Effect of the Modifiable Temporal Unit Problem on the Trends of Climatic Forcing and NDVI data over India

RAVI MAURYA
March, 2013

IIRS SUPERVISOR
Mr. Prasun Kumar Gupta

ITC SUPERVISOR
Dr. Raul Zurita Milla

Effect of the Modifiable Temporal Unit Problem on the Trends of Climatic Forcing and NDVI data over India

RAVI MAURYA
Enschede, The Netherlands [March, 2013]

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Geoinformatics

IIRS SUPERVISOR	**ITC SUPERVISOR**
Mr. Prasun Kumar Gupta	Dr. Raul Zurita Milla

THESIS ASSESMENT BOARD:
Chairperson : Prof. M.G. Vosselman
ITC Professor : Prof.Dr. M.J. Kraak
External Examiner : Dr. Surya S. Durbha, CSRE (IIT-M)

Indian Institute of Remote Sensing
Indian Space Research Organisation
Department of Space, Government of India,
ISO 9001-2008 Certified

FACULTY OF GEO-INFORMATION SCIENCE AND EARTH OBSERVATION, UNIVERSITY OF TWENTE, ENSCHEDE, THE NETHERLANDS

DISCLAIMER

DEDICATED TO THREE MOST IMPORTANT FACTORS OF MY LIFE –

HARD WORK, HEALTH AND MY FAMILY

Abstract

Extraction of valuable information with the help of trend analysis from long time series of spatial data demands precision and great amount of scientific computation. The trends themselves are interesting estimators of studying spatial and temporal changes in climate and its effects at global and regional scales. Climate change assessment and evaluation is a subject of intensive scientific research. India being a predominantly agrarian country, also ranks amongst the top ten countries with the largest forest area coverage, has a huge dependence on rainfall for the agricultural sector. Geoscientists study climatic records to identify spatial patterns and temporal trends. Understanding climate change and its effect on vegetation is a pre-requisite to design sustainable mitigation and adaptation strategies. Considering the space-time variation of climatic parameters and vegetation over India, the choice of temporal aggregation level is as vital as choice of scale for spatial aggregation as it might lead to unreliable or unrealistic results. The present study was done to study the effect of Modifiable Temporal Unit Problem (MTUP) which arises due to temporal aggregation. The concept of MTUP is fundamental because the way in which temporal units are defined influences the results of the analysis. Trend detection at multiple temporal granularities such as daily, monthly and so on, provides a useful and representative way of depicting the basic characters of the changes. A detailed study of these temporal trends at different temporal granularities was carried out in this work.

25 years (from 1981-2005) long historical data for Rainfall and Temperature (Climatic forcing) gridded data, developed by the Indian Meteorological Department was used in this study. Normalized difference vegetation index (NDVI) derived from satellite imagery which provides a reliable monitoring system for terrestrial plant productivity was used from GIMMS. Parametric test- Ordinary Least Square Estimation and Non-Parametric tests- Mann-Kendall Test followed with Sen's Slope Estimator and Cox-Stuart Test were used to trend detection to statistically quantify the significant trends in the time series data. At different temporal granularities, the significant trends were observed for climatic forcing and NDVI data both to establish any relationship among them. For extraction of spatial information related to these significant temporal trends, the Indian subcontinent was studied by dividing it into 21 Agro-Ecological Zones depending on the physiographic, soil type, climate and growth period of vegetation for homogenous regions. Similarly, India was sub-divided into six homogenous summer monsoon rainfall zones for rainfall to study significant trends. Seven homogenous temperature regions were also delineated for India to study the effect of MTUP. The results were able to explore that the choice of selected temporal granularity and statistical methods are the key parameters which needs to be chosen carefully for such analysis. The end results of this research work were the significant trend maps which were helpful in analyzing spatial patterns in varying trends across different aggregation levels to show the effect of MTUP on NDVI and climatic forcing data over India.

One more outcome of this study was the development of a new trend analysis software tool named as AVSTAT 1.0 built on entirely open source tools and technologies with the help of Python Programming languages which has helped to carry out present analysis efficiently.

Index Terms- *Trend analysis, Climatic Forcing, NDVI, Temporal Aggregation, Modifiable Temporal Unit Problem, Parametric and Non-parametric statistical tests.*

Acknowledgements

A research of this kind requires resources, support and motivation. I therefore take this opportunity to acknowledge all those people who have encouraged and supported me during the entire period of this M.Sc. programme.

It's unimaginable to achieve anything without love and support of the family; No amount of gratitude would suffice for the unconditional support and unfailing faith that my parents have shown by supporting me throughout my life. Mere words are not enough for everything they have done so far for me. I would like to thank both my sisters and my brother and his family, who have supported me since childhood. I would be forever indebted for their love and support.

I would like to acknowledge that I am purely blessed to have you in my life Bimalpreet. You have contributed immensely and inspired me to achieve this milestone, thanks for supporting me in toughest of times with your unconditional love and care.

I would like to express my sincere sense of gratitude to my ITC Supervisor, Dr. Raul Zurita-Milla, for his concerns, comments, suggestions and constructive criticisms for my work throughout this thesis phase. Thanks for your feedback on my work which has helped to bring this thesis to its final form.

I would like to thank my IIRS Supervisor, Mr. Prasun Kumar Gupta for his guidance. I highly appreciate your constructive criticism that has always pushed me to work hard and learn more than ever. Your comments have helped me to carry out my work properly.

I would also like to thank Dr. Nicholas Hamm for his constructive criticism which has helped me to organize my work in a better way that has helped me to finish it well on time.

I would also like to thank Dr. P. S. Roy, Former Director-IIRS and especially Dr. Y.V.N Krishna Murthy, Director -IIRS for inspiring me during my stay at IIRS and providing great institutional and educational facilities.

I would like to thanks all faculty members of IIRS, Geoinformatics division for sharing their knowledge during the course modules. I would like to thanks Mr. P. L. N. Raju, Group Head, Remote Sensing & Geoinformatics Group and Dr. S. K. Srivastav, Head, Geoinformatics Department for their help during the M.Sc. programme.

Thanks to all my colleagues in IIRS and ITC for making this study experience truly a memorable and pleasant one. Shine, Madhur, Rahul, Mohit, Shankar, Anudeep, Suman, Akhil, Pavan Vijjapu, Abhishek, Sai, Vaibahv, Deepak, JJ, Shreya, Dinesh,Vimal, Raj, Sangeeta, Manuel, Federico and many others have very special place in my life and I have learnt so much from everyone. I would like to thank everyone who have left special imprint in my life so far.

Ravi Maurya

Table of contents

List of figures

List of tables

1. Introduction

1.1. Background

India is largely an agrarian country with approximately 70 percent of the population reliant directly or indirectly on agriculture (National Portal Content Management Team, 2011). The gross domestic product, which is an indicator of performance of an economy, is highly contributed by the agricultural sector of India. This represented a significant 14 percent of the total economic growth in India in year 2011-12. In many of the Indian states like Madhya Pradesh, Punjab and Haryana, Uttar Pradesh, Bihar etc. there is a huge dependence on rainfall either for rain fed agriculture or for irrigation. More than sixty percent of the Indian population's livelihood is from rain fed areas. The Indian summer monsoon rainfall (ISMR) is a major climatic component through which India receives about 80 percent of its total rainfall during the summer monsoon season (from June to September). Recent IPCC (Intergovernmental Panel on Climate Change) reports and other studies have indicated a probability of 10 to 40 percent loss in crop production in India with decrease in irrigation water and increase in temperature by 2080-2100 [Parry et al., 2007; Aggarwal, 2008]. Due to the vagaries of rainfall, more than 68 percent of the net sown area in the country is drought prone, out of which 50 percent is severe in nature [Alley et al., 2007]. The surface temperatures in India are increasing at the rate of 0.4 degrees Celsius per hundred years, particularly during the post-monsoon and winter season according to recent studies [Samui and Kamble, 2011]. Concerning predictions by using scientific models for mean winter temperatures have shown an increase by as much as 3.20 degrees Celsius in the 2050s and 4.50 degrees Celsius by 2080s. Summer temperatures are expected to increase by 2.20 degrees Celsius in the 2050s and 3.20 degrees Celsius in the 2080s. At this rate India could lose million tons of major crops produced every year with every rise of 1 degree Celsius temperature throughout the growing period. Even higher losses are expected in case if irrigation would decrease in future. Natural calamities induced by climate change like droughts, floods, tropical cyclones, heavy precipitation events, hot extremes, and heat waves are known to negatively impact agricultural. Visible signs of decrease in yields due to change in global weather has already shown in many regions in India. Variation and trends in rainfall and temperature have significant political and social impacts as Indian agriculture is largely controlled by variations in climate seasons. Climatic parameters (rainfall and temperature) are also referred as Climatic forcing. The changes in climatic forcing give rise to serious concerns to agriculture which has direct implications on food security and economy of India. The majority of the Indian subcontinent can be classified into three categories: forest area, other vegetation, and non-vegetation areas [Jeyaseelan et al., 2007]. Forest area has all types of species of forest and natural systems. Other vegetation areas consist of mainly maintained agriculture regions in India. Non-vegetation areas represents urban, water, snow etc. Over a long period of time climate change is also responsible for a significant decline in forest area in India. Many other reasons were also responsible for the deforestation in past years. Over the last 20 years, deforestation trends have shown a significant decline in India. According to United Nations report from 2010, India's forest as well as woodland cover area has increased significantly [Food and Agriculture Organization of the

United Nations (FAO), 2012]. According to the FAO and Global Forest Resources Assessment 2010 India ranks amongst the 10 countries with the largest primary forest area coverage in the world (the other nine being Australia, Brazil, China, Canada, Democratic Republic of the Congo, Indonesia, Sudan, Russian Federation and United States of America). With the evolution of remote sensing, various indices are derived to study changes in vegetation at global and local scales. The study of vegetation growth and sustainability is commonly done using Normalized Difference Vegetation Index (NDVI) by the researchers. NDVI is one of the most classical indices used in many studies due to its long time availability. NDVI reflects vegetation vigour and is a measure to describe the vegetation health. The relationships between NDVI and climatic forcing have been sufficiently demonstrated in many studies done previously across the world [González-Alonso et al., 2003; Ji and Peters, 2003; SERGIO, 2006; Vicente-Serrano et al., 2010; Julien et al., 2011].

This study intends to determine whether significant changes in NDVI could be associated to changes in climatic forcing. As variations in NDVI would indicate impact of climate change on vegetation growth, it could be used as an indicator to study agricultural vulnerability. Although a significant change in climatic forcing does not necessarily imply a significant change in NDVI and vice versa. Any significant increase or decrease in trends of NDVI in the absence of any significant increase or decrease in climatic forcing presented the possibility that some other factor might be responsible for the change in NDVI. For example, deforestation in India between 1970's to 1980's were showing significant negative trend in NDVI but they were more or less human induced changes rather than caused by climate change. These changes were due to industrialization and growth in urbanisation in the post independence period and not necessarily due to climate change. With the evolution of Remote sensing and Geographic Information Systems, the availability of satellite data and ground station data, its archival and utilization for such studies has increased tremendously. Trend detection in a time series from large data archives and the evaluation of its statistical significance and magnitude is an important tool for information extraction both at global and local scales. This importance is amplified in case of impact of climatic variables and their dynamic relationship with vegetation growth.

Recent studies have demonstrated that the statistical significance of a trend, changes drastically by the behaviour of the time series [Fatichi et al., 2009]. Trend analysis must avoid common statistical pitfalls such as the violation of assumptions for most statistical analyses (i.e., linear regression), including normality, homogeneity of variance, and serial autocorrelation [De Beurs and Henebry, 2004]. In this study a combination of different statistical estimators are used for trend detection. These statistical tests were carefully chosen to avoid such problems. .One parametric statistical test i.e. Ordinary Least Square is applied in order to test for trends in time series for climatic forcing and NDVI [De Jong et al., 2011]. The trend detection results will be further compared with the results obtained by using two different nonparametric trend detection methods: Mann-Kendall test followed by Sen's slope estimator to evaluate the magnitude of trend and Cox-Stuart test respectively [Guhathakurta and Saji, 2012; Mondal et al., 2012; Chandrasekaran et al., 2003; Fatichi et al., 2009; Paul and Sarkar, 2012].

1.1.1. Long term NDVI time Series analysis

Monitoring vegetation change over a long time is critical to understand gradual or long-term changes, such as ecosystem degradation due to agricultural over-use, human induced changes and deforestation which can be detected and characterized with trend analysis. NDVI is a very useful index in this context. The chlorophyll pigments exhibits two maximum absorption radiation zones; one is the blue region of the spectrum (0.43 micrometers) and another in the red region (0.66 micrometers). The mesophyll of the leaves - provided with irregularly shaped cells which constitute a surface with large inter-cellular spaces - is very reflective of the radiation incident in the infrared region (0.75-1.1 micrometers). Thus, the response of the green vegetation (in a good physiological and healthy state) is characterized by a substantial absorption in the red region and a large reflection in the near infrared region of the electromagnetic spectrum. It has also been observed that the vegetation which is unhealthy, ageing or subject to conditions of stress, which increases its reflectance in the red region of the spectrum while it decreases in the nearby infrared [González-Alonso et al., 2003; Ji and Peters, 2003]. Trend analysis is also used to find relationship and affect of climatic forcing on NDVI. Time series analysis for trends in NDVI are used for many purposes, such as phenological change [White et al., 2009], assessment of ecological response to global warming [Pettorelli et al., 2005], land cover change [Hüttich et al., 2007] or desertification [*Symeonakis and Drake*, 2004; *Bai et al.*, 2008]. There are many applications in the field of remote sensing and geographic information systems where time series analysis of NDVI has been used to study vegetation. Some of the most important applications are drought monitoring and monitoring vegetation status which is commonly used in assessments of productivity of natural and agricultural lands at global and local scales. Large historical datasets are required in these applications which involve complex inter-relationships with the climatic factors. For an example, from these applications, Drought is one of the sinister hazards of nature. Drought always starts with the lack of precipitation (or may not) which affect soil moisture, groundwater, streams, ecosystems and human beings. Due to the prominent reduction of the rainfall, the capability to carry out the chlorophyll function on the part of the vegetation is remarkably reduced. This event is confirmed by the spectral response provided by the affected vegetation covers. With the help of such spectral indication from vegetation and its study using time series analysis, the information for monitoring vegetation change can be obtained. Crop sustainability and growth patterns for agricultural area are also studied with the help of time series analysis. Statistical assessments of these changes are done for planning and adaptive strategies for future. Long time series data availability for NDVI helps in monitoring vegetation sustainability in forest area and other vegetation areas. Time series analysis also helps in monitoring deforestation in the forest areas. Gradual changes like loss of endangered forest species are also detected by time series analysis.

1.1.2. Climatic forcing Trend analysis

Considering, the space-time variations of climatic parameters over a region, trend analysis for change detection is one of the reliable methods [Jain and Kumar, 2012; Paul and Sarkar, 2012]. The spatial and temporal patterns of temperature and rainfall are predominantly influenced by the latitude, with the temperature decreasing gradually from equatorial to the Polar Regions. These patterns are appreciably modified by the land-sea distribution, climatic seasons and topography. Topography has a profound effect on spatial patterns of precipitation and temperature both globally and regionally. Trend analyses for different topographic regions have shown different patterns for trends variations. Another very useful and representative way of depicting changes in the basic character of climate is to study the changes in rainfall and temperature means for daily or monthly data [Dash et al., 2009]. Generally, to study the variations in climate at regional levels major seasons are considered [Rajeevan et al., 2006; Kothawale et al., 2010]. Climatic Seasons are fundamentally due to sun-earth orbital geometry, and are generally based on the associated thermal/moisture regimes for specific locations. From a climatic point of view, India is a tropical country dominated by different climatic seasons. Many trend analysis studies in past decade involving climate change were done for India [Gadgil et al., 2004; Aggarwal, 2008; Mishra et al., 2012].

According to National climate centre reports from the Indian meteorological department, the climate change is projected to continue and is expected to be accompanied by changes in extreme climate events and weather conditions [Guhathakurta and Saji, 2012]. Yet quantitative knowledge about these changes is very limited. In this present context, it is important to know how the climatic changes induced in the past are affecting the present extreme events in rainfall and detected changes in temperature by many research works. Variation in trends for climatic forcing are quantified with the help of trend analysis for change detection.

The trend analysis has helped scientists to find some serious implications of climate change in India. Due to the change in climate the coastal states of Maharashtra, Goa and Gujarat would face a grave risk from sea level rise. Damage to coastal infrastructure and other property including agricultural land are expected because of this. In the state of Maharashtra, the business capital of India, over 1.3 million people are at risk. Goa could be the worst hit, losing a large percentage of its total land area if these predictions will happen. A one meter rise in sea level will adversely affect 7 per cent of the population in Goa (Planning Commission Report, 2010). Similar results show that extreme rainfall events are increasing in states like Madhya Pradesh in Central India. These extreme events cause serious threat to vegetation as well to human population. Thus effective trend analysis for long time series climatic data is immensely important to detect changes in climate.

1.1.3. Modifiable Temporal Unit Problem

Generally, both climatic forcing and NDVI contains strong seasonal characteristics and have tendency to show autocorrelation which create problems in any change detection analysis. For example, if we consider temperature or rainfall data from ground stations, both data shows strong cycles. In case of temperature, it is usually low at night and remains higher during the day time. When we consider seasonal cycles, it is usually very low in winter seasons across the country but is very relatively very high in some part of countries in summer season. Similar to temperature, rainfall experienced by the country observes a maximum in the monsoon season where as post monsoon seasons are significantly less wet. There are signs of long term trends in both rainfall and temperature which are associated with global warming. If we consider the temporal resolution for our observation to be every 24 hours at afternoon time every day, we will miss the daily cycle completely. Again, if we choose to fix our temporal resolution for observation annually, we are going to miss all seasonal variations throughout the year as well as the daily cycles. NDVI also show seasonal variation throughout the year in forest areas. The agriculture regions also show significant variations in case of major crop seasons. If we consider our temporal resolution more than the time estimated for crop growth and harvesting period, we might not be able to assess the changes in NDVI. The choice of temporal resolution is as vital as choice of spatial resolution for any study. The temporal resolution of the data used is the key factor when working with periodic data. All these important facts show the importance of choosing optimum temporal resolution for the analysis. This issue can be taken care of by temporal aggregation by creating temporal aggregates of the data. In general, the data can be aggregated over fixed number of bins (years or months or days). Aggregating the data like this will create temporal units which are modifiable. These temporal units may influence the model fitted parameters and can also affect the amount of change detected. This issue is also termed as Modifiable Temporal unit Problem (MTUP). MTUP is analogous to Modifiable Areal Unit problem (MAUP) which arises due to variation in spatial scale, yet it is formally not developed to address issues that can be applied as a standard [Devillers and Goodchild, 2010]. The issue of Modifiable Temporal Unit Problem (MTUP) can be remediated if we address these three important aspects – duration (how long), temporal resolution (how often), and the point in time (when), to study the NDVI and climatic forcing together for temporal analysis. In this research work, the effect of MTUP is studied on the temporal trends of climatic forcing and vegetation indices derived from remotely sensed data. The issue of MTUP has to be addressed as temporal units influence the results of the analysis [De Jong and De Bruin, 2012]. Various studies are done for different regions to study changes in climatic variability at different spatial and temporal scales [Julien et al., 2011; Jain and Kumar, 2012]. Results for these studies have shown a great amount of uncertainties and inconsistencies when the spatial and temporal scales were changed [Goswami et al., 2006; Ghosh et al., 2009]. For example, trend analysis carried out for Madhya Pradesh, one of the biggest states in India has shown presence of extreme rainfall events over past decades and also predicts larger variations for future. When a similar study was done at all India level, the results were found out to be quite contradictory to the former study. This shows that spatial scale also plays an important role. Temperature and rainfall variations observed annually at all India level shows very less variations, but extreme rainfall and temperature events are reported in specific seasons. The pre-monsoon seasons are getting hotter and cold waves experienced during winter seasons have increased. This clearly supports the importance to studying these changes at different temporal scales. In this study, we have concentrated on studying the temporal aspects of these changes and how choice of temporal aggregation level may affect the results of the analysis. The solution to this problem is critical as there are different ways to handle it but it has no standard solution for various problems faced in such analysis [Beurs and Henebry, 2005]. Aggregation or disaggregation both in terms of spatial and temporal aspects is one of the key challenges involved in these studies.

1.2. Problem statement and Motivation

Because of critical socio-economic dependency of climatic forcing on vegetation in India, trend analysis involving historical data can be very crucial in change assessment. But few problems are faced by researchers during such analysis. One of the problems is combining distinct data due to difference in their spatial and temporal resolution which is always an area of concern for researchers. To do a study how climatic forcing and NDVI trends are varying over Indian subcontinent is always a challenge in itself due to the topographic and climatologically diversity which tightly controls these variations. How much temporal sampling is required to study the climatic changes is always been subjected to discussions. Same is true for choice of temporal resolution for observation. Aggregating data temporally is one of the ways where these issues can be handled. But aggregating data like this will give rise to MTUP and subsequently affects the results obtained. Another problem in these studies is the choice of statistical methods used for the trend analysis [Bettini and Ruffini, 2003; Fatichi et al., 2009]. This choice is also a critical aspect that may lead us to spurious statistical results for the trend analysis, and moreover, to misleading interpretation of the data. A detailed study to statistically establish and quantify significant trends and a comparative analysis of results obtained from different statistical estimators can be very helpful to understand correlation between NDVI and climatic forcing data by aggressing issues related to MTUP at multiple temporal granularities. The knowledge of trends analyzed in this time series analysis may provide information about the future evolution of the process or at least on the modifications occurred. IPCC’s projection on climate change depicts macro level scenarios. Hence, it is required to downscale and analyse them at regional levels. Furthermore, study for localized impacts on agriculture, forests and allied sectors should be done. The implications of climate change could be responsible for additional stress on ecological and socioeconomic systems that are already under tremendous pressures due to industrialization, economic development and rapid urbanization in India post independence. Hence these factors have inspired to do a study which is helpful in studying the effect of temporal aggregation.

1.3. Innovation

MTUP is a relatively new problem in the fields of remote sensing and geographic information systems [Çöltekin et al., 2011]. Though it is not addressed formally as MTUP, but it is known and experienced in some works involving different temporal scales mainly in the fields of econometrics [Zellner and Montmarquette, 1971; Wei, 1978; Gotway and Young, 2002; Buishand et al., 2004; Cotofrei and Stoffel, 2009]. To study the MTUP effects at varying temporal granularity is one of the key innovations of this research work. Since we have considered all of India subcontinent region, the results may vary from the previously done trend analysis studies on a relatively smaller study area, such as analysis done at Indian states level. We have also tried to find out if there is any correlation between the trends observed between NDVI and climatic forcing in various AEZ. Major seasonal aspects in case of agriculture (crop seasons- Rabi (December- Feburary), Kharif (July-September) and Zaid (March-June)) are taken into account in this study. Trend analysis is also done for rainfall in homogenous monsoon rainfall regions in India. Similar analysis is also done in this study for temperature in homogeneous temperature regions in India. Temperature and rainfall variations in all seasons (winter, pre-monsoon, monsoon and post-monsoon) are covered in present study to provide enough temporal sampling to study the seasonal variations. The problem arises due to temporal aggregation level is one the key challenges addressed here with the help of studying these changes at multiple temporal granularities to establish correlation between NDVI and climatic forcing data. Temporal granularity is an indispensible attribute of time which is usually fixed by the scientist/analyst when observations are made [Çöltekin et al., 2011]. The temporal granularities are defined by differences in time of observations. In terms of temporal scales some granularities are finer or coarser with respect to other granularities. A new framework is also proposed in this study to use different statistical estimators for the trend analysis to extensively study and compare the trends thus observed. Combinations of both parametric and non-parametric tests are used for the analysis to assess their sensitivity towards the data. The proposed approach may seem a little more laborious but with the large uncertainties present and the growing importance of trend significance justify this work. Another innovation targeted in this study is to develop a comprehensive self-developed software tool for trend analysis using open source geo-spatial tools and technologies which will help in automating the whole trend analysis process.

1.4. Research objectives

The main research objective of this study is to study variations in significant trends for climatic forcing and NDVI at different temporal granularities. These trends may help us to identify spatial and temporal patterns which may associate change in climatic forcing and NDVI over India. The sub objectives of this research are: -

- To study the MTUP effects that arises due to temporal aggregation in climatic forcing and NDVI data over India.
- To quantify and compare the statistically significant temporal trends obtained by different statistical methods used for trend analysis in this study.
- To evaluate different parametric and non-parametric trend analysis methods those are used to derive significant trends in climatic forcing and NDVI.

1.5. Research Questions

For the fulfilment of the objectives, the present study will answer the following questions:

- How do the significant trends in climatic forcing and NDVI data vary when calculated at multiple temporal granularities?
- Which temporal granularities yield the most or least statistically significant trends in climatic forcing and NDVI?
- Which trend analysis method is more sensitive to the selected temporal granularity?
- Does the variation in trends in Agro-ecological zones shows any relationship among climatic forcing and NDVI?

1.6. Structure of the thesis

This thesis comprises of six chapters. Chapter 1 explains the basic concepts of trend analysis for NDVI and climatic forcing data and further deals with the problem statement, research objectives and research questions. Chapter 2 discusses the literature reviewed and referred for accomplishing this study. It briefly explains the concepts and techniques which are employed and why they are used in this study. Chapter 3 gives the detailed description of the study area and its significance. It provides a very informative overview to the geography, climate as well as biodiversity in a concise manner. The other section of this chapter provides a detailed overview of the data sets used in this study. Chapter 4 provides a detailed overview about the general methodology followed in this work to accomplish all research objectives. The subsection provides all necessary details and steps how each data sets is processed. Each statistical method is explained in this section in detail. In Chapter 5, the self built software tool AVSTAT 1.0 is discussed which is used for the present study. Chapter 6 deals with the results obtained during the execution phase of this work. These results are carefully documented, properly formatted and evaluated before adding in the main body of this thesis. Detailed discussions and explanations for the results thus obtained are provided in this section. In Chapter 7 answer to research questions are provided and suggestions and recommendations for future work are discussed. Due to page limit constraints, some of the trend analysis results obtained from this study are documented in the APPENDIX-1 section for further discussion. The readers are requested to refer to this section.

2. Literature Review

This chapter deals with all the literature and previous work revised to make this research work possible. The knowledge of trends analyzed in any time series may provide information about the future evolution of the process or at least on the modifications occurred. The evaluation of trends in NDVI and climatic forcing time series has always received a great interest from the scientific community professionals and even from companies involved in long-term design of infrastructures and risk analysis. In the fourth assessment report of the IPCC in 2007 trend detection and evaluation of its magnitude has been acknowledged significantly with the growing interest of assessment of climate change.

2.1. Inferences from trend analysis results for NDVI and Climatic Forcing

Recent IPCC reports and many other studies have indicated probability of significant loss in major crop production in India with decrease in irrigation water and increase in temperature in near future [Alley et al., 2007; Parry et al., 2007; Aggarwal, 2008]. The historical trends analysis for yields of crops using regional statistics, long-term fertility experiments, crop simulation models and field experiments in many regions have shown a declining trend during last three decades in India. This may be partly related to the gradual change in weather conditions during last two decades. Trend analysis results by studies conducted in some states have shown concerning results. In lower hills of Himachal Pradesh, a substantial declining trend in Apple yield has been observed due to non-fulfilment of chilling requirement essential for proper flowering and fruiting. In Rajasthan, a 2 degrees Celsius rise in temperature was observed which has resulted in reduced production of pearl millet by 10 to15 percent in past decade. A study conducted in Madhya Pradesh, the biggest state in central India which is the major producers of soybean involving trend analysis have shown interesting relationship between this particular crop and climate variables. Soybean is grown on 77 percent of agricultural land in this state which has been found to be dubiously benefited if there will be an increase in carbon dioxide in the atmosphere. If the concentration doubles, the yields could go up by as much as 50 percent. However, if this increase in carbon dioxide is accompanied by an increase in temperature, as expected, then the yields could actually go down substantially. If the maximum and minimum temperatures go up by 1 degrees Celsius and 1.5 degrees Celsius respectively, the increase in yield is expected to come down to 35 percent [Pathak, 2009]. Changes in climate in tropical and temperate regions have been found to be highly sensitive to food crop productions. Most of the world’s supply of staple food crops such as rice and maize is produced in the tropics where climate vary dramatically from year-to-year. With growing population there has been an increasing trend expected in food demands of wheat and rice ranging from 103.6 to 122.1 million tons for rice and 85.8 to 102.8 million tons for wheat in 2010 to 2020. With the help of trend analysis, the projected wheat production shows steady trend up to 2020 and thereafter it shows decreasing trend in all wheat growing regions of India. Northern India shows a slight increasing trend up to 2020 and then a decreasing trend for wheat production. Similarly eastern and rest of India have shown decreasing trends for rice and wheat crop productions [Gadgil et al., 2004; Lilleor et al., 2005; Aggarwal, 2008].

The majority of the Indian population's livelihood has shown dependency on rain fed areas, where rainfall plays a vital role in crop productions. Monsoon rainfall variation has a very soaring effect on the national food grain production. During deficit monsoon rainfall years the food grain production has reduced significantly. According to trend observed by studies, it would not be possible to provide irrigation for more than 50 percent of the existing cultivated area in the future [Sharma et al., 2008]. According to NATCOM report (2007), monsoon rainfall has shown significant increasing trend along west coast, north Andhra Pradesh and northwest India and a declining trend was observed over east Madhya Pradesh, north-east India and parts of Gujarat and Kerala. However, at all India level no significant trend has been observed.

Not all agricultural regions in India receive a substantial amount of rainfall every year and thus they are not ideally dependent on irrigation through rainfall only. The backup support plan is through major river channels through manmade canals and other artificial ways. Northern regions like Punjab and Haryana have canal support systems for agriculture. Neighbouring states like Rajasthan receives very less rainfall throughout the year and thus depends heavily on canal systems for agriculture [Sharma et al., 2006]. In the South, a few districts like Telangana and Rayalaseema in Andhra Pradesh uses bore well and dug well for agriculture. This situation has been experienced by most part of the countries. This has triggered an increasing in usage of bore wells, which in turn resulted in heavy depletion of ground water table. The total area for Kharif crops as well as the cropping pattern has been changed in favour of water intensive remunerative crops which have resulted in creating problems of irrigation water. This has caused further depletion of ground water since last three decades in Andhra Pradesh and many other states. There has been a wide gap observed in productivity levels of crops between rain fed and irrigated areas in India [Wani et al., 2003]. Post independence, due to green revolution in India, there was an abrupt increase in the usage of fertilizer and pesticide application. That has enhanced the productivity level in irrigated areas but they have failed to produce the same impact in rain fed areas [Gadgil and Rao, 2000; Gadgil et al., 2004]. These studies are clear indication of how climatic forcing and vegetation are tightly coupled in many regions of India [Wassmann et al., 2009]. Climate change has affected agriculture in India by inducing changes in the soil, pests and weeds [Vahini and Shobha, 2012]. For instance, changes in precipitation, runoff, and evaporation have affected the amount of moisture in the soil.

Reliable seasonal forecasts of crop yield would be of real benefit to government planners, agri-business and farmers. The impacts of climate change also pose a serious threat to food security and needs to be much better understood. Therefore, developing models that will be able to produce crop forecasts a season ahead is crucial for future food security, especially in vulnerable regions. Hence, it is necessary to find out strategies that can help in attaining and sustaining high levels of production in the context of climatic variability [Sarma et al., 2008].

Such trend analysis studies were not only related to agriculture, they are also helpful in assessing the potential threats to human population. Due to the change in climate, the coastal states of Maharashtra, Goa and Gujarat would face a grave risk from sea level rise which has been predicted by scientists. Damage to coastal infrastructure and other property including agricultural land are expected because of this. In the state of Maharashtra, the business capital of India, over 1.3 million people are expected to be at risk. Goa could be the worst hit, losing a large percentage of its total land area if these predictions happen to be true. A one meter rise in sea level will adversely affect 7 per cent of the population in Goa (Planning Commission Report, 2010).

All these studies have clearly shown that how trend analysis helps in change and causal assessment of impact of climatic changes. These studies have also helped us to understand that results obtained from localized studies at region level done so far will may show different results obtained from studying these changes at country level [Singh et al., 2005; Gupta and Seth, 2007; Kelkar and Bhadwal, 2007; Gupta et al., 2009; Ladha et al., 2009; DEVI and Sumathi, 2011]. Climatic forcing study should be studied according to the homogenous regions as well which has been planned in this study. There is a need to correlate NDVI and climatic forcing at regional level and thus Agro-ecological zones may help in this regard.

2.2. Effects of Spatial and Temporal Aggregation: MAUP and MTUP

Advancements in remote sensing now permit fast and easy data acquisitions and access to spatial data at several different resolutions. In many studies across the world, different types of data have been collected at different scales and resolutions. This has been one of the major areas of concern in analysis [Gotway and Young, 2002]. The major issue is in combining these spatially and temporally unmatched data sets. Many statistical issues are also associated with combining such data for modelling and inferences [Shellman, 2004]. The choice of an appropriate spatial and temporal scale for the study of climatic processes has been extremely important because mechanisms essential to the spatial and temporal dynamics for any variable at one scale may be unimportant or inoperative at another. The relationships between variables at selected scale may be obscured or distorted when viewed from another scale both spatially and temporally [Goswami et al., 2006; Ghosh et al., 2009; de Jong et al., 2011]. These facts are proven true in the study of human, animal, and plant populations and has led many researchers in sociology, agriculture, ecology, geography, statistics, and environmental sciences to consider scale issues in detail [Kendall and Yule, 1950].

In many cases, spatial aggregation is necessary to create consequential units for analysis. This aspect has been described by Yule and Kendall, who stated that “geographical areas chosen for the calculation of crop yields are modifiable units and necessarily so. Since it is impossible (or at any rate agriculturally impractical) to grow wheat and potatoes on the same piece of ground simultaneously we must, to give our investigation any meaning, consider an area containing both wheat and potatoes and this area is modifiable at choice” [Kendall and Yule, 1950]. This implicitly means that a spatial scale which is suitable to study one phenomenon is not always essentially suitable to study other phenomenon. Openshaw and Taylor (1979) first coined the term modifiable areal unit problem, referred as the MAUP [Openshaw and Taylor, 1979; Devillers and Goodchild, 2010]. Many studies have illustrated the MAUP as two interconnected problems. The first problem referred to as the scale effect or aggregation effect. It arises as different inferences are obtained when the same set of data is grouped into increasingly larger areal units and vice-versa. The second problem, often termed as the grouping effect or the zoning effect. It arises due to unusual formations of the areal units leading to differences in unit and shape at the similar scales and hence results in the variations in results [Openshaw and Taylor, 1979; Openshaw and Rao, 1995; Jelinski and Wu, 1996]. Both these issues can be, and often are, present in a single analysis. Reviewing such studies was necessary for this study as three different datasets of different spatial resolutions are used. It has been proved by many studies that the choice of temporal resolution is critical as it defines the time units for observation. Temporal analysis focuses on discovering contributory relationships among events that are ordered in time and hence time and unit of observation is important [Silvestrini and Veredas, 2008]. Here temporal granularity is one solution which has been explained by few studies in the field of econometrics and computer science. By focusing on different levels of temporal granularities, information can be extracted [Cotofrei and Stoffel, 2009].

Similar to spatial aggregation, there are consequences of temporal aggregation in time series models [Wei, 1978; Buishand et al., 2004]. In general, the data is aggregated over fixed number of units may be in years or months or days. Aggregating the data like this will create temporal units which are modifiable. These units influence the analysis and also affect the amount of change detected. This issue has been termed as Modifiable Temporal unit Problem [Çöltekin et al., 2011]. MTUP is analogous to MAUP yet it has not been formally developed to address issues that can be applied as a standard. The issue of Modifiable Temporal Unit Problem (MTUP) can be remediated three important aspects are considered for any time series analysis – duration (how long), temporal resolution (how often), and the point in time (when).

Data aggregation is done to simplify the large data sets by summarizing groups of data elements. Meaningful patterns can often achieve by repeated cycles of aggregation process. But, the consequences of this process are MAUP and MTUP as already explained. The availability of related work which involves issues of MTUP is relatively less because this problem has recently been addressed [Çöltekin et al., 2011]. A related study has been done to study linear trends in seasonal vegetation time series and the modifiable temporal unit problem over part of Australia [De Jong and De Bruin, 2012]. Their results show that linear regression can be used to quantify trends in cyclic data using Ordinary least squares (OLS). They have shown how the temporal unit affects the estimation of model parameters and how the amount of absolute change that was attributed to MTUP has been estimated. The issues of MTUP are studied in the field of econometrics (financial studies involving time series data). Likewise different temporal aggregation algorithms have been discussed in the field of computer science as well [Tao et al., 2004; Zhang, 2006; Rahman, 2008] . These algorithms are based on temporal logic for data mining which are controlled by temporal constraints. The unit of observation, starting and end point affect the results same as in case of remote sensing data.

2.3. Robust Statistical Methods for Trend Analysis

Many statistical issues have been associated with modelling and inferences attained from time series analysis [McCuen, 2002; Shellman, 2004; Sheskin, 2004]. These issues arise when assumptions for most statistical analyses have been violated such as data normality, homogeneity of variance and serial autocorrelation [Beurs and Henebry, 2005]. Other problem has been faced in trend analysis studies which is sometimes termed as "spurious regression" because the models fitted to data are essentially not suitable for the type of model used [De Jong and De Bruin, 2012]. Generally, linear regression models have been used to quantify trends in time series analysis, although the results are influenced by the presence of outliers and, thus, failed to prove the robustness of the models [Muhlbauer et al., 2006; Reza et al., 2011; de Jong et al., 2011; de Jong and de Bruin, 2012]. The conventional trend analysis has been done on the non-parametric regime on the basis of the correlation studies, ordinary least square method, generalized least square methods and by applying the Autoregressive methodology etc. This choice has proved to be a critical aspect that may lead to spurious statistical results in the regression estimates and, and moreover, to misleading interpretation of the data [Muhlbauer et al., 2006]. Considering these problems, rank based trend analysis has proved to be much superior to conventional methods like ordinary least squares. The Mann-Kendall test statistics has been among the most widely used and extensive methods for detecting linear trends in climatic variations [Partal and Kahya, 2006]. This test is based on the order statistics and is therefore less sensitive to the outliers. Like other trend tests, the Mann-Kendall test assumes observations to be independent and identically distributed. The test statistic in the Mann-Kendall test follows a standard normal distribution. In Mann-Kendall test the null hypothesis is that the data are independent and randomly ordered. Therefore the significance of trends at a desired significance level can be evaluated by comparing its value with standard normal variate. The impact of serial correlation on the Mann-Kendall test has been observed to results in increase or decrease in the rejection rate of the null hypothesis [Hamed and Ramachandra Rao, 1998; SHENG et al., 2003]. This has been observed that this factor considerably reduces the power of the test. This test has been used in number of studies and helped in trend detection for various regions across the globe (Alley et al., 2007; Fatichi et al., 2009; Hamed & Ramachandra Rao, 1998; Hamed, 2008; Helsel & Hirsch, 2002; Hirsch, Alexander, & Smith, 1991; Koutsoyiannis & Montanari, 2007; Maragatham, 2012; Mondal et al., 2012; Yue & Wang, 2004; Zhang et al., 2013). Another test has been revised for this study which belongs to non-parametric trend test family. The Cox-Stuart test which is used in trend detection, allows to verify if a variable has a monotonically tendency (reject of null hypothesis of trend absence). The power of any statistical has been defined as the probability of rejecting the null hypothesis. This test has been found to be very close to the sign test for two independent samples [Cox and Stuart, 1955; Berryman et al., 1988; Conover, 1999; Helsel and Hirsch, 2002; Fatichi et al., 2009; Supit et al., 2010]. The test statistic is expected to follow a binomial distribution; and hence the standard binomial test is used to calculate the significance. The Cox-Stuart test has been widely applicable because one of the assumptions of this test is the mutual independence of the observations. It is unbiased, requires minimum of assumptions and proved to be very consistent in a statistical sense.

2.4. Open source Technologies and GIS customization

Python is a modern, powerful programming language which follows object-oriented principles. It has high level data structures, which makes it very efficient. Python's elegant syntax, together with its dynamic nature makes it an excellent language for scripting and fast application development. It is capable of supporting a wide range of applications from causal scripting and lightweight tools to full-fledged systems. The supporting packages such as numpy (also called as Numerical Python) which comprises of numpy array as well as a set of accompanying mathematical functions, has been widely adopted in academia, national laboratories and industry, with applications ranging from gaming to space exploration/ numpy provides a high level abstraction for numerical computation without compromising performance [Van Der Knijff et al., 2010]. Similarly, GDAL package is used to create and manipulate both with raster as well as vector data. GDAL is an open source library for reading and writing raster geospatial data formats, and is released under the free software license by the Open Source Geospatial Foundation (www.gdal.org).Other packages such as scipy (also called as scientific python), statsmodel etc have been used to do statistical computation. Likewise the other packages such as matplotlib, PIL, numpy-MKL, scikits.timeseries, statsmodels, PyQt, wxPython and FWTools247 have proved their utilities in many research works.

Various gaps were noticed while revising the work done related to trend analysis with time series data;

- Combining incompatible data different in terms of spatial and temporal resolution.
- Effects of temporal aggregation in case of larger study areas need to be studied more.
- There was lack of temporal sampling in many studies and effective usage of temporal granularity was not considered for change detection.
- Sufficient emphasis on statistical estimation of trends using different statistical tests was commonly missing in these studies. This only means that subtle combinations of different statistical tests could have provided better analysis.
- Relatively smaller study areas have been considered and localized changes are not studied exhaustively to determine the reasons responsible for observed changes in the trends.
- A comprehensive open source software tool for trend analysis can also be designed as mostly proprietary tools are generally used to carry out such analysis.

3. Study Area, Data and Tool

This chapter presents the study area and data used in this research work. Section 3.1 describes the study area; section 3.2 describes the data used.

3.1. Study area

The Indian subcontinent has been chosen for the present study. Much of India's biodiversity stems from its diverse geographical landscape The Indian subcontinent is located within -38° 00 North to 7° 00 North and 64° 00 East to 95° 00 East and it has an area of 3,287,263km2 of which 90.44 percent is land and 9.56 percent is water. India is a country in South Asia. It is the seventh-largest country by geographical area.

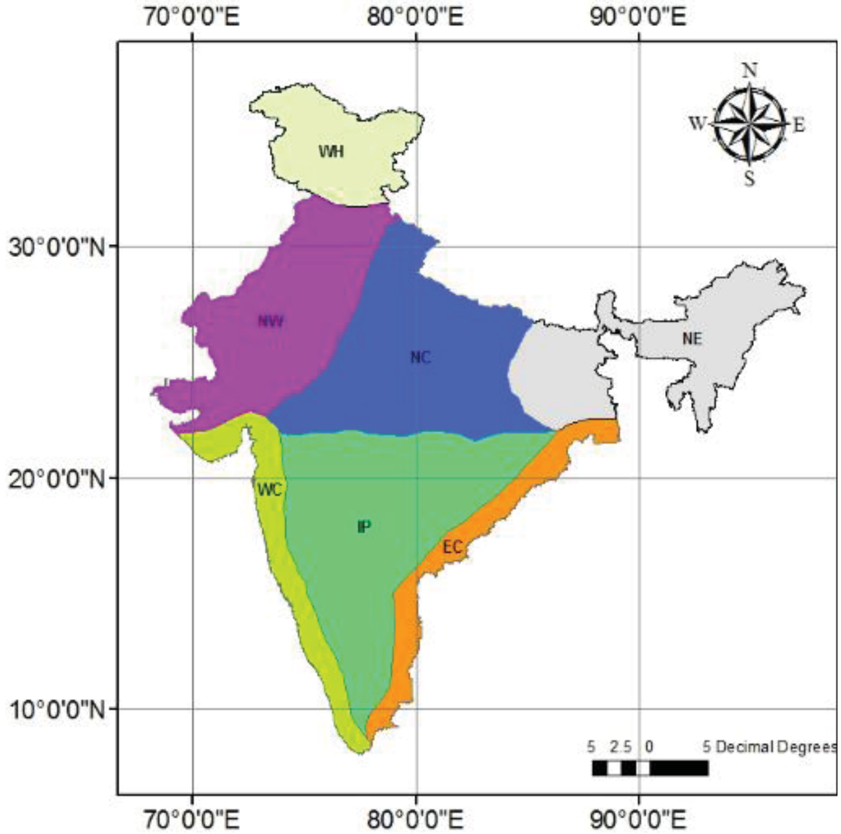
Figure 3.1: Political boundaries for Indian states and union territories

India is bound by the Bay of Bengal in the East and Arabian Sea in the West and South-West as shown in Figure 3.1. These two seas and the Indian Ocean in the South, bring moisture into the country. From the North, the country is bound by the Himalayan mountain ranges. India also shares many of its geographical features and biodiversity with many neighbouring nations including Bangladesh, Bhutan, China, Myanmar, Nepal, Pakistan and Sri Lanka. It shares land borders with Burma and Bangladesh to the east; and Pakistan to the West; China, Nepal, and Bhutan to the north-east. In the Indian Ocean, India is in the surrounding area of Sri Lanka and the Maldives. India's Andaman and Nicobar Islands share a maritime border with Thailand and Indonesia. India occupies 2.4% of the world's land area and supports over 17.5% of the world's population. Rajasthan is the biggest state in terms of area and Lakshadweep is smallest while Uttar Pradesh has the highest population in the country.

3.1.1. Geography and Climate

The land of India can be divided into seven regions: The northern Himalayan mountain ranges, , The Thar Desert, The Indo-Gangetic plain, Central Highlands and the Deccan Plateau, Mainland mountain ranges, East Coast, West Coast, Bordering seas and islands. Of these regions, the Himalayas, the Indo-Gangetic plain and the Western Ghats, contains a significant amount of biodiversity. The climate of India defies easy generalization, comprising a broad range of weather conditions across a large geographic scale and diverse topography. India hosts six major climatic subtypes, ranging from alpine tundra and glaciers in the north, to desert in the west, to humid tropical regions supporting rain forests in the southwest and the island territories. India has six climatic zones: Montane, Tropical wet and dry, Humid subtropical, Tropical wet, Semi-arid and Arid. The nation has four seasons: Winter (January and February), Summer (March to May), Monsoon (rainy) season (June to September), and a Post-monsoon period (October to December). The Indian climate is strongly influenced by the Himalayas and the Thar Desert, both of which constrain the economically and culturally essential summer and winter monsoons. The Himalayas avert cold Central Asian katabatic winds from blowing in, keeping most of the Indian subcontinent warmer than most locations at similar latitudes. The Thar Desert plays a vital role in attracting the moisture-laden south-west summer monsoon winds that, between June and October, provide the majority of India's rainfall. India has three major crop seasons because of these climatic variation namely- Rabi (December-February), Kharif (July-October) and Zaid(March - June).

3.1.2. Homogenous Temperature Regions in India

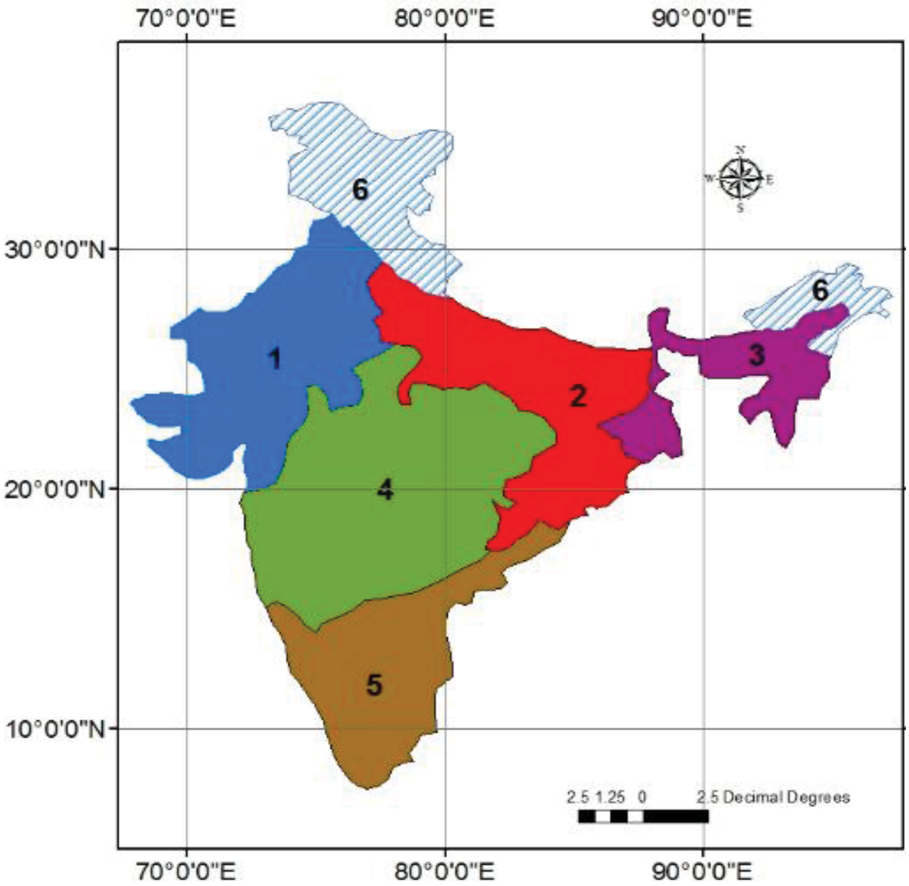


WH	Western Himalayas
NW	North-West
NC	North-Coast
WC	West-Coast
IP	Indian-Peninsular Region
EC	East-Coast
NE	North-East

Figure 3.2: Homogeneous Temperature Regions in India
Source: - Indian Institute of Tropical Meteorology
(An Autonomous Body under the Ministry of Earth Sciences, Govt. of India)

Indian subcontinent region is categorised into these seven homogeneous regions, viz., Western Himalaya (WH), Northwest (NW), Northeast (NE), North Central (NC), East coast (EC), West coast (WC) and Interior Peninsula (IP). Using geographical, topographical and climatologically features these homogenous regions were subjectively identified and demarcated [Hingane et al., 1985; Kothawale and Kumar, 2005]. Figure 3.2. shows Homogeneous Temperature Regions in India. Although, temperature change can be an direct result of extreme climate and weather events but during a season and over a region it is a gradual process where temperature conditions show continuous increasing or decreasing trends over a period of time. A temperature condition up to certain spatial extent remains same unless there is heterogeneity in the geography and topography. Based on these conditions, these homogenous regions were identified. In this study, these homogenous regions are considered to study the variations in significant trends observed over India during 1981-2005. Trend analysis was carried out using different statistical estimators to study the variation in significant trends in each of these homogenous temperature regions.

3.1.3. Homogenous Regional Summer Monsoon Rainfall Zones in India



1	North-West
2	Central North-East
3	North-East
4	West Central
5	Peninsular Region
6	Hilly Region

Figure 3.3: Homogenous Summer Monsoon Rainfall zones in India
Source: - Indian Institute of Tropical Meteorology
(An Autonomous Body under the Ministry of Earth Sciences, Govt. of India)

According to the availability of rainfall data from twenty-nine meteorological sub-divisions across all regions in India, five homogenous regions of rainfall were delineated based on the rainfall received by these regions in the Monsoon season. These regions are 1- North-West (NW), 2 - West Central (WC), 3 - Central Northeast (CNE), 4 - Northeast (NE) and 5 - Peninsula (PN) as shown in figure 3.3. The region 6 is the hilly region in India where the data availability is not significant due to the high altitude and many other reasons. These areas were chosen after optimizing the similar rainfall and circulation characteristics of each region and the criteria's adopted were 1) sub-divisions contiguity 2) percentage contribution of specific seasonal rainfall to the annual rainfall 3) coefficient of variability of rainfall 4) inter-correlations of sub-divisional rainfall 5) characteristics of principal component of the sub-divisional rainfall and 6) sub-divisional rainfall's relationship with regional/global circulation parameters.

3.1.4. Agro-Ecological zone over India

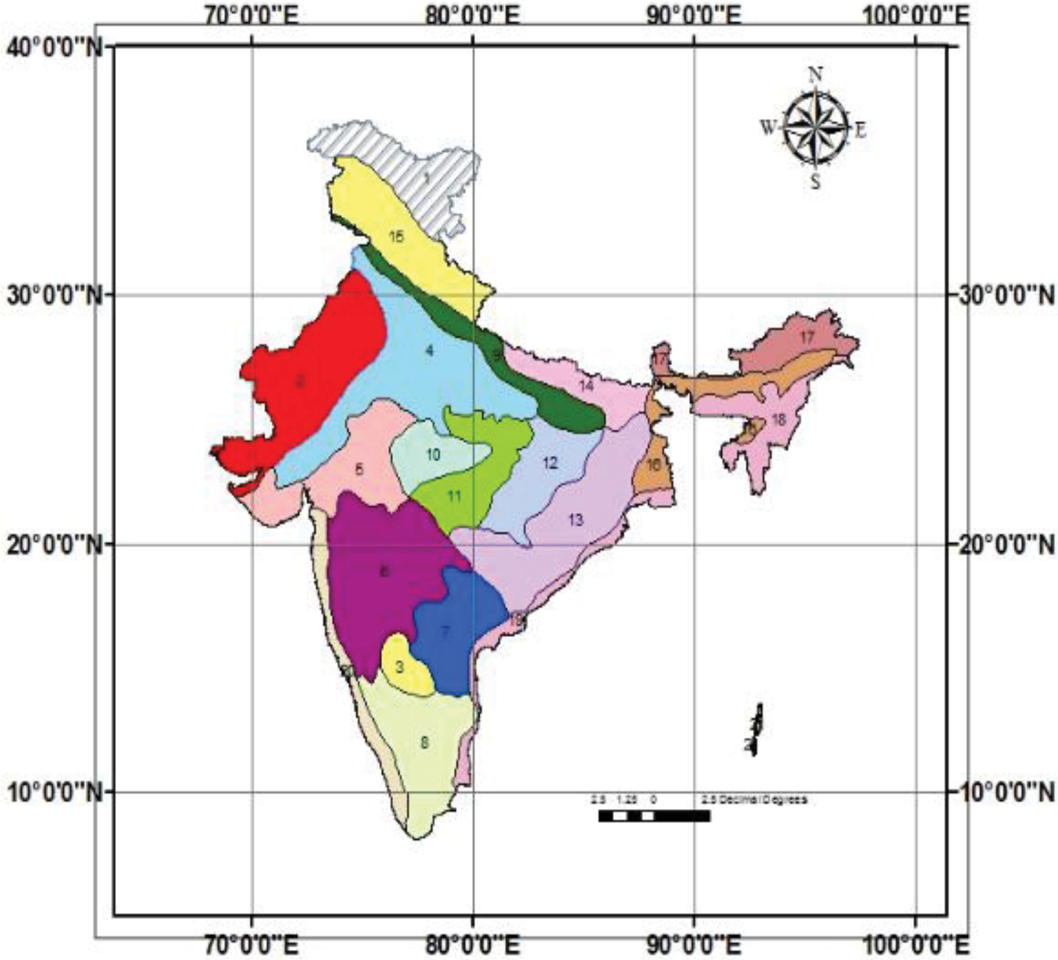


Figure 3.4: Agro-Ecological Zones
Source: - National Bureau of Soil Survey & Land Use Planning
(Indian Council of Agricultural Research – ICAR)

Figure 3.4. shows different Agro-ecological zones in India. Agro-Ecological Zone (AEZ) is a systematic assessment of the soil and climatic resources which is a pre-requisite for formulating efficient land use plan for various regions in India. Mapping of the various agro- ecological regions will help in identifying appropriate cropping patterns for a particular region. To assess yield potentialities of different crops, crop combinations in different agro-ecological regions/zones are delineated. National bureau of soil survey and land use planning- ICAR have differentiated twenty-one such zones on the basis of different ecosystems, physiographic, soil type, climate and growth period for vegetation. Here an effort is made to explore significant trends in NDVI and also in climatic forcing at different temporal aggregation levels to asses any significant change in these zones for 1981-2005 in India. Table 3.1. shows the specific ecosystems, physiographic, soil type, climate and growth period for vegetation for each AEZ.

Table 3.1: Specifications of different Agro-Ecological Zones in India

Id	Zone	Physiographic	Soil	Climate	Growth Period
1	Arid ecosystem	Western Himalayas	Shallow skeletal soils	Arid	< 90
2	Arid ecosystem	Western plain	Desert & saline soils	Arid	< 90
3	Arid ecosystem	Deccan plateau	Mixed red & black soils	Arid	< 90
4	Semiarid ecosystem	Northern plain	Alluvium - derived soils	Semi - arid	90 – 150
5	Semiarid ecosystem	Central highlands	Medium & deep black soils	Semi - arid	90 – 150
6	Semiarid ecosystem	Deccan plateau	Shallow & medium black soils	Semi - arid	90 – 150
7	Semiarid ecosystem	Deccan plateau	Mixed red & black soils	Semi - arid	90 – 150
8	Semiarid ecosystem	Eastern Ghats	Red loamy soils	Semi - arid	90 – 150
9	Sub humid ecosystem	Northern plain	Alluvium - derived soils	Sub humid	150 – 180
10	Sub humid ecosystem	Central highlands	Medium & deep black soils	Sub humid	150 – 180
11	Sub humid ecosystem	Deccan plateau	Mixed red & black soils	Sub humid	150 – 180
12	Sub humid ecosystem	Eastern plateau	Red & yellow soils	Sub humid	150 – 180
13	Sub humid ecosystem	Eastern plateau	Red loamy soils	Sub humid	150 – 180
14	Sub humid ecosystem	Eastern plain	Alluvium - derived soils	Sub humid	180 – 210
15	Sub humid ecosystem	Western Himalayas	Brown forest & podzolic soils	Sub humid	180 – 210
16	Humid per humid ecosystem	Assam & Bengal plain	Alluvium - derived soils	Semi - arid	> 210
17	Humid per humid ecosystem	Eastern Himalayas	Brown & red hill soils	Per humid	> 210
18	Humid per humid ecosystem	North-eastern hills	Red & lateritic soils	Per humid	> 210
19	Coastal ecosystem	Eastern coastal plain	Coastal alluvium - derived soils	Sub humid	> 210
20	Coastal ecosystem	Western Ghats	Red & lateritic soils	Per humid	> 210
21	Islands ecosystem	Islands	Red loamy soils	Per humid	> 210

3.2. Data

Three different types of data were used in this study as shown in Table 3.2. Their main characteristics are briefly described and discussed in sections 3.2.1, 3.2.2 and 3.2.3. respectively.

