Spatio-Temporal Eco-Environmental Vulnerability Assessment in Agro-Climatic Zone-III of Bihar Region

काशी हिन्दू विश्वविद्यालय BANARAS HINDU UNIVERSITY

AN INSTITUTION OF NATIONAL IMPORTANCE ESTABLISHED BY AN ACT OF PARLIAMENT

THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

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in

Agricultural Engineering

(Soil and Water Conservation Engineering)

Supervisor
Prof. Anupam Kumar Nema

Submitted by
Vikash Singh

DEPARTMENT OF FARM ENGINEERING
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UNDERTAKING FROM THE CANDIDATE

I, **Vikash Singh,** a Ph.D. scholar **(ID No. PF-18049)** registered and pursued my research work under the supervision of **Prof. Anupam Kumar Nema** , Professor, Department of Farm Engineering, Institute of Agricultural Sciences, Banaras Hindu University, for full term and hereby submitting the thesis entitled **"Spatio-Temporal Eco-Environmental Vulnerability Assessment in Agro-Climatic Zone-III of Bihar Region"** for the award of Ph.D. degree.

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ANNEXURE – E

[See Clause XIII.2 (b) (iii)]

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I, **Vikash Singh, ID No. PF-18049, Enrollment No. 390171** certify that the work embodied in this Ph.D. thesis is my own bonafide work carried out by me under the supervision of **Prof. Anupam Kumar Nema** and the external supervision of **Dr. Arpit Chouksey**, Water Resource Department, IIRS, ISRO, Dehradun , for a period from **August 2018 to December 2021** at Department of Farm Engineering, Institute of Agricultural Sciences, Banaras Hindu University, Varanasi (UP) and Indian institute of Remote Sensing, ISRO Dehradun (Uttarakhand). The matter embodied in this Ph.D. thesis has not been submitted for the award of any other degree/diploma.

I declare that I have faithfully acknowledged, given credit to and referred to the research workers wherever their works have been cited in the text and the body of the thesis. I further certify that I have not willfully lifted up some other‟s work, para, text, data, results, etc. reported in the journals, books, magazines, reports, dissertations, theses, etc., or available at web-sites and included them in this Ph. D. thesis and cited as my own work.

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

Supervisor
(Prof. Anupam Kumar Nema)

(Signature of the HOD/Coordinator of the School with seal)

ANNEXURE – F
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By

Vikash Singh

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It's my heart turn

It's my pleasure to glance back and recall the path one traveled during the day of hard work and perseverance. Interdependence is definitely more valuable than independence. This thesis is the result of three year and three months of work whereby I have been accompanied, supported and guided by many people. I would like to thanks everyone who, knowingly or otherwise, has provided support, encouragement and assistance along the way. First and foremost, praises and thanks to ***GOD, the Almighty****, for having bestowed upon me good health, courage, inspiration, zeal and for his showers of blessing throughout my work to complete the research successfully.*

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Last but not least the outset, being the student of this great institution, I bow my head with great reverence to the lotus feet of ***Bharat Ratna Mahamana Pandit Madan Mohan Malviyaji,*** *the founder of the great temple of Goddess* ***"SARASWATI"*** *for students like us to worship her and improve our lives.*

Any omission in this brief acknowledgment does not mean a lack of gratitude.

Date:

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CONTENTS

LIST OF ABBREVIATIONS AND SYMBOLS

Abbreviation/Symbol	Description
%	Percentage
AHP	Analytical Hierarchy Process
CGWB	Central ground Water Board
CI	Consistency Index
CR	Consistency Ratio
CWC	Central Water Commission
DEM	Digital Elevation Model
EVI	Eco-environmental Vulnerability Index
EVSI	Eco-environmental Vulnerability Integrated Index
FAO	Food and Agriculture Organization
GOI	Government of India
IDW	Inverse Distance Weighting
IIRS	Indian Institute of Remote Sensing
IMD	Indian Meteorological department
ISRO	Indian Space Research Organization
Km	Kilometer
LANDSAT	Land Satellite
Lat.	Latitutde
Long.	Longitude
LULC	Land Use Land Cover
Max	Maximum
Min	Minimum
Monsoon	June - September
MSL	Mean Sea level
NBSSLUP	National Bureau of soil survey and land use Planning
PCA	Principal component Analysis
Post-monsoon	October to November
Pre-monsoon	March to May
RI	Random Consistency Index
SPCA	Spatial Principal Component Analysis
SPI	Standardized Precipitation Index
SWAT	Soil and Water Assessment Tool
Tmax	Maximum temperature
Tmin	Minimum Temperature
USA	United States of America
WMO	World Meteorological Organization

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PREFACE OF THE THESIS

This thesis is written as the final draft for doctorate degree in agricultural Engineering, specialization in soil and water conservation engineering with the primary aim to **Spatio-Temporal Eco-Environmental Vulnerability Assessment in Agro-Climatic Zone-III of Bihar Region**. I hope the results will be helpful for our environmental and climate change policy makers. So, the present study deals with assessment of spatial and temporal variation in the level of eco-environmental vulnerability in southern Bihar region.

The work described in the thesis has been carried out in between August, 2018 to December, 2021 at Banaras Hindu University and Indian Institute of Remote Sensing under the supervision of Dr. Anupam Kumar Nema, Professor, Department of Farm Engineering, Institute of Agricultural Sciences, BHU, Varanasi and Dr. Arpit Chouksey, Scientist, WRD, IIRS, ISRO, Dehradun.

Chapter I envisages the introduction, which provides much of the general background and overview of drought severity and environmental vulnerability conditions. The Chapter identifies the research gaps and specifies the objectives for the research work.

Chapter II reviews the literature on important work done in the past on the subject and explains the research work carried out by different workers in India and abroad.

Chapter III explains the details of the study area, the materials required and methods adopted in research work to accomplish the defined objectives.

Chapter IV discusses the results and discussion of the research work performed for achieving the objectives.

Chapter V summarizes the research work and lists the conclusions drawn from the present investigation.

The sections on Bibliography deals with the details of references consulted during the entire investigation.

(Vikash Singh)

Chapter I

INTRODUCTION

1.1 Background of the Research

Human beings and their environment have been closely related with each other since the evolution of life on the Earth. In this symbiotic relationship, initially the human beings have attempted to adjust themselves with the surroundings but have subsequently changed the environment abruptly, due to their continuous demanding needs. This has created an imbalance in many ecological systems and thereby has created several anthropogenic vulnerabilities in the environment.

In the twentieth century the continuous rise in the emission of green house gas, have contributed in making the situation more vulnerable in most countries and ensures the unavoidable negative impact of climate change on the human surroundings (Bolin B., 1998; Wigley T. *et al*., 1996). Globally, climate change can, and is resulting in the occurrence of unavoidable extreme climatic events, like droughts, floods, earthquakes, landslides, cloud bursting etc. (Fussel, H.M. *et al*., 2006; Rajesh, S. *et al*., 2014). It has mixed impacts in different regions like change in crop selection and cropping pattern, water supplies availability, biodiversity of vegetation and forest, political and social system and several other modifications in the regional economy (Summary for policy makers: WGII, Fifth Assessment Report, 2014). All of these extreme and unexpected events, caused by the climatic change, indicate that our environment is becoming more and more vulnerable day by day.

Firstly, the need for developing and evaluating environmental vulnerability index was considered at the Global Summit on “Small Island States” organized at Barbados in 1994 (SOPAC EVI, Manual). In the meet the United Nations formally expressed the extreme desire for the development of such an index and evaluating it at country level in the Barbados action plan. In the index developing process, the selection of indicators was a very intellectual and crucial work as the indicators should be a true representative of the environment of any country. Finally after detailed data analysis, 57 indicators were found to be capable to assess the vulnerability index. This included 39 risk indicators, 5 resilience indicators and 13 environmental degradation indicators. The advantages of developing such an index was that the vulnerability can be regionalized country wise and consequently planning, management and financial aid for mitigation projects can be processed and contributed.

Since 1994, the area of environmental vulnerability by external and internal factors has been a topic of active research in different aspects. Environmental vulnerability indicates the extent of risk; the natural environment has been put into danger. The eco-environment symbolizes the condition of environment with respect to human beings. The attributes at risk consists of ecosystems, human population and the bio-physical processes, influenced by anthropogenic events (Kaly *et al*., 2002). The vulnerability is precisely expressed in terms of the level of sensitivity, extent of exposure and the adaptive and flexible capacity of the system to adjust itself according to the potential change in the surroundings. The assessment of environmental vulnerability is carried out for comprehensive analysis and evaluation of the resource system influenced by the existing natural conditions and interrupted by human activities (Fan *et al*., 2009).

The southern and south-eastern part of Asia, which harbors many people below poverty line, sustaining on availability of marginalized resources has experienced frequent and continuous extreme weather and climatic events in the last decades (Dev, S.M., 2011).

India has also been the witness of extreme inevitable impacts of climate change. Cruz *et al*. (2007), carried out a research work on the environment of India and found it to be more vulnerable to the change of climate. The country is quite vulnerable to the change of climate and its impact on sectors such as forestry, agriculture, water resources and the health sector, etc. has been well reported by many researchers (Fussel, H.M. *et al*., 2006; Rajesh, S. *et al*., 2014; Summary for Policymakers: WGII, Fifth Assessment Report (AR5), 2014; Dev, S.M., Mumbai, India, 2011).The Gross Domestic Product (GDP) and food security of India is highly affected by floods and drought caused by extreme and erratic rainfall events, indicating the importance of rainfall variability in making Indian economy (Wigley, T.M.L. *et al*., 1996).

In the world, India ranks higher in list of most drought vulnerable countries with a drought frequency of at least once in every three years during the last decades (FAO 2002, World Bank 2003). Drought is a complex hazard and one of the major challenges to life affecting social as well as economic progress. The damage contribution in terms of percentage to agriculture with respect to other sectors due to the events of severe drought was found to be around 22% (FAO, 2015). The drought impact, as compared to different natural calamities is more severe. The categorization of drought can be expressed as its regional extent, severity condition and duration of persistence. The severity indicates how intensely the area is hit by the hazard; the persistence shows the continuous existence of drought (WMO, 2016 and GWP, 2016).

The attributes indicating impacts of drought comprises of soil water depletion, stream flow reduction, storage in reservoir and level of groundwater as well as lake (Dracup *et al*., 1980). The various spatiotemporal drought factors were integrated for drought vulnerability assessment in the drought-prone region of Bundelkhand, Madhya Pradesh (Kar *et al*., 2018). The spatial and temporal drought analysis using 3-m SPI is very helpful to detect the onset and withdrawal of the drought event and the drought prone areas (Kar *et al*., 2018). The drought severity is taken as an important factor for the drought propagation analysis as compared other indexes, which help in advance, policy makers to detect this phenomenon (Kar *et al*., 2016).

Ghosh *et al*. (2014) analysis drought severity in southern Bihar and concluded that the region south of river Ganga faces drought severity during Kharif season every year because of delayed onset of monsoon and uneven spatial variation of rainfall. The drought severity of pre-monsoon season is found to more severe as compared to that of the post monsoon condition of drought. The months of June, July and even October are found to be the most drought prone times. The ten most drought affected districts of Bihar that are: (i) Kaimur, (ii) Rohtas, (iii) Aurangabad, (iv) Buxar, (v) Bhojpur, (vi) Gaya, (vii) Jahanabad, (viii) Patna, (ix) Siwan and (x) Gopalganj.

Department of agriculture of Bihar government (2014, a) conducted a research study on the drought condition of Bihar. The work covered the whole 38 districts of Bihar for the analysis from 2009 to 2013. It resulted that twenty-six districts in 2009, all of the thirty-eight districts in 2010, twenty five districts in 2012 and thirty-three districts in 2013 were affected by the natural hazard. These research works indicate that drought vulnerability is increasing in the south Bihar region.

On the other hand the population pressure in Bihar is relatively higher than other states of India (Thorpe *et al*. 2007, Minhas & Samra, 2003). The decadal growth of population in the state (25.1%) is also much higher with respect to the India (17.6%) and the number of person per km2 (1102) is almost three times that of the average national population density (382, per km2) (Government of Bihar 2012). Such pressure puts much negative pressure on forestry, water resources, agriculture farming and biodiversity (Carney 1998), which caused household vulnerability, since the reach to products of forest, possession of land and its ownership are important indicators of households' condition, as majority of the population depends on them for their livelihood (Vincent & Cull 2010). From 2001 and 2012, the drought events cause reduction in the yield of paddy, on average, by 450 kg/ha in a district, in addition the paddy crop area felt by nearly 4750 ha. The effect on production is indeed very high and indicates critical vulnerability of the primary kharif crop in the state (Kishore, A., Joshi, P.K. & Pandey, D., 2015). In 2008, the Bihar government launched a large scheme, known as conditional cash transfer (CCT) scheme to mitigate the impact of drought on crop area and production in the state. Almost three million farmers applied for the diesel subsidy in the paddy season of 2013, and since its launch, the scheme has delivered USD 284 million to farmers in drought-affected areas of the state (Department of Agriculture, Bihar, 2014, b). This is one of the largest CCT schemes meant to mitigate the impact of drought on crop production anywhere in the developing world, implemented by the government of Bihar (Kishore, Joshi, & Pandey, 2014)..

This indicates that the environment of south Bihar is becoming vulnerable for the human being due the combine effect of drought, population pressure and other factors that should be analyzed. Thus a research study is required to evaluate the spatiotemporal decadal change in the environmental vulnerability level of the state, particularly focussing on drought severity, using multi criteria decision analysis techniques, so that an early step can be taken to mitigate the inevitable impact.

1.2 Statistical Approach for Analysis

Several statistical and non-statistical methods have been conceptualized to analyze the level and severity of vulnerability. Mathematical modelling (Wilson *et al*., 2005), comprehensive evaluation method (Goda and Mastuoka, 1986), fuzzy evaluation method (Enea and Salemi, 2001), grey evaluation method (Hao and Zhou, 2002), artificial neural network (Dzeroski, 2001) and spatial multi-criteria evaluation (SMCE) (Enete *et al*., 2010) have been used for qualitative and quantitative assessment of environmental vulnerability. The analysis of environmental vulnerability is a multi-dimensional technique which is necessary to determine the inter-relationship of all the influencing factors and to evaluate dominating factors. Principal Component Analysis (PCA) also known as factor analysis is a powerful statistical tool to reduce the dimensionality of input datasets and extract the existing relationship, by creating composite of all the input variables, however, it doesn't evaluate the result spatially. On the other hand, remote sensing and GIS is used to develop the map of several variables and analyze their spatial distributions, but it is very difficult to find out the relationship in between different attributes, using GIS. The integration or combination of GIS and PCA, hence termed as spatial principal component analysis (SPCA), can be used to reveal the detailed spatial tendencies and contribution of the factors in the vulnerability. SPCA has been used in many environmental research works for finding the relationships among different indicators (Calais *et al*., 1996; Yu *et al*., 1998). Shi *et al*. (2009) used SPCA to evaluate the effects of land use and land cover change on the quality of environment. Li *et al*. (2006 a, b) concludes the technique to be useful approach for environmental vulnerability assessment. Using SPCA, an eco-environmental vulnerability index can be determined based on the linear correlation coefficients and the percentage contribution of several factors can also be estimated (Parinet *et al*., 2004). Due to all such special features of the SPCA technique, it was applied for environmental vulnerability assessment in the present research work.

The accuracy of the vulnerability evaluation cannot be guaranteed by the SPCA alone, which is based on the concept of dimension reduction of input datasets. So in addition to SPCA the evaluation process must be done by some other method to validate the result.

The Analytic Hierarchy Process (AHP) developed by Thomas Saaty (1980), is an effective technique for solving the complex and multi-dimensional decision making problems. It is based on the principles of decomposition, comparative judgment and priorities synthesis. It allows the decision maker to define priorities and make the best solution in the given constraints, by providing aid in determining the weight for each variable of all class and sub-class.

Chunsheng, W. *et al*. (2018) evaluate the ecological vulnerability in their study area using the two methods of Fuzzy analytical method and analytical hierarchy process and find the combination of the two models as useful for the vulnerability assessment. Venkatesh, R. *et al*. (2020) applied AHP technique for monitoring of eco-environmental vulnerability in watershed region in India and found it as an effective technique.

1.3 Objectives

The present research work has been planned to address the identified problems using SPCA and AHP techniques, in south Bihar Agro-Climatic Zone-III with the following objectives:

1. To evaluate drought severity using Standard Precipitation Index (SPI) in the study area,
2. To assess the eco-environmental vulnerability of the study area using Remote Sensing and G.I.S software.

3. To analyse the spatiotemporal decadal change in the environmental vulnerability level.
4. To prepare the rebuilding planning as per the identified major problems and resource availability in the study area.

Chapter II

REVIEW OF LITERATURE

A detailed review of drought severity, environmental vulnerability, spatiotemporal decadal change in vulnerability level and rebuilding planning to mitigate the impact of different types of vulnerabilities, carried out by various researchers has been summarized under the following headings:

2.1 Drought concept and different approaches to evaluate its severity,

2.2 Different approaches to vulnerability,

2.3 Statistical methods for vulnerability assessment and

2.4 Rebuilding planning to mitigate the impact of vulnerability.

2.1 Drought concept and different approaches to evaluate its severity

According to the World Meteorological Organization (WMO, 1986), drought is defined as a sustained period of deficiency in the amount of precipitation. The UN Convention to Combat Drought and Desertification (UN Secretariat General, 1994) documented drought as the natural phenomenon that prevails when precipitation falls significantly below the normal levels, resulting in serious hydrological imbalances that adversely affect the agriculture production resource systems. The Food and Agriculture Organization (FAO, 1983) of the United Nations considers drought as a hazard and defines it in terms of the percentage of years when crops fail to yield effectively due to the unavailability of required moisture condition. The encyclopedia of climate and weather (Schneider, 1996) conceptualized drought as an extended period that may be a season, a year or several years when there is a deficit in rainfall relative to the normal rainfall of the area. Gumbel (1963) defined drought as the smallest annual value of daily stream-flow. Palmer (1965) described drought as a condition when there is a significant deviation from the normal hydrologic conditions of the area. Linseley et al. (1959) defined drought as a sustained period of time without significant rainfall. Undoubtedly, drought is a condition of deficit in rainfall, but this concept is very controversial among researchers of different region across the globe as per their climatic conditions.

In USA according to Conrad (1944), a period of twenty consecutive days or more without 6.4 mm or more of precipitation in 24 hours during the season of March to September, is considered as drought situation. In Indian condition, the India Meteorological Department (IMD) defines drought in any area, when the rainfall deficiency in that area is greater than 26% of its long term normal rainfall. In order to have the concept of drought very clear, its definition have been classified in different categories as meteorological drought, agriculture drought, hydrological drought, socio-economic drought and groundwater drought. Meteorological drought is defined as a lack of precipitation over a region for a period of time. Precipitation has been commonly used for the analysis of meteorological drought (Pinkeye, 1966; Santos, 1983; Eltahir, 1992). Hydrological drought is related to a period with inadequate surface and subsurface water resources for established water uses of a given water resources management system. Stream-flow data have been widely applied for hydrologic drought analysis (Dracup et al., 1980; Sen, 1980; Zelenhasicand Salvai, 1987). Agricultural drought, usually, refers to a period with declining soil moisture and consequent crop failure without any reference to surface water resources. Socio-economic drought is associated with failure of water resources systems to meet water demands and thus associating droughts with supply of and demand for an economic good (American Meteorological Society, 2004). Socio-economic drought occurs when the demand for an economic good exceeds supply as a result of a weather related shortfall in water supply. When groundwater system is affected by drought, firstly groundwater recharge and then groundwater levels and ground-water discharge decrease. Such droughts are called groundwater droughts and generally occur on a time scale of months to years (van Lanen and Peters, 2000). For groundwater, the total amount of water available is difficult to define. Even if it can be defined, in most groundwater systems, negative impacts of storage depletion can be felt, long before the total storage is depleted (van Lanenand and Peters, 2000; Calow et al., 1999). Therefore, most often a groundwater drought is defined by the decrease in groundwater level (Chang and Teoh, 1995; Eltahir and Yeh, 1999).

2.1.1 Drought vulnerability

Pandey et al. (2010) proposed a technique for the assessment of vulnerability towards drought, by utilizing hydrological, meteorological and topographical factors in Sonar watershed area of Ken river basin system of Madhya Pradesh. To integrate the variables, they assigned weight on a common scale of 0 to 5; 0 indicating the least grade of vulnerability and 5 as the critical situation. The method and the results are found to be very effective and helpful in evaluating the drought vulnerability.

Thomas et al. (2015) analyzes the spatial and temporal variation of different characteristics of drought using Standardized Precipitation Index (SPI) in the drought prone region, Bundelkhand. The region consists of thirteen districts from two states, Uttar Pradesh and Madhya Pradesh, lying in the central part of India. The 3-month scale of SPI was used for the meteorological drought assessment. The spatial variation was performed by interpolating the findings in GIS environment. The 3-month scale of SPI is found to be very effective in performing the meteorological drought assessment. The results are very helpful for the state and central government agencies in prioritizing the district while applying the drought mitigation plan and management techniques.

Jain et al. (2015) applied a multi-approach methodology for drought vulnerability assessment using climatic, hydrological, topographical, and hydrological factors with spatial and temporal resolution. All of the input variables were weighted on a common scale and integrated for computation of the vulnerability at hydrological response units (HRUs) of the Ken River basin in the Bundelkhand region of central India. The vulnerability was quantified by performing the calculation of an index termed as “Integrated Drought Vulnerability Index (IDVI)”. The soil and water assessment (SWAT) model has been used for extracting the HRUs. The higher value of IDVI indicates the HRUs with relatively higher grade of vulnerability to drought and vice versa. The higher elevation is found to be drought prone due to less availability of water resources.

Murthy (2015) used input datasets of temperature, soil type, cropping pattern, irrigation intensity and land holding capacity of Andhra Pradesh state of India to evaluate the impact of drought vulnerability on agriculture. Agricultural drought vulnerability was analyzed at block level through indicators symbolizing sensitivity, exposure and adaptive capacity components in the study area. The 205 blocks of the state are found to be severely affected by the agriculture drought.

Thomas et al. (2016) calculated the drought vulnerability index (DVI) for Bearma basin of Madhya Pradesh using multi-dimensional input attributes. The total of nine indicators was considered in the study to be the true representative of the vulnerability. The selected input variables were slope degree, land use, soil texture, water utilization map, river reach, rainfall departure, ground water availability, soil moisture availability and surface water availability. The water utilization was based on the settlement and population density, river reach was conceptualized using elevation map, soil moisture was represented by 3-month scale of SPI and availability of surface water was indicated by 6-month scale of SPI. The attributes were scaled in the range of 0 to 10; 0 for less vulnerable and 10 for the most vulnerable input indicator. Finally the DVI was computed in the raster calculator of GIS environment. The DVI map was graded as negligible, slightly, moderate, highly and critically vulnerable. Nearly 35% of area comes under the moderate and the same percentage of area is found to be in slightly vulnerable grade. About 25% were highly vulnerable and less than 1.5% zone was under critically vulnerable level.

Krakauer et al. (2019) applied trend in drought over northeastern region of United States. The time series data of drought were created by calculating Standardized Precipitation Evapotranspiration Index (SPEI) for the study area. Since SPEI indicates integrated effect of precipitation, evaporation and transpiration, the different input datasets was required for its computation. Precipitation was the main input along with temperature and other climatic variables like wind speed, sunshine hours etc. They found the SPEI index to be more effective over SPI which is based on precipitation as the input only, in drought trend analysis but also consider it to be a little more complex in calculation over SPI. Linear regression technique was applied to detect trends in characteristics of drought; drought frequency, duration, severity and magnitude as calculated for SPEI 1-month to 12-month time scales. The primary finding was that, when we go continuously to longer SPEI timescales, the frequency of drought gets reduced.

Temam et al. (2019) performed trend test in drought over Ethopia region. For drought data creation, they calculated four (4) indices; SPI, SPEI, Palmer Drought Severity Index (PDSI) and Z-index. The core finding of the trend analysis was that there is a shift of late-season precipitation into dry season in the south-western and south-central parts of Ethiopia.

Dharumarajan et al. (2018) presented a study to develop desertification vulnerability index (DVI) and predict the different process governing the desertification processes in Anantapur District, India, based on machine language techniques. Climate, land use, soil, and socio-economic parameters were used to prepare DVI by a multivariate index model. The computed DVI along with other climate, terrain, and soil properties were used as explanatory variable to predict the desertification processes by applying a random forest model. About 14.2% of the area was created as a training dataset in 9 places for modeling and remaining area was tested for prediction of desertification processes. About 13% area is found to be affected by desertification. The findings are also found to be effective in rebuilding planning to reduce the impact of desertification on agriculture production.

Hoque et al. (2020) conducted a study in the north-western region of Bangladesh. It comprises 16 drought-prone districts of Bangladesh under two divisions, namely, Rajshahi and Rangpur. A total of 17 criteria under 4 drought categories, namely, meteorological, agricultural, hydrological and socio-economic, were selected. The four relevant criteria (annual precipitation, temperature, reference evaporation and humidity) were selected for meteorological drought mapping. Wind speed and sunshine duration are important in evapotranspiration and in drought evaluation. Five influencing criteria, namely, land use and land cover (LULC), soil moisture, soil texture, geomorphology and slope, were selected for agricultural drought mapping. Four criteria, namely, surface water bodies, groundwater, drainage density and elevation, were used for hydrological drought vulnerability mapping. In addition the four criteria, namely, agriculture-dependent population, population density, percentage of irrigated land and the number of deep tube wells are considered for socio-economic drought vulnerability mapping. AHP was used to calculate the weights for each criterion and drought types using pair-wise comparison matrices. Individual categories of drought and overall drought vulnerability maps were developed using the weighted overlay technique. The produced maps effectively defined the spatial extents and levels (e.g. normal, mild, moderate, severe and extreme) of drought vulnerability. The findings suggest that the proposed approach is highly effective in mapping comprehensive drought vulnerability for formulating strong drought mitigation strategies.

Hazbavi et al. (2017) conducted a study in the Shazand Watershed (1740 sq. km.) of south west of Markazi Province, Iran. The rainfall data was taken from the Ministry of Energy and was used for the calculation of SPI as developed by McKee et al. (1993) to categorize observed rainfall as a standardized departure with respect to a rainfall probability distribution function. A frequency distribution of precipitation data was built to determine the SPI at the study stations for the period of 1977–2014. The SPI values have been calculated at monthly time scale using Drought Index Package (DIP) software. Three risk indicators, namely Rel (frequency), Res (ability to recover) and Vul (vulnerability) are calculated in the context of drought through the analysis of spatial and temporal variation of the SPI. In this context, the Rel (frequency), Res (ability to recover) and Vul (vulnerability) of each rain gauge station of the Shazand Watershed from a SPI as drought index assessment were computed. The results are found to be very effective and useful, introducing a new approach to assess the drought vulnerability.

Guhathakurta et al. (2017) has assessed meteorological drought all over India during the southwest monsoon season and for the northeast monsoon season over five meteorological subdivisions of India for the period of 1901–2015 using standardized precipitation index (SPI). The standardized precipitation index (SPI) has been computed by fitting a Gamma probability density function to the frequency distribution of precipitation summed over the time scale for each district. Whenever all India southwest monsoon rainfall was less than −10% or below normal, for those years all India SPI was found as −1 or less. Composite analysis of SPI for the below normal years, viz., less than −15% and −20% of normal rainfall years indicate that during those years more than 30% of country’s area was under drought condition, whenever all India southwest monsoon rainfall was –15% or less than normal. Trend analysis of monthly SPI for the monsoon months identified the districts experiencing significant increase in drought occurrences. Significant positive correlation has been found with the meteorological drought over most of the districts of central, northern and peninsular India, while negative correlation was seen over the districts of eastern India.

