C (2020) The response of maize, sorghum, and soybean yield to growing phase climate revealed with machine learning. *Environ Res Lett* 15:094013
- IPCC, Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, Caud N, Chen Y, Goldfarb L, Gomis MI, Huang M (2021) Climate change 2021: the physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change. 2021;2
- Kang Y, Khan S, Ma X (2009) Climate change impacts on crop yield, crop water productivity and food security—a review. *Prog Nat Sci* 10(1912):1665–1674
- Konduri VS, Vandal TJ, Ganguly S, Ganguly AR (2020) Data science for weather impacts on crop yield. *Front Sustainable Food Syst* 19:452
- Kukul MS, Irmak S (2018) Climate-driven crop yield and yield variability and climate change impacts on the US Great Plains agricultural production. *Sci Rep* 22(1):1–8
- Liaw A, Wiener M (2002) Classification and regression by random Forest. *R news*. 3;2(3):18–22
- Lobell DB, Asseng S (2017) Comparing estimates of climate change impacts from process-based and statistical crop models. *Environ Res Lett* 4(1):015001
- Lobell DB, Ortiz-Monasterio JI, Asner GP, Matson PA, Naylor RL, Falcon WP (2005) Analysis of wheat yield and climatic trends in Mexico. *Field Crops Res* 94(2–3):250–256
- Lobell DB, Sibley A, Ivan Ortiz-Monasterio J (2012) Extreme heat effects on wheat senescence in India. *Nat Clim Change* 2(3):186–189
- Lu J, Carbone GJ, Gao P (2017) Detrending crop yield data for spatial visualization of drought impacts in the United States, 1895–2014. *Agric for Meteorol* 1:237:196–208
- MacCarthy DS, Traore PS, Freduah BS, Adiku SG, Dodor DE, Kumhar SK (2022) Productivity of soybean under projected climate change in a Semi-arid region of West Africa: sensitivity of current production system. *Agronomy* 24(11):2614
- Madhukar A, Dashora K, Kumar V (2021) Climate trends in temperature and water variables during wheat growing season and impact on yield. *Environ Processes* 8:1047–1072
- Matiu, Matiu M, Ankerst DP, Menzel A et al (2017) 2017. Interactions between temperature and drought in global and regional crop yield variability during 1961–2014. *PloS one*. 26;12(5):e0178339
- Mohanty M, Sinha NK, McDermid SP, Chaudhary RS, Reddy KS, Hati KM, Somasundaram J, Lenka S, Patidar RK, Prabhakar M, Cherukumalli SR (2017) Climate change impacts vis-a-vis productivity of soybean in vertisol of Madhya Pradesh. *J Agrometeorology* 1(1):10–16
- Mohapatra S, Mohapatra S, Han H, Ariza-Montes A, López-Martín MD (2022) Climate change and vulnerability of agribusiness: assessment of climate change impact on agricultural productivity. *Front Psychol* 26:13:955622
- Moore FC, Baldos UL, Hertel T (2017) Economic impacts of climate change on agriculture: a comparison of process-based and statistical yield models. *Environ Res Lett* 12(6):065008
- Murari KK, Mahato S, Jayaraman T, Swaminathan M (2018) Extreme temperatures and crop yields in Karnataka, India. *Rev Agrarian Studies*. 2018;8(2)
- Novikova LY, Bulakh PP, Nekrasov AY, Seferova IV (2020) Soybean response to weather and climate conditions in the Krasnodar and Primorye territories of Russia over the past decades. *Agronomy* 10(9):1278
- Ortiz-Bobea A, Wang H, Carrillo CM, Ault TR (2019) Unpacking the climatic drivers of US agricultural yields. *Environ Res Lett* 14:064003
- Paszke A, Gross S, Massa F, Lerer A, Bradbury J, Chanan G, Killeen T, Lin Z, Gimelshein N, Antiga L, Desmaison A (2019) Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems* 32
- Paymard P, Bannayan M, Haghighi RS (2018) Analysis of the climate change effect on wheat production systems and investigate the potential of management strategies. *Nat Hazards* 91:1237–1255
- Peichl M, Thober S, Meyer V, Samaniego L (2018) The effect of soil moisture anomalies on maize yield in Germany. *Nat Hazards Earth Syst Sci* 18:889–906
- Petersen LK (2019) Impact of climate change on twenty-first century crop yields in the U.S. *Climate* 7:40
- Porter JR, Gawith M (1999) Temperatures and the growth and development of wheat: a review. *Eur J Agron* 10(1):23–36
- Powell JP, Reinhard S (2016) Measuring the effects of extreme weather events on yields. *Weather Clim Extremes* 1:12:69–79
- Praveen D, Palanivelu K (2017) Spatiotemporal analysis of projected impacts of climate change on the major C3 and C4 crop yield under representative concentration pathway 4.5: insight from the coasts of Tamil Nadu, South India. *PLoS ONE* 12(7):e0180706
- Rao BB, Chowdary PS, Sandeep VM, Pramod VP, Rao VU (2015) Spatial analysis of the sensitivity of wheat yields to temperature in India. *Agric for Meteorol* 15:200:192–202
- Robert M, Thomas A, Sekhar M, Badiger S, Ruiz L, Raynal H, Bergez JE (2017) Adaptive and dynamic decision-making processes: a conceptual model of production systems on Indian farms. *Agricultural Syst* 1:157:279–91
- Sadok W, Jagadish SK (2020) The hidden costs of nighttime warming on yields. *Trends Plant Sci* 25(7):644–651
- Schierhorn F, Hofmann M, Gagalyuk T, Ostapchuk I, Müller D (2021) Machine learning reveals complex effects of climatic means and weather extremes on wheat yields during different plant developmental stages. *Clim Change* 169(3–4):39
- Sharma RK, Kumar S, Vatta K, Dhillon J, Reddy KN (2022) Impact of recent climate change on cotton and soybean yields in the south-eastern United States. *J Agric Food Res* 9:100348
- Shenoda JE, Sanad MN, Rizkalla AA, El-Assal S, Ali RT, Hussein MH (2021) Effect of long-term heat stress on grain yield, pollen grain viability and germinability in bread wheat (*Triticum aestivum* L.) under field conditions. *Heliyon*, 7(6).
