# Prediction of Impact of Climate Change on Agricultural Production through Land Suitability Analysis

**Ph.D. Thesis**

By

**BUSHRA PRAVEEN**

**DISCIPLINE OF ECONOMICS**

**INDIAN INSTITUTE OF TECHNOLOGY INDORE**

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# Prediction of Impact of Climate Change on Agricultural Production through Land Suitability Analysis

**A THESIS**

*Submitted in partial fulfillment of the requirements for the award of the degree*
***Of***
**DOCTOR OF PHILOSOPHY**

*By*
**Bushra Praveen**

**DISCIPLINE OF ECONOMICS**

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# INDIAN INSTITUTE OF TECHNOLOGY INDORE

I hereby certify that the work which is being presented in the thesis entitled <**Prediction of Impact of Climate Change on Agricultural Production through Land Suitability Analysis**> in the partial fulfillment of the requirements for the award of the degree of **DOCTOR OF PHILOSOPHY** and submitted in the **DISCIPLINE OF ECONOMICS, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from Dec 2016 of joining to November 2021 under the supervision of Dr. Pritee Sharma, Professor, School of Humanities and Social Sciences (HSS) Indian Institute of Technology Indore.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

Bushra Parveen

04 November 2021

**signature of the student with date**
**(BUSHRA PRAVEEN)**

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This is to certify that the above statement made by the candidate is correct to the best of my/our knowledge.

Pritee

04 November 2021

Signature of Thesis Supervisor #2 with date

**(Dr. PRITEE SHARMA)** **(NAME OF THESIS SUPERVISOR)**

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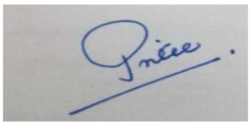
<**BUSHRA PRAVEEN**> has successfully given his/her Ph.D. Oral Examination held on **<12.July.2022>**.



Signature of Thesis Supervisor #2 with

15.July.2022

**(Dr PRITEE SHARMA)** **(NAME OF THESIS SUPERVISOR)**

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## Synopsis

## Introduction

Climate change is widespread, rapid, and intensifying, with many climatic trends now irreversible, at least for the present time frame. The attribution of these changes to human influence has been further strengthened by the latest much-anticipated Intergovernmental Panel on Climate Change IPCC report (IPCC., 2021; Climate Change., 2021[1]).

Human-induced climate change is already affecting many weather and climate extremes globally. Evidence of observed changes in extremes includes increasing incidences of heat waves, heavy precipitation, droughts, and tropical cyclones. Changes in precipitation trend and severity (Li et al., 2019; Storch et al., 1993; Rahman and Islam, 2019) and meteorological drought are also evident.

Climate change is also one of the most pressing problems of the twenty-first century, threatening the capability of humanity to fulfil fundamental human needs as well as detrimental to human health. The most visible signs of climate change. According to the United Nations World Food Program, changes in rainfall patterns have led to an increased likelihood of crop failure, and extreme weather events such as droughts, floods, and storms can exacerbate food security problems globally (Climate Impacts on Food Security and Livelihoods in Asia, UN World Food Program.,2016).

Further, changes in the hydrological cycle with respect to precipitation strength and duration are leading to concomitant region-specific extreme drought or flooding (Meresa et al., 2016; Oguntunde et al., 2017). Studies reveal that crop production and productivity have decreased significantly, especially in third-world countries, resulting in food insecurity, famine, malnutrition, and other socio-economic issues escalated by livelihoods and habitat destruction. (Nath and Behera, 2011; Ho et al., 2018; Sarkar et al., 2019). Climatic stress will put significant pressure on many developing Asian countries which have to simultaneously meet the demands of rising populations, using finite and often degraded soil and water resources that are predicted to be further stressed by the impacts of climate change (Rosegrant et al., 2018). This is about 85% of Indian farmers and marginal and small

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[1] The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change)

landholders (Agricultural Census, 2011 http://agsccences.nic.in) and about 60% of the net sown area is under rainfed agriculture.

Indian agriculture is highly vulnerable to climate change, which will considerably affect the cropping system, livestock, fisheries, poultry, soil, pests, and diseases. It is inevitable that climate change will have a critical impact on Indian agriculture in the coming years. It will negatively impact some important crops that would lead the country to food insecurity. Further, as about 85% of Indian farmers and marginal and small landholders (Agricultural census, 2011 http://agsccences.nic.in) and about 60% of the net sown area is under rain-fed agriculture, the climate crisis will also lead to long-term socio-economic impacts for rural India. Thus, efficient measures for adaptation and climate change resilient agricultural practices are critically required.

The key focus of this thesis is the creation of integrated climate change-agricultural production evaluation models to understand the impacts of change in climate variables on Indian agriculture across 34 meteorological regions across India and also forecast productivity and land suitability in the regions. The thesis initially evaluates patterns of rainfall transitions and long-term meteorological droughts across India.  Several non-parametric trend analysis approaches, such as the Mann-Kendall measure, Innovative trend analysis (ITA), and the LOWESS curve, were used to investigate the proof of rainfall reduction. To detect the presence of change in the rainfall results, change point detection techniques such as the Pettitt test, standard normal homogeneity test, and Buishand range test were used.

The European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-5 reanalysis data was used to determine the causes of the rainfall transition. A long-term meteorological drought has been estimated using the standard precipitation index for twelve-month (SPI)-12. Similarly, the Mann-Kendall test and creative pattern analysis and innovative trend analysis (ITA) were used to predict overall trends in long-term meteorological datasets. The Morelet wavelet transition was used to detect the meteorological drought's periodicity. Then, in order to determine the impact of climate change on crop production, first, we did an innovative trend analysis (ITA) for historical trend analysis, and then multiple regression and Pearson's correlation coefficient were used to describe each crop's production in the light of climate change. Climate variables and crop production in India were estimated and forecasted using the artificial neural network (ANN) and ARIMA models up to 2030. Mean absolute error

(MAE), mean absolute percentage error (MAPE), Mean squared error (MSE), and root-mean-square error (RMSE) error values were used to quantify the error. Finally, various fuzzy logic operators and a hybrid fuzzy-Analytic Hierarchy Process (AHP) model were used to create agriculture-suitability maps. The Morris model-based global sensitivity analysis, the random forest-based and Pearson's correlation coefficient methodology were used to investigate the impact of input variables on the final agriculture map.

Results reveal that but for seven divisions during the study years, most meteorological divisions had declining annual and seasonal precipitation trends. Eleven divisions recorded a statistically significant reduction in rainfall pattern at a (p0.05) during the monsoon season, while the declining rainfall trend during the winter and pre-monsoon seasons was negligible.

In order to analyze the impact of long-term meteorological drought on agriculture (SPI-12), the Standard Precipitation Index, for example, referring to accumulation periods of twelve months, was used to predict long-term meteorological drought for 34 sub-divisions. The innovative trend analysis (ITA) and wavelet transformation findings showed that meteorological drought has recently (mostly after 1980) increased in almost all subdivisions, whereas these sub-divisions previously had mild to no drought conditions.

In terms of crop yields, we find that yields for Bajra, Cotton, Gram, Jowar, Maize, Ragi, Wheat, Tea, and Rice improved in a consistent and statistically relevant ($p<0.01$) way. The growth of rapeseed and barley showed a significant ($p<0.01$) and monotonic downward pattern. The demand for the rest of the crops followed a similar upward pattern. According to the trend study, the production of many edible food grains such as rice, wheat, Bajra, jowar, and ragi has increased dramatically. ANN projections have forecasted future agricultural and temperature factors in India for the years 2017–2030. The forecasted rainfall trend has not improved substantially. The ANN model, on the other hand, has discovered a significant improvement in the expected temperature trend. Production of barley, ahar, linseed, and rapeseed would be decreased. To summarize, all crop production will increase in the future as temperatures rise and rainfall trends change, with the exception of barley, arhar, linseed, and rapeseed.

According to the Fuzzy map for agricultural suitability study, 16.76 percent (546019.2 km2) area would be highly suitable for agriculture, including some parts of the south-west, along with 8.04 % of the area incredibly suitable for agriculture. Only 15.52 percent (55722.6 km2) of the total area is equally suitable for agriculture by 2030. On the other hand, about 6.11

percent of agricultural land, or 19.067.2 km2, would be deemed extremely unacceptable, while the remaining 53.55 percent, distributed in the northern, central, southern, and western zones, would be deemed moderately inappropriate (1744325 km2) by the year 2030.

Temperature and precipitation were the most influential variables in the agricultural suitability studies, while evapotranspiration was the least influential predictor. This study can greatly assist in the development and establishment of background for agricultural climate research for regional studies in India. This research also illustrates the capability of geospatial technology as well as the pooling of various themes of land, soil, temperature, and topographic data that can be incorporated into GIS. The study demonstrates a way to obtain more precise results for agricultural productivity analysis under changing climatic conditions.

**Figure 1** Delineates the framework for the research work of the thesis in terms of key steps, methodology, and key insights.

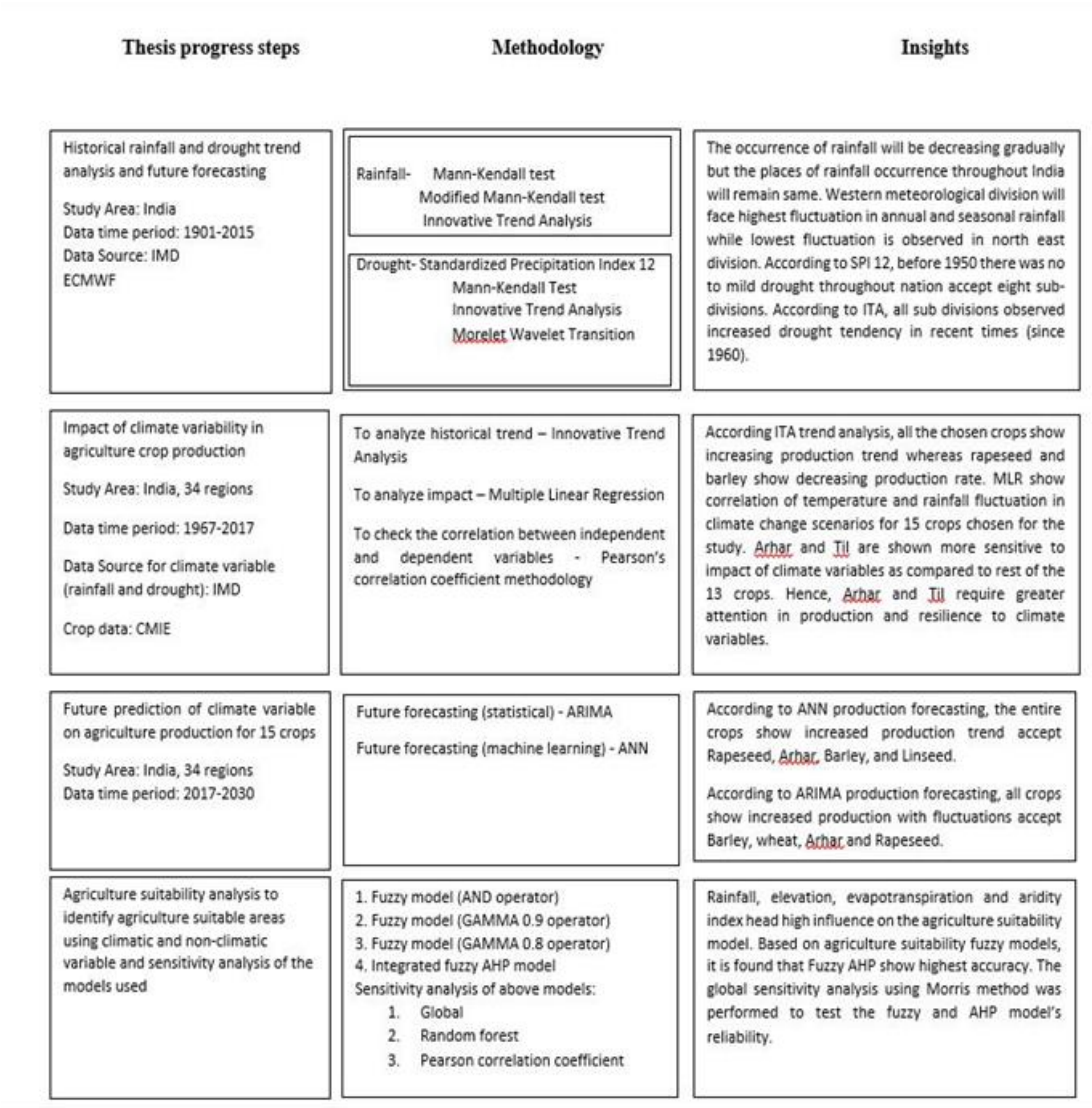


**Fig 1:** Conceptual Framework of the Study

## Literature Review

Climate change is one of the most pressing problems of the twenty-first century, threatening fundamental human needs as well as human health. Changes in precipitation trend and severity (Li et al., 2019; Storch et al., 1993; Rahman and Islam, 2019) and meteorological drought are the most visible signs of climate change. The study was conducted since heavy weather events and moderate to severe drought has a big impact on humans. The precipitation and meteorological drought patterns have been taken into account in the study. (Westra et al., 2014). The trend analysis of rainfall (Partal and Kahya, 2006; Addisu et al., 2015; Neil and Notodiputro, 2016; Singh and Srivastava, 2016); temperature (Arora et al., 2005; Karanurun and Kara, 2011; Meshram et al., 2018) and other climatic variables on different spatial scales will help in the construction of future climate scenarios.

According to the United Nations World Food Program, agricultural systems are highly sensitive to the climate given their high reliance on rain-fed production. Changes in rainfall patterns can increase the likelihood of crop failure and result in production declines. Higher temperatures in key producing areas typically result in reduced yields of desirable crops whilst extreme weather events such as droughts, floods, and storms can exacerbate food security problems (Climate Impacts on Food Security and Livelihoods in Asia, UN World Food Program.,2016).

Agriculture has been severely impacted by climate change across the world. The need for food has risen over time as India's population has grown. On the other hand, climate change has a detrimental influence on agricultural productivity, resulting in hunger, food shortages, farmer suicides, and other problems. References, As a result, sustainable agriculture management and water supply management are crucial for feeding billions of people. Based on this reasoning, the goal of this study is to investigate trends analysis, climate change and its impact on agricultural production in current and future scenarios. This research also resulted in the development of an agricultural model that is suited for smart agriculture techniques. Several approaches have been used to achieve these goals.

**Research Gap**

Based on the research in the previous literature, the following research gaps were identified:

- Previous research (Imran et al.,2014; Nikhil et al.,2014; Shrestha et al.,2012) has primarily used linear regression for analyzing climatic variation and very few studies have been undertaken using the Mann-Kendall test (Ahmed et al., 2017; Wu and Qian 2017) for exploring the climate change. But in the present study, recently developed innovative trend analysis (ITA), along with several versions of Mann-Kendall tests (MK test, modified MK test, trend-free pre-whitening MK test), and also linear regression have been used for analyzing the change in climatic parameter for whole India. Only a few studies (Gao et al.,2018; Wang et al.,2013) have shown that for climate change, but this thesis utilises ERA-5 reanalysis data from the European

Centre for Medium-Range Weather Forecasts (ECMWF) to establish the reasons of rainfall causes.

- Many studies have only incorporated precipitation changes for analysing the climate change (Adeyeri et al.,2017; Okonkwo et al.,2014; Nkiaka et al.,2017) while in the present study, the meteorological drought has been used to investigate climate change using advanced statistical techniques like wavelet transformation and trend analysis.

- Most of the studies have used average data for analyzing climate change, but in this thesis, all monthly data since 1901-2017 have been analyzed using heat maps.
- Previous research has only focused on climate change, but did not focus on the impact of climate change on agriculture production. Even, some research theoretically analyze the impact of climate change on agriculture, but in this thesis, impact of climate change in terms of rainfall and temperature on the production of 15 crops individually analyzed for whole India using multi linear regression (MLR).
- Many researchers have used statistical models like ARIMA, ARMA for forecasting future climate change, but in this thesis, statistical as well as machine learning algorithm like artificial neural network have been used not only for forecasting climate, but also for agriculture productions.
- Some studies done by different researchers all over the world (Wolf et al., 1996; Jagtap et al., 2002) have modeled agriculture suitability model in context of climate change for whole country, but in this thesis, the agriculture suitability modeling in context of climate change have been prepared at regional level using fuzzy logic and other advanced techniques for deriving recommendation for smarter agricultural practices under changing climatic conditions at more granular level.

Therefore, this thesis provides a comprehensive research on change in climatic parameters for whole India meteorological zone wise along with its impact on agriculture productivity, the study also forecasts future scenario for agriculture production and recommendation for proposing smart agriculture under climate change through land suitability study.

**Research objectives**

Based on the previous literature survey, the research gaps and research questions have been found out for the present research. Therefore, considering the discussion about climate change and its effect on agriculture productivity, the following questions have been raised:

- Is there any evidence that climatic factors such as rainfall, drought intensity, and temperature change over time across different regions?
- How does climate change affect agricultural production, crop-wise and zone-wise?
- How can future conditions of climatic variables and agriculture production be estimated?
- What will be the likely future scenario for climatic variables and agricultural production?
- In the light of current climatic conditions, what will be the potential regions in India for suitable agricultural production?

As a result, the following objectives have been developed to address both research questions and research gaps.

- To measure climate change in India in terms of changes in rainfall and meteorological drought at the regional level using the most updated data.
- To investigate the impact of climate change on Indian agriculture production.
- To forecast the impacts of changes in climatic parameters on agriculture production till 2030.
- To develop agriculture suitability models for identifying potential agriculturally viable areas in changing climatic conditions.

**Data and method**

In the present study, a variety of databases have been used to explore the effects of climate change. The database has been classified in terms of objectives and chapters. The details of databases have been used as follows:

*Chapter 3*: In this chapter, rainfall data has been used to explore climate change in terms of rainfall reduction and the lengthening of meteorological drought. The study collected rainfall and temperature data for the time period 1901 to 2015 from IMD India, New Delhi.

*Chapter 4*: In this chapter, temperature and rainfall data from 1901 to 2015 are presented. The continuous data were used for this study, which covered the years 1976 to 2016, to investigate the impact of climate change on agriculture production; fifteen major crops were considered which account for over 75% of the total cropping area.

*Chapter 5*: In this chapter, future forecasting has been made for the meteorological variables and crops produced using the same data as in Chapter 3.

*Chapter 6*: In this chapter, several databases have been used. For agriculture suitability work data was collected from various sources such as soil types (https://soilgrids.org/), soil erosion data ISRIC, world soil information, DEM DIVA-GIS 90meter, aridity ISRIC, world soil information and Land use land cover Oak Ridge National Laboratory (ORNL) Distributed

Active Archive Center (DAAC) (https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1336).Note: *Different resolution effects of several data have been solved using resampling effects.*

**Methodology**

In this thesis, the methods have been prepared objectively. The section below provides a brief description of the methods that have been employed for dealing with the research gaps.

*First objective*: To deal with the first objective, several methods have been employed. First, to explore the evidence of rainfall reduction, several non-parametric trend analysis methods have been utilized, such as the Mann-Kendall test, Innovative trend analysis, and LOWESS curve. Change point detection techniques, such as the Pettitt test proposed by Pettitt, (1979), the standard normal homogeneity test (SNHT) proposed by Alexandersson and Moberg, (1997), and the Buishand range test, have been employed to detect the presence of change in the rainfall data series for thirty-four meteorological subdivisions. To identify the causes of rainfall change, the European Centre for Medium-Range Weather Forecasts (ECMWF), ERA-5 (http://apps.ecmwf.int/ datasets/data/interim-full-daily) provided atmospheric oscillations on rainfall pattern variation, winter and summer precipitations, and moisture divergence on 1.25° x 1.25° grids from 1979 to 2015 on 1.25° x 1.25° grids. Since 1979, the ERA5-Interim is the most recent ocean-atmospheric transition reanalysis dataset available. In addition, to assess the impact of cloud cover on rainfall variance, a low cloud cover dataset was obtained from the ECMWF ERA5 data. To detect a long-term change, the heat map was used. On the other hand, the standard precipitation index (SPI)-12 has been used to estimate long-term meteorological drought. Similarly, to estimate the overall trend in the long-term meteorological datasets, the Mann-Kendall test and innovative trend analysis (ITA) have been used. Morelet wavelet transformation has been used to detect periodicity analysis of the meteorological drought.

*Second objective:* The second objective was to explore the impact of climate change on agriculture productions. Therefore, first, the overall trend for each climatic variable and crop production has been measured using innovative trend analysis. Then, to assess the effect of climate change on crop production, multiple regressions have been applied for explaining each crop production in the context of climate change.

*Third objective*: Using datasets from 1967 to 2016, this chapter used an artificial neural network (ANN) and ARIMA models to estimate and forecast climatic variables and crop production in India up to 2030. The comparison of expected and real values of crop production and climatic variables using ANN and ARIMA has been evaluated to explore the performance of the model with suitable mean absolute error (MAE), mean absolute percentage error (MAPE), Mean squared error (MSE), and root-mean-square error (RMSE) error values.

*Fourth objective*: In this chapter, numerical data, reanalysis data, satellite data, vector data have been used for preparing the agriculture suitability models. However, numerical data like rainfall and temperature have been converted into raster format by using kriging methods. On the other hand, vector data like soil types have been rasterized using spatial analyst tools in ArcGIS. Other observational data like evapotranspiration, wind speed have been modelled by NASA.Topographical data like slope, aspects, topographic roughness index (TWI), SPI have been extracted from SRTM DEM using the QGIS software package and spatial analyst tool of ArcGIS. On the other hand, soil-related data like RUSLE based gross soil erosion, soil qualities have been modelled by ISRIC World Soil Information, which has been directly downloaded from the ISRIC website. The land use land cover (LULC) map has been created using an artificial neural network model. Finally, these datasets were integrated using the different operators of fuzzy logic and hybrid fuzzy-AHP model for preparing agriculture suitable maps. On the other hand, the influence of the input variables on the final agriculture map has been explored using Morris model-based global sensitivity analysis, random forest and also Pearson’s correlation coefficient technique.

**Empirical results (Brief Summary)**

*First objective*: The findings revealed that, except for seven divisions during the study periods, most meteorological divisions exhibited diminishing annual and seasonal precipitation trends. For the monsoon season, 11 divisions reported a strong rainfall decreasing pattern ($p<0.05$), while the declining rainfall trend for the winter and pre-monsoon seasons was negligible. The average rainfall trend decreased by around 8.45 percent overall. For the various meteorological units, the likely year of greatest change varied, and the maximum change occurred mainly after 1960. Between 1901 and 1950, there was a growing trend in rainfall, but after 1951, there was a substantial decrease in rainfall. The results of the LOWESS curve show an increasing trend of annual rainfall up to 1965, but a declining pattern of rainfall after 1970. The results of the LOWESS curve for the winter season revealed that for the periods 1935-1955 and 1980-1998, a growing rainfall trend was observed. Between 1955 and 1998, there was a sharp drop in the pattern. In the case of the summer and monsoon seasons, the curve shows that a downward trend began after 1960. Since 1995, there has been a downward trend in post-monsoon rainfall. Many of the meteorological division's rainfall forecasts for the next 15 years showed a substantial reduction in rainfall. According to the ECMWF ERA5 reanalysis data, increasing/decreasing precipitation convective volume, elevated low cloud cover, and insufficient vertically integrated moisture divergence could have influenced rainfall change in India. SPI-12 the Standardized Precipitation Index (12 months), on the other hand, was used to estimate long-term meteorological drought for 34 sub-divisions to investigate its effect on agriculture. The results of the ITA and wavelet transformation revealed that the meteorological drought has recently risen in almost all sub-divisions, while in the past, these sub-divisions had moderate to no drought conditions.

*Second objective:* The innovative trend analysis (ITA) for climate variables and agricultural production has been examined for the years 1967 to 2016. The value is interpreted by the assigned variables as shown by trend indicators and their respective slopes. The trend indicator values for rainfall and temperature are 0.42025 and 0.05126, respectively, indicating that neither temperature nor rainfall had a noticeable trend. Cotton, Gram, Jowar, Maize, Ragi, Wheat, Tea, and Rice all showed a consistent and important (P0.01) upward trend in demand. Rapeseed (ITA D value -8.54) and Barley (ITA D value -28.93) both showed a major ($P<0.01$) and monotonic decrease in yield. The rest of the crops showed a similar upward trend in demand. Despite having limited agricultural land and low technical growth, most edible food grains such as rice, wheat, Bajra, jowar, and Ragi have increased significantly. As a result of increasing agricultural activity, the impact of climate change cannot be observed by direct observation.

Multiple correlation coefficients have been calculated for fifteen crops and climatic variables. The results show a very strong influence (coefficient determination values) between Ragi (0.862), Rapeseed (0.836), Tea (0.85), Wheat (0.815), Rice (0.811), and Jowar (0.815), indicating high crop production with the current temperature and rainfall pattern. Cotton (0.665), Gram (0.603), Barley (0.788), and Maize (0.621) production all show a strong connection. Crops of moderate strength, such as barley (0.597) and til (0.401), need a precise structure for yield and processing. The Arhar (0.298) crop has a weak relationship, indicating that it would take more attention in terms of productivity and climate change resilience. Temperature and rainfall variations had little impact on the production of groundnut and linseed. Although many crops responded differently to the climatic variables, Arhar and Til (one of India's two main crops in terms of cropping production) were found to be more vulnerable to the effects of climate change as compared to the other thirteen major crops studied.

*Third objective*: It is essential to check the performance of the model by predicting existing data before it is used for forecasting. If real data and forecast data have a similar relationship with lower error values, it may be used for further analysis. By refining the variables of ANN, the current research predicted climatic variables and different crops and discovered that the real and expected data of climatic variables and 15 different crops were very similar. With R2 values greater than 0.82, the association between real and expected values of all 15 crops and two climatic variables was extremely high. But for rice (0.86) and barley (0.82), the majority of the crops had R2 correlations greater than 0.92. The association between real and expected temperature and rainfall values was also very high (R2>0.82). The effects of these errors indicate that the model's efficiency in predicting climatic parameters and crop yields is adequate and can be used for future forecasting.

Future forecasts of agriculture and climate variables in India have been made by ANN models for the period 2017-2030. The pattern of predicted rainfall has not significantly changed. Instead, the ANN model has discovered a large increase in the predicted temperature pattern. Barley, Arhar, Linseed and Rapeseed production will be reduced. Though output is to be significantly increased to 2030, Rice, Ragi, Tea, Maize, Jowar, Bajra and Cotton. From 2017-2030 Til, Groundnut and Gram have examined moderated future-growing demand trends. In conclusion, except for barley, arhar, linseed, and rapeseed, all other crop production will increase in the future as temperatures rise and rainfall patterns shift.

*Fourth objective:* This chapter summarizes the findings of the land suitability zone for agriculture. In India, the area and percentage coverage of the various agricultural suitability zones per km2 have been computed. Following that, 14 fuzzy data layers were superimposed on this land suitability map to assess the overall agricultural suitability using the Fuzzy AND, Fuzzy Gamma 0.9, Fuzzy Gamma 0.8, and Integrated AHP models. The Fuzzy map showed, that for certain areas of the southwest, the dominance was strongly suitably 16.76% (546019.2 km2), the field was extremely suitable for 8.04% (261936.3 km2) and the surroundings were fairly suited to 15.52% (55722.6 km2). Around 6.11 percent of them, or

19.067.2 km2, were deemed highly inappropriate, while a moderately inappropriate sector, which was located in northern, middle, southern, and western areas, remaining 53.55 percent (1744325 km2). The global sensitivity analysis using the Morris method was performed in this thesis to evaluate the FUZZY and AHP models' reliability. The farm suitability models are used as dependent variables, while 14 influencing variables as independent variables were introduced. We also carried out a global sensitivity test based on the factors affecting variables that were derived to examine the most sensitive independent variable in the modelling of agricultural suitability areas. The most influential variables of the agricultural suitability area were temperatures and precipitation, while the lowest responsible predictor was evapotranspiration.

**The policy implications of the thesis**

The present study is significant in terms of India because it is the first time that agriculture suitability mapping has been comprehensively performed at the national level. Furthermore, the above research would significantly aid in the new climate of agricultural research on a regional scale.

Sustainable agriculture is one of the most effective solutions to tackle the adverse impacts of climate change. The study integrates inputs from remote sensing, GIS, and machine learning algorithms, to provide insights for smart and sustainable agriculture practices that alleviate the impacts of climate change**.** The Fuzzy map showed that for certain areas of the southwest the dominance was strongly suitable at 16.76% (546019.2 km2), and the field was extremely suitable for 8.04% (261936.3 km2), and the surroundings were fairly suited to 15.52% (55722.6 km2). At around 60 % of the total agricultural land suitability, there will be a high to mild inappropriate risk. Around 6.11 percent of them, or 19.067.2 km2, were deemed highly inappropriate, while a moderately inappropriate sector, which was located in northern, middle, southern, and western areas, accounted for the remaining 53.55 percent (1744325 km2).

The global sensitivity analysis using the Morris method was performed in this thesis to evaluate the FUZZY and AHP models' reliability. The agriculture suitability model developed through the study has an enormous capacity to propose smart agriculture management plans, which aid in achieving sustainability in agriculture and allied sectors while maximizing land productivity to assist vulnerable and disadvantaged farmers who are suffering from the effects of climate change. Agriculture suitability (potentiality) can be extended to incorporate food security, nutrition, energy, and employment concerns for a more holistic evaluation of climate change impacts and the best prospects of resilience under climatic stress.

The present study on agricultural land suitability maps relying on FAO guidance would be extremely useful to India's agriculture policymakers in expanding the projects to new areas. Since cropland has strong suitability for S1 categories (46 percent), there is a massive opportunity to harness agro forestry in cropland areas in India. Future policies can rely on this study in identifying agricultural suitability in the context of climatic sensitivity. This will give a regional as well as a national cohesive picture of required future adaptive and mitigation measures.

**LIST OF FIGURES**

## LIST OF TABLES

**ACRONYMS**

AHP- The Analytic Hierarchy Process

ALSA- land suitability analysis in agriculture

ANN- Artificial Neural Network

CC-Climate Change

CMIE – Centre for Monitoring Indian Economy

CSP-Crop suitability map

DEM-Digital elevation model

ECMWF- European Centre for Medium-Range Weather Forecasts

FAO- Food and Agriculture Organization of the United Nations

GHGs-Greenhouse Gasses

GIS- Geographic Information System

IMD -Indian Meteorological Department

INDIASTAT-Statistics from India

IPCC- Intergovernmental Panel on Climate Change

ITA- Innovative Trend Analysis

MAE- Mean Absolute Error

MAPE- Mean Absolute Percentage Error

MK- Mann-Kendall

MLP- Multi-layer Perception

MoSPI- Ministry of Statistics and Programme Implementation

MSE- Mean Squared Error

RMSE- Root Mean-Square Error

RS-Remote Sensing

SNHT- Standard Normal Homogeneity Test

UNFCCC- United Nations Framework Convention on Climate Change

WMO-World Meteorological Organization

Division- Denote states one or more based on IMD

SPI-12- The Standardized Precipitation Index (12 months)

LULC-Land Use Land Cover

NDVI-Normalized Difference Vegetation Index

TRI- Topographic roughness index

ET- Evapotranspiration

AR4 -Fourth Assessment Report of the IPCC

NDVI- Normalised Differential Vegetation Index

# Chapter 1

# INTRODUCTION

## 1.1. Introduction

The broad concern of this study is to examine the impacts of climate change on agriculture production in India. We initially do a historical trend analysis of change in climatic variables, followed by evaluating the impacts of climatic variables on agriculture production and further future prediction using statistical and machine learning methodologies.

## 1.2. Literature Review

Climate change has prompted heated debate among researchers, requiring several investigations into historical changes that have occurred since the beginning of the industrial revolution, as well as the projected future impact of anthropogenic and natural activity on the climatic variables. Many studies provide evidence for changes in climatic parameters over time. Spinoni et al. (2014) showed that all of these drought characteristics have risen dramatically in Africa, East Asia, southern Australia, and the Mediterranean region. Long-term droughts deplete river storage and groundwater volumes, resulting in a slew of social and environmental consequences. Based on the most recent comprehensive report (IPCC, 2014a) by the Intergovernmental Panel on Climate Change (IPCC), existing greenhouse gas pollution would exacerbate global warming and trigger long-term shifts in the climate environment, increasing the likelihood of extreme events. As a result of these conditions, droughts may become more frequent and severe around the world (Dai, 2013), putting a strain on water resources. Drought is a complex and difficult to quantify phenomenon. This is because it is time-dependent and its characterization is based on different components of the water cycle, and drought consequences vary over time. In recent times, several studies have been conducted to assess the impact of climate change on meteorological, agricultural, and hydrological droughts in different parts of the world, using a number of metrics depending on the type of drought (Mishra and Singh, 2010; Zargar et al., 2011; Pedro-Monzonis et al., 2015). Several drought indexes can be used to predict and reflect drought. Current scientific tools such as the Standardized Precipitation Index (SPI), Palmer Severity Index, Crop Moisture Index, and Reclamation Drought Index are used to calculate drought indices. Thousands of datasets on precipitation, stream flow, and other The The compiled water management metrics are compiled into a simple, broad representation of the drought index values. Although the benefits and drawbacks of these indexes for analyzing historical droughts have been widely studied (Alley, 1984; Dai, 2011; Hayes, 1999), few researchers have looked at the traditional metrics' fundamental flaws in a non-stationary, climate change context. Although none of the main indexes is superior to the others in all cases, some are better suited to such applications than others. Each of the indexes has a different purpose depending on the need (Othman et al. 2016). McKee et al (1993).'s Standardized Precipitation Index (SPI), which has been commonly used in numerous countries, is without a doubt the most well-known index for calculating meteorological drought. Since it can be calculated over a number of time scales and used to analyze different drought classes, this drought index is one of the most accurate and versatile drought indices. Moreover, the SPI calculates drought conditions solely using precipitation data, making it easier to estimate than complex indices and allowing for comparisons of drought conditions across regions and time periods. Because of its intrinsic probabilistic nature, the SPI is an ideal candidate for drought risk analysis. To accomplish this aim, many authors preferred the SPI trend. Easy drought indexes, on the other hand, do not disclose the true situation; thus, researchers must employ sophisticated techniques to investigate the true state of the drought situation in India.

Climate change has affected wildlife and people around the globe, as shown by increasing temperatures, increasingly erratic rainfall, recurrent drought, sea-level rise, and glacier melting (Mehta et al., 2018). As a result, crop production and productivity have decreased significantly, especially in third-world countries, resulting in food insecurity, famine, malnutrition, and other issues, as their livelihoods are primarily dependent on agricultural crop production (Nath and Behera, 2011; Ho et al., 2018; Sarkar et al., 2019). As a result, it's critical to look into the effects of climate change on agricultural crop production, especially in countries like India. Effects of climatic variability on agricultural outputs are often calculated using three approaches: biophysical, hedonic, and panel data. The biophysical approach, also known as crop modeling methodology, is the most critical and common of the three approaches (Adams et al., 2013; Aggarwal, 2009; Kurukulasuriya et al., 2006; Lal, 2000).Apart from that, the hedonic or Ricardian approach has been used to investigate long-term phenomenal temperature changes in cropping systems while taking adaptation into account (Mendelsohn and Dinar, 2009; Deschênes and Greenstone, 2007; Kurukulasuriya et al., 2006). Furthermore, a common tool for quantifying the effects of climate change on agricultural production is the panel data approach. Climate change can have a variety of effects on the economy. For example, high rainfall variability causes flood irregularity and intensity, resulting in a large number of crop losses. The foregoing approach is used to quantify the relationship between climate change and agricultural production. The rise in mean sea level caused by rising surface temperatures affects the lives of people living in coastal areas around the world. According to the IPCC (2007), global temperatures will rise by 1–6 oC by 2100. As a result, increased heat intensity and erratic precipitation patterns would have a significant effect on crop production (Aggarwal, 2008). Climate change would thus have a significant impact on food production around the world, including in India, resulting in food insecurity (Meeting, 2006).

There have been numerous studies that show the negative impact of climate change on cropping patterns and crop development in India, but only a few studies using observational techniques have been conducted on this subject. Kumar and Parikh (2001) estimated the production of wheat, maize, barley, sorghum, and arhar, among other important crops. Owing to their high climate sensitivity, these crops are vulnerable to adversity, making them crucial for India's food security. Furthermore, due to the increased temperature, the yield of commercial crops such as cotton, sesamum, and sugarcane has decreased since 1990 (Singh 2012). It is expected that by 2060, climate change will result in a decrease in potato and paddy production, possibly jeopardizing food security for the country's nearly one billion people. Any temperature variation below the average has a negative and numerically significant impact on linseed output (Singh 2012). According to Kumar et al. (2011), irrigated areas of maize, mustard, wheat, rice, and sorghum in the seaside district, the north-eastern region, and the Sahyadriregion, or the Western Ghats, have been decreasing due to the negative effects of climate variations. According to Hundal (2007), as the mean temperature increased by 1–3 oC above the normal range, paddy and wheat yield decreased by 3% and 10%, respectively, within the Punjab province. The unpredictability of precipitation patterns has adversely slowed the cropping of Jowar in Karnataka, resulting in food insecurity among farmers. According to Geethalakshmi et al. (2011), due to temperatures reaching a maximum of 40°C, paddy crop yield in Tamilnadu has decreased by more than 41%.

According to Srivastava et al., (2010), due to phenomenal atmospheric variance, the production of the monsoonal crop sorghum in central India and southern central India will decline by 14 percent and 2 percent by 2025, respectively,. due to phenomenal atmospheric variance. Growing ambient heat has a substantial negative impact on the productivity of rice, maize, jowar (sorghum), Bajra, and barley, according to empirical evidence (Kalra et al., 2008; Geethalakshmi et al., 2011). The agricultural production of has a gloomy An increase in the maximum degree of heat has a negative impact on the production of gram and ragi, but the processed production of wheat and tur has increased significantly due to an increase in the maximum degree of heat (Kumar and Parikh, 2001; Kaur and Hundal, 2007). According to Kapur et al., (2009), a 30 percent reduction in crop production could occur in the middle of the twenty-first century as a result of the intensification of surface warming combined with a shift in precipitation levels, which could lead to a decline in arable land, causing crop production stresses in India. Climate variability has a negative impact on agricultural crop production, according to evidence. Furthermore, the majority of observational research has only looked at a single crop or a few crops with minimal geographical scope.

As a result, determining the ultimate impact of climate variability on major food crops, as well as an emphasis on viable and safe crop production options, has become critical for ensuring food security in India (Hollaender, 2010). Our research seeks to test the hypothesis that agricultural productivity in India is climate-sensitive, with changes in rainfall and temperature trends having a significant impact on food grain production.

The food crop is the source of the most calories and protein in the world's food supply. Precise agricultural productivity prediction can be very useful for the grain circulation market, drought prevention, and food conservation. As global temperatures rise, the subsequent changes in rainfall trends have a significant effect on crop production. As a result, crop water supply is largely determined by rainfall distribution. Furthermore, heavy and excessive rainfall may have negative consequences, including massive flooding that destroys vegetation, and crop yields that are reduced due to water scarcity in drought climates. Therefore, forecasting agricultural production is also useful for handling farming activities, including planning fertilizer applications for the crops. India is the world's leading producer of many grains, including rice and wheat. However, recent climate change has had a negative impact on agriculture. As a result, accurate and timely agricultural productivity prediction in India is critical, given the country's major impact on agricultural production, national food security, and even global food security.

Crop yield estimation has been the subject of extensive research. For crop yield prediction at regional scales, researchers either utilize weather/climate data, satellite remote sensing. database, or both. Several researchers have looked into the connections between different climatic conditions and various crops. As a result of the exponential growth of emerging technology, crop models and decision tools have become a critical component of precision agriculture around the world. To forecast grain yields in different countries, statistical and process-based models have been developed (Asseng et al., 2017, 2015; Newlands et al., 2014; Potgieter et al., 2016; Zheng et al., 2014). The key inputs to both empirical and process-based models involve climate factors including temperature, precipitation, and solar radiation. Traditional mathematical models forecast yields by creating regression models among weather variables (temperature, precipitation, solar radiation, and so on) and calculating yields over time. The findings of such regressions did demonstrate how climatic variables influenced yields, but their relative lower explanatory potential has been widely debated.

Machine learning, on the other hand, has proven its effectiveness in data mining and agricultural analyses, such as crop type classification and yield estimation, as an alternative statistical model. Crop yield is determined by the interaction of spatial and temporal changes in variables as these models have a good ability to handle multi-dimensional datasets. As a result, machine learning methods can be useful in helping to improve yield prediction models. This perspective has been supported by a number of recent publications around the world. Many of the forecast approaches used in crop forecasts under climate change include Adaptive Neuro-fuzzy Interference System (ANFIS), Support Vector Machines (SVM), Data Mining (DM), Genetic Programming (GP), and Artificial Neural Network (ANN). ANN is considered to be a good alternative for the majority of complex problems in these approaches. They solve dynamic relationships between crop production and interconnected parameters that linear systems can't solve. An artificial neural network (ANN) is a type of computer program that mimics the functions of the human brain. These programmes learn to function by evaluating their examples for a given task. As a result, tailoring a neural network to a specific problem is extremely important. The formation of a neural network is therefore of great importance for a specific issue. When properly trained, however, neural networks can easily model relationships even with a larger number of variables.

Rainfall, temperature, humidity, and sunshine hours are only a handful of the many kinds of weather and climatic influences that influence crop production. As a result, there are several studies in the literature that use ANN to determine the relationship between climatic conditions and agricultural yield all over the world. Not only is ANN used to consider climatic conditions, but it was also used to distinguish food crops. However, only a few

ANN-based studies in the context of food grain production are available India. However, to the best of the authors' knowledge, no research has been conducted in India to determine crop harvest (yield) in relation to different climatic factors. As a result, this thesis aims to better understand the links between climatic factors and food grain production in India.

Agricultural food products remain in perpetual demand (OECD/FAO 2019) because of an increasing population (Sands et al., 2014; Mozumdar, 2012), rapid urbanisation and urban growth (UN, 2018), a rapid increase in productivity on agricultural land (Sands et al., 2020) and climate change (Fukase & Martin 2020); Talukder et al., 2020; Anderson et al., 2020; P.Leisner, 2020). As a result, world food demand is projected to rise by 70% by 2050. (UNESCO, 2017). The need to reduce and eliminate fossil fuel consumption (Popp et al., 2014; R.Quentin et al., 2015), which is putting more pressure on agricultural land through the demand for biofuel and bio-based products, is exacerbating the situation (WWAP, 2017; Alalwanet al., 2019; Bos & Broeze, 2020; Gursel et al., 2020). This rising demand for agricultural goods has resulted in the exhaustion of global land resources in recent decades (Lambin & Meyfroidt, 2011), which not only causes agro-ecological problems (Hathaway, 2016), but also jeopardises agricultural sustainability (Hunter, 2017). To address these issues and promote optimal utilization of the land resources, planning through agricultural suitability assessment has proven to be very useful (Song & Zhang, 2021; Ahmed et al., 2016: Yohannes & Soromessa, 2018).

Land suitability appraisal is the method of evaluation and aggregation of the suitability of particular areas of land for defined uses (Liu et al., 2006). It is a tool for deciding the factors that inhibit a given crop from growing (Halder, 2013; Chozom & Nimasow 2021). Land suitability evaluation involves both qualitative valuations of topography, vegetation, climate, hydrology, and soil properties, as well as quantitative valuations that rely more on yield estimates (Mosleh et al., 2017; El Baroudy, 2016). Typically, this land suitability appraisal is performed separately for each crop type (Herzberg et al., 2019).

One of the most important and basic aspects of the agricultural suitability evaluation process is the selection of criteria (Tercan & Dereli, 2020; Zolekar, & Bhagat, 2015). For agricultural suitability zonation, Pilevar et al. (2020) used climatic factors such as temperature, topographic factors such as slope and elevation, and soil characteristics such as soil texture, soil PH, and electric conductivity, among others. However, Seng et al., (2009), however, showed that the alkalinity, acidity, water storage profile, and waterlogging characteristics of soil are essential factors for mapping agricultural suitability. Similarly, Akinci et al. (2013) show that the soil classification category, land capacity level and subclass, height, slope, soil density, rockiness, and stoniness are all important factors to consider when assessing land suitability. Seyedmohammadi et al., (2019) have used climatic characteristics such as mean daily maximum and minimum temperatures for the coldest month, as well as mean temperature at various stages of crop development; soil characteristics such as depth, gypsum and calcium carbonate content, PH, electrical conductivity, exchangeable sodium percentage, and topographic characteristics of slope for agricultural suitability. Finally, for land suitability evaluation, Sahoo et al., (2018) consider various geological and hydrometeorological characteristics such as rainfall, ET, NDVI, LULC, soil, soil moisture, groundwater level, geology, slope, and elevation. Considering the findings of the previous research, the current research employs climatic characteristics such as rainfall, temperature, wind speed, ET, and aridity; topographic characteristics such as slope, aspect, elevation, and TRI(Topographic roughness index); soil characteristics such as soil quality, soil composition, soil erosion, and the amount of soil organic carbon; and finally, LULC parameters to determine land suitability.

Comprehending ALSA (Agricultural Land Suitability Analysis) is critical for a variety of research studies and policy applications aimed at achieving food security and long-term growth. We classify ALSA as a modern system in this article (De la Rosa & C. A. V. D., 2002). Conventional ALSA approaches are principally qualitative,quantitative, and parametric, primarily based on a number of edaphic biophysical variables. Modern ALSA frameworks provide a new set of approaches for dealing with MCE, GIS, and remote sensing for vast amounts of data, as well as Decision Support Systems (DSS) (Gilliams et al., 2005) wherein the ALSA operations are incorporated. GIS-based land-use suitability analysis can be classified into three groups, as per Malczewski (2004): (i) computer-assisted overlay modeling, (ii) multi-criteria assessment methods, and (iii) soft computing or geo-computation, also known as Artificial Intelligence (AI) methods. GIS-based MCE could be described as a method for combining and transforming spatial data or input into a decision map or output (Malczewski, 1999). The MCE procedures provide a link between the input and output maps. GIS-MCE could demonstrate a rational and objective approach for making decisions in agriculture (Feizizadeh & Blaschke, 2013). The procedures include the use of spatial data, the decision maker's interests, and data preference manipulation according to established decision rules (Akıncı et al., 2013). In addition, combining MCE techniques with artificial intelligence techniques, such as combining AHP and fuzzy logic, can increase modelling efficiency. In the present study, different operators of fuzzy logic and MCE integrated fuzzy logic (AHP-fuzzy logic) were performed to mapthe agricultural land suitability mapping.

ALSA has received substantial support from agricultural and spatial scientists since the development of the Food and Agricultural Organization's (FAO) land assessment system (FAO, 1976). Current advances in geographic information sciences, mathematical modelling and spatial processing can help understand this (Heumann, Walsh, & McDaniel, 2011). The classification system used by ALSA is based on FAO guidelines (FAO, 1976), with classes andcategories. Highly Suitable, Moderately Suitable, and marginally Suitable, as well as Currently Not Suitable and Permanently Not Suitable, are the suitability classes (FAO, 1976; FAO, 2007). Suitability could be interpreted in two ways in this context. The first is concerned with the condition of a given area's current or present physiography, which has not improved. The second is the probable suitability of a region for specific purposes by alteration of one or more land features (such as decreasing soil water saturation by drainage or minimising excessive slope through terracing) (Wang, et al., 1990). The classification aids tactical land-use decision-making when conflicting goals are being weighed. The successful and long-term optimization of land resources for agriculture has been needed (Nijbroek & Andelman, 2015). The recent controversy on sustainable agriculture, or agricultural systems that increase yield without adversely affecting the environment or demanding the transformation of extensive non-agricultural land, includes agro-ecological and socio-economic intensifications (Pretty & Bharucha, 2014).

### 1.3. Research Gap

Based on the research on the previous literature, the following research gaps have been found, which have been incorporated into this thesis:

- Previous research has only used linear regression for analyzing climatic variation, and very few studies have been undertaken using the Mann-Kendall test for exploring climate change. But in the present study, we recently developed innovative trend analysis (ITA), along with several versions of Mann-Kendall tests (MK test, modified MK test, trend free Pre-whitening MK test) and also linear regression have been used for analyzing climate change.

Very few studies have shown the reasons for climate change, while in this thesis, the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-5 reanalysis data is used to determine the causes of rainfall transition.

Many studies have only incorporated precipitation changes for anlysing the climate change, while in the present study, the meteorological drought has been used to investigate climate change using advanced statistical techniques like wavelet transformation and trend analysis.

Most of the studies have used average data for anlyzing climate change, but in this thesis, all monthly data since 1901-2017 has been analyzed using a heat map.

Previous research has only focused on climate change but did not focus on the impact of climate change on agriculture production. Even, some research theoretically analyzes the impact of climate change on agriculture, in this thesis, the impact of climate change in terms of rainfall and temperature on the production of 15 crops is individually analyzed using multi-linear regression (MLR).

Many researchers have used statistical models like ARIMA, ARMA for forecasting future climate change, but in this thesis, statistical as well as machine learning algorithms like artificial neural networks have been used not only for forecasting climate, but also for agriculture production evaluation.

There are very few studies that have modeled agriculture suitability models in the context of climate change for the whole country and none has been for India, but in this thesis, the agriculture suitability modeling in the context of climate change have been prepared using fuzzy logic and advanced techniques has been prepared at national level.

Therefore, this thesis provides comprehensive research on climate change, its impact on agriculture production, future scenarios of climate change and agriculture production, and the preparation of land suitability maps that can be used for smarter management of agricultural activities under climate change.

## 1.4. Research Questions and Objectives

Based on the previous literature survey, the following research gaps and research questions have been elucidated.

- What is the relationship between agriculture and climatic variables?
- Is there any evidence that climatic factors such as rainfall and temperature have changed over time?
- What effect does climate change have on agricultural productivity?
- How can future conditions of climatic variables and agriculture productivity be estimated?
- What is the likely future scenario for climatic variables and agricultural productivity?
- In the light of current climatic conditions, what are the potential areas in India for suitable agricultural production?

As a result, the following objectives have been developed to address both research questions and research gaps.

**The Specific Objectives of this study are:**

- To measure climate change in India in terms of changes in rainfall and meteorological drought.
- To investigate the impact of climate change on Indian agriculture production
- To predict and forecast the climatic parameters and agriculture production
- To develop agriculture suitability models for identifying potential agriculturally viable areas in the sense of current climatic conditions.

## 1.5. Database and Methods

### Data

In the present study, a variety of databases have been used to explore the effects of climate change. The database has been classified in terms of objectives and chapters. The details of databases have been used as follows:

*Data used for chapter 2:* In this chapter, rainfall data has been used to explore climate change in terms of rainfall reduction and the lengthening of meteorological drought. For both modeling, rainfall data has been used. The India Meteorological Department (IMD) has divided the country into thirty-four meteorological sub-divisions, each with its own set of climatic data collected at various meteorological stations. The thirty-four meteorological sub-divisions are the focus of the current research. In this analysis, we used IMD to collect rainfall data for 115 years (1901–2015) by meteorological subdivision. There were no missing values in the study's data because it was constant.

*Data used for chapter 3:* The Indian Meteorological Department (IMD) database of the Government of India has been used to acquire meteorological subdivision-level temperature and rainfall data from 1901 to 2015. The continuous data were used for this study, which covered the years 1976 to 2016, with no missed values. To investigate the impact of climate change on crop production, sixteen major crops were considered, including Bajra, rice, wheat, barley, arhar, ragi, maize, jowar, gram, and mustard, as well as non-food grain crops such as linseed, sugarcane, groundnut, rapeseed, cotton, til, and tea, which account for over 75% of the total cropping area. Using a panel econometric study from 1967 to 2016, we used per unit area as a dependent variable to estimate the effects of climate change on cropping patterns and production. The development dataset was provided by the Centre for Monitoring the Indian Economy (CMIE).

*Data used for chapter 4:* For this chapter, similar data as in Chapter three has been used. In this chapter, future forecasts have been made for the meteorological variables and crop production using the same data as in chapter three.

*Data used for chapter 5:* In this chapter, several databases have been used. Therefore, the details of the databases have been presented in a tabular format.

| **Data types** | **Sources** | **Resolution** |
|---|---|---|
| Rainfall | IMD (1901-2015) | - |
| Temperature | IMD | - |
| Wind speed | Giovanni (https://giovanni.gsfc.nasa.gov/giovanni/) | 1° |
| Evapotranspiration | Giovanni (https://giovanni.gsfc.nasa.gov/giovanni/) | 1° |

| | | |
|---|---|---|
| Soil organic carbon | Soil organic carbon stock in t/ha for 0-30cm depth intervals. (https://maps.isric.org/mapserv?map=/map/ocs.map) | 250 meter |
| Soil Types | Reference soil group (2006), soil grid (https://soilgrids.org/) | - |
| Soil Nutrient Qualities | Fischer, G., F. Nachtergaele, S. Prieler, H.T. van Velthuizen, L. Verelst, D. Wiberg, 2008. *Global Agro-ecological Zones Assessment for Agriculture (GAEZ 2008)*. IIASA, Laxenburg, Austria and FAO, Rome, Italy. | 250m |
| Soil erosion | ISRIC, world soil information | 250m |
| DEM | DIVA GIS | 90meter |
| Aridity | ISRIC, world soil information | 250m |
| Land use land cover | Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center (DAAC) (https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1336) | 100 m |

*Different resolution effects of several datasets have been solved using resampling effect*

**1.6. Methodology**

In this thesis, the methods have been prepared objectives wise. The brief details of the methods have been employed for dealing with the research gaps.

*For the first objective*, to deal with the first objective, several methods have been employed. First, to explore the evidence of rainfall reduction, several non-parametric trend analysis methods have been utilized, such as the Mann-Kendall test, Innovative trend analysis, and LOWESS curve. Change point detection techniques, such as the Pettitt test proposed by Pettitt (1979), the standard normal homogeneity test (SNHT) proposed by Alexandersson and Moberg, (1997), and Buishand rangetests have been employed to detect the presence of change in the rainfall data series for thirty-four meteorological sub-divisions. To identify the causes of rainfall change, the European Centre for Medium-Range Weather Forecasts

(ECMWF), ERA-5 (http://apps.ecmwf.int/ datasets/data/interim-full-daily) provided atmospheric oscillations on rainfall pattern variation, winter and summer precipitations, and moisture divergence on 1.25° 1.25° grids from 1979 to 2015 on 1.25° 1.25° grids. Since 1979, the ERA5-Interim is the most recent ocean-atmospheric transition reanalysis dataset available. In addition, to assess the impact of cloud cover on rainfall variance, a low cloud cover dataset was obtained from the ECMWF ERA5 data. The heat map was used to detect a long-term change.

On the other hand, the standard precipitation index (SPI)-12 has been used to estimate long-term meteorological drought. Similarly, to estimate the overall trend in the long-term meteorological datasets, the Mann-Kendall test and innovative trend analysis (ITA) have been used. Morelet wavelet transformation has been used to detect the periodicity analysis of the meteorological drought.

*In the second objective***,** the second objective was to explore the impact of climate change on agriculture production. Therefore, first, the overall trend for each climatic variable and crop production has been measured using innovative trend analysis. Then, to assess the effect of climate change on crop production, multiple regressions have been applied to explain each crop's production in the context of climate change. Similarly, Pearson’s correlation coefficient technique has been applied to explore the association between climatic variables and crop production.

*In the third objective***,** using datasets from 1967 to 2016, used ANN and ARIMA models to estimate and forecast climatic variables and crop production in India up to 2030. The comparison of expected and real values of crop production and climatic variables using ANN and ARIMA has been evaluated to explore the performance of the model with suitable MAE, MAPE, MSE, and RMSE error values.

*In the Fourth Objectives***,** in this chapter, numerical data, reanalysis data, satellite data, and vector data have been used for preparing the agriculture suitability models. However, numerical data like rainfall and temperature has been converted into raster format by using kriging methods. On the other hand, vector data like soil types has been rasterized using The The spatial analyst tool in ArcGIS Other observational data like evapotranspiration and wind speed have been modelled by NASA and have been directly downloaded from Geovanni (https://giovanni.gsfc.nasa.gov/giovanni/). Topographical data like slope, aspects, TWI, SPI have been extracted from SRTM DEM using QGIS software package and spatial analyst tool of ArcGIS. On the other hand, soil-related data like RUSLE based gross soil erosion, soil quality have been modeled by ISRIC World Soil Information, which has been directly downloaded from the ISRIC website. The LULC map has been created using an artificial neural network model. It was collected from Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center (DAAC) (https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1336). Finally, these datasets were integrated using the different operators of fuzzy logic and a hybrid fuzzy-AHP model for preparing agriculture-suitable maps. On the other hand, the influence of the input variables to the final agriculture map has been explored using Morris model-based global sensitivity analysis and also Pearson's correlation coefficient technique.

### 1.7. Empirical Results (Brief Summary)

*In the first objective,* the findings revealed that, except for seven divisions during the study periods, most meteorological divisions exhibited diminishing annual and seasonal precipitation trends. For the monsoon season, 11 divisions reported a strong rainfall decreasing pattern ($p<0.05$), while the declining rainfall trend for the winter and pre-monsoon seasons was negligible. The average rainfall trend decreased by around 8.45 percent overall. For the various meteorological units, the likely year of greatest change varied, and the maximum change occurred mainly after 1960. Between 1901 and 1950, there was a growing trend in rainfall, but after 1951, there was a substantial decrease in rainfall. The results of the LOWESS curve show an increasing trend of annual rainfall up to 1965 but a declining pattern of rainfall after 1970. The results of the LOWESS curve for the winter season revealed that for theperiods 1935–1955, and 1980–1998, a growing rainfall trend was observed. Between 1955 and 1998, there was a sharp drop in the pattern. In the case of the summer and monsoon seasons, the curve shows that a downward trend began after 1960. Since 1995, there has been a downward trend in post-monsoon rainfall. Many of the meteorological divisions' rainfall forecasts for the next 15 years showed a substantial reduction in rainfall. According to the ECMWF ERA5 reanalysis data,increasing or decreasing precipitation convective volume, elevated low cloud cover, and insufficient vertically integrated moisture divergence could have influenced rainfall change in India. SPI-12, on the other hand, was used to estimate long-term meteorological drought for 34 sub-divisions to investigate its effect on agriculture. The results of the ITA and wavelet transformation revealed that the meteorological drought has recently risen in almost all sub-divisions, while in the past, these sub-divisions had moderate to no drought conditions.