Neto et al. (2021) completed the research work, which seeks to evaluate TRMM-estimated rainfall data's performance for monitoring the behavior and spatiotemporal trends of meteorological droughts over Paraíba State, based on the standardized precipitation index (SPI) from 1998 to 2017. The 78 rain gauge-measured and 187 TRMM-estimated rainfall time series were used, and trends of drought behavior, duration, and severity at eight-time scales were evaluated using the Mann–Kendall and Sen’s slope tests. Daily data were accumulated at a monthly level to calculate the SPI and to develop the drought analysis. The eight SPI values were used to monitor droughts at multiple time scales: SPI-1, SPI-3 and SPI-6 for short-term droughts; SPI-9 and SPI-12 for medium-term droughts; and SPI-18, SPI-24 and SPI-48 for long-term droughts. All drought metrics (DD, DS, DI) and drought time series (behavior, DDS, DSS) were computed based on these time series (8 scales × 265 times series). The results show that the TRMM-estimated rainfall data accurately captured the pattern of recent extreme rainfall events that occurred over Paraíba State. Drought events tend to be drier, longer-lasting, and more severe in most of the state. The greatest inconsistencies between the results obtained from rain gauge-measured and TRMM-estimated rainfall data are concentrated in the area closest to the coast.

Bisht et al. (2019) conducted a study to evaluates the drought characteristics in India over projected climatic scenarios in different time frames i.e., near-future (2010-2039), mid-future (2040-2069), and far-future (2070-2099) in comparison with reference period (1976-2005). Standardized Precipitation Evapo-transpiration Index (SPEI), a multi-scalar drought index was used owing to its robustness in capturing drought conditions while accounting the temperature. Gridded rainfall and temperature data provided by India Meteorological Department (IMD) was used to perform bias correction of 9 Global Climate Models (GCMs) from Coupled Model Inter-comparison Project Phase 5 (CMIP5) project. Quantile mapping was used to correct the daily rainfall data at seasonal scale whereas daily temperature data was corrected at monthly scale. To analyze drought characteristics over India; severity, duration, and area under drought were studied. Drought severity and durations were estimated using 'run theory' given by Yevjevich. To study the areal extent of drought, fraction of area under drought were computed by identified drought affected grids (for moderate and above moderate drought, separately) across all the months of a time. The frequency analysis using L-moments approach was employed to estimate the drought severity and duration of various return periods. L-moments approach to estimate parameters for distribution is reported to be superior to other methods. The study reveals an increasing trend in drought severity, duration, occurrences, and the average length of drought under warming climate scenarios.

Shah et al. (2020) selected two basins to test the applicability of Integrated Drought Index (IDI) in India. Sabarmati River Basin (SRB) is located in the arid and semiarid zone of western India, which drains into the Arabian Sea. On the other hand, Brahmani River Basin (BRB) is located in the tropical subtropical region and drains into the Bay of Bengal. They developed an Integrated Drought Index (IDI) that combines the response of meteorological, hydrological, and agricultural droughts and accounts for groundwater storage. They integrated the 12 month Standardized Precipitation Index (SPI), 4 month Standardized Runoff Index (SRI), 1 month Standardized Soil moisture Index (SSI), and 1 month Standardized Groundwater Index (SGI) to develop IDI. They characterized the major retrospective droughts during 1952–2017 using IDI for both the basins. To characterize droughts the attributes determined were; onset, termination, duration, maximum and mean intensity and the areal extent. The study estimated the percentage area affected by droughts by taking the ratio of total grids with IDI less than −0.8 to the total number of grids in a basin. The results identified different categories (abnormally dry, moderate, severe, extreme, and exceptional) based on the IDI ranges. The key finding was that the three most severe droughts occurred in 1966, 1979, and 2010 in the Brahmani basin.

Madhu et al. (2015) carried out an investigation over six temperature homogeneous regions of India, viz., Northwest (NW), North Central (NC), Northeast (NE), West Coast (WC), East coast (EC) and Interior Peninsula (IP). Six temperature homogeneous regions of India were chosen to calculate evapotranspiration (ET) using Hargreaves and Samani method on a monthly basis. Break Trend Analysis has been applied to the annual and seasonal ETs of the respective homogeneous regions as well as for whole India and the factors contributing for the changes in ET have been analyzed. The monthly rainfall data for all India, collected from the IMD is used for the comparison with the ET during drought years. The Standardized Reconnaissance Drought Index (RDIst) (Tsakiris and Vangelis, 2005) and Aridity (Thornthwaite and Mather, 1955) has been calculated for all India. By considering the data of Reconnaissance Drought Index (RDI), Rainfall, Advanced Very High Resolution Radiometer (AVHRR) Normalized Difference Vegetation Index (NDVI) for South West (SW) monsoon (June to September) and Rice yield (major Khariff crop yield) of all India, the research investigated the variations in ET during drought years. The trend analysis of seasonal and annual ET over the test regions have shown significant (levels of 0.05 to 0.01) increase over the past 107 years of the study period (1901 to 2007). The enhancement in ET is found to be 2.9 mm/decade over India and with a maximum in West Coast India (6 mm/decade), followed by Northwest India (3.9 mm/ decade). The increasing trends in ET may be due to the increase in difference of maximum and minimum temperatures over these regions, which is of the order of 0.64 °C/ decade on all India scale. The analysis of ET in drought years consistently shows higher values in the years when India suffered under moderate and severe droughts.

Shah et al. (2020) applied the well calibrated and evaluated Variable Infiltration Capacity Simple Groundwater Model (VIC-SIMGM) to simulate soil moisture, runoff, and groundwater storage variability in India for the 1951–2016 periods. They used Variable Infiltration Capacity model (VIC) with the Simple Groundwater Model to simulate hydrological variables required to construct IDI. Gridded precipitation was developed using observations from 6,995 rain gauge stations located across India using the inverse distance weighting (IDW) interpolation scheme. The research divided India into eight clusters that have similar drought characteristics. The study estimated the IDI for the 1951–2016 periods for each grid in the study domain. The majority of clusters in India experience the onset and termination of droughts during the summer monsoon season (June–September). The analysis of moisture back trajectories using the Hybrid Single Particle Lagrangian Integrated Trajectory (HYSPLIT) model showed that the Arabian Sea and Bay of Bengal are the two major moisture sources for the identified clusters in India. Droughts based on 1 month IDI that affect a majority of drought clusters are associated with the positive phase of El Nino Southern Oscillations (ENSO) and Indian Ocean Dipole (IOD).

Mishra et al. (2020) conducted a study to simulate root-zone soil moisture to identify flash droughts in India for 1951–2018 periods. The research shows that flash droughts predominantly occur during the monsoon (June to September) in India. More than 80% of the country-level flash droughts occurred during the monsoon season in India. The study used vegetation parameters in the form of the land use and land cover information which is globally developed using at 1 km spatial resolution. Overall, the result was that flash droughts can be localized, large-scale, and region-specific posing challenges for crop production and water management in India. The major country-level flash droughts occurred during the monsoon season of 1979, 2001, 1958, and 1986. About 10%–15% of rice (Oryza sativa) and maize (Zea mays) grown area in each year is affected by flash droughts during the monsoon season in India.

Shah et al. (2021) focused on the identified problem that anthropogenic activities associated with intensive irrigation, reservoir storage, and groundwater pumping has substantially altered the hydrological cycle, environment, and regional climate in India. To address the cause of the problem they use calibrated and evaluated Community Water Model (CWM) in order to quantify the influence of human activities on agricultural (estimated using soil moisture) and hydrological (estimated using runoff) droughts in India during 1951-2016. The simulations using the CWM were conducted for the Natural (without human influence) and Human (with the human influence of irrigation, reservoir storage, and groundwater pumping) scenarios. The dominant influences of human activities on agricultural and hydrological droughts were found during the monsoon and post-monsoon seasons. The findings have a contrasting effect of human activities on agricultural and hydrological droughts. While human activities reduced the intensity of agricultural droughts, hydrological droughts are intensified under the Human scenario.

Jaiswal et al. (2015) applied statistical methods for change point identification and trend detection in climatic parameters (indicative of drought). The climatic parameters taken into account for the analysis were minimum temperature, maximum temperature, relative humidity, wind speed, sunshine hour and pan evaporation. For the change point detection absolute homogeneity checks were performed using four tests i.e., Standard normal homogeneity test (SNHT), Pettitt's test, Buishand range test and von Neumann ratio test and finally method proposed by Winingaard et al. (2003) was used. The trend test was performed using linear regression test, Man-Kendall test and Spearman's rho test for three periods of P-1 (up to 1995), P-2 (1986 to 2012) and P-3 (1971 to 2012) at Raipur, the capital of Chhattisgarh state of India. Some of the core findings of the research were: the minimum temperature indicated a significant falling trend in April month, June to October months and on annual time series data at 5 % level of significance, in the first period till 1995 (P-1); the trend in wind speed historical data showed a significant falling trend for all three periods P-1, P-2 and P-3 in nearly all datasets at monthly, seasonal and annual scales.

2.2 Different approaches to conceptualize vulnerability

Environmental vulnerability indicates that up-to what extent, the natural environment has been put into risk and danger. The eco-environment symbolizes the condition of environment with respect to human beings. The attributes at risk consists of ecosystems, human population and the bio-physical processes, influenced by anthropogenic events (Kaly et al., 2002). The vulnerability is precisely expressed in terms of the level of sensitivity, extent of exposure and the adaptive and flexible capacity of the system to adjust itself according to the potential change in the surroundings. The assessment of environmental vulnerability is carried out for comprehensive analysis and evaluation of the resource system influenced by the existing natural conditions and interrupted by human activities (Fan et al., 2009). Eco-environmental vulnerability is the outcomes of complex phenomenon and processes, influenced by topographical vulnerability, hydro-meteorological vulnerability, land resource vulnerability and socio-economic vulnerability. In general there is no fix rule to define that how many indicators are required to evaluate the eco-environmental vulnerability level of any region. The selection of indicators completely depends on data availability and the regional cause of vulnerability of the area of interest (Lai et al., 2001; Li et al., 2006).

2.2.1 Agriculture vulnerability

Kumar et al. (2016) has assessed the agricultural vulnerability of five villages in Madhubani district of Bihar. The research has been carried out using Focus group (FGD) technique. Total of thirty FGDs comprising of female, male and mix group were formed in the selected five villages. Agricultural vulnerability has been assessed using twelve sub-factors organized into three main factors (a, b, c). The selection and classification of indicators were as; (a) climatic and soil factors: i) drought, ii) flood, iii) soil degradation, iv) heat stress, v) erratic rainfall; (b) biological factors: vi) insect, vii) disease, viii) weed; (c) social factors: ix) financial crunch, x) unavailability of quality inputs, xi) farm machinery unavailability and xii) unavailability of man power. To compute the vulnerability score, the values were scaled between '0' for less vulnerable to '1' for high vulnerable. Extent or level of vulnerability was computed based on the index-score as: (a) low, for score value less than or equal to 0.33, (b) medium, for score value ranging between 0.34 to 0.66 and (c) high, for the index value greater than or equal to 0.67.The results concluded that the level of agriculture vulnerability was low in one village (Khairi) and medium in the rest four villages.

Bharti et al. (2017) has conducted a study to evaluate the agricultural vulnerability in Kosi region of Bihar. The study was conducted for 1976 to 2015 time periods and was further analyzed into four different periods of: (i) 1976-1985, (ii) 1986-1995, (iii) 1996-2005 and (iv) 2006-2015. Eight districts (Supaul, Saharsa, Madhepura, Araria, Purnea, Katihar, Khagaria, and Kishanganj) of Kosi region of Bihar were considered for the study. Three different methods of (i) simple average method, (ii) Patnaik and Narayanan's method of equal weight (Patnaik and Narayanan, 2005), and (iii) expert judgment method were employed for the computation of vulnerability index. The vulnerability was considered to be a function of demographic, climatic, agriculture and occupational parameters. All of the selected indicators were classified into four groups as: (a) indicators of exposure, (b) indicators of historical hazard, (c) indicators of future hazard and (d) indicators of vulnerability as discussed below:

Selected indicators of exposure were: net sown area, rural population density, small and marginal farmers, SC/ST population and cross-bred cattle. Selected indicators of historical hazard were: drought proneness, flood proneness and cyclone proneness. Selected indicators of future hazard were: Change in annual rainfall, Change in June rainfall, Change in July rainfall, Change in number of rainy days, Change in maximum temperature, Change in minimum temperature , Change in incidence of unusually hot days, Change in incidence of unusually cold days, Change in frequency of occurrence of frost, Change in drought proneness, Change in incidence of dry spells of >= 14 days, Change in 99 percentile rainfall, Change in number of events with >100 mm in 3 days, Change in average highest rainfall in a single day as % to annual normal, Change in average highest rainfall in three consecutive days as % to annual normal Selected indicators of vulnerability were: annual rainfall, degraded and waste land , available water holding capacity of soil, ground water availability, livestock density, literacy, gender gap, self-help groups, net irrigated area, road connectivity, electrification, market access, fertilizer use, income and income inequity. The indicators were normalized to bring all of them to a common scale and to make them unit-free by computing Z-scores. The indices of determinants of risk viz., hazard, exposure and vulnerability were then combined to build an index of risk with the calculated weights for all the four components of risk: historical hazard, future hazard, exposure and vulnerability. The results obtained through this process were found to agree with those obtained by applying weights derived through factor analysis and were also presented to various stakeholders.

Ahmed et al. (2021) performed a research work that aims to enhance the detection of agricultural vulnerability conditions in a heterogeneous environment, taking Bangladesh as a case study. The normalized difference vegetation index (NDVI) and land cover products from the Moderate Resolution Imaging Spectro-radiometer (MODIS) satellite images have been incorporated to compute the vegetation index. In this study, a modified vegetation condition index (m-VCI) has been proposed to enhance the estimation of agricultural vulnerability. Firstly, the heterogeneity of the landscape is investigated. Secondly, land cover variability is considered in delineating the m-VCI for separating the water-stressed croplands areas from other land covers and vegetation. Thirdly, a comparative analysis is done between the m-VCI and the traditional VCI, the result is evaluated using precipitation and crop yield. Fourthly and lastly, multiyear m-VCI maps are input to compute a composite map of areas indicating the levels of vulnerability to agriculture. Various land cover classification approaches have been used to detect geographic features. The NDVI has also been used as a good indicator for the classification of vegetation, and has been used to detect stressed or damaged crops. The VCI values close to 0% (zero) indicate an extreme dry condition, whereas the VCI values between 50% and 100% indicate normal vegetation conditions. The vulnerability to agriculture was found due to the unavailability of water resources during the cropping season caused by the frequent occurrence of the drought events.

2.2.2 Environmental vulnerability

Nandy et al. (2015) assesses the vulnerability of environment in ecological development zone of the Great Himalayan National Park (GHNP), located in western Himalaya. The indicators from different dimensions were selected for the research work as: land use/land cover (LULC), forest canopy density, distance to roads, distance to settlements, slope degree, aspect and elevation. The decadal change analysis was done for the time-scale of 1990-2000 and 2000-2010. The vulnerability was found to be increasing continuously and requires an urgent proper mitigation plan to be adopted. Based on the numerical outputs, the vulnerability of the region was categorized into five classes: potential, slight, medium, high, and severe. The primary factor responsible for the increase in vulnerability overtime was land use/land cover change in the study area due to hydro-electric power projects, construction of roads, and other infrastructure developments. Forest fire and decreased forest canopy density are other major contributing factors responsible for the increase in the environmental vulnerability.

Liou et al. (2017) have used total of 12 indicators grouped into four primary determinants for eco-environment vulnerability assessment in Vietnam using primarily Landsat data. The twelve indicators used were (i) normalized differential moisture index (NDMI), (ii) normalized differential water index (NDWI), (iii) distance from hydrological network, (iv) land surface temperature (LST), (v) land use land cover (LULC), (vi) normalized differential vegetation index (NDVI), (vii) distance from urbanized area, (viii) normalized differential built-up index (NDBI), (ix) Urban thermal field variance index (UTFVI), (x) elevation, (xi) slope angle and (xii) slope aspect. The indicators are found to be the nearly good representative of the regional environment. It also indicates the new approach of remote sensing and GIS to evaluate the vulnerability very effectively.

Gupta et al. (2020) compute spatial socio-environment vulnerability index (SSEVI) caused by the climatic change at different altitudes in the Himalayan region of India. Total of thirteen indicators were selected from different dimensions like climatic parameters, physical and biological variables and socio-economic attributes. The principal component analysis (PCA) and entropy weight method were applied for the final vulnerability map creation in GIS environment. Finally the vulnerability index map was projected over DEM to analyze the findings at different altitudes. This approach was found to be very effective in analyzing the results of vulnerability at different elevation. This will help in effective planning and management of natural resources.

Venkatesh et al. (2020) compute eco-environmental vulnerability index with aim to monitor the vulnerability and analyze the different severity levels zone-wise. The research was carried out in Pombar watershed of Tamilnadu state of India. The results were found very useful in managing the basin for sustainable development.

Haiying et al. (2007) performed an analysis of land use/cover changes and environmental vulnerability of the Birahi Ganga sub-watershed in the Garhwal Himalaya, India. They used satellite-based Landsat MSS and TM image. An index termed as Environmental Vulnerability Integrated Index (EVSI) has been applied to grade in five level (least, low, slight, moderate and severe) using cluster standards that shows higher EVSI greater the vulnerability. The results indicate that environment is becoming vulnerable due to the increasing built-up and deforestation.

Nguyen et al. (2019) proposed a study for mapping of globally vulnerable environment that has been caused by combined effect of human interferences and natural hazards. In this study GIS software has been used for quantification of vulnerability for which five parameters have been analyzed such as topography, hydrometeorology, natural hazards, and land resources. Finally, vulnerability has been categorized in six levels very low, low, medium, and medium high, high and very high. The primary finding indicates that very high vulnerability area prevails in Asia.

Kuchimanchi et al. (2019) conducted a study in the area that was located in the Sangamner taluka of Ahmednagar district and Paithan talukas of Aurangabad district, in Maharashtra, India. The stratified random sampling (based on biophysical characteristics) was used to choose three villages in Ahmednagar and three villages in Aurangabad districts out of a cluster of villages in both locations. The biophysical characteristics include the location of villages within the catchment, topography (slope), soil erosion status, natural vegetation cover, wastelands, water-body spread area, and the groundwater status. The vulnerabilities were assessed using the Community Driven Vulnerability Evaluation Program Designer (CoDriVEPD) tool, which is a participatory tool for assessing vulnerabilities of communities, villages and landscapes to climatic and non-climatic risks for locale-specific adaptation plans. The application of the tool has four methodological steps: (1) sector analysis, (2) mapping climate risks, impact & responses, (3) sensitivity analysis of indicators & response mechanisms and (4) multidimensional vulnerability code. Within this context, the current study presents how agrarian livelihoods in rural Maharashtra have been transforming to adapt to both the changing climate and non-climatic drivers. A community engaging vulnerability assessment tool was used to explore the climate risks and vulnerabilities of different social groups. Insights indicate that vulnerability is socially differentiated and across farmer categories and social groups. Caste and social standing play a significant role in access to resources, land ownership, livelihoods choices and approaches – impacting their vulnerability to climate change. The study concludes that vulnerability assessments need to be conducted at lower scales, as climate risks vary even within small clusters of villages.

Pandey et al. (2017) focused study area was Srinagar and adjoining regions in the Garhwal Himalayas, the western part of the Indian Himalayas and lies in Pauri Garhwal (Pauri block) and Tehri Garhwal (Devprayag block) districts of Uttarakhand state of India. The evaluation was conducted through proposing and testing indices for vulnerability (Climate Vulnerability Index – CVI) and adaptation (Current Adaptive Capacity Index – CACI) based on the assumption that a community is an active dynamic entity and has tremendous capability to address the impacts of climate change through an ability to make adjustments based on perceived experiences. The approach is based on a total of 44 indicators for developing CVI and CACI. Data for the analysis were collected from randomly selected households located away from district headquarters (ADH) and near district headquarters (NDH). Each dimension was measured based on associated socio-environment-specific indicators for assessing vulnerability and sustainability at community level. The results showed that ADH households had higher human capital and natural capital vulnerability than NDH households. In contrast, NDH households had higher social capital and financial capital vulnerability than ADH households.

2.3 Statistical methods for vulnerability assessment

Several statistical and non-statistical methods have been conceptualized to analyze the level and severity of vulnerability. Mathematical modelling (Wilson et al., 2005), comprehensive evaluation method (Goda and Mastuoka, 1986), fuzzy evaluation method (Enea andSalemi, 2001), grey evaluation method (Hao and Zhou, 2002), artificial neural network (Dzeroski, 2001) and spatial multi-criteria evaluation (SMCE) (Enete et al., 2010) have been used for qualitative and quantitative assessment of vulnerability. Principal Component Analysis (PCA) also known as factor analysis is a powerful statistical tool to reduce the dimensionality of input datasets and extract the existing relationship. The combination of GIS and PCA, termed as spatial principal component analysis (SPCA), can be used to reveal the detailed spatial tendencies and contribution of the factors in the vulnerability. The accuracy of the vulnerability evaluation cannot be guaranteed by the SPCA alone, which is based on the concept of dimension reduction of input datasets. The Analytic Hierarchy Process (AHP) developed by Thomas Saaty (1980), is an effective technique for solving the complex and multi-dimensional decision making problems. It is based on the principles of decomposition, comparative judgment and priorities synthesis. It allows the decision maker to define priorities and make the best solution in the given constraints, by providing aid in determining the weight for each variable of all class and sub-class.

2.3.1 Spatial Principal Component Analysis (SPCA)

Gupta, K. et al. (2020) assessed the vulnerability of environment towards society in the view of climatic change at different elevations in the Himalayan region of India. Based on the pilot study and literature reviews 22 indicators indicating the 3-dimensions of the vulnerability i.e., for exposure (6 attributes), sensitivity (8 parameters) and adaptive capacity (8 variables), were initially selected. Thereafter principal component analysis (PCA) was performed to finalize the best contributing indicators in the 3 dimension approach. The entropy method was adopted for providing weights to the different indicators. The Manush approach introduced by Mishra and Nathan (2018), a method derived from human development index (HDI) was used for the vulnerability index computation. The Manush method was based on the concept of dispersion from ideal; a highly efficient system has least dispersion from the ideal and vice versa. The Inverse Distance Weighting (IDW) technique was used for interpolation in GIS environment for analyzing the spatial variation of the SSEVI index in the study area. The PCA along with Entropy weighing method was found very useful and efficient in deriving the environment related SSEVI index.

Kang et al. (2015) analyzed the variation in ecological vulnerability for the north Shaanxi, region of China using SPCA model in the GIS environment. Six indicators were selected for the analysis as: soil erosion, land use, climate, topography, social economy and vegetation index. The Natural Break Classification (NBC) was applied to classify the ecological vulnerability index computed by the SPCA model in the area of research. Five classes were defined as heavy, medium, light and slight vulnerable region. The EVI value of the eight countries in southern region was found to be lower than that of the twelve countries of the northern areas. The SPCA model was found very useful in zoning the vulnerability defined by EVI index.

Ainong et al. (2006) conducted a research study in mountainous region of China for evaluation of eco-environmental vulnerability using SPCA on GIS platform. The EVI index for eco-environmental vulnerability analysis was computed by introducing a numerical model linked with geographical information system (GIS) and remote sensing (RS) environment. The SPCA statistical method was used for the model evaluation using GIS software. As it can been seen in the flowchart, nine indicators were selected for the research as: slope, drought index, elevation, accumulated temperature, land use, soil, vegetation, soil-water erosion and population density. The index was computed for the years of 1972, 1986, and 2000 to detect the temporal variation in the vulnerability level, classified into 5 grades from heavy to potential. The spatiotemporal dynamic change of eco-environmental vulnerability in the last thirty years from 1972 to 2000 were discussed and analyzed. The findings of this study concluded that the SPCA method integrated with remote sensing (RS), and GIS, evaluates the mountainous region's vulnerability towards the ecological environment very effectively and also justify the mountain-river belt natural relationship.

Gulrez et al. (2017) proposed methods of principal component analysis and heat vulnerability index for assessment of heat wave for 640 districts in India. Many health problems of peoples in India are increasing because of heat wave. We evaluated demographic, socioeconomic, and environmental vulnerability factors and combined district level data from several sources including the most recent census, health reports, and satellite remote sensing data. Satellite data was extracted from the ISRO server's "Bhuvan" tool where the average vegetation fraction and Normalized Difference Vegetation Index (NDVI) images were layered with a district level India shape-file and the variables (mean, median, maximum, minimum, range, and standard deviation) were calculated for each of the district polygons using GIS software. Land cover was assessed through Vegetation Fraction (VF) and Normalized Difference Vegetation Index (NDVI). Studies have documented the protective influence of green cover from heat island effects and heat deaths and these have been included in other indices. The variables were integrated for each of the 640 districts to create a composite Heat Vulnerability Index (HVI) for India. Out of the total 640 districts, the analysis identified 10 and 97 districts in the very high- and high-risk categories (> 2SD and 2-1SD HVI) respectively. Mapping showed that the districts with higher heat vulnerability are located in the central parts of the country.

2.3.2 Analytical Hierarchy Process (AHP)

Venkatesh et al. (2020) performed the AHP method for the eco-environmental vulnerability assessment in Pombar watershed, situated in Tamilnadu region of India. The indicators were grouped into four criteria and sub-criteria. The four primary classes were: (A1) land resource, (A2) hydro-meteorological, (A3) socio-economic and (A4) topographical attributes. The priority vector was synthesized using the pair wise comparison matrix for the four class and their sub classes. The weight defined for the four groups were 0.321 for A1, 0.197 for A2, 0.331 for A3 and 0.151 for A4 group. The researchers concluded the AHP technique to be one of the best methods in indentifying the dominating factors and computing the vulnerability assessment index.

Nandy et al. (2015) applied AHP in Himalayan region of Himachal Pradesh (H.P) for computing environmental vulnerability index. Total of seven indicators were selected and pair wise comparison matrix was synthesized to calculate the weight of each input variables. The indicators were Land use/Land cover (LULC), slope, aspect, elevation, forest canopy density, distance from settlements and distance from roads. The computed priority vector showed LULC as the most contributing indicator with a weight of 0.355 (35.5%) and elevation as the least contributing parameter, having a weight of 0.023 (2.3%). The AHP technique was found to be very efficient in determining the contribution of each variable in making the environment vulnerable. The findings were very helpful for the government as well as for the private bodies working in the field of environment rebuilding.

Chakraborty and Joshi (2016) considered 594 districts in India for their study to natural vulnerability and climate-induced disasters using analytical hierarchy process as a multi-criteria decision mapping method. They used AHP to measure the vulnerability in terms of exposure, sensitivity, and adaptive capacity for the districts (Zila) in India. For the mapping of districts, vulnerable to natural and climate-induced disasters, composite vulnerability index approach has been used and vulnerability indices have been calculated. By aggregating the relative indices of exposure, sensitivity, and adaptive capacity, the cumulative composite vulnerability index has been calculated to categorize the highest and lowest vulnerable regions in India at the sub-national level (districts). The methods adopted and result concluded is found to be very effective and useful for the current and future planning and management of the natural resources to have the sustainable development.

2.4 Rebuilding planning to mitigate the impact of vulnerability:

Rebuilding planning is required to mitigate the impact of vulnerable conditions caused by a number of factors. The vulnerability exists in a number of different forms as: agriculture vulnerability, drought vulnerability, socio-economic vulnerability, hydro-meteorological vulnerability, topographical vulnerability etc. These all forms of vulnerabilities are the cause for the overall increasing vulnerability to environment.

Wilhite et al. (2005,b) summarized the ten step process followed by National Drought Mitigation Centre (NDMC) for drought vulnerability mitigation; the same is also available on the website of the NDMC ***(http://drought.unl.edu/portals/docs/ 10StepProcess).*** The description of the 10-step process is as follow:

1. Appoint a task force for to implement the management and mitigation plan against the impact of drought,
2. State the objectives and purpose of the drought mitigation plan clearly,
3. Seek stakeholders input and resolve the conflicts,
4. Identify inventory resources available and groups at risk,
5. Prepare and write the mitigation plan step-wise,
6. Identify research needs and fill institution gaps,
7. Integrate the scientific concepts with that of the government policies,
8. Publicize the drought mitigation plan and build awareness,
9. Develop education programs and awareness and
10. Evaluate the efficacy and revise the implementations of the drought mitigation plans.

