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Quantitative Investigation of Drought Impacts on Agriculture and Relation with Socioeconomic Security of Farmers

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Dedicated with gratitude

to all the farmers who keep us alive

and in solidarity

with all the girls struggling for basic right of education

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Abstract

Recurring droughts and its dire consequences on the agriculture sector is challenging the socioeconomic security of farmers in agrarian countries like India. The complex, multidimensional, spatially extensive, and water extreme phenomenon of drought is one of the costliest natural disasters which is anticipated to be frequent and more severe in the warming world. The profound impacts of droughts include agriculture failures, groundwater depletion, water scarcity and economic losses, which is specifically threatening the agriculture, and allied businesses. Under the deteriorating socioeconomic status of farmers subject to frequent droughts, especially in central parts of India, drought assessment holds a paramount importance. Multiple climatic and hydrologic factors are responsible for droughts and vegetation conditions, where meticulous attribution of these primary drivers and understanding of their integrated effect is crucial for holistic drought quantification and disaster contingency planning. Despite well-established system of drought management in India, which is typically univariate and depends on analysis of multiple variables, the process has its own limitations, where this integrated effect is typically overlooked, frequently leading to ambiguous drought categorization.

In the present study, dynamics and variability in vegetation and its interlinkage with regional drought characteristics were analyzed in the form of greening and browning trends along with discerning it's governing factors in the central state of Maharashtra in India. Furthermore, using the confounding primary drought drivers, a novel multivariate Joint Drought Index (JDI) was proposed for seasonal agriculture drought classification which shall provide a unique perspective for drought monitoring and mitigation by increasing the accuracy of drought severity analysis in India and beyond. In addition, by utilizing economic data and taking farmers suicides as an index showing the socioeconomic status of farmers, the possible relation between vegetation variability, dynamics in hydroclimatic variables, droughts, and role of JDI in the farmer's socioeconomic status is also discussed. The outcomes of this study should provide crucial insights for policymakers in India and around the world and should be valuable for revisiting the drought management plans and creating efficient mitigation system in areas facing harsh conditions because of droughts.

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List of acronyms and abbreviations

LAI: Leaf Area Index

NDVI: Normalized Difference Vegetation Index

GB: Greening and Browning

LA: Leaf Area

NCLA: Net Change in Leaf Area

MODIS: Moderate Resolution Imaging Spectroradiometer

IMD: India Meteorological Department

IGBP: International Geosphere Biosphere Program

MK: Mann-Kendall

GWS: Groundwater Storage

GW: Groundwater

GLDAS: Global Land Data Assimilation System

GRACE: Gravity Recovery and Climate Experiment

CLSM: Catchment Land Surface Model

VIC: Variable Infiltration Capacity

CGWB: Central Groundwater Board

GA: Geographical Area

CA: Cropped Area

CP: Crop Production

GMIA: Global Map of Irrigated Areas

SPEI: Standardized Precipitation Evapotranspiration Index

SSI: Standardized Soil Moisture Index

SGI: Standardized Groundwater Index

SRI: Standardized Surface Runoff Index

SPI: Standardized Precipitation Index

SM: Soil Moisture

JDI: Joint Drought Index

AIC: Akaike Information Criterion

BIC: Bayesian Information Criterion

PCA: Principal Component Analysis

PC: Principal Components

GDP: Gross Domestic Product

MSP: Minimum Support Price

APMC: Agriculture Produce Market Committee

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CHAPTER 1
Introduction

1. Introduction

1.1. Background

The multifaceted phenomenon of drought is one of the most expensive natural disaster that has an impact on many economic sectors at once (WMO, 2016). Drought is normally defined as drier than normal conditions and generally explained in terms of deficiency of precipitation over an extended period of time (season or more) (Mishra & Singh, 2010). Although droughts are a normal part of the climate and can occur in any climate regime around the world, rising temperatures are expected to increase the likelihood of droughts, especially in the arid and semiarid regions of Asia according to recent reports by Intergovernmental Panel on Climate Change (IPCC AR6, Pörtner et al., 2022). Drought has remarkable effects on various agriculture, environmental and socioeconomic spheres which pose challenges of water availability, livestock issues, industrial water supply, livelihood security, health issues, political instability and intensifying agricultural crisis. Not only these, but drought also affects personal security of the community in drought prone areas, especially related to agriculture and allied activities, who depend on the supply of water for their daily activities. India, which holds an important place in the global food security has been experiencing droughts once in every three years since last few decades and is facing most devastating outcomes of the droughts (Mishra & Singh, 2010; Mohanty & Wadhawan, 2021).

Nearly 1.3 billion people live in India, 80% of whom reside in areas that are particularly vulnerable to natural catastrophes. Since 2005, both the frequency and the severity of extreme climatic events have grown by up to 200% in these areas (Mohanty & Wadhawan, 2021). India is one of the most drought prone countries in the world which has been experiencing consecutive droughts with increased recurrence in recent times, where central regions are particularly highly susceptible to increased drought events (Mallya et al., 2016; World Bank, 2003). Rainfed agriculture makes drought impacts even more severe owing to high sensitivity to meteorological anomalies, especially considering the limited irrigation infrastructure in India (Government of India, 2016). Drought impacts usually depend on the socioeconomic context of the region and vulnerability of the exposed entities. India has more than 70% of its population dependent on agriculture and allied businesses (https://www.fao.org/india/fao-in-india/india-at-a-glance/en/), where agriculture is notoriously unstable industry subject to climate change and extreme weather conditions. The agriculture and consequently socioeconomic security of Indian farmers is in threat subject to synergistic impacts of multiple factors such as climate change, persistent droughts, erratic rains, groundwater over abstraction as well as market uncertainties, inadequate irrigation infrastructure, and high agricultural input costs (machinery, electricity, seeds, fertilizers, etc.) which contribute to instability and remain prime concerns of the farmers as well as policymakers in the region. Unfortunately, despite being an agrarian country, India has been facing catastrophe of farmer suicides since last few decades, mainly subject to droughts and agriculture failures which hamper their financial status and inevitably their socioeconomic security (Nagaraj et al., 2014). More than 350 thousand farmers have committed suicide in the past two decades in India surrendering to stress related to persistent agricultural uncertainties (NCRB, 2021). Considering the scenarios of hydro-climatological uncertainties and key role of agriculture in the life of various classes of society, drought impact assessment and mitigation hold a paramount importance for India, especially with respect to socioeconomic security of farmers and other stakeholders of agriculture and allied businesses, in order to alleviate human suffering.

Drought is generally categorized in different types (meteorological, agriculture, hydrological, groundwater, socioeconomic drought, etc.) where the selection of indicators accurately reflecting and representing the situation of drought impacts being experienced in the region is extremely crucial (WMO, 2016). India has well established drought management system which works based on drought manual developed by the Ministry of Agriculture, Cooperation and Farmers Welfare (Government of India, 2016). Multiple drought indicators are prescribed for drought analysis by the manual related to rainfall, agriculture, soil moisture, hydrology, and remote sensing, despite of which drought is often observed based mainly on the meteorological indicator. Additionally, based on the severity of the drought in each of these indicators, droughts are classified as severe, moderate, or normal to set the triggers and the drought declaration is made to initiate the government response in terms of financial waivers, alternate employment generation, cattle camps, fodder supply, etc. A range of interlinked hydrometeorological processes are responsible for meteorological anomalies and aggravating surface or groundwater unavailability, which makes the regional conditions significantly drier than the normal, potentially to the damaging extent. Meteorological droughts can propagate to other kinds of droughts such as agriculture, hydrological and groundwater, which may take time to reflect and can have major impact on the regional drought characteristics when persisted for longer duration. Despite prime influence of groundwater storage variability on drought propagation, exacerbated by groundwater depletion in India (Asoka et al., 2017; Asoka & Mishra, 2020; Mishra & Asoka, 2011; Rodell et al., 2009), its consideration in the drought analysis is largely ignored. Considering the stringent conditions for obtaining financial help from the government and complexities involved in the assessment using multiple univariate indicators, the process of drought management, specifically drought declaration is very tricky, where inconsistent data availability and complex interaction between hydroclimatic variables make it more challenging. Often discrepancies have been observed in the drought declaration and actual drought conditions which results in denial of the crucial financial aid and assistance to the marginalized communities seeking governmental help in case of the disaster (Aadhar & Mishra, 2022; Bhardwaj & Mishra, 2021). Therefore, an efficient drought detection mechanism which can effectively integrate the multiple aspects of droughts responsible for regional drought conditions is extremely important for drought adaptation and mitigation. This makes understanding of primary drivers of regional droughts and consequently vegetation variability crucial for improving the accuracy of drought detection and reconfiguring drought mitigation measures.

An important indicator signaling the interlinkage between droughts, regional climatic conditions, and human interference is variability and trends in vegetation. Notwithstanding high repercussions of droughts on agriculture, croplands have been found to be primarily responsible for most of the increasing trend in vegetation in the form of greening all over the world (Chen et al., 2019; Emmett et al., 2019; Mishra & Mainali, 2017; Zhu et al., 2016), mainly subject to anthropogenic activities (land use, irrigation, improved agricultural practices etc.). Meticulous attribution of vegetation variability, its primary drivers, and droughts, especially in drought-prone areas, holds a crucial importance in disaster contingency planning and its mitigation measures along with socioeconomic security of the region. However, knowledge of primary drivers of vegetation variability and their interlinkage with regional drought characteristics remains largely unexplored which can potentially improve detection of integrated effect of various drought drivers. In addition, socioeconomic factors that are unrelated to the physical nature of droughts make drought assessment more complicated by influencing the impacts related to drought exposure and vulnerability. Thus, it is also crucial to comprehend how droughts affect different classes of society, particularly farmers, in order to take action to lessen the effects of future droughts.

1.1.1. Framework of drought response and mitigation in India

The drought management in India is mainly divided in three phases as guided by manual of drought management in India (Government of India, 2016); 1. Drought monitoring, 2. Drought declaration, and 3. Drought response and relief (**Figure 1.1**). The drought response and drought relief measures are initiated after the declaration of drought. The drought response is implemented by inter-coordination of various departments such as agriculture, water management, finance, health etc. The primary aim of the response and relief measures provided by the government is to minimize the immediate hardships caused to farmers and other communities. Most importantly, formal declaration of drought is required to initiate measures related to drought relief such as remission of land revenue and other taxes and dues, deferment and restricting crop loans, agriculture input subsidies, and financial assistance from the National Disaster Response Fund.

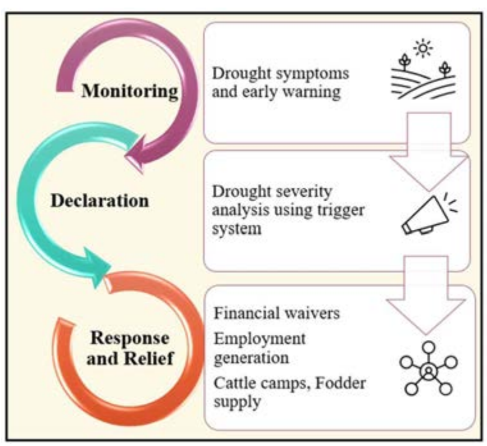

Figure 1.1: Schematic of drought monitoring and mitigation measures in India according to manual of drought, 2016, Government of India.

Some of the important relief measures undertaken by the state government at different administrative levels (village, district, division, and state) are as follows:

Government relief measures: Submission of the memorandum of assistance to the central government by state governments, increased frequency of crisis management group meetings, setting up control room for drought management, vital decisions like deferment/rescheduling/fresh loans, compensation for losses, financial assistance made available through bank transfer, assistance for purchasing of inputs required for farming, checking up on inflation, implementation of relief assistance and mitigation programs, information management and media coordination, evaluation and documentation of impact assessment and responses taken by the government,

Agriculture: movement of water and fodder through various transportation such as railways, ensuring availability of seeds, fodders and nutrients to the farmers, subsidies on seeds for second/third sowings, provision of custom hiring centers for farm machineries, activating the farmer call centers and farmer portals, providing extension services from local/regional agricultural universities to advice farmers on crop varieties, selection of seeds, soil and water conservation measures based on the drought situations, guidance on contingency and agronomic practices, energy support for uninterrupted power supply, activating alternate employment generation schemes for agricultural communities, cattle camps and fodder supply,

Water resource management: water budgeting and prioritization of the water use among sectors, regulating water use at household and village level, renting private water resources, such as well for public use, water supply through tankers,

Health, food, waivers and concession: taking help from various self-help groups called 'Anganwadi' to monitor health and nutritional status of population, specifically children, financing opening of additional Anganwadis when deemed necessary, preventive measures for loss of human/cattle life on account of potential disaster, implementing 'Mid-day Meal Schemes' for children even in vacation for drought affected areas, starting community kitchens to help old, disabled, and distressed population, provision of gratuitous assistance in cash or food, waivers and concessions, school fee waivers, maintaining health and hygiene by preventing spread of diseases (contamination of water at source, wrong storage practices may lead to water borne diseases).

1.2. Goals and Objectives

Amidst the significance of the knowledge of primary drought drivers, inherent limitations of traditional drought indices, need of improved drought declaration mechanism and relation of drought assessment with socioeconomic security of farmers, this thesis is predominantly divided into three parts trying to address three main questions: 1) What are the primary drivers of vegetation variability and thereupon their role in shaping regional drought conditions, 2) how to improve the drought detection methodology using the primary climatological and vegetation drivers, and 3) what is the significance of climate variability, droughts and improved drought detection in the socioeconomic security of farmers? The central Indian state of Maharashtra, which is extremely susceptible to drought is utilized as a case study in this thesis to explore the aforementioned issues. The research done for this thesis should offer crucial information for revisiting drought mitigation plans in areas facing such harsh hydroclimatic conditions and will be helpful in creating efficient drought management systems on various global platforms. Different chapters of this thesis are presented as follows:

In Chapter two, Leaf Area Index (LAI), which depicts vegetation conditions by displaying the amount of leaf area per unit ground area is used to understand the various drivers of variability in vegetation. Here, leaf area variability, trends in leaf area index, increase and decrease in leaf area represented as greening and browning, their relationship with droughts, and trends and variability in precipitation and groundwater storage is discussed. Moreover, this chapter also investigates the role of irrigation infrastructure and various other factors in greening and browning, necessarily in vegetation variability.

In chapter three, using the primary drivers of vegetation variability as investigated in chapter two, a novel method of drought severity classification in the form of multivariate joint drought index (JDI) is discussed. Here, drought characteristics such as onset, duration, termination, and severity are also analyzed based on the newly developed index which integrates the responses of different drought drivers in the region.

Further in chapter four, the role of greening and browning, trends and variability in hydro-climatological variables, droughts, and role of proposed method of drought severity analysis on the socioeconomic security of farmers, along with role of agriculture and droughts in the economy of the state is discussed. By taking number of farmer suicides as an index representing the grim situation of farmers, the dreadful effects of droughts, central role played by agrarian crisis and inefficient state interventions on the socioeconomic security of farmers is primarily discussed, along with possible solutions for improvement of their status. Finally, chapter five concludes the thesis with a summary and an outline of future study.

CHAPTER 2
Unraveling the multiple drivers of trends and variability in vegetation

This chapter is published in Bageshree et al., (2022b)*,*

Bageshree, K., Abhishek, Kinouchi, T. (2022b). Unraveling the Multiple Drivers of Greening-Browning and Leaf Area Variability in a Socioeconomically Sensitive drought prone region. *Climate*, *10*(5). https://doi.org/https://doi.org/10.3390/cli10050070

2. Unraveling the multiple drivers of trends and variability in vegetation

2.1. Background and motivation

Vegetation is an important ecological parameter with a unique response for each terrestrial ecosystem formed by the interaction of global-scale drivers to regional and local climatic conditions (Xue & Su, 2017; Zhu et al., 2016). Satellite-derived observations of vegetation indices such as Normalized Difference Vegetation Index (NDVI) and Leaf Area Index (LAI) have been widely used to study global as well as regional trends in vegetation, to clarify the vegetation response to natural environmental changes and human interference (Chakraborty et al., 2018; de Jong et al., 2011, 2012; Emmett et al., 2019; Gemitzi et al., 2019; Mishra et al., 2015; Murthy & Bagchi, 2018; Parida et al., 2020; Sarmah et al., 2018). For example, Zhu et al., (2016) analyzed the global LAI trend and reported CO_2 fertilization effect as the major contributor (70%) to the global greening trend, whereas Chen et al. (2019) revealed the contribution of human land-use practices for the same. Mishra et al., (2015) discussed the role of human impact on vegetation trends in African savanna and examined the spatial variability in vegetation morphology attributed to moisture availability, fire regimes, and land-use practices. Emmett et al., (2019) studied the greening and browning (GB; increase and decrease in leaf area, respectively) patterns in northern latitude forests and accounted precipitation as a key driver for greening. Furthermore, the study Sarmah et al., (2018) in South Asia revealed a greening trend mainly in irrigated croplands driven by anthropogenic activities (agricultural advancements) during summer and winter monsoon seasons. The GB study on the Himalayas also found the dominant greening patterns in rainfed and irrigated agricultural areas, where browning was found to be mainly related to the pre-monsoonal droughts (Mishra & Mainali, 2017).

Many of the GB studies show that climatic variability and anthropogenic factors are mainly responsible for the trend in vegetation, where the significant role of agriculture in greening is primarily discussed. However, rigorous attribution of leaf area variability to its key drivers, particularly in extensively agricultural but drought-prone areas, have not been discussed so far in the literature. LAI, defined as leaf area (LA) per unit ground area, has the potential to quantitatively analyze the vegetation dynamics in the form of net gain or loss in the leaf area. The quantification of the LA statistics, such as increasing or decreasing trends, spatiotemporal variability, and the response to climatic (precipitation) and anthropogenic (land use and irrigation) variability, is not only important for understanding human-ecosystem interaction, disaster contingency planning and its mitigation measures but also for socioeconomic security of any region. Several studies have focused on quantifying the change in the vegetation response to climatic conditions and its driving factors (e.g., Baudena et al., 2008; Tadesse et al., 2014; Zhong et al., 2019; Zhu et al., 2016), while others have studied climatic variabilities (mainly precipitation) responsible for droughts (Chen et al., 2020; Guhathakurta & Rajeevan, 2008; Guhathakurta & Saji, 2013; Mallya et al., 2016; Niranjan Kumar et al., 2013; Trenberth et al., 2014). However, the comprehensive characterization of the trend and spatiotemporal variability of vegetation, their controlling factors, and the impact on various socioeconomic aspects is still lacking, particularly in drought-prone regions like India.

India is an agrarian country where 68% of cropped area is vulnerable to droughts (Government of India, 2016) that cause great economic losses and hamper the social security of related stakeholders (mainly agriculture and allied activities). The future warming climate may increase the frequency and extent and intensify the severity of droughts in India, where drought-induced deadly famines in the past two centuries have disrupted the socioeconomic security of the region (Aadhar & Mishra, 2018; Mishra et al., 2019). The consequence of droughts is different for different classes of the society where the agricultural communities, especially farmers, get directly affected, impairing their social and mental status, and eventually forcing them to take extreme measures such as suicide. Mallya et al., (2016) showed that droughts are becoming widespread and are increasing their duration and severity in vulnerable regions of central India, specifically in the state of Maharashtra, where more than 70,000 farmers have ended their lives surrendering to the agrarian stress caused due to droughts during 2000 to 2018 (NCRB, 2021). About 64% of the population predominantly depends on agriculture and allied activities in Maharashtra (Udmale et al., 2014) (e.g., animal husbandry and livestock, dairy, horticulture etc.), where even minor delays in the Southwest monsoon (June-

September) and episodic but prolonged dry spells have cumulatively caused severe droughts over the years (Kulkarni et al., 2016), ultimately leading to a huge socioeconomic loss in terms of agricultural failures, migrations, loss of livestock, and political instability in the region. The lack of adequate infrastructure for irrigation and poor administrative management exaggerate the effects of these adverse events during the droughts (Kulkarni et al., 2016). Furthermore, groundwater, which is the primary source of irrigation in the state, has been overexploited, resulting in highly declining groundwater storage in the region (Abhishek & Kinouchi, 2021, 2022; Asoka et al., 2017; Asoka & Mishra, 2020). Cumulative effects of erratic rains, prolonged and widespread droughts, agricultural and market uncertainties, and limited irrigation facilities are increasingly challenging the sustainability in agriculture and are few of the prime concerns for the policymakers in the region, where their interconnection and interdependency remains largely unexplored. Under such dynamic and complex feedback from natural and anthropogenic drivers, disentangling the impacts of these confounding factors is imperative for assisting the policymakers in ensuring socioeconomic and food security.

Knowing the devastating effects of droughts, the question arises whether the land surfaces of these drought-prone regions, especially vegetation in agricultural areas, are sustainably maintained and operated, what are the key factors and drivers dominating the vegetation conditions, and what is their role in shaping the regional drought conditions and thereupon in the socioeconomic status of the farmers. Although several studies have used LAI for GB analysis for global (e.g., Chen et al., 2019; Zhang et al., 2017) and regional (e.g., Gemitzi et al., 2019; Mishra & Mainali, 2017; Zhong et al., 2019) scales, to the best of our knowledge, no study has been carried out to analyze the spatiotemporal variability of LA, its governing factors and more importantly their possible implications and role in the regional drought conditions in the socioeconomically sensitive and agriculturally dominant drought-prone areas like the state of Maharashtra. Therefore, the specific objectives of this chapter are:

(i) To quantify the trend and variability in LAI in the form of greening-browning and net change in leaf area (NCLA) due to heterogeneous responses of vegetation cover to climatic conditions under the influence of human interaction,

(ii) To categorize the vegetation land covers responsible for LAI trends,

(iii) To understand the spatiotemporal characteristics of precipitation and groundwater and their influence on LA variability

(iv) To analyze the influence of water availability (and irrigation infrastructure) on LA distribution

2.2. Material and Methods

2.2.1. Study Area

Maharashtra is the third-largest Indian state in terms of geographical area (380,851 km^2), second largest in population, and the largest economy. It lies in Peninsular India between 22° N and 15.5° N and 72.5° E and 81° E (**Figure 2.1**(a) inset). The mountain ranges called Sahyadri (also known as the Western Ghats) geographically divide the state into two main parts, namely Kokan to the West and Deccan Plateau to the East. Sahyadri, with an average elevation of 1200m, runs parallel to the West coast and almost perpendicular to the incoming monsoon stream resulting in the highest rainfall in the Kokan region. There are six administrative divisions in the state, namely Amravati, Aurangabad, Kokan, Nagpur, Nashik, and Pune (**Figure 2.1**(a)). The climate in Maharashtra is tropical with four distinct seasons: the rainy season also known as monsoon (June to September), postmonsoon (October to December), winter (January and February), and summer season (March to May). Out of the total geographical area of the state, around 77% is agricultural land, 17% is grasslands, 3% is forests, and the remaining land is primarily urban areas, shrublands, barren lands, and water bodies (**Figure 2.1**(b)). The central part of Maharashtra is dominated by agricultural land-use practices, whereas the areas under grasslands are concentrated in Kokan and Pune divisions. The maximum forest cover in Maharashtra is in Nagpur division, mainly in the Garhchiroli district, consisting of more than half of the state's total forest cover (**Figure 2.1**(b)).

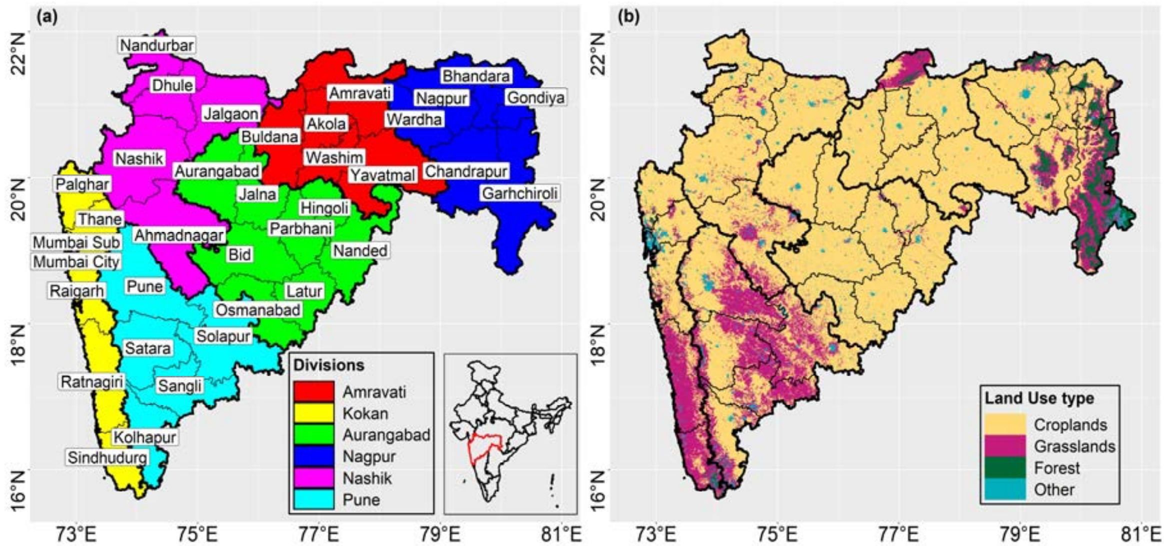

Figure 2.1: (a) Six administrative divisions of the Maharashtra state, (b) International Geosphere-Biosphere Program (IGBP) land-use classification.

2.2.2. Data and Methodology

A schematic of various data sources, methods, and analyses carried out in this study is shown in **Figure 2.2**, and details are explained in the sections below.

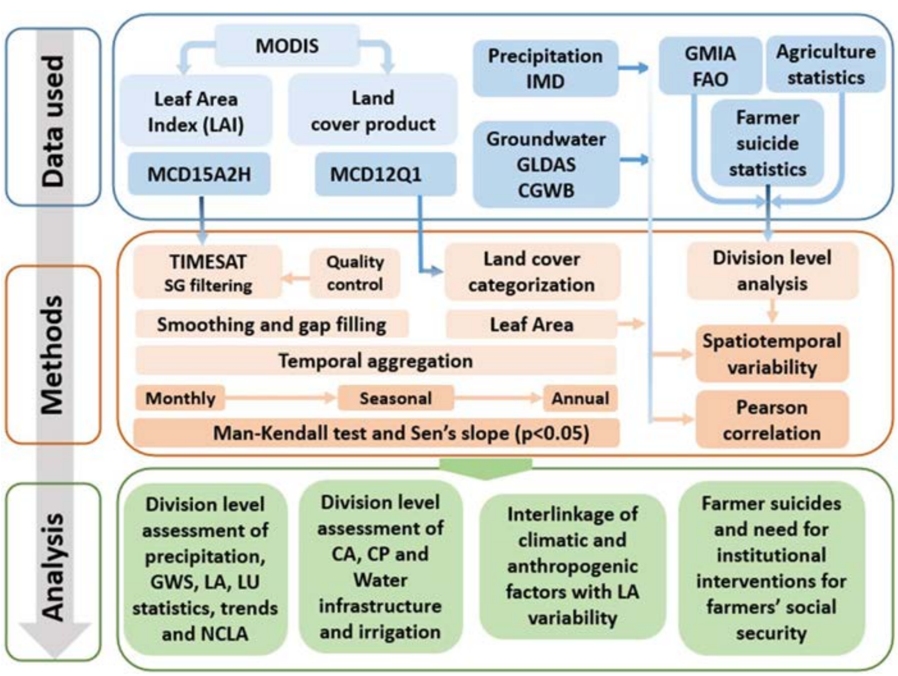

Figure 2.2: Schematic of various data sources, methods, and analysis carried out in this study.

2.2.2.1. MODIS LAI product (MCD15A2H)

LAI was obtained from the MODIS MCD15A2H (https://lpdaac.usgs.gov/products/mcd15a2hv006/) version 6, which is a combined product of LAI and Fraction of Photosynthetically Active Radiation (FPAR) and is available from July 2002 (Myneni et al., 2015). MCD15A2H v6 is a well calibrated and validated product providing the highest quality LAI datasets with minimum residual contamination arising from aerosols, clouds state, shadow, and snow cover (Chen et al., 2019; Lyapustin et al., 2014; Zhang et al., 2017). Here, we used the 'AppEARS' tool by NASA LP-DAAC to obtain 500m resolution, 8-day composites of MCD15A2H, assign the projections, convert the HDF file format to GIS friendly .tiff files, and then clip the LAI retrievals by mask to finally obtain the images with required extent and projection (AppEEARS Team, 2019). Despite the reduced uncertainties compared to the earlier MODIS products, the LAI retrieval accuracy tends to be affected by the theoretical uncertainties in the algorithm (main or empirical backup), BRDF representation, and the atmospheric corrections (Didan et al., 2016; Yan et al., 2021; Y. Zhang et al., 2017). In our case, about 89% of the retrieved images had the best quality for more than 80% of the pixels in the image. The quality of the remaining 11% images was essentially compromised by the seasonal monsoon clouds. The adaptive Savitzky-Golay filter in TIMESAT environment, which allocates more weightage to the good quality pixels, removes spikes and outliers, and fits a quadratic polynomial to all points in a moving window, was used for noise removal and gap filling (Eklundh & Jonsson, 2017; Jonsson & Eklundh, 2017; Jönsson & Eklundh, 2004; Kandasamy et al., 2013). The resulting LAI time series was aggregated to monthly, seasonal (corresponding to the four seasons: Monsoon (JJAS), Postmonsoon (OND), Winter (JF) and Summer (MAM)), and annual time series for further analysis.

2.2.2.2. MODIS land cover product (MCD12Q1)

The land cover data was obtained from MCD12Q1 land cover product by MODIS (https://lpdaac.usgs.gov/products/mcd12q1v006/), which provides global coverage of annual land cover classifications developed by using a supervised classification of MODIS reflectance data (Friedl & Sulla-Menashe, 2019). We used the 500m resolution, International Geosphere-Biosphere Program (IGBP) classification provided in the

MCD12Q1 product, which has 17 types of land cover data, and further aggregated them into four major biome types viz., croplands (croplands and natural vegetation), grasslands (grasslands and savannas), forests (evergreen needle-leaf forests, evergreen broad-leaf forests, deciduous broad-leaf forests, and mixed forests), and others (open and closed shrub-lands, woody savannas, permanent wetlands, urban areas, and water bodies). To know the types of the land cover showing the significant trends, following the method by Chen et al., (2019), the land cover type at the start of the analysis, i.e., for the year 2003, was considered as a static map to define, classify, and further analyze the land cover statistics for trends and net change in leaf area.

2.2.2.3. Trend analysis and net change in leaf area

We used Mann-Kendall (MK) test for the trend analysis in LAI time series during the past 16 years from June 2003 to May 2019 (June to May corresponds to the water year which coincides with the two agricultural seasons, i.e., Kharif (June to September) and Rabi (October to May)). The non-parametric MK test is widely used to analyze the presence of a monotonic positive or negative trend in the target variable (Chen et al., 2019; Dhorde et al., 2017; Mishra & Mainali, 2017; Zhu et al., 2016).

Prior to the trend analysis, we tested the monthly time series dataset for seasonality and autocorrelation and removed them using the method proposed by Yue and Wang (Yue & Wang, 2004). The data were first detrended and effective sample size (ESS) was calculated using the significant serial correlation coefficients. The ESS was then used to correct the variance of the MK test and the Z statistic, and the new p-values were calculated according to the corrected variance (Yue & Wang, 2004). We used the ‘modifiedMK’ package in the R environment (Patakamuri & O’Brien, 2020) to process the data for a significance level of 95% ($p<0.05$). The magnitude of the trend was calculated with the help of Sen’s slope, which is used to calculate the linear rate of change in the variable (Kumar Sen, 1968).

The Net Change in Leaf Area (NCLA) was calculated as,

$$NCLA = \sum_{i=1}^{n} Tr_i \times A_i \times N \tag{2.1}$$

where Tr_i is the magnitude of the trend of pixel i, A_i is the area of the pixel i in km^2, N is the length of the analysis period (192 for monthly, and 16 for seasonal), and n is the number of pixels with a significant trend. The statistically significant positive and negative trends contribute to greening and browning, respectively. The NCLA considers both greening and browning of leaf areas to arrive at the net change. Statistically insignificant trends have zero contribution to NCLA.

2.2.2.4. Precipitation data

The daily gridded (0.25°×0.25°) precipitation dataset (Pai et al., 2014) was retrieved from the India Meteorological Department (IMD; https://www.imdpune.gov.in/). Long-term means of the monthly, seasonal, and annual datasets were further calculated from the daily precipitation data of 30 years from 1989 to 2019. The IMD daily precipitation data has been developed by using a network of 6955 rain gauge stations pan-India and applying the Inverse Distance Weighted Interpolation (IDW) scheme (Shepard, 1984). Since precipitation is an important climatic driver influencing the trends and variability in vegetation, we analyzed the annual and seasonal monotonic trends in precipitation using the MK test ($p<0.05$), evaluated the interannual as well as seasonal variability along with its correlation with groundwater and LA and its relationship with LA variability, trends in LAI and variations in the NCLA.

2.2.2.5. Groundwater data

We used daily groundwater storage (GWS) time series from Global Land Data Assimilation System (GLDAS) version 2.2 to understand the relationship between LA and GWS and the associated seasonal and annual variability. Version 2.2 of GLDAS assimilates the terrestrial water anomaly observation from Gravity Recovery and Climate Experiment (GRACE) to produce 0.25° gridded datasets of land surface fluxes by simulating the Catchment Land Surface Model (CLSM) (Li et al., 2020; Bailing Li et al., 2019; Rodell et al., 2004). The daily GWS data was aggregated into monthly, seasonal, and annual time series from 2003 to 2019 for further analysis related to spatiotemporal GWS and LA variability.

Moreover, to understand the GWS dynamics and trends due to local heterogenic activities of water abstraction, in-situ groundwater level data was obtained from Central

Ground Water Board (CGWB) (India-WRIS, http://www.india-wris.nrsc.gov.in/wris.html) from June 2003 to May 2019. Data from more than 7,000 wells was obtained and filtered for temporal continuity (observations with two or more consecutive gaps were not considered) and outliers to obtain reliable observations (Abhishek & Kinouchi, 2021). The number of the filtered wells was between 440 to 600 depending on the season. The station-level GW consists of quarterly observations (January, May, August, November), i.e., one data value in each season. Thereafter, the trend statistics for seasonal groundwater levels were estimated by the MK trend test ($p<0.05$).

To further comprehend the interconnection between climatic and anthropogenic factors, Pearson's correlation (r) was used to examine the correlation between precipitation and LA, precipitation and GWS, and LA and GWS. To evaluate the response of vegetation and GWS to the precipitation, lagged correlations were also estimated.

2.2.2.6. Statistical data of irrigation, agriculture, and forest cover

Since the vegetation conditions, primarily associated with agriculture, are highly dependent on water availability, irrigation statistics in terms of the percentage of area equipped with infrastructure for irrigation were analyzed to explore the effect of the irrigation on the variations in the NCLA. These statistics were retrieved from version 5 of the Global Map of Irrigated Area (GMIA) provided by the Food and Agriculture Organization (FAO, http://www.fao.org/aquastat/en/geospatial-information/global-maps-irrigated-areas/latest-version/) (Stefan et al., 2013). Furthermore, we analyzed the relationship of cropped area, cropping intensity, and crop production with the LA variability and trends in LAI, precipitation, and GWS. The data related to agricultural statistics were obtained from the Economic Survey Department, Government of Maharashtra (https://mahades.maharashtra.gov.in/) and Department of Agriculture and Cooperation (http://krishi.maharashtra.gov.in/). To investigate the change in forest cover during the study period, information on forest cover was obtained from the Ministry of Environment, Forest, and Climate change (https://fsi.nic.in/).