*In the second objective*, the ITA for climate variables and agricultural production has been examined for the years 1967 to 2016. The value is interpreted by the assigned variables as shown by the trend indicators and their respective slopes. The trend indicator values for rainfall and temperature are 0.42025 and 0.05126, respectively, indicating that neither temperature nor rainfall had a noticeable trend. Cotton, gram, jowar, maize, ragi, wheat, tea, and rice all showed a consistent and important (p-value 0.01) upward trend in demand. Rapeseed (ITA D value of -8.54) and barley (ITA D value of -28.93) both showed a major ($P<0.01$) and monotonic decrease in yield. The rest of the crops showed a similar upward trend in demand. Despite having limited agricultural land and low technical growth, most edible food grains such as rice, wheat, Bajra, jowar, and ragi have increased significantly (Table 3). As a result of increasing agricultural activity, the impact of climate change cannot be observed by direct observation.

Multiple correlation coefficients have been calculated for fifteen crops and climatic variables. The results show a very strong influence (coefficient determination values) between Ragi (0.862), Rapeseed (0.836), Tea (0.85), Wheat (0.815), Rice (0.811), and Jowar (0.815), indicating high crop productivity with the current temperature and rainfall pattern. Cotton (0.665), Gram (0.603), Barley (0.788), and Maize (0.621) production all show a strong connection. Crops of moderate strength, such as barley (0.597) and til (0.401), need a precise structure for yield and processing. The Arhar (0.298) crop has a weak relationship, indicating that it would require more attention in terms of productivity and climate change resilience. Temperature and rainfall variations had little impact on the production of groundnut and linseed. Although many crops responded differently to the climatic variables, Arhar and Til (one of India's two main crops in terms of crop production) were found to be more vulnerable to the effects of climate change as compared to the other thirteen major crops studied.

*In the third objective,* it is essential to check the performance of the model by predicting existing data before it is used for forecasting. If real and forecast data have a similar relationship with lower error values, it may be used for further analysis. By refining the variables of ANN, the current research predicted climatic variables and different crops and discovered that the real and expected data of climatic variables and 15 different crops were very similar. With R2 values greater than 0.82, the association between real and expected values of all 15 crops and two climatic variables was extremely high. But for rice (0.86) and barley (0.82), the majority of the crops had $R^2$ correlations greater than 0.92. The association between real and expected temperature and rainfall values was also very high (R2>0.82). The effects of these errors indicate that the model's efficiency in predicting climatic parameters and crop yields is adequate and can be used for future forecasting.

Future forecasts of agriculture and climate variables in India have been made by ANN models for the period 2017–2030. The pattern of predicted rainfall has not significantly changed. Instead, the ANN model has discovered a large increase in the predicted temperature pattern. Barley,arhar, linseed and rapeseed production will be reduced. Though output is to be significantly increased to 2030, rice, ragi, tea, maize, jowar, bajra, and cotton. From 2017 to 2030, Til ,Groundnut, and Gram have examined moderated future-growing demand trends. In conclusion, except for barley, arhar, linseed, and rapeseed, all other crop production will increase in the future as temperatures rise and rainfall patterns shift.

*In the Fourth Objectives*, This chapter summarises the findings of the land suitability zone for agriculture. In India, the area and percentage coverage of the various agricultural suitability zones per km2 have been computed. Following that, 14 fuzzy data layers were superimposed on this land suitability map to assess the overall agricultural suitability map using the Fuzzy AND, Fuzzy Gamma 0.9, Fuzzy Gamma 0.8, and Integrated AHP models. The Fuzzy map showed, for certain areas of the south-west the dominance was strongly suitable at 16.76% (546019.2 km2), the field was extremely suitable for 8.04% (261936.3km2), and the surroundings were fairly suited to 15.52% (55722.6 km2). Around 6.11 percent of them, or 19.067.2 km2, were deemed highly inappropriate, while a moderately inappropriate sector, which was located in the northern, middle, southern, and west areas, remaining 53.55 percent (1744325 km2). The global sensitivity analysis using the Morris method was performed in this thesis to evaluate the FUZZY and AHP models' reliability. The farm suitability models are used as dependent variables, while 14 influencing variables as independent variables were introduced. We also carried out a global sensitivity test based on the factors affecting variables that were derived to examine the most sensitive independent variable in the modelling of agricultural suitability areas. The most influential variables in agriculture are suitability area were temperatures and precipitation, while the lowest responsibility predictor was evapotranspiration.

## 1.8. Major Findings

*In the first objective*, in different meteorological sub-divisions, rainfall has decreased substantially since 1960 and 1975. The change detection techniques revealed that the entire rainfall time series (1901–2015) for 34 sub-divisions has a change point, which varies between 1950 and 1980 for various sub-divisions. This means that a rapid change or shift in the historical pattern or trend has been detected in the time series of rainfall records. The pattern detection findings accurately quantified that, with the exception of North-East India, all meteorological sub-divisions experienced a slightly negative trend between 1960 and 1980, indicating a decrease in rainfall over time. The best approaches for trend identification were also examined, including the MK test, MMK test, Sen's slope estimator, and innovative trend analysis, in addition to the trend detection results. The ITA outperformed other pattern detection methods, according to the findings. In addition, the current chapter looks at climate change in terms of meteorological drought patterns and trends. SPI-12 was used to measure the long-term time series of meteorological drought. The drought pattern or tendency for 34 sub-divisions has been increasing over time, according to long-term meteorological drought data. Most sub-divisions have recently seen an increase in drought, while some have seen moderate or no drought in the past.

*In the second objective*, there was no noticeable trend in temperature or rainfall according to the trend predictor values for rainfall and temperature. The yield of Bajra, Cotton, Gram, Jowar, Maize, Ragi, Wheat, Tea, and Rice increased in a monotonic and significant ($P<0.01$) way. Rapeseed and barley development demonstrated a major ($P<0.01$) and monotonic downward trend. The rest of the crops showed a similar upward trend in demand. Many edible food grains, such as rice, wheat, Bajra, jowar, and ragi, have increased dramatically, according to the pattern report. Crops such as groundnut, linseed, maize, ragi, rapeseed, and barley show that the models' predictions are accurate in terms of production and climatic variables. The estimated crop production and climatic factors have a close relationship. Maize has the highest multiple correlation coefficient of crop production, indicating that it has a greater affinity and tolerance to potential changing climatic factors such as temperature and rainfall. Wheat, Tea, Jowar, Cotton, and Gram have several correlation coefficients, indicating that temperature factors have little impact on their productivity and sustenance. The rest of the crops have very good multiple associations, meaning that their productivity will rise in the future as climatic variables shift.

*In the third objective*, using a panel dataset spanning 1967 to 2016, this study looked at the climatic vulnerability of Indian agricultural crop production. Temperature and precipitation datasets were used to plan crop production. In India, there was a mixed outcome due to climatic variability that differed due to various regional, tribal, and socio-economic factors. As a result of varying agro-climatic conditions, agricultural crop production varies across the region. The ANN model provides an admissible finding for further forecasts by comparing observed and expected values at the 95 percent confidence stage. Inevitably, the model will be used to comprehend upcoming plans, policy-making, and schedule reductions in the country's agro-based cropping systems. The model's outputs are critical for determining crop calendars dependent on local climatic conditions. Meanwhile, the crop produced is suffering from the negative consequences of climatic change, such as frequent precipitation occurrences, which would undoubtedly necessitate a change in the cropping pattern.

*In the Fourth Objectives*, in this study, the GIS modelling concept was used to connect several themes from diverse sources of information that have a significant connection to agricultural practices. In the GIS domain, computer-based analysis of various datasets and their computational appraisal significantly aids decision-making. Furthermore, global sensitivity analysis and machine learning-based sensitivity analysis can help in the detection of the most sensitive variables. To achieve strong agricultural yields, land and agriculture management can be optimised based on the effects of sensitivity analysis. As a result, the agriculture suitability model has a huge potential for proposing smart agriculture management plans that help achieve resilience in agriculture and related sectors while maximising land productivity to help poor and marginalized farmers who are suffering from the impact of climate change. The agriculture suitability (potential) model is viewed as a promising choice for meeting food, nutrition, resources, and work demands while still protecting the environment.

### 1.9. Importance of the Study

The present research has a variety of importance. Therefore, the study's importance has been classified into two classes, such as methodological importance and objective importance. The methodological importance has been identified from all objectives. In the first objective, several trend analysis techniques have been used, and among them, innovative trend analysis appeared as best method to detect trends in the climatic data. This method, for the first time, has been applied in the whole India. Even, several non-parametric techniques, wavelet analysis, and satellite image based reanalysis have been used, which is totally new in the Indian context. In case of objective two, multiple regressions have been used to assess the effect of climate change on agricultural production. This technique is technically sound for assessing the relationship between several input variables and one target variable. For the objective three, machine learning algorithms like ANN and robust statistical techniques like ARIMA have been used to forecast the climatic variables and agriculture variables. The application of machine learning for forecasting both climate and agricultural production is totally new in India and technically very robust. In the case of the last objective, fuzzy logic and an integrated fuzzy-AHP model have been used to prepare an agriculture suitable model considering several standard databases, which is technically very robust and new. Very rare studies have been conducted to prepare agriculture suitability models in not only India but also around the world. Therefore, the present thesis employs many technically sound and robust techniques for dealing with the objectives.

On the other hand, in the case of objective importance, rainfall changes in thirty-four meteorological stations have been identified using robust techniques. Long-term rainfall changes on a micro scale. Pattern and periodicity of meteorological drought have been identified for 34 meteorological stations. Therefore, to obtain evidence of climate change, this research contributes significantly to the literature on climate change. Similarly, the impact of climate change on each crop has been assessed in the study. The forecasting of future climatic conditions and agricultural production using machine learning algorithms will be a turning point for agriculture management and water resource management. In the last, identification of probable agriculture suitability under the present climatic, topographic, hydrologic, and pedogenic conditions will contribute a new dimension to exercise a smart agriculture practice. The agriculture suitability model also contributes a sensitivity analysis, which can be helpful for proposing management plans.

### 1.10. Limitations of the study

- In the first objective, since the research has made significant contributions to the fields of climate change and agricultural economics, it does have certain limitations. In the case of the first goal, rainfall data from 34 meteorological stations was used for the analysis, with each station covering an entire state and, in some cases, several states. As a result, only one station in a state or multiple stations in multiple states cannot adequately classify the evidence of climate change. Rainfall data collected at the district or block level can be very accurate for assessing climate change. Many advanced drought indices are available for forecasting meteorological drought, but due to a lack of funding, the SPI index has been selected for drought estimation.

- In the second objective, in the case of the second goal, only 50 years of data were used to investigate the impact of climate change on agricultural production. At least 100 years of evidence must be used. Due to a lack of data, only two climatic factors, such as rainfall and temperature, have been used to investigate the impact of climate change. However, in order to produce more precise data, the modelling should contain, in addition to rainfall and temperature, humidity, evapotranspiration, wind speed, and solar days.
- In the third objective, just 50 years of data were used to train machine learning models for predicting future climatic conditions and agricultural development in the case of the third goal. To obtain reliable prediction results, at least 100 years of time series data are needed. Ensemble machine learning algorithms, on the other hand, have seen widespread use around the world. As a result, these algorithms can be used to achieve precise results.
- In the Fourth Objectives, In the case of the fourth target, modelling was done using moderate resolution satellite images. However, in developing countries such as India, obtaining high-resolution data is both rare and costly. Though data with a moderate resolution is free. However, in order to achieve a sufficiently reliable agriculture model, high-resolution data must be used. The modelling, on the other hand, has made use of fuzzy logic and fuzzy-AHP. Machine learning, on the other hand, can yield reliable results. As a result, in order to apply machine learning algorithms, a comprehensive survey across the country is needed, which is very expensive. As a result, in order to achieve highly reliable suitability models, these issues must be resolved.

### 1.11. Organisation of the thesis

The thesis is organised into six chapters. The first and second chapters provide an introduction and a literature review, respectively. The third shows the first objective analysis, next three (fourth, fifth, and sixth) consist of second, third,and fourth objectives main analysis. The seventh chapter provides the thesis conclusion, major findings, and policy suggestions for future recommendation. This section provides a thesis outline and shows the broader parts of each of the chapters.

- Chapter 1: Introduction

This chapter builds the basis for the present doctoral thesis work. It introduces the area of climate change, links it with agriculture studies, and shows the impacts of climate change on agriculture production. Thereafter, existing literature is reviewed,and a research problem is identified. Research questions and objectives are formed. Thereafter, datasets, variable descriptions, and methodology strategies are identified.

- Chapter 2: Literature review

All four objectives will be covered in Chapter 2, which will cover the overall literature review with the following all four objectives,

- Chapter 3: Assess the Climate Change in India in terms of Rainfall Change and Meteorological Drought.

Chapter 3, which will cover the first objective, This objective will cover the assessment of climate change in India in terms of rainfall and drought trends. Firstly, we used trends using machine learning techniques and key results from these studies.

- Chapter 4: Climate change and its impacts on Indian agriculture

The second objective, which will be covered in Chapter 4, will be to investigate the impacts of climate change on Indian agriculture (15 crops) based on climatic parameters, that is, rainfall and temperature, and we used both food grains and non-food grain crops. Firstly, we used ITA innovative trend analysis to check the trend of existing data and then multiple regression and key results from these studies,

- Chapter 5: Predicting and forecasting of climatic factors and agricultural production

This will be the third objective of this, which will cover the prediction of climatic variables such as rainfall and temperature and agriculture production (15 crops) till 2030 using artificial neural networks (ANN-MLP), a technique of machine learning and ARIMA, a statistical technique, and it is found that ANN is more accurate than ARIMA. So, in this chapter, the literature and key findings are added.

- Chapter 6: Recommendation of suitable agricultural sites in reference to climate change and other factors.

Chapter 6 provides an overview of agriculture suitability in India to know the areas where agriculture could be a good idea and recommend suitable agricultural sites in reference to climate change and other factors. We used remote sensing and GIS techniques in this chapter. A land suitability analysis for agriculture created using fuzzy logic and the (AHP) analytical hierarchy process found that fuzzy logic is good for best accuracy. Agriculture suitability is important to determining agricultural cropping patterns, preparation, and activities in the future for modeling agricultural suitability for the entire country of India. The global sensitivity study using the Morris approach was used to investigate the models' reliability.

- Chapter 7: Findings, conclusions, and policy implications

An overall synthesis of all the chapters is used in this chapter to derive major findings, conclusions, policy implications, and future scope of this study.

# Chapter 2

# Climate Change and Agricultural Production: A Theoretical and Empirical Review

The current chapter examines theoretical and empirical research on the influence of climate change on agricultural sector sectors. In this review, we review the research on the impacts of climate change on agricultural yield, agricultural output, and productivity of various crops, as well as future predictions in a broad overview of global climate change. The current chapter gives a broad review of existing literature on climate change and its implications for agricultural production, global food security, and concomitant developmental indicators like poverty. This is followed by a review of empirical studies related to the effects of climate change. We examine research that looks at agricultural output losses as a result of climate change in various economies. There is also a comprehensive assessment of the literature on climate change and its impact on agriculture, rather than the causes of climate change and a prediction-based review. In the concluding part, we outline a brief review of previous studies and gaps in the literature that motivated this research.

## 2.1. General Overview of Climate Change in the World as well as India

Climate change is one of the most challenging issues facing the globe today. Significant changes in the average values of meteorological variables such as precipitation and temperature, for which averages have been estimated over a long time, are characterised as climate change (WMO 1992). Climate change poses a serious danger to the world's food and nutritional security. Because of the greenhouse effect, when greenhouse-gas emissions in the atmosphere rise, the temperature rises as well. The average world temperature is steadily rising and is expected to climb by 2 °C by 2100, resulting in significant global economic losses.

According to the existing literature, researchers have differing viewpoints on climate change and its effects on agriculture and other economic sectors. According to Bosello and Zhang (2005) the link between climate change and agriculture is complicated and rising temperatures will affect production patterns. Research by Gbetibouo and Hassan (2005) also prove that agriculture is also a more susceptible sector to climate change, both physically and monetarily, than other sectors of the economy. Alam et al. (2011) mentioned that climate change produces low productivity, crop damage, and high production costs, resulting in lower farmer income, increased inequality, and high poverty levels, as well as a reduction in farmer participation in agriculture. numerous researchers like (Gbetibouo & Hassan, 2005); Rosegrant (2008); Masters et al. (2010); Fofana (2011) mentioned that climate change has a substantial negative influence on agricultural productivity, and it is more damaging to poor countries when compared to developed nations. In this regards, Girardet and Bree (2009) reported that many rich nations may profit from climate change, while most underdeveloped countries will face numerous challenges. Greg et al. (2011) explained that due to a lack of assets and sufficient insurance coverage, climate change affects the living situations of those who are already vulnerable, particularly in emerging nations. Arndt et al. (2012) reviewed that climate change presents highly complex and several challenges for developing countries, particularly for low income countries. The study also found that economic structure, geographical and agro-ecological characteristics of the country are also responsible for climate sensitivity. Eid et al. (2006) observed that in Egypt, a rise in temperature would have a detrimental impact on agriculture revenue. Mano and Nhemachena (2007) estimated that Increases in temperature have a negative impact on net farm revenues, whereas increases in precipitation have a favourable impact. The table provides a brief overview of historical trend analysis of climatic variable using different methodologies literature in the field.

Table: Historical trend analysis of climatic variables and their findings

| **Authors** | **Study area** | **Variable used for analyzing climate change** | **Publication year** | **Main findings** |
|---|---|---|---|---|
| (Jha et al., 2021) | Bihar, India | precipitation, temperature, and solar radiation. | 2021 | |
| (Mahmood, 1997) | Bangladesh | temperature | 1997 | temperature will lead to affect the crop production by altering the phenological days |

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|---|---|---|---|---|
| (Sharma & KUMAR, 2005) | The North Western Himalayas (India) | | | Variability in rainfall may cause flooding conditions |
| (Wang et al., 2018) | South Asia | Rainfall and temperature | 2018 | effect of climate change in the production and yield of four major crops globally, i.e., maize, rice, wheat, and soybean |
| (Tesfaye et al., 2017) | South Asia | monthly maximum and minimum temperatures | 2017 | It is projected that climate change would reduce rain-fed maize yield by an average of 3.3–6.4% in 2030 and 5.2–12.2% in 2050 and irrigated yield by 3–8% in 2030 and 5–14% in 2050 if current varieties were grown |
| (Arshad et al., 2017) | Pakistan | temperature and cumulative precipitation for each crop's growing season | 2017 | This study focuses on there is a negative effect of both season-long and terminal heat stress on rice and wheat, though wheat is considerably more sensitive than rice |

| | | | | |
|---|---|---|---|---|
| (Deschênes & Greenstone, 2007) | USA | minimum and maximum temperature, or precipitation and relative humidity | 2007 | to measure the economic impacts of climate variability on agriculture in the United States. And find out both negative as well as positive |

Climate change has the greatest impact on agriculture. Based on the previous literature, it can be concluded that climatic variability has an impact internationally. Many researchers have conducted country-specific studies and discovered that particular crops are severely impacted when climatic fluctuations are greater.

The significant impacts of climate change on agriculture can be attributed to rainfall reduction as well as highly irregular rainfall occurrences and monotonically increasing temperatures. Even in India, the evidence of climate change has been observed as per previous research. But very few studies have looked at the rainfall, temperature, and meteorological drought for the whole country. Therefore, we identify the use of meteorological variables for identifying climate change in India as one of the research gap to be further investigated through research.

Table: Literature on the technical aspects for climate change

| **Authors** | **Study area** | **Methods for analyzing climate change** | **Publication year** | **Pros** | **Cons** |
|---|---|---|---|---|---|
| Talukdar et al. | Whole India | MK test | 2020 | Shows the increasing and decreasing trends of rainfall | |

| | | | | | |
|---|---|---|---|---|---|
| Upaka (2019), Ghulam(2015), Deepak (2017), Jamaluddin(2015, Bedartha(2017) | | Mann kendall (MK )Method | | • Not affected by missing data.<br>• Perform better when the time series period is longer | Not suitable for seasonal weather like winter |
| Mujtaba (2017) Aida (2015) Abiodun(2017) | | Spearman's rho tests | 2017 | Able to examine the median and mean of lowest and highest rainfall | Complex formula which may leads to misinterpretation |
| Lucia (2017) Ghulam (2015) Deepak (2017) | | Sen's slope estimation | | Shows the increasing and decreasing trends of rainfall | Moderate results |
| (Karpouzos et al., 2010) | Pieria Region (Greece) | Mann–Kendall Trend Test | | This method is also suitable for finding the trend with non-normally distributed time series data, which contain outliers and nonlinear trends | |

| | | | | | |
|---|---|---|---|---|---|
| (Fraile, 1993) | Geneva | Mann–Kendall Trend Test | | most appropriate test, was used to determine the positive or negative trends in the climatic variables | |
| (Quiring, 2009) | USA | SPI | 2009 | Several drought indicators, in particular, have been created across the world. Some of these indices (e.g., SPI) are based only on precipitation, while others are based on a mix of multiple agro-hydro climatic factors. All of these drought indicators are used to track three different forms of drought: meteorological, hydrological, and agricultural. | |

| | | | | | |
|---|---|---|---|---|---|
| (Westmacott & Burn, 1997) | west-central Canada | Mann–Kendall Trend Test | 1997 | To assess climate change severity implications on the Churchill–Nelson River Basin in central Canada, they utilised the Mann-Kendall trend test and a regionalization technique. | |

Many researchers have used various tests to determine the causes of climate change, such as the MK test, the Sen Slope estimator, and SPI indices for rainfall and drought. After reviewing the literature, we discovered that the nonparametric M–K test and Sen's slope estimator, which are widely used tests for trend analysis, are more accurate.

**2.2. Climate Change and Agriculture**

Agriculture as sector is the most susceptible to climate change due to its vast size and susceptibility to weather variables, resulting in significant economic consequences. Changes in climatic events such as temperature and rainfall have a substantial impact on agricultural output. In the near future, climate change is expected to intensify. In Pakistan's Punjab region, the minimum and maximum temperatures are expected to rise throughout the Kharif and Rabi seasons. The average maximum and minimum temperatures are expected to climb by 1–3.3 °C and 2–3 °C respectively throughout the Kharif season while in Rabi, in models done for the upcoming mid-century (2040–2069), it is expected to climb by 2.1–3.5 °C and 2–3 °C, respectively. There have also been forecasts of rainfall fluctuations in the areas, particularly during the Kharif season (25–35 percent); during the rabi season, the differences are small (Bokhari et al., 2017). According to PRECIS, temperature minimums and maximums in Punjab, India, are expected to climb by the middle and end of the twenty-first century (Providing Regional Climates for Impact Studies). Furthermore, very high temperatures (heat waves) are expected from March to June, as well as extreme cold temperatures (frost) in December and January (Kaur, 2016). With an extra 0.5°C of warming, extremes in meteorological parameters, such as minimum temperature, maximum temperature, and precipitation, are expected to occur more frequently and with greater severity in China. Furthermore, if global warming is limited to 1.5 degrees Celsius, weather extremes will be reduced (Chen & Sun, 2018). Temperature and precipitation extremes, on the other hand, are more likely to occur in the near future as a result of global warming. Extreme precipitation events, such as severe rain or drought, are influenced by the topography of a place. Drought in southern Africa and South America will be less severe, but increased average river flows owing to persistent high rains will be more likely in South and East Asia. The Indus River Basin's rainfall pattern is expected to show uneven regional and seasonal variability. In the upper Indus basin, precipitation is expected to increase, whereas in the lower basin, it is expected to drop. Furthermore, the higher basin is expected to warm faster than the lower basin (Rajbhandari et al., 2015). In the northeastern United States, there is a chance of more warm extremes, fewer cold extremes, and stronger precipitation extremes in the future. Increased emissions will exacerbate these effects. Increased precipitation intensity and frequency has an influence on soil erosion, which will be exacerbated in northeast China as greenhouse-gas emissions rise (Y.-G. Zhang et al., 2010). Anomalies in precipitation have a negative impact on agriculture, particularly in underdeveloped countries. It has a major impact on agricultural yields as well as farmland acreage. According to research, the nearly 9% rate of agricultural growth in the developing world during the previous two decades is attributable to dry anomalies, as farmers extend their acreage to compensate for yield losses(Zaveri et al., 2020). Global warming would represent a serious danger to global food security, but if it is kept to 1.5 degrees Celsius, the vulnerability of 76 percent of poor nations will be decreased compared to the same regions at 2 degrees Celsius(Betts et al., 2018). Due to climate change's massive influence on agriculture output, ensuring food for the world's population is a difficult challenge (World Population Review 2020). To meet the population's food and nutritional needs by 2050, global agricultural production must increase by 60% annually from 2005/2007 to 2050, with a 77 percent increase in poor nations and a 24 percent increase in wealthy ones(Alexandratos & Bruinsma, 2012). Climate change is known to have a negative impact on agricultural productivity, and it is predicted that worldwide cereal production of maize and wheat will decrease by 3.8 percent and 5.5 percent, respectively, as a result of climate change (Lobell et al., 2011). Because of climatic factors, plants have to face several abiotic stresses such as salinity, drought, heat stress, cold stress, etc (Malhi et al., 2021). Climate change has a number of negative consequences, including water scarcity, soil fertility loss, and insect infestations in crops(Baul & McDonald, 2015). Therefore, a list of literature has been presented in table 3, which depicts the effect of climate change on agricultural production in India.

Table 3 Effect of climate change on agricultural production in India.

| **Authors and publication year** | **Study area** | **Climatic variables and crop production** | **Main findings** | **Main findings** |
|---|---|---|---|---|
| Talukdar et al. (2021) | Maharashtra | Rainfall and wheat | 2021 | Due to decreasing rainfall by 10mm causes the wheat production by 10% during the period of 1990-2020 |
| (Botai et al., 2016) | South Africa | Temperature Rainfall | 2016 | Increased rainfall variablity and high temperatures are the current major variables predicted to have a substantial influence on South African agriculture productivity. |

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|---|---|---|---|---|
| (Alexandratos & Bruinsma, 2012) | global level | Wheat, maize and Temperature Rainfall | 2012 | Climate change is expected to have a detrimental influence on agricultural output, with global cereal production of maize and wheat expected to drop by 3.8 percent and 5.5 percent, respectively, as a result of the shift. |
| (Baul & McDonald, 2015) | Nepal | temperature, rainfall | 2015 | Study shows that Water shortages, soil fertility loss, and pest infestations in crops are all negative impacts of climate change. |
| (Rajbhandari et al., 2015). | Indus river basin india | Precipation and temperature | 2015 | Precipitation is predicted to rise in the upper Indus basin while decreasing in the lower basin. |

| | | | | |
|---|---|---|---|---|
| Kumar and Parikh (2001) | India | temperature, rainfall Wheat, maize, Barley, sorghum, and arhar | 2001 | Wheat, maize, barley, sorghum, and arhar were among the crops whose output was assessed in this study. Due of their great climatic sensitivity, these crops were vulnerable to hardship. |
| (Hollaender, 2010). | India | temperature, rainfall and mix crops | 2010 | study found at testing the hypothesis which says, agricultural output in the country of India has climate-sensitivity in nature, and any variation in rainfall precipitation and temperature patterns significantly influence the production of the food grain |

**Literature on the forecasting of climate change and agricultural production**

The majority of studies on how climate change affects agriculture productivity are focused on future CO2 concentrations. In the Indo-Gangetic Plains for the 2050s, (Ortiz et al., 2008) discussed how wheat can adapt to climate change and suggested that while global warming is beneficial for wheat crop production in some regions; it may reduce productivity in critical temperature areas, making it critical to develop heat-tolerant wheat germplasm to mitigate climate change. With DSSAT 3.5, (Luo et al., 2003) explored the effects of climate change on wheat productivity (Decision Support System for Agro technology Transfer). CERES-Wheat simulations were run in Southern Australia for the 2080s under various CO2 levels, and the results suggest that wheat yields will rise under all CO2 levels, and drier locations will be more suitable for wheat cultivation but will likely have worse wheat quality. In South Africa, (Walker & Schulze, 2006) used the CERES-Maize model to predict crop sustainable production in smallholders under various climate scenarios using the Mann-Kendall non-parametric test, and the results show that increasing inorganic nitrogen and rainwater harvesting can increase crop yield for smallholders over time. In the Volta Basin, (Droogers et al., 2004) used the SWAP and HadCM3 climate models to study climate change impacts on rice production in seven basins under A2 and B2 scenarios, and the results suggest that rice yields are anticipated to rise by about 45 percent and 30 percent, respectively, for A2 and B2 scenarios. Climate change has varied effects on agricultural production in different locations; in some, it will rise, while in others, it will drop, depending on the area's latitude and irrigation application. Crop production may be enhanced by applying irrigation and increasing precipitation throughout the growing season; nevertheless, crop output is more susceptible to precipitation than temperature. If water supply is limited in the future, soil with a high water retention capacity will be more suited to reducing drought frequency and increasing agricultural yields. (Cuculeanu et al., 2002). This study suggests that because crop rotation periods may be reduced as a result of climate change, farmers must consider crop types, sowing dates, crop densities, and fertiliser levels when planting crops. The beneficial impacts of climate change on agriculture include increased CO2 concentrations, longer agricultural growing periods at higher latitudes, and highland ecosystems; the negative effects include increased insect and disease incidence, as well as soil degradation due to temperature change. Many climate models have been created to anticipate the effects of climate change, with greater spatial resolution climate models proving to be more effective in forecasting future climatic scenarios. Temperatures are expected to rise in the future, although precipitation may increase or decrease depending on the location of the research area.

Many researchers employ many types of models for prediction, such as statistical models or machine learning models for forecasting. To get the best outcome, we compared statistical and machine learning ANN and ARIMA models for prediction.

**Literature on the agricultural suitability modeling in the context of climate change**

One of the most important and basic aspects of the agricultural suitability evaluation process is the selection of criteria (Tercan & Dereli, 2020; Zolekar, & Bhagat, 2015). For agricultural suitability zonation, Pilevar et al. (2020) used climatic factors such as temperature, topographic factors such as slope and elevation, and soil characteristics such as soil texture, soil PH, and electric conductivity, among others. However, Seng et al., (2009), however, showed that the alkalinity, acidity, water storage profile, and water logging characteristics of soil are essential factors for mapping agricultural suitability. Similarly, Akinci et al. (2013) show that the soil classification category, land capacity level and subclass, height, slope, soil density, rockiness, and stoniness are all important factors to consider when assessing land suitability. Seyed mohammadi et al., (2019) have used climatic characteristics such as mean daily maximum and minimum temperatures for the coldest month, as well as mean temperature at various stages of crop development; soil characteristics such as depth, gypsum and calcium carbonate content, PH, electrical conductivity, exchangeable sodium percentage, and topographic characteristics of slope for agricultural suitability. Finally, for Land suitability evaluation, Sahoo et al., (2018)consider various geological and hydrometrological characteristics such as rainfall, ET, NDVI, LULC, soil, soil moisture, groundwater level, geology, slope, and elevation.

Modeling agricultural land suitability at a regional scale is critical for developing the most effective long-term management system. Several studies have applied the GIS technique and AHP methods to analyze the land suitability. For instance evaluated by using AHP in GIS, the land suitability for agriculture production in Turkey's Yusufeli district was determined. They claim that the soil depth is insufficient for agricultural production and that the erosion rate is excessive. (Zolekar & Bhagat, 2015) used slope degree, soil data, and the IRS P6 LISS-IV dataset to create a GIS-based multicriterion decision-making method framework for agriculture in the hilly zone. (Kazemi et al., 2016) used a combined GIS–AHP technique to assess land suitability for rain-fed Faba-bean cultivation in Golestan Province, north of Iran. They found that the most critical elements for rain-fed faba bean production were climate, topography, and soil data. With climate, topography, soil, and remote-sensing data in mind, (Ostovari et al., 2019) utilised a combination of AHP and GIS to assess site suitability for rapeseed cultivation. They found that soil characteristics had the highest specific weight, indicating that they were the most effective. A fuzzy set is a quantitative approach for assessing the degree of ambiguity in a complex system (Zadeh, 1996). The fuzzy set was applied for the land suitability assessment studies (Banai 1993; Sicat et al. 2005; Keshavarzi 2010) said that there are certain benefits to using a fuzzy-set technique: (1) allows you greater freedom in determining the set's object boundary; (2) inclusion is based on a degree of proximity to the ideal point, and (3) an element's partial membership in a set is taken into consideration. Sicat et al., 2005) used fuzzy modelling and farmers' expertise to estimate land suitability maps for agriculture production in the Nizamabad area of India. In the Ziaran area of Iran, (Keshavarzi et al., 2010) employed fuzzy-set theory to assess land suitability. They demonstrated that by using a fuzzy-set approach, land continuity in various land classes could be continuously shown. In the Yellow River Delta,(Wu et al., 2019), they used a fuzzy logic model to analyse soil quality and evaluate the geographical distribution of land-use types. Their findings reveal that the research site's usage of land resources should be carefully planned. In terms of managing weights of land characteristics and computing the land suitability rating, the AHP or fuzzy-set approaches performed very poorly. Hence, (Keshavarzi 2010) and (Zhang et al. 2015) employed AHP for determining weights of land feature for developing fuzzy membership functions. As a result, combining AHP, fuzzy set, and GIS approaches might be a powerful way to improve the accuracy of land suitability evaluation for a specific crop production. The goal of this work was to create a Geostatistical–AHP–Fuzzy set in GIS methods to assess land suitability evaluation for the entire country in order to identify whether areas are more or less appropriate for agriculture based on climatic and non-climatic elements under recent climatic circumstances.

Taking into account the findings of the previous research, the current research employs climatic characteristics such as rainfall, temperature, wind speed, ET, and aridity; topographic characteristics such as slope, aspect, elevation, and TRI; soil characteristics such as soil quality, soil composition, soil erosion, and the amount of soil organic carbon; and finally, LULC parameters to determine land suitability in India. Agriculture is a key source of revenue and the bulk of people's lives are based on it. Smallholder farmers' productivity and livelihoods can be enhanced by identifying suitable agricultural zones and comprehending climate-related concerns. These findings are likely to help with mitigation planning and policy discussions, as well as more informed and scientifically based decision-making for these selected crops. We came to the conclusion that integrating fuzzy–AHP–Geostatistics in a GIS is a practical and effective method to improve land-use planning for agricultural reasons.

### 2.3. Summary and Concluding Remarks

The current chapter provides an extensive literature review regarding climate change and its impacts on agriculture production. In the first section, we have reviewed the theoretical and empirical literature on climate change. Most studies show that there is a significant and negative effect on all sectors of the economy, as indicated by gross domestic product (GDP), specifically for agricultural production and food security at the global level. In the second section, we provided empirical results estimating the impact of climatic factors on agricultural productivityat a global level. The review of literature reveals how climatic variables such as rainfall and temperature are important for crop production in both negative and positive terms followed by a study of future prediction models built by researchers globally.

Based on existing literature, we understand that the agricultural sector is very sensitive to climate change throughout the world. Most of the studies give a clear indication that climate change decreases agricultural productivity or net revenue in the different regions of India, other developing and developed countries. Climate change in future may accentuate the food security issue, and can decrease the employment opportunities and increase poverty in India. In India, a number of studies estimated the effect of climate change on various crops. Most of studies show that climate change has decreased the agricultural productivity or net revenue of most food grain crops in different regions of India.

However, we could not find any study which evaluates the impact of climatic factors such as rainfall and temperature on agriculture production for all the major food grain and cash crops (commercial crops) at a macro level in India or future prediction with a comparative analysis using ARIMA and ANN. Land suitability analysis is a method of determining how suitable or acceptable a given area is for a specific land use (such as growing a certain crop variety) in a given venue. Land suitability techniques have been used widely in agricultural regions to find best management practice previous studies show that many researches have been carried out on the land suitability assessment using statistical models in different parts of the world. In addition, In India, few studies were taken places for land suitability analysis, but as a whole In this country, any kind of land suitability analysis has not been carried out. Agriculture suitability mapping has also not been carried out in India. As a result of the research void, the existing studies mainly concentrate on a small geographic region or district. The current study creates zone-wise agriculture suitability maps for the entire country.

Based on the identified gaps in existing literature, we have conducted this study that initially performs a comprehensive historical trend analysis for variation in key climatic variables in India, followed by investigating the effect of climatic factors on selected crops, including future prediction till 2030. The study in also creates a recommendation-based agriculture suitability analysis work to find the best agriculture suitable regions using climatic and non-climatic variables for the whole country. This study provides key insights to decision makers and interested stakeholders with a detailed assessment of climate trend analysis and impacts on agriculture production and future predictions towards improved crop production and food security.

# Chapter 3

## ASSESS THE CLIMATE CHANGE IN INDIA IN TERMS OF RAINFALL CHANGE AND METEOROLOGICAL DROUGHT

### 3.1. Introduction[2]

This study analyzes and forecasts long-term spatiotemporal changes in rainfall and meteorological drought for the period 1901–2015 across India at a meteorological divisional scale using the Mann-Kendall (MK) test, the Pettitt test, and Sen's innovative trend analysis. Precipitation and meteorological changes have been considered as the proxy of climatic change parameters in this study. Therefore, assessing the changes in proxy climatic variables (rainfall and meteorological drought) can establish the fact of climate change in India. To estimate the changes in climatic parameters, several sophisticated statistical and machine learning techniques have been employed, such as Mann-Kendall (MK test), the Pettitt test, Sen's innovative trend analysis (ITA), and artificial neural network (ANN). To do so, the long-term rainfall time series has been divided into two periods based on change point analysis to explore the changes in rainfall trends prior and afterward the change point. To examine the trend and pattern of rainfall for the entire basin, the kriging interpolation model was applied in the ArcGIS domain. The results showed that most meteorological divisions exhibited a declining rainfall trend on annual and seasonal scales except for seven divisions during the study periods. Out of 17 divisions, 11 divisions showed a significant rainfall declining trend for the monsoon season ($p<0.05$), while the declining rainfall trend was insignificant for the winter and pre-monsoon seasons. Overall, the annual rainfall trend had a decline of about 8.45 percent. The probable year of maximum change was diverse for the different meteorological divisions, and the maximum change occurred primarily after 1960. The increasing rainfall trend was observed during the period 1901-1950. In constrast, a significant decline had detected in the rainfall trend after 1951. The rainfall forecast for the next 15 years for all the meteorological divisions' also exhibited a significant decrease in The

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[2] This chapter is published as follows:
Praveen, B., Talukdar, S., Mahato, S., Mondal, J., Sharma, P., Islam, A. R. M. T., & Rahman, A. (2020). Analyzing trend and forecasting of rainfall changes in india using non-parametrical and machine learning approaches. Scientific reports, 10(1), 1-21. https://www.nature.com/articles/s41598-020-67228-7

rainfall forecast for the next 15 years for all the meteorological divisions' also exhibited a significant decrease in rainfall. The results derived from ECMWF ERA5 reanalysis data exhibited that increasing/decreasing precipitation convective rate, elevated low cloudcover, and inadequate vertically integrated moisture divergence might have influenced on change of rainfall in India. On the other hand**,** SPI-12 was used to estimate the long-term meteorological drought for 34 sub-divisions to explore its effect on the agriculture activities. The results of ITA and wavelet transformation showed that the meteorological drought for almost all sub-divisions has been increased very recently, while in the past, these sub-divisions observed mild to no drought conditions. Finding of the study has some implications in water resources management considering the limited availability of water resources and increase in the future water demand.

## 3.2. Review of Literature

One of the key challenging issues of the 21$^{st}$ century is the changing climate, which has threatened the basic needs as well as the health of humans. The most significant evidence of climate change can be observed in the changes in the pattern and intensity of precipitation (Li et al., 2019; Storch et al., 1993; Rahman and Islam, 2019) and meteorological drought. The precipitation and meteorological drought pattern have been getting consideration in the research because the extreme precipitation events and mild to severe drought affect people significantly (Westra et al., 2014). The precipitation and meteorological drought patterns of the world have changed significantly during recent decades, especially in the countries of the mid-latitudes (IPCC, 2013). Hence, a complete understanding of the precipitation pattern and meteorological drought in the changing environment will help in better decision-making and improve the adapting-capacity of the communities to sustain the extreme weather events.

The major climate variables such as rainfall and temperature, along with meteorological drought are used to detect climate change because the spatio-temporal pattern of water resource availability significantly depends on these variables (Taxak et al. 2014). The availability of the water resources significantly depend on the precipitation and the temperature, and variability of rainfall has significantly increased, as reported in (Afzal et al. 2015). The Spatio-temporal changes in rainfall pattern can cause floods and drought which ultimately results in loss of life, property and biodiversity. Therefore, the study of historic trends in rainfall and its distribution are noteworthy to the climatologist and water resources planners (Kundzewicz et al. 2007). In many parts of the world, the precipitation pattern has significantly changed during recent decades (IPCC, 2013). In the assessment reports of 2007 and 2014 by the Intergovernmental Panel on Climate Change has shown how the climate is adapting for the production of water supplies around the globe and on a regional basis. It has been quite clearly demonstrated in recent studies that hydrological cycle changes have resulted in changes in intensity and precipitation frequency which, depending on the area of influence, have led to a severe drought or flood (Meresa et al., 2016; Oguntunde et al., 2017). New et al. (2001) reported that the amount of rainfall occurrences has attenuated across the globe during 20th century and it is getting poorer in the 21st century. Kumar and Jain (2011) have demonstrated that 15 basins out of 22 basins of India have recorded a decrease in the annual trend of rainfall occurrences and the number of rainy days during the last century. Studies indicate that extreme precipitation events have increasedin the northern and north-western parts of India while they have decreased in the southern parts of India (Roy, 2009; Goswami et al., 2006). Further, several studies indicate that, the pattern and trend of rainfall have changed in India during the last century (Nikumbh et al., 2019; Paul et al., 2016; Roy, 2009; Guhathakurta and Rajeevan, 2008; Roy and Balling, 2007).

Drought occurs when there is insufficient water for normal uses for an extended period of time. When a region's precipitation is consistently below normal, this is known as a drought. It has the potential to have a major effect on the affected region's biodiversity and agriculture. While droughts can last for years, even a brief period of severe drought can inflict substantial economic damage (Oliver, 2005). Agricultural drought, according to the World Meteorological Organization (WMO), is described as "a long-term rainfall deficiency affecting a wide area for one or more seasons or years, reducing primary production in rain-fed agriculture”. Climate change has sparked intense discussion among scientists, necessitating several studies into the historical changes that have arisen since the dawn of the industrial era, as well as the projected future effects of anthropogenic and natural activities on climate. Spinoni et al. (2014) demonstrated that all of these drought features have increased significantly in Africa, East Asia, and southern Australia as well as in the Mediterranean region in order to illustrate improvements to worldwide dryness, length, and severity between 1951 and 2010. Droughts that last for a long time will deplete reservoir storage and groundwater levels, resulting in a wide variety of socioeconomic and environmental consequences. According to the Intergovernmental Panel on Climate Change's (IPCC) most recent study (IPCC, 2014a), current greenhouse gas emissions will accelerate global warming and create long-term changes in the climate system, increasing the risk of severe events. Droughts can become more common and extreme across the world as a result of these conditions (Dai, 2013), with an increasing effect on water supplies. Drought is a dynamic and hard to measure phenomenon. This is due to the fact that its characterization is based on various components of the water cycle, and drought effects change over time, making it time-dependent. Numerous research has been undertaken in recent years to measure the possible effect of climate change on meteorological, agricultural, and hydrological droughts in various parts of the world, using a variety of indicators based on the form of drought (Mishra and Singh, 2010; Zargar et al., 2011; Pedro-Monzonis et al., 2015). Drought can be estimated and represented by several drought indices. Drought indices are generally determined using existing scientific methods such as the Standardized Precipitation Index (SPI), Palmer Severity Index, Crop Moisture Index, and Reclamation Drought Index. Thousands of datasets on rainfall, stream flow, and other water resources metrics are combined into an easily understood, broad representation of these drought index values. While the advantages and disadvantages of these indexes for analyzing historical droughts have been extensively explored (Alley, 1984; Dai, 2011; Hayes, 1999), few scholars have examined the standard metrics' basic shortcomings in a non-stationary, climate change sense. Some indices are more suited to such applications than others, despite the fact that none of the major indices is clearly superior to the others in all situations. Depending on the need, each of the indices functions in a different way (Othman et al. 2016). The Standardized Precipitation Index (SPI) introduced by McKee et al. (1993), which has been widely used in various countries, is without a doubt the most well-known index for measuring meteorological drought. This drought index is one of the most reliable and useful drought indices because it can be measured over a variety of time scales and can be used to analyze various drought groups. Furthermore, the SPI uses only precipitation data for calculation, making it simpler to quantify than complex indices and allowing for comparison of drought conditions across regions and time spans. The SPI is an excellent candidate for drought risk analysis because of its inherent probabilistic structure. Several authors chose the SPI trend to achieve this goal. However, simple drought indices do not reveal the actual scenario; therefore, researchers need to use sophisticated techniques to explore the actual condition of the drought situation in India.

Numerous statistical methods have been developed and applied to detect the trend-shift in climatic and hydrological parameters. Thus, several parametric and non-parametric techniques were developed, but researchers have favored the non-parametric methods over the parametric (Sonali and Kumar, 2013). Consequently, non-parametrictests such as the

Mann-Kendall (MK) statistical test (Kendall, 1975; Kendall, 1955) have been widely used to detect trend-shifts in the fields of hydrology and climatology. Following this, several other parametric & non-parametric statistical methods were used to identify the abrupt change point in the climatic and hydrologic time series data. The non-parametric Standard Normal Homogeneity Test (SNHT) (Alexandersson and Moberg,1997), the Buishand ranges test (Buishand, 1982) and the Pettitt's test (Pettitt, 1979) were frequently used to detect abrupt change point from the time series data.

Sen (2012, 2014) recently introduced an innovative trend analysis (ITA) method for identifying trends in environmental, hydrological, and meteorological variables. Martnez-Austria et al. (2015) used data linear adjustment, Spearman test, and ITA to examine temperature and heat wave patterns in Northwest Mexico, and all of the tests revealed the presence of a heating mechanism with rising high temperatures. The Mann–Kendall test, linear regression model, and ITA were used by Saploglu et al. (2014) to investigate the transition in monthly and annual river flows. The findings were the same with all three methods. Furthermore, the study discovered a strong connection between the Mann–Kendall test and ITA. At the 5% level observed by the Mann–Kendall test, a trend line shorter than 36 must be statistically important. ITA was used by Kisi and Ay (2014) to detect patterns of low, medium, and high values of water quality parameters in the Kizilirmak River in Turkey, and the findings were similar to the Mann–Kendall test results. They demonstrated that the ITA method would identify certain no-clear-trends discovered by the Mann–Kendall test. The findings were the same with all three methods. Furthermore, the study discovered a strong connectionbetween the Mann–Kendall test and ITA. At the 5% level observed by the Mann–Kendall test, a trend line shorter than 36 must be statistically important. ITA was used by Kisi and Ay (2014) to detect patterns of low, medium, and high values of water quality parameters in the Kizilirmak River in Turkey, and the findings were similar to the Mann–Kendall test results. They demonstrated that the ITA method would identify certain no-clear-trends discovered by the Mann–Kendall test. Furthermore, the graphical representation may reveal important hidden sub-trends. Previous research, on the other hand, only defined patterns in a qualitative manner, limiting the precision and comparability with other studies. As a result, a trend estimation algorithm is needed.

Although numerous studies have already examined the country-level changes in rainfall and meteorological drought in India during the past two decades (Kumaret al., 2010; Roy, 2009; Guhathakurta and Rajeevan, 2008), no comprehensive research has been conducted to determine the trend analysis and periodicity over the whole of India. Thus, this study has been designed to study the rainfall and meteorological drought trends across India for 115 years (1901–2015). The previous studies considered only the MK test and change point detection techniques using SNHT, Pettitt's test, and Buishand range test for the different parts of India. But in this study, the non-parametric MK as well as change detection techniques, ITA, periodicity analysis have been considered, followed by temporal analysis by splitting the available record into two sub-periods, pre and post change point (before 1960s and post 1960s). 1960 period) for the whole India. This study also considered a detailed analysis of climate change from the point of view of rainfall pattern using different statistical techniques.

## 3.3. Methodology

### 3.3.1. Study Area and data source

India is located in the South Asia between 8.4$^{o}$ and 37.6$^{o}$N latitude and 68.7$^{o}$ and 97.25$^{o}$E longitude. Himalayas in north separate India from rest of the Asia while Arabian Sea, Bay of Bengal and Indian Ocean makes the Western, Eastern and Southern limits, respectively. The country experiences almost all types of climate due to its vast size and location (Sharma et al., 2019).The presence of Himalayas in north which runs east to west not only provides scenic beauty but also influences its climatic condition. The total area of country is about 3.2 million sq. km.India along with its neighboring countries like Pakistan, Srilanka, Bangladesh and Myanmar is also called Monsoon Asia due to their unique monsoon type climate. The country has some of the world's coldest (Drass Valley), hottest (Thar Desert) and wettest (Mawsynram) places on the earth.

India meteorological Department (IMD) has classified the whole country into thirty-four meteorological sub-division where the climatic data have been recorded at different meteorological stations (Figure 3.1a). The present work is done on these thirty-four meteorological sub-division. In this study, we have collected meteorological sub-division wise 115 years (1901–2015) rainfall data from IMD. The data used in the study was continuous with no missing values.

### 3.3.2. Method for Drought Estimation

The Standardized Precipitation Index (SPI) is widely used at the moment due to its ease of calculation and interpretation. A simple calculation is better than applying difficult hydrological indices for showing dryness (Oladipio, 1985). SPI is a quick and effective way to look at drought climatology (Lloyd-Hughes and Saunders, 2002). McKee et al. (1993) improved the Standardized Precipitation Index (SPI) as a method for recognizing and monitoring territorial droughts. If the SPI remains consistently negative and reaches amplitude of -1.0 or below, a drought occurs. McKee et al. claim that the occurrence ends when the SPI becomes positive (1993). The SPI designation for drought cruelty is seen in Table 3.1 (McKee et al., 1995). The standardized precipitation sequence is represented by the X1, X2, and Xn series, and SPI is calculated using the given equation no 1 (Omondi, 2014). Here, Xij denotes the seasonal precipitation at the ith station and jth observation, Xim denotes the seasonal average over the long term, and indicates the standard deviation.

$$SPI = \left(\frac{X_{i,j} - X_{i,m}}{\sigma}\right)$$

The meteorological drought was quantified and characterized in this analysis using a twelve-month (SPI-12) sequence from 1901 to 2015.

Table 3.1: SPI value ranges for different meteorological drought conditions (McKee et al., 1995).

| SPI values | Drought Category |
|---|---|
| 0 to −0.99 | Mild drought |
| −1.00 to −1.49 | Moderate drought |
| −1.50 to −1.99 | Severe drought |
| −2.00 | Extreme drought |

**3.3.3. Method for Trend Analysis**

The MK test (Kendall 1975; Kendall 1955) is a non-parametric test based on rank system used to detect the changes in time series data, especially hydro-climatic data due to their strong nature for the any kind of data as well as low sensitivity to any sudden change (Yue and Hashino 2003; Yue and Wang 2002). To perform this test, it is essential to verify the serial correlation of data series (Jenkins & Watts 1968). A positive serial correlation can support the expected number of bogus positive products in the MK test (Von Storch, 1995). Thus, the serial correlation must be excluded prior to applying the MK test. To eliminate the serial correlation, the trend free pre-whitening (TFPW) technique proposed by Yue and Wang (2002) has been used.

The MK test technique used in this study can be expressed as eq. 2.1:

$$S = \sum_{i=1}^{n} \sum_{j=i+1}^{n} \operatorname{sgn}(K_j - K_i) \tag{2.1}$$

Where,

$$\operatorname{sgn}(K_j - K_i) = \begin{pmatrix} 1 & if\,(K_j - K_i) & \rangle 0 \\ 0 & if\,(K_j - K_i) & = 0 \\ -1 & if\,(K_j - K_i) & \langle 0 \end{pmatrix}$$

In a time series, $K_i$, *i = 1, 2, 3, ……….n*, the value of S is supposed to be similar as the normal distribution with a mean 0 and while the discrepancy of statistics S has been computed using eq. 2.2:

$$\operatorname{var}(s) = \left[ \frac{n(n-1)(2n+5) - \sum_{y=1}^{x} t_y (t_y - 1)(2t_y + 5)}{18} \right] \tag{2.2}$$

The $Z_{MK}$ value is used to find out that the time series information is demonstrating a significant trend or not. The $Z_{MK}$ value is computed using eq. 2.3:

$$Z_{MK} = \begin{pmatrix} \dfrac{S-1}{\sqrt{\operatorname{var}(S)}} & if & S\rangle 0 \\ 0 & if & S = 0 \\ \dfrac{S+1}{\sqrt{\operatorname{var}(S)}} & if & S\langle 0 \end{pmatrix} \tag{2.3}$$

The positive and negative values of Z in a normalized test statistic reflect increasing and decreasing trend, respectively, while a 0 (zero) Z value reflects a normal distributed data series.

**3.3.4. Method for Change Point Detection**

Different methods have been applied to examine the existence of the abruptly shifting change points in the time series climatic and hydrological data (Kundzewicz et al. 2007;

Radziejewski et al. 2000). Pettitt test proposed by Pettitt, (1979) and standard normal homogeneity test (SNHT) proposed by Alexandersson and Moberg, (1997) have been applied to identify any sudden shift of annual and seasonal rainfall of all the meteorological divisions of India.

**Pettitt Test:** It is a distribution-free rank based test used to discover noteworthy changes in the mean of the time series. It is more helpful when the hypothesis testing about location of a change point is not necessary. This test has been used extensively to identify the changes observed in climatic and hydrological data series (Gao et al. 2011; Zhang and Lu 2009). When length of a time series is represented by *t* and the shift take place at m years, the consequential test statistics are expressed as given in Equation (2.1).The statistic is similar to the Mann- Whitney statistic, which characterized by two samples, such as k1, k2…, km and km+1, k2…, kn:

$$U_{t,m} = \sum_{i=1}^{m} \sum_{j=t+1}^{t} \operatorname{sgn}(K_i - K_j) \quad \text{------- (2.4)}$$

Where $\operatorname{sgn}$ in equation 2.1 is defined by equation 2.2:

$$\operatorname{sgn}(K_i - K_j) = \begin{pmatrix} 1 & if\,(K_i - K_j) & \rangle 1 \\ 0 & if\,(K_i - K_j) & = 0 \\ -1 & if\,(K_i - K_j) & \langle 1 \end{pmatrix} \quad \text{------------------- (2.5)}$$

The test statistic *Ut,m* is calculated from all haphazard variables from 1 to *n*. The majority of distinctive change points are recognized at the point where the magnitude of the test statistic |*Ut,m*| is highest.

$$Z_T = Max_{1 \le t \langle m} \left| U_{t.m} \right| \quad \text{------------------------ (2.6)}$$

The probability of shifting year is estimated when |*Ut,m*| is maximum following equation 2.7:

$$P = 1 - \exp\left(\frac{-6Z^2{}_T}{K^2 + K^3}\right) \quad \text{------------- (2.7)}$$

If the *p*-value is less than the significance level α, the null hypothesis is considered to be rejected.

**Standard Normal Homogeneity Test (SNHT):** Also known as Alexanderson test, this test is applied to detect sudden shift or presence of change point in time series climatic and hydrologic datasets. The change point or change is detected following equation 2.5:

$$T_s = T_m \ , 1 \leq m < n \qquad (2.8)$$

The change point refers to the point, when $T_s$ attains maximum value in the data series. The $T_m$ is derived using equation 2.6:

$$T_m = \overline{m z_1} + (n-m)\overline{z}_1, m = 1, 2, ...., n \quad \text{------------- (2.9)}$$

Where, $$\bar{z}_1 = \frac{1}{m}\sum_{i=1}^{n} \frac{(M_i - \overline{M})}{s} \quad \text{--------------- (2.10)}$$

Where $\underline{m}$ represents the mean and $s$ represents the standard deviation of the sample data.

**Buishand Rang Test:** Also called Cumulative Deviation test, it is calculated based on the adjusted biased sums or cumulative deviation from mean. The change point is detected using the following equations:

$$R_0^* = 0 \ and \ \mathrm{R}_m^* = \sum_{t=1}^{m} P_t - P_{mean}) \quad \text{----------------------- (2.11)}$$

$$m = 1, 2.........., n$$

Where, $$R_m^{**} = \mathrm{R}_m^* / \sigma$$

$$S = Max\left|R_m^{**}\right| - Min\left|R_m^{**}\right|, 0 \leq m \leq n \quad \text{----------------(2.12)}$$

The $S/\sqrt{n}$ is then estimated using the critical values proposed by Buishand, (1982).

### 3.3.5. Methods for Innovative Trend Analysis

The time series rainfall trend in India was detected using an innovative trend analysis proposed by Sen (2012). The approaches, on the other hand, are plotted using a Cartesian coordinate system and a sub-section time series. As a result, the time series was split into two sections: 1901–1957 and 1958–2015. In an increasing order, all segments became fixed. The first sub-series (xi) were typically applied to the x axis, while the second sub-series (yi) were typically added to the y axis. If the data is plotted above the 1: 1 line, it means that there is no trend, but if the data is plotted on the 1:1 line, it indicates that the moment series is increasing, and if the data is plotted below the 1:1 line, it indicates that the moment series is decreasing (Ay and Kisi 2015; Şen 2014).The trend change slope of that time series would be lower if the scatter plot is closer to the 1:1 point, and the further away from the 1:1 tier it is, the higher the excitement change incline in the time series (Sen 2012). The ITA method's straight-line trend slope is often illustrated as the following expression (en 2015):

$$s = \frac{1}{n}\sum_{i=1}^{n} \frac{10(\bar{y}-\bar{x})}{n}$$ ------------------(2.13)

Where s is the indicator of trend, with the positive value representing an increasing trend while negative value represents the decreasing trend. ȳ as well as x̄ would be the arithmetic average of the first sub-series (xi) and also second sub-series (yi), and n is the number of data products collected. The indicator is multiplied by 10 for comparison with MK test (Wu and Qian, 2016).