Cai et al. (2015) presents a decision-support framework based on a coupled simulation and stochastic optimization model through a case study area in the Frenchman Creek basin (FCB), part of the Republican River basin to address the two problems: whether climate change aggravate the risk of drought at the local scale or current infrastructures is sufficient to mitigate the damage of future drought or is in-advance infrastructure expansion needed for future drought preparedness?. A complex watershed simulation model is established and converted into a statistical surrogate model for computational feasibility. Modeling scenarios of the future climate are developed from multiple general circulation models (GCMs) and regional climate models (RCMs) under different greenhouse gas emission scenarios to represent the various possible climatic conditions in the midterm (2040s) and long-term (2090s) time horizons. The result of the case study shows that current facilities are not enough to mitigate the damage under future climate conditions, indicating the requirement for infrastructure investment.

Chapter III

MATERIALS AND METHODS

The present chapter discusses with the details of study area, datasets used and the methodology adopted to accomplish the objectives of the work entitled "Spatio-Temporal Eco-Environmental Vulnerability Assessment in Agro-climatic Zone - III of Bihar Region".

3.1 Description of the Study area

This study has been carried out in southern region of Bihar state. The Bihar state lies on the eastern part of India, between 83°30´E to 88°00´E longitudes and 21°58´N to 27°3´N latitudes, with a geographical area of 94.2 thousand square kilometer.

It is divided by river Ganges into two parts, the north Bihar with an area of 53.3 thousand square kilometer, and the south Bihar (study area) having an area of 40.9 thousand square kilometer. The study area (south Bihar) represents 25.75% of the total area of the state. The location map of the area of interest has been shown in Figure 3.1.

Based on soil characterization, rainfall, temperature and terrain, three main agro-climatic zones in Bihar have been identified by Food and Agriculture Organization. These are: Zone – I (North West alluvial plain), Zone – II (North East alluvial plain), and Zone-III (A, B) (south Bihar, alluvial plain), each with its own potential and prospects.

The whole south Bihar comes under Agro-Climatic zone –III consisting of seventeen districts. It has been further sub-classified as Agro-climatic zone III (A) and Agro-climatic zone III (B). The districts of Agro-climatic zone III (A) are Sheikhpura, Munger, Jamui, Lakhisarai, Bhagalpur and Banka. The districts that comprises Agro-climatic zone III (B) are Rohtas, Bhojpur, Buxar, Bhabhua, Arwal, Patna, Nalanda, Nawada, Jehanabad, Aurangabad and Gaya.

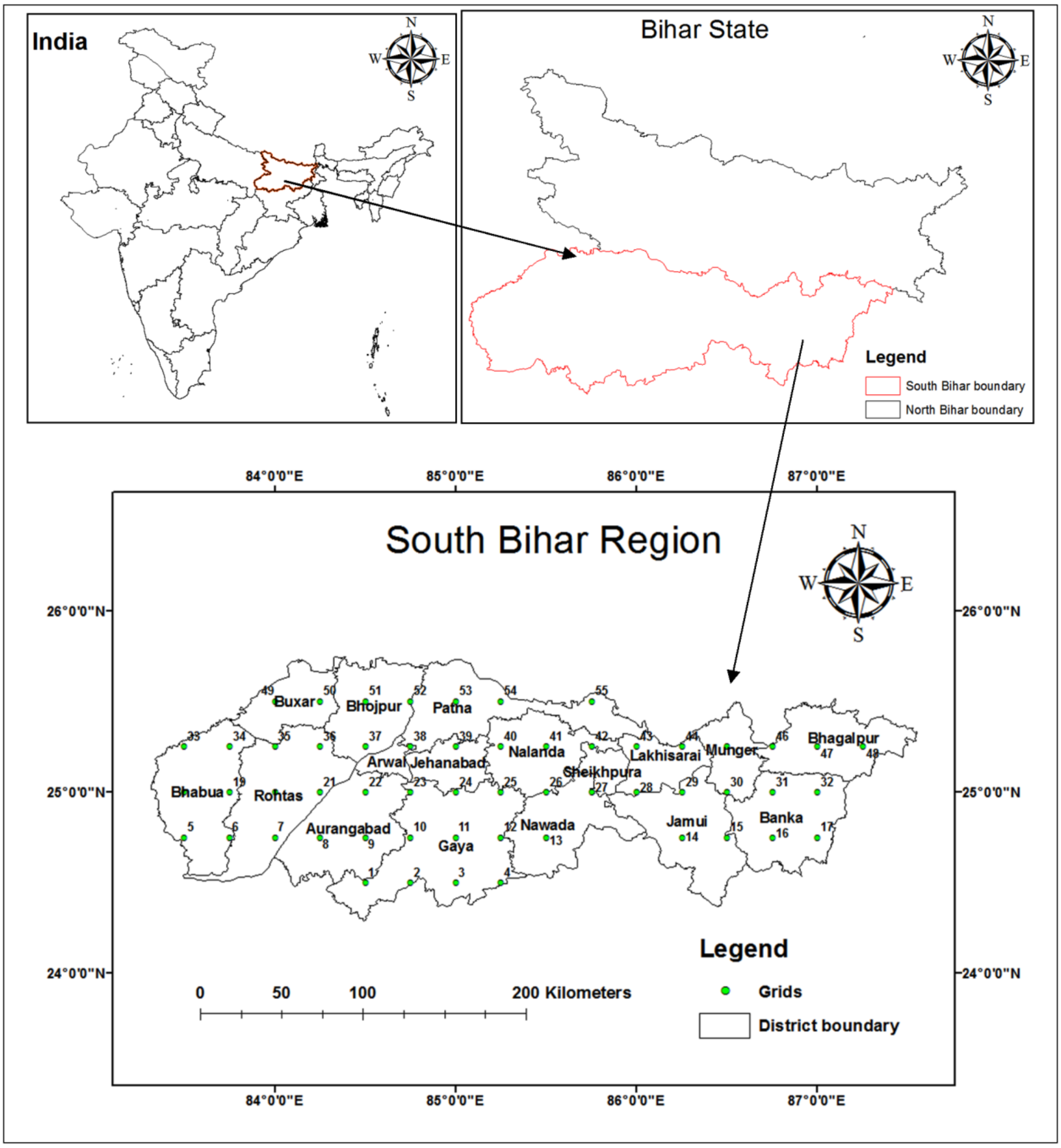

Figure 3.1 Location map of the study area

3.1.1 Climate

The region lies in a subtropical and temperate zone, which comes under middle Indo-Gangetic plain. The type of climate in the zone is humid-subtropical and the average annual rainfall is 1102.1 mm. There are four seasons that persist in the region are (i) cold weather season (December to February), (ii) hot weather season (March to May), (iii) southwest monsoon (June to September) and (iv) retreating southwest monsoon (October to November). The study area is drained by six rivers as: (i) Karmnasa, (ii) Sone, (iii) Punpun, (iv) Kiul-harhar, (v) Badua and (vi) Chandan. All these rivers drain into the main Ganga stem (Report of the special task force on Bihar, 2008, G.O.I).

3.1.2 Soil type and topography

The soils are mostly medium to heavy textured throughout the depth of the profiled. There are no marshy lands in this zone. The main broad soil association groups recognized in this zone are (i) recent alluvial calcareous soils, (ii) Tal land soils, light grey, dark grey medium to heavy textured soils, (iii) old alluvial reddish yellow, yellowish-grey centenary soils, (iv) old alluvial grey, grayish-yellow, heavy texture soils with cracking nature, (v) recent alluvial yellowish to reddish-yellow non-calcareous non-saline soils, (vi) old alluvial yellowish to red-yellow soils of foothills, and (vii) old alluvial saline and saline-alkali soils (Report of the special task force on Bihar, G.O.I, 2008).

According to the soil map collected from national bureau of soil survey and land use planning (NBSS and LUP), more than fifty-percent area is under clayey type soil, nearly forty percent area is under loamy soil, four-percent is covered by loamy skeletal soil and less than one percent lies under sandy soil. The southern region of the study is at relatively more height. Hence the land’s slope is towards north east with gentle slope gradient and moderate to low gradient.

3.2 Data acquisition

The datasets used for the research work are: digital elevation model (DEM), rainfall, land use and land cover map (LULC), LANDSAT satellite data, soil map, groundwater level, temperature data and India census data. The details of the datasets applied in the research work, with their resolution and sources have been mentioned in the Table 3.1.

Table 3.1: Datasets applied in the research work with their sources

S.No.	Data	Resolution	Years	Sources
1	DEM	30m	2000	SRTM, https://www.usgs.gov.in
2	Rainfall	0.25 degree	1901-2016	https://mausam.imd.gov.in
3	LULC	100m	1995, 2005	https://earthdata.nasa.gov.in
4	LANDSAT	30 m	2015	https://www.usgs.gov.in
5	Soil map	100m	2011	NBSS and LUP
6	Groundwater	Station-wise	1995-2015	http://cgwb.gov.in
7	Temperature	1 degree	1951-2016	https://mausam.imd.gov.in
8	India Census	District-wise	1901, 2001, 2011	www.indiacensus.gov.in

3.3 Methodology

The present research work has been carried out in the agro-climatic zone-III of Bihar state, which covers the whole southern region of Bihar, comprising of seventeen districts. As per the research objectives, the methodology involves the evaluation of drought severity, assessment of environmental vulnerability, detection of decadal change in the vulnerability level and finally designing the mitigation plan as per the grade of vulnerability on priority basis. The details of the applied methods for the research work have been described below.

3.3.1 Drought condition analysis in the study area:

To evaluate the severity of drought as the first objective, the sequence of the applied methods were: firstly rainfall departure analysis for identification of drought years, secondly, rainfall probability analysis using Weibull's plotting position formula for determining the drought prone grids, and then lastly computation of standard precipitation index (SPI) to evaluate and monitor the drought events.

3.3.1.1 Identification of drought years

Rainfall departure is a good indicator for the identification of wet or dry zones (Kar et al., 2016). A grid is considered to be affected by severe drought, in case, the annual rainfall received that year, is less than 75% of its normal value , as per Indian Meteorological Department (Appa Rao, 1986). A similar work has been done by Kar et al., (2016), on identification of the drought years, using the rainfall departure analysis in Dhasan basin, M.P. In the research, the method based on the departure analysis of annual rainfall has been employed for drought year assessment; the same was suggested by Indian meteorological department (IMD) (Report of Irrigation Commission, 1972). The annual rainfall departure was computed by subtracting the normal annual rainfall (R_m) from the mean annual rainfall (R_i) for that year. The percentage departure (D_i) is subsequently computed by dividing the rainfall departure by the normal annual rainfall for various grids and multiplied by 100 to express into percentage, as given by Equation 3.1.

$$D_i = \left(\frac{R_i - R_m}{R_m}\right) * 100 \qquad (3.1)$$

Where,

D_i = Annual rainfall departure for the i_{th} year (%),

R_i = Annual rain fall for i_{th} year,

R_m = Normal annual rainfall for the years of research

In general, the year having annual rainfall departure more than or equal to 25% is considered to be a drought year. However the severity of drought has been further classified according to percentage deviations from the normal rainfall and grouped into four severity classes as given in Table 3.2 (Kar et al., 2016). The departure analysis of annual rainfall has been computed for all the fifty-five grids of the agro-climatic zone-III and consequently the drought years have been detected.

Table 3.2: Drought severity classification based on percentage of departure

Drought severity Class	Rainfall departure (%)
Mild Drought	-10 to -20
Moderate Drought	-20 to -25
Severe Drought	-25 to -50
Extreme Drought	Less than -50

3.3.1.2 Identification of drought prone zones

The probability analysis of rainfall was performed using Weibull's plotting position formula for detecting the drought-prone zone in Dhasan basin, M.P and is found very useful (Kar et al., 2016). The result help drought mitigation steps to be implemented on a priority basis. In this study the probability analysis was carried out for fifty-five grids of the research area by arranging the annual rainfall in the decreasing order and ordering it from 1901 to 2016. The first entry takes order of 1 and the last entry as N, and finally the plotting position formula was fitted to the ordered data. Consequently, the plots between the probability of exceedance and the corresponding magnitude of annual rainfall were prepared. By using the Equation 3.2, the probability of exceedance is estimated.

$$P = \left(\frac{m}{n+1}\right) * 100 \qquad (3.2)$$

Where;

P = Probability of exceedance (%)

m = Order of rainfall in the series

N = Total number of rainfall events in the series.

The probability of occurrence for rainfall equivalent to 75% of mean annual rainfall as well as the 75% dependable annual rainfall was computed and analyzed for analyzing drought conditions. A grid was considered to be drought prone if the probability of occurrence of 75% mean annual rainfall was less than 80% otherwise the area was not considered as drought prone (CWC, 1982).

3.3.1.3 Drought severity assessment using SPI

In the present research work the spatial and temporal variation of drought and its characteristics has been evaluated using standardized precipitation index (SPI) for fifty-five grids, covering the study area for the time period of 1902 to 2016 i.e., for 115 years. The standardized precipitation index was developed by T.B. McKee et.al, of Colorado State University in 1993. It is very easy to compute, as it takes precipitation as the only input. It is based on the long term historical data of precipitation. This monthly time series record is fitted to a probability distribution, and further converted into a normal distribution to ensure the mean value of SPI to be zero (Edwards and McKee, 1997). The World Meteorological Organization (WMO) also recommends that all hydrological and meteorological centers at national level should use the SPI for effective monitoring of onset and termination of dry periods (Press report December 2009, WMO No. 872). Indian meteorological department (IMD) has also started monitoring of drought situations using SPI at monthly scale district-wise, since January, 2013 (www.imdpune. gov.in/hydrology/ Drought_Monitoring).

Dipanwita Dutta et.al (2015) applied SPI for agricultural drought assessment in Rajasthan (India) and found it as very effective and useful. The 3m-SPI is considered to reflect the soil moisture deficit and surplus effectively (T. Thomas et al., 2014). The spatial and temporal analysis of drought characteristics using 3-m SPI is very helpful to detect the onset and withdrawal of the drought event (Kar et al., 2018).

The Index is based on the probability of rainfall and is very flexible and so can be performed for multiple time scales. It can be computed from 1 to 72 months. Statistically speaking, 1–24 months is the most practically effective range of application (Guttman, 1994, 1999). These timescales indicates the condition, produced by drought on the availability of the water resources in different forms. The soil moisture conditions are reflected by shorter time-scale whereas the longer-scales of SPI are used as an indication of the storage of water in reservoirs, groundwater and in stream-flow. To analyze the availability of water in different forms, McKee et.al (1993) computed the SPI for 3-, 6-, 12-, 24- and 48-month scales of time.

In this study work SPI computation has been performed for 1-, 3-, 6- and 12-month timescales to analyze the all types of drought condition. Generally speaking, the shorter time scale, SPI-1 will indicate early warning condition in terms of meteorological drought. The intermediate timescales of SPI-3 will represent the soil moisture (or agriculture) and hydrological drought condition is represented by SPI-6. The groundwater drought conditions will be represented by relatively longer timescale of SPI-12.

The stepwise SPI statistical procedure developed by Edwards and Mc Kee (1997) has been summarized in the following ten steps:

i. Mean of precipitation can be computed as;

$$\overline{X} = \sum_{i}^{n} \frac{X_i}{N_i} \tag{3.3}$$

$\sum Xi$ = sum of all precipitation values (mm); Ni = no of non-zero observations.

ii. Standard Deviation $sd = \sqrt{\frac{\sum (x_i - \overline{x})^2}{N_i}}$ (3.4)

iii. Log mean $X_{ln} = \ln(\overline{x})$ (3.5)

iv. $U = X_{ln} - \sum_{i}^{n} \frac{\ln(X_i)}{N_i}$ (3.6)

v. $\alpha = \frac{1+\sqrt{1+4*\frac{U}{3}}}{4*U}$ (3.7)

vi. $\beta = \frac{\overline{X}}{\alpha}$ (3.8)

vii. Cumulative probability $G(x) = \int \frac{(x(\alpha-1)e^{\frac{x}{\beta}})}{\beta(\alpha)\,\Gamma(\alpha)} d\,x$ (3.9)

viii. $q = \frac{m}{N}$ (3.10)

m = number of zero values in observations; N = total no of observations.

ix. Final cumulative probability $H(x) = q + (1 - q)G(x)$ (3.11)

x. The cumulative probability H (x) is then transformed to standard normal random variable Z with mean zero (0) and standard deviation (sd) of one 1,which is the value of SPI (Edwards and Mc Kee (1997).

The positive and negative values of SPI indicate wet and dry conditions respectively. The onset of drought takes place, at any time the value of SPI is negative continuously and reaches an intensity of -1.0 or less and terminates when the value takes positive sign. The SPI values range and the corresponding drought intensity levels proposed by Mc Kee et al. (1993) were adopted in this study as depicted in Table 3.3. The SPI intensity has been further classified for drought severity conditions as in Table 3.4.

Table 3.3: SPI intensity classifications for soil moisture conditions

SPI values	≥ 2.0	1.5 - 1.99	1.0 - 1.49	-0.99 - 0.99	-1.0 - -1.49	-1.5 – -1.99	≤ -2.0
Soil moisture	Extremely wet	Very wet	Moderately wet	Normal	Moderately dry	Severely dry	Extremely dry

Table 3.4: Drought severity classification based on SPI intensity

S.No.	SPI intensity	Drought condition
1	-0.5 to -0.99	Mild drought
2	-1.0 to -1.49	Moderate drought
3	-1.5 to -1.99	Severe drought
4	≤ -2.0	Extreme drought

3.3.1.4 Drought events monitoring

The monitoring of historical drought events is required, in order to analyze the drought severity pattern in the study area. The analysis will provide help in effective planning and management. For monitoring of the drought, the onset, termination, severity and intensity of the events has been estimated. As the SPI computation has been performed at fifty five grids, for four different timescales of 1, 3, 6 & 12, it will be very complex to monitor all the grids for all the timescales. So the grids facing maximum drought events based on intermediate scales of SPI (SPI-3 and SPI-6) with durations greater or equal to three months (≥3 months) has been considered for monitoring purpose.

3.3.2 Eco-environmental vulnerability assessment:

The assessment of eco-environmental vulnerability index (EVI) has been performed by using the analytical hierarchy process (AHP) and spatial principal component analysis (SPCA) techniques for three selected decadal years of 1995, 2005 and 2015.

3.3.2.1 Selection of Indicators for EVI computation

Eco-environmental vulnerability is the outcomes of complex phenomenon and processes, influenced by topographical factors, hydro-meteorological factors, land resource factors and socio-economic factors. In general there is no fix rule to define that how many variables are required to evaluate the eco-environmental vulnerability level of any region. The selection of indicators completely depends on data availability and the vulnerability of the area of interest (Lai et al., 2001; Li et al., 2006; Wang et al., 2008; Song et al., 2010).

Yuei-An Liou et al (2017) have used total of 12 indicators, grouped into four primary determinants for eco-environment vulnerability assessment in Vietnam country, using LANDSAT satellite data. Anh Kim Nguyena et al (2017) have taken into account 16 variables grouped into four classes (i) topography (ii) hydro-meteorology, (iii) social-economics and (iv) land resource to assess the vulnerability grade in Vietnam region, using analytical hierarchy process(AHP) on GIS platform. Similarly different researchers have used different number of indicators either satellite or secondary data or a combination of both in their study area, based on the availability of dataset resource and the severity and types of problems dominating in the research area.

The present study takes into account a total of four (**4**) group variables (indicators) classified into **21** sub-group variables (indicators) to evaluate the eco-environment vulnerability level, based on the identified problems in the research area, as below:

(i) Topographical,

(ii) Land resource,

(iii) Hydro-meteorological and

(iv) Socioeconomic indicators.

The elevation, slope degree and slope aspect has been considered for the topographical group indicator. The seasonal rainfall, rainfall departure, number of rainy days, minimum temperature, maximum temperature, groundwater, soil moisture and proximity to river has been used to compute hydro-meteorological group indicator. Land resource group indicator has been considered to be the primary function of land use and land cover (LU/LC), soil texture and soil depth. The socio-economic group variable (indicator) consists of population, population density, decadal growth rate, literacy and literacy gender gap in the study area.

3.3.2.2 Data input maps preparation

The Dem map has been processed for creating elevation, slope degree and slope aspect map. The land use and land (LULC) cover map for the year 2015 has been developed by classifying LANDSAT data. The point datasets of seasonal rainfall, rainy days, rainfall departure, temperature and ground-water datasets (below ground level, BGL) has been interpolated using inverse distance weight (IDW) method for developing their variables input maps in the environment of Arc-GIS software (10.1). Similarly the district-wise socio-economic point data, collected from www.indiacensus.gov.in, has been interpolated using IDW technique to create the corresponding socioeconomic input maps. For the soil moisture map the 3-month SPI of October month has been used and processed. The proximity to river map has been developed using buffer tool on the drainage network map. The rest other input maps have been collected from different sources as already mentioned in Table 3.1.

3.3.2.3 EVI computation using AHP

The Analytic Hierarchy Process (AHP) developed by Thomas Saaty (1980), is an effective technique for solving the complex and multi-dimensional decision making problems. It allows the decision maker to define priorities and make the best solution in the given constraints, by providing aid in determining the weight for each class and variables. The overall process of the AHP can be expressed in six sequential steps (Saaty, 1980; Saaty and Vargas, 2001; Bhushan and Rai, 2007) as discussed below:

(i) Firstly a hierarchical structure of the decision making problem is constructed,

(ii) Secondly, decision tables for pair-wise comparisons matrix at each level of the structure are defined based on literatures review using a preference scaling Table 3.5.

(iii) Thirdly, the pair wise comparison matrix that reveal the relative importance of all decision variables at step-2 are organized into a square matrix with 1 as the value of the diagonal variables. If the value of a criterion (i,j) is more than 1, it indicates that the i^{th} row is relatively more preferred than the j^{th} column and vice-versa.

(iv) Fourthly, priority vector were determined by normalizing the eigen-vector associated with the largest eigen-value (λ_{max}) of the judgment matrix.

(v) Fifthly, the degree of consistency of the square matrix of order n is evaluated.

For this, firstly the consistency index (CI) is calculated by using Equation 3.12.

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \tag{3.12}$$

This CI is compared with average of resulting consistency (RI). The RI is depends on the order of the matrix as given in Table 3.6. Then the consistency ratio (CR) was calculated by using Equation 3.13.

$$CR = \frac{CI}{RI} \tag{3.13}$$

Table 3.5 Preference rating scale

Numerical Rating	Judgments of Preferences
9	Extremely preferred
8	Very strongly to extremely
7	Very strongly preferred
6	Strongly to very strongly
5	Strongly preferred
4	Moderately to strongly
3	Moderately preferred
2	Equally to moderately
1	Equally preferred

Table 3.6 Average random consistency (RI)

Size of Matrix	1	2	3	4	5	6	7	8	9	10
Random Consistency	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The AHP tolerates inconsistency up-to some extent. If this consistency index reaches above the required level then the pair-wise comparison matrix is required to be re-examined. It is suggested that the value of CR should be less than 0.1 so that the matrix has a reasonable consistency (Saaty, 1980; Saaty and Vargas, 2001; Bhushan and Rai, 2004).

After ensuring all of the conditions of the AHP method, the weight of the group and sub-group variables are confirmed as per the priority vectors computed from their pair-wise comparison matrix. Finally algebraic computation is performed to integrate the multi-dimensional variables at group and sub-group levels to create the composite map.

In the present study, “eco-environmental vulnerability” as the decision making problem, is deconstructed into four groups consisting of: (B_1) topographical, (B2) land resource, (B3) hydro-meteorological and (B4) socio-economic. The pair-wise comparison matrix is performed for sub-group and group variables based on the review of literatures and logical analysis in the area of interest. Following AHP technique, the eco-environmental index (EVI) map is created based on their generated stack and each component’s weight with support of the algebra computation using Equation 3.14.

$$\mathrm{EVI} = \sum(B_1 * W_1 + B_2 * W_2 + B_3 * W_3 + B_4 * W_4) \qquad (3.14)$$

Where B_1 is the topographical, B_2 is the land recourses, B_3 is the hydro-meteorological and B_4 is the socio-economical factors and Wi, i = 1, 2, 3, 4 are their corresponding global weights. B1, B2, B3, B4 are calculated by using Equation 3.15.

$$B_i = \sum_{i=1}^{n}(v_i w_i) \qquad (3.15)$$

Where v is the i^{th} variable, w_i is the weight for the variable and n is the total number of variables (i = 1, 2, 3, . . . n) in the group Bi.

3.3.2.3.1 Pair-wise comparison matrix of indicators:

The indicator maps developed for the different parameter are continuous in nature and needs to be reclassified so that weight for their sub-class can be determined. The weighing scheme for the sub-class of topographical, land resource, hydro-meteorological and socio-economical indicators has been depicted in Table 3.7, 3.8, 3.9 and Table 3.10 respectively, along with the proper references of the research paper followed for the findings.

The higher the elevation the more vulnerable are the zones with scarce facilities of education, hospitality, water supply and other resources. At higher slope, the land will be more steep and unstable, will provide less opportunity time for water infiltration, will be more susceptible to erosion due to high runoff and thus will contribute in making the environment more vulnerable. The same approach has been followed for the rest sub-indicators.

In case of land resource sub-indicators, the deeper soil is more acceptable with higher water holding capacity as it will make the soil more productive for agriculture. For the same reason clayey texture of soil has been considered to be less vulnerable as compared to the sandy soil. The built-up contribute in heat island effect, reduce the water recharge capacity of land and so have been considered to increase the vulnerability by different researchers. In the same way the sub-class of all the indicators has been given weight, in the light of the concept that the area is drought prone, water availability will be profit-full.