Table 3.2: Data Description

Data	Spatial Resolution (in Degrees)	Temporal Resolution (in Days)	Data Availability
NDVI	0.072	15	1981-2005
Temperature	1	1	1981-2005
Rainfall	0.5	1	1981-2005

3.2.1. NDVI Data

The Normalized Difference Vegetation Index, NDVI, was first suggested by Tucker in 1979 as an index of vegetation health and density.

$$\mathrm{NDVI} = (\lambda_{\mathrm{NIR}} - \lambda_{\mathrm{RED}})/(\lambda_{\mathrm{NIR}} + \lambda_{\mathrm{RED}}) \qquad \text{Equation (3.1)}$$

Where, λ_{NIR} and λ_{RED} are the reflectance in the NIR and Red bands respectively. NDVI reflects vegetation vigour, percent green cover, Leaf Area Index (LAI) and biomass. It is the most commonly used vegetation index. NDVI values range from -1.0 to +1.0 and are unit-less.Values greater than 0.1 generally denote increasing in the greenness and intensity of vegetation. Values between 0 and 0.1 are usually characteristic of rocks and bare soil, and values less than 0 sometimes indicate ice-clouds, water-clouds, and snow. Vegetated surfaces typically have NDVI values ranging from 0.1 in deserts up to 0.8 in dense tropical rain forests. NDVI is a measure to describe the greenness as well as the starting point to calculate the fraction of vegetation cover. The lack of greenness is termed as browning effect which shows the downward trend in growth and sustainability of vegetation [De Jong et al., 2011; de Jong and de Bruin, 2012].

The NOAA-AVHRR – NDVI composite which is provided by the Global Inventory Modelling and Mapping Studies (GIMMS) was downloaded from the University of Maryland Global Land Cover Facility Data distribution centre. 25-year satellite records of Maximum value composite (MVC) data sets were used in this study. The continental files of Eurasia having an image size of 2000 × 1250 was acquired and the study area was extracted out [Tucker et al., 2004, 2005]. These (MVC) shows changes in terrestrial vegetation. The GIMMS dataset is composited at a 15-day time step. The 15a composite is the maximum value composite from the first 15 days of the month, and the second (15b) is from days 16 through the end of the month. The coverage is global for all land areas except Greenland and Antarctica. The data are given in an 8km Albers Equal Area Conic projection, Clarke 1866 ellipsoid, and in geographic coordinates, WGS84 datum at 0.0727 degree resolution per pixel. The data are available from July 1981 through December 2006. NDVI values have been scaled to values ranging from -1000 to 1000, water pixels are assigned the value of -10000, and masked pixels are -5000. We have used data from July 1981 to December 2005.

GIMMS-NDVI has been corrected for variations arising from [Tucker et al., 2004]:

- residual sensor degradation and sensor inter-calibration differences
- distortions caused by persistent cloud cover globally
- solar zenith angle and viewing angle effects due to satellite drift
- volcanic aerosols
- missing data in the Northern Hemisphere during winter using interpolation due to high solar zenith angles
- Low signal to noise ratios due to sub-pixel cloud contamination and water vapour.

3.2.2. Rainfall Data

From the Indian Metrological Department (IMD) a coarse resolution 0.5 degree gridded ~ approximately equivalent to 55 kilometres, daily rainfall data for Mesoscale Meteorological Studies over the Indian subcontinent region for 1981-2005 has been used in this study [Rajeevan and Bhate, 2009]. This data product is the first version of IMD 0.5 degree gridded daily rainfall data developed in 2008 collected by 6000 quality controlled rain-gauge stations over India. The data is arranged in 69x65 grid points which were created by interpolating the station data. The starting point of the grid is 6.50 North and 66.50 East which was quite unconventional from the way the data is provided. The data files were transposed and rotated to match orientation as same as other data sets. From this point, there are 69 data points towards east and 65 data points towards north. The data is available in one binary file for each year. Daily mean rainfall data values are stacked in the form of multi-band data layers. For the leap year, data layers for 366 days were created. For the present study the data files in .GRD format were chosen which were then converted into .IMG format which is compatible with python programming language for further usage.

A well tested interpolation method named Shepard's method was used to interpolate the station data into regular grids of 0.5 degrees. In the Shepard's method, interpolated values were computed from a weighted sum of the observations [Shepard, 1968; Rajeevan and Bhate, 2009]. Given a grid point, distance from this point to a given station was calculated and referred as the search distance. For search distances greater than or equal to the radius of influence, the grid point value was assigned a special code when there were no stations located within that distance. In this method, interpolation was limited to the radius of influence. A predetermined maximum value limits the number of data points used, which in the case of high data density reduced the effective radius of influence. They have also considered to locally modifying the scheme for including the directional effects and barriers. In this interpolations method, no initial guess was required. According to IMD, since the data density is not kept uniform, there is a possibility of temporal in-homogeneity. This temporal in-homogeneity results due to mainly two problems. During the data preparation by IMD, the network of rainfall stations considered were not kept spatially distributed. Moreover, for the same time period, the rain-gauge stations selected were not kept constant throughout the process. They have selected about 3500 stations on an average for the daily analysis. However the data density varied from year to year. This inconsistency has resulted in missing pixel value problem at boundary regions in India mainly in the Himalayan, North-East and South-East regions. The data quality was examined and compared with other high resolution rainfall data set developed at the Research Institute for Humanity and Nature (RIHN) -Japan. The project was named as Asian Precipitation- Highly Resolved Observational Data Integration towards Evaluation of the Water Resources (APHRODITE). Under this project a high resolution 0.25 degree and 0.5 degree data sets were developed. IMD rainfall data was thus made available for research work after several comparisons and quality control evaluations. The utility of this data set is already proved in many studies related to metrological studies [Guhathakurta and Saji, 2012; Maragatham, 2012; Goswami et al., 2006; Krishnamurthy and Shukla, 2008; Ghosh et al., 2009; Rahman et al., 2009; Rajeevan and Bhate, 2009; Jain and Kumar, 2012].

3.2.3. Temperature Data

Another data set from IMD, a very coarse resolution 1 degree gridded ~ approximately equivalent to 110 kilometres, daily temperature data was used for this study [Srivastava et al., 2009]. The daily temperature (Minimum, Maximum and Mean) data were collected from 395 quality controlled stations over India. IMD has prepared this data set for the period 1969-2005 for research purposes. For this particular study, only Mean temperature datasets have been considered and used for a selected period of 25 years from 1981-2005. This data has been arranged in 32x35 grid points. The unit of temperature is in degrees Celsius(C). For the leap year, data for 366 days were created. The data is available in binary and text format for every year.

IMD at present maintains around 550 well distributed surface observatories in the entire country, where daily surface air temperature observations (maximum and minimum) are taken. These data are compiled, digitized, quality controlled and archived at the National Data Centre (NDC) of IMD. Only those stations which have minimum 10 years of data, at least for 300 days in a year, were selected for the data preparation. The data were subjected to basic quality checks like greater than exceeding known extreme values, rejecting values, same temperature values for many consecutive days and minimum temperature greater than maximum temperature. A filter was used to flag unusual high values which allowed values only in the range mean and standard deviation for further data preparation. The flagged values were further examined for spatial continuity before rejection. After putting these quality checks, 395 stations were selected for the development of the gridded data set.

They have used a modified version of the Shepard's angular distance weighting Algorithm [Shepard, 1968] for the data preparation. Others have also employed the same interpolation method for creation of gridded temperature data sets because of its efficiency and flexibility [Kiktev et al., 2003; Caesar et al., 2006]. This interpolation method took spatial correlation structure of the station data into consideration for data preparation. Therefore, the inter-station correlations were calculated to determine the distances over which observed temperature anomalies are related. For each pair of 395 stations lying within 2000 kilometres, for each month, correlation was calculated and then put together according to their separation over a distance of 100 kilometres. A two-degree polynomial function was fitted to the mean correlation values over each 100 kilometres interval. For interpolation of the station data, the radius of influence was estimated as the Correlation Length Scale (CLS), which is defined as the distance at which the mean correlation, represented by the fitted function, fell below certain range of value. Angular distance weighting calculate the weighting of each station. The assignment of weights of the station is according to its distance from a grid point, with the CLS controlling the rate at which the weight decreases away from the grid point. To select the stations that will contribute to each grid point value, stations lying in the radius up to the CLS were selected. Within the CLS distance, the weighted sum of the closest four to a maximum of ten stations to each grid point has been used to estimate the grid point temperature values. If there are more than ten stations within the CLS distance, then only those ten closest stations to the grid point having maximum correlations were used. Missing pixel value problem at boundary regions in India was observed mainly in the Himalayan, North-East and South-East regions similar to rainfall data.

This temperature data set has been cross validated to estimate errors associated with the interpolation technique used. The root mean square errors were less than 0.5 degree Celsius over most parts of the country. The hilly areas have shown relatively larger errors for the obvious reason of height and data scarcity in those areas. According to IMD, this data set is validated against other monthly mean temperature data sets prepared by Cort Willmott & Kenji Matsuura of University of Delaware (www.cdc.noaa.gov). This data set contained monthly temperature data for 0.5 degrees resolution for the period 1951-1999. The correlation coefficients between this data set the daily data set developed by IMD, for monthly/annual mean temperature values for the common period 1969-1999 were prepared. Correlation coefficients between the two sets were of the order of 0.8 at most of the grids. Daily temperature data at a coarse resolution are useful for analyzing extreme climate changes. For environmental modelling applications and validation of climate model simulations the IMD temperature datasets have shown their efficiency in many studies [Kothawale and Kumar, 2005; Rajeevan et al., 2006; Aggarwal, 2008; Rajeevan and Bhate, 2009; Kothawale et al., 2010; Aggarwal et al., 2012; Jain and Kumar, 2012].

4. Methods

This chapter describes the research methodology followed for executing this study for trends analysis of NDVI and climatic forcing over India at multiple temporal granularities to study the MTUP effect.

4.1. Methodology flow chart

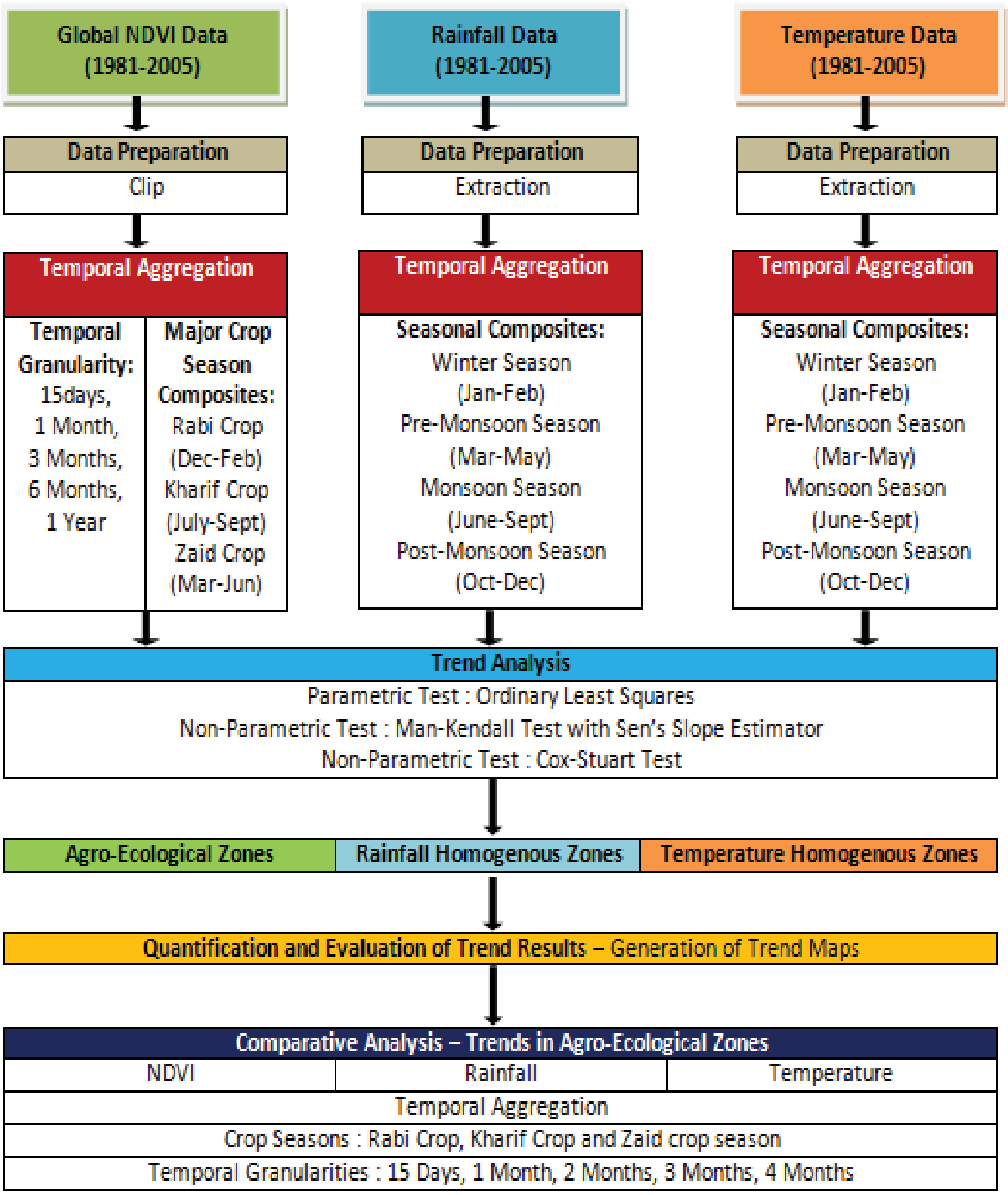


Figure 4.1: General Methodology

This section provides an overview of the methodology adopted for the study. The flowchart of the methodology followed for this study is shown in Figure 4.1. As discussed in chapter three, NDVI and climatic forcing data were acquired for 1981-2005. The initial pre-processing steps, those including extraction of NDVI data for Indian subcontinent region is done by clipping data with Indian political boundaries shape file from the global files. A pre-processing step for climatic forcing data was performed to extract daily mean rainfall and temperature data from the annual grided data files provided by IMD. The next step was the creation of temporal aggregates at multiple temporal aggregation levels. For this data sets were added at desired levels to obtain new raster images by taking the mean of the data. All three datasets were temporally aggregated depending on seasonal and non-seasonal aspects. For example, NDVI datasets were aggregated non-seasonally (at intervals of 1 month, 3 months, 6 months and annually). It was followed by seasonal-major crop seasons (Rabi, Kharif and Zaid) temporal aggregates. Similarly, climatic forcing data was also aggregated for same crop seasons. Furthermore, climatic forcing was aggregated according to major climatic seasons in India. When all the datasets were temporally aggregated, trend analysis was carried out at multiple granularities and evaluation and quantification of significant was done with the help of combination of parametric and non-parametric statistical estimators. The detailed explanation of the methods followed for trend analysis is explained in the following sections of this chapter.

4.2. Data Preparation

4.2.1. NDVI

As discussed in chapter 3, the NDVI dataset is available as MVC twice a month from July 1981 to December 2006. A total of 588 file were processed in this study. The continental file of Eurasia was extracted from the ftp location. These datasets were provided in GeoTIFF format with global coverage. The global mosaic files have the 4950 columns and 2091rows. With AVSTAT, the Indian subcontinent area was clipped with the shape file and a new raster data subset was created from each global file.. Figure 4.2. represents flowchart how NDVI data was processed.

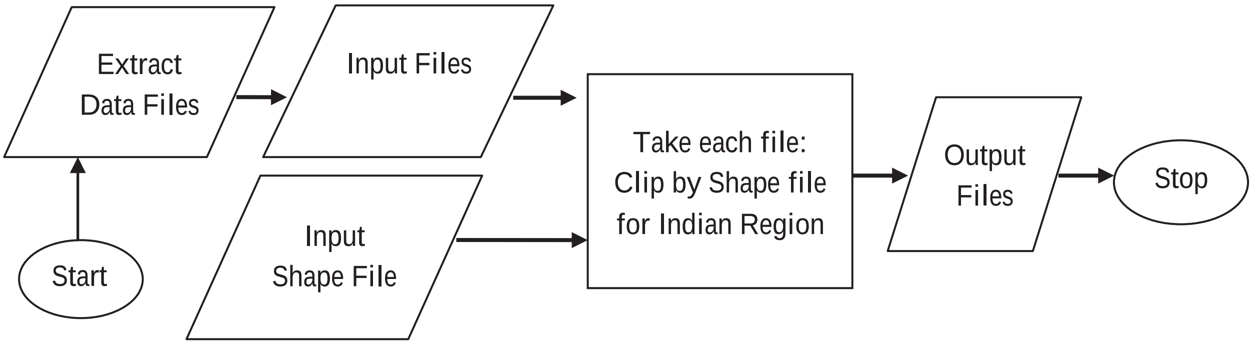


Figure 4.2: Flowchart for NDVI data preparation

4.2.2. Rainfall Data

The daily mean rainfall data was available in binary and text format for every year in the .GRD format which as not compatible with python and GDAL libraries. Each yearly file contained the daily data values in the form of multiple bands stacked in one file. First the data files were transposed and rotated for the orientation and geo-referencing purpose. Then these files were converted to GeoTIFF/IMG format. Once these files were converted, with the help of AVSTAT, daily mean rainfall data raster files were created. Figure 4.3. shows the process how the mean rainfall daily data raster files were created.

Figure 4.3: Flowchart for daily mean rainfall data extraction

4.2.3. Temperature Data

Similar to rainfall data preparation technique discussed in previous section, the daily mean temperature raster files for each day from 1981-2005 were created with the help of AVSTAT. For leap years, 366 data files were created. Figure 4.4. shows the flowchart to extract daily mean temperature from the yearly data file.

Figure 4.4: Flowchart for daily mean rainfall data extraction

4.3. Temporal Aggregation

After extraction and creation of the data sets in the data preparation phase, the next step done was to create the temporal aggregates at multiple granularities carefully selected for trend analysis. Temporal aggregation was also done using GDAL and python libraries.

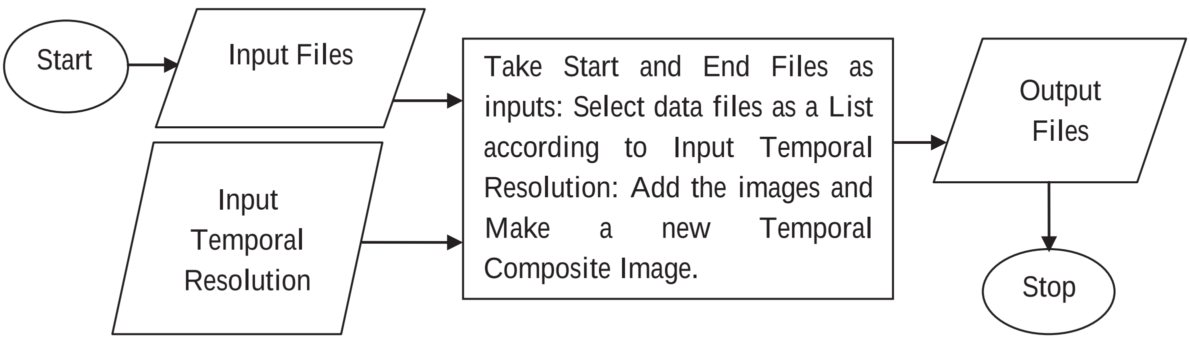


Figure 4.5: Flowchart for Temporal aggregation Tool

A new algorithm was designed for executing this important step. Figure 4.5. shows how temporal aggregation is carried out in this study. All the data files were stacked to form a data cube. From this data cube, first the start time from where the data should be aggregated to the end time i.e. up to which time it should be aggregated was taken as input. Once this list is selected according to the temporal resolution i.e. in this case it is the number of files to be combined in order to form a new temporal aggregate, mean of every pixel was calculated and a new raster dataset was created. This algorithm for temporal aggregation is specifically designed in order to deal with data insufficiency problem like missing pixel value. In the case of missing pixel value, a window size of 4 by 4 pixels was considered. Only the valid pixel values were taken into consideration, the window mean is substituted to the missing pixel value and then only it is aggregated. The temporal aggregates resulted from this algorithm were consistent having no missing pixel value.

4.4. Trend Analysis

This section deals with the one of the most significant aspects of this study. In this section, the methods selected for trend analysis are discussed in details. Considering the explanations provided in chapter 1 and 2, from the research point of view the trend analysis is "a process that analyze periodic variables to discover and establish relationships between them which would help in efficient monitoring of these complex, periodic processes to find any irregularities and abrupt changes."

As discussed earlier, the choice of statistical estimator was vital for this study. These methods were selected based on the extensive literature review done and in accordance with many studies done previously by scientists and researchers. The statistical tests which are used in this study are commonly available in many geo-statistical tools and libraries like R software etc. But, accept the parametric test - linear regression which was available in Scipy (also called as scientific python) other non-parametric tests used here were not available. The algorithms for both the non-parametric test were designed using different packages available with python. These packages were GDAL, matplotlib, numpy (called as numerical python), PIL(Python Imaging Library), numpy-MKL, Scipy, scikits-timeseries, statsmodels. The theories behind these tests are explained in the following sections.

4.4.1. Linear Regression

Regression analysis is a used for statistically estimating the relationships between different variables. Linear regression includes different techniques for analyzing variables. It mainly focuses on the relationship between a dependent variable and typically one or more independent variables. When any one of the independent variables is varied keeping the other independent variables constant, how the value of dependent variable changes can be estimated with the help of regression analysis. Generally, given the independent variables, it estimates the conditional expectation of the dependent variable. The dependent variable y_i is a linear combination of the parameters [McCuen, 2002; Shellman, 2004; Sheskin, 2004]. For example, in linear

regression for modelling n data points there is one independent variable: x_i, and two parameters, β_0 and β_1:
Straight line:

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i \ , \quad i = 1, \ldots, n \qquad \text{Equation(4.1)}$$

ε_i is an error term and the subscript i indexes an observation. Given a random sample from the population, we estimate the population parameters to obtain the sample model:

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i \qquad \text{Equation(4.2)}$$

The residual, $e_i = y_i - \hat{y}_i$, is the variation between the value of the dependent variable predicted by the model, $\hat{y}_i$, and the true value of the dependent variable, y_i.
Ordinary least squares is another method for estimation which is used in this study. This method obtains parameter estimates that minimize the sum of squared residuals as:

$$\mathrm{SSE} = \sum_{i=1}^{n} e_i^2 \qquad \text{Equation(4.3)}$$

Minimization of this function results in a set of normal equations, a set of simultaneous linear equations in the parameters, which are solved to yield the parameter estimators, $\hat{\beta}_0$, $\hat{\beta}_1$. In the case of simple regression, the formulas for the least squares estimates are

$$\hat{\beta}_1 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2} \text{ and } \hat{\beta}_1 = \bar{y} - \hat{\beta}_1 \bar{x} \qquad \text{Equation(4.4)}$$

where $\bar{x}$ is the mean of the x values and $\bar{y}$ is the mean of the x values [Helsel and Hirsch, 2002; McCuen, 2002].

Figure 4.6. shows how significant slope value maps are generated. At 95% significance level, pixels with p-values less than 0.05 were considered pixels showing significant positive trends in the time series. p-values values higher than 0.05 were attributed to negative significant trends.

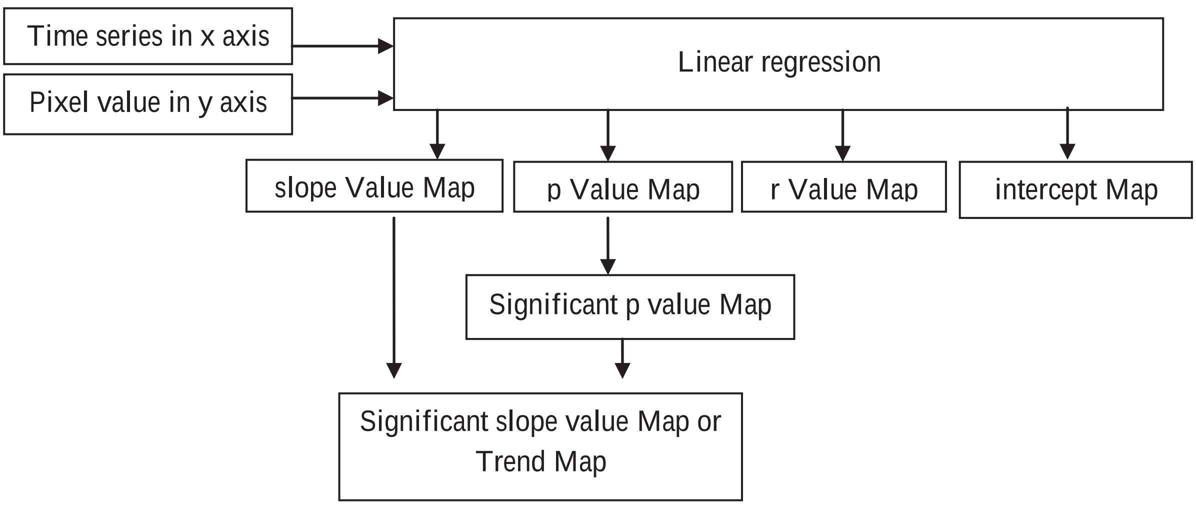


Figure 4.6: Flowchart for Trend analysis using Ordinary Least Squares

For generating significant slope maps for trend detection, slope values for each pixel in the time series were calculated. Negative and positive slopes show subsequent decreasing and increasing trends respectively. Pixels with zero slope means there was significant trend. After the logical operations, significant trend maps were generated from the p-value and slope value maps. Figure 4.7. also shows the same logical steps performed in the algorithm for this test.

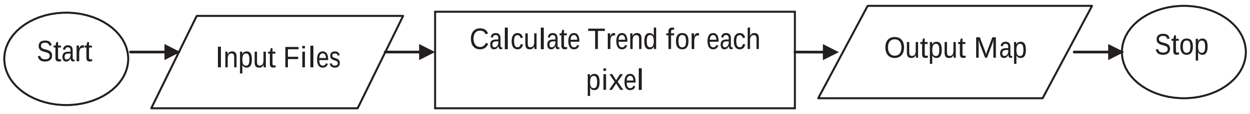


Figure 4.7: Flowchart- Trend analysis tool using AVSTAT

4.4.2. Mann-Kendall Test

In the present study, trend analysis was done using non-parametric Mann-Kendall test [McCuen, 2002; Shellman, 2004; Sheskin, 2004]. This is a very strong statistical method which used in many works for studying the spatial variation and temporal trends of long time-series. A non parametric test is taken into consideration because it can evade the problem roused by data skew. Man-Kendall test was a preferred choice for this study because it takes properties of distribution of data and problems like autocorrelation into account. Mann-Kendall test had been formulated by Mann (1945) as non-parametric test for trend detection and the test statistic distribution had been given by Kendall (1975) for testing non-linear trend and turning point. Hirsch, Slack, and Smith (1982) and Taylor and Loftis (1989) provide assessment of the Kendall non-parametric test [Hirsch et al., 1991; Helsel and Hirsch, 2002]. This test is intended to assess the randomness of the data sequence. The test if designed to detect a monotonically increasing or decreasing trend in the data rather than an episodic or abrupt event.

Autocorrelation: Trend detection in a series is affected by the presence of a positive or negative autocorrelation. With a positive autocorrelation in the series, possibility of trend detection is more, which may not be always true. Alternatively, this is opposite for negative autocorrelation in a series, where a trend is not detected. The coefficient of autocorrelation ϱ_k of a discrete time series for lag k is projected as

$$\varrho_k = \frac{\sum_{t=1}^{n-k}(x_t - \bar{x}_t)(x_{t+k} - \bar{x}_{t+k})}{\left[\sum_{t=1}^{n-k}(x_t - \bar{x}_t)^2 \times \sum_{t=1}^{n-k}(x_{t+k} - \bar{x}_{t+k})^2 \times\right]^{1/2}} \qquad \text{Equation}(4.5)$$

where x_t and Var (x_t) are considered as the sample mean and sample variance of the first $(n-k)$ terms respectively, and $\bar{x}_{t+k}$ and Var (x_t+ k) are the sample mean and sample variance of the last $(n-k)$ terms respectively. Further, the hypothesis of serial independence is tested by the lag-1 autocorrelation coefficient as $H_0 : \varrho_1 = 0$ against $H_1 : |\varrho_1| > 0$ using

$$t = |\varrho_1| \sqrt{\frac{n-2}{1-\varrho_1^2}} \qquad \text{Equation}(4.6)$$

where the t test statistic has a Student's t -distribution with $(n-2)$ degrees of freedom. At the significance levelα, if $|t| \geq t_{\alpha/2}$, then the null hypothesis about the serial independence is rejected.

Mann-Kendall Test:: The Mann-Kendall statistic S is given as

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_i) \qquad \text{Equation(4.7)}$$

The application of trend test is done to a time series x_i that is ranked from i = 1,2,……… n -1 and x_j, which is ranked from $j = i$ +1,2,………n. Each of the data point x_i is taken as a reference point which is compared with the rest of the data points x_j so that,

$$\operatorname{sgn}(x_j - x_i) = \begin{cases} +1, > (x_j - x_i) \\ 0, = (x_j - x_i) \\ -1, < (x_j - x_i) \end{cases} \qquad \text{Equation(4.8)}$$

It has been documented that when $n \geq 8$, the statistic S is approximately normally distributed with the mean.

$$E(S) = 0 \qquad \text{Equation(4.9)}$$

The variance statistic is given as

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(i)(i-1)(2i+5)}{18} \qquad \text{Equation(4.10)}$$

Where t_i is is considered as the number of ties up to sample i. The test statistics Z_c is computed as

$$Z_c = \begin{cases} \dfrac{S-1}{\sqrt{Var(S)}} & S = 0 \\ \dfrac{S-1}{\sqrt{Var(S)}} & S < 0 \end{cases} \qquad \text{Equation(4.11)}$$

Z_c here follows a standard normal distribution. A positive (negative) value of Z signifies an upward (downward) trend. A significance level $\propto$ is also utilised for testing either an upward or downward monotone trend (a two-tailed test). If Z_c appears greater than $Z_{\propto/2}$ where $\propto$ depicts the significance level, then the trend is considered as significant.

Modified Mann–Kendall test: In the presence of autocorrelation, Pre-whitening is done for detecting a trend in a time series. Nonetheless, pre-whitening assures to reduce the rate of detection of significant trend in the MK test. Thus, the Modified MK test has been used for trend detection of an auto correlated series. In this study, the autocorrelation between ranks of the observations ϱk was estimated after subtracting an estimate of a non-parametric trend such as Sen's median slope from the data. Significant values of ϱk were used for calculating the variance correction factor n/n_s^* , as the variance of S is underestimated for the positively auto correlated data:

$$\frac{n}{n_s^*} = 1 + \frac{2}{n(n-1)(n-2)} \times \sum_{k=1}^{n-1} (n-k)(n-k-1)(n-k-2)\varrho_k \qquad \text{Equation}(4.12)$$

Where n represents the actual number of observations, n_s^* is represented as an effective number of observations to account for the autocorrelation in the data and ρ_k is considered as the autocorrelation function for the ranks of the observations. The corrected variance is then calculated as

$$V^*(S) = V(S) \times \frac{n}{n_s^*} \qquad \text{Equation}(4.13)$$

where $V(S)$ is from Equation (6). The rest is same as in the MK test.

Sen's Slope Estimator Test: The magnitude of trend is predicted by the Sen's estimator. Here, the slope (Ti) of all data pairs is computed as (Sen, 1968)

$$T_{i=} \frac{x_j - x_k}{j-k} \quad , \quad \text{For } i = 1,2,3, \ldots .N \qquad \text{Equation}(4.14)$$

where x_j and x_k are considered as data values at time j and k ($j > k$) correspondingly. The median of these N values of T_i is represented as Sen's estimator of slope which is given as:

$$Q_i = \begin{cases} T_{\frac{N+1}{2}} & N \text{ is odd} \\ \frac{1}{2}\left[T_{\frac{N}{2}} + T_{\frac{N+2}{2}}\right] & N \text{ is even} \end{cases} \qquad \text{Equation}(4.15)$$

Sen's estimator is computed as $Q_{med} = T(N+1)/2$ if N appears odd, and it is considered as $Q_{med} = \left[T_{N/2} + T_{(N+2)/2}\right]/2$ if N appears even. At the end, Q_{med} is computed by a two sided test at 100 $(1-\propto)\%$ confidence interval and then a true slope can be obtained by the non-parametric test.

Positive value of Q_i indicates an upward or increasing trend and a negative value of Q_i gives a downward or decreasing trend in the time series.

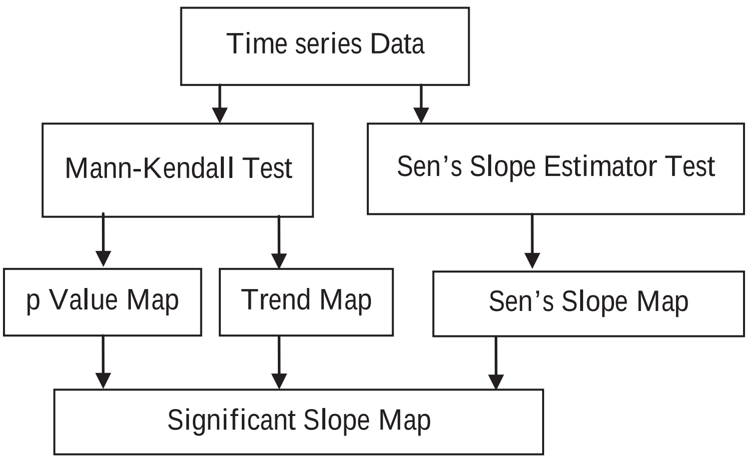


Figure 4.8: Flowchart for Trend Analysis using Mann-Kendall Test

Figure 4.8. shows the logical steps used in the algorithm designed for Mann-Kendall Test for the present study. Mann-Kendall Test detects the presence of trend in the time series and provides p-values. In the present study 95% significance level is chosen for the hypothesis testing. With the help of Sen's slope estimator, slope was calculated for each pixel in the time series data over India. This slope signifies the presence of negative or positive significant trend if it is less than zero or more than zero. Slope value equal to zero signifies presence of no significant trend in the time series. With the help of p-values, and sen's slope value significant slope map which are also termed here as trend maps were generated to shows significant trends over India.

4.4.3. Cox – Stuart Test

The Cox-Stuart test is useful for detecting trends in a sequence of independent measurements on a single random variable. The null hypothesis is that, no trend exists in the series. One of the three alternate hypotheses is possible:

1) An upward or downward trend exists
2) An upward trend exists
3) A downward trend exists

An alternative 2) and 3) indicates that the direction of the trend is known a priori. If the null hypothesis is accepted, the results indicate that the measurements within the ordered sequence are identically distributed [McCuen, 2002; Shellman, 2004; Sheskin, 2004]. The test is concluded as follows:

N measurements are recorded sequentially ($\mathrm{i} = 1,2,3, \ldots\ldots, \mathrm{N}$) in an order relevant to the intent of the test, such as with respect to the time that the measurements were made or their ordered locations along the some axis.

Data are paired by dividing the sequence into parts so that $\mathrm{x_i}$ is paired with $\mathrm{x_j}$ where $\mathrm{j} = \mathrm{i} + (\mathrm{N}/2)$ if N is even and $\mathrm{j} = \mathrm{i} + 0.5(\mathrm{N} + 1)$ if N is odd. This produces n pairs of values. If N is an odd integer, the middle value is not used.

For each pair, denote the case where $\mathrm{x_j} > \mathrm{x_i}$, as a $+$, where $\mathrm{x_j} < \mathrm{x_i}$ as a $-$, and where $\mathrm{x_j} = \mathrm{x_i}$ as a 0. If any pair produces a zero, n is reduced to the sum of the number of $+$ and $-$ values. The values of the test statistics is the number of $+$ signs. If the null hypothesis is true, a sequence is expected to have the same number of $+$ and – values.

The assumption of a binomial variate apply, so the rejection probability can be computed for the binomial distribution with $\mathrm{p} = 0.5$, if an increasing trend is specified in the alternative hypothesis, Then rejection of $\mathrm{H_0}$would occur for a large number of positive$+$ values; thus the rejection region is the upper tail. If a decreasing trend is expected, then a large number of negative values are expected; so the rejection region is in the lower tail. Consideration of both the tails was done, for a two-sided alternative.

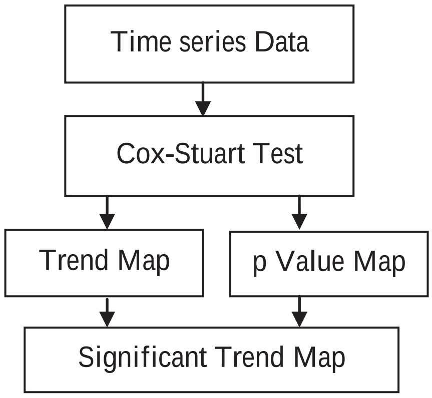


Figure 4.9: Flowchart for Trend Analysis using Cox-Stuart Test

Figure 4.9. shows the working of Cox-Stuart test algorithm which is developed for the present study. As discussed earlier, Cox-Stuart test's efficiency for detecting trends in a time series. A Boolean value map termed as trend map is generated from the long time series data. P-value map from the test is also computed from these data as well. At 95% significance level, significant trend maps were generated by logically operations with trend maps and p-value maps.

4.5. Comparative Analysis

The results of the trend analysis performed were done considering the spatial variations of Indian subcontinent. This was done on the basis of different homogenous summer monsoon rainfall regions, homogenous temperature regions and agro-ecological zones delineated in India on the basis of several criteria. Different significant trends were observed at multiple granularities in these zones. The results thus obtained by these methods are discussed in the next chapter.

5. GIS Tool

This research work is carried out with the help of a self-developed tool named as AVSTAT 1.0 (A Very Simple Trend Analysis Tool) for trend analysis using open source geo-spatial tools and technologies which has helped in automating the whole trend analysis process.

5.1. GIS Tool for trend analysis

In almost every scientific study, implementation and realizations of concepts are mainly done with the help of software tool these days. With the development of robust software technologies in the recent times, development of customized tools for common users has increased. These tools and technologies help to keep abreast to the latest developments and give birth to new scientific innovations [Bachmann et al., 2011]. Geo-spatial technologies are capable of handling large volumes of spatial data in distributed environments which is helpful in scientific studies. A lot of work has been attempted using geo-spatial frameworks and technologies, although very few open source tools are built entirely upon open source technologies [Rao et al., 2009][Van Der Knijff et al., 2010]. There is a common belief that many open source software tools have only specific capabilities to serve the user specific requirements. To prove this convention wrong, this was one of the motivations to build a build a comprehensive tool like AVSTAT 1.0 to serve all requirements which were needed in this present study. AVSTAT 1.0 is a customised application software tool which is designed specifically with minimum number of menus/user interface to help even a non-technical user to operate and obtain results for trend analysis.

5.2. Python and GIS

Python was developed by Guido van Rossum at Centrum voor Wiskunde en Informatica (CWI) in The Netherlands and released for the first time in 1991. There are many tools available for GIS customization like C# and .NET, Arc Macro Language (AML), Arc Objects, VBA and COM, Java, Python etc. Python programming language and its supporting packages are used extensively to build AVSTAT. Python is designed to be an easy-to-use, easy-to-learn dynamic scripting language. Python provides many opportunities for integration among GIS computing systems [Steiniger and Hunter, 2012]. Python's cross-platform capabilities and ease of integration with other languages viz. C, FORTRAN, and java, has made it quite successful among the software and scientific community. Python follows object oriented principles like other robust programming languages which makes it highly efficient.

5.3. Graphical User Interfaces for Python

For any tool, a GUI (Graphical user Interface), is mandatory, which helps the users to perform the tasks in an easier manner. Python has a large number of GUI frameworks like Tkinter and other cross platform options as well like WxPython, PyQt, etc. (www.pypi.python.org). For the present study, WxPython and PyQt are chosen because of their functionality and support.

Wxpython is a cross-platform GUI toolkit for python. It supports python programmers with robust functionality to develop GUI's with ease. PyQt is a python binding of the cross-platform GUI toolkit Qt. PyQt is implemented as a Python plug-in. PyQt is developed by the British firm Riverbank computing. The main advantages of PyQt are that it is quite fast and follows object oriented approach for design and development. PyQt uses a mechanism called signal, to communicate events and messages between objects. Using PyQt, it is much easier to control communication between objects in a flexible manner (http://pypi.python.org/pypi/PyQt).

5.4. AVSTAT 1.0

All the computational logic is designed with the help Python and libraries like GDAL (Geo-spatial Data Abstraction Library), matplotlib, numpy (called as numerical python), PIL (Python Imaging Library), numpy-MKL, scipy (scientific python), scikits-timeseries and statsmodels for building AVSTAT. The GUI was designed with the help of PyQt. AVSTAT features three basic tools used in the present study. The first tool is named as data-preparation tool and it provides functionalities like data extraction, clipping and creating geo-referenced raster datasets. GDAL is used which is an open source library for reading and writing raster geospatial data formats, and is released under the free software license by the Open Source Geospatial Foundation (www.gdal.org). The second tool incorporated in AVSTAT is temporal aggregation tool. The designing principle for this tool is quite simple and GDAL and numpy packages are used for creating temporal aggregates by adding datasets for different time periods. Last featured tool of AVSTAT is named as trend analysis tool which was built using scipy, scikits-timeseries, statsmodels, numpy and GDAL capabilities. This tool helps in statistical evaluations done in the present study for trend analysis. The design and working of AVSTAT is discussed in detail here. Figure 5.1. shows a snapshot of AVSTAT's home page when the application is launched. This tool is platform independent and tested on Windows platform.

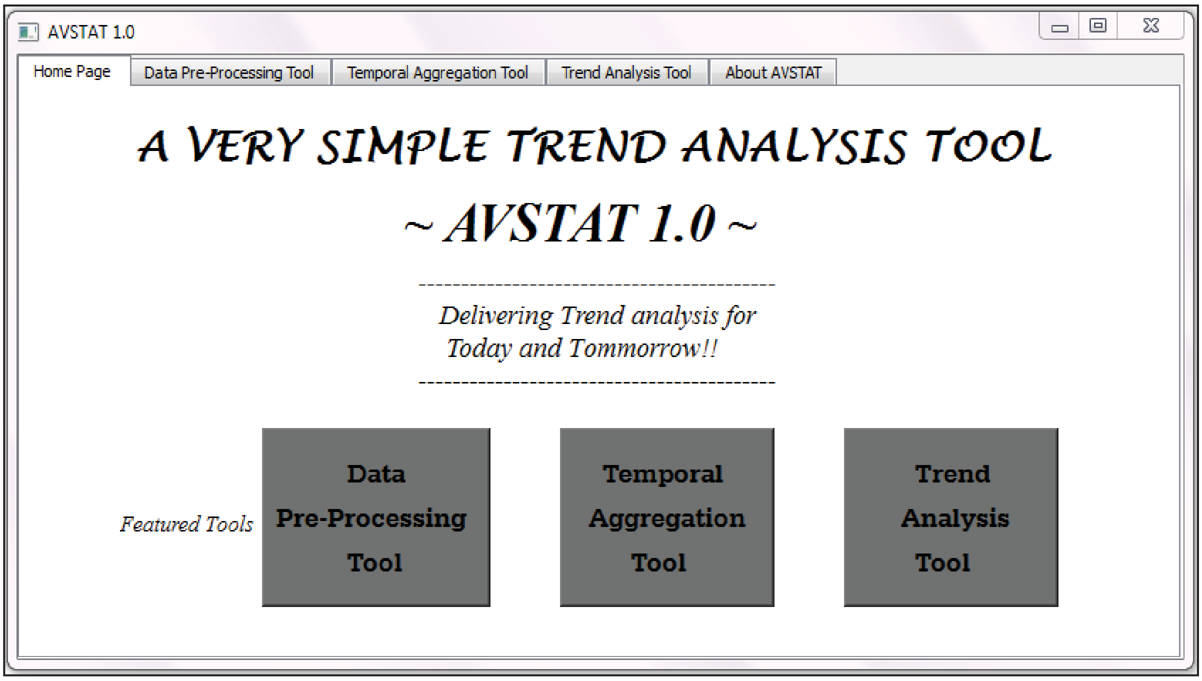


Figure 5.1: Snapshot of AVSTAT 1.0 – A Very Simple Trend Analysis Tool

In the Data Pre-Processing Tool, there are two sub menus; the first sub-page is providing functionality to do the pre-processing functions on NDVI data as shown in figure 5.2. This functionality is developed using python programming language and other open source libraries freely available such as GDAL (Geospatial Data Abstraction Library).

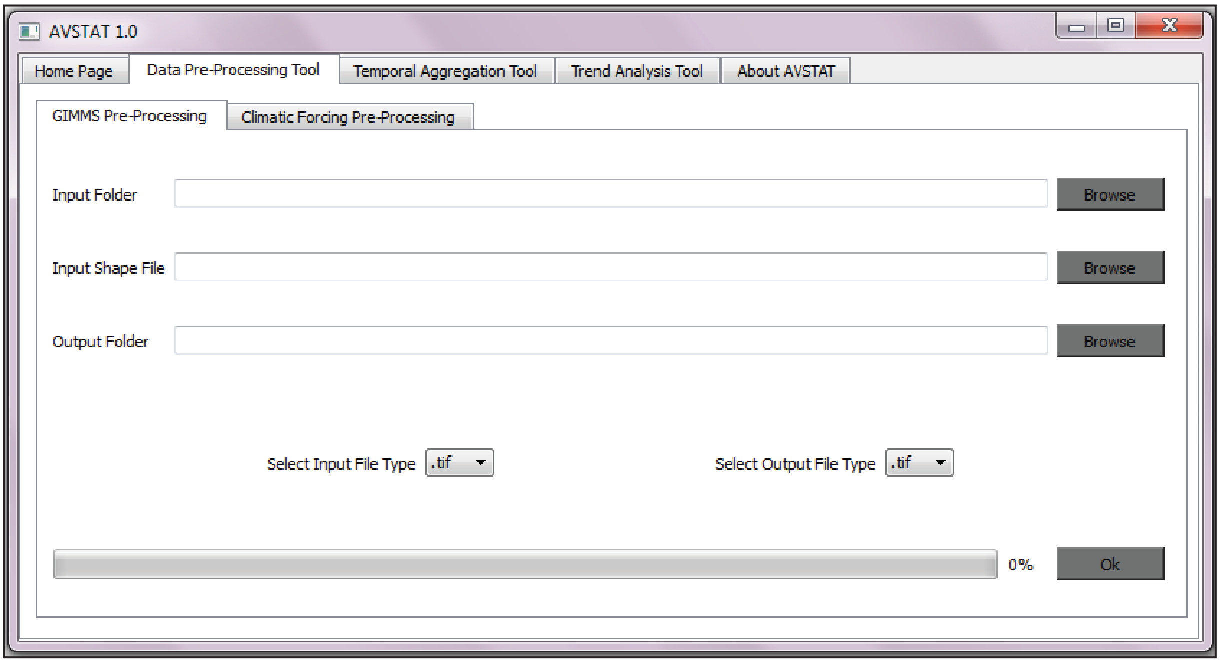


Figure 5.2: NDVI pre-processing through AVSTAT 1.0

With the help of this tool, the global NDVI data was clipped with a polygon shape file representing the boundary of Indian subcontinent. This tool supports several types of image formats such as .img, .tif, etc file formats. This tool will generate geo-referenced raster images.

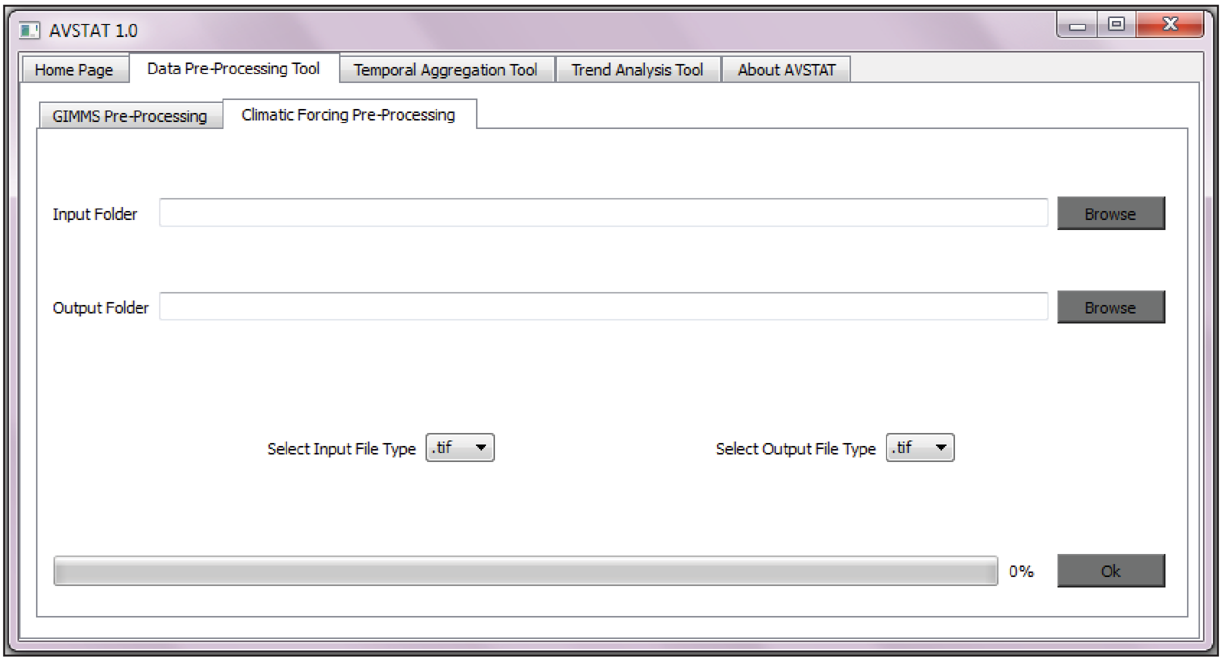


Figure 5.3: Flowchart for daily mean rainfall data extraction

The climatic forcing data is provided as yearly composites having same number of bands as daily data. With the help of AVSTAT's climatic forcing pre-processing functionality, for each day, a new raster data file with mean rainfall values for whole Indian subcontinent was created. Once the user specifies the format for the output daily raster data, depending on how many days bands are present in the annual file, the tool will generate same number of geo-referenced daily data files.

The next tool which is featured in AVSTAT is the temporal aggregation tool. After extraction and creation of the data sets in the data preparation phase, the next step done was to create the temporal aggregates at multiple granularities which are carefully selected for trend analysis. Temporal aggregation tool is also designed using GDAL and python libraries like numpy. The designed tool for temporal aggregation takes geo-referenced raster data image files as inputs.

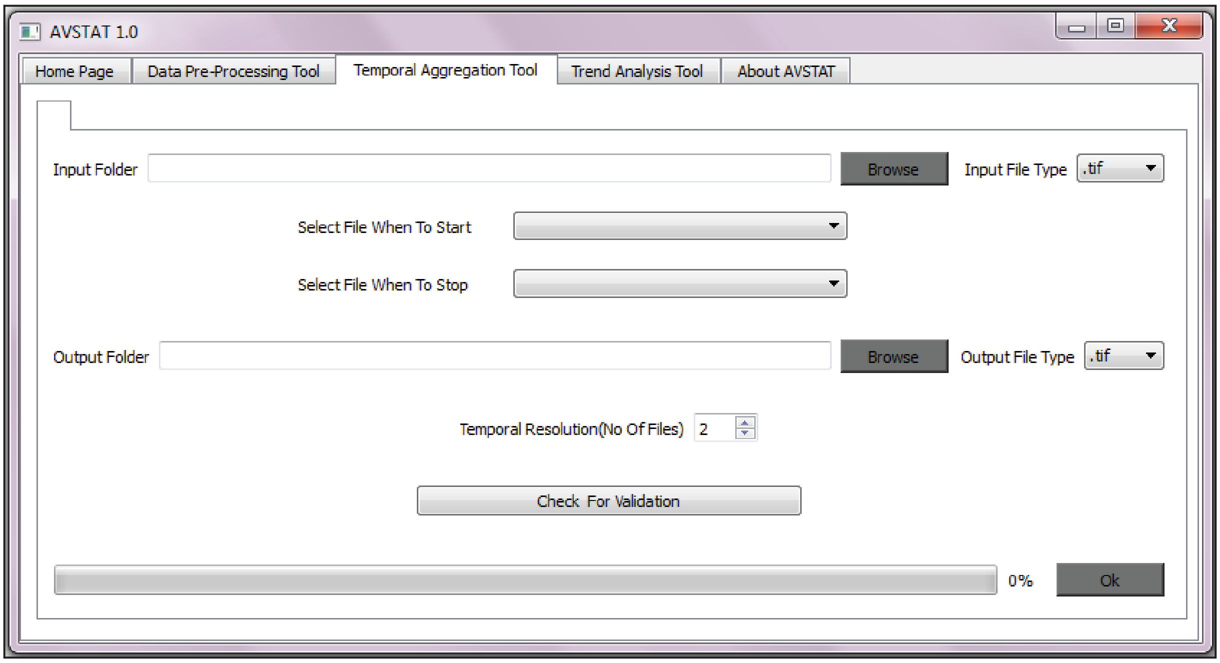


Figure 5.4: Snapshot of Temporal aggregation Tool in AVSTAT 1.0

The graphical user interface for the temporal aggregation tool is shown in Figure 5.4. A new algorithm was designed for this tool, firstly a list of all the files was prepared and these files were stacked to form a data cube. Then only those numbers of files will be selected from the complete file list which is equivalent to the temporal resolution selected by the user. The tool only takes those selected number of files and compute the mean from the pixel values according to the temporal resolution. There is a check for validating the inputs and output location which must be specified prior to the execution. This is done to avoid inconsistencies during the creation of new temporal subsets for further analysis. A new geo-referenced raster data image is created as the end product. This tool is designed in such a way because it provide the flexibility to address the issue of MTUP which can be tackled only if we address these three important aspects – duration (how long), temporal resolution (how often), and the point in time (when), together for temporal analysis.

Once the temporal aggregation is done at selected levels, AVSTAT is also designed to do the trend analysis. Three statistical estimators are used for the analysis. This tool is one of the major achievements of the present study as these tests were not available as standard functions in python. R software is renowned to provide all these statistical tests as standard in-built functions but python libraries only provide limited functionalities in terms of statistical analysis like linear regression. Other two tests were developed exclusively by designing desired algorithm in python.

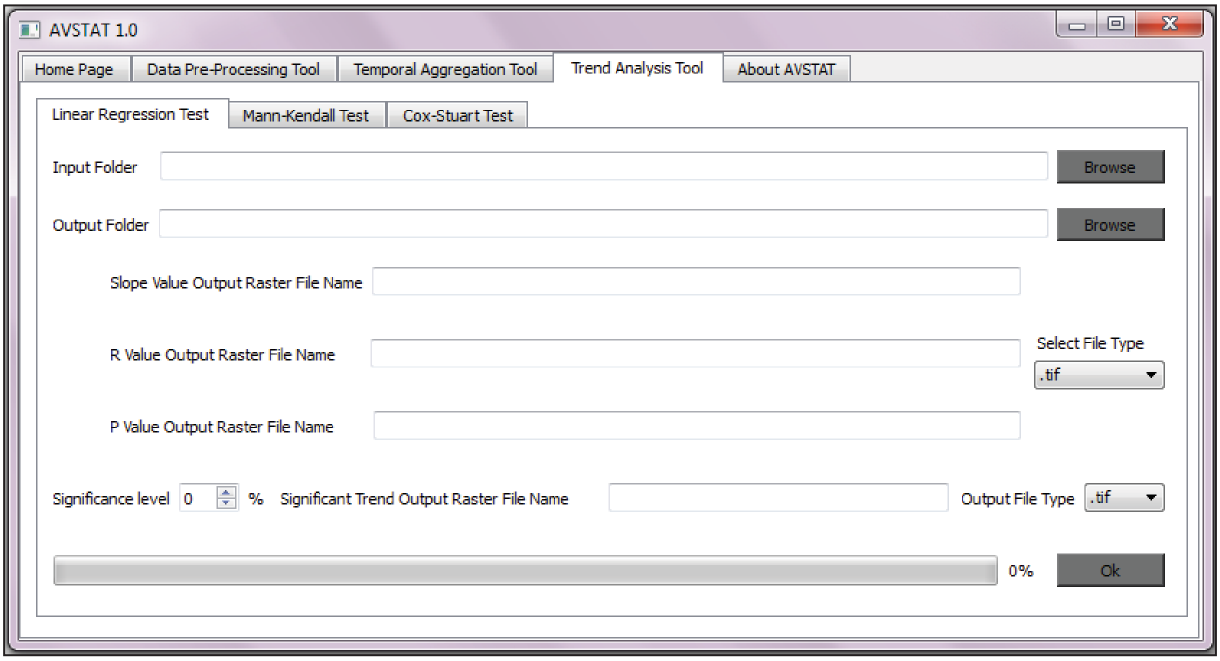


Figure 5.5: Snapshot from AVSTAT for Ordinary Least Squares

Figure 5.5. shows the snapshot from the AVSTAT which shows how a user will interact with the system to generate significant trend maps using linear regression. Slope value map, p-value, r-value maps and significant slope value maps can be generated. These files can be saved into a wide range of file formats such as .tif, .png, .gif, .img etc. The user will also provide the significance level at which hypothesis will be tested for trend analysis.