2.3. Results and Discussion

2.3.1. Trends in Leaf Area Index (LAI)

2.3.1.1. Trend in monthly composite LAI

About 51% of the total geographical area (GA) of the Maharashtra state showed a statistically significant trend in the monthly composite LAI, with 42.31% and 8.45% of the area showing significant positive and significant negative trends, respectively, during the study period (**Table 2.1** and **Figure 2.3**). The percentage of GA showing a significant trend is highest in the Pune division (>70%), while it is lowest in the Nagpur and Aurangabad divisions (**Table 2.1** & **Figure 2.3**(a)). Pertaining to the higher positive trends over negative trends in all the divisions except for Nagpur, where both the trends are comparable (~18-20% each), each division contributes to the greening of the state. Pune and Nagpur divisions contribute the most to the positive (32.19%) and negative (36.42%) trends in LAI in the state, respectively (**Figure 2.4**(a & b)).

Table 2.1: Percentage of geographical area showing significant trends in monthly MK analysis from 2003-04 to 2018-19 (positive, negative, and total) in each division of Maharashtra state.

Division	Positive trend (%)	Negative trend (%)	Total trend (%)
Amravati	41.42	3.77	45.20
Aurangabad	31.13	8.90	40.03
Kokan	55.46	8.88	64.34
Nagpur	19.79	18.30	38.09
Nashik	37.78	9.73	47.51
Pune	74.03	1.23	75.27
Total (Maharashtra)	42.31	8.45	50.76

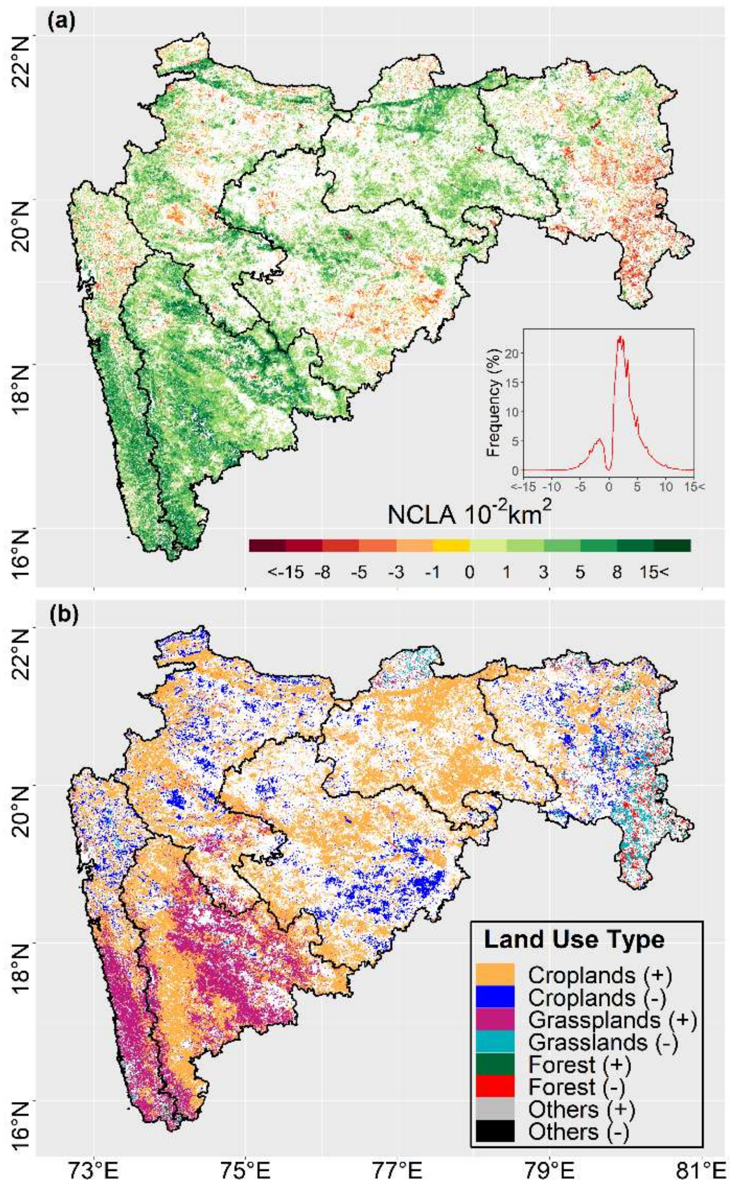

Figure 2.3: (a) Net Change in Leaf Area (NCLA) and (b) Land use of each pixel showing significant positive (+) and negative (–) trends in MK trend analysis ($p<0.05$) on monthly time series from 2003-04 to 2018-19. Inset figure in (a) shows the frequency distribution of pixels (NCLA). White areas have insignificant contribution in NCLA.

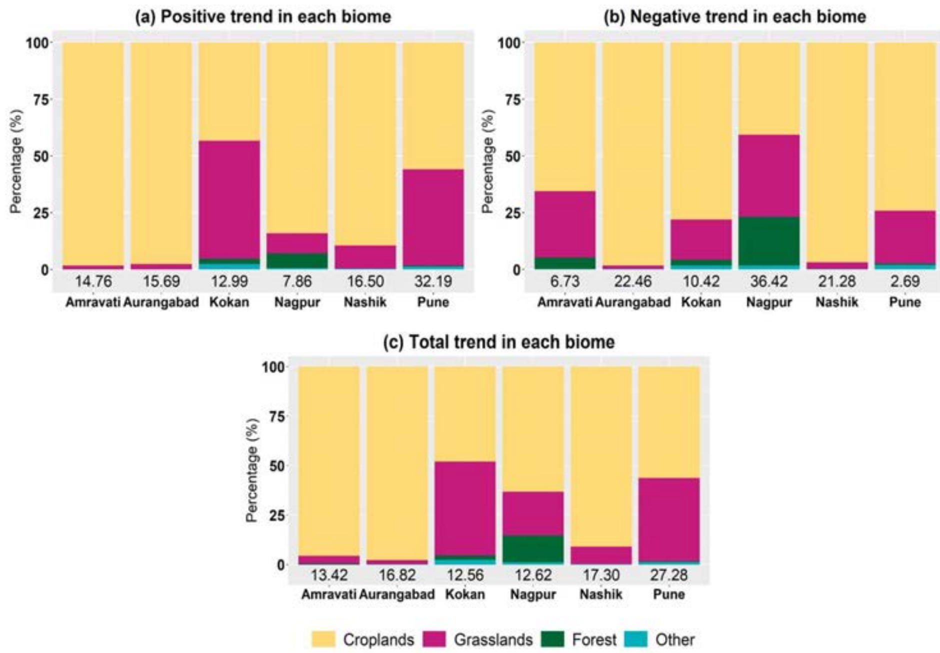

Figure 2.4: Percentage contribution of each biome in significant trends ((a) positive, (b) negative, and (c) total) of each division in monthly trend analysis. (The number below the bars denotes the contribution of each division in respective significant trends for the whole of Maharashtra)

Furthermore, using the land use map of the year 2003 as static, we found that more than 70% of the significant trend is represented by croplands (both positive and negative), followed by grasslands and forests (**Table 2.2** & **Figure 2.3**(b)). Within the same biome, forest areas showed a comparatively large percentage (8.42%) of significant negative trend compared to significant positive trend (<1%) (**Table 2.2**), which can be explained by the joint influence of natural disasters like forest fires and the human activities of deforestation, clearcutting for industries, and agricultural intensification in the state (https://fsi.nic.in/). The coastal regions of Kokan and Pune divisions showed significant trends because of croplands and grasslands (nearly 48% each in Kokan and 56% and 42% in Pune division), whereas the Deccan Plateau region consisting of Amravati, Aurangabad, and Nashik divisions mainly showed significant trends due to agriculture (96%, 98% and 91% respectively) (**Figure 2.4**(c) & **Figure 2.5**(a)). The browning trend in Nagpur division is mainly contributed by croplands and grasslands followed by forests, whereas greening is mainly attributed to croplands (**Figure 2.4**(a & b)). Although the trends are prominent due to croplands over the state, about 50% of the total area under croplands showed significant trend while ~66% and 36% of area under grasslands and forests showed significant trend respectively. We also observed the percentage of positive and negative trends within each biome and found that all biomes have a higher contribution to greening (~84%) except for forests (browning ~64%) (**Table 2.2**).

Table 2.2: Percentage contribution of each biome to significant positive, negative, and total trend in monthly LAI trend analysis for Maharashtra state. The numbers in brackets under each biome represent the percentage of positive and negative trend within that biome.

Area	**Trend**	**Croplands (%) (1)**	**Grasslands (%) (2)**	**Forests (%) (3)**	**Other (%) (4)**	**Total area showing significant trend (km²) (5)**
Maharashtra state	Positive	74.82 (83.87)	23.40 (86.32)	0.96 (36.31)	0.81 (81.07)	161130.80
	Negative	72.05 (16.13)	18.58 (13.68)	8.42 (63.69)	0.95 (18.93)	32176.75
	Total	74.36	22.60	2.20	0.83	193307.50

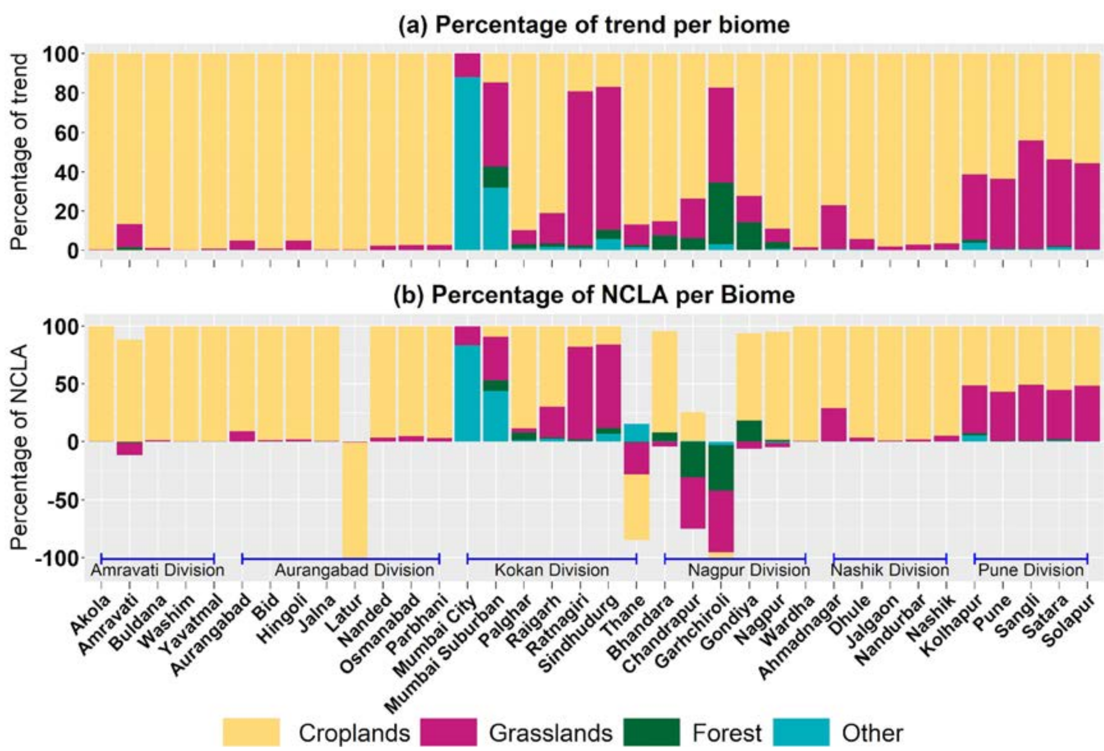

Figure 2.5: Percentage contribution of each biome per district to (a) significant monthly LAI trend ($p< 0.05$) and (b) NCLA.

Table 2.3: Net Change in Leaf Area (NCLA) per division and in each biome based on monthly MK trend analysis during 2003-04 to 2018-19. (Geographical area (GA) is calculated based on number of pixels in each division in the static map multiplied by the area of pixel)

Division	Geographical Area (km²)	NCLA (km²)				
		Croplands	Grasslands	Forest	Others	Total
Amravati	57405	2487.04	-92.32	-11.55	-0.02	2383.15
Aurangabad	81231	1942.74	73.32	0	-0.26	2015.81
Kokan	37741	817.38	1988.40	71.33	92.82	2969.93
Nagpur	64026	558.60	-453.64	-287.64	-22.98	-205.66
Nashik	70381	2041.92	276.99	-0.23	1.57	2320.26
Pune	70066	4273.65	3570.77	48.16	102.50	7995.08
Total (Maharashtra)	380851	12121.34	5363.53	-179.94	173.63	17478.57

Maharashtra state showed greening as a whole during 2003-2019 with a net gain of 17.478×10^3 km^2 of LA (~91 km^{2}month^{-1}, **Table 2.3**). The cropland greening in the state is more prominent irrespective of the higher contribution of croplands in the negative trend than other biomes (**Table 2.2**), resulting in the addition of LA. Greening is most notable due to the Pune division, which added LA at the rate of 41.64 km^{2}month^{-1}, contributing to 45.75% of the total NCLA of the state, mainly due to croplands and grasslands (**Table 2.3** and **Figure 2.5**(b)). The Pune division contributed the most (35.26%) to the NCLA in croplands, followed by the Amravati division (20.52%), whereas Kokan and Nagpur divisions had meager contributions (**Table 2.3**). Browning hotspots in the croplands are mainly observed in Nashik and Aurangabad divisions (**Figure 2.3**(b) and **Figure 2.4**(b)). The contribution of each biome to addition and reduction in LA revealed that both Aurangabad and Nashik divisions had almost equal reductions in LA in croplands (27% and 25% of negative change due to croplands only, respectively, **Table 2.4**). The Nagpur division, where the negative trend is largest (**Table 2.1**), experienced a loss in the LA at the rate of 1.07 km^2 month^{-1} because of grasslands and forests (the LA in croplands increased irrespective of the browning trend due to comparatively high greening in croplands) (**Table 2.3** and **Table 2.4**).

Table 2.4: Positive, negative, and total NCLA in each biome in each division observed for monthly MK trend analysis from 2003-04 to 2018-19.

Division	Biome	Positive NCLA (km^2)	Negative NCLA (km^2)	Total NCLA (km^2)
Amravati	croplands	2628.64	-141.61	2487.04
	grasslands	35.08	-127.39	-92.31
	forests	2.14	-13.69	-11.55
	others	0.23	-0.25	-0.02
Aurangabad	croplands	2536.48	-593.74	1942.74
	grasslands	83.30	-9.98	73.32
	forests	0.00	0.00	0.00
	others	0.49	-0.75	0.26
Kokan	croplands	1110.99	-293.61	817.38
	grasslands	2084.73	-96.33	1988.40
	forests	95.42	-24.09	71.33
	others	103.89	-11.07	92.82
Nagpur	croplands	1036.65	-478.05	558.60
	grasslands	134.45	-588.09	-453.64
	forests	154.35	-441.99	-287.64
	others	6.41	-29.39	-22.98
Nashik	croplands	2588.04	-546.12	2041.92
	grasslands	289.76	-12.77	277.00
	forests	0.62	-0.86	-0.23
	others	2.18	-0.60	1.57
Pune	croplands	4396.43	-122.78	4273.65
	grasslands	3615.13	-44.36	3570.77
	forests	56.19	-8.03	48.16
	others	104.94	-2.44	102.50
Total (Maharashtra)	croplands	14297.24	-2175.89	12121.34
	grasslands	6242.45	-878.92	5363.53
	forests	308.73	-488.66	-179.94
	others	218.14	-44.50	173.63

2.3.1.2. Trend in seasonal LAI

The MK trend analysis on seasonal LAI time series for monsoon, postmonsoon, winter and summer seasons revealed that more than 20% of the state shows a significant trend in each season except in monsoon (~14% of GA of the state) (**Figure 2.6**). The highest trend is observed in the postmonsoon season, where 22% of the state is greening, whereas only 1% is browning (**Figure 2.6**). The trends in each season are primarily represented by croplands for Amaravati, Aurangabad, Nashik, and Nagpur divisions (>90% of the total trend in each division for each season) except in monsoon for Nagpur division (79% of the total trend in the division) (**Figure 2.7**). The maximum percentage of total trends in each season in the Pune and Kokan divisions are uniformly shared by croplands (~56% and ~45%, respectively) and grasslands (~40 and ~50%, respectively). Although the NCLA was positive in each season for all the divisions (**Table 2.5**), postmonsoon season shows prominent browning clusters in croplands of the Aurangabad division (**Figure 2.6**(b) and **Figure 2.7**(b)). Districts experiencing negative trends have negative NCLA in respective seasons with comparatively lower magnitude than positive NCLA, which has resulted in greening of all the divisions in each season.

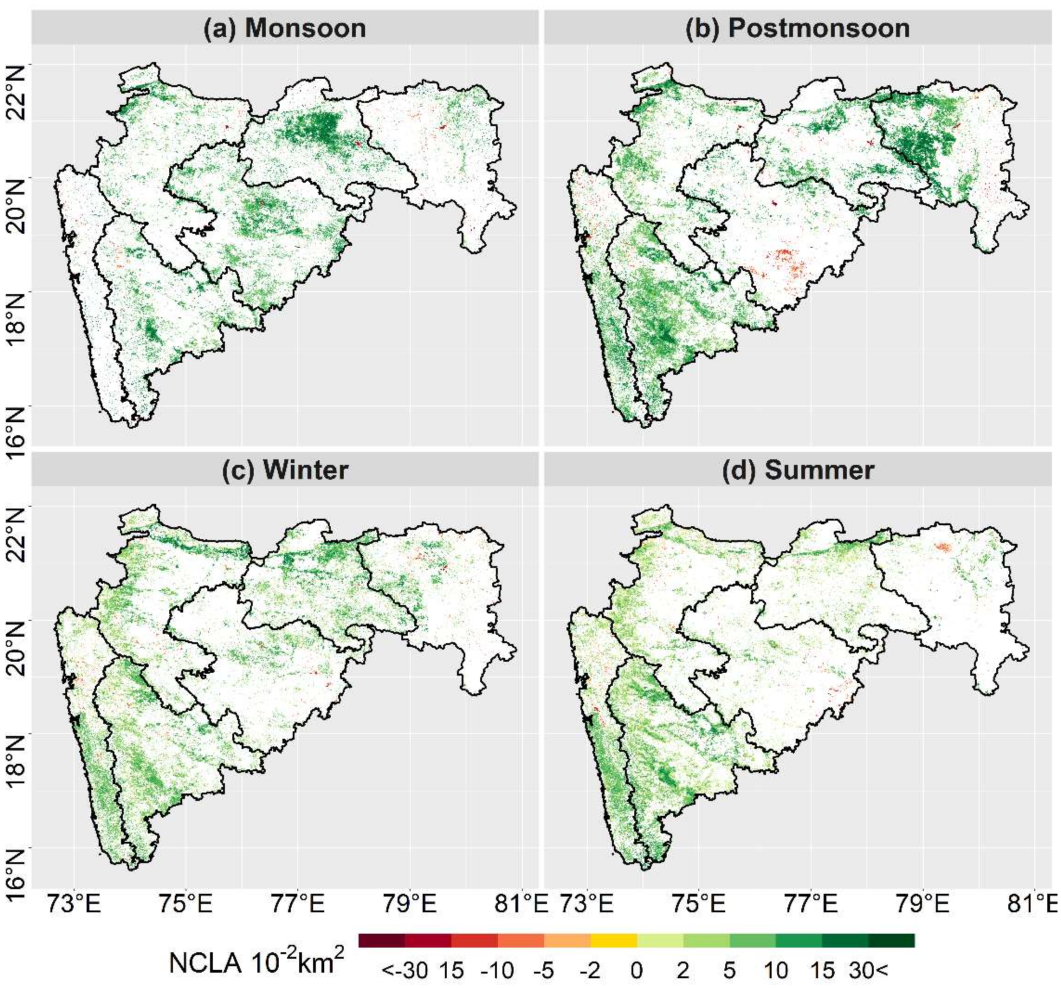

Figure 2.6: Net Change in Leaf Area (NCLA) by MK trend analysis ($p < 0.05$) on seasonal LAI time series for (a) monsoon (June-September), (b) postmonsoon (October-December), (c) winter (January-February), and (d) summer (March-May) from 2003-04 to 2018-19.

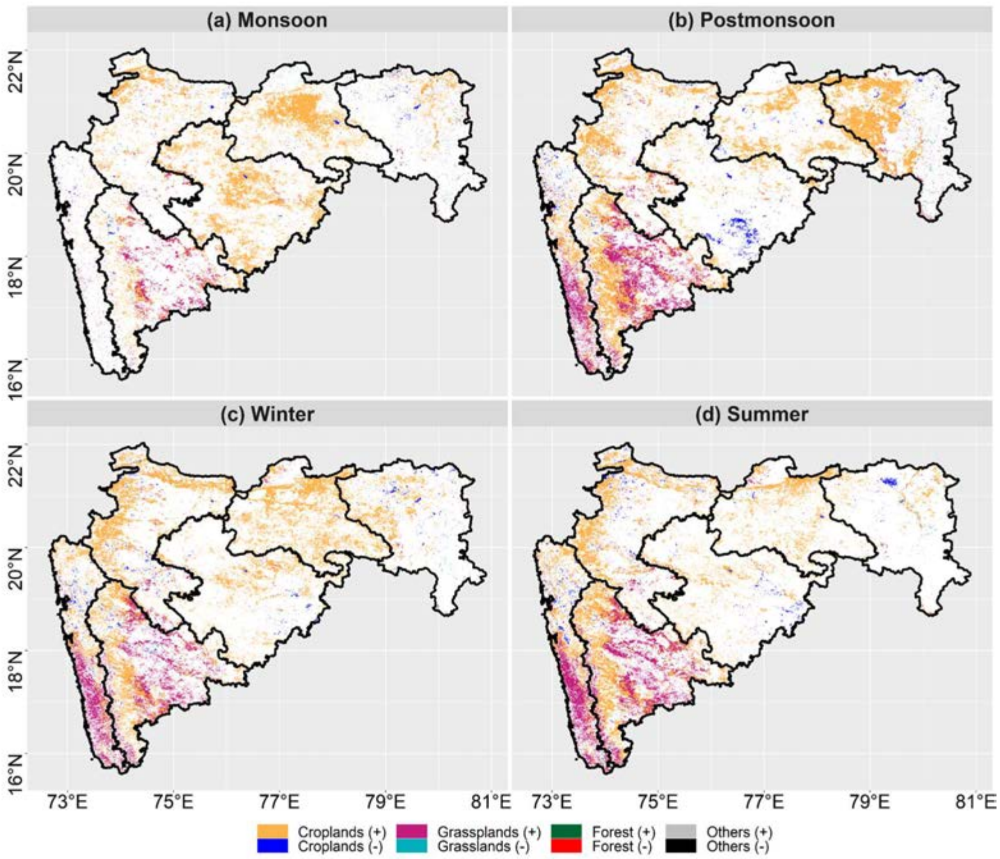

Figure 2.7: Land use by areas showing significant positive (+) and significant negative (-) trends in seasonal LAI time series from 2003 to 2019 ($p < 0.05$) in (a) monsoon (June-September), (b) postmonsoon (October-December), (c) winter (January-February) and (d) summer (March-May)

Table 2.5: NCLA in seasonal trend analysis per division during 2003-04 to 2018-19.

Division	NCLA (km^2)			
	Monsoon	Post-monsoon	Winter	Summer
Amravati	5396.90	3864.30	3890.43	1248.13
Aurangabad	5995.66	1446.83	1758.65	824.59
Kokan	401.42	3146.49	2244.24	2972.06
Nagpur	1234.49	7212.30	1189.41	460.74
Nashik	2681.66	4233.09	3637.24	2040.35
Pune	3903.89	8765.23	4343.04	6400.61

In both monthly and seasonal LAI trend analysis, the state prominently showed greening, where the agricultural land-use was mainly responsible for the trend as well as NCLA (**Figure 2.3**(b), **Figure 2.7**, **Table 2.4**, and **Table 2.5**), which is also consistent with other studies (Chen et al., 2019; Sarmah et al., 2018).

2.3.2. Leaf area variability during 2003-2019

The monthly average LA over Maharashtra state varies seasonally with a gradual increase after the commencement of monsoon in June (1.86 x 10^5 km^2) and reaches its highest in September (6.20 x 10^5 km^2) (**Figure 2.8**(a)). Annual assessment during the study period revealed that the total LA of the region was highest in the year 2017-18 (3.60 x 10^5 km^2) and lowest in the year 2003-04 (2.82 x 10^5 km^2) (**Figure 2.8**(b)). The LA variability is primarily driven by agriculture, where more than 70% of the LA of the state is represented by croplands (71.2% croplands, 18.4% grasslands, 9.4% forests, and the remaining others).

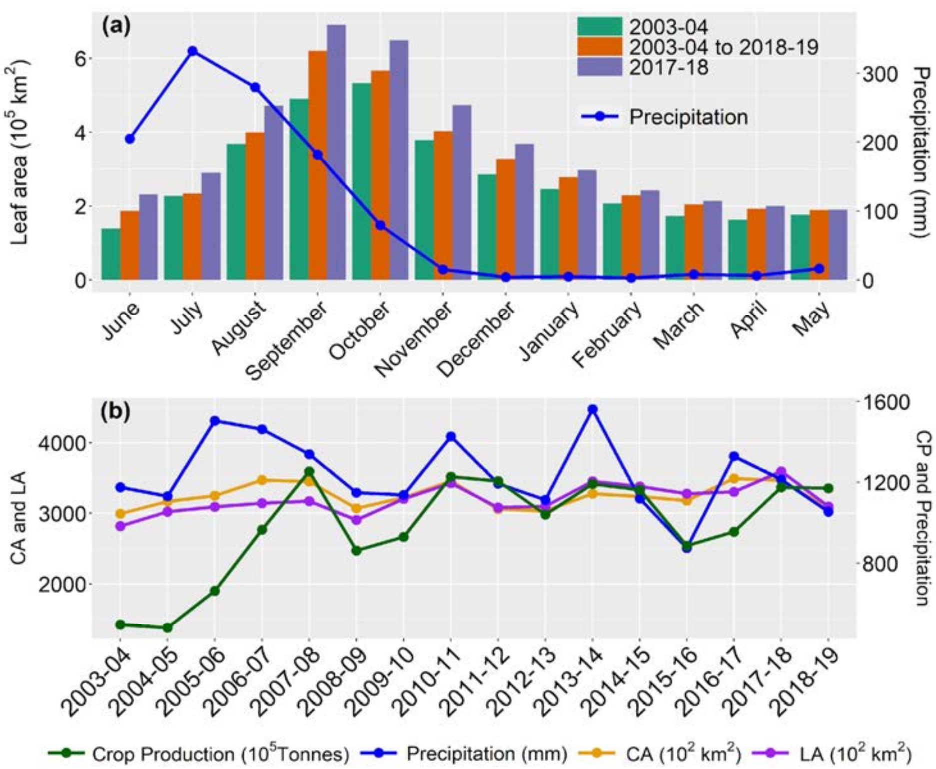

Figure 2.8: (a) Monthly average LA for the years 2003-04, 2017-18, and during 2003-2019, and mean monthly precipitation during 2003-2019. (b) Annual CP, precipitation, CA, and LA during 2003-2019 over Maharashtra state.

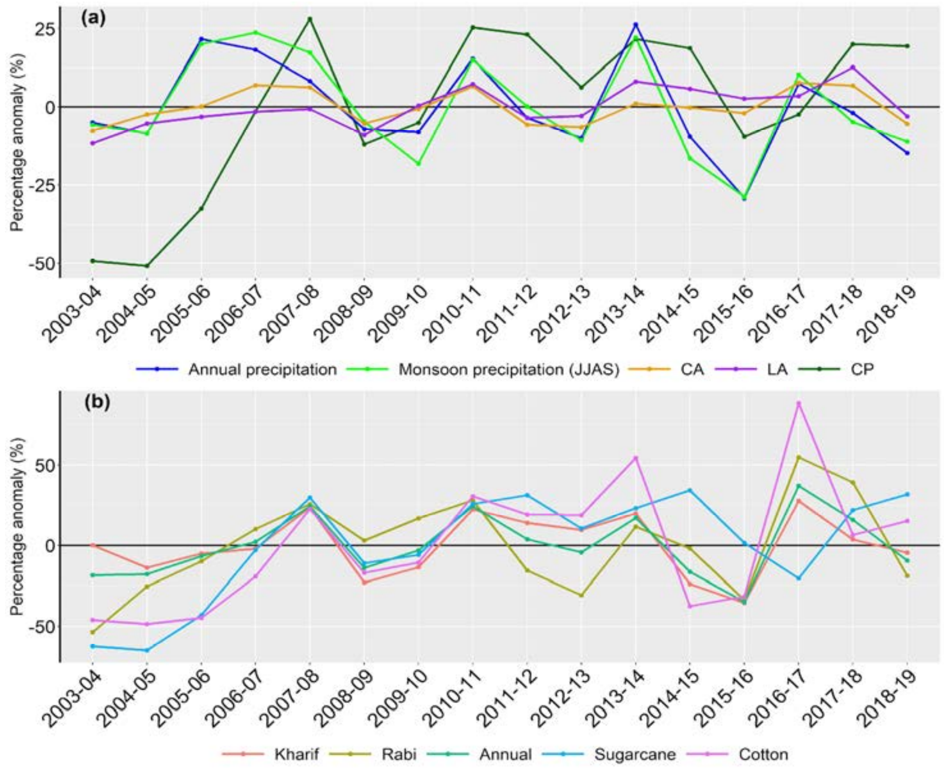

Figure 2.9: Percentage anomaly in (a) precipitation, cropped area, leaf area, and crop production and (b) Kharif CP, Rabi CP, annual CP (Kharif + Rabi), sugarcane CP, and cotton CP in the state during 2003-04 to 2018-19.

The total CA in the state under primary crops like food-grains, cereals, pulses, oilseeds, sugarcane, and cotton was stable with an annual variation of ±7.7% during 2003-04 to 2018-19 and was maximum in 2016-17 and minimum in 2003-04 (**Figure 2.9**(a)). In 2003-04, CA and CP were lower by 7.7% and ~49% than their respective long-term average, whereas in 2017-18, the same were higher by 6.8% and 20% (**Figure 2.9**(a)). Although the CA was the highest in 2016-17, it was not well reflected in the increase in total annual CP attributable to the decreased sugarcane production, which accounts for about 69% of the total annual CP (**Figure 2.9**(b)). Similarly, despite the similarity in CA and precipitation in 2003-04 and 2012-13, the difference in CP is mainly highlighted by increased sugarcane CP of the state in 2012-13 by 193% than in 2003-04.

The annual cropped area (CA) and annual crop production (CP) of the state showed a good correlation with the annual LA in croplands (r = 0.75 and 0.64, respectively). Even though LA can potentially be a good representative of the crop conditions, crop yield is difficult to ascertain from the LA as LA represents number of leaves in the area while crop yield is the measurement of harvested agriculture production. The satellite-derived vegetation indices such as LAI typically capture biomass status. The yield is however obtained when this photosynthetic assimilate is transferred from leaves to grain (Mondal et al., 2014) which depends on the hydro-climatic conditions at the time, which may result in varying correlations between the yield and satellite derived index. While investigating the relationship between LA and CP in the state, a weak correlation was observed in different divisions in the Kharif season, while it was stronger for the Rabi season (**Table 2.6**). Difference in the identification of crop type and land use for agriculture, fluctuations in the LA due to crop varieties other than those used in the statistical data of CP in each season (such annual crop sugarcane), monsoon precipitation variability affecting the crop calendar of different crops in different years, inclusion of nontarget vegetation in the LA estimation as well as cloud coverage in the monsoon season might be responsible for lower correlation between LA and CP in Kharif season. Nevertheless, LA variability and largescale greening in agriculture can be effectively investigated by the CP statistics representing the influence of various hydro-climatological factors on agriculture with close relation to the actual field circumstances.

Table 2.6: Correlation between crop production (CP) and cropland leaf area (LA) in each division and for the whole state in Kharif and Rabi seasons, and on annual basis.

Season	Amravati	Aurangabad	Kokan	Nagpur	Nashik	Pune	Maharashtra
Kharif	-0.11	0.08	-0.26	-0.42	0.57	0.34	0.04
Rabi	0.61	0.72	-0.12	0.49	0.78	0.86	0.77
Annual	0.33	0.43	-0.12	0.30	0.68	0.69	0.64

2.3.3. Spatiotemporal characteristics and trend in precipitation

Maharashtra state receives most of its annual rainfall from the Southwest monsoon, from June to September, and possesses a large spatial variation in the rainfall distribution across the state (**Figure 2.10**). The state frequently faces droughts, with the Central (mainly Aurangabad division) and Eastern (mainly Amravati division) parts being comparatively more vulnerable to droughts than Northern and Western parts (**Figure 2.11**). This variability in the rainfall also affects the availability of natural (streamflow, aquifers) and artificial (storage tanks, dam reservoirs) water storage for irrigation, which affects the irrigated area in rainfall deficit years.