Table 3.7: Weighing scheme for the sub-class of topographical indicators

Indicators	Class	Weight	References
Elevation (m)	0 -75	1	Sahoo et al., 2015
	75 - 150	3	Choudhary et al., 2017
	150 - 300	5	Li et al., 2005
	300 - 400	7	Yang et al., 2021
	400 - 654	9	Nandy et al., 2015
Slope (Degree)	0 - 2	1	Sahoo et al., 2015
	2 - 6	3	Choudhary et al., 2017
	6 - 12	5	Li et al., 2005
	12 - 30	7	Yang et al., 2021
	30 -72.9	9	Yuan et al., 2008
Aspect	Flat (-1)	1	Sahoo et al., 2015
	North (0 -22.5)	2	Choudhary et al., 2017
	Northeast (22.5 - 67.5)	4	Li et al., 2005
	East (67.5 - 112.5)	7	Yang et al., 2021
	Southeast (112.5 - 157.5)	6	Yuan et al., 2008
	South (157.5 - 202.5)	5	Nandy et al., 2015
	Southwest (202.5 - 247.5)	1	
	West (247.5 - 292.5)	2	
	Northwest (292.5 - 337.5)	3	
	North (337.5 - 360)	4	

Table 3.8: Weighing scheme for sub-class of land resource indicators

Indicators	Class	Weight	References
Land use and Land cover	Water bodies	1	Li et al., 2005 Yang et al., 2021 Yuan et al., 2008 Nandy et al., 2015
	Forest area	3	
	Crop land	5	
	Grass land	7	
	Built-up	9	
Soil depth	Shallow	7	Nandy et al., 2015 Iqra et al., 2020 Thomas et al., 2015 Rao et al., 2019
	Moderate deep	5	
	Deep	3	
	Water bodies	1	
Soil texture	Sandy	9	Li et al., 2005 Yang et al., 2021 Yuan et al., 2008 Nandy et al., 2015 Iqra et al., 2020
	Loamy	5	
	Clayey	3	
	Loamy skeleton	7	
	Water bodies	1	

Table 3.9: Weighing scheme for sub-class of hydro-meteorological indicators

Indicators	Class	Weight	References
Rainfall (mm)	< 300	1	Yang et al., 2021
	300 - 400	3	Zhao et al., 2018
	400 - 500	5	Thomas et al., 2015
	500 - 600	7	Rao et al., 2019
	> 600	9	
Rainfall departure (%)	> -10	1	Li et al., 2005
	-10 - -20	3	Zhao et al., 2018
	-20 - -25	5	Thomas et al., 2015
	-25 - -50	7	Rao et al., 2019
	< -50	9	
Rainy days (number)	< 20	9	Thomas et al., 2015
	20 - 23	7	Rao et al., 2019
	23 - 26	5	
	26 -30	3	
	> 30	1	
Ground water availability (bgl, m)	1 - 2.5	1	Thomas et al., 2015 Rao et al., 2019
	2.5 -3.5	3	
	3.5 - 4.5	5	
	4.5 - 5.5	7	
	> 5.5	9	
Proximity to River (m)	< 500	1	Machiwal et al., 2010
	500 - 1000	3	Thomas et al., 2015
	1000 - 1500	5	
	1500 - 2000	7	
	> 2000	9	
Max. Temperature (^{o}C)	< 30.5	1	Sahoo et al., 2015
	30.5 - 32.5	3	Choudhary et al., 2017
	32.5 - 34.5	5	Li et al., 2005
	34.5 - 35.5	7	Zhao et al., 2018
	> 35.5	9	Iqra et al., 2020
Min. Temperature (^{o}C)	12 -13	1	Li et al., 2005
	13 - 14	3	Zhao et al., 2018
	14 - 15	5	Iqra et al., 2020
Soil moisture availability	Normal	1	Li et al., 2005
	Mild	3	Nandy et al., 2015
	Moderate	5	Zhao et al., 2018
	Severe	7	Iqra et al., 2020
	Extreme	9	Thomas et al., 2015

Table 3.10: Weighing scheme for sub-class of socioeconomic indicators

Indicators	Class	Weight	References
Population ($1*10^5$)	< 10	1	Li et al., 2005 Iqra et al., 2020 Thomas et al., 2015
	10 - 20	3	
	20 - 25	5	
	25 - 30	7	
	> 30	9	
Population density (No. of persons/km^2)	< 500	1	Li et al., 2005 Iqra et al., 2020 Thomas et al., 2015
	500 - 700	3	
	700 - 900	5	
	900 - 1100	7	
	> 1100	9	
Decadal growth rate (%)	< 20	1	Li et al., 2005 Iqra et al., 2020
	20 - 22	3	
	22 - 24	5	
	24 - 26	7	
	> 26	9	
Literacy (%)	< 45	9	Rao et al., 2019
	45 - 50	7	
	50 - 55	5	
	55 - 65	3	
	> 65	1	
Literacy gender gap (%)	5 - 10	3	Rao et al., 2019
	10 - 15	5	
	15 - 20	7	
	> 20	9	

In the analysis of group variables the socio-economic indicator with literacy as one of its sub-group indicator, has been considered to be of utmost importance as the literate society will be able to manage to stand-up and progress in any vulnerable conditions, using their multi-skills of creating income for livelihood, followed by the hydro-meteorological factors that depends mainly upon the water source availability, which is the basic requirement for agriculture and socio-economic activities. Thereafter the preference has been provided to land resource factor and the least to topographical factors, as the area is nearly leveled with gentle slope gradient. The matrix used for the weighing scheme for group variables has been given in Table 3.11. A similar work and weighing scheme preference for socio-economic, hydro-meteorological, land resource and topographical group variables has been adopted by different researchers in their study area (Nandy et al, 2015; Thomas et al, 2016; Nguyen et al, 2016; Zhao et al, 2018; Nguyen et al 2019; Gupta et al, 2020; Venkatesh et al, 2020).

Table 3.11: Weighing scheme for integrating group variables

Indicators	1	2	3	4	Weight
1.Topographical	**1**	**0.5**	**0.4**	**0.36**	**0.120**
2.Land Resource	**2**	**1**	**0.67**	**0.63**	**0.221**
3. Hydro-meteorological	**2.5**	**1.5**	**1**	**0.90**	**0.314**
4. Socio-economics	**2.8**	**1.6**	**1.1**	**1**	**0.345**

Consistency Ratio (C.R) = 0.0062 (<0.1); So acceptable.

In the analysis of topographical factors, the elevation (DEM) of the study area has been considered to be more contributing in defining the factor as it directly affect the agriculture and socio-economic activities followed by slope and the slope aspect has been taken to be least affecting. In case of land resource factors LULC has been given more weight followed by soil texture and soil depth. While comparing the seasonal variables of hydro-meteorological factor the summer monsoon (monsoon) has been given more preference and minimum weight has been provided to the summer season as per their direct importance to the agriculture sector and indirect to the socio-economic development. The groundwater is the ultimate stable source of water supply particularly in non-monsoon season followed by river water (surface-water). The soil moisture is dominating in monsoon season and has been computed using SPI-3. Similarly rainfall attributes (rainfall, rainy days and rainfall departure) are important in monsoon season only. However water supply is required throughout the year. So it is very logical to provide more weight to groundwater which ensures the availability of water throughout the year followed by surface water (proximity to river) and then soil moisture, rainfall attributes and finally temperature variables. A similar preference has been adopted for sub-groups of hydro-meteorological factor by Thomas et al (2015) for drought vulnerability analysis in Bundelkhand region.

In the process of comparing socio-economic variables, the literacy gender gap (difference of total literacy and female literacy) has been considered to be more dominating followed by literacy, since the literate female educates the whole family and consequently the entire community, which will ultimately promotes awareness regarding the government management policies that will help in effective implementation of mitigation plan to counter balance the vulnerable environment produced by drought, flood, increased population, the shortage of food supply etc.

The matrix used for the weighing scheme for different subgroup variables has been provided from Table 3.12 to Table 3.16. The final weight for all group and subgroup variables has been list up in Table 3.17. Following AHP technique, the eco-environmental vulnerability map was created based on generated stack and each component's weight with support of the algebra computation using Equation 3.16.

$$EVI = \sum(B_1 * W_1 + B_2 * W_2 + B_3 * W_3 + B_4 * W_4) \qquad (3.16)$$

Where B_1 is the topographical, B_2 is the land recourses, B_3 is the hydro-meteorological and B_4 is the socio-economical factors and W_i, i = 1, 2, 3, 4 are their corresponding global weights. B_1, B_2, B_3, B_4 are calculated by using Equation 3.17.

$$B_i = \sum_{i=1}^{n}(v_i w_i) \qquad (3.17)$$

Where v is the i^{th} variable, w_i is the weight for the variable and n is the total number of variables (i = 1, 2, 3, . . . n) in the group Bi.

Table 3.12: Weighing scheme for integrating topographical variables (B1)

Indicators	1	2	3	Weight
1.Elevation	1	2	4	0.55
2. Slope	0.5	1	3	0.32
3. Aspect	0.25	0.33	1	0.12

Consistency Ratio (C.R) = 0.0158 (<0.1); So acceptable.

Table 3.13: Weighing scheme for integrating land resource variables (B2)

Indicators	1	2	3	Weight
1.LULC	1	2	3	0.539
2.Soil texture	0.5	1	2	0.297
3. Soil depth	0.334	0.5	1	0.164

Consistency Ratio (C.R) = 0.0079 (<0.1); So acceptable.

Table 3.14: Weighing scheme for integrating seasonal hydro-meteorological variables

Seasons	1	2	3	4	Weight
1. Winter	1	2	0.334	0.5	0.17
2. Summer	0.5	1	0.25	0.334	0.10
3. Monsoon	3	4	1	2	0.45
4. Post-monsoon	2	3	0.50	1	0.28

Consistency Ratio (C.R) = 0.0138 (<0.1); So acceptable.

Table 3.15: Weighing scheme for integrating hydro-meteorological variables (B3)

Indicators	1	2	3	4	5	6	7	8	Weight
1.Rainfall	1	0.5	0.34	0.25	0.167	2	2	0.2	0.053
2.Rainy days	2	1	0.5	0.5	0.25	2	2	0.34	0.074
3.Rainfall departure	3	2	1	0.334	0.25	2	2	0.25	0.090
4.Soil moisture availability	4	2	3	1	0.25	3	2	0.34	0.130
5.Ground water availability	6	4	4	4	1	5	6	3	0.338
6.Maximum temperature	0.5	0.5	0.5	0.34	0.2	1	2	0.2	0.048
7.Minimum temperature	0.5	0.5	0.5	0.5	0.167	0.5	1	0.2	0.040
8.Proximity to River	5	3	4	3	0.34	5	5	1	0.228
Consistency Ratio (C.R) = 0.0756									

Table 3.16: Weighing scheme for integrating socioeconomic variables (B4)

Indicators	1	2	3	4	5	Weight
1. Population	1	0.5	0.333	0.167	0.143	0.072
2. Population density	2	1	0.500	0.333	0.200	0.104
3. Decadal growth rate	3	2	1.000	0.500	0.333	0.158
4. Literacy (%)	6	3	2	1	0.5	0.265
5. Literacy gender gap (%)	7	5	3	2	1	0.402

Consistency Ratio (C.R) = 0.0100 (<0.1); So acceptable.

Table 3.17: Weighing scheme for all group and sub-group indicators to evaluate eco-environment vulnerability index using AHP method

Group No.	**Group Indicators**	**Group weight (W_i)**	**Sub-group Indicators**	**Local weight (w_i)**
B1	Topographical	0.120	Elevation	0.55
			Slope	0.32
			Slope aspect	0.12
B2	Land Resource	0.221	Land use and Land cover	0.53
			Soil texture	0.29
			Soil depth	0.16
B3	Hydro-meteorological	0.314	Rainfall	0.05
			Rainy days	0.07
			Rainfall departure	0.09
			Soil moisture availability	0.13
			Ground water availability	0.33
			Maximum temperature	0.05
			Minimum temperature	0.03
			Proximity to River	0.23
B4	Socio-economics	0.345	Population	0.07
			Population density	0.10
			Decadal growth rate	0.16
			Literacy	0.26
			Literacy gender gap	0.40

3.3.2.4 EVI assessment using SPCA

The analysis of eco-environmental vulnerability is a multi-dimensional task which is based on the inter-relationship of all the influencing factors. Both principal component analysis (PCA) and geographic information system (G.I.S) has their own limitations, whenever used independently in research work. The PCA is a statistical tool that neither takes spatial datasets nor provides the spatial interpretation of the result. Similarly GIS is mainly used for spatial analysis, it doesn't perform statistical calculation on the data. The combined technique of GIS and PCA, known as spatial principal component analysis (SPCA), can be used effectively for EVI computation by performing both spatial as well as statistical analysis on the input maps and interpreting the results in the same fashion. Li et al. (2006 a, b) concluded SPCA to be useful and effective method for the assessment of vulnerability to the environment. The SPCA method can be used to calculate an eco-environmental vulnerability index based on the linear correlation coefficients (Parinet et al., 2004).

In the current research work SPCA technique has been applied for the vulnerability assessment. The evaluation processes of EVI index using SPCA method have been summarized in the following steps (Li et al. 2006 a, b):

(1) Firstly, to standardize primary data

(2) Secondly to create a covariance matrix R of each variable,

(3) Thirdly, to compute an eigenvalue λ_i of matrix R and its corresponding eigenvectors α_i .

(4) Fourthly, the linear combination is used to group eigenvectors and put out m (say) numbers of principal components and finally using algebra computation to create EVI map.

In the ARC-GIS software environment, the Principal component analysis (PCA) function is used to transform the multivariate input data in a stack to a single multi layer band with a new co-ordinate system whose axes are rotated with respect to the original one. The PCA text data file is also created which consists of the corelation matrix, eigenvector and eigenvalue of each principal component. According to the cumulative contribution of principal components, the numbers of components are selected and SPCA is performed using the band arithmetic function. The EVI index is computed as sum of weighted principal components using the Equation 3.18.

$$\mathrm{EVI} = \alpha_1 Y_1 + \alpha_2 Y_2 + \alpha_3 Y_3 \ldots\ldots + \alpha_m Y_m \qquad (3.18)$$

In the formula, Yi is the. i_{th} principal component, while α_i is its corresponding contribution.

The higher EVI value indicates the relatively more vulnerable eco-environment. Since the index map takes a continuous value, it should be classified into grades and the classification should be objective and logical in sense. Histogram is an effective graphical tool to analyze the statistical distribution of the classes and clusters in the space (Apan, 1997). Following the histogram approach the EVI map is classified into five levels. The potential, slight, light, medial and heavy vulnerability has been graded as I, II, III, IV and V as listed in Table 3.18. The classified EVI map will be more interpreting as it will allow the quantification of the vulnerability grade-wise as well as zone-wise.

Table 3.18: Grading of Eco-environmental vulnerability

Evaluation level	Grade	Feature description
Potential vulnerability	I	Very Stable ecosystem, great anti-interference ability, rich soil, and relatively low altitude.
Slight vulnerability	II	Stable ecosystem and anti-interference ability, rich soil, and relatively low altitude.
Light vulnerability	III	Relatively unstable ecosystem, low literacy region, bad quality soil, and less availability of water source.
Medial vulnerability	IV	Highly unstable ecosystem, poor water source availability, deteriorated soil, and higher population density and low literacy rate.
Heavy vulnerability	V	Extremely unstable ecosystem and poor water source availability, deteriorated soil, sparse vegetation, very high population density and very low literacy rate.

3.3.3 Analysis of decadal variation in vulnerability

The spatiotemporal decadal change in the vulnerability levels were analyzed district-wise for the periods of 1995-2005, 2005-2015 and 1995-2015, focusing the third objective.

3.3.3.1 Spatiotemporal decadal change in EVI level

Li et al., (2006, a) and S. Nandy et.al (2015), analyzed decadal change in environment vulnerability level from 1990 to 2000 and from 2000 to 2010 by computing an eco-environmental vulnerability integrated index (EVSI).

This study also analyses spatiotemporal decadal change by computing the Eco-environmental Vulnerability Integrated Index (EVSI) value. The EVSI is computed using the Equation 3.19.

$$\mathrm{EVSI_j} = \sum_{i=1}^{n} (\mathrm{P_i}) * \frac{\mathrm{A_i}}{\mathrm{S_j}} \qquad (3.19)$$

In this formula, n is the number of valuation grade, EVSIj is the EVSI in unit j, Ai the occupied area of grade i in analysis unit j, Sj is the total area of analysis unit j, and Pi is the rating value of grade i. The Table 3.19 has been followed for rating the vulnerability grades.

Table 3.19: Rating value for different grades

Evaluation level	Grade	Rating Value
Potential vulnerability	I	1
Slight vulnerability	II	2
Light vulnerability	III	3
Medial vulnerability	IV	4
Heavy vulnerability	V	5

3.3.4 Designing mitigation plan

The rebuilding plan is designed to mitigate the impact of the vulnerability level as per the identified problem in the region, to achieve the fourth and the last objective.

3.3.4.1 Rebuilding planning

The EVI map is created using AHP and SPCA techniques. The gradation of the vulnerability was done as potential (grade I), slight (grade II), light (grade III), medial (grade IV), and heavy (grade V). The district wise regionalization of EVI index was done to plan mitigation steps. The contribution percentage of different variables was found using AHP method. The most dominating factor was given the first priority while preparing the rebuilding plan and so on to least contributing factors. There are two distinct phases in planning; the first is the long term planning in which strategies can be devised, and precautions can be taken to reduce the impact, the second phase is the action taken during the onset of the event to reduce the adverse effect.

Drought management policies included agricultural planning and practices with consideration of overall water requirement can be proposed in case vulnerability of drought prevails within the agro climatic zone. The ill effects of drought can be alleviated by adopting proper crop management strategies up-to a considerable extent. These strategies may vary from moisture conservation to manipulation of plant population, and even mid-season corrections. Rainfall also can be harvested in either farm ponds or in village tanks and can be recycled. The focus in mitigation should be on measures like improvement in agriculture, management of wasteland, development of water resource and animal husbandry.

Watershed management measures in conjunction with structural measures such as check dams, detention basins, etc. can be proposed in eco-environmental rebuilding planning for the study area. The principle of planning is to take strict protection measures for heavy vulnerable regions, focal protection steps for light and medial vulnerable zones and comprehensive developing techniques for slight vulnerable areas.

Chapter IV

RESULTS AND DISCUSSION

The present chapter discusses with the results and discussion for the work entitled "Spatio-Temporal Eco-Environmental Vulnerability Assessment in Agro-climatic Zone (III) of Bihar Region". Firstly the chapter discusses with the results for drought analysis, secondly, it covers the outcomes of the environmental vulnerability, their decadal change and finally describes the proposed adaptable mitigation plan as per the resource availability.

4.1 Results for drought analysis

The methods adopted for the drought analysis has been already mentioned in section 3.3.1 of chapter 3. The outcomes are for the identification of drought years, drought prone zones, drought severity assessment using standardized precipitation index (SPI) and finally it's monitoring using the SPI at grid level for the periods of 115 years from 1902 to 2016. The detailed results and discussion for the work objectives has been described section wise as below:

4.1.1 Identification of drought years

The percentage departure of rainfall from normal annual rainfall has been computed to identify the drought years based on the data for the period of 116 years from 1901-02 to 2015-16 at grid level in the study area. The departure of rainfall in the positive direction indicates wet conditions whereas the departure in a negative direction indicates the condition of drought. The result shows that maximum annual rainfall departure of -82.99% was observed during the year 1978-79 (with mean annual rainfall as 1137.74 mm) for the grid-32 (Banka district) and second most rainfall departure of -80.35% is observed during the year 1948-49 (with mean annual rainfall as 932.53 mm) for the grid 52 (Patna district).

However, the minimum rainfall departure of -39.76 % has been observed for the grid 28 (Lakhisarai district) during 1953-54 (with mean annual rainfall as 1096.31

mm). The complete summary of rainfall departure for all the fifty-five grids consisting of all seventeen districts has been tabulated in Table 4.1. It can be concluded from Table 4.1, that grid forty-seven (G-47) of Bhagalpur district faces a maximum number of sixty-two drought events with the drought frequency of at least once in 1.9 years and the grid 2 of Gaya district faces the second highest of fifty-two (52) drought events during the study period, while grid 11 (G-11) of Gaya district and grid 24 (G-24) of Jehanabad district is at lowest position with only 35 drought events.

If we consider the findings at the district level, then on an average, Arwal district is the one that faces a maximum number of forty-nine (49) drought events and Bhagalpur district is at second position with forty-eight (48) drought events, while Buxar district is at the lowest position with only thirty-six to thirty-seven (36.5) drought events in the study area. The bar graph of annual rainfall departure at grids 2, 11, 24, 28, 32, 47, and 52 are given from Figure 4.1 to 4.7 respectively and the diagram indicating maximum rainfall departure for all grids in the period of 116 years from 1901 to 2016 is shown in Figure 4.8.

As the south-west monsoon is the only big contributor of rainfall in the study area, the deficit/weak south-west monsoon was primarily responsible for the regular occurrence of drought and subsequent water stress in the study area, thereby adversely affecting the major agricultural operations. The rainfall departure analysis also resulted that the drought occurs once in every two to three years in the agro-climatic zone.

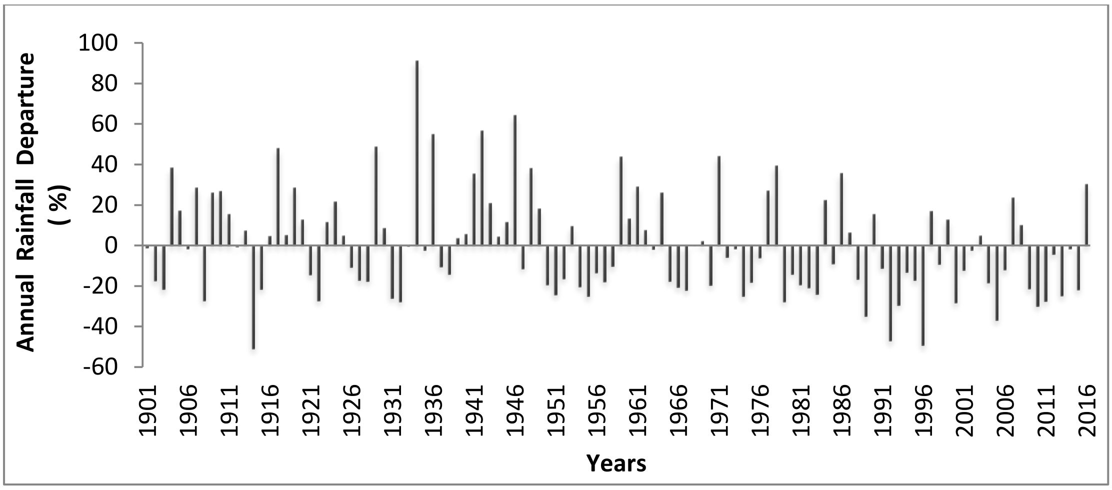

Figure 4.1 Annual rainfall departures at grid 2 (Gaya district)

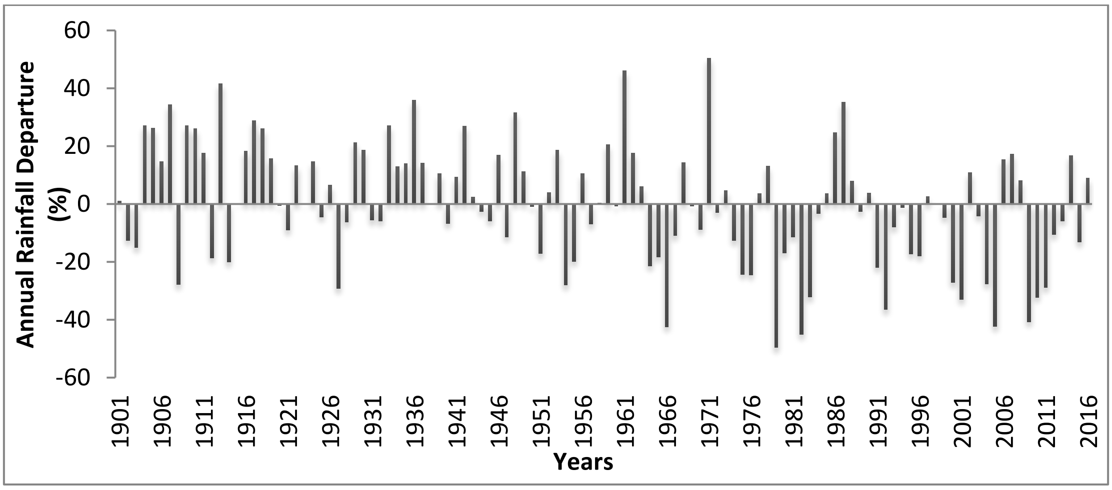

Figure 4.2 Annual rainfall departures at grid 11(Gaya district)

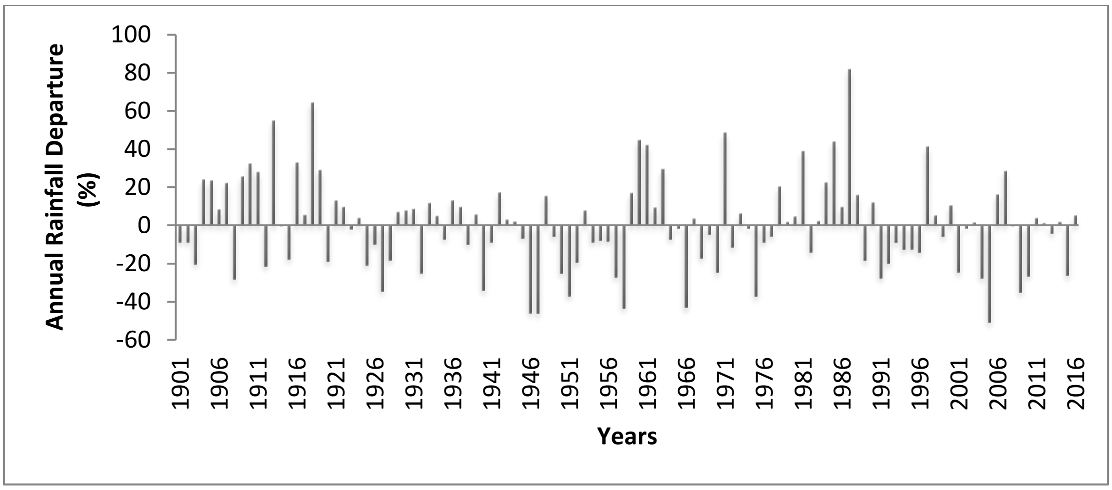

Figure 4.3 Annual rainfall departures at grid 24 (Jehanabad district)

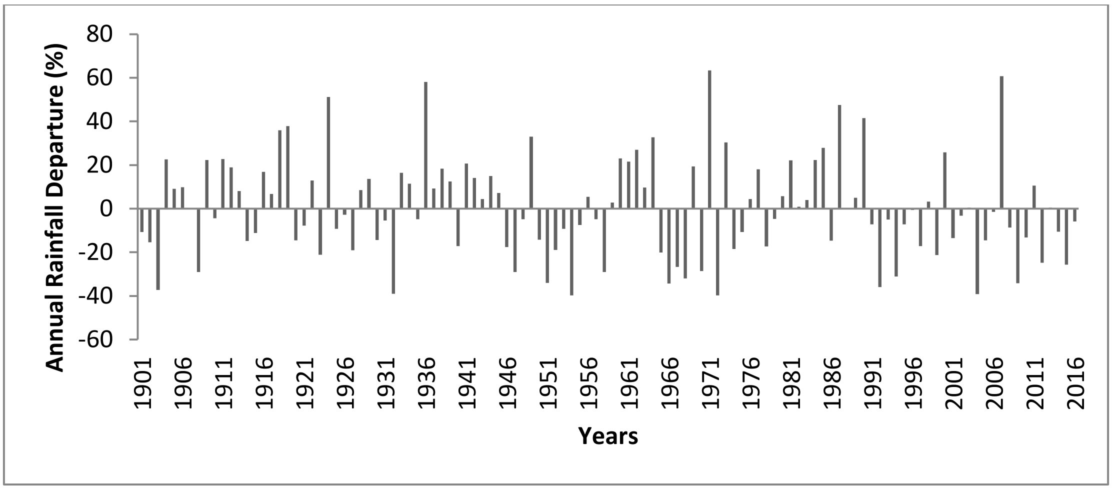

Figure 4.4 Annual rainfall departures at grid 28 (Lakhisarai district)

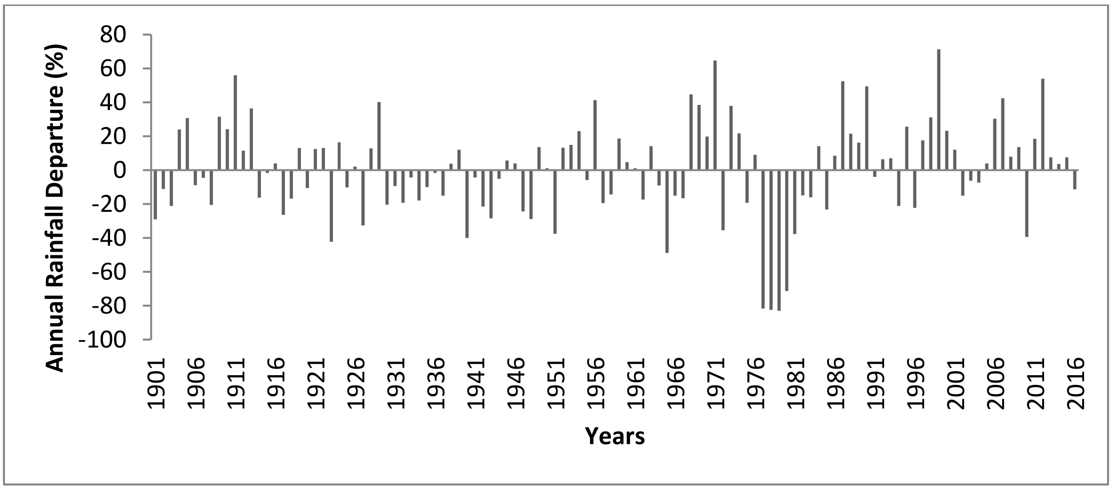

Figure 4.5 Annual rainfall departures at grid 32 (Banka district)