Figure 5.6. shows the snapshot of the AVSTAT in which Mann-Kendall test is used for the trend analysis. Same as in case of linear regression, user can operate this tool to generate the significant trend maps. This test is accompanied by Sen's slope estimator to evaluate the magnitude of the significant trend. The algorithm for this test was self developed using scipy, statsmodel, scikits-timeseries and numpy packages available with python.

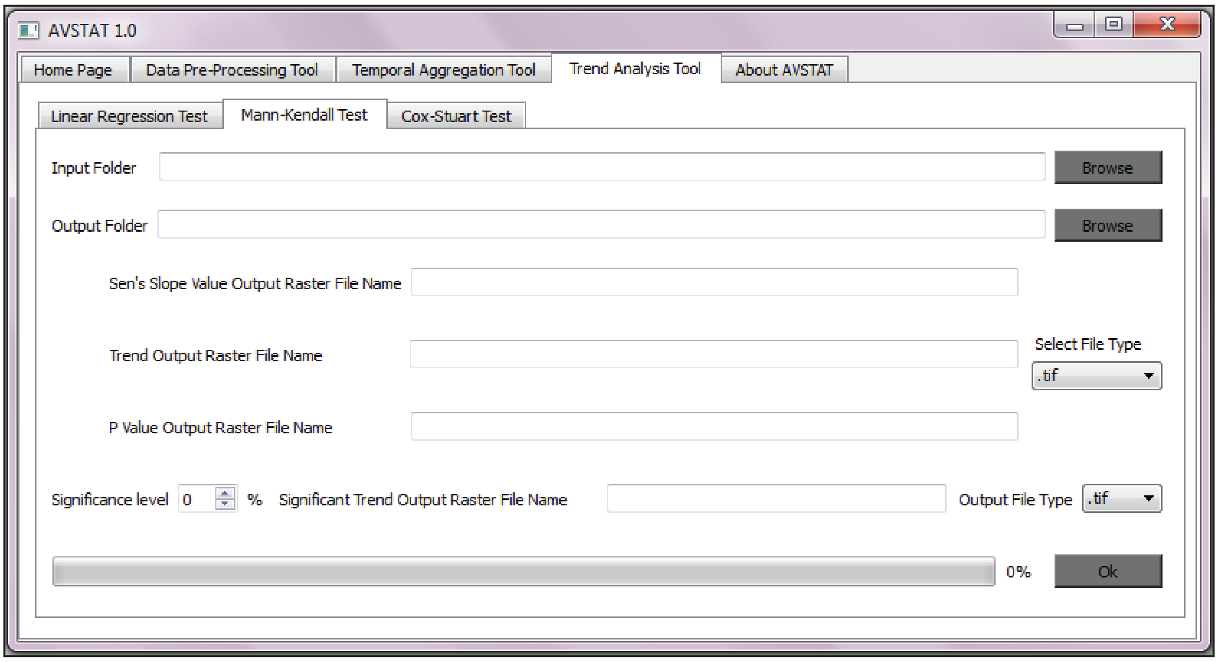


Figure 5.6: Snapshots from AVSTAT for Trend Analysis using Mann-Kendall Test

Figure 5.7. shows the snapshot of AVSTAT for trend analysis using Cox-Stuart Test in the present study. The last page of AVSTAT which is labelled as About AVSTAT contains the basic information about AVSTAT 1.0.

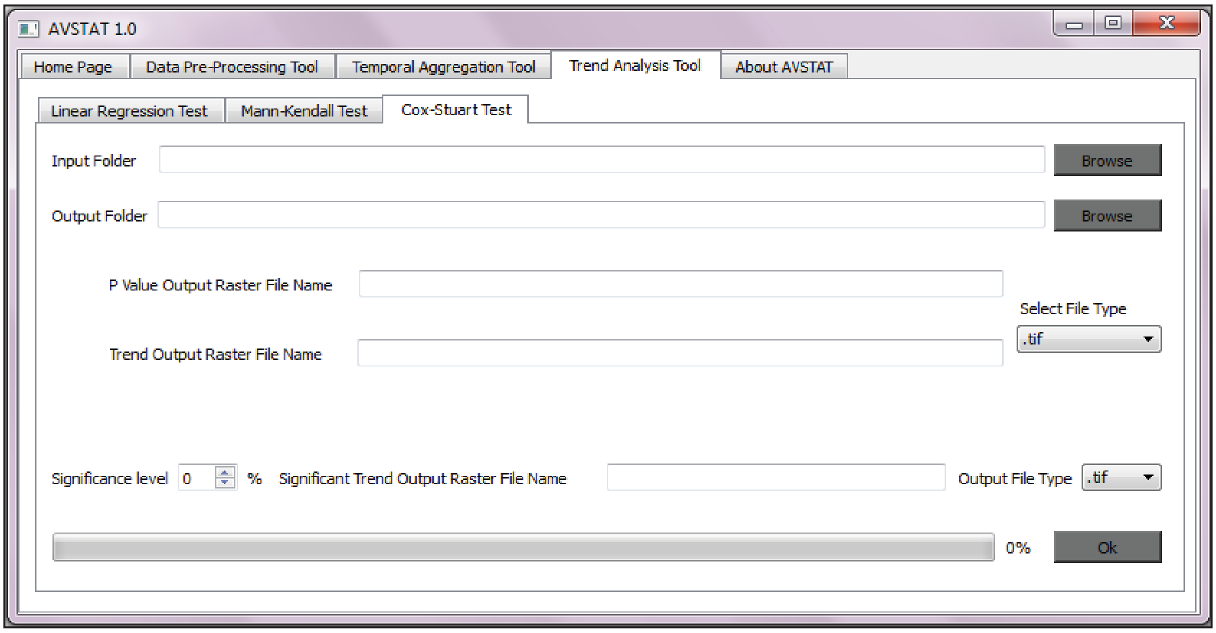


Figure 5.7: Snapshot from AVSTAT for Trend Analysis using Cox-Stuart Test

6. Results and Discussions

This chapter presents the results and discussions obtained from the trend analysis performed at multiple temporal granularities for the NDVI and the climatic forcing data. Due to large amount of results obtained from wide varieties of temporal granularities, all results are not shown in this section; however complete results are incorporated in the APPENDIX -1 section for further references.

6.1. Trends in NDVI and Climatic Forcing at various Temporal Granularities over India

Both NDVI and climatic forcing data sets were subjected to the trend analysis with both parametric and non-parametric tests. With the help of the tool for the trend analysis in this study, significant trend maps showing positive trend, negative trend and no trend were produced. The significant trends maps were helpful in visualizing the variation in trends when operated at multiple granularities. As shown in Figure 6.1., the trends at multiple temporal granularities were quantified and areas showing significant positive trends are depicted using the green colour. Areas showing significant negative trends are depicted in red colour. Areas where no significant trends were found are given no colour. NDVI was temporally aggregated at five different temporal aggregation levels such as fifteen day; one month; three months; six months and also to yearly composites. In a specific case, when seasonality is not considered while temporally aggregating data, those composites are termed as non-seasonal temporal composites in this study.

The results show two very important facts here, first, the variation in amount of trends detected by different statistical estimators. While linear regression (referred as LR) detects 43.75 percent of the total area in Indian subcontinent having significant positive trends, Mann-Kendall test (referred as MKT) detects only 41.41 percent area which corresponds to significant positive trend. Cox-Stuart test (referred as CST) results differs from other tests by showing only 32.24 percent areas as significant positive trends when aggregated annually. So, it is quite evident from these results that the choice of statistical method for any trend analysis is important as the results obtained may vary from different methods. Second important observation is, in terms of subsequent increase and decrease in amount of trends detected. At multiple temporal aggregation level, due the MTUP effect, there are subtle changes in percentage of areas where significant trends were observed. From Figure 6.1. and Table 6.1., with the increase in temporal granularity from one month to six months, the area showing positive trends have decreased by approximately 7.4 percent from 33.22 percent to 25.82 percent. This 7.4 percent area corresponds to approximately 473.60 square kilometre area. When the same data is temporally aggregated at yearly level, the area showing positive trends comes out to be 43.75 percent which has increased by more than 10 percent and 18 percent when observed at one month and six months respectively. When temporal granularity is doubled, from six months to 1 year, the area corresponding to positive trends becomes more than twice from 12.14 percent to 32.24 percent according to CST. Importantly, areas showing significant positive trends were least observed at

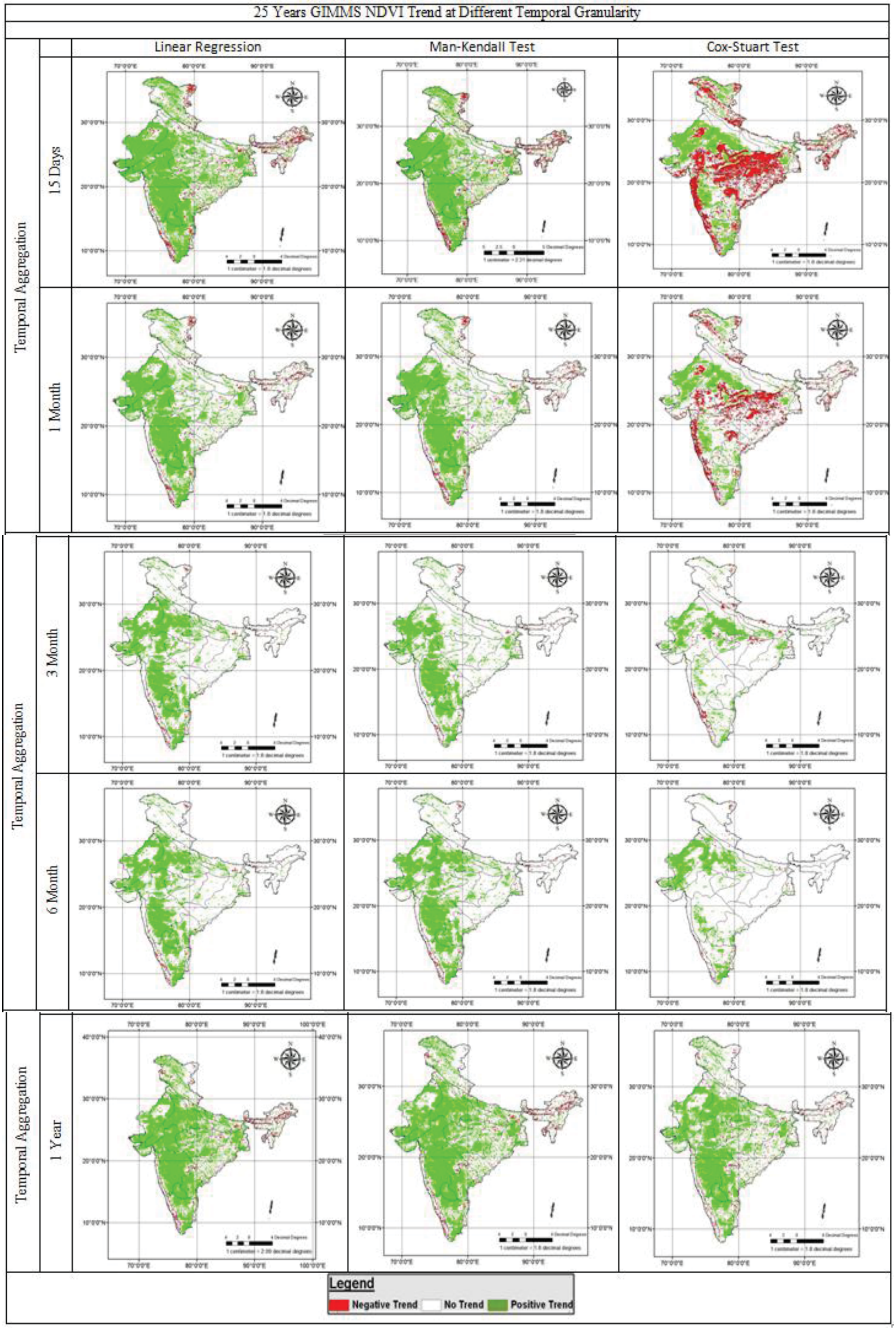


Figure 6.1: Trend Maps for NDVI data at different Temporal Granularities

3 months temporal granularity. At same temporal granularity, most regions in India show no significant trends. Maximum area showing significant negative trends were observed at 15 days by CST. From these trend maps, mainly North-Eastern states Arunachal Pradesh, Assam and Manipur were showing significant negative trends for vegetation. Very high percentages of negative trends were also observed by CST in Madhya Pradesh, Jharkhand, Chhattisgarh, Orissa and along the west coastal regions at 15 days and 1 month temporal granularities. All three tests confirm that, Southern states like Tamil Nadu, Kerala, Karnataka and very small regions in Andhra Pradesh were showing significant positive trends. Central Indian states, Maharashtra, Gujarat, regions of Madhya Pradesh were also confirms the presence of significant positive trends. Rajasthan, regions of Punjab and Haryana in northern India shows positive trends. Uttar Pradesh, Bihar and Jharkhand show absence of significant trends at one month, 3 months, and 6 months temporal granularities confirmed by all the three tests.

At different temporal aggregation levels, the variation in significant positive trends in percentage area is shown in the Figure 6.2. LR and MKT have detected almost same percentage of area, whereas CST has shown less area where positive trends were detected. CST has detected that most regions in India have shown negative trends in NDVI. When data was temporally aggregated to yearly level, there is significant increase of more than 25 percent area which corresponds to significant positive trends.

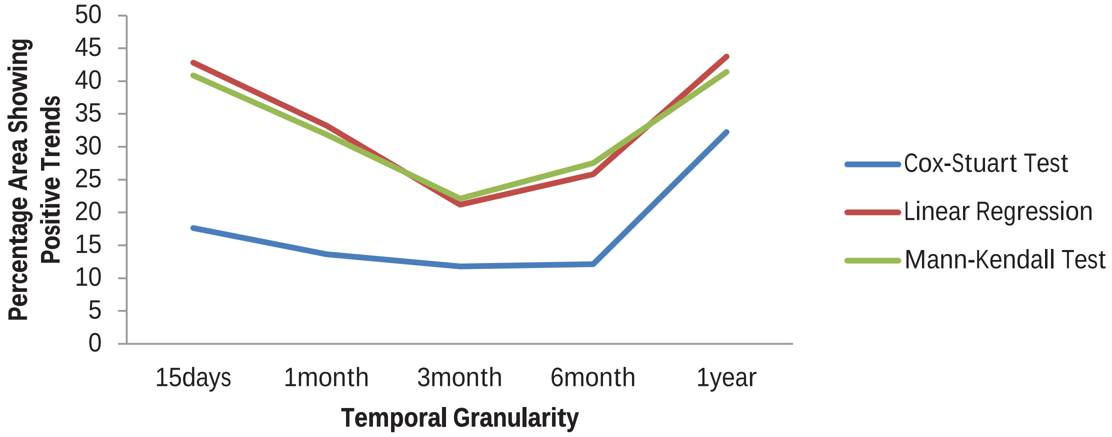


Figure 6.2: Effect of Temporal Aggregation on NDVI data at multiple temporal granularities

An effort was made to study these varying trends at multiple granularities for the major crop seasons in India. The major crops seasons Kharif and Rabi are of approximately 3 months whereas the Zaid crop season if of 4 months. To provide a sufficient temporal sampling for the analysis, different temporal granularities such as 15 days, 1 months and 3 months were chosen carefully to cover Rabi and Kharif crop season. For Zaid crops season, selected temporal granularities were 15days, 1 month, 2 months and 4 months respectively. Please refer to section 1.1 in APPENDIX-1 to see the trend maps for different crop seasons.

Table 6.1: Area in percentage showing Significant Trends in NDVI over India

Non-Seasonal Aggregates

Temporal Granularity	Linear Regression	Mann-Kendall Test	Cox-Stuart Test
15days	42.80	40.88	17.62
	5.34	6.01	25.92
	51.86	53.10	56.47
1month	33.22	31.85	13.65
	2.79	3.18	14.35
	63.98	64.97	71.99
3months	21.17	22.12	11.78
	0.94	0.96	2.19
	77.89	76.91	86.02
6months	25.82	27.50	12.14
	1.17	1.13	0.81
	73.01	71.37	87.06
1year	43.75	41.41	32.24
	3.62	3.39	2.65
	52.63	55.20	65.11

Zaid Crop

Temporal Granularity	Linear Regression	Mann-Kendall Test	Cox-Stuart Test
15days	44.50	43.33	59.81
	4.89	6.72	6.42
	50.62	49.95	33.77
1month	36.20	35.46	47.63
	2.48	3.90	5.18
	60.85	60.64	47.19
2months	30.26	28.72	40.03
	1.74	2.13	3.47
	68.00	69.15	56.49
4 months	39.90	37.40	28.27
	2.90	2.82	1.94
	57.20	59.78	69.79

Positive Trends
Negative Trends
No Trends

Kharif Crop

Temporal Granularity	Linear Regression	Mann-Kendall Test	Cox-Stuart Test
15days	35.27	35.75	18.76
	5.73	6.51	4.47
	59.55	57.74	76.77
1month	24.57	24.54	9.47
	3.68	4.19	2.52
	71.74	71.28	88.02
3month	23.50	22.52	13.25
	3.65	3.61	2.23
	72.85	73.87	84.52

Rabi Crop

Temporal Granularity	Linear Regression	Mann-Kendall Test	Cox-Stuart Test
15days	43.91	41.90	44.97
	8.21	9.08	15.48
	47.88	49.02	39.55
1month	36.44	34.66	37.26
	4.95	5.40	10.35
	58.60	59.94	37.26
3month	34.25	31.94	22.34
	4.02	3.85	4.03
	61.73	64.21	73.62

Table 6.1 shows the percentage area in square kilometres from the total area covered by Indian subcontinent which is showing significant trends. In trend analysis for the non seasonal composites, as much as 42.80 percent and 40.88 percent of the area were observed to show positive trends according to LR and MKT but as per CST it indicates only 17.62 percent area

showing positive trends. 25.92 percent was reported to show negative trends in NDVI over India by CST when observed at 15 days temporal granularity.

Figure 6.3. shows the variation in trends reported by different statistical estimators. Similar to Kharif season, trends for Rabi season have also shown consistent results. All tests confirm that approximately 40 percent of the area is showing positive trends when observed at 15 days. As we increase the temporal granularity to 1 month, there was a sharp decline of approximately 10 percent in each test for positive trends. While observations were made at 1 month, about 60 to 74 percent area shows no significant trends.

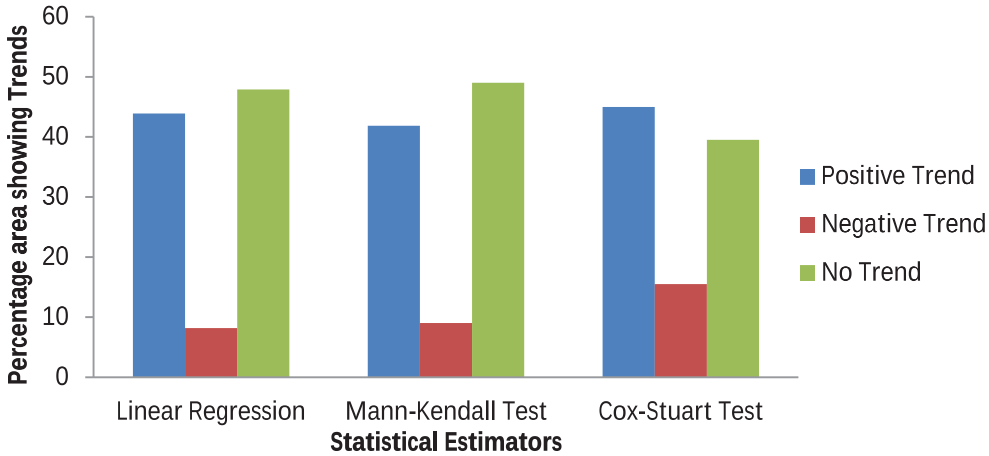


Figure 6.3: Area in percentage showing trends in NDVI for Rabi Crop when aggregated at 15 days over India

From Table 6.1. and Figure 6.4. for Kharif crop season, both LR and MKT were reported to have approximately same percentage of trends with a very small deviation of less than 1 percent, whereas, the results from CST were showing a decrease in trends for more than 50 percent as compared to other tests. For Kharif Season, very low percentage of less than 7 percent recorded over India show negative trends for all selected temporal granularities. Absence of significant trends was found between 57 percent to 88 percent area. Mostly North-Eastern regions in India showed significant negative trends in this crop season. Major crop producing states like Punjab and Haryana, Maharashtra, Rajasthan, Karnataka, Andhra Pradesh and few regions in Uttar Pradesh and Madhya Pradesh were showing significant positive trends in Kharif season.

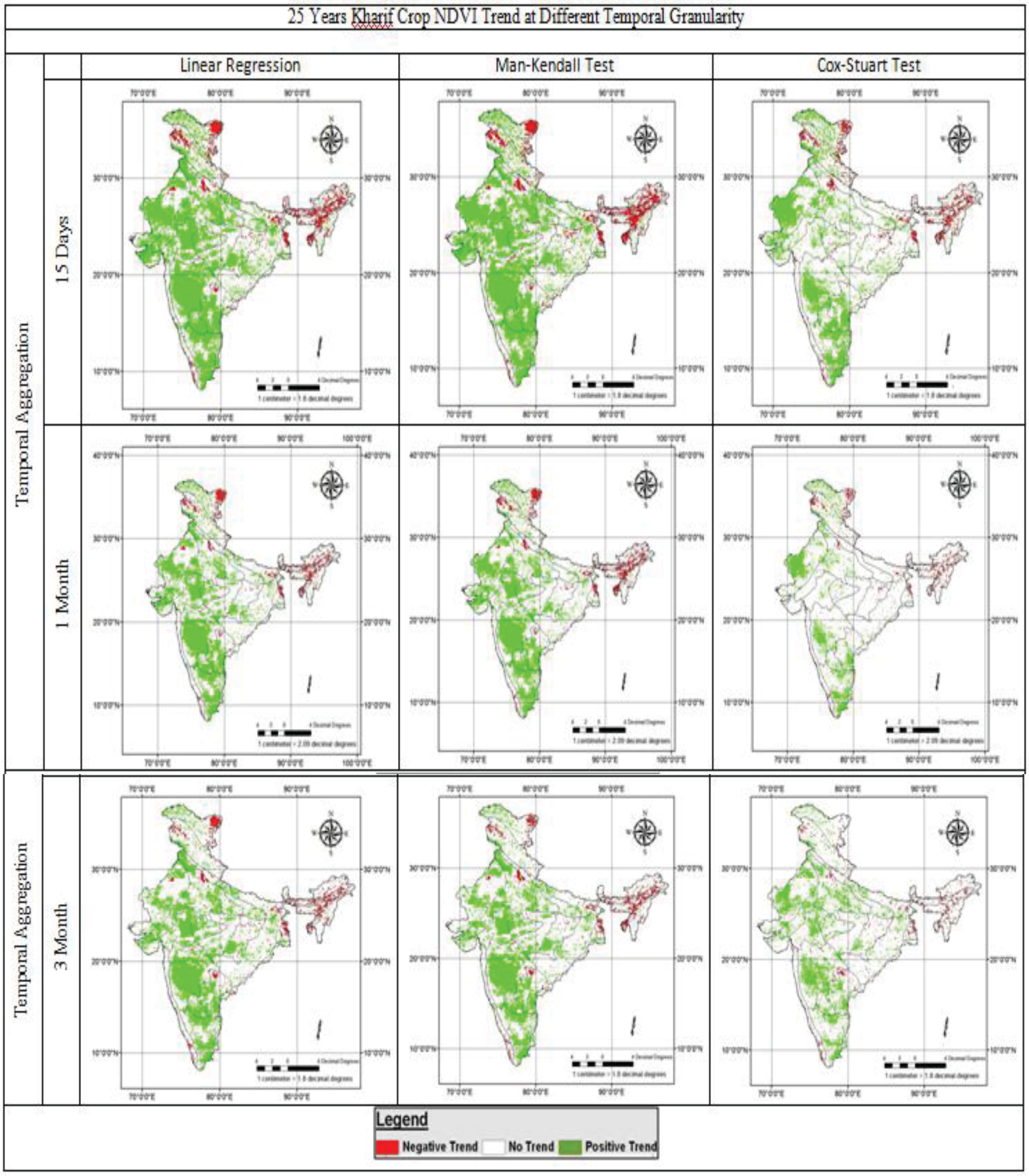


Figure 6.4: Trend Maps to show variations in Kharif Crop season at different Temporal Granularities

From Figure 6.5. Tamil Nadu and other states in South India were moderately showing positive trends, whereas states like Uttar-Pradesh, Bihar, Orissa, Chhattisgarh, West-Bengal and north-eastern regions have shown absence of significant trends in India for Rabi crop season. Significant negative trends were observed along the West-Coastal areas in India mainly in Karnataka and Kerala and North-Eastern region.

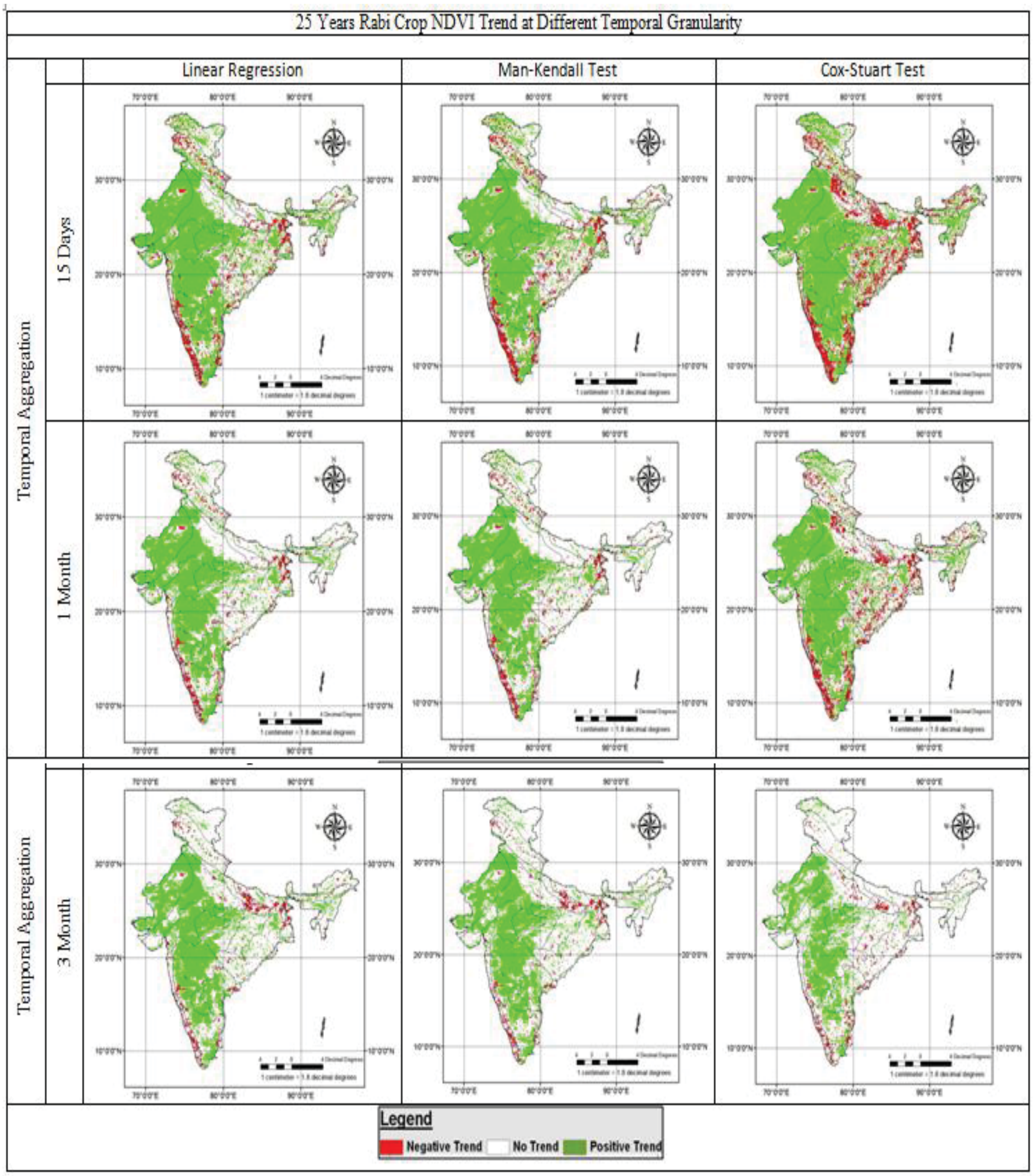


Figure 6.5: Trend Maps to show variations in Kharif Crop season at different Temporal Granularities

From Figure 6.6. for Zaid crop season, CST confirms that nearly 60 percent in the subcontinent shows positive trends for NDVI which is by far the highest predicted value in this study. CST happens to report relatively higher values in case of positive trends for 15days, 1 month and 3 month temporal aggregation levels as nearly as 10 percent more than the amount of positive trends reported by LR and MKT respectively. But there is a sharp decline when trends were observed at 4 months, while LR reports 39.90 percent and MKT reports 37.40 percent, CST shows only 28.27 percent area to show positive trends.

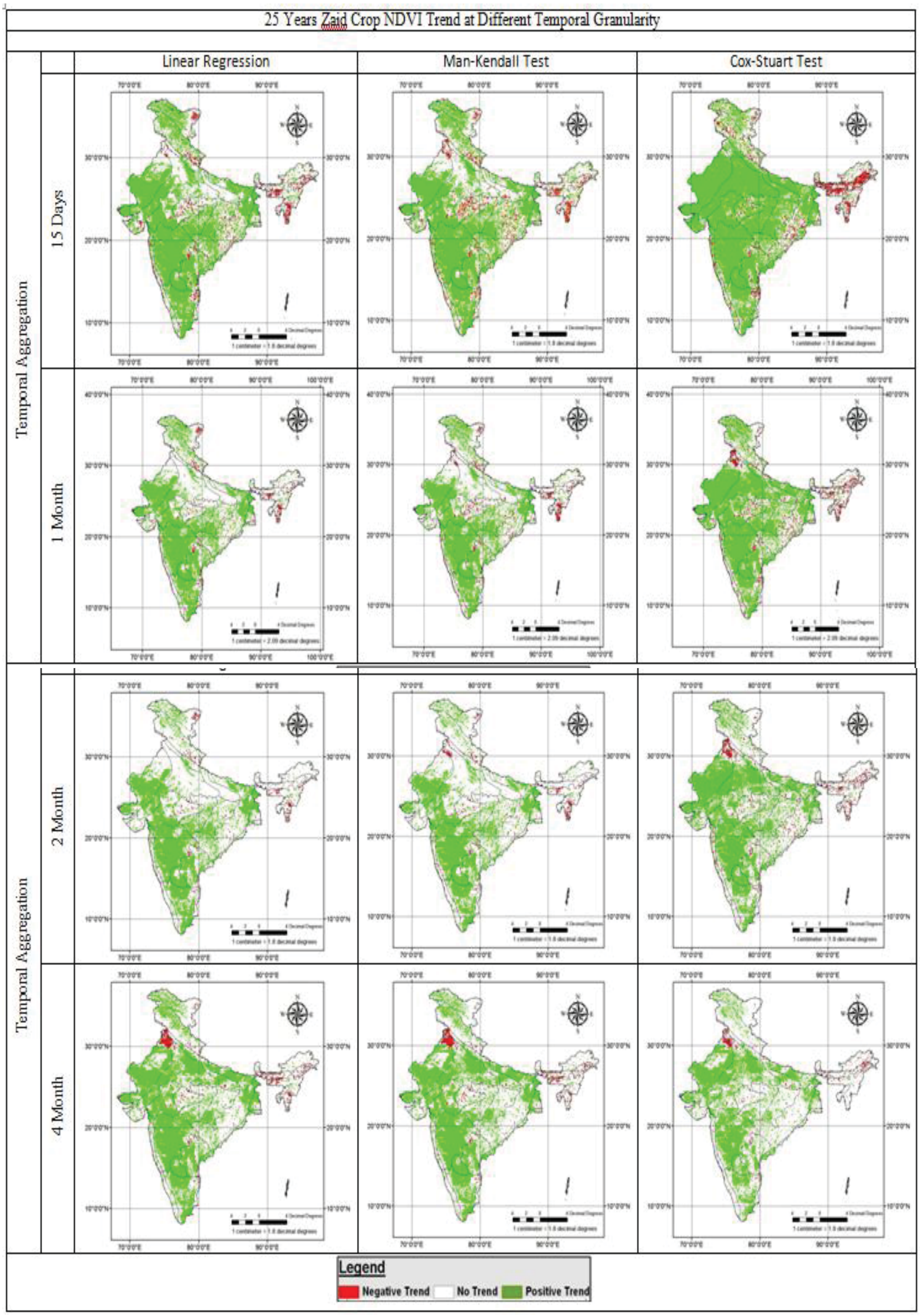


Figure 6.6: Trend Maps to show variations in Kharif Crop season at different Temporal Granularities

Zaid crops season comes in middle of the year and mainly supplementary crops are grown during this period. Due to high temperature and less rainfall conditions during this crop season is a major reason for states like Uttar Pradesh, Rajasthan, Punjab and Haryana and regions in Madhya Pradesh for showing no significant trends. Towards the western and southern regions of India, significant positive trends were observed in Maharashtra, Karnataka, Kerala, Tamil Nadu, Gujarat and some parts of Andhra Pradesh.

To establish relationship betweeen NDVI and climatic forcing over whole Indian subcontinent is a trivial task for any researcher. One of the main motives for this study was to establish any relationship which could possibly relate effect of change in climatic forcing on changes on NDVI. But, this necessarily does not imply that the trends in NDVI were direct results of variation in trends of climatic forcing. To study this, an effort was made to understand the variation in trends for rainfall and temperature over India for the major crop seasons. The climatic forcing data corresponding to the same time period was chosen and studied at same temporal aggregation levels as previously done in the case of NDVI. Trend maps for rainfall and temperature for major crop seasons were generated and documented in APPENDIX -1 section for further reference.

Table 6.2: Variations in Rainfall and Temperature trends for Kharif crop Season over India

Rainfall Trends for Kharif Crop Season			
Temporal Granularity	**Linear Regression**	**Mann-Kendall Test**	**Cox-Stuart Test**
15days	13.83	5.84	4.00
	6.55	7.83	6.95
	79.62	86.33	89.05
1month	11.67	4.16	2.64
	5.44	5.52	2.80
	82.89	90.33	94.56
3month	3.60	2.40	1.36
	4.64	4.24	2.48
	91.77	93.37	96.16

Temperature Trends for Kharif Crop Season			
Temporal Granularity	**Linear Regression**	**Mann-Kendall Test**	**Cox-Stuart Test**
15days	14.36	16.30	12.43
	4.42	4.42	2.21
	81.22	79.28	85.36
1month	10.77	11.33	10.22
	3.59	3.59	0.83
	85.64	85.08	88.95
3month	11.05	11.88	8.84
	2.49	3.59	1.93
	86.46	84.53	89.23

In Table 6.2., variation in significant trends in terms of percentage area for rainfall and temperature is shown for Kharif crop season. For rainfall, LR shows 13 percent and 11 percent of the total area having positive trends. Consistent negative trends between 2 to 8 percent were recorded by each method. Less than 3 percent of the area shows significant positive trends when observed at 3 months. For temperature, minimum area corresponding to positive trend was reported as 8 percent and maximum was 16 percent by MKT. For both rainfall and temperature, very consistent results were observed from each statistical test as 80 percent to 95 percent of the total area show absence of significant trends over India. Both rainfall and temperature show very low significant negative trends for most regions of the country. Temperature trend maps showed presence of significant positive trends for North-East regions. For the same temporal granularities and region, significant negative trends were observed in rainfall. Interestingly, the trends maps generated at multiple granularities showed presence of significant negative trends in NDVI over North-East regions. Lack of rainfall and increase in temperature conditions over North-East regions might be held responsible for presence of significant negative trends in NDVI. If these facts are not true, then these negative trends also may result because of deforestation in that region. In Orissa, significant negative trends were observed for both rainfall and temperature, but trends maps during Kharif cop seasons failed to show presence of any significant trends for NDVI. Please refer to trend maps in section 1.1.5 and 1.1.8. in APPENDIX-1 for spatial variations of significant trends in Kharif season.

Similarly, variation in significant trends in rainfall and temperature were also observed for Rabi crop season over India as shown in Table 6.3. LR and MKT were able to detect that less than 2 percent area shows presence of significant positive trends in India for rainfall. Similarly, only 6 to 9 percent area was detected to show significant negative trends for rainfall. But CST predicted that 37.09 percent and 24.38 percent area corresponds to significant positive trends, whereas 47.72 percent and 33.73 percent area shows significant negative trends when observed at 15days and 1 month respectively which shows high uncertainty. These significant trends decreased by a substantial margin when observed at 3 months as compared to 15 days. Positive trends were observed in temperature in some parts of North-East regions. Negative trends were observed in rainfall as well. But no conclusive spatial patterns were observed in this crop season for significant trends in NDVI to correlate it to climatic forcing. Please refer to trend maps in section 1.1.6 and 1.1.9. in APPENDIX-1 for spatial variations of significant trends in Rabi season.

Table 6.3: Variations in Rainfall and Temperature trends for Rabi crop season over India

Rainfall Trends for Rabi Crop Season			
Temporal Granularity	Linear Regression	Mann-Kendall Test	Cox-Stuart Test
15days	1.28	0.48	37.09
	7.59	9.83	47.72
	91.13	89.69	15.19
1month	0.96	0.24	24.38
	6.47	7.99	33.73
	92.57	91.77	41.89
3month	0.56	0.16	4.64
	6.63	6.95	8.07
	92.81	92.89	87.29

Temperature Trends for Rabi Crop Season			
Temporal Granularity	Linear Regression	Mann-Kendall Test	Cox-Stuart Test
15days	21.82	11.60	19.61
	0.00	0.00	3.31
	78.18	88.40	77.07
1month	8.84	6.63	15.19
	0.00	0.00	1.10
	91.16	93.37	83.70
3month	19.89	20.72	5.52
	0.83	0.55	0.00
	79.28	78.73	94.48

Table 6.4. shows variations in Rainfall and Temperature trends for Zaid crop season. These trends were analysed at 4 different temporal granularities due the prolonged season of approximately 4 months before the onset of ISMR. Significant temperature trends have shown

that there were relatively no significant changes in the temperature over most parts in India when observed at 15 days, 1 month and 2 months.

Table 6.4: Variations in Rainfall and Temperature trends for Zaid crop season over India

Rainfall Trends for Zaid Crop Season			
Temporal Granularity	**Linear Regression**	**Mann-Kendall Test**	**Cox-Stuart Test**
15days	7.35	3.84	23.02
	9.99	11.27	16.79
	82.65	84.89	60.19
1month	4.64	1.76	7.59
	9.11	9.43	8.55
	86.25	88.81	83.85
2 month	3.60	0.72	0.08
	7.67	7.35	0.40
	88.73	91.93	99.52
4months	7.11	6.63	4.48
	9.03	6.63	2.32
	83.85	86.73	93.21

Temperature Trends for Zaid Crop Season			
Temporal Granularity	**Linear Regression**	**Mann-Kendall Test**	**Cox-Stuart Test**
15days	1.38	2.21	2.21
	0.00	0.28	0.00
	98.62	97.51	97.79
1month	0.83	0.83	1.10
	0.00	0.00	0.28
	99.17	99.17	98.62
2 month	0.83	0.83	0.83
	0.00	0.00	0.00
	99.17	99.17	99.17
4months	16.30	14.92	8.84
	0.00	0.00	0.00
	83.70	85.08	91.16

Although when observed at 4 months, no significant negative trends were found but a moderate 8 percent to 16 percent area showed positive trends in temperature in the Western Himalaya regions. For rainfall, significant negative trends were observed from all the tests in Western Himalaya region. NDVI also shows presence of positive trends in this region. This region is not recognized for agriculture but may be due to increase in temperature and less rainfall there was presence of positive trends in NDVI. No conclusive spatial patterns were observed in this crop season for other regions in India and hence it was not possible to correlate NDVI and climatic forcing. Please refer to trend maps in section 1.1.7 and 1.1.10. in APPENDIX-1 for spatial variations of significant trends in Zaid season.

6.2. Trends in Climatic Forcing at various Temporal Granularities over India

Climate change is not an immediate result of extreme climate and weather events but is a gradual process where climatic conditions show continuous increasing or decreasing trends over a period of time. Pre-dominantly four seasons exists in India, in which winter season stays almost for two months from January and February with intense snowfall in the high altitude regions and cold waves in the plain areas. Pre-monsoon season is expected to be the hottest time of the year over almost all regions. Hot weather is supported by intense heat waves which may cause serious societal impacts, particularly on human health as well as to vegetation growth in growing periods. The relief from intense summer is provided by the onset of ISMR which is largely responsible for irrigation purposes as well. Extreme rain events are reported by many regions in India in the past few decades. Moderate temperature conditions are experienced in post-monsoon season. All these seasons have specific temperature ranges that that may or may not vary yearly. An effort was made to study the trends by temporally aggregating data to 10 days, 15 days and 1 month.

6.2.1. Trends in Rainfall data at various Temporal Granularities over India

Table 6.5. shows percentage area showing significant trends in rainfall over India in different climatic seasons at different temporal aggregation levels. LR and MKT have detected 1 to 2 percent of total area showing significant positive trends, and nearly 5-8 percent area for negative trends across all aggregation levels for winter season. In the winter season, significant negative trends are prominently observed in Jammu and Kashmir, Arunachal Pradesh and some parts of West-Central Zones. CST detected very high 25 to 43 percent area for positive trends. CST has detected large areas in central India. Madhya Pradesh, Chattisgarh, Orissa and many other states were observed to show negative trends in rainfall.

Table 6.5: Percentage area showing Significant Trends in Rainfall over India in different climatic seasons at multiple granularities

Winter Season (Jan-Feb)			
Temporal Granularity	Linear Regression	Mann-Kendall Test	Cox-Stuart Test
10days	2.48	0.80	43.25
	7.99	7.91	37.17
	89.53	91.29	19.58
15days	1.92	0.56	38.37
	6.87	8.71	27.10
	91.21	90.73	34.53
1month	1.44	0.64	24.46
	5.68	5.52	9.35
	92.89	93.84	66.19

Monsoon Season (Jun-Jul-Aug- Sep)			
Temporal Granularity	Linear Regression	Mann-Kendall Test	Cox-Stuart Test
10days	17.51	12.23	9.91
	6.08	5.92	8.79
	76.42	81.85	81.29
15days	15.43	9.43	6.71
	5.60	6.24	6.08
	78.98	84.33	87.21
1month	13.11	6.47	3.36
	4.72	4.88	3.28
	82.17	88.65	93.37

Pre-Monsoon Season (Mar-Apr- May)			
Temporal Granularity	**Linear Regression**	**Mann-Kendall Test**	**Cox-Stuart Test**
10days	6.71	4.24	35.41
	16.55	14.07	37.81
	76.74	81.69	26.78
15days	5.28	3.76	25.10
	16.23	13.59	28.78
	78.50	82.65	46.12
1month	2.88	2.00	13.27
	14.79	13.11	14.39
	82.33	84.89	72.34

Post-Monsoon Season (Oct-Nov-Dec)			
Temporal Granularity	**Linear Regression**	**Mann-Kendall Test**	**Cox-Stuart Test**
10days	0.48	0.32	29.02
	9.67	11.75	49.96
	89.85	87.93	32.61
15days	0.08	0.16	16.47
	8.15	10.07	42.53
	91.77	89.77	41.01
1month	0.00	0.00	4.48
	7.99	10.07	27.34
	92.01	89.93	68.19

Please refer to the trend maps documented in section 1.2. in APPENDIX section. In the pre-monsoon season, prominent spatial pattern in significant negative trends in Jammu and Kashmir, Himachal Pradesh, Punjab and Uttaranchal were observed across all temporal aggregation levels. Goa and some regions in Maharashtra, Karnataka, and Kerala showed presence of positive trends during pre-monsoon season. Again CST has shown larger areas to show significant trends over India especially in Maharashtra and Gujarat. The most important season for Indian subcontinent is the onset of Monsoon rainfall. Prominent spatial pattern was observed in South Indian states like Tamil Nadu, Kerala, Karnataka, and Andhra Pradesh for showing positive trends in monsoon season by linear regression. Some region in Maharashtra also shows positive trends during monsoon season. In Goa and along the coast lines of Karnataka and Kerala, negative trends were observed. Regions in Rajasthan have shown presence of negative trends by all tests. Unlike winter season and pre-monsoon season, regions in Jammu and Kashmir have shown positive trends in monsoon season. In the monsoon season, more than 10 percent of areas showing positive trends were detected by all tests but the areas decreases with increase in temporal granularities as shown in Figure 6.7. CST was showing greater areas for both significant positive and negative trends than LR and MKT for rainfall across all seasons.

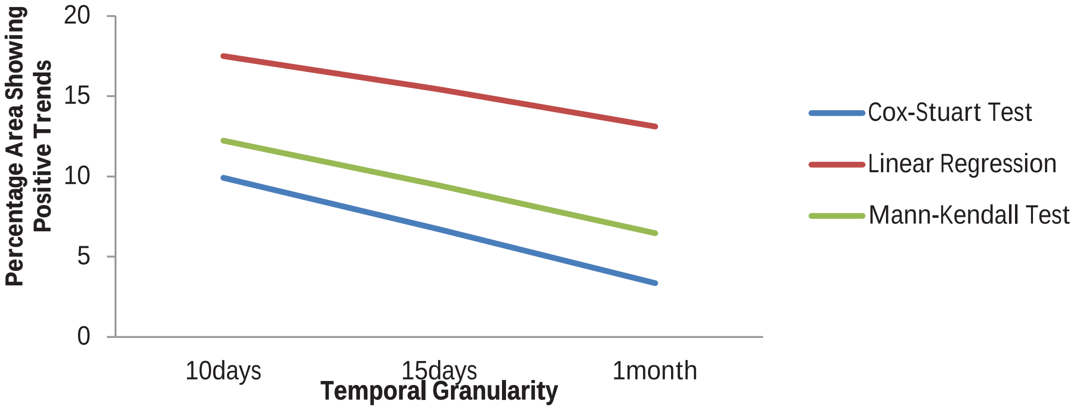


Figure 6.7: Effect of Temporal Aggregation on Positive Trends in Monsoon season Rainfall data

Negligible positive trends were observed in post-monsoon seasons by LR and MKT as shown in Figure 6.8. But negative trends were detected in Jammu and Kashmir which confirms decrease in rainfall for this region in post monsoon season. Similar negative trends were also observed in some areas of Tamil Nadu and Andhra Pradesh.

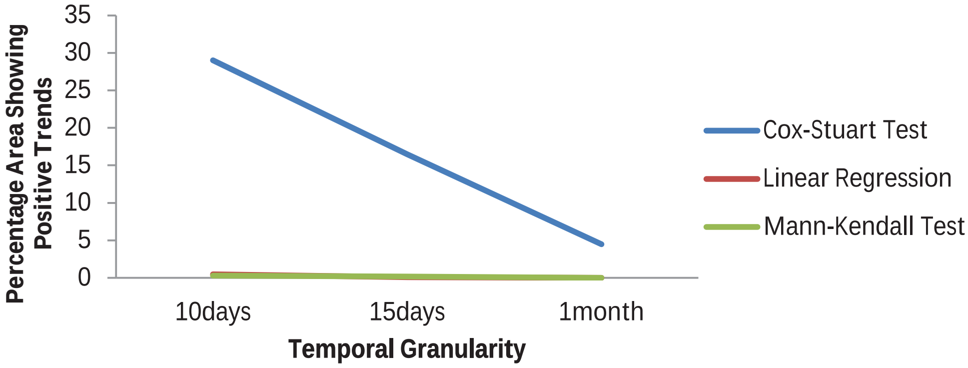


Figure 6.8: Effect of Temporal Aggregation on Positive Trends in Post-monsoon season Rainfall data

6.2.2. Trends in Temperature data at various Temporal Granularities over India

A Similar approach for trend estimation was used to study the trends in temperature at different temporal granularities. The variations in trends in climatic seasons were quantified with the help of trend analysis tool and significant trend maps were generated. The trend maps generated are documented in section 1.3. in APPENDIX -1 section of this thesis. Figure 6.9. shows percentage area showing significant trends in temperature over India in Winter Season observed at temporal granularity of 10 days.

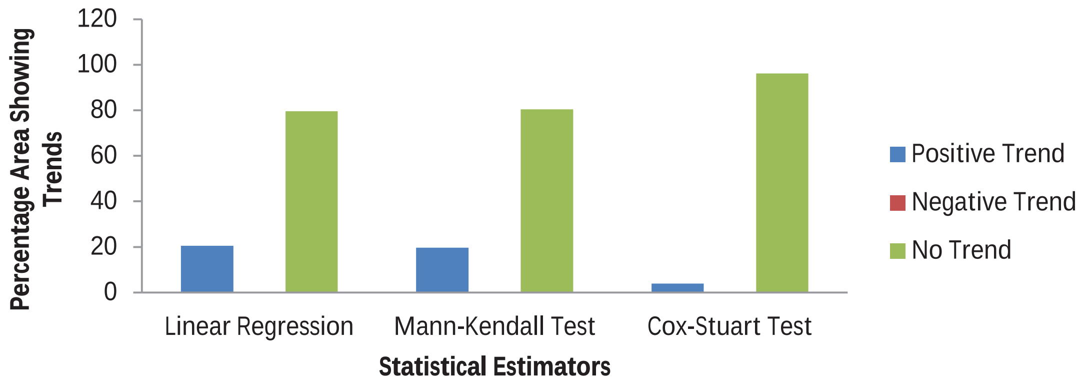


Figure 6.9: Percentage area showing significant trends in temperature in Winter Season (Temporal granularity - 10 days)

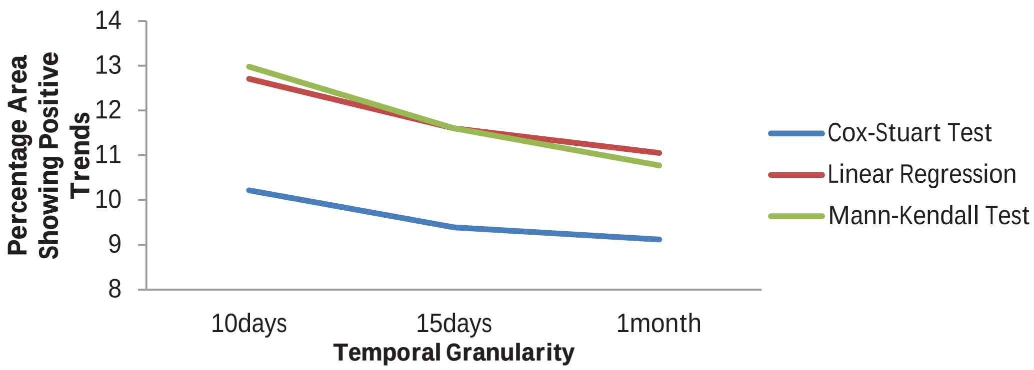


Figure 6.10: Effect of Temporal Aggregation on Positive Trends in Monsoon season Temperature data

Figure 6.10. and Figure 6.11. shows the effect of temporal aggregation on temperature in monsoon and winter seasons respectively. All three tests confirm a significant decrease in the area showing positive trends with increase in temporal granularity in monsoon period. In the winter season, MKT and CST both shows marginal increase in the area showing positive trends when temporal granularity was increased from 15 days to 1 month, whereas LR reports a 10 percent decline in the area with increase in temporal granularity.

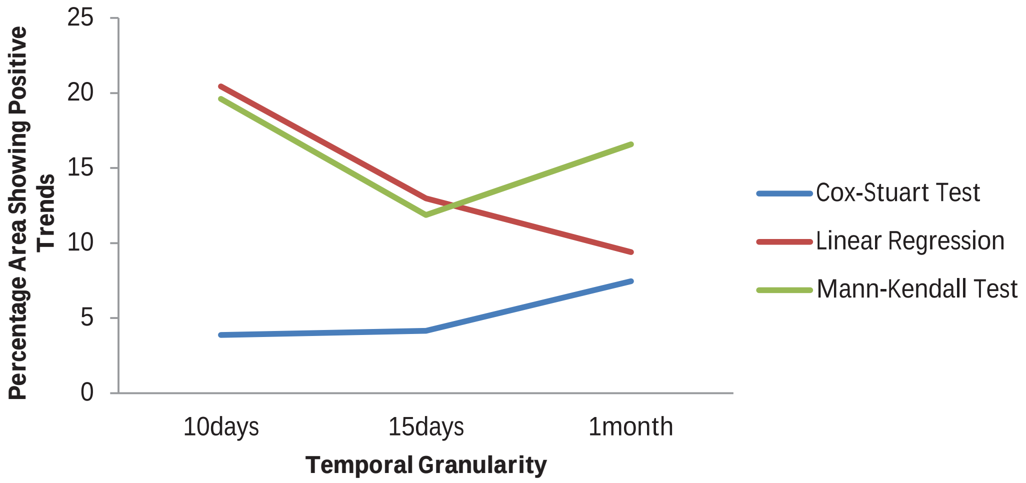


Figure 6.11: Effect of Temporal Aggregation on Positive Trends in Winter season Temperature data

From Table 6.6. no significant negative trends were detected in winter season for 1981-2005 India. Significant positive trends were observed in Jammu and Kashmir and Himachal Pradesh. Due to this increase in temperature in Himachal Pradesh in winter season, production of apple was reported to have declined because low temperature is required for fruiting. Significant positive trends were observed along the coast line areas in Gujarat, Maharashtra, Goa, Karnataka, Kerala, Tamil Nadu and some part of Andhra Pradesh in winter season.

In the pre-Monsoon season, more than 30 percent of the area showed positive trends according to LR and MKT. But with the increase in temporal granularities, the area decreases to only 1 percent, as confirmed by all the tests. In the pre-monsoon season Jammu and Kashmir, Himachal Pradesh, Punjab and Haryana, Uttaranchal, some regions in Rajasthan, Uttar Pradesh, and Gujarat were reported to show significant positive trends when observed at lower temporal granularities.

For the whole monsoon season, 9 percent to 13 percent of the total area shows positive trends and most of the Indian subcontinent regions show absence of significance trends. During the monsoon season, Orissa was reported to show significant negative trends by MKT. Bihar; regions in north-east like Assam, Meghalaya, and Manipur were reported to show significant positive trends in the monsoon season.

In the Post-Monsoon season, no positive or negative trends were observed and almost around 98 percent of the total area shows absence of significant trends. No spatial patterns were observed in post-monsoon seasons as almost all regions were showing absence of significant trends.

Table 6.6: Percentage area showing Significant Trends in Temperature over India in different climatic seasons at multiple granularities

Winter Season (Jan-Feb)			
Temporal Granularity	Linear Regression	Mann-Kendall Test	Cox-Stuart Test
10days	20.44	19.61	3.87
	0.00	0.00	0.00
	79.56	80.39	96.13
15days	12.98	11.88	4.14
	0.00	0.00	0.00
	87.02	88.12	95.86
1month	9.39	16.57	7.46
	0.00	0.00	0.83
	90.61	88.40	91.71

Monsoon Season (Jun-Jul-Aug- Sep)			
Temporal Granularity	Linear Regression	Mann-Kendall Test	Cox-Stuart Test
10days	12.71	12.98	10.22
	3.04	5.52	3.31
	84.25	81.49	86.46
15days	11.60	11.60	9.39
	1.10	3.59	0.55
	87.29	84.81	90.06
1month	11.05	10.77	9.12
	0.55	2.21	0.55
	88.40	87.02	90.33

Pre-Monsoon Season (Mar-Apr- May)			
Temporal Granularity	Linear Regression	Mann-Kendall Test	Cox-Stuart Test
10days	30.39	38.40	1.66
	0.83	1.10	1.66
	68.78	60.50	96.69
15days	13.26	12.71	1.38
	0.83	0.83	0.83
	85.91	86.46	97.79
1month	1.10	0.28	0.28
	0.28	0.00	1.10
	98.62	99.72	98.62

Post-Monsoon Season (Oct-Nov-Dec)			
Temporal Granularity	Linear Regression	Mann-Kendall Test	Cox-Stuart Test
10days	0.83	0.83	2.21
	0.28	3.04	2.49
	98.90	96.13	95.30
15days	0.83	0.83	1.38
	0.00	0.00	1.38
	99.17	99.17	97.24
1month	0.83	0.83	2.49
	0.00	0.00	1.10
	99.17	99.17	96.41

The results reported in sections 5.1 and 5.2. were able to show the variation in trends at multiple temporal granularities at all India level in both NDVI and climatic forcing across different seasons chosen for the analysis. Different zones where homogenous patterns were observed in climatic forcing and NDVI were selected in the present study. Information provided by Indian Institute of Tropical Meteorology and National Bureau of Soil Survey & Land Use Planning were used. Results of the trend analysis in these zones are discussed in sections 5.3 and 5.4 respectively.