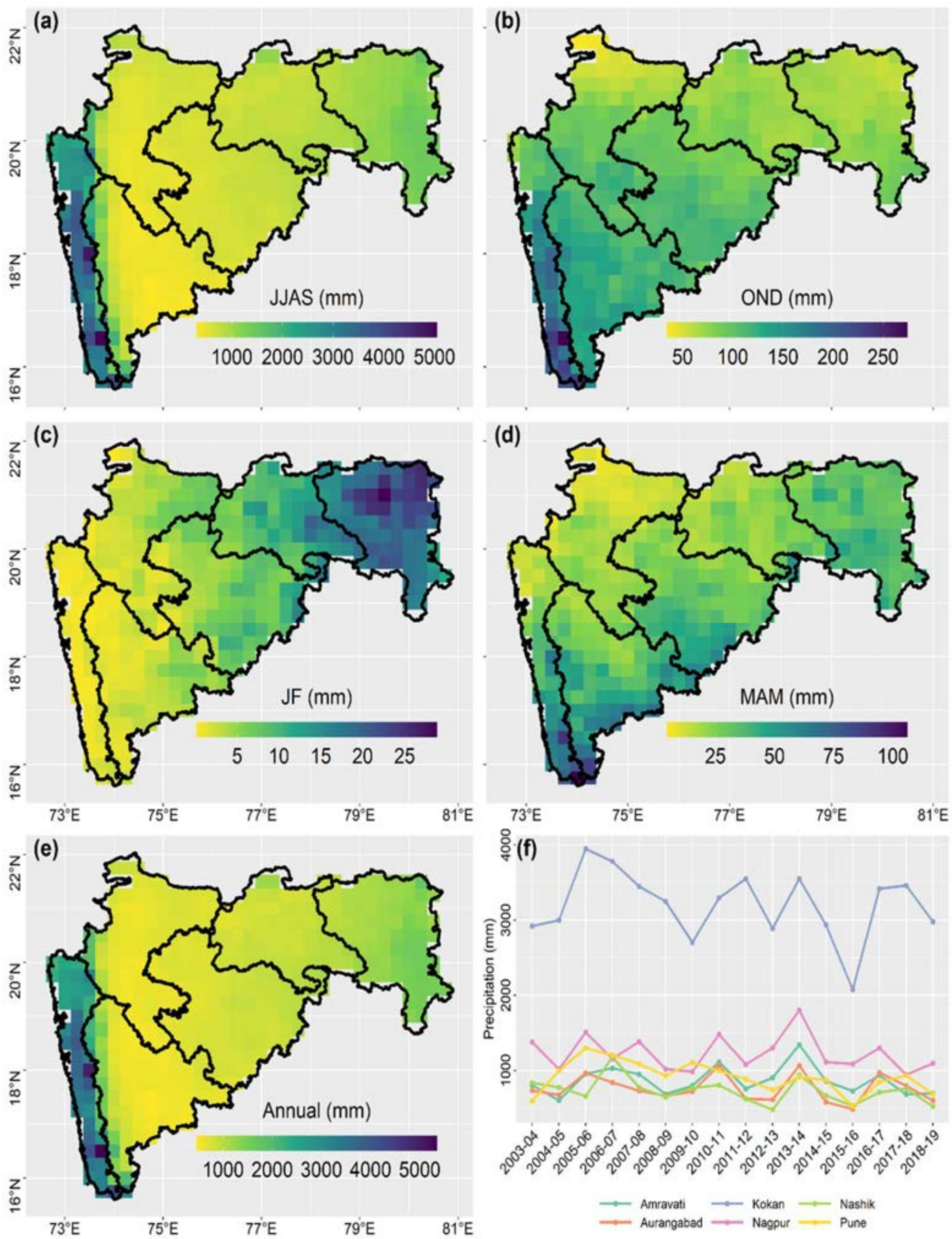

Figure 2.10: Long-term mean (averaged over 1989-90 to 2018-19) of precipitation distribution in (a) monsoon (June-September), (b) postmonsoon (October-December), (c) winter (January-February), (d) summer (March-May) and (e) annual. (f) Annual precipitation in each division from 2003-04 to 2018-19

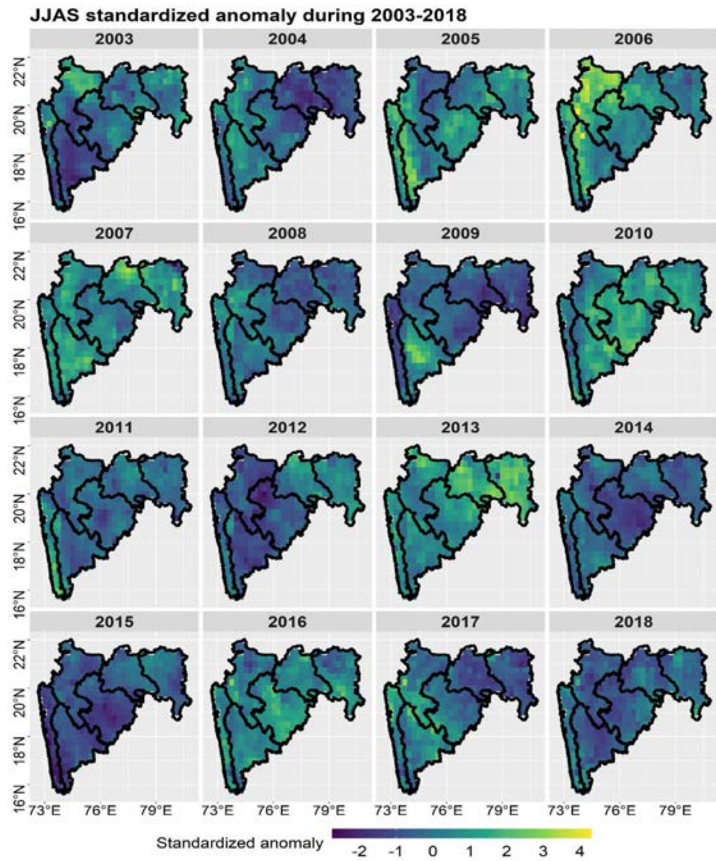

Figure 2.11: Spatial distribution of standardized monsoon rainfall anomaly (normalized by standard deviation) during 2003 to 2018. Standardized anomaly less than -1 is considered as a drought situation for that pixel area.

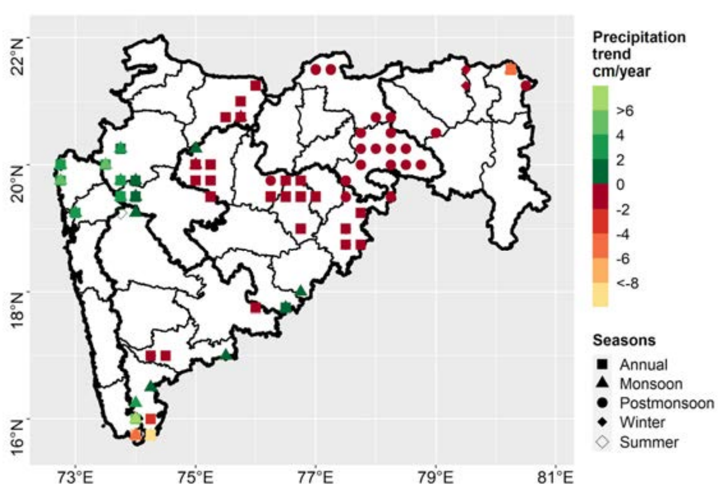

Figure 2.12: Significant trend ($p<0.05$) in $0.25° \times 0.25°$ gridded precipitation dataset, analyzed during 1989-2019 for annual (June-May) and monsoon, postmonsoon, winter, and summer seasons.

Here, the significant spatiotemporal trends in precipitation were analyzed to understand its effect on LA variability. Results show an increasing trend in the monsoon and annual (June-May) rainfall concentrated mainly on the northern parts of the Kokan division (in the coastal region, 94% of the annual rainfall occurs in monsoon) (**Figure 2.12**). In contrast, parts of the Aurangabad division are experiencing a decreasing trend in the annual rainfall (**Figure 2.12**). Postmonsoon rainfall, which is also a source of irrigation for rabi crops, is experiencing a decreasing trend, particularly in the Amravati and eastern parts of the Aurangabad division (**Figure 2.12**). The inter-annual, as well as spatial variability of the rainfall within the state, is quite large (**Figure 2.9**(a), **Figure 2.10** and **Figure 2.11**). We found a distinct pattern in the response of the seasonal vegetation to the rainfall. In the Kharif season, we observed a positive correlation between LA in croplands in Nashik and Pune divisions, a negative correlation in Kokan and Nagpur divisions, and an insignificant correlation in Aurangabad and Amravati divisions (**Table 2.7**). Conversely, in the Rabi season and annually, the respective LA in each division showed positive correlation with the precipitation except for annual LA and precipitation in Kokan division. The undermined LAI quality in Kokan division, especially in monsoon season, along with difference in the resolution of compared datasets, may be the reason behind the negative correlations in the division. To further understand the role of lags in the response of LA to precipitation, we checked the correlations in monthly time series LA (croplands) and precipitation after removing the seasonality. Results show that in the central and eastern districts of Maharashtra, the LA is positively correlated with the precipitation with one and three months of lag time, respectively (**Figure 2.13**(a)).

Table 2.7: Pearson's correlation between seasonal (Kharif and Rabi) and annual cropland LA, precipitation and GWS in subdivisions of Maharashtra.

Division	Precipitation and LA			Previous Monsoon Precipitation			GWS and LA		
	Kharif	Rabi	Annual	Rabi LA	Rabi GWS	Rabi CP	Kharif	Rabi	Annual
Amravati	-0.09	0.50	0.54	0.59	0.84	0.51	0.19	0.62	0.50
Aurangabad	0.06	0.65	0.66	0.65	0.73	0.71	0.39	0.80	0.71
Kokan	-0.44	0.31	-0.24	-0.02	0.17	0.10	-0.44	0.34	-0.04
Nagpur	-0.33	0.50	0.29	0.43	0.86	0.17	-0.19	0.36	0.03
Nashik	0.11	0.69	0.33	0.18	0.59	0.14	0.34	0.75	0.65
Pune	0.33	0.50	0.52	0.42	0.55	0.54	0.19	0.77	0.60
Total (Maharashtra)	-0.13	0.64	0.42	0.43	0.70	0.42	0.05	0.78	0.44

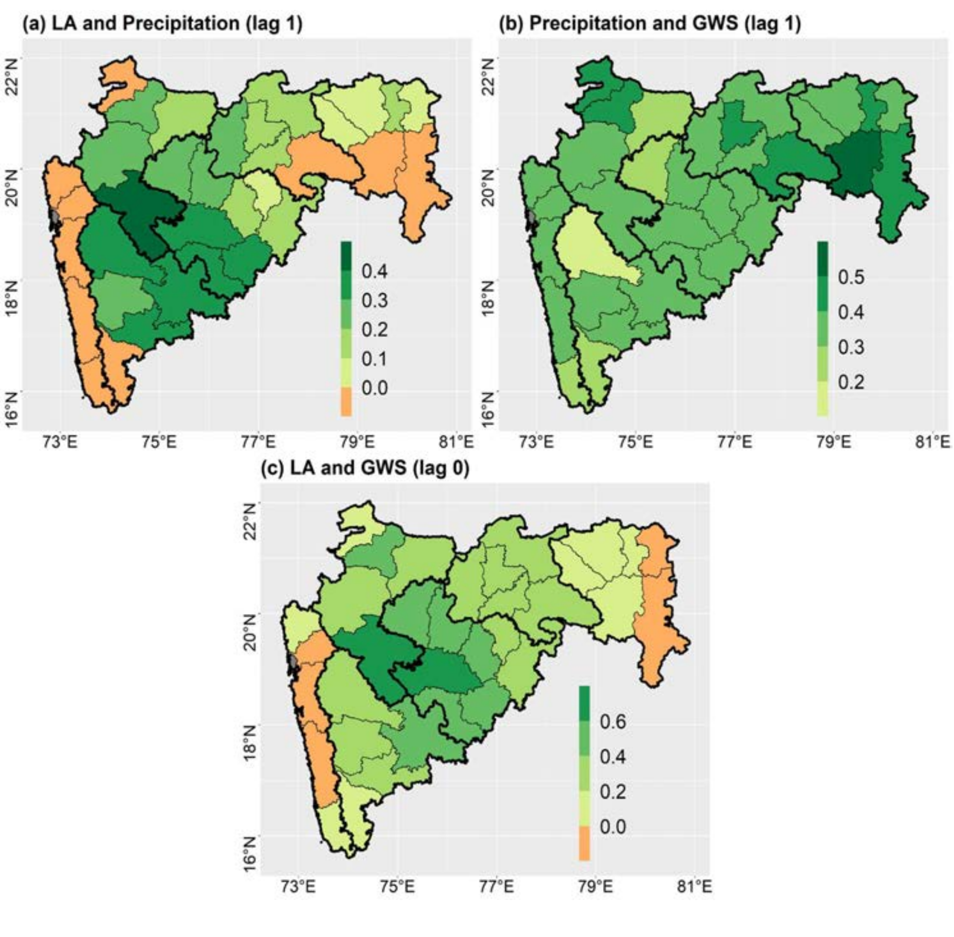

Figure 2.13: District-wise Pearson correlation coefficient between (a) monthly cropland LA and precipitation with one month lag time, (b) precipitation and monthly GWS with one month lag time, and (c) cropland LA and monthly GWS with zero lag during 2003-04 to 2018-19. Seasonality was removed from all the datasets before analyzing the correlation.

The rainfall anomaly in the monsoon season affects the LA and crop production in Kharif and Rabi season by affecting the plant available water and groundwater recharge, which is the prime source of irrigation (mainly during Rabi season) in the state. In addition, one or two dry spells in the growing season can have a huge negative impact on agriculture as rainfall variability is critical for rainfed agriculture. The correlation of LA and GWS in Rabi season to the preceding monsoon precipitation showed a moderate correlation in all districts except Kokan (and lower correlation for LA in Nashik division but still positive, **Table 2.7**). CP in Rabi season also moderately correlates with the previous monsoon (stronger in Aurangabad division), suggesting a role of monsoon precipitation in Rabi agriculture in the form of reservoir storages, aquifer recharge, and stream flows.

The lack of stronger quantitative correspondence between LA in monsoon with precipitation underscores the involvement of factors other than the precipitation (such as advanced crop management technologies, use of groundwater, water management in case of dry spells, use of fertilizers, etc.) in the vegetation growth. Similar interactions between precipitation and vegetation are also reported by various regional and global studies (Liu et al., 2015; Milesi et al., 2010; Mondal et al., 2014; Sarmah et al., 2018). We observed the reductions in the LA in respective drought years (**Figure 2.9**(a)) with a consistently increasing trend in LAI in the state. Although LA is dominated by croplands where CP is primarily constrained mainly by water availability, the trends in precipitation and LAI cannot be consistently linked. Therefore, we infer that the spatial and interannual variations in the rainfall, particularly in monsoon, are closely related to the LA and influence the LA variability and distribution in the state.

2.3.4. Groundwater storage and Leaf Area variability

The increased dependency of agriculture on groundwater is inevitable to sustain the effects of consistent rainfall anomalies in the state. While analyzing the role of groundwater in LA variability, it was observed that the seasonal cropland LA in Kharif season in most parts across the state shows a good correspondence with the seasonal GWS (**Table 2.7**). The correlation is comparatively stronger in the Rabi season over the state (**Table 2.7**). Due to the concentrated rainfall in the monsoon season (81-94% of annual rainfall), agriculture in Maharashtra depends heavily on alternate sources of water (especially groundwater) during the non-monsoon months, i.e., Rabi season. The groundwater recharge is also highly dependent on the monsoon rainfall as high correlations can be observed for GWS in the Rabi season to the previous monsoon precipitation (**Table 2.7**). However, the positive correlations in most of the divisions in the Kharif season also underscores the increased dependency of seasonal agricultural activities on groundwater considering the erratic rainfall patterns. The monthly precipitation and GWS over the state are generally positively correlated with one-month lag (**Figure 2.13**(b)), while the monthly cropland LA and GWS are in phase (zero lag), suggesting the consistent use of groundwater in agriculture (**Figure 2.13**(c)). Inadequate irrigation infrastructure coverage of the state (Government of India, 2018) (**Figure 2.17**, further discussed in section 2.3.5) makes groundwater extraction inevitable during dry periods, further amplified by the lack of implementation of GW withdrawal and usage regulations. The GW pumping in the region is not restricted to only shallow aquifers or for a particular month, but farmers obtain water from deep aquifers by uncontrolled abstraction to sustain the deficit in the availability of water for crops whenever required. The heterogeneous behavior and local influence of GW extraction are also evident from the simultaneous increasing and decreasing trends in GW levels in each season across the state (**Figure 2.14**).

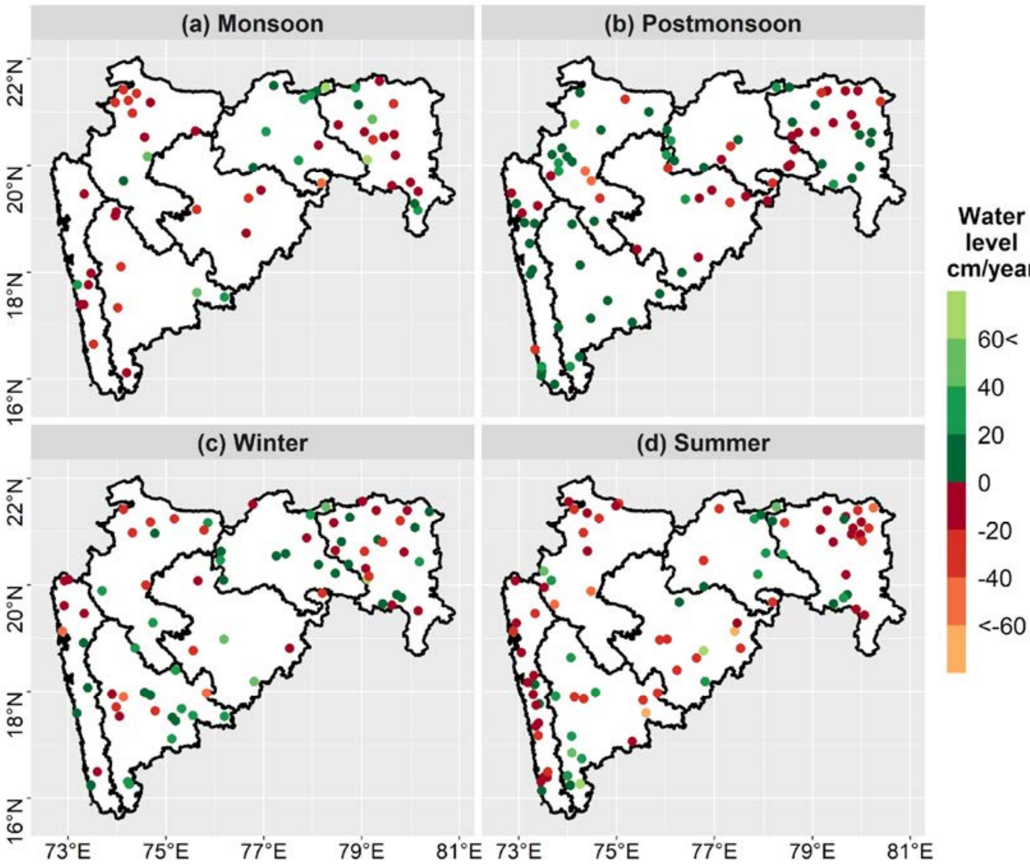

Figure 2.14: Significant trend in well levels by MK trend analysis ($p<0.05$) in each season; (a) monsoon, (b) postmonsoon, (c) winter, and (d) summer over the state. The in-situ groundwater table data shows significant decreasing or increasing trends in all parts of the state in each season, signifying the localized and seasonal influence of groundwater abstraction.

The variations in the rainfall are directly reflected in GWS, where persistent and consecutive droughts for two or more years can reduce GW recharge and increase consequential exploitation of the available GWS (**Figure 2.11**, **Figure 2.15** and **Figure 2.16**(a)). For example, the drought of 2012 reduced the GWS in Kokan, Nashik, Pune, and Aurangabad division but increased in Amravati and Nagpur division due to spatial variability of the rainfall in monsoon (**Figure 2.11**, **Figure 2.15** and **Figure 2.16**(a)). However, consecutive droughts in 2014 and 2015 reduced GWS all over the state due to less/no replenishment (**Figure 2.16**(a and b)). Irrespective of higher GWS in 2013-14, the use of GW for agriculture in 2014-15 on account of deficient rainfall distribution and less/no recharge due to drought in 2015 monsoon (**Figure 2.11**) resulted in declined GWS in both monsoon and Rabi seasons of 2015 (**Figure 2.16**(b)). The GW extraction often exceeds the recharge due to exploitation for irrigation (Abhishek & Kinouchi, 2021, 2022; Asoka et al., 2017; Asoka & Mishra, 2020; Rodell et al., 2009; Shah et al., 2003), which is not only threatening the water security of the state but also affects CP and can alter the patterns of greening in the state. Considering the complex interactions between precipitation and use of GWS for irrigation, where precipitation anomalies trigger excessive GW extraction and affect the GW recharge, together with increasing dependency of agriculture on groundwater, groundwater turns out to be one of the primary drivers for leaf area variability in the region.

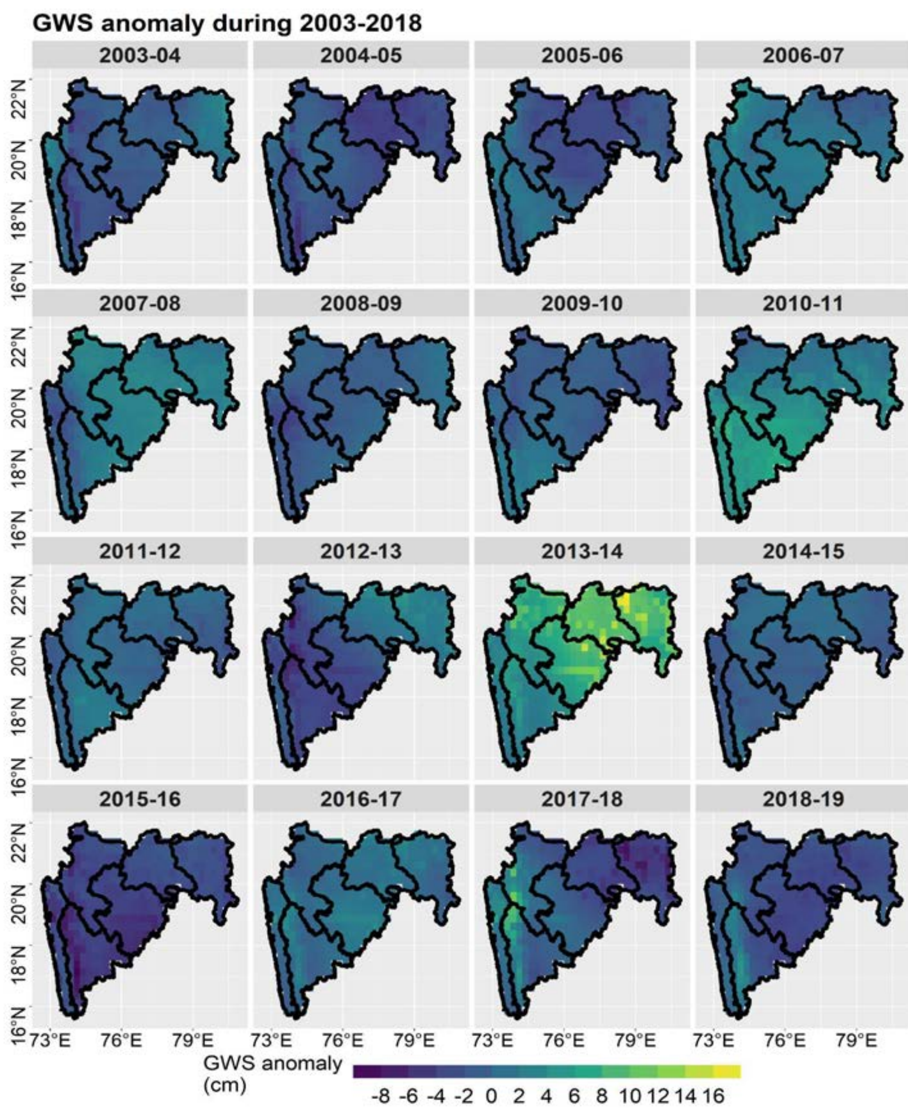

Figure 2.15: Spatial distribution of GLDAS groundwater storage anomaly from 2003-04 to 2018-19.

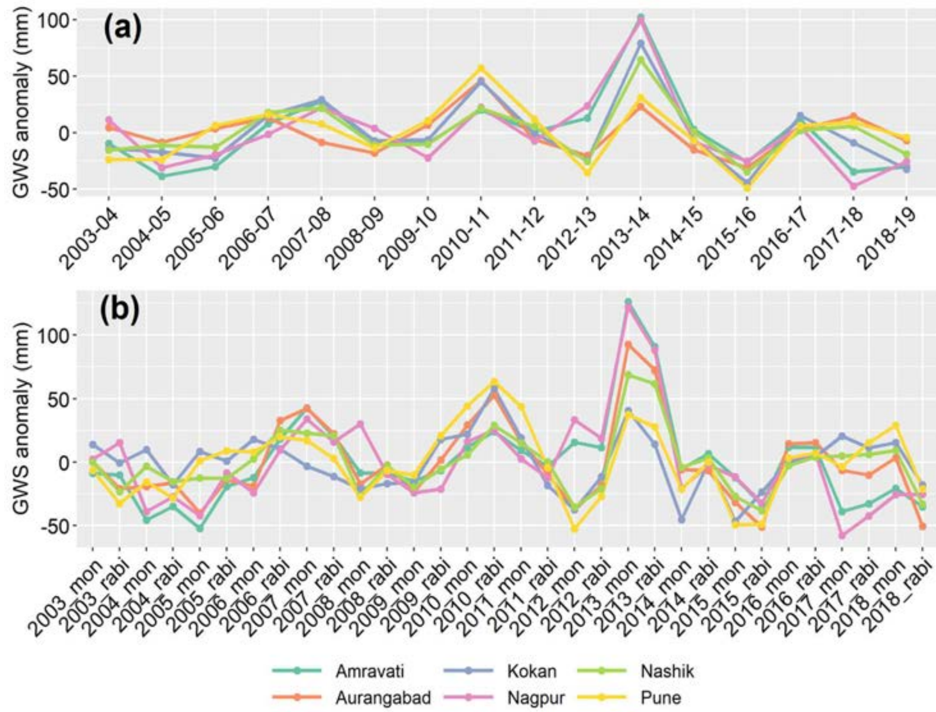

Figure 2.16: Time series of (a) annual GWS anomaly and (b) GWS anomaly in Kharif and Rabi seasons (Kharif: June-September, Rabi: October-May) from 2003-04 to 2018-19 in each division.

2.3.5. Irrigation infrastructure, CA, CP, and LA variability

2.3.5.1. Irrigation infrastructure and water availability

Ancillary irrigation data, obtained from the GMIA by FAO shows that the western regions of the Maharashtra state, consisting of Pune and Nashik divisions, show a comparatively higher percentage of area equipped for irrigation (AEI) (19% and 16% of GA, respectively) than the rest of Maharashtra (**Figure 2.17**(a)). Availability of assured water resources in the form of better irrigation facilities reduces the sole dependency on rainfall and improves the agriculture production, which is well reflected in the greening over these two divisions, which accounts for nearly 59% of total NCLA (**Table 2.3**). Although the irrigation coverage of the Kokan division is the least in the state (~3%), the overall water availability is very high (**Table 2.8**) pertaining to the abundant rainfall from the southwest monsoon. For Aurangabad and Amravati divisions, where the percentage of AEI is very low (14% and 5%, respectively), the dependency on GWS for irrigation is very high as more than 90% of the area is irrigated by groundwater in several districts (**Figure 2.17**(b)). These two divisions are very vulnerable to droughts as the water availability is well below 3000 m^3 ha^{-1}, making it a water-deficit region (Government of Maharashtra, 2013, **Table 2.8**). The north-eastern parts of the Nagpur division are mainly irrigated through surface water irrigation (AEI~20%), while the western part (Nagpur and Wardha district, AEI 13% and 9%, respectively) is dependent on GW for irrigation (70-89%) (**Figure 2.17**). However, the declining trends in GW levels in this region (**Figure 2.14**) underscore the inefficient functioning of the available surface water irrigation systems and increased dependency on groundwater.

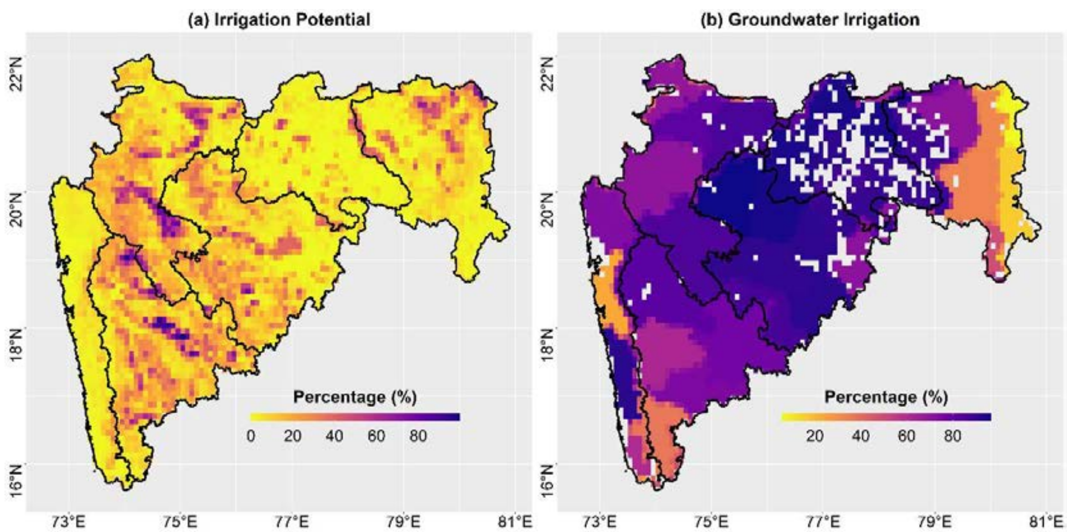

Figure 2.17: Irrigation data obtained from GMIA-FAO. (a) Area equipped for irrigation as a percentage of the total area of the cell (AEI) showing irrigation potential, and (b) Area irrigated by groundwater (AEI_GW) expressed as a percentage of AEI (white colored area represents No-data pixels). AEI includes both surface and GW irrigation where water extracted from wells, tube-wells, boreholes, or springs is considered as groundwater, and water extracted from rivers, reservoirs, lakes, streams, dams, canals, ponds, or tanks is considered as surface water.

Table 2.8: Water availability per capita and per hectare in subdivisions of Maharashtra state (CCA-Culturable Command Area). Data is compiled from the Kelkar committee's report on balanced regional development issues in Maharashtra (Government of Maharashtra, 2013). Water availability is estimated based on inter-state awards on water sharing of major river basins and natural water availability.

Division and state	Water availability per ha of CCA (m^3ha^{-1})	Water availability per capita (m^3)	Percentage of non-irrigation water use (%)	Category of water availability
Amravati	1974	624	8	Deficit
Aurangabad	1383	438	10	Deficit
Kokan	36507	2283	80	Very high
Nagpur	5818	1331	18	Abundant
Nashik	3695	734	22	Normal
Pune	3531	686	15	Normal
Maharashtra state	5587	1121	21.5	Normal

2.3.5.2. Annual CA and CP

The annual CP of primary crops in the state increased by 135% during 2003-2004 to 2018-19 with a marginal increase of about 2.5% in CA, whereas the crop productivity increased by 129.6% (**Table 2.9**). The fertilizer use increased by 89% from 2003-04 ($32.42x10^5$ MT) to 2016-17 ($61.2x10^5$ MT) with annual variations depending on the corresponding CA (http://krishi.maharashtra.gov.in/1039/General-information). The total annual CP is strongly correlated (r = 0.78) with the fertilizer application (**Figure 2.18**). Some deriving factors for the increase in the overall CP across the state can be the adoption of better-quality seeds, increased use of fertilizers, and increased cropping intensity. Our observations about cropping intensity are consistent with results reported by Ray & Foley, (2013), where the cropland harvest frequency, represented as the ratio of annually harvested cropland to the total standing cropland, showed a significant increase in India from 1.08 to 1.21 harvests per year during 2000 to 2011. The cropping intensity, represented as the percentage of gross cropped area to net sown area in the study region, increased from 126.19 in 2000-01 to 137.34 in 2018-19, which further ascertains the increased frequency of cropping in the region (Economic Survey Reports of Maharashtra, https://mahades.maharashtra.gov.in/publications.do?pubId=ESM).

Table 2.9: Percentage of relative change in CA (ΔCA), CP (ΔCP) and productivity (ΔProductivity) of Kharif, Rabi, sugarcane, and cotton and change in total annual CA, CP, and productivity (including Kharif, Rabi, sugarcane, and cotton) from 2003-04 to 2018-19. (Estimated from annual agriculture statistic reports, http://krishi.maharashtra.gov.in/1238/District-Level. Kharif and Rabi crops include food-grains, cereals, pulses, and oilseeds).

Division	Kharif			Rabi			Sugarcane			Cotton			Total		
	ΔCA	**ΔCP**	**ΔProductivity**	**ΔCA**	**ΔCP**	**ΔProductivity**	**ΔCA**	**ΔCP**	**ΔProductivity**	**ΔCA**	**ΔCP**	**ΔProductivity**	**ΔCA**	**ΔCP**	**ΔProductivity**
Amravati	-12.52	-12.56	-0.04	127.43	152.45	11.00	-58.61	-61.07	-5.93	-7.42	90.80	106.10	3.10	0.52	-2.50
Aurangabad	-11.92	-29.24	-19.67	-35.39	-3.73	48.99	183.71	170.52	-4.65	79.16	88.69	5.32	-10.25	68.32	87.54
Kokan	-15.61	-18.83	-3.81	-26.72	-38.72	-16.37	0	0	0	0	0	0	-16.57	-19.67	-3.71
Nagpur	-11.95	14.07	29.54	18.86	143.16	104.58	125.47	153.90	12.61	129.82	299.75	73.94	5.00	45.13	38.23
Nashik	-7.69	15.57	25.20	33.95	114.42	60.07	142.17	352.20	86.73	103.37	98.94	-2.18	17.07	186.67	144.87
Pune	12.51	22.74	9.10	1.12	132.48	129.91	170.57	270.18	36.81	-85.52	-89.84	-88.07	13.77	235.75	195.12
Maharashtra	-9.05	-4.62	4.87	1.11	75.09	73.15	162.79	249.73	33.09	52.72	114.06	40.16	2.46	135.26	129.61

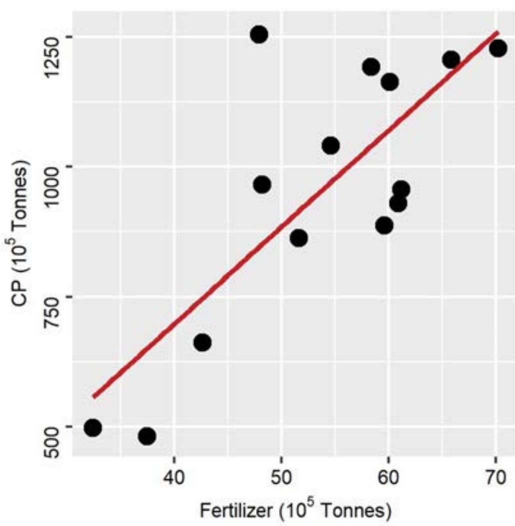

Figure 2.18: A scatterplot showing correlation between CP and fertilizer use in the state during 2003-04 to 2016-17 (r=0.78).

2.3.5.3. Greening in Western Maharashtra

The Pune division dominated the annual CP of the state, sharing approximately 49% of the total CP with average annual productivity of 8332 kg ha^{-1} primarily attributed to the high production of sugarcane (89% of total CP of the division, **Table 2.10**), whose production increased by 270% during the study period (**Table 2.9**). All the divisions showed a decrease in CA in the Kharif season except for the Pune division, which also showed a maximum increase in total annual production (**Table 2.9**). Similarly, the annual CP of Nashik division also increased, mainly attributed to sugarcane, which shares more than 60% of the total annual CP of the division (**Table 2.9**, **Table 2.10**). About 64% of the total annual production of sugarcane in the state comes from Pune division and 17% from Nashik division, which together has about 74% of the state's CA under sugarcane, of which 70.5% is well equipped for irrigation (Government of India, 2018). Not only sugarcane but Kharif and Rabi production of both divisions also showed a significant increase during the period of analysis (**Table 2.9**). Better irrigation coverage, availability of water, and increase in harvested area, CP, and productivity can be the synergetic reasons behind the high greening trend in croplands and NCLA in western Maharashtra (**Figure 2.3**, **Figure 2.17**, **Table 2.8**, and **Table 2.9**).

Table 2.10: Percentage of average contribution of each crop type in total annual CP during 2003-04 to 2018-19.

Division	Food-grains (%)	Cereals (%)	Pulses (%)	Oilseeds (%)	Sugarcane (%)	Cotton (%)
Amaravati	28.76	13.74	15.03	24.66	12.10	5.71
Aurangabad	15.41	11.04	4.37	5.86	61.59	1.74
Kokan	49.25	48.20	1.05	0.42	1.08	0
Nagpur	36.83	30.03	6.80	12.75	11.00	2.59
Nashik	16.62	14.60	2.02	1.73	63.73	1.30
Pune	4.80	4.40	0.40	1.19	89.21	0
Total Maharashtra	12.78	10.25	2.53	3.90	69.54	0.99

2.3.5.4. Greening-Browning in Central and Eastern Maharashtra

There are prominent browning clusters in croplands in the southern parts of Aurangabad division and Nashik division (**Figure 2.3**(a)), which are primarily irrigated through groundwater (**Figure 2.17**(b)). However, the magnitude of browning in Aurangabad division is high, particularly for the Latur district, resulting in a loss of LA during 2003-2019 (**Figure 2.5**(b)). The unpredictability and unreliability of assured water supply through public irrigation schemes (canals, reservoir storage, etc.) in these divisions have forced farmers to search for and over-rely on the sources of water on their own (e.g., digging multiple and deeper tube wells for groundwater pumping, direct lifting from reservoirs, lakes, or ponds, etc.), which puts excess pressure on the available GW resources leading to its overexploitation. Despite an increased area under sugarcane in the Aurangabad division, the increase in production is not very high compared to Pune and Nashik divisions (**Table 2.9**). About 98% of the total significant trend in LAI in the Aurangabad division is mainly because of croplands (**Figure 2.4**). Although the NCLA is still positive in Aurangabad division (except in Latur district), its contribution to the total NCLA of the state (**Table 2.3**) is limited (11.5%) because of significant browning hotspots (**Figure 2.3**(a)). The huge impacts of droughts in Aurangabad division are mainly associated with the poor strategic planning and administrative management of available water resources in the division (Government of Maharashtra, 2013; Kulkarni et al., 2016; Udmale et al., 2014), which has set off the browning trend in LAI with a reduction in LA. The variability in monsoon rainfall makes this division highly vulnerable to droughts and has huge impact on the CP (Kulkarni et al., 2016; Kulkarni & Gedam, 2018). For example, the drought of 2015 (**Figure 2.11**) caused more than 50% of CP loss compared to the average CP of the division and water scarcity, where even the drinking water had to be supplied to Latur district through trains (PTI, 2016).