### 3.3.6. Methods for Rainfall Changes

To calculate atmospheric oscillations on rainfall trend variation, winter and summer precipitations and moisture divergence during 1979–2015 on 1.25°×1.25° grids were obtained from the European Centre for Medium Range Weather Forecasts (ECMWF), ERA-5 (http://apps.ecmwf.int/ datasets/data/interim-full-daily). The ERA5-Interim is the most recent ocean-atmospheric changes reanalysis datasets available since 1979 forwards. In addition, low cloud cover dataset was also derived from the ECMWF ERA5 data to assess the effect of cloud cover on rainfall variation (Rahman and Islam, 2019). We have quantified the influence of atmospheric circulation changes on the trend patterns in rainfall. At first, we have detected a recent significant change point of annual mean rainfall based on Pettit test for the period 1979–2015 in India and observed that the mean rainfall has a change point after 2000. Then, the change in circulation of the two periods before and afterword the changes are quantified by subtracting 1979–2000 from 2001 to 2015 using the ECMWF ERA5 reanalysis data. The GrAd software was used to prepare the spatial maps.

### Morlet wavelet transformation

Wavelet transform analysis (Li et al. 2013) is one type of reliable mechanism for determining the original periodicity of nonstationary signals and detecting variance over several time scales (Liang et al. 2014; Torrence and Compo 1997). The convolution of xn with a scaled and interpreted wavelet ($\eta$) yields the wavelet transform attributable to a time series $xn$ ($n$ = 0, . . . , $N - 1$):

$$W_n(\xi) = \sum_{\gamma=0}^{N-1} X_\gamma(\psi)^* \left[\frac{(\gamma - n)\delta t}{\xi}\right]$$

The Morlet wavelet equation is given as follows: (Torrence and Compo 1997).

$$\psi(\eta) = \pi^{\frac{-1}{4}} e^{i\omega_0\eta} e^{\frac{-\eta^2}{2}}$$

Where ξ represents the time scale, ω0 the non-dimensional frequency captured to be 6 since it satisfies the admissibility condition ( Farge, 1992), $\eta$ expresses the time, $\delta t$ indicates the time interval, and $\psi*[(\gamma - n)\delta t/\xi]$ is the complex conjugate of the wavelet function $\psi[(\gamma - n)\delta t/\xi]$. To pick the initial vibration periodicities, the actual segment of $(\xi)$ and the modulus square of the Morlet Wavelet (wavelet spectral power), $(\xi)$, are widely used. The signal magnitude and stage of certain properties in different time scales are shown in the actual portion of the Morlet Wavelet, while wavelet spectral power depicts the signal's power on function time scales Wang et al. (2013). Wavelet spectral strength at several scale $(\xi)$ can be quantified by:

$$P_n(\xi) = |W_n(\xi)|^2$$

Wavelet variance can be assessed by the total of the square of wavelet coefficients in time field:

$$Var(\xi) = \sum_{n=0}^{N-1} \quad |W_n(\xi)|^2$$

Present study utilized this method for periodicity analysis of drought.

### 3.4. Empirical Findings

## Modelling of Climate Change by analyzing rainfall pattern

### Descriptive Analysis of Annual rainfall

We calculated the descriptive statistics of the annual rainfall since 1901 to 2015 for thirty-four meteorological sub-divisions of India. Results show that the South Indian meteorological divisions i.e. Kerala, Tamil Nadu, and Konkan & Goa have observed the highest average rainfall (3396.64 mm. 2930 mm. and 2974 mm. respectively). While, the minimum average rainfall has been recorded in the sub-divisions of West India meteorological divisions i.e. West Rajasthan (288.74 mm.), Saurashtra and Kutch (494.27 mm.), Haryana (535.47 mm.), Delhi and Chandigarh (596.16 mm.). The standard deviation of rainfall for whole India varies from 1242.04 to 108.99 mm. The highest variation (standard deviation) in rainfall was observed in Arunachal Pradesh meteorological sub-division, followed by Coastal Karnataka (480.98 mm.), Konkan & Goa (478. 49 mm.), while the minimum variation was recorded in Western Rajasthan (108.99 mm., followed by North Interior Karnataka (135.33 mm), Haryana Delhi and Chandigarh (142.64 mm). The skewness of the rainfall ranges from -0.81 to 1.05 for all sub-divisions of India. The negative skewness was found in Tamil Nadu (-0.81), Bihar (-0.39), Konkan & Goa (-0.21), Jharkhand (-0.15), West Uttar Pradesh (-0.09), East Madhya Pradesh (-0.02) and Madhya Maharashtra (-0.001). While rest of the meteorological sub-divisions were observed positive skewness.

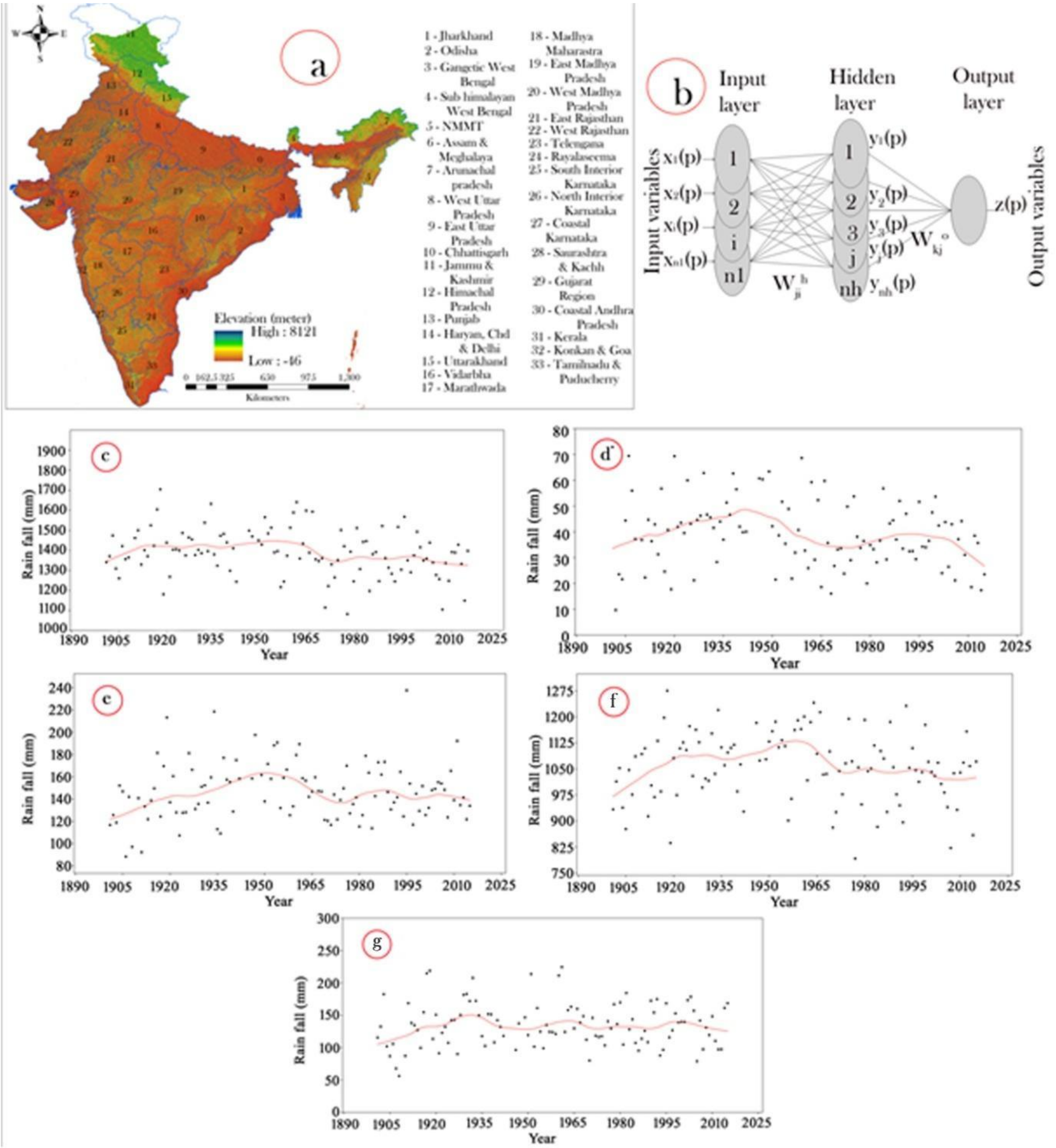


**Figure 3.1**: (a) Geographical location of the study area; (b) the schematic structure of Artificial Neural Network (ANN); LOWESS curve on annual and seasonal rainfall where figure (c) shows annual rainfall, (d) winter (e) summer (f) monsoon and (g) post monsoon rainfall.

The arithmetic mean is not significant (robust) to local variations (Duhan and Pandey 2013). Therefore, LOWESS regression curve was applied on the seasonal rainfall to minimize the local variation. A cluster of researchers used this statistical method and achieved satisfactory findings over the arithmetic mean. The findings of LOWESS curve indicate an increasing pattern of annual rainfall up to 1965, while a decreasing pattern of rainfall was found after the year 1970. (Figure 3.1c). The findings of LOWESS curve for the winter season (Figure 3.1d) showed that the increasing rainfall pattern was observed for the periods of 1935-1955 and 1980-1998. A sudden decrease in the trend was observed after 1955 and 1998. In the case of summer and monsoon season (Figure 3.1e, 1f), the curve indicates that the negative trend was observed after the 1960. The identical result was found in the work of Goyal (2014). Whilst, in the case of post-monsoon (Figure 3.1g), the LOWESS regression curve indicates the positive trend was found during 1925-1935 and 1955-1965. The negative trend for post monsoon was observed after 1995.

**Long Term Pattern and variation of average annual and seasonal rainfall** we used the coefficient of variation techniques to explore the rainfall variation for all meteorological sub-divisions. The figure 2a-e showed the spatial mapping of variations of average annual and seasonal rainfall over India using ordinary kriging interpolation method which is geo-statistical approach. The findings of spatial mapping of rainfall variation showed that the meteorological sub-divisions of Western India were recorded highest rainfall fluctuations. The minimum rainfall fluctuation was registered in Assam and Meghalaya (11.35%) metrological divisions, followed by Sub-Himalayan meteorological divisions like West Bengal (12.25%), Orissa (12.92%) and extreme South Indian divisions like Kerala (14.16%), Coastal Karnataka (14.42%) and North Interior Karnataka (14.67%). These results indicate that these states have been experiencing very less inconsistent rainfall trend for 115 years. While, the highest rainfall variation was found in Saurashtra and Kutch (41.14%), followed by Western Rajasthan (37.75%), Arunachal Pradesh (33.23%) and Gujarat region (30.46%) indicating the irregular occurrences of rainfall throughout the year.

The analysis of distribution and fluctuation of rainfall over Indian meteorological divisions' show that the occurrence of winter season rainfall was comparatively less than the other seasons during 1901-2015. The maximum variation of rainfall was reported in Konkan & Goa (253.37%), followed by Coastal Karnataka (187.70%), Gujarat region (185.12%), Saurashtra & Kutch (174.88%) and Madhya Maharashtra (162.06%) indicating the unstable incidence of rainfall in these meteorological units. More consistent rainfall with low variations was observed in Himachal Pradesh (41.89%), followed by Arunachal Pradesh (43.15%), Uttarakhand (48.69%) and Assam & Meghalaya (52.21%) meteorological units (Figure 2.2c). Result show that, the rainfall in summer season had not recorded a significant variation, whilst the maximum variations of rainfall was observed in the meteorological divisions of Western India. The lowest rainfall variation was found in the meteorological divisions of Northeastern India and extreme South India.

The study of diverge distribution of rainfall over India for monsoon season indicates that the maximum rainfall was registered in Saurashtra & Kutch (42.67% and 157.64%), followed by West Rajasthan (39.93% and 145.35%), Arunachal Pradesh. Whereas, the highest rain fall variation in post-monsoon season was found in Punjab (36.18% and 138.65%), followed by Gujarat region (31.38% and 127.66%) indicating unstable rainfall incidences (Figure 3.2d and 3.2e). The lowest rainfall fluctuation of monsoon season was recorded in the meteorological divisions of Assam & Meghalaya (12.69%), followed by Orissa (13.34%), Sub Himalayan West Bengal (13.94%) and Coastal Karnataka (15.29%). While, in the post-monsoon season, the lowest rainfall fluctuation was observed in Kerala (26.21%), followed by Tamil Nadu (29.46%) and South Interior Karnataka (36.44%).

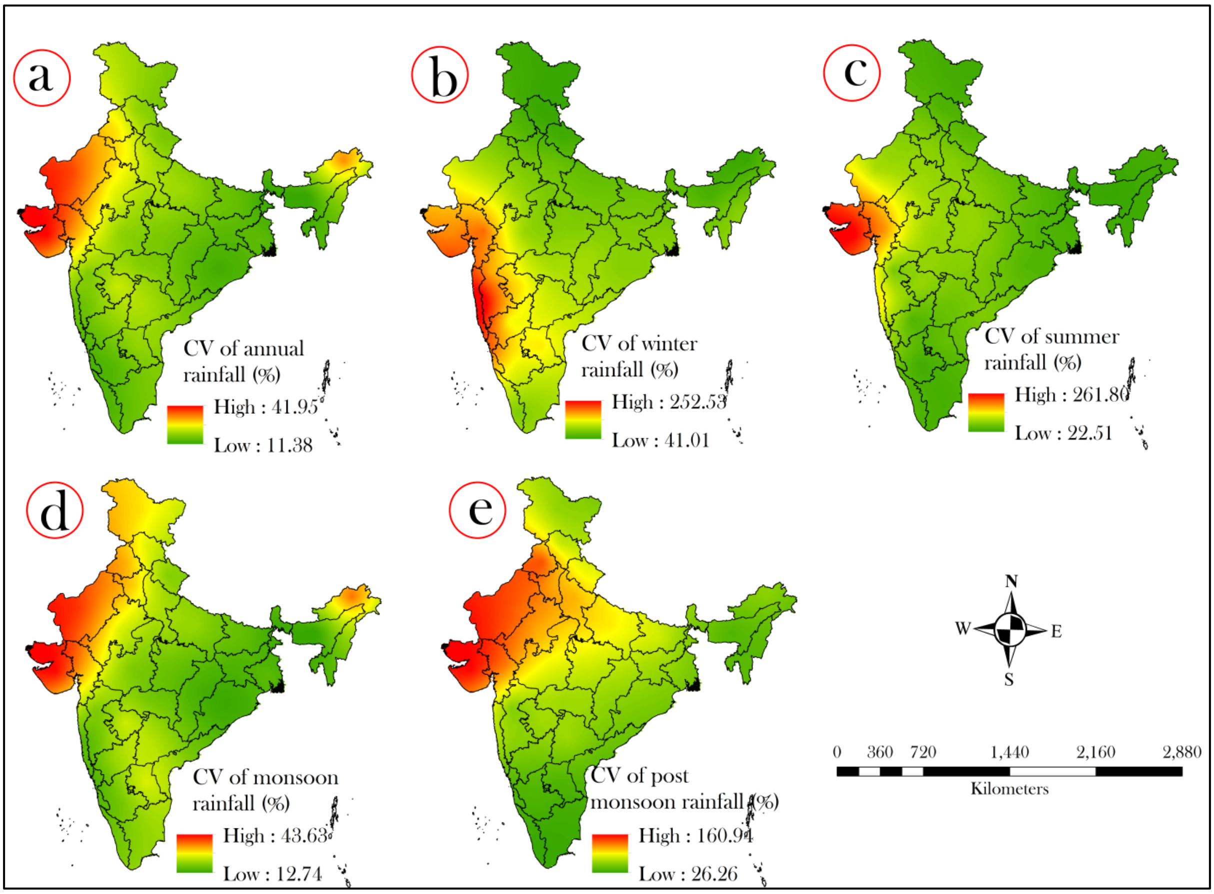


**Figure 3.2**: Meteorological subdivision wise spatial variations using the coefficient of variation (CV) in annual and seasonal rainfall where figure (a) shows annual, (b) winter, (c) summer, (d) monsoon, and (e) post monsoon rainfall pattern

### Meteorological sub-division wise trends of Annual and Seasonal Rainfall

We calculated the annual and seasonal rainfall trend for thirty-four meteorological sub-divisions using non-parametric Mann-Kendall test (Table 3.1). The table 3.1 shows the five shades of brown color based on the intensity of z value of Mann-Kendall test at 0.05 significance level which indicates that darker the shade of brown color, higher the negative z value and vice-versa. Results show that five sub divisions for annual rainfall were found in very dark shade zones (Nagaland Mizoram Manipur & Tripura, East Madhya Pradesh, Jharkhand, East Uttar Pradesh, Chhattisgarh and Kerala) which suggests that these sub-divisions were experienced highly negative trend of rainfall (less than -2 of z value). The z value of MK test ranges from 0 to -2 (which indicates decreasing nature of rainfall), could be found in eight meteorological sub-divisions, i.e. Bihar, Orissa, Assam & Meghalaya, West Uttar Pradesh, Uttarakhand, Himachal Pradesh, Vidarbha and East Rajasthan (dark brown color in Table 3.1). The z value having the positive trend varies from 0 to 2 which were observed in the eleven meteorological sub-divisions that implies the increasing nature of rainfall over these divisions, while the six meteorological sub-divisions recorded z values more than 2 (very light shade of brown color in Table 3.1), which indicates the significant increase of rainfall over time in these meteorological units.

**Table 3.1**: Results of the MK test (Z) and the percentage change estimation for annual and seasonal rainfall for the period of 1901–2015

| State | Annual | Monsoon | Post Monsoon | Summer | Winter |
|---|---|---|---|---|---|
| Arunachal Pradesh | -1. | -1.21 | -0.54 | -0.98 | -0.21 |
| Assam & Meghalaya | -1.99 | -3.45 | 0.44 | -0.51 | -1.33 |
| Nagaland, Manipur, Mizoram & Tripura | -2.74 | -1.33 | 0 | 3.27 | 3.01 |
| Sub Himalayan West Bengal & Sikkim | 0.32 | 2.53 | -0.08 | 0.82 | -0.06 |
| Gangetic West Bengal | 2.41 | -1.36 | -0.44 | -0.28 | -0.68 |
| Orissa | -1.19 | -2.08 | 0.37 | -0.52 | -1.28 |
| Jharkhand | -2.42 | -1.6 | 0.54 | 2.23 | -0.7 |
| Bihar | -1.77 | -2.03 | -1.24 | -0.14 | -1.28 |
| East Uttar Pradesh | -2.74 | -0.79 | -0.98 | -0.09 | -1.33 |
| West Uttar Pradesh | -1.28 | -1.87 | -1.42 | 0.8 | -0.79 |
| Uttarakhand | -1.38 | 0.63 | -1.42 | 0.8 | -0.79 |
| Haryana, Delhi & Chandigarh | 0.58 | 0.65 | 1.1 | 0 | -0.55 |

| | | | | | |
|---|---|---|---|---|---|
| Punjab | 0.36 | -2.38 | 0.39 | 0.24 | -0.54 |
| Himachal Pradesh | -0.99 | 0.05 | -0.06 | 2.28 | 1.16 |
| J & k | 0.56 | -0.88 | -1.62 | -0.57 | -1.59 |
| West Rajasthan | 0.69 | 0.28 | 1.25 | -0.29 | 0.55 |
| East Rajasthan | -1.03 | -2.23 | -0.63 | -0.96 | -0.53 |
| West Madhya Pradesh | 0.02 | 0.38 | -0.16 | -0.27 | -0.24 |
| East Madhya Pradesh | -2.70 | -0.74 | -0.24 | -0.82 | -0.43 |
| Gujarat Region | 0.58 | 0.69 | 1.5 | -0.51 | -0.14 |
| Saurashtra & Kutch | 1.65 | 1.52 | 2.25 | -1.34 | 0.2 |
| Konkan & Goa | 2.26 | 2.26 | -1.52 | -0.59 | -1.79 |
| Madhya Maharashtra | 3.32 | 3.68 | -1.82 | -2.46 | -0.34 |
| Marathwada | 0.26 | 0.24 | 0.04 | -1.49 | -1.84 |
| Vidarbha | -0.80 | -0.44 | 0.55 | -0.65 | -0.79 |
| Chhattisgarh | -3.14 | -2.09 | 0.6 | -1.65 | -0.39 |
| Coastal Andhra Pradesh | 1.08 | 1.52 | -0.12 | 0.62 | -0.5 |
| Telengana | 2.01 | 1.74 | -0.38 | 1.58 | 2.42 |
| Rayalseema | 1.45 | 1.22 | -0.89 | 2.36 | 0.57 |
| Tamilnadu | 0.65 | 1.22 | 0.3 | 0 | 0 |
| Coastal Karnataka | 2.69 | 2.31 | 0.44 | -0.64 | 0.56 |
| North Interior Karnataka | 1.45 | 1.17 | -0.82 | -2.14 | 0.86 |
| South Interior Karnataka | 2.80 | 3.93 | -0.5 | -1.64 | 0.03 |
| Kerala | -2.15 | -2.33 | 1.73 | 0.76 | 0.44 |

**Index of detected trend**

| >2 | 2-0 | 0 – (-2) | < -2 |
|---|---|---|---|
| | | | |

The two meteorological division (Madhya Maharashtra and North Interior Karnataka) for summer season and seven meteorological divisions (Assam & Meghalaya, Orissa, Bihar, Punjab, East Rajasthan, Chhattisgarh and Kerala) for monsoon season were recorded highly negative trend in rainfall having z value <-2 (very dark shade rows in Table 3.1). On the other hand, no meteorological divisions for winter and post-monsoon season were recorded as highly negative trend (z value <-2) in rainfall, while most of the sub-divisions were detected as negative trend of rainfall having the z value 0f 0 to -2 (dark shade rows in table 1).

**The Change Point Detection analysis for annual and seasonal rainfall**

The above-mentioned analysis (Table 3.1) explained that few meteorological sub-divisions were detected as significant negative trend having the z value of >-2. However, several researchers claimed that the actual trend could not be detected if we apply the MK test on overall hydro-climatic datasets and they highly recommended to apply the change detection techniques before the application of MK test. Hence, we utilized change detection methods like Pettitt test, SNHT test and Buishand range test for detecting the abrupt change point in the rainfall datasets in thirty-four meteorological sub-divisions (Table s1). The supplementary table 3.1 shows that the annual and seasonal rainfall of all meteorological sub-divisions had the abrupt change points which were detected by mentioned three change detection techniques. Furthermore, we selected the change point for annual and seasonal rainfall in each sub-divisions based on the performances (p value) of these tests (Table s1). Therefore, these abrupt change points suggest that the rainfall datasets had no monotonous trend. The selected change point for seven meteorological sub-divisions (East Uttar Pradesh, West Uttar Pradesh, Punjab, and Gujarat region, Saurashtra & Kutch, Coastal Andhra Pradesh and Tamil Nadu) were after 1990s. The nineteen meteorological sub-divisions had the abrupt change point during the period of 1950-1980. The abrupt change point year for the rest of the meteorological divisions were detected before 1940.

| **Meteorological sub-divisions** | **Changepoint based on SNHT test** | **Changepoint based on the Pettitt test** | **Changepoint based on a Buishand′s range** | **Selected change point (Year) based on the performance of the test** |
|---|---|---|---|---|
| Arunachal Pradesh | 1965 | 1965 | 1968 | 1965 |
| Assam & Meghalaya | 1961 | 1961 | 1961 | 1961 |
| Nagaland, Manipur, Mizoram & Tripura | 1976 | 1961 | 1976 | 1976 |
| Sub Himalayan West Bengal & Sikkim | 1908 | 1910 | 1910 | 1910 |
| Gangetic West Bengal | 1974 | 1967 | 1967 | 1972 |
| Orissa | 1968 | 1966 | 1966 | 1966 |

| | | | | |
|---|---|---|---|---|
| Jharkhand | 2013 | 1966 | 1966 | 1966 |
| Bihar | 2013 | 1954 | 1954 | 1954 |
| East Uttar Pradesh | 1995 | 1990 | 1990 | 1990 |
| West Uttar Pradesh | 1974 | 1990 | 1990 | 1990 |
| Uttarakhand | 1976 | 1976 | 1976 | 1976 |
| Haryana, Delhi & Chandigarh | 1905 | 1956 | 1956 | 1956 |
| Punjab | 2002 | 1941 | 2002 | 2002 |
| Himachal Pradesh | 1972 | 1972 | 1972 | 1972 |
| J & k | 1905 | 1954 | 1954 | 1954 |
| West Rajasthan | 2001 | 1983 | 1983 | 1983 |
| East Rajasthan | 1966 | 1966 | 1966 | 1966 |
| West Madhya Pradesh | 1962 | 1962 | 1978 | 1962 |
| East Madhya Pradesh | 1927 | 1932 | 1927 | 1827 |
| Gujarat Region | 2007 | 2007 | 1926 | 2007 |
| Saurashtra & Kutch | 2009 | 1979 | 2009 | 2009 |
| Kankan & Goa | 1926 | 1931 | 1931 | 1931 |
| Madhya Maharashtra | 1930 | 1930 | 1930 | 1930 |
| Marathwada | 1931 | 1931 | 1931 | 1931 |
| Vidarbha | 1968 | 1968 | 1968 | 1968 |
| Chhattisgarh | 1966 | 1966 | 1966 | 1966 |
| Coastal Andhra Pradesh | 2007 | 1915 | 2007 | 2007 |
| Telengana | 1924 | 1957 | 1957 | 1957 |
| Rayalseema | 1994 | 1979 | 1979 | 1979 |
| Tamilnadu | 2008 | 2008 | 1951 | 2008 |
| Coastal Karnataka | 1950 | 1950 | 1950 | 1950 |
| North Interior Karnataka | 1946 | 1946 | 1950 | 1946 |
| South Interior Karnataka | 1957 | 1957 | 1957 | 1957 |

| | | | | |
|---|---|---|---|---|
| Kerala | 1967 | 1967 | 1967 | 1967 |

*Table* s1(supplementary 1). The abrupt change point year for the meteorological sub-divisions using SNHT test, Pettitt test and Buishihand's range test.

**Change point wise annual and seasonal variation analysis:**

We computed the annual and seasonal rainfall variation in pre and post change point wise for all meteorological sub-divisions to explore the dynamics of the intensity of annual and seasonal rainfall variations after the change point. Therefore, we can consider this change point wise rainfall variation analysis as a validating method for the relevancy of uses of the change point methods and further research. Hence, to prove this statement, we computed and prepare the spatial map of annual and seasonal rainfall variation for pre change point (figure 3a-e) and post change point (figure 3f-j) using coefficient of variation method. Results show that highest fluctuation (25% to 239.02%) in annual and seasonal rainfall was observed in the sub-divisions of Western India and North-Western India (3a-e). Whereas, the minimum fluctuation in annual and seasonal rainfall having the CV of 0.36% to 7.76% was observed in the sub-divisions of North Eastern India, Eastern India and Northern India indicating the consistent rainfall occurrence in these region.

The findings of annual and seasonal rainfall analysis in post change point phase show that the large areas of the country like the sub-divisions of western India, central India, and south western India were observed high fluctuation having the CV of 22% to 209.82%. In the case of monsoon and post monsoon season, the sub-divisions of north western were experienced by high variation of rainfall suggesting the high tendency of inconsistently rainfall occurrences in these regions. While the lowest rainfall variation having the CV of 0.75% to 11.64% was recorded in sub-divisions of north-eastern India, north India, east India of winter and summer rainfall and central India of post monsoon rainfall. The intensity of minimum rainfall variation range was increased in post change point phase which suggests that inconsistency rainfall events were observed. However, in the post change point phase, the area coverage of lower variation of rainfall incidences were reduced significantly that implies the climate change and validation of the application of change point detection methods.

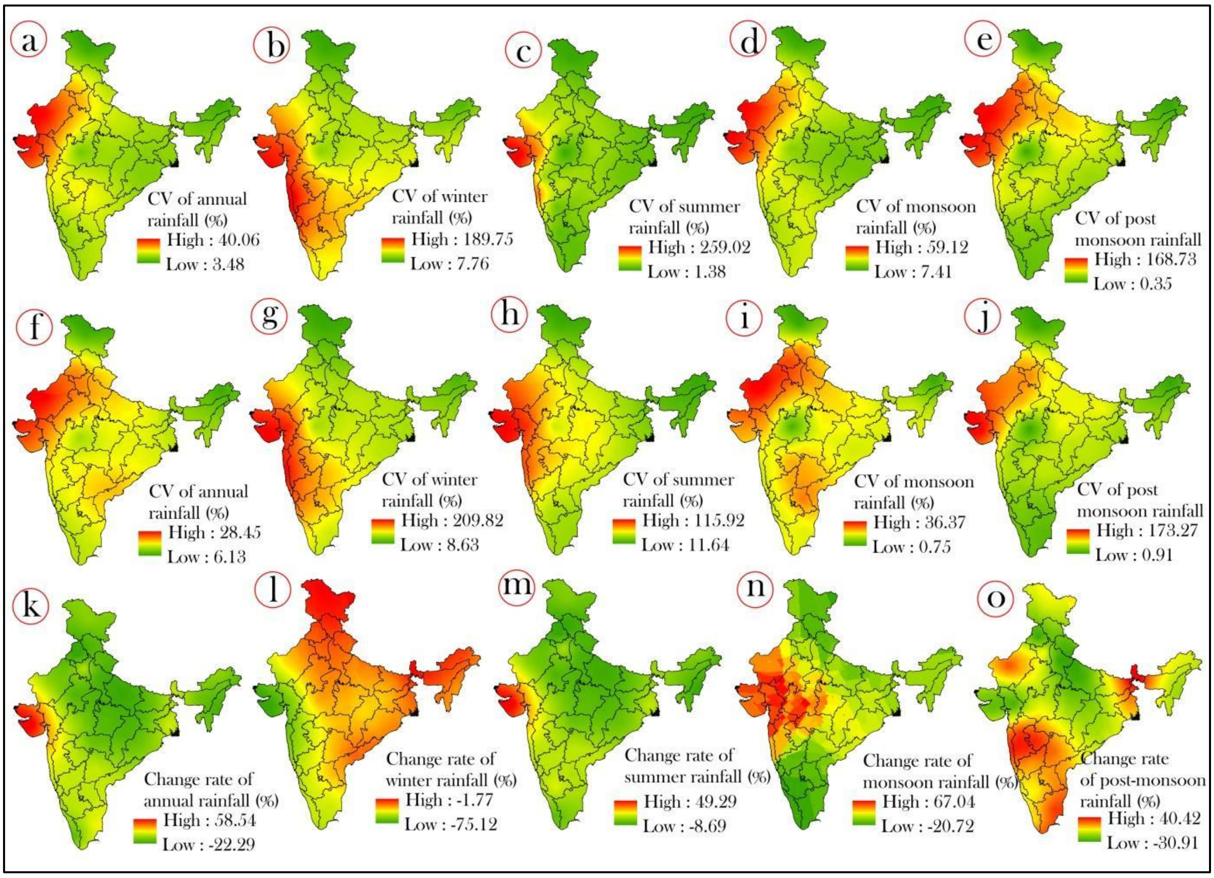


**Figure 3.3:** Spatial variation of rainfall measured using the coefficient of variation for pre-change point where figure (a) shows annual rainfall, (b) winter, (c) summer, (d) monsoon, and (e) post monsoon; post-change point where figure (f) shows annual rainfall, (g) winter (h) summer (i) monsoon and (j) post monsoon; spatial changes in the rate of rainfall where figure (k) shows annual rainfall, (l) winter (m) summer (n) monsoon and (o) post monsoon.

**Rainfall change rate analysis:**

In the present study, we computed the rainfall change rate for annual and seasonal rainfall in all meteorological sub-divisions based on the calculation between the rainfall data of pre and post change point phase. The figure 3.3k-o shows the spatial mapping of rainfall change rate for annual and seasonal rainfall. Results show that sub-divisions of western India were observed the highest change rate (47% to 58.54%) in annual rainfall, while the sub-divisions of whole country except West India were registered the highest change rate (-0.5% to -1.77%) in winter rainfall. In case of summer and monsoonal rainfall, the sub-divisions of western were observed highest negative change rate (34.22% to 67.04), while the south India and north east India were recorded highest negative change rate in post monsoon rainfall. Furthermore, the north India and central India was recorded minimum change rate, whereas, the western India of winter and post-monsoon rainfall. This analysis signifies that the amounts of rainfall occurrences were decreased significantly after change point.

**Change point wise seasonal rainfall trend analysis:**

We applied MK test on the datasets of pre and post change point of seasonal rainfall in each of the meteorological sub-divisions as per the recommendation of many scientists. The table 3.2 reported the seasonal rainfall trend for pre change point in all sub-divisions. Results show that eight meteorological sub-divisions in monsoon, six sub-divisions in post monsoon, fourteen sub-divisions in both summer and winter season were recorded negative trend having the z value of 0 to -2 (dark shade of brown color rows in table 3.2). While, three sub-divisions in summer and four sub-divisions in winter seasons were recorded highly negative trend having z value of <-2 (very dark shade of brown color rows in Table 3.2). Rest of the meteorological sub-divisions was detected as positive trend (lighter shade of brown color in Table 3.2) except one division (Sub Himalayan west Bengal & Sikkim) which detected has no trend. From the analysis, it can be stated that non-monsoonal seasons were recorded with declining trend.

**Table 3.2:** Meteorological subdivision wise trend for pre-change point

| **Meteorological subdivision** | **Z value for Pre Change Point** | | | |
|---|---|---|---|---|
| | **Monsoon** | **Post Monsoon** | **Summer** | **Winter** |
| Arunachal Pradesh | -0.41 | -1.31 | -0.15 | -0.26 |
| Assam & Meghalaya | 0.11 | 0.52 | -0.36 | -1.52 |
| Manipur, Mizoram, Nagaland & Tripura | 2.07 | 0.59 | 0.30 | 0.40 |
| Sikkim &Sub Himalayan West Bengal | 0.00 | 0.00 | 0.00 | 0.00 |
| Gangetic West Bengal | -1.07 | 0.73 | -2.55 | -0.56 |
| Orissa | 1.03 | 1.44 | -1.79 | -0.45 |
| Jharkhand | 0.49 | 1.39 | -1.61 | 0.00 |
| Bihar | 0.08 | 1.11 | -0.31 | 1.72 |
| East Uttar Pradesh | 1.07 | 1.40 | 0.02 | -0.54 |
| West Uttar Pradesh | 1.40 | 1.24 | 0.35 | -1.14 |
| Uttarakhand | 0.69 | 0.98 | 0.97 | 0.83 |
| Haryana, Delhi & Chandigarh | -0.21 | -0.14 | -0.69 | -0.59 |
| Punjab | 2.31 | 0.02 | 0.06 | -0.50 |
| Himachal Pradesh | 1.19 | 2.34 | 1.74 | 2.04 |
| J & k | -0.56 | 0.13 | -0.41 | 0.18 |
| West Rajasthan | 0.57 | -0.75 | -1.04 | 0.41 |
| East Rajasthan | 1.64 | -0.07 | -1.19 | -1.86 |
| West Madhya Pradesh | 2.66 | 0.22 | -1.12 | -1.46 |

| | | | | |
|---|---|---|---|---|
| East Madhya Pradesh | 1.18 | 0.66 | -0.50 | 1.29 |
| Gujarat Region | -0.25 | 1.17 | -2.60 | -2.45 |
| Saurashtra & Kutch | 0.30 | 1.49 | -2.74 | -2.90 |
| Konkan & Goa | 0.46 | 0.68 | -0.73 | 0.22 |
| Madhya Maharashtra | 0.62 | 0.24 | -0.26 | 0.02 |
| Marathwada | -1.04 | 0.30 | -0.23 | 0.84 |
| Vidarbha | 1.76 | 1.13 | 0.90 | -1.08 |
| Chhattisgarh | 2.18 | 1.32 | 0.08 | -0.91 |
| Coastal Andhra Pradesh | 1.36 | -0.21 | -0.29 | 0.30 |
| Telengana | 0.72 | 1.24 | 1.11 | 0.41 |
| Rayalseema | 0.33 | -0.62 | 0.66 | -3.69 |
| Tamilnadu | 0.45 | -0.66 | -1.97 | -2.94 |
| Coastal Karnataka | -0.03 | 0.66 | 1.20 | -1.06 |
| North Interior Karnataka | -1.24 | 0.15 | 0.05 | 0.81 |
| South Interior Karnataka | -0.59 | -0.15 | -0.11 | -0.61 |
| Kerala | -0.66 | -1.23 | 3.12 | -0.12 |

Index of detected trend

| >2 | 2-0 | 0 – (-2) | < -2 |
|---|---|---|---|
| | | | |

The Table 3.3 showed the trend analysis using MK test for post-change point seasonal rainfall. Seventeen meteorological sub-divisions in monsoon, eighteen sub-divisions in post monsoon, eighteen sub-divisions in summer and twenty two sub-divisions in winter seasons were observed the negative trends having the z value of 0 to -2 indicating that a declining trend of rainfall was recorded over huge area in the post-change phase than the pre-change point phase (dark shade of brown color rows in Table 3.3). The number of meteorological divisions with negative trend of rainfall increases in the post change point as compared to the pre change point (Table 3.3). This circumstance implies that the declining trend of rainfall was increased manifold after post change point which shows the sign of climate change. On the other hand, rest of the meteorological sub-divisions experienced the insignificant positive trend having the z value of <0.5.

**Table 3.3**: Meteorological subdivision wise trend for post-change point

| **Meteorological subdivision** | **Z Value for Post Change Point** | | | |
|---|---|---|---|---|
| | **Monsoon** | **Post Monsoon** | **Summer** | **Winter** |
| Arunachal Pradesh | 0.28 | -0.72 | -0.31 | -0.64 |
| Assam & Meghalaya | 0.67 | 0.36 | -0.36 | -0.74 |

| | | | | |
|---|---|---|---|---|
| Manipur, Mizoram, Nagaland & Tripura | 0.19 | 0.44 | -0.51 | -1.33 |
| Sikkim &Sub Himalayan West Bengal | -1.87 | 0.00 | 3.27 | 3.01 |
| Gangetic West Bengal | -0.77 | -0.08 | 0.82 | -0.06 |
| Orissa | 1.08 | -0.44 | -0.28 | -0.68 |
| Jharkhand | 0.30 | 0.37 | -0.52 | -1.28 |
| Bihar | -0.13 | 0.54 | 2.23 | -0.70 |
| East Uttar Pradesh | -1.43 | -1.24 | -0.14 | -1.29 |
| West Uttar Pradesh | -0.63 | -0.98 | -0.09 | -1.33 |
| Uttarakhand | 1.19 | -1.42 | 0.80 | -0.79 |
| Haryana, Delhi & Chandigarh | -1.69 | -1.42 | 0.80 | -0.79 |
| Punjab | 1.04 | 1.10 | 0.00 | -0.55 |
| Himachal Pradesh | 0.70 | 0.39 | 0.24 | -0.54 |
| J & k | 0.14 | -0.16 | 0.13 | 0.26 |
| West Rajasthan | -0.34 | -0.06 | 2.28 | 1.16 |
| East Rajasthan | 0.26 | -1.62 | -0.57 | -1.59 |
| West Madhya Pradesh | -0.44 | 1.25 | -0.29 | 0.55 |
| East Madhya Pradesh | -1.25 | -0.63 | -0.96 | -0.53 |
| Gujarat Region | -0.87 | 1.50 | -0.51 | -0.14 |
| Saurashtra & Kutch | 0.00 | 2.25 | -1.34 | 0.20 |
| Konkan & Goa | -0.89 | -1.52 | -0.59 | -1.79 |
| Madhya Maharashtra | 0.71 | -1.82 | -2.46 | -0.34 |
| Marathwada | -1.12 | 0.04 | -1.49 | -1.84 |
| Vidarbha | 0.79 | 0.55 | -0.65 | -0.79 |
| Chhattisgarh | -0.28 | 0.60 | -1.65 | -0.39 |
| Coastal Andhra Pradesh | 0.94 | -0.12 | 0.62 | -0.50 |
| Telengana | -1.44 | -0.38 | 1.58 | 2.42 |
| Rayalseema | 0.18 | -0.89 | 2.36 | 0.57 |
| Tamilnadu | -0.64 | 0.30 | 0.00 | 0.00 |
| Coastal Karnataka | -0.09 | 0.44 | -0.64 | 0.56 |
| North Interior Karnataka | -0.58 | -0.82 | -2.14 | 0.86 |
| South Interior Karnataka | 0.26 | -0.50 | -1.64 | 0.03 |
| Kerala | 0.28 | 1.73 | 0.76 | 0.44 |

**Index of detected trend**

| >2 | 2-0 | 0 – (-2) | < -2 |
|---|---|---|---|
| | | | |

**Innovative trend analysis for seasonal rainfall:** Several researchers suggested that a non-parametric statistical technique like mann-kendall test has many drawbacks like the presence of serial correlation within the data sets, non-linearity and most importantly sample size which could have ability to influence the result. Therefore, Sen (2012) developed innovative trend method which can overcome the mentioned drawbacks, especially the problem sample size. Sen (2012) reported that innovative trend can effectively able to detect the trend on any numbers of sample size and presence of serial correlation. Hence, we used innovative trend to calculate the trend for seasonal rainfall (winter, summer, monsoon and post monsoon) in thirty-four meteorological sub-divisions (Supplementary figure 3.1-3.4) we computed D value of innovative trend to compare the intensity of trend achieved by MK test. The spatial mapping using D values of innovative trend for seasonal rainfall was presented in figure 3.4. However, the supplementary Table 3.3 showed the slope value of innovative trend for seasonal rainfall in all meteorological sub-divisions. The findings indicate that the negative trend was detected in the sub-divisions of north eastern, central and southern India for summer season. The results were quite identical with the findings of MK test, but the magnitudes of the trend were different which stated that the region was experienced strong negative trend (figure 3.3). Although the highly positive trend was detected in the sub-divisions of Rajasthan part and Jammu-Kashmir region which does not imply that the rainfall occurrences was increased, but the regions were received more or less consistent amount of rainfall throughout the time periods, while little amount of rainfall was increased in few years over these regions which is the reason for positive trend. However, in case of monsoon rainfall, the negative slope of innovative trend was detected in the sub-divisions of North Eastern part, Eastern part and some parts of the central India, whereas, rest of the sub-divisions were detected as insignificant positive slope of trend. The sub-divisions of North Eastern states, Bihar, Orissa, Jharkhand, Western Ghats and Punjab regions were experienced very strong negative slope of innovative trend, on the other hand, rest of the part were recorded insignificant positive slope of trend for post monsoon rainfall. In case of winter rainfall, the meteorological sub-divisions of Central part of India, Southern India, Western Ghats regions were observed the negative trend, while the sub-divisions of North Eastern, Western and Eastern part of India were experienced positive slope of trend. Therefore, the findings of MK test and innovative trend analysis were highly identical, however, few states where no significant trend were detected using MK test, but in the case of innovative trend, those region were come under negative trend. However, the findings from both trend detected methods clearly stated that India has been experiencing fewer downpours than the expected rainfall since last 30 years that clearly points out about the climate change. Several researches established that innovative trend can able to detect trend effectively over the others non-parametric test (Debanli et al. 2016; Kisi and Ay 2014; Cui et al. 2017; Sonali and Kumar 2013). Therefore, we considered innovative trend as a tool of intensity of trend measurement over the other techniques and results show that the highly negative trend was detected in most of the sub-divisions indicate about the climate change.

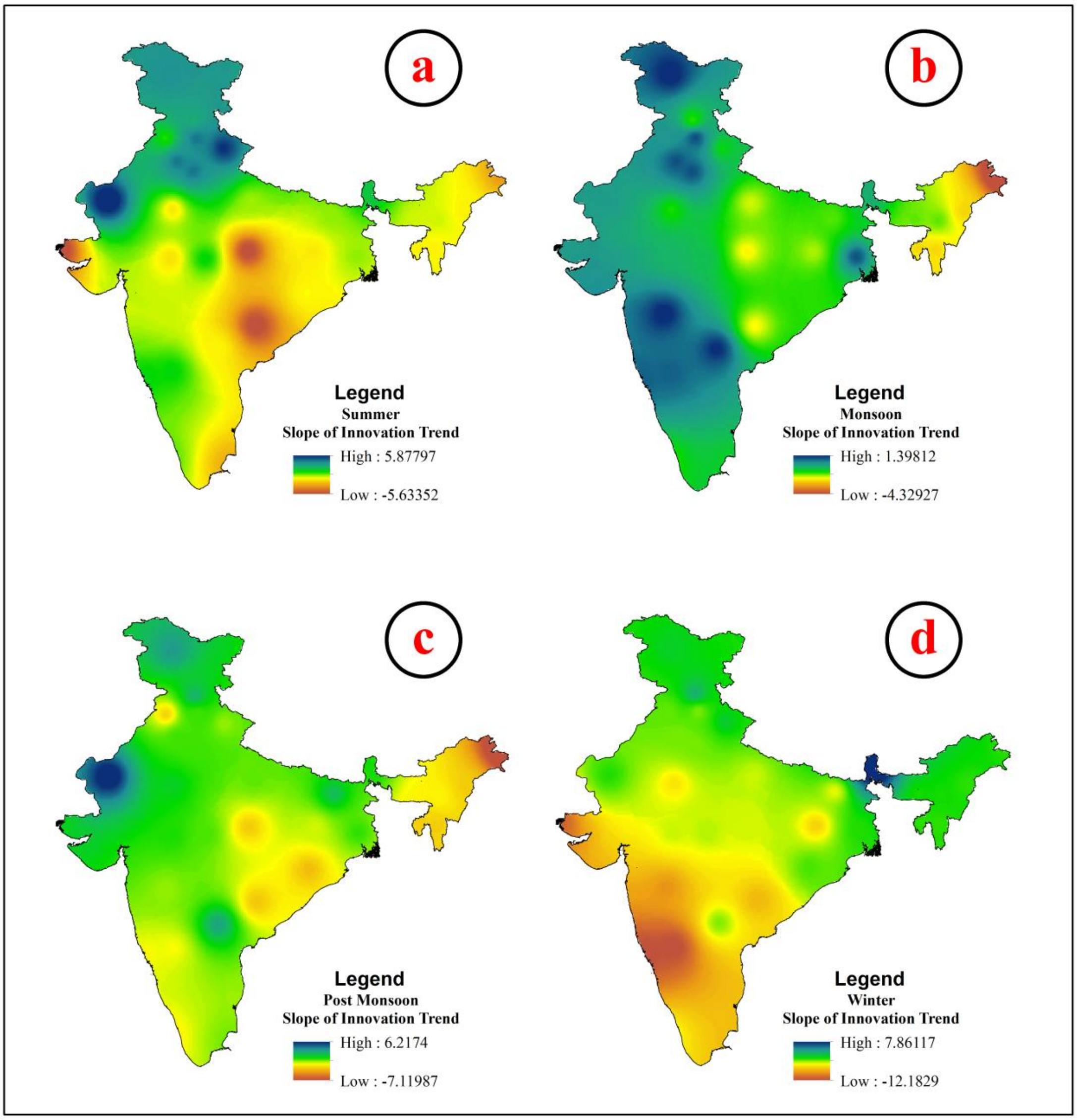


**Figure 3.4:** the spatial variation of slope of innovative trend for (a) summer, (b) monsoon, (c) post monsoon and (d) winter

**Micro level rainfall change rate analysis:**

In the present study, we attempted to analyze the change rate of annual rainfall for each and every year in thirty-four meteorological sub-divisions. We computed the change rate by calculating the departure of year wise average rainfall from the long-term average rainfall. The heat map was used to show the dynamics of year wise rainfall change rate for all sub-divisions (Figure 3.5). The intensity of change rate was represented by the shades of red and green color indicating the highly negative change rate and vice versa. Results show that the after 1970, all meteorological sub-divisions were observed the negative departure in almost all years from long-term average rainfall by 50 mm.-2000 mm. (Figure 3.5). While the sub-divisions of North-Eastern India and North India were recorded positive change rate only for few years because of the occurrences of excessive rainfall that was happened occasionally by monsoon burst, ELSO effect (Kripalini et al. 2003) and local climatic effect. The highest negative change rate was observed in the sub-divisions like Arunachal Pradesh, Nagaland Manipur, Mizoram & Tripura, Kerala, Western Uttar Pradesh, Rajasthan, Uttarakhand and Himachal Pradesh by more than -2000 mm. The positive change rate was mainly detected before change detection year or 1970 in all sub-divisions. The positive change rate was varied from 0-2000mm. However, few sub-divisions like Kerala, Nagaland Manipur Mizoram & Tripura, and Coastal Karnataka.

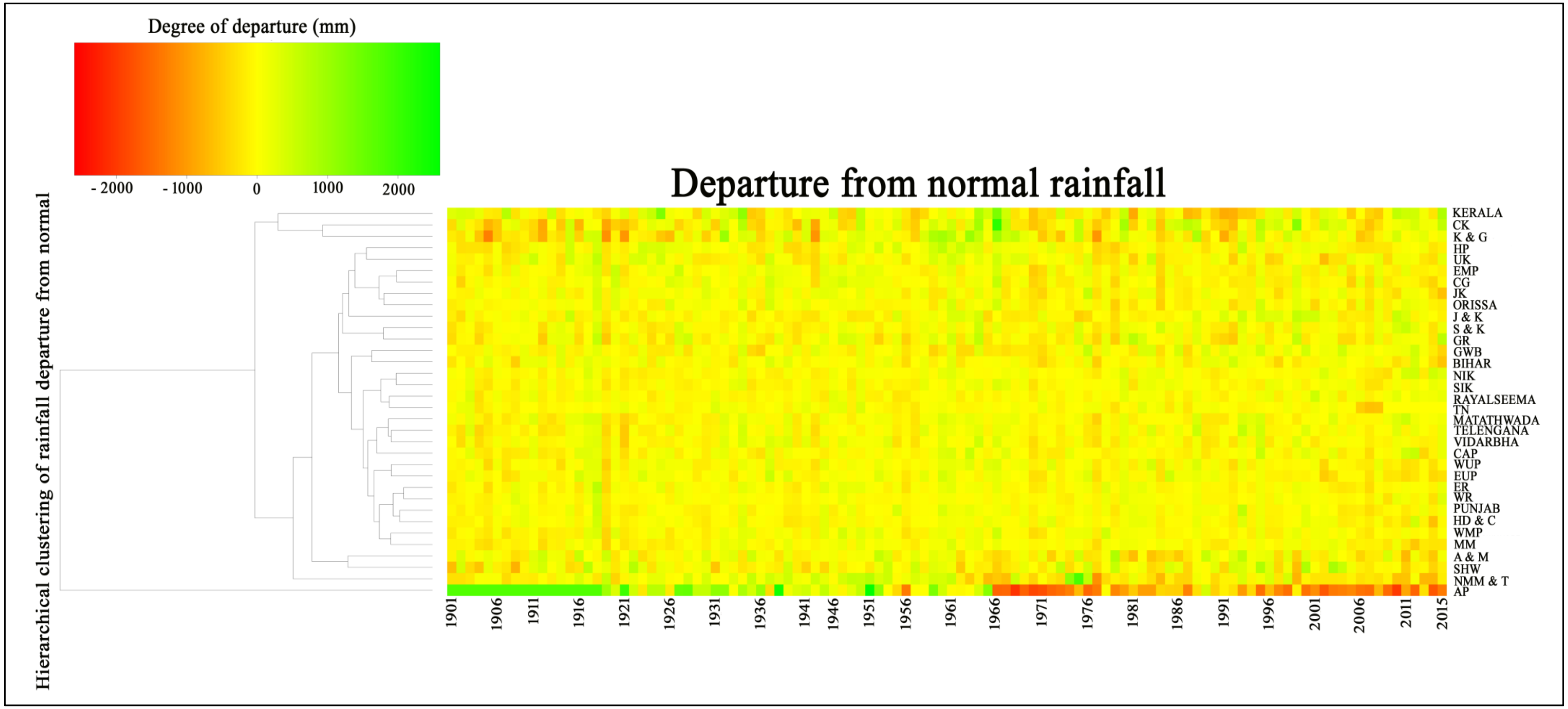


**Figure 3.5**: Heatmap represents the departure of rainfall from normal rainfall for all meteorological subdivision. (N.B. CK- Coastal Karnataka, K & G – Konkan and Goa, HP- Himachal Pradesh, UK- Uttarakhand, EMP- Eastern Madhya Pradesh, CG- Chhattisgarh, JK – Jharkhand, J & K – Jammu and Kashmir, S & K- Saurashtra and Kachcha, GR – Gujarat region, GWB – Gangetic West Bengal, NIK – North Interior Karnataka, SIK – South Interior Karnataka, TN – Tamilnadu, CAP – Coastal Andhra Pradesh, WUP – western Uttarpradesh, EUP – Eastern Uttarpradesh, ER – Eastern Rajasthan, WR – Western Rajasthan, HD & C- Haryana Delhi and Chandigarh, WMP – WesternMadhyapradesh, MM – MadhyaMadhyapradesh, A & M- Assam and Meghalaya, SHW – Sub Himalaya West Bengal, NMM & T- Nagaland, Manipur, Mizoram and Tripura, AP- Arunachal Pradesh.

### 3.4.1Modelling of climate change by analyzing meteorological drought pattern

## Estimation of drought

The current research estimated the Standardized Precipitation Index (SPI) for the long term historical span of 115 years from 1901 to 2015 to measure long term (12 months) meteorological drought scenarios in 34 sub-divisions of India (Figure 3.61a-f). SPI-12 showed that in the past (before 1950), mild to no drought conditions existed in all sub-divisions except eight sub-divisions like Jammu Kashmir, Rayalseema, South interior Karnataka (Figure 3.6c, d,f). In the study area, about 26 sub-divisions observed severe to very severe drought since 1980, such as Arunachal Pradesh, Nagaland Manipur Tripura, Orissa, Assam Meghalaya (figure 3.7a), Jharkhand, Uttar Pradesh (figure 3.6b), Rajasthan, Madhya Pradesh (Figure 3.6c), Vidarbha, Tamil nadu (figure 3.6d), and Kerala (figure 3.61e). Highly severe drought (SPI value >-1.5) have been found in recent times in Nagaland Manipur Tripura, Sub-Himalayan West Bengal (figure 3a), western Rajasthan (Figure 3.6c), Tamilnadu (Figure 3.6d), Kerala (Figure 3.6f). On the other hand, recently, no drought or mild drought can be observed in Gangetic West Bengal Sikkim (Figure 3.6a), Jharkhand (Figure 3.6c), Saurashtra, Madhya Maharashtra (Figure 3.6d), Rayalseema (figure 3.6e), Central Karnataka, and North Interior Karnataka (Figure 3.6f). While, before 1950s, most of the meteorological sub-divisions observed no drought or mild drought. Only 5 meteorological sub-divisions have observed severe drought before 1950s, especially in West Bengal, which cause famine.