6.3. Trends in Homogenous Temperature Regions in India

In this section, trends in temperature for all seasons will be discussed. These trends were detected for the seven homogeneous regions - Western Himalaya (WH), Northwest (NW), Northeast (NE), North Central (NC), East coast (EC), West coast (WC) and Interior Peninsula (IP).

Table 6.7: Percentage Area showing Significant trends for Homogenous Temperature Regions in India

WINTER SEASON	Cox-Stuart Test							Linear Regression							Mann-Kendall Test						
	WH	NW	NC	IP	WC	EC	NE	WH	NW	NC	IP	WC	EC	NE	WH	NW	NC	IP	WC	EC	NE
10days	25	0	0	0	0	0	0	83	10	0	8	33	20	0	67	8	0	13	35	23	0
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	75	100	100	100	100	100	100	17	90	100	92	67	80	100	33	92	100	87	65	77	100
15days	21	0	0	0	2	0	4	46	5	0	3	24	10	0	33	5	0	3	24	10	0
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	79	100	100	100	98	100	96	54	95	100	97	76	90	100	67	95	100	97	76	90	100
1Month	0	0	0	13	13	23	0	21	5	0	1	20	3	0	71	5	0	9	24	20	0
	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	100	100	100	87	87	77	93	79	95	100	99	80	97	100	29	95	100	91	76	80	100

PRE-MONSOON SEASON	Cox-Stuart Test							Linear Regression							Mann-Kendall Test						
	WH	NW	NC	IP	WC	EC	NE	WH	NW	NC	IP	WC	EC	NE	WH	NW	NC	IP	WC	EC	NE
10days	4	0	0	0	0	0	0	92	56	26	1	15	3	20	92	68	39	1	13	7	43
	0	0	0	1	7	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0
	96	100	100	99	93	100	100	8	44	74	99	85	97	80	8	32	61	99	85	93	57
15days	4	0	0	0	0	0	0	79	17	9	0	7	0	2	54	21	12	0	4	0	4
	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	96	100	100	99	98	100	100	21	83	91	100	93	100	98	46	79	88	100	96	100	96
1Month	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	100	100	100	100	98	100	100	96	100	100	100	100	100	100	100	100	100	100	100	100	100

MONSOON SEASON	Cox-Stuart Test							Linear Regression							Mann-Kendall Test						
	WH	NW	NC	IP	WC	EC	NE	WH	NW	NC	IP	WC	EC	NE	WH	NW	NC	IP	WC	EC	NE
10days	0	0	0	0	2	0	48	0	0	0	4	13	0	52	0	0	0	1	11	0	54
	13	0	3	5	0	10	0	13	0	0	1	2	10	0	13	0	2	10	4	10	2
	88	100	97	95	98	90	52	88	100	100	95	85	90	48	88	100	98	88	85	90	43
15days	0	0	0	0	0	0	48	0	0	0	1	9	0	50	0	0	0	1	9	0	52
	8	0	0	0	0	0	0	8	0	0	0	0	0	0	8	0	0	8	0	10	0
	92	100	100	100	100	100	52	92	100	100	99	91	100	50	92	100	100	91	91	90	48
1Month	0	0	0	0	0	0	46	0	0	0	0	7	0	50	0	0	0	0	7	0	48
	0	0	0	0	0	0	2	4	0	0	0	0	0	0	4	0	0	4	0	10	0
	100	100	100	100	100	100	52	96	100	100	100	93	100	50	96	100	100	96	93	90	52

POST-MONSOON SEASON	Cox-Stuart Test							Linear Regression							Mann-Kendall Test						
	WH	NW	NC	IP	WC	EC	NE	WH	NW	NC	IP	WC	EC	NE	WH	NW	NC	IP	WC	EC	NE
10days	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	21	0	0	0	0	0	4	0	2	0	0	0	0	0	25	2	0	0	0	0	2
	79	100	100	100	100	100	93	100	98	100	100	100	100	100	75	98	100	100	100	100	98
15days	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	92	100	100	100	100	100	93	100	100	100	100	100	100	100	100	100	100	100	100	100	100
1Month	0	0	0	0	7	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	100	100	100	100	93	100	96	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 6.7. shows the percentage area in the respective homogenous temperature regions where significant trends were detected. In the winter season, NC and NE regions were showing no significant trends during 1981-2005. No significant negative trends were detected in any of the regions for the winter season. High significant positive trends were detected in WH region by all the tests. In the pre-monsoon season, no significant trends were observed at high temporal granularity such as 1 month. EC region and WC regions shows no significant trends as well. Again high percentages of positive trends were only reported in WH by MKT and LR. In the monsoon season, NE region shows that almost 50 percent of the area shows high positive trends. Only NE region shows significant positive trends. Regions of WH, NW, NC and EC show no positive trends at any temporal granularity. For post-monsoon season, none of the homogenous regions were reported to show significant positive trend. More than 20 percent of the area in WH is reported to show significant negative trends in the WH region by MKT and CST.

6.4. Trends in Homogenous Regional Summer Monsoon Rainfall Zones in India

As discussed in chapter 3, homogenous regions for summer rainfall are 1- North-West (NW), 2 - West Central (WC), 3 - Central Northeast (CNE), 4 - Northeast (NE), 5 - Peninsula (PR) and 6 - Hilly region (HR).

Percentage area showing significant trends in the homogenous rainfall regions are shown in Table 6.8. From the six identified regions, high percentage of area showing positive trends were reported in PR region by LR at all temporal granularities. Similarly, HR region also shows more than 15 percent area where positive trends were observed. Trend maps for the variation in trends for monsoon season are shown in Figure 6.12.

Table 6.8: Percentage Area showing Significant trends for Homogenous summer monsoon rainfall regions in India

MONSOON SEASON																		
	Cox-Stuart Test						Linear Regression						Mann-Kendall Test					
	NW	CNE	NE	WC	PR	HR	NW	CNE	NE	WC	PR	HR	NW	CNE	NE	WC	PR	HR
10days	13	9	7	3	11	21	2	6	8	12	63	30	6	6	7	6	19	37
	12	5	12	2	6	20	5	8	12	3	7	5	5	7	14	2	7	6
	75	87	81	94	83	59	93	86	80	85	30	66	88	87	79	92	75	57
15days	6	6	6	4	8	14	2	5	8	10	57	25	4	5	7	6	15	27
	6	3	9	1	4	14	4	7	12	3	6	5	6	6	15	2	7	8
	85	91	85	95	88	72	94	89	80	87	37	70	90	89	78	92	79	65
1Month	1	3	6	3	4	5	1	5	7	9	47	21	1	6	7	4	7	19
	4	3	6	2	5	2	4	6	10	3	5	3	4	5	11	2	6	6
	95	94	88	95	91	93	95	90	83	88	47	76	94	90	82	94	87	75

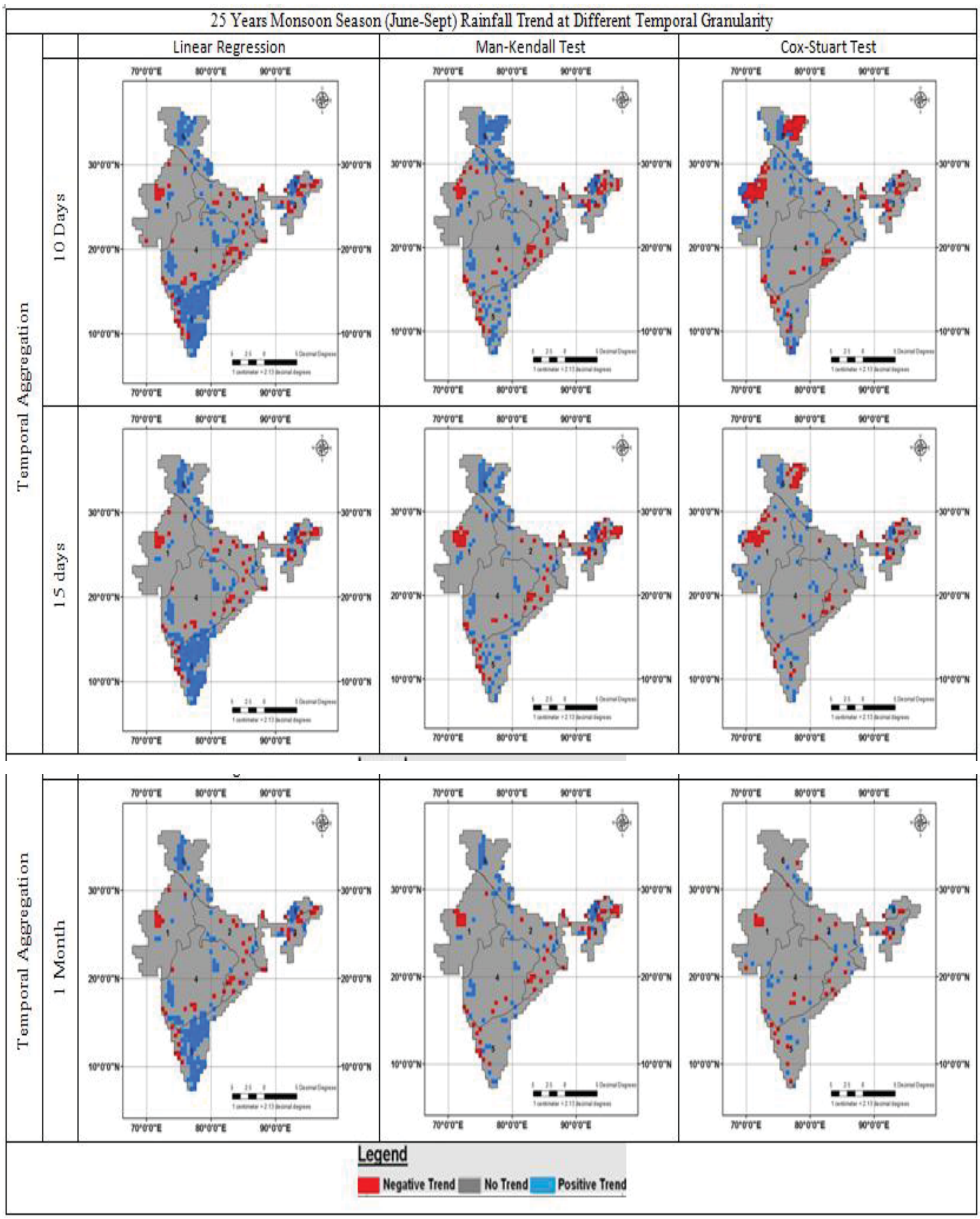


Figure 6.12: Trend Maps showing Significant Positive, Negative or No trend for Homogenous summer monsoon rainfall regions in India

Mostly all the regions show very less significant negative trends. NW, CNE, NE and WC regions shows that almost 85 percent of the areas show absence of significant trends at all temporal granularities. Figure 6.13. shows percentage area showing significant positive trend for different homogenous regions reported by CST.

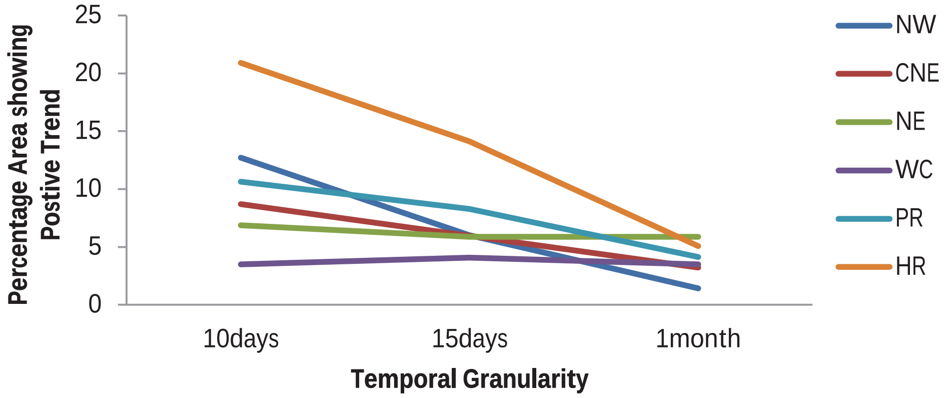


Figure 6.13: Percentage Area showing Significant Positive trend for different Homogenous regions by CST

6.5. A comparative study - Trends in Agro-Ecological zone over India

An effort was made to study variations in trends for both NDVI and climatic forcing in the AEZ in India for 1981-2005. This is part of the comparative study was done to identify which zones were able to show the relationship between NDVI and climatic forcing. For the comparative analysis, both NDVI and climatic forcing were temporally aggregated on the basis of major crop seasons in India. Trend analysis was done on the data and results were statistically determined with the help of different statistical estimators used in the study. Zone number 21 is not considered in case of trends for temperature and rainfall. The trend graphs generated to study the variations in trends are shown in section 1.4 in APPENDIX -1. Figure 6.14, 6.15, 6.16 shows significant trends in Agro-Ecological zones in India for Kharif Crop Season by Mann-Kendall Test at 15days, 1 month and 3 month temporal granularities respectively.

More than 50 percent of the area in AEZ- 2(Punjab and Haryana, Rajasthan), 3(Karnataka), 5(Regions in Madhya Pradesh), 6(Maharashtra), 7(Andhra Pradesh) and 8(Tamil Nadu) were observed to show significant positive trends for NDVI, whereas AEZ 16(Region in West-Bengal), 17(Arunachal Pradesh) and 18(Nagaland, Mizoram, Manipur etc.) were observed to show more than 20 percent area for significant negative trends. These facts may be accounted to show relationships with climatic forcing in case Karnataka and Tamil Nadu as the rainfall and temperature both shows relatively high percentage of areas showing positive trends as compared to other zones detected by MKT during Kharif season . In case of temperature, AEZ 16, 17, 18 show very large areas with significant positive trends but same regions do not show presence of positive trends in case of NDVI.

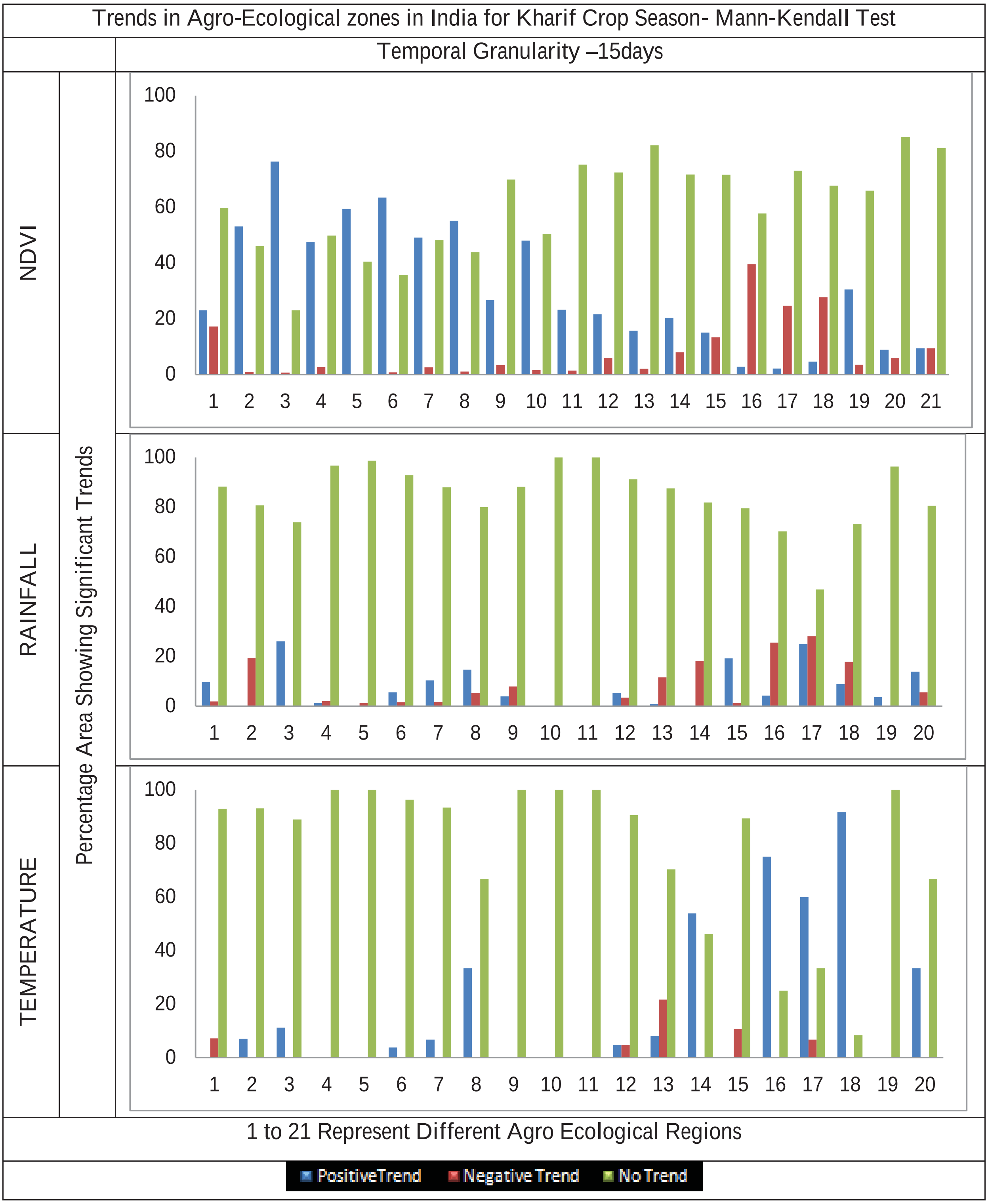


Figure 6.14: Trends in Agro-Ecological zones in India for Kharif Crop Season- Mann-Kendall Test

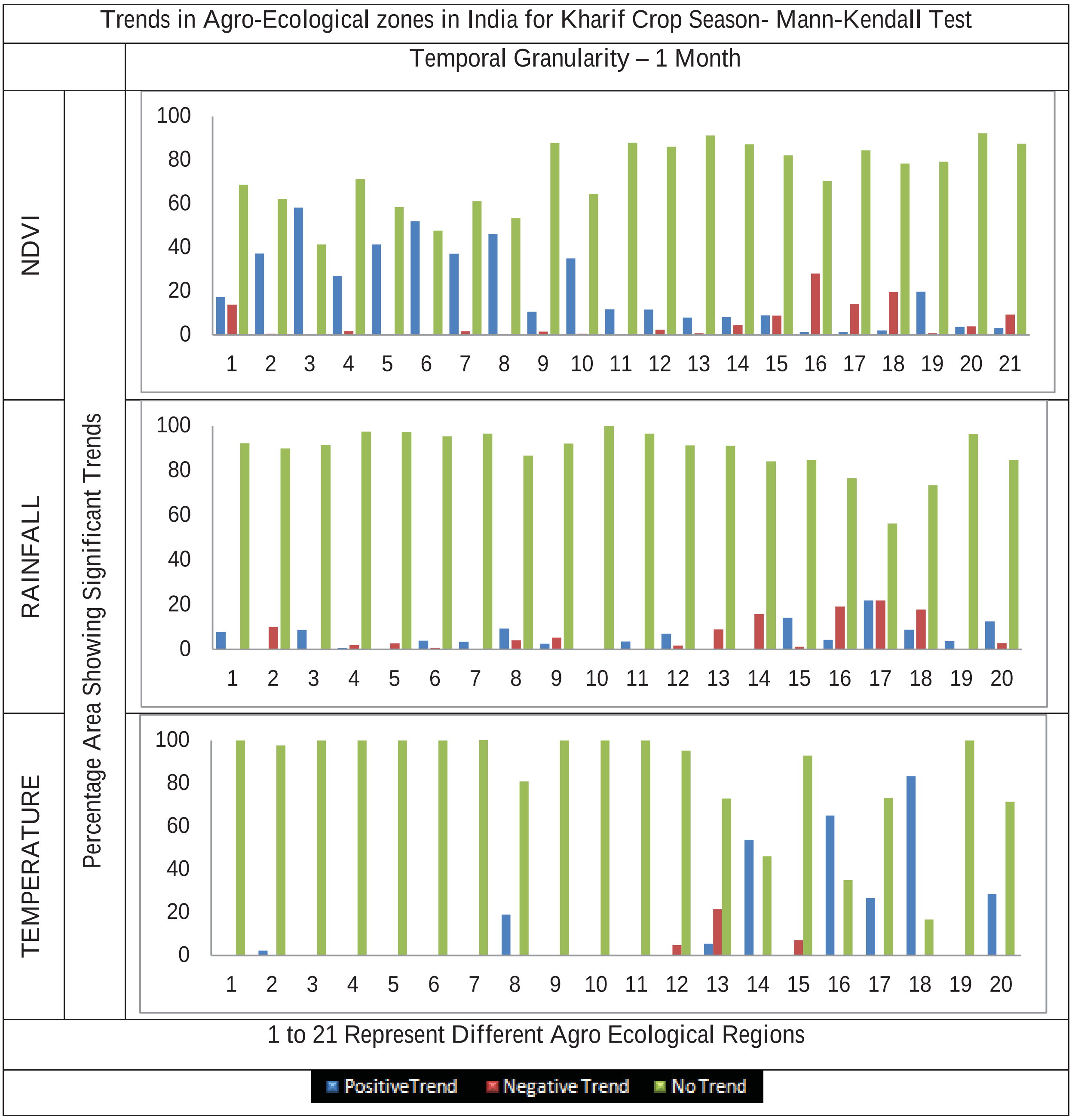


Figure 6.15: Trends in Agro-Ecological zones in India for Kharif Crop Season at 1 month temporal granularity - Mann-Kendall Test

At temporal granularity-1 month, AEZ 1 to 12 shows negligible significant trends in temperature and rainfall for the Kharif season. A decline was observed in percentage area showing positive trends when observed at 15 days as shown in figure 6.15. Large areas of more than 40 percent have shown significant positive trends in AEZ 3(Karnataka), 5(Region of Madhya Pradesh) and 8 (Tamil Nadu). 20 percent areas was reported in AEZ 2(Punjab and Haryana), 4(Uttar Pradesh and Bihar), 6(Maharashtra), 7(Andhra Pradesh) and 10(region in Madhya Pradesh) for significant positive trends. AEZ 14(Bihar), 16(West Bengal) and 18(Nagaland, Mizoram) reports more than 40 percent area to show significant trends in temperature whereas these trends were not present in NDVI for same zones.

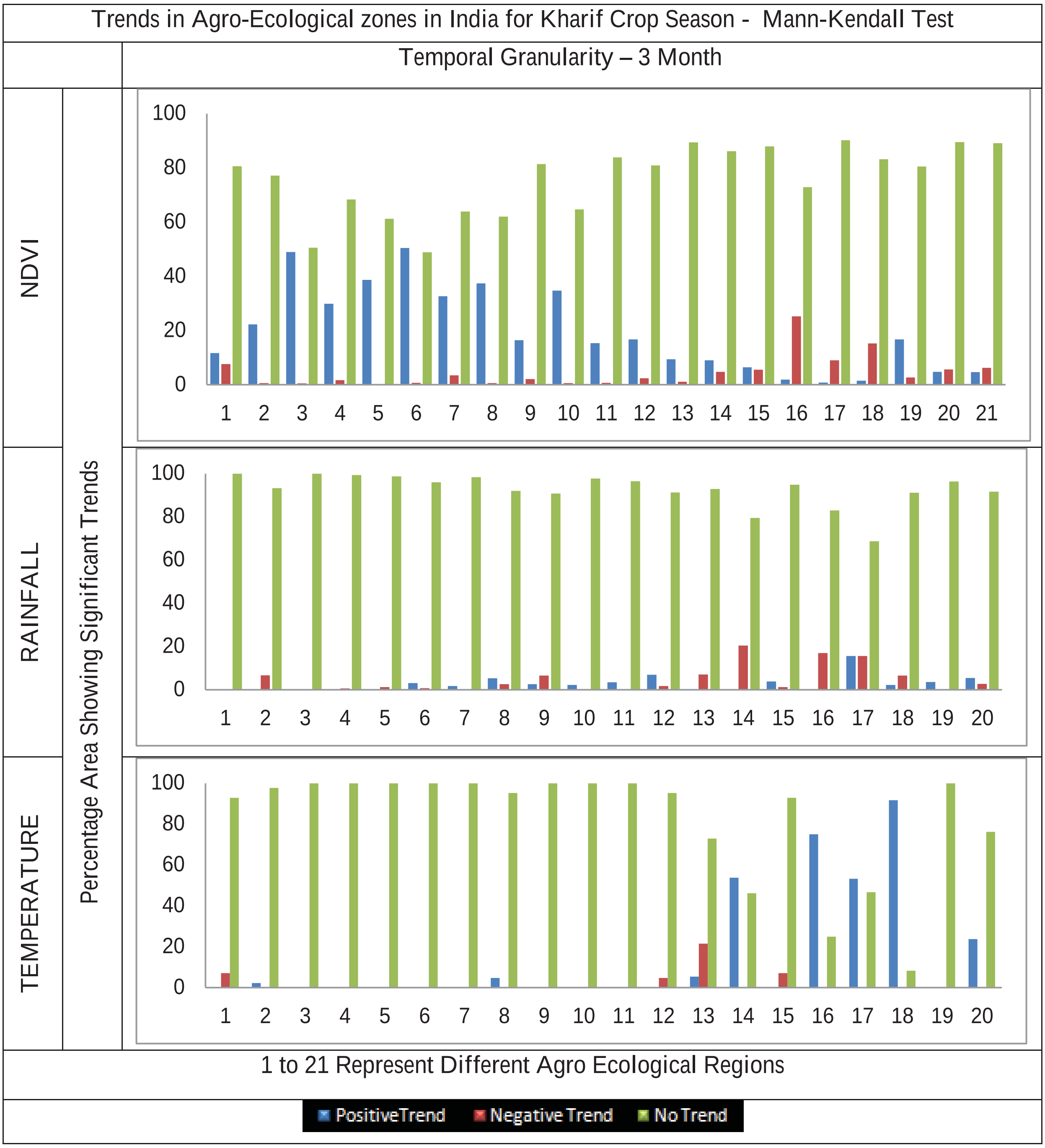
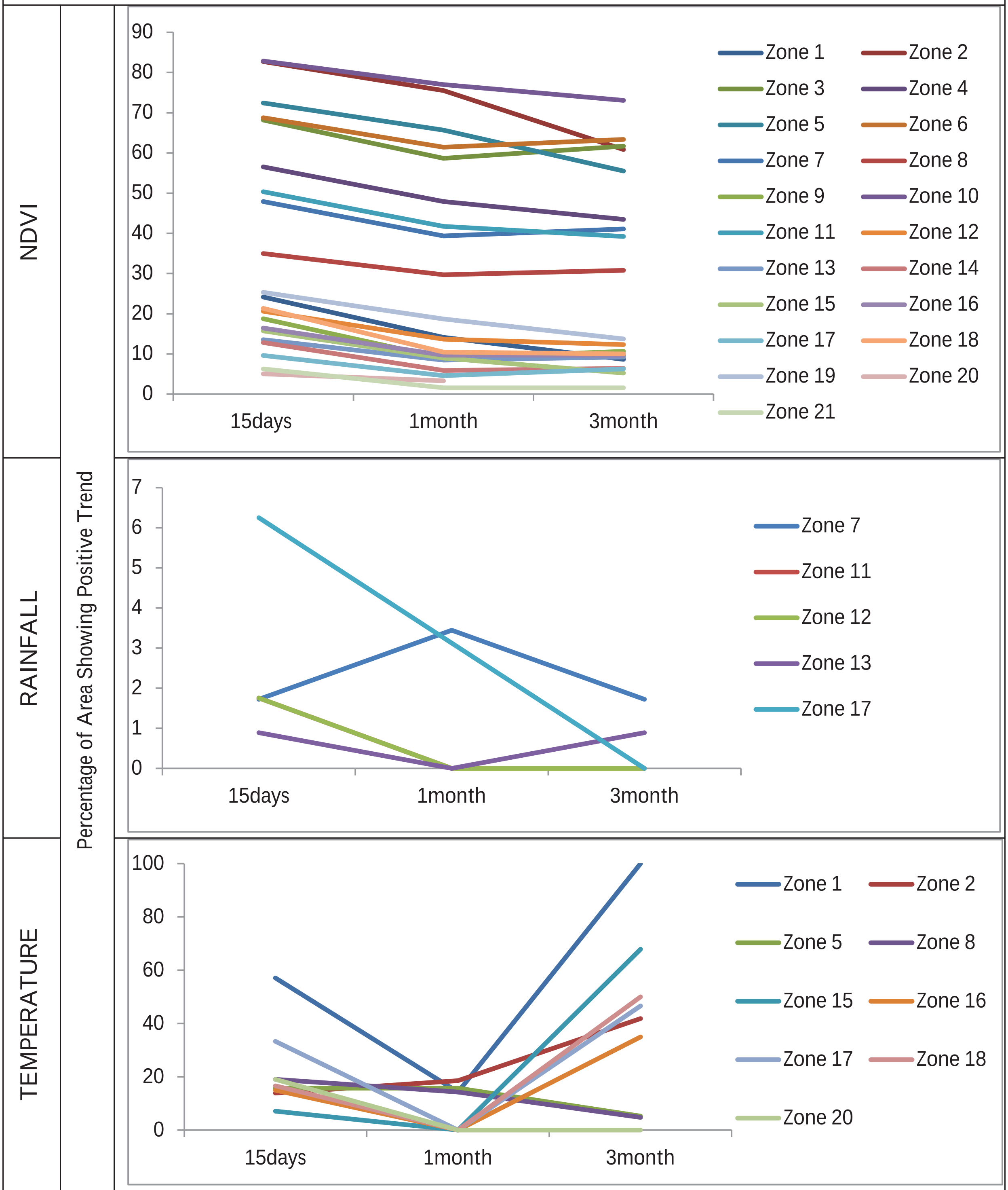


Figure 6.16: Trends in Agro-Ecological zones in India for Kharif Crop Season at 3 month temporal granularity - Mann-Kendall Test

Similar to the results shown at 15 days and 1 month, the trends continues to show almost identical results for the same AEZ at 3 months temporal granularity as shown in Figure 6.16. There is an increase in the area showing positive trends in temperature for AEZ 14(Bihar), 16(West Bengal), 17(Arunachal Pradesh) and 18(Nagaland, Mizoram) respectively. Similarly, trend analysis was done for Rabi and Zaid seasons as well at different temporal granularities. The results are documented in the APPENDIX -1 section of this thesis for further references.

Temporal Aggregation effect on Trends observed in Agro-Ecological zones in India for NDVI, Rainfall and Temperature

Rabi Crop Season – Mann-Kendall Test



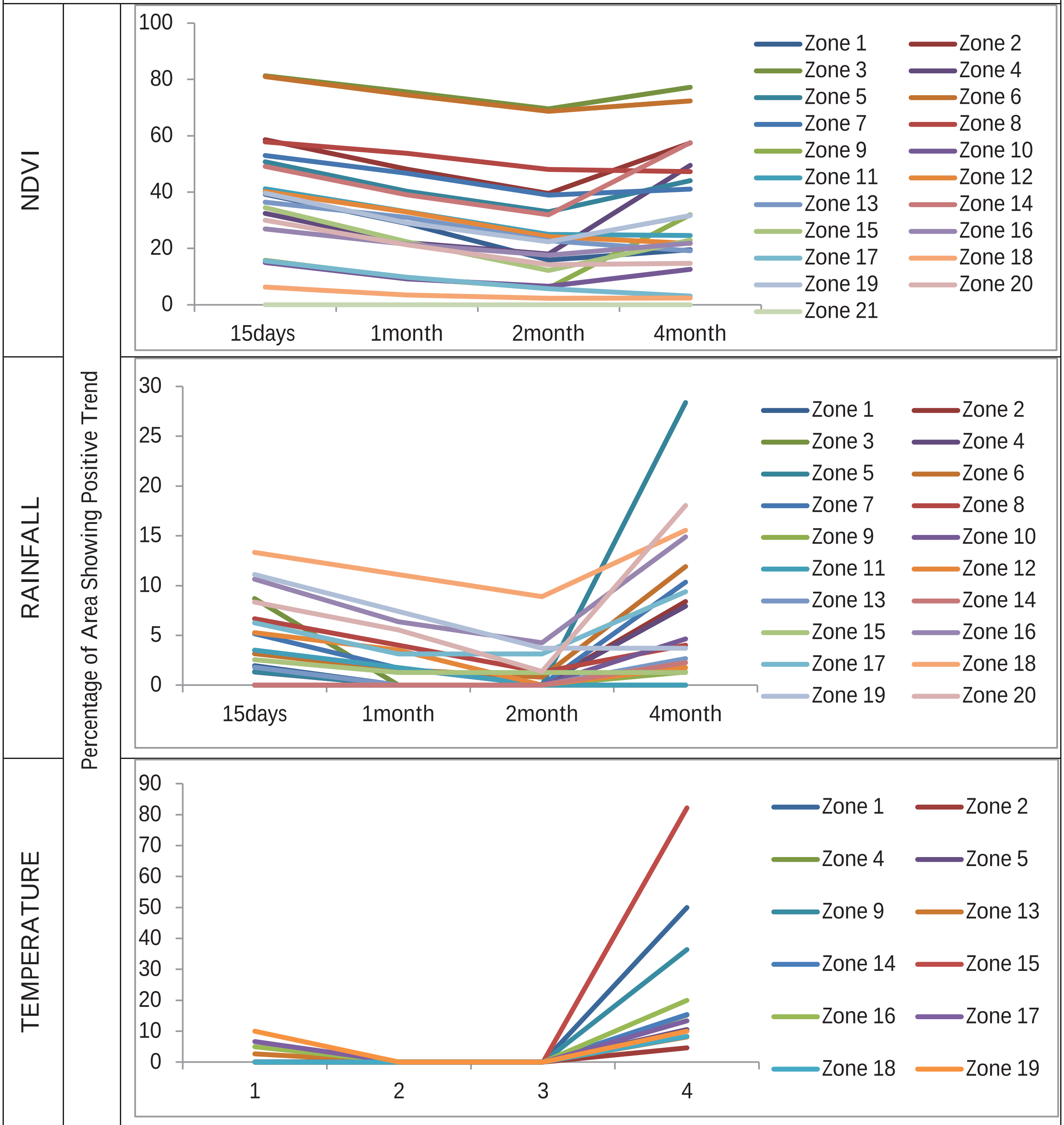
- Agro Ecological Zones where there was no Positive Trend detected are not shown here

Zones 1 to 21 Represent Different Agro Ecological Regions

Figure 6.17: Temporal Aggregation effect on Trends observed in Agro-Ecological zones in India for NDVI, Rainfall and Temperature in Rabi Crop Season – Mann-Kendall

Temporal Aggregation effect on Trends observed in Agro-Ecological zones in India for NDVI, Rainfall and Temperature

Zaid Crop Season – Mann-Kendall Test



- Agro Ecological Zones where there was no Positive Trend detected are not shown here

Zones 1 to 21 Represent Different Agro Ecological Regions

Figure 6.18: Temporal Aggregation effect on Trends observed in Agro-Ecological zones in India for NDVI, Rainfall and Temperature in Zaid Crop Season – Mann-Kendall

Figure 6.17. and Figure 6.18. show effect of temporal aggregation on trends observed in Agro-Ecological zones in India for NDVI, Rainfall and Temperature in Rabi Crop Season detected by

Mann-Kendall test. In Rabi season there is significant decrease in areas showing positive trends as detected by MKT with the increase in temporal granularity.

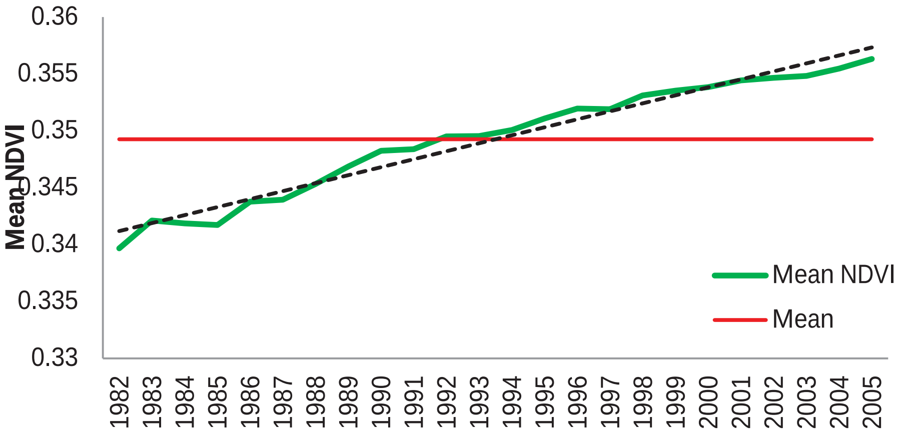


Figure 6.19: Mean NDVI for annual temporal aggregates

Figure 6.19. shows mean NDVI of yearly temporal aggregates and mean NDVI throughout 1981-2005. This shows a linear increasing trend in NDVI for 1981-2005.

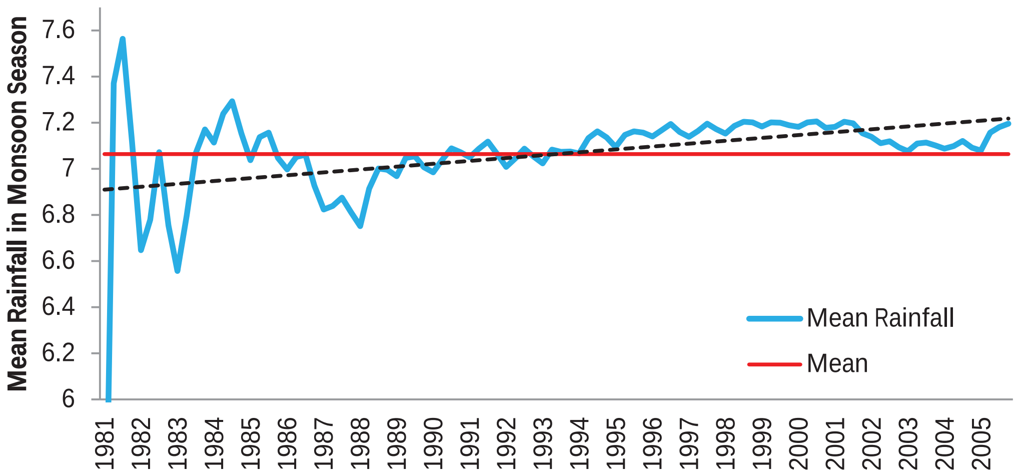


Figure 6.20: Variation in Mean Rainfall during monsoon season
Temporal Granularity– 1 month

Figure 6.20. shows the variation of mean rainfall by aggregating the rainfall data to a monthly level for the monsoon season in India. The mean calculated throughout this period is represented as by the red line. Overall, rainfall variations during this season are not showing much significant changes. According to reports from National Climatic centre in India, there is not much significant change in the rainfall received during monsoon periods.

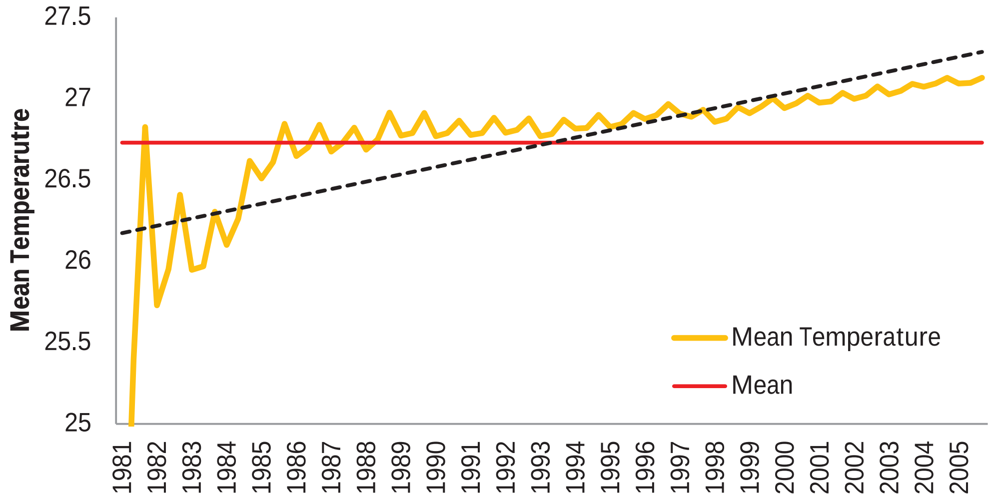


Figure 6.21: Variation in Mean Temperature during Pre-monsoon season
Temporal Granularity– 1 month

Figure 6.21. shows variation in temperature during the pre-monsoon season in India. Temperature variations when observed at 1 month temporal granularity shows an increasing trend during this season. The temperature in Northern regions like Punjab and Haryana, Rajasthan, Delhi, Uttar Pradesh etc. were also reported to record increase in temperature before the onset of monsoon period. The heat waves in Orissa, Madhya Pradesh in the pre-monsoon seasons were largely responsible for large number of deaths recorded. These variations were studied as they depict the behaviour in change for climatic variables. Increasing trends were observed in case of NDVI in all major crop seasons. For temperature, all seasons except pre-monsoon seasons were showing results for less variation. Rainfall results were showing downward trends in both pre-monsoon and winter seasons during 1981-2005.

The trend analysis results are documented in section 1.4. of APPENDIX-1. All the results are not shown and discussed in this section because of the page count, but it is quite evident from the results that all zones do not show any direct relationship between NDVI and climatic. Zone 1-12 which are mostly regions in Jammu and Kashmir, Punjab and Haryana, Uttar Pradesh, Bihar, Gujarat, Maharashtra, Andhra Pradesh, Tamil Nadu and Chhattisgarh have shown positive trends for NDVI whereas AEZ 14-19 which are regions in Bihar, Himachal Pradesh, Uttaranchal, Assam, Arunachal Pradesh, Andhra Pradesh and Orissa have shown significant positive trends for temperature. Net areas corresponding to significant trends for rainfall in AEZ is very less and thus do not provide any spatial pattern to conclude facts from them.

The significant trend results obtained from this study have helped to reach conclusions and provided answer to all the research posed to this work.

7. Conclusions and Recommendations

This chapter contains the conclusions and recommendations derived from this research work. Knowledge of the temporal and spatial distribution and changing patterns in vegetation and climatic forcing parameters are basic and important requirement for the planning and management of natural resources in today's world. To study the effect of MTUP, temporal sampling is very important. Three aspects have to be addressed if variations caused by MTUP are studied. First, the duration (how long), i.e. for how much period of time, is taken for observation. Second, the temporal resolution (how often), i.e the basic unit of observation in any temporal analysis. Finally, the point in time (when), i.e. when is the observation made, which is generally the seasonal or non seasonal component of the process. Time series data for 25 years was temporally analysed at multiple temporal granularities for seasonal changes in various zones. This has sufficiently addressed all the three important aspect to quantify the trends in NDVI and climatic forcing to study the MTUP effect.

From the results obtained, it can be concluded that temporal aggregation affects the observed trends significantly which was the main objective of this study. The study also aimed at statistically quantifying these significant trends, which was achieved by using different statistical tests. Different parametric and non-parametric tests were able to successfully quantify the trends in NDVI and climatic forcing in India as well as in homogenous regions. The trends thus observed were able to show clear distinction on the efficiency of these statistical tests. All objectives of this study were completed successfully.

The trend maps generated were helpful in analyzing the spatial pattern of how these significant trends vary at multiple temporal granularities. The main inferences drawn from the trend analysis done on the non-seasonal temporal aggregates can be expressed with the help of spatial patterns in significant trends. Prominent positive trends were observed in North-west and south Indian states like Rajasthan, Punjab and Haryana, Maharashtra, Karnataka, Tamil Nadu and Andhra Pradesh. All these states are major contributors in agricultural sector. Presence of positive trends in these regions had positive socio-economic impact in state like Punjab and Haryana. During 1981-2005 Punjab and Haryana have proved to be the most productive state in India. This was possible because of the use of canal system and artificial irrigation techniques employed by farmers in these regions. North-East regions have shown presence of significant negative trends during 1981-2005. This might have been caused by deforestation in these regions during the 80's and early 90's until strict rules against deforestation were put in place India through Nature Conservation Acts. It is quite evident from the results that direct relationship between rainfall and temperature with NDVI is not conclusive. In Kharif crop season rain fed areas like Maharashtra, Madhya Pradesh, Uttar Pradesh, Andhra Pradesh, Tamil Nadu, Karnataka, Rajasthan, Gujarat were the main states where significant positive trends were observed at all temporal granularities. Rice, millets, sugarcane, soybean etc are the major crops for Kharif season. Madhya Pradesh, the major producer of soybean has shown increase in production of soybean from 80's which is also confirmed by the results of this study by observing positive trends during Kharif season.

Similarly, regions of Rajasthan, Maharashtra, Andhra Pradesh, Tamil Nadu, Karnataka, Punjab and Haryana showed significant positive trends in Rabi season. The crops in Rabi season are taken after the monsoon season. So the productivity of these crops is heavily dependent on monsoon rainfall. After Rice, Wheat which is second in terms of total production tonnage is produced in this season. Punjab and Haryana are the largest contributors of wheat production in India. States like Orissa, Uttar Pradesh and Bihar were observed to show no significant trends during Rabi seasons. This was may be due to severe droughts and increase in temperature in past decades. Orissa was reported to be majorly affected by droughts during 80's and 90's. Due to shortage in rainfall received every year during monsoon, the production of wheat has shown a decline in Bihar and Uttar Pradesh. Coastal Areas of Maharashtra, Karnataka and Kerala were found to show negative trends in Rabi season. These states faced extreme rainfall events during the monsoon seasons that can be attributed as a major reason behind negative trends shown during these 25 years. During Zaid crop season, very high percentage of the total area was showing positive trends for NDVI. Madhya Pradesh, Maharashtra, all South Indian states were showing significant positive trends during 1981-2005. Punjab and Haryana showed presence of negative trends during the same period. Because of the presence of canal based irrigation support system for agriculture, these states are acknowledged as major producers in India in all seasons. No significant trends were observed along the west-coast regions such as Kerala, Goa and Karnataka etc. Similarly trends in Climatic forcing were also analysed with the help of different statistical methods to show the spatial variation in significant trend at multiple granularities. Jammu and Kashmir, Tamil Nadu and Karnataka are the major states where positive trends were observed in winter season for rainfall. Similar variations were observed in temperature for winter and pre-monsoon seasons. According to IMD, there is no significant increase or decrease is detected in the monsoon rainfall experienced by the country. But according to NATCOM reports, monsoon rainfall has shown significant increasing trend along west coast, regions of Andhra Pradesh and North-West India and a declining trend was observed over East Madhya Pradesh, North-East India and parts of Gujarat and Kerala. However, at all India level no significant trends were observed. This spatial variation in trends is because of the MTUP effect due to temporal aggregation. Generally, because these studies are done at either annual level or season specific, gradual changes may not be detected due to insufficient temporal sampling. Similarly, temperature trend analyses results were also observed to show spatial patterns in significant trends over India. North-East regions showed positive trends during Kharif crop. Whereas rise in temperature is observed in Rajasthan, Gujarat, and Jammu and Kashmir was confirmed by positive trends in Rabi season. Throughout Zaid season, no significant trends were observed. These spatial patterns in significant trends may help in identifying which regions are at higher risks so as to prepare better management plans and adaptive strategies. These variations in patterns are very critical from agriculture and hydrological point of view. In spite of increasing trends in monsoon rainfall, there are decreasing trends in first five months of the years (winter and pre-monsoon seasons). Increasing significant trends in temperature have resulted in heating and may effect in shortage of ground water and also soil moisture. This will eventually affect NDVI and that is why studying these changes are important.

The second research question is related to the choice of temporal granularity which can be accounted for providing most or least statistically significant trends in NDVI and climatic forcing. Temporal aggregation is required to be carried out carefully in order to avoid spurious results. Coarser/Higher aggregation levels tend to overestimate the amount of trends detected in such analysis. It may also results in higher variations in terms of significance of observed trends as well. Sufficient temporal sampling is critically required to obtain significant trends but different temporal granularities tend to shows variation in the detected significant trend because of the MTUP effect. So the choice of temporal granularity is subjected to the discretion of the analyst and it is largely dependent on data for which the trend analysis is done. In present study, with the increase or decrease in temporal granularity, considerable increase or decrease in significant trends was observed. In this study, seasonal variations were considered for selecting temporal granularities. For future work, growth period of vegetation may be considered while doing trend analysis. This might provide better understanding on which temporal granularity will account for most or least statistically significant trends.

For any trend analysis, the choice of statistical method for evaluation and quantification of trends is very critical. In this study, consistent results were obtained by Linear Regression and Mann-Kendall test across multiple temporal granularities, but results obtained by Cox-Stuart test were sometimes highly uncorrelated in terms of net area detected for presence of significant trends. The main advantage of using this test is that, it is based on the order statistics and is therefore less sensitive to the outliers. The Mann-Kendall test assumes observations to be independent and identically distributed. These properties make MKT a strong statistical test which is among the most widely used and extensive methods for detecting trends. Therefore, MKT was preferred and considered to be the most reliable statistical estimators used in this study.

An effort was made to determine whether significant changes in NDVI could be associated to changes in climatic forcing in Agro-ecological zones. Variations in NDVI could be used as an indicator. These variations would indicate impact of climate change. Although a significant change in climatic forcing does not necessarily imply a significant change in NDVI and vice versa (as other factors might be responsible for the change in NDVI). The results obtained in the AEZ for NDVI and climatic forcing was not able to directly relate them. Although, few AEZ were showing high percentage of significant trend, but there was absence of significant trends in corresponding zones for climatic forcing.

A genuine scientific research gives rise to more questions than it could possibly answer. This work has also raised questions for further research. The problem in combining distinct data at different spatial and temporal resolution will always gives rise to MAUP and MTUP. Just as this study was able to provide facts to explore MTUP, the next advancement must be a combination of MAUP and MTUP which is referred to Modifiable Spatio-Temporal Unit Problem (MSTUP). A similar analysis to the one presented in this work could be done by involving spatial aggregation/disaggregation to study combined effects of spatial and temporal aggregation on NDVI and climatic forcing data. Analysis done at similar spatial resolution could better indicate how these variables have changed for a particular location in a region. The solution to this issue can be achieved by aggregating the data, but it would result in loss of spatial information i.e. agriculture land may be classified with forest area and vice-versa. Other alternative is Disaggregation, which has proved to be very trivial due to the geographical and topographic diversity of Indian subcontinent. But these issues may be addressed with the help of statistical up-scaling/downscaling techniques.

During this study, few problems related to data used were also encountered. There were missing data values for boundary regions in case of climatic forcing data. During the temporal aggregation, these missing values have caused computational errors. These problems were identified and resolved by designing efficient algorithm which was capable of handling such problem. The large size of the NDVI datasets posed a computational efficiency problem. Although Python is a robust language, but high computational time was taken in trend analysis by AVSTAT. Low temporal granularity means more number of files and thus results in more computational time taken by the tool. For example, time taken for the trend analysis at lowest temporal granularity – 15days, by Linear Regression and Cox-Stuart was only few minutes to generate results whereas Mann-Kendall test took more than 2 hours. The efficiency of AVSTAT depends on the number of files to be processed. The algorithms designed for these statistical tests have to be optimized to increase the computational efficiency. This allows further customisation of the AVSTAT tool.

Even though all the proposed research objectives for this study were achieved, the following few areas could still be explored:

- Spatial aggregation/disaggregation to make all datasets at equal spatial scale will help to efficiently relate NDVI and climatic forcing. These can be achieved by statistical up-scaling/downscaling techniques.
- A wide variety of other robust statistical tests can be used.
- New technologies can be used to develop trend analysis tools.
- Other high resolution datasets can be used.

References

Aggarwal, P. K. (2008), Global climate change and Indian agriculture: impacts, adaptation and mitigation, *Indian Journal of Agricultural Sciences*, *78*(11), 911.

Aggarwal, S. P., V. Garg, P. K. Gupta, B. R. Nikam, and P. K. Thakur (2012), CLIMATE AND LULC CHANGE SCENARIOS TO STUDY ITS IMPACT ON HYDROLOGICAL REGIME, *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XXXIX-B8*, 147–152, doi:10.5194/isprsarchives-XXXIX-B8-147-2012.

Alley, R., T. Berntsen, N. L. Bindoff, Z. Chen, A. Chidthaisong, P. Friedlingstein, J. Gregory, G. Hegerl, M. Heimann, and B. Hewitson (2007), IPCC 2007: summary for policymakers, *Climate change*, 1–18.

Bachmann, A., H. Bergmeyer, and A. Schreiber (2011), Evaluation of aspect-oriented frameworks in Python for extending a project with provenance documentation features, *The Python Papers*, *6*(3), 3.

Bai, Z. G., D. L. Dent, L. Olsson, and M. E. Schaepman (2008), Proxy global assessment of land degradation, *Soil Use and Management*, *24*(3), 223–234, doi:10.1111/j.1475-2743.2008.00169.x.

Berryman, D., B. Bobée, D. Cluis, and J. Haemmerli (1988), NONPARAMETRIC TESTS FOR TREND DETECTION IN WATER QUALITY TIME SERIES1, *JAWRA Journal of the American Water Resources Association*, *24*(3), 545–556.

Bettini, C., and S. Ruffini (2003), Direct granularity conversions among temporal constraints, *J. UCS*, *9*(9), 1123–1136.

De Beurs, K. M., and G. M. Henebry (2004), Trend analysis of the Pathfinder AVHRR Land (PAL) NDVI data for the deserts of Central Asia, *Geoscience and Remote Sensing Letters, IEEE*, *1*(4), 282–286.

Beurs, K. M. de, and G. M. Henebry (2005), A statistical framework for the analysis of long image time series, *International Journal of Remote Sensing*, *26*(8), 1551–1573, doi:10.1080/01431160512331326657.

Buishand, T. A., M. V. Shabalova, and T. Brandsma (2004), On the choice of the temporal aggregation level for statistical downscaling of precipitation, *Journal of climate*, *17*(9), 1816–1827.

Caesar, J., L. Alexander, and R. Vose (2006), Large-scale changes in observed daily maximum and minimum temperatures: Creation and analysis of a new gridded data set, *Journal of geophysical research*, *111*(D5), D05101.

Chandrasekaran, S., O. Cooper, A. Deshpande, M. J. Franklin, J. M. Hellerstein, W. Hong, S. Krishnamurthy, S. R. Madden, F. Reiss, and M. A. Shah (2003), TelegraphCQ: continuous dataflow processing, in *Proceedings of the 2003 ACM SIGMOD international conference on Management of data*, pp. 668–668. [online] Available from: http://dl.acm.org/citation.cfm?id=872857 (Accessed 14 February 2013)

Çöltekin, A., S. De Sabbata, C. Willi, I. Vontobel, S. Pfister, M. Kuhn, and M. Lacayo (2011), Modifiable Temporal Unit Problem, in *ISPRS/ICA workshop "Persistent problems in geographic visualization"(ICC2011), Paris, France*, vol. 2. [online] Available from: http://www.geo.unizh.ch/~sdesabba/docs/ModifiableTemporalUnitProblem.pdf (Accessed 17 August 2012)

Conover, W. J. (1999), Some tests based on the binomial distribution, *Practical nonparametric statistics, 3rd ed. John Wiley and Sons, Inc., New York, NY*, 123–178.

Cotofrei, P., and K. Stoffel (2009), Time Granularity in Temporal Data Mining, *Foundations of Computational, Intelligence Volume 6*, 67–96.

Cox, D., and A. Stuart (1955), Some quick sign tests for trend in location and dispersion, *Biometrika*, 80–95.

Dash, S. K., M. A. Kulkarni, U. C. Mohanty, and K. Prasad (2009), Changes in the characteristics of rain events in India, *Journal of Geophysical Research*, *114*(D10), D10109.

Van Der Knijff, J. M., J. Younis, and A. P. J. De Roo (2010), LISFLOOD: a GIS- based distributed model for river basin scale water balance and flood simulation, *International Journal of Geographical Information Science*, *24*(2), 189–212, doi:10.1080/13658810802549154.

DEVI, M. G., and V. Sumathi (2011), EFFECT OF NITROGEN MANAGEMENT ON GROWTH, YIELD AND QUALITY OF SCENTED RICE (Oryza sativa L.) UNDER AEROBIC CONDITIONS, *Journal of Research ANGRAU*, *39*(3), 81–83.

Devillers, R., and H. Goodchild (2010), *Spatial data quality from process to decisions*, CRC Press, Boca Raton [Fla.]. [online] Available from: http://dx.doi.org/10.1201/b10305 (Accessed 20 August 2012)

Fatichi, S., S. M. Barbosa, E. Caporali, and M. E. Silva (2009), Deterministic versus stochastic trends: Detection and challenges, *Journal of Geophysical Research*, *114*(D18), D18121.

Food and Agriculture Organization of the United Nations (FAO) (2012), *The state of the world's forests 2012*, FAO, Rome.

Gadgil, S., and S. P. Rao (2000), Farming strategies for a variable climate-A Challenge, *Current Science*, *78*(10), 1203–1215.