The Amravati division showed an increase in Rabi and cotton production while a decrease in Kharif and sugarcane production during 2003-04 to 2018-19 (**Table 2.9**). Although the total CP in Kharif in Amravati division decreased, division level analysis showed a substantial increase in CA and CP of oilseeds (increase of 194% in area and 160% in production). About 96% of the total trend in LAI in the division is because of croplands (**Figure 2.4**), where the NCLA is highest in the monsoon season (**Table 2.5**). The magnitude of change of CP for Amravati division, however, is far below compared to western Maharashtra (**Table 2.9**), which is relatively better equipped with irrigation, whereas NCLA is still comparable with the Nashik division (**Table 2.3**). However, there are no significant browning hotspots in the Amravati division considering the insufficient irrigation coverage and constraints on natural water availability (water deficit region, **Table 2.8**). De-centralized and scattered shifting to a more suitable cropping pattern for natural water availability and partial reduction in high water-consuming crops like sugarcane might have helped Amravati division to gain LA. Similarly, Nagpur division also showed an increase in annual CP attributed mainly to Rabi cropping (**Table 2.9**), where NCLA in the division was highest in the postmonsoon season (**Table 2.5**), observed mainly in croplands (**Figure 2.7**(b)).

2.3.6. Drought management and leaf area variability

Unequal natural water availability and difference in the irrigation provisions between western, and central and eastern regions of the Maharashtra state primarily made distinction in the capacities of farmers to advance their agricultural practices, which resulted in greater degree of greening in the western regions compared to rest of the state. Central regions of Maharashtra are particularly highly vulnerable to droughts and predominantly depend on groundwater storage for irrigation. Precipitation and groundwater storage, which are primary drivers of leaf area variability in the state, are also responsible for shaping the regional drought characteristics. Measures like groundwater quantification and rationing, groundwater development and replenishment, crop patterns parallel to water availability of the region, protective irrigation to avoid effects of abnormal rain conditions, watershed development and improved irrigation facilities are few of the measures to improve the water efficiency and reduce the effects of droughts in the region. Furthermore, in view of complex drought management framework in India as explained in chapter one, when studying drought features of regions like Maharashtra, it becomes impractical and non-viable to ignore the role of groundwater storage variability in analyzing regional drought characteristics, considering the role of groundwater in leaf area variability, especially in agriculture. Additionally, the socioeconomic security of farmers depends on the multiple scenarios of climatic uncertainties hampering agriculture sector, which are further aggravated by market fluctuations and shortcomings of policy interventions (discussed in detail in chapter four). Due to this, it is necessary to address the unpredictability and consequences of trends and variability in the vegetation drivers and create drought management systems that comprehensively take into account these vegetation factors.

2.4. Conclusion

In this chapter, the trend analysis on the Leaf Area Index (LAI) and quantification of Net Change in Leaf Area (NCLA) in the drought-prone Maharashtra state of India was carried out for a period of 16 years from June 2003 to May 2019. Here, the Mann-Kendall (MK) trend test was used to investigate the influence of the climatic (e.g., precipitation) and anthropogenic (e.g., agriculture water use) factors on the vegetation response and the greening (increase in LA) clusters and browning (decrease in LA) hotspots were further identified. In addition, the spatiotemporal variability in LA as a consequence of the trends and variations in precipitation and GWS was also discussed along with the statistical data of irrigation and agriculture. Major findings of this chapter are summarized below:

1. Land use for agriculture primarily caused greening as well as browning trends (>70%) in LAI where the state was found to be greening at a rate of approximately 91 km^2 per month during the period of analysis.

2. Increased crop productivity and cropping intensity, better quality seeds and increased use of fertilizers, access to irrigation, and water availability (both precipitation and groundwater) helped in greening the state. In contrast, poor irrigation coverage and frequent droughts were primarily responsible for browning. The difference in the crop productivity between Western (Pune and Nashik) and the rest of Maharashtra highlights the importance of assured water availability for irrigation.
3. Spatial and interannual variations in the precipitation and GWS are the primary drivers of the LA variability in Maharashtra. Their seasonal variations play a dominant part than their long-term trends, affecting the crop productions, LA variability, and consecutively the socioeconomic status of farmers.
4. There is an urgent need of reconfiguring drought management system in India, which traditionally rely on the precipitation anomalies for severity analysis, by contemplating the significant role of groundwater storage on the vegetation variability which also influences the regional drought traits.

The results of this chapter may provide a blueprint for the multidimensional studies in other drought-prone regions of India and other developing countries and be valuable in dealing with complicated issues related to policy modifications and increasing trends in the deterioration of the socioeconomic status of the farmers. In view of current drought management system in India which mainly considers meteorological indicator for drought severity analysis, the current chapter provides a crucial insight for significance of other vegetation drivers (such as groundwater storage variability) which plays crucial role in shaping the regional drought characteristics. Additionally, the primary vegetation drivers as explained in this chapter will further be used for developing a novel method for drought severity analysis and will be discussed in detail in the next chapter.

CHAPTER 3
Multivariate drought index for drought classification using primary vegetation drivers

This chapter is published in Bageshree et al., (2022a),

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3. Multivariate drought index for drought classification using primary vegetation drivers

3.1. Background and motivation

Droughts are spatially extensive water extreme events with multidimensional impacts that have incurred a huge cost in related damages in the past century, with multifold devastation in worldwide economies (Guha-Sapir et al., 2021; UNCCD, 2022; Wilhite, 2000). This widespread water scarcity is increasing year by year, pertaining to population growth, agricultural expansion, and growing water demands for energy and industrial sectors, exaggerating the pronounced and multifarious impacts of droughts (Mishra & Singh, 2010). The droughts in specific areas of the world are projected to increase in severity as well as intensity in the near future, subject to climate shifts towards warmer temperatures, decrease in precipitation, and an increase in evapotranspiration (Aadhar & Mishra, 2018; Bloomfield et al., 2019; Dai, 2013). On the backdrop of progressively detrimental effects of climate change, drought assessment, especially in countries such as India, is of paramount importance, considering its exclusively agrarian economy. Despite being a global agriculture powerhouse, about 68% of cropped area in India is highly vulnerable to drought, with 33% being chronically drought-prone (Government of India, 2016), where compounding effects of droughts have caused an immense loss in terms of agriculture failures, food insecurities, widespread distress issues, and even farmer suicides (Bageshree et al., 2022b; Merriott, 2016; Nagaraj et al., 2014; Talule, 2020b, 2021). The societal impacts of droughts are more persistent and prolonged than other natural calamities, which see great migrations, water scarcity, political instabilities, livestock issues, women, and health-related problems, along with intensifying agricultural crises (Iyer, 2021). India has also faced miserable famines owing to droughts in the past century (Mishra et al., 2019). Moreover, unsustainable extraction of groundwater, which is the primary source of irrigation in India, is expected to further magnify the agricultural stress under the threat of climate change, disturbing the routine agricultural activities to a great extent (Asoka & Mishra, 2020; Bageshree et al., 2022b; Rodell et al., 2009). Considering these profound social, economic, and hydro-climatological impacts of the droughts on multiple aspects of life, comprehensive and efficient drought monitoring, and mitigation, along with a subsequent assessment of drought severity, is imperative to maintain the socioeconomic security in India.

Unfortunately, a comprehensive universal definition of drought is difficult to formulate, considering its diverse range of drivers and impacts. This has led to the classification of drought in multiple domains (meteorological, agricultural, hydrological, groundwater, social, etc. (Aghakouchak et al., 2015)), hindering the inclusion of the integrated effect of various critical parameters and thorough determination of drought characteristics (such as onset, end, and duration) using a single indicator. The conventional approach of drought quantification is mainly dependent on ground-based hydro-meteorological data. Multiple indices have been developed to date for drought monitoring, including traditional ones, such as Palmer Drought Severity Index (Palmer, 2010), Standardized Precipitation Index (SPI; Mckee et al., 1993), Standardized Precipitation, Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010), and remote-sensing-based indices, such as Normalized Difference Vegetation Index (NDVI; Burgan et al., 1996; Kogan, 1990), Vegetation Health Index (VHI; Kogan, 1995), Vegetation Condition Index (VCI; Kogan & Sullivan, 1993), Evaporative Stress Index (ESI; Anderson et al., 2007, 2011), and many more (WMO, 2016). The accuracy of these traditional approaches is mainly constrained by the data gaps, inadequate monitoring network, and data unavailability in required spatiotemporal scales. Remote-sensing-based indices, on the other hand, provide fine-resolution, near real-time, and consistent data observations, which are advantageous over traditional methods and provide unique drought monitoring opportunities (Aghakouchak et al., 2015). However, all these indices rely on a single surface or subsurface water storage and vegetation character irrespective of the combined effect from other hydro-climatological parameters, thus failing to capture the integrated water deficit effect, which may have a further intensifying effect on the overall drought situation. Amid these challenges in drought analysis, researchers recently have also focused on integrating the information from multiple hydroclimatic variables to optimize the drought monitoring efforts to provide a more robust method to capture diverse vegetation responses across the ecosystems (Aghakouchak et al., 2015; Mishra & Singh, 2010; Wardlow et al., 2017). For example, the Vegetation Drought Response Index (VegDRI; Brown et al., 2008; Tadesse et al., 2005) integrates climate (precipitation) and satellite-based observations (NDVI), along with biophysical information, whereas Microwave Integrated Drought Index (MIDI; Zhang & Jia, 2013) integrates precipitation, soil moisture, and surface temperature. Similarly, Multivariate Standardized Drought Index (MSDI; Hao & Aghakouchak, 2014) integrates precipitation and soil moisture information, while the Combined Drought Indicator (CDI) (Sepulcre-Canto et al., 2012) combines SPI and anomalies of soil moisture and fraction of Absorbed Photosynthetically Active Radiation (fAPAR). Due to complex physical interconnections between natural energy fluxes, a single indicator may not satisfactorily define the drought characteristics, highlighting the importance of multivariate drought analysis.

As explained in chapter one, drought monitoring in India is implemented using a drought manual (Government of India, 2016) developed by the Ministry of Agriculture and Farmers Welfare, which deals with multiple individual indices (e.g., precipitation anomalies, NDVI/VCI, crop area anomalies, hydrological indices, such as streamflow and reservoir storage, etc.) to set the thresholds/triggers to initiate the government relief measures. Pertaining to the complexities involved in the declaration of drought using these triggers, the process is challenging for the state governments, where discrepancy has often been observed in the declaration and the on-ground situations of droughts (Bhardwaj & Mishra, 2021; Gupta et al., 2011). These inherent ambiguities and inconsistencies in the drought conditions by different indices make the judgment very strenuous and intricate, where the final decision regarding the drought status is subjective to the assumptions of local authorities responsible for analyzing the drought. In addition, the identification and characterization of droughts become even more complex in the region of groundwater overexploitation, which, unlike surface water, is not commonly visible (Abhishek & Kinouchi, 2022). While discussion in chapter two of present thesis along with numerous other studies have indicated the unsustainable groundwater use leading to its depletion and its impact on magnifying drought conditions in India (Asoka et al., 2017; Bageshree et al., 2022b; Dangar et al., 2021; Mishra & Asoka, 2011; Panda & Wahr, 2016; Rodell et al., 2009), due to the lack of continuous spatiotemporal groundwater data, it has often been ignored in the drought assessment, monitoring, and declaration, despite heavy dependence of agriculture on groundwater for irrigation. Recently, the development of global land surface models has made the continuous gridded datasets of hydroclimatic variables easily and freely available, which can be used for data-sparse regions (Rodell et al., 2004). This avoids the simulation of complex hydrological models for data inputs, as postprocessed satellite observations are proven useful in drought characterization, especially with the help of Gravity Recovery and Climate Experiment (Girotto et al., 2017; Shah & Mishra, 2020). Monitoring droughts using these variables is a reliable alternative to the in situ measurements, especially for groundwater drought (Li et al., 2020; Li et al., 2019; Li & Rodell, 2015; Rodell et al., 2004; Wardlow et al., 2017).

In this chapter, a novel multivariate drought index is developed considering multi-dimensional hydro-climatological drought propagation, and the applicability of the developed index is studied for the spatiotemporal drought characterization in the highly drought-prone Marathwada region (Aurangabad division) of central India which was subject to browning trend in vegetation as discussed in chapter two. Here, two approaches were used for the construction of the joint index which are principal component analysis (PCA) and copula. With a goal of reducing the complexity involved in the current drought monitoring methods of India and to efficiently analyze the interdependence of hydroclimatic variables in drought classification, the specific objectives of this study are

(i) development of a multivariate Joint Drought Index (JDI) incorporating meteorological (SPEI), agricultural (SSI), groundwater (SGI), and hydrological (SRI) conditions,
(ii) to define onset, termination, and duration of drought, and
(iii) spatiotemporal analysis of drought severity.

Here, the relevance of land surface model (LSM) outputs for the development of multivariate drought index, which is unexplored so far, especially for tropical semiarid regions, was also validated.

3.2. Materials and Methods

3.2.1. Data

The data related to the hydro-climatological variables used in this study was first obtained from various sources and then the standardized index of each variable was formed. These indices were then integrated into the joint drought index (JDI), which was further compared with the seasonal crop production. A schematic of these data sources and methods employed in this study is illustrated in **Figure 3.1** and discussed in detail in the following sections.

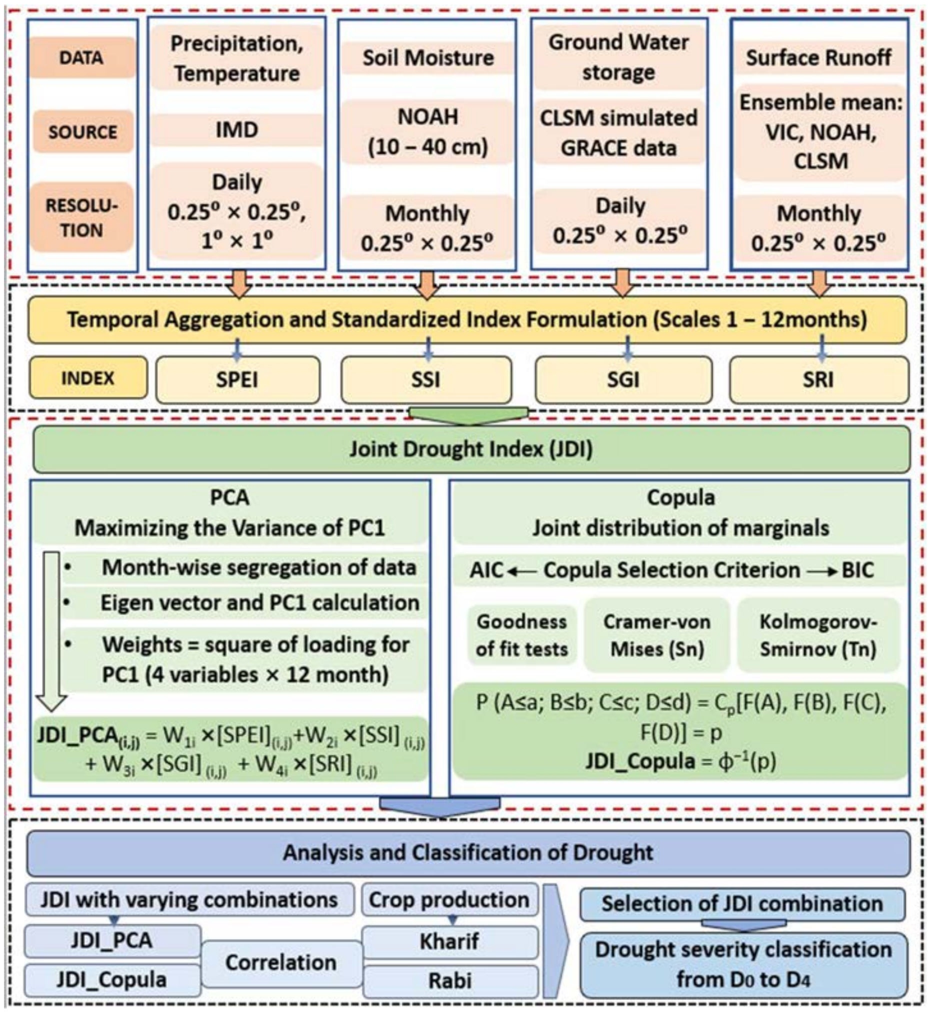

Figure 3.1: A schematic diagram depicting the methodology, various data sources, and the analyses conducted in this study. JDI_PCA and JDI_Copula represent the joint drought index derived from the PCA and Gaussian copula methods. Please refer to Section 3.2 for the abbreviation related to various data sources and the drought indices.

3.2.1.1. Precipitation and Temperature

The effect of temperature and resulting evapotranspiration in drought propagation is highly important in arid climates, which is not contemplated in the commonly used Standardized Precipitation Index (SPI) (Mckee et al., 1993). To account for this, the Standardized Precipitation Evaporation Index (SPEI) was used in constructing the JDI, which comprehends the changes in the evaporative demand of plants caused by temperature fluctuations (Vicente-Serrano et al., 2010; Wardlow et al., 2017). SPEI is a multi-scalar index based on climatic water balance, having similar properties as SPI but also incorporating temperature data to define drought characteristics.

Daily gridded precipitation data of 0.25° (Pai et al., 2014) were obtained from the India Meteorological Department (IMD, https://www.imdpune.gov.in/), which uses Inverse Distance Weighted Interpolation scheme proposed by Shepard (D. S. Shepard, 1984) on a dense network of 6955-gauge stations. The climatological variations in the precipitation, especially in the leeward side of the Western Ghats of the central west coast of India, are more realistic in IMD data than other existing datasets (Pai et al., 2014). The $1° \times 1°$ minimum and maximum temperature data of 30 years, from 1990 to 2020, were also retrieved from IMD, which was developed by using the modified version of Shepard's angular distance weighting algorithm (Shepard, 1968) to interpolate 395 quality-controlled stations' temperature data. This dataset was then re-gridded to 0.25° using bilinear interpolation to make it spatially consistent with other datasets.

3.2.1.2. Soil Moisture

Soil moisture (SM) mainly drives the drought-induced vegetation stress, where plants reduce transpiration to conserve water as a result of depletion in available soil moisture towards the wilting point (Moran, 2004; Wardlow et al., 2017). The Global Land Data Assimilation System (GLDAS) SM data products are found to be potentially efficient and reliable in capturing the temporal variations in the SM characteristics (Bi et al., 2016; Mishra et al., 2018; Zhang et al., 2021). Moreover, in India, the GLDAS SM data products generally follow the characteristics of monsoon rainfall, and the general features and variations in the datasets broadly match with the spatiotemporal variations in the rainfall and, therefore, have been used in several regional studies (Mishra et al., 2014, 2018; Rodell et al., 2004; Sathyanadh et al., 2016). Despite varying definitions of soil layers in different GLDAS models (VIC, NOAH, and CLSM), we found a strong correlation ($r > 0.9$) between their SM retrievals.

Although the depth/thickness required for proper representation of soil moisture content for agricultural droughts is still under exploration (Arora & Boer, 2003; Qiu et al., 2014, 2016), we considered the layer between 10 and 40 cm below ground level by NOAH, which will better represent the soil moisture conditions due to ancillary sources, such as local rainfall or irrigation, avoiding quick saturation of upper layers and lags in the lower layers. Thus, to incorporate the soil moisture drought in JDI, 0.25°, monthly standardized soil moisture drought index (SSI) was constructed from 2000 to 2020, using the method proposed by Mckee et al., (1993), which is also preferred by many researchers to study SM drought (Hao & AghaKouchak, 2013; Hao & Singh, 2015; Hu et al., 2021; Kulkarni et al., 2020; Ma et al., 2014; Shah & Mishra, 2020).

3.2.1.3. Groundwater Storage

As discussed in chapter two, more than 90% of the irrigation in central parts of India is through groundwater (Bageshree et al., 2022b), making its availability crucial for agricultural activities, while little attention is given to its management and inclusion in the regional drought analysis. Groundwater droughts often take time to reflect after the meteorological drought is manifested due to inherent complexities in the aquifer response and may persist for a longer period (Balacco et al., 2022). Effects are exacerbated due to high water demand and excessive use of available resources, especially in the case of droughts, which negatively offsets the availability of water for vegetation growth. Thus, groundwater potentially shapes the regional drought conditions.

GLDAS provides 0.25° gridded groundwater storage (GWS) data products by assimilating the terrestrial water anomaly observations from Gravity Recovery and Climate Experiment (GRACE) via simulating the Catchment Land Surface Model (CLSM) (Li et al., 2020; Li et al., 2019). The GLDAS groundwater storage data have been commonly used by researchers to study drought in regional, arid, or small-scale areas (Li & Rodell, 2015; Ouma et al., 2015; Wang et al., 2020). The advantage of GLDAS groundwater storage data is that they do not require any pre- or postprocessing to obtain the GWS and are temporally consistent (without data gaps) with comparatively finer resolution. Thus, 0.25° gridded daily GWS data were obtained from GLDAS version 2.2 from 2003 to 2020 and were further aggregated into monthly time series to construct the standardized groundwater index (SGI; Hao & Singh, 2015; Mckee et al., 1993; Shah & Mishra, 2020).

3.2.1.4. Surface Runoff

For holistic assessment of drought characteristics, surface runoff is an important indicator suggested in the drought manual of India for planning and mitigation (Government of India, 2016), bearing direct impacts of the hydrological anomalies. The issue of data availability for such critical variables is potentially solved by global-scale terrestrial models, such as GLDAS, where the uncertainties in the runoff estimates can be greatly reduced by the ensemble mean of surface runoffs from different models in the suite (Bai et al., 2016; Qi et al., 2020).

The 0.25° monthly surface runoff data were obtained from three models of GLDAS: VIC, NOAH, and CLSM between 2000 and 2020, and their ensemble mean was used to construct the monthly standardized runoff index (SRI; Hao & Singh, 2015; Mckee et al., 1993; Shah & Mishra, 2020).

3.2.1.5. Crop Production

Agriculture bears the direct brunt of droughts with immediate impacts adversely affecting the crop yield. Consequently, crop losses and limited productivity are often observed in drought situations (Panu & Sharma, 2002). We used seasonal crop production data (food-grains, cereals, pulses, and oilseeds) in the Kharif and Rabi seasons as an indicator against which the accuracy of the developed integrated index JDI was verified. Statistical data related to crop production (CP) were obtained from the Economic Survey Department, Government of Maharashtra (https://mahades.maharashtra.gov.in/) and the Department of Agriculture and Cooperation (http://krishi.maharashtra.gov.in/).

3.2.1.6. Administrative Boundaries

Data related to state- and district-level administrative boundaries were obtained from the latest version (3.6) of the Database of Global Administrative Areas (GADM, https://gadm.org/).

In view of the minimal influence of reservoir operations in the region during droughts and considering the high dependency on groundwater, the effect of irrigation and reservoir storage was not considered in the analysis.

3.2.2. Methodology

3.2.2.1. Principal Component Analysis (JDI_PCA)

Principal component analysis (PCA) is widely used to describe the dominant patterns in the observational data (Hao & Singh, 2015; Hidalgo et al., 2000; Keyantash & Dracup, 2004; Kulkarni et al., 2020). Using linear combinations of the variables, new orthogonal (independent to each other) variables, i.e., PCs, can be constructed without losing much information from each variable. In this study, the Joint Drought Index (JDI) was constructed by extracting the essential hydrologic information from each variable integrated in the JDI in the form of PC1, i.e., first principal component (Maity, 2018). In PCA, the PCs are determined such that the variance of any i^{th} PC is maximum and sum of the square of loadings is unity (eigenvectors) (Maity, 2018). The square of loadings can serve as the percentage contribution by each variable in the joint index, which were thus estimated with the help of the eigenvector. This contribution was represented in the form of weights. This process was followed for each month separately and the weights of four variables (SPEI, SSI, SGI, and SRI) for 12 months were estimated (total 48) (Keyantash & Dracup, 2004; Kulkarni et al., 2020). The JDI using PCA for i^{th} month and j^{th} year is represented by $JDI\_PCA_{(i,j)}$, where:

$$JDI\_PCA_{(i,j)} = W_{1i} \times [SPEI]_{(i,j)} + W_{2i} \times [SSI]_{(i,j)} + W_{3i} \times [SGI]_{(i,j)} + W_{4i} \times [SRI]_{(i,j)} \quad (3.1)$$

For each grid point, W_{1i}, W_{2i}, W_{3i}, and W_{4i} are the weights for i^{th} month (i = 1 to 12) for SPEI, SSI, SGI, and SRI, respectively, which are multiplied by the respective index for i^{th} month and j^{th} year. Moreover, to account for the different response time of each variable to the existing hydro-climatological conditions, we executed a new approach of integrating these indices in JDI, which involves using various combinations of the involved indices, which may have different temporal scales. The combination of the variables having a maximum correlation with the seasonal crop yield is then selected for further analysis (further discussed in Section 3.2.2.3).

3.2.2.2. Copula (JDI_Copula)

Copulas are often used to derive the joint distribution of multiple variables using their one-dimensional marginal distribution (Hao & Aghakouchak, 2014; Hao & Singh, 2015; Kavianpour et al., 2018; Nelson, 2006). Copulas are efficient in modeling the general dependence between multivariate data (Ayantobo et al., 2019; Kao & Govindaraju, 2008, 2010; Song & Singh, 2010), where, out of copula families, meta-elliptical copulas (Gaussian and Student-*t*) are found to be a better fit for modeling joint distribution of more than two variables (Kao & Govindaraju, 2008; Ma et al., 2014). Assuming SPEI, SSI, SGI, and SRI as random variables, Gaussian copula was used to find the joint distribution of multivariate drought index. Using Sklar's theorem (Sklar,

$$P\,(A \le a;\, B \le b;\, C \le c;\, D \le d) = C_p[F(A), F(B), F(C), F(D)] = p \tag{3.2}$$

1959), if p is the joint cumulative probability of random variables, A, B, C, and D, then there exists a copula C_p, such that:

where, F(A), F(B), F(C), and F(D) are marginal cumulative distribution functions of the random variables, i.e., SPEI, SSI, SGI, and SRI in this study. The inverse of the joint cumulative probability p will give the joint drought index JDI represented as JDI_Copula, which can be written as:

$$\text{JDI\_Copula} = \varphi^{-1}(p) \tag{3.3}$$

where φ is the standard normal distribution function. The detailed interpretations of the copulas can be found in Hao & AghaKouchak (2013), and Nelson (2006). The classical penalized criterion based on log-likelihood, viz., Akaike and Bayesian information criterion (AIC and BIC), which discourages the overfitting, was used to select the appropriate copula from various copula families (e.g., Gaussian, t-copula, Joe, Clayton, and Gumbel) (Delignette-Muller & Dutang, 2015). AIC and BIC are common methods to measure the fitting biases in copulas (Ma & Sun, 2011). Moreover, Cramer–von Mises (Sn) and Kolmogorov–Smirnov (Tn) are two classical goodness-of-fit tests often considered to fit the continuous distributions (Delignette-Muller & Dutang, 2015; Genest et al., 2006). These statistical methods were considered to check the goodness of fit for the proposed cumulative distribution function. For the construction of joint distribution, a copula is acceptable when the *p*-value of the goodness-of-fit tests is greater than 0.05.

3.2.2.3. Integration of the Indices in JDI

Multivariate distributions, in general, are mainly focused on statistical properties of drought indices without concern for physical processes that cause a certain time lag (Hao & Singh, 2015; Minea et al., 2022). In this study, the effect of time lag in response of different variables to climatic conditions (Apurv et al., 2017; Shah & Mishra, 2020; Shukla & Wood, 2008) was incorporated by forming JDI with combinations of these variables with different time scale, ranging from 1 to 12 months (1, 2, 3, 4, 6, and 12 months for SPEI, 1 to 3 months for SSI, and 1 to 4 months for SRI and SGI). In total, 288 unique combinations of these indices having different temporal scales were used to generate JDI based on PCA and copula.

Since seasonal crop conditions are directly associated with the prevailing drought conditions, crop production data can presumably be used as an indicator to analyze the accuracy of JDI. Although crop production data can be obtained from multiple sources such as satellite or model based, the temporal resolution of these data products (mainly annual) are quite distant from the objective of this chapter which requires seasonal agriculture output (Kim et al., 2021). Moreover, seasonal crop yield for small regions like Marathwada is difficult to accurately ascertain from satellite data due to local variations in crop conditions and differences in how the seasons are defined along with uncertainty involved in the identification of crop type and cropped area. These factors may prevent proper capture and representation of cropped area and yield in satellite data. Similar limitations are observed in relation with LAI and CP where LA represents number of leaves in the area, while crop yield is the measurement of harvested agriculture production which is directly associated with the drought impacts on regional agriculture. Government crop production data on the other hand is directly obtained from the farmers and is more closely related to the actual field conditions and drought circumstances, which therefore was further used in the analysis. The mean drought intensity of JDI for each season (Kharif and Rabi) was correlated to the standardized crop yield of the respective season to analyze the potential of JDI to capture the drought characteristics. A JDI combination having the highest correlation with the crop yield is assumed to represent the actual drought conditions better than other combinations. We also evaluated the JDI against each integrated index to understand whether the responses of each variable are satisfactorily captured through the integration. The combination giving a highest correlation with the seasonal CP and capturing the optimal response (having the highest correlation with each of its integrated variables) from the integrated variables is then finally selected for the analysis for each season. It is possible that the combination of variables in JDI giving the highest correlation with the seasonal crop yield is different in both seasons. In such a case, different time scale combinations are considered to define JDI and categorize drought in the respective season.

The previous chapter has verified the consistent use of groundwater for irrigation in the Maharashtra state of India, along with its role in vegetation response to hydro-climatological changes (Bageshree et al., 2022b). Soil moisture is another important indicator conveying immediate water stress faced by vegetation due to lack of irrigation. As groundwater storage and provision of irrigation can greatly influence the vegetation conditions in the region as discussed in chapter 2, crop conditions can vary substantially depending on the monthly state of these two variables. Hence, a 1-month scale was set for SSI and SGI in deciding the seasonal combination for JDI, along with varying scales of SPEI and SRI. For better representation and easy comparisons, the scales of variables used in the development of JDI are included in the JDI nomenclature, along with the method used. The numbers include the index name representing the temporal scales of SPEI, SSI, SGI, and SRI in the order of appearance. For example, JDI_PCA_3_1_1_3 represents JDI_PCA using SPEI (3 months), SSI (1 month), SGI (1 month), and SRI (3 months).

Here, the drought classification scheme by Svoboda et al. (2002), based on the percentile approach for magnitude category thresholds, was adopted for JDI classification (**Table 3.1**), which is also preferred by many researchers for related studies (Hao & Aghakouchak, 2014; Mo, 2011; Shah & Mishra, 2020). The possible impacts of droughts which can be observed on agriculture and water resources for different categories of JDI are also explained in the **Table 3.1**. It should however be noted that the impacts of droughts cannot be constrained to certain severity classes and may intermix depending on various factors such as local climatological conditions, stages of crop growth, adopted water management practices in the view of drought onset, previous status of available water resources and soil moisture etc. Crop stress and agriculture failures are instantaneous indicators of impacts on agriculture whereas hydrological effects of drought involving availability of water resources may take time to reflect and even persist for longer period.

Table 3.1: Drought classification categories for JDI and description of possible impacts (but not restricted to) on agriculture and water resources.

JDI	Description	Category	Impact on agriculture	Impact on water resources
−0.50 to −0.79	Abnormally Dry	D0	Slows down farm activity and crop growth, temporary wilting	Increased evapotranspiration, decreased flow
−0.80 to −1.29	Moderate drought	D1	Lowers crop quality, damage to crops, premature wilting	Water shortages for drinking, agriculture, and industries
−1.30 to −1.59	Severe drought	D2	Severe crops losses more likely	Low water storage in reservoirs, groundwater starts depleting, restrictions and regulations on water use
−1.60 to −1.99	Extreme drought	D3	Extreme crop losses, affected food security	Dead storage in reservoirs, drinking water scarcity, strict restrictions
−2.0 or less	Exceptional drought	D4	Widespread crop losses and agriculture failures	Extreme water scarcity, water emergency

3.2.3. Case Study Region

In this study, the semiarid region of Aurangabad division, also known as Marathwada, from central state of Maharashtra in India was considered for the development of the JDI (**Figure 3.2**). Maharashtra is the largest economy state in India, where more than 60% of the state population depends on agriculture and allied businesses (**Figure 3.2**a, Economic Survey Reports of Maharashtra, https://mahades.maharashtra.gov.in/publications.do?pubId=ESM). The region is highly susceptible to drought vulnerabilities and has often seen farmers suicides related to drought and agriculture failures (Bageshree et al., 2022b; Government of Maharashtra, 2013; Talule, 2021). Due to Sahyadri mountain ranges running parallel to the west seacoast, the state is mainly divided into two parts: Western Ghats of Kokan to the west and Deccan plateau to the east. A similar distinction is formed in terms of precipitation, which is highly influenced by the Arabian branch of the monsoon coming perpendicular to the Ghats. Marathwada is located in the leeward side of the Sahyadri and consists of eight districts—Aurangabad, Beed, Latur, Osmanabad, Parbhani, Hingoli, Beed, and Nanded (**Figure 3.2**b), with an area of about 69,899 km^2. The region has a tropical-semiarid climate with four distinct seasons: monsoon (June–September), post-monsoon (October–December), winter (January–February), and summer (March–May). The average annual precipitation of Marathwada is minimum in the state (811 mm), more than 80% of which occurs during four months of monsoon season (**Figure 3.3**).