- Sobol WT (1993) Analysis of variance for ‘component stripping’ decomposition of multiexponential curves. *Comput methods programs in biomed*, 39(3–4), 243–257

- Sobol IM (2001) Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Math Comput Simul* 55(1–3):271–280
- Strobl C, Boulesteix AL, Kneib T, Augustin T, Zeileis A (2008) Conditional variable importance for random forests. *BMC Bioinformatics* 9:1–1
- Subramaniam AR (1983) Agro-ecological zones of India. *Archives for meteorology, geophysics, and bioclimatology. Ser B* 32(2):329–333
- Tigchelaar M, Battisti DS, Naylor RL, Ray DK (2018) Future warming increases probability of globally synchronized maize production shocks. *Proc Nat Acad Sci* 26;115(26):6644–9
- Tirivarombo S, Osupile D, Eliasson P (2018) Drought monitoring and analysis: standardised precipitation evapotranspiration index (SPEI) and standardised precipitation index (SPI). *Phys Chem Earth Parts A/B/C* 106(1):1–0
- Ullah A, Nadeem F, Nawaz A, Siddique KH, Farooq M (2022) Heat stress effects on the reproductive physiology and yield of wheat. *J Agron Crop Sci* 208(1):1–7
- Van Oort PA, Zhang T, De Vries ME, Heinemann AB, Meinke H (2011) Correlation between temperature and phenology prediction error in rice (*Oryza sativa* L). *Agric for Meteorol* 15(12):1545–1555
- Vicente-Serrano SM, Gouveia C, Camarero JJ, Beguería S, Trigo R, López-Moreno JJ, Azorín-Molina C, Pasho E, Lorenzo-Lacruz J, Revuelto J, Morán-Tejeda E (2013) Response of vegetation to drought time-scales across global land biomes. *Proc Nat Acad Sci* 110(1):52–7
- Vogel E, Donat MG, Alexander LV, Meinshausen M, Ray DK, Karoly D, Meinshausen N, Frieler K (2019) The effects of climate extremes on global agricultural yields. *Environ Res Lett* 14:054010
- Webber H, Ewert F, Olesen JE, Müller C, Fronzek S, Ruane AC, Bourgault M, Martre P, Ababaei B, Bindi M, Ferrise R, Finger R, Fodor N, Gabaldón-Leal C, Gaiser T, Jabloun M, Kersebaum K-C, Lizaso JJ, Lorite IJ, Manceau L, Moriondo M, Nendel C, Rodríguez A, Ruiz-Ramos M, Semenov MA, Siebert S, Stella T, Stratonovitch P, Trombi G, Wallach D (2018) Diverging importance of drought stress for maize and winter wheat in Europe. *Nat Commun* 9:4249
- Yu Y, Huang Y, Zhang W (2013) Projected changes in soil organic carbon stocks of China's croplands under different agricultural managements, 2011–2050. *Agric Ecosyst Environ* 15(178):109–120
- Zampieri M, Ceglar A, Dentener F, Toreti A (2017) Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. *Environ Res Lett* 12:064008
- Zaveri E, Lobell D (2019) The role of irrigation in changing wheat yields and heat sensitivity in India. *Nat Commun* 10(1):9
- Zhang XY, Trame MN, Lesko LJ, Schmidt S (2015) Sobol sensitivity analysis: a tool to guide the development and evaluation of systems pharmacology models. *CPT: Pharmacometrics Syst Pharmacol* 4(2):69–79
- Zhao C, Liu B, Piao S, Wang X, Lobell DB, Huang Y, Huang M, Yao Y, Bassu S, Ciaia P, Durand JL, Elliott J, Ewert F, Janssens IA, Li T, Lin E, Liu Q, Martre P, Müller C, Peng S, Peñuelas J, Ruane AC, Wallach D, Wang T, Wu D, Liu Z, Zhu Y, Zhu Z, Asseng S (2017) Temperature increase reduces global yields of major crops in four independent estimates. *Proc Nat Acad Sci* 114(35):9326–9331

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