Gadgil, S., P. N. Vinayachandran, P. A. Francis, and S. Gadgil (2004), Extremes of the Indian summer monsoon rainfall, ENSO and equatorial Indian Ocean oscillation, *Geophysical Research Letters*, *31*(12), L12213.

Ghosh, S., V. Luniya, and A. Gupta (2009), Trend analysis of Indian summer monsoon rainfall at different spatial scales, *Atmospheric Science Letters*, *10*(4), 285–290, doi:10.1002/asl.235.

González-Alonso, F., J. M. Cuevas, A. Calle, J. L. Casanova, and A. Romo (2003), Drought monitoring in Spain during the period 1987-2001, using NOAA-AVHRR images., pp. 435–437, Millpress Science Publishers.

Goswami, B. N., V. Venugopal, D. Sengupta, M. S. Madhusoodanan, and P. K. Xavier (2006), Increasing Trend of Extreme Rain Events Over India in a Warming Environment, *Science*, *314*(5804), 1442–1445, doi:10.1126/science.1132027.

Gotway, C. A., and L. J. Young (2002), Combining incompatible spatial data, *Journal of the American Statistical Association*, *97*(458), 632–648.

Guhathakurta, P., and E. Saji (2012), Detecting changes in rainfall pattern and seasonality index vis-à-vis increasing water scarcity in Maharashtra,

Gupta, A. K., S. S. Nair, and V. K. Sehgal (2009), Hydro-meteorological disasters and climate change: conceptual issues and data needs for integrating adaptation into environment and development framework, *Earth Science India*, *2*(2), 117–132.

Gupta, R., and A. Seth (2007), A review of resource conserving technologies for sustainable management of the rice–wheat cropping systems of the Indo-Gangetic plains (IGP), *Crop protection*, *26*(3), 436–447.

Hamed, K. H. (2008), Trend detection in hydrologic data: The Mann–Kendall trend test under the scaling hypothesis, *Journal of Hydrology*, *349*(3), 350–363.

Hamed, K. H., and A. Ramachandra Rao (1998), A modified Mann-Kendall trend test for autocorrelated data, *Journal of Hydrology*, *204*(1), 182–196.

Helsel, D. R., and R. M. Hirsch (2002), *Statistical methods in water resources*, US Geological survey Reston, Va.

Hingane, L. S., K. Rupa Kumar, and B. V. Ramana Murty (1985), Long-term trends of surface air temperature in india, *Journal of Climatology*, *5*(5), 521–528, doi:10.1002/joc.3370050505.

Hirsch, R. M., R. B. Alexander, and R. A. Smith (1991), Selection of methods for the detection and estimation of trends in water quality, *Water Resources Research*, *27*(5), 803–813.

Hüttich, C., M. Herold, C. Schmullius, V. Egorov, and S. A. Bartalev (2007), Indicators of Northern Eurasia's land-cover change trends from SPOT-VEGETATION time-series analysis 1998-2005, *International Journal of Remote Sensing*, *28*(18), 4199–4206, doi:10.1080/01431160701442054.

Jain, S. K., and V. Kumar (2012), Trend analysis of rainfall and temperature data for India, *Current Science(Bangalore)*, *102*(1), 37–49.

Jelinski, D. E., and J. Wu (1996), The modifiable areal unit problem and implications for landscape ecology, *Landscape ecology*, *11*(3), 129–140.

Jeyaseelan, A. T., P. S. Roy, and S. S. Young (2007), Persistent changes in NDVI between 1982 and 2003 over India using AVHRR GIMMS (Global Inventory Modeling and Mapping Studies) data, *International Journal of Remote Sensing*, *28*(21), 4927–4946.

Ji, L., and A. J. Peters (2003), Assessing vegetation response to drought in the northern Great Plains using vegetation and drought indices, *Remote Sensing of Environment*, *87*(1), 85–98.

De Jong, R., and S. de Bruin (2012), Linear trends in seasonal vegetation time series and the modifiable temporal unit problem, *Biogeosciences*, *9*(1), 71–77, doi:10.5194/bg-9-71-2012.

De Jong, R., S. de Bruin, A. de Wit, M. E. Schaepman, and D. L. Dent (2011), Analysis of monotonic greening and browning trends from global NDVI time-series, *Remote Sensing of Environment*, *115*(2), 692–702, doi:10.1016/j.rse.2010.10.011.

Julien, Y., J. A. Sobrino, C. Mattar, A. B. Ruescas, J. C. Jimenez-Munoz, G. Soria, V. Hidalgo, M. Atitar, B. Franch, and J. Cuenca (2011), Temporal analysis of normalized difference vegetation index (NDVI) and land surface temperature (LST) parameters to detect changes in the Iberian land cover between 1981 and 2001, *International Journal of Remote Sensing*, *32*(7), 2057–2068.

Kelkar, U., and S. Bhadwal (2007), South Asian regional study on climate change impacts and adaptation: implications for human development, *Human Development Report 2007/2008*.

Kendall, M. G., and G. U. Yule (1950), *An introduction to the theory of statistics*, Charles Griffin & Company.

Kiktev, D., D. M. Sexton, L. Alexander, and C. K. Folland (2003), Comparison of modeled and observed trends in indices of daily climate extremes, *Journal of Climate*, *16*(22), 3560–3571.

Kothawale, D. R., and K. R. Kumar (2005), On the recent changes in surface temperature trends over India, *Geophys. Res. Lett.*, *32*(18), L18714, doi:10.1029/2005GL023528.

Kothawale, D. R., J. V. Revadekar, and K. Rupa Kumar (2010), Recent trends in pre-monsoon daily temperature extremes over India, *Journal of earth system science*, *119*(1), 51–65.

Koutsoyiannis, D., and A. Montanari (2007), Statistical analysis of hydroclimatic time series: Uncertainty and insights, *Water Resources Research*, *43*(5), W05429.

Krishnamurthy, V., and J. Shukla (2008), Seasonal persistence and propagation of intraseasonal patterns over the Indian monsoon region, *Climate Dynamics*, *30*(4), 353–369.

Ladha, J. K., V. Kumar, M. M. Alam, S. Sharma, M. K. Gathala, P. Chandna, Y. S. Saharawat, and V. Balasubramanian (2009), Integrating crop and resource management technologies for enhanced productivity, profitability, and sustainability of the rice-wheat system in South Asia, *Integrated crop and resource management in the rice–wheat system of South Asia'.(Eds JK Ladha et al.) pp*, 69–108.

Lilleor, H. B., X. Giné, R. Townsend, and J. Vickery (2005), Weather insurance in semi-arid India, *Commodity Risk Management Group, Agricultural and Rural Development Department, The World Bank, Washington, DC*.

Maragatham, R. S. (2012), TREND ANALYSIS OF RAINFALL DATA-A COMPARATIVE STUDY OF EXISTING METHODS, [online] Available from: http://www.cibtech.org/J%20PHYSICS%20MATHEMATICAL%20SCIENCES/PUBLICATIONS/2012/Vol%202%20No.%201/005%20trend%20.....pdf (Accessed 14 February 2013)

McCuen, R. H. (2002), *Modeling hydrologic change: statistical methods*, CRC.

Mishra, V., B. V. Smoliak, D. P. Lettenmaier, and J. M. Wallace (2012), A prominent pattern of year-to-year variability in Indian Summer Monsoon Rainfall, *Proceedings of the National Academy of Sciences*, *109*(19), 7213–7217.

Mondal, A., S. Kundu, and A. Mukhopadhyay (2012), RAINFALL TREND ANALYSIS BY MANN-KENDALL TEST: A CASE STUDY OF NORTH-EASTERN PART OF CUTTACK DISTRICT, ORISSA, [online] Available from: http://www.cibtech.org/J%20GEOLOGY%20EARTH%20ENVIRONMENT/PUBLICATIONS/2012/Vol%202%20No%201/8-JGEE-12-Airban%20M.pdf (Accessed 14 February 2013)

Muhlbauer, A., P. Spichtinger, and U. Lohmann (2006), Robust statistical methods in climate trend analysis, [online] Available from: http://www.meteo.physik.uni-muenchen.de/dkt/abstracts/klimaparameter/muehlbauer_v.pdf (Accessed 14 February 2013)

Openshaw, S., and L. Rao (1995), Algorithms for reengineering 1991 Census geography, *Environment and planning A*, *27*, 425–425.

Openshaw, S., and P. Taylor (1979), A million or 80 Correlation Coefficient: Three Experiments on the Modifiable Areal Unit problem, *WRIGLEY N.(éd.)*.

Parry, M. L., O. F. Canziani, J. P. Palutikof, P. J. van der Linden, and C. E. Hanson (2007), *IPCC, 2007: climate change 2007: impacts, adaptation and vulnerability. Contribution of working group II to the fourth assessment report of the intergovernmental panel on climate change*, Cambridge University Press, Cambridge.

Partal, T., and E. Kahya (2006), Trend analysis in Turkish precipitation data, *Hydrological Processes*, *20*(9), 2011–2026.

Pathak, H. (2009), Greenhouse gas mitigation in rice-wheat system with resource conserving technologies, *Plenary Session*, 373.

Paul, S., and P. K. Sarkar (2012), Spectral Information Enhancement Using Wavelet-Based Iterative Filtering for in Vivo Gamma Spectrometry, *Radiat Prot Dosimetry*, doi:10.1093/rpd/ncs171. [online] Available from: http://rpd.oxfordjournals.org/content/early/2012/08/10/rpd.ncs171 (Accessed 14 February 2013)

Pettorelli, N., J. O. Vik, A. Mysterud, J.-M. Gaillard, C. J. Tucker, and N. C. Stenseth (2005), Using the satellite-derived NDVI to assess ecological responses to environmental change, *Trends Ecol. Evol. (Amst.)*, *20*(9), 503–510, doi:10.1016/j.tree.2005.05.011.

Rahman, N. (2008), Updating Data Warehouses with Temporal Data,

Rahman, S. H., D. Sengupta, and M. Ravichandran (2009), Variability of Indian summer monsoon rainfall in daily data from gauge and satellite, *Journal of Geophysical Research: Atmospheres*, *114*(D17), n/a–n/a, doi:10.1029/2008JD011694.

Rajeevan, M., and J. Bhate (2009), A high resolution daily gridded rainfall data set (1971–2005) for mesoscale meteorological studies, *Curr. Sci*, *96*(4), 558–562.

Rajeevan, M., J. Bhate, J. D. Kale, and B. Lal (2006), High resolution daily gridded rainfall data for the Indian region: Analysis of break and active monsoon spells, *Current Science*, *91*(3), 296–306.

Rao, K. R. M., I. Bakshihov, and B. S. Sokhi (2009), A Customized GIS application for Dehradun Tourist Information System,

Reza, Y. M., K. D. Javad, M. Mohammad, and S. Ashish (2011), Trend Detection of the Rainfall and Air Temperature Data in the Zayandehrud Basin, *Journal of Applied Sciences*, *11*, 2125–2134.

Samui, R. P., and M. V. Kamble (2011), Climate change and agriculture over north east India., *SATSA Mukhaptra Annual Technical Issue*, *15*, 40–47.

Sarma, A., T. L. Kumar, and K. Koteswararao (2008), Development of an agroclimatic model for the estimation of rice yield, *Journal of the Indian Geophysical Union*, *12*(2), 89–96.

SERGIO, M. (2006), Spatial and temporal analysis of droughts in the Iberian Peninsula (1910–2000), *Hydrological sciences journal*, *51*(1), 83–97.

Sharma, B. R., B. Sharma, K. V. Rao, K. P. R. Vittal, and U. A. Amarasinghe (2006), Realizing the potential of rainfed agriculture in India, *Draft prepared for the IWMI-CPWF project on 'Strategic Analysis of National River Linking Project of India*.

Sharma, B. R., K. V. Rao, K. P. R. Vittal, and U. A. Amarasinghe (2008), Converting rain into grain: Opportunities for realizing the potential of rain-fed agriculture in India, *Strategic Analyses of the National River Linking Project (NRLP) of India Series 2*, 239.

Shellman, S. M. (2004), Time series intervals and statistical inference: The effects of temporal aggregation on event data analysis, *Political Analysis*, *12*(1), 97–104.

SHENG, Y., P. Pilon, and B. Phinney (2003), Canadian streamflow trend detection: impacts of serial and cross-correlation, *Hydrological Sciences Journal*, *48*(1), 51–63.

Shepard, D. (1968), A two-dimensional interpolation function for irregularly-spaced data, in *Proceedings of the 1968 23rd ACM national conference*, pp. 517–524, ACM.

Sheskin, D. (2004), *Handbook of parametric and nonparametric statistical procedures*, CRC PressI Llc.

Silvestrini, A., and D. Veredas (2008), *Temporal aggregation of univariate and multivariate time series models: A survey*, Temi di discussione (Economic working papers), Bank of Italy, Economic Research and International Relations Area. [online] Available from: http://ideas.repec.org/p/bdi/wptemi/td_685_08.html (Accessed 17 August 2012)

Singh, R. K., S. K. Saha, and S. Kumar (2005), Soil Conservation Prioritization of Watershed based on Erosional Soil Loss and Morphometric Analysis using Satellite Remote Sensing & GIS–A case Study, *Indian Institute of Remote Sensing (NRSA), Dehradun: Map India*.

Srivastava, A. K., M. Rajeevan, and S. R. Kshirsagar (2009), Development of a high resolution daily gridded temperature data set (1969-2005) for the Indian region, *Atmospheric Science Letters*, n/a–n/a, doi:10.1002/asl.232.

Steiniger, S., and A. J. Hunter (2012), Free and open source GIS software for building a spatial data infrastructure, *Geospatial Free and Open Source Software in the 21st Century*, 247–261.

Supit, I., C. A. Van Diepen, H. L. Boogaard, F. Ludwig, and B. Baruth (2010), Trend analysis of the water requirements, consumption and deficit of field crops in Europe, *Agricultural and Forest Meteorology*, *150*(1), 77–88.

Symeonakis, E., and N. Drake (2004), Monitoring desertification and land degradation over sub-Saharan Africa, *International Journal of Remote Sensing*, *25*(3), 573–592, doi:10.1080/0143116031000095998.

Tao, Y., G. Kollios, J. Considine, F. Li, and D. Papadias (2004), Spatio-temporal aggregation using sketches, in *Data Engineering, 2004. Proceedings. 20th International Conference on*, pp. 214–225, IEEE.

Tucker, C. J., J. E. Pinzon, and M. E. Brown (2004a), Global inventory modeling and mapping studies, *Global Land Cover Facility, University of Maryland, College Park, Rep. NA94apr15b*, (11).

Tucker, C. J., J. E. Pinzon, M. E. Brown, and E. Molly (2004b), Global inventory modeling and mapping studies (GIMMS) satellite drift corrected and NOAA-16 incorporated normalized difference vegetation index (NDVI), monthly 1981-2002, *University of Maryland*.

Tucker, C. J., J. E. Pinzon, M. E. Brown, D. A. Slayback, E. W. Pak, R. Mahoney, E. F. Vermote, and N. El Saleous (2005), An extended AVHRR 8-km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data, *International Journal of Remote Sensing*, *26*(20), 4485–4498.

Vahini, S., and S. Shobha (2012), PESTICIDE RESIDUE CONTENT OF SELECTED WHOLE AND PROCESSED FOOD GRAINS OF SCARCE RAINFALL ZONE OF ANDHRA PRADESH, *The Global users can now retrieve the articles from Journal on the repository of Commonwealth Agricultural Bureaux International (CABI) on*, 96.

Vicente-Serrano, S. M., S. Beguería, and J. I. López-Moreno (2010), A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index, *Journal of Climate*, *23*(7), 1696–1718.

Wani, S. P., H. P. Singh, T. K. Sreedevi, P. Pathak, T. J. Rego, B. Shiferaw, and S. R. Iyer (2003), Farmer-participatory integrated watershed management: Adarsha watershed, Kothapally India-an innovative and upscalable approach, *Journal of SAT Agricultural Research*, *2*(1), 1–27.

Wassmann, R., S. V. K. Jagadish, K. Sumfleth, H. Pathak, G. Howell, A. Ismail, R. Serraj, E. Redona, R. K. Singh, and S. Heuer (2009), Regional vulnerability of climate change impacts on Asian rice production and scope for adaptation, *Advances in Agronomy*, *102*, 91–133.

Wei, W. W. S. (1978), *Some Consequences of Temporal Aggregation in Seasonal Time Series Models*, NBER Chapters, National Bureau of Economic Research, Inc. [online] Available from: http://ideas.repec.org/h/nbr/nberch/4333.html (Accessed 20 August 2012)

White, M. A. et al. (2009), Intercomparison, interpretation, and assessment of spring phenology in North America estimated from remote sensing for 1982–2006, *Global Change Biology*, *15*(10), 2335–2359, doi:10.1111/j.1365-2486.2009.01910.x.

Yue, S., and C. Wang (2004), The Mann-Kendall test modified by effective sample size to detect trend in serially correlated hydrological series, *Water Resources Management*, *18*(3), 201–218.

Zellner, A., and C. Montmarquette (1971), A study of some aspects of temporal aggregation problems in econometric analyses, *The Review of Economics and Statistics*, 335–342.

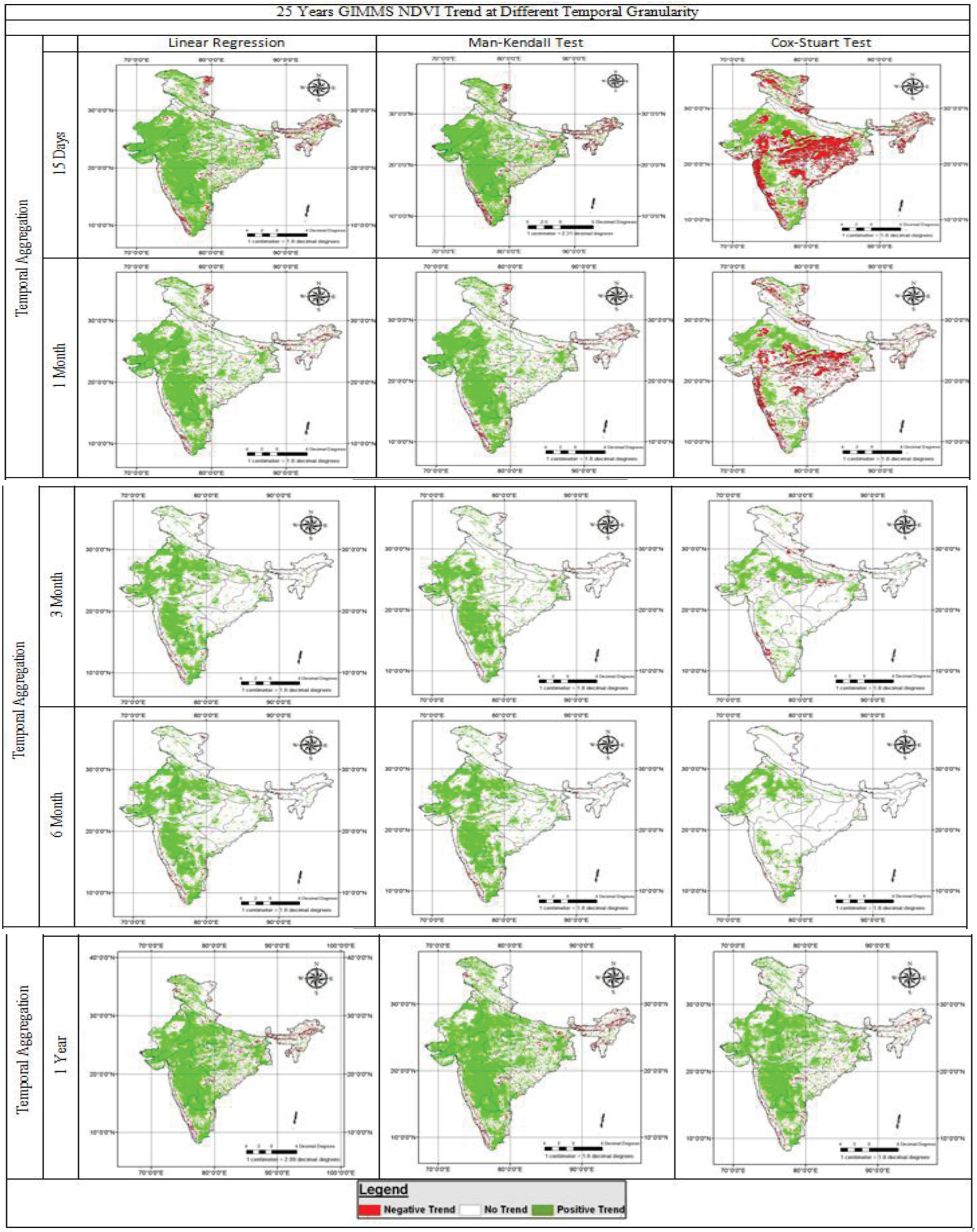
Zhang, J. (2006), Spatio-temporal aggregates over streaming geospatial image data, *Current Trends in Database Technology–EDBT 2006*, 32–43.

Zhang, L., C. Podlasly, Y. Ren, K.-H. Feger, Y. Wang, and K. Schwärzel (2013), Separating the effects of changes in land management and climatic conditions on long-term streamflow trends analyzed for a small catchment in the Loess Plateau region, NW China, *Hydrological Processes*.

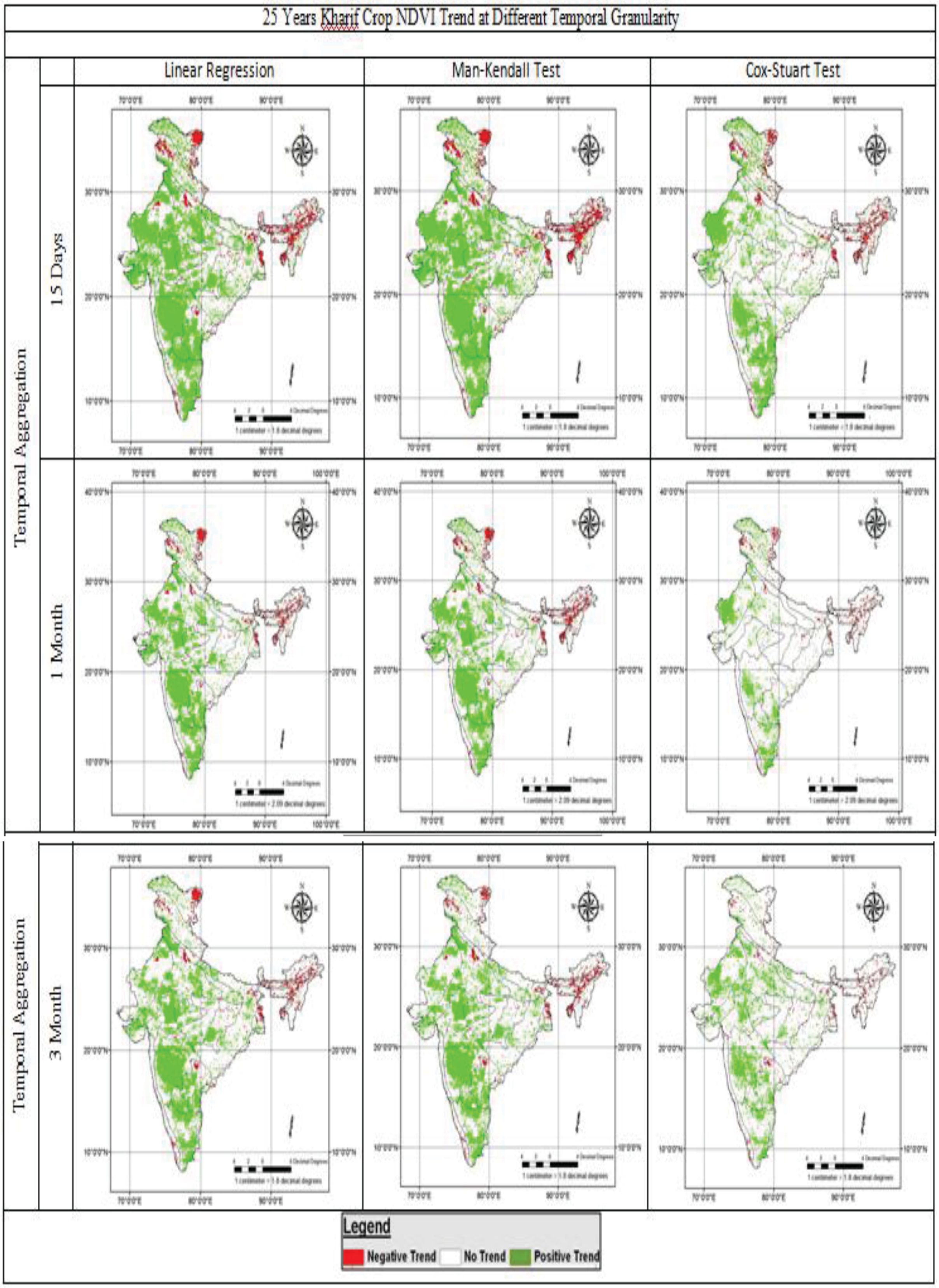
APPENDIX – 1

1.1. Trends in NDVI at multiple temporal granularities.

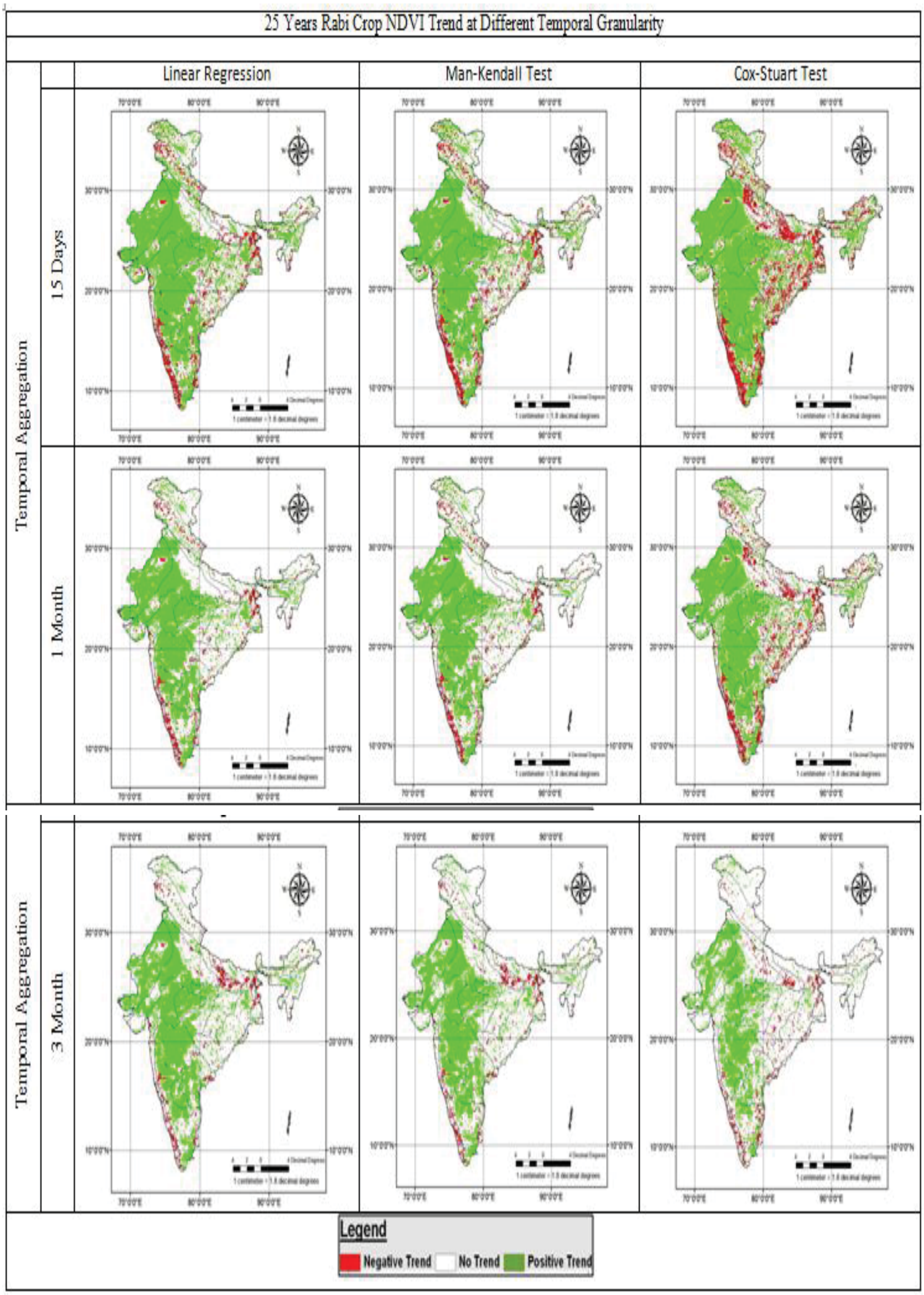
1.1.1. Trends in Non seasonal temporal composites at multiple temporal granularities



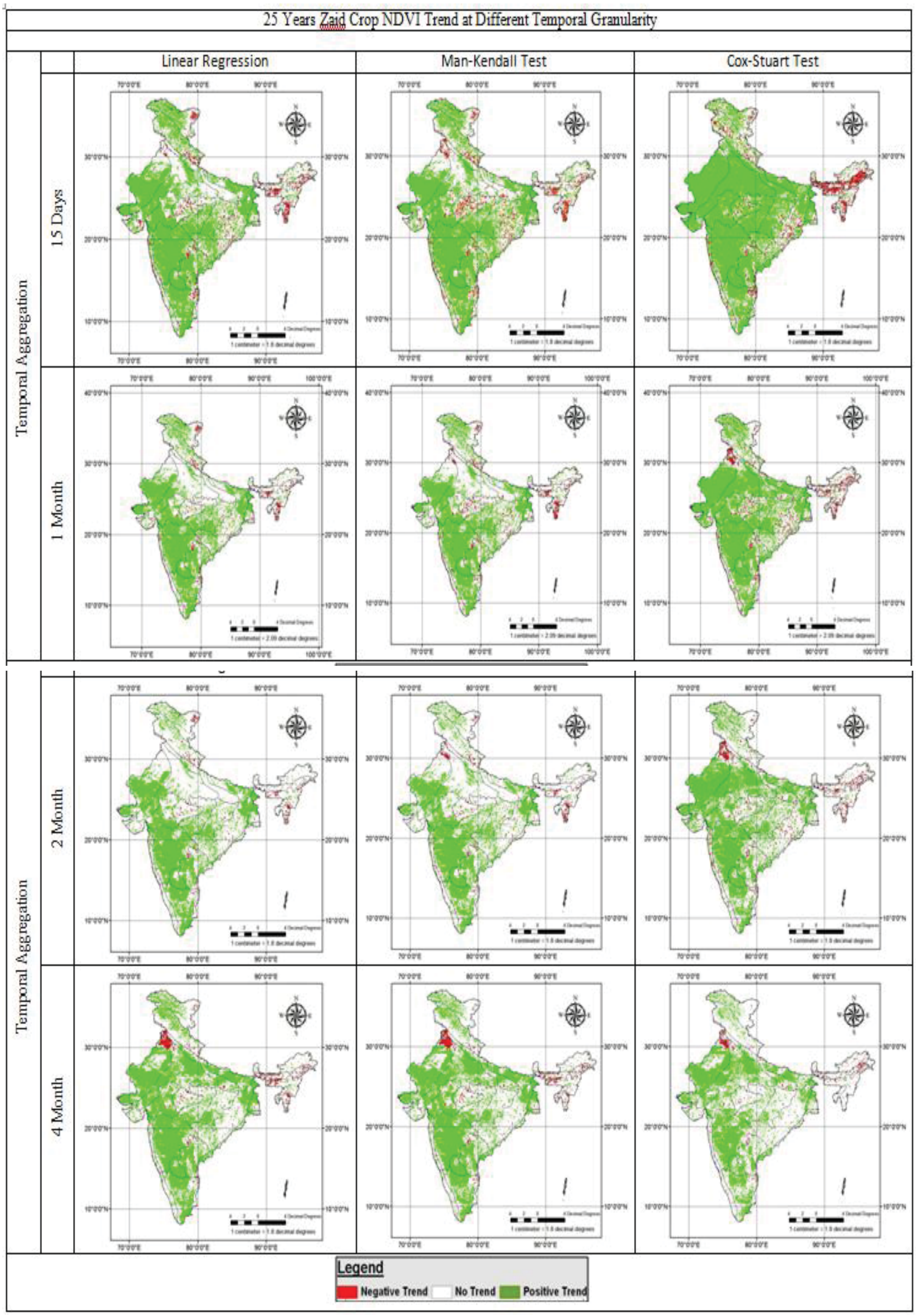
1.1.2. Trends in NDVI for Kharif Crop Season at multiple temporal granularities



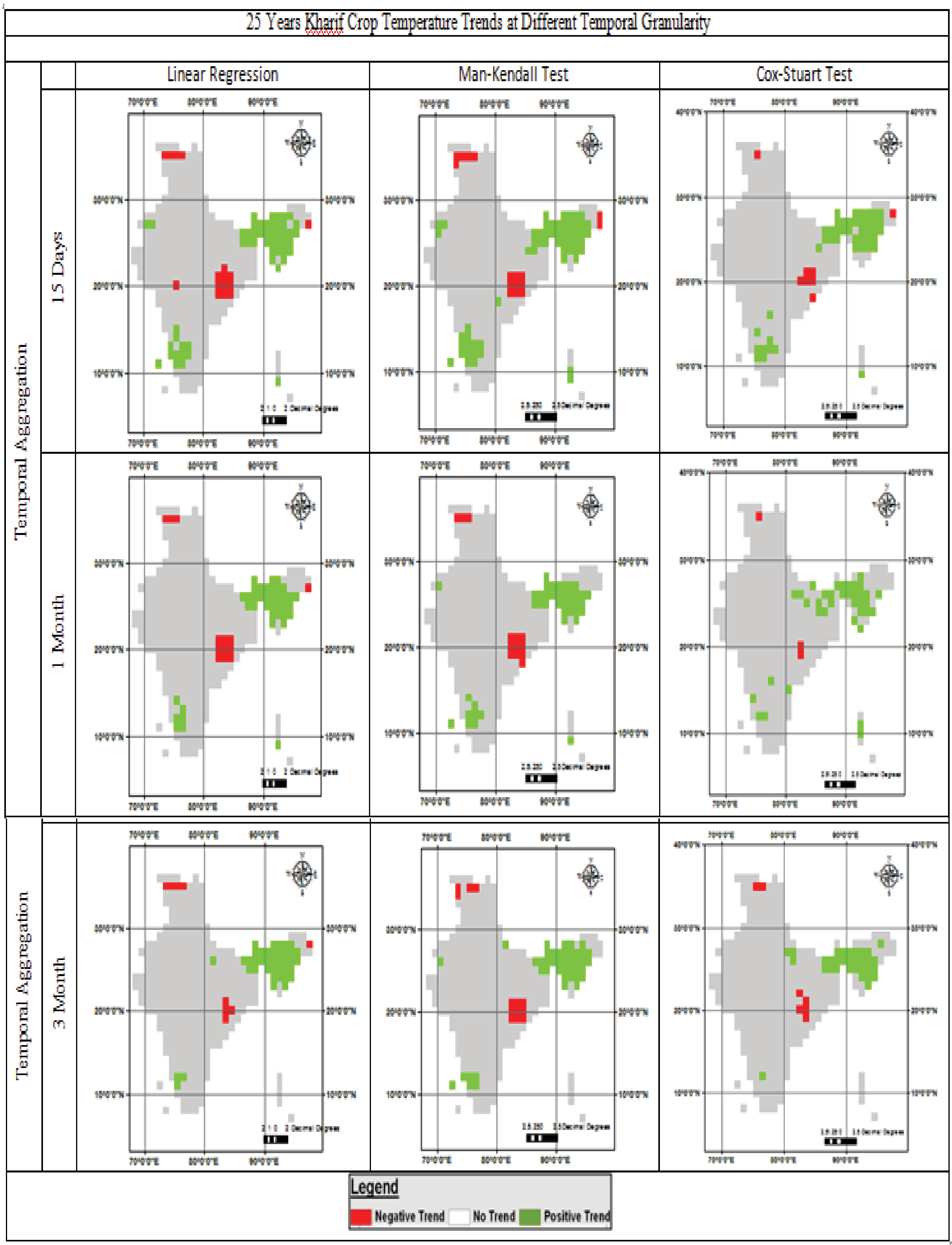
1.1.3. Trends in NDVI for Rabi Crop Season at multiple temporal granularities



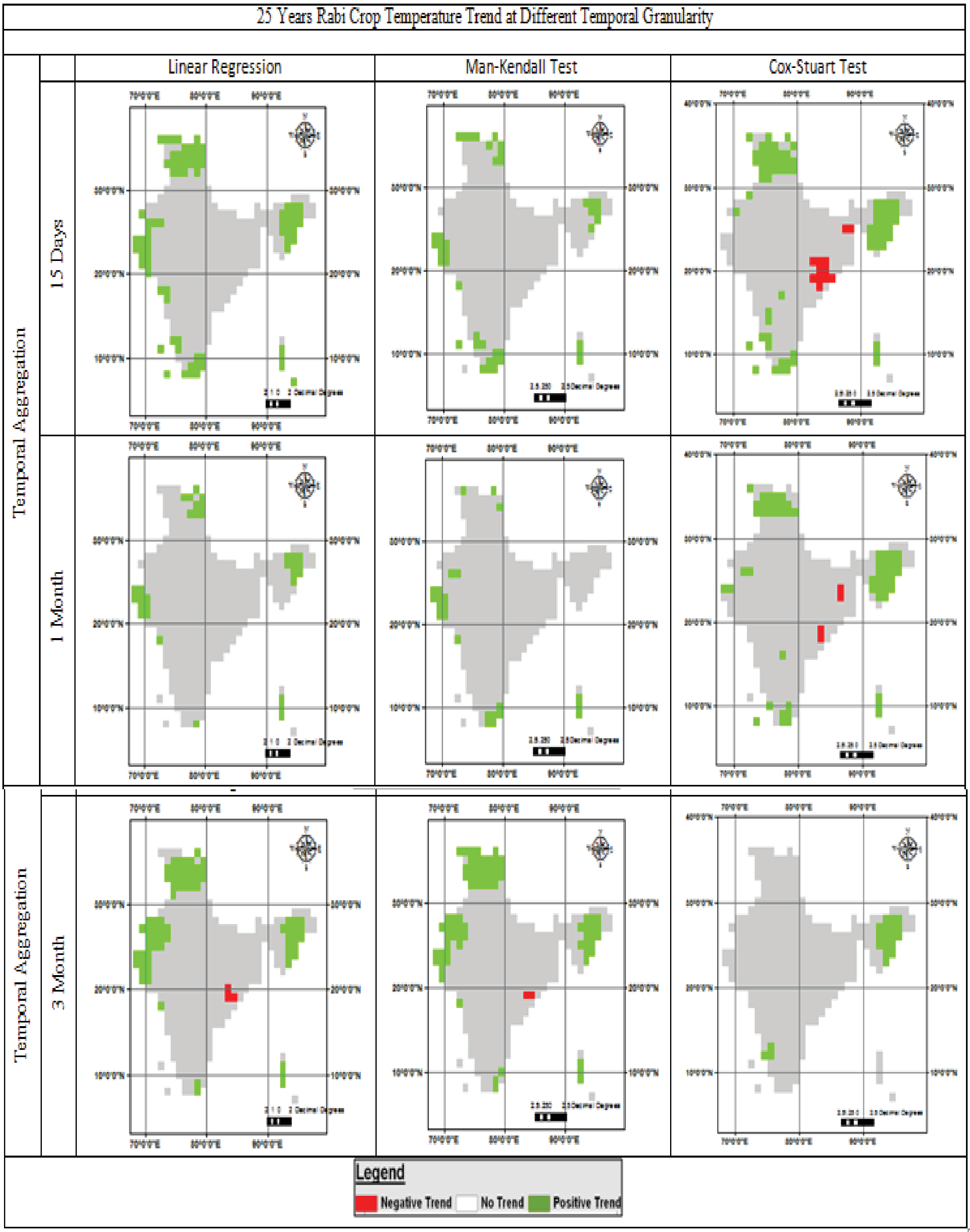
1.1.4. Trends in NDVI for Zaid Crop Season at multiple temporal granularities



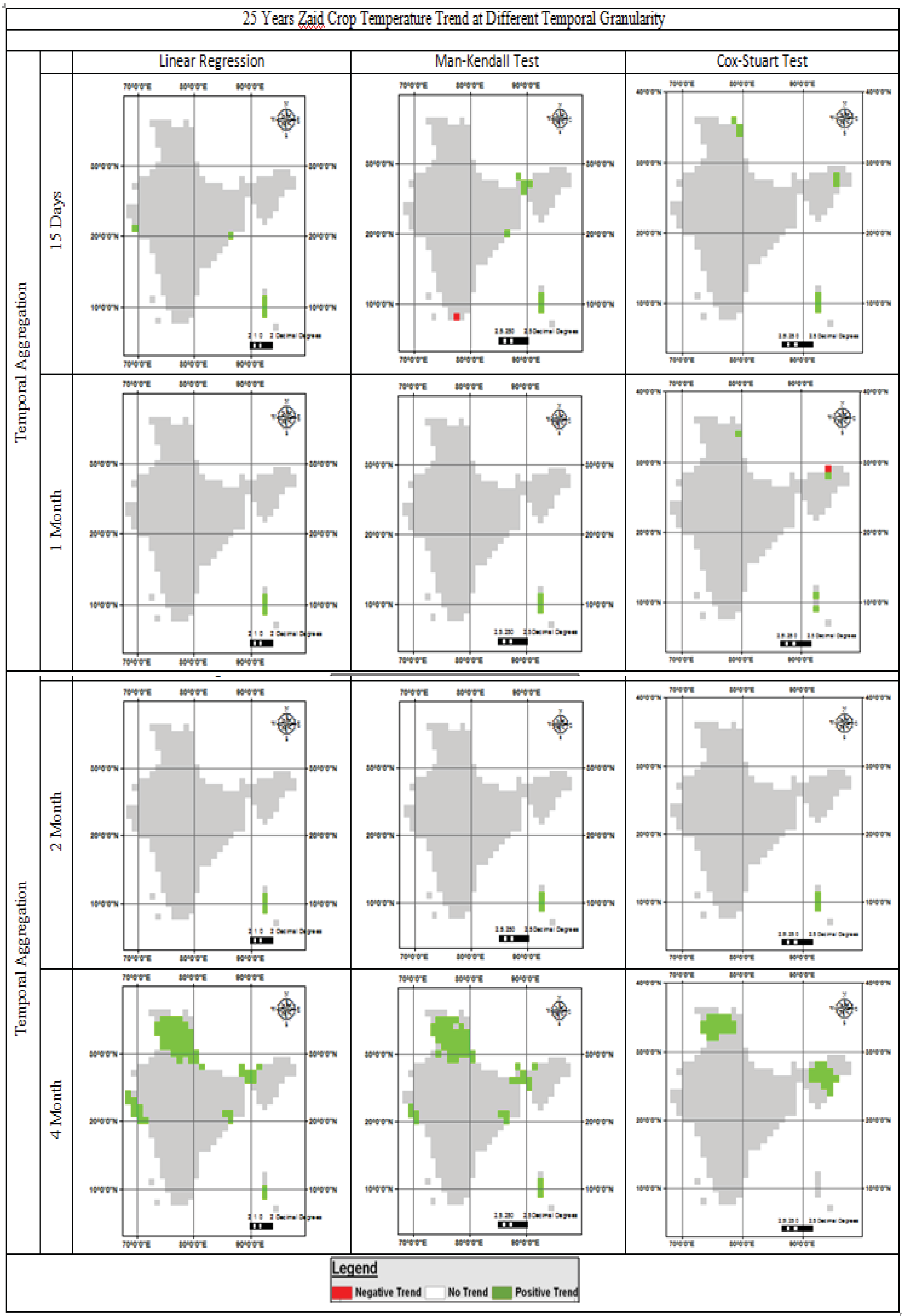
1.1.5. Trends in Temperature for Kharif Crop season at multiple temporal granularities



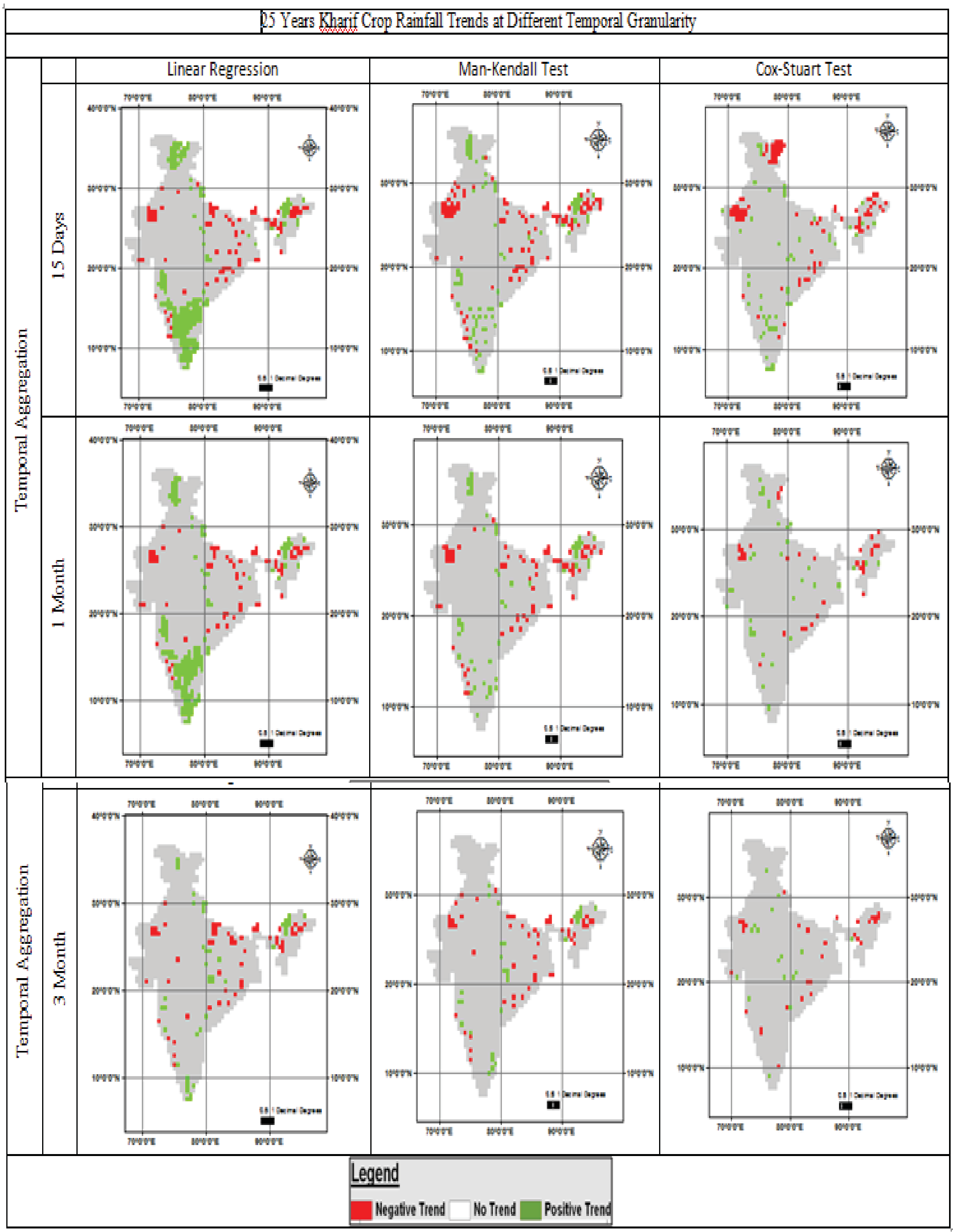
1.1.6. Trends in Temperature for Rabi Crop season at multiple temporal granularities



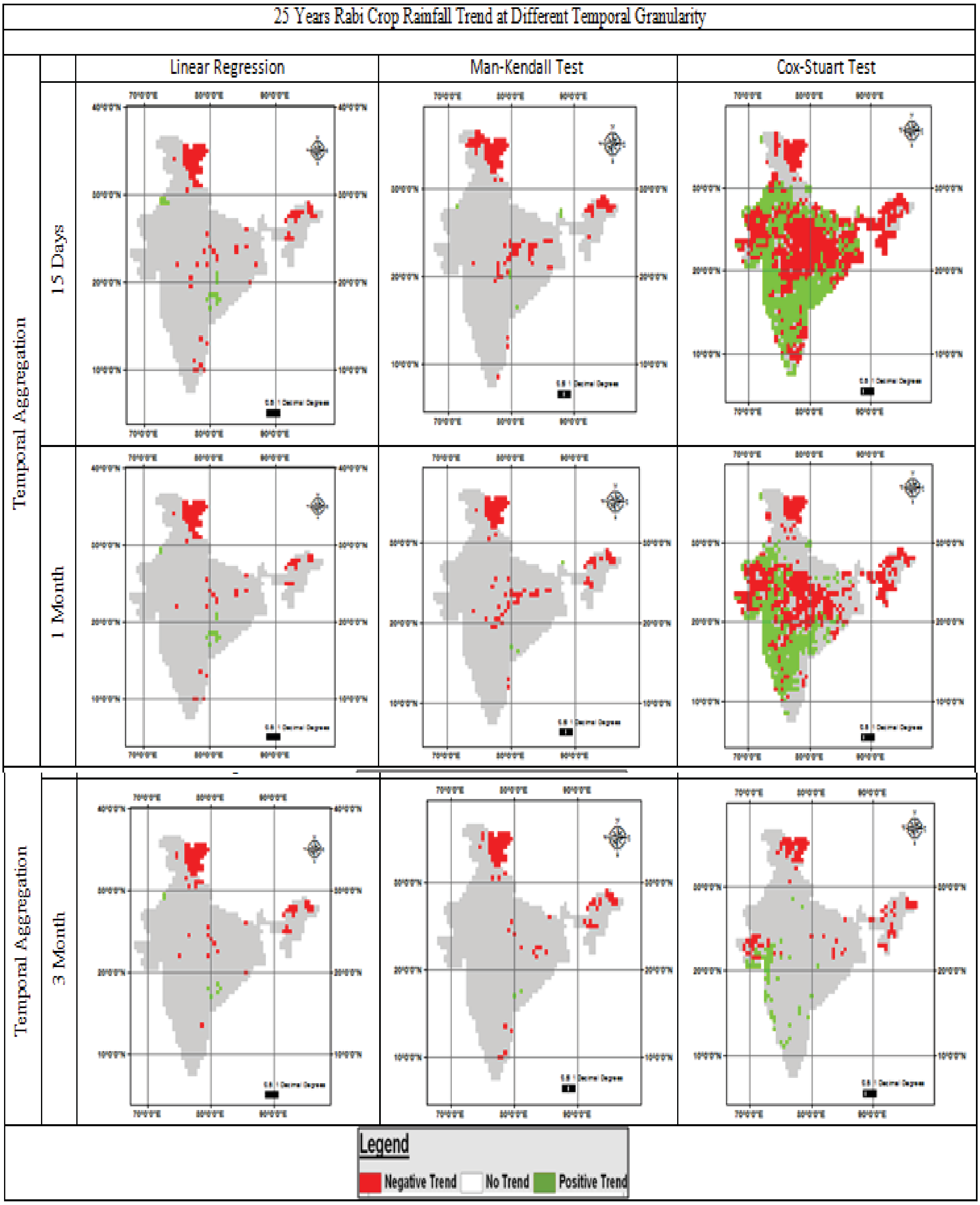
1.1.7. Trends in Temperature for Zaid Crop season at multiple temporal granularities



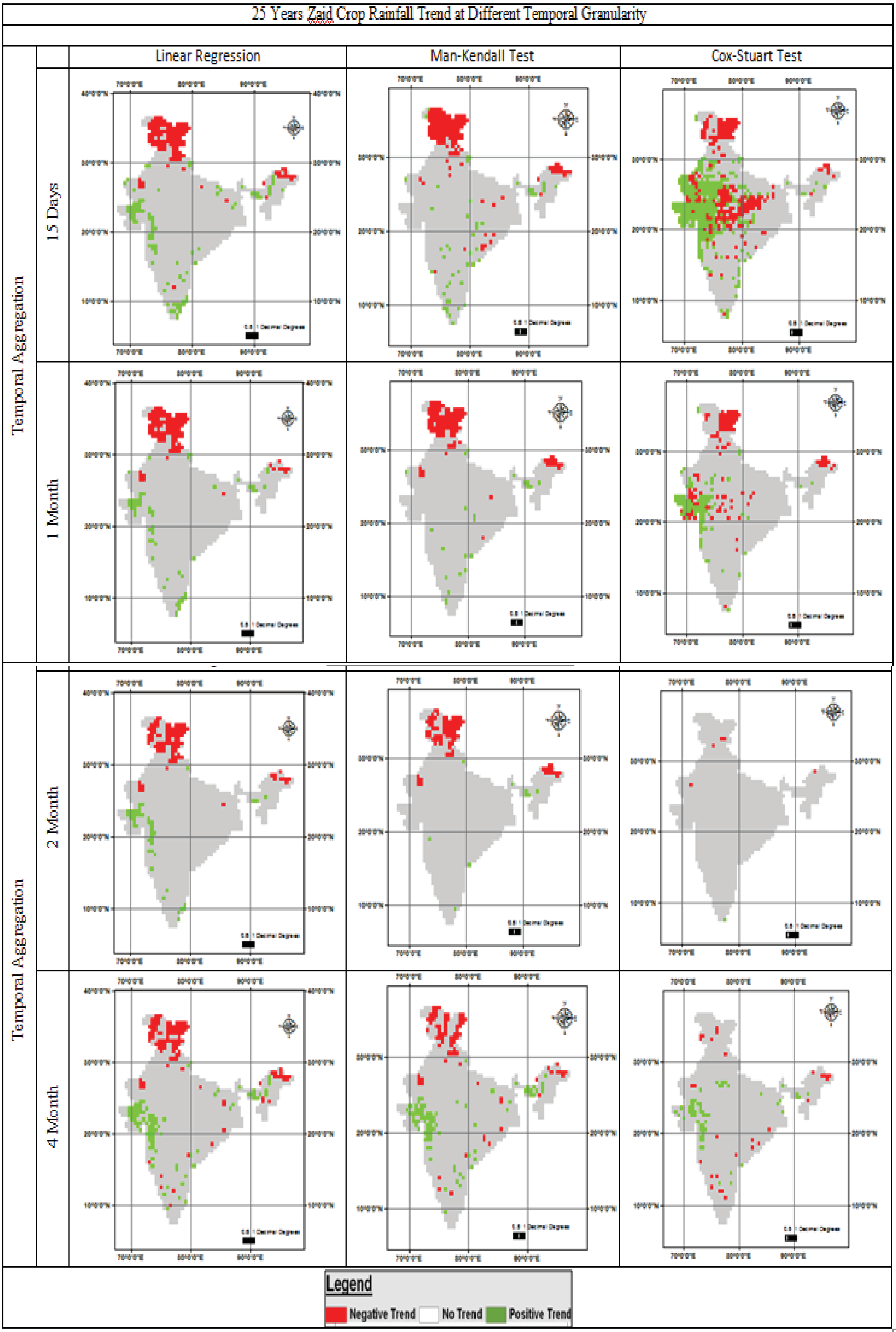
1.1.8. Trends in Rainfall for Kharif Crop season at multiple temporal granularities