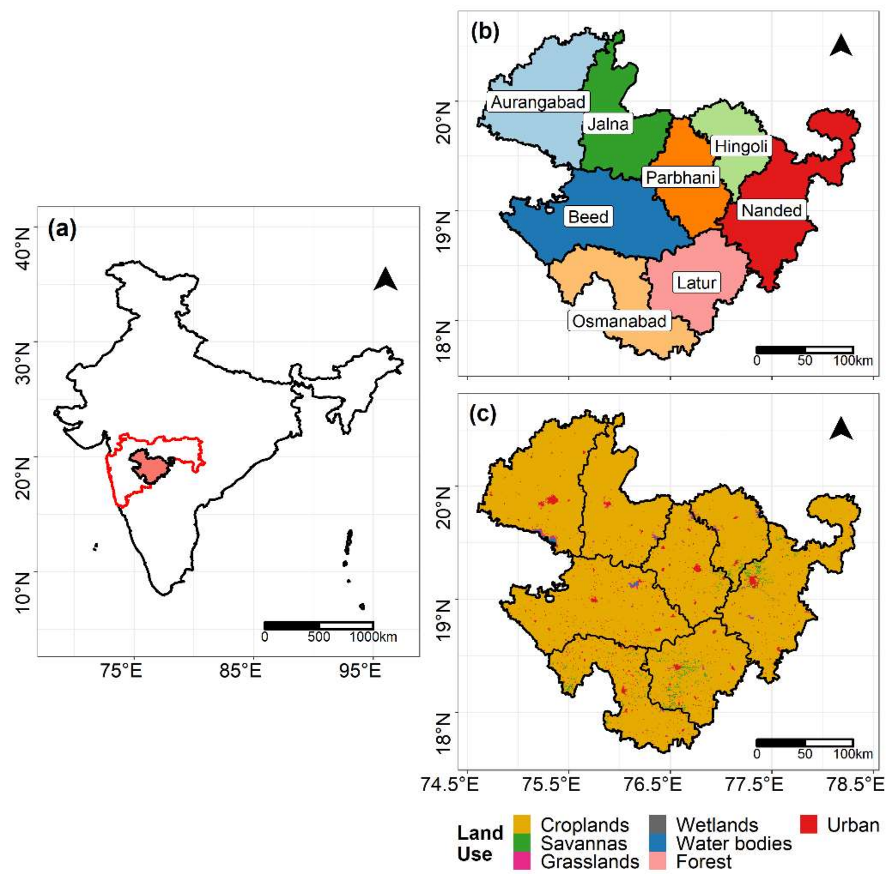

Figure 3.2: (**a**) Location of the study area. Black and red borders represent India and the state of Maharashtra, respectively, while the filled area represents Marathwada region. (**b**) Administrative map of Aurangabad division (Marathwada) with eight districts. (**c**) MODIS land cover product MCD121Q1, International Geosphere-Biosphere Program (IGBP) classification in Marathwada illustrated for the year 2019.

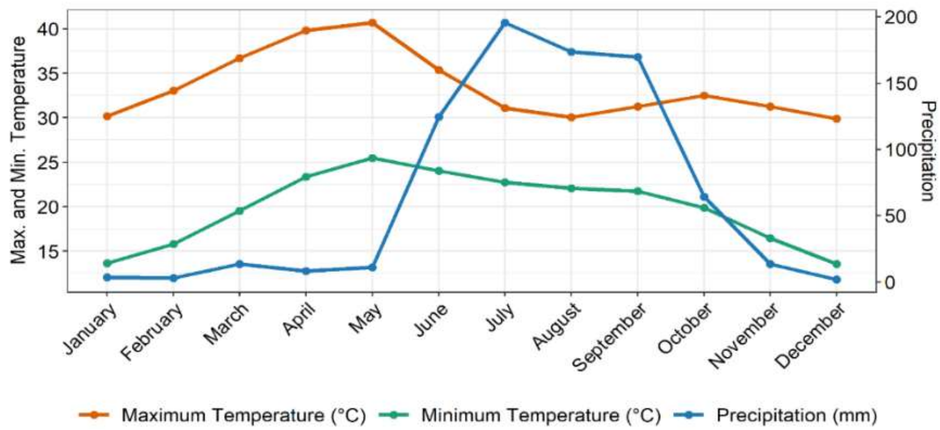

Figure 3.3: Long term (1989-2020) mean monthly precipitation and minimum and maximum temperature in Marathwada.

There are two main agriculture seasons of the region: Kharif (coincides with monsoon season, i.e., June–September) and Rabi (October–March). Monsoon rainfall is crucial for agriculture, as it is mainly rainfed, where post-monsoon rainfall also plays a key role in the Rabi season and aquifer recharge. Out of four months of monsoon season, Marathwada receives the highest rainfall in July, with August and September having similar intensities (**Figure 3.3**). The maximum and minimum monthly temperatures for the region are observed in May (~41 °C) and in December (~13 °C), respectively (**Figure 3.3**). Marathwada is underlain by a hard rock aquifer system, where even minor fluctuations in the monsoon rainfall may exaggerate the prevailing drought conditions (Abhishek & Kinouchi, 2021; Xiong et al., 2022), ultimately hampering the various aspects of the agriculture sector. The land is primarily used for agriculture (**Figure 3.2**c), where food grains, cereals, pulses, and oilseeds are mainly grown. The arid hydro-climatological conditions are similar over the whole region, which is highly vulnerable to water deficit conditions, further aggravated by lack of adequate infrastructure and developmental backlogs (Bageshree et al., 2022b; Government of Maharashtra, 2013), where, during 2003–2020, some or the whole of the region was frequently subject to negative precipitation anomalies (which often leads to different types of droughts) (**Figure 3.4**). Moreover, as investigated in chapter two, the division was subject to browning trend in the vegetation from the periodic droughts, which makes it ideal to validate the effectiveness of the JDI.

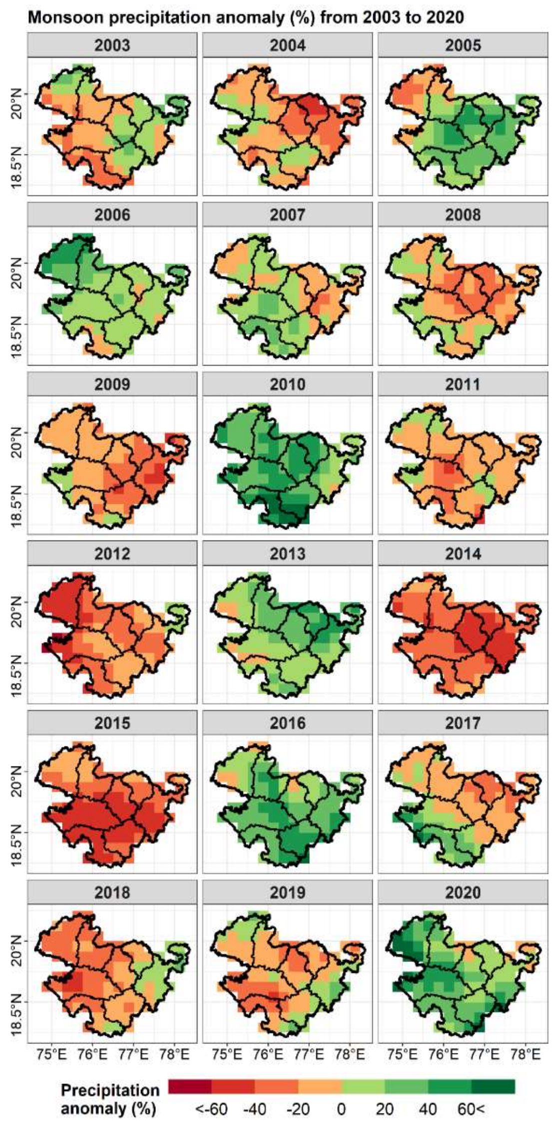

Figure 3.4: Monsoon precipitation anomaly over Marathwada from 2003 to 2020.

3.3. Results

3.3.1. Selected Combination of Indices for JDI

Amidst all the combinations of SPEI, SSI, SGI, and SRI used to construct JDI, the combination of SPEI (3 months), SSI (1 month), SGI (1 month), and SRI (3 months), represented as 3_1_1_3, was best correlated to CP in Kharif season in both methods, i.e., JDI_PCA and JDI_Copula (**Figure 3.5**a,b and **Table 3.2**).

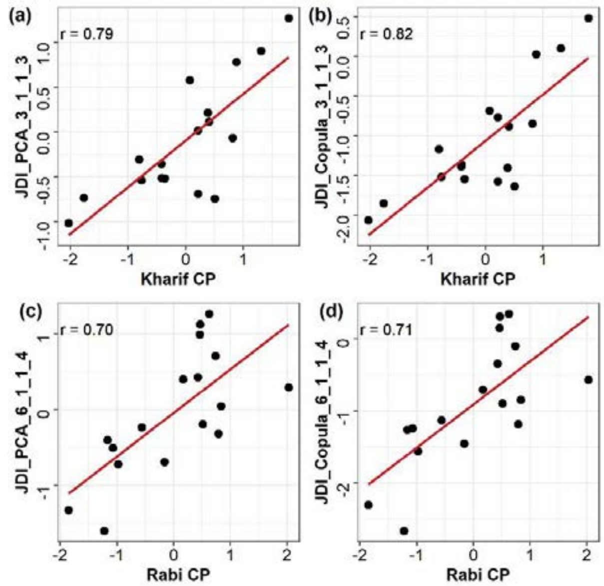

Figure 3.5: Correlation of mean drought intensity by JDI_PCA and JDI_Copula with the seasonal crop production (CP) in (**a**,**b**) Kharif season and in (**c**,**d**) Rabi season. The scales of the integrated indices in JDI_PCA and JDI_Copula in Kharif (3_1_1_3) and in Rabi (6_1_1_4) season are in the order of SPEI, SSI, SGI, and SRI.

Table 3.2: Correlation of mean drought intensities by JDI_PCA and JDI_Copula with standardized crop productions in Kharif and Rabi seasons for different combinations of the integrated indices (First column represents the scales of the indices integrated within JDI in the order as mentioned. For e.g., 3_1_1_1 represents combination of SPEI (3 months), SSI (1 month), SGI (1 month) and SRI (1 month) for construction of JDI).

SPEI_SSI_SGI_SRI	JDI_PCA		JDI_Copula	
	Kharif CP	**Rabi CP**	**Kharif CP**	**Rabi CP**
3_1_1_1	0.80	0.59	0.80	0.54
3_1_1_2	0.79	0.58	0.80	0.56
3_1_1_3	**0.79**	0.59	**0.82**	0.60
3_1_1_4	0.78	0.63	0.80	0.62
4_1_1_1	0.76	0.62	0.77	0.57
4_1_1_2	0.75	0.62	0.78	0.59
4_1_1_3	0.76	0.62	0.80	0.61
4_1_1_4	0.75	0.64	0.78	0.65
6_1_1_1	0.70	0.70	0.71	0.63
6_1_1_2	0.70	0.70	0.73	0.65
6_1_1_3	0.71	0.70	0.75	0.68
6_1_1_4	0.70	**0.70**	0.73	**0.71**
12_1_1_1	0.64	0.71	0.63	0.66
12_1_1_2	0.65	0.72	0.66	0.68
12_1_1_3	0.66	0.71	0.69	0.70
12_1_1_4	0.66	0.72	0.66	0.73

Similarly, in Rabi season, a combination of SPEI (6 months), SSI (1 month), SGI (1 month), and SRI (4 months), represented as 6_1_1_4, had the highest correlation with Rabi CP and could be considered to best represent the corresponding drought conditions (**Figure 3.5**c,d and **Table 3.2**). Furthermore, to evaluate the potential of JDI to incorporate feedback from each integrated variable and to strengthen the choice of the combination, the correlation between the JDIs to each of its four constituent indices was estimated. We found that both JDIs were able to capture the responses from each hydroclimatic variable with strong correlation (**Table 3.3**). Although overall correlations of the integrated variables (SPEI, SSI, SGI, and SRI) with JDIs gave comparable responses (**Table 3.3**), the correlation of larger scale SRI (3–4 months) with JDI is stronger (r~0.8) than the shorter scale (r~0.5 to 0.7) attributable to the increased accumulation period. Among the hydroclimatic variables used in this study, surface runoff was highly correlated with precipitation (r~0.9), while SM and GWS were highly correlated to precipitation with lagging by 1 month (r~0.8) and 2 months (r~0.8), respectively.

Table 3.3: Correlation of JDI_PCA and JDI_Copula with their integrated indices for different combinations.

Index	**JDI_PCA combination (SPEI_SSI_SGI_SRI)**							
	3_1_1_1	**3_1_1_2**	**3_1_1_3**	**3_1_1_4**	**4_1_1_1**	**4_1_1_2**	**4_1_1_3**	**4_1_1_4**
SPEI	0.85	0.86	**0.88**	0.84	0.87	0.87	0.88	0.89
SSI	0.90	0.89	**0.88**	0.90	0.91	0.90	0.90	0.89
SGI	0.77	0.74	**0.74**	0.76	0.79	0.77	0.77	0.77
SRI	0.55	0.74	**0.84**	0.83	0.52	0.70	0.79	0.84
Index	**6_1_1_1**	**6_1_1_2**	**6_1_1_3**	**6_1_1_4**	**12_1_1_1**	**12_1_1_2**	**12_1_1_3**	**12_1_1_4**
SPEI	0.90	0.89	0.90	**0.90**	0.89	0.88	0.88	0.88
SSI	0.92	0.92	0.91	**0.91**	0.90	0.90	0.90	0.89
SGI	0.81	0.80	0.80	**0.80**	0.86	0.85	0.85	0.85
SRI	0.44	0.60	0.73	**0.79**	0.36	0.53	0.66	0.73
Index	**JDI_Copula combination (SPEI_SSI_SGI_SRI)**							
	3_1_1_1	**3_1_1_2**	**3_1_1_3**	**3_1_1_4**	**4_1_1_1**	**4_1_1_2**	**4_1_1_3**	**4_1_1_4**
SPEI	0.79	0.82	**0.83**	0.81	0.80	0.82	0.83	0.84
SSI	0.81	0.82	**0.84**	0.85	0.81	0.83	0.85	0.85
SGI	0.71	0.74	**0.77**	0.78	0.72	0.75	0.77	0.79
SRI	0.68	0.75	**0.80**	0.79	0.67	0.75	0.79	0.81

Index	6_1_1_1	6_1_1_2	6_1_1_3	6_1_1_4	12_1_1_1	12_1_1_2	12_1_1_3	12_1_1_4
SPEI	0.77	0.79	0.83	**0.84**	0.74	0.76	0.79	0.80
SSI	0.81	0.83	0.85	**0.86**	0.81	0.83	0.85	0.85
SGI	0.73	0.76	0.79	**0.80**	0.75	0.78	0.81	0.82
SRI	0.67	0.73	0.77	**0.79**	0.63	0.70	0.74	0.76

3.3.2. JDI Based on PCA (JDI_PCA)

The weight of each parameter used for the selected JDI_PCA for average Marathwada in each season and for each month is provided in **Table 3.4**. Comparing the contribution of each variable, SPEI and SSI were found to be important variables in both seasons, having higher weights, while the weightage for SGI was higher in Rabi season than Kharif season (**Table 3.4**). This can also be seen in the spatial distribution of weight components over the region, associated with the increased use of groundwater in the Rabi season (**Figure 3.6** and **Figure 3.7**). We observed that drought intensity estimated by PCA is, in general, an average of the intensities of the integrated variables. In each season, the average weight allocated by PCA to each index is quite comparable (0.26~0.29) (**Table 3.4**), except for SGI in Kharif and SRI in Rabi, which have lower weights (average of the season, 0.18 and 0.19, respectively) than other variables in respective seasons.

Table 3.4: Weights of indices for JDI_PCA_3_1_1_3 for Kharif and JDI_PCA_6_1_1_4 for Rabi season over Marathwada.

Month	Kharif (June–September)			
	SPEI (3 months)	**SSI (1 month)**	**SGI (1 month)**	**SRI (3 months)**
June	0.27	0.30	0.19	0.23
July	0.29	0.29	0.17	0.25
August	0.29	0.26	0.19	0.26
September	0.29	0.27	0.15	0.29
Month	**Rabi (October–March)**			
	SPEI (6 months)	**SSI (1 month)**	**SGI (1 month)**	**SRI (4 months)**
October	0.29	0.25	0.25	0.21
November	0.28	0.27	0.26	0.19
December	0.27	0.27	0.25	0.21
January	0.28	0.27	0.24	0.21
February	0.27	0.30	0.29	0.13
March	0.28	0.30	0.26	0.16

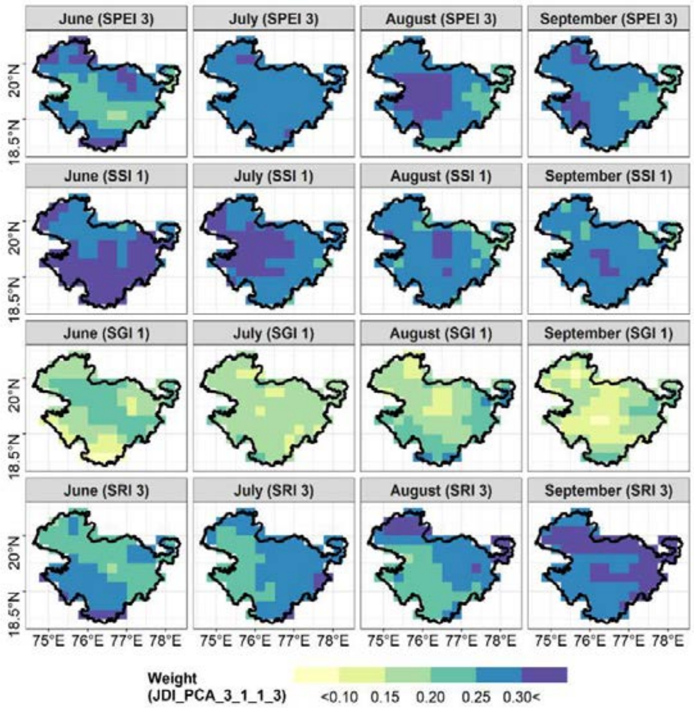

Figure 3.6: Weight allocation to each hydroclimatic variable in each month by PCA in Kharif season (JDI_PCA_3_1_1_3).

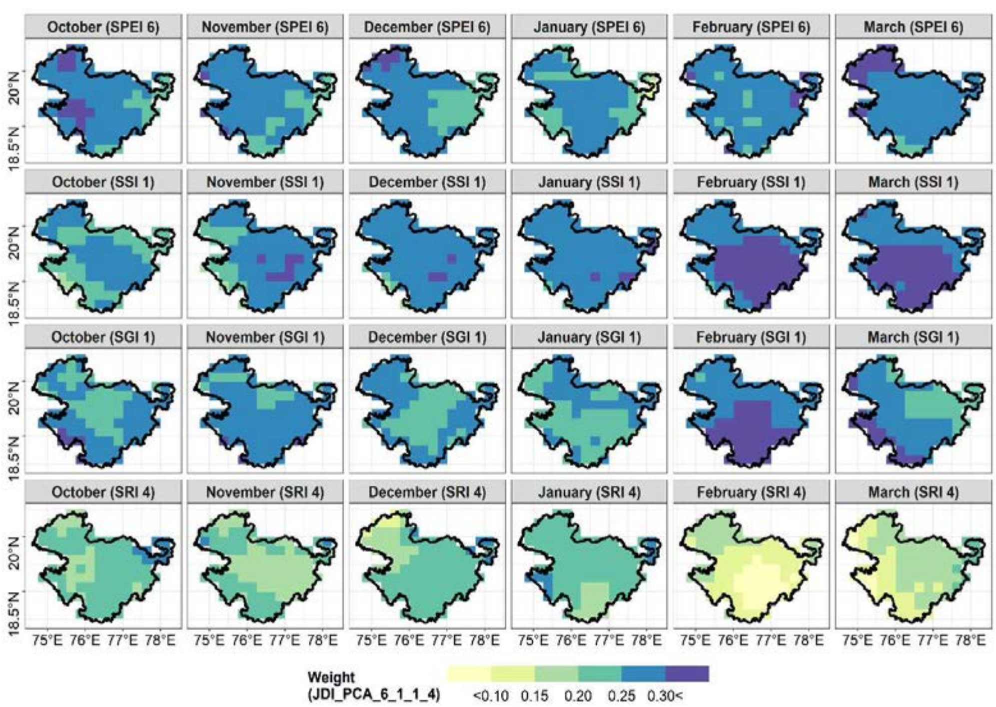

Figure 3.7: Weight allocation to each hydroclimatic variable in each month by PCA in Rabi season (JDI_PCA_6_1_1_4).

Apart from monthly weights, JDI_PCA using seasonal weights (four weights per season, total eight for Kharif and Rabi) was also evaluated using the same process as discussed in Section 3.2.2.1, where a similar phenomenon was observed when SGI was given higher weight in Rabi than in Kharif season (**Table 3.5**). It should be noted that the intensities by JDI_PCA using monthly and seasonal weights were very highly correlated ($r > 0.95$; **Figure 3.8**), subject to the similarity in weights for the integrated indices. Despite this similarity, to even capture any slight changes in the JDI response to monthly variations in the hydro-climatic variables, monthly weights were used in this analysis.

Table 3.5: Seasonal weights of indices for JDI_PCA in Kharif (scale 3_1_1_3) and Rabi (scale 6_1_1_4) season. For each season, weights were obtained by applying PCA separately over seasonal data points (June-September of each year for Kharif and October to March for Rabi), where 4 weights per season (1 for each variable) were generated (total 8).

Scale of variables for each season	SPEI	SSI	SGI	SRI
3_1_1_3 (June-September)	0.29	0.28	0.17	0.26
6_1_1_4 (October-March)	0.28	0.28	0.26	0.19

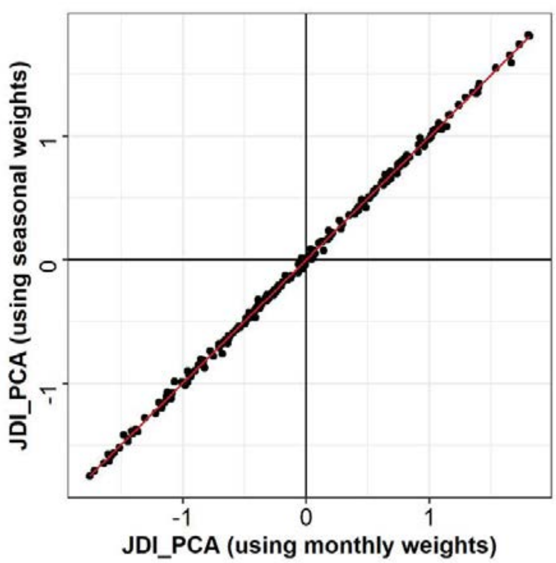

Figure 3.8: Scatterplot of JDI_PCA intensities using monthly weights and seasonal weights obtained by process discussed in section 3.2.2.1 on monthly data and seasonal data of each year during 2003-2020.

3.3.3. JDI Based on Copula (JDI_Copula)

The classical AIC and BIC criteria show that, among the selected family of copulas, Gaussian copula can best represent the joint distribution of hydroclimatic variables (**Table 3.6**). The JDI_Copula using Gaussian transformation for Kharif, and Rabi season also satisfies the Sn and Tn statistics, with a *p*-value greater than 0.05. Spatially, 99% of grid points over the region satisfy the Sn and Tn criteria in Kharif season, while, in Rabi season, the percentage is 97% and 90%, respectively (**Figure 3.9**). Moreover, as the scale of SPEI in JDI increases, the number of grid points satisfying the goodness-of-fit criterion decreases (85% and 81% of grid points satisfy Sn and Tn criterion, respectively, for JDI_Copula_12_1_1_4).

Table 3.6: Akaike information criterion (AIC) and Bayesian information criterion (BIC) statistics for different types of copulas.

AIC	Gaussian	t-Copula	Joe	Clayton	Gumbel
JDI_Copula_3_1_1_3	−427.09	−424.65	−231.44	−256.62	−297.00
JDI_Copula_6_1_1_4	−433.36	−430.86	−248.73	−290.79	−327.24
BIC	**Gaussian**	**t-copula**	**Joe**	**Clayton**	**Gumbel**
JDI_Copula_3_1_1_3	−411.86	−405.91	−218.42	−281.12	−284.74
JDI_Copula_6_1_1_4	−417.22	−411.06	−252.95	−296.89	−327.91

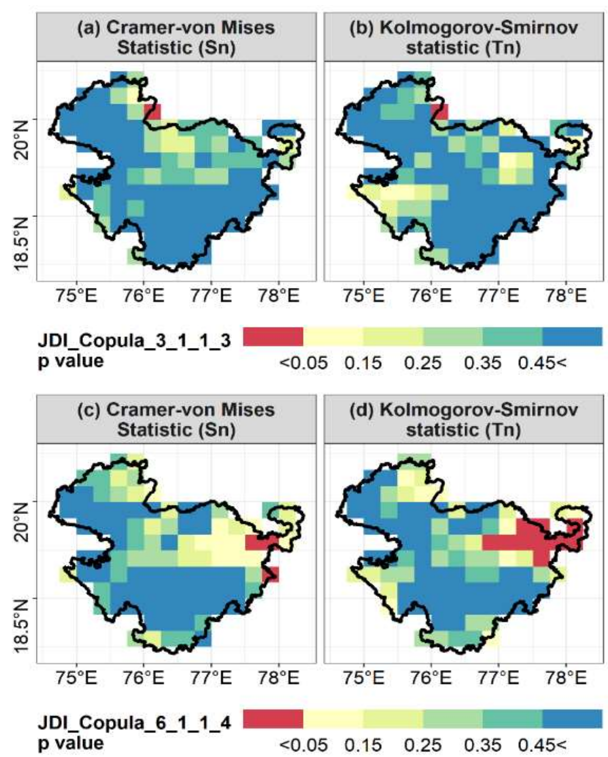

Figure 3.9: Significance value (p value) for Cramer-von Mises statistic (Sn) and Kolmogorov-Smirnov statistic (Tn) for gaussian copula in Kharif season (a & b; JDI_Copula_3_1_1_3) and Rabi season (c & d; JDI_Copula_6_1_1_4).

It was observed that JDI_PCA and JDI_Copula are highly correlated with each other (r > 0.95) in both seasons (**Figure 3.10**). **Figure 3.11** shows the time series of both the JDIs in the Kharif and Rabi seasons, along with the variables used for the integration. If there is a drought in any one of the integrated variables, there is a higher chance of its detection by copula than PCA, as copula constitutes a larger probability space (Hao & AghaKouchak, 2013; Nelson, 2006). Notwithstanding the normal conditions in other variables, if there is drought in a single integrated variable, JDI_Copula will indicate a drought situation (for example, in year 2005 in **Figure 3.11**(a and b), due to severe conditions in SGI, JDI_Copula displayed more severe intensities than JDI_PCA). More severe behavior is displayed when all the variables are excessively diverted towards the negative side, where JDI_Copula will show exceptional drought conditions compared to the integrated variables (for example, the years 2015 and 2018 in **Figure 3.11**(a and b)). JDI_PCA, on the other hand, tries to optimize the responses from the individual variables through linear transformation by taking maximum information from each integrated variable in the form of a principal component and, consequently, the weight component (**Figure 3.11**).

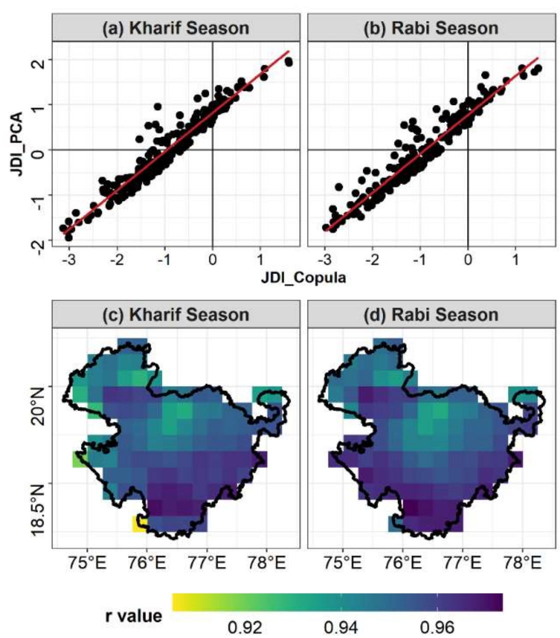

Figure 3.10: Scatterplot showing correlation between JDI_PCA and JDI_Copula for Kharif (scale 3_1_1_3) and Rabi (scale 6_1_1_4) season for average Marathwada (a & b, r~0.95) and spatial correlation of the same in each season (c & d).

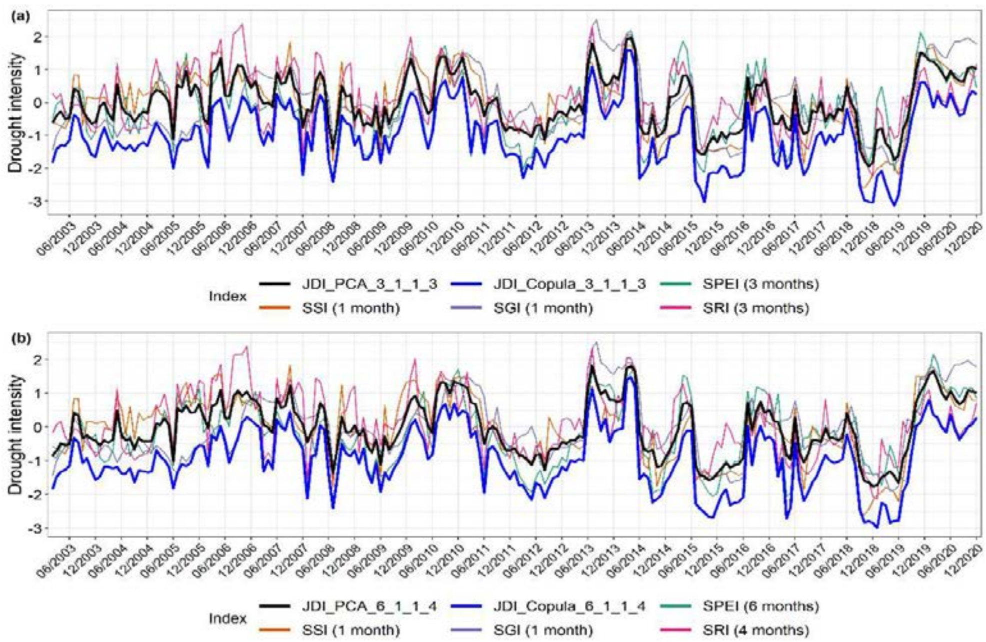

Figure 3.11: Time series of JDI_PCA and JDI_Copula during 2003 to 2020 for scales (**a**) 3_1_1_3 and (**b**) 6_1_1_4, where the scales are in the order of SPEI, SSI, SGI, and SRI, along with time series of the integrated indices SPEI, SSI, SGI, and SRI with their respective scales.

Finally, when the seasonal intensities of JDI_PCA and JDI_Copula were plotted against the seasonal CP, it was observed that the drought intensities of JDI and CP in each season corroborate with each other signifying the effectiveness of JDI in capturing the integrated response of hydro-climatological drivers responsible for shaping regional drought conditions and consequently the agriculture production (**Figure 3.12**). The relative changes in drought intensities broadly match with CP in each season where the effect of climatological conditions in different stages of crop growth along with other factors such as water management (for e.g., temporary provisions of water to save the crops, such as by tankers) by farmers, quality of seed, fertilizer use etc., might also play an important role in overall harvested agriculture production. Nevertheless, JDI combinations used here for the analysis of seasonal drought conditions provide crucial insights of the regional drought severity and propagation by efficiently incorporating the responses from the primary drought drivers in the region.

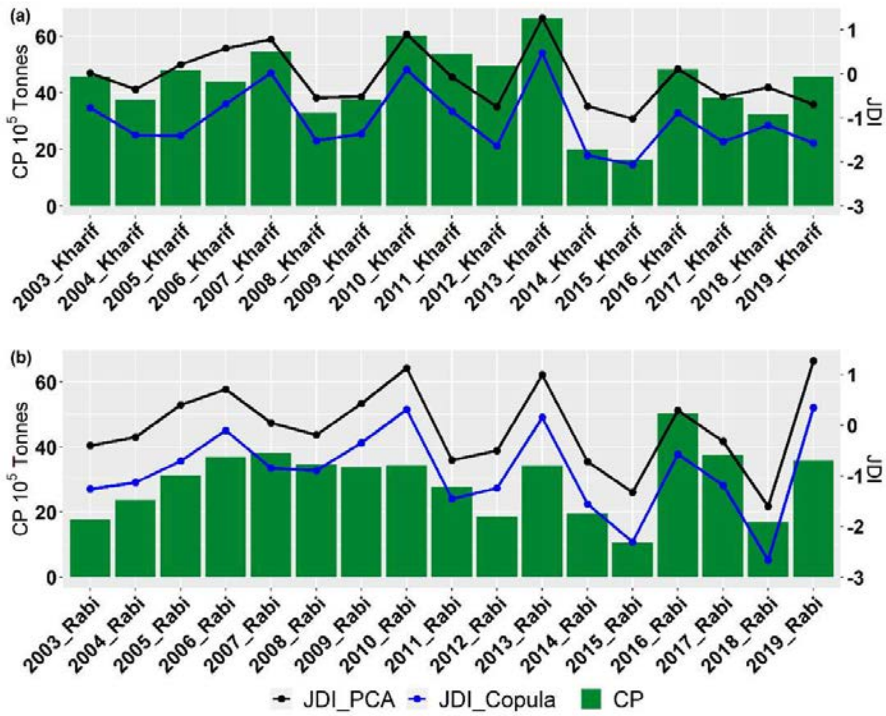

Figure 3.12: Seasonal drought intensities by JDI_PCA and JDI_Copula over Marathwada in (a) Kharif and (b) Rabi season in each year along with seasonal CP in respective years.

3.3.4. Seasonal Analysis of the Drought Intensities

3.3.4.1. Kharif Season

During four months of the Kharif season, JDI_PCA detected a minimum of three, while JDI_Copula detected a minimum of nine drought events in June and September, respectively. One interesting finding is that, despite receiving ample monsoon rainfall (**Figure 3.3**), the month of August witnessed the highest drought frequency (number of drought events) in both methods (**Figure 3.13**a). We found that the detection of drought events using JDI_Copula was much higher than that of JDI_PCA pertaining to more severe drought intensities. Spatially, Marathwada showed a minimum of seven droughts in each month per pixel detected by JDI_Copula, which is just two in the case of JDI_PCA (except for few pixels showing only one drought in January and February (**Figure 3.14**a, b)).

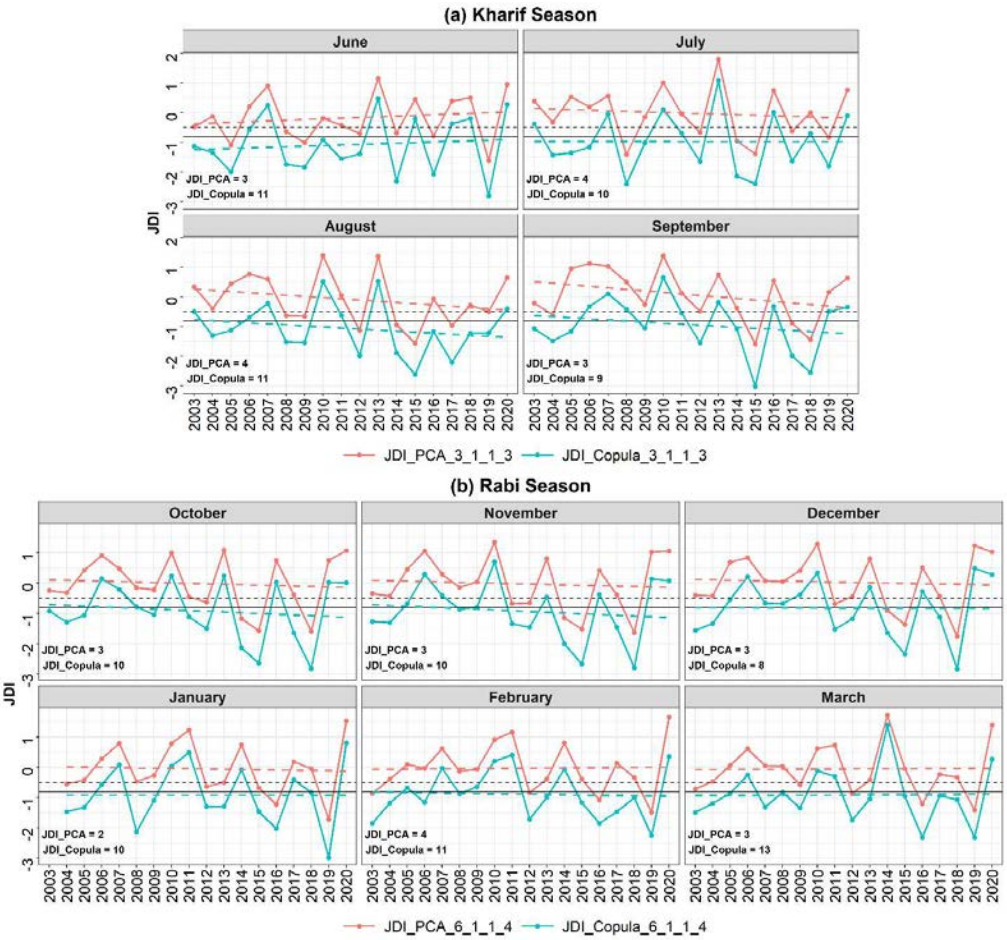

Figure 3.13: Time series of JDI_PCA and JDI_Copula in each month of (a) Kharif (June to September) and (b) Rabi (October to March) season during 2003 to 2020. Number of moderate to exceptional drought events captured by JDI_PCA and JDI_Copula are noted in bottom left of each panel. Colored dashed lines represent linear trend in each variable while black dashed and solid lines represent abnormally dry (JDI = -0.5) and moderate drought (JDI = -0.8), respectively.