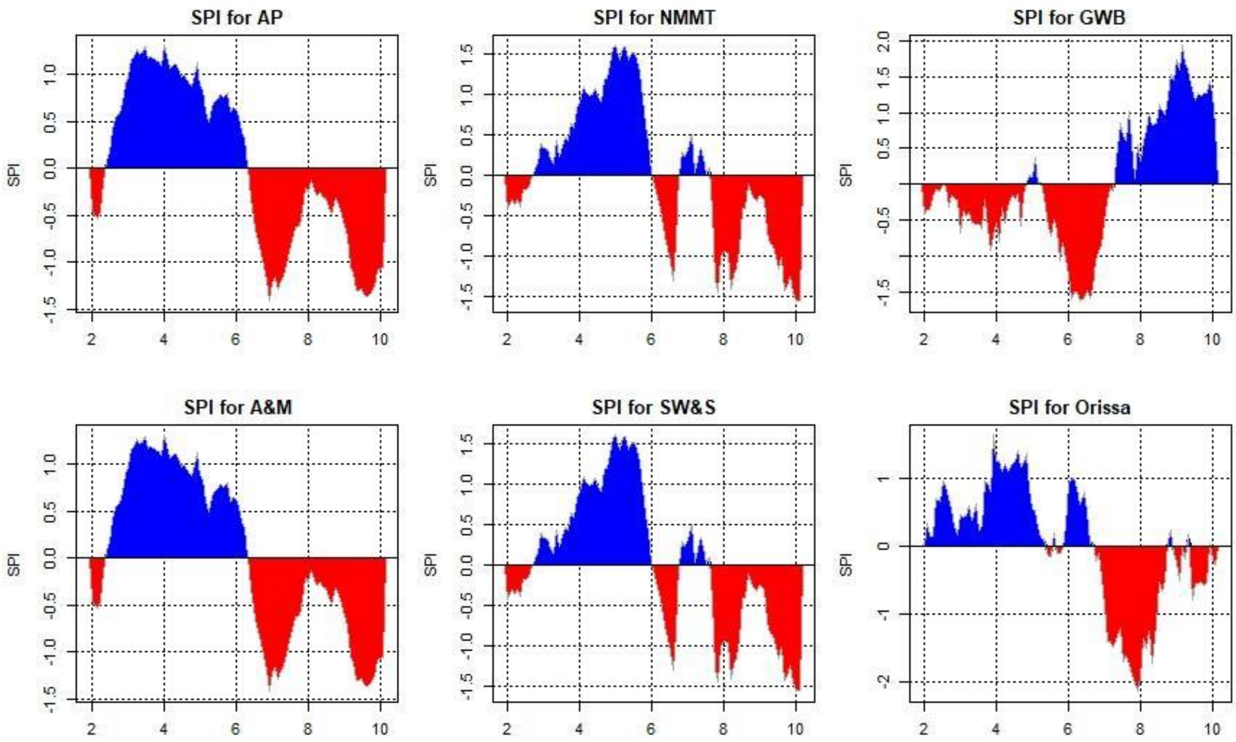


**Figure: 3.6a**: Drought estimation for Arunachal Pradesh (AP), Nagaland Manipur Tripura (NMMT), Gangetic West Bengal Sikkim (GWB), Assam Meghalaya (A&M), Sub-Himalayan West Bengal (SW&S), and Orissa

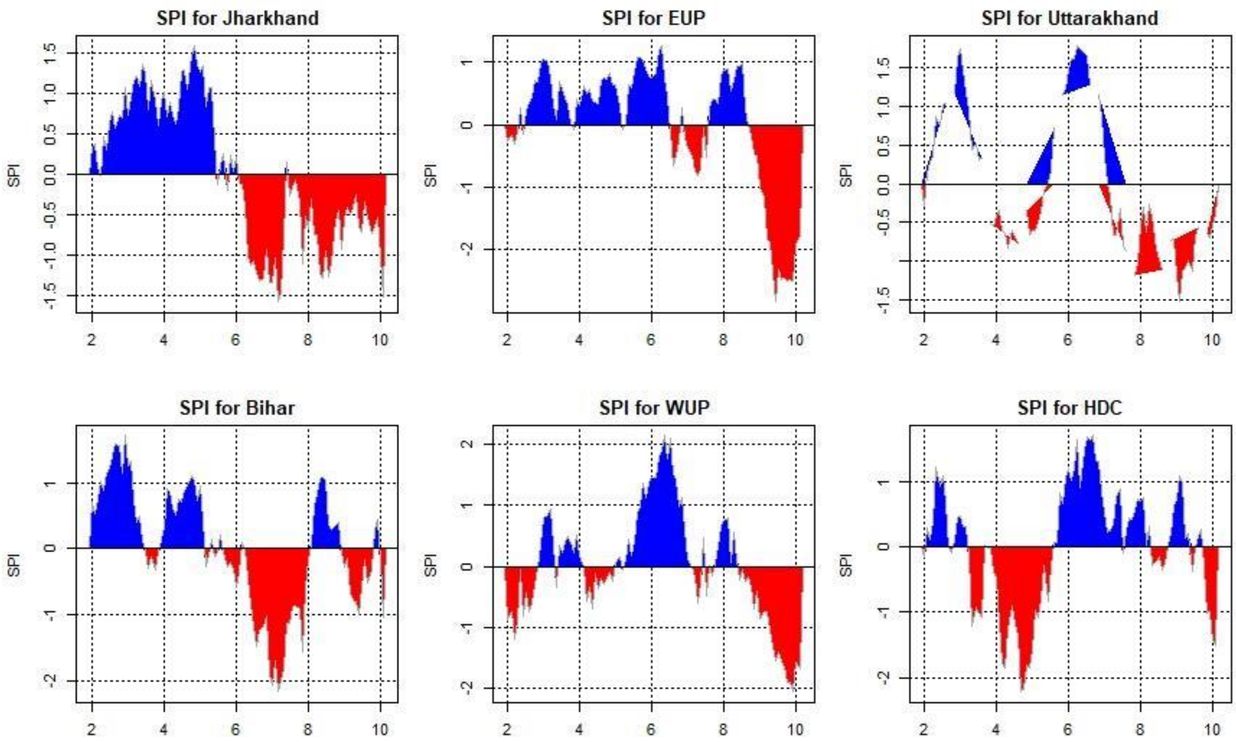


**Figure 3.6b**: Drought estimation for Jharkhand, Eastern Uttar Pradesh (EUP), Uttarakhand, Bihar, Western Uttar Pradesh (WUP), and Haryana Delhi Chandigarh (HDC)

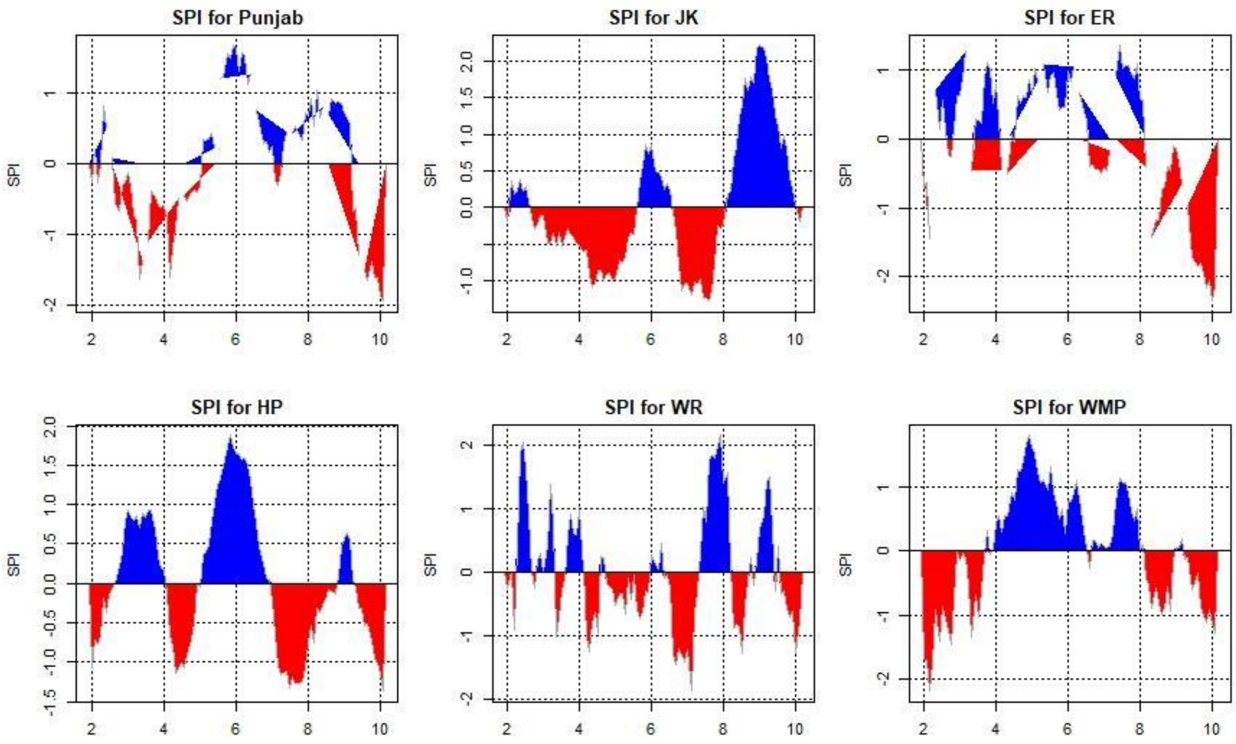


**Fig 3.6c:** Drought estimation for Punjab, Jammu and Kashmir, Eastern Rajasthan (ER), Himachal Pradesh (HP), Western Rajasthan (WR), Western Madhya Pradesh (WMP)

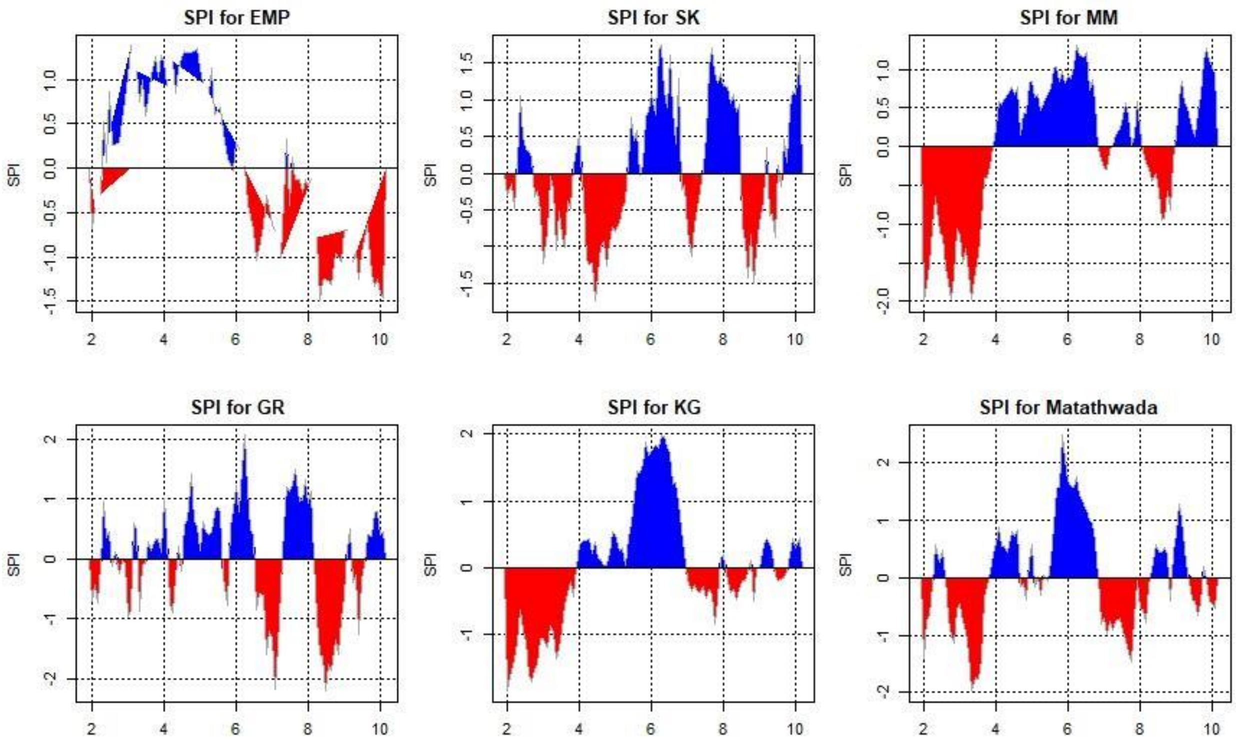


**Fig 3.6d**: Drought estimation for Eastern Madhya Pradesh (EMP), Saurashtra Kankan (SK), Madhya Maharashtra (MM), Gujarat Region (GR), Konkan Goa (KG), Marathwada

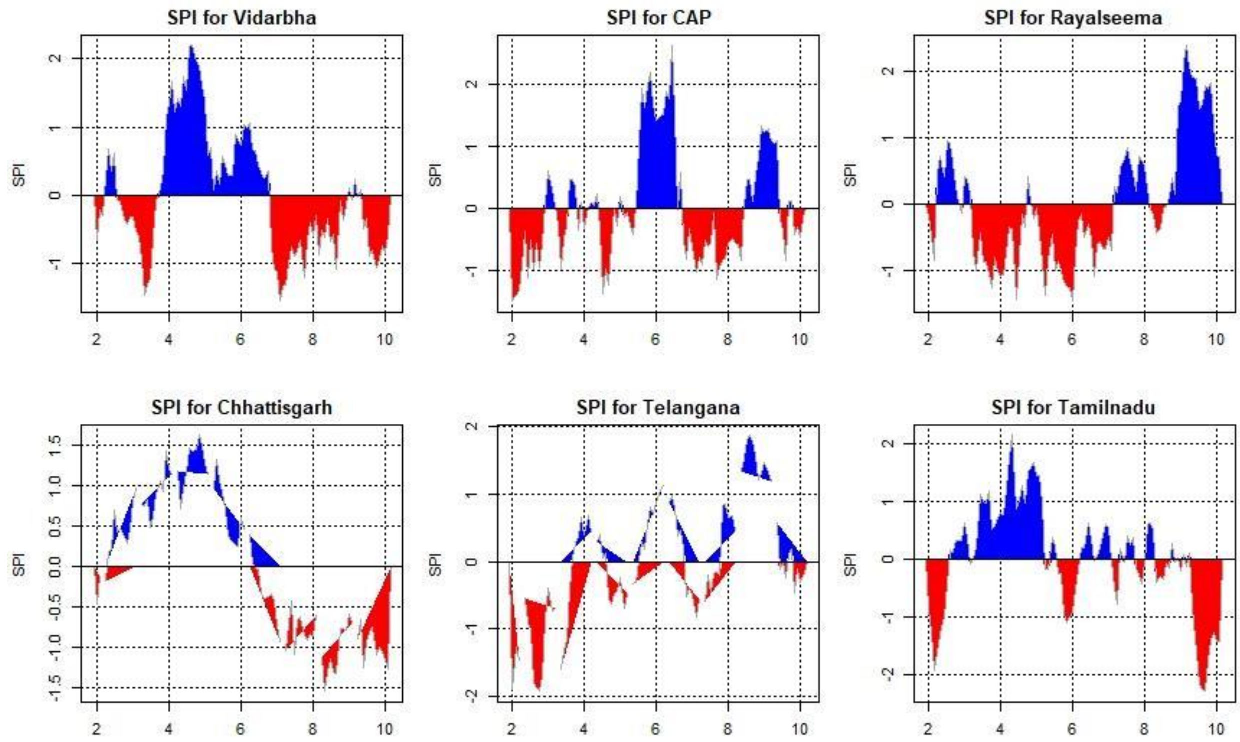


**Figure 3.6e**: Drought estimation for Vidarbha, Coastal Andhra Pradesh (CAP), Rayalseema, Chhattisgarh, Telengana, Tamil nadu

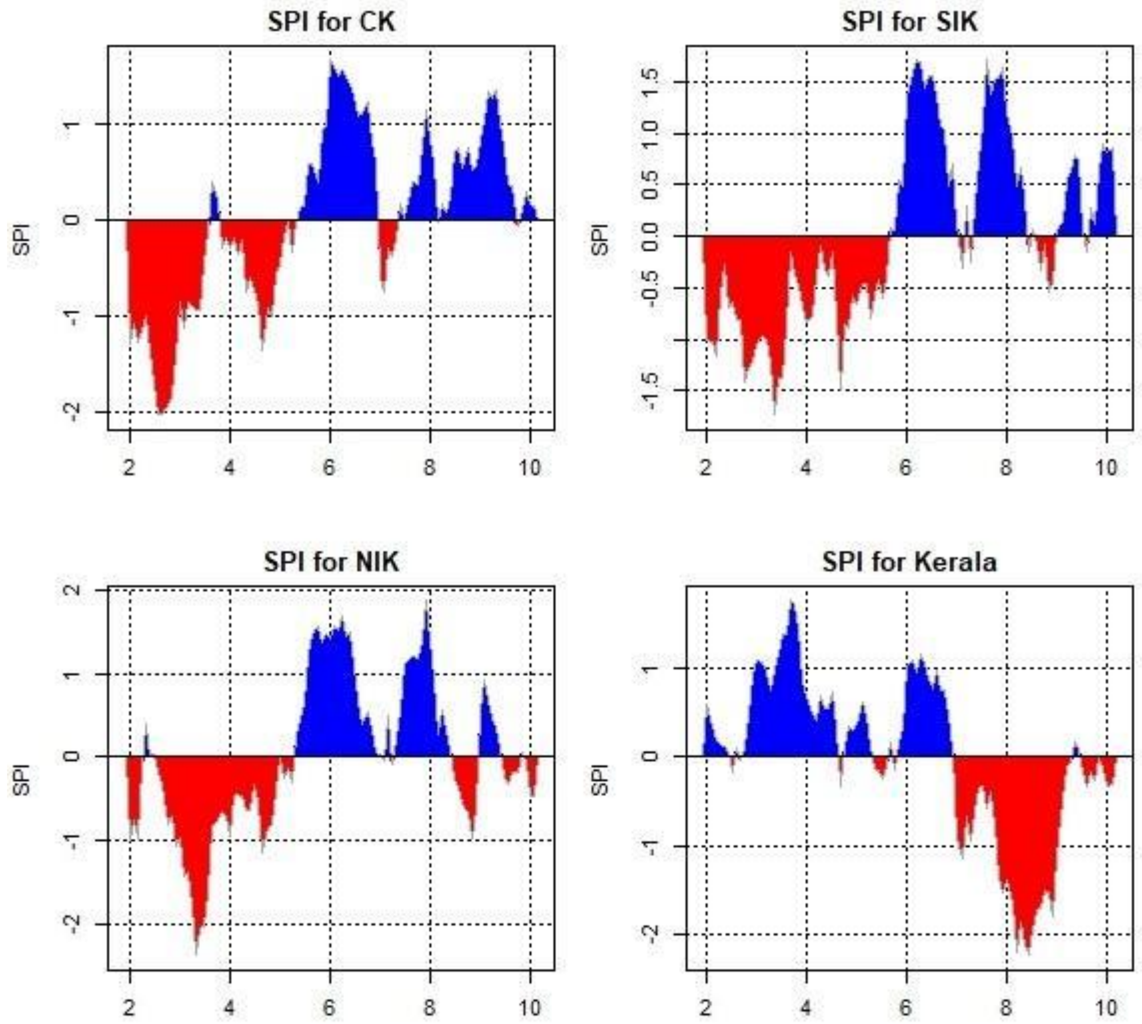


**Fig 3.6f:** Drought estimation for Coastal Karnataka (CK), South Interior Karnataka (SIK), North Interior Karnataka (NIK), Kerala

### 3.4.2Trend detection for long-term drought pattern

Long-term meteorological drought conditions were estimated using SPI-12 drought indices for the period of 1901-2015. The time series drought reveals only the overall situation of meteorological drought over time. But it cannot be quantified how much meteorological drought has been increased or decreased. Therefore, the trend analysis techniques should be utilized to obtain the quantification of the time series meteorological drought. Although several parametric and non-parametric statistics are available to quantify the drought scenario. While many researchers reported that ITA outperforms other trend detection techniques for capturing the trend along with hidden trend. Therefore, the ITA has been applied in the present research to quantify the overall drought conditions. Although very rare studies have been conducted yet in India for measuring the trend in meteorological drought conditions. Figure 3.7a-f showed the graphical format of the ITA based trend detection results for 34 meteorological sub-divisions of India.

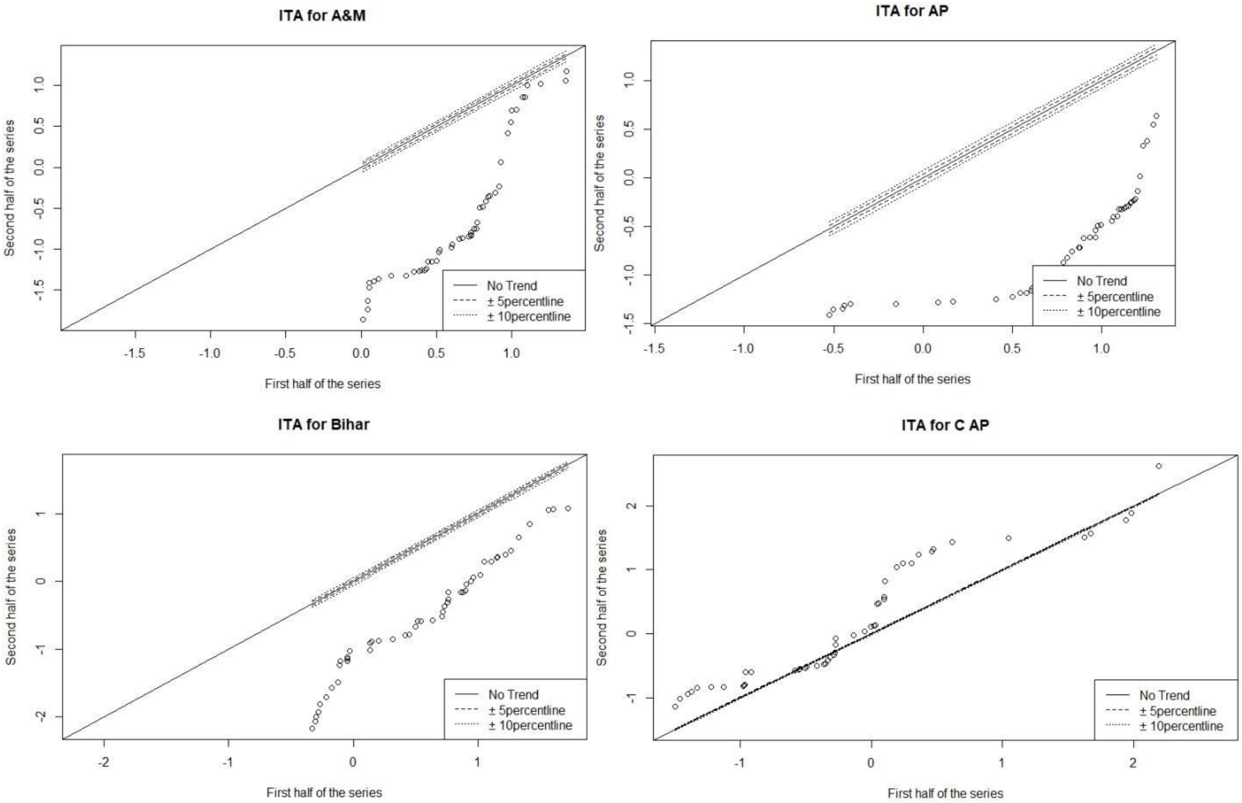


**Figure 3.7a**: Trend analysis using ITA for Assam Meghalaya, Arunachal Pradesh, Bihar, and Coastal Andhra Pradesh

Figure 3.7a showed the ITA based trend detection findings of Assam Meghalaya, Arunachal Pradesh, Bihar, and Coastal Andhra Pradesh. Except coastal Andhra Pradesh, rest of three sub-divisions observed increasing tendency of drought very recently, while in the past these sub-divisions observed lesser drought. On the other hand, coastal Andhra Pradesh observed drought throughout the study period.

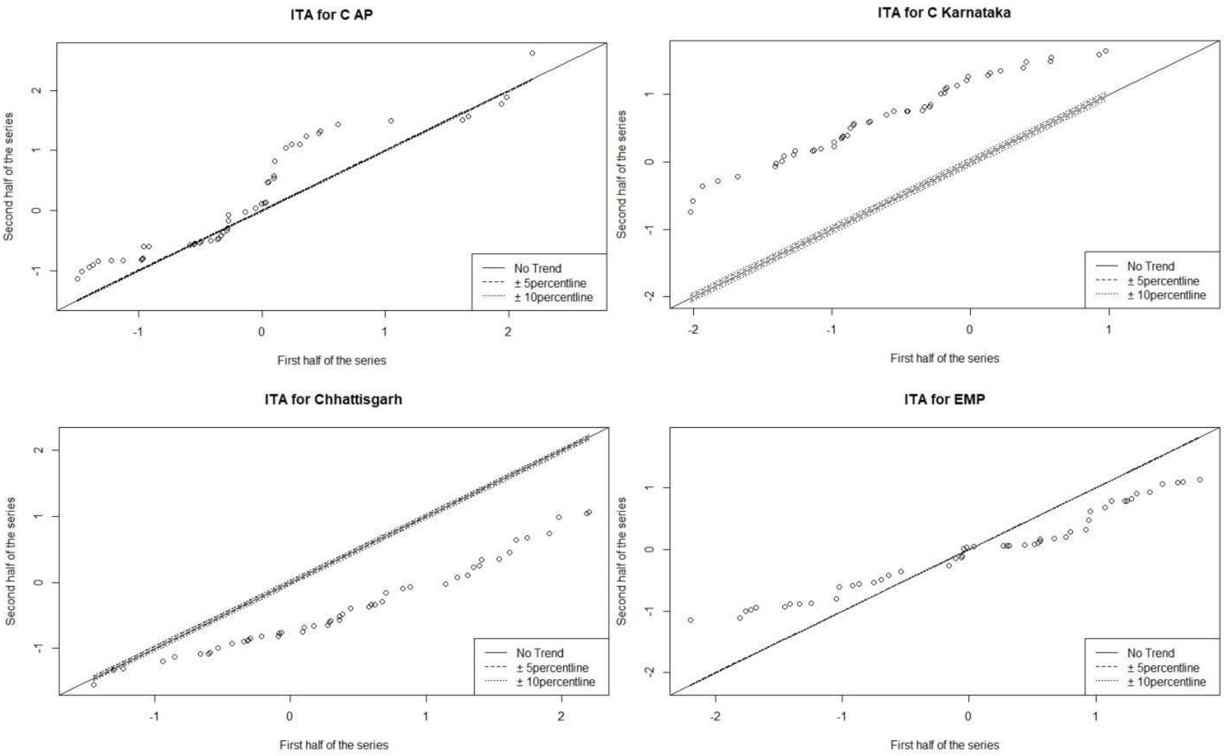


**Figure: 3.7b** Trend analysis using ITA for Coastal Karnataka, Chhattisgarh, and Eastern Madhya Pradesh

Figure 3.7b showed the ITA based trend detection findings of Coastal Karnataka, Chhattisgarh, and Eastern Madhya Pradesh. All sub-divisions observed increasing tendency of drought very recently, while in the past these sub-divisions observed lesser drought. On the other hand, coastal Karnataka observed drought throughout the study period.

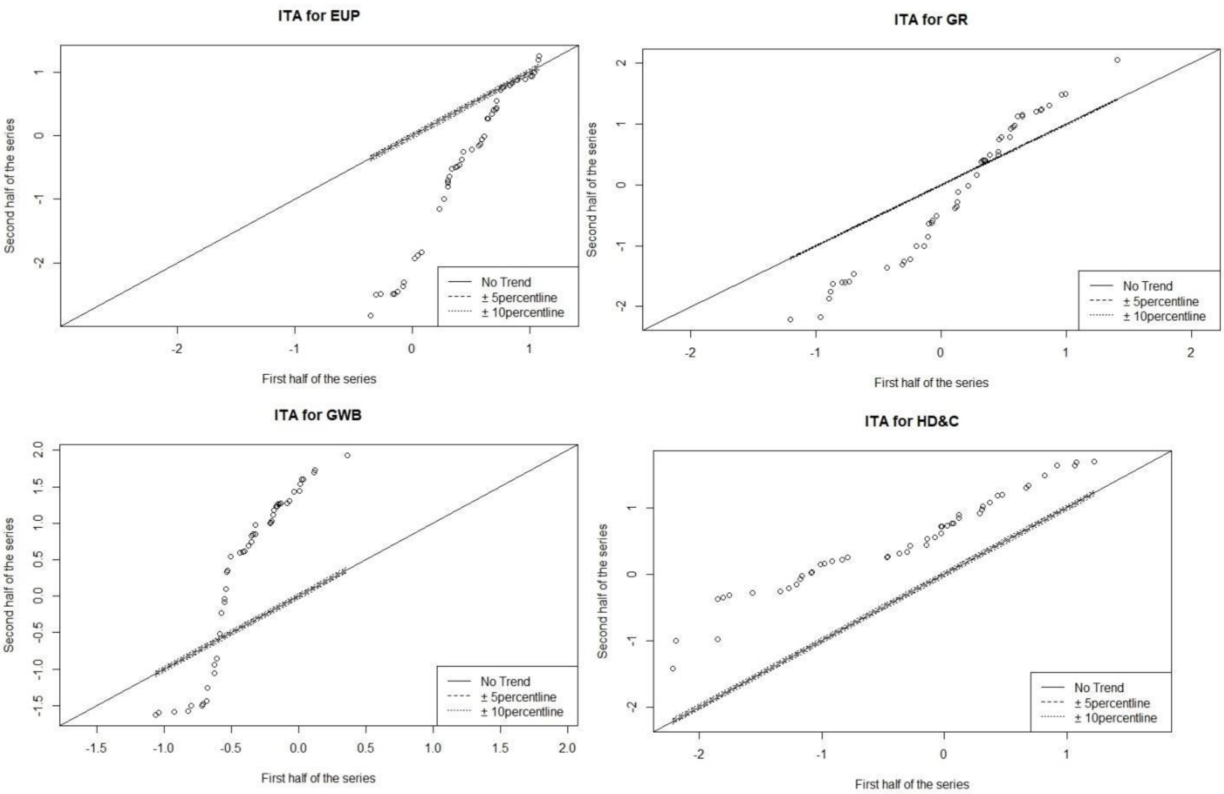


**Figure 3.7c**: Trend analysis using ITA for Eastern Uttar Pradesh, Gujarat region, Gangetic West Bengal, Haryana Delhi Chandigarh

Eastern Uttar Pradesh, Gujarat region, Gangetic West Bengal, Haryana Delhi Chandigarh's ITA-based trend detection findings are seen in Figure 3.7c. All sub-divisions have recently seen an increase in drought, while in the past, these sub-divisions have seen less drought. HD&C, on the other hand, endured drought during the study period.

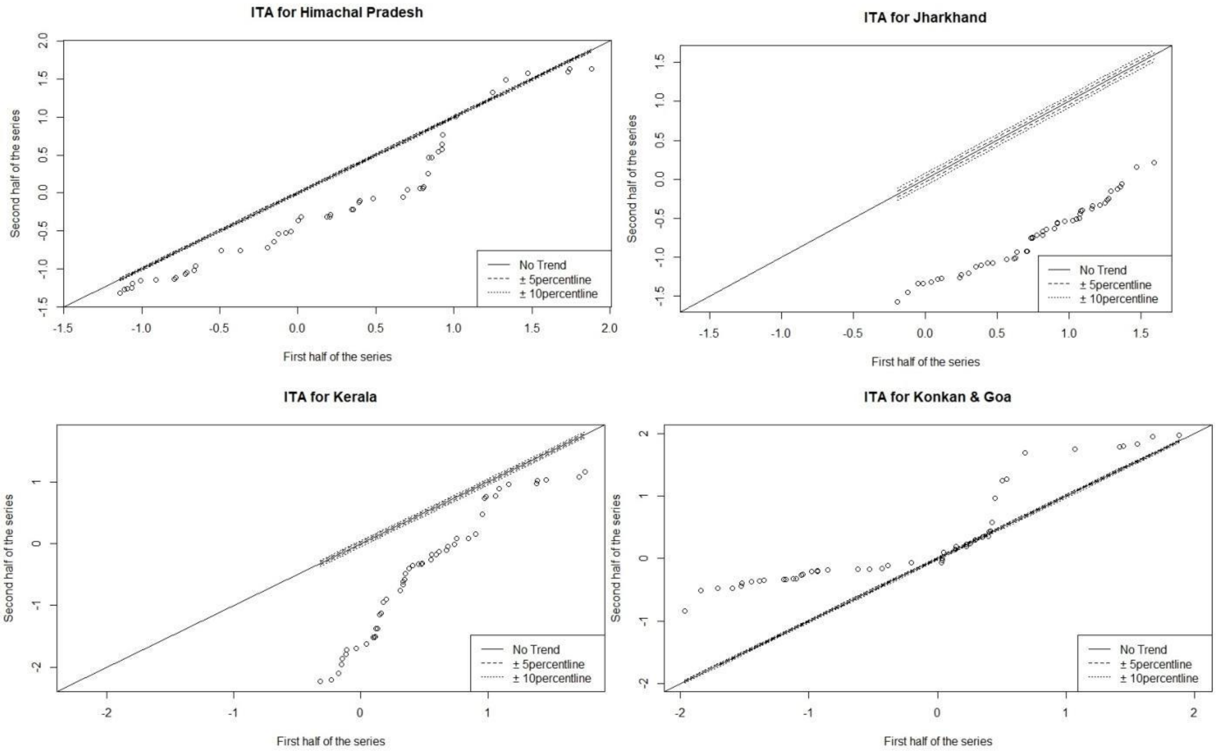


**Figure 3.7d:** Trend analysis using ITA for Himachal Pradesh, Jharkhand, Kerala, and Konkan & Goa

Figure 3.7d reveals the ITA-based trend detection results for Himachal Pradesh, Jharkhand, Kerala, and Konkan & Goa. Both sub-divisions have recently seen an increment in drought, although they have previously seen less drought. Drought hit coastal Karnataka during the study time, on the other hand.

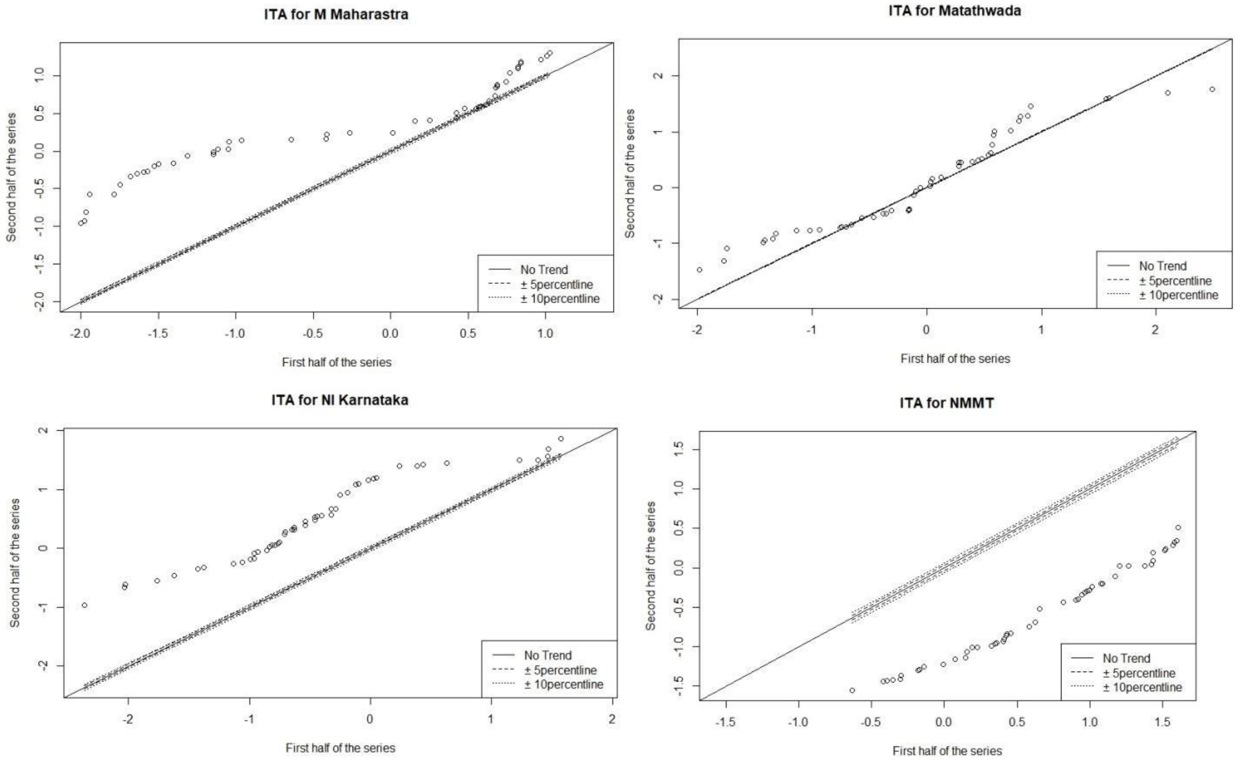


**Figure 3.7e:** Trend analysis using ITA for Madhya Maharashtra, Marathwada, North interior Karnataka, and Nagaland Manipur Tripura

The findings of ITA-based trend detection for Madhya Maharashtra, Marathwada, North interior Karnataka, and Nagaland Manipur Tripura are shown in Figure 3.7e. Both sub-divisions have recently undergone a rise in drought, despite having historically experienced fewer droughts. On the other hand, a severe drought struck Madhya Maharashtra, Karnataka, for the duration of the study period.

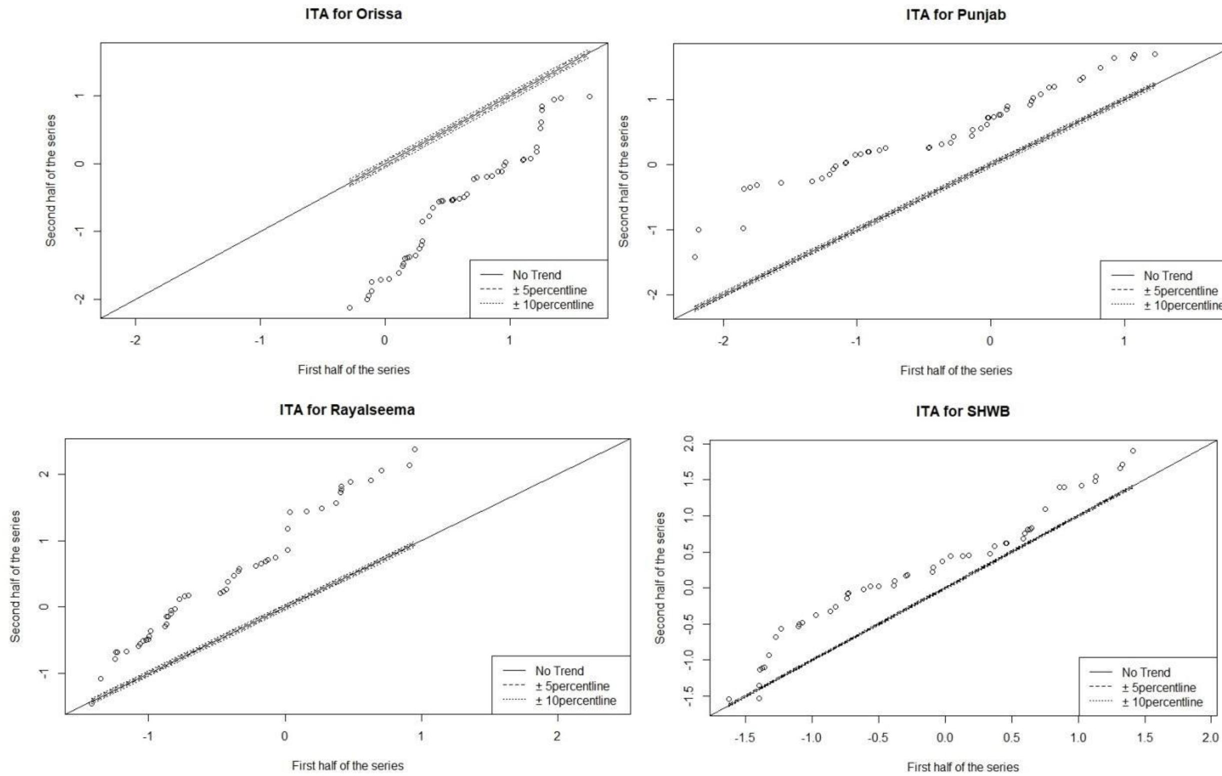


**Figure 3.7f:** Trend analysis using ITA for Orissa, Punjab, Rayalseema, and Sub-Himalayan West Bengal

Figure 3.7f displays the effects of ITA-based trend detection in Orissa, Punjab, Rayalseema, and Sub-Himalayan West Bengal. Despite having traditionally seen fewer droughts, both sub-divisions have recently seen an increase in drought. An extreme drought, on the other hand, hit all three sub-divisions for the length of the study period, with the exception of Orissa.

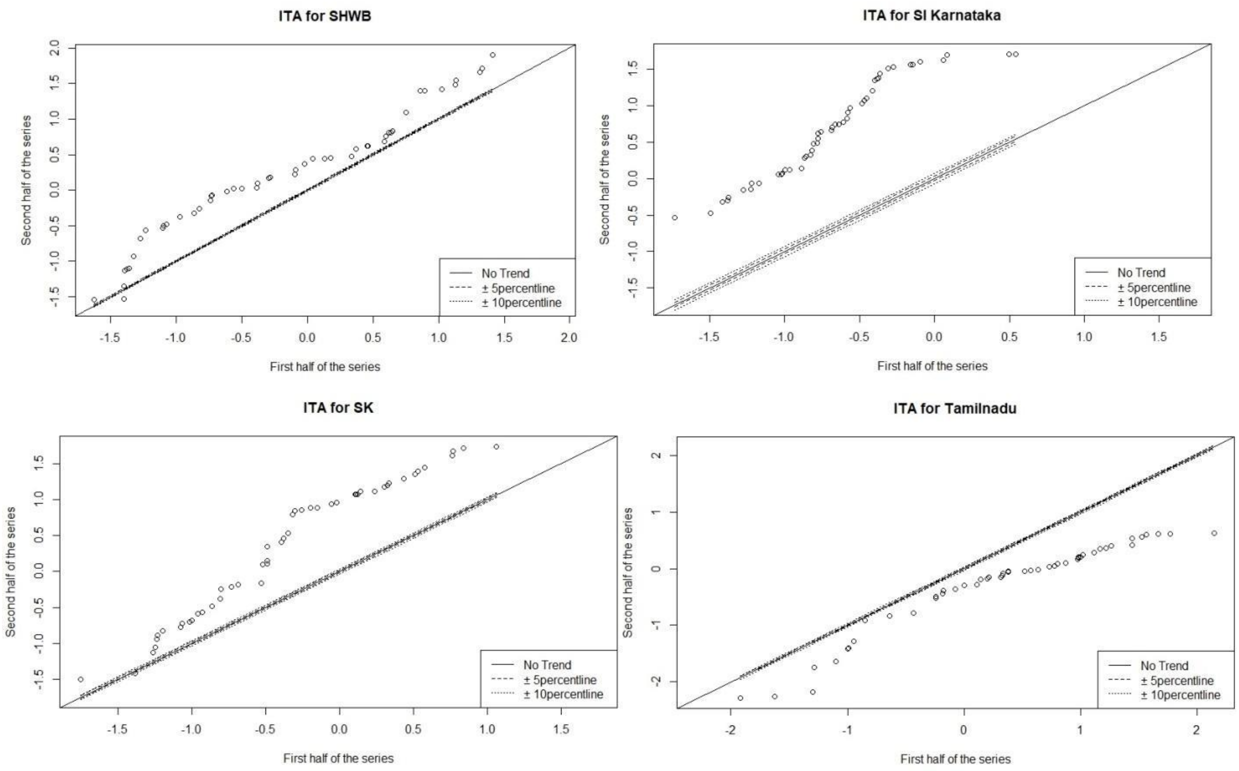


**Figure 3.7g**: Trend analysis using ITA for South Interior Karnataka, Saurashtra, and Tamilnadu

The results of ITA-based pattern identification in South Interior Karnataka, Saurashtra, and Tamilnadu are seen in Figure 3.7g. Despite seeing fewer droughts in the past, both sub-divisions have recently undergone a rise in drought. With the exception of Tamilnadu, all three sub-divisions endured significant drought for the duration of the study period.

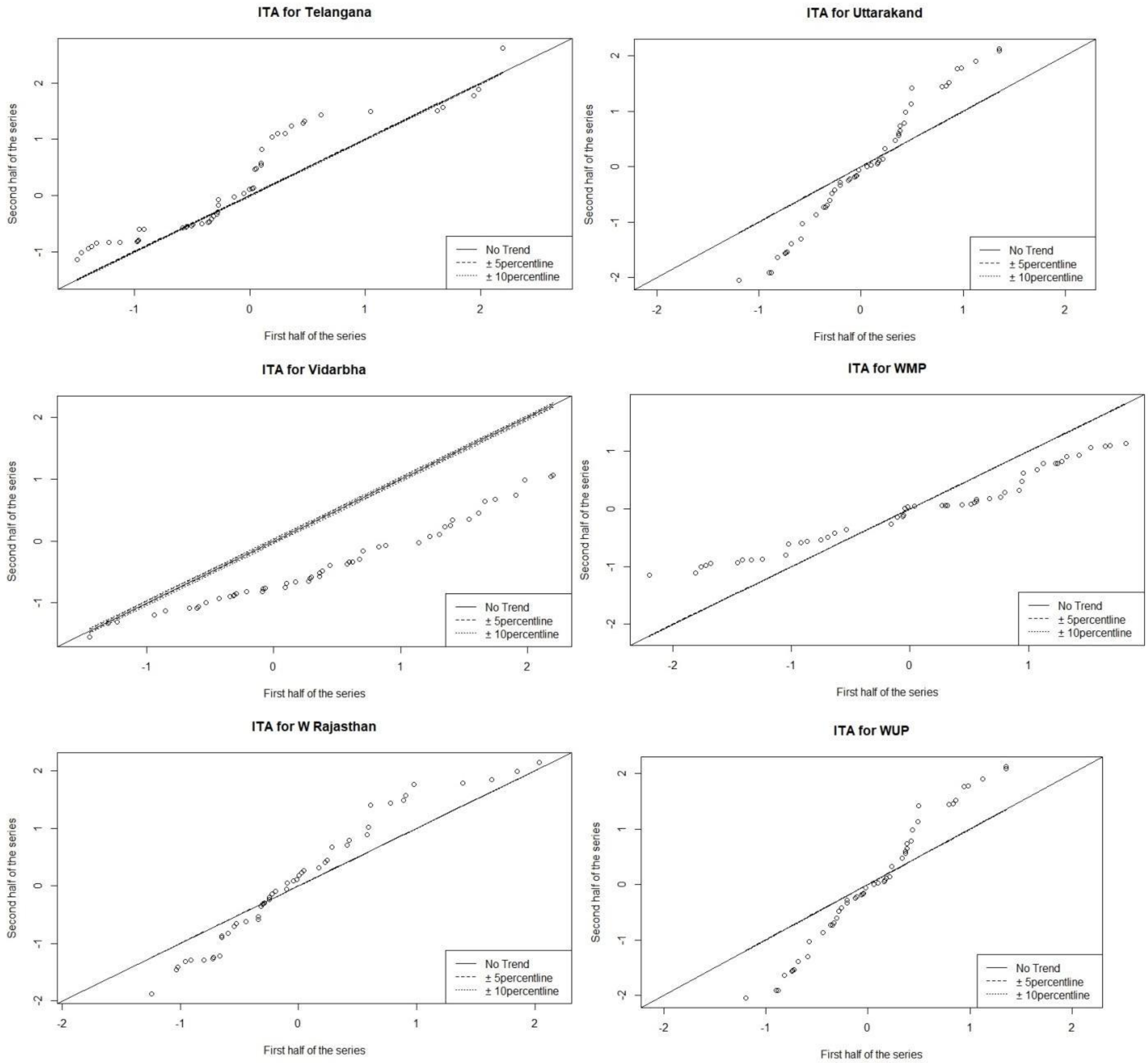


**Figure 3.7h:** Trend analysis using ITA for Telengana, Uttarakhand, Vidarbha, West Madhya Pradesh, West Rajasthan, and West Uttar Pradesh

Figure 3.7h shows the effects of ITA-based trend detection in Telengana, Uttarakhand, Vidarbha, West Madhya Pradesh, West Rajasthan, and West Uttar Pradesh. Despite seeing less drought in the past, both sub-divisions have seen an increase in drought lately.

### 3.4.3Periodicity analysis of meteorological drought pattern

At the SPI -12's 95 percent confidence standard, the CWT was used to distinguish the periodic variance. In Figure 3.8a-f, the SPI -12's wavelet power spectra (WPS) are shown. The power of the WT for annual rainfall using Morlet mother wavelets is seen in Figures 3.8a-f. These absolute values squared provide information about relative power at a given time and scale, resulting in a two-dimensional image. These statistics represent the true oscillations of each wavelet rather than the wavelet magnitudes. By using white- or red-noise baseline spectra, the black contours in those figures reflect the 0.05 significance level. White-noise or red-noise models may be used to model a variety of geophysical time series. The lag-1 is the contrast between the time series and a year-shifted version of the same time series, which is the current time unit. Since the analysed time series are limited in duration, there would be errors at the start and end of the wavelet power spectra by definition. Torrence and Compo (1998) suggested padding the end of the time series with zeroes only before using the WT and then deleting those zeros afterwards. In these numbers, the bend area represents the cone of influence, where zero padding reduced variation. When dealing with cyclic sequences, there is no need to pad with zeroes, because there are no impact cones in this situation. The Morlet wavelet has a higher frequency resolution than other wavelets, which is one of its advantages over other wavelets. In comparison to other wavelets such as the Mexican Cap, Paul, and D, researchers discovered that using the Morlet wavelet was better at detecting and localising different important events in hydro-meteorological data.

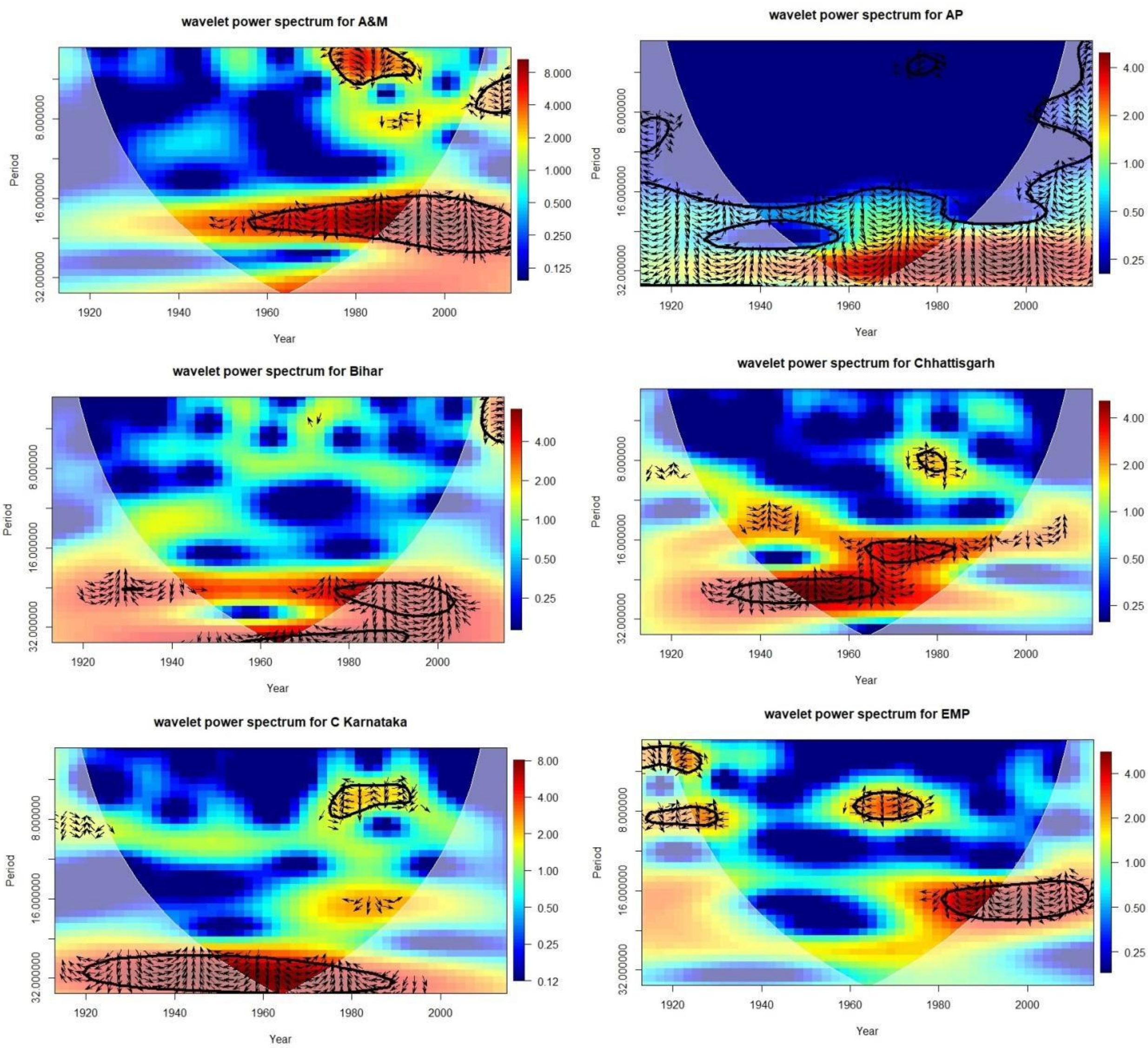


**Figure 3.8a:** Periodicity analysis using wavelet transformation for Assam Meghalaya, Arunachal Pradesh, Bihar, Chhattisgarh, Coastal Karnataka, and Eastern Madhya Pradesh

Figure 3.8a shows the periodicity analysis for Assam Meghalaya, Arunachal Pradesh, Bihar, Chhattisgarh, Coastal Karnataka, and Eastern Madhya Pradesh. The CWT indicates that thirty two-year frequency variability dominated the time series, especially after 1960 (Assam Meghalaya), Bihar, Eastern Madhya Pradesh. (Figure 3.8a). This means that annual pattern uncertainty was elevated prior to 1960. It then became frail until 1995, when it recovered its dominance. Furthermore, the findings presented by CWT suggest that the 2-year and 8-year periodicities have an effect on TP patterns (Figure 3.8a)

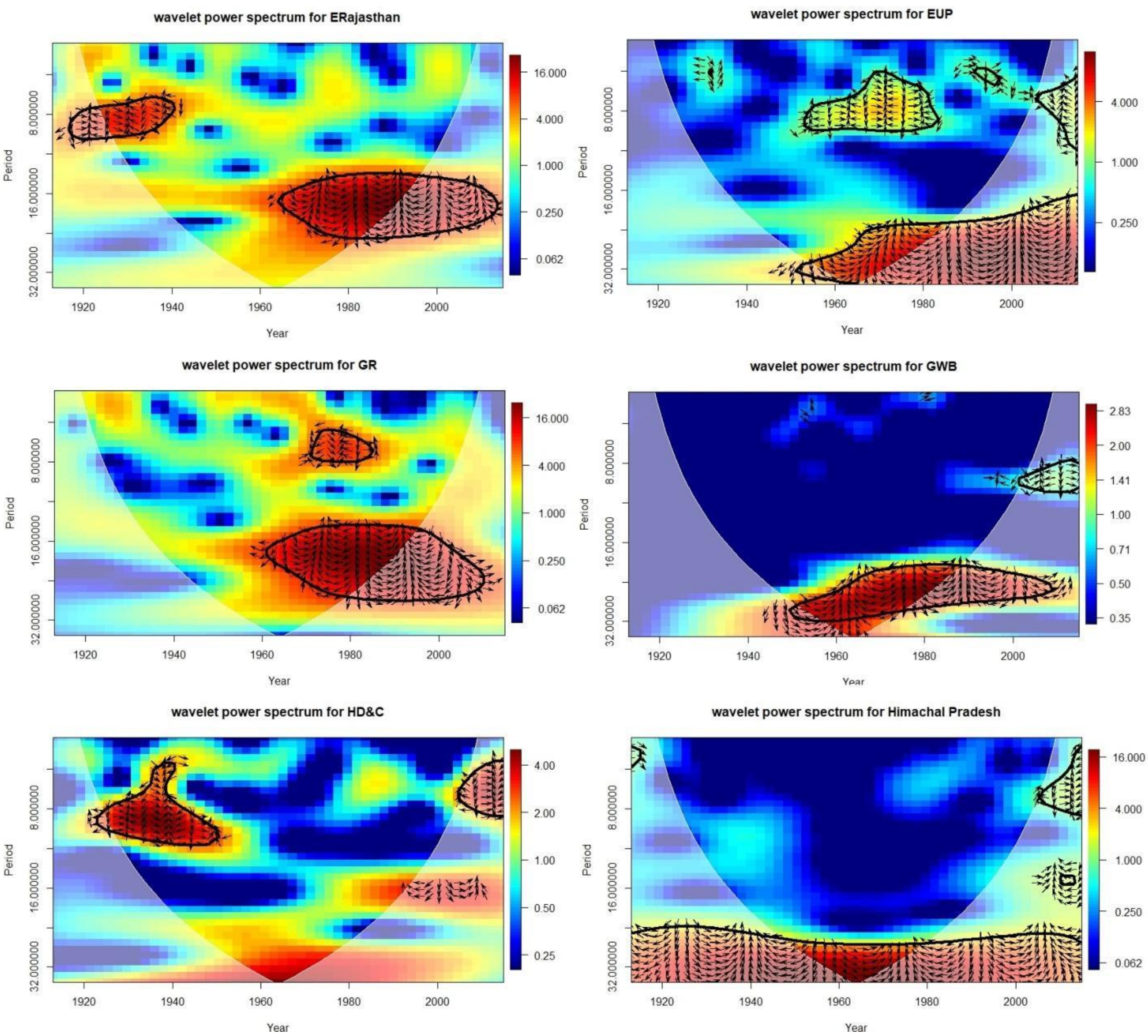


**Figure 3.8b** Periodicity analysis using wavelet transformation for Eastern Rajasthan, Eastern Uttar Pradesh, Gujarat Region, Gangetic West Bengal, Haryana Delhi Chandigarh, and Himachal Pradesh

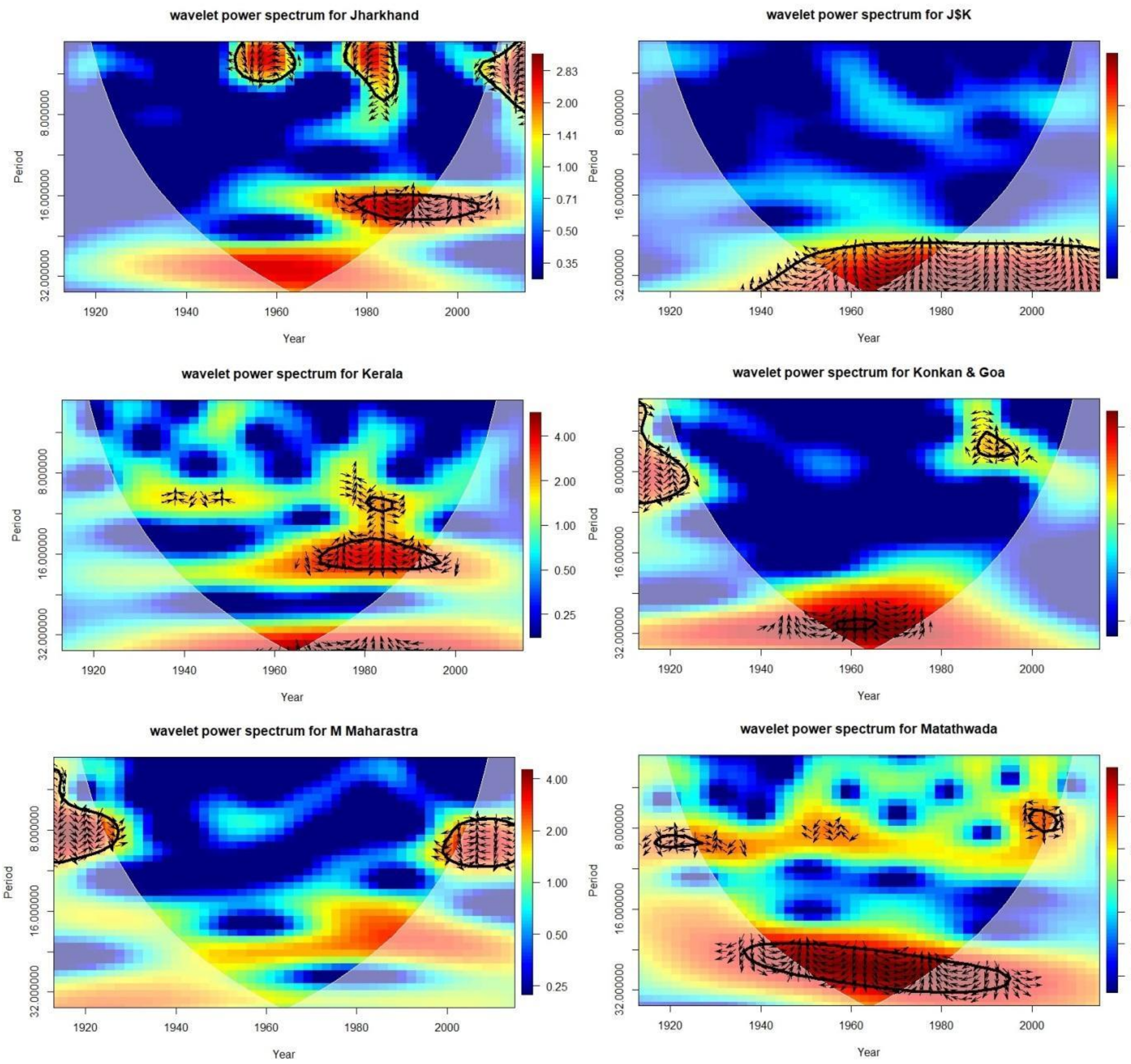


**Figure 3.8c** Periodicity analysis using wavelet transformation for Jharkhand, Jammu & Kashmir, Kerala, Konkan & Goa, Madhya Maharashtra, and Marathwada