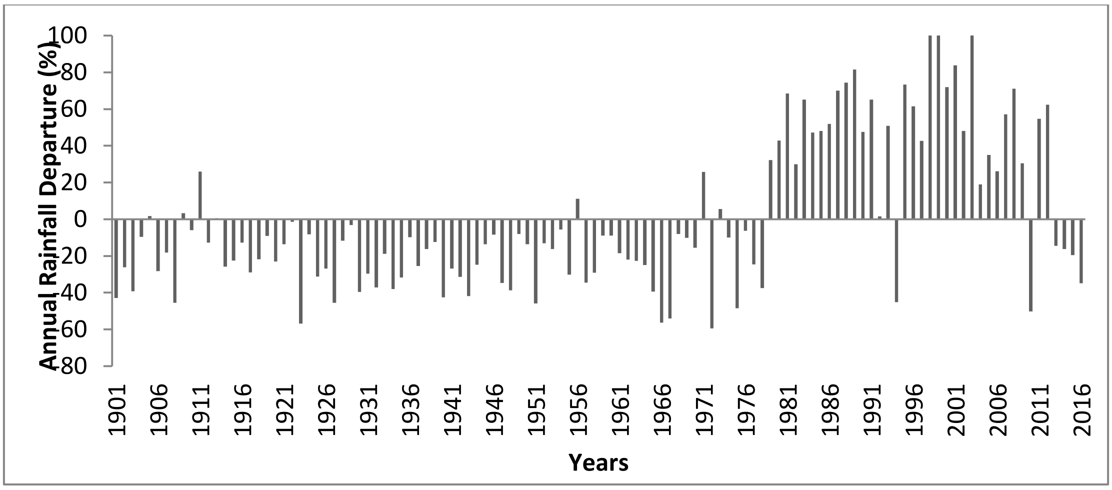

Figure 4.6 Annual rainfall departures at grid 47 (Bhagalpur district)

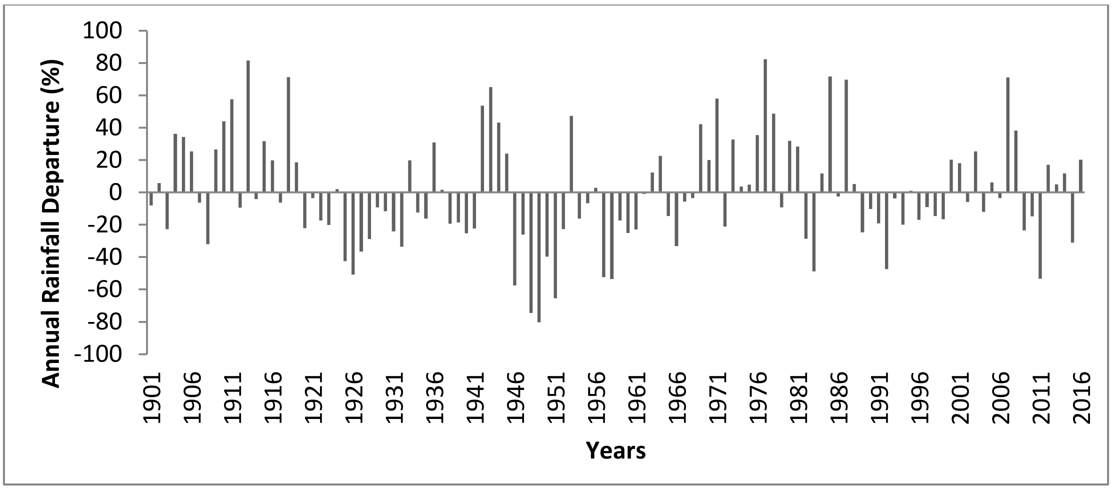

Figure 4.7 Annual rainfall departures at grid 52 (Bhojpur district)

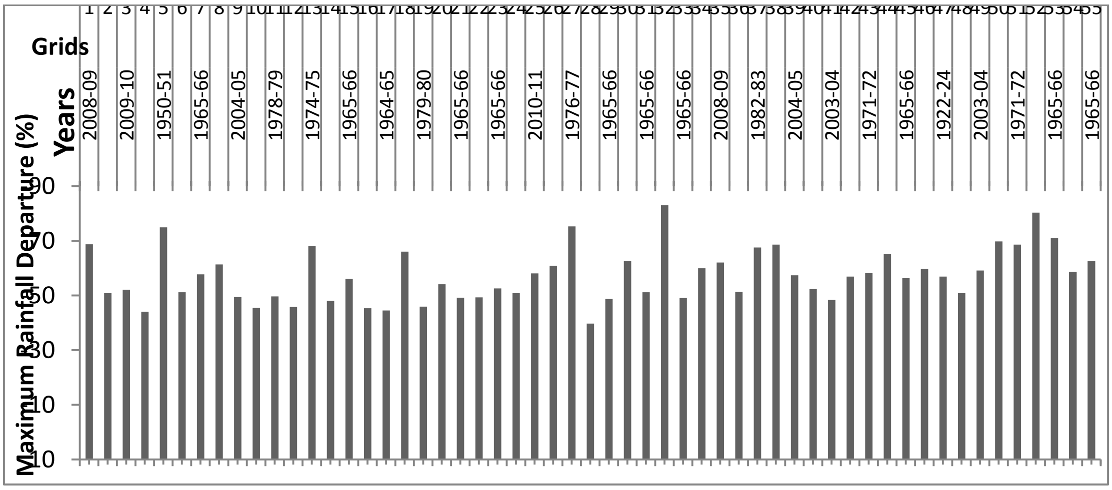

Figure 4.8 Maximum rainfall departure at grids from 1901-2016

Table 4.1 Summary of annual rainfall departure analysis

AGR Zone	Districts Names	Grid No.	Data Available	Drought Frequency	Drought Years	Maximum Departure	Departure Year	Drought Condition
A	Arwal	G-38	116	2.37	49	-68.62	1965-66	Extreme
A	Aurangabad	G-8	116	2.97	39	-61.34	1965-66	Extreme
		G-9	116	3.05	38	-49.44	2004-05	Severe
		G-22	116	2.64	44	-49.27	1965-66	Severe
B	Banka	G-16	116	2.9	40	-45.37	1965-66	Severe
		G-17	116	2.76	42	-44.52	1964-65	Severe
		G-31	116	3.05	38	-51.22	1965-66	Extreme
		G-32	116	2.7	43	-82.99	1978-79	Extreme
A	Bhabhua	G-5	116	3.14	37	-74.96	1950-51	Extreme
		G-6	116	2.9	40	-51.13	1978-79	Extreme
		G-18	116	2.47	47	-66.06	1965-66	Extreme
		G-19	116	2.76	42	-45.98	1979-80	Severe
		G-33	116	3.05	38	-49.13	1965-66	Severe
		G-34	116	2.64	44	-59.96	1965-67	Extreme
B	Bhagalpur	G-46	116	2.97	39	-59.7	1922-23	Extreme
		G-47	116	1.87	62	-56.89	1922-24	Extreme
		G-48	116	2.69	43	-50.85	1965-66	Extreme
A	Bhojpur	G-37	116	2.42	48	-67.57	1982-83	Extreme
		G-51	116	2.9	40	-68.62	1971-72	Extreme
A	Buxar	G-49	116	3.23	36	-59.15	2003-04	Extreme
		G-50	116	3.14	37	-69.79	1971-72	Extreme
A	Gaya	G-1	116	3.05	38	-68.76	2008-09	Extreme
		G-2	116	2.23	52	-50.85	2013-14	Extreme
		G-3	116	2.58	45	-52.08	2009-10	Extreme
		G-4	116	2.83	41	-44.07	1965-66	Severe
		G-10	116	2.9	40	-45.47	2004-05	Severe
		G-11	116	3.32	35	-49.62	1978-79	Severe
		G-12	116	3.14	37	-45.77	1965-66	Severe
		G-23	116	2.47	47	-52.6	1965-66	Extreme
		G-24	116	3.32	35	-50.79	2004-05	Extreme
		G-25	116	2.52	46	-58.1	2010-11	Extreme
B	Jamui	G-14	116	2.83	41	-47.99	1965-66	Severe
		G-15	116	2.97	39	-56.07	1965-66	Extreme
		G-29	116	3.05	38	-48.77	1965-66	Severe
A	Jehanabad	G-39	116	2.9	40	-57.34	2004-05	Extreme
	Lakhisarai	G-28	116	2.83	41	-39.76	1953-54	Severe
B		G-43	116	2.64	44	-58.19	1971-72	Extreme
		G-44	116	2.9	40	-65.08	1976-77	Extreme
B	Munger	G-30	116	2.76	42	-62.48	1965-66	Extreme
		G-45	116	2.76	42	-56.28	1965-66	Extreme
A	Nalanda	G-40	116	3.14	37	-52.31	2004-05	Extreme
		G-41	116	2.64	44	-48.38	2003-04	Severe
A	Nawada	G-13	116	2.83	41	-68.16	1974-75	Extreme
		G-26	116	2.7	43	-60.92	1922-23	Extreme
A	Patna	G-52	116	2.37	49	-80.35	1948-49	Extreme
		G-53	116	2.47	47	-71.01	1965-66	Extreme
		G-54	116	2.97	39	-58.73	1965-66	Extreme
		G-55	116	2.64	44	-62.5	1965-66	Extreme
A	Rohtas	G-7	116	2.83	41	-57.71	1965-66	Extreme
		G-20	116	2.58	45	-54.11	1965-66	Extreme
		G-21	116	2.64	44	-49.24	1965-66	Severe
		G-35	116	2.9	40	-62.09	2008-09	Extreme
		G-36	116	2.52	46	-51.35	1965-66	Extreme
B	Sheikhpura	G-27	116	2.97	39	-75.31	1976-77	Extreme
		G-42	116	2.76	42	-56.93	1945-46	Extreme

The spatial variation map of drought attributes (drought years, drought frequency and maximum departure) and rainfall attributes (normal annual rainfall and 75% dependable rainfall) has been prepared to visualize and analyze the result more effectively. The inverse distance weighed (IDW) interpolation technique has been used to interpolate the grid result of all the above discussed parameters, up-to the extent of the area of interest, on ARC GIS platform. Figure 4.9 shows the spatial variation of drought years in the districts of South Bihar agro-climatic zone III (A) and III (B). It indicates that more than fifty percent of the area faces drought in the range of 40-45 years in the study period of 116 years. The Drought greater than sixty years are mainly concentrated in Bhagalpur district of zone-III (B), no patches of zone-III (A) faces drought years in this category, this indicates the severity of the Bhagalpur district and nearby area.

The spatial variation of drought frequency in the study area has been shown in Figure 4.10. Drought frequency is inversely proportional to the number of drought years and the same can be seen by comparing Figure 4.9 and Figure 4.10. The grid 47 of Bhagalpur district with drought return of once in less than two years, put the adjoining area of the grid in severe drought frequency zone with a return period of once in 2-2.5 years. The visual interpretation indicates that more than 70% areas are under drought frequency of 2.5 to 3 years.

The Figure 4.11 depicts the spatial variation of maximum annual rainfall departure percentage throughout the period of 1901-2016 years. Most area faces departure in the range of -60 to -50 (%).

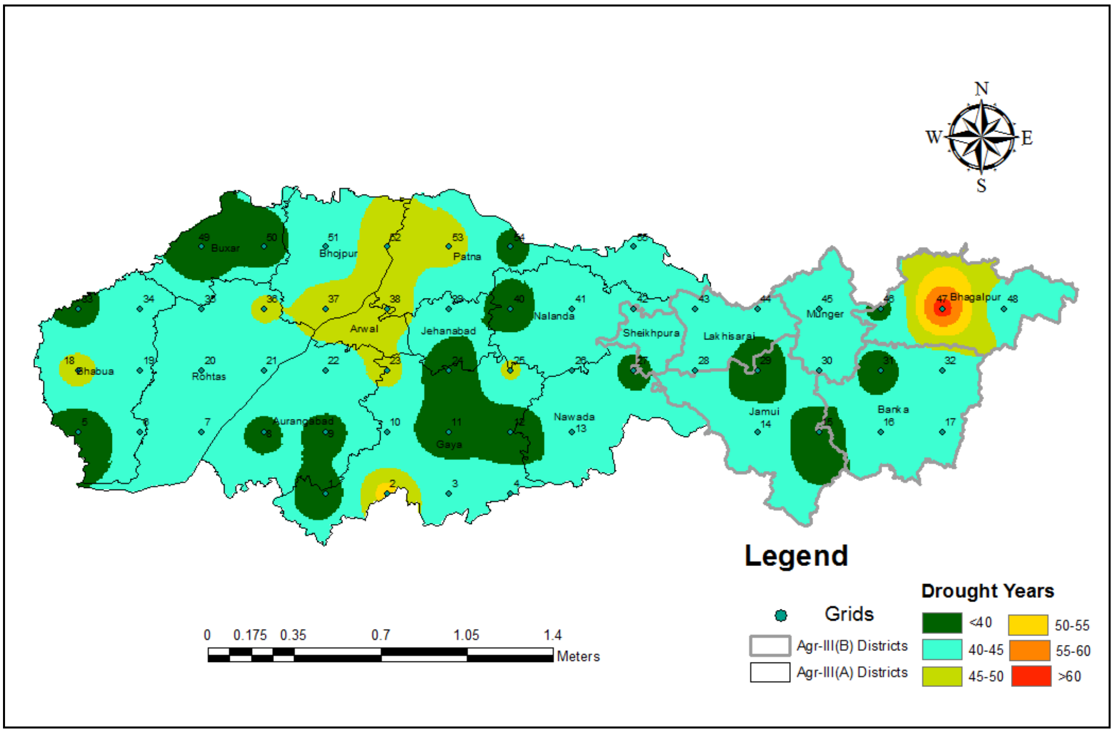

Figure 4.9 Spatial variation map of droughts years

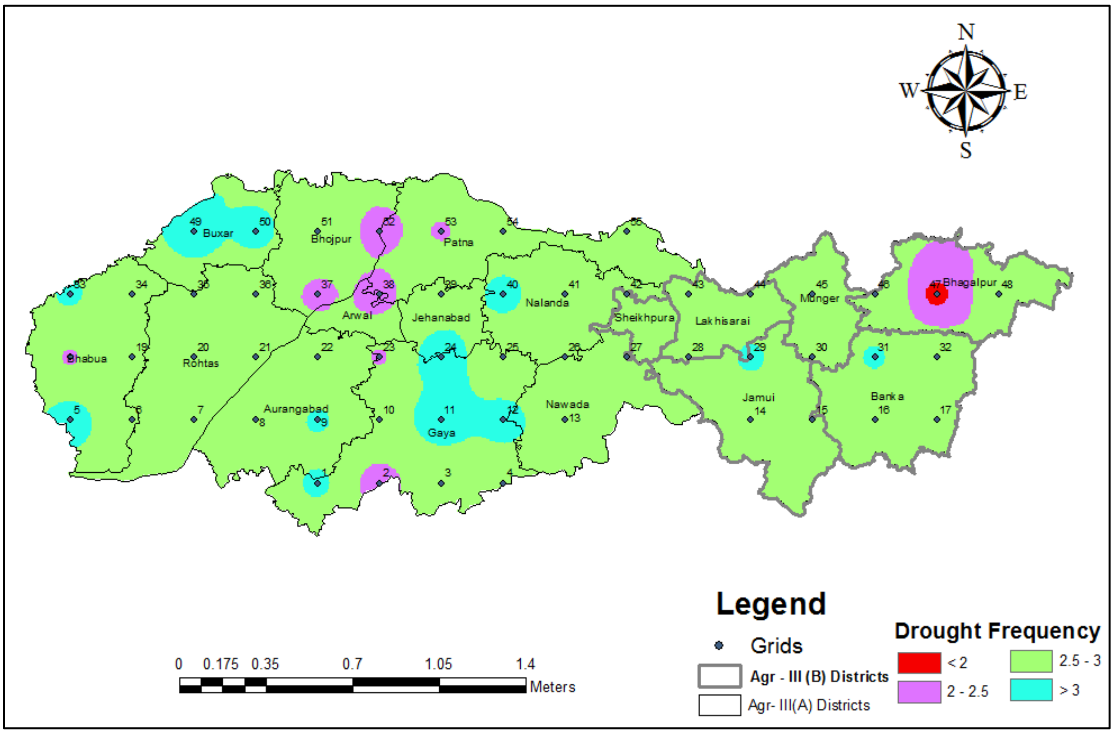

Figure 4.10 Spatial variation map of drought frequency

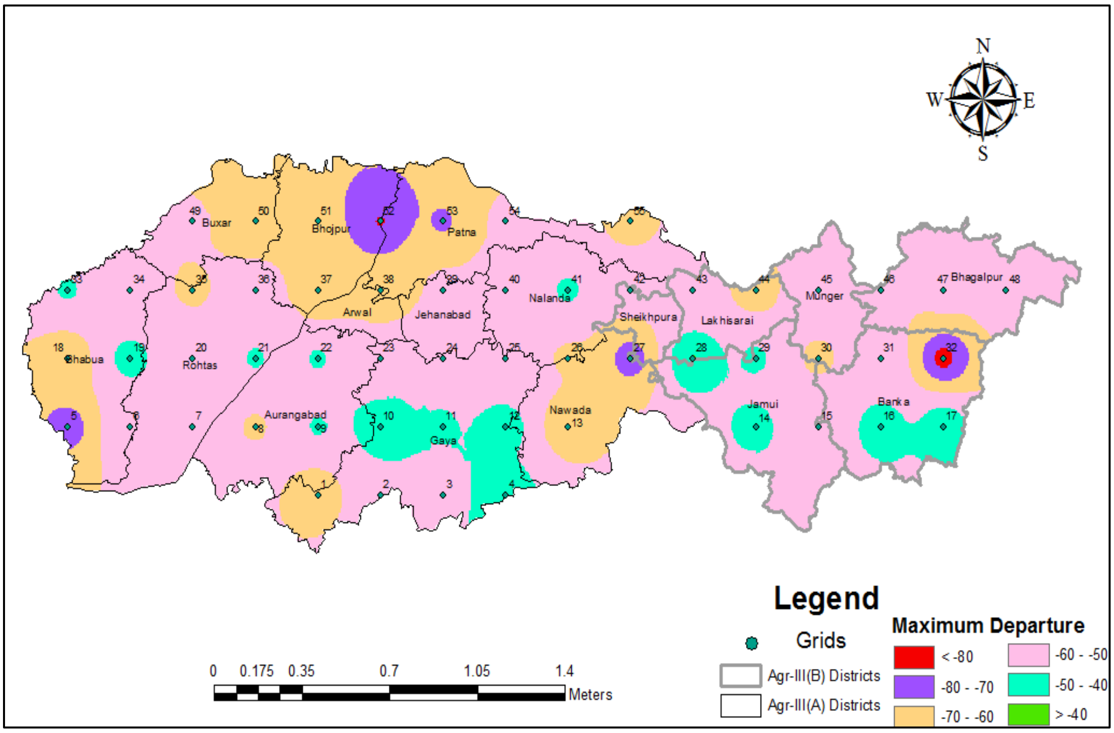

Figure 4.11 Spatial variation map of maximum departure

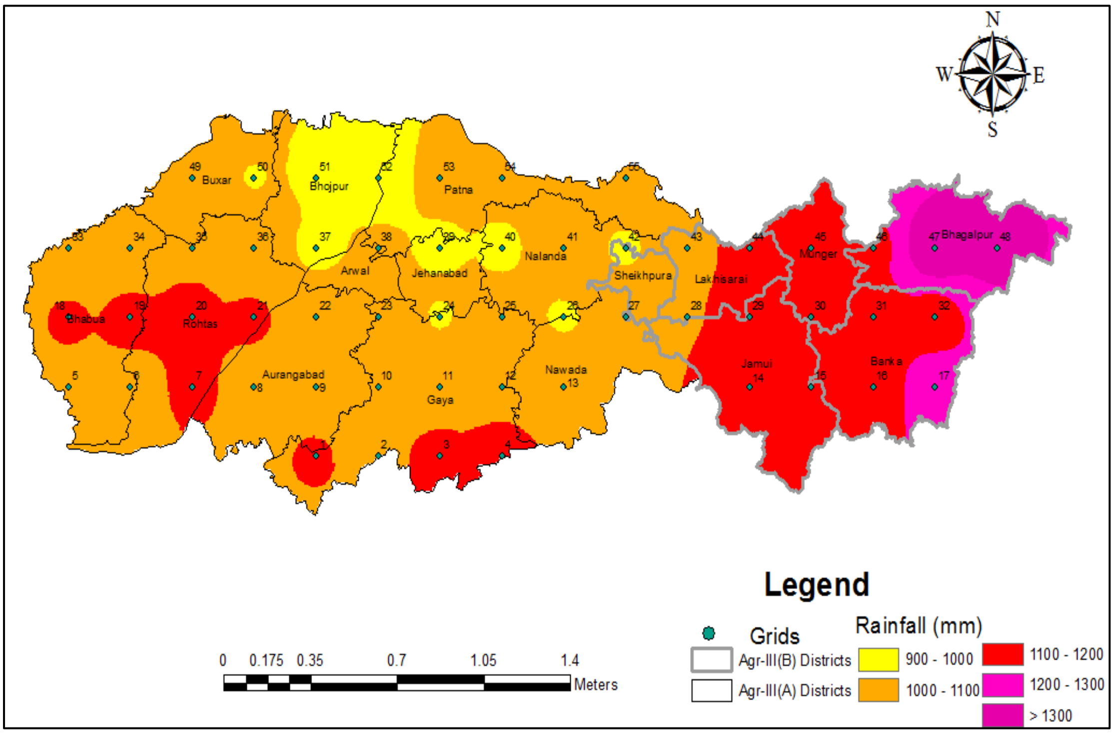

Figure 4.12 Spatial variation map of normal annual rainfall (mm)

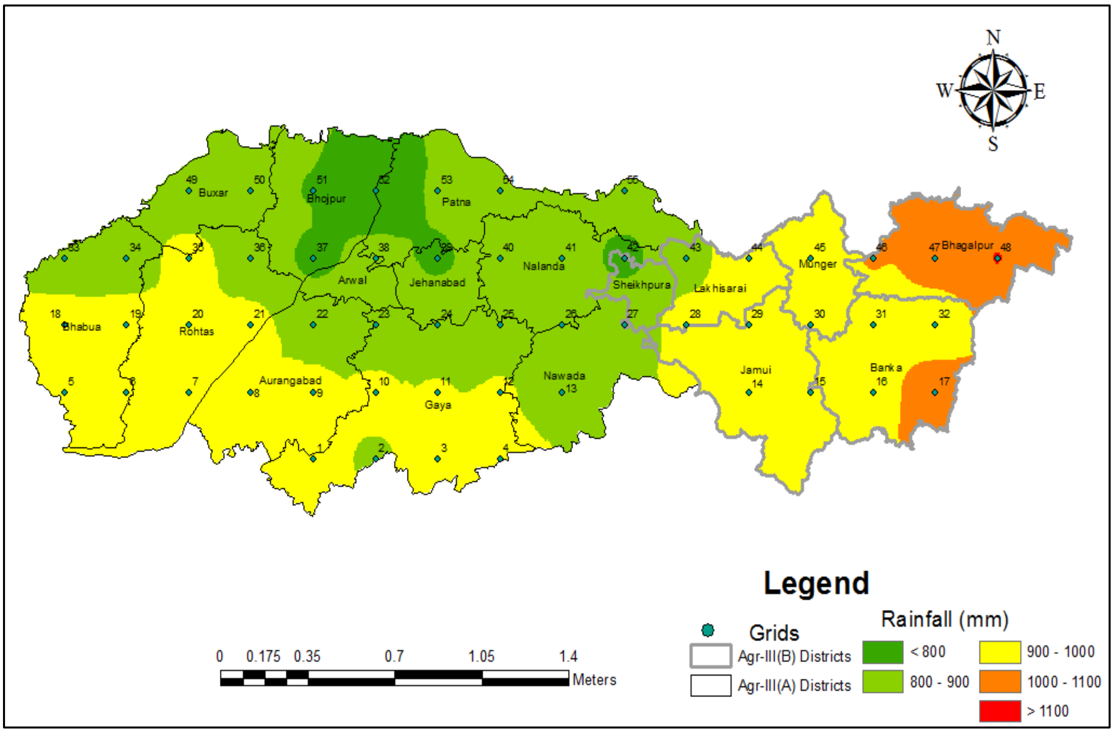

Figure 4.13 Spatial variation map of 75% dependable rainfall (mm)

The Figure 4.12 shows the spatial variation of normal mean rainfall in the districts of South Bihar agro-climatic zone. Most part of the agro-climatic zone-iii (b) has normal rainfall of 1100-1200 (mm) while in the zone-iii (a) the normal rainfall varies in between 1000 – 1100 (mm). The most eastern part of the study area shows the normal annual rainfall greater than 1200 mm and so on.

The Figure 4.13 shows the spatial variation of 75% of dependable rainfall in the study period. Most part of the zone-III (B) shows the dependable rainfall in the range of 900-1000 mm while most part of zone-III (A) shows the dependable rainfall to vary from 800-900 mm. This indicates that the western portion of the study area can survive even with the low amount of rainfall, while the eastern portion requires relatively higher amount of rainfall to fulfill the water needs and thus is more vulnerable to drought.

4.1.2 Identification of drought prone zones:

To detect the drought-prone zones at fifty-five grids in the study area, the probability analysis of rainfall was carried out using Weibull's plotting position formula. The statistics so concluded based on the probability distribution of annual rainfall for the grids is tabulated in Table 4.2. It is observed that there is a considerable variation in the 75% dependable rainfall values from a maximum of 1101.67 mm at grid 48 (Bhagalpur district) to a minimum of 726.14 mm at grid 52. The bar graph showing the variation in the 75% dependable rainfall from the grid to the grid is shown in Figure 4.20. This indicates that rainfall distribution at neighboring grids have a wide variation, where one station receiving more than its normal rainfall and at the same time other station may experience rainfall deficiency. The probability of occurrence of rainfall equivalent to 75% of normal was obtained from the probability distribution chart, which varies from the grid to grid. From the probability analysis, it is indicative of the fact that the areas influenced by grids 37, 42, 45 and 47 are drought-prone (probability of 75% mean rainfall being less than 80%) and faced water scarcity and droughts. So efforts should be focused on the four grids for drought preparedness, mitigation, and management measures. The graph depicting the probability distribution of the annual rainfall at grids 37, 42, 45, 47, 48, and 52 have been given from Figure 4.14 to 4.19.