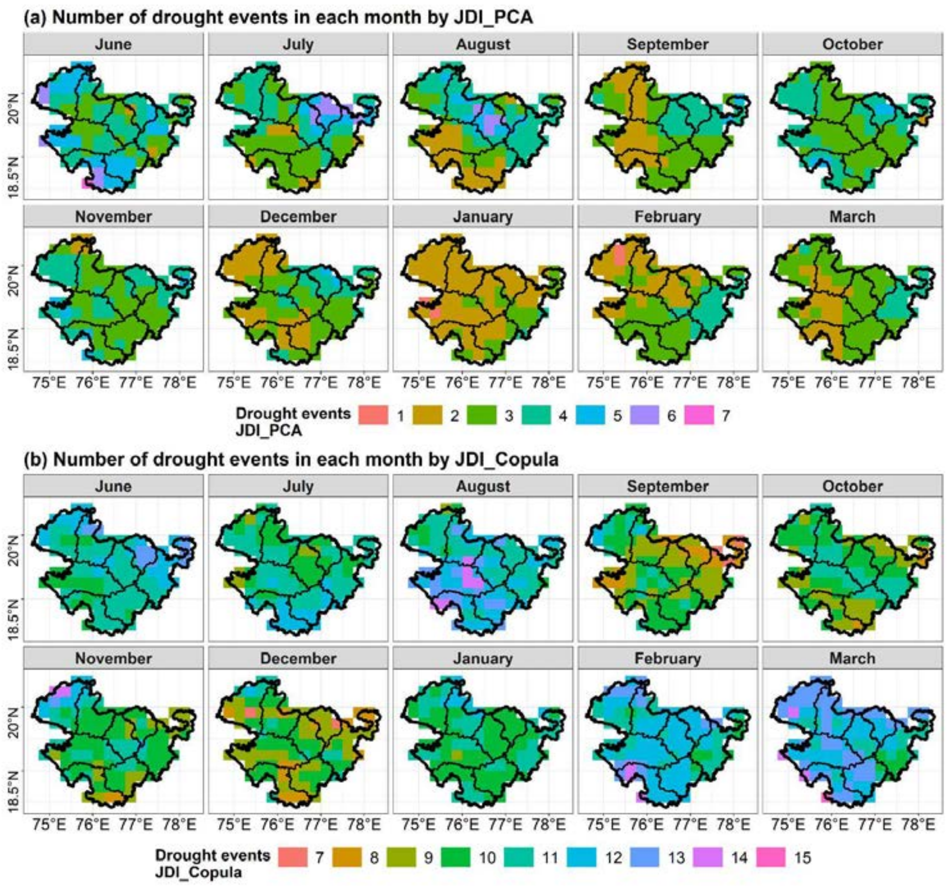

Figure 3.14: Number of moderate to exceptional drought events in each month of Kharif and Rabi season during 2003 to 2020 using (a) JDI_PCA and (b) JDI_Copula.

The drought conditions in any month of the Kharif season are crucial for farmers, as they affect overall crop performance for the season. The analysis of the spatial distribution of various drought events detected by JDI_PCA revealed that, in year 2015, 100% of the Marathwada region was under moderate to extreme drought, except for June (**Figure 3.15** and **Figure 3.16**a). The onset of the monsoon in the year 2015 was normal, with no drought conditions in June (**Figure 3.15**). However, the remaining months of the season experienced severe to extreme drought conditions, especially in the southern part of the region, causing overall Kharif crop losses of more than 60% (**Figure 3.17**), where parts of Osmanabad district also recorded exceptional drought conditions in August. Similar characteristics of the 2015 drought were also registered by JDI_Copula, with some differences in the drought intensities (JDI_Copula showed exceptional drought conditions over the entire region, **Figure 3.16**b and **Figure 3.18**). In both methods, a linear decreasing trend in drought severity was observed in the Kharif season (except for June), which suggests an increase in drought intensities and frequency (**Figure 3.13**a). However, the trend was not significant.

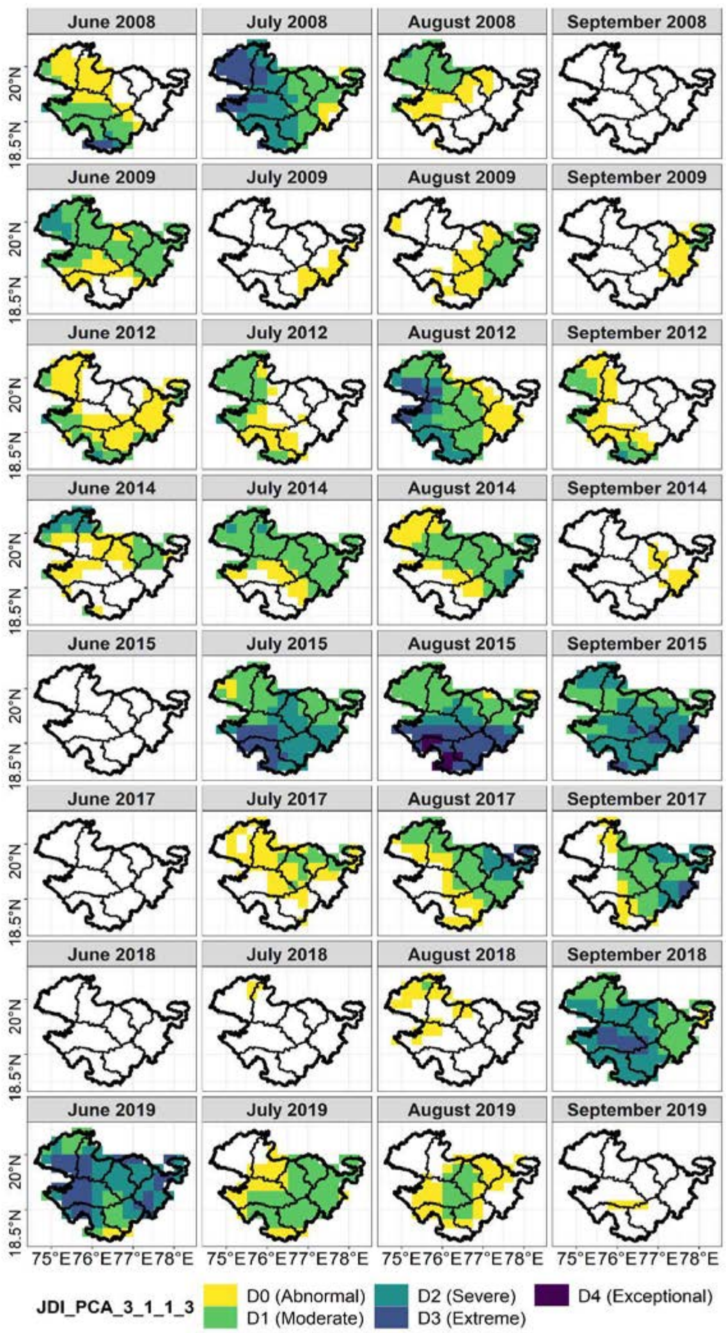

Figure 3.15: Spatial distribution of drought severity over Marathwada in Kharif season of different drought years detected by using JDI_PCA. Various subfigures are vertically stacked for better comparison among different years (white areas represent no drought condition).

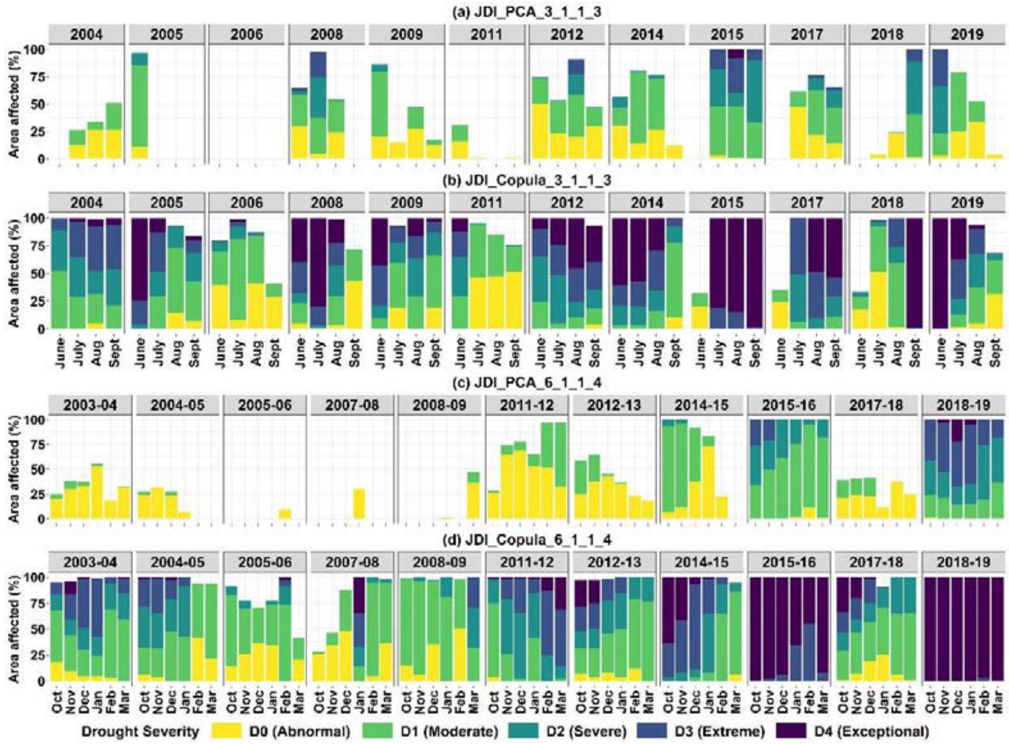

Figure 3.16: Percentage of drought area in each month of Kharif (**a**,**b**) and Rabi (**c**,**d**) season for different drought events during 2003 to 2020 using PCA (**a**,**c**) and copula (**b**,**d**). Drought severity varies from D0 (yellow bars with least severity) to D4 (dark blue bars with highest severity).

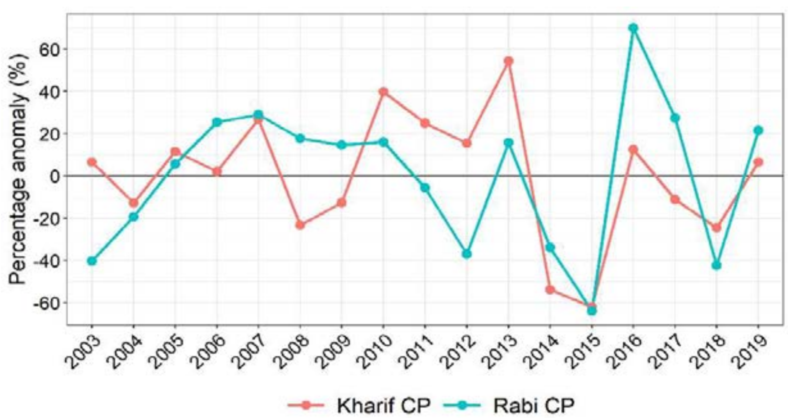

Figure 3.17: Crop production (CP) anomaly in Kharif and Rabi season during 2003-2019.

In most of the drought years recorded by JDI_Copula, 100% of the region showed drought conditions ranging from moderate to exceptional categories, with certain pockets having at least abnormally dry conditions (**Figure 3.16**b and **Figure 3.18**). JDI_Copula exhibited a tendency to show exceptional drought conditions in cases of severe droughts in JDI_PCA by encapsulating every response of the integrated variables. This resulted in higher drought intensities by JDI_Copula, such as in the last three months of the Kharif season of 2015, where 100% of the area was shown to be under exceptional drought conditions (**Figure 3.16**b and **Figure 3.18**).

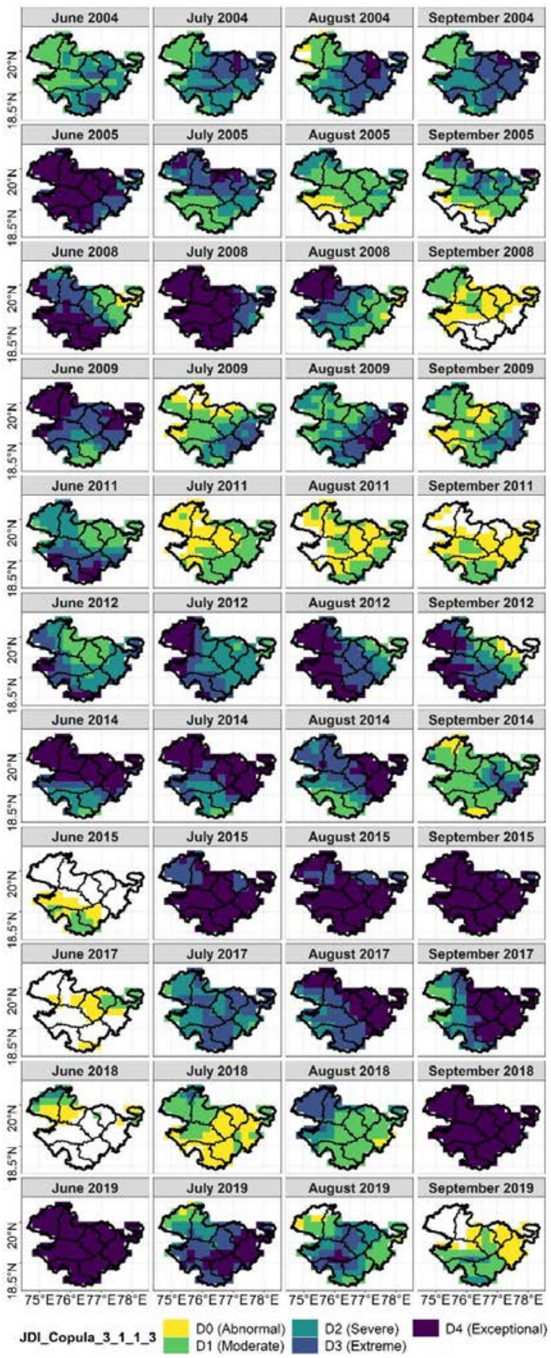

Figure 3.18: Spatial distribution of drought severity in Kharif season of different drought years detected by using JDI_Copula.

The difference in the intensities of the drought severity by both methods is especially evident in the initial years of the analysis (**Figure 3.16**). For example, in 2005, JDI_PCA showed moderate drought conditions in Kharif season in the month of June, while the conditions were exceptional by JDI_Copula during the same period, while, in other months, only JDI_Copula showed drought conditions with varying intensities over the region, with no drought detection by JDI_PCA (**Figure 3.16**a,b). Detailed analysis of the integrated variables for the Kharif season of 2005 showed that the entire region of Marathwada was under meteorological drought in June, while only Aurangabad district in the northwest suffered from moderate to abnormal drought conditions in three months of the season (**Figure 3.19** for SPEI 3, 2005). In the same year, groundwater displayed severe drought conditions covering the entire area during the same period, whereas SSI and SRI exhibited normal conditions, except for June (**Figure 3.19** for SSI 2005, SGI 2005, and SRI 2005). As PCA allocates lower weights to SGI in Kharif season and pertaining to comparatively higher contribution from other integrated variables (**Table 3.4**), JDI_PCA averages the responses, and the drought severity was not significant by JDI_PCA in 2005, except for June. Consequently, by capturing this groundwater drought, JDI_Copula exhibited exceptional to moderate drought conditions throughout the season of 2005. In conclusion, JDI_Copula was more efficient in capturing the groundwater drought than JDI_PCA.

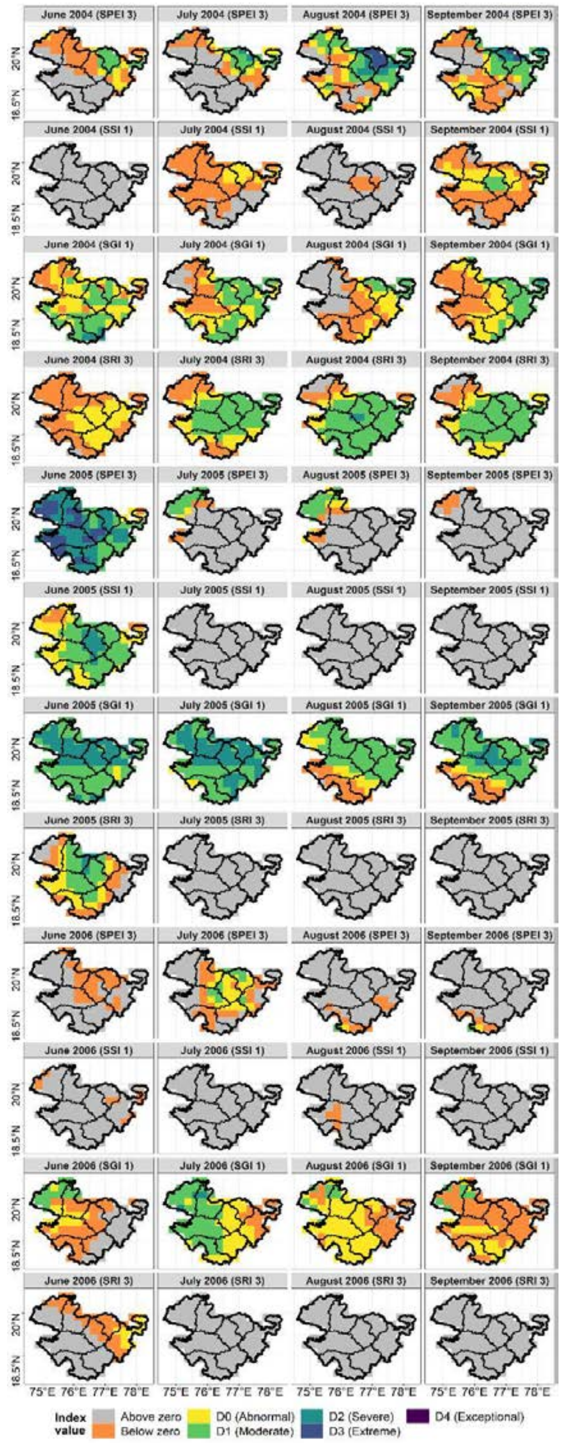

Figure 3.19: Spatial drought severity over Marathwada in Kharif season in each index i.e., SPEI (3 months), SSI (1 month), SGI (1 month) and SRI (3 months) for the year 2004, 2005 and 2006.

3.3.4.2. Rabi Season

Rabi season in Marathwada primarily depends on the groundwater for irrigation and lasts for about six months, from October to March. We observed similar characteristics of JDI_PCA and JDI_Copula in the Rabi season as those in Kharif, where JDI_Copula was able to record a higher number of drought events than JDI_PCA (**Figure 3.13**b and **Figure 3.16**c,d). The number of drought occurrences is lower in December (JDI_Copula) and January (JDI_PCA) compared to other months, which, again, increased in February and March as the season progressed (**Figure 3.13**b).

In the Rabi season, JDI_PCA showed abnormal to moderate drought conditions in most of its captured events (**Figure 3.20**). During these events, 100% areal coverage over the study area was observed for only two drought years, i.e., 2015–2016 and 2018–2019, with more severe intensities than the rest of the events (**Figure 3.16**c and **Figure 3.20**; 2015–2016 represents Rabi season from October 2015 to March 2016. Same for other years). JDI_Copula, on the other hand, showed 100% of the area under drought during most of the events by capturing the integrated response of the involved hydroclimatic variables and water storage deficits, with higher drought intensities than JDI_PCA (**Figure 3.16**d and **Figure 3.21**). Rabi seasons of 2015–2016 and 2018–2019 were particularly critical for Marathwada. Pertaining to higher (negative) precipitation anomalies in the Kharif season of 2015, the Rabi season of 2015–2016 experienced severe to exceptional drought conditions throughout (**Figure 3.20** and **Figure 3.21**), bringing down the Rabi CP to about 65% of the average (**Figure 3.17**). Likewise, in 2018–2019, the drought conditions were extreme to exceptional during the whole season, covering the entire area and causing a loss of around 42% in the Rabi CP (**Figure 3.17**, **Figure 3.20**, and **Figure 3.21**). During both years, the preceding Kharif season had suffered from severe to exceptional drought conditions. However, in 2018–2019, with respect to drought in the earlier Kharif season, the crop area was already lowered by about 35% (https://mahades.maharashtra.gov.in/). This may be one of the reasons behind comparatively less loss of Rabi production in 2018–2019, despite having severe drought conditions compared to 2015–2016.

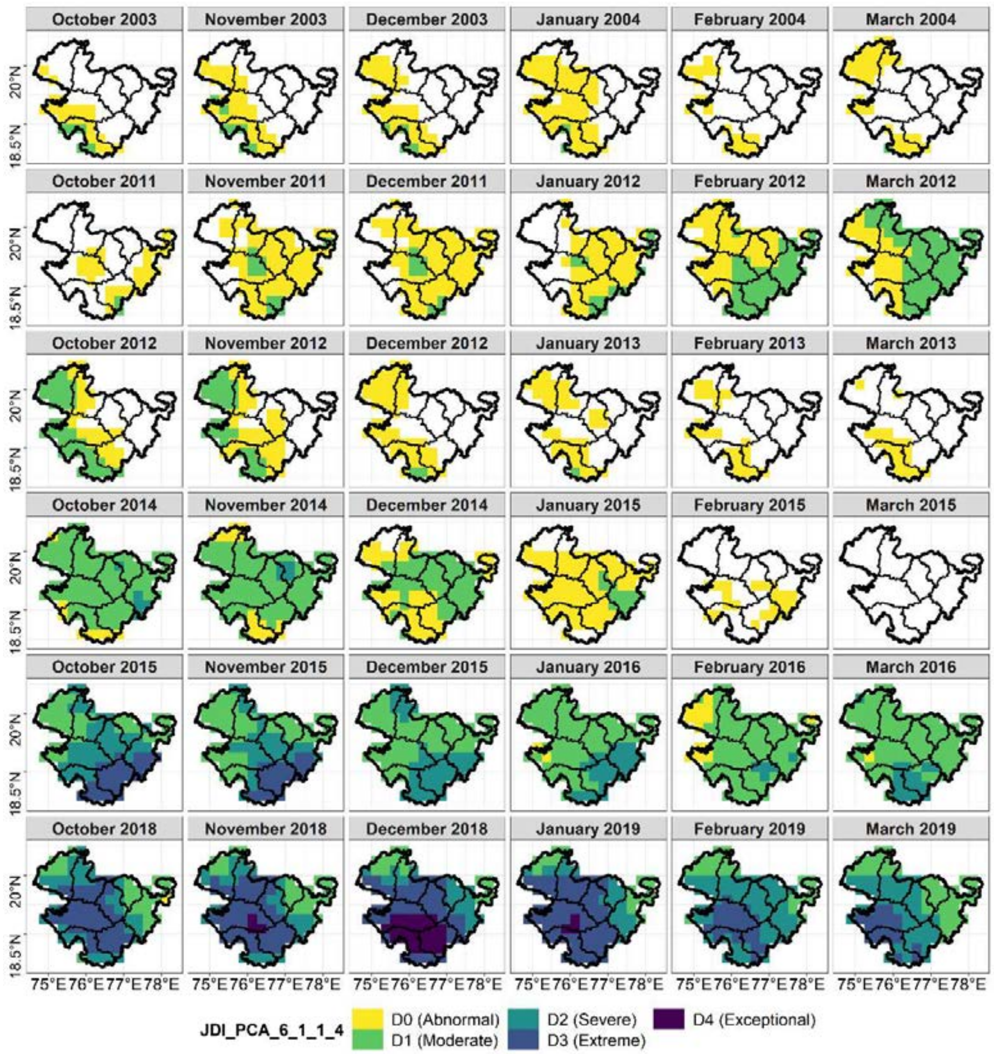

Figure 3.20: Spatial distribution of drought severity in Rabi season of different drought years detected by using JDI_PCA.

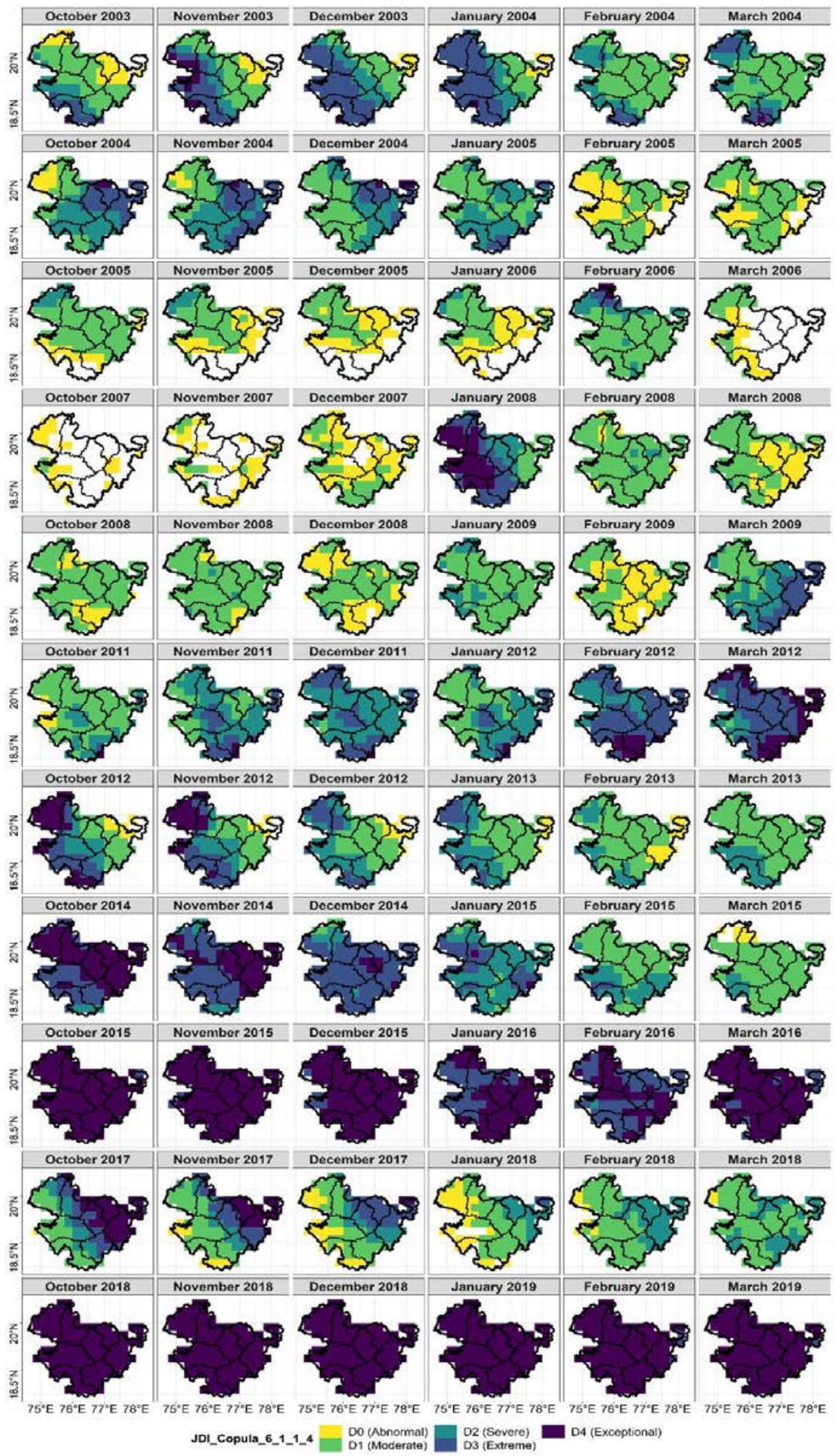

Figure 3.21: Spatial distribution of drought severity over Marathwada in Rabi season of different drought years detected by using JDI_Copula.

3.3.5. Multiseason and Multiyear Droughts

Multiseason droughts gravely impact the ability of the farmers to deal with drought situations by seizing their financial capabilities due to agriculture losses in the current season in conjunction with the previous one. During 18 years of analysis, Marathwada was subject to several drought events spanning multiple seasons and sometimes extending up to years (**Figure 3.22**). We considered the season to be drought-affected when the drought conditions were observed for three consecutive months in both the seasons and in any of the three months for the Kharif season. If the drought situation possesses sporadic breaks of one or two months owing to the anonymously heavy localized precipitation, those months were also included in the drought duration. For April and May, scale 6_1_1_4, in continuation to Rabi season, was considered to analyze the drought intensity. Here, we use the same drought categorization scheme as mentioned in **Table 3.1** to estimate the drought occurrences using both methods (**Figure 3.22**(a)) and also compare the responses of standardized JDI_PCA and standardized JDI_Copula in drought severity analysis **Figure 3.22**(b).

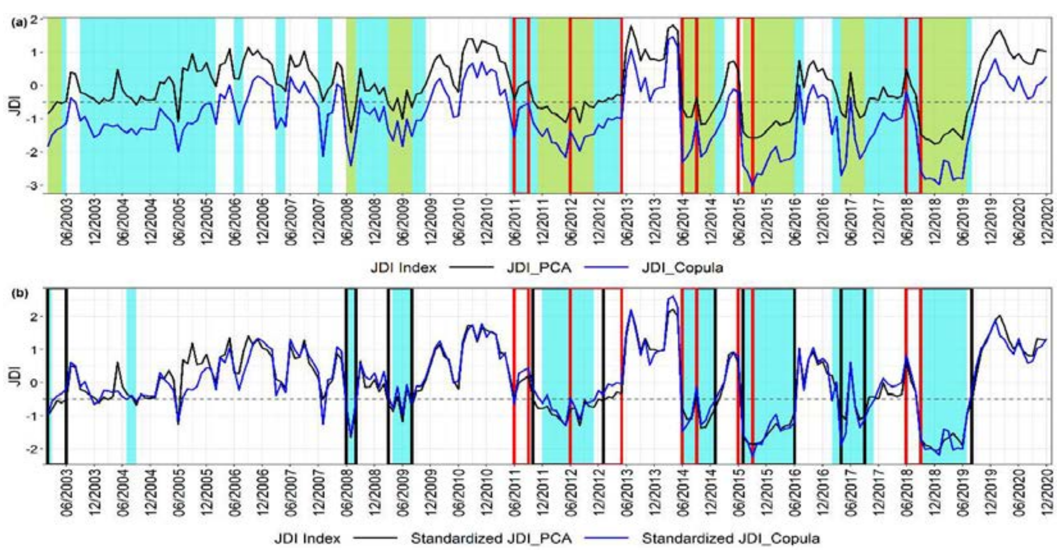

Figure 3.22: (a) Continuous time series of JDI_PCA and JDI_Copula from 2003 to 2020 with scale 3_1_1_3 for June–September and scale 6_1_1_4 from October to May. Green and blue shaded regions represent drought periods for JDI_PCA and JDI_Copula, respectively, where green areas overlap blue areas each time. (b) Continuous time series of standardized JDI_PCA and standardized JDI_Copula. Black rectangles represent drought events in standardized JDI_PCA while blue shaded regions represent drought events in standardized JDI_Copula. In both subfigures, JDI intensity below -0.5 is considered as drought event and red rectangles show the declared drought events mentioned in Table 3.7.

Considering the difference in the recorded intensities by both the methods as discussed in section 3.3.4, multiyear droughts recorded by JDI_Copula persisted longer and were more severe than those by JDI_PCA. For example, a 13-month drought was recorded by JDI_PCA, which started from November of the Rabi season of 2011–2012 and continued to the Kharif season in 2012, with a slight extension in the following Rabi season (**Figure 3.22**(a)). The same drought was recorded by JDI_Copula, starting from Kharif in 2011 and ending in Rabi 2012–2013, with a duration of about 24 months (**Figure 3.22**(a)). Similarly, with a gap of a few months in Rabi season of 2014–2015, the drought starting in 2014 also continued till the Rabi season of 2015–2016, making 2015 the most critical drought year in Marathwada (**Figure 3.22**(a), Kulkarni et al., 2016). Although there is no specific crop season in the summer months of April and May, severe drought conditions in these months increase the land surface temperature and soil moisture demands of the following Kharif season. Similar behavior can be observed in the persistent drought conditions in 2017, which started in February 2017 and continued till the end of the Kharif season. Although there are no particularly abnormal drought conditions shown by JDI_PCA for the remaining season of 2017–2018, the conditions were below normal, causing soil moisture deficit and stress in the crops, which caused a decrease in the Rabi CP compared to the previous year (**Figure 3.17**). In contrast, JDI_Copula discerned the multiyear drought conditions from February 2017 until August 2019, covering drought conditions of years 2017–2018, as well as the severity of drought in 2018–2019 (**Figure 3.22**(a)). JDI_Copula also unveiled the incessant multiyear drought conditions starting from February 2003 to August 2006, together with some recoveries in Kharif of 2003 and in end of the Rabi season of 2005–2006, which were typically absent in JDI_PCA (**Figure 3.22**(a)). Although below normal (JDI = 0) conditions can be observed for JDI_PCA for a majority of this period, the drought severity detected by JDI_PCA was negligible. Detailed analysis for each integrated index for this period suggests abnormal groundwater conditions over this region, which was satisfactorily captured by JDI_Copula (**Figure 3.19** and **Figure 3.23**). These results compare well with the recorded CP anomalies. The Rabi CP in 2003–2004 and 2004–2005 was lower by 40% and 20%, respectively, while, for 2005–2006, it was slightly higher by 5% (**Figure 3.17**). Despite abnormal groundwater conditions in Kharif in 2005, other variables contributed to improving the CP by approximately 11%, which, again, decreased in 2006, mostly due to the persistent groundwater anomalies and drought conditions in the initial months of the season (**Figure 3.17** and **Figure 3.19**). Although category D0 leans towards the recovery of the drought, prolonged exposure to abnormal conditions causes many lingering hazards (environmental, social, etc.).

Furthermore, acknowledging that JDI_PCA and JDI_Copula appear to be interchangeable by adding or subtracting a constant, where threshold value can make a difference in the areas under drought analyzed by each index, we compared drought areas shown by standadized JDI_PCA and standardized JDI_Copula (**Figure 3.22(b)**). We found that standardized JDI indices of both methods shows similar drought severity and drought durations (**Figure 3.22(b)).** More about difference in the behavior of JDI_PCA and JDI_Copula is further discussed in **section 3.4**.