1.1.9. Trends in Rainfall for Rabi Crop season at multiple temporal granularities

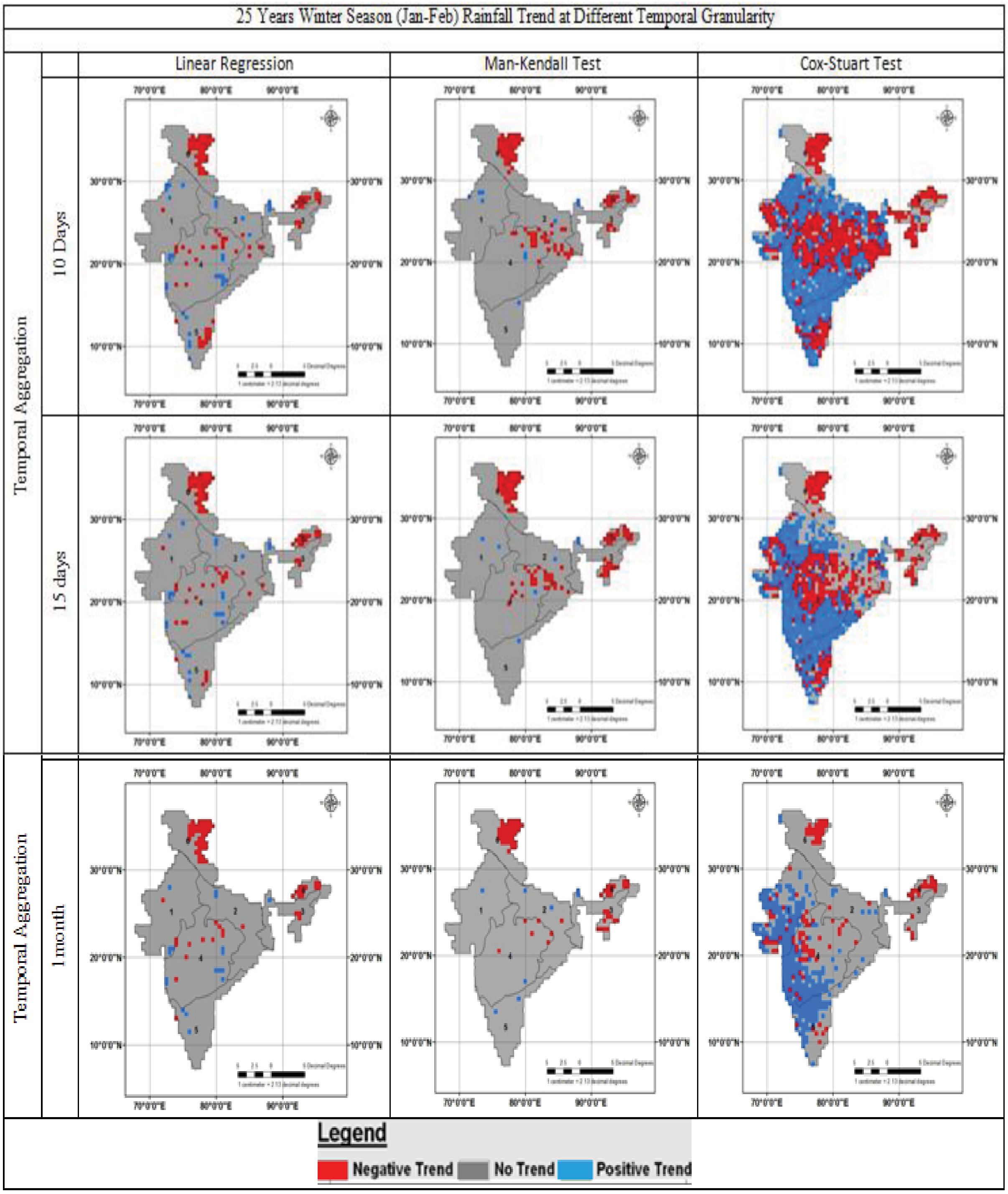


1.1.10. Trends in Rainfall for Zaid Crop season at multiple temporal granularities

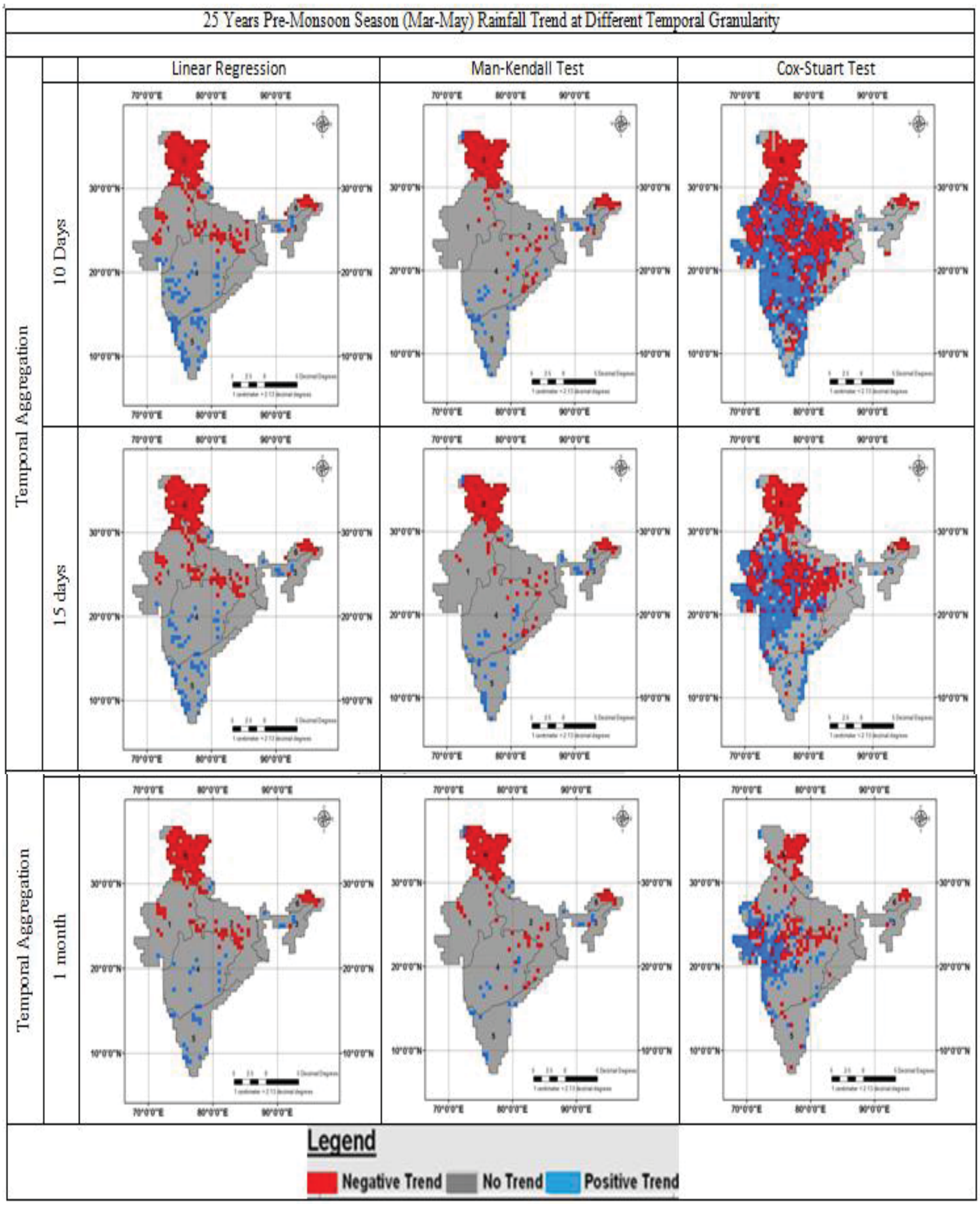


1.2. Trends in Rainfall at multiple temporal granularities.

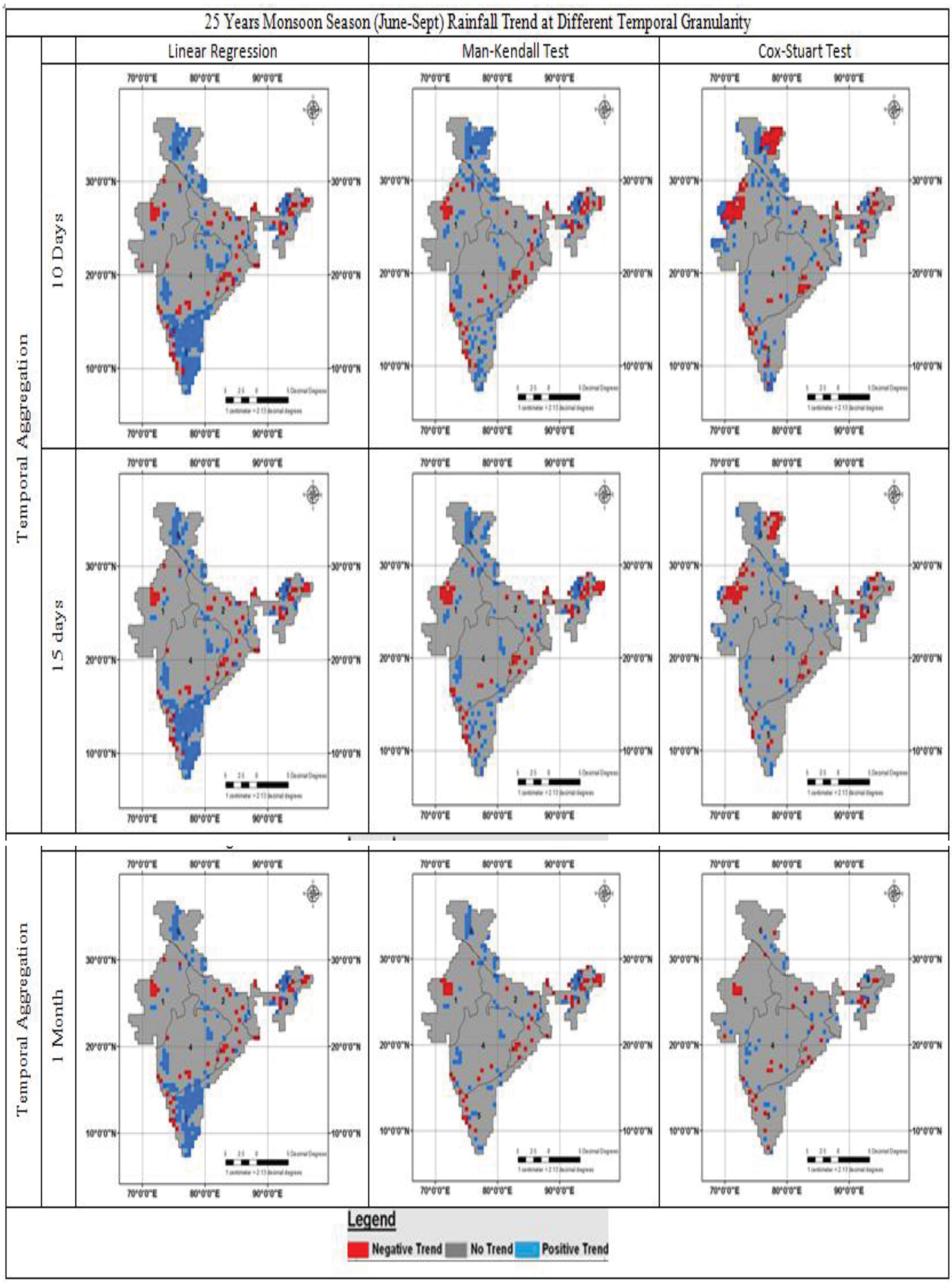
1.2.1. Trends in Rainfall for Winter Season (Jan-Feb) season at multiple temporal granularities



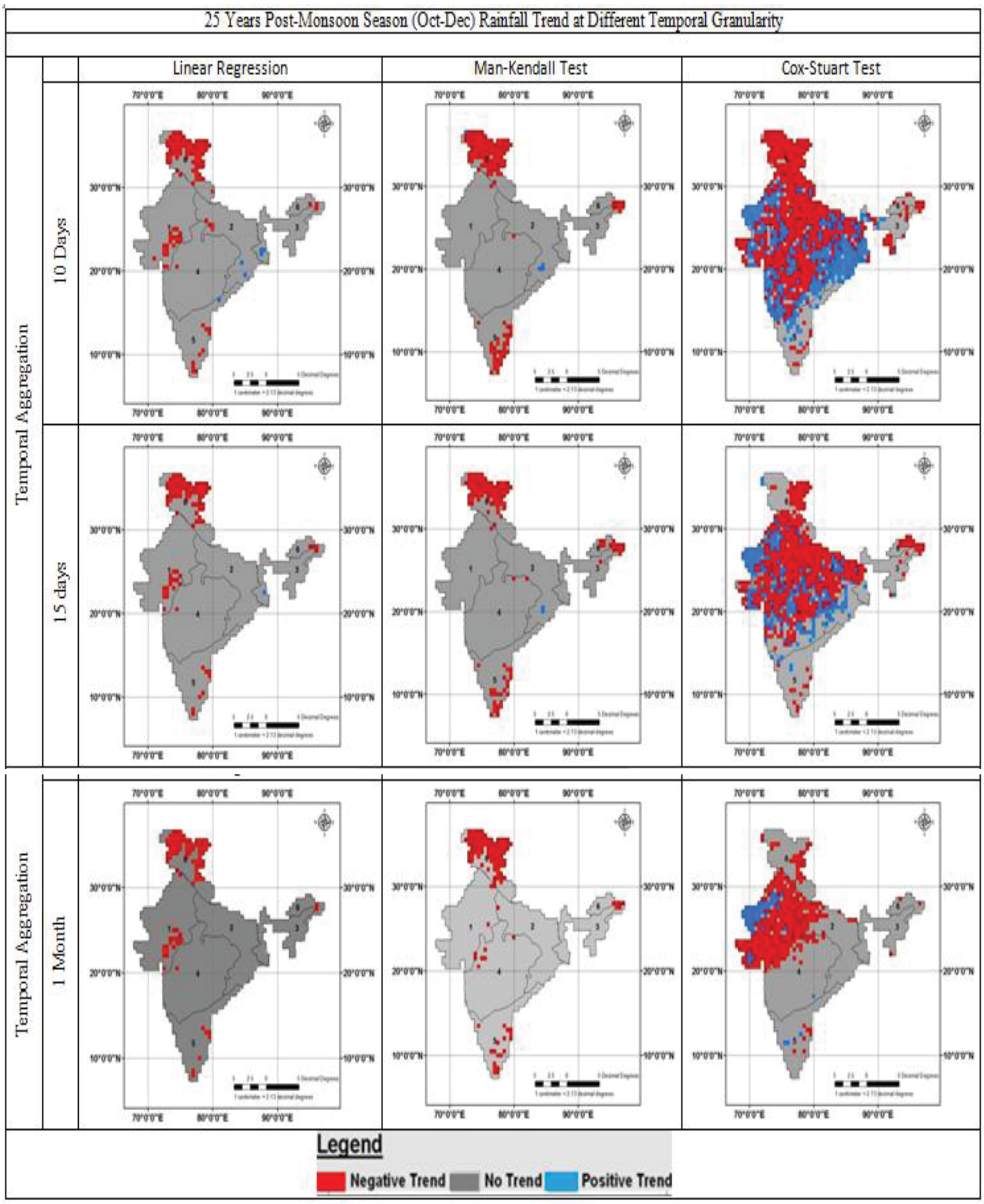
1.2.2. Trends in Rainfall for Pre-Monsoon Season (Mar-May) season at multiple temporal granularities



1.2.3. Trends in Rainfall for Monsoon Season (Jun-Sep) season at multiple temporal granularities

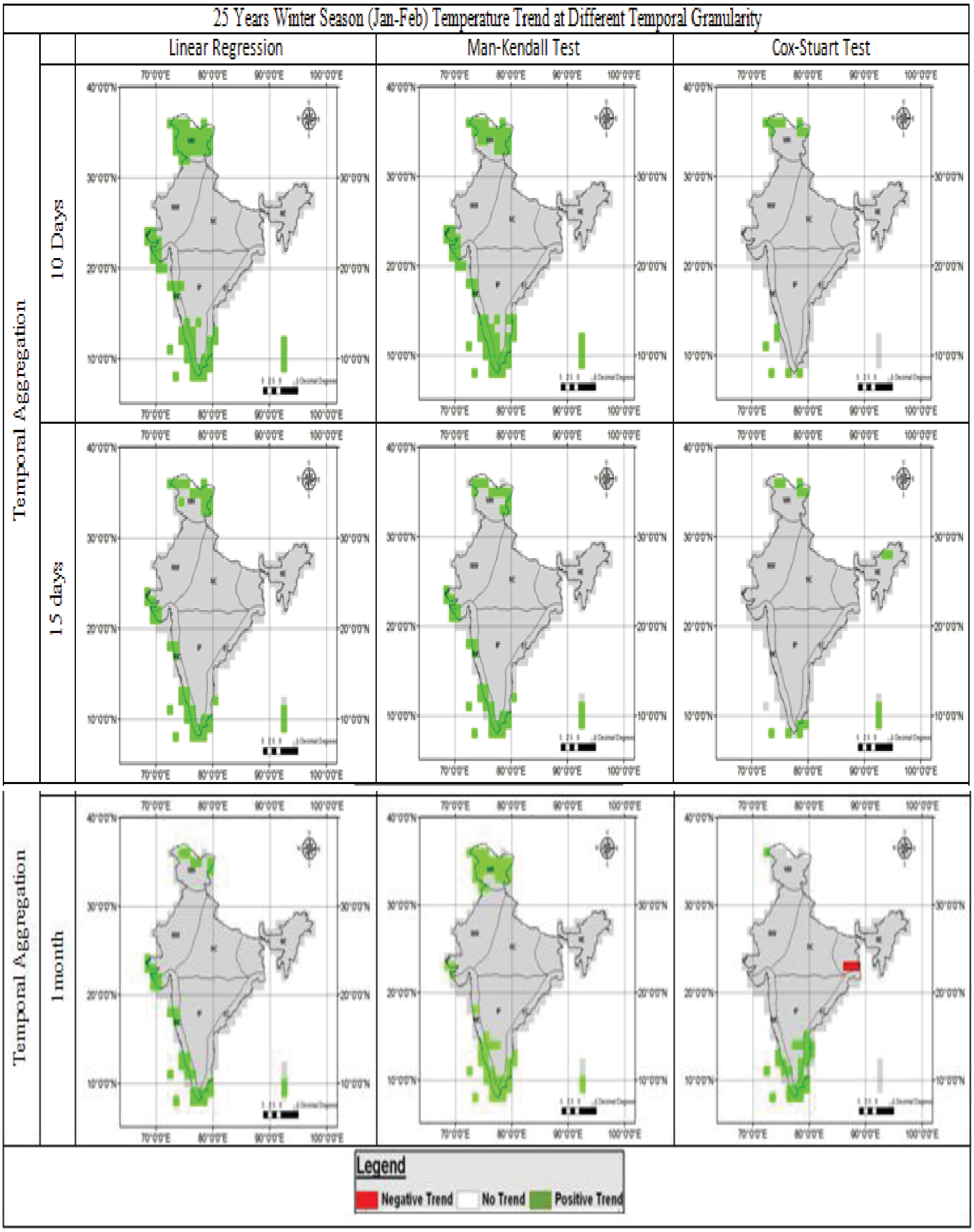


1.2.4. Trends in Rainfall for Monsoon Season (Jun-Sep) season at multiple temporal granularities

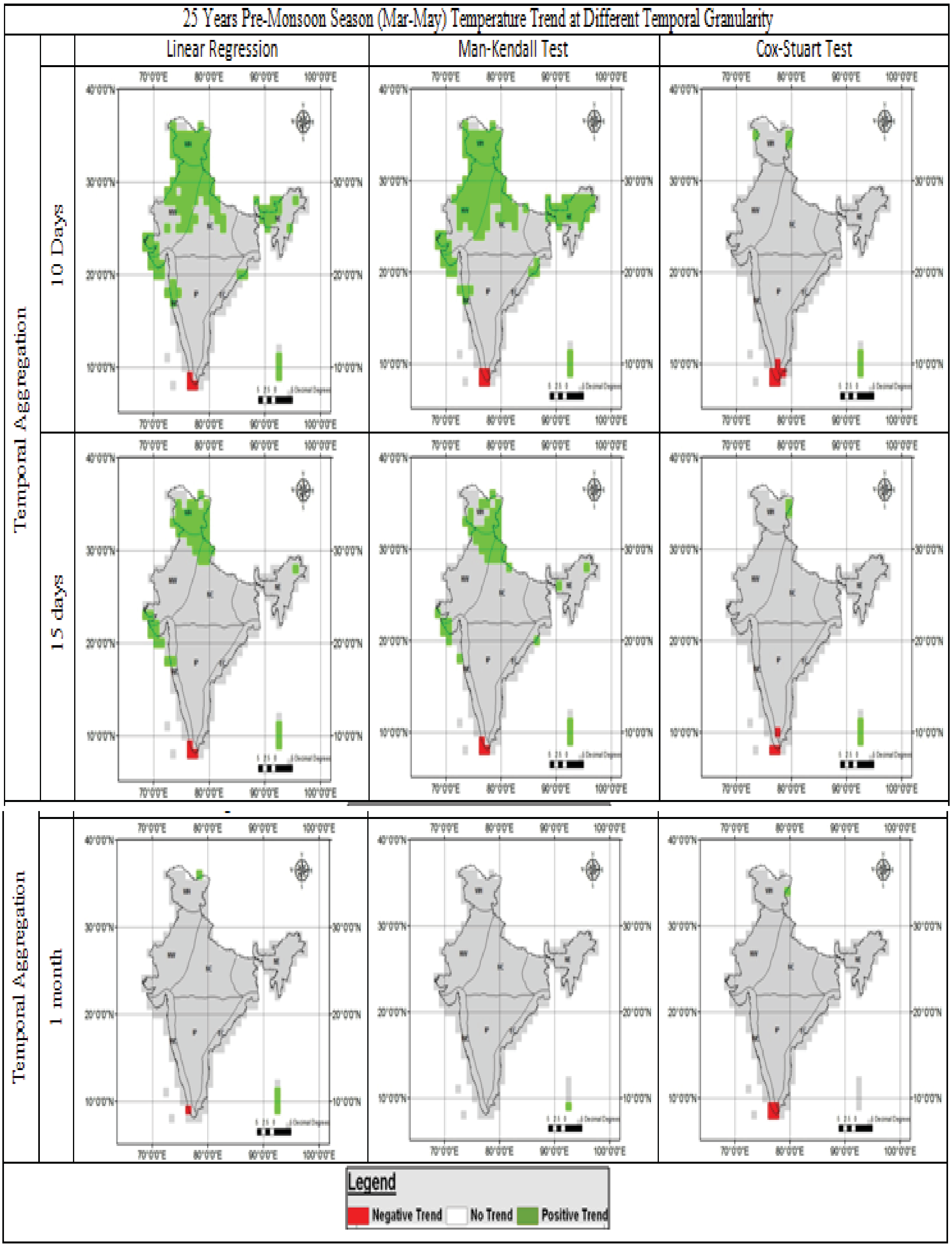


1.3. Trends in Temperature at multiple temporal granularities.

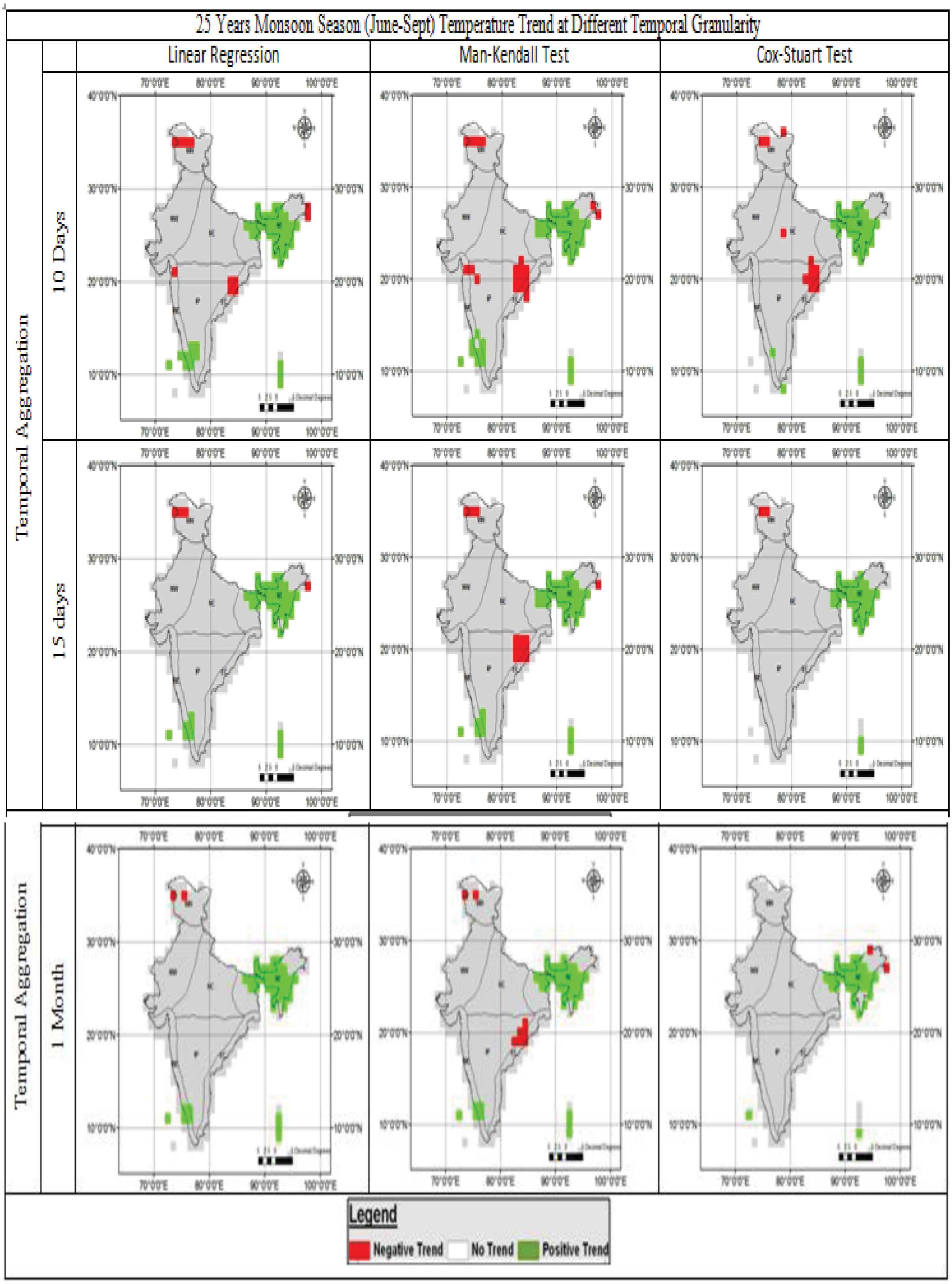
1.3.1. Trends in Temperature for Winter Season (Jan-Feb) season at multiple temporal granularities



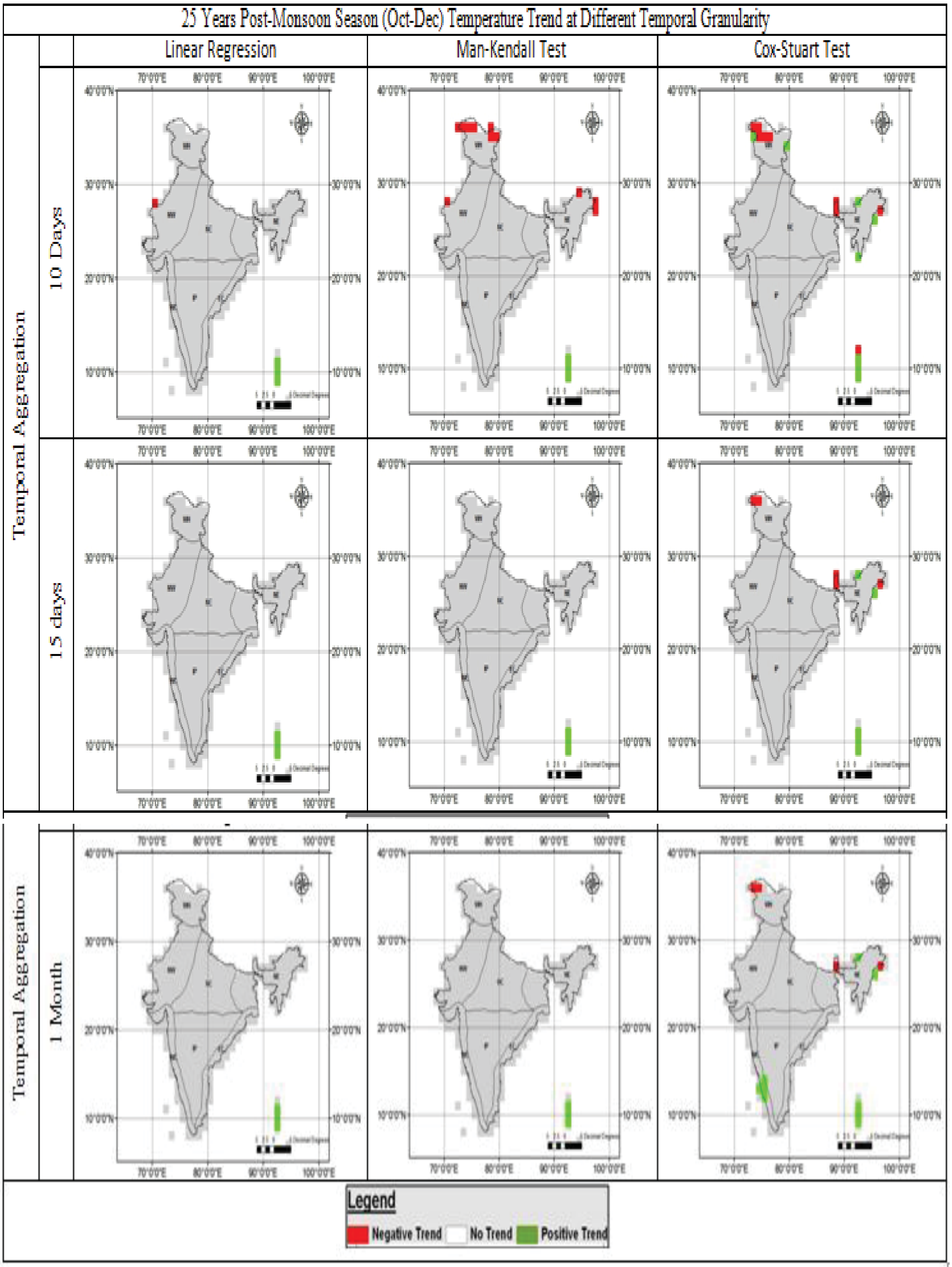
1.3.2. Trends in Temperature for Pre-Monsoon Season (Mar-May) season at multiple temporal granularities



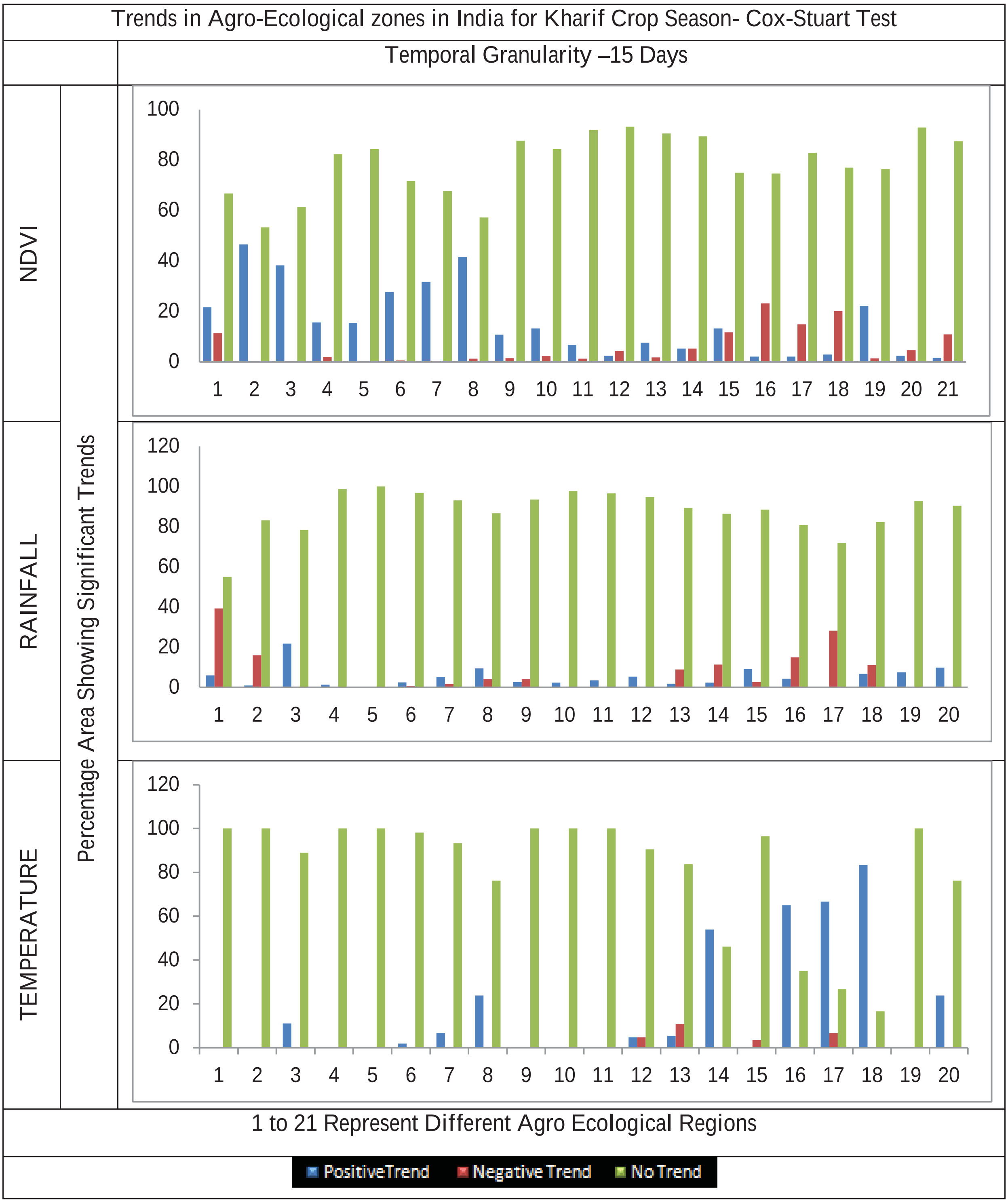
1.3.3. Trends in Temperature for Monsoon Season (Jun-Sep) season at multiple temporal granularities



1.3.4. Trends in Temperature for Post-Monsoon Season (Oct-Dec) season at multiple temporal granularities



1.4. Trends in NDVI at multiple temporal granularities.

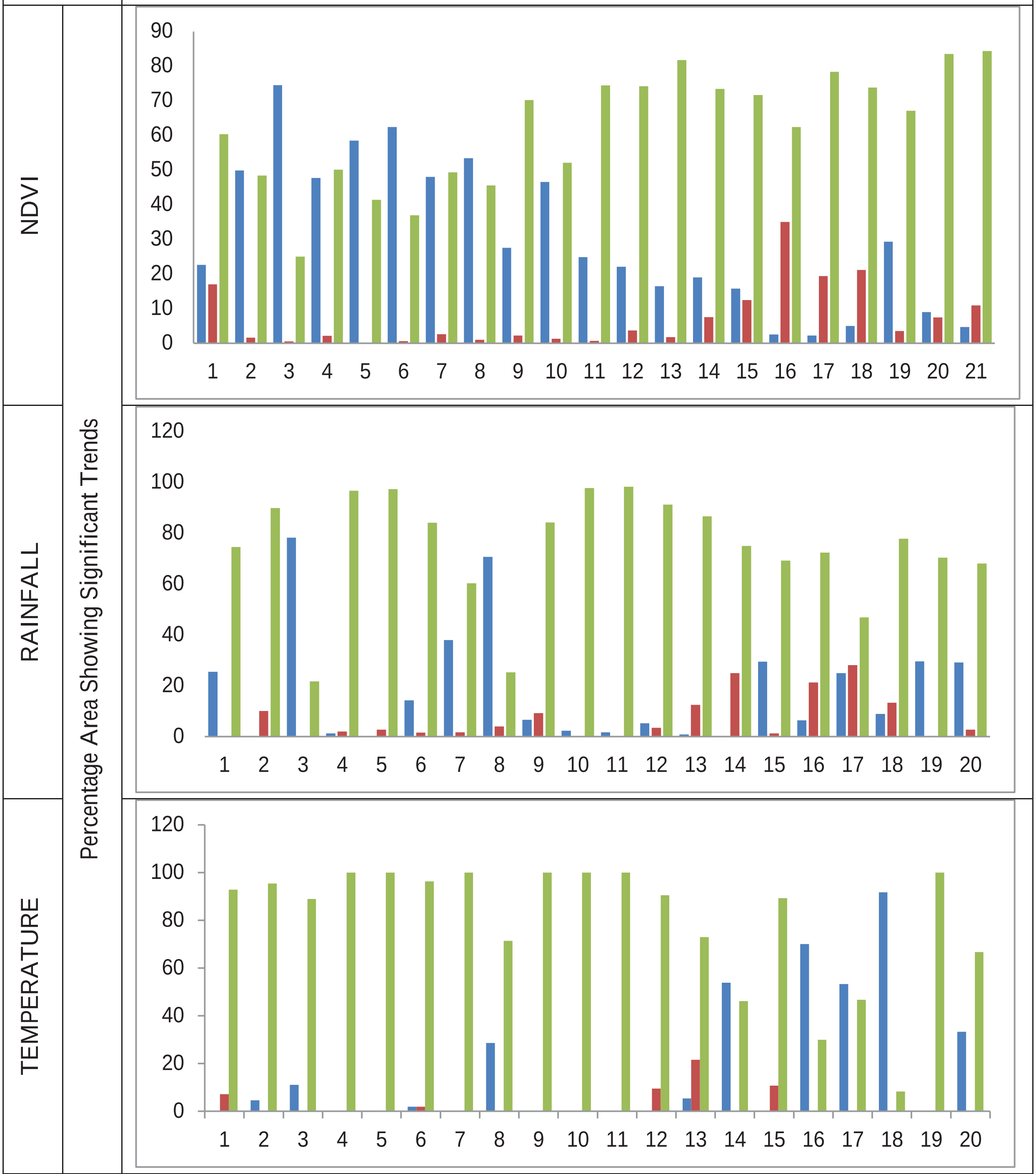


Zone 2, 3 and 8 are showing more than 30 percent area corresponding to positive trends for NDVI. More than 10 percent significant trends are observed in zones 1617, and 18.

For rainfall zone 1 and 17 shows significant negative trends in more than 20 percent area. More than 50 percent area shows positive trends in zones 14, 16, 17 and 18.

Trends in Agro-Ecological zones in India for Kharif Crop Season- Ordinary Least Squares

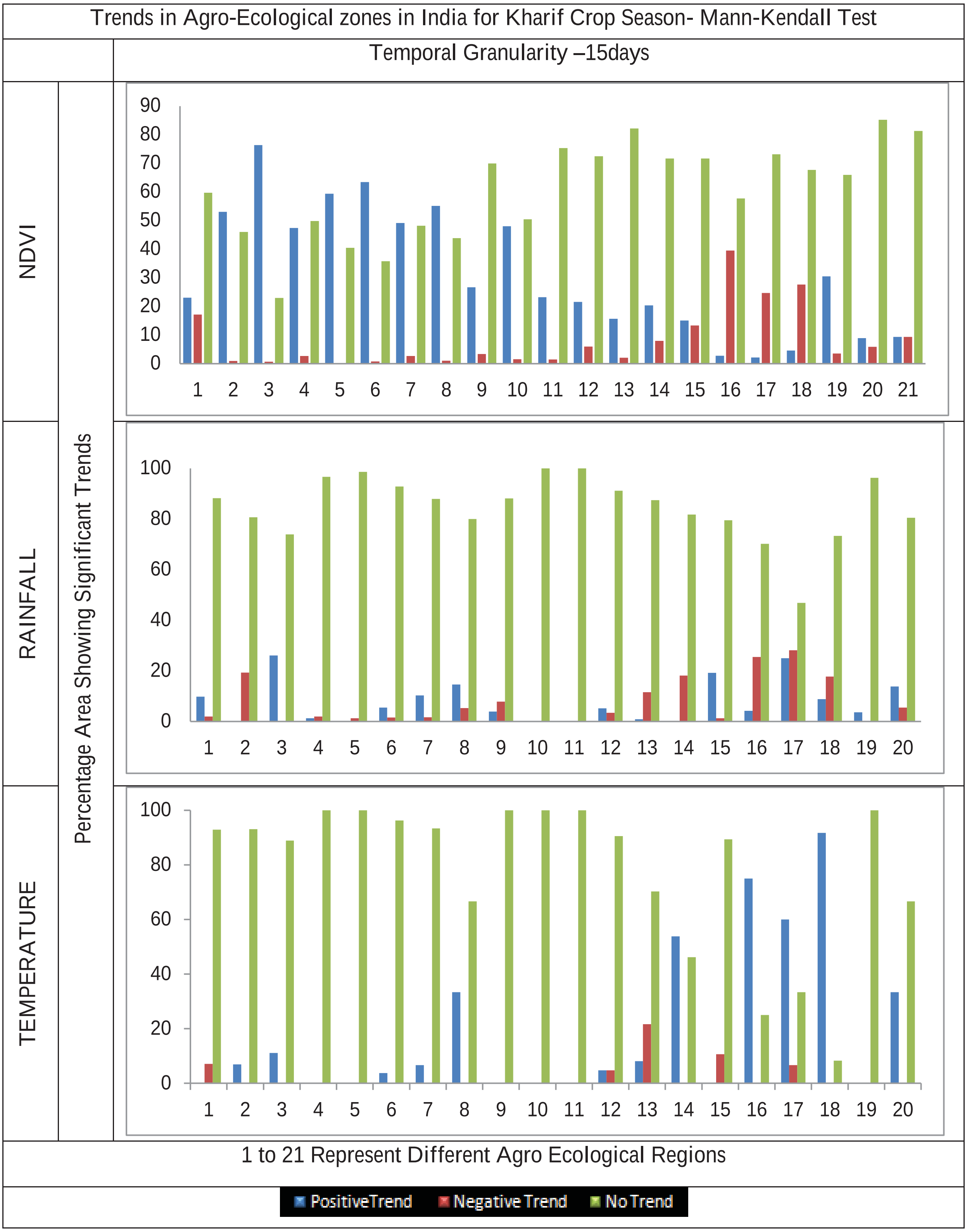
Temporal Granularity –15days



1 to 21 Represent Different Agro Ecological Regions

PositiveTrend Negative Trend No Trend

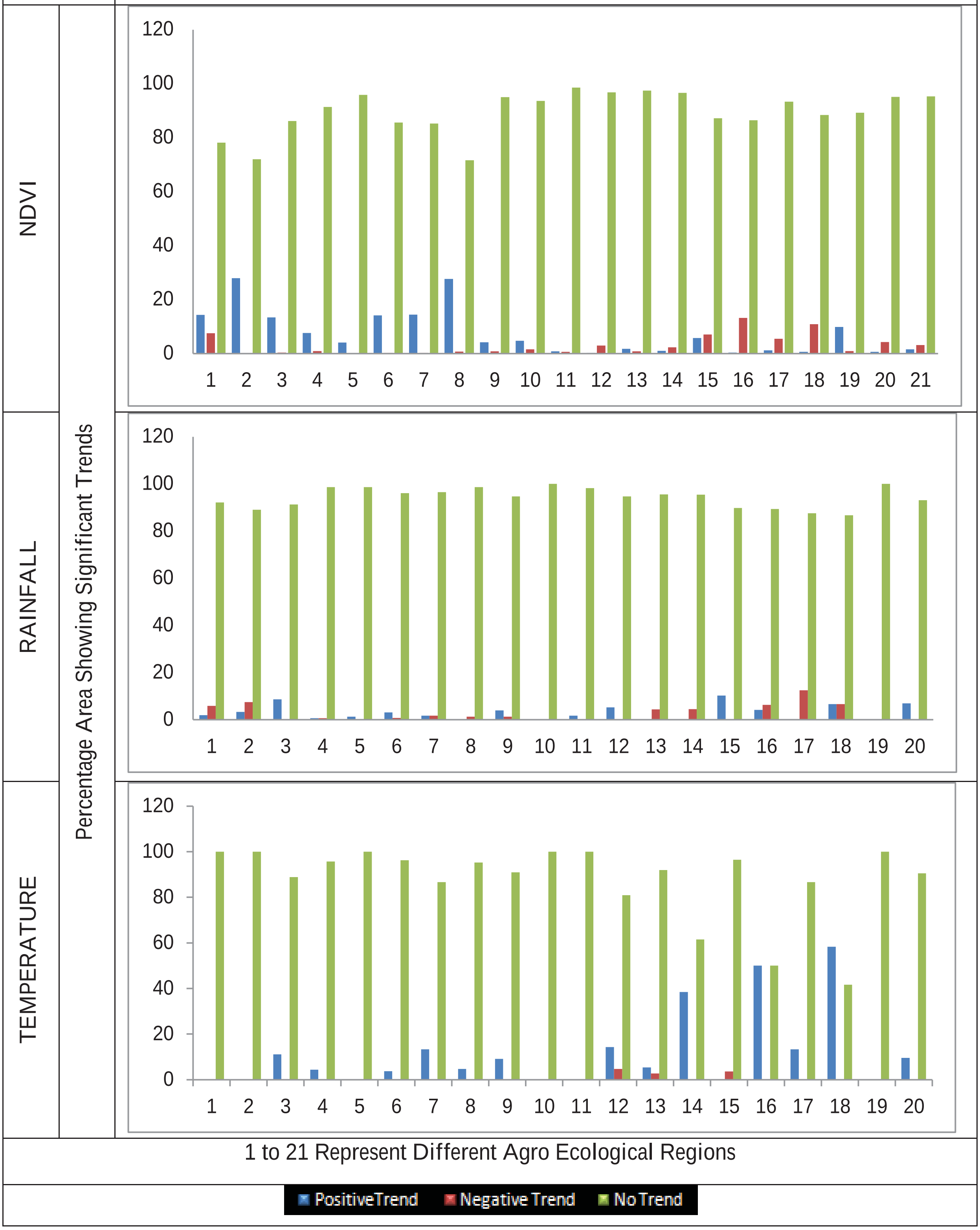
Zones 3, 5, 6 and 8 shows more than 50 percent area for positive trends in NDVI.
Zone 16, 17 and 18 shows more than 20 percent area corresponding to negative trends in NDVI.
Whereas zone 3 and 8 confirms presence of positive trends in more than 50 percent areas
More than 50 percent significant positive trends were found in zone 16, 17 and 18 for temperature.



Zones 2, 3, 5 and 6 shows more than 50 percent area for positive trends in NDVI.
Zone 16, 17 and 18 shows more than 20 percent area corresponding to negative trends in NDVI.
Whereas zone 3 and 17 only shows 20 percent areas for positive trends for rainfall.
More than 60 percent significant positive trends were found in zone 16, 17 and 18 for temperature

Trends in Agro-Ecological zones in India for Kharif Crop Season- Cox-Stuart Test

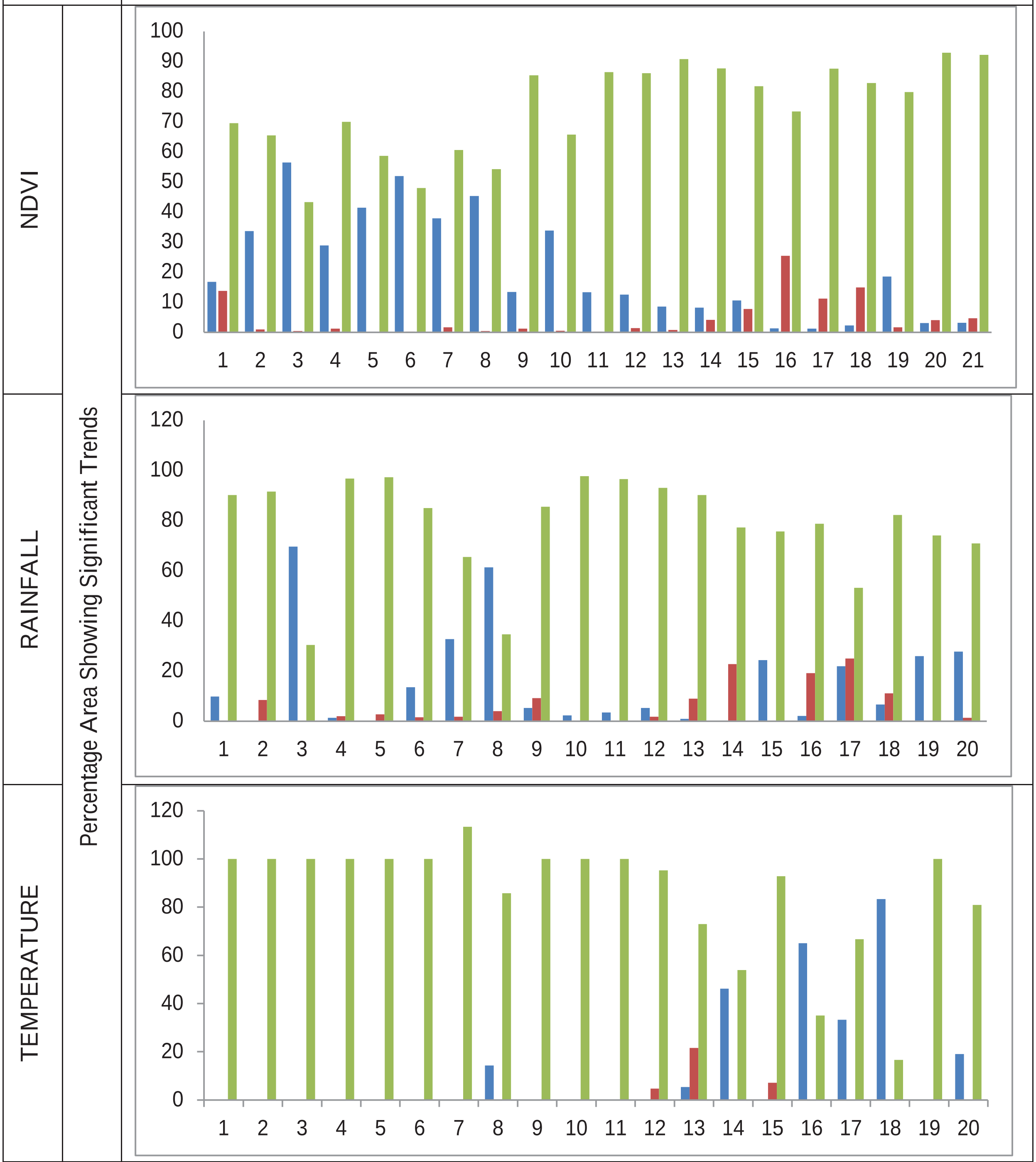
Temporal Granularity – 1 Month



1 to 21 Represent Different Agro Ecological Regions

Trends in Agro-Ecological zones in India for Kharif Crop Season- Ordinary Least Squares

Temporal Granularity – 1 Month



1 to 21 Represent Different Agro Ecological Regions

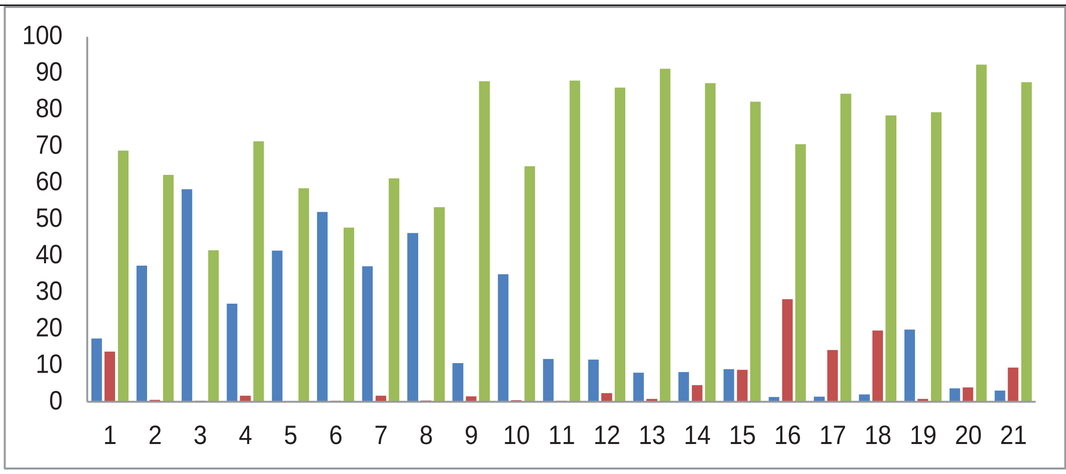
PositiveTrend NegativeTrend No Trend

Trends in Agro-Ecological zones in India for Kharif Crop Season- Mann-Kendall Test

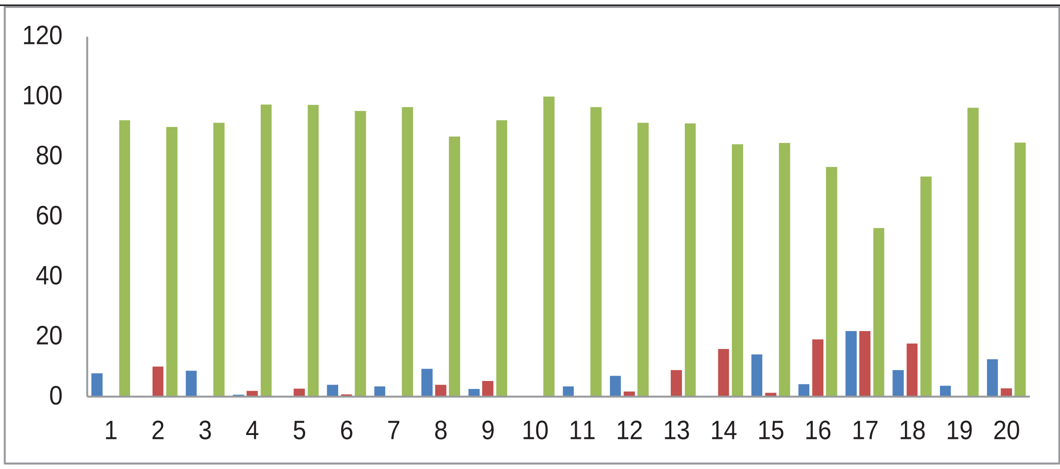
Temporal Granularity – 1 Month

Percentage Area Showing Significant Trends

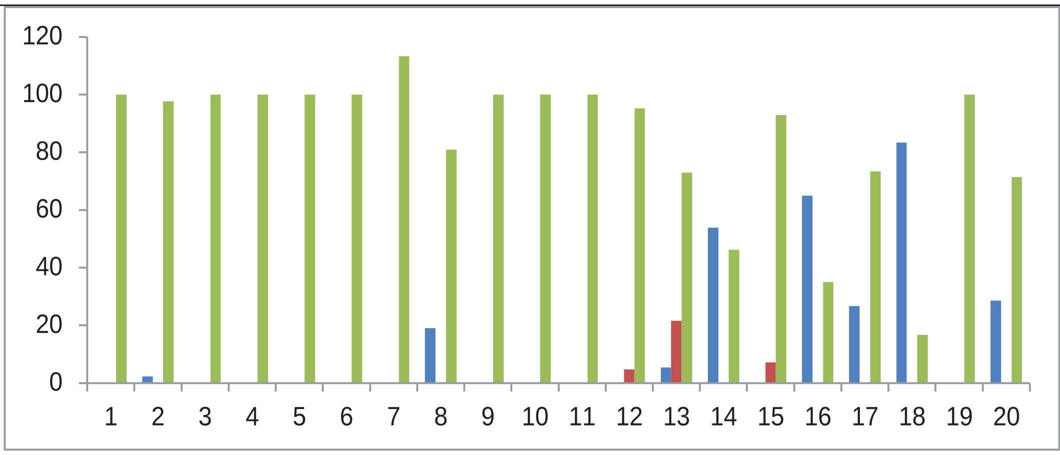
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

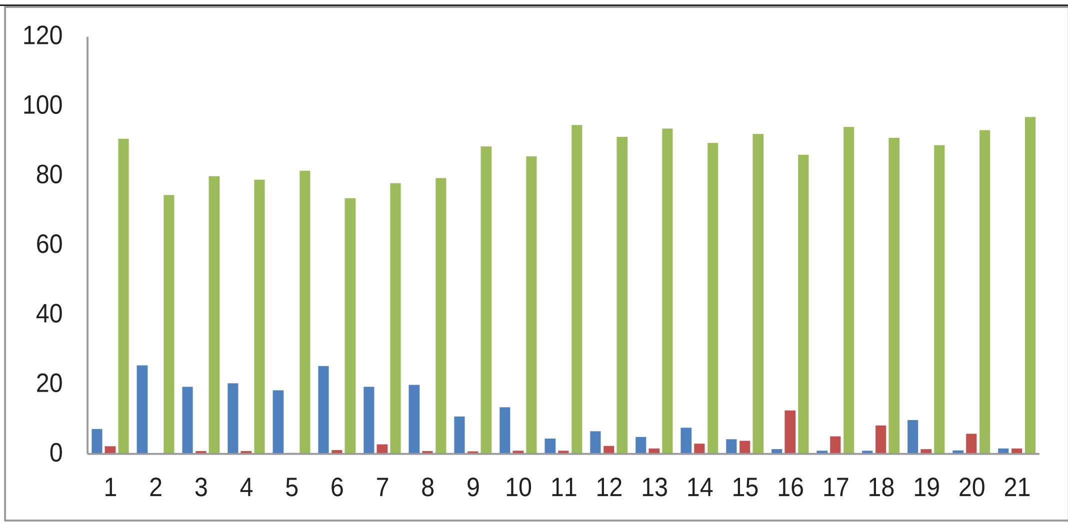
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Kharif Crop Season - Cox-Stuart Test