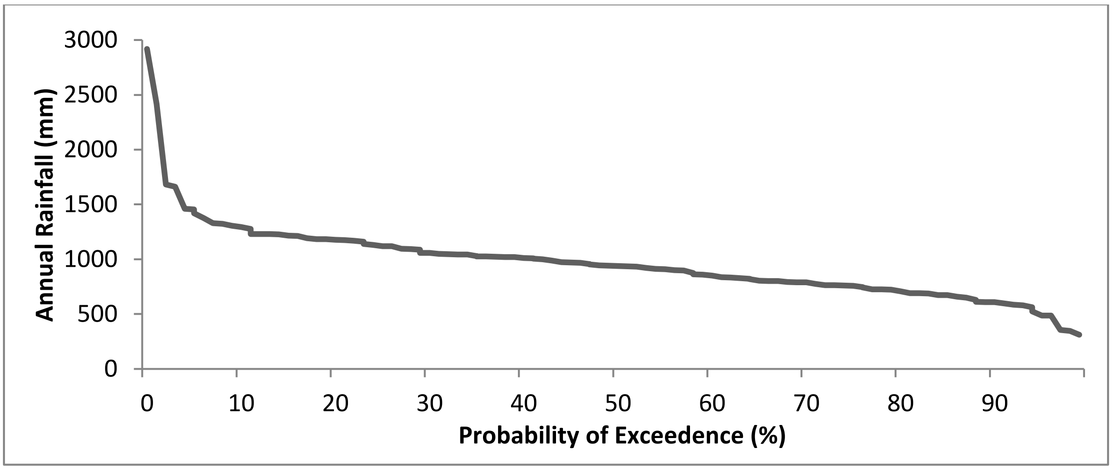

Figure 4.14 Probability distribution of annual rainfall (mm) at grid 37 (Bhojpur district)

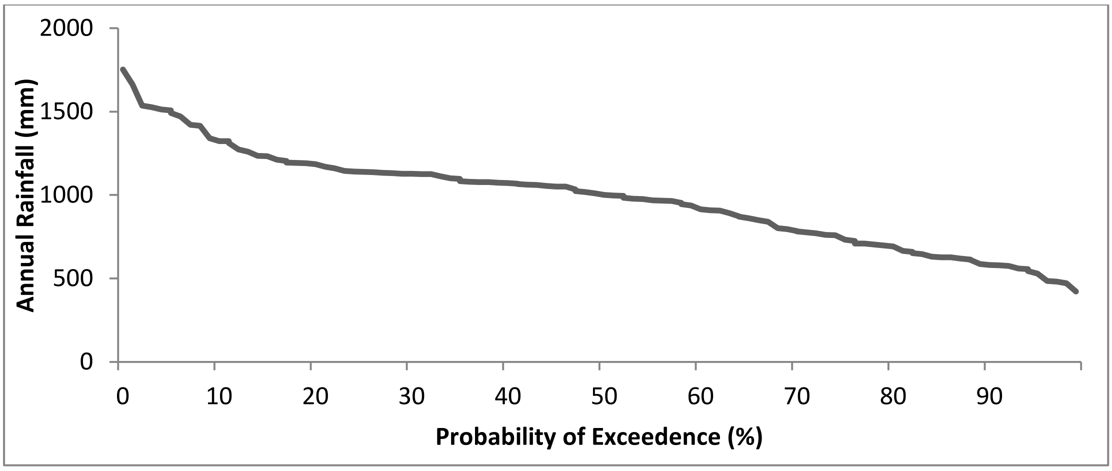

Figure 4.15 Probability distribution of annual rainfall (mm) at grid 42 (Sheikhpura district)

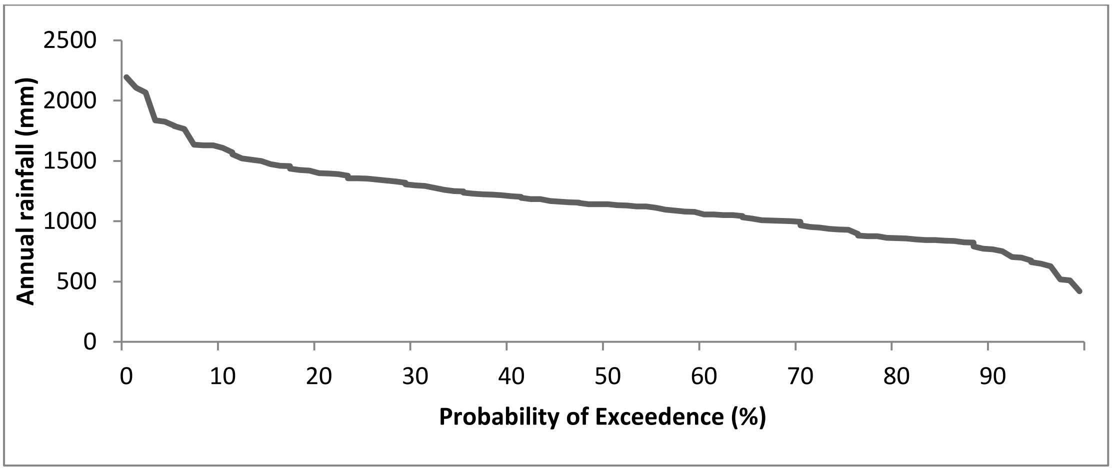

Figure 4.16 Probability distribution of annual rainfall (mm) at grid 45 (Munger district)

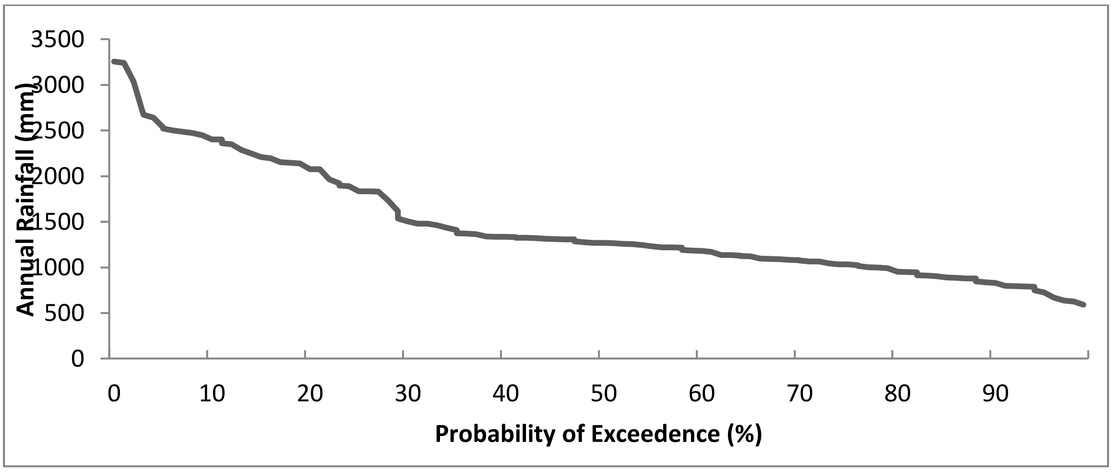

Figure 4.17 Probability distribution of annual rainfall (mm) at grid 47 (Bhagalpur district)

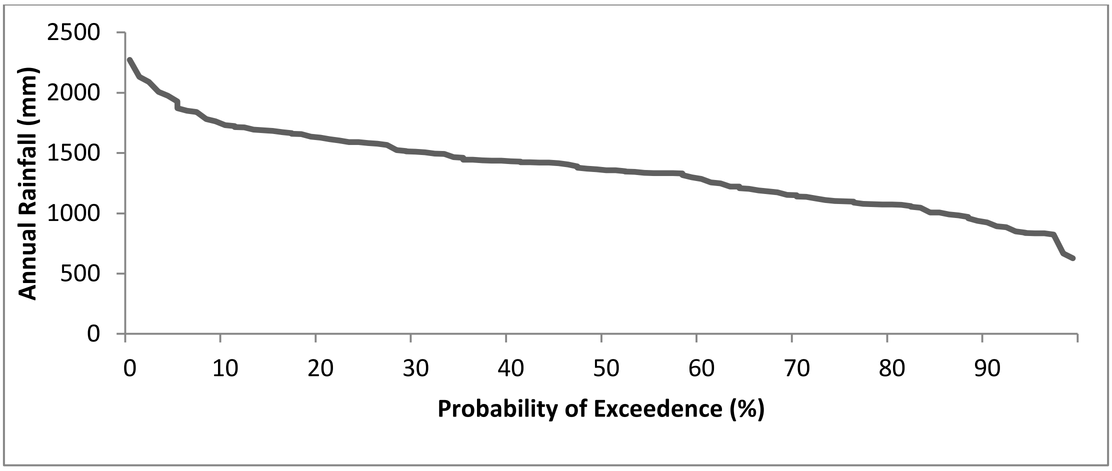

Figure 4.18 Probability distribution of annual rainfall (mm) at grid 48 (Bhagalpur district)

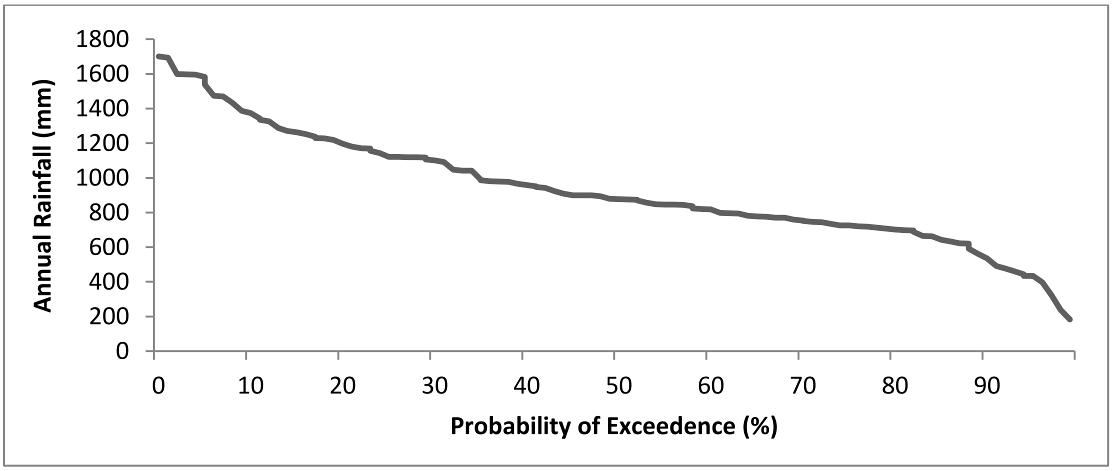

Figure 4.19 Probability distribution of annual rainfall (mm) at grid 52 (Patna district)

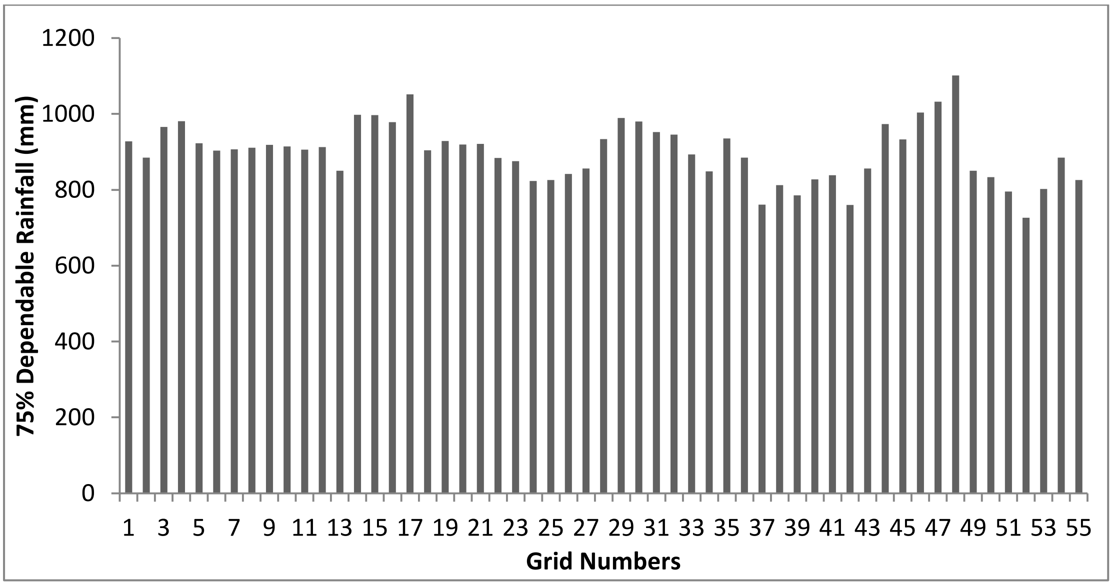

Figure 4.20 Variation of 75 % dependable rainfall (mm) at grids

Table 4.2 Probability distribution of annual rainfall at grids

Grid No.	Normal Annual Rainfall (mm)	75% of Normal Annual Rainfall (mm)	75% Dependable Rainfall (mm)	Probability of Occurrence of Rainfall equivalent to 75% of Normal (mm)	Drought Condition
1	1106.69	830.02	928.18	> 80%	Normal
2	1086.63	814.97	884.76	> 80%	Normal
3	1133.85	850.39	965.34	> 80%	Normal
4	1165.52	874.14	981.31	> 80%	Normal
5	1098.71	824.03	922.65	> 80%	Normal
6	1069.47	802.10	903.47	> 80%	Normal
7	1109.38	832.03	906.39	> 80%	Normal
8	1079.11	809.33	910.65	> 80%	Normal
9	1084.75	813.56	918.35	> 80%	Normal
10	1094.18	820.63	914.48	> 80%	Normal
11	1037.19	777.90	905.92	> 80%	Normal
12	1079.47	809.60	912.56	> 80%	Normal
13	1043.38	782.53	850.68	> 80%	Normal
14	1186.21	889.66	997.54	> 80%	Normal
15	1184.41	888.31	997.04	> 80%	Normal
16	1162.47	871.85	978.42	> 80%	Normal
17	1249.56	937.17	1052.09	> 80%	Normal
18	1108.87	831.65	904.07	> 80%	Normal
19	1125.17	843.88	928.33	> 80%	Normal
20	1138.95	854.21	919.37	> 80%	Normal
21	1119.11	839.33	921.16	> 80%	Normal
22	1047.13	785.35	884.12	> 80%	Normal
23	1054.91	791.18	875.56	> 80%	Normal
24	991.70	743.77	823.12	> 80%	Normal
25	1024.20	768.15	826.03	> 80%	Normal
26	987.36	740.52	841.45	> 80%	Normal
27	1028.46	771.35	856.17	> 80%	Normal
28	1096.30	822.23	934.00	> 80%	Normal

Grid No.	Normal Annual Rainfall (mm)	75% of Normal Annual Rainfall (mm)	75% Dependable Rainfall (mm)	Probability of Occurrence of Rainfall equivalent to 75% of Normal (mm)	Drought Condition
29	1134.07	850.56	989.78	> 80%	Normal
30	1150.61	862.96	979.87	> 80%	Normal
31	1135.56	851.67	952.56	> 80%	Normal
32	1137.74	853.31	945.67	> 80%	Normal
33	1039.17	779.38	892.96	> 80%	Normal
34	1028.19	771.15	848.40	> 80%	Normal
35	1098.53	823.90	935.09	> 80%	Normal
36	1063.19	797.39	884.48	> 80%	Normal
37	965.68	724.26	761.26	< 80%	Drought Prone
38	1013.68	760.26	812.60	> 80%	Normal
39	986.06	739.55	784.97	> 80%	Normal
40	980.50	735.37	827.73	> 80%	Normal
41	1046.45	784.83	838.73	> 80%	Normal
42	978.15	733.61	759.75	< 80%	Drought Prone
43	1063.79	797.84	855.91	> 80%	Normal
44	1132.96	849.72	973.17	> 80%	Normal
45	1163.42	872.56	932.56	< 80%	Drought Prone
46	1163.70	872.78	1003.74	> 80%	Normal
47	1454.24	1090.68	1032.70	< 80%	Drought Prone
48	1357.41	1018.05	1101.67	> 80%	Normal
49	1009.49	757.12	850.63	> 80%	Normal
50	995.72	746.79	833.03	> 80%	Normal
51	986.50	739.88	795.51	> 80%	Normal
52	932.52	699.39	726.14	> 80%	Normal
53	1033.74	775.31	801.90	> 80%	Normal
54	1038.24	778.68	884.83	> 80%	Normal
55	1069.82	802.37	825.84	> 80%	Normal

4.1.3 Drought severity assessment using SPI

The drought events and their duration have been computed using SPI. The drought durations have been classified into extreme, severe, moderate and mild as per severity classification. The drought events have been categorized in three different grades; (i) for drought prevailing one month only, (ii) for drought prevailing continuously two months only and (iii) for drought prevailing continuously three or more than three months. The drought events existing continuously three or more than three months indicates the most severe condition as all the conserved and saved water will be exhausted in the mean time.

Referring to Figure 4.21 and Figure 4.22, the SPI-1 results show that grid 32(Banka district) faces maximum times extreme drought with total duration of 27 months. The grid 47 of Bhagalpur district suffers highest number of total drought periods of 366 months and also faces maximum drought events of grade-iii of 33 events with total of 230 drought events. The grid 16 faces maximum number of 252 drought events with 20 events of grade-iii. The SPI-1 analysis shows the nature of meteorological drought prevailing in the area based on one month cumulative rainfall.

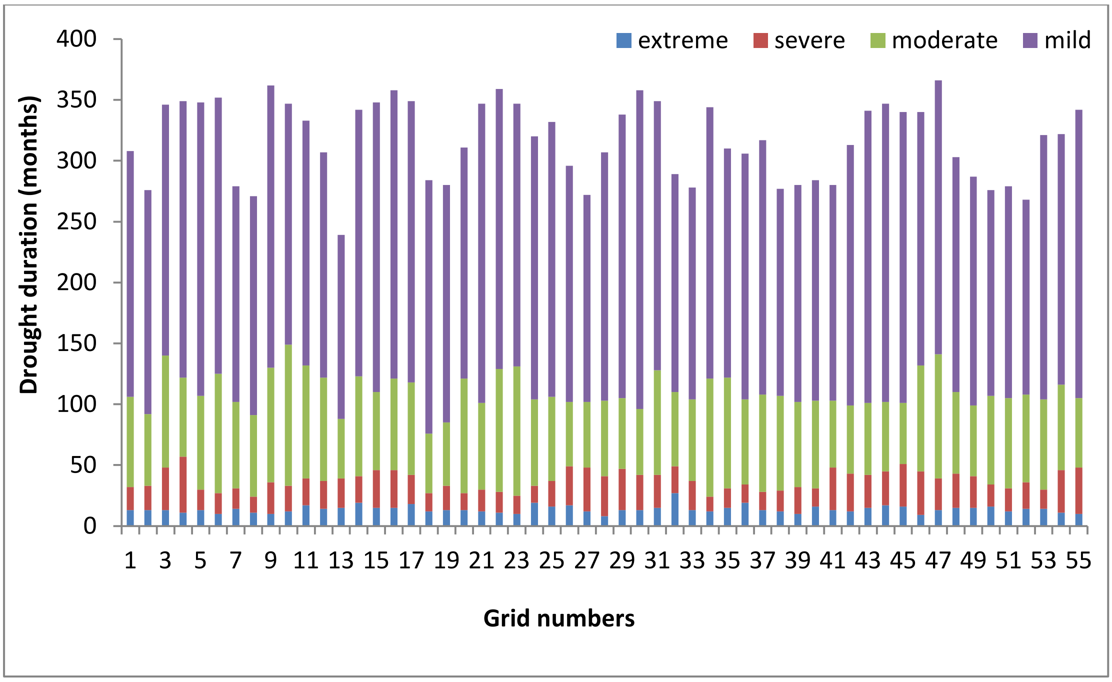

Figure 4.21 Drought durations for all grids based on SPI-1

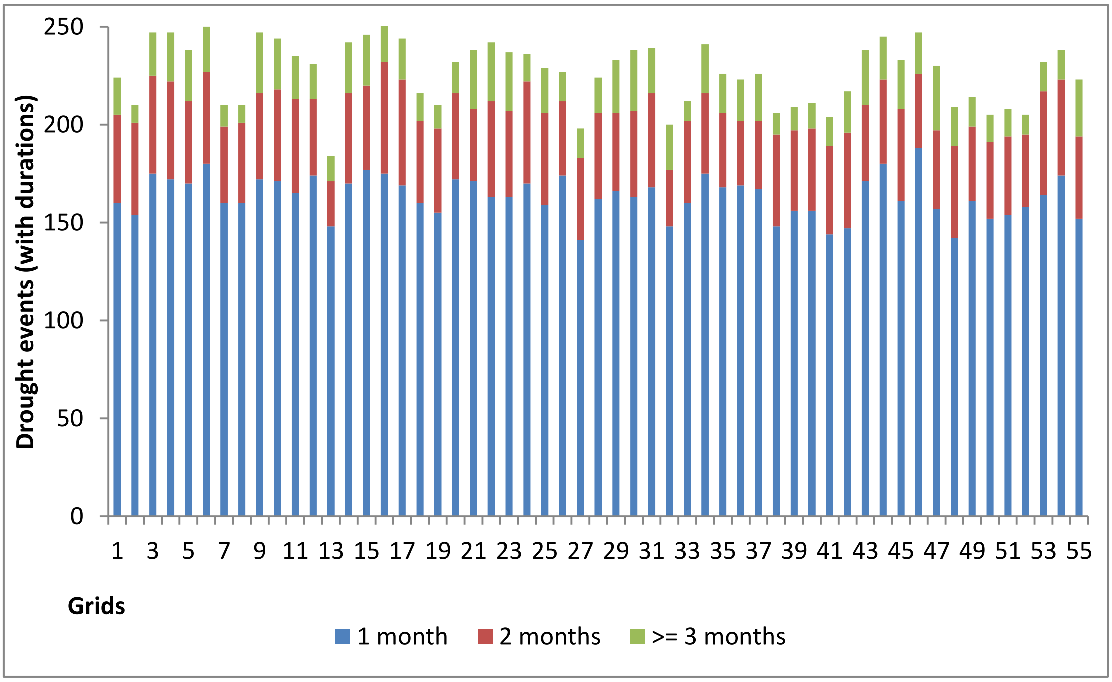

Figure 4.22 Drought events prevailing continuously for months for all grid based on SPI-1

The condition of soil moisture or agriculture drought is indicated by the 3-month scale of SPI (Thomas et al., 2014). Referring to Figure 4.23 and Figure 4.24, the SPI-3 results show that grid 32 face maximum number of extreme drought duration of 41 months. The grid 47 of Bhagalpur district suffers highest number of total drought periods of 438 months with 18 as extreme months. The grid 25 faces maximum of 73 drought events of grade-iii with total drought events of 168.

Referring to Figures 4.25 and 4.26, the SPI-6 results shows that grid 11 and grid 54 faces highest number of extreme drought condition for 51 months while the grid 14 faces maximum of 429 drought months. The grid 2 suffers highest number of 58 extreme drought events. The grid 19 faces maximum drought events of 133 with 48 as extreme events. The SPI-6 analysis shows the behavior of hydrological drought prevailing in the area (Angelidis et al., 2012).

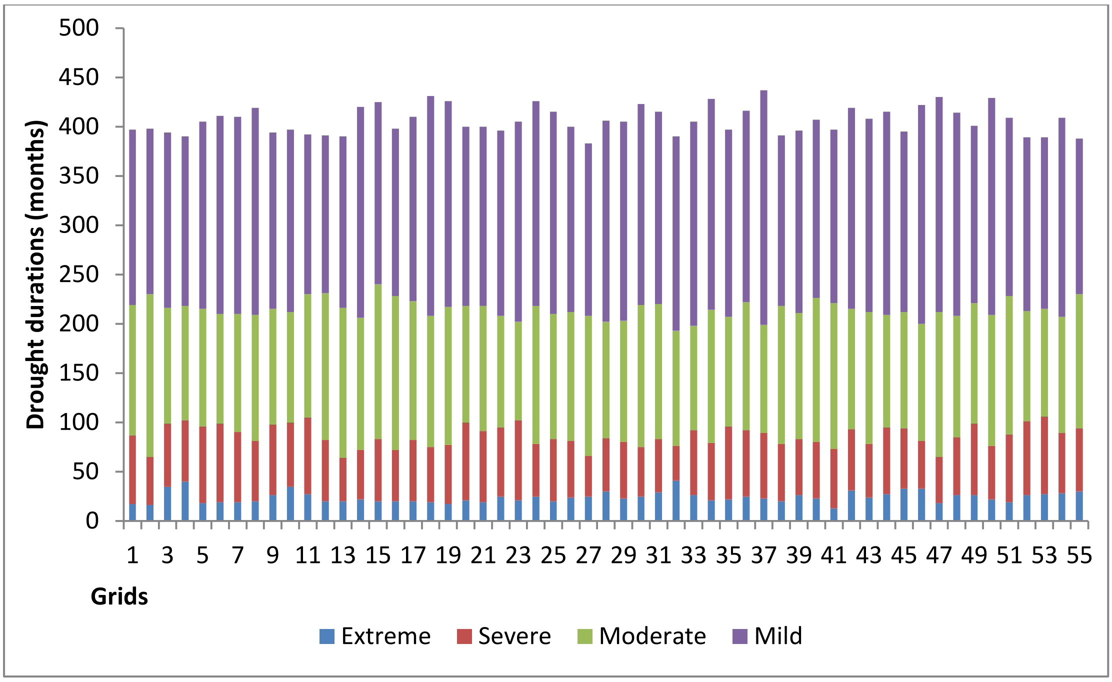

Figure 4.23 Drought durations for all grids based on SPI-3

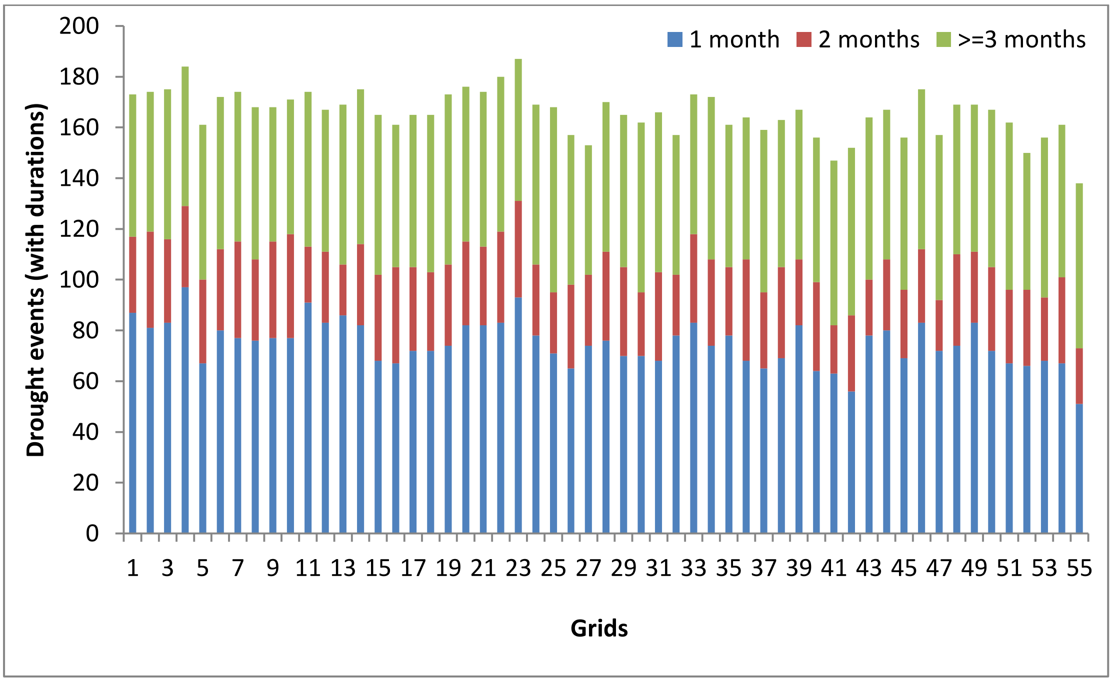

Figure 4.24 Drought events prevailing continuously for months based on SPI-3 for all grids

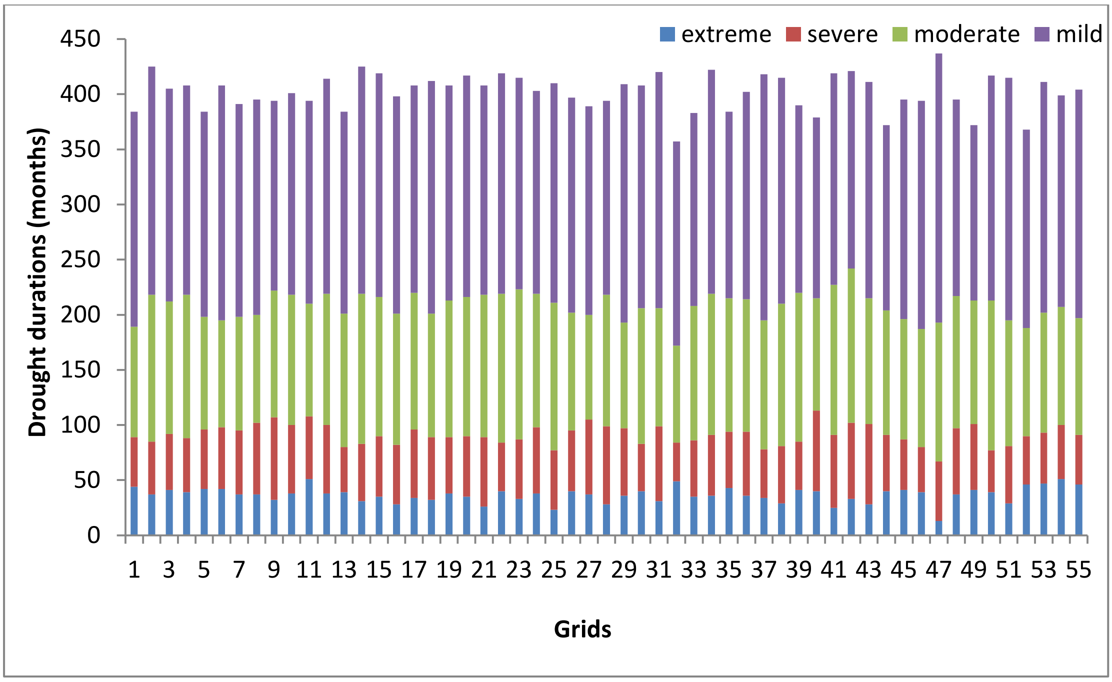

Figure 4.25 Drought durations for all grids based on SPI-6

The SPI-12 analysis shows the nature of groundwater drought prevailing in the area (Angelidis et al., 2012). Referring to Figures 4.27 and 4.28, the SPI-12 results show that grid 11 faces maximum number of extreme drought condition for 60 months while the grid 2 faces maximum of 499 drought months.