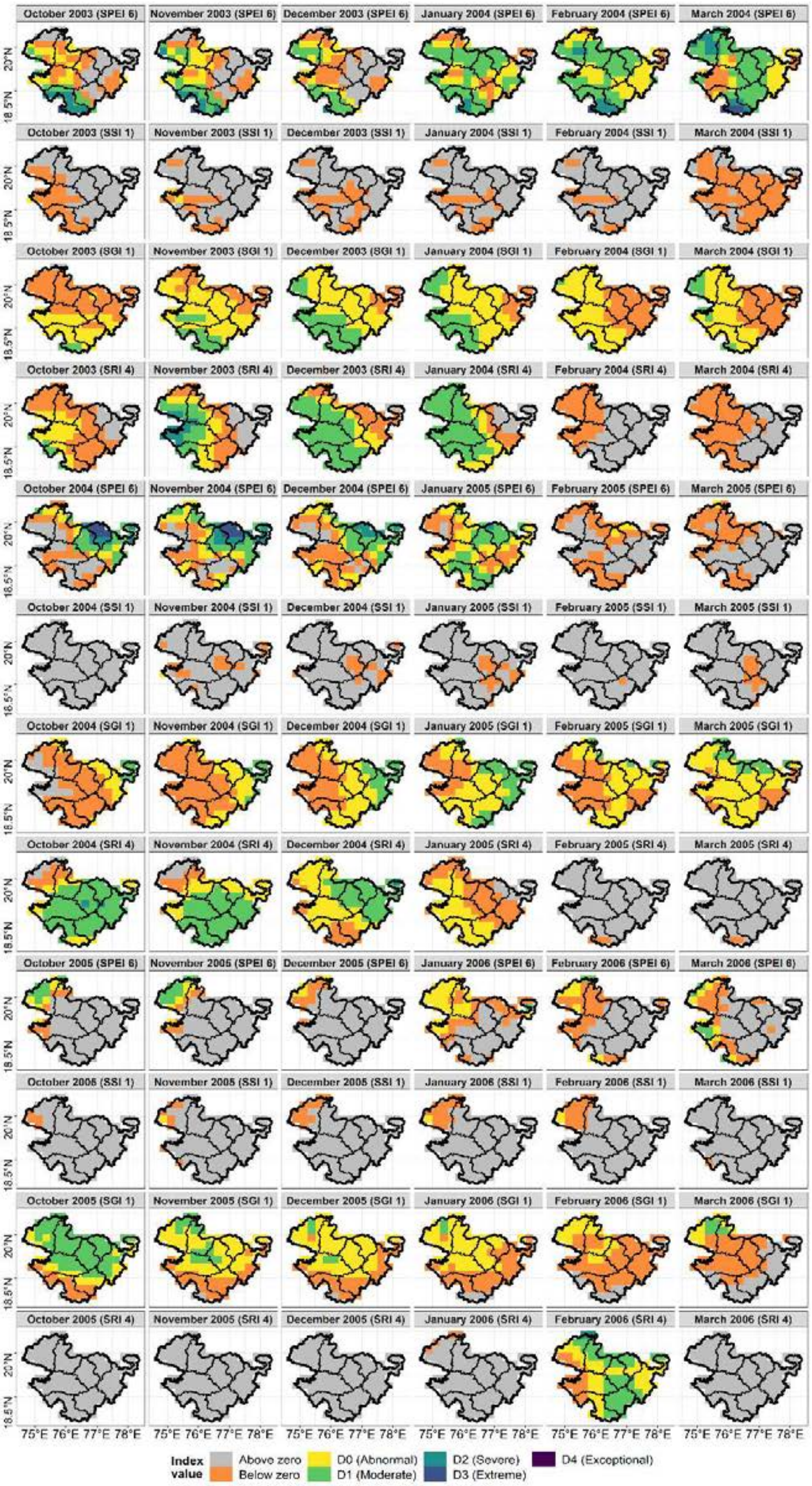

Figure 3.23: Spatial drought severity in Rabi season in each index i.e., SPEI (6 months), SSI (1 month), SGI (1 month) and SRI (4 months) for the year 2003-04, 2004-05 and 2005-06.

3.3.6. Historical declared drought events

As discussed in **section 1.1.1**, the drought declaration is an important step in initiating the response and relief measures by the government. The historical declared drought events for Kharif and Rabi season in the study area are available during 2011-2020 as listed in **Table 3.7**, which are shown in red rectangles in **Figure 3.22**(a & b). As can be seen from **Figure 3.22**(a), all the drought events in Kharif and Rabi season are well captured by JDI_Copula while JDI_PCA primarily captured major drought events of Kharif season in 2012, 2014 and 2015. However, severe drought appearances as captured by multivariate index JDI, especially in Rabi season (such as in years 2011-12, 2014-15, 2015-16 and 2018-19 in **Figure 3.22**(a), and 2011-12, 2015-16 and 2018-19 in **Figure 3.22**(b)), as well as Kharif season of 2017 (**Figure 3.22**(a & b) does not seem to be declared in respective years. Moreover, the drought events captured by JDI corroborate well with the seasonal CP (**Figure 3.12**) signifying the effectiveness of JDI in regional drought analysis. This shows the potential of JDI in enhancing the drought severity analysis and drought declaration, which will be valuable in disseminating the crucial governmental assistance to the drought affected communities.

Table 3.7: Declared drought events by government of Maharashtra in different districts of Marathwada during 2011 to 2020 in Kharif and Rabi seasons (Ministry of Agriculture and Farmers Welfare, https://agricoop.nic.in/).

District	Kharif (June to September)					Rabi (October to March)
Aurangabad		2012	2014	2015	2018	2012-13
Jalna		2012	2014	2015	2018	2012-13
Beed		2012	2014	2015	2018	2012-13
Latur	2011	2012	2014	2015	2018	
Osmanabad	2011	2012	2014	2015	2018	2012-13
Nanded		2012	2014	2015	2018	
Parbhani		2012	2014	2015	2018	
Hingoli		2012	2014	2015	2018	

We observed that JDI_Copula was highly effective in analyzing the drought conditions covering multiple drought parameters compared to JDI_PCA and can, therefore, be used to predict the CP anomalies in the respective season.

3.3.7. Prediction of CP from JDI

The significant association between CP and JDI can be established for copulas through a regression equation, where the *p*-values for both the intercept and the slope were significant ($p < 0.05$; while, for PCA, $p > 0.05$ for the intercept). Thus, JDI_Copula_3_1_1_3 was used to predict the CP in the Kharif season with Equation (3.4) and JDI_Copula_6_1_1_4 for Rabi CP prediction using Equation (3.5).

$$\text{Kharif CP} = 1.21 + 1.14 \times \text{JDI\_Copula\_3\_1\_1\_3}\ (r = 0.82) \tag{3.4}$$

$$\text{Rabi CP} = 0.76 + 0.84 \times \text{JDI\_Copula\_6\_1\_1\_4}\ (r = 0.71) \tag{3.5}$$

The CP is particularly sensitive for JDI values in Kharif season associated with the volatile monsoon precipitation characteristics and its influence on the indices integrated in the JDI (deviation of ±0.1 in JDI shows fluctuation of ~22.8% and ~16.8% in Kharif and Rabi CP, respectively).

3.4. Discussion

The multivariate drought indices JDI_PCA and JDI_Copula prove to be potentially competent and coherent in capturing the responses of each integrated hydroclimatic variable and overall water deficit conditions of the study region in the case of drought. Although different combinations of SPEI (3 and 6 months), SSI (1 month), SGI (1 month), and SRI (3 and 4 months) were used for the development of JDI, there is no fixed effective and common (applicable everywhere) combination of indices to construct the joint index. Closely related combinations were found to exhibit comparable correlations with the crop yield and showed similar drought intensities (**Table 3.2** and **Figure 3.24**a–d). However, when the time scale of the integrated index is longer, it often involves conditions that no longer influence the current hydrological situations, which can result in higher correlation between the JDI and the CP (Shukla & Wood, 2008, for example, scale 12_1_1_4 in **Table 3.2**).

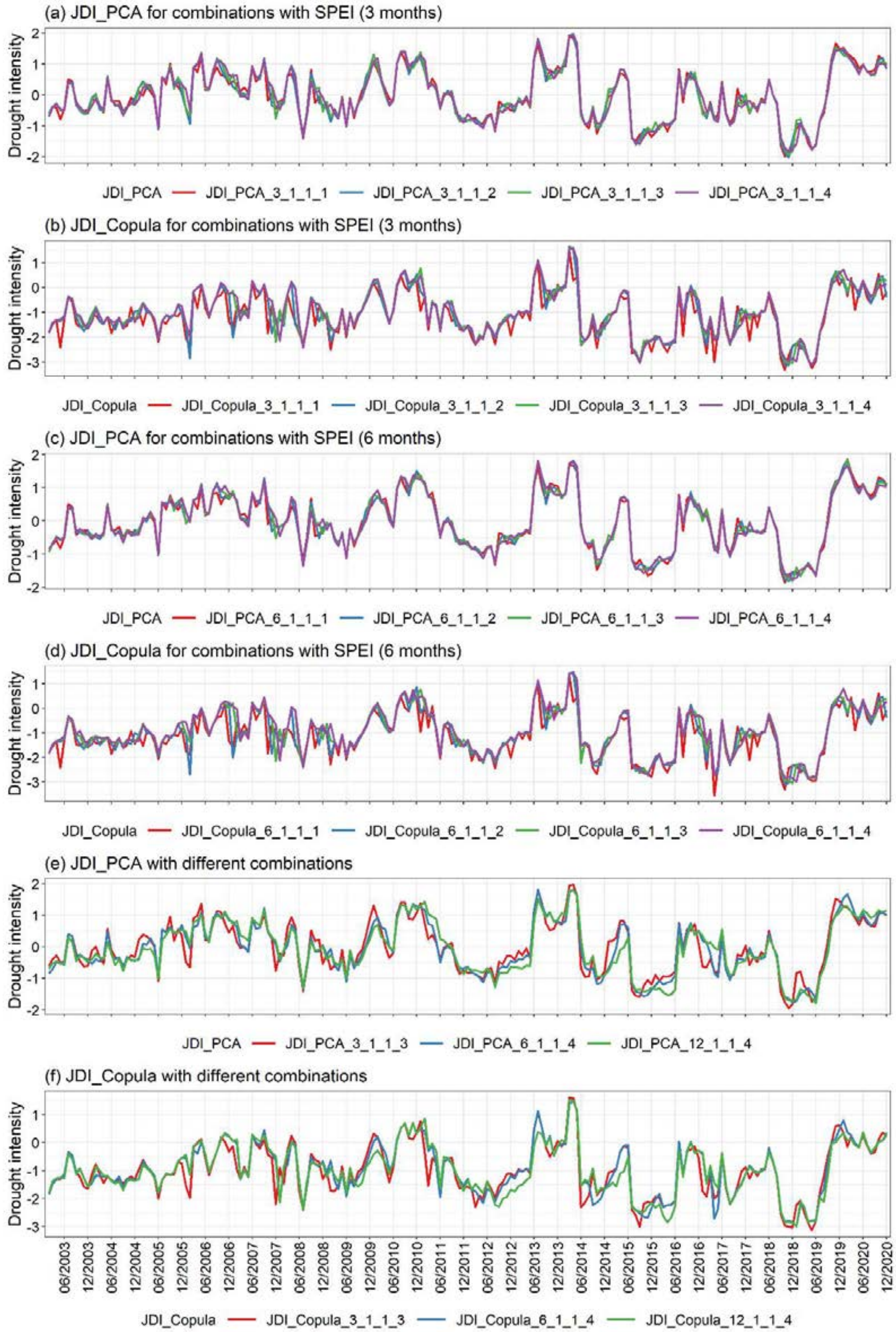

Figure 3.24: Time series of JDI_PCA and JDI_Copula with different combinations of integrated indices.

JDI with different combinations of integrated indices are found to be highly correlated with each other (r~0.83 to 0.98). The difference in these JDIs lies in the persistence of the drought with change in the scale of any variable in the combination as the drought progresses (**Figure 3.24**e,f). When there is a difference in the accumulation period (scale) of any one index of the combination, the response of JDI differs accordingly. Shorter scale indices attain positive values more quickly, while longer scale indices persist over a longer period (**Figure 3.24**e,f). For example, JDI_PCA, as well as JDI_Copula for the shorter scale (3_1_1_3), show higher drought intensity for June 2014, while longer scale indices (6_1_1_4 and 12_1_1_4) remain at comparatively lower intensities (**Figure 3.24**e,f for June 2014). Moreover, partial drought recoveries are captured more effectively by JDI having lower scale SPEI by reducing the drought intensities, while JDI with 12-month SPEI still shows severe drought conditions (e.g., from December 2015 to June 2016, **Figure 3.24**e,f). Drought intensities in Kharif season are more efficiently captured by scale 3_1_1_3 by both JDIs than scale 6_1_1_4 (e.g., Kharif 2014 and 2015 in **Figure 3.24**e,f), while, for Rabi season, scale 3_1_1_3 shows higher intensities than scale 6_1_1_4 (e.g., Rabi season 2005–2006, 2010–2011, and 2016–2017, **Figure 3.24**e,f).

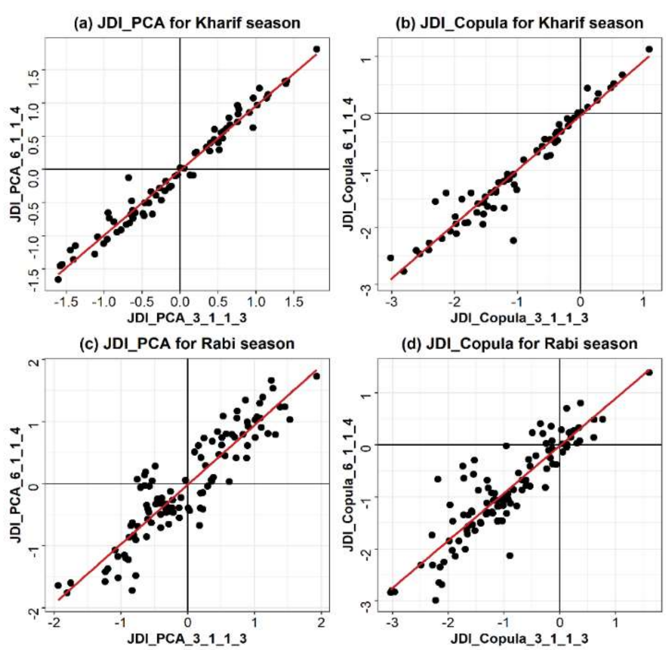

Figure 3.25: Scatterplot of JDI_PCA and JDI_Copula for scales 3_1_1_3 and 6_1_1_4 analyzed for Kharif months (a and b) and Rabi months (c and d).

While JDI intensities for Kharif season are more comparable for both the scales (3_1_1_3 and 6_1_1_4) used in this analysis (**Figure 3.25**a,b), there is higher variability of drought intensities in Rabi season (**Figure 3.25**c,d). This shows that separate indices, using appropriate scale variables for integration, used to define the seasonal drought characteristics provide more realistic results than using a single index for analyzing the drought for the whole year. An area under drought by differently scaled JDIs also shows variations with higher persistence of JDIs involving longer scale indices (**Figure 3.26**). Moreover, the area under drought by JDI_PCA varies considerably with JDI_Copula, where 100% of the area is frequently under drought (**Figure 3.26**).

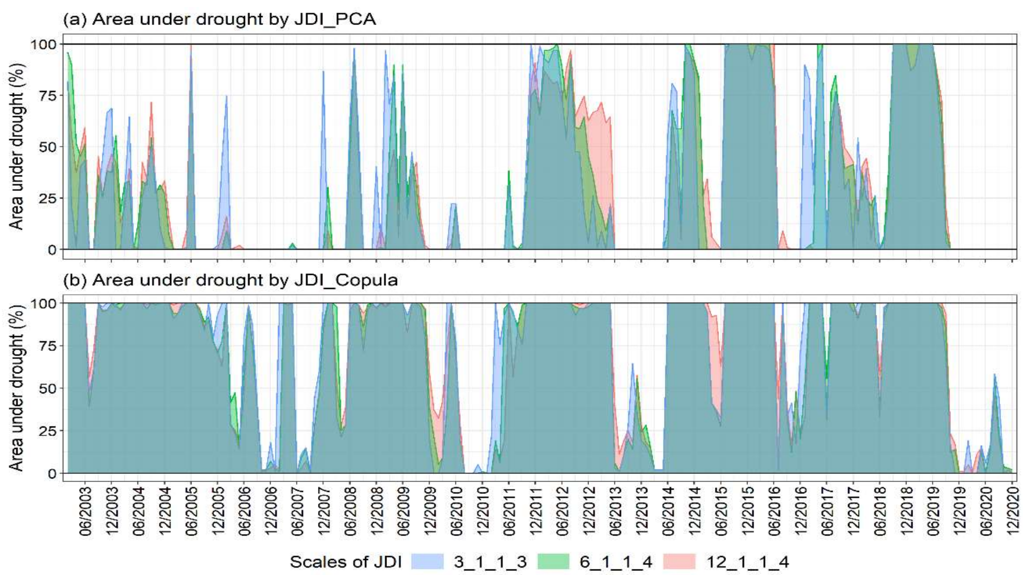

Figure 3.26: Area under drought for scales 3_1_1_3, 6_1_1_4 and 12_1_1_4 (representing scales for variables in order of the SPEI, SSI, SGI, and SRI) using (**a**) JDI_PCA and (**b**) JDI_Copula.

The probability of agricultural drought occurrence increases with increase in the severity of meteorological drought (Xu et al., 2021). Integrated indices, such as JDI, play an important role in capturing the drought conditions created by different hydro-climatological abnormalities. The periodic precipitation spells may improve the meteorological drought conditions temporarily depending on the precipitation volume, subsequent meteorological conditions, crop growing stage, and cropping seasons and patterns. However, it may not ameliorate the agricultural, groundwater, or hydrological drought conditions, as observed for the initial years of the analysis. JDI as presented in this chapter incorporates the responses from each of the primary variables integrated withing the index and enhances the user's comprehension of the characteristics of the droughts. JDI_Copula in particular is more efficient in capturing the groundwater drought than JDI_PCA, as observed in this analysis. However, as copula tries to consider the critical responses from each integrated variable, JDI_Copula might give lower estimates, even in wet periods, similar to the higher estimates in the case of droughts.

PCA and copula both possess the potential to be included in the drought management system of India, avoiding separate judgment of individual indices, which may not always capture the integrated effect. Groundwater, being the main source of irrigation, has major influence on the drought conditions in the region as observed by JDI_Copula. JDI_PCA's limitation lies in the fact that it is essentially a linear combination of the drought indices assumed to represent maximum information from each variable through the variance (Hao & Singh, 2015). JDI_Copula, on the other hand, preserves the marginal distributions of the integrated variables and their dependence structure. Although both JDIs are highly correlated and have a similar direction of drought intensity, the captured drought intensity varies considerably, with JDI_Copula frequently showing exceptional drought conditions. Similar observations were reported by other studies, indicating the ability of copula-based integrated index to capture extreme drought conditions better than other methods (e.g., entropy) (Azhdari & Bazrafshan, 2022). However, this may not be advisable for the mitigation measures, as this overestimation may stress the official resources to always deal with extreme conditions. Determination of the threshold for the drought categorization is, however, a subjective assumption, where upscaling or downscaling the threshold may result in changes in the drought severities and areas under drought. Nevertheless, the standardized JDI_Copula and standardized JDI_PCA (removing the mean and dividing by standard deviation) give more similar drought intensities and drought durations (**Figure 3.22**(b)), where extreme behaviors are better captured by JDI_Copula (**Figure 3.27**).

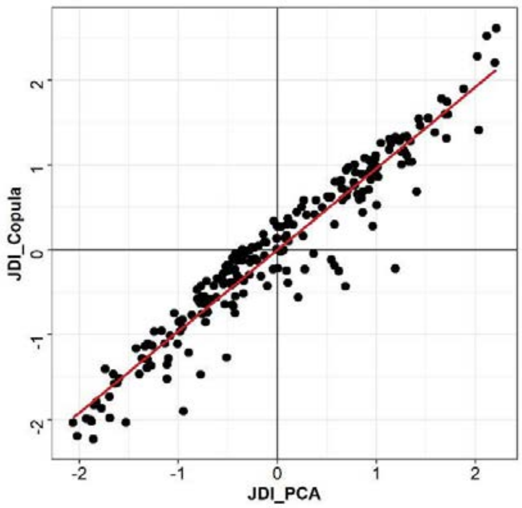

Figure 3.27: Scatterplot of standardized JDI_PCA and standardized JDI_Copula obtained by removing the mean and dividing by standard deviation. The red line is the regression line. Scale of the integrated indices from June-September is 3_1_1_3 and for October-May is 6_1_1_4 (order of the variables: SPEI, SSI, SGI, and SRI).

The difference in the severity reported by both methods using same drought threshold is evident from **Figure 3.22**(a), where we can see that all of the declared drought events are well captured by JDI_Copula by incorporating response from each integrated index while severity showed by JDI_PCA is very less with failure of recognition of drought in some cases, such as drought of 2011 in Kharif season in southern districts of Latur and Osmanabad (**Figure 3.28**) and drought of 2012-13 in Rabi season in eastern districts of Aurangabad, Jalna, Beed and Osmanabad (**Figure 3.29**). Despite difference in reported severity conditions (where standardized indices of JDI_PCA and JDI_Copula show similar drought characteristics), both methods possess potential to analyze the drought situation in the region where JDI_Copula is recommended for evaluating the overall drought conditions with due consideration to the response from every critical variable in the region, whereas JDI_PCA can be used to inspect the average integrated response of regional drought characteristics. In addition, qualitative investigation of drought impacts is as necessary as quantitative analysis in the view of varying socioeconomic parameters of the region by involving local experts, agriculturists, and climatologists along with various farmer groups. Multidisciplinary considerations in the drought analysis can further help in improving the current methods and for deciding the future drought mitigation strategies.

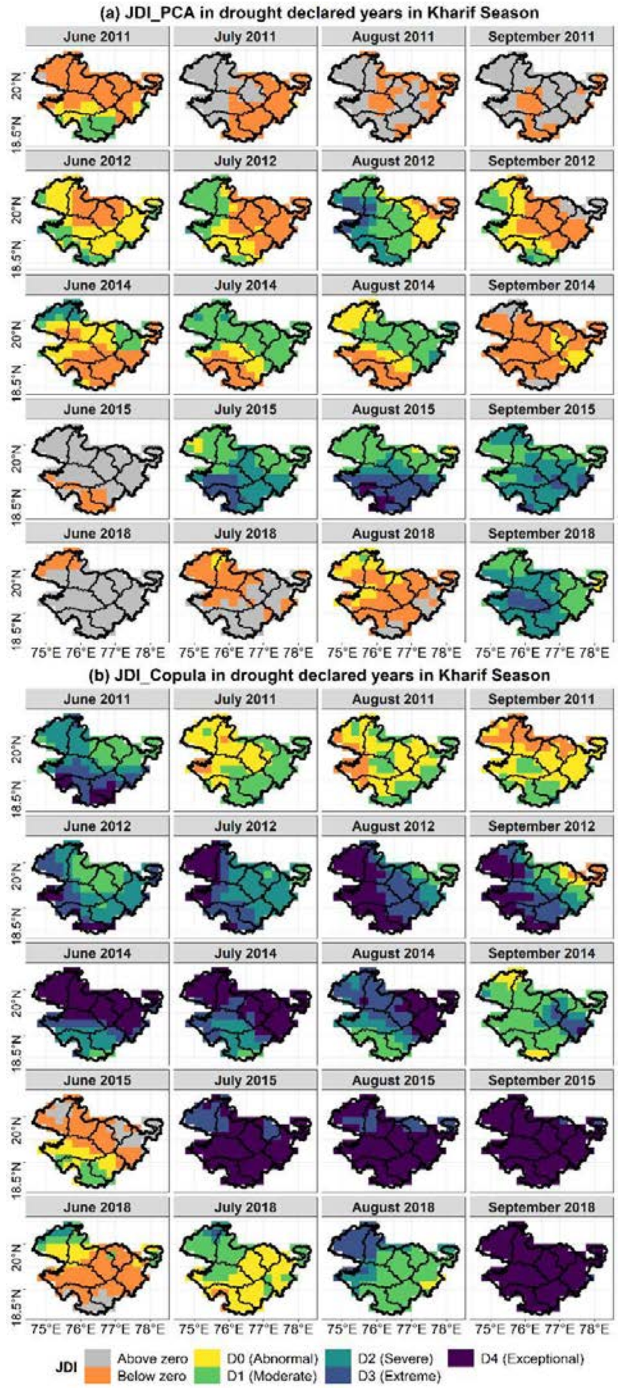

Figure 3.28: Spatial distribution of drought severity in Kharif season for declared drought events during 2011-2020 by using (a) JDI_PCA and (b) JDI_Copula

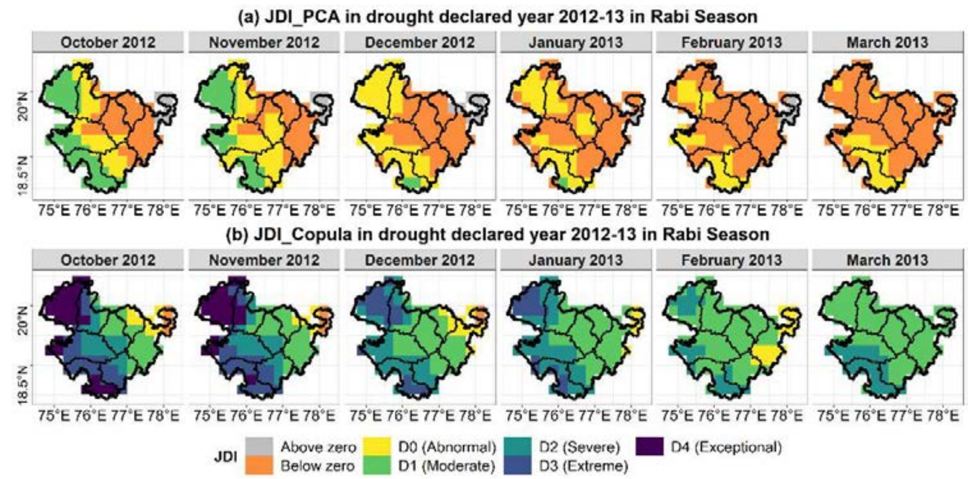

Figure 3.29: Spatial distribution of drought severity in Rabi season for declared drought events during 2011-2020 by using (a) JDI_PCA and (b) JDI_Copula

3.5. Limitations and Future Scope

Although multivariate drought indices, such as JDI, enhance the collective detection of various types of droughts, they may not overpower the ability of the univariate indices to apprehend the drought characteristics, nor are they inherently superior. When a single drought type, such as meteorological, is to be analyzed, a single standardized index, such as SPI/SPEI, can still give better insights. Moreover, independent hydrological model simulations at regional scales may provide more sophisticated inputs for integrated indices than readily available LSM outputs, which needs further research. Here, we recognize that longer time-series data would be more beneficial for standardized indices of GLDAS model outputs, which also reflect the associated uncertainties. Nevertheless, JDI displays the potential to be used for the assessment of local hydro-climatological conditions, leading to improved current and future drought assessment techniques. Fine-resolution vegetation indices, such as NDVI and VCI, can also be used along with JDI for enhanced spatial details of drought conditions. The lack of high-resolution and seasonal CP data hinders the accuracy in the assessment of drought severity. However, the approach of using a separate multivariate index for each season, representing the seasonal crop conditions by the highest correlation, as discussed in this study, will be beneficial in drought mitigation over any region by increasing the accuracy of drought detection. Weekly monitoring, particularly in Kharif season, may be beneficial in the timely detection of drought aggression and effective mitigation measures. Socioeconomic drought, although difficult to include in multivariate index, should be contemplated in future drought analysis, considering its grave impacts.

3.6. Conclusion

In this chapter, a multivariate joint drought index (JDI) was developed by integrating standardized indices representing meteorological (SPEI), soil moisture (SSI), groundwater (SGI), and surface runoff (SRI) drought by using PCA and Gaussian copula. Various combinations of these indices were analyzed for correlation with seasonal crop production (CP), and the combination showing the highest correlation was selected for the assessment of drought conditions in the Marathwada region of central India. The key findings of this study are as follows:

1. Unlike traditional indices, JDI efficiently captured the combined effect of drought variability in the study region. Moreover, the dynamics of seasonal CP and JDI corroborate each other, showing the advantages of using separate JDI for drought analysis in each season. JDI_Copula performed better in detecting the extreme drought characteristics by each integrated variable by preserving their dependence structure than JDI_PCA, which averaged the responses.
2. Groundwater, being the primary source of irrigation, is an important driver of droughts over Marathwada, shaping the regional drought characteristics. JDI successfully captured this contribution, revealing its potential to support local-scale decision making and the ability to be evolved for any region having different hydroclimatic conditions by integrating locally critical inputs.
3. Multivariate indices are more efficient in capturing overall water deficit from multiple drought-related indices compared to a univariate index. JDI, as presented in this chapter, can play a crucial role in drought analysis with improved accuracy of detection of each drought type and comprehensive inclusion of various seasonal drought characteristics.
4. JDI proves to be efficient in detecting the onset, termination, and duration of drought based on the integrated effect of multiple drought indicators,

which otherwise was difficult to analyze. Out of drought characteristics captured by both the methods, droughts of the years 2015–2016 and 2018–2019 were the most severe in the study region.

5. The results of this study also highlight the importance of a multidisciplinary approach in drought classification, which can play a crucial role in policy formation and food security, by providing a timely and accurate estimation of drought characteristics by reducing the inherent inconsistencies in the traditional methods. This is also important for the socioeconomic security of vulnerable regions, such as Marathwada, experiencing increased suffering of the farmers.

The novel approach of seasonal drought categorization for holistic quantification of drought conditions, as presented in this study, should provide a unique perspective to drought monitoring by increasing the accuracy of drought severity analysis worldwide. As discussed in **section 1.1.1**, in India, the majority of the government assistance in case of drought is prioritized based on the drought severity where drought declaration plays a crucial role. Multivariate indices such as JDI will be advantageous for assessing the drought severity and delivering the most essential help to agricultural communities in case of drought events. Furthermore, JDI can play a significant role in the agriculture sector, especially in the life of farmers by protecting their socioeconomic security in case of drought events by improving the drought detection, which is further discussed in the next chapter.

CHAPTER 4
Socioeconomic security of farmers and relation with greening-browning and droughts

Parts of this chapter are published in Bageshree et al., (2022b)*,*

Bageshree, K., Abhishek, Kinouchi, T. (2022b). Unraveling the Multiple Drivers of Greening-Browning and Leaf Area Variability in a Socioeconomically Sensitive drought prone region. *Climate*, *10*(5). https://doi.org/https://doi.org/10.3390/cli10050070

4. Socioeconomic security of farmers and relation with greening-browning and droughts

4.1. Farmers suicides as an index

Maharashtra state frequently faces extensive and prolonged droughts, where the impacts are often found to be exacerbated when it is in proximity to the previous drought, as discussed in the previous chapters. Farmers, being the key stakeholders of agriculture and allied businesses, are undoubtedly affected the most by such widespread disasters. Persistent drought calamities resulting in agriculture failures seize the opportunities for farmers to recover from the aftermath, continuing the brutal cycle of their socioeconomic perils. The financial stress as a result of the agrarian crisis is very deeply rooted in Maharashtra state of India which frequently experience fluctuations in the Gross Domestic Product (GDP) of the state, especially in case of drought years (Iyer, 2021). Farmers of the state are well aware of the drought and its socioeconomic and environmental impacts. However, their drought adaptation capacities and understandings differ depending on their economic status (Udmale et al., 2014). Shrinking crop productivity, drinking water scarcity, loss of employment, reduction in household income, food scarcity, malnutrition, affected schooling of children, migrations etc. are common socioeconomic impacts faced by the famers which are generally known. However, compound effect of the aforementioned factors is manifested in most unfortunate, tragic, and concerning footprint of aggravated drought ramification in the form of farmer suicides, subject to hopelessness and sense of loss related to droughts and consequent agriculture failures.

Suicide is a cry of desperation which throws a light on the grim situation of socioeconomic situation of farmers, where this alarming issue is often considered as an index for agriculture related issues and other analyses (Nagaraj, 2008; Singh et al., 2022; Talule, 2013, 2020a). More than 350 thousand farmers have died by suicide in the past two decades in India (NCRB, 2021). During the same period, the depression and anxiety among the farmers were also registered all over the Maharashtra state, which was mainly associated with the persistent agriculture uncertainties (Iyer, 2021; NCRB, 2021; Talule, 2021). There are climatic, financial, as well as social angles involved in this issue. The farmer's distress is so widespread that despite efforts from the government and NGOs to pre-identify their mental status through door-to-door surveys by public health workers, especially in drought years and offering counseling could not reduce the number of suicides. Recognition of cause and deeper impacts of such issues is very important in scientific discussions where knowledge of interlinkage of climatic and anthropogenic factors and drought mitigations measures as discussed in previous chapters can play a pivotal role in strategic planning, policymaking, and efficient drought recovery, saving stressed farmers from survival threats. Such information is crucial for convincing policy makers for additional investments in drought preparedness, monitoring, and mitigation. Thus, taking farmers suicide as an index showing the socioeconomic status of farmers, to the best possible, this chapter discusses the possible relation between greening and browning explored in chapter two, role of the joint drought index as developed in chapter three along with the central role played by the agrarian crisis in the farmer's socioeconomic status, acknowledging the unsteady relationship between the various factors involved such as crop production, irrigation cover and agriculture related policies. In addition, the effects of droughts on the economy of the agriculture and allied businesses sector and overall GDP of the state are also discussed along with plausible measures to improve the drought mitigation measures in the region.

4.2. Data

Statistical information on farmer suicides was retrieved from National Crime Records Bureau (https://ncrb.gov.in/) to understand the complex interplay between various hydro-climatological drivers (precipitation, groundwater storage etc.), drought mitigation measures and farmers' socioeconomic status in the region, while information about various farmer welfare schemes was obtained from the reports prepared by the Ministry of Agriculture and Farmers Welfare, Government of India (https://agricoop.nic.in/). The statistics related to economy of the state such as Gross Domestic Product (GDP) and per capita income was obtained from the economic survey reports (https://mahades.maharashtra.gov.in/) of the Maharashtra state. (Note: Due to changes in the methodology after 2011-12 and unavailability of separate GDP for each sector, Gross value added (GVA) by each sector is considered as GDP for simplicity in representation, where GDP = GVA + taxes - subsidies)

4.3. Droughts and economy of Maharashtra

4.3.1. Economical aspects of various sectors

The Maharashtra state is the largest contributor to the national income with an approximate 14% share in the national GDP (https://mahades.maharashtra.gov.in/). The economy of the state is mainly contributed by three sectors: Agriculture and allied businesses (referred as agriculture henceforth), Industries, and Services sector sharing about 11%, 33% and 56% of the state GDP, where primary source of income for more than 60% of the state's population is related to agriculture and allied activities. The agriculture sector primarily consists of crops, livestock, forestry and logging, fishing, aquaculture etc., while the industry sector is mainly contributed by mining, manufacturing, electricity, gas, water supply, construction, and other utilities. The highest growing services sector is made up of trade, hotels and restaurants, transport, storage, communication, and services related to broadcasting, financial, real estate and professional services, public administration, defense, and other services. Out of these three sectors, the services sector showed the highest growth rate (9%) during 2004-05 to 2018-19 followed by industry sector (8%), whereas the average growth rate of agriculture sector was 4% while the state was growing at an average rate of 8%.

4.3.2. Economy of Agriculture sector

The primary sector of the state economy i.e. agriculture showed significant variations during 2004 to 2019 with a dip in the GDP of the sector in case of drought years (**Figure 4.1**(a)) along with decrease in its share in the total GDP of the state in respective years (**Figure 4.1**(b)). Moreover, this sector shows prominent fluctuations in the growth performance when compared with other sectors, where services sectors managed a steady growth, while fluctuations in the industry sector are mainly associated with the manufacturing sectors requiring raw materials from the agriculture sector (**Figure 4.2**(a)). The direct impact of droughts on agriculture is in the form of crop failures, leading to a decrease in overall crop production which significantly affects the growth rate of the sector. The average growth rate of agriculture sector was better till 2011-12 (5.8%) which saw two dips owing to droughts which then dropped to 2.4% in the later period which had multiple drought events including consecutive drought years 2014-2015.