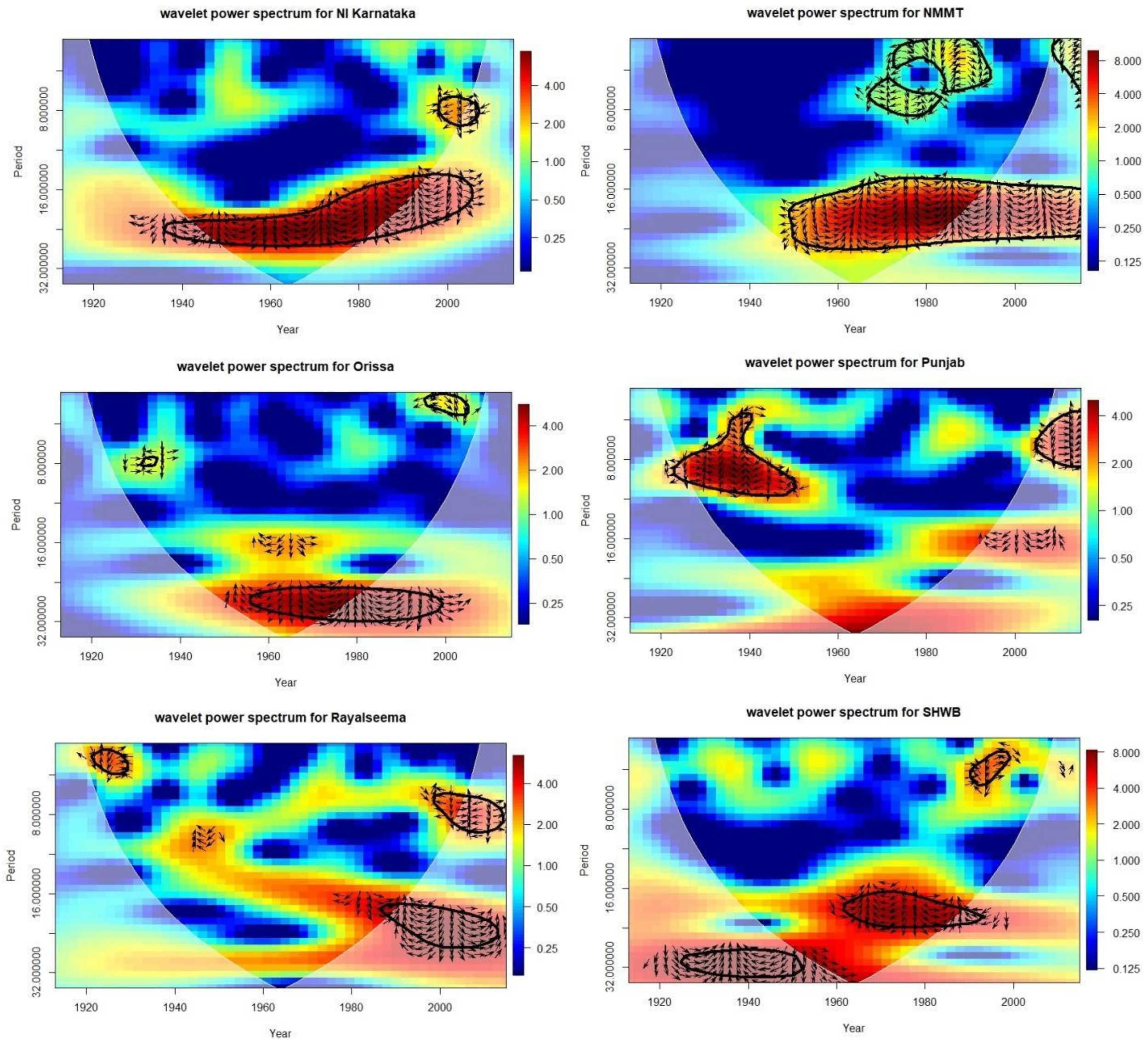


**Figure 3.8d** Periodicity analysis using wavelet transformation for North Interior Karnataka, Nagaland Manipur Tripura, Orissa, Punjab, Rayalseema, and Sub-Himalayan West Bengal

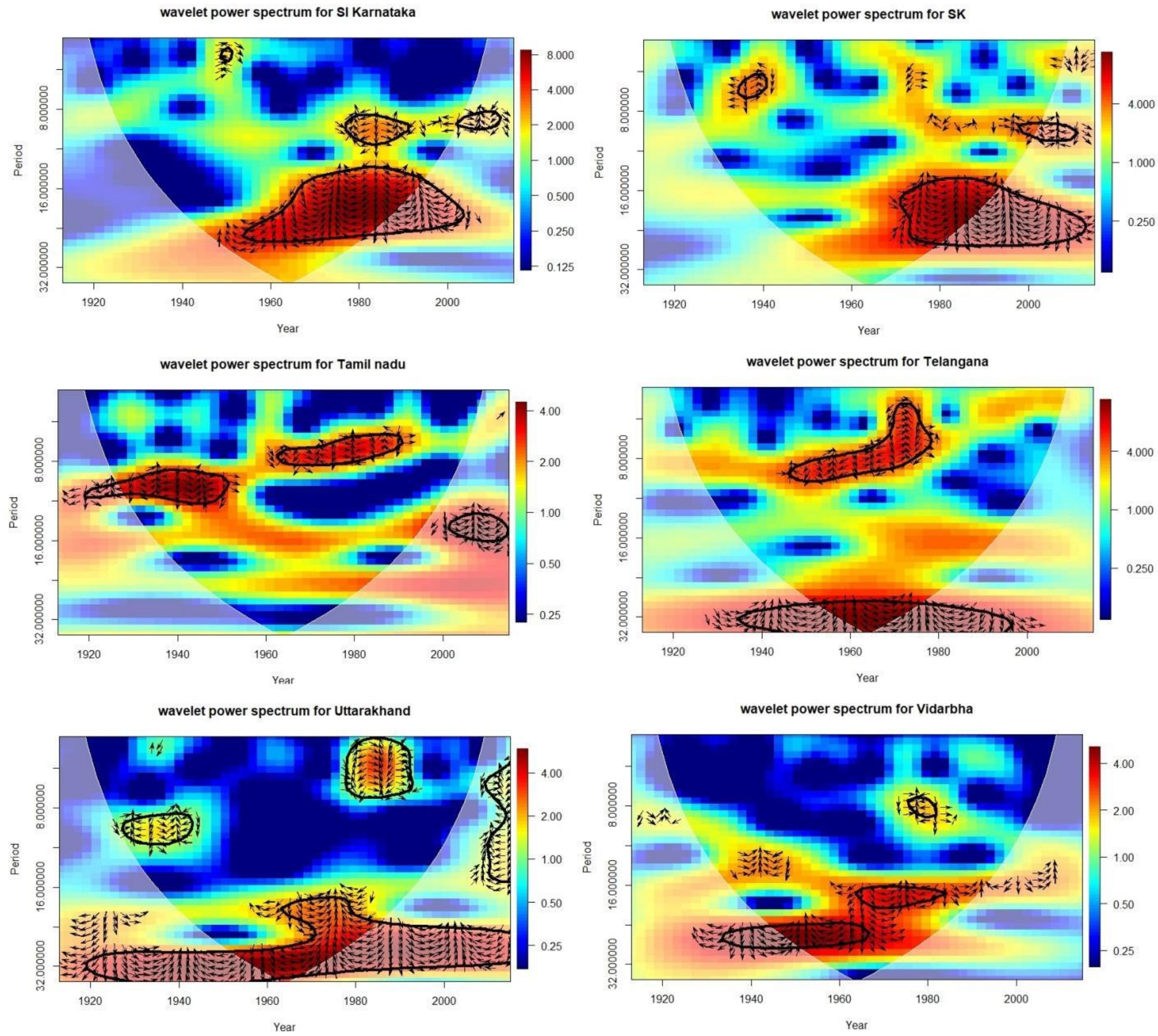


**Figure 3.8e** Periodicity analysis using wavelet transformation for South Interior Karnataka, Saurashtra, Tamilnadu, Telengana, Uttarakhand, and Vidarbha

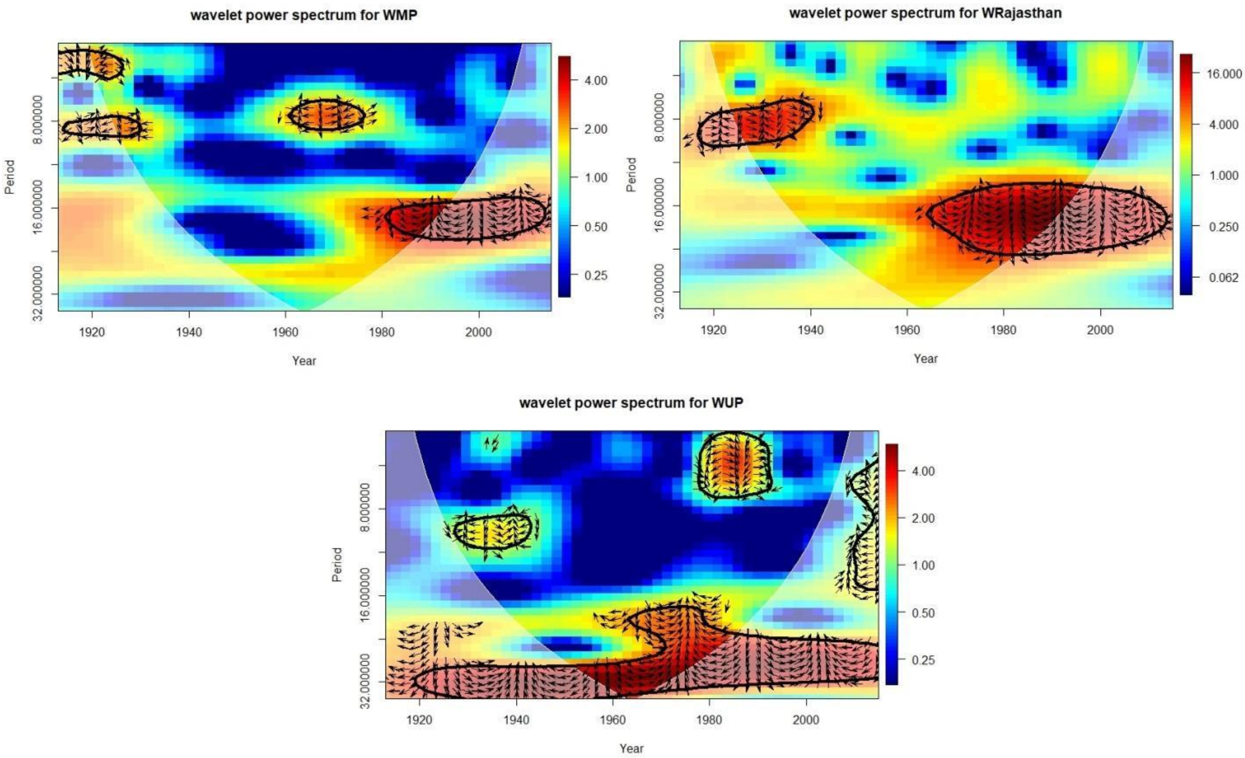


**Figure 3.8f** Periodicity analysis using wavelet transformation for West Madhya Pradesh, West Rajasthan, and West Uttar Pradesh

However, the findings of periodicity analysis for 34 meteorological sub-divisions showed that the variability has been disturbed mostly after 1960 for most of the sub-divisions. These sub-divisions observed strong power during the period indicating higher disturbance in the time series data. Therefore, in practical, it can be stated that after 1960, the meteorological drought has been increased with varying intensities for different sub-divisions. Finally, it can be concluding that due to the effect of climate change; the rainfall has been reduced significantly, which in turn caused drought conditions. These severe drought conditions in different parts of India have been evidently revealed using periodicity analysis.

**Climate change modeling**

India encompasses large areas with moderate to high convective precipitation, while low convective rainfall rate occurred which was brought excessive moisture from the Indian Ocean to the in-land areas, which is unfavorable for the formation of rainfall (Figure 3.9). This caused a decreased in mean rainfall during monsoon season, which has been distributed in the extreme southern and mid-central divisions of the country (Figure 3.9). The northeasterly wind was strengthened in the whole country, which reduced the invasions of cooler air, led to decline in rainfall all over India in the winter season. By contrast, most of the divisions had moderate to high mean convective precipitation rate, which increased rainfall to some extent. The low cloud has increased all over the India, and a few cloud covers will enhance the consolidation impact of atmosphere on the solar radiation, and hence it leads to declining rainfall trend. Moreover, high mean total precipitation rate has been influencing across the country except for eastern division, which triggered uneven downdraft pattern and leading to more clear sky days during the recent study period (1979-2017). Most of the regions in India exhibited a declining vertically integrated moisture divergence which triggered by a significant decreasing rainfall changes.

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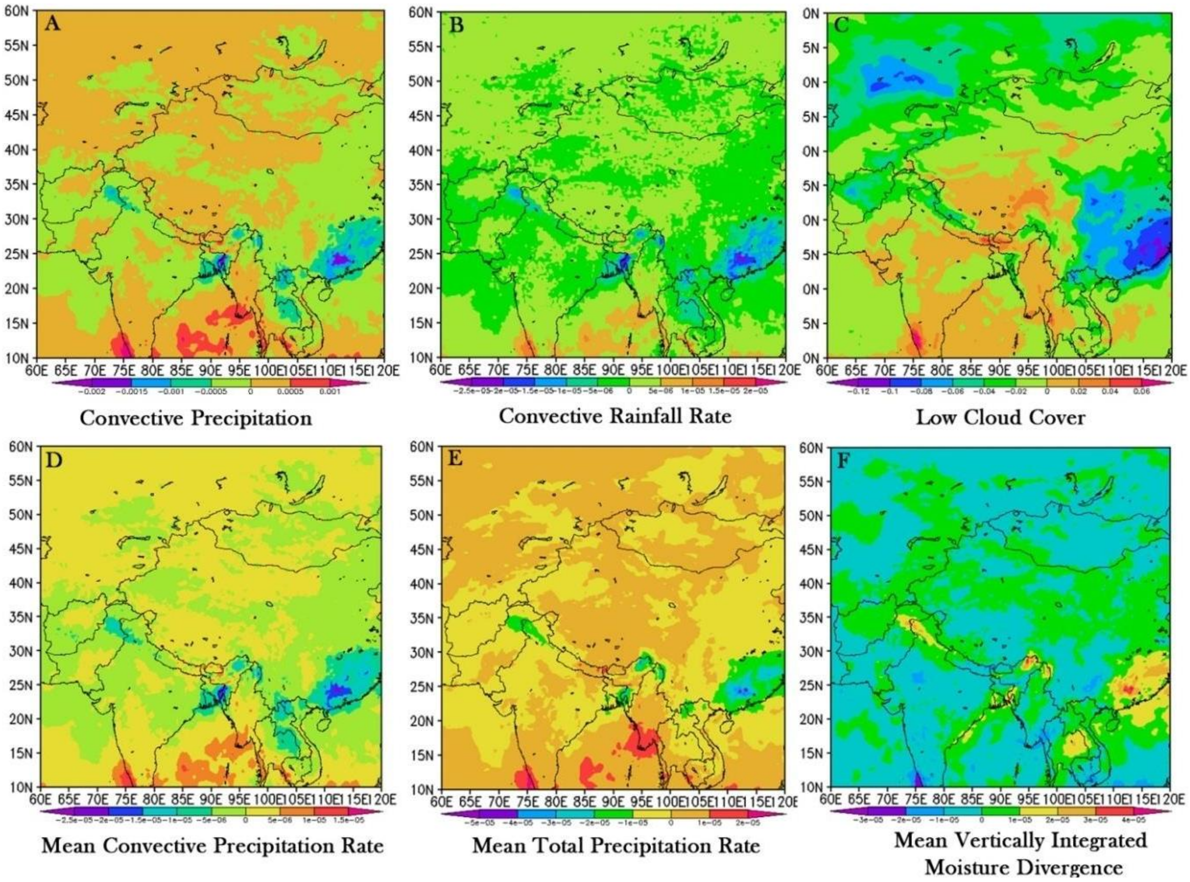



**Figure 3.9**: Spatial variations of differences inconvective precipitation in monsoon season, convective rainfall rate in winter season, low cloud cover, mean convective precipitation rate, mean total precipitation rate, and mean vertically integrated moisture divergence between the recent period of 2001-2015 and 1979–2000.

### 3.5. Conclusion & Summary

Based on the above findings, the finding of the present chapter can be summarized as follows:

The rainfall has been reduced significantly after 1960-1975 periods in different meteorological sub-divisions. The change detection techniques showed that the whole time series rainfall (1901-2015) for 34 sub-divisions has a change point, which is ranging from 1950-1980 for different sub-divisions. This indicates that the time series rainfall data has observed a sudden change or shift from historical pattern or trend. The trend detection results truly quantified that after 1960-1980, all meteorological sub-divisions, except North-East India, have observed significantly negative trend, which indicates the reduction of rainfall over time. Along with trend detection findings, the best methods for trend detection were also analysed among MK test, MMK test, Sen's slope estimator, and Innovative trend analysis. The results showed that ITA outperformed other trend detection techniques. The present chapter also investigates the climate change in terms of meteorological drought pattern and its trend. The long-term time series meteorological drought was estimated using SPI-12. The long-term meteorological drought for 34 sub-divisions showed that the drought pattern or trend has been increased over time. The drought pattern or trend has been quantified using ITA methods and Periodicity analysis. Results showed that most of sub-divisions observed increasing tendency of drought very recently, while those have observed mild to no drought pattern in the past. On the other hand, disturbance in variation in the time series of meteorological drought has also indicated increasing of meteorological drought over time, which can be the results of climate change. The effects of various factors, such as temperature and rainfall, will be discussed in the next chapter. Which crops are sensitive to these factors and their effects on agriculture production.

# Chapter 4

# IMPACT OF CLIMATE CHANGE ON AGRICULTURE PRODUCTION

## 4.1. Introduction

This study analyzes the climatic variation and its impacts on Indian agricultural (fifteen crops) productions using a panel dataset from 1967-2016. Crop productions were designed according to temperature and rainfall datasets. First we did Innovative trend analysis (ITA). Trend analysis refers to analysis on its past trends in any sector. It allows one to predict what might happen to the upcoming years in the future. Further, multiple regression was performed to assess the impacts of temperature and rainfall on crop production. Finally two different tools (ANN and ARIMA) were used to predict the production till 2030 and the outcome of both analyses were compared. The prediction work is discussed in next chapter.

## 4.2. Review of Literature

Climate change is expected to adversely impact agricultural crop production, which is heavily reliant on climatic conditions and fluctuations (Kumar and Gautam, 2013; 2014). Climate change has also affected wildlife and populations around the globe, as demonstrated by rising temperatures (Cramer et al., 2018), increasingly erratic rainfall (Mehta et al., 2018), recurrent drought (Mehta et al., 2018), sea-level rise (Ho et al., 2018), and glacier melting (Mehta et al.,2018). While climatic factors fluctuate naturally, anthropogenic greenhouse gas emissions, deforestation, urbanisation, advanced industrial growth, use of modern machinery and technology, advanced economic enlargement, and transportation have intensified the impacts in recent decades. (Ahmad et al., 2011). As a result, crop production and productivity have decreased significantly, notably in third-world countries (Sarkar et al., 2019), resulting in food insecurity (Ho et al., 2018), drought (Sarkar et al., 2019), malnutrition (Ho et al., 2018), and other issues, as these countries' livelihoods are primarily dependent on agricultural crop production (Nath and Behera, 2011). However, climatic conditions in mid-latitude developing countries may vary due to the use of advanced agricultural technologies, reduced reliance on agriculture, and increased knowledge of agricultural science such as crop rotation and mixed farming, among other factors (Cramer et al., 2018).Therefore, investigating the repercussions of climate variation over agricultural crop production is preeminent, especially for countries like India.

The outturns of climatic variations on agricultural productions are being measured using three approaches mostly as biophysical, hedonic, and panel data. Among three approaches, the most important and popular method is the biophysical approach and also known as crop modeling technique (Adams et al., 2013; Aggarwal, 2009; Kurukulasuriya et al., 2006; Lal, 2000; Rao and Sinha, 1994; Rosenzweig and Iglesias, 1994; Reilly et al., 1994; Aggarwal and Sinha, 1993; Kane et al., 1992). Apart from this, the hedonic or Ricardian approach has been applied to explore the long-term phenomenal variations of climate in cropping system of production while considering adaptation (Mendelsohn, 2014; Mendelsohn et al., 2010; (Mendelsohn and Dinar, 2009; Deschênes and Greenstone, 2007; Kurukulasuriya et al., 2006; Kumar and Parikh, 2001).

Furthermore, the panel data approach is also a popular method to quantify the reverberations of climate variation upon agricultural productivity (Okiyama et al. 2013; Tokunaga et al. 2015). The change in climatic variables may influence the economy in various ways. For example, high fluctuation of rainfall leads to irregularity and severity in floods, resulting in decline in the crop production. The interrelation of climate change and agricultural productivity are quantified through the aforementioned technique. The increase in surface temperature raises the mean sea level that affects the livelihood of inhabitants in the coastal regions of the world. IPCC (2007) projected that the temperature will increase by 1º-6ºC by 2100. Consequently, the rise of the degree of heat intensity and irregular precipitation patterns will possess a severe impact on crop productivity (Aggarwal, 2008). Therefore, climate change has been severely affecting food production throughout the world including India, which causes food insecurity (Meeting, 2006; FAO, 2008).

There have been many types of research that report the negative consequences of the climate variation over cropping patterns as well as crop production in India, but only a few studies have been performed using empirical techniques regarding this issue. Kumar and Parikh (2001) have estimated production of a few prominent crops which are named as Wheat, maize, Barley, sorghum, and arhar. These crops were prone to adversity due to high climate sensitivity; therefore, it is also critical for the security of food of India. In addition to this, the productions of commercial crops like cotton Sesamum, and sugarcane have also been declined since 1990 (Singh 2012) due to the elevated temperature. It is estimated by 2060 and found that the changes in climate would result in a decline in the production of potato and paddy and potentially endanger food safety for nearly one billion population of the country. Food grain at any fluctuation in temperature below the normal has a dismal and numerically noteworthy influence on linseed production (Singh 2012). Kumar et al. (2011) reported that irrigated areas of maize, mustard, Wheat, Rice, and sorghum in the seaside region, Northeastern Region, and Sahyadri region or the Western Ghats have been declining because of the negative effects of climatic variations,

Hundal (2007) stated, as the mean temperature spiral by 1º-3º C above normal range it will result in decreasing of paddy and wheat production by 3 percent and 10 percent respectively in  the state of Punjab. The unreliable pattern of precipitation has inimically slowed down the cropping of Jowar in Karnataka that led to food insecurity among farmers (Kaul and Ram, 2009). According to Geethalakshmi et al. (2011), the production of paddy crop in Tamilnadu has declined by more than 41% due to the temperature reaching the maximum 40ºC. Furthermore, Saseendran et al. (2000) projected the paddy crop and temperature in the state of Kerala up to 2049 and found that temperature would cross 50ºC which would significantly decline the production of paddy in the state. Saseendran et al. (2000) reported that rising of each 1-degree temperature would reduce crop production by up to 6 percent. Srivastava et al., (2010) argued that the production of monsoonal crop i.e. sorghum may decline at  14 percent and 2 percent respectively by the year 2020 in regions of central India and southern central India only in response to the phenomenal climatic variance.

Empirical evidence clearly indicates that rising in atmospheric heat has significantly dismissive consequences over the production of Rice, maize, Jowar (sorghum), Bajra and Barley (Kalra et al., 2008; Geethalakshmi et al., 2011). The agricultural production for  Gram along with  Ragi would also decreasedue to increase in the maximal  degree of heat, however, the produced output of Wheat and Tur have increased firmly due to the increase in the maximal intensity of heat  (Kumar and Parikh, 2001; Kaur and Hundal, 2007).

Kapur et al., (2009) estimated a potential 30% reduction in crop production in the middle of 21st as intensification occurred in surface warming with a change in the rate of precipitation, which could lead to a decline in arable land triggering crop production stresses in India. Evidence shows climate variability has negatively influenced agricultural crop production. Moreover, most of the empirical studies have either covered single crops or multiple crops with limited geographical coverage. Therefore, it has found to be imperative to determine the overall effect of climate variability over major food grains along with a focus on profitable and sustainable crop production choices for ensuring food security in India (Hollaender, 2010). Our study aims at testing the hypothesis which says, agricultural output in India is climate- sensitive, and any variation in rainfall precipitation and temperature patterns significantly influence the production of the food grain. The development of a proper policy guideline related to the irrigation system and better crop management systems, can alleviate some of the negative consequences of climate sensitiveness on Wheat, paddy, sorghum, Tur , and Bajra, along with managing the food safety in India (Kar and Kar, 2008; Singh, 2012; Ranuzzi and Srivastava, 2012, Sing; 2012).

The development of the agricultural sector executes a pivotal share in overall socio-economic wellbeing of the people in India. Critically, the account of agricultural share in Gross Domestic Product (GDP) as well as in employment has been reduced in times. Although, the benefit of cropping systems is still highly significant and important for economic development (Mall et al., 2006). In India, extensive work has been done during the past few decades assessing nature and magnitude in crop yield fluctuations with a focus on climate change issues in the last decade. Nevertheless, those cited works have primarily dealt with impact of climate change on only few selected crops. In this study, we did ITA to check the trend of climatic factors and have performed a comprehensive analysis of impacts of climatic variations on fifteen different crops, than we applied a multiple linear regression model to assess the impacts of climatic variables on agriculture production.

### 4.3. Data Description

Amongst the leading countries of South Asian region India is the one which is situated from 8°4 to 37°6 north latitude and 68°70 to 9°25o east longitude to the northern portion of equator, circumambient by the water bodies on three sides - on the West by the Arabian Sea, the Bay of Bengal on the East and on the South by Indian Ocean. (Database of the Government of India)

In this study to examine the effect of climate change on crop production major crops has taken into consideration, for example Bajra, rice, wheat, barley, arhar, Ragi, maize, jowar, gram, and mustard plus grain crops which are non-food like linseed, sugarcane, groundnut, rapeseed, cotton, Til and tea, covering over 75 percent of the total cropping land. In this analysis, continuous data was used for a period from 1967 to 2016, with no missing values.

To estimate the climate change impacts on the agriculture production, we have considered per unit area of production as the dependent and climatic variable of temperature and rainfall variable as independent variables for an econometric analysis. The crop production data was obtained from Centre Monitoring Indian Economy (CMIE) and IndiaStat databases.

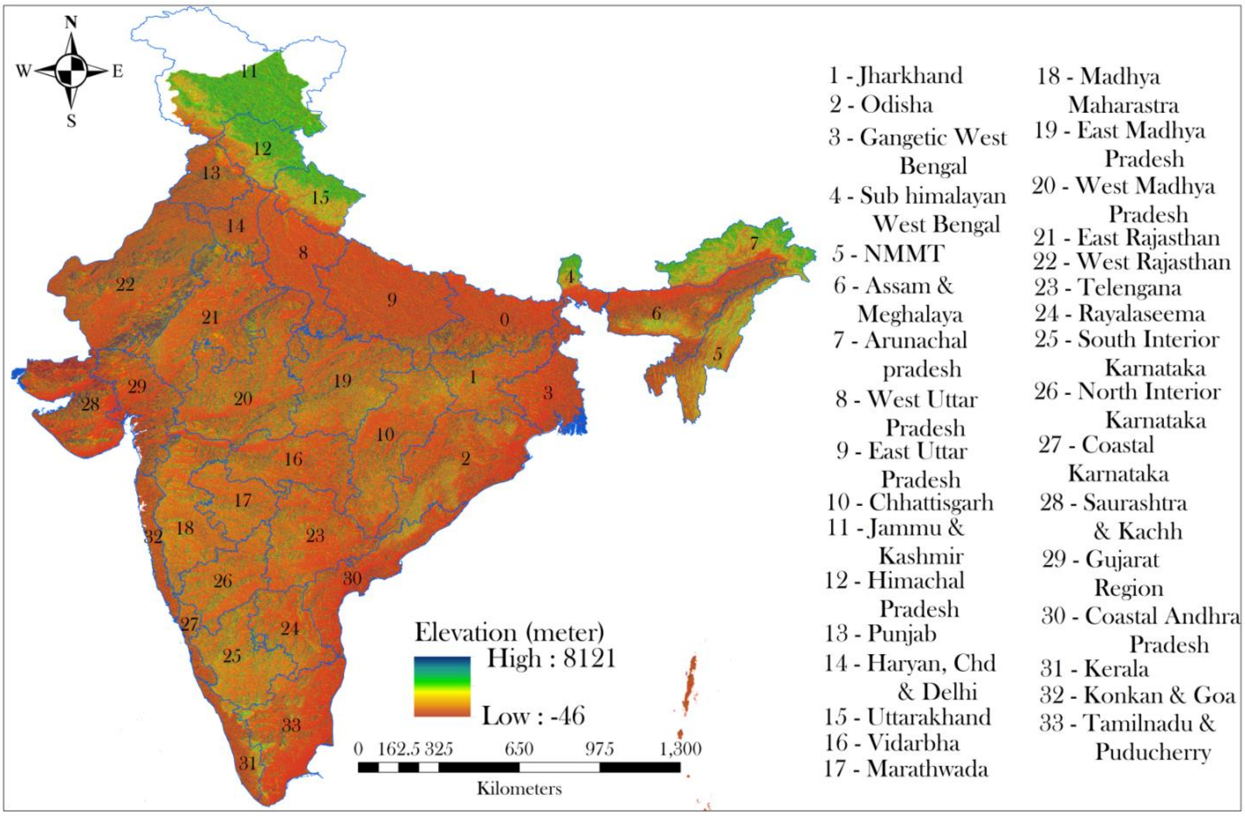



**Figure 4.1**: Geographical location of the study area

## 4.4. Methodology

### Descriptive statistics of the climatic variables and crops production

The data analysis was performed using basic statistical techniques like mean, standard deviation, kurtosis, and skewness to explore the real situation of these variables. In this study, the descriptive statistical techniques have been applied to the climatic variables and agricultural production for the period 1967 to 2016.

### Innovative trend analysis method

As suggested by Sen (2012), when two similar time series are plotted against each other, all points on the Cartesian coordinate system (Figure 4.2) are scattered on the 1:1 line regardless of their distribution form, sample length, serial dependency, or trend form. If the data points collected on the 1:1 (45°) line in the scatter plot indicate they were trendless (data without trend). If the data points fall above the upper triangular area, the line of 1:1, it will be aforementioned that the statistic undergoes a trend of upliftment. If the data points accumulated lower the line of 1:1 in the triangular area, it can be concluded that a declining trend was there in the series of time (Sen, 2012; Sen 2015) The value (absolute) of the distinction between the y and x values of a point is that the horizontal or perpendicular distance from the one, it suggests that the amount of an enlarging or a reducing trend. The key benefits of revolutionary approaches can be understood with a fact that they are not based on any assumptions such as serial correlation, non-normality, sample size, and low, medium, and high data trends could be detected with fewer efforts through the approach (Sen,2014; Kisi, 2015). So, it is useful for measuring a trend, as well as the climate change and agricultural production variations averagely.

Over the years, a numbers of researchers have used ITA frequently for identifying trend on hydrological and climatological parameters (Balasmeh et al. 2019; Güçlü et al. 2018; Zhou et al. 2018; Kisi et al. 2018; Wu and Qian 2017; Cui et al. 2017; Mohorji et al. 2017; Dabanli et al. 2016; Ay and Kisi 2015). Kisi and Ay (2014) applied the Mann-Kendall (MK) test and ITA in Kizilirmak River, Turkey for analyzing the trends of parameters for water quality. The author has used the successful application of the ITA technique for trend assessment. Kisi (2015) implied the ITA method over six stations in Turkey to assess the trend system on monthly pan evaporation data and observed the negative and positive trend over the study area. Cui et al. (2017) used the ITA method, MK test, linear regression method, and Sen's slope estimator to analyze the trend in annual and seasonal rainfall and temperature of the Yangtze River Basin, China, and those climatic variables were increased significantly was reported. According to the author, the ITA approach was utilised for the first time in whole India for agricultural research in this study.

## 4.5. Empirical Result and Discussion

*Descriptive statistics analysis of climatic variables and different crop production*

The descriptive statistics have been provided in Table 4.1. Table 4.1 summarizes the fundamental properties of all the variables which are under study. The climatic variables of mean annual rainfall and temperatures were 1388.56 mm and 24.87 ° C, respectively. Negative kurtosis found at all climatic and agricultural variables, except Til, Barley, Ragi and Gram. The observed kurtosis values ranged from -1 to 1 for all variables except Temperature, Rice, Jowar, Bajra, Barley and Wheat. This demonstrates that the data is acceptable for further analyses. Rainfall, Rice, Jowar, and Wheat showed negative skewness and the rest of the variables showed positive and moderate skewed distribution (Table 4.1).

**Table 4.1**: Descriptive analysis of the climatic variables and crop production

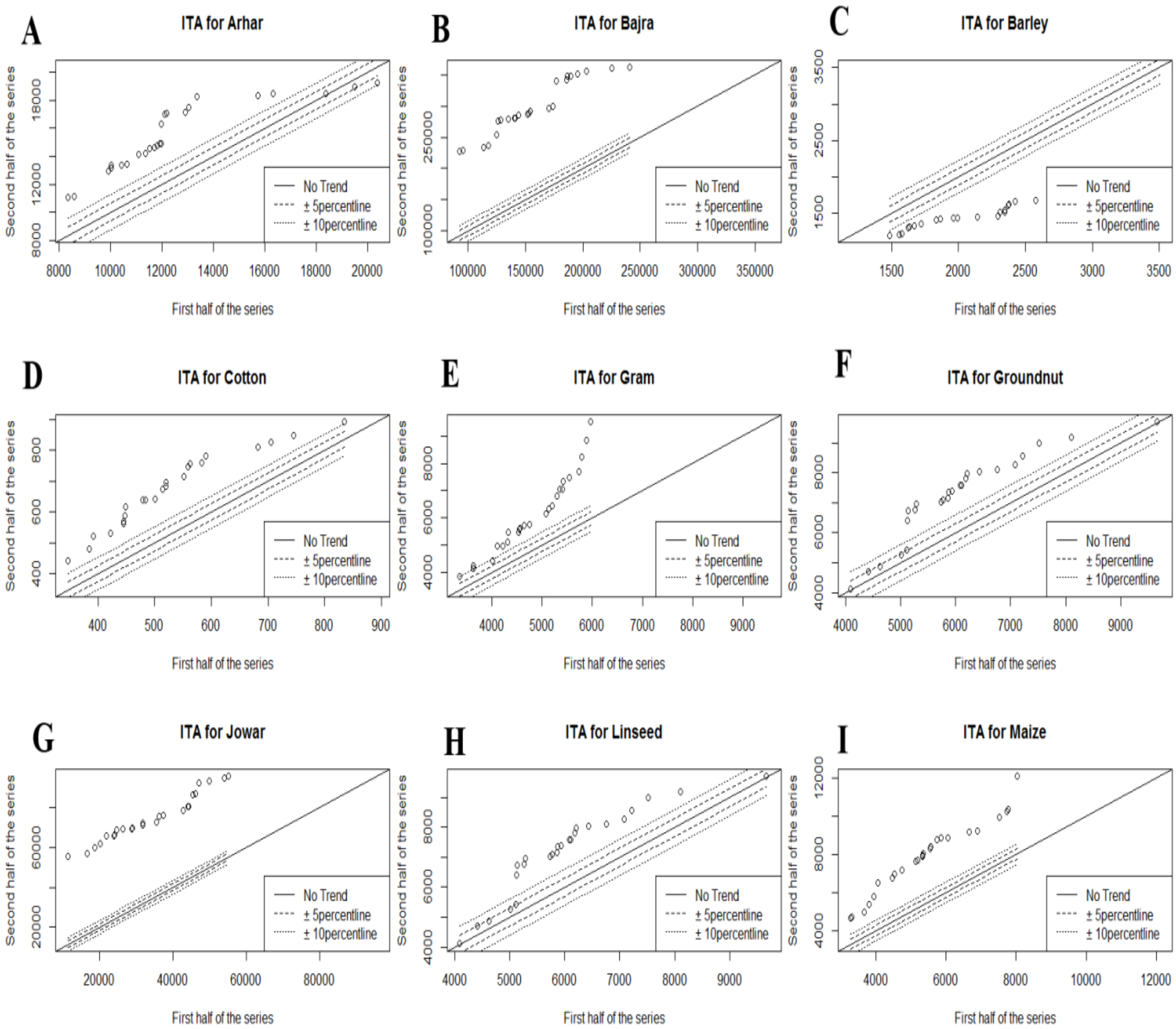
| Climatic Variables and production of various crops | Descriptive statistics | | | | | |
|---|---|---|---|---|---|---|
| | **Mean** | **Standard Deviation** | **Kurtosis** | **Skewness** | **Minimum** | **Maximum** |
| Rainfall | 1388.56 | 108.11 | -0.15 | -0.21 | 1131.86 | 1611.18 |
| Temperature | 24.87 | 0.86 | -1.29 | 0.63 | 23.74 | 26.46 |
| Cotton | 591.75 | 138.15 | -0.77 | 0.37 | 347.70 | 893.00 |
| Rice | 70172.27 | 22622.23 | -1.29 | -0.02 | 30437.90 | 106645.50 |
| Tea | 728.47 | 231.10 | -0.63 | 0.37 | 376.00 | 1208.70 |
| Rapeseed & Mustard | 315.71 | 133.17 | -1.00 | 0.33 | 125.50 | 597.80 |
| Linseed | 6595.12 | 1437.33 | -0.61 | 0.26 | 4091.60 | 9713.90 |
| Maize | 6636.81 | 2057.97 | -0.37 | 0.40 | 3271.90 | 12109.30 |
| Arhar | 14050.71 | 3145.08 | -0.93 | 0.28 | 8347.10 | 20368.10 |
| Sesamum (Til) | 1990.48 | 2648.94 | 0.62 | 1.53 | 31.80 | 8178.70 |
| Jowar | 54306.49 | 23826.01 | -1.12 | -0.01 | 11392.80 | 95849.80 |
| Groundnut | 6595.12 | 1437.33 | -0.61 | 0.26 | 4091.60 | 9713.90 |
| Bajra | 227464.73 | 81291.28 | -1.23 | 0.10 | 92826.10 | 362332.80 |
| Barley | 1855.98 | 546.55 | 1.04 | 1.24 | 1196.10 | 3503.60 |
| Ragi | 10912.51 | 5693.94 | 0.07 | 1.11 | 4893.60 | 24259.50 |
| Wheat | 54306.49 | 23826.01 | -1.12 | -0.01 | 11392.80 | 95849.80 |
| Gram | 5492.08 | 1346.31 | 0.95 | 0.97 | 3356.30 | 9526.30 |

### 4.5.1Trend analysis of the Climatic variables and crops production

The results of the ITA for climate variables and agriculture production for the period of 1967-2016 have been provided in Table 4.2. The allocated variables shown by trend indicators and their respective slopes interpret the value. The trend indicator values of rainfall and temperature are 0.42025 and 0.05126, respectively, which indicates that there was no significant trend in temperature and rainfall. Bajra, Cotton, Gram, Jowar, Maize, Ragi, Wheat, Tea and Rice showed monotonic and significant ($P<0.01$) increasing trend of production (Figure 4.2). Rapeseed (D value of ITA is -8.54) and Barley (D value of ITA is -28.93) showed significant ($P<0.01$) as well as monotonic (Figure 3.2) decreasing trend of its production. Rest of the crops also showed increasing trend of its production (Figure 3.2 and Table 4.2). The trend analysis showed that most edible food grains like Rice, Wheat, Bajra, Jowar and Ragi have increased significantly (Table 4.2), despite having low agricultural land and very low technological development. Therefore, due to rising production of agriculture, the result of climate change cannot be detected from direct observation.

**Table 4.2**: Results of the ITA method for climatic variables and different crops

| **Variables** | **Trend Indicator** | **Slope** | **Variables** | **Trend Indicator** | **Slope** |
|---|---|---|---|---|---|
| Rainfall | 0.42025 | 0.07595 | Til | 84.411 | 6.9289 |
| Temperature | 0.05126 | 0.529 | Jowar | 1633.41 | 12.0498 |
| Cotton | 5.61328 | 2.69052 | Groundnut | 45.7965 | 1.90101 |
| Rice | 1556.21 | 7.67065 | Bajra | 5593.93 | 8.87696 |
| Tea | 15.2262 | 7.07355 | Barley | -28.932 | -3.2616 |
| Rapeseed | -8.5438 | -5.0555 | Ragi | 335.932 | 12.509 |
| Linseed | 45.7965 | 1.90101 | Wheat | 1633.41 | 12.0498 |
| Maize | 97.7765 | 4.51448 | Gram | 54.0624 | 2.80622 |
| Arhar | 116 | 2.30145 | | | |


A
ITA for Arhar
B
ITA for Bajra
C
ITA for Barley
D
ITA for Cotton
E
ITA for Gram
F
ITA for Groundnut
G
ITA for Jowar
H
ITA for Linseed
I
ITA for Maize
No Trend
± 5percentline
± 10percentline
Second half of the series
First half of the series

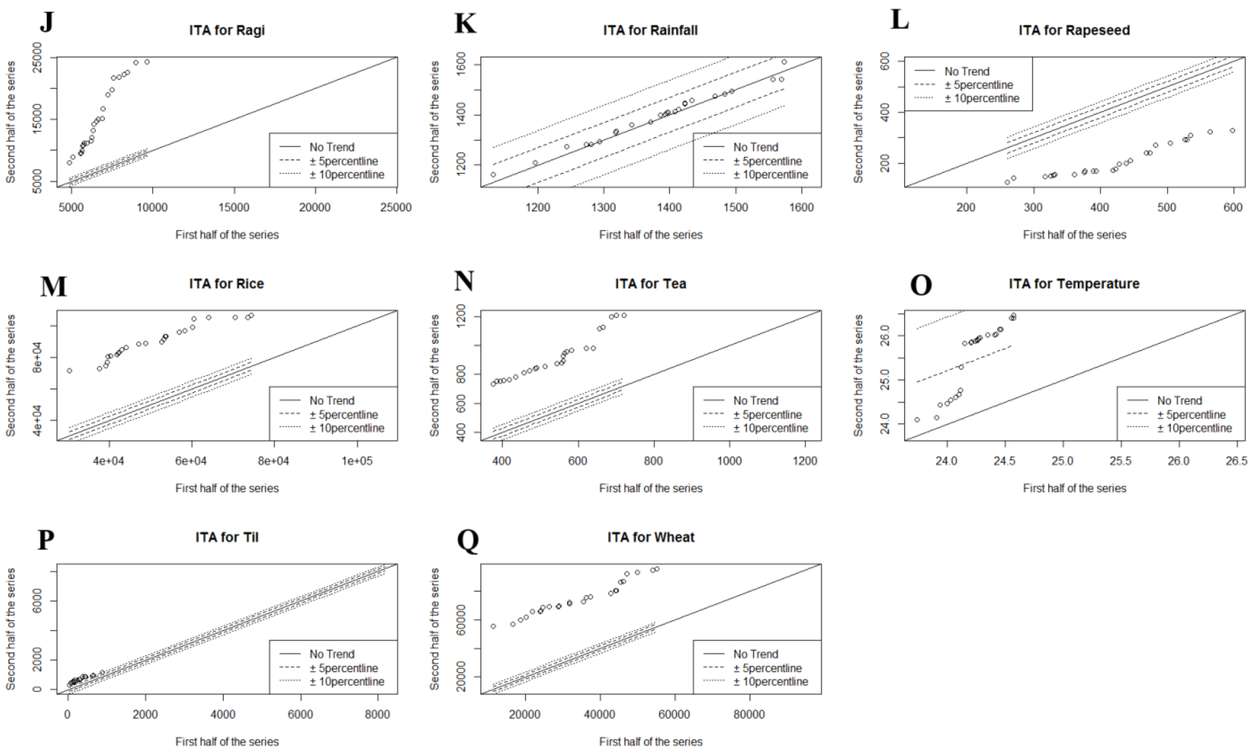



**Figure 4.2**: Innovative trend analyses of climatic variables and agricultural production

**Relationship between climatic factors and crop production**

**Table 4.3**: Multiple linear regression results of temperature and rainfall impacts on crop production

| **Crops** | **Coefficient of determination** | **$R^2$-adjusted** | **Multiple correlation coefficient** |
|---|---|---|---|
| Arhar | 0.089 | 0.07 | 0.298 |
| Bajra | 0.62 | 0.612 | 0.788 |
| Barley | 0.356 | 0.343 | 0.597 |
| Cotton | 0.442 | 0.43 | 0.665 |
| Gram | 0.364 | 0.35 | 0.603 |
| Groundnut | No relation | | |
| Jowar | 0.664 | 0.657 | 0.815 |
| Linseed | No relation | | |

| | | | |
|---|---|---|---|
| Maize | 0.385 | 0.372 | 0.621 |
| Ragi | 0.743 | 0.738 | 0.862 |
| Rapeseed | 0.699 | 0.692 | 0.836 |
| Rice | 0.657 | 0.650 | 0.811 |
| Til | 0.161 | 0.143 | 0.401 |
| Tea | 0.722 | 0.716 | 0.85 |
| Wheat | 0.664 | 0.657 | 0.815 |

In this we used Multiple correlation coefficients for given fifteen crops and climatic variables have been estimated (Table 4.3) and found that some crops are sensitive to the climatic variables variation of. For the crops Ragi (0.862), Rapeseed (0.836), Tea (0.85), Wheat (0.815), Rice (0.811) and Jowar (0.815) indicating sensitivity to temperature and rainfall variation. Moderate sensitive to climatic variable observed in Cotton (0.665), Gram (0.603), Barley (0.788) and Maize (0.621) production Barley (0.597) and Til (0.401). Arhar (0.298) crop shows low sensitivity towards climatic variables (rainfall and temperate) of relationship which means it requires more attention for its production and resistance against climate change. Groundnut and linseed showed no identical correlation with temperature and rainfall variability on their productivity. Although several crops reacted differently to the climatic variables, among the 15 main crops, Arhar and Til (which are one of two main crops of India in terms of cropping production) were found more vulnerable to the consequences of climate change by comparing them to the other thirteen major crops in this study.

### 4.5.2 Relationship between future climatic variables and crops production

**Table 4.4**: Multiple regression results of future temperature and rainfall to estimate crop yields

| **Crops** | **Coefficient of determination** | **$R^2$-adjusted** | **Multiple correlation coefficient** |
|---|---|---|---|
| Arhar | 0.534** | 0.495 | 0.731 |
| Bajra | 0.382* | 0.331 | 0.618 |
| Barley | 0.952** | 0.949 | 0.976 |
| Cotton | No relation | | |
| Gram | No relation | | |
| Groundnut | 0.977** | 0.975 | 0.988 |
| Jowar | No relation | | |
| Linseed | 0.972** | 0.97 | 0.99 |
| Maize | 0.979** | 0.977 | 0.989 |
| Ragi | 0.959** | 0.955 | 0.979 |
| Rapeseed | 0.924** | 0.918 | 0.961 |
| Rice | 0.856** | 0.854 | 0.925 |
| Til | 0.846** | 0.853 | 0.919 |
| Tea | No relation | | |
| Wheat | No relation | | |

*In.NB."** indicates 0.05* indicates a 0.01 level of significance.*

Correlation between future climatic variables and crop production has been undertaken by using multiple regression analysis (Table 4.4). The result indicates a diverse situation for all these crops. The multiple regression analysis shows the higher degree of adjustment $R^2$ in crops like groundnut (0.988), linseed (0.97), maize (0.977), ragi (0.955), rapeseed (0.918), and barley (0.976), which means the prediction for the models fits well for the accuracy of production and climatic variables relationship (Table 3.4). The relationship between predicted crop production and climatic variables is strong. The lowest relationship has been observed for the Bajra crop, with 0.33 $R^2$values (Table 4.4). The performance of Arhar represents a moderate correlation with climatic variables. The highest multiple correlation coefficient of crop productivity is measured in maize (0.989). That means this crop shows greater affinity and resistance against the future changing climatic variables of temperature and rainfall. Multiple correlation coefficients of wheat, tea, jowar, cotton, and gram indicate no effect of climate variables on these crops in terms of production and sustenance. Arhar (0.731) and Bajra (0.618) crops show moderate strength of multiple correlations, which means these crops require attention for their production and response to changing climatic variables. The rest of the crops show a very strong multiple correlation with a coefficient >0.91 indicating that in the future the production of these crops will be increased with the change of climatic variables.

### 4.6. Conclusion & Summary

This study analyzed the climatic variation and its impacts on of Indian agricultural crop productions using a panel dataset from 1967-2016. Crop production was designed according to temperature and rainfall Datasets. First we did ITA to check the trend then multiple regressions to check the impacts of temperature and rainfall on crop production. Next we did prediction using ANN and ARIMA a comparison work till 2030, prediction work added in the fourth chapter.

The results of the ITA for climate variables and agriculture production for the given period study are discussed as the allocated variables are shown by trend indicators and their respective slopes interpret the value. The trend indicator values of rainfall and temperature are 0.42025 and 0.05126, respectively, which indicates that there was no significant trend in temperature and rainfall but the food grains crops production such as Bajra, Cotton, Gram, Jowar,maize, Ragi, Wheat,tea, and Rice showed monotonic and significant ($P<0.01$) increasing trend of production. Rapeseed (D value of ITA is -8.54) and Barley (D value of ITA is -28.93) showed significant ($P<0.01$) as well as monotonic decreasing trend of its production. Rest of the crops also showed increasing trend of its production. The trend analysis showed that most edible food grains like Rice, Wheat, Bajra, Jowar and Ragi have increased significantly, despite having low agricultural land and very poor technological development. Therefore, due to rising of agriculture products, the result of climate change cannot be detected from direct observation.

Multiple correlation coefficients for given fifteen crops and climatic variables have been estimated and the results reflect very strong correlation (r values $\geq$ 0.8) for the crops of ragi, rapeseed, tea , wheat, rice and jowar indicating high crop productivity with the existing nature of temperature and rainfall pattern. Strong correlation ($0.6 \leq r < 0.8$) observed in Cotton (<0.665), gram (0.603), barley and maize production. A crop like barley (0.597) and til (0.401) shows moderate correlation ($0.4 \leq r < 0.6$) and requires accurate framework for its yield and production. Arhar (0.298) crop shows low strength of relationship ($r < 0.4$) which means it requires more attention for its production and resistance against climate change. Groundnut and Linseed showed no correlation with temperature and rainfall. Among the 15 main crops, Arhar and Til were found more vulnerable to the consequences of climate change in comparison to the other thirteen major crops in this study.

Meanwhile, the agriculture production has now been facing adverse impact of climatic shifting with respect to irregular rainfall pattern occurrences which will definitely lead to an adjustment in the cropping pattern. Based on the empirical results, the following key suggestions can be drawn for handling the issue in India. First, the intensity of cropping patterns possibly will rise the cycle of Crops inevitably that will increase food production in the country. Second, the policymaker may furthermore need to increase additional irrigation facilities for enhancing agriculture production Along with food security. Third, the availability of fertilizers and government expenditure on agriculture is very important to mitigate the badeffects of climate alteration (ADB, 2012; Hollaender, 2010). Next, any addition to the consumption of organic fertilizers will possibly enhance the proliferation and efficiency of agricultural products such as wheat, gram, rice, arhar, jowar, maize, ragi, and barley. Finally, forecasting results show that some crops like wheat, rice, cotton, tea, arhar, and somegram, sesamum (Til), Jowar, groundnut, and sugarcane Bajra are very sensitive which are positive with the climatic change as an increase in temperature or rainfall increases its production. However, future research can be conducted at the regional scale and local level, which may help to stabilize the sustainable agriculture sector in the long run.

# Chapter 5

# PREDICTING AND FORECASTING OF CLIMATIC FACTORS AND AGRICULTURAL PRODUCTION

## 5.1. Introduction

In this study, the analysis explored the effects of climate variations over 15 different food-grain and non-food grain crops production of India using the econometric model from 1967-2016 and to forecast these crops output using the Artificial Neural Network (ANN) and ARIMA models up to 2030. Comparison between the existence values of crops production and climatic variables with that of the predicted values by ANN and ARIMA demonstrated a strong correlation, and its performance evaluated by acceptable error values of MAE, MAPE, MSE and RMSE. Hence, these two models are used to forecast the grain productions and climatic variables. Forecasting by ANN and ARIMA model explored that except Barley, Arhar, Linseed and Rapeseed all the other crops production will be increased in upcoming future with the increase of temperature and changes in rainfall pattern. Meanwhile, results also unfold that if the temperature increases, rainfall will become more unstable that will trigger the reduction of crops production. The outcomes of the study can aid in insights into sustainable agricultural crop productions of India, and livelihood patterns, particularly among minor and marginal agricultural families.

## 5.2. Review of Literature

Climate change is a trending topic that has an effect on agricultural crop production, which is heavily reliant on climatic conditions and fluctuations (Kumar and Gautam, 2013; 2014). Climate change has also affected wildlife and people around the globe, as demonstrated by rising temperatures (Cramer et al., 2018), increasingly erratic rainfall (Mehta et al., 2018), recurrent drought (Mehta et al., 2018), sea-level rise (Ho et al.,2018), and glacier melting (Mehta et al.,2018). Climatic factors fluctuate naturally as well as anthropogenic practices such as greenhouse gas emissions, deforestation, urbanisation, advanced industrial growth, use of modern machinery and technology, advanced economic enlargement, and transportation. All these factors have intensified the climatic fluctuations in recent decades (Ahmad et al., 2011). As a result, crop production and productivity have decreased significantly, notably in third-world countries (Sarkar et al., 2019) where livelihoods are primarily dependent on agricultural crop production (Nath and Behera, 2011), resulting in food insecurity (Ho et al., 2018), drought (Sarkar et al., 2019), malnutrition (Ho et al., 2018), and other issues. However, climatic conditions in mid-latitude countries may vary due to the use of advanced agricultural technologies, reduced reliance on agriculture, and increased knowledge of agricultural science such as crop rotation and mixed farming (Cramer et al., 2018). Therefore, investigating the repercussions of climate variation over agricultural crop production is preeminent, especially for countries like India.

The outturns of climatic variations on agricultural productions are being measured using three approaches mostly as biophysical, hedonic, and panel data. Among three approaches, the most important and popular method is the biophysical approach and also known as crop modeling technique (Adams et al., 2013; Aggarwal, 2009; Kurukulasuriya et al., 2006; Lal, 2000; Rao and Sinha, 1994; Rosenzweig and Iglesias, 1994; Reilly et al., 1994; Aggarwal and Sinha, 1993; Kane et al., 1992). Apart from this, the hedonic or Ricardian approach has been applied to explore the long-term phenomenal variations of climate in cropping system of production while considering adaptation (Mendelsohn, 2014; Mendelsohn et al., 2010; (Mendelsohn and Dinar, 2009; Deschênes and Greenstone, 2007; Kurukulasuriya et al., 2006; Kumar and Parikh, 2001). Furthermore, the panel data approach is also a popular method to quantify the reverberations of climate variation upon agricultural productivity (Okiyama et al. 2013; Tokunaga et al. 2015).The change in Climate may influence the economy in various ways. For example, high fluctuation of rainfall leads to irregularity and severity in floods, resulting in decline in the crop production. The interrelation amidst climate change and agricultural productivity are quantified through the aforementioned technique. The increase in surface temperature raises the mean sea level that affects the livelihood of inhabitants in the coastal regions of the world. IPCC (2007) projected that the temperature will increase by 1º-6ºC by 2100. Consequently, the rise of the degree of heat intensity and irregular precipitation patterns will possess a severe impact on crop productivity (Aggarwal, 2008). Therefore, climate change has been severely affecting food production throughout the world including India, which causes food insecurity (Meeting, 2006; FAO, 2008).

There have been many types of research that report the negative consequences of the climate variation over cropping patterns as well as crop production in India, but only a few studies have been performed using empirical techniques regarding this issue. Kumar and Parikh (2001) have estimated production of a few prominent crops which are named as Wheat, maize, Barley, sorghum, and arhar. These crops were prone to adversity due to high climate sensitivity; therefore, it is also critical for the security of food of India. In addition to this, the productions of commercial crops like cotton, sesamum, and sugarcane have also been declined since 1990 (Singh 2012) due to the elevated temperature. It is estimated and found that the changes in climate would result in a decline in the production of potato and paddy and potentially endanger food safety for nearly one billion population of the country by 2060. Any fluctuation in temperature below the normal has a dismal and numerically noteworthy influence on linseed production (Singh 2012). Kumar et al. (2011) reported that irrigated areas of maize, mustard, Wheat, Rice, and sorghum in the seaside region, North Eastern Region, and Sahyadri region or the Western Ghats have been declining because of the negative effects of variations which have been occurring in climate.