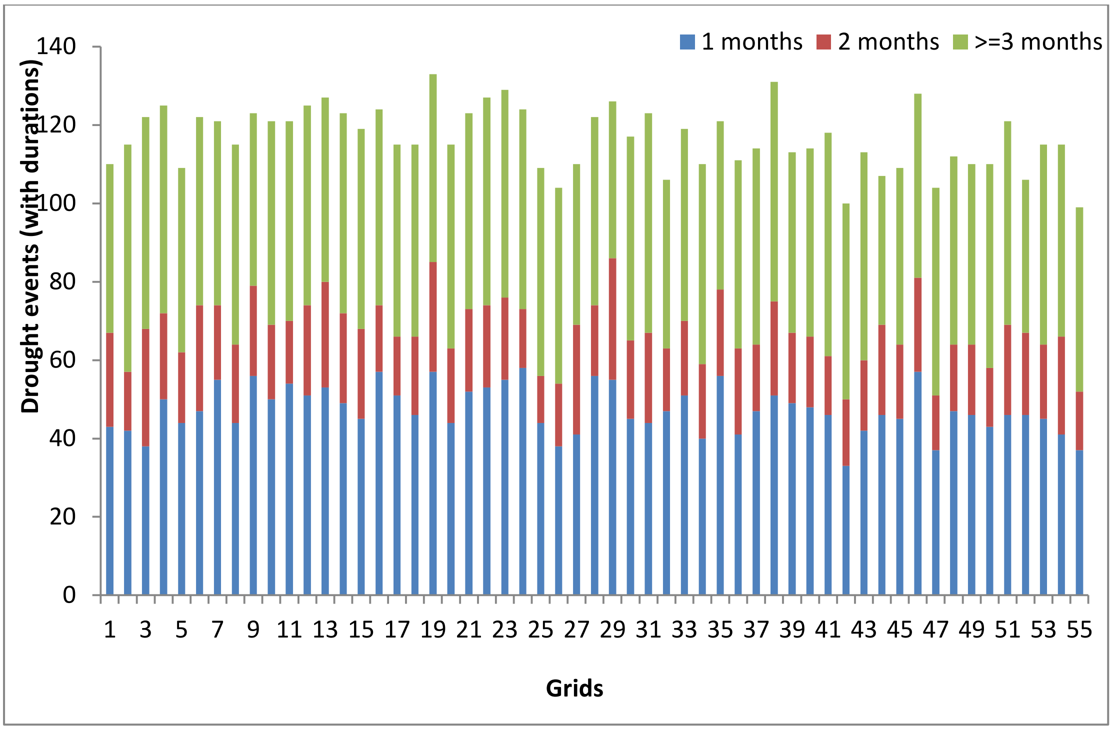

Figure 4.26 Drought events prevailing continuously for months based on SPI-6 for all grids

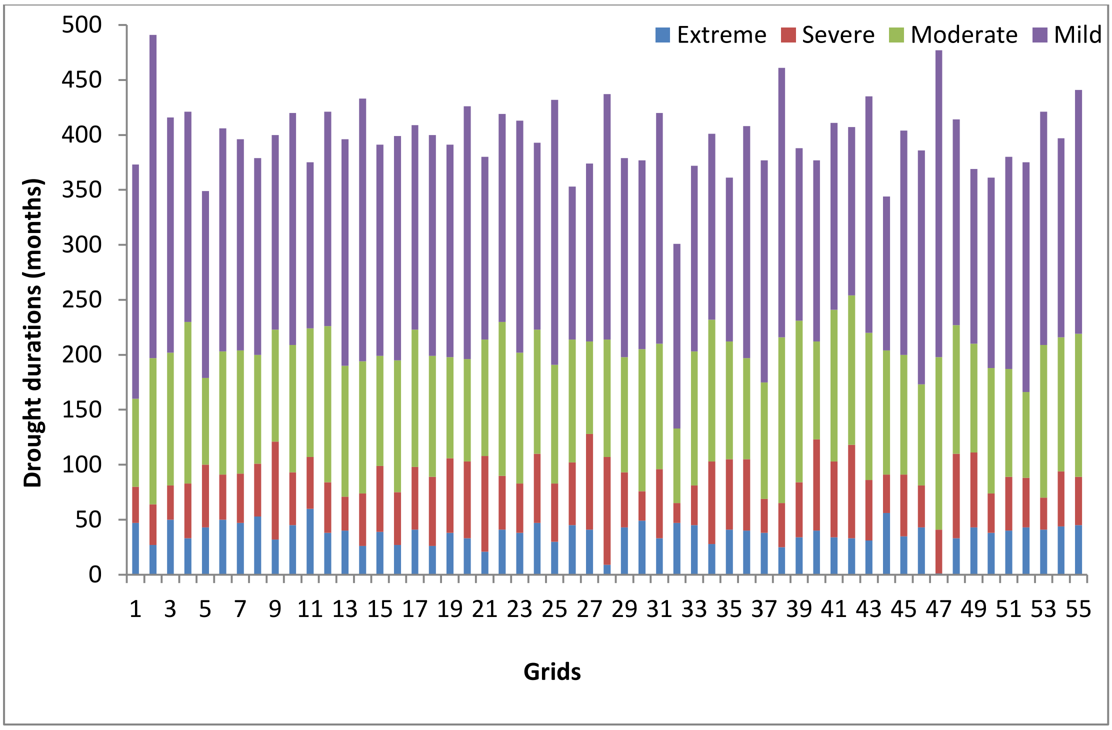

Figure 4.27 Drought durations for all grids based on SPI 12

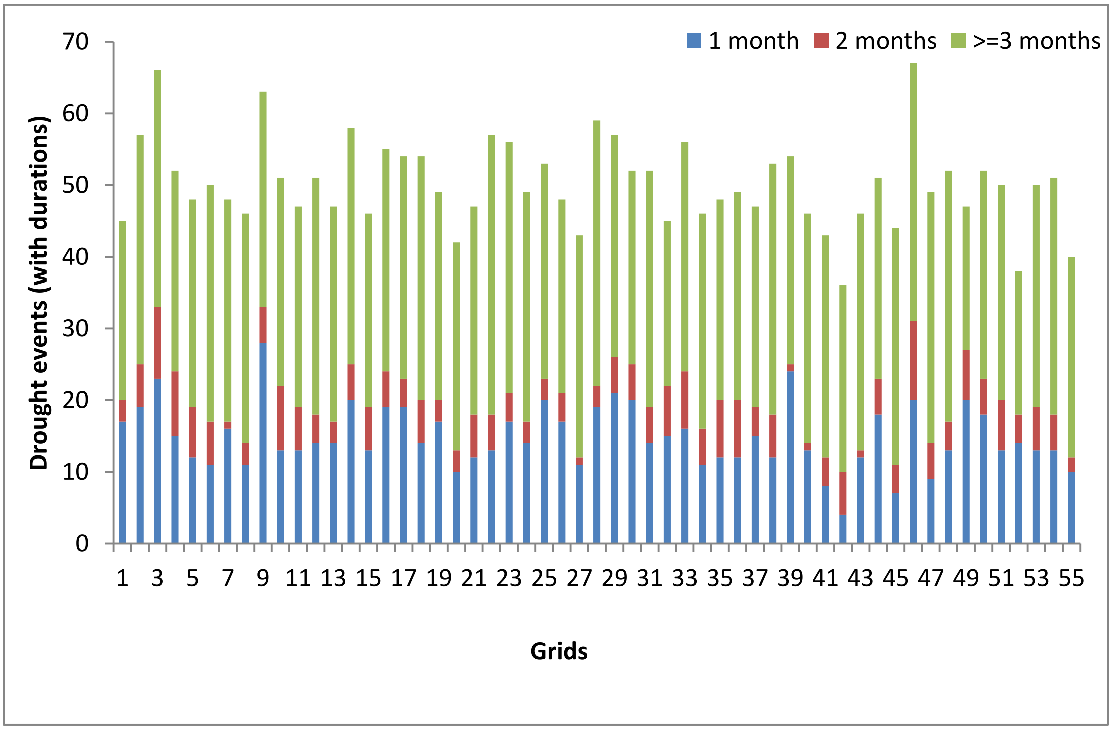

Figure 4.28 Drought events prevailing continuously based on SPI 12 for all grids

The grid 22 (Aurangabad district) suffers highest number of 39 of grade-iii drought events with total number of fifty-seven (57) events and four hundred thirty-two (432) drought months where forty-one (41) are under extreme period. The grid 46 faces maximum of 67 drought events with 36 as grade-iii events and duration of 389 months with 43 as extreme months.

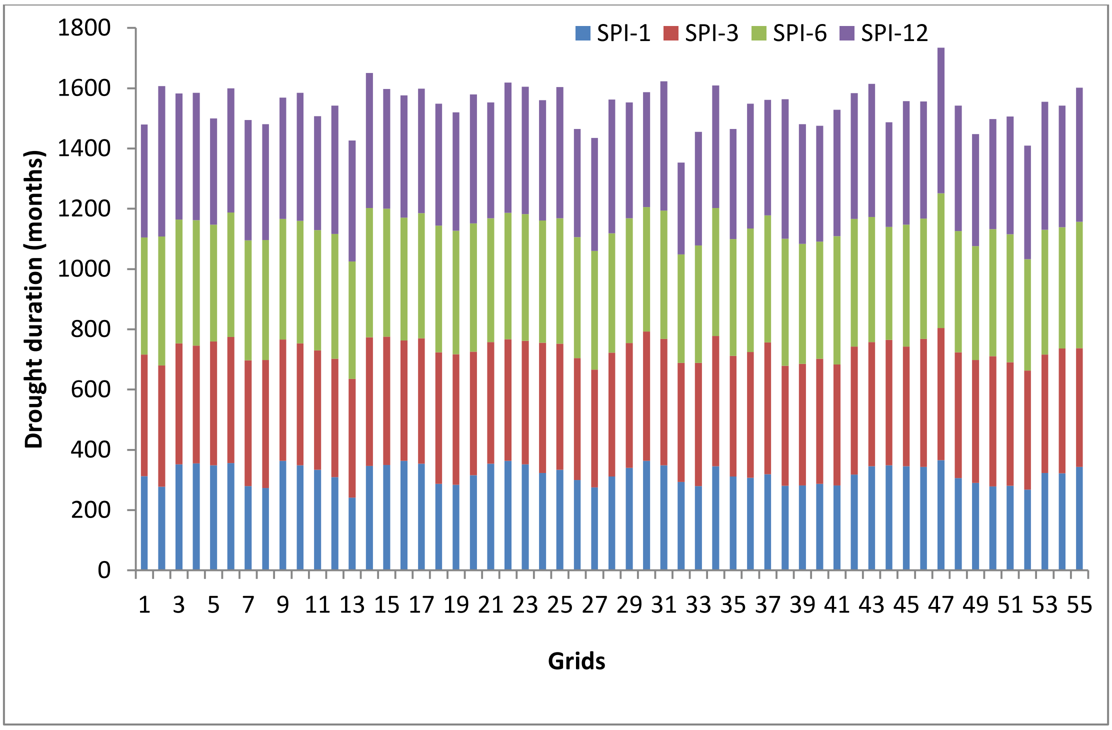

Figure 4.29 Total drought durations (months) for different timescales of SPI for all grids

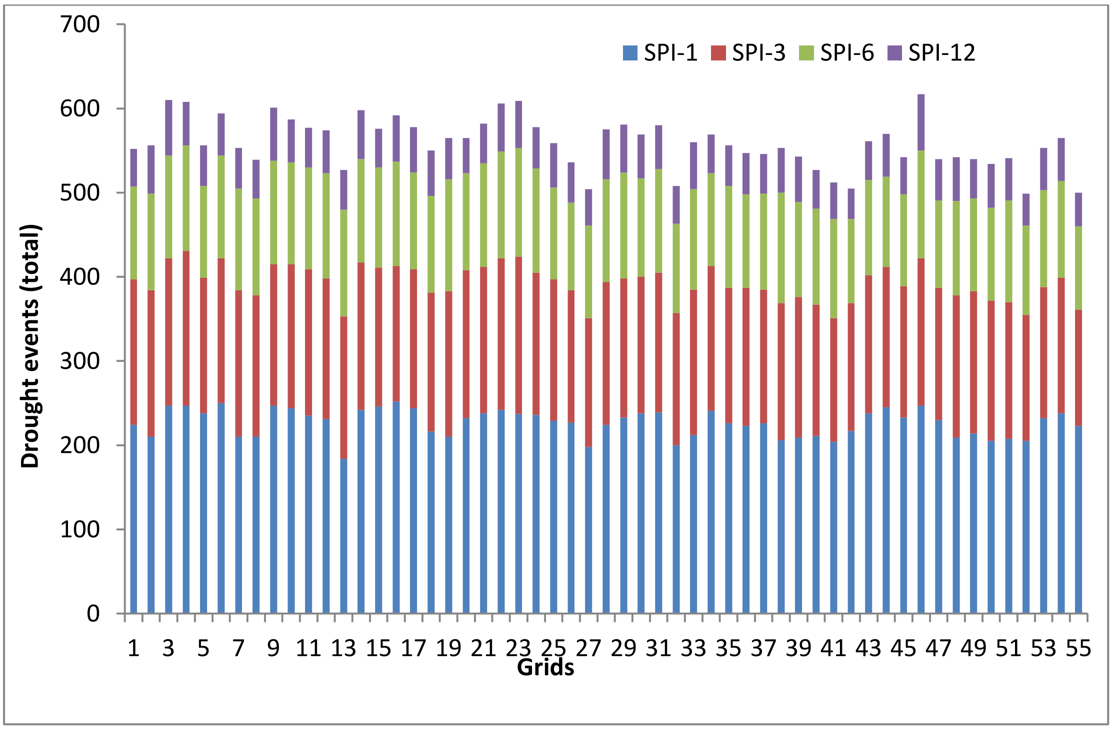

Figure 4.30 Total drought events by different timescales of SPI for all grids

Figure 4.29 shows the variations of total drought durations by different timescales of SPI for all grids. The grid 22 faces maximum period of meteorological drought period of 364 months while the soil moisture deficit as well as the hydrological drought prevails maximum in grid 47 and the grid 2 suffers highest groundwater drought period of 499 months as indicated by 1-, 3-, 6- and 12- month scale of SPI respectively.

Figure 4.30 shows the variation of drought events by different timescale of SPI. The events of meteorological drought are highest in grid 16 (252 events), while agriculture as well as surface water drought events is maximum in grid 23 (187 and 129 events respectively) and lastly the grid 46 faces maximum of 67 events of groundwater drought as indicated by 1-, 3-, 6- and 12- month scales of SPI respectively.

The south-west monsoon season is the main rainy season over the entire study region. About 86% of the total rainfall amount is received in the period of the southwest monsoon season (June to September), about 2% is received in the winter season (December to February) and about 6% comes in the pre-monsoon moths (March, April and May) and about 6% in post monsoon periods (October to November). The delay in the onset of the south-west monsoon is the primary cause for the occurrence of drought and the extension of its duration. In addition, the erratic nature and the deficit in the amount of the monsoon rainfall also causes drought.

4.1.4 Spatial analysis of drought frequency

The drought frequency is an important characteristic to analyze the drought vulnerability in the study area. It is computed by simply dividing the period of study (1902 to 2016, 115 years) with that of drought events. Since the drought events which prevail continuously for three or more than three months are considered to be more severe, have been considered for frequency analysis.

Figure 4.31 shows the spatial variation of meteorological drought frequency that varies from 3.48 to 12.77. It indicates that the drought event occurs at least once in 3.48-12.77 years. The lower value indicates that more severe drought condition prevails in that district. The Eastern region of south Bihar is more severe to the drought as compared to west part of south Bihar, as the drought frequency is low in the area.

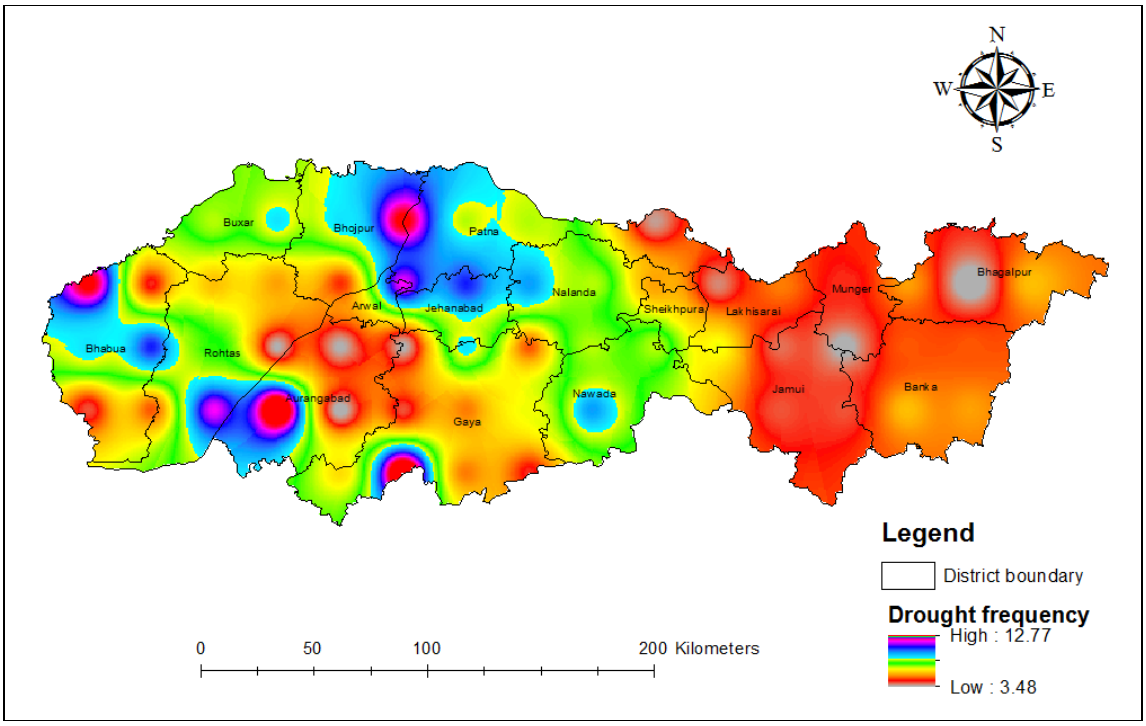

Figure 4.31 SPI-1 based meteorological drought frequency

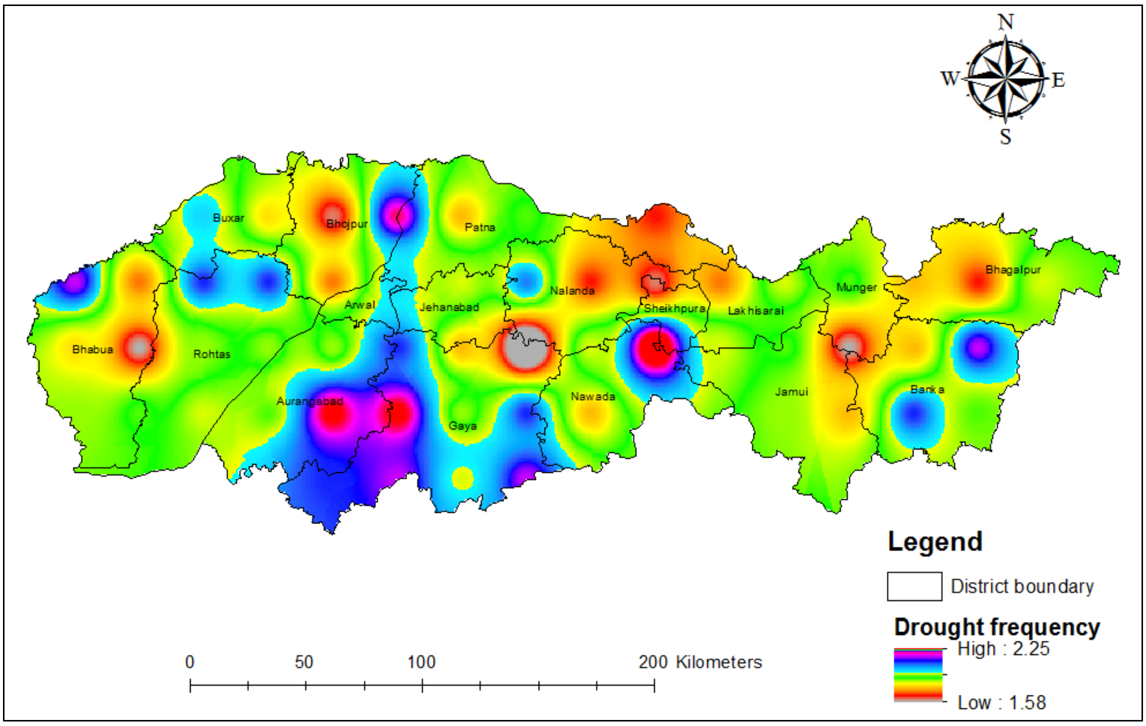

Figure 4.32 SPI-3 based agriculture drought frequency

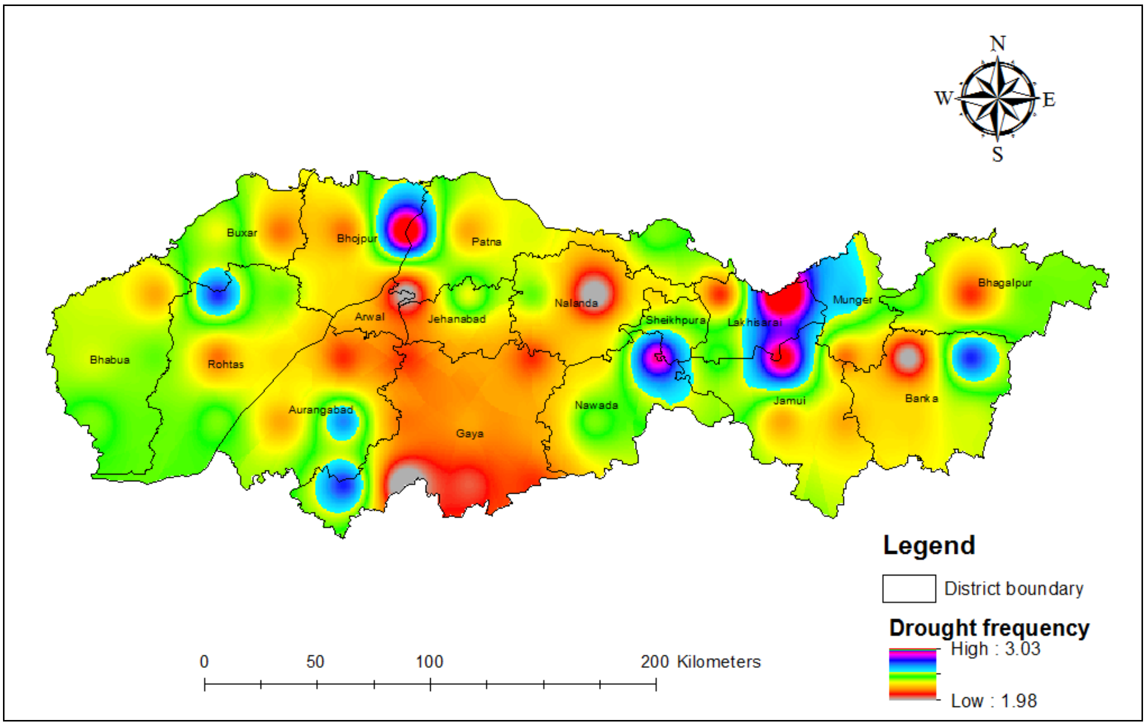

Figure 4.33 SPI-6 based hydrological drought frequency

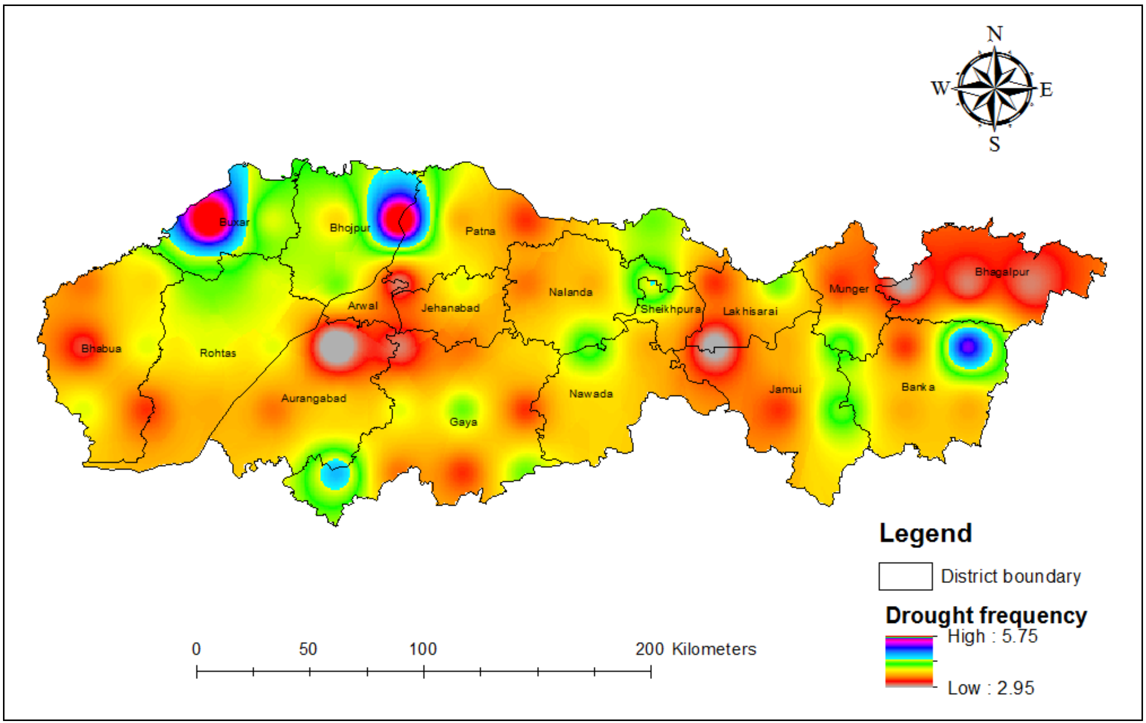

Figure 4.34 SPI-12 based groundwater drought frequency

Figure 4.32 shows the spatial variation of agriculture drought frequency that varies from 1.58 to 2.25. It indicates that the drought event occurs at least once in 1.58 to 2.25 years. The Figure shows that some parts of Gaya, Bhabhua, Nalanda and Munger are more severe to the occurrence of the drought events, while in most region the drought frequency is in between once in 1.58 to 2.25 years. The spatial variation of hydrological drought frequency that varies from 1.98 to 3.03 is shown in Figure 4.33. It indicates that the drought event occurs at least once in 1.98 - 3.03 years. The Figure shows that most parts of Gaya district are under severe condition with very low frequency. Figure 4.34 shows the spatial variation of groundwater drought frequency that varies from 2.95 to 5.75. It indicates that the drought event occurs at least once in 2.95 to 5.75 years. The Figure (4.34) shows that most eastern districts of the study area i.e., Bhagalpur, Munger, Jamui and Lakhisarai districts are under severe condition with low drought frequency.