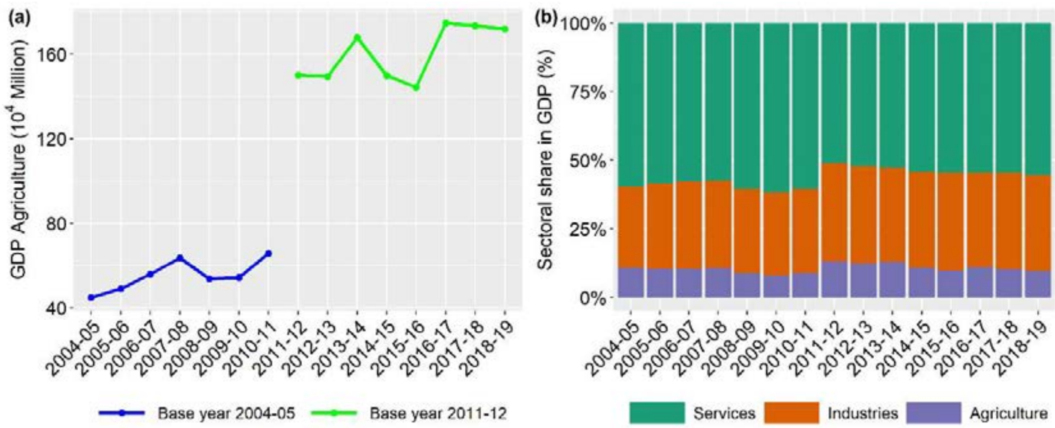

Figure 4.1: (a) GDP of agriculture sector for the state of Maharashtra (INR) (b) Share of each sector in the state GDP (Base year for calculation of GDP from 2004-05 to 2010-11 is 2004-05 and from 2011-12 to 2018-19 is 2011-12)

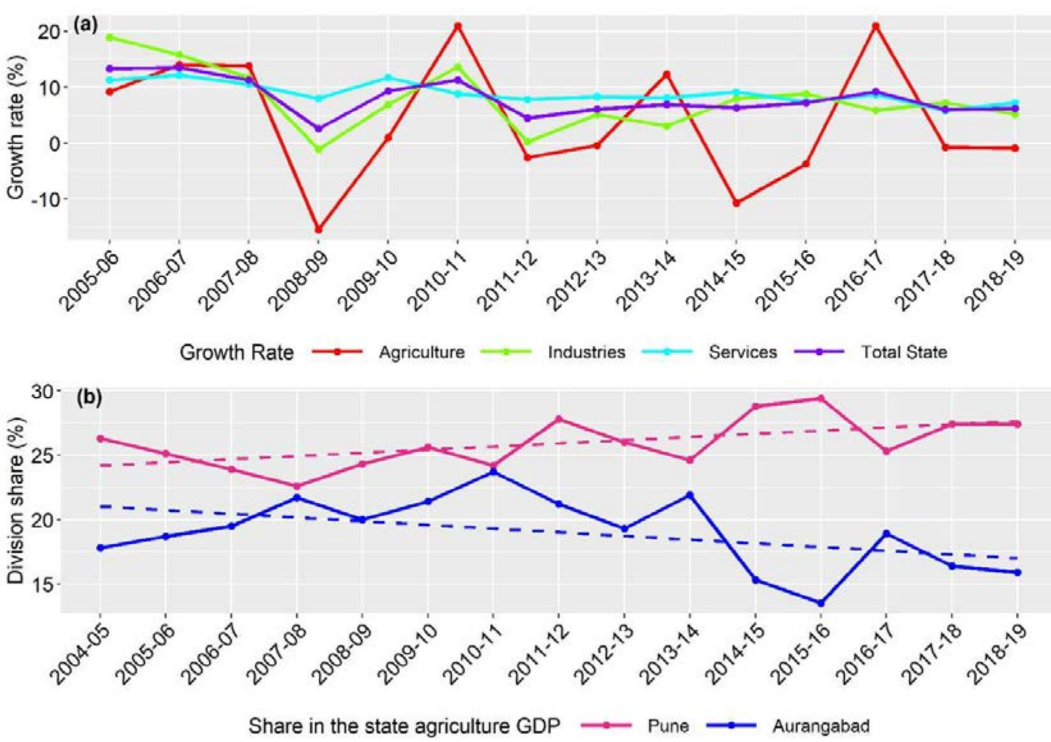

Figure 4.2: (a) Sector-wise annual growth rates in the GDP of Maharashtra state (b) Share of Pune and Aurangabad division in the GDP of the agriculture sector of the state

The state's hydro-climatic conditions and physical features separate it into mostly western and other regions, where rainfall variability has considerable effects (section 2.3.3). The Pune division from the western region is the prime contributor of increase in leaf area and shows maximum greening in the state owing to better irrigation facilities, agricultural practices, and overall water availability as discussed in the chapter two. As an inevitable effect, on economical aspect, Pune division also shares maximum contribution (26%) to the state GDP of agriculture sector, which further shows an increasing trend (**Figure 4.2**(b)). On the other hand, the share of Aurangabad division, which experienced browning in some regions and has approximately 19% contribution in the state GDP of agriculture sector, is witnessing a decreasing trend in its share (**Figure 4.2**(b)). The Aurangabad division is highly susceptible to drought conditions emerging from multiple factors such as inadequate irrigation facilities, declining groundwater storages, along with absence of efficient state policy interventions which further exacerbate the situation (discussed in further sections). The GDP of agriculture sector in the Aurangabad division is highly influenced by drought situations arising from multivariate factors, which witness peaks and troughs parallel to the drought situation in the region, which are successfully captured by JDI developed in the chapter three (**Figure 4.3**(a)). The state agriculture sector is highly vulnerable to droughts and is frequently suffering from the aftermath showing poor performance in the overall economy affecting the socioeconomic security of related stakeholders. Moreover, despite the increase in overall productivity of the state as discussed in section 2.3.5, with increasing index of agriculture production (compared to average production of 1979-82), the share of agriculture in the state GDP is not increasing (**Figure 4.3**(b)), where studies have found decreasing share of agriculture in the overall economy of India attributed to droughts and rainfed agriculture in last few decades (Deshpande, 2022).

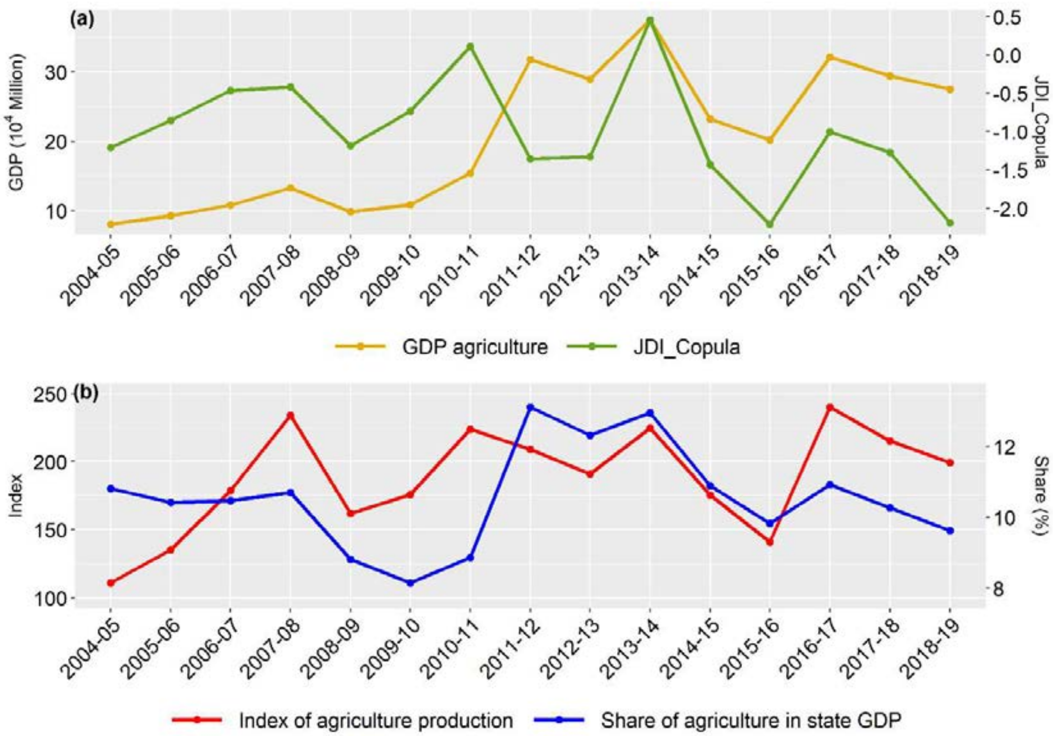

Figure 4.3: (a) GDP of agriculture sector for Aurangabad division along with multivariate Joint Drought Index (JDI_Copula) obtained from chapter three, (b) Index of agriculture production for Maharashtra (compared to average production of years 1979-82=100), and share of state agriculture sector in the state GDP

4.3.3. Difference in the development of western and central region

The effects of droughts are predominantly evident and harsh in the central divisions of Aurangabad and Amravati which are already suffering from developmental backlog (Government of Maharashtra, 2013) due to extreme hydroclimatic conditions. Considering the agrarian nature of these divisions, this underdevelopment is increasing cause of social unrest, threatening the socioeconomic security in the region. The backwardness of the central divisions is evident in the economic growth compared to other divisions of the state, highlighted by the per capita income of the districts in these divisions. The lowest per capita income districts are generally located in the Aurangabad and Amravati division except for Garhchiroli district from Nagpur division, while highest per capita income districts are in Kokan and Pune division. The average per capita income of Aurangabad and Amravati division is 65,410 and 60,435 INR, while Kokan and Pune division have per capita income of 157,147 and 112,230 INR respectively, showing remarkable difference of 114% in the average income per person in these divisions. In addition, the industry sector which is the second highest contributor to the state GDP is again dominated by the western regions with about 78% contribution in the state GDP. Recently the services sector has been seen as a stable source of income, which is not much affected by the shocks of droughts and shows steady growth. However, the western region once more reaps the benefits of the services sector, contributing as high as 76% in the GDP of the sector.

It is proverbial to claim that the growth of any region is inhibited by natural disasters such as droughts impeding its ability to thrive, where the greatest impacts are always endured by the agriculture sector. The decreasing share of agriculture in the state GDP shows the decreasing employment in the sector, where squeeze and push effect can be observed when agriculture labor moves to other sectors. This can be a temporary or permanent employment creating a large mass of migrant workers, especially in the drought years. Maharashtra sees a large migration of agriculture related population from central regions, especially from Aurangabad to Pune region in search of alternate employment (Iyer, 2021). The migrant population must migrate from their places to live in uncertain situations, most of the times keeping their elderly and children behind, tremendously affecting their mental stability and socioeconomic security (Iyer, 2021). The declining contribution of the agriculture sector is largely compensated for by the growth in the services sector over the years which attracted the agriculture labor. However, the overall fluctuations in the growth of GDP are largely influenced by shocks in the agriculture sector in drought years which are transmitted to the overall economic growth of the state. The unsatisfactory performance of agriculture in the drought years puts farmers in the dubious cycle of economic perils. This not only affects their financial security but also compromises their social standing by making them unsuited for a variety of activities. Not everyone survives this brutal print of drought on their socioeconomic status breaking them from their will to live. Drought years heap the misery and worsen the life struggles for farmers discernable from the decrease in economic activities of agriculture sector and increase in the farmer suicides in the respective years. Although agriculture failures are primary reason for decreasing share of agriculture in the state economy, multiple factors are responsible for shaping the agriculture scenarios and affecting the socioeconomic status of farmers which are discussed in the further sections.

4.4. Factors affecting socioeconomic security of farmers

4.4.1. Climatic and anthropogenic factors

Enduring hydroclimatic changes and high dependency on rainfall with poor irrigation coverage, combined with inadequate irrigation infrastructure as discussed in chapter two (**Sections 2.3.3, 2.3.4, and 2.3.5**), have made Maharashtra highly vulnerable to droughts, which has ultimately led to agriculture failures and farmers' suicides. Since farmer suicides involve a complex interplay between a multitude of social and environmental parameters, it is difficult to disentangle the various governing factors. It can be argued that the basis of all problems stems from erratic rainfalls and agricultural uncertainties, and the role of policy interventions also cannot be ignored. Crop failures leading to indebtedness are considered to be the primary cause of farmer suicides in Maharashtra (more than 95% of the distressed farmers used credit money for cultivation) (Chinnasamy et al., 2019; Dongre & Deshmukh, 2012; NCRB, 2021; Talule, 2020b), where maximum number of suicides are observed in Amravati and Aurangabad division (Mishra, 2006; Talule, 2020a).

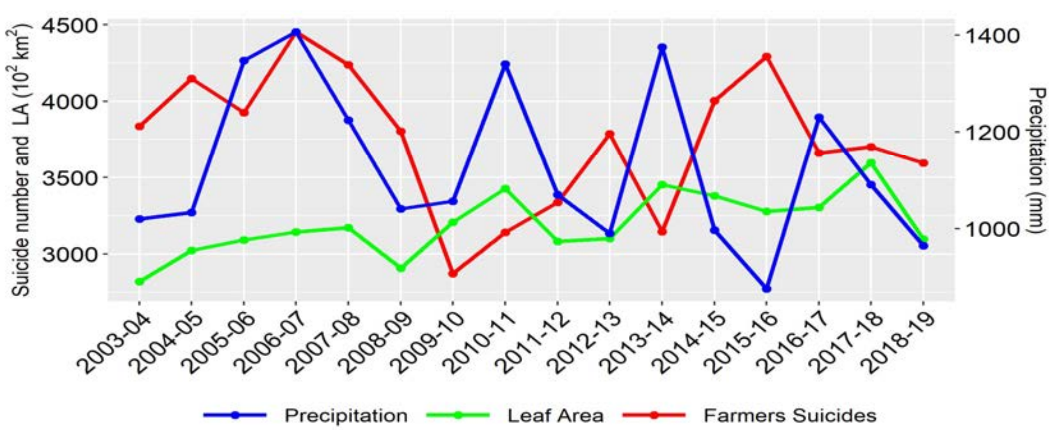

Figure 4.4: Number of farmers suicides, total leaf area and precipitation in each year from 2003 to 2018 in Maharashtra state.

Figure 4.4 shows the number of farmer suicides and precipitation in each year from 2003-2018 along with total leaf area in the state in each year. The farmer suicides have a significant share of 24% on average in total number of suicides (including other occupations and categories) in Maharashtra during the period of analysis, where the percentage share of farmers in total number of suicides moves parallel with the number of farmer suicides in Figure 4.4. The state witnessed two pronounced farmer suicide peaks in the years 2006 and 2015. It is interesting to note that both peaks represent different issues related to socioeconomic security of farmers. The number of suicides seems to be inversely proportional to the observed rainfall, with a rising tendency during drought/low rainfall years (e.g., 2004, 2012, 2014, 2015, 2017, and 2018). The highest number of suicides can be observed in the first peak of 2006, which then dampened to again increase after 2009, where the suicides were mainly observed in the cotton grower communities of Aurangabad and Amravati divisions. Despite better rainfall and crop production, the reduced prices as the effect of economic liberalization policies which had opened the global markets and imports of cotton without equipping the farmers for global competition (Mitra & Shroff, 2007), and failure of state procurement mechanisms initiated a wave of farmer suicides during the first peak (Pande & Savenije, 2016; Shah et al., 2021a; Talule, 2020a, 2021). Cotton farming requires assured irrigation and costly pest management mechanisms which have often been hampered by inadequate irrigation facilities (~3% area under cotton is irrigated, https://mahades.maharashtra.gov.in/) and impaired seed quality leading to stunted growth and low-quality output. Around 2002, a new genetically modified variety of cotton (known as Bt cotton) was introduced, which was costly, and the results depended on the irrigation quality, which showed better results in adjacent states such as Gujarat (better equipped with irrigation facilities) than Maharashtra (Mitra & Shroff, 2007; Shah et al., 2021b; Talule, 2020a). Within India, the cotton yield in Maharashtra was one of the lowest compared to other states showing lower competence of Maharashtra farmers for global markets (Mitra & Shroff, 2007). The absence of effective and meaningful state policies was also evident in 2016, when a production glut (especially in cotton, **Figure 2.9**b) followed by lower commodity prices resulted in a large number of suicides. State procurement mechanisms and enforcement of the minimum support price (MSP) are critical in the case of production gluts but are not in place in Maharashtra and require significant revitalization to include more crop varieties in the procurement basket (Shah et al., 2021a; Talule, 2020a, 2021). The debt waiver schemes were helpful to slow down the number after 2006 which again increased in the second peak during 2015 owing to consecutive droughts in 2014 and 2015. During the drought years, farmers even try second or third sowings in an attempt to survive the drought, exhausting all their savings in the hope of good produce. However, if that does not help in the current year, they become forced to move to cash crops like sugarcane in the next year to compensate for the loss, which is a gamble in drought-prone regions considering high water requirements of such crops. This cycle can be observed from the fact that farmers' suicides increase sharply during rainfall deficit/drought years than years with normal rainfall (**Figure 4.4**), which is also true in case of GWS (correlation of farmer suicides and GWS during 2003-2019 is r = -0.4, which shows that decrease in GWS is also responsible for the increased stress and anxiety in farmers due to inability to supply water to the crops) as rainfall deficit causes depletion of GWS by less recharge and more extraction. Pande and Savenije (Pande & Savenije, 2016) suggest that the distress of smallholder farmers (holding less than 2 to 5 ha of farmland) because of poor irrigation facilities and low water storage capacity is mainly responsible for farmers' suicides in Maharashtra. Similar observations have also been made by other researchers (Government of Maharashtra, 2013; Kulkarni et al., 2016; Shah et al., 2021a; Talule, 2013, 2020a). Apart from the climate uncertainties, price volatility, increasing fertilizer prices, indebtedness, commercialization, competition to global markets with inadequate irrigation facilities, lack of assured water supply, interrupted power supply, increased input costs, declined credits from financial institutions due to previous unpaid loans or lack of credibility (considering persistent agriculture failures), and private moneylenders are some of the other factors affecting socioeconomic security of the farmers. The significant share of farmers in total number of suicides displays an urgent need of strategic and concentrated planning in alleviating these stressors where mere fluctuations in the number cannot be considered as a decisive break in deteriorating status of farmers.

4.4.2. Trends in vegetation: Greening-browning

In Maharashtra, the western regions, which are comparatively richer in agriculture production, share the largest part of the greening trends, while relatively backward districts of Aurangabad division lacking in irrigation and overall development still see a browning trend in LAI (**Figure 2.3**). Contrary to the observed greening trends, the socioeconomic developmental backlog in the state is the highest in Aurangabad and Amravati divisions (Government of Maharashtra, 2013). The increase in CP and productivity in these divisions is also lower compared to western Maharashtra which are richer in agriculture production safeguarded by overall water availability (**Table 2.8** and **Table 2.9**). This is also evident in the per capita income difference of about 114% between these regions as discussed in **section 4.3.3**. Aurangabad and Amaravati come under deficit water conditions with lowest per capita water availability in the state (438 and 624 m^3 per capita, respectively), which greatly affects its drought coping capabilities (**Table 2.8**), where maximum number of farmer suicides are observed in these two divisions (Talule, 2020a). The farmer suicides in non-irrigated croplands are far more than those with access to irrigation according to recently available reports by the Maharashtra state (80% of farmer suicides are from non-irrigated landholdings), where, as discussed in section 2.3.5.1, the irrigation cover in these divisions is very low which is mainly dependent on the groundwater. Despite the greening trends and increase in leaf area in the state, there is significant difference in the status of agriculture in western and rest of the Maharashtra in the form of irrigation infrastructure, increase in crop productivity and overall water availability, which consequently affects the farmers socioeconomic security.

Given the paucity of water resources and observed browning trends, investment in infrastructural development for irrigation is recommended, specifically in water-scarce regions of Maharashtra. Additionally, it is necessary to adopt sustainable strategies for water allocation and crop management consistent with the natural variability of rainfall at the earliest, as irrigation has the potential to improve CP, income, and employment in agriculture, which will enable farmers to gain stability and maintain their socioeconomic status which will help in curbing the extreme behaviors such as suicides.

4.4.3. Drought severity classification and drought declaration

The drought vulnerability of Indian agriculture sector is a cause of concern, especially among the farmers considering the agriculture driven economy of the nation. The recent widespread, severe and multiseason droughts have perturbed the farmers and escalated their apprehensions, especially related to drought monitoring and mitigation mechanism in India. In the process of drought management, drought declaration, based on multiple indices, plays an important role in initiating the government relief measures for drought affected areas as discussed in chapter one (Government of India, 2016).

However, recent media reports and research studies have shown the lacunas in this declaration method involving assessment of multiple indices to analyze the drought situation, which is time consuming, inefficient and inaccurate, where often critical variables like groundwater are neglected due to unavailability of consistent data (Aadhar & Mishra, 2022; Bhardwaj & Mishra, 2021). Drought declaration is a key factor for farmers to receive government help in the form of relief measures like financial waivers, alternate employment schemes, cattle camps, school fees waivers, increased subsidies, water supply etc. These factors are very important for farmers' socioeconomic security. Failure of acceptance of drought existence at government level leaves farmers at their own risk to cope with the drought hazards, fueling their distress. Multivariate joint drought index JDI, as proposed in chapter three, has potential to ease down these sufferings by improving the accuracy of drought detection and categorization. Integrated indices, such as JDI, play an important role in capturing the drought conditions created by different hydro-climatological abnormalities, thus improving the accuracy of drought detection. JDI reasonably incorporates responses of all the integrated variables and, thus, puts forward an improved understanding of the drought onset, which is crucial for employing the mitigation strategies by the governing agencies. As farmer suicides show increase in case of drought years, JDI, by improving the drought detection will be crucial in maintaining the socioeconomic status of the farmers.

Considering the wide impacts of droughts and their involved complexity, qualitative depictions of drought impacts are as necessary as quantitative analysis. Synergizing the regional expert knowledge from local bodies, agriculturists, and climatologists is also critical for drought categorization and can play an important role in the interpretation of multivariate indices like JDI to correctly capture the drought impacts. Furthermore, such multidisciplinary considerations will also play a critical role in identifying weak links in the drought monitoring system and for future mitigation strategies (Orimoloye, 2022), especially in vulnerable regions, such as Aurangabad division (commonly known as Marathwada).

4.5. Suggested measures for better water management

The natural water availability across the Maharashtra state is unequal, where western region enjoys its availability while the central part struggles to manage the available resources (**Table 2.8**). Divisions like Pune, with comparatively better irrigation facilities outperform other divisions in the annual CP (the highest increase in productivity by 195%, **Table 2.9**) and Net Change in Leaf Area (NCLA). Given the high productivity of sugarcane (often referred to as cash crop), this high water-consuming crop (20000-25000 m^3 ha^{-1}) which constitutes significant proportion of annual crop production in the state, is grown in a somewhat unplanned manner in the region (**Table 2.10**). However, conscious, and planned management of sugarcane is necessary by incorporating technologically advanced irrigation methods (e.g., drip irrigation) along with regionwide crop-specific targeted productivity which will also ensure the water availability for other native crops and limit the exploitation of the available resources. Additionally, more attention should be paid to conjugative water infrastructure development and upscaling the irrigation efficiency of the water-scarce regions to reduce their vulnerability to erratic rainfall patterns. In water deficit years, it is crucial to maintain at least the minimal crop water supply to farms which can help sustain the standing crops and reduce the farmer distress. The water security will encourage farmers to even try new crop patterns which are less vulnerable to the erratic climates considering local agroecology. This can be achieved through the expansion of irrigation parallel to natural water availability in the region. Deliberate efforts should be made to increase crop productivity, especially in the Kharif season (as it entirely depends on monsoon precipitation, where delays or dry spells severely affect the CP), where protective irrigation (to protect the crops in case of erratic rains) can be one of the possible ways to ensure water supply in case of long dry spells. There is an inequality in the distribution of irrigation water across different crops (Sugarcane > 70%, cereals ~21%, food grains ~18%, pulses ~11%, and cotton and oilseeds ~3%, out of total existing irrigation infrastructure, https://mahades.maharashtra.gov.in/) across the state (Government of India, 2018; Shah et al., 2021a), which also needs to be addressed for enhanced crop patterns as per water availability of the region. Measures like groundwater development and replenishment, GW quantification and rationing, micro-irrigation practices, watershed development, advanced agricultural practices, and sustainable crop patterns can further help reduce the vulnerability and increase the water efficiency of these regions. This will propel the growth in agriculture and help in better CP and productivity, which will enhance the greening in croplands and maintain the regional food security along with socioeconomic security of farmers.

4.6. Need for institutional interventions for farmers security

For an efficient, prompt, and need-based adaptation to climate change and prevailing farming practices, effective and authentic exchange of the information and technology at the farm level is a prerequisite. Interactive intervention programs, including various stakeholders, and focusing on a dynamic implementation of farmer-friendly and sustainable scientific advancements are essential for farmer's socio-economic security. In the current era of rapidly developing technology, open-source platforms will play an important role in establishing and facilitating the local farmers' need-based knowledge transfer and integrating multiple domains such as meteorology, soil science, agriculture, sustainable water use, and social security. Multimodal approaches for knowledge exchange, revitalization of the existing infrastructure for monitoring, developing, disseminating, and supporting adoption by farmers can benefit them by boosting their confidence in the system, which will, in turn, reduce the feeling of isolation leading to suicides. Despite multiple efforts being taken by the government (annual reports by Ministry of Agriculture and Farmers Welfare, https://agricoop.nic.in/), they are not reflected in increasing the irrigation efficiency of the region or stabilizing the water resource availability. Schemes such as debt/loan waivers when announced, especially in drought years, are crucial for farmers. However, such schemes provide merely temporary relief to farmers and not a sustainable solution to the root cause. Moreover, implementation of MSPs, efficient and effective Agriculture Produce Market Committees (APMC) to prevent exploitation of farmers from the intermediaries possess huge importance in the farmers socioeconomic security. Measures such as improved health care facilities, increasing the farmer's income, credit provisions, subsidized fertilizers, uninterrupted electricity, better rural-urban road connections, support to families in distress, supporting livestock care, creating awareness against suicide, responsible media reporting of suicides, reducing access to alcohol and addictions, etc. are also crucial along with state-level comprehensive policy interventions for the abatement of farmers' distress issues.

4.7. Summary and future directions

The persistent trend in farmers' suicides indicates the urgent need for focused efforts to develop irrigation infrastructure, policy modifications and improved drought management mechanism explicitly based on leaf area fluctuations and multivariate drought analysis as highlighted in this thesis. The greening in croplands, as revealed in chapter two, is a ray of hope for the agriculture sector as well as for the farmers. However, it does not offset the pressing need to reconfigure the uncertainties and complexities involved in the agricultural practices and drought management and mitigation measures to better deal with climate variabilities, where share of agriculture in the state GDP is showing a declining trend. Using the information of variability and trends in LAI, GWS, and precipitation along with drought categorization methods in the form of multivariate index JDI as discussed in this study, an educated understanding of agriculture scenarios can be made, enabling the farmers and policymakers to observe the cropping patterns, agricultural water demand, availability, and the source, which can be used in modifications and improvements in the current water management policies and understand the dynamics of the agriculture to offer sustainable solutions.

One of the primary reasons for farmer's suicides is a financial crisis or indebtedness, which is exaggerated due to persistent agriculture failures and climate uncertainties and ultimately hamper their socioeconomic status. It can be argued that many of these issues, if not all, can be eased with good agricultural produce and timely government help, which will not push the farmers into the debt trap. The financial stability among the farmers, which is primarily driven by climatic variability, is the central element in their mental stability, which can be achieved through assured gains from farming, which is possible through an assured water supply. Water management techniques like watershed management, equitable irrigation distribution, and sustainable groundwater management along with improved crop patterns parallel to water availability of the region have the potential to convert the distressing factors for farmers into assured incentives. Management of drought in case of drought years is also very important in view of its direct relation to agriculture failures, where drought declaration plays a crucial role in ensuring the farmers socioeconomic stability for the season. Policy reforms, together with these techniques, can give farmers hopes and improved incomes which will reduce their proneness to indebtedness which in turn will facilitate the improvement of the distress of farmers, diverting them from taking extreme steps such as suicides.

Considering the intertwined factors involved, picking a single factor contributing the most to the socioeconomic security of farmers is not feasible. Although for some years the suicides are mainly triggered by policy-level issues, the state is chronically drought-prone, where the suicides are mainly related to agriculture failures and related distress. Although we can see a decline in the number of farmer suicides in some years, we cannot say it is a decisive break in the trend of declining socioeconomic condition of farmers until the existing climate vulnerabilities are there without an exhaustive but explicit attribution to all of them.

Given the myriad of confounding drivers, the quantitative assessment of policymaking, various socioeconomic indicators and its effects is exceedingly difficult, driving this chapter to qualitatively analyze the time series of the farmer suicides, viable policymaking facilitation, and role of droughts in the economy of agriculture in the state. In view of the high socioeconomic vulnerability of the Maharashtra state, this chapter will be pertinent in addressing the sensitive aspect of farmer suicides with descriptive analysis of the various factors involved.

CHAPTER 5
Conclusion and future study

5. Conclusion and Future Study

The complex and multifaceted phenomenon of drought not only threatens food security by persistent agriculture failures but also affects the socioeconomic security of its key stakeholders i.e., farmers. For comprehensive drought analysis and mitigation, the knowledge of local influencing factors driving drought propagation is pertinent for effective drought categorization. Till now, the knowledge of vegetation response to the external influencing factors has either been carried out on a global scale that puts forward bulk estimates or precipitation is primarily discussed, where other regional driving factors may have a greater influence on the vegetation response. Given the socioeconomic sensitivity of India to precipitation and other factors, there is an urgent need for a quantitative assessment of the commonly anticipated factors (for e.g., precipitation, GWS, cropping intensity, crop productivity, and irrigation) and their complex interplay, especially in the regions highly vulnerable to droughts. This is the first time the relation between greening-browning in vegetation, and their driving factors in drought-prone areas along with the implications on farmers' socioeconomic harmony, are discussed for agrarian states like Maharashtra in central India. Furthermore, using these confounding drought drivers, a multivariate joint drought index (JDI) is proposed for holistic drought quantification by integrating the response from each primary driver.

In chapter two, trends, and variability in the MODIS leaf area index (LAI) time series, along with spatiotemporal patterns in precipitation, groundwater storage, agriculture statistics, and irrigation infrastructure, were analyzed to identify their influences on the vegetation response and to understand the dynamics of primary drivers. The state showed greening attributed mainly to agricultural practices with a net gain of 17.478×10^3 km^2 of leaf area during the period of analysis. Maximum greening was observed in irrigated croplands, attributable to increased crop productivity, whereas inadequate irrigation facilities with erratic rainfall patterns and droughts were primarily responsible for cropland browning. Here, the dynamics and variability of vegetation response was discerned by incorporating a spectrum of synergistic feedbacks from multiple confounding drivers, where the quantitative distinction in leaf area change was governed by an uneven distribution of water availability across the administrative divisions. The results of chapter two will play a decisive role in establishing a framework for drought impact assessment and policymaking in Maharashtra state as well as for the multidimensional studies in other drought-prone regions of India and other developing countries requiring serious attention to multiplex issues related to policy modifications and deteriorating status of key stakeholders of agriculture. While the trend in LAI in Maharashtra state was mainly explored in this chapter focusing on the impact of climatic and anthropogenic factors on agriculture, the climatic and policy-related study of trends in LAI in various biomes could be investigated in future studies.

With the help of confounding drivers of vegetation dynamics in the semi-arid regions of Maharashtra, analyzed in chapter two, chapter three deals with the development of a multivariate joint drought index (JDI) for a better representation of drought severity assessment, enabling users to understand the integrated effect of multiple drought characteristics by assimilating the critical information from the constituent variables. The result of the present analysis mainly discusses the JDI characteristics by two methods: PCA and Copula, and implications of the JDI on the drought monitoring and mitigation measures. The drought intensities captured by JDI are more realistic than the traditional ones, where groundwater drought is effectively captured in JDI which is commonly neglected despite the dominant role of groundwater for irrigation in the study region. The chapter also gives insights into multiple characteristics of droughts including onset, duration, severity, and termination, by this novel drought index. The multidisciplinary approach of drought management as presented in this chapter is predominantly important in decision making and government response to droughts, especially in socioeconomically sensitive regions of India. Future study shall focus on using the regional hydrologic models for providing inputs to the multivariate index along with using fine resolution data which can also be extended to a country level by incorporating regional driving factors. Development of a new drought classification scheme for JDI should also be considered for future study to better understand and compare the responses of integrated variables using different methods.

Chapter four discusses the role of droughts, trends, and dynamics in hydroclimatic variables, irrigation infrastructure, agriculture related policies and multivariate drought analysis in the socioeconomic security of the farmers, along with economy of the state and various divisions. Despite the observed greening trends as discussed in chapter two, the study region witnessed a high number of farmer suicides related to droughts and agriculture failures addressing the crucial need to reconfigure the irrigation infrastructure and comprehensive policy interventions for abatement of farmer distress. Moreover, the decreasing share of agriculture in the state economy further highlights the stress on the sector, which gets echoed in the socioeconomic security of the farmers. Although it is difficult to point out a single driving factor for jeopardizing the socioeconomic security of farmers, indebtedness, and agriculture failures along with inadequate and insecure water availability for irrigation and inefficient policy interventions are some of the key factors fueling the distress in farmers. Improved water management and timely and efficient state interventions along with modified agricultural techniques can help in dampening the harsh aftereffects of droughts and securing the farmers social and economic status. In future, an index shall be developed based on the socioeconomic condition of the region, representing the socioeconomic drought which will be beneficial in understanding the effects of droughts on community related to agriculture and allied businesses, which will be advantageous in initiating the government response to droughts and formulate new policies.

The quantitative assessment of vegetation dynamics and proposed framework for drought classification and management using multivariate drought index along with descriptive analysis of factors affecting the socioeconomic security of farmers by incorporating a spectrum of dynamic feedback from multiple confounding drivers as discussed in this thesis will be valuable in providing important insights to the policymakers for efficient and effective drought management and drought proofing of susceptible areas in India and worldwide.

6. Acknowledgements and Data availability

The datasets utilized in this study are duly cited in the respective chapters. The datasets used are mainly obtained from the sources as follows:

MODIS MCD15A2H: https://lpdaac.usgs.gov/products/mcd15a2hv006/), MODIS MCD12Q1: https://lpdaac.usgs.gov/products/mcd12q1v006/, India Meteorological Department IMD: https://www.imdpune.gov.in/, Global Land Data Assimilation System (GLDAS) version 2.2: https://disc.gsfc.nasa.gov/datasets?keywords=GLDAS, Central Ground Water Board (CGWB) India-WRIS: http://www.india-wris.nrsc.gov.in/wris.html, Global Map of Irrigated Area (GMIA) by FAO: http://www.fao.org/aquastat/en/geospatial-information/global-maps-irrigated-areas/latest-version/), Economic Survey Department, Government of Maharashtra: https://mahades.maharashtra.gov.in/, Department of Agriculture and Cooperation: http://krishi.maharashtra.gov.in/, Ministry of Environment, Forest, and Climate change: https://fsi.nic.in/. Database of Global Administrative Areas GADM: https://gadm.org/, National Crime Records Bureau: https://ncrb.gov.in/, Ministry of Agriculture and Farmers Welfare: (https://agricoop.nic.in/).

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