Hundal (2007) stated that a mean temperature spiral by 1º-3º C above normal range resulted in decrease of paddy and wheat production by 3 percent and 10 percent respectively inside the state of Punjab. The unreliability in the pattern of precipitation occurrences has inimically slowed down the cropping of Jowar in Karnataka that led to food insecurity among farmers (Kaul and Ram, 2009). According to Geethalakshmi et al. (2011), the production of paddy crop in Tamilnadu has declined by more than 41% due to the temperature reaching the maximum 40ºC. Furthermore, Saseendran et al. (2000) projected the paddy crop and temperature in the state of Kerala up to 2049 and found that temperature would cross 50ºC which would significantly decline the production of paddy in the state. Saseendran et al. (2000) reported, rising of each 1-degree temperature would reduce crop production by up to 6 percent. Srivastava et al., (2010) argued that the production of monsoonal crop i.e. sorghum may decline at 14 percent and 2 percent respectively by the year 2020 in regions of central

India and southern central India only in response to the phenomenal climatic variance. Empirical evidence clearly indicates that rising in atmospheric heat has significantly dismissive consequences over the production of Rice, maize, Jowar (sorghum), Bajra and Barley (Kalra et al., 2008; Geethalakshmi et al., 2011). The agricultural produce for Gram along with Ragi has a gloomy effect due to increase in the maximal degree of heat, however, the produced output of Wheat and Tur have increased firmly due to the increase in the maximal intensity of heat (Kumar and Parikh, 2001; Kaur and Hundal, 2007). Kapur et al., (2009) estimated a potential 30% reduction in crop production in the middle of 21st as intensification occurred in surface warming with a change in the rate of precipitation, which could lead to a decline in arable land triggering crop production stresses in India. Evidence shows climate variability has negatively influenced agricultural crop production. Moreover, most of the empirical studies have either covered single crops or multiple crops with limited geographical coverage. Therefore, it has found to be imperative to determine the overall effect of climate variability over major food grains along with a focus on profitable and sustainable crop production choices for ensuring food security in India (Hollaender, 2010). Our study aims at testing the hypothesis which says, agricultural output in the country of India has climate- sensitivity in nature, and any variation in rainfall precipitation and temperature patterns significantly influence the production of the food grain. The development of a proper policy guideline related to the irrigation system, that will have possibly alleviated the detrimental consequences of climate sensitiveness on Wheat, paddy, sorghum, Tur , and Bajra, along with managing the food safety in India (Kar and Kar, 2008; Singh, 2012; Ranuzzi and Srivastava, 2012, Sing; 2012).

The development of the agricultural sector executes a pivotal share in overall socio-economic wellbeing of the people in India. Critically, the account of agricultural share in Gross Domestic Product (GDP) as well as in employment has been reduced in times. Although, the benefit of cropping systems is still highly significant and important for economic development (Mall et al., 2006). In a country like India, extensive works have been done during the past few decades assessing nature and magnitude in crop yield fluctuations with a focus on climate change issues in the last decade. Nevertheless, those cited works were concentrated over the reverse impact of climate change ability on some of the selected crops only. Considering limited coverage in earlier studies till the time, we have set two broad objectives here, first one; to analyze the repercussions of climate variability over different crops and measure the robustness of the methods using different statistical techniques.

Another objective is to simulate and estimate the future climatic factors and the trends in different crop production using the Artificial Neural Network (ANN).

The application of ANN to forecast future production is a comparatively new contribution to the agricultural sector. The ANN establishes relationships to develop and formulate models for the future prediction in crop productivity (Pachepsky et al., 1996). Climate Change is a threat to food production with wider impact on social and economic development of a nation (Matsui, 1997). Occurrences of extreme weather events have significantly affected the yield and the crop growth (Zhang et al., 2016). An agricultural assessment and management technique requires accurate yield prediction nowadays. ANN model investigates the yield for particular climatic conditions (Wan et al., 2006). The innovative trend analysis (ITA) produces extensive interpretations regarding trends and variation of precipitation (Alifujiang et al., 2020). Climate change has impacts on temperature, precipitation, and runoff and soil moisture. Innovative trend analysis records yields and reliable results from different parts of the world (Sen et al., 2016). To determine the disparity of Temperature and precipitation trends at regional and national scale ITA method is most reliable and produces more viable results (Cui et al., 2017).

The novelty of this current research work is that the application of ANN and ARIMA which is used to forecast of upcoming production and also it is a comparatively modern contribution in the agricultural sector as the country like India. Moreover, past studies mostly have done on some specific crops but here analyzed the impact and forecasting on various oil seed crop, cash crop and grain crop. Therefore, the study will be completely favorable as it worked on national and regional level in India. Therefore, depending on the past literatures and research gaps, the aims of the present research are: (i); to analyze the repercussions of climate variability over different crops and measure the robustness of the methods using different statistical techniques, (ii) to simulate and estimate the future climatic factors and the trends in different crop production using the Artificial Neural Network (ANN) and ARIMA.

## 5.3. Methodology

### Artificial Neural Network (ANN)

The ANN is a statistical model that is abstract and black box. It's been used in a variety of areas, covering decision-making, pattern analysis, automated control systems, robotics, and many others (Conforti et al., 2014). Complex, non-linear, and unbalanced data sets are no problem for it. As a result, it can mimic human brain activity and also generalise and model output from a vast range of complex inputs. As a result, scholars from all over the world have been widely used to solve problems in a variety of fields. The ANN model will act as an expert, identifying complex statistical patterns that non-experts are unable to identify. It will function on categorical, constant, and binary data while remaining true to the data's assumptions and characters (Wang et al., 2016).

Numerous neural network models have been extensively used (Moayedi et al., 2019; Harmouzi et al., 2019; Sevgen et al., 2019; Falah et al., 2019; Termehet al., 2018; Zhao et al., 2018; Garosi et al., 2019; Huang et al., 2018). The multilayer perceptron (MLP) architecture based on feed-forward was used in this analysis. Each layer includes several neurons or nodes, each of which is bound to the next layer's nodes with a certain weight. It is their role to pass knowledge. As a result, the neural network has been developed. The MLP trains the network using the back propagation algorithm until the expected and performance values of the network are as similar as possible. As a result, the results are produced by the ANN model.

Table 5.1: Calculated variables of the algorithms for different climatic and crops used in the study

| | Number of Inputs (Lag) | Number of hidden layer | Seed | Activation function in hidden unit | Number of iteration | Learning algorithm | Learning rate | Momentum |
|---|---|---|---|---|---|---|---|---|
| Rainfall | 10 | 8 | 15 | Sigmoid | 2000 | Back propagation | 0.1 | 0.2 |
| Temperature | 15 | 8 | 15 | Sigmoid | 2000 | Back propagation | 0.1 | 0.2 |
| Cotton | 10 | 8 | 15 | Sigmoid | 2000 | Back propagation | 0.1 | 0.2 |
| Rice | 15 | 8 | 15 | Sigmoid | 2000 | Back propagation | 0.1 | 0.2 |
| Tea | 10 | 8 | 15 | Sigmoid | 2000 | Back propagation | 0.09 | 0.2 |
| Rapeseed & Mustard | 10 | 8 | 10 | Sigmoid | 2000 | Back propagation | 0.1 | 0.2 |
| Linseed | 15 | 8 | 10 | Sigmoid | 1500 | Back propagation | 0.09 | 0.2 |
| Maize | 10 | 8 | 12 | Sigmoid | 2000 | Back propagation | 0.1 | 0.2 |
| Arhar | 15 | 8 | 20 | Sigmoid | 2000 | Back propagation | 0.09 | 0.2 |
| Sesamum (Til) | 15 | 8 | 5 | Sigmoid | 2200 | Back propagation | 0.1 | 0.23 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Jowar | 15 | 9 | 20 | Sigmoid | 42000 | Back propagation | 0.19 | 0.4 |
| Groundnut | 10 | 8 | 20 | Sigmoid | 3200 | Back propagation | 0.19 | 0.3 |
| Bajra | 15 | 9 | 20 | Sigmoid | 50000 | Back propagation | 0.19 | 0.42 |
| Barley | 15 | 8 | 20 | Sigmoid | 5000 | Back propagation | 0.19 | 0.22 |
| Ragi | 10 | 8 | 20 | Sigmoid | 30000 | Back propagation | 0.19 | 0.22 |
| Wheat | 15 | 8 | 22 | Sigmoid | 38000 | Back propagation | 0.18 | 0.22 |
| Gram | 15 | 7 | 20 | Sigmoid | 1000 | Back propagation | 0.19 | 0.22 |

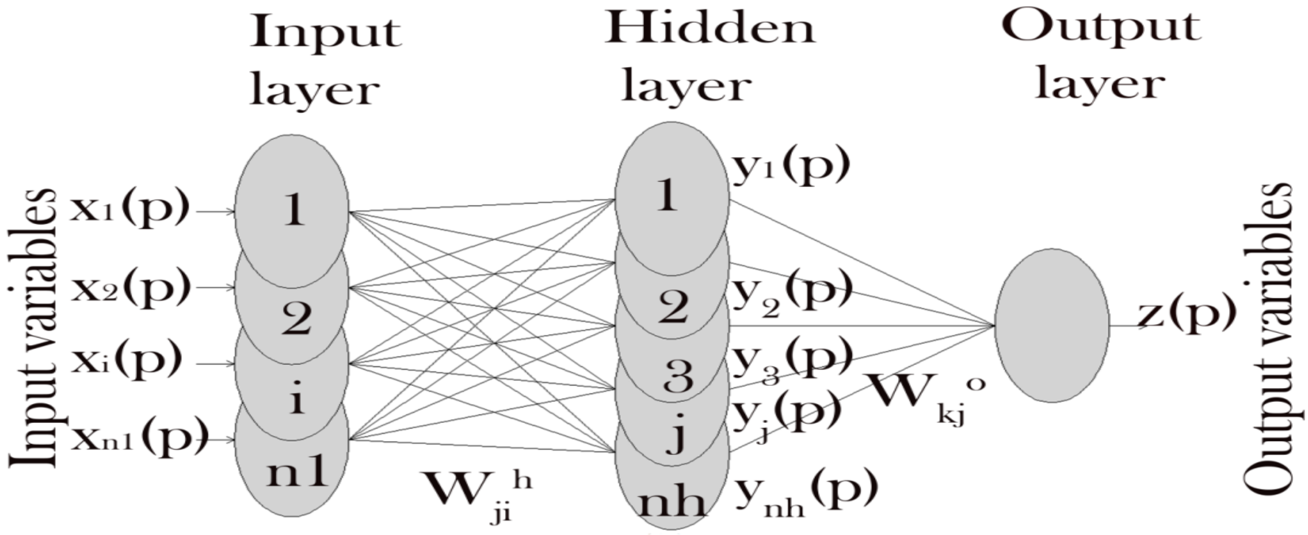



Figure 5.1: The schematic structure of an Artificial Neural Network (ANN)

**ARIMA**

A time series is a compilation of data obtained at frequent intervals over time. Time series analysis is a mathematical approach that uses such statistical results. Many decisions in hydrological processes and decisions about water resource exploitation are dependent on time series estimation and interpretation. The first goal of time series analysis is to consider or model the random function that contributes to the series observation, and the second goal is to forecast future series values based on the past values. In hydrology and water management, linear models account for the bulk of time series models. The Autoregressive Integrated Moving Average (ARIMA) model is the most standard framework of time series analysis. The method must be static to use the previous time series models, so the ARIMA model was created to solve this problem. The time series of previous models was believed to be unchanged. The absolute number of roots in a static time series is greater than one. If the time series is not static, it must be differentiated in order for it to become static. When a non-static time series is separated d times with a p times autoregressive process and a q times moving average process, the ARIMA (p, q, d) time series is obtained. The Box-Jenkins approach is another name for the ARIMA modeling technique. In 1976, Box-Jenkins developed a prediction method known as ARIMA modelling. ARIMA is a tool for generating time series results. The data production method, according to this principle, links mathematical interactions between past and current variables. The most important aspect of this modeling is deciding the process form and degree. A tool for deciding these characteristics is provided by Box-Jenkins.

### 5.4. Empirical Findings

#### 5.4.1Prediction and forecasting of climatic variables and 15 different crops using ANN

It is essential to check the performance of the model by predicting existing data before it is used for forecasting. If there find a close adjacency between actual data and predicted data with lower error values, then it can be used for further analyses. Present study predicted climatic variables and different crops by optimizing the variables of ANN and found that there existed very close adjacency between actual and predicted data of climatic variables and 15 different crops (Figure 5.2). Correlation between actual and predicted values of all the 15 crops and 2 climatic variables showed very strong correlation with $R^2$ values greater than 0.82. Except Rice (0.86) and Barley (0.82), rest of the crops showed higher correlation of $R^2$ greater than 0.92. Correlation between actual and predicted values of temperature and rainfall also showed very strong correlation ($R^2$>0.82). Table 5.2 shows the MAE, MAPE, RMSE and MSE between actual and predicted values of crops and climatic variables. The results of these errors suggest that the performance of the model for predicting climatic parameters and different crop productions is good enough and proved to be used for future forecasting.

**Table 5.2:** Model performance evaluation using different error measures

| **Error Measures** | Rainfall | Temperature | Cotton | Rice | Tea | Rapeseed | Linseed | Maize | Arhar | Sesamum | Jowar | Groundnut | Sugarcane | Bajra | Barley | Ragi | Wheat | Gram |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mean absolute error** | 2.68 | 0.082 | 5.47 | 155 | 14.01 | 5.85 | 23.1 | 42.63 | 54.32 | 54.59 | 85.07 | 3.76 | 63.12 | 84.21 | 14.58 | 68.24 | 39.58 | 10.08 |
| **Mean absolute percentage error** | 0.19 | 0.33 | 0.96 | 0.85 | 1.74 | 2.62 | 2.86 | 0.74 | 0.36 | 8.02 | 0.13 | 0.055 | 4.78 | 0.032 | 0.96 | 0.65 | 0.068 | 0.16 |
| **Root mean squared error** | 5.92 | 0.1 | 9.13 | 19 | 17.49 | 8.71 | 11.34 | 57.96 | 74.88 | 71.9 | 104.14 | 5.03 | 16.32 | 98.16 | 17.77 | 84.13 | 64.02 | 14.29 |
| **Mean squared error** | 35.15 | 0.011 | 83.34 | 380 | 306.21 | 76.03 | 95.36 | 3359 | 5607.6 | 5183.42 | 1084.5 | 25.32 | 152.18 | 963.6 | 315.8 | 7078.65 | 4099.78 | 204.45 |

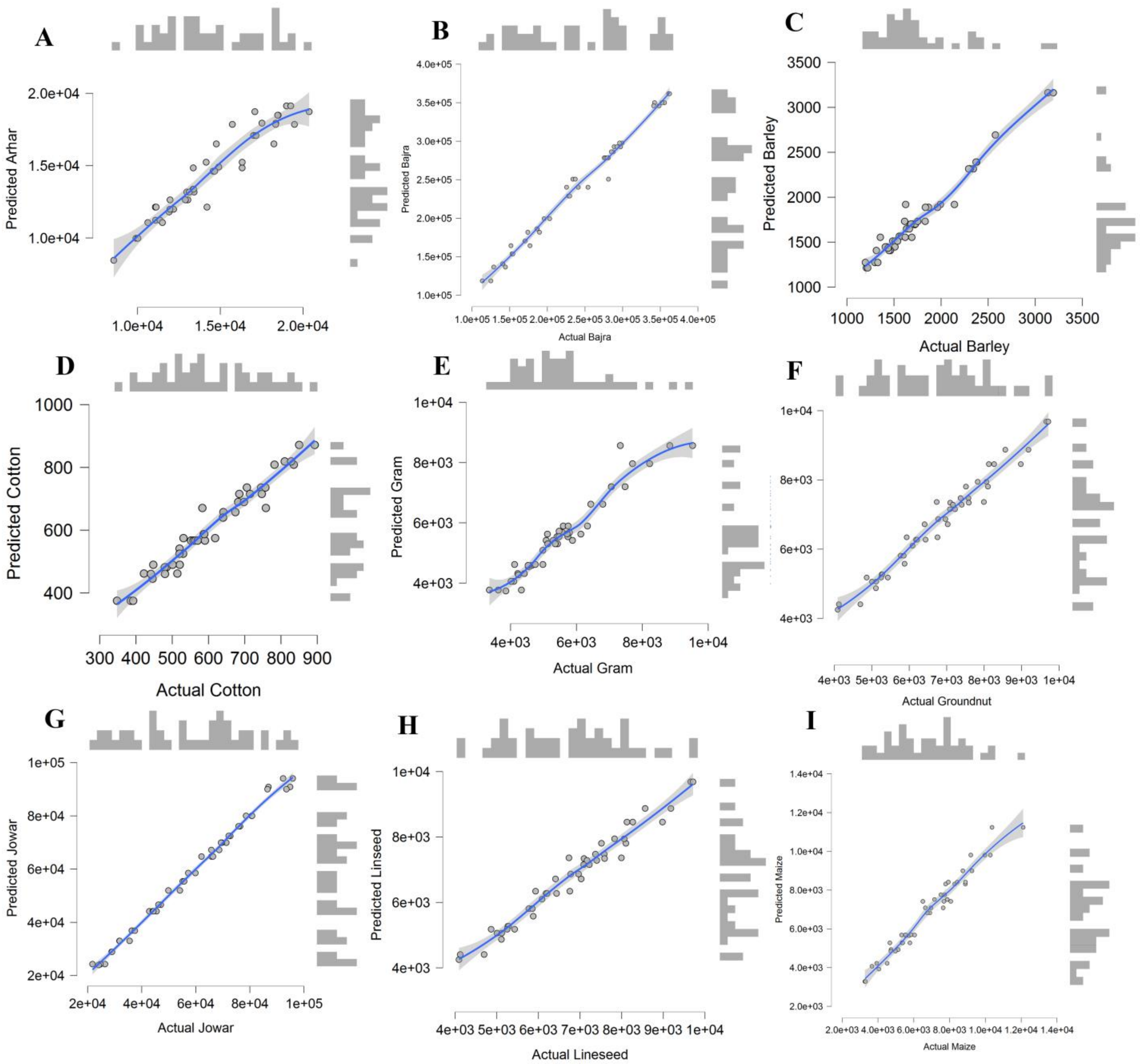



**Figure5.2:** Comparison between actual and predicted values of climatic variables and different crops (Continued)

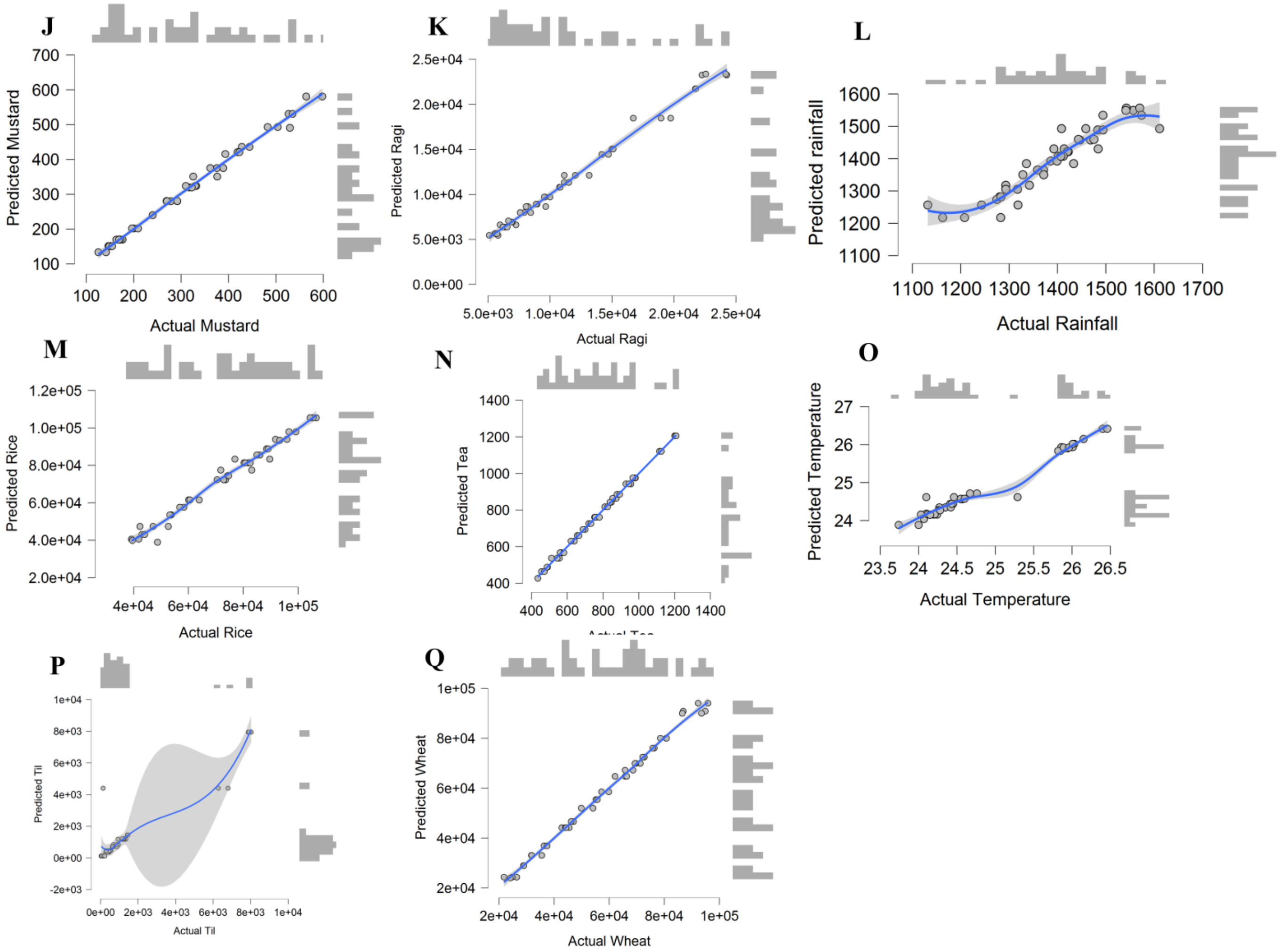
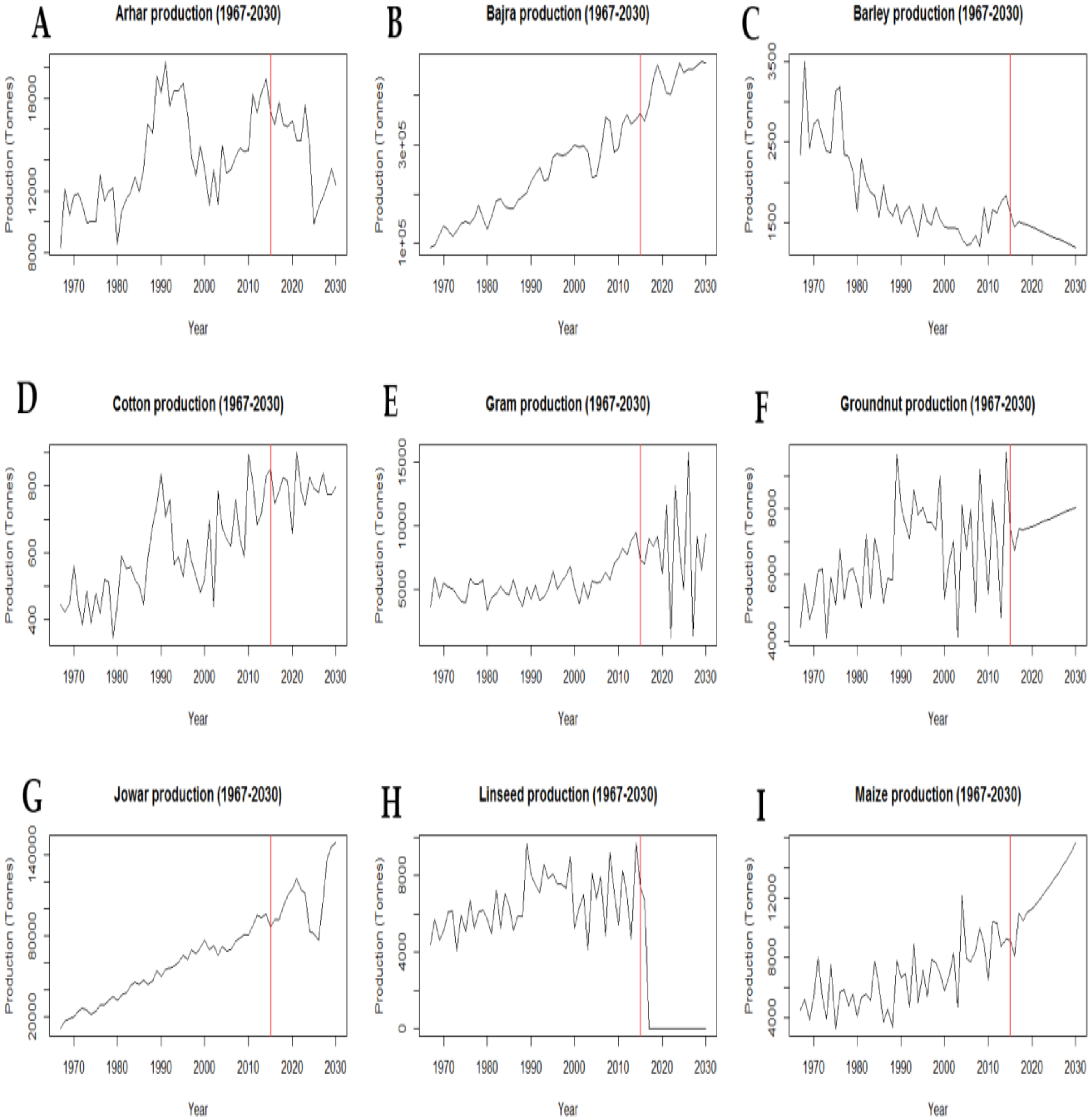



**Figure 5.2**: Comparison between actual and predicted values of climatic variables and different crops


A
Arhar production (1967-2030)
B
Bajra production (1967-2030)
C
Barley production (1967-2030)
D
Cotton production (1967-2030)
E
Gram production (1967-2030)
F
Groundnut production (1967-2030)
G
Jowar production (1967-2030)
H
Linseed production (1967-2030)
I
Maize production (1967-2030)
Production (Tonnes)
Year
1970
1980
1990
2000
2010
2020
2030

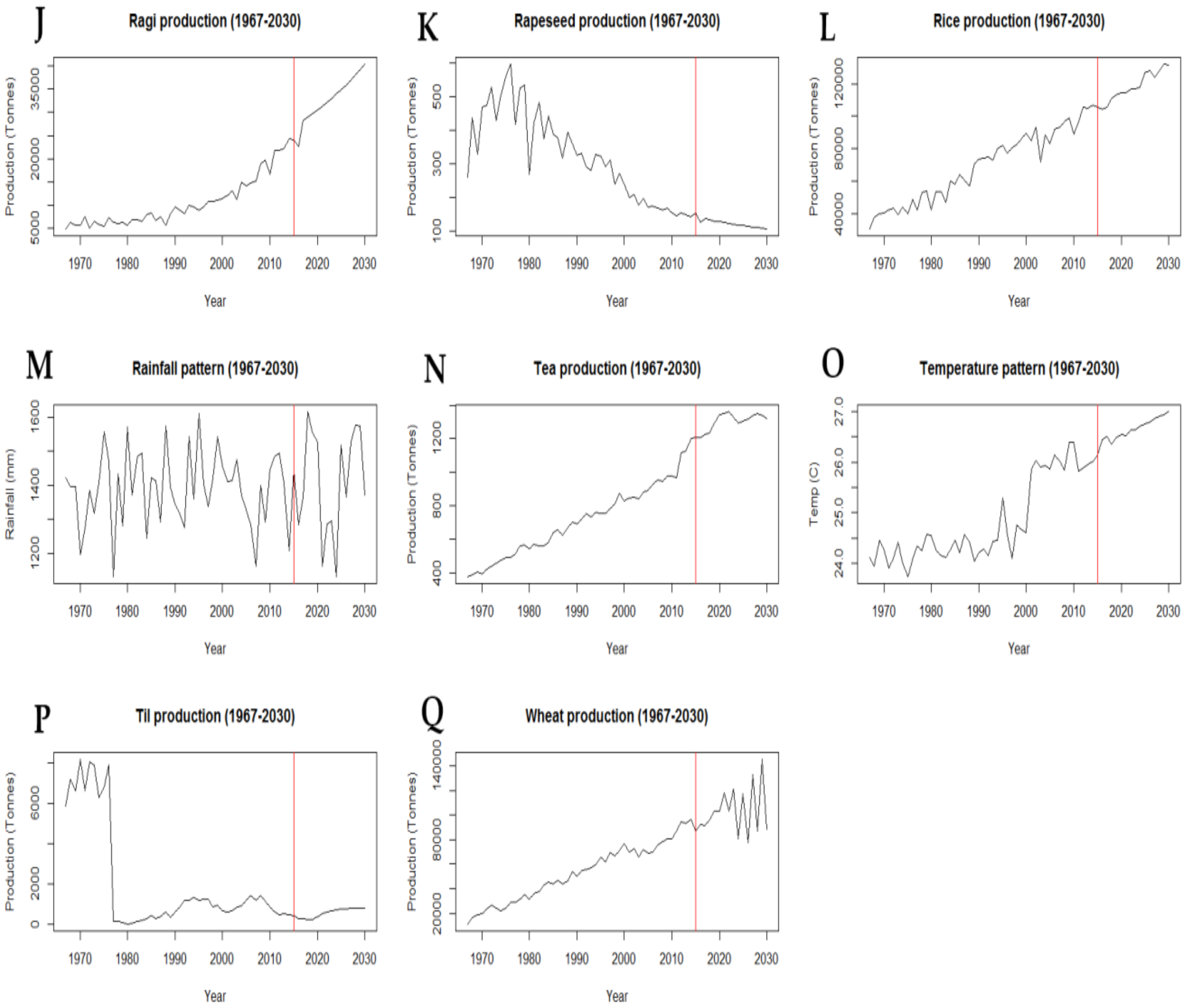



**Figure 5.3**: Forecasting of climatic variables and 15 different crops using machine learning algorithms of ANN model

Future forecasting of crop production and climatic variables in India for the period of 2017–2030 has undertaken using the ANN model (Figure 5.3). No significant change of trend of future rainfall has observed. On the contrary, significant increasing trend of future temperature has found by ANN model. Production of Barley, Arhar, Linseed and Rapeseed will be decreased. Whereas, production of Rice, Ragi, Tea, Maize, Jowar, Bajra and Cotton will be highly increased by 2030. Moderate future increasing trend of production of Til, Groundnut and Gram from 2017-2030 has explored. In conclusion, except Barley, Arhar, Linseed and Rapeseed all the other crops production will be increased in future with the increase of temperature and change of rainfall pattern.

### 5.4.2Prediction and forecasting of climatic variables and 15 different crops using ARIMA

We used ARIMA methods to predict climatic parameters and crop production up to 2030. Before using the model to forecast, it is important to validate its efficiency by forecasting current data. It is addressed that if real results and expected data are closely matched, and error measurements mean that the model's accuracy is satisfactory, we can use it for further analysis. By refining the parameters of ARIMA, we were able to forecast climatic parameters and various crops, and we discovered that the real and expected climatic parameters and crops were very similar (Figure 5.4). The coefficient of determination indicates that the ARIMA performed admirably.

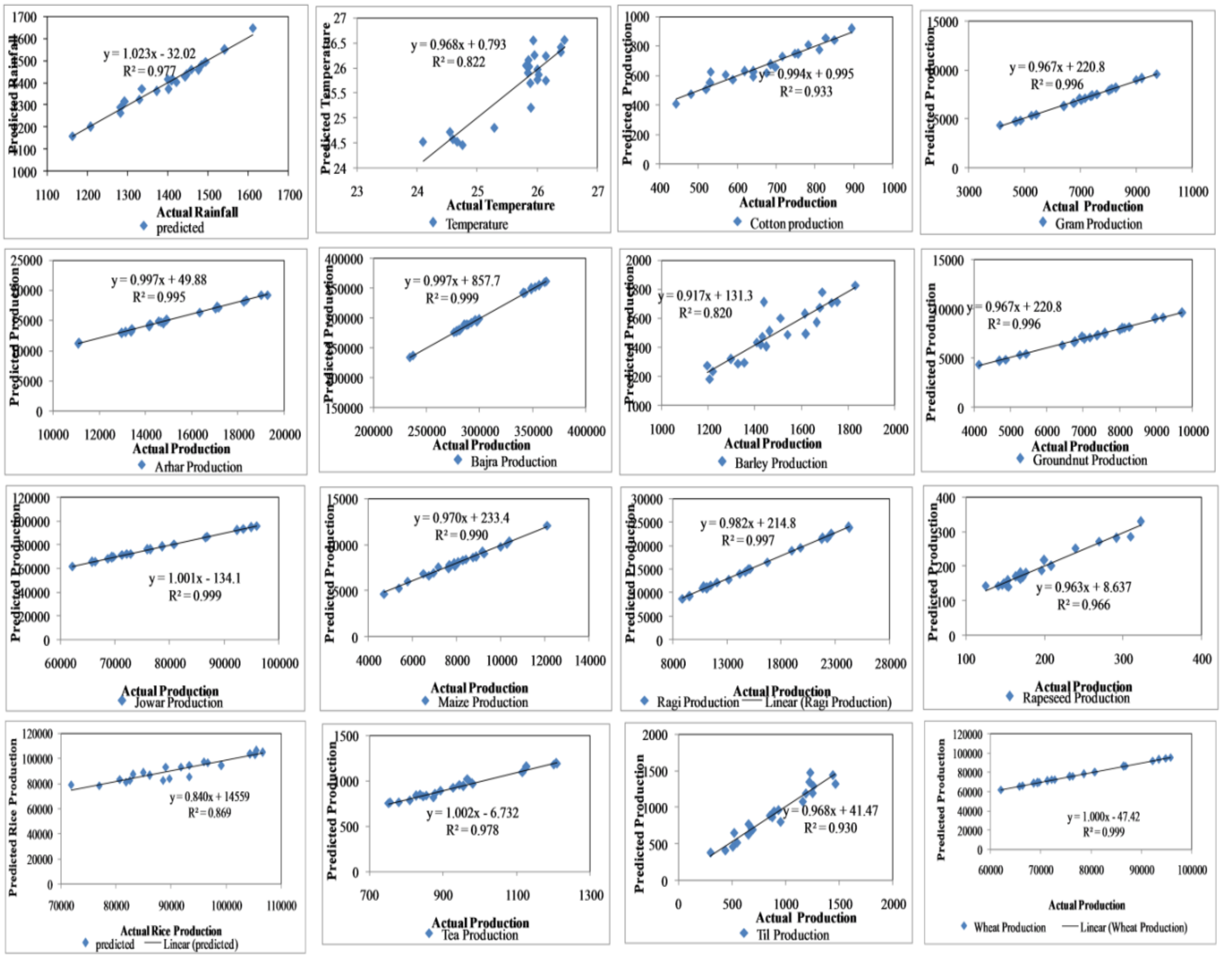


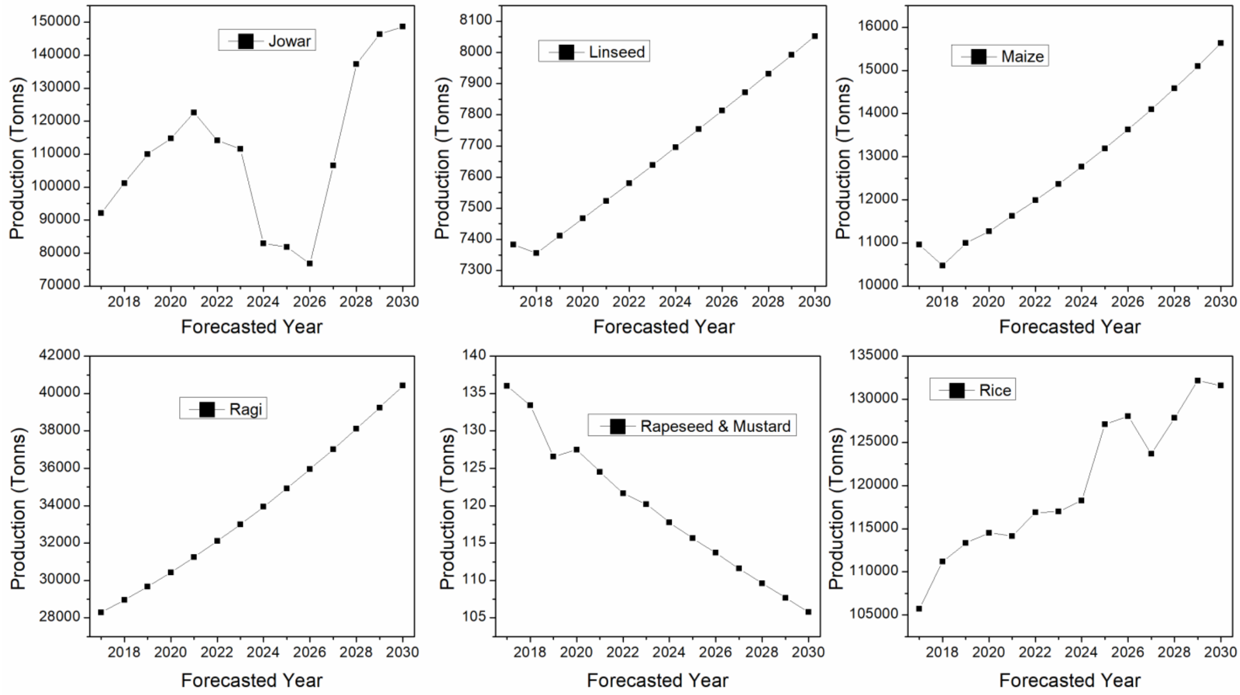

**Figure 5.4** the comparison between actual and predicted values of climatic parameters and different crops

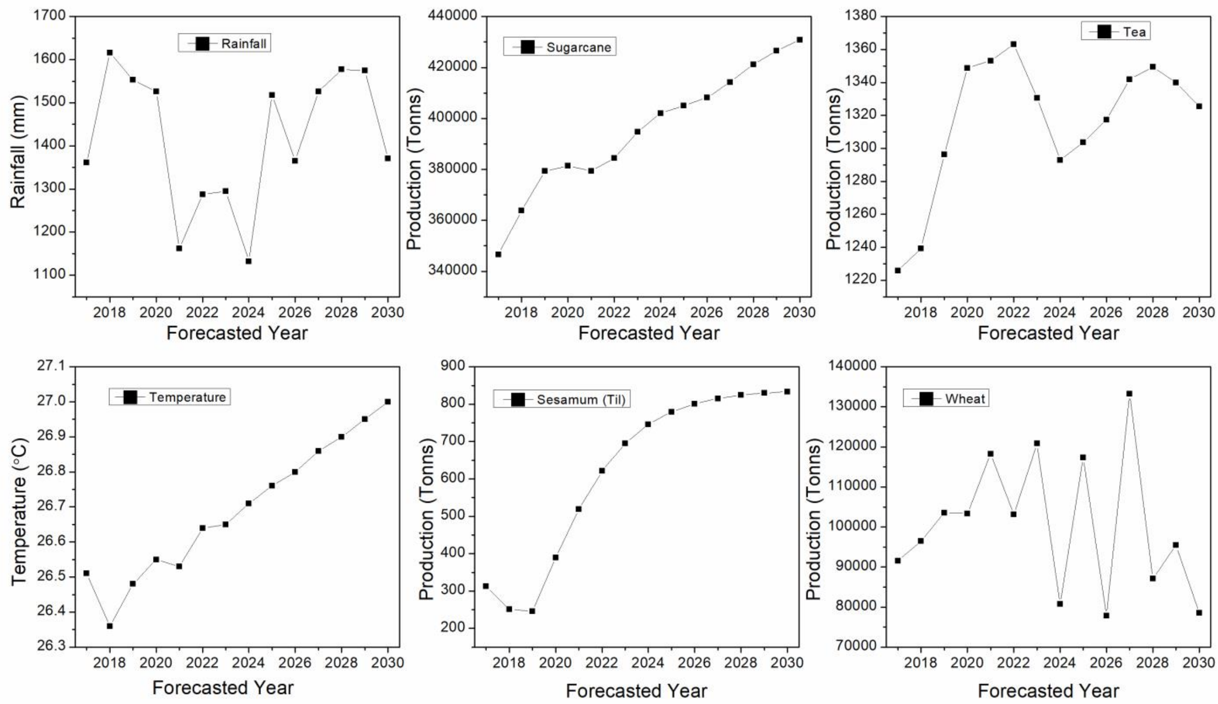
We used mean absolute error, mean absolute percentage error, root means squared error, and mean squared error to quantify the difference between real and expected values of climatic parameters and crop production. The effects of these errors indicate that the model's efficiency in forecasting climatic parameters and crop yields is very high. Table 5.3 predicts that, with rising temperatures, rainfall will dip marginally by 2030. On the other hand, projected production of some crops including Gram, Sesamum (Til), Jowar, Groundnut, Sugarcane Bajra are projected to increase, whereas some crops such as Arhar, wheat, rice cotton and tea production, which are climate sensitive, will be most adversely impacted by temperature increases. We looked at how fluctuations in rainfall and rising temperatures have affected various crops in different ways (Table 5.3). Increased temperatures and rainfall have helped Arhar as the conditions during the vegetation cycle are very humid and wet (Table 5.3).

**Table 5.3** shows the forecasting of crops using temperature rainfall from 2017 to 2030 for different crops

| Forecasted Year | Dlog (Temp) | Dlog(rainfall) | Cotton | Rice | Tea | Rapeseed & Mustard | Linseed | Maize | Arhar | Sesamum (Til) | Jowar | Groundnut | Sugarcane | Bajra | Barley | Ragi | Wheat | Gram |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Dlog(Prod) | D(Prod) | Dlog(Prod) | Dlog(Prod) | Dlog(Prod) | Dlog(Prod) | Dlog(Prod) | Dlog(Prod) | D(Prod) | Dlog(Prod) | D(Prod) | D(Prod) | D(Prod) | Dlog(Prod) | D(Prod) | Dlog(Prod) |
| 2017 | 26.51 | 1360.983 | 782.7198 | 105722.2 | 1225.73 | 136.02 | 7382.88 | 10958.84 | 17806.21 | 312.76 | 92138.49 | 7382.88 | 346657.3 | 379557.9 | 1511.4 | 28297.99 | 91506.49 | 8989.405 |
| 2018 | 26.36 | 1615.96 | 826.1507 | 111169.2 | 1239.408 | 133.42 | 7355.34 | 10471.1 | 16289.05 | 250.91 | 101183.5 | 7355.34 | 363848.6 | 429692.6 | 1486.6 | 28954.39 | 96468.31 | 8404.586 |
| 2019 | 26.48 | 1553.112 | 811.6937 | 113331.2 | 1296.319 | 126.55 | 7411.05 | 10995.43 | 16143.58 | 245.86 | 109953.2 | 7411.05 | 379336.2 | 460812 | 1461.7 | 29667.69 | 103539.8 | 9149.445 |
| 2020 | 26.55 | 1525.696 | 656.3143 | 114518.9 | 1348.764 | 127.51 | 7467.18 | 11267.17 | 16531.4 | 389.28 | 114783.8 | 7467.18 | 381393.6 | 432618.7 | 1436.8 | 30432.85 | 103384.1 | 6278.099 |
| 2021 | 26.53 | 1161.904 | 898.1491 | 114148.4 | 1353.14 | 124.53 | 7523.74 | 11628.98 | 15228.44 | 518.96 | 122560 | 7523.74 | 379409.6 | 405073.4 | 1412 | 31245.98 | 118248.7 | 11647.89 |
| 2022 | 26.64 | 1287.554 | 786.772 | 116898.8 | 1363.129 | 121.67 | 7580.73 | 11987.65 | 15295.69 | 621.25 | 114142.9 | 7580.73 | 384521.8 | 402963.7 | 1387.1 | 32104.11 | 103108.1 | 1196.801 |
| 2023 | 26.65 | 1294.861 | 740.8432 | 116977.5 | 1330.675 | 120.2 | 7638.15 | 12369.89 | 17537.66 | 695.28 | 111553.5 | 7638.15 | 394711.2 | 433520.9 | 1362.2 | 33005 | 120853.3 | 13187.51 |
| 2024 | 26.71 | 1132.248 | 823.8914 | 118246.7 | 1292.947 | 117.79 | 7696.00 | 12769.61 | 14822.77 | 746.02 | 82982.43 | 7696 | 402036.7 | 465048.7 | 1337.4 | 33947 | 80755.41 | 8148.999 |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2025 | 26.76 | 1518.031 | 791.8264 | 127096.4 | 1303.662 | 115.64 | 7754.29 | 13189.82 | 9892.923 | 779.64 | 81826.32 | 7754.29 | 404967.7 | 445671.8 | 1312.5 | 34928.96 | 117388.2 | 4959.362 |
| 2026 | 26.8 | 1365.574 | 780.1965 | 128033.1 | 1317.45 | 113.71 | 7813.02 | 13631.1 | 10929.33 | 801.44 | 76789.32 | 7813.02 | 408140.8 | 452607.9 | 1287.6 | 35950.11 | 77844.89 | 15793.11 |
| 2027 | 26.86 | 1525.765 | 838.2129 | 123709.4 | 1341.844 | 111.61 | 7872.20 | 14094.78 | 11588.9 | 815.39 | 106520.6 | 7872.2 | 414242.1 | 453215.7 | 1262.8 | 37010.02 | 133233.5 | 1325.01 |
| 2028 | 26.9 | 1577.47 | 774.7671 | 127839.7 | 1349.464 | 109.62 | 7931.83 | 14582.12 | 12355.39 | 824.25 | 137332.4 | 7931.83 | 421231.3 | 461472 | 1237.9 | 38108.55 | 87060.03 | 9167.557 |
| 2029 | 26.95 | 1574.487 | 771.7588 | 132163.1 | 1339.811 | 107.69 | 7991.90 | 15094.45 | 13413.91 | 829.83 | 146332.7 | 7991.9 | 426625.5 | 467511.7 | 1213 | 39245.75 | 95430.2 | 6525.247 |
| 2030 | 27 | 1371.015 | 795.0386 | 131587.6 | 1325.559 | 105.76 | 8052.44 | 15633.23 | 12423.93 | 833.35 | 148701.8 | 8052.44 | 430858.5 | 464921.4 | 1188.2 | 40421.91 | 78529.35 | 7431 |


Jowar
Linseed
Maize
Ragi
Rapeseed & Mustard
Rice
Production (Tonns)
Forecasted Year


Rainfall
Sugarcane
Tea
Temperature
Sesamum (Til)
Wheat
Rainfall (mm)
Production (Tonns)
Temperature (°C)
Forecasted Year

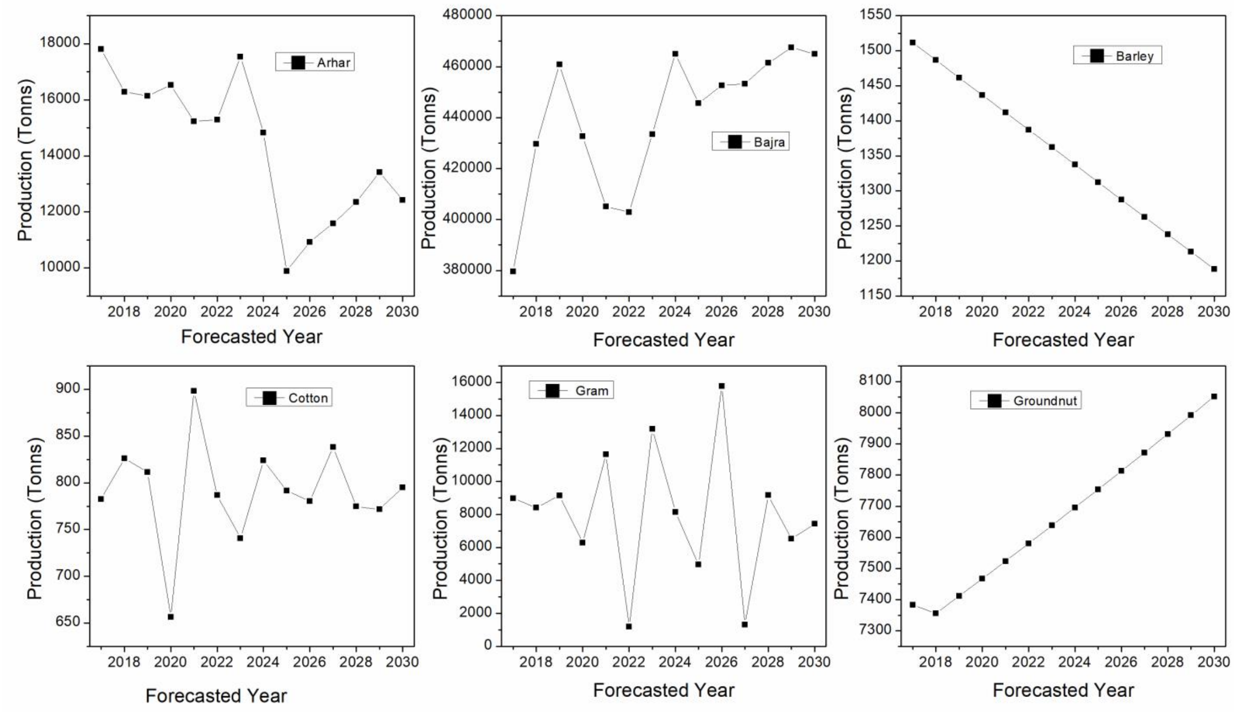



**Figure 5.5**: Forecasting of climatic variables and 15 different crops using ARIMA model

**Comparisons between ANN and ARIMA**

Both ANN and ARIMA model are different mathematically. ANN is a machine learning model, while the ARIMA is a statistical model. Both the model has been used for forecasting the time series datasets. In the era of artificial intelligence, it is expected that ANN would perform better than any statistical techniques. But many researchers recommended that ARIMA can perform like ANN. Therefore, in the present study, both the models have been utilized. The error measures between actual and predicted data for both models showed that the performances of the both models are satisfactory. But quantitatively it can be stated that ANN model outperforms ARIMA model.

## 5.5. Discussion

Indian economy is mainly based on agricultural activities. Climate change is a worldwide common issue which puts adverse impacts on agricultural production, environmental activities, and socio-economic systems and so on. It is very imperative to assess the trend of past climatic variables (specially temperature and rainfall) as well as several crops and past along with future correlation of crops production with the changing climatic variables. Most of the researches has undertaken to assimilate the immensity and phenomena of gains or crops yields failures at local levels as well as national level associated with climatic variability in past far from recent decades and limited researches have been done in India in recent time (Sinha and Swaminathan, 1991; Abrol et al., 1991; Aggarwal and Sinha, 1993; Rao and Sinha, 1994; Aggarwal and Kalra, 1994; Mathauda and Mavi, 1994; Gangadhar Rao et al., 1995; Mohandass et al., 1995; Saseendran et al., 1999; Aggarwal and Mall, 2002; Mall and Aggarwal, 2002; Attri and Rathore, 2003; Aggarwal, 2003; Mall et al., 2004). Present study has undertaken these tasks. ITA explored no significant trend of climatic variables, whereas most of the crops showed significant increasing trend for the period of 1967-2016. The actual emphasize of this study is that it observed input data for the past 50 years to forecast the future crop yields. It attained that the stochastic trend in Indian crop yields can be largely narrated by the power of weather kinetics, an excellent outcome considering that the weather variables potentially significant for crop yields. Most identical strong positive correlation with past climatic variables observed by Ragi (0.862), Rapeseed (0.836), Tea (0.85), Wheat (0.815), Rice (0.811) and Jowar (0.815) assessed by multiple regression analysis. Arhar and Til showed low strength of correlation with climatic variables. The wheat performance in India influenced by climatic variance has been observed to be reduced due to the detrimental consequences of temperature over the crop during the filling of grain and maturity stage of the growth is stated by Gangadhar Rao and Sinha (1994). The outcomes here demonstrate the grain filling duration sensitivity to temperature plays a crucial role in defining the impacts of change in climate on the productivity of crop. It is projected by Mall et al. (2006) that the production of crops in India will not be in danger till 2050; however, by the year 2080, the cropping pattern and its system will be challenged due to the climatic variability caused by climate change. Mall and Singh (2000) reported that minor temperature fluctuations during the growing season of cropping have affected annual Wheat yield over the years. Pathak et al. (2003) assessed that intensifying of minimum temperature and notable negative trends in solar radiations have decreased the cropping of the yields of Wheat and Rice in India's Gangetic plains. Proliferation at the lowest temperatures increases the crop requirements for maintenance respiration and further decreases net yield and growth (Aggarwal, 2003). Kumar et al. (2004) assessed Indian crop-climate relationships with historical crop production data for major crops such as Sorghum, Rice, Wheat, Sugarcane, Groundnut Oilseed, Pulses and Cereals and notable association of crops production with summer precipitation. Performance evaluation of ANN model for future forecasting done by comparison of actual and predicted values of climatic variables and 15 crops in conjunction with MAE, MAPE, MSE and RMSE. Sharma et al. (2018) used ANN algorithm for predicting the relationship between potato late blight and weather variables in developing countries. Alvarez (2016) also utilized the ANN model for predicting the Wheat production in Argentine Pampas to exploring the relation of crops yields with climatic and soil factors. The comparison of actual and predicted values by ANN model showed a good figure which indicates the past data and the used ANN model can be used for further forecasting. Except, Barley, Arhar, Linseed and Rapeseed all the crops production will be significantly increased in future for 2017-2030 with the increase of temperature and rainfall. Kartika et al. (2016) found an increasing trend of future Oil Palm production in Kalimantan using ANN model. There found a very strong correlation of future crops production and climatic variability for the period of 2017-2030 except Arhar and Bajra (these showed moderate correlation), While the production of Cotton and Gram will not be affected with the change of temperature and rainfall pattern. Use of ANN model for predicting and forecasting crops production in association with climatic variables is so far a new assessment in India and still scare throughout the world.  This study demonstrates that the climatic variables are the effective determinants of the long-run growth rate of crops yields. Therefore, it is hoped that this research will give an insight for the development and management of agriculture and the field of agriculture in India to overcome the possible impacts of the climate change.

### 5.6. Conclusion & Summary

This study has analyzed the climatic sensitivity in Indian agricultural crops production using a panel dataset from 1967-2016. Crop productions were designed according to temperature and precipitation datasets. There found a mixed result in India with diverse climatic variability which also differs because of different geographic, territorial, socio-economic facets. Therefore, agricultural crops production also differs throughout the country due to diverse agro-climatic conditions. Comparing observed and predicted values at the 95 percent confidence level, the ANN model provides an admissible result for further forecasting. Inevitably, the model accommodates to understand forth coming proposals, policy-making, and plan alleviations in agro based cropping systems in the country. The outputs of the model are vital for fixing up of crop calendars based on the local climatic conditions. Meanwhile, the crop produce is going through bad effects of climatic shifting with respect to irregular precipitation occurrences which will definitely lead to an adjustment in the cropping pattern.

On the basis of empirical outcome, the aforementioned key suggestions may be delineated for handling issues of food security inside India. First, the intensity of cropping patterns perhaps may upraise the sequence of agro based products inevitably that will increase food production in the country. Second, the policymaker is required to increase additional irrigation conveniences for enhancing crop produce and food safety alongside. Third, the availability of fertilizers and government expenditure in agriculture is essential to pacify bad impacts of climate variance (ADB, 2012; Hollaender, 2010). Fourth, incorporation of substitutes in the consumption of biotic fertilizers may perhaps enhance the efficiency in agricultural products such as Gram, Wheat, Rice, Arhar, Barley, Ragi, Jowar and Maize. Fifth and last, predicted outcome exhibits, fewer crops such as Rice, Wheat, Tea, Cotton and Arhar and Jowar; some Gram, Sesamum (Til), Groundnut, and Bajra, Sugarcane found very sensitive which are positive with the climatic change as an increase in temperature or rainfall increases its production. However, future studies could be led at the territorial and zonal level, so that it might assist in regulating sustainable cropping in the long run.

## CHAPTER 6

## RECOMMENDATION SUITABLE AGRICULTURAL SITES IN REFERENCE TO CLIMATE CHANGE AND OTHERS FACTORS

### 6.1. Introduction

Land suitability analysis is a method of determining how suitable or acceptable a given area is for a specific land use (such as growing a certain crop variety) in a given venue. Land suitability techniques have been used widely in agricultural regions to find best management practices. For modeling agricultural suitability for the entire country of India,) we used different operators of fuzzy logic and integrated fuzzy logic with AHP to model agricultural suitability for the entire India and used different operators of fuzzy logic and integrated fuzzy logic with AHP to model agricultural suitability. The global sensitivity analysis using the Morris methodology was used to investigate the models' stability, because validation is not feasible. The land suitability study for agriculture using climatic, topographic, and soil quality criteria is the best way to distinguish between zones where agricultural operations are extremely appropriate and those where they are not.. The agriculture management strategy can be formulated using land suitability study in order to achieve optimum agricultural productivity. A land suitability analysis for agriculture is therefore a critical tool for determining agricultural cropping patterns, preparation, and activities in the future.Agricultural food products remain in perpetual demand (OECD/FAO 2019) because of an increasing population (Sands et al., 2014; Mozumdar, 2012), rapid urbanisation and urban growth (UN, 2018), a rapid increase in productivity on agricultural land (Sands et al., 2020) and climate change (Fukase & Martin 2020), and (Talukder et al., 2020; Anderson et al., 2020; P.Leisner, 2020). As a result, world food demand is projected to rise by 70% by 2050 (Bocchiola et al., 2019; UNESCO, 2017). The need to reduce and eliminate fossil fuel consumption (Popp et al., 2014; R.Quentin et al., 2015), which is putting more pressure on agricultural land through the demand for biofuel and biobased products, is exacerbating the situation (WWAP, 2017; Alalwan etal., 2019; Bos & Broeze, 2020; Gursel et al., 2020). This rising demand for agricultural goods has resulted in the exhaustion of global land resources in recent decades (Lambin & Meyfroidt, 2011), which not only causes agro-ecological problems (Hathaway, 2016), but also jeopardises agricultural sustainability (Hunter, 2017). To address these issues and optimally utilzse the land resources, planning through agricultural suitability assessment is of paramount importance (Song & Zhang, 2021; Ahmed et al., 2016: Yohannes & Soromessa, 2018).