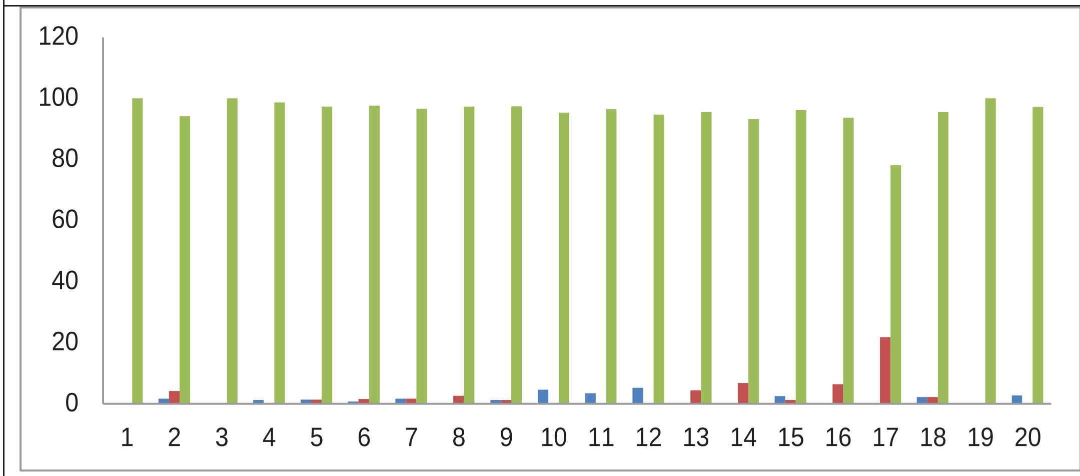
Temporal Granularity – 3 Month

Percentage Area Showing Significant Trends

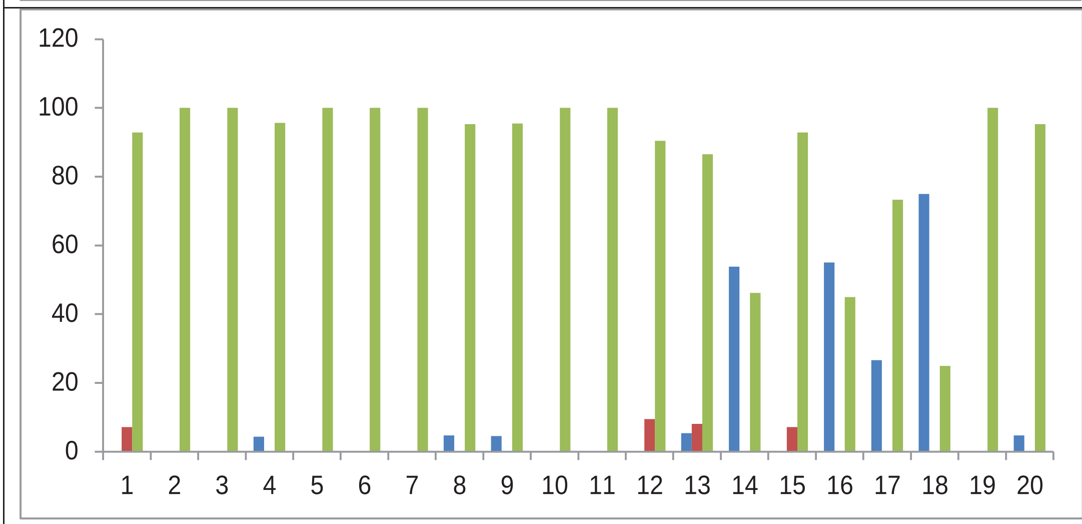
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

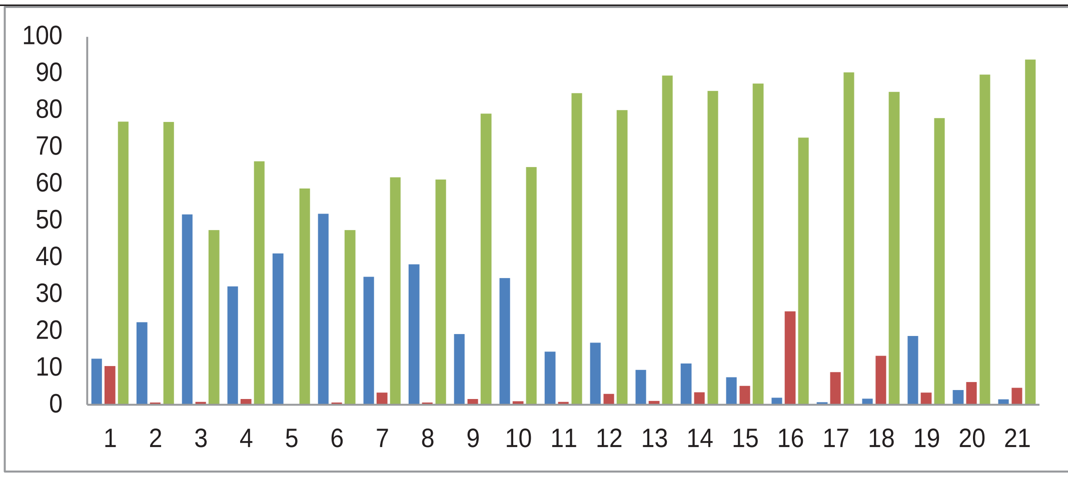
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Kharif Crop Season - Ordinary Least Squares

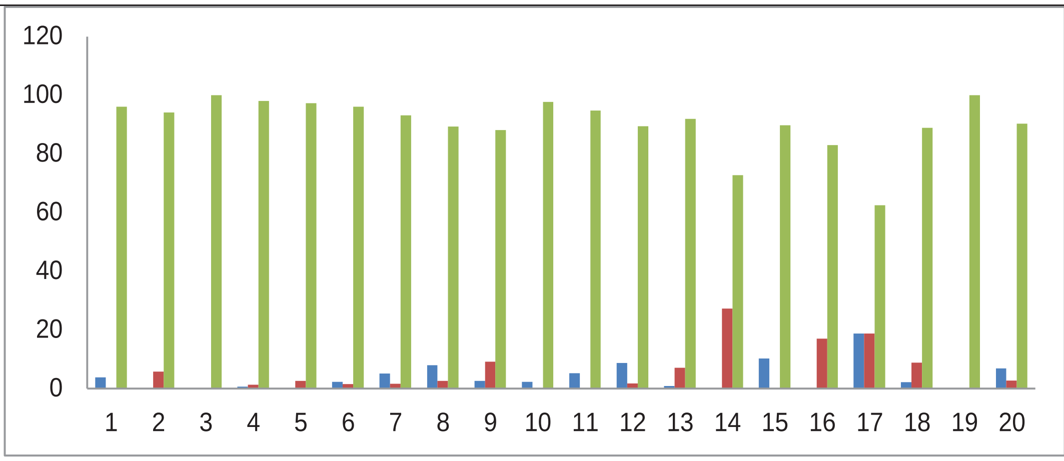
Temporal Granularity – 3 Month

Percentage Area Showing Significant Trends

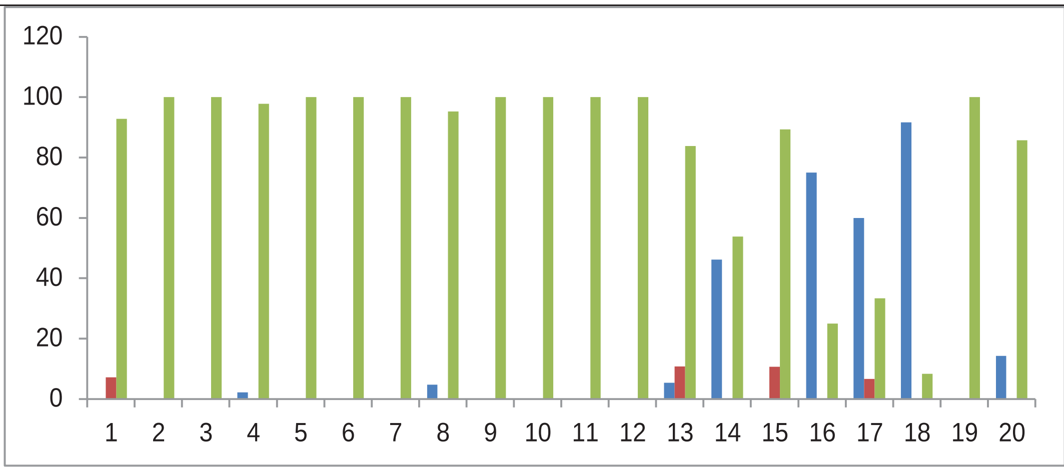
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

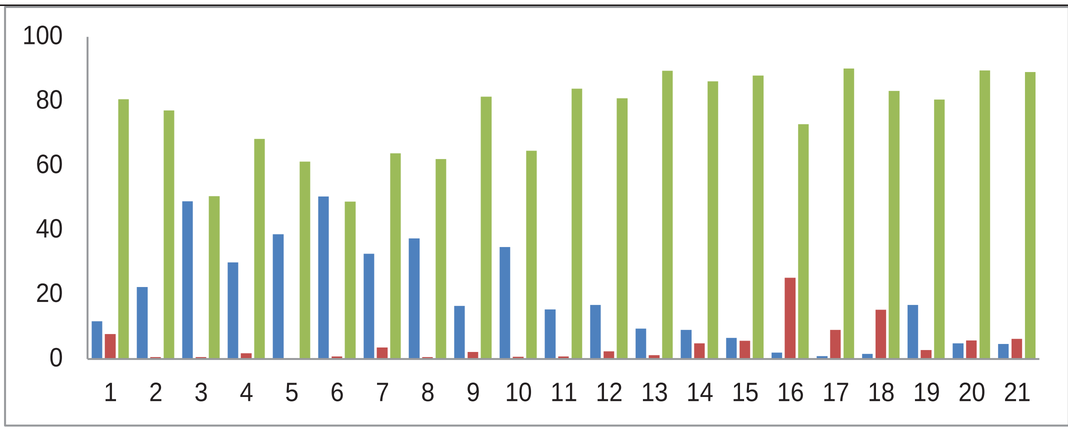
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Kharif Crop Season - Mann-Kendall Test

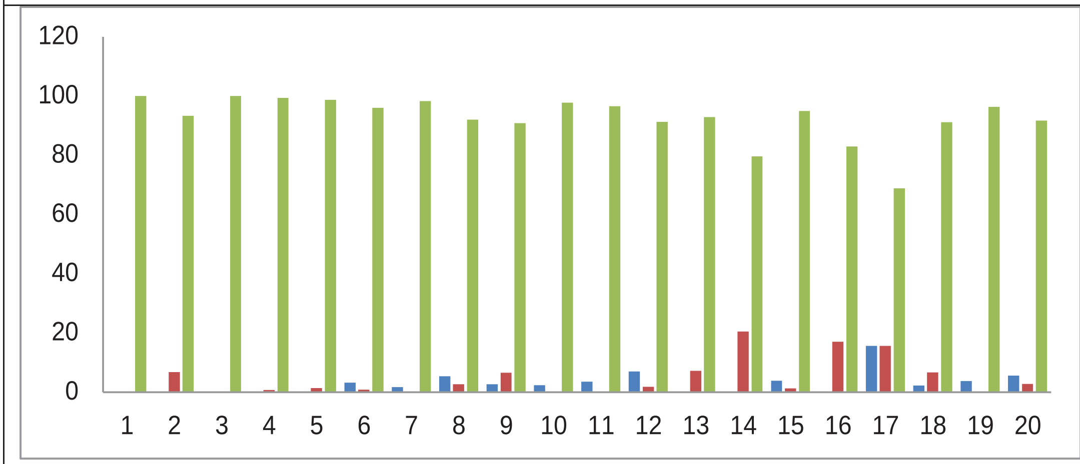
Temporal Granularity – 3 Month

Percentage Area Showing Significant Trends

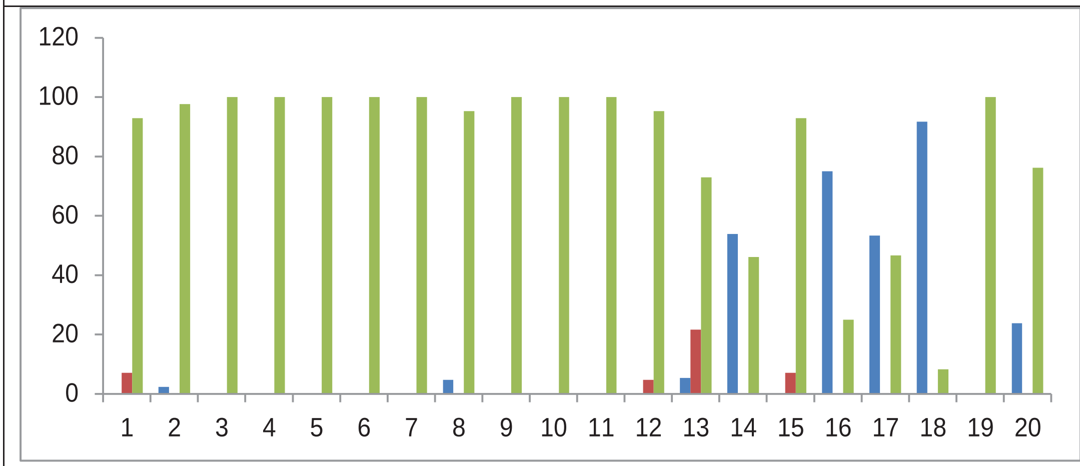
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

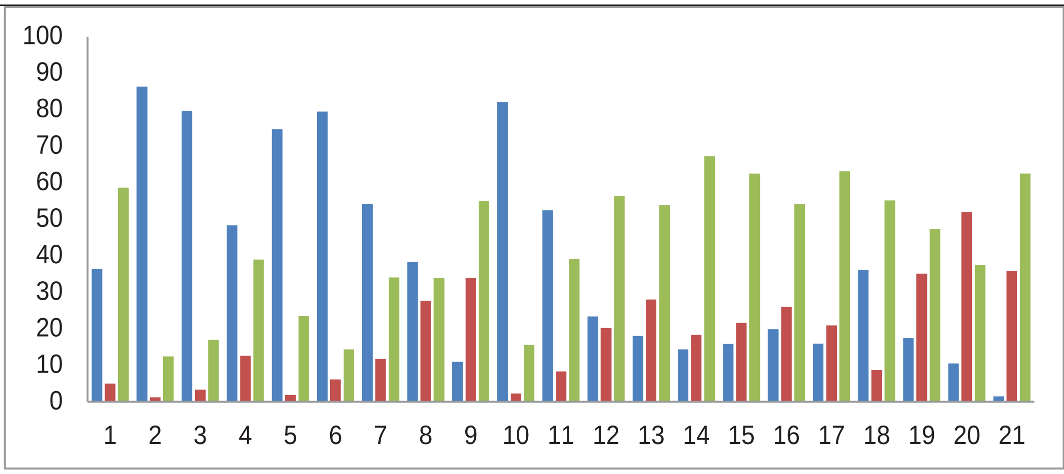
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Rabi Crop Season - Cox-Stuart Test

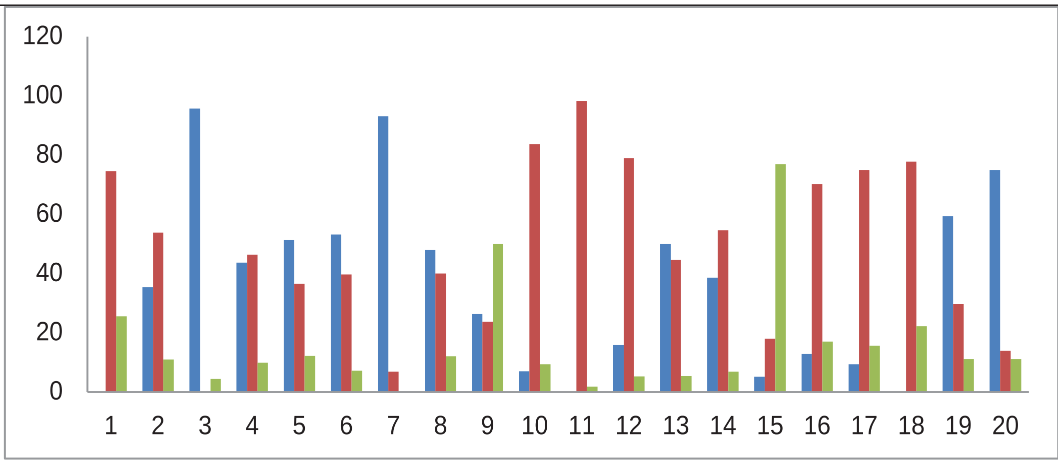
Temporal Granularity – 15days

Percentage Area Showing Significant Trends

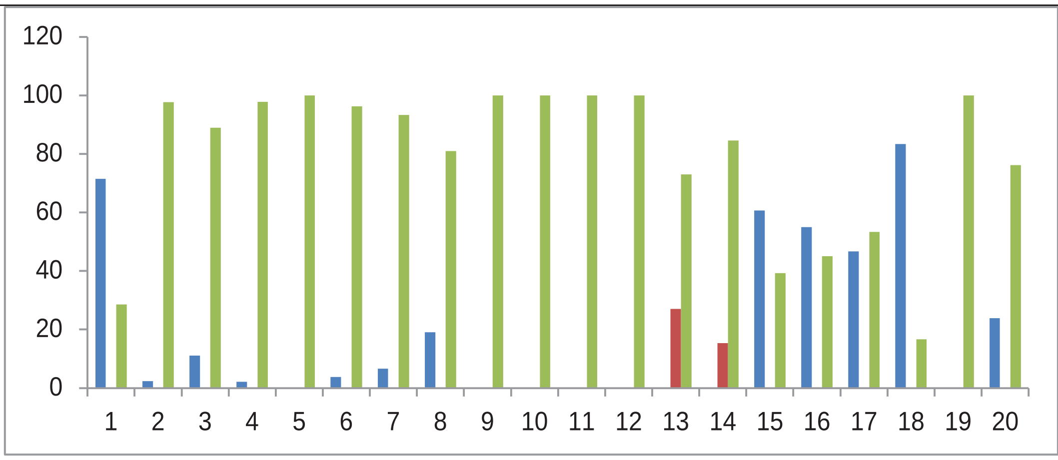
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

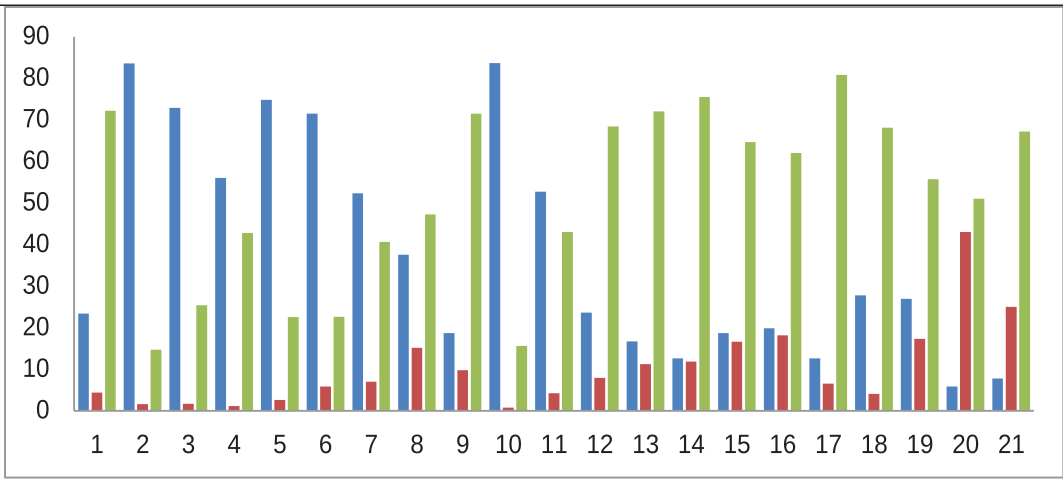
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Rabi Crop Season - Ordinary Least Squares

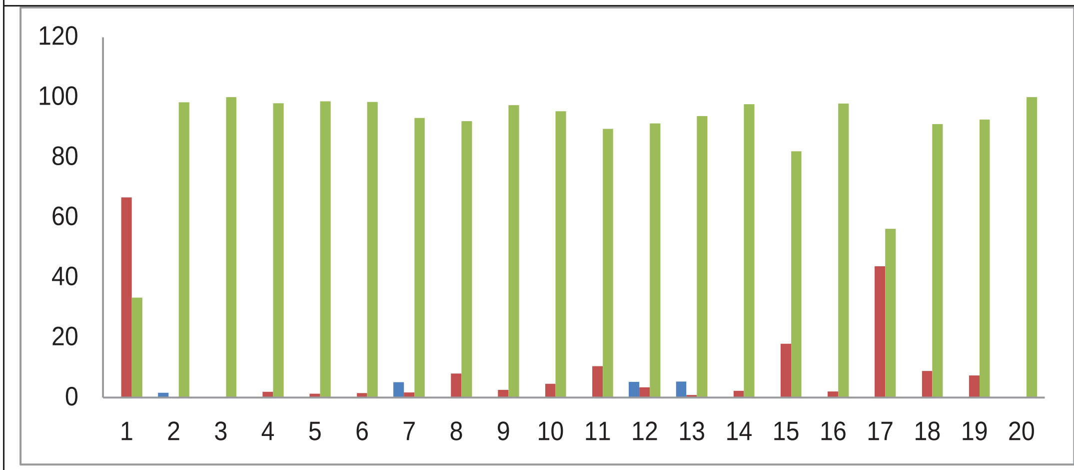
Temporal Granularity – 15days

Percentage Area Showing Significant Trends

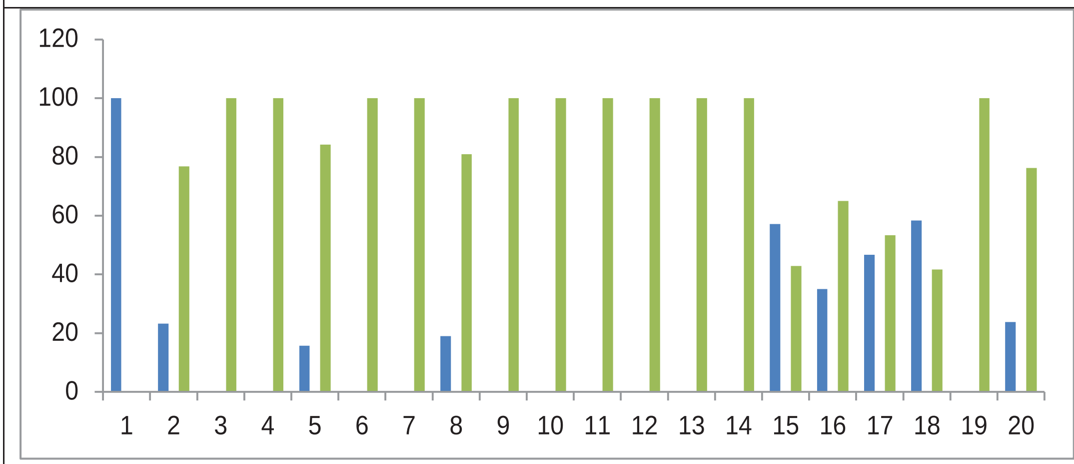
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

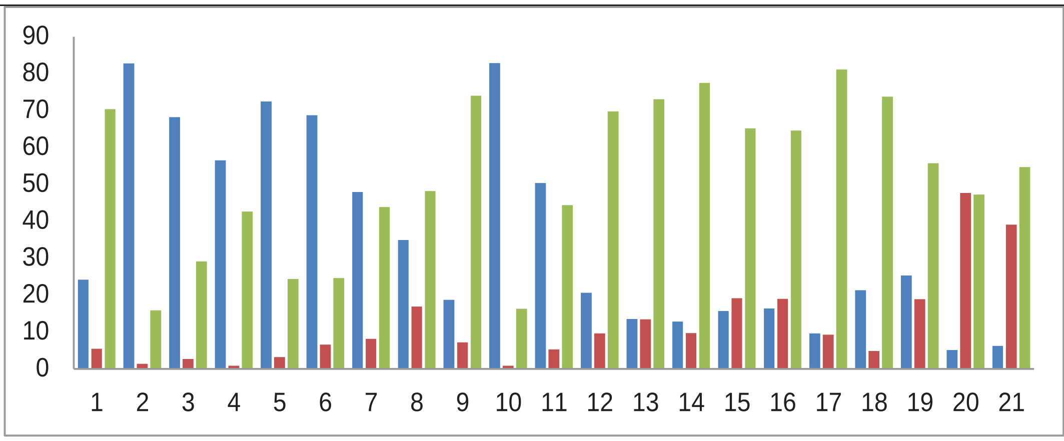
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Rabi Crop Season - Mann-Kendall Test

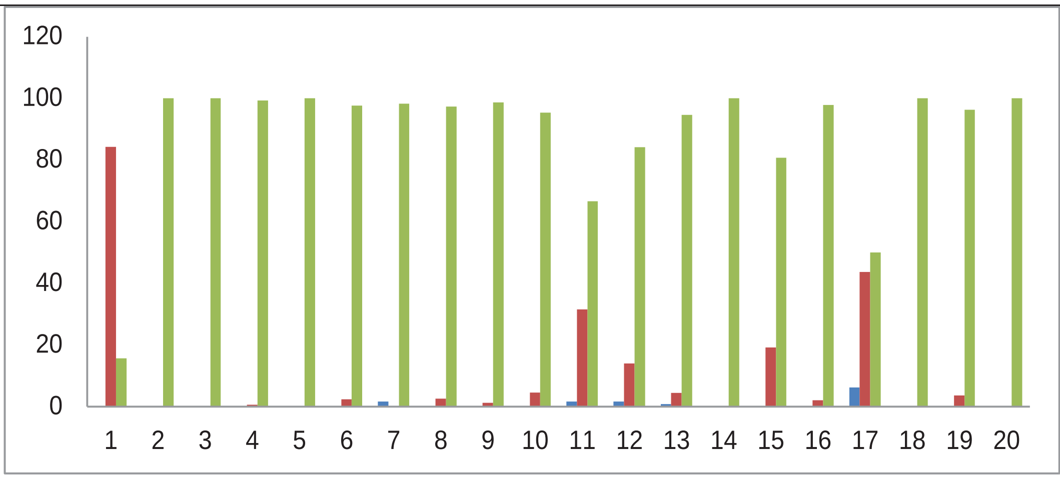
Temporal Granularity – 15days

Percentage Area Showing Significant Trends

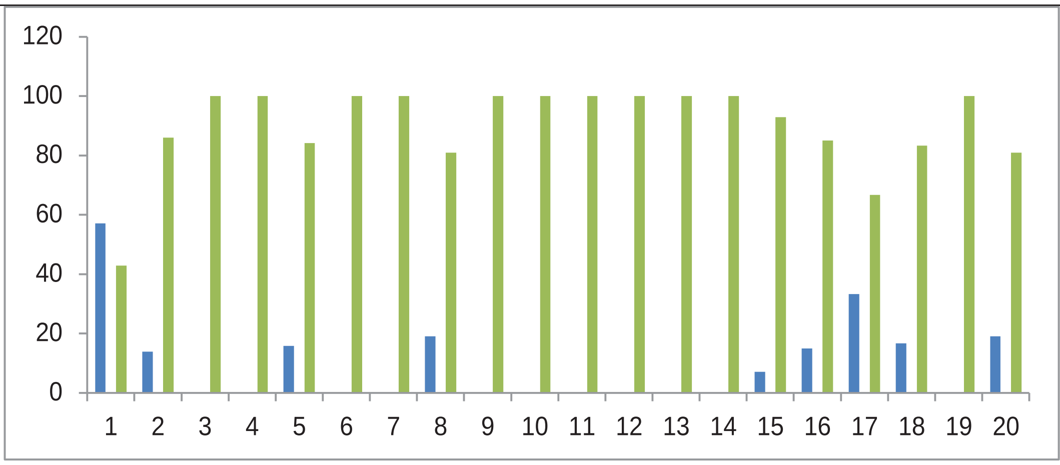
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

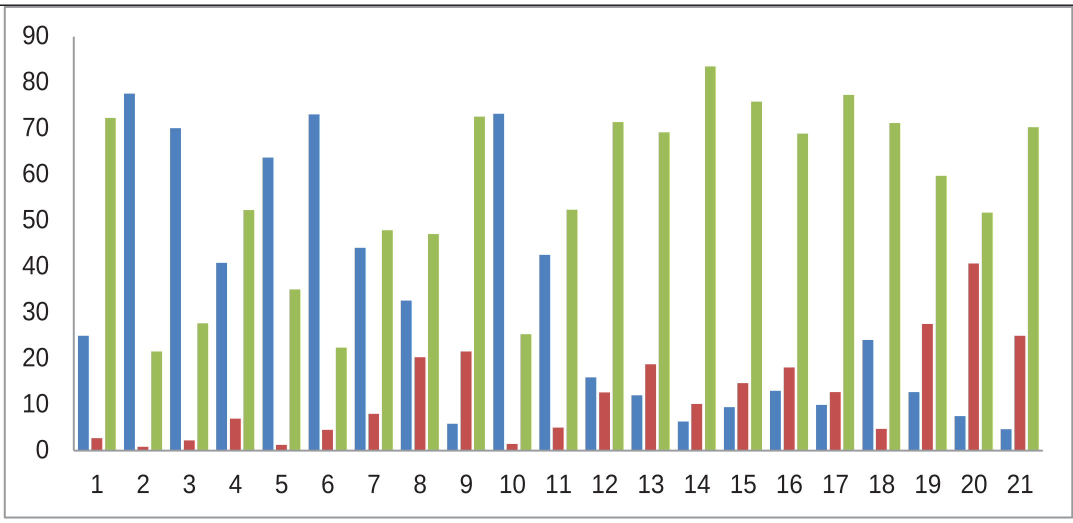
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Rabi Crop Season – Cox-Stuart Test

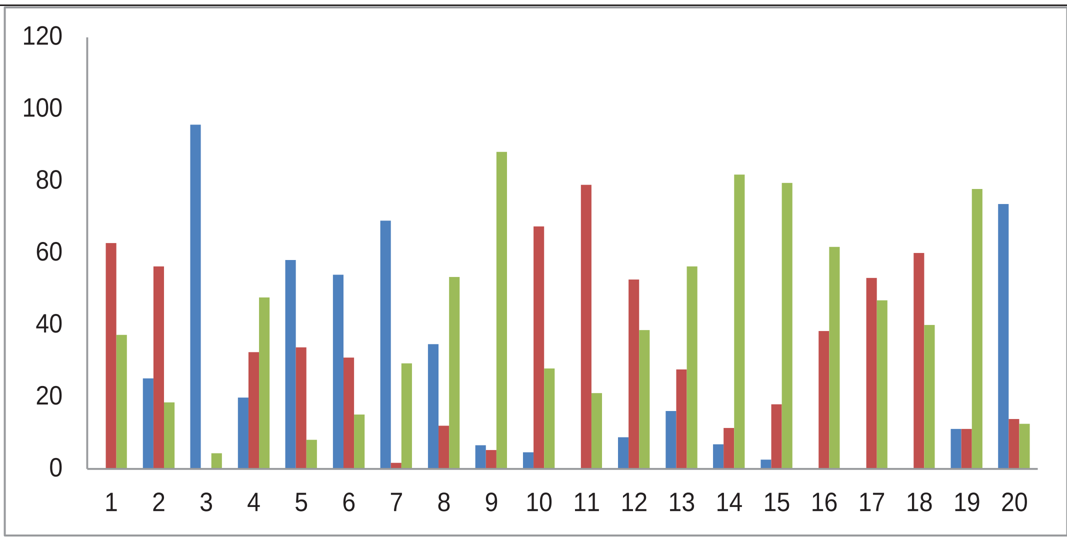
Temporal Granularity – 1month

Percentage Area Showing Significant Trends

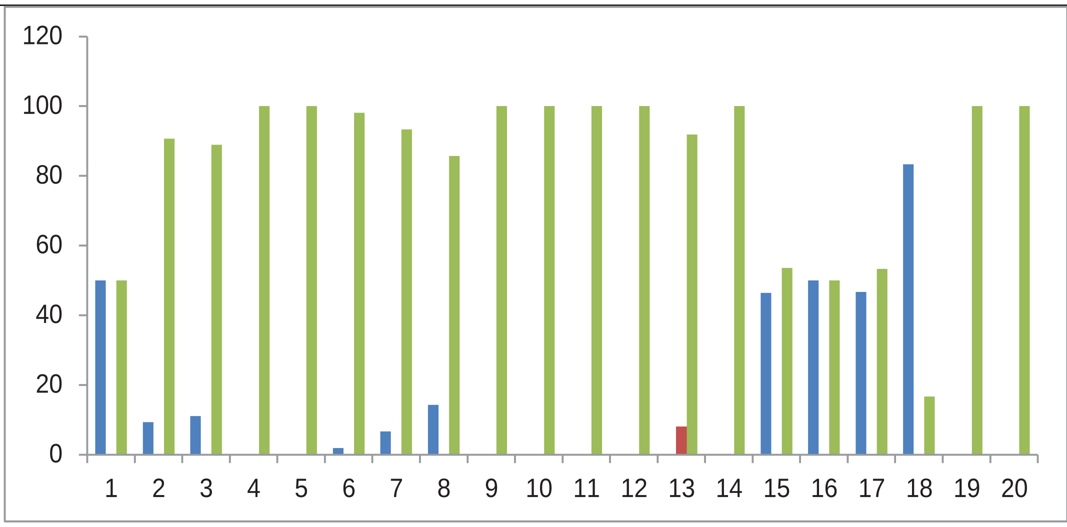
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

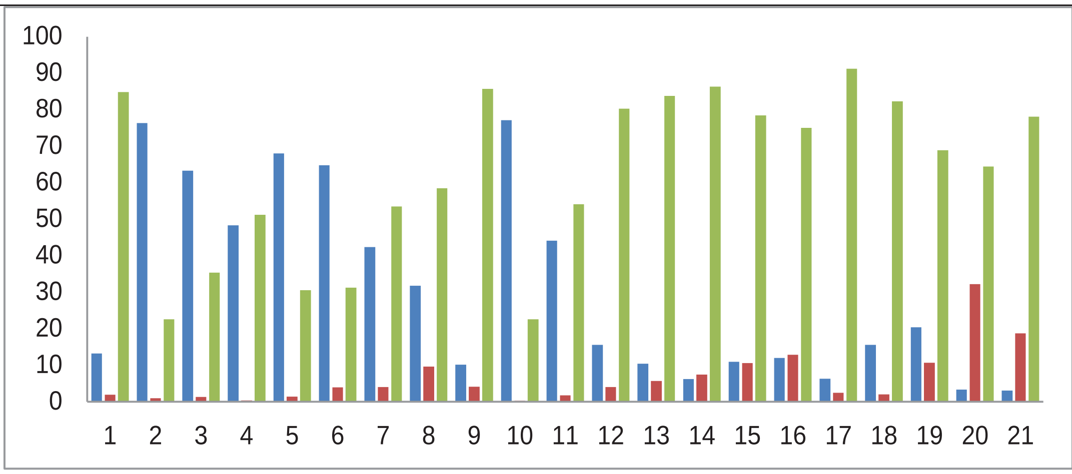
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Rabi Crop Season – Ordinary Least Squares

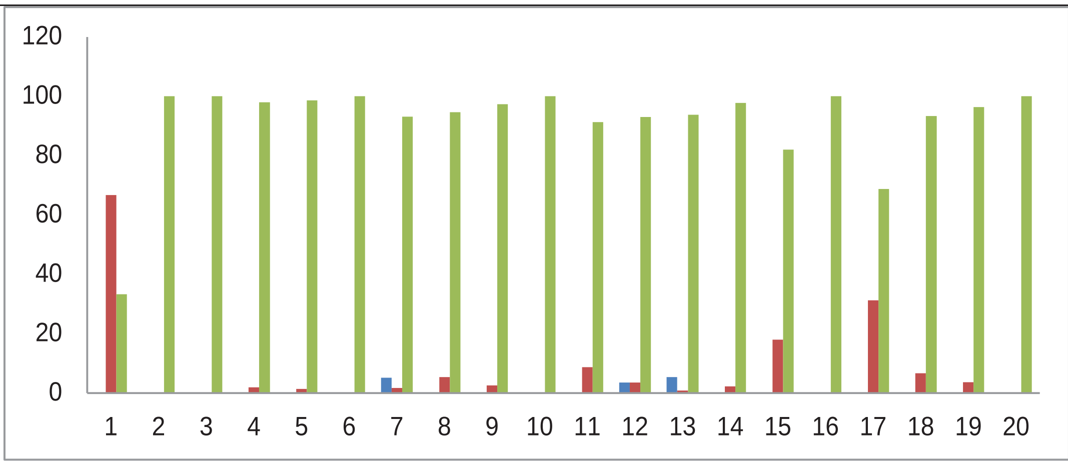
Temporal Granularity – 1month

Percentage Area Showing Significant Trends

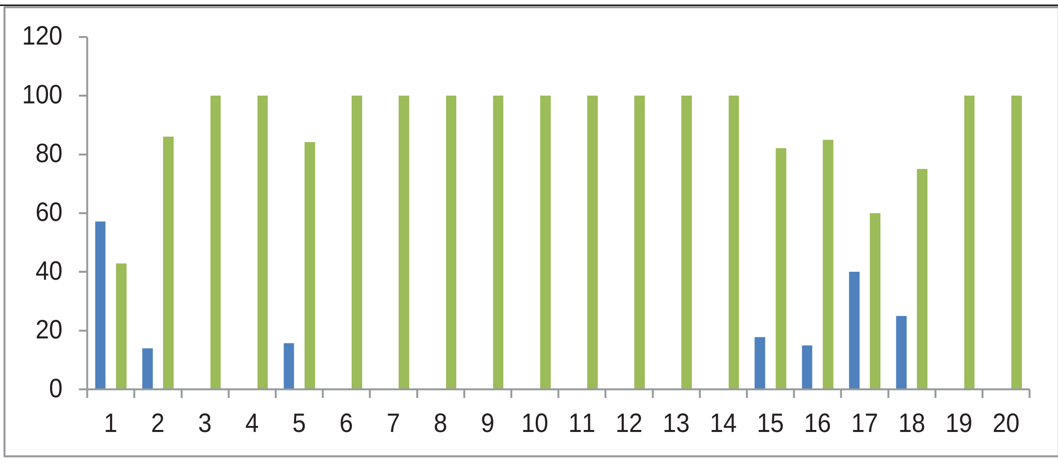
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

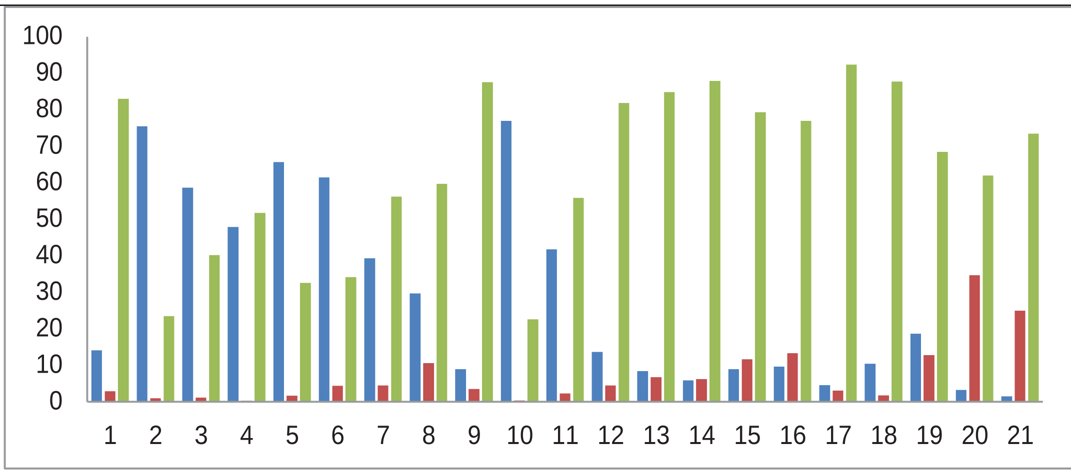
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Rabi Crop Season - Mann-Kendall Test

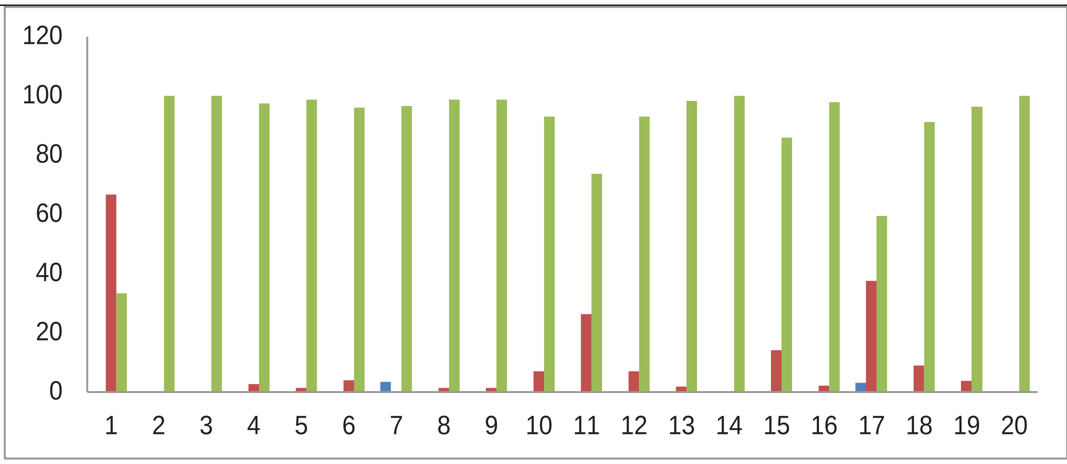
Temporal Granularity – 1month

Percentage Area Showing Significant Trends

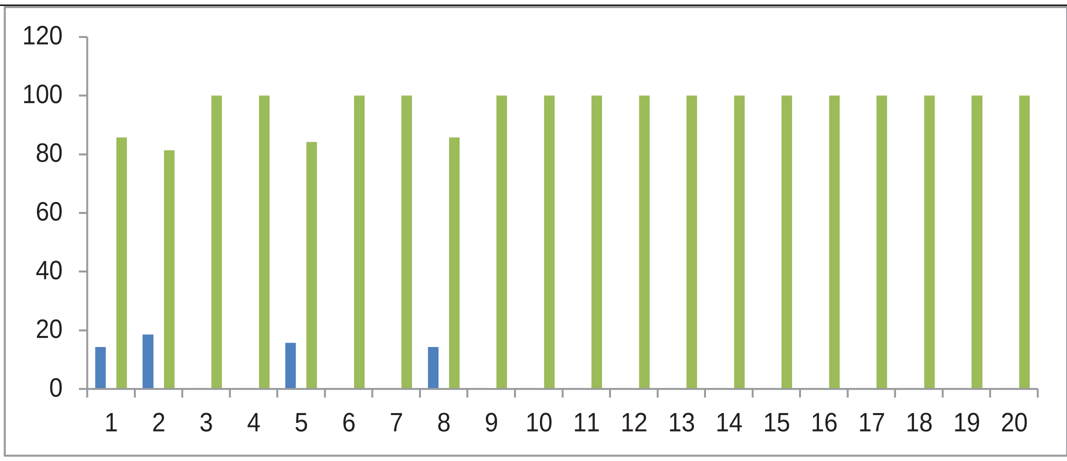
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

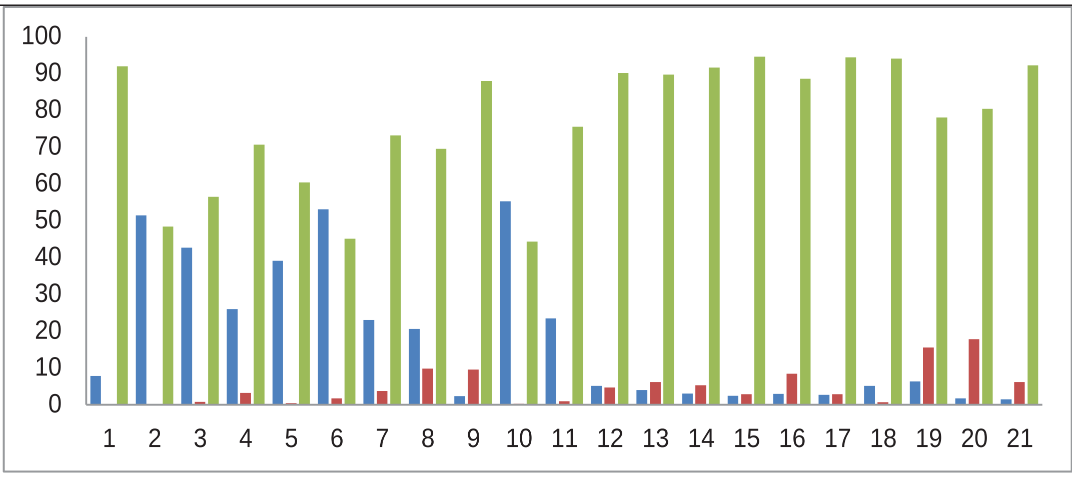
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Rabi Crop Season – Cox-Stuart Test

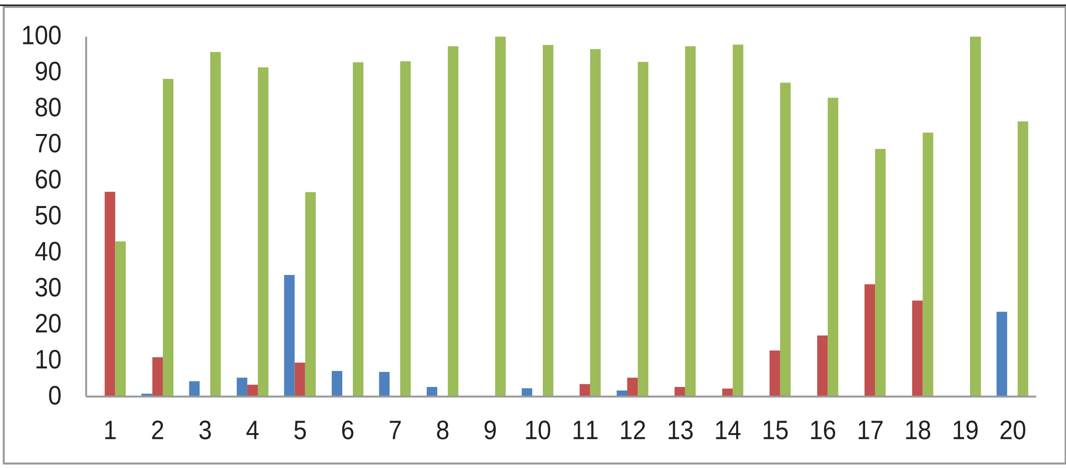
Temporal Granularity – 3 Month

Percentage Area Showing Significant Trends

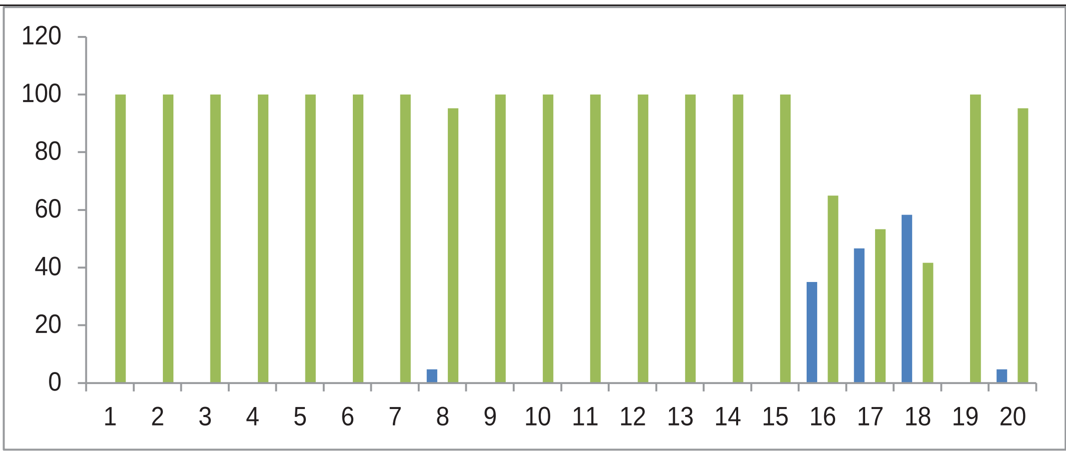
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

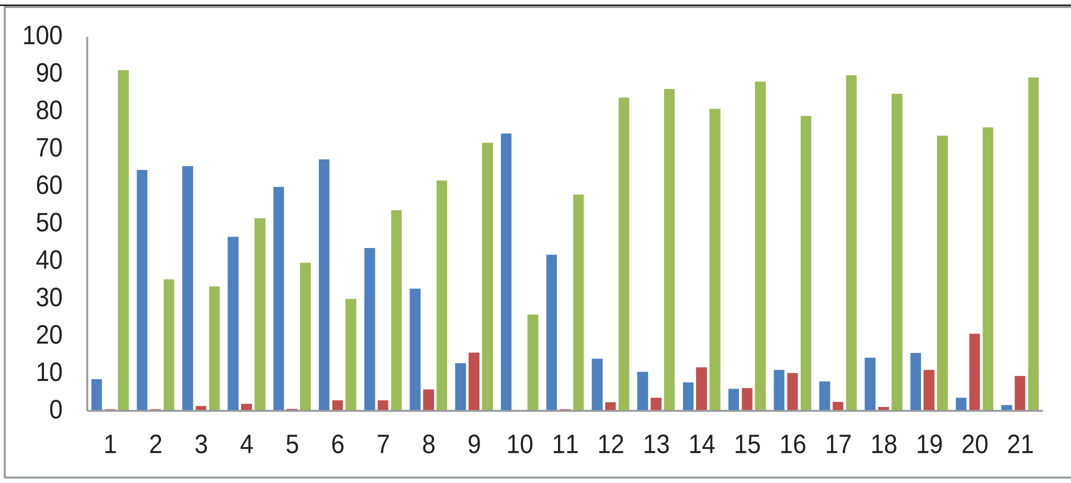
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Rabi Crop Season – Ordinary Least Squares

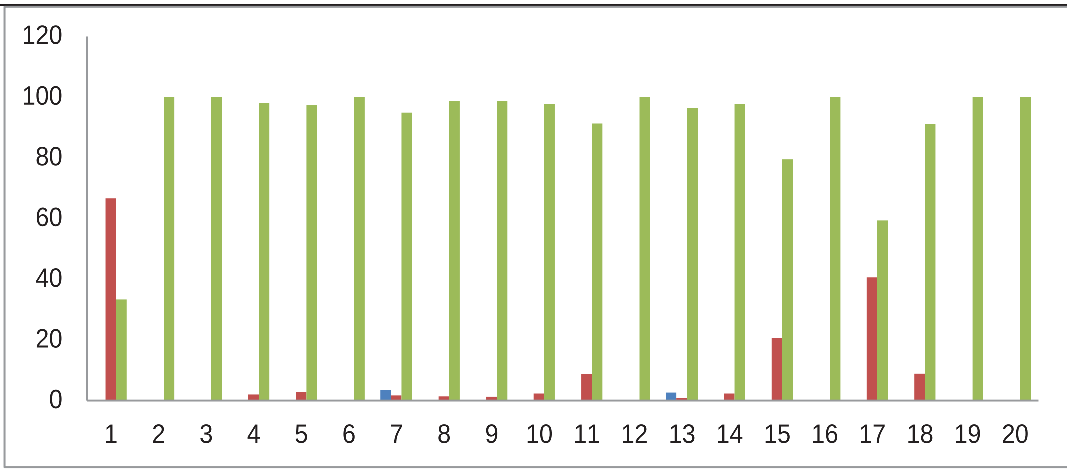
Temporal Granularity – 3 Month

Percentage Area Showing Significant Trends

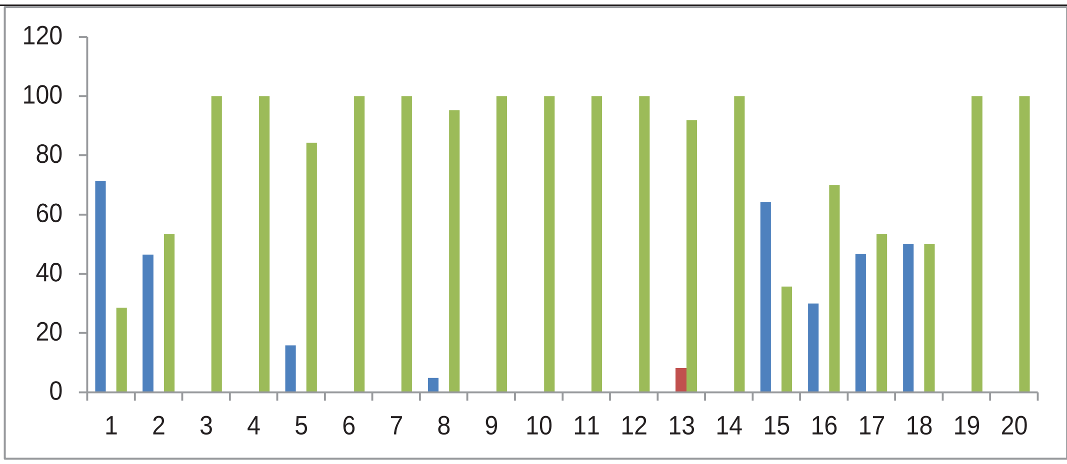
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

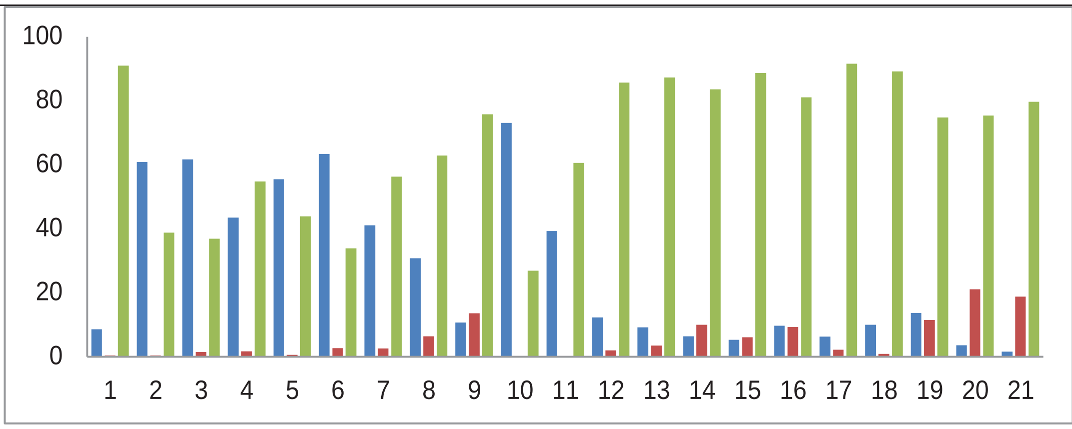
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Rabi Crop Season - Mann-Kendall Test

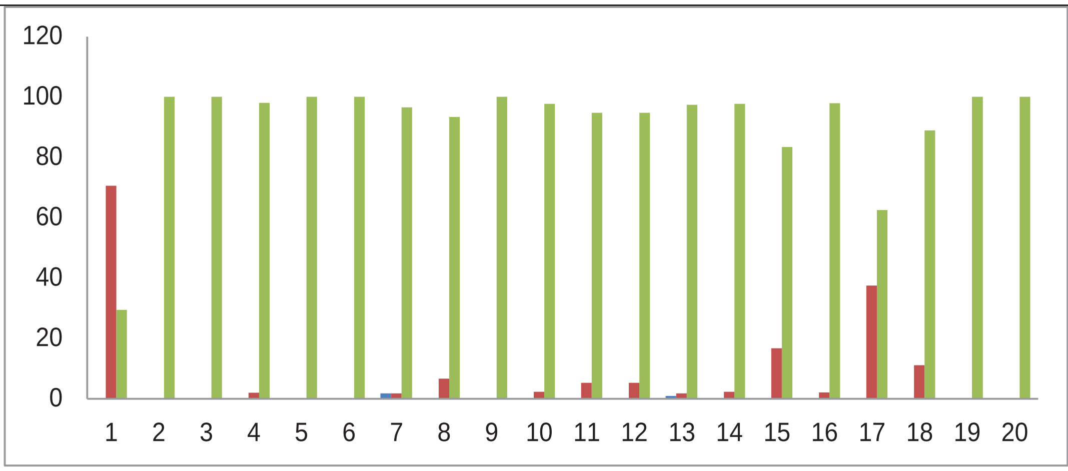
Temporal Granularity – 3 Month

Percentage Area Showing Significant Trends

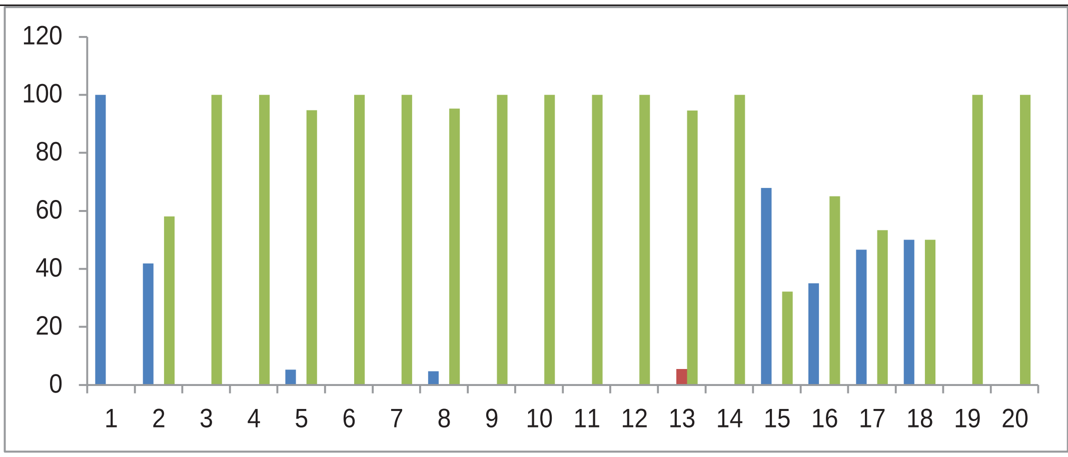
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

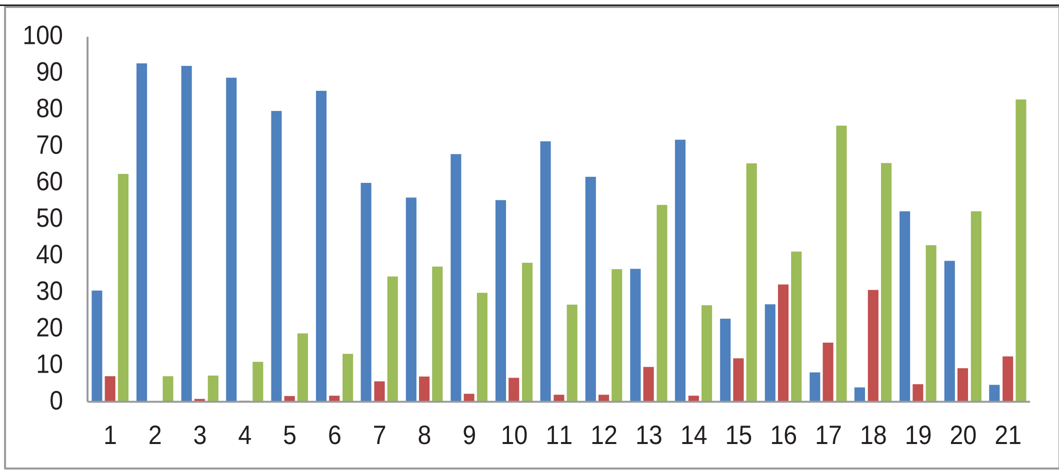
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Zaid Crop Season – Cox-Stuart Test

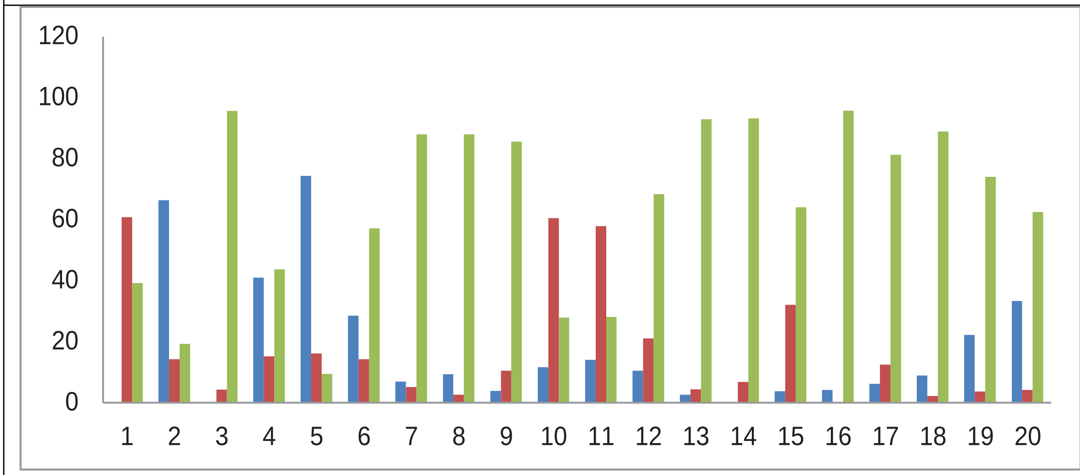
Temporal Granularity – 15days

Percentage Area Showing Significant Trends

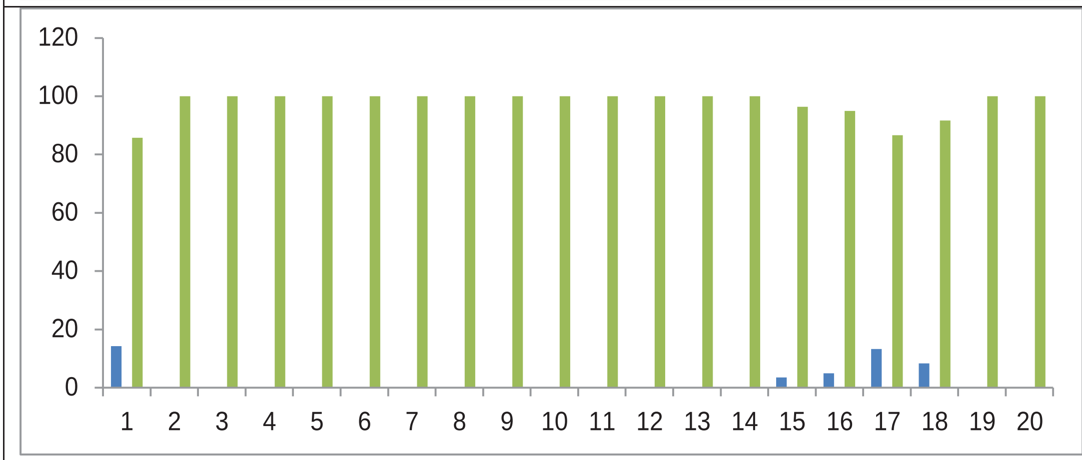
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

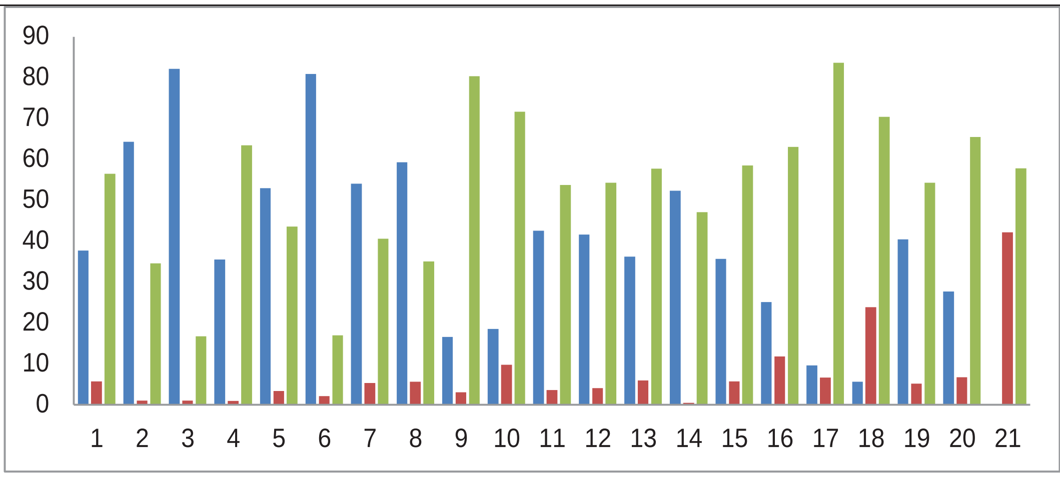
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Zaid Crop Season - Ordinary Least Squares

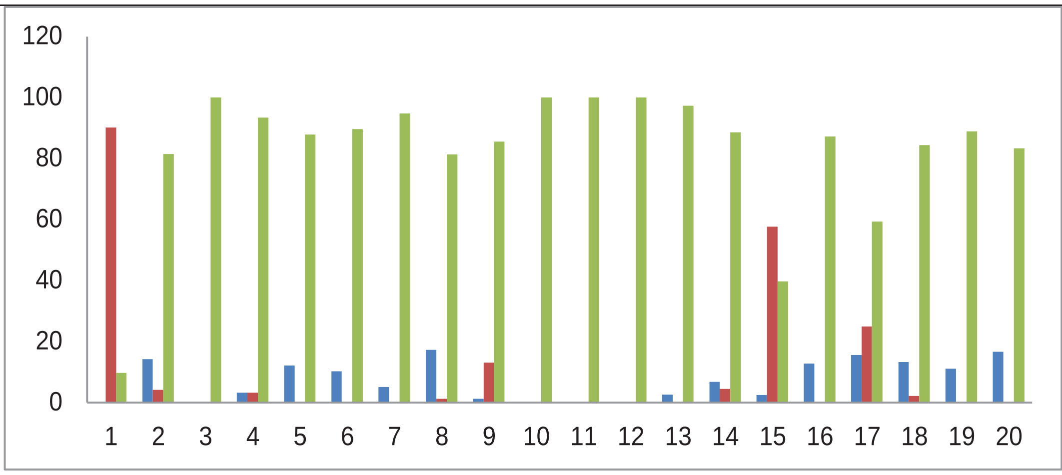
Temporal Granularity – 15days

Percentage Area Showing Significant Trends

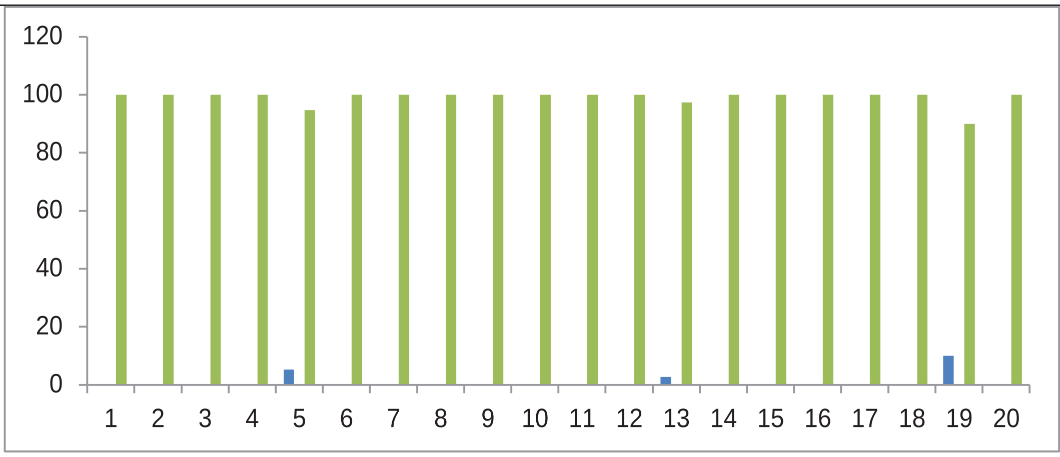
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

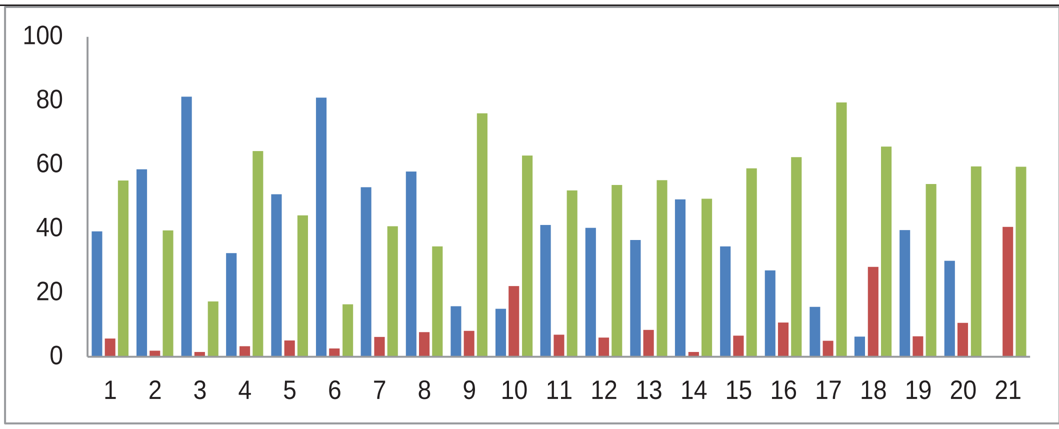
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Zaid Crop Season - Mann-Kendall Test

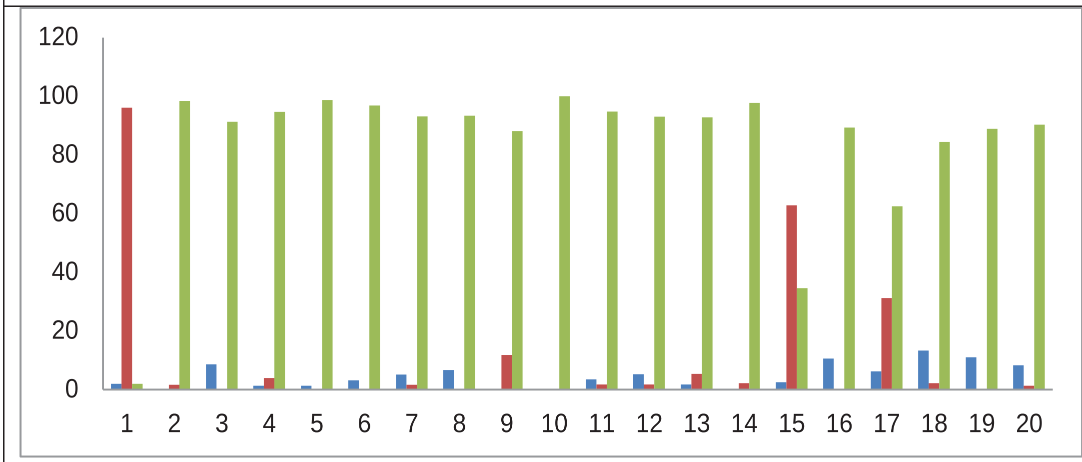
Temporal Granularity – 15days

Percentage Area Showing Significant Trends

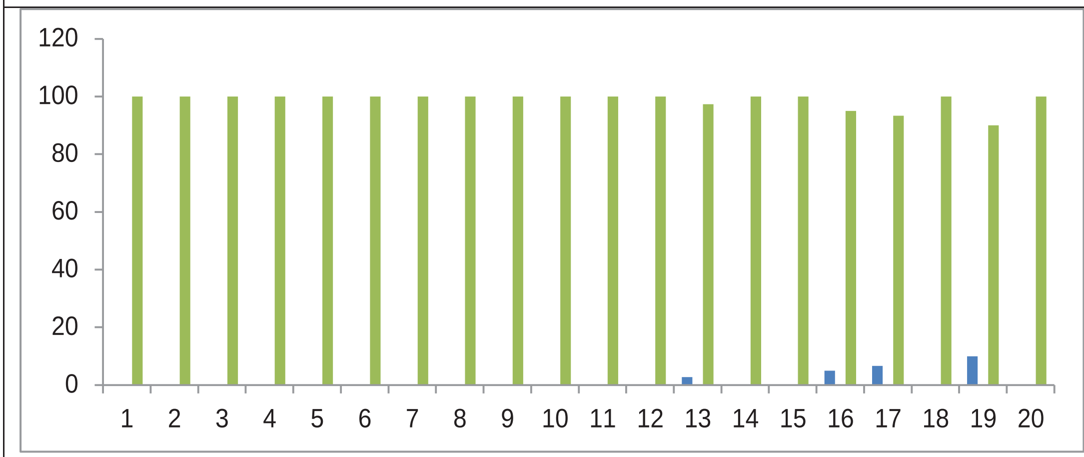
NDVI



RAINFALL



TEMPERATURE

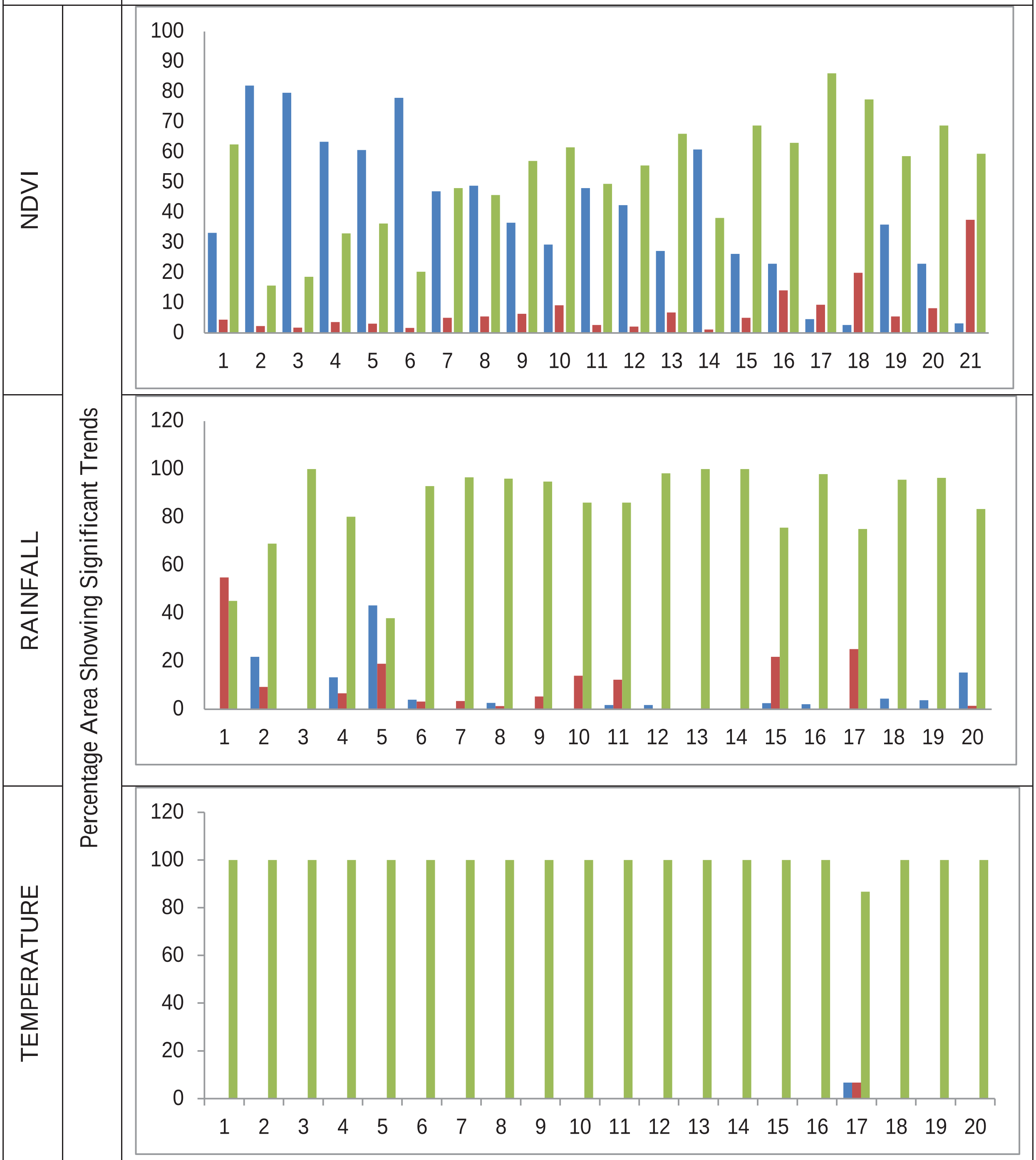


1 to 21 Represent Different Agro Ecological Regions

PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Zaid Crop Season - Cox-Stuart Test

Temporal Granularity – 1 Month



1 to 21 Represent Different Agro Ecological Regions

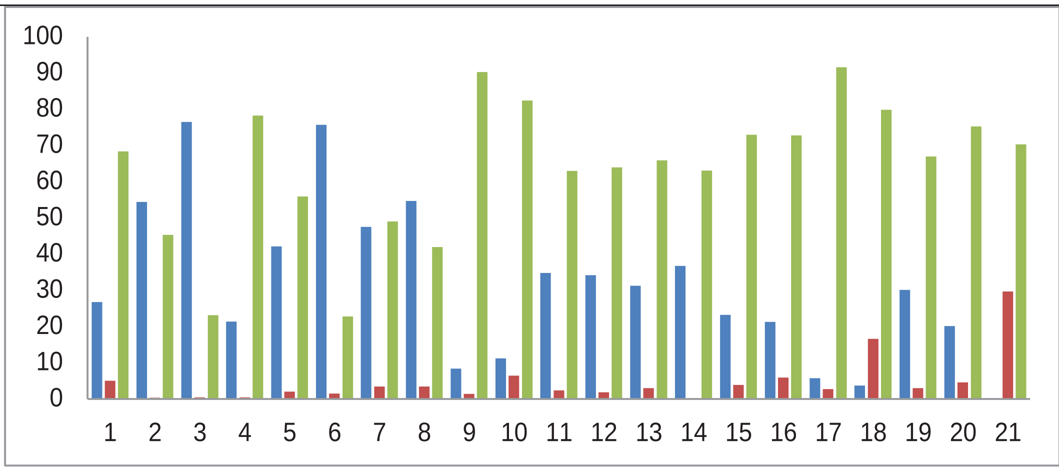
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Zaid Crop Season - Ordinary Least Squares

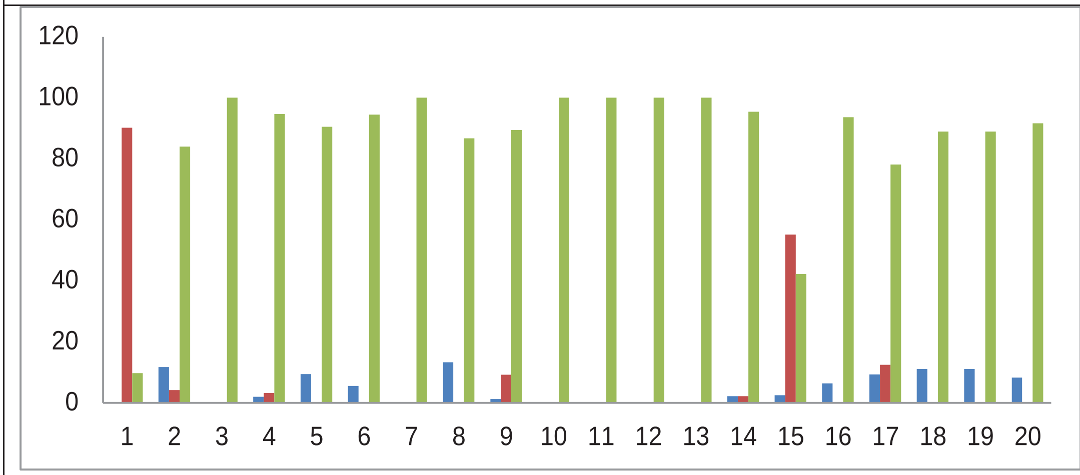
Temporal Granularity – 1 Month

Percentage Area Showing Significant Trends

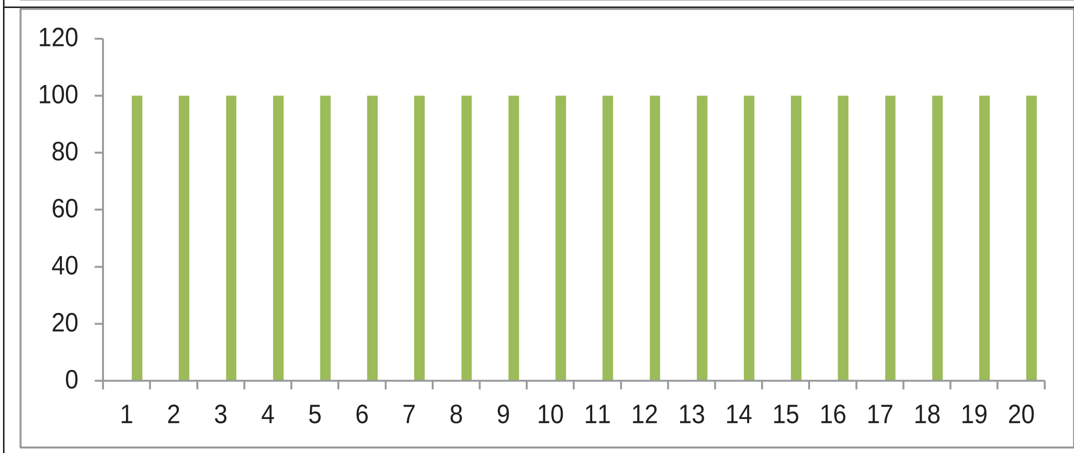
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

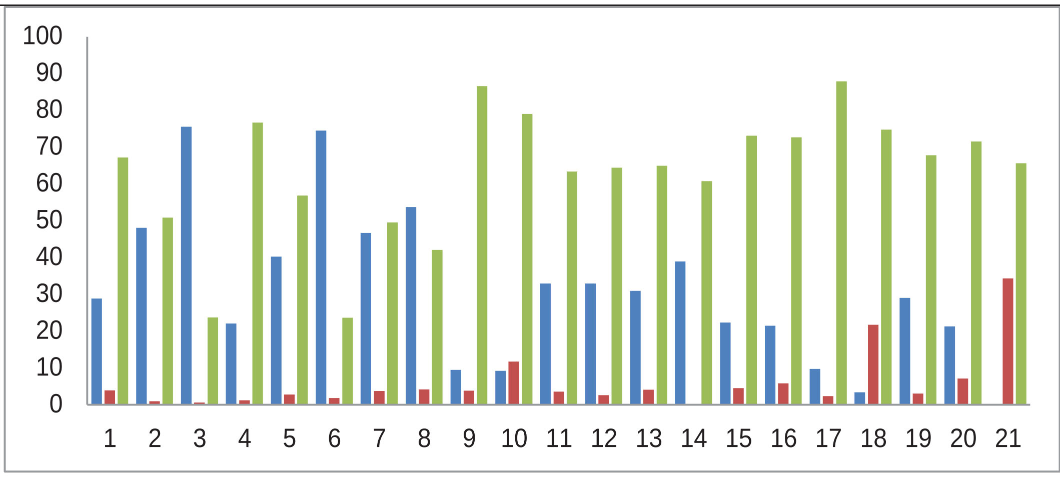
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Zaid Crop Season - Mann-Kendall Test

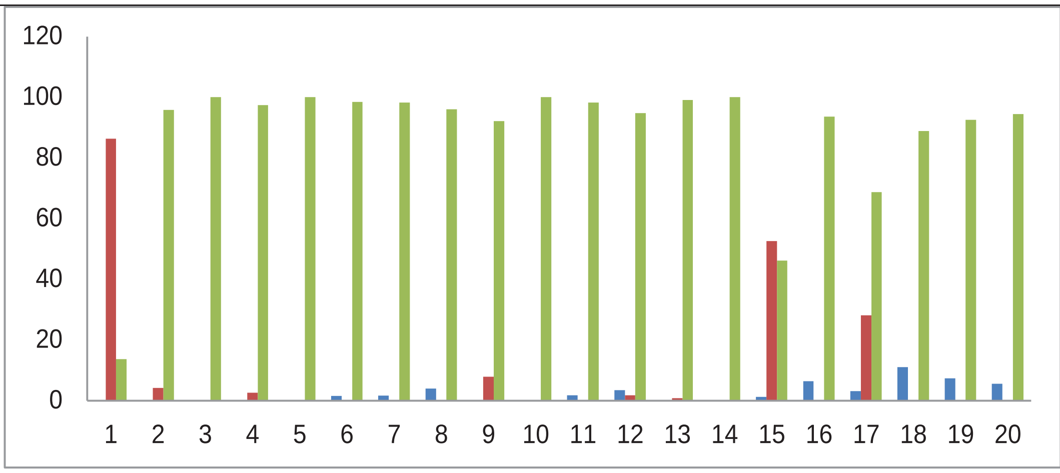
Temporal Granularity – 1 Month

Percentage Area Showing Significant Trends

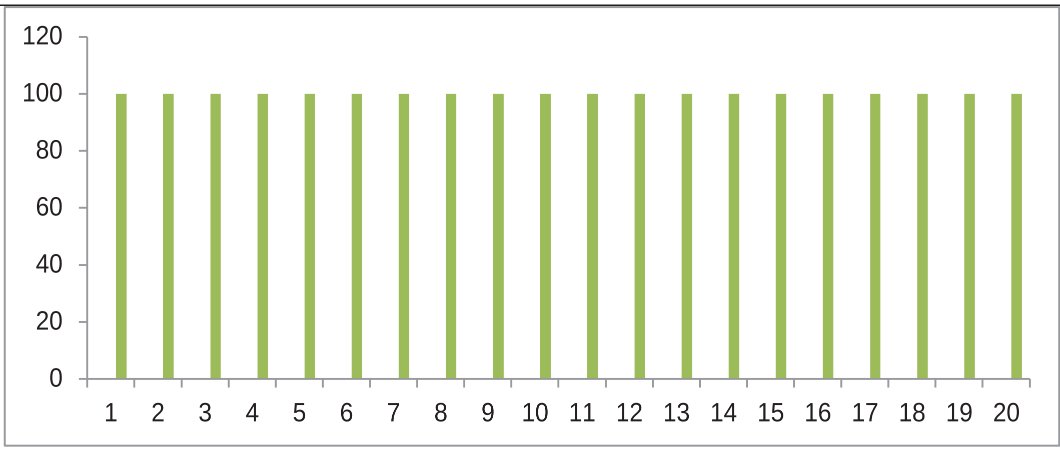
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

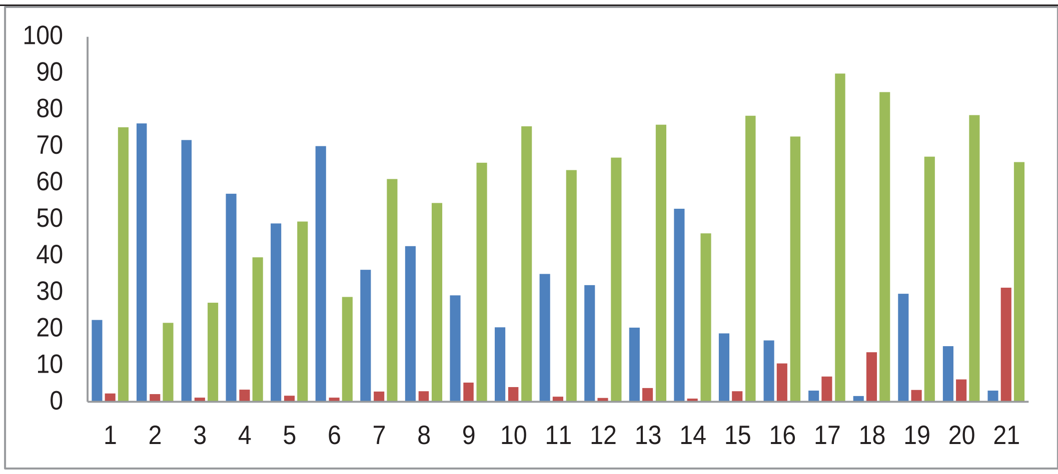
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Zaid Crop Season - Cox-Stuart Test

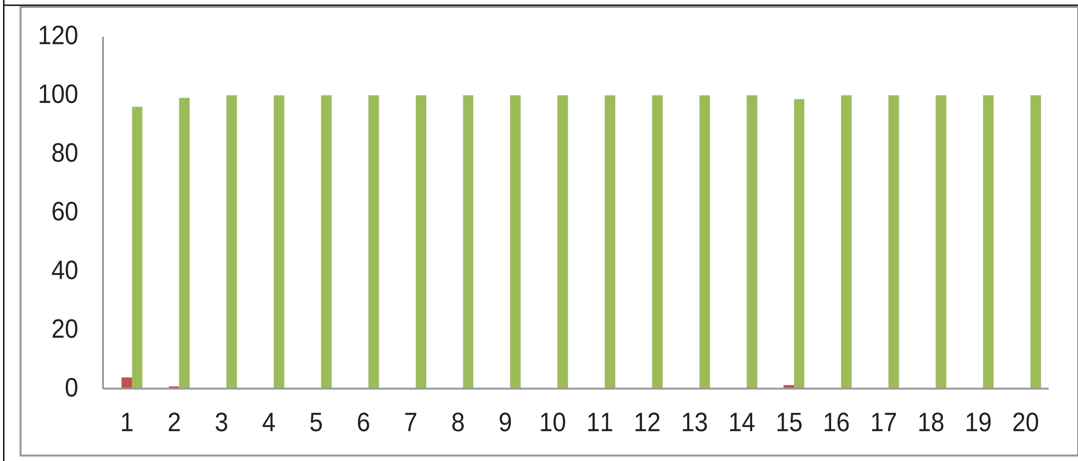
Temporal Granularity – 2 Month

Percentage Area Showing Significant Trends

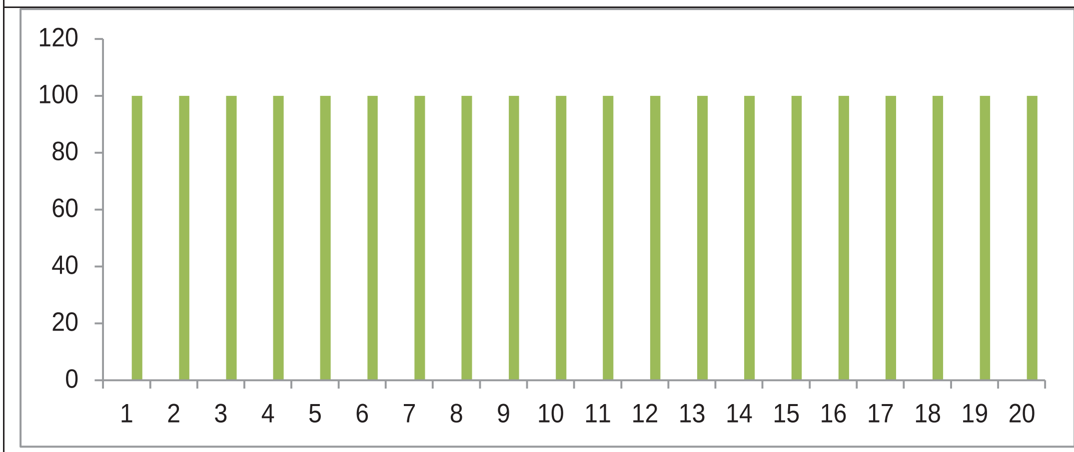
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

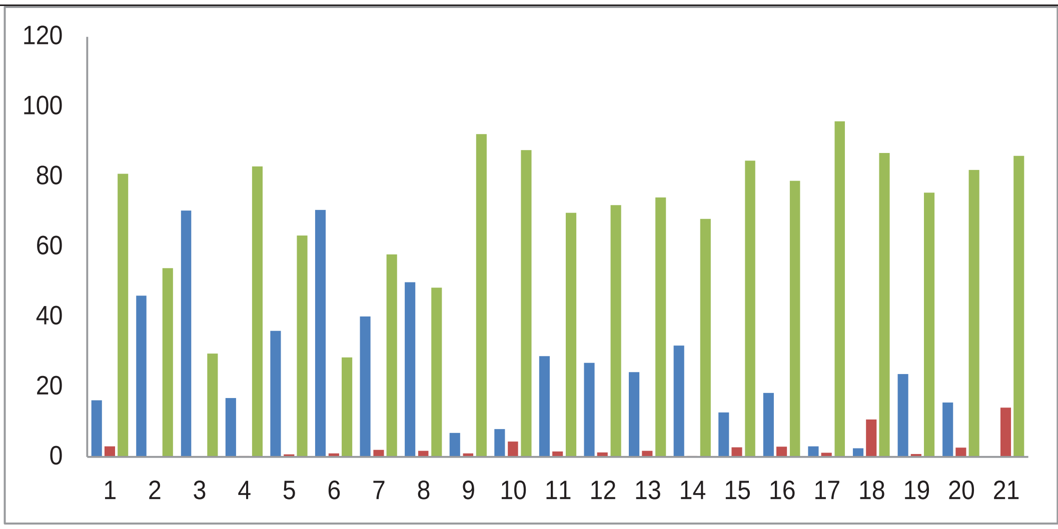
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Zaid Crop Season - Ordinary Least Squares

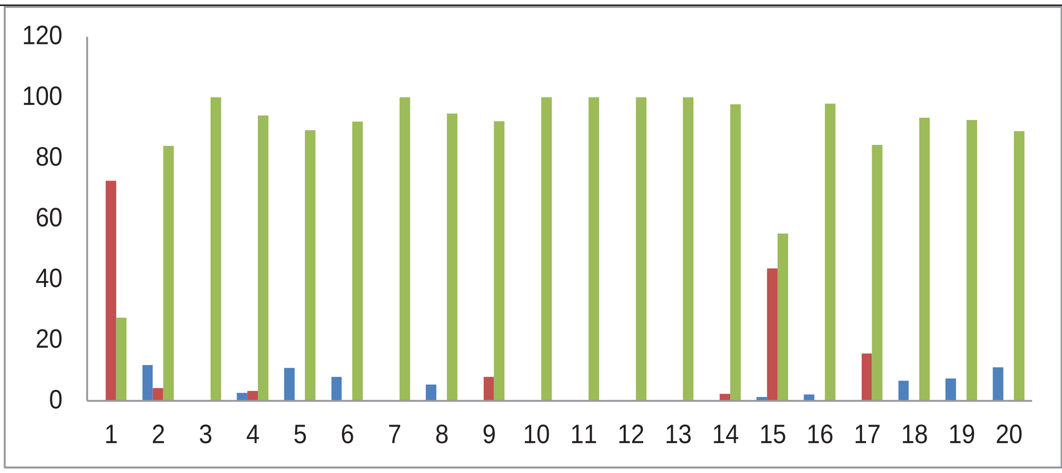
Temporal Granularity – 2 Month

Percentage Area Showing Significant Trends

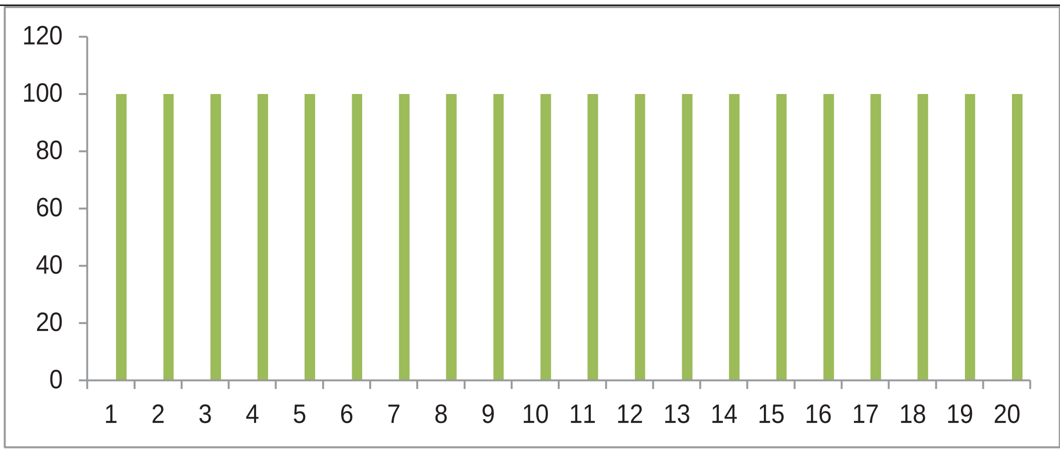
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

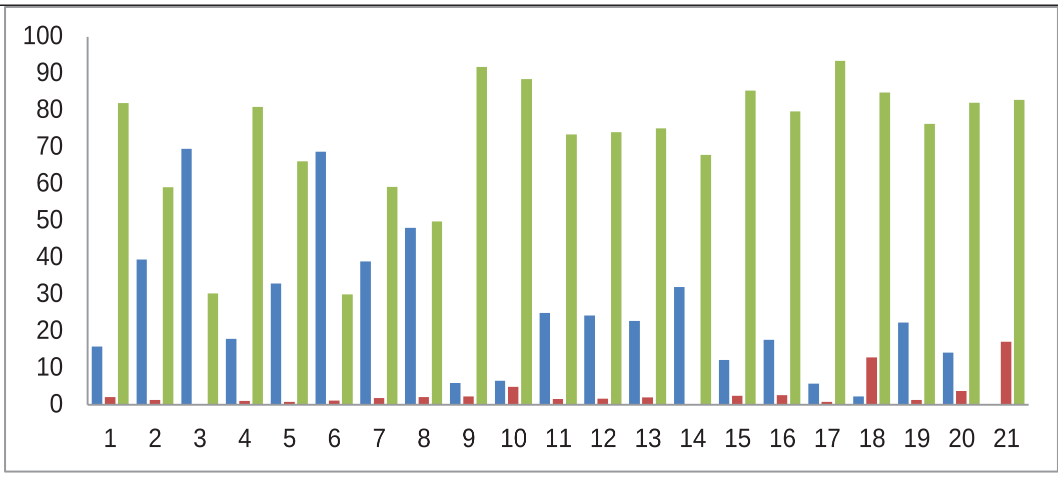
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Zaid Crop Season - Mann-Kendall Test

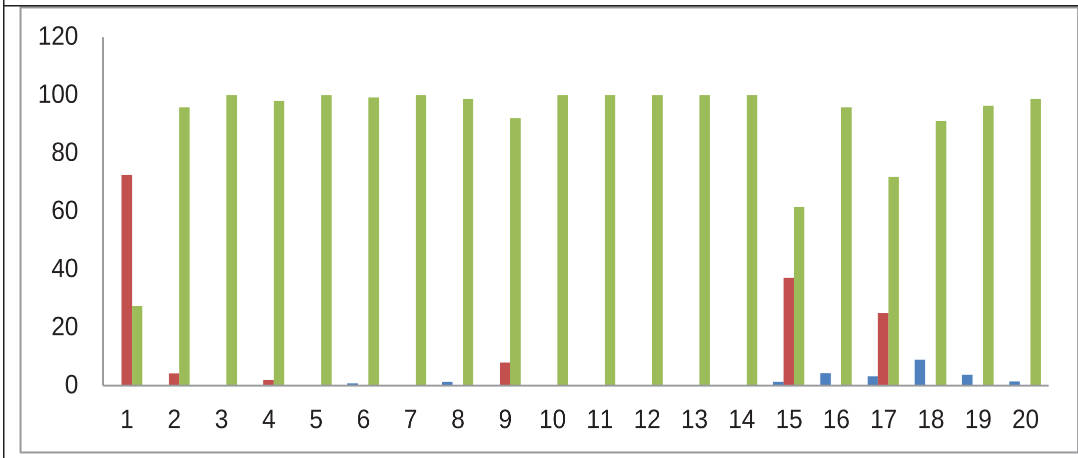
Temporal Granularity – 2 Month

Percentage Area Showing Significant Trends

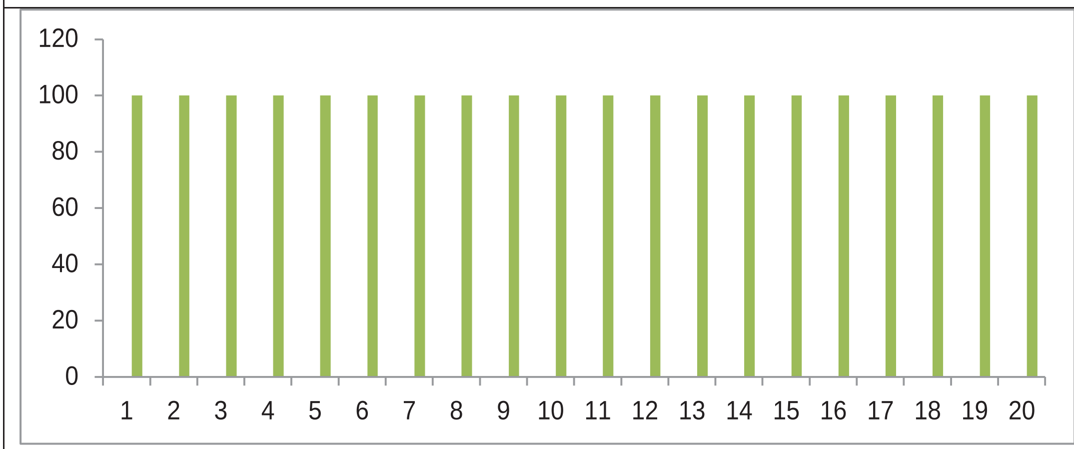
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

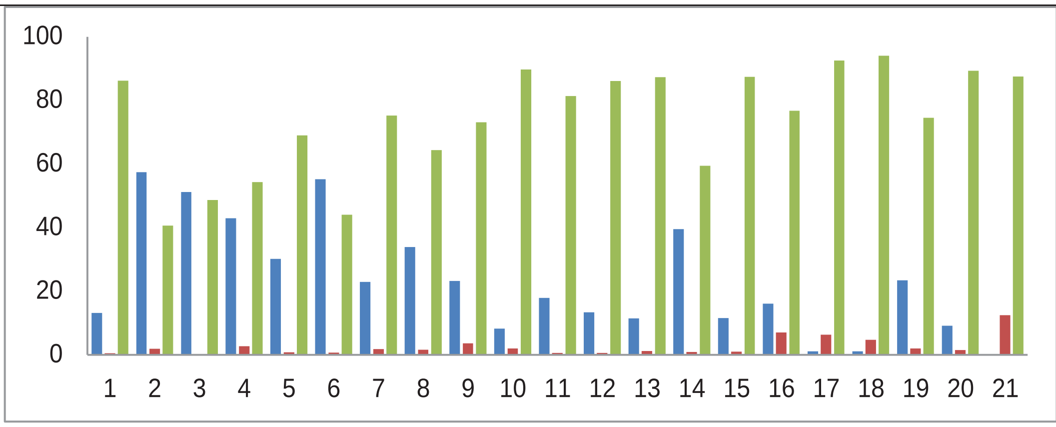
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Zaid Crop Season - Cox-Stuart Test

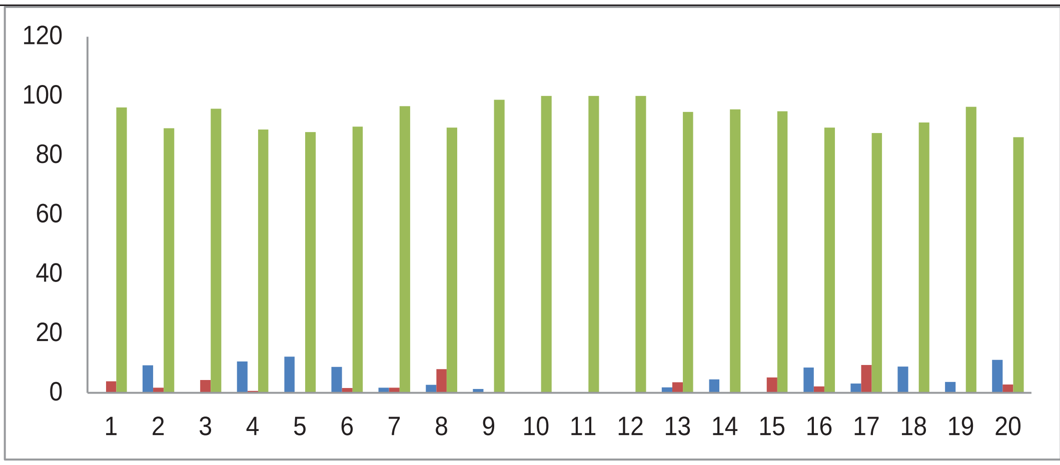
Temporal Granularity – 4 Month

Percentage Area Showing Significant Trends

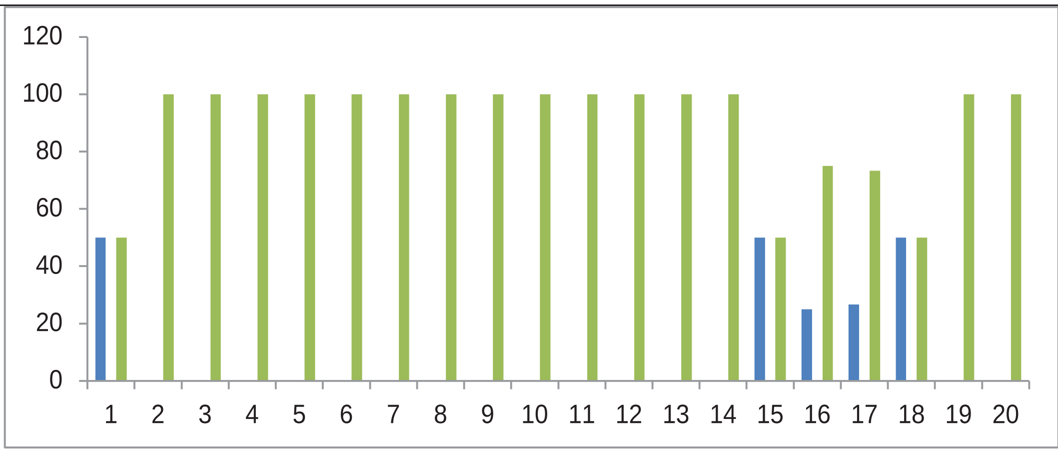
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

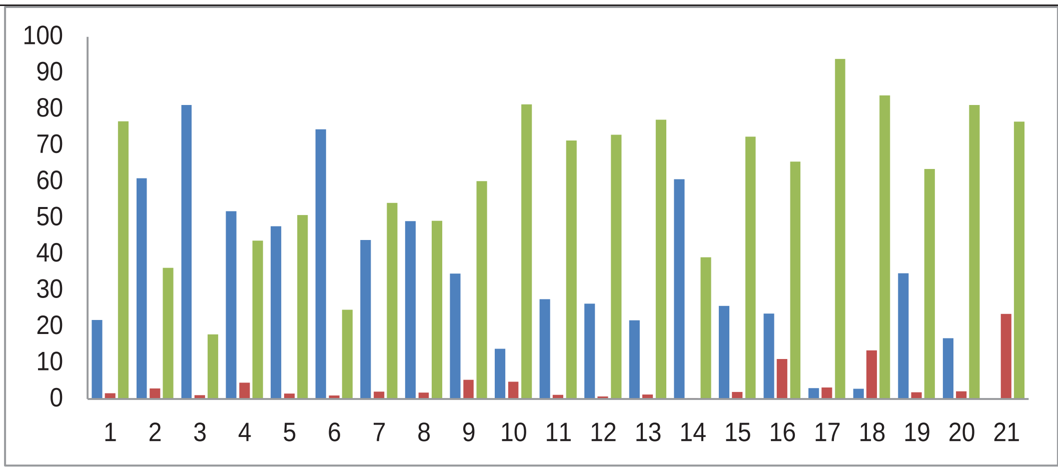
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Zaid Crop Season - Ordinary Least Squares

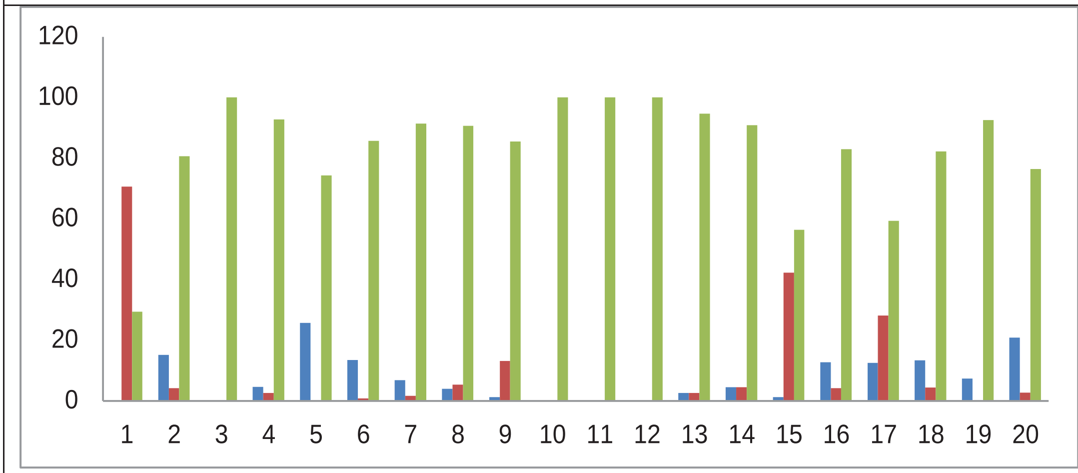
Temporal Granularity – 4 Month

Percentage Area Showing Significant Trends

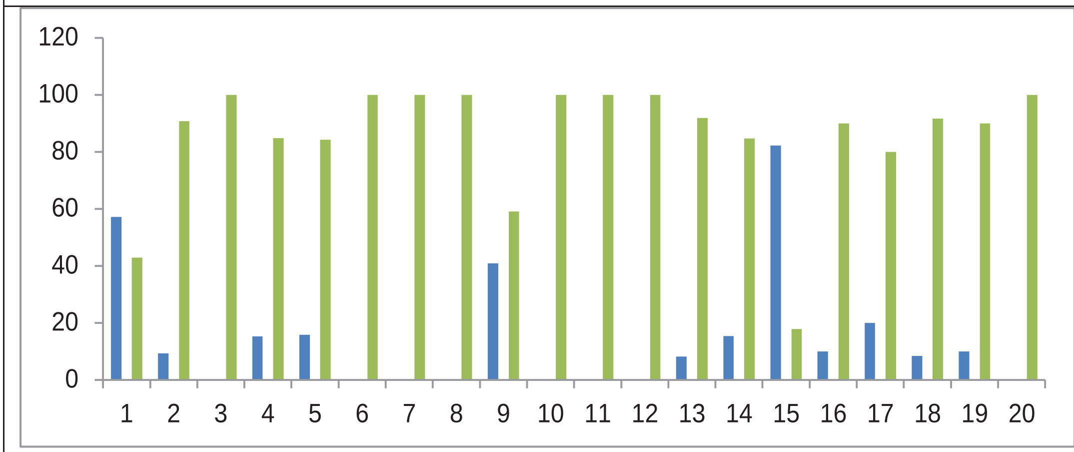
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

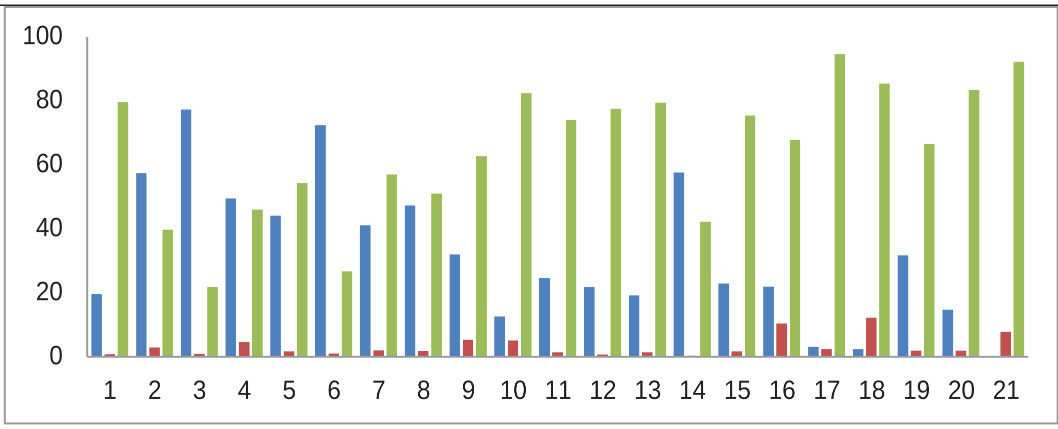
PositiveTrend Negative Trend No Trend

Trends in Agro-Ecological zones in India for Zaid Crop Season – Mann-Kendall Test

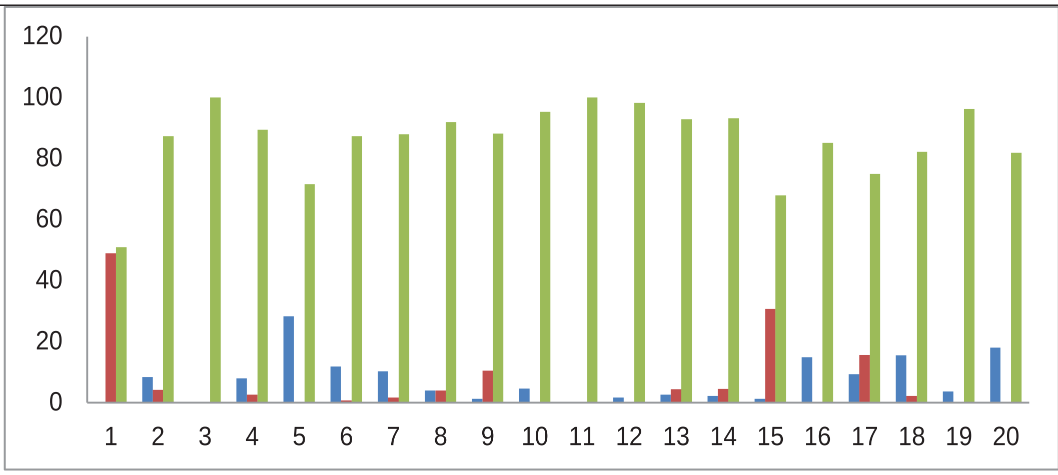
Temporal Granularity – 4 Month

Percentage Area Showing Significant Trends

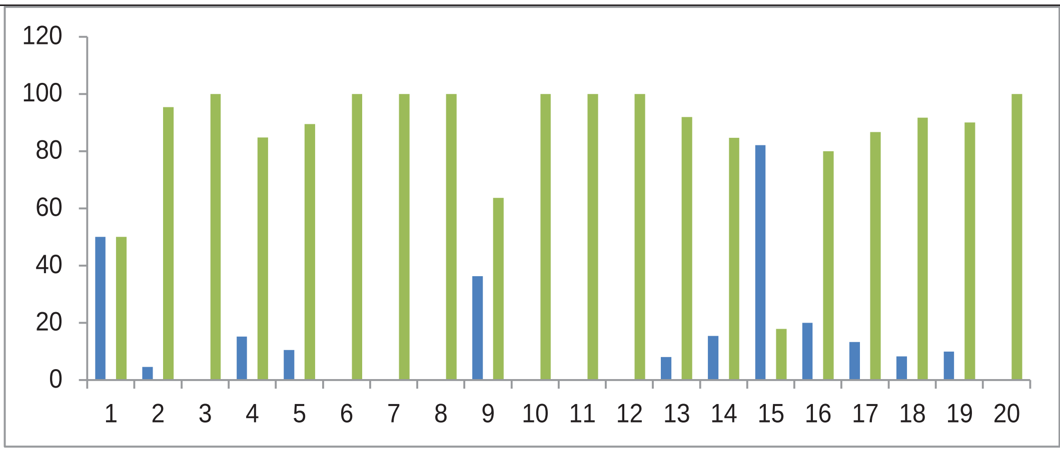
NDVI



RAINFALL



TEMPERATURE



1 to 21 Represent Different Agro Ecological Regions

PositiveTrend Negative Trend No Trend