Land suitability appraisal is the method of evaluation and aggregation of the suitability of particular areas of land for defined uses (Liu et al., 2006). It is a tool for deciding the factors that inhibit a given crop from growing (Halder, 2013; Chozom & Nimasow 2021). Land suitability evaluation involves both qualitative valuations of topography, vegetation, climate, hydrology, and soil properties, as well as quantitative valuations that rely more on yield estimates (Mosleh et al., 2017; El Baroudy, 2016). Typically, this land suitability appraisal is performed separately for each crop type (Herzberg et al., 2019).

One of the most important and basic aspects of the agricultural suitability evaluation process is the selection of criteria (Tercan & Dereli, 2020; Zolekar, & Bhagat, 2015). For agricultural suitability zonation, Pilevar et al. (2020) used climatic factors such as temperature, topographic factors such as slope and elevation, and soil characteristics such as soil texture, soil PH, and electric conductivity, among others. Seng et al, (2009), however, showed that the alkalinity, acidity, water storage profile and water logging characteristics of soil are essential factors for mapping agricultural suitability. Similarly, Akinci et al. (2013) show that the soil classification category, land capacity level and subclass, height, slope, soil density, rockiness, and stoniness are all important factors to consider when assessing land suitability. Seyedmohammadi et al., (2019) have used climatic characteristics such as mean daily maximum and minimum temperatures for the coldest month, as well as mean temperature at various stages of crop development; soil characteristics such as depth, gypsum and calcium carbonate content, PH, Electrical conductivity, exchangeable sodium percentage, and topographic charcteristics of slope for agricultural suitability. Finally, for Land suitability evaluation, Sahoo et al., (2018) considers various geological and hydrometrological characteristics such as rainfall, ET, NDVI, LULC, soil, soil moisture, groundwater level, geology, slope, and elevation. Taking into account the findings of the previous research, the current research employs climatic characteristics such as rainfall, temperature, wind speed, ET, and aridity; topographic characteristics such as slope, aspect, elevation, and TRI; soil characteristics such as soil quality, soil composition, soil erosion, and the amount of soil organic carbon; and finally, LULC parameters to determine land suitability.

The choice of a precise and efficient algorithm for determining land suitability has a big influence on current and future land use planning (Gardner et al., 2021; Pilevar et al., 2010).

The paramatric method of Sys et al., (1991) and the FAO (1976) land evaluation system, which combine terrain data, climatic and soil properties, have recently been used among the conventional approaches for agricultural suitability assessment (Bagherzadeh & Gholizadeh, 2016; Bagheri Bodaghabadi et al., 2016). Other methods include multi-criterion evaluation (MCE), which considers several criteria at the same time and yields promising outcomes (Zolekar, & Bhagat, 2015; Sarkar et al., 2013). The best approach for multi-criteria decision systems is AHP, which is built on a hierarchical structure that reflects the relative value and relationships of variables (Saaty, 1980; Ustaoglu & Aydnoglu, 2020). Fuzzy set theory method is the most widely used strategies to eliminate any inaccurate information and uncertainties in decision making by using AHP for land suitability (Mardani et al., 2015; Sitorus and Brito-Parada, 2020). The combination of AHP and Fuzzy logic results in an effective algorithm (Pilevar et al., 2020), which has been commonly used in land suitability evaluation (Mandal et al., 2020; Ustaoglu & Aydnoglu, 2020; Bahrani et al., 2016; Akinci et al., 2013).

In addition, combining MCE techniques with artificial intelligence techniques, such as combining AHP and fuzzy logic, can increase modelling efficiency. Because MCE and AHP techniques have flaws, particularly in the case of pairwise comparisons, where certainty is lacking (Huang et al. 2008). Furthermore, even though it integrates expert intelligence, the AHP approach does not depict human insight. In order to overcome these shortcomings, the FAHP approach was proposed. Fuzzy logic applications are constantly expanding (Özkan et al., 2020), and its convergence with AHP is proving to be an effective technique with improved precision for land suitability evaluations (Tashayo et al., 2020). The approach has been applied to a variety of issues, including site selection (Erturul and Karakaşolu 2008), tourism management (Wang et al. 2013), machine-tool selection (Durán and Aguilo 2008), supply chain management (Jakhar and Barua 2014), arms selection (Dadeviren et al. 2009) and energy systems management (Durán and Aguilo 2008). FAHP methods have been used in many research but only a very few reports have documented the method's use in agriculture suitability modelling (Salvacion, 2019; Tashayo et al. 2020; Nabati et al., 2020). Therefore, in the present study, different operators of fuzzy logic and MCE integrated fuzzy logic (AHP-fuzzy logic) were performed to map the agriculture land suitability mapping.

Previous studies show that many researches have been carried out on the land suitability assessment using statistical models in different parts of the world. In addition, In India, only a handful of studies have undertakenland suitability analysis. Moreover, most studies concentrate primarily on a small region but agriculture suitability mapping has also not been carried out in India at national level. The current study aims to perform zone wise agriculture suitability mapping for the entire country. The key features of the current study to address the research gaps are: (i) Use of different operators of fuzzy logic and integrated fuzzy logic with AHP to model agricultural suitability for the entire India (ii) The study uses global sensitivity analysis using the Morris methodology to investigate the models' stability, because validation is not feasible. The following outcomes were achieved:

- General: The work leads to increasing the robustness of expertise by designing and applying methods to a previously unstudied field on agriculture suitability mapping for the entire country.
- Regional: Agriculture suitability mapping has not yet been completed in the entire country. As agriculture is a major pillar of the Indian economy, this form of work is important in proposing management plans. The results of this work will be a beneficial framework to enhance land and agricultural management for earth scientists, government authorities and stakeholders.
- Methodical: Several fuzzy operators, such as AND, OR, and GAMMA, were used in the present study, along with integrated AHP-based fuzzy logic for agriculture suitability mapping, which has not yet been extended to agriculture land suitability mapping. Furthermore, to the best of the authors' knowledge, this is the first research in which sensitivity analysis using the Morris approach was used to explore the relationship between parameters and models.

## 6.2. Data Sources and Methods

### 6.2.1. Data sources and rationale for selecting the data

This study was conducted using data from all states of India (Fig. 6.1). Rainfall, temperature, wind speed, evapotranspiration, soil organic carbon, soil types, soil nutrient qualities, gross soil erosion, elevation, aspect, slope, aridity index, and land use land cover were chosen as criteria for agricultural land suitability in this analysis. The above parameters were derived from various sources with varying resolutions. Table 1 contains information about the data sources. The resolution effects have been eliminated by the use of resampling techniques. We employed a variety of resampling approaches in this work, including nearest neighbour and cubic convolution. For discrete datasets such as land use, land cover, soil types, and nutrient quality, the nearest neighbour approach has been employed. It is used for discrete datasets since the values of the cells will not change. In the present research, cubic convolution was utilised for continuous datasets because it calculates a cell's new value by fitting a smooth curve through the 16 closest input cell centres. It has less geometric distortion than the raster produced by the nearest neighbour resampling method. We utilised elevation as a basis parameter with a lower resolution (90 metres) for resampling and converted all values to 90 metres. Different resolution effects have been removed in this way. All parameters were resampled at 100 metres, such as land usage and land cover, in this analysis(Abrol et al., 1991).

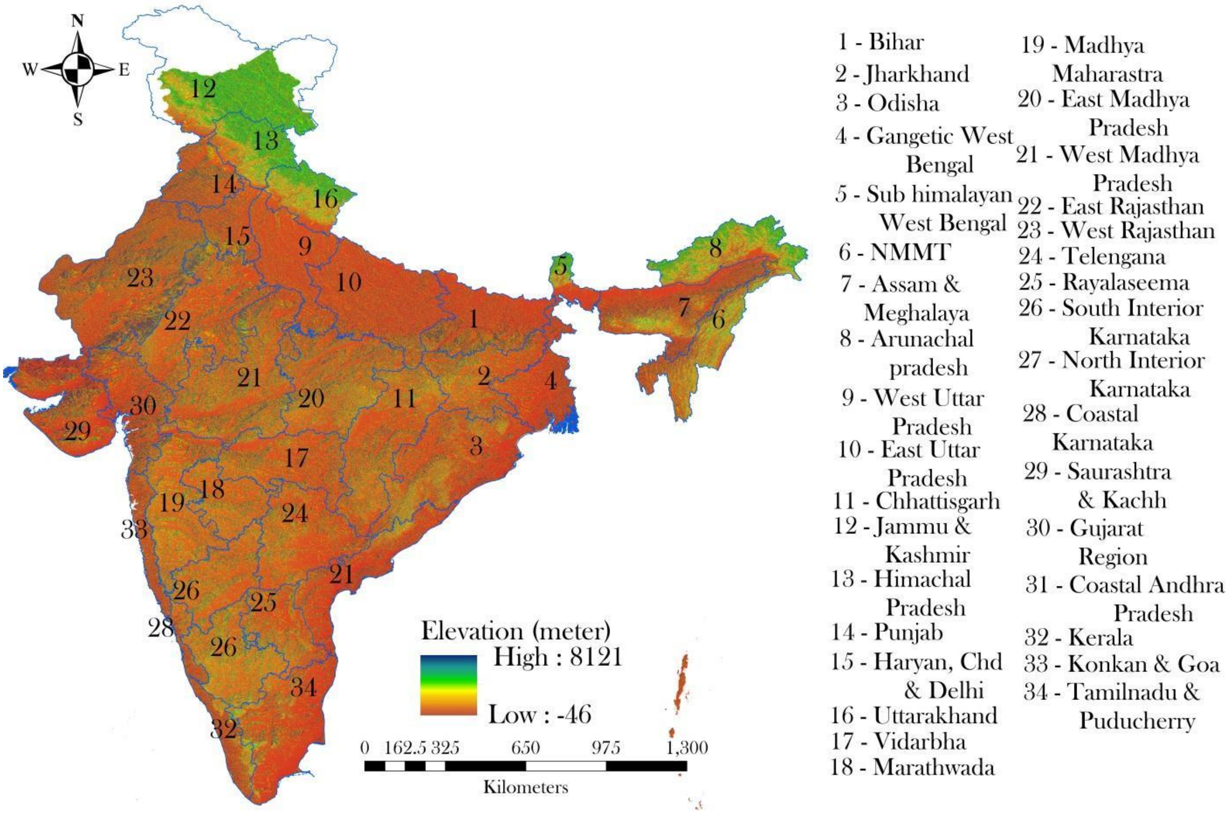



**Figure 6.1** Location of the study area.

**Table:6.1** Details of data sources for agriculture suitability modelling

| Data types | Sources | Resolution |
|---|---|---|
| Rainfall | IMD (1901-2015) | - |
| Temperature | IMD | - |
| Wind speed | Giovanni (https://giovanni.gsfc.nasa.gov/giovanni/) | 1° |
| Evapotranspiration | Giovanni (https://giovanni.gsfc.nasa.gov/giovanni/) | 1° |

| | | |
|---|---|---|
| Soil organic carbon | Soil organic carbon stock in t/ha for 0-30cm depth intervals. (https://maps.isric.org/mapserv?map=/map/ocs.map) | 250 meter |
| Soil Types | Reference soil group (2006), soil grid (https://soilgrids.org/) | - |
| Soil Nutrient Qualities | Fischer, G., F. Nachtergaele, S. Prieler, H.T. van Velthuizen, L. Verelst, D. Wiberg, 2008. *Global Agro-ecological Zones Assessment for Agriculture (GAEZ 2008)*. IIASA, Laxenburg, Austria and FAO, Rome, Italy. | 250m |
| Soil erosion | ISRIC, world soil information | 250m |
| DEM(Digital elevation model) | DIVA GIS | 90meter |
| Aridity | ISRIC, world soil information | 250m |
| Land use land cover | Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center (DAAC) (https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1336) | 100 m |

The method for determining land suitability has been extended by emphasizing on numerous essential factors that affect crop production. A multitude of variables must be considered in order to produce accurate and robust sustainable agriculture management. Therefore, to help policies and land planning strategies for adequate crop production, an integration of the various factors is required. As a result, a suitability research technique was designed to distinguish each conditioning factor based on the associated positive and negative effects in terms of crop yield. Climate, topography, and soil characteristics were defined in the current study based on their effect on crop yield. In view of these factors, the suitability of land was achieved in agricultural mapping. The reasons for selecting the variables for agricultural land suitability modelling are detailed below:

Climate change has had a more negative effect on crop production than positive effects across a large variety of regions, according to the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) (IPCC, 2014). Climate change would have a significant effect on water availability and supply by altering rainfall, evaporation, runoff, and soil moisture storage, as well as causing significant temperature volatility (Olesen & Bindi, 2002). When the average precipitation is somewhat smaller or greater than the optimal, major problems may occur from drowning to poorer productivity. Aside from the impact of high and low rainfall on cropping trends, events such as coastal floods are expected to decrease the amount of land suitable for cultivation. Farmers are still struggling to respond to these environmental changes, despite the fact that nearly all crops are seasonal and dependent on rainfall (Singh et al., 2014). Droughts, floods, erratic precipitation patterns, heat waves, and other severe events have risen as a result of the extreme rise in temperature around the world. According to a study released by the United Nations Environment Programme in 2017, drought and dissertification have resulted in the abandonment of 500 million hectares of farmland (Arora, 2019). The direction and velocity of the wind have a big impact on crop development. As a result, decent crop yields necessitate optimum windspeed (Zabihi et al., 2015). Evapotranspiration is an essential element of the soil water equilibrium and it plays a significant role in assessing agricultural yield potential. Crop productivity will likely decline as the crop growth cycle is shortened as a result of rising temperatures, lack of moisture, and soil water scarcity (Bhatt and Hossain, 2019). Therefore, to propose reliable land suitability model for smart agriculture practice, it is nesseasry to know spatial pattern of evapotraspiration.

The evaluation of topographical criteria offers knowledge about the land's limits for agricultural development.Topographic indicators, such as elevation, slope, aspect, index of topographical ruggedness, are important factors that affect the crop substantially. Elevation variations have a bearing on soils, microclimatic impacts, and other processes that can influence land suitability (Yi and Wang, 2013). Generally, food crop yield was inversely proportional to elevation (Minda et al., 2018). Crops and pulses such as rice, jute, wheat, and maize could be at risk as altitude rises. Since low altitude areas are suitable for these food and commercial crops. While few fruits are suitable for high altitude, plain regions are widely recommended for food and commercial crops in order to feed a large population. Since the degree of sunlight intensity is influenced by the aspect, the southern and western aspects are commonly considered to be the most suitable for agriculture (Akinci et al. 2013). The slope has a major impact on plant structure as well as soil erosion. The slope is essential for both the surface and the internal soil water drainage, since both features perform a significant role in crop growth (Yi and Wang, 2013). For these reasons, topographical criteria should be taken into account when developing smart agriculture management plans.

For agricultural development and long-term soil usage, the physical properties of the soil are critical. The ability of the roots to absorb the soil solution as well as the ability of the soil to provide it to the roots determine the quantity and rate of water, oxygen, and nutrient absorption by plants, both of which have a significant impact on the health of vegetation, including crops. As a result, when proposing agricultural and irrigation management policies, soil properties such as soil types, soil nutrient conditions, the presence of soil organic carbon, and soil degredation should be taken into account. 1As a result, when proposing agricultural management policies, the spatial pattern of soil erosion region should be taken into account.

Aridity index is another important parameter which provides a numerical indicator of the degree of water scarcity which is most frequently related to natural vegetation and crop distribution. As a result, it should be considered when modelling land suitability in agriculture. Land availability can be determined by understanding existing land use. Land use data aids in determining an area's viability for a specific cropping method (Akpoti et al., 2019). As a result, it must be taken into account before determining suitability for agriculture. Based on these discussion, we have chose the mentioned parameters for agriculture suitability modelling.

**6.2.2. ALAS modeling**

**Data filtering**

In the present study, before proceding for modeling, data filtering has been performed. Data filtering or feature selection is very essential as redundant data can produce erronous results. In this study we used multicolinearity analysis for data filtering. Some approaches for measuring multicollinearity include variance inflation factors (VIF), tolerance (TOL), linear support vector machine, and chi-square (Talukdar et al. 2021). In this study, tolerance and VIF were employed to assess multicollinearity among the variables. It's worth mentioning that variables with collinearity concerns should be removed before modelling in order to achieve high accuracy results. The greater the collinearity, the larger the VIF. To evaluate multicollinearity, the coefficient of determination was determined using rice production data (a proxy for existing agricultural appropriate regions) as response variables and suitability indicators as predictor factors in a linear regression analysis.

**6.2.3. Methods for fuzzy logic and FAHP**

The following steps have been performed to implement the fuzzy logic and FAHP for generating ALSA.

*Step-1: Development of hierarchical structure*

In this phase, a literary survey and expert opinion relevant to the field of research are used to implement the AHP process. The next step is the creation of a matrix of judgement through comparison of pairs and evaluations by decision makers and experts. The matrices were checked for consistency, and eigen values and eigen vectors were measured in order to compare element priority (Li et al. 2009). Following this, the consistency of the matrix decisions in the pairwise evaluation is verified. If the consistency test fails, the initial values of the pairwise comparison matrix must be changed. In the present study, the CI and other evaluating factors are: consistency 1%, CI is 0.01316, RI is 0.0146, CI/RI is 0.9.

*Step-2: Determination of degree of membership and computation of fuzzy evaluation matrix*

The fuzzy membership function (MF) is determined by the fuzzy set theory based on the spatial relationships of the conditioning variables in fuzzy logic in decision-making. Zadeh's (1965) fuzzy logic is a soft computing approach designed to solve problems of uncertainty and/or imprecision, which may be implicit in the problem or applied as a way of grappling with complexity (Magdalena, 2010;). In contrast to boolean logic, fuzzy logic has a membership value that ranges from 0 to 1, while boolean logic has a membership value that is either 0 or 1. (Dubey et al., 2013). The 0 values indicate that the desired value is not a member of that set, while the value 1 indicates that the desired value is absolutely a member of that set. Other values range from 0 to 1 depending on their level of membership. One of the biggest challenges of fuzzy research is that the type of membership and its criteria are not determined using the optimum approach. These membership functions are usually chosen based on decision-makers' interests in the study field (Shahabi et al. 2015).

The variables in fuzzy set theory can be given a membership value ranging from 0 to 1, which indicates the degree of MF. The linear membership function (MF) is used in the ArcGIS software to establish the fuzzy map of each parameter. For all parameters (figure 2), the maximum and minimum values of the membership functions are evaluated; for example, the MF value for a DEM less than 100 m is 1, the value for a DEM greater than 5000 m is MF = 0, and MF is computed between 0 and 1 for DEM values between 100 and >7000 m. In the same way, the magnitudeof other parameters is determined by the minimum and maximum MF values. For each parameter between 0 and 1, membership functions were specified based on Table 6.2. As a result, all agriculture land suitability conditioning variables were scaled from 0 (lesser suitable) to 1 (highly suitable).

*Step-3 final mapping*

The final agricultural suitability mapping in this study was accomplished in two ways: (1) the agriculture suitable conditioning parameters were fuzzified using membership functions, and then different fuzzy operators, such as ‘AND,' ‘GAMMA 0.8,' and ‘GAMMA 0.9,' were used to integrate all the fuzzified parameters and generate final agriculture suitability maps in ArcGIS 10.8 software. (2) In ArcGIS software, the weights for all parameters obtained from FAHP algorithms were easily integrated using the weighted sum technique.

**6.2.4.Sensitivity analysis**

The sensitivity analysis was carried out in this study because ground truth evidence for validating the land suitability model for agriculture is sparse and difficult to come by. As a result, a sensitivity analysis was performed to express the robustness and precision of the suitability models. Sensitivity analysis was performed in three different ways in this study: (1) global sensitivity analysis using the Morris model, (ii) random forest dependent sensitivity analysis, and (iii) Pearson's correlation coefficient.

*Global sensitivity analysis using Morris model*

Morris (1991) devised the Morris one-at-a-time approach (MOAT) for parameter screening as a global sensitivity analysis method. The overall effect and interaction effect of all input parameters are computed using the mean m and standard deviation s of the gradients of all input parameters, which have been sampled from the r MOAT path, as the theoretical basis of this process. All input parameters were modified by the same relative amount using this global sensitivity process. Morris' procedure differs from conventional OAT research in that it takes into account adjusting the variable in question between two model simulations (Morris 1991; Campolongo et al. 2000).

*Random forest-based feature selection technique*

Breiman's Random Forest (RF) (Breiman, 2001) is one of the most commonly used efficient ensemble supervised algorithms. The regression problem, classification, and unsupervised learning can all be solved with this algorithm. It's been widely used in a variety of fields, including natural hazard modelling, hydrology, LULC classification, and finance (Salam and Islam 2020; Chen et al., 2019; Talukdar and Pal, 2020). In the present study, RF offers two distinct important metrics for ordering variables and variable choice, mean decrease accuracy (MDA) and mean decrease Gini (MDG). When the values of a variable become randomly permuted relative to the original data, MDA evaluates the significance of the variable by evaluating the change in prediction accuracy. MDG is the total of all Gini impurity reductions caused by a particular variable (when that variable is used to generate a split in the Random Forest), normalised by the number of trees.

This approach was used in the present analysis to determine the weight or control of the various parameters in describing the expected agriculture land suitability models. We computed the variables influence against different agriculture suiability models. Therefore, the agriculture suitability models have been treated as target variables. To implement the RF model, we set the following optimized parameters: seed-5, number of trees- 500, number of variables tried at each split- 3, interation- 200, out of bag estimate error rate: 11.32%. To the best of the authors' knowledge, this is the first work in the study field to use RF-based sensitivity analysis to identify the model's most sensitive parameters.

*Pearson correlation-based sensitivity analysis*

The Pearson correlation coefficient was used to assess the relationship between ten parameters and land suitability approaches. We used SPSS (version 22) tools to conduct correlation coefficient analysis on ten parameters and land suitability models in this analysis.

The whole work has been summarized in figure 6.2.

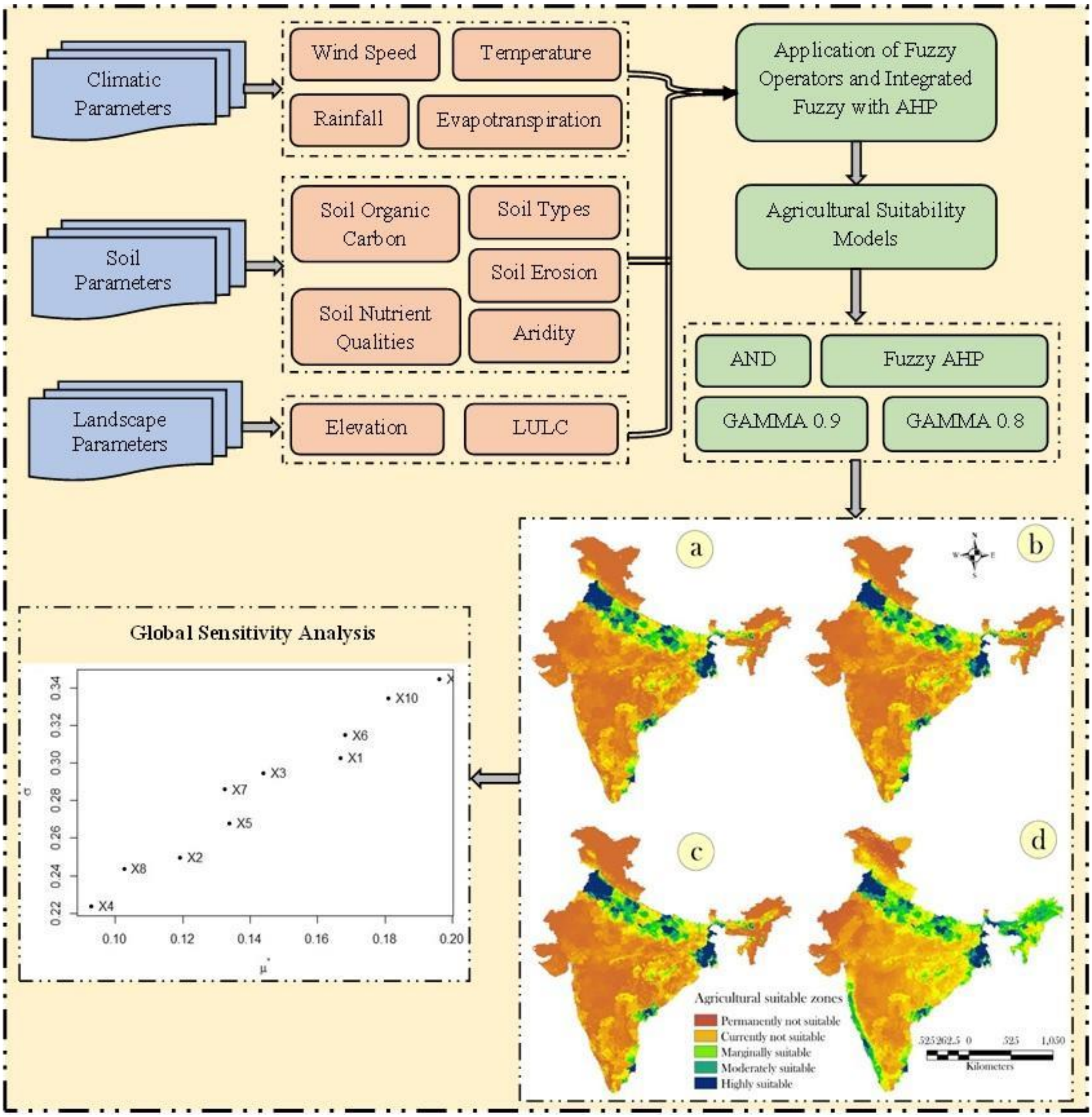



**Figure 6.2:** The Summary of the Whole Work

## 6.3. Results

### 6.3.1. Data filtering analysis

A multicollinearity test was used in this work to see whether there was a connection between the conditioning factors using variance inflation factors (VIF) and the tolerances technique for selecting agriculture suitability conditioning factors (Table 2). VIF > 10 or tolerance 0.1 indicates a multicollinearity concern in conditioning factors (Mallick et al. 2021). There was no collinearity among the 14 conditioning factors impacting the agriculture suitable model, according to the multicollinearity test findings (Table 2).

**Table 6.2** Diagnosis of multicollinearity for agricultural suitability conditioning factors

| Coefficients[a] | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Collinearity Statistics | |
| | | B | Std. Error | Beta | | | Tolerance | VIF |
| 1 | (Constant) | -.194 | .745 | | -.261 | .794 | | |
| | Elevation | 10.356 | .847 | .381 | 12.227 | .000 | .112 | 8.941 |
| | Slope | 6.039 | .399 | .249 | 15.128 | .000 | .402 | 2.485 |
| | Aspect | 4.699 | .286 | .177 | 16.451 | .000 | .944 | 1.060 |
| | TRI | 5.443 | .670 | .195 | 8.123 | .000 | .188 | 5.331 |
| | Rainfall | 8.666 | .392 | .320 | 22.108 | .000 | .518 | 1.931 |
| | Temperature | 4.003 | .962 | .080 | 4.160 | .000 | .292 | 3.420 |
| | Wind speed | 3.599 | .469 | .125 | 7.670 | .000 | .411 | 2.431 |
| | Evapotranspiration | 3.066 | .514 | .102 | 5.968 | .000 | .371 | 2.695 |
| | Soil qualities | .126 | .352 | .005 | .358 | .721 | .597 | 1.674 |
| | SOM | .505 | .460 | .012 | 1.098 | .273 | .876 | 1.141 |
| | Soil types | .320 | .377 | .011 | .850 | .396 | .708 | 1.412 |
| | Soil erosion rate | -.554 | .366 | -.019 | -1.513 | .131 | .660 | 1.516 |
| | LULC types | .618 | .368 | .024 | 1.677 | .094 | .537 | 1.864 |
| | Aridity index | .260 | .481 | .009 | .541 | .589 | .412 | 2.426 |
| a. Dependent Variable: Rice production | | | | | | | | |

#### 6.3.2. Description of data layers

*Climatic parameters*

The study region has a humid to desert environment with a southwest monsoon system. Rainfall is an important factor in determining the suitability of agricultural land. We used ArcGIS 10.2 software to generate a rainfall map using rainfall data from an Indian meteorological station and the kriging interpolation methodology. In the studied area, yearly rainfall ranges from 0 to 345 mm ((Figure 6.3a). Another important factor that influences crop output is temperature. The yearly temperature ranges from 30.2 degrees Celsius to -18.3 degrees Celsius (Figure 6.3b). In comparison to other locations, the northernmost area had greater temperatures. Evapotranspiration has an impact on agricultural water resource management as well. The northern and eastern portions of the nation had lower evapotranspiration, whereas the central and northwestern areas had more evapotranspiration (Figure 6.3c). Another critical factor in determining land suitability is wind speed. The wind speed ranges from 0.5 to 10.3 knots per second on a yearly basis (Fig. 6.3d). Wind speeds were found to be greater and lower in the research area's northern and centre part.

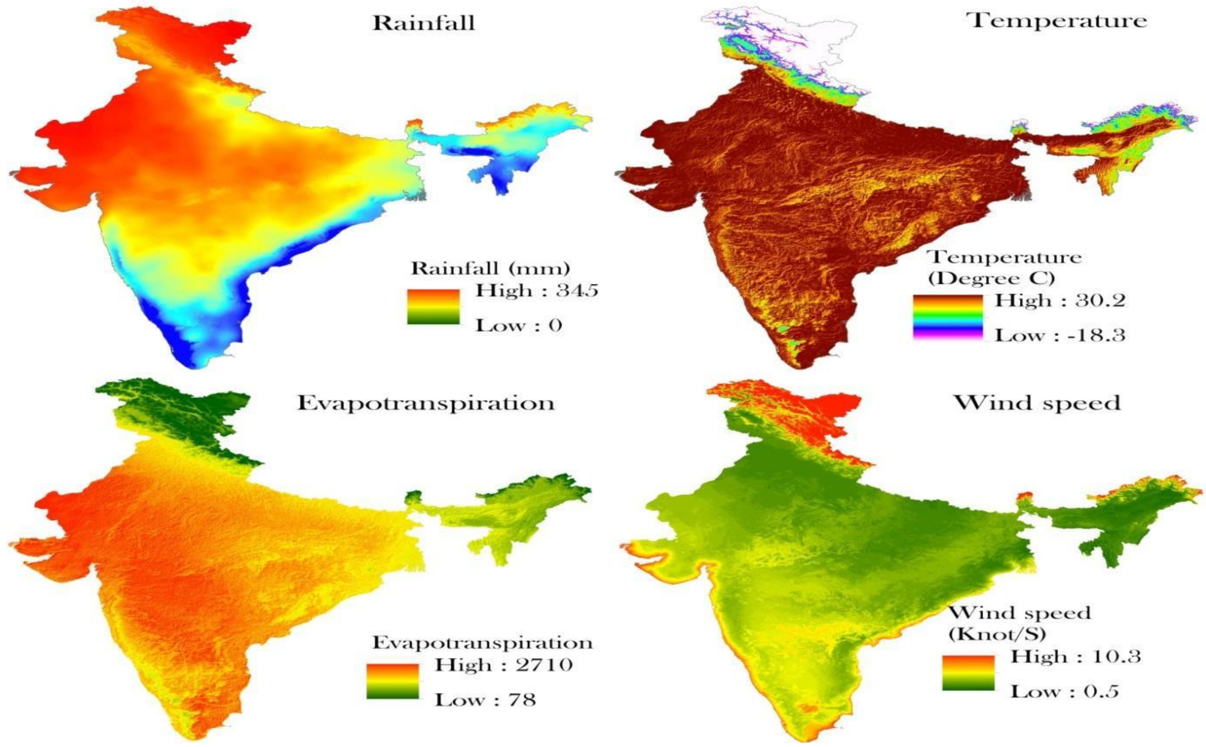



**Figure 6.3:** The climatic parameters for agriculture suitability mapping using (a) annual average rainfall (2017), (b) annual average temperature (2017), (c) average evapotranspiration, (d) wind speed (continued).

*Topographic parameters*

Elevation and slope were recognised as critical topographic characteristics in this investigation. The topographic factor has a significant influence on farming mechanisation. The elevation factor affects climatic data such as precipitation and temperature. Crop growth and dispersion are greatly influenced by elevation above sea level. The greater height is found in the northern and certain parts of the eastern hilly regions, whereas the rest of the

Deccan plateau is at a lower elevation (Figure 6.4a). The elevation varies from 800 to 900 metres above mean sea level (AMSL) and accounts for more than a third of the research area. Crop yield benefits with a low slope. In the southern and southwestern areas, extremely softly sloped lands (1–3 degree) were discovered, according to the slope study. Gently sloping lands (3-8 degrees) were found in the middle areas, whereas moderate to high slope lands (>8 degrees) were found throughout the study, mostly in the northern and eastern parts (Figure 6.4b). Aspect is the compass direction that a slope faces in relation to land owing convergence. The aspect map was made up of eleven classes (Figure 6.4c). The degree of elevation variation between close cells of a digital elevation map is indicated as the topographic roughness index (TRI). It is based on the research area's local terrain. The northern margin and a small portion of the eastern region had greater TRI, whereas the rest of the study area had lower TRI (Figure 6.4d).

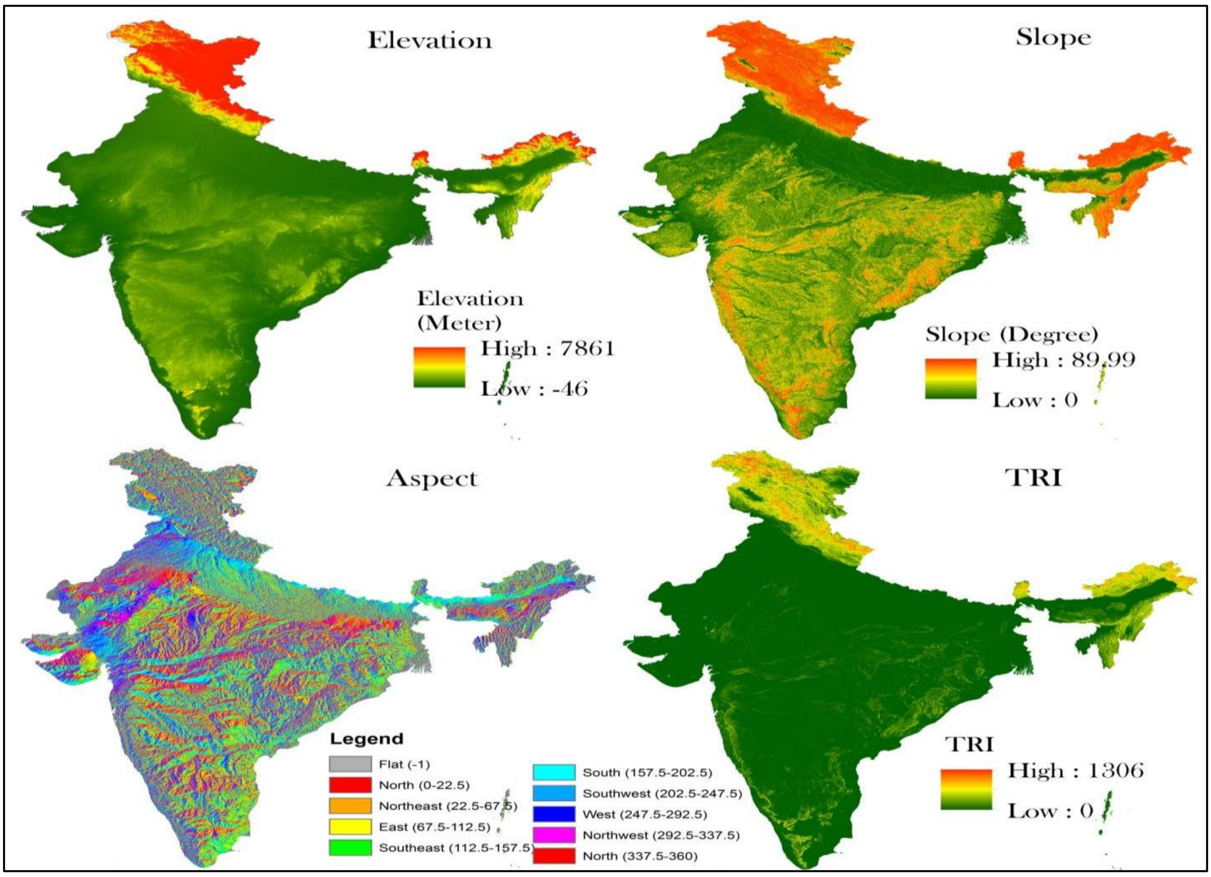



**Figure 6.4**: Topographical parameters for agriculture suitability modeling, (a) Elevation, (b) Slope, (c) Aspect, and (d) TRI

*Soil related parameters*

Soil organic carbon (SOC) is important for soil fertility, a complex water-nutrient tradeoff in the plant root zone, and land deterioration (Bandyopadhyay et al., 2009). It changes with elevation, slope, and rainfall, as well as soil variability and management on a geographical scale. Higher altitude, steeper slopes, and higher rainfall produce lower altitude, slope, and rainfall than lower altitude, slope, and rainfall. The greater SOC is found in the eastern part of the country, whereas the lower SOC is found in the northwest (Fig.6.5a). Soil erosion is also an important factor in determining agricultural suitability. Soil erosion occurs mostly in higher elevation areas, notably in a small fraction of the northern region, although it also occurs irregularly across the study territory (Fig. 6.5b). There were seven types of soil quality employed in this study (Fig. 6.5c). This soil quality is critical for effective low-input farming and, to a lesser extent, intermediate-input farming. There are several diagnostics for nutritional availability. Texture/Structure, Organic Carbon (OC), pH, and Total Exchangeable Bases (TEB) are all important topsoil (0-30 cm) features. The most significant factors to consider for the subsoil (30-100 cm) are texture/structure, pH, and TEB. The soil parameters that affect soil nutrient availability are connected to some extent. As a result, to represent soil, the most limiting soil feature is merged with the average of the remaining less limiting soil qualities in the evaluation. The study region showed nutrient availability in most sections of the nation, but toxicity and rooting conditions in the northern and eastern regions. Soil types are one of the most important determinants of land suitability (Islam et al., 2021). In this study, we used a soil map from the United States Geological Survey (USDA) and divided it into six soil types using USDA soil taxonomy (Figure 6.5d). Entisols and Inceptisols are often found in the research region, according to the soil taxonomy model (USDA, 2010).

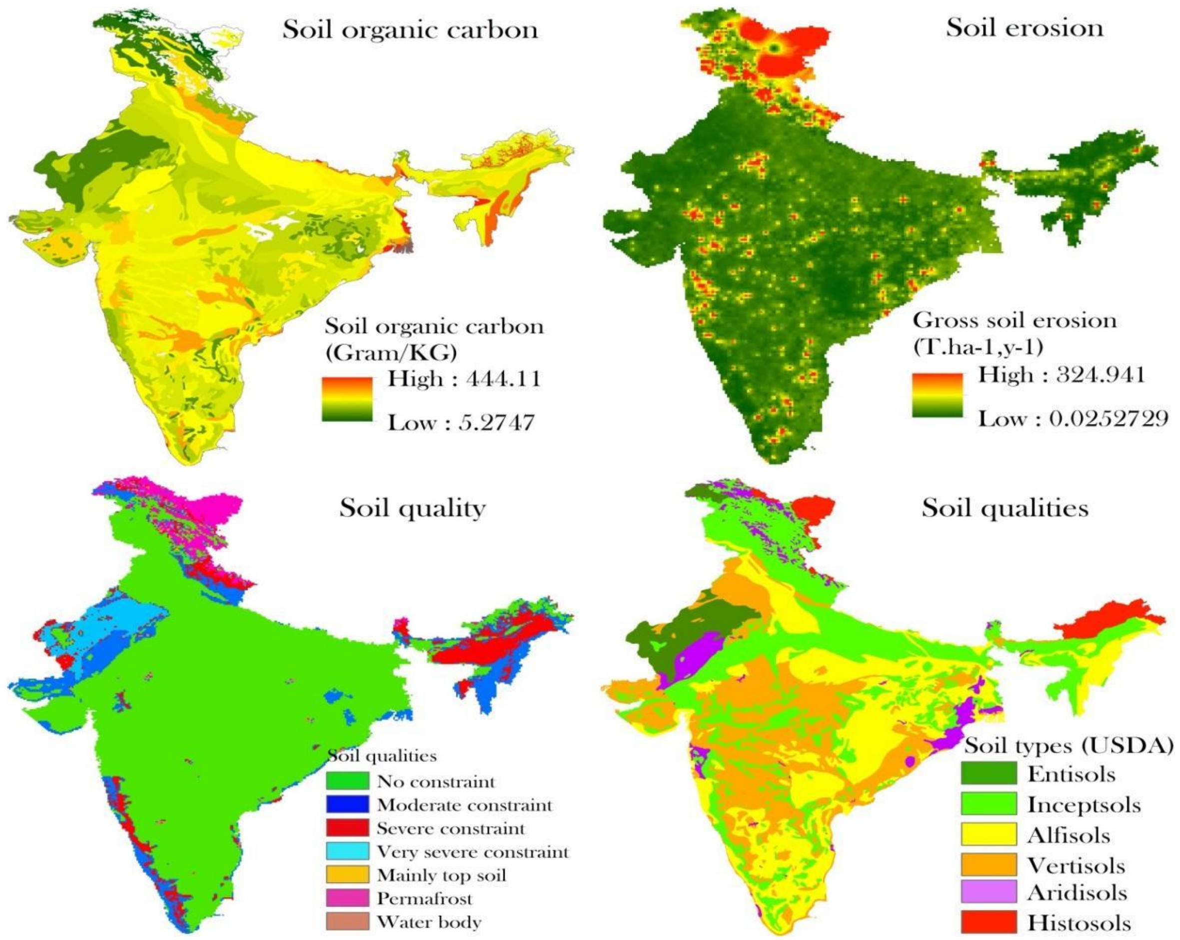



**Figure 6.5:** Soil related parameters, (a) Soil organic carbon, (b) Gross soil erosion, (c) Soil nutrient quality, (d) Soil types

*Land use related parameters*

Aridity is one of the most essential aspects of land suitability. A high degree of aridity was discovered in the eastern and a small section of the southwestern regions, while a low level of aridity was discovered in the central and northwestern areas (Figure 6.6a). The land pattern, desertification, and evapotranspiration are all influenced by land use/land cover (LULC) (Yalcin et al., 2011). For evaluating agricultural suitability zones, the LULC map is crucial. The LULC map (Figure 6.6b) included 19 classes, and the area was calculated in Table 6.2.

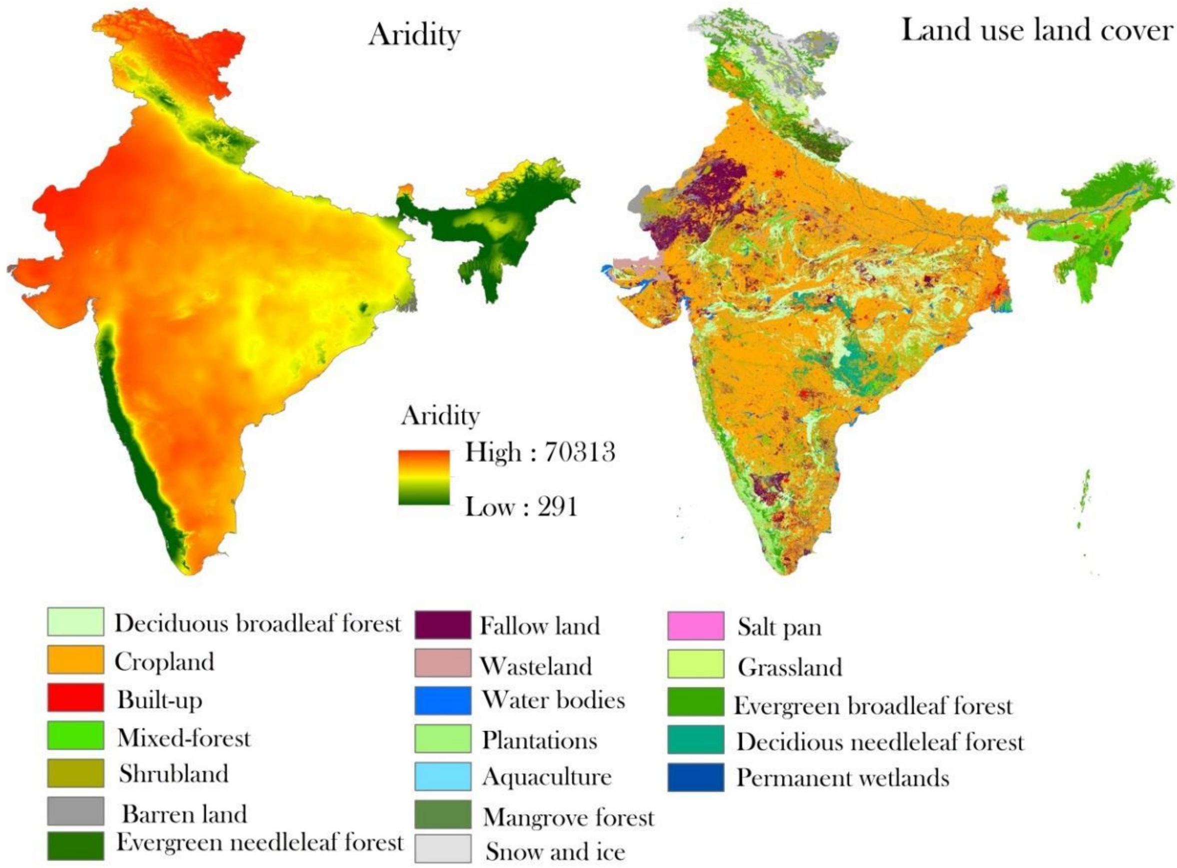



**Figure 6.6:** Parameters for agricultural suitability modeling, (a) aridity, (b) land use land cover type

**Table 6.3:** Computation of area coverage under different land use land cover types.

| LULC categories | Pixel count | Area (km2) | Area (%_ |
|---|---|---|---|
| Deciduous broadleaf forest | 31533579 | 315335.8 | 17.18 |
| Cropland | 16253929 | 162539.3 | 8.86 |
| Built-up | 4719281 | 47192.81 | 2.57 |
| Mixed forest | 15219101 | 152191 | 8.29 |
| Shrubland | 18713333 | 187133.3 | 10.20 |
| Barren land | 10296149 | 102961.5 | 5.61 |
| Fallow land | 22352184 | 223521.8 | 12.18 |
| Wasteland | 4232325 | 42323.25 | 2.31 |
| Water bodies | 10860343 | 108603.4 | 5.92 |
| Plantations | 7916282 | 79162.82 | 4.31 |

| | | | |
|---|---|---|---|
| Aquaculture | 21530 | 215.3 | 0.01 |
| Mangrove forest | 118022 | 1180.22 | 0.06 |
| Salf pan | 9136 | 91.36 | 0.00 |
| Grassland | 5533971 | 55339.71 | 3.02 |
| Evergreen broadleaf forest | 18317906 | 183179.1 | 9.98 |
| Deciduous needle leaf forest | 5740966 | 57409.66 | 3.13 |
| Permanent wetlands | 386825 | 3868.25 | 0.21 |
| Snow and ice | 9310845 | 93108.45 | 5.07 |
| Evergreen needle leaf forest | 1969561 | 19695.61 | 1.07 |

#### 6.3.3. Fuzzification of the data layers

A fuzzy inference system consists of four essential components: a rule basis, a fuzzifer, an inference engine, and a defuzzifer. A fuzzy set is a rule-based model that functions as an active system. To prepare an inference from fuzzy rules, an inference engine is used (Ostovari et al. 2016). To map a fuzzy dataset for the output of crisp parameters, defuzzification is used. The fuzzy membership tool reclassifies or converts the input data to a 0 to 1 scale depending on the likelihood of belonging to a specific set. Sigmoid, inverted sigmoid, linear, and parabolic types of membership functions were used in our research. In addition, the Mamdani fuzzy inference system was used in this study (Mamdani, 1977). To begin, climatic, soil, topography, and land use parameters were translated into fuzzy-set data with numerical values ranging from 0 to 1 using various fuzzy membership functions (Supplementary figures 6.1-6.4).

#### 6.3.4. Agriculture suitability modeling

Figure 6.7 shows the findings of the land suitability zone for agriculture, and Table 6.4 shows the area and percentage coverage of the various agricultural suitability zones in India. The final agricultural suitability map was created by superimposing 14 fuzzy data layers on this land suitability map using Fuzzy AND, Fuzzy Gamma 0.9, fuzzy Gamma 0.8, and Integrated AHP models (Fig. 6.7a-d). According to the Fuzzy (AND operator) map, 16.76 percent (546019.2 km2) of the study area is very highly suitable, with the exception of a small piece in the southwest, 8.04 percent (261936.3 km2) is moderately suitable, and 15.52 percent (505722.6 km2) is marginally suitable. Approximately 6.11 percent (199067.2 km2) has been assessed to be currently not suitable, with the remaining 53.55 percent (1744325 km2) being permanently not suitable, concentrated in the northern, central, southern, and western areas.

According to the Fuzzy (Gamma 0.9 operator) model, 59.69 percent (1944325 km2) of the study area is permanently unsuitable, 4.02 percent (131067.2 km2) is currently not suitable, and 14.45 percent (405722.6 km2) is marginally suitable. In some parts of the research area's eastern region, 7.05 percent (229936.5 km2) is assessed to be moderately suitable, while 15.76 percent (546019.2 km2) is assessed to be highly suitable (Figure 6.7b). According to the Fuzzy (Gamma 0.8 operator) map, 16.15 percent (526019.2 km2) of the region is permanently not suitable, 7.42 percent (241936.5 km2) of the territory is currently not suitable, and 14.91 percent (485722.6 km2) of the region is marginally suitable. Only the easternmost region of the nation is home to 4.97 percent (162067.2 km2) of moderately suitable, with the remaining 56.53 percent (1841325 km2) of highly appropriate land dominating the rest of the nation (figure 6.7c). According to the integrated AHP model, 19.78 percent (644324.7 km2) of the study area is permanently not suitable in the northernmost region, 19.87 percent (647265.6 km2) is currently not suitable in the northernmost region, and 20.05 percent (676012.6 km2) is marginally suitable in the northwestern and central parts of the area. Similarly, 20.10 percent (671592.1 km2) is determined to be moderately suitable in the northeastern sections of the area, while the remaining 20.20 percent (617875.3 km2) is discovered to be in the highly suitable category in India's eastern region (Figure 6.7d).

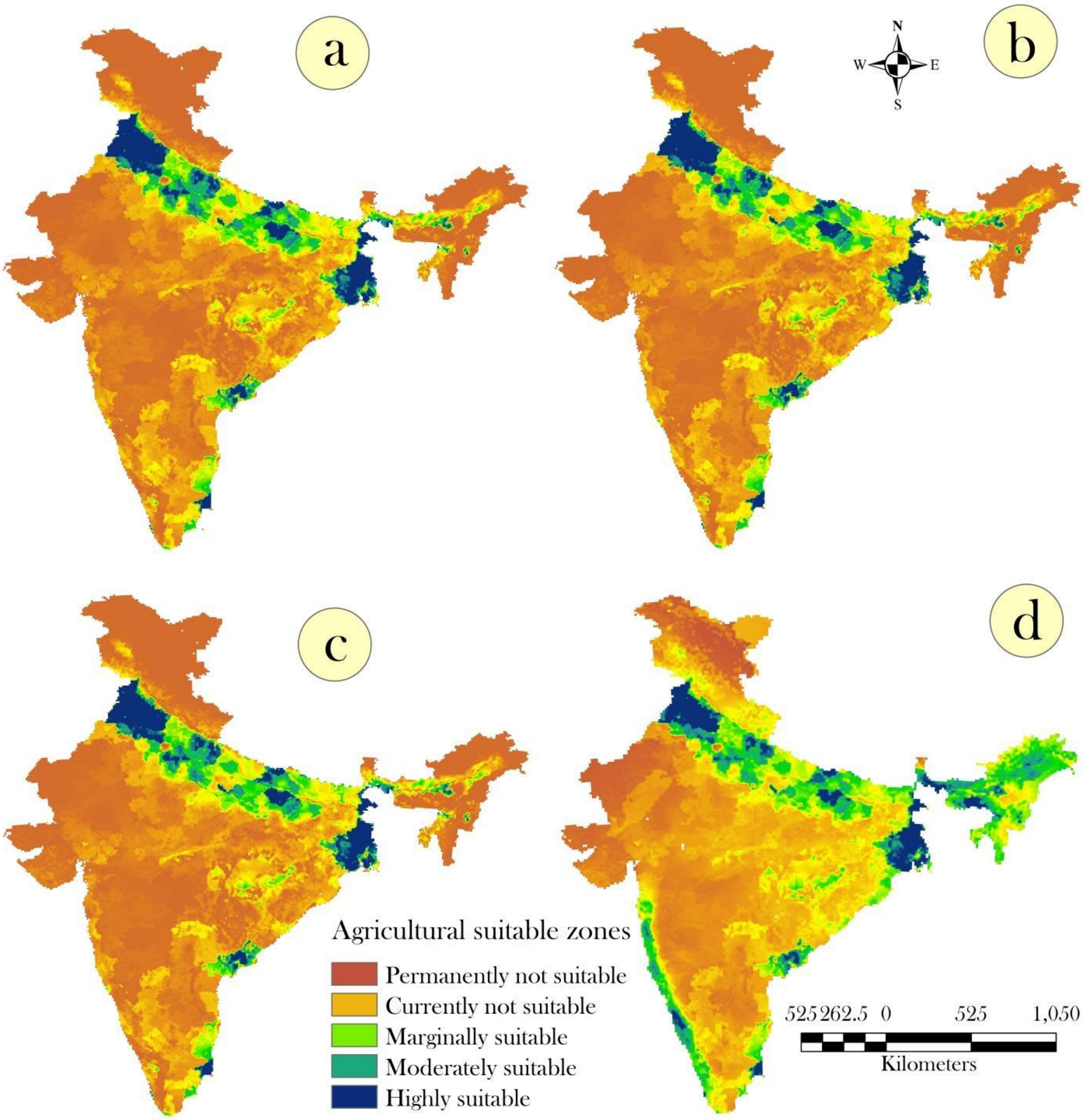



**Figure 6.7:** Agriculture suitability modeling using (a) fuzzy AND, (b) fuzzy gamma 0.9, (c) fuzzy gamma 0.8, (d) fuzzy AHP

**Table 6.4** Computation of area coverage different agriculture suitability zones

| Agricultural suitability zones | Area ($km^2$) | | | |
|---|---|---|---|---|
| | Fuzzy AND | Gamma 0.9 | Gamma 0.8 | Fuzzy AHP |
| Permanently not suitable | 1744325 (53.56%) | 1944325 (59.7%) | 1841325 (56.53%) | 644324.7 (19.78) |

| | | | | |
|---|---|---|---|---|
| Currently not suitable | 199067.2 (6.11%) | 131067.2 (4.02%) | 162067.2 (4.97%) | 647265.6 (19.87%) |
| Marginally suitable | 505722.6 (15.53%) | 405722.6 (12.46%) | 485722.6 (14.91%) | 676012.6 (20.76%) |
| Moderately suitable | 261936.5 (8.04%) | 229936.5 (7.06%) | 241936.5 (7.42%) | 671592.1 (20.62%) |
| Highly suitable | 546019.2 (16.76%) | 546019.2 (16.76%) | 526019.2 (16.15%) | 617875.3 (18.98%) |

Some climatic parameters in the current study, such as rainfall, temperature, humidity, and evapotranspiration, are time variable or vary with time. As a result, these parameters might have an effect on the model over time. As a consequence, we used historical rainfall and temperature data (1990-2000) as input data for ALSA modelling to propose a dependable and precise agricultural suitable model. Historical humidity and evapotranspiration data, on the other hand, are not accessible. As a result, we maintained the same humidity and evapotranspiration levels as before. The FAHP model was then utilised to build a time variant agriculture appropriate model (Figure 8). The results reveal that the time variant ALSA model and the FAHP model based ALSA are quite comparable. Then, using ArcGIS software's 'band collection statistic' tool, we used the correlation coefficient approach (Table 6.4). It indicates that the fuzzy AND, fuzzy GAMMA0.8, and 0.9 models are more than 50% comparable to the time variant model (Table 6.4). It is, nevertheless, more than 80% identical to the FAHP-based ALSA model. As a result, time variant parameters can have an impact on the ALSA model to some level. As a result, the authors propose that long-term climate data be used for agriculture suitability modelling in order to achieve extremely robust and trustworthy results.

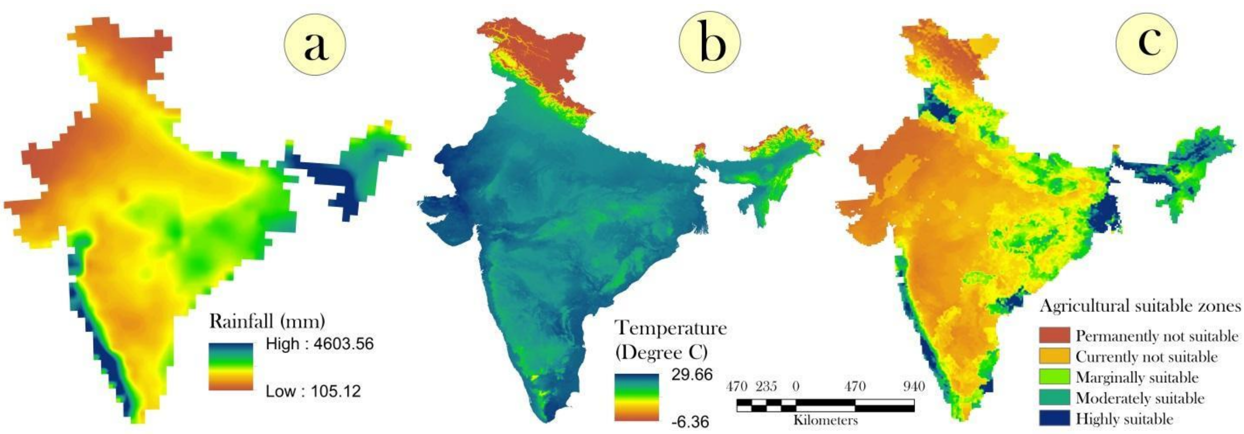


**Figure 6.8** Historical average rainfall (a) and temperature (b) used for FAHP based ALSA (c)

**Table 6.5**Correlation coefficient among five ALSA models

| | AND | Gamma0.8 | Gamma0.9 | FAHP | Time variant model |
|---|---|---|---|---|---|
| AND | 1 | 0.99348 | 0.99504 | 0.82338 | 0.5264 |
| Gamma0.8 | 0.99348 | 1 | 0.99848 | 0.81918 | 0.52898 |
| Gamma0.9 | 0.99504 | 0.99848 | 1 | 0.82288 | 0.53266 |
| FAHP | 0.82338 | 0.81918 | 0.82288 | 1 | 0.80645 |
| Time varient model | 0.5264 | 0.52898 | 0.53266 | 0.80645 | 1 |

**6.4 Ground validation**

Ground validation is critical for any type of prediction model. However, for some types of complicated prediction models, ground data is extremely sparse and difficult to come by. As a result, proxy ground data may be utilised to evaluate and test the models' reliability. Ground data on agricultural suitability zones are not accessible in the present research. As a result, we used several key crop production gridded historical data (1997-2003), such as rice, wheat, potato, pulses, and tea, as proxies (latest data is unavailable) (figure 6.9). Visually, the Indo-Gangetic plain is very fertile, and the majority of crops have been farmed. Figure 6.9 indicates that rice, wheat, and potato output were all quite high in these areas. While tea and pulsenes were abundant on the western and eastern ghats, As a result, these areas are also productive and suitable for farming. In India's complicated situation, determining an agriculturally suitable zone based on certain crops is extremely challenging. As a result, four agriculture-appropriate models have been compared to the production of these five key crops (Table 6.6). It indicates that the FAHP model, rather than other models, has a strong association with these crops. Other models have a positive relationship with these crops as well. As a result, depending on the model's present state, it may be claimed that FAHP outperformed other models.

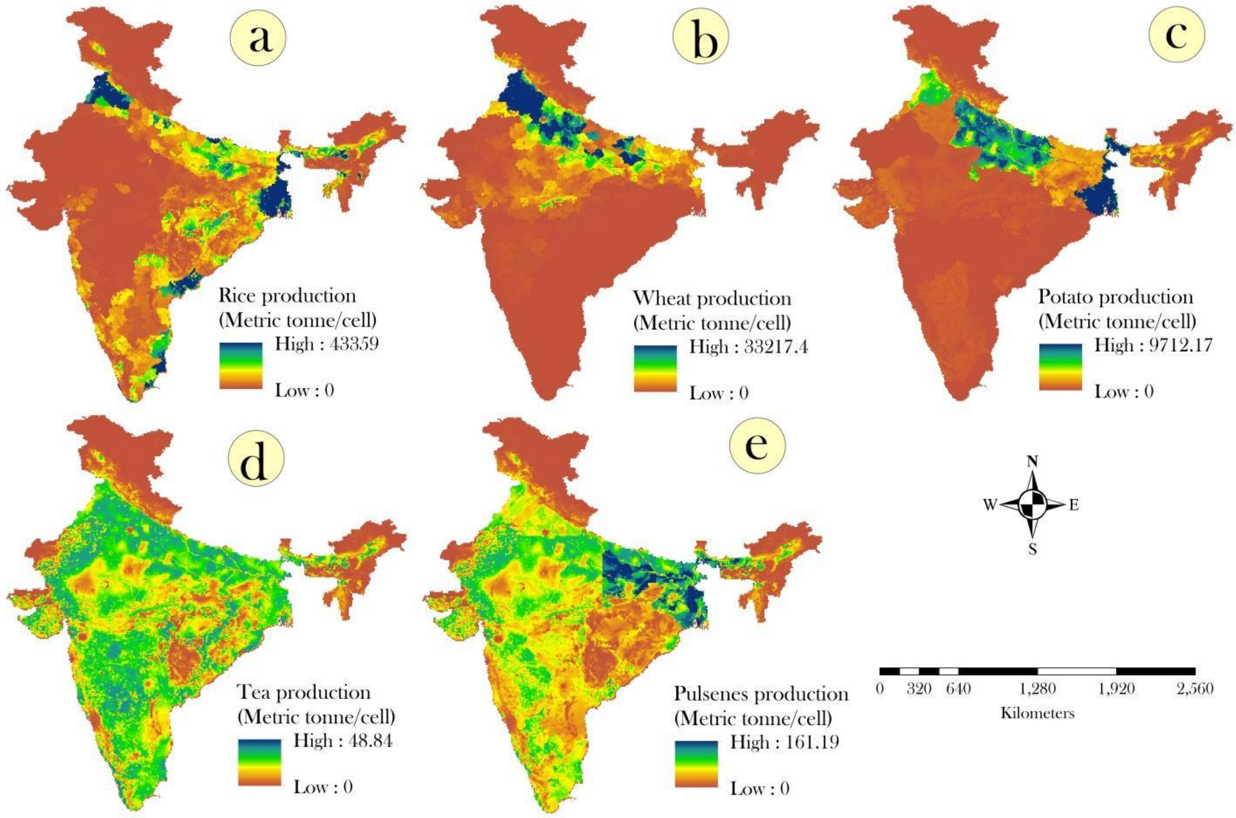



**Figure 6.9.**Production of major crops of India, such as (a)rice, (b) wheat, (c) potato, (d) tea, and (e) pulses for 1997-2003

**Table 6.6.**Correlation between agricultural suitability models and major crops

| | Fuzzy AND | Gamma 0.9 | Gamma 0.8 | FAHP | Potato | Pulsenes | Rice | Tea | Wheat |
|---|---|---|---|---|---|---|---|---|---|
| Fuzzy AND | 1 | 0.823 | 0.819 | 0.824 | 0.563 | 0.287 | 0.738 | 0.224 | 0.561 |
| Gamma0.9 | 0.823 | 1 | 0.998 | 0.995 | 0.640 | 0.441 | 0.842 | 0.397 | 0.752 |
| Gamma0.8 | 0.819 | 0.998 | 1 | 0.993 | 0.599 | 0.425 | 0.842 | 0.393 | 0.762 |
| FAHP | 0.824 | 0.995 | 0.993 | 1 | 0.641 | 0.448 | 0.837 | 0.405 | 0.756 |
| Potato | 0.563 | 0.640 | 0.599 | 0.641 | 1 | 0.507 | 0.557 | 0.303 | 0.357 |
| Pulsenes | 0.287 | 0.441 | 0.425 | 0.448 | 0.507 | 1 | 0.393 | 0.810 | 0.287 |
| Rice | 0.738 | 0.842 | 0.842 | 0.837 | 0.557 | 0.393 | 1 | 0.358 | 0.379 |
| Tea | 0.224 | 0.397 | 0.393 | 0.405 | 0.303 | 0.810 | 0.358 | 1 | 0.296 |
| Wheat | 0.561 | 0.752 | 0.762 | 0.756 | 0.357 | 0.287 | 0.379 | 0.296 | 1 |

### 6.4.1. Sensitivity analysis

For four agricultural suitability models, sensitivity analysis was done utilising different machine learning algorithms and statistical approaches, including global sensitivity analysis, RF, and Pearson's correlation approaches (Figure 6.7-6.9). The agricultural suitability models (produced using fuzzy operators and fuzzy AHP) were employed for the sensitivity analysis. The target variables were land suitability models, while the independent factors were fourteen agriculture suitability conditioning factors. We randomly gathered data from the target and independent variables based on 5000 points before doing sensitivity analysis. We used the retrieved data to do a sensitivity analysis to see how the independent factors affected the modelling of the target variable or land suitability models.

#### 6.4.2. Global sensitivity analysis

The Morris technique was used to conduct a global sensitivity analysis to test the dependability of the Fuzzy and AHP models in this study. As dependent factors, agricultural suitability models are used, while 14 influencing variables are included as independent factors. We did a global sensitivity analysis based on the extracted factor affecting factors to determine the most sensitive independent variable for modelling agricultural suitability zones in the research region. Four models were used to assess the effects of independent factors on agricultural suitability zones. Because ground-based monitoring is not feasible, sensitivity analysis is essential. Temperature, TRI, and soil quality were identified using the Fuzzy AND model as critical indicators that account for agricultural land suitability zones. Wind speed, on the other hand, has the least impact on agriculturally appropriate models (Figure 6.10a). Temperature, elevation, rainfall, and aspect were anticipated to be significantly affecting variables for agricultural suitability by the Fuzzy Gamma 0.9 model, whereas soil quality was anticipated to be the least influencing element for the research region (Figure 6.10b). Soil quality, soil organic carbon, and temperature were determined as strongly responsible for agricultural suitability using Fuzzy gamma 0.8. The Fuzzy gamma model, on the other hand, identified TRI as the least responsible variable (Figure 6.10c). The most influential markers for agricultural adaptability zone were found to be temperature and rainfall, whereas evapotranspiration was shown to be the least responsible variable (Figure 6.10d).

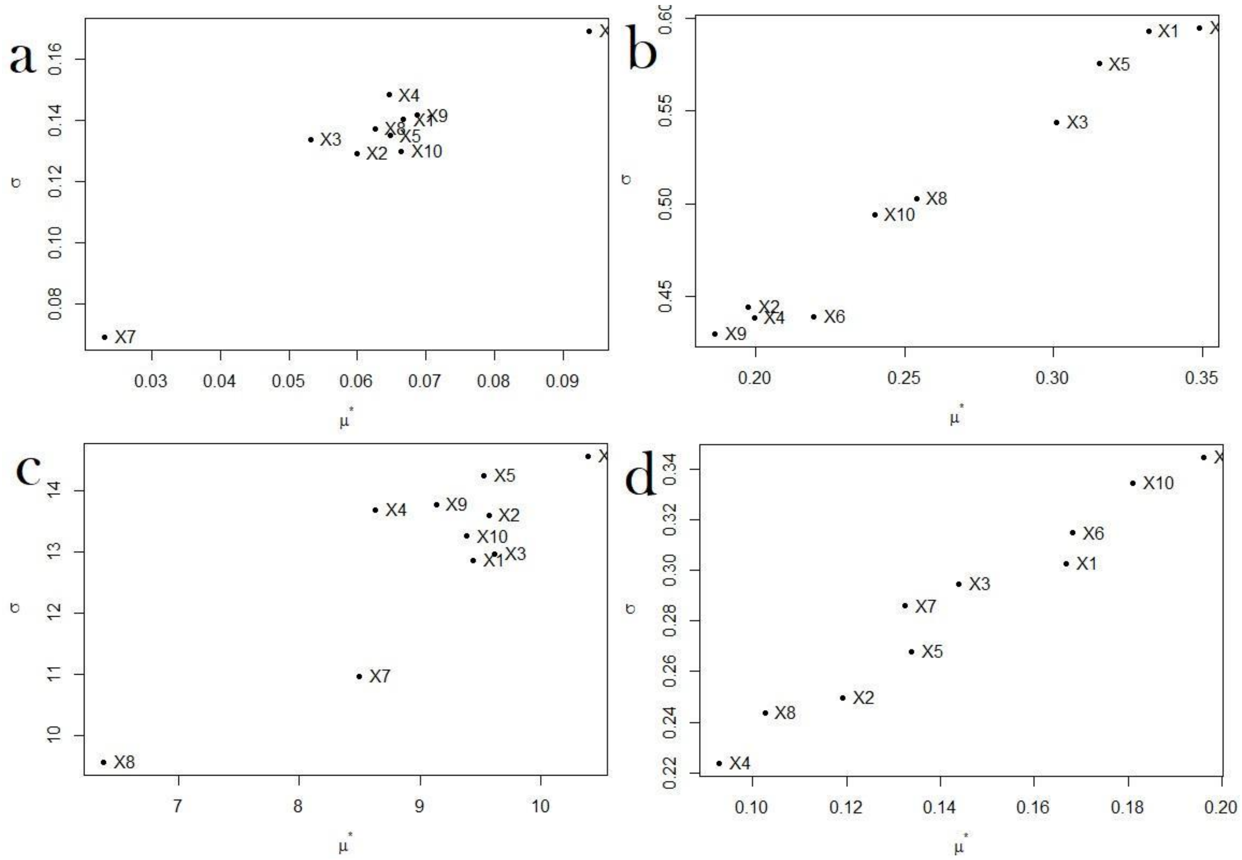


**Figure 6.10:** Global sensitivity analysis using (a) fuzzy AND, (b) Gamma 0.9, (c), and FAHP (d) Gamma 0.8. (N.B. X1-Elevation, X2-Slope, X3-Aspect, X4-TRI, X5-Rainfall, X6-Temperature, X7-Wind Speed, X8-Evapotranspiration, X9-Soil organic carbon, X10-Soil types, X11-Gross soil erosion, X12-LULC types, X13-Aridity).

#### 6.4.3. RF based sensitivity analysis

In this work, we utilised two RF model error matrices, MDA and MDG, to determine the relevance of factors versus agricultural suitability models (figure 6.11). In this study, four agricultural suitable models were used as target variables, and the relevance of predictor factors was calculated for each of the stated models. The sensitivity analysis of the fuzzy AND model is depicted in Figure 6.11a. According to the MDA and MGD values, the aridity index, rainfall, temperature, evapotranspiration, and soil quality are the most sensitive factors, whereas aspect and soil organic matter are the least susceptible. Figure 6.11b, on the other hand, depicts the sensitivity analysis of the GAMMA0.8 model. It shows that the most sensitive factors are aridity index, rainfall, temperature, evapotranspiration, and elevation, whereas the least sensitive ones are aspect and gross soil erosion. Figure 6.11c also displays the sensitivity analysis of GAMMA0.9, which demonstrates that the results are equal to GAMMA0.8. Finally, figure 6.8d depicts the FAHP model's sensitivity analysis. The most sensitive factors are evapotranspiration, temperature, soil organic matter, slope, and rainfall, whereas TRI and soil characteristics are less susceptible. As a result, evapotranspiration and temperature are the most ubiquitous sensitive factors, whereas rainfall, soil organic matter, and slope are the most dynamic sensitive parameters. As a result, in order to provide solid sustainable management plans for eradicating hunger, these indicators should be examined on a regular basis.

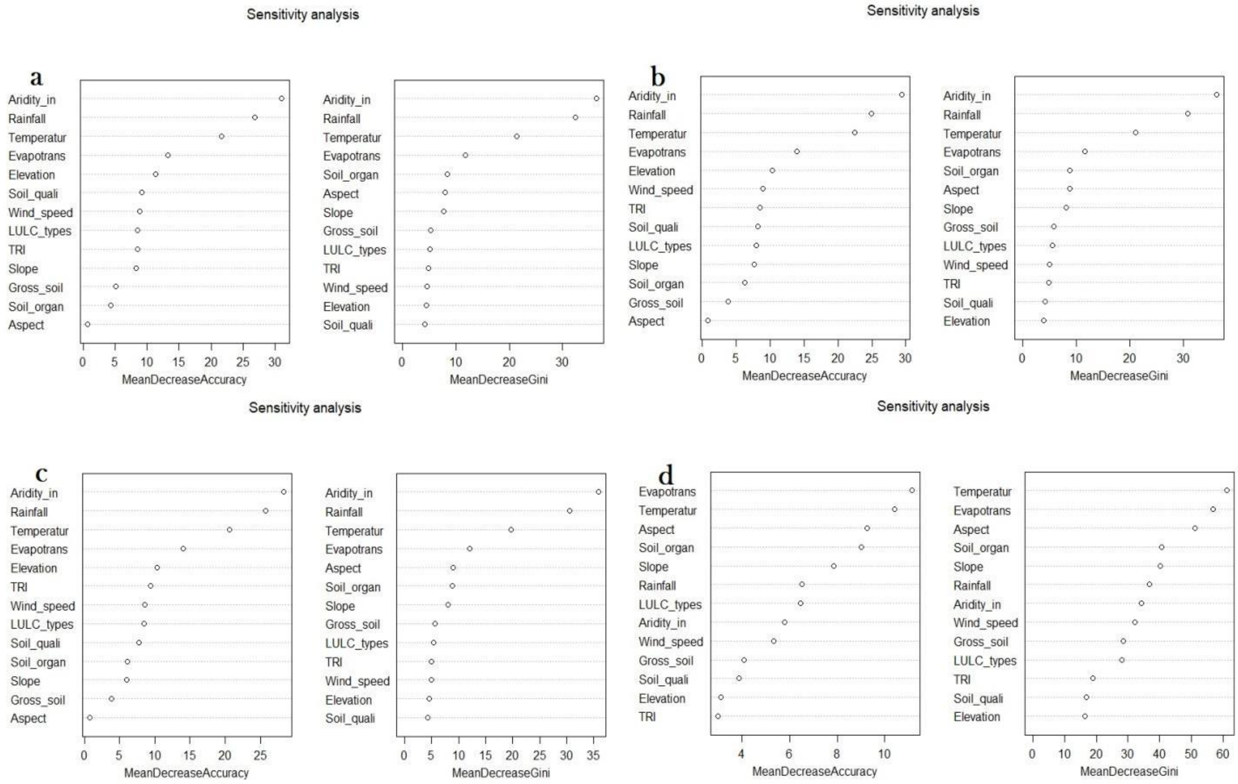



**Figure 6.11:** Random forest-based sensitivity analysis using (a) fuzzy AND, (b) Gamma 0.9, (c) Gamma 0.8, and (d) FAHP

### 6.4.4. Correlation coefficient based sensitivity analysis

Using Pearson's correlation coefficient, we calculated the relationship between the land suitability model and the independent variables for four agricultural suitability models (Figure 12). At the significance level of 0.01, Figure 6.12a revealed that aridity index had a greater correlation (r: 0.59), followed by rainfall (0.51), and evapotranspiration (0.34), while soil types had a very insignificant negative influence on agricultural suitability models. On the other hand, similar to fuzzy AND model, gamma 0.8 and gamma 0.9 identified that aridity index, rainfall, and evapotranspiration had most influence on the agricultural suitable models (Figure 6.12b, c). In the case of fuzzy AHP model, elevation, TRI, slope, rainfall, temperature, wind speed, LULC, and soil erosion had most influence (Figure 6.12d). Based on this analysis, it can be stated that rainfall, elevation, slope, evapotranspiration, aridity index had high influence on the agricultural suitability model.

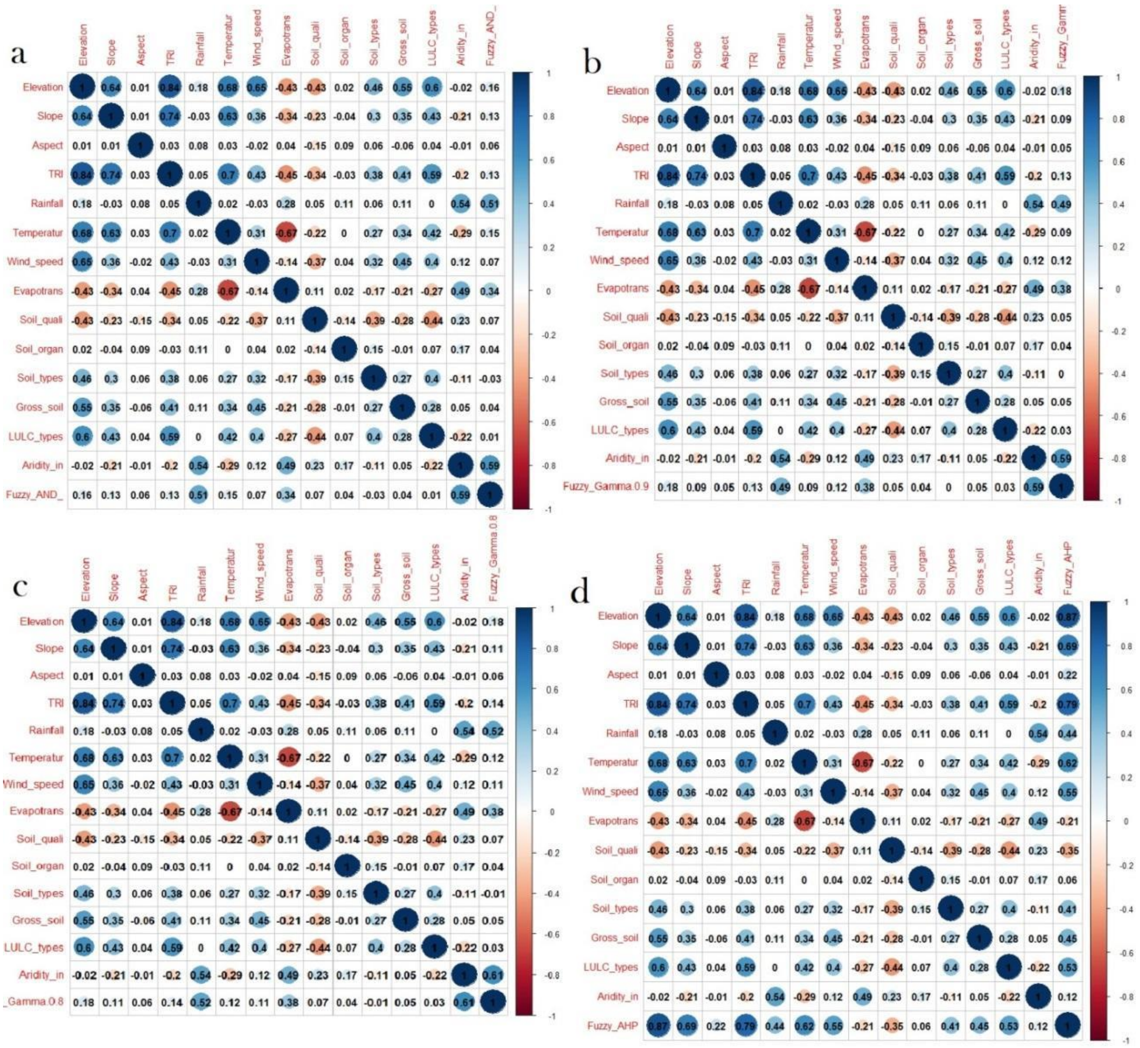



Figure 6.12: Correlation coefficient based sensitivity analysis using (a) fuzzy AND, (b) Gamma 0.9, (c) Gamma 0.8, and (d) FAHP

### 6.5. Conclusion & Summary

This work proposes (agricultural land suitability analysis) ALSA's state-of-the-art and future prospects. The SDG2 focuses on "ending hunger," "achieving food security," and "promoting sustainable agriculture." Food security can be attained through sustainable agriculture, which will eventually lead to the abolition of hunger. Climate change, on the other hand, is increasing the pressure on agricultural areas by causing calamities such as drought and flooding. To feed a growing population until 2050 and beyond, a significant transformation in global food and farming systems is required. Agricultural Land Suitability Analysis is a method of evaluating appropriate agricultural land in order to promote sustainable agriculture and food security in order to end hunger. ALSA, on the other hand, must be implemented with full understanding of and consideration for current and future climate change consequences. As a result, ALSA is an essential prerequisite for sustainable agriculture and food security in the face of climate change. As a result, in this work, we propose hybrid models for constructing ALSA as well as reliability testing.A closer look at the area and percentage coverage of the country's agricultural land suitability zones reveals that there is a lot of difference between the agricultural suitability zones in India (Table 3). Just 16 to 20% of the research area in eastern and northeastern areas, as well as a limited portion of southwestern regions, is designated as "moderately suitable," while more than half of the study area is designated as "highly unsuitable." The region and percentage coverage of ‘marginally suitable' lands ranges slightly, ranging from 14.45 percent to 20.05 percent.

To maximize crop yields across India, it is critical to identify suitable agricultural land for various crops. As a result, a large number of studies have estimated the suitability of agricultural land in existing works (FAO 1976; Fontes et al. 2009; Bandyopadhyay et al. 2009; Grassano et al. 2011; Akinci, Ozalp, and Turgut. 2013; Zolekar and Bhagat 2015; Kazemi, Sadeghi and Akinci 2016; Kazemi and Akinci. 2018; Ostovari et al. 2019; Pilevar et al. 2020; Ramamurthy et al., 2020; Rukanee et al., 2020; Saha et al., 2021). Topographic conditions, climate variables, soil characteristics, and local expert knowledge all play a role in crop production on agricultural land (Grassano et al. 2011). Temperature, soil quality, rainfall, soil organic carbon, and elevation, as shown in Figures 5.7-5.9, are important factors in increasing crop yield in farming practice.

Some previous studies have used fuzzy sets to determine land suitability (Zhang et al., 2015; Keshavarzi et al., 2010; Braimoh and Stein, 2004). The fuzzy set model has many advantages, including the ability to (i) convert all data to a range of 0–1, which is an excellent mechanism for solving different magnitudes at various data layers, and (ii) generate a detailed land suitability assessment for each crop production on a continuous scale in various land categories using fuzzy membership functions. Many researchers have used the combined Fuzzy set with the AHP approach to measure the weights of contributing variables in recent decades (Zhang et al. 2015; Kazemi, Sadeghi and Akinci 2016; Pilevar et al. 2020). The weighting of factors in our research can be compared to other studies including Kazemi, Sadeghi, and Akinci (2016), Ostovari et al. (2019), and Pilevar et al. (2020), which found that soil factors are an important factor in modelling land suitability for maize crop production. Temperature, soil quality, and rainfall, according to the Morris method, play a critical role in agricultural suitability for the entire country. Temperature and soil properties are primarily influenced by elevation, which can be linked to land suitability. Increasing elevation raises the likelihood of frost, cooler temperatures, and a decrease in plant growth months.

The most sensitive variables are temperature, soil quality, elevation, and rainfall, resulting in a highly suitable to marginally suitable region for crops. High wind speed (northern parts of the area), evapotranspiration (western and southern portions), and TRI (northern and eastern locations) limitations, on the other hand, curtailed the country's agricultural crop production capacity (Figure 9). Ahmed and Jeb (2014) reported similar results. Rainfall, temperature, and soil organic content, on the other hand, were identified as limiting factors in the suitability of a micro-water watershed for sorghum production (Mohan, 2008). The northern, north-central, and western parts of the country are called environmentally sensitive zones that must be preserved and protected. As a result, farming operations are prohibited on these fields. It is recommended that land managers and decision-makers prioritise those extremely suitable areas in context of states. Nevertheless, micro-level planning, like district and block level can be encouraged. It can be fruitful for achieving SDGs.

The AHP-Fuzzy logic method has been effective in combining data layers with a variety of subjective knowledge. One disadvantage of uniting both forms of knowledge is determining the general importance or weight of all parameters in the multi-criteria decision-making process. Some criteria must be considered concurrently, but few criteria have an unfavourable impact on agricultural suitability. The weights of parameters were well allocated in our analysis, as inferred by the AHP-Fuzzy logic tool. This method is an important model for scientifically integrating heterogeneous datasets and calculating weight, thus assessing any inconsistency in this appraisal. This result is in line with the findings of several previous studies (Kumar and Shaikh, 2012; Akinci et al., 2013; Zhang et al., 2015; Jamil et al., 2018), which used AHP in land suitability studies but improved their efficiency by incorporating fuzzy logic theory. Finally, farming managers and land-use developers will use the proposed model to identify alternate land uses/land covers for particular crop production. When compared to traditional agricultural suitability appraisal models, AHP-Fuzzy logic analysis of agricultural suitability evaluation has the advantage of being able to render appraisals at the national level by appraising each data unit individually. As a result, it is possible to determine the contribution of each soil, climatic, and topographic aspect to the assessment and make the results applicable to each landowner.

Our study's innovation in comparison with previous reports focusing on a global sensitivity analysis on agricultural suitability throughout India using the integrated fuzzy logic-AHP model, Morris method and machine learning based sensitivity. To achieve optimum crop yield, however, significant attention should be given to crop selection that is well suited to the agro-ecological conditions as well as proper land management.

There are a few flaws in this report. First, combined fuzzy-AHP results are based on a subjective assessment of the relative significance of the two variables, and associations between variables can be overlooked. Second, how the data layers and parameters are treated affects the validity of agricultural suitability assessment. Other considerations, such as agricultural land availability and the social context, should also be taken into account. One of the most complex aspects of this type of work is incorporating social perspectives into the spatial demonstration. As a result, these viewpoints need to be explored further.

### 6.6. Policy Implication

The GIS modelling concept was used in this analysis to link numerous themes from various sources of knowledge that have a significant relationship to agriculture practices. Decision-making is greatly aided by computer-based study of different databases and their conceptual assessment in the GIS domain. Furthermore, machine learning-based sensitivity analysis and global sensitivity analysis will aid in the identification of the most sensitive variables. Land and agriculture management can be optimised based on the results of sensitivity analysis to achieve good agricultural yields. As a result, the agriculture suitability model has an enormous capacity to propose smart agriculture management plans, which aid in achieving sustainability in agriculture and allied sectors while maximising land productivity to assist vulnerable and disadvantaged farmers who are suffering from the effects of climate change. Agriculture suitability (potentiality) model is seen as a promising option for meeting food, nutrition, energy, and job demands while still protecting our threatened environment.

Our study on agricultural land suitability maps relying on FAO guidance would be extremely useful to India's agriculture policymakers in expanding the projects to new areas. Since cropland has a strong suitability for S1 categories (46 percent), there is a massive opportunity to harness agroforestry in cropland areas. In India, over 80% of farmers are small landowners, and the majority of them depend on rain for their agricultural practices. During the monsoon season, they only use the ground for agricultural purposes. Due to a lack of irrigation, land is not used for agriculture for the remainder of the period. The rainwater harvest scheme would enable the preservation of soil moisture on the land before the next harvest season, when combined with different soil and water management activities at the watershed level. Several such research have been reported, that have modified crop cultivation scenarios at the local levels (Ahmad and Goparaju 2017b). The present study is significant in terms of India because it is the first time that agriculture suitability mapping has been performed at the country level. Furthermore, the above research would significantly aid in the creation and establishment of new agriculture centers for further research on a regional scale. This study demonstrates the capability of geospatial technologies as well as the pooling of different themes of land, soil, climate, and topographic data that could be taken into the scope of GIS. If integrated logically, GIS modelling software has immense possibilities for evaluating land potentiality in terms of its productivity for such particular uses. There is a need to assess India's land potential at different levels (village, district, and state) using key themes/layers/parameters that will substantially aid in crop productivity and variety. This will allow us to get accurate outcomes and better direction for future studies.

# CHAPTER 7

## Summary and Conclusions

This doctoral thesis is a compilation of four objectives to examine the impact of climatic variation on agriculture production in India. Chapter 2 presents the first objective where we comprehensively analyse trend of rainfall and temperature to show the climate change pattern. The analysis was done using statistical and machine learning methodologies. Chapter 3 provides the impacts of climatic factors on agriculture in this we use fifteen crops data including food and non-food grains crop to estimate what are the impacts of change in climatic on the productivity of these crops. This analysis used ITA for trend and multiple regression for impacts assesment. Chapter 4 develops a forecasting model to study the impacts of climatic variables on agriculture production till 2030. Chapter 5 methodology to build the agriculture suitability models which can assist in comprehensive a recommendations for land use management under climate induced constrains by areas are suitable or not suitable for existing agricultural practices in India.

The present chapter is organised as follows: Section 7.1 summarizes the thesis with the main findings of each objectives. Section 7.2 draws policy implications. Section 7.3 elaborates upon contributions of the study. Section 7.4 delineates limitations of the thesis and outlines directions for future research. 7.5 provide the concluding remarks.

### 7.1. Overall Summary

Climate change is today's most urgent concerns, as it has  either changed or is in the process of altering the earth's ecosystems.. While climate change has been a constant process on Earth, the rate of fluctuation has increased substantially in recent years, probably the last 100 years or so. Agriculture has been severely impacted by climate change across the world. The need for food is on rise for India due to growing population trends.On the otherhand, climate change is having detrimental influence on agricultural productivity, resulting in hunger, food shortages, farmer suicides, and other problems. As a result, sustainable agriculture management and water supply management are crucial for feeding billions of people. Based on this reasoning, the goal of this study is to investigate climate change and its impact on agricultural production in current and future scenarios. This research also resulted in the development of an agriculture suitability model that can be used for smart agriculture management under climate change stressed conditions expected in future. Several approaches have been used to achieve these goals. To begin, the proof of rainfall reduction was investigated using a variety of non-parametric trend analysis techniques. Change point detection methods were utilised to detect the presence of changes in the rainfall results. The ERA-5 reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF) was used to investigate the reasons of the rainfall shift. The standard precipitation index (SPI)-12 was used to calculate the long-term meteorological drought. In long-term meteorological datasets, the Mann-Kendall test and innovative trend analysis (ITA) were employed to forecast overall trends. The periodicity of the meteorological drought was detected using the Morelet wavelet transition. Multiple regression and Pearson's correlation coefficient were then used to describe each crop's production in light of climate change in order to estimate the influence of climate change on crop output. The ANN and ARIMA models were used to estimate and forecast climate variables and agricultural production in India up to 2030. Finally, agriculture-suitability maps were created using different fuzzy logic operators and a hybrid fuzzy-AHP model. According to the findings, most meteorological divisions exhibited falling annual and seasonal precipitation patterns during seven of the research years. 11 divisions had a significant drop in rainfall ($p<0.05$) during the monsoon season, but the declining rainfall trend throughout the winter and pre-monsoon seasons was insignificant. SPI-12 was used to forecast long-term meteorological drought for 34 sub-divisions in order to assess the impact of long-term drought on agriculture. The results of the ITA and wavelet transformations revealed that meteorological drought has lately grown in virtually all sub-divisions, despite the fact that these sub-divisions previously experienced mild to no drought. There was no obvious trend in temperature or rainfall, according to the trend indicator readings for rainfall and temperature. The yields of Bajra, cotton, Gram, Jowar, maize, Ragi, wheat, tea, and rice have all increased in a consistent and statistically significant ($P<0.01$) fashion. Rapeseed and barley revealed a significant ($P<0.01$) and monotonic decreasing tendency in their development. The output of various edible food grains, including as rice, wheat, bajra, jowar, and ragi, has grown substantially, according to the trend research. For the years 2017-2030, ANN predictions have predicted future agricultural and temperature parameters in India. The projected rainfall pattern has not much improved. On the other hand, the ANN model has revealed a substantial improvement in the predicted temperature trend. Production of barley, amaranth, linseed, and rapeseed has also declined. To summarise, with the exception of barley, Arhar, linseed, and rapeseed, all crop production will grow in the future but as they show a strong correlation with as temperatures rise and rainfall patterns shift greater efforts will have to be made for maintaining good productivity levels. According to the Fuzzy map, in certain areas of the south-west, the land was highly suitable for 16.76 percent (546019.2 km2), the region was amazingly suitable for 8.04 percent (261936.3 km2), and the surrounds were similarly good for 15.52 percent (55722.6 km2). The remaining 53.55 percent, spread throughout the northern, central, southern, and western zones, were considered somewhat unsuitable (1744325 km2). In the agricultural suitability field, temperatures and precipitation were the most influential factors, whereas evapotranspiration was the least influential predictor. Furthermore, this research will aid in the creation and building of new agriculture research centres for regional study. This study demonstrates the power of geospatial technology as well as the pooling of diverse land, soil, temperature, and topographic data topics that can be used into GIS. This research would aid us in obtaining more exact results and provide better direction for future research.

### 7.1.1. Main Findings of the Thesis

The main findings of the thesis are as follows. Based on the above findings, the summary of the present chapter can be summarized as follows:

In the first objective, in different meteorological sub-divisions, rainfall has decreased substantially since 1960 and 1975. The change detection techniques revealed that the entire rainfall time series (1901-2015) for 34 sub-divisions has a change point, which varies between 1950 and 1980 for various sub-divisions. This means that a rapid change or shift in the historical pattern or trend has been detected in the time series rainfall records. The pattern detection findings accurately quantified that, with the exception of North-East India, all meteorological sub-divisions experienced a slightly negative trend between 1960 and 1980, indicating a decrease in rainfall over time. The best approaches for trend identification were also examined, including the MK test, MMK test, Sen's slope estimator, and Innovative trend analysis, in addition to the trend detection results. ITA outperformed other pattern detection methods, according to the findings. In addition, the current chapter looks at climate change in terms of meteorological drought patterns and trends. SPI-12 was used to measure the long-term time series meteorological drought. The drought pattern or tendency for 34 sub-divisions has been increasing over time, according to long-term meteorological drought data. Most sub-divisions have recently seen an increase in drought, while some have seen moderate or no drought in the past.

In the second objective, there was no noticeable trend in temperature or rainfall, according to the trend predictor values for rainfall and temperature. The yield of Bajra, Cotton, Gram, Jowar, Maize, Ragi, Wheat, Tea, and Rice increased in a monotonic and significant ($P<0.01$) way. Rapeseed and barley development demonstrated a major ($P<0.01$) and monotonic downward trend. The rest of the crops showed a similar upward trend in demand. Many edible food grains, such as rice, wheat, Bajra, jowar, and Ragi, have increased dramatically, according to the pattern report. Crops such as groundnut, linseed, maize, Ragi, rapeseed, and barley show that the models' predictions are accurate in terms of production and climatic variables. The estimated crop production and climatic factors have a close relationship. Maize has the highest multiple correlation coefficient of crop production, indicating that it has a greater vulnerability to potential changing climatic factors such as temperature and rainfall. Wheat, Tea, Jowar, Cotton, and Gram have several correlation coefficients, indicating that temperature factors will also have impact on their productivity and sustenance.

In the third objective, using a panel dataset spanning 1967 to 2016, this study looked at the climatic vulnerability of Indian agricultural crop production. Temperature and precipitation datasets were used to plan crop production. In India, there was a mixed outcome due to climatic variability that differed due to various regional, tribal, and socio-economic factors. As a result of varying agro-climatic conditions, agricultural crop production varies across the region. The ANN model provides an admissible finding for further forecasts by comparing observed and expected values at the 95 percent confidence stage. Inevitably, the model will be used to comprehend upcoming plans, policy-making, and schedule reductions in the country's agro-based cropping systems. The model's outputs are critical for determining crop calendars dependent on local climatic conditions. Meanwhile, the crop produce is suffering from the negative consequences of climatic change, such as frequent precipitation occurrences, which would undoubtedly necessitate a change in the cropping pattern.

In the Fourth Objectives, in this study, the GIS modelling concept was used to connect several themes from diverse sources of information that have a significant connection to agricultural practises. In the GIS domain, computer-based analysis of various datasets and their computational appraisal significantly aids decision-making. Furthermore, global sensitivity analysis and machine learning-based sensitivity analysis can help in the detection of the most sensitive variables. To achieve strong agricultural yields, land and agriculture management can be optimised based on the effects of sensitivity analysis. As a result, the agriculture suitability model has a huge potential for proposing smart agriculture management plans that help achieve resilience in agriculture and related sectors while maximising land productivity to help poor and marginalised farmers who are suffering from the impact of climate change. The agriculture suitability (potentiality) model is viewed as a promising choice for meeting food, nutrition, resources, and work demands while still protecting the environment

**7.1.2. Synthesis of the Empirical Results**

Except for seven divisions over the research periods, most meteorological divisions had declining annual and seasonal precipitation patterns, according to the data. 11 divisions showed a significant drop in rainfall (p 0.05) during the monsoon season, but the declining rainfall trend throughout the winter and pre-monsoon seasons was insignificant. Overall, the average rainfall trend fell by 8.45 percent. The anticipated year of greatest change varied per climatic unit, with the highest change occurring primarily after 1960. There was a rising tendency in rainfall from 1901 and 1950, however after 1951, there was a significant reduction in rainfall. The LOWESS curve shows an increasing tendency in annual rainfall from 1965 to 1970, but a falling pattern after that. The findings of the LOWESS curve for the winter season indicated a rising rainfall trend for the years 1935-1955 and 1980-1998. There was a significant decrease in the pattern between 1955 and 1998. The graph demonstrates that a decreasing tendency began after 1960 in the summer and monsoon seasons. There has been a decreasing trend in post-monsoon rainfall since 1995. Rainfall projections over the next 15 years from many meteorological divisions suggest a significant decrease. Increasing/decreasing precipitation convective volume, increased low cloud cover, and inadequate vertically integrated moisture divergence, according to ECMWF ERA5 reanalysis data, might have affected rainfall variations in India. In order to examine the impact of long-term meteorological drought on agriculture, SPI-12 was used to estimate long-term meteorological drought for 34 sub-divisions. The ITA and wavelet transformation results indicated that meteorological drought has lately increased in virtually all sub-divisions, although these sub-divisions previously had mild to no drought conditions.

For the years 1967 to 2016, the ITA for climatic factors and agricultural productivity was investigated. The assigned variables, as demonstrated by trend indicators and their corresponding slopes, interpret the value. The trend indicator readings for rainfall and temperature are 0.42025 and 0.05126, respectively, suggesting that neither temperature nor rainfall are showing any apparent trend. Cotton, Gram, Jowar, maize, Ragi, wheat, tea, and rice all exhibited a steady and significant (P0.01) increase in production. Both rapeseed (ITA D value -8.54) and barley (ITA D value -28.93) yields decreased significantly (P 0.01) and monotonically. The production for the remainder of the crops followed a similar increasing trend. Most edible food grains such as rice, wheat, Bajra, jowar, and Ragi have risen considerably despite limited agricultural acreage and poor technical progress (Table 3). The influence of climate change cannot be noticed directly as a result of increased agricultural activities. For fifteen crops and meteorological factors, multiple correlation coefficients were computed. The results reveal that Ragi (0.862), Rapeseed (0.836), Tea (0.85), Wheat (0.815), Rice (0.811), and Jowar (0.815) have a very significant effect (coefficient determination values), indicating good crop production with the current temperature and rainfall pattern. Cotton (0.665), Gram (0.603), Barley (0.788), and Maize (0.621) are all related in terms of output. Crops with a moderate yield and processing need, such as barley (0.597) and wheat (0.401), require a precise structure. The Arhar (0.298) crop has a poor connection, suggesting that it might benefit from more attention in terms of production and climate change resistance. Variations in temperature and rainfall had minimal effect on groundnut and linseed output. Although several crops responded differently to the environmental factors, Arhar and Til (two of India's two primary cropping crops) were shown to be more sensitive to the impacts of climate change than the other thirteen key crops investigated.

Before using the model for forecasting, it is critical to test its effectiveness by predicting existing data. It may be utilised for further research if real data and projected data exhibit a similar connection with reduced error levels. The current study predicted climatic factors and different crops by refining ANN variables, and revealed that the real and expected data of climatic variables and 15 different crops were highly comparable. The correlation between real and expected values of all 15 crops and two meteorological factors was exceptionally strong, with R2 values larger than 0.82. The majority of the crops, however, had R2 correlations better than 0.92, with the exception of rice (0.86) and barley (0.82). The correlation between actual and predicted temperature and rainfall was likewise extremely strong ($R2 > 0.82$) due to that they are more sensitive to variation in climatic variables. The model's effectiveness in predicting climatic factors and crop yields is sufficient, and it may be utilised for future forecasting, according to the consequences of these mistakes. ANN models have forecasted future agricultural and climatic factors in India for the years 2017-2030. The forecasted rainfall pattern has not changed much. The ANN model, on the other hand, has identified a significant rise in the anticipated temperature trend. Production of barley, Arhar, linseed, and rapeseed will be decreased. Rice, Ragi, tea, maize, Jowar, Bajra, and cotton production will all be considerably enhanced by 2030. Til, Groundnut, and Gram looked at modest future-growing demand patterns from 2017 to 2030. To summarise, every crop output will grow in the future, with the exception of barley, amaranth, linseed, and rapeseed, as temperatures rise and rain falls.

The findings of the land suitability zone for agriculture are summarised in this chapter. The size and percentage coverage of various agricultural suitability zones per km2 has been calculated in India. Following that, the Fuzzy AND, Fuzzy Gamma 0.9, Fuzzy Gamma 0.8, and Integrated AHP models were superimposed on this land suitability map to analyse the overall agricultural suitability map. The Fuzzy map revealed that the dominance was highly appropriate for specific regions of the south-west, with 16.76 percent (546019.2 km2), the field was extremely suitable for 8.04 percent (261936.3 km2), and the surrounds were reasonably suitable for 15.52 percent (55722.6 km2). Around 6.11 percent of them, or 19.067.2 km2, were judged very improper, while a moderately problematic sector, which included areas in the north, centre, south, and west, accounted for 53.55 percent (1744325 km2). This thesis used the Morris approach to do a global sensitivity analysis to assess the FUZZY and AHP models' dependability. As dependent factors, the farm suitability models are employed, while 14 influencing variables are included as independent variables. We also ran a global sensitivity test using the derived factors influencing variables to look at the most sensitive independent variable in the agricultural suitability area modelling. Temperatures and precipitation were the most influential factors in the agricultural suitability region, whereas evapotranspiration was the least influential predictor.

### 7.2. Policy Implications &suggestions

Climate change, dubbed the "defining challenge of our time," is expected to have significant "impacts on environmental and human systems across all continents and seas." These effects are expected to devastate India, a nation with 7500 kilometres of coastline, large swaths of low-lying land, high population density, weak infrastructure, and a persistent reliance on agriculture as a source of income. Himalayan glaciers have begun to recede as a result of the 1°C warming that has already happened since pre-industrial times, and there has been a significant rise in the frequency and intensity of heat waves, droughts, extreme rainfall events, and floods. If the globe warms to between 2.6°C and 3.2°C, as the UN climate secretariat predicts based on existing nation commitments, India would face significant, pervasive, and permanent repercussions — not just for people and ecosystems, but also for economic development, livelihoods, and well-being. Climate change, for example, is expected to lower agricultural revenues in India by 15-25 percent by the end of the century. Therefore, India should rethink its policy regarding climate change in two ways; first is regarding how to tackle climate change, and second is about the alternative option to maintain the agriculture productivity in context of climate change.

Solar energy, energy efficiency, sustainable housing, water, ecosystem preservation in the Himalayas, reforestation, sustainable agriculture, and strategic knowledge management may all be used to combat climate change and its consequences. Adaptation measures are a critical component of this comprehensive climate plan. The first two sectors (solar energy and energy efficiency) are primarily concerned with climate protection, but the others, particularly agriculture and knowledge management, incorporate adaptation components. The following is a list of the adaption objectives.

While the sustainable agriculture is one of major element to tackle climate change. With the integration of remote sensing, GIS, and machine learning algorithms, smart and sustainable agriculture can be proposed. The GIS modelling concept was used in this analysis to link numerous themes from various sources of knowledge that have a significant relationship to agriculture practises. Decision-making is greatly aided by computer-based study of different databases and their conceptual assessment in the GIS domain. Furthermore, machine learning-based sensitivity analysis and global sensitivity analysis will aid in the identification of the most sensitive variables. Land and agriculture management can be optimised based on the results of sensitivity analysis to achieve good agricultural yields. As a result, the agriculture suitability model has an enormous capacity to propose smart agriculture management plans, which aid in achieving sustainability in agriculture and allied sectors while maximising land productivity to assist vulnerable and disadvantaged farmers who are suffering from the effects of climate change. Agriculture suitability (potentiality) model is seen as a promising option for meeting food, nutrition, energy, and job demands while still protecting our threatened environment.

The present study on agricultural land suitability maps relying on FAO guidance would be extremely useful to India's agriculture policymakers in expanding the projects to new areas. Since cropland has a strong suitability for S1 categories (46 percent), there is a massive opportunity to harness agroforestry in cropland areas. In India, over 80% of farmers are small landowners, and the majority of them depend on rain for their agricultural practises. During the monsoon season, they only use the ground for agricultural purposes. Due to a lack of irrigation, land is not used for agriculture for the remainder of the period. The rainwater harvest scheme would enable the preservation of soil moisture on the land before the next harvest season, when combined with different soil and water management activities at the watershed level. Several such research have been reported, that have modified crop cultivation scenarios at the local levels (Ahmad and Goparaju 2017b).

Adaptation is an important factor that will minimize the severity of the impact of climate change on future crop production (IPCC 2007). Potential adaptation strategies should thus be developed and consistently evaluated to effectively cope with climate risk.

Finally, the effect of climate change on crop yield is considerable and poses serious threats not just to farmers but also to regional food security, especially given the rapidly growing population which necessitates the production of more food. Ultimately, the solution to climate change lies in the effective deployment of adaptive strategies that could mitigate the impacts of climate change. The implications of the analysis and findings of this study are to pave the way towards a more proactive agricultural management planning with regards to climate change and its impending impacts on food security in the region.

### 7.3 Major Contributions

The major contributions are:

Şen’s innovative trend analysis (ITA) (Şen 2012) Due to its ability to show the results in graphical style, the innovative trend analysis technique is a very important tool for detecting patterns in rainfall time series data. The findings of this study might aid researchers in better understanding the annual and seasonal variations of rainfall in the study region, as well as serve as a basis for future research. In this study the best trend detection technique (ITA) has been identified. The ITA has been used across India to detect rainfall trends and meteorological droughts. This is the first research of its kind in India, according to the author.

The periodicity of rainfall and meteorological drought has been obtained. The complete research points to climate change, and there's a chance that droughts like these will become more prevalent in the study region in the future. The findings of this study will aid planners in developing good water resource policies, as well as forecasting tools that will offer prior warnings.

Most Indian states are badly impacted by repeated and long-term droughts, which have a wide range of negative consequences for water supplies, ecosystems, and socioeconomic development. As a result of this natural danger, agricultural production is also diminished. Droughts cannot be prevented; however their early detection can assist to reduce their negative consequences. To guarantee efficient usage and sound enhancement of water resources, economic advancement, and agricultural activity, it is important to study the spatiotemporal features and severity of droughts.

Łabędzki L (2007) in our research, we utilised SPI. The SPI is often regarded as the most efficient and dependable indicator for predicting drought.

The effect of climatic variables on fifteen crop productions has been assessed using multiple linear regressions.

The climatic variable such as temperature, rainfall and crop production have been forecasted up to 2030 using artificial neural network and statistical model (ARIMA) a comparative study could help to make decision the accuracy of result.

There are many studies done on agriculture suitability in India in different or specific region but as a whole country this work done first time as per author's knowledge

The world's population is projected to reach approximately 10.9 billion by 2021, there is important to farmers have a mandate to feed the growing population by sustainably increasing food production. Cropland identification and classification exercises address questions such as "where", "why" and "when" a particular crop is grown for a specific area to date, Land suitability analysis is a process applied to determine a specific area's suitability for considered use; it reveals the suitability of a site regarding its intrinsic characteristics (suitable or unsuitable).After that, land suitability mapping can be used to address the questions "where" in terms of land and resource use; hence establishing conditions favourable for sustainable production of a particular crop.

Agriculture suitability models have been generated using different fuzzy operators and integrated fuzzy-AHP algorithms. The contribution of several parameters for agriculture suitability models have been evaluated using Morris-model based sensitivity analysis and machine learning based algorithms.

This study is useful for conceiving complementary studies required to determinate and understands the relationship between climate variability and availability of the water resources.

## 7.4. Limitations and Directions for Future Research

This study aimed at estimating impact of climatic factors on agricultural studies in India; however, given the paucity of time and data availability, the study could not include some other important estimation which might have been useful. Therefore, the study acknowledges following limitations in the present analysis.

The fact that agriculture is also a cause for climate change and environmental degradation. The study also could not include impacts of food prices, general inflation, government regulation in agricultural markets,

We could not include factors like any government policies on climate change and food security, however, government expenditure on agriculture and allied activities for analysis,
There are many additional factors like solar radiation, sunshine, wind speed, hail storm, humidity, fog, concentration of carbon dioxide, and other weather patterns, which directly or indirectly affect the agriculture production system and climate change study, however, these variables were not included in the present study, and

We could not include information on natural disasters (e.g. floods, earthquakes, and crop disease etc.) which have a negative and significant impact on agricultural productivity, food security and vulnerability of the poor in terms of loss of livelihood.

Although research has contributed significantly to the disciplines of climate change and agricultural economics, it does have certain limits. Rainfall data from 34 meteorological stations were utilised in the study for the first aim, with each station covering an entire state and, in some circumstances, several states. As a result, categorising evidence of climate change using either one station in a state or numerous sites in multiple states is impossible. For measuring climate change, rainfall data gathered at the district or block level can be highly precise. Many sophisticated drought indices are available for forecasting meteorological droughts, however the SPI index was chosen for drought estimates due to a lack of funds.

Only 50 years of data were utilised to study the influence of climate change on agricultural productivity for the second aim. At least 100 years of evidence must be utilised to investigate the specific conditions of climate change. Only two climatic parameters, such as rainfall and temperature, have been utilised to examine the impact of climate change due to a lack of data. However, in order to provide more exact data, the modelling should include humidity, evapotranspiration, wind speed, and solar days in addition to rainfall and temperature.

In the case of the third aim, just 50 years of data were utilised to train machine learning models for forecasting future climatic conditions and agricultural development. To achieve better prediction results, at least 100 years of time series data is necessary. On the other hand, ensemble machine learning techniques have found extensive application across the world. As a result, these algorithms may be utilised to provide very accurate results.

For the fourth target, modelling was done using intermediate quality satellite photos. In poor countries like India, however, obtaining high-resolution data is both difficult and expensive. Although data with a moderate resolution is free, high resolution data is necessary to construct an agriculture model that is sufficiently believable. Machine learning, on the other hand, may offer reliable results. Fuzzy logic and fuzzy-AHP have been employed in modelling. As a result, using machine learning algorithms necessitates a countrywide survey, which is highly costly. As a result, in order to build highly reliable and suitable models, these challenges must be addressed.

One recommendation could be that hybrid techniques approaches that combine traditional and modern methodologies (e.g., MCDM, CSM, and MLMs)—are needed to efficiently identify homogeneous zones, especially for (NUS) Neglected and Underutilized Species. Hybrid land evaluation systems may be useful in dealing with complications like severe variability, intermittency, and socio-economic variables that are involved in the production of Neglected and Underutilized Species.

Methods differ in their robustness and simplicity. To enhance mapping accuracy, future studies could explore using data with a higher resolution. This will aid in the delineation of land suitability in marginalised agricultural communities, which are notoriously diverse. Sensors aboard unmanned aerial vehicles can be used to verify satellite-derived data and produce high-resolution pictures. The utilisation of data obtained from blockchain, cloud computing, big data, and IoT technologies can increase the accuracy and relevance of land suitability, particularly in high-risk regions.

The use of new predictive technologies in forecasting should be the focus of future research. The bulk of resource allocation studies used rudimentary GIS tools, according to the findings. Future research should concentrate on integrating the GEPIC model with additional approaches to analyse geographical distribution and boost crop output. The GEPIC model is used to forecast crop output levels by integrating near-real-time changes in the agricultural environment and combining it with other approaches for better decision-making.

## 7.5. Concluding Remarks

Exploration of the spatiotemporal distribution and changing pattern of climatic variables in any area is a basic and necessary necessity for the management and planning of water resources, sustainable agricultural growth, and other sectors. As a result, the current study used 115 years of long-term annual and seasonal rainfall data from thirty-four meteorological sub-divisions to investigate the variability and trend analysis of climatic variables in several ways, including overall data, change point wise (pre and post change point), and change point wise (pre and post change point). The total annual and seasonal variability of climatic variables was largest in Western India's sub-divisions, while it was lowest in Eastern and North India, according to the current study. According to the results of the MK test on overall annual and seasonal climatic variables, the sub-divisions of North-East, South, and Eastern India showed a significant negative trend, whereas the sub-divisions of Sub-Himalayan Bengal, Gangetic Bengal, Jammu & Kashmir, Konkan & Goa, Madhya Maharashtra, and Marathwada showed a positive trend.

As a result of the detailed study, it is clear that after 1970, virtually all of the sub-divisions showed a negative trend and significant variability. Even the year-by-year analysis indicated which year and how much climate factors were deviated. As a result, these detailed historical data for the entire country are extremely useful for planning. The forecasting of upcoming events, which can be found in any area such as finance, water resources, and, most significantly, climatology, is one of the most remarkable characteristics of developmental planning in recent times. As a result, in the current study, advanced AI models such as artificial neural networks were used to anticipate rainfall, as well as other climatic variables and agricultural production, for all meteorological sub-divisions. The outcomes of the predicting suggest that in 2030, 15% of rainfall and agriculture production would be reduced, indicating that worrying conditions will emerge for both the environment and the living world.

Whether it is agriculture or manufacturing, India's economy is completely reliant on the weather. As a result, water is a critical component of India's progressive economy. The world's rainfall, temperature, and drought patterns have all been disrupted as a result of climate change. As a result, several researches have been conducted in industrialised nations in order to assess the pattern of climate changes and establish management plans appropriately. However, in India, there has been very little research in this area. The current study provides all elements of climatic variability and trend for overall and change point wise annual and seasonal, change rate since the change point year, year wise departure, and future situation, as well as the causes of climate change in India. Technically, the current study included a number of advanced procedures that have been praised by experts all around the world for their ability to provide high-precision results. This sort of research has never been done for the entire country of India. As a result, the current study can serve as a complete package for Indian planners when it comes to developing strategies for small and large size locations.

Scientists from other countries can conduct research similar to the current study to formulate management plans for the sustainable development of water resource-based sectors and the environment because they require a large amount of data for developing plans, which can be in any field such as hydrology or climatology.

However, in this study, we examined thirty-four meteorological sub-divisions for the research, but micro level data such as district-level data should be included to be more accurate. After that, the extremely precise micro level management strategy will be implemented. Planners will also benefit from a grid-based rainfall study utilising cutting-edge microwave remote sensing technologies. To acquire very high quality forecasting data, ensemble machine learning techniques and deep learning techniques such as the long-short-term memory (LSTM) network can be employed.

The present study is significant in terms of India because it is the first time that agriculture suitability mapping has been performed at the country level. Furthermore, the above research would significantly aid in the creation and establishment of new agriculture centers for further research on a regional scale. This study demonstrates the capability of geospatial technologies as well as the pooling of different themes of land, soil, climate, and topographic data that could be taken into the scope of GIS. If integrated logically, GIS modelling software has immense possibilities for evaluating land potentiality in terms of its productivity for such particular uses. There is a need to assess India's land potential at different levels (village, district, and state) using key themes/layers/parameters that will substantially aid in crop productivity and variety. This will allow us to get accurate outcomes and better direction for future studies.

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