The reason behind this will be that the monsoon comes from Southwest and withdraw from the Northeast region of the region. The southern Bihar region receives rainfall primarily due to low pressure zones and monsoon depressions originating in the Bay of Bengal during the southwest monsoon. The southwest monsoon sets in over the eastern parts of the state by about the middle of second week of June and covers the entire Bihar state by the end of the second week of June. The withdrawal of the southwest monsoon begins from the northern parts of the region in the first week of October and the monsoon completely withdraws from the state by the mid October.

4.1.5 Drought events monitoring:

The results of SPI-3 and SPI-6 shows that grid 25 and grid 2 faces maximum drought events with duration ≥ 3 months respectively (Table 4.3), so the events for the grids (25 and 2) have been considered for the monitoring. The onset of drought event starts when the SPI value becomes less than -0.5 and ends when it becomes greater than -0.5. The magnitude of a drought event is the positive sum of SPI severity for the drought periods. The intensity of any drought event is determined by dividing the magnitude of the event by the period of the drought months. Referring to Table 4.3, the SPI-3 analysis for the grid 25 (Gaya district), the drought event (64 no.) is found to be of maximum durations of 12 months from May 2005 to April 2006 and was also of maximum magnitude of 16.57 with an average intensity of 1.38, while, the drought event (60 no.) was of maximum intensity of 1.84 with a magnitude of 5.52 that prevails for three months from February 1999 to April 1999. The variation of intensity of SPI-3 for the grid 25 for the 115 years is shown in Figure 4.35.

Table 4.3 Drought events with duration ≥ 3 months based on SPI-3 and SPI-6 for all grids

Grids No.	SPI-3 Events	SPI-6 Events	Grids No.	SPI-3 Events	SPI-6 Events
1	56	43	**29**	60	40
2	55	**58**	**30**	67	52
3	59	54	**31**	63	56
4	55	53	**32**	55	43
5	61	47	**33**	55	49
6	60	48	**34**	64	51
7	59	47	**35**	56	43
8	60	51	**36**	56	48
9	53	44	**37**	64	50
10	53	52	**38**	58	56
11	61	51	**39**	59	46
12	56	51	**40**	57	48
13	63	47	**41**	65	57
14	61	51	**42**	66	50
15	63	51	**43**	64	53
16	56	50	**44**	59	38
17	60	49	**45**	60	45
18	62	49	**46**	63	47
19	67	48	**47**	65	53
20	61	52	**48**	59	48
21	61	50	**49**	58	46
22	61	53	**50**	62	52
23	56	53	**51**	66	52
24	63	51	**52**	54	39
25	**73**	53	**53**	63	51
26	59	50	**54**	60	49
27	51	41	**55**	65	47
28	59	48	-	-	-

Table 4.4 Drought events monitoring based on SPI-3, with durations ≥ 3 months for the grid 25

Event no.	Onset	Termination	Durations	Magnitude	Intensity
1	May-1903	Sep-1903	5	8.01	1.6
2	Jan-1904	Apr-1904	4	3.36	0.84
3	Aug-1908	Nov-1908	4	3.29	0.82
4	Dec-1909	Mar-1910	4	2.94	0.74
5	Aug-1912	Nov-1912	4	3.26	0.82
6	Nov-1914	Jan-1915	3	3.64	1.21
7	Jul-1915	Oct-1915	4	2.99	0.75
8	Jan-1918	Mar-1918	3	3.72	1.24
9	Aug-1920	Oct-1920	3	4.08	1.36
10	Mar-1921	Jul-1921	5	5.18	1.04
11	Sep-1923	Nov-1923	3	1.98	0.66
12	Feb-1925	Apr-1925	3	3.88	1.29
13	Jun-1927	Nov-1927	6	9.25	1.54
14	Aug-1928	Nov-1928	4	4.72	1.18
15	Mar-1930	Jun-1930	4	3.22	0.81
16	May-1932	Sep-1932	5	5.02	1
17	May-1935	Jul-1935	3	5.33	1.78
18	Oct-1938	Jan-1939	4	4.54	1.14
19	Jun-1940	Nov-1940	6	6.51	1.09
20	Mar-1941	May-1941	3	3.34	1.11
21	Apr-1943	Jun-1943	3	2.53	0.84
22	Oct-1944	Dec-1944	3	2.19	0.73
23	Jun-1945	Sep-1945	4	4.55	1.14
24	Jul-1946	Oct-1946	4	6.29	1.57
25	Feb-1947	Dec-1947	11	12.09	1.1
26	Oct-1950	Dec-1950	3	4.14	1.38
27	Mar-1951	May-1951	3	4.01	1.34
28	Aug-1951	Nov-1951	4	3.76	0.94
29	Jan-1952	Mar-1952	3	3.69	1.23
30	May-1954	Aug-1954	4	4.7	1.18
31	Oct-1957	May-1958	8	6.73	0.84
32	Jul-1958	Sep-1958	3	3.22	1.07
33	Jan-1960	Mar-1960	3	3.86	1.29
34	Jun-1960	Aug-1960	3	2.81	0.94
35	Jan-1963	Apr-1963	4	4.63	1.16
36	May-1965	Aug-1965	4	3.7	0.93
37	Jul-1966	Nov-1966	5	8.91	1.78
38	Jun-1967	Sep-1967	4	5.85	1.46

39	Sep-1968	Nov-1968	3	3.47	1.16
40	May-1972	Aug-1972	4	5.24	1.31
41	Jan-1974	Apr-1974	4	3.87	0.97
42	Apr-1975	Jun-1975	3	2.65	0.88
43	Jan-1976	Apr-1976	4	3.74	0.94
44	Dec-1976	Mar-1977	4	3.83	0.96
45	Dec-1981	Feb-1982	3	3.28	1.09
46	Jul-1982	Sep-1982	3	3.14	1.05
47	Aug-1983	Oct-1983	3	2.89	0.96
48	Feb-1985	Jun-1985	5	4.99	1
49	Jan-1986	Mar-1986	3	2.78	0.93
50	Sep-1986	Nov-1986	3	2.89	0.96
51	Mar-1987	Jun-1987	4	4.59	1.15
52	Dec-1987	Feb-1988	3	2.23	0.74
53	Jan-1989	Apr-1989	4	2.73	0.68
54	Jul-1991	Sep-1991	3	2.26	0.75
55	Mar-1992	Jun-1992	4	4.34	1.09
56	Sep-1992	Jan-1993	5	6.39	1.28
57	Aug-1994	Nov-1994	4	3.4	0.85
58	Apr-1995	Aug-1995	5	5.68	1.14
59	Jan-1997	Apr-1997	4	3.73	0.93
60	Feb-1999	Apr-1999	3	5.52	**1.84**
61	Jan-2000	Mar-2000	3	2.06	0.69
62	Dec-2000	May-2001	6	9.19	1.53
63	Aug-2004	Nov-2004	4	6.21	1.55
64	May-2005	Apr-2006	**12**	**16.57**	1.38
65	Oct-2008	Apr-2009	7	11.64	1.66
66	Jul-2009	Sep-2009	3	4.54	1.51
67	Feb-2010	Apr-2010	3	4.33	1.44
68	Jul-2010	Oct-2010	4	3.87	0.97
69	Jul-2011	Dec-2011	6	13.1	2.18
70	Jan-2013	Mar-2013	3	2.79	0.93
71	Jul-2013	Sep-2013	3	4.51	1.5
72	Oct-2014	Dec-2014	3	2.22	0.74
73	Jul-2015	Dec-2015	6	8.02	1.34

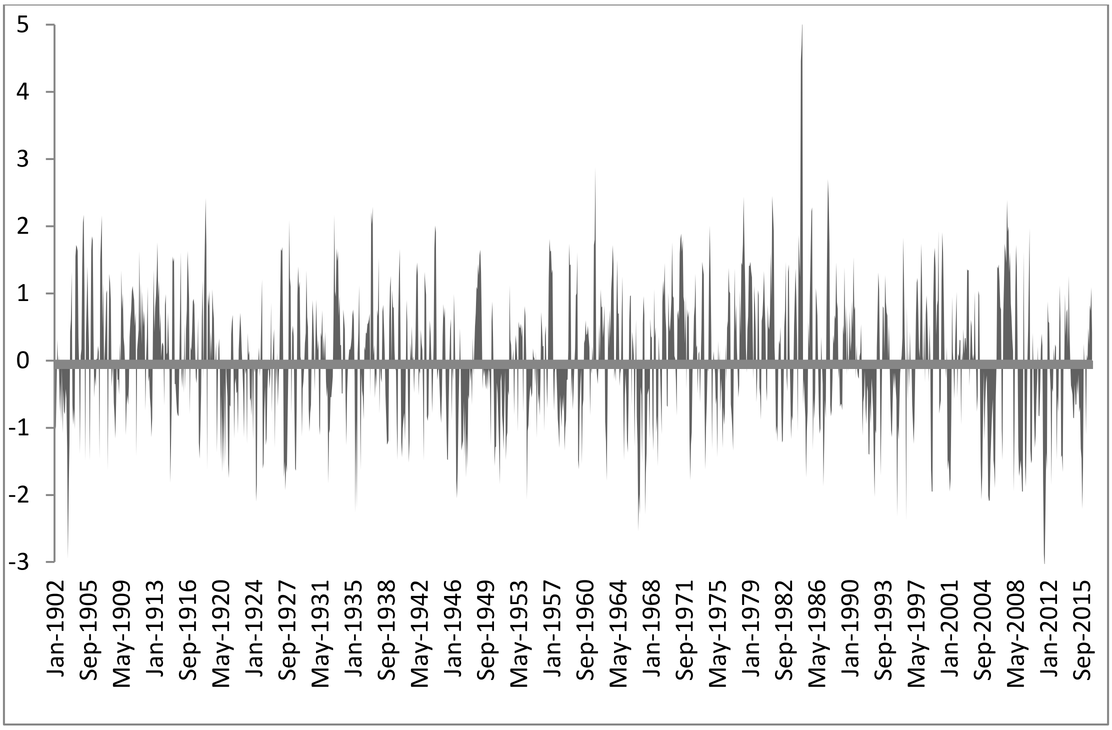

Figure 4.35 SPI-3 values for the grid 25

Referring to Table 4.5, the results of SPI-6 (grid 2) shows that the drought event (42 no.) was of maximum durations of 19 months from June 1992 to December 1993 and was also of maximum magnitude of 30.49 with an average intensity of 1.60, while, the drought event (45 no.) was of maximum intensity of 1.96 with a magnitude of 23.46 that prevails for twelve months from June 1996 to May 1997. The variation of intensity of SPI-6 for the grid 2 (Gaya district) for the 115 years is shown in Figure 4.36.

Table 4.5 Drought events monitoring based on SPI-6 with durations ≥ 3 months for the grid 2

Event no.	Onset	Termination	Durations	Magnitude	Intensity
1	Jun-1903	Dec-1903	7	7.20	1.03
2	Aug-1908	Feb-1909	7	8.12	1.16
3	Jun-1914	Feb-1915	9	16.99	1.89
4	Aug-1915	Feb-1916	7	7.24	1.03
5	Mar-1921	Jul-1921	5	6.04	1.21
6	Feb-1922	Dec-1922	11	13.64	1.24
7	Mar-1923	May-1923	3	3.49	1.16
8	Jul-1927	Nov-1927	5	5.38	1.08
9	Sep-1928	Feb-1929	6	6.77	1.13
10	Jun-1931	Jan-1932	8	8.32	1.04
11	May-1932	Dec-1932	8	9.76	1.22
12	Feb-1936	Apr-1936	3	2.72	0.91
13	Sep-1950	Mar-1951	7	5.67	0.81
14	Sep-1951	Mar-1952	7	7.53	1.08
15	Jul-1952	Dec-1952	6	3.75	0.63
16	Mar-1953	May-1953	3	4.29	1.43
17	Jul-1954	Dec-1954	6	4.98	0.83
18	Jun-1955	Dec-1955	7	6.67	0.95
19	Feb-1956	Apr-1956	3	3.59	1.20
20	Jul-1956	Sep-1956	3	2.57	0.86
21	Sep-1957	Nov-1957	3	2.16	0.72
22	Jan-1958	Mar-1958	3	3.52	1.17
23	Apr-1963	Sep-1963	6	6.32	1.05
24	May-1965	Nov-1965	7	4.75	0.68
25	May-1966	Jul-1966	3	2.52	0.84
26	Sep-1966	Nov-1966	3	2.25	0.75
27	Sep-1967	Nov-1967	3	2.32	0.77
28	Jan-1969	Apr-1969	4	3.75	0.94
29	Aug-1970	Jan-1971	6	6.21	1.04
30	Jun-1972	Sep-1972	4	2.42	0.61
31	Apr-1974	Jun-1974	3	7.00	2.33
32	Aug-1974	Nov-1974	4	2.93	0.73
33	Sep-1975	Jun-1976	10	9.14	0.91
34	Aug-1979	Feb-1980	7	8.19	1.17
35	Sep-1981	Feb-1982	6	5.88	0.98
36	Aug-1982	Feb-1983	7	6.87	0.98
37	Aug-1983	Dec-1983	5	5.08	1.02
38	Feb-1985	Sep-1985	8	11.10	1.39
39	Apr-1987	Jun-1987	3	5.63	1.88
40	Sep-1988	Dec-1988	4	3.34	0.84
41	Apr-1989	Jan-1990	10	13.35	1.34
42	Jun-1992	Dec-1993	**19**	**30.49**	1.60
43	Dec-1994	Feb-1995	3	3.24	1.08

44	Apr-1995	Nov-1995	8	10.77	1.35
45	Jun-1996	May-1997	12	23.46	**1.96**
46	Mar-1999	May-1999	3	3.27	1.09
47	Aug-2000	May-2001	10	11.31	1.13
48	Dec-2001	Feb-2002	3	2.32	0.77
49	Apr-2002	Jul-2002	4	3.46	0.87
50	Jul-2004	Dec-2004	6	4.31	0.72
51	Apr-2005	Dec-2005	9	12.10	1.34
52	Feb-2006	May-2006	4	6.05	1.51
53	Dec-2008	Nov-2009	12	15.89	1.32
54	Mar-2010	Dec-2010	10	11.27	1.13
55	Jul-2011	Dec-2011	6	6.42	1.07
56	Mar-2012	Jun-2012	4	5.36	1.34
57	Jul-2013	Dec-2013	6	8.47	1.41
58	Sep-2015	Mar-2016	7	7.66	1.09

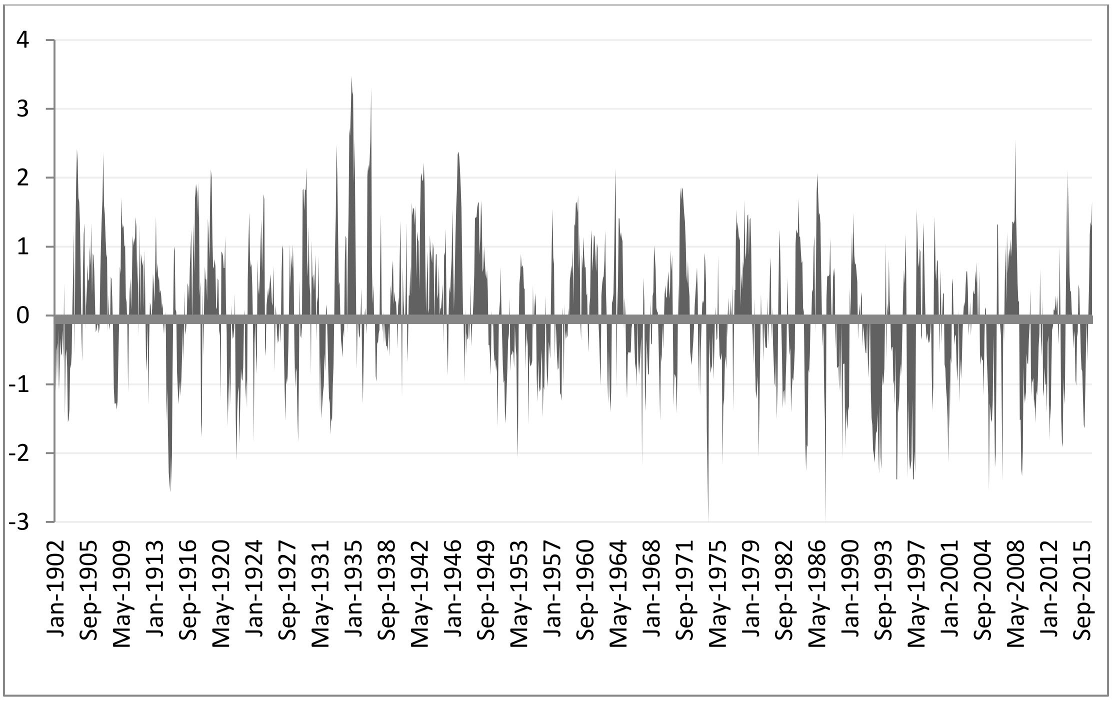

Figure 4.36 SPI-6 Values for the grid 2

4.2 Analysis of results of eco-environmental vulnerability assessment:

For the assessment of eco-environmental vulnerability index (EVI), firstly indicators are selected; secondly, their pair-wise comparison matrix has been performed using analytical hierarchy process (AHP). Lastly AHP and spatial principal component analysis (SPCA) techniques has been applied for the vulnerability evaluation for the selected three decadal years of 1995, 2005 and 2015. The detailed methodology has been depicted in section 3.3.2 of chapter 3. The results and discussion for the same have been discussed below:

4.2.1 Indicator result maps

This study considers a total of four (**4**) group indicators, classified into **21** sub-group indicators to evaluate the eco-environment vulnerability. The main indicators are (i) topographical, (ii) land resource, (iii) hydro-meteorological and (iv) socio-economical.

For topographical vulnerability analysis three indicators has been considered as: elevation, slope and slope-aspect. The elevation map indicates that the southern part of the study area is at higher elevation with gentle slope towards the north-east (NE) direction. The same can be validated from the drainage network map, which symbolizes the direction of the natural water flow from higher to lower elevation. The result maps for the topographical indicators and drainage network have been shown from Figure 1 to Figure 4 in Appendix-I.

The land resource vulnerability has been considered to be the primary function of land use and land cover, soil texture and soil depth. The indicator result maps for analyzing the land resource vulnerability has been given from Figure 5 to Figure 9 in Appendix-I. The LULC map has been prepared for 1995, 2005 and 2015. While the soil texture and soil depth has been considered to be nearly constant unlike LULC and so the only map has been used for the three decades analysis. The hydro-meteorological vulnerability has been computed using rainfall, rainfall departure, rainy days, soil moisture and groundwater availability condition, proximity to river, minimum and maximum temperature indicator maps. The hydro-meteorological indicators are variable in nature and so have been prepared for all the three decadal years as shown from Figure 10 to Figure 30 in Appendix-I. The socio-economic vulnerability map has been computed using population, population density, decadal growth rate, literacy and literacy gap indicator maps. The results for the indicator maps have been shown from Figure 31 to Figure 45 in Appendix-I.

4.2.2 Analysis of results for group indicators

The sub-indicator maps has been integrated in raster calculator based on their priority vector as determined from their pair-wise comparison matrix analysis using AHP. Thus a way four group indicator maps have been created as: topographical vulnerability map, land resource vulnerability map, hydro-meteorological vulnerability map and socio-economic vulnerability map. The group indicator maps have been shown from Figure 4.37 to Figure 4.46 respectively.

The topographical vulnerability map (Figure 4.37) shows the southern region of the study area to be more vulnerable along with some patches of Munger and Lakhisarai district. This is due to the presence of moderately dissected Kaimur, Mirzapur and Rajmahal hills in the southern region and eroded Kharagpur hills in the Munger and Lakhisarai districts.

The land resource vulnerability map (from Figure 4.38 to Figure 4.40) for all the three decades, is mainly concentrated to southern region of Banka, Bhabua and Jamui districts and some patches of Bhagalpur district. There is no significant variation in the land resource vulnerability from 1995 to 2015. The regional land resource vulnerability is due to the presence of rocks and sandy soil in these regions that make the soil unproductive for agriculture.

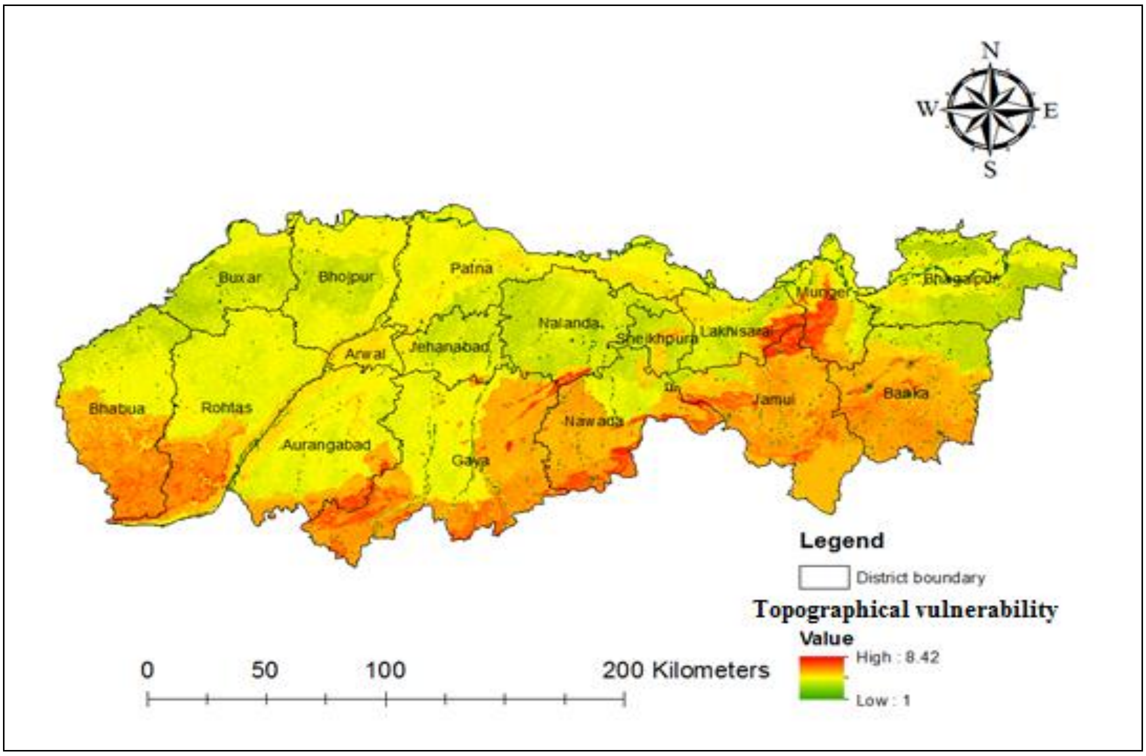

Figure 4.37 Topographical vulnerability map

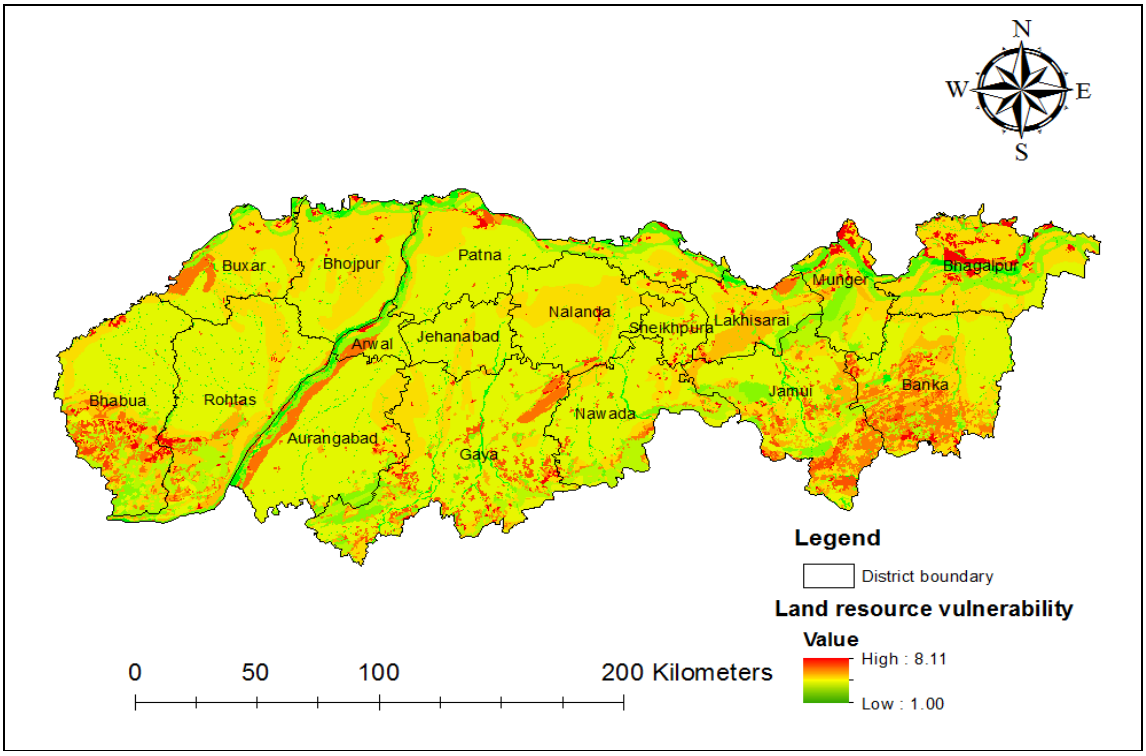

Figure 4.38 Land resource vulnerability map (1995)

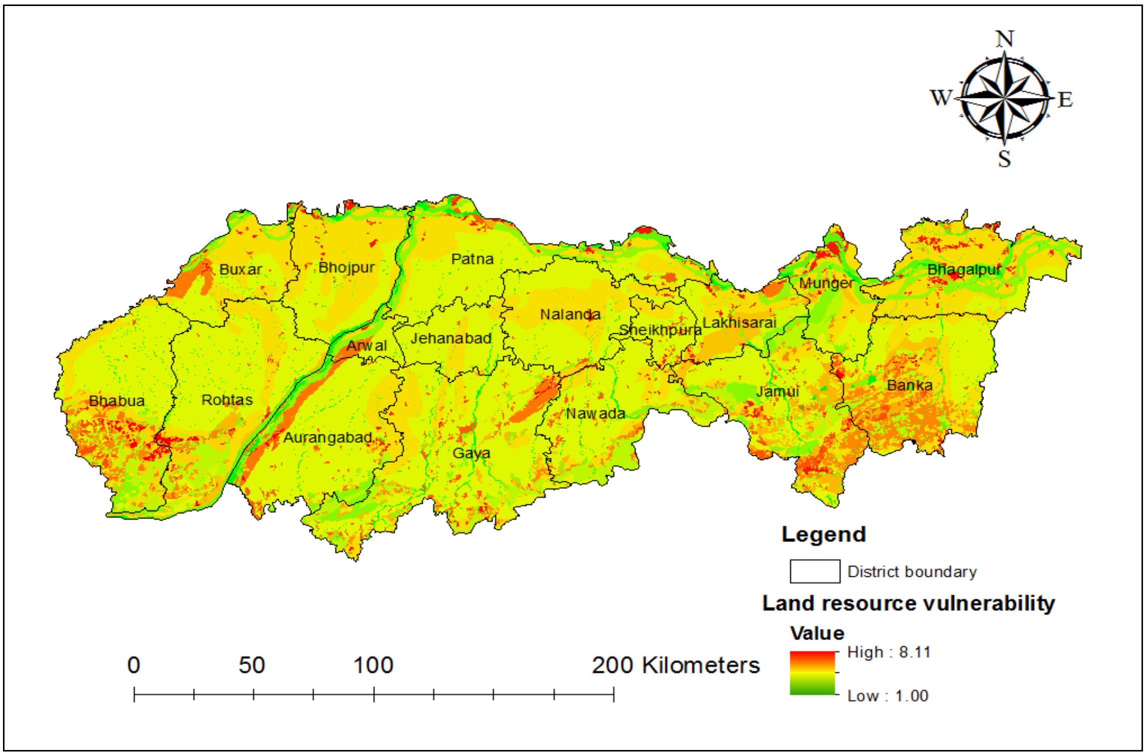

Figure 4.39 Land resource vulnerability map (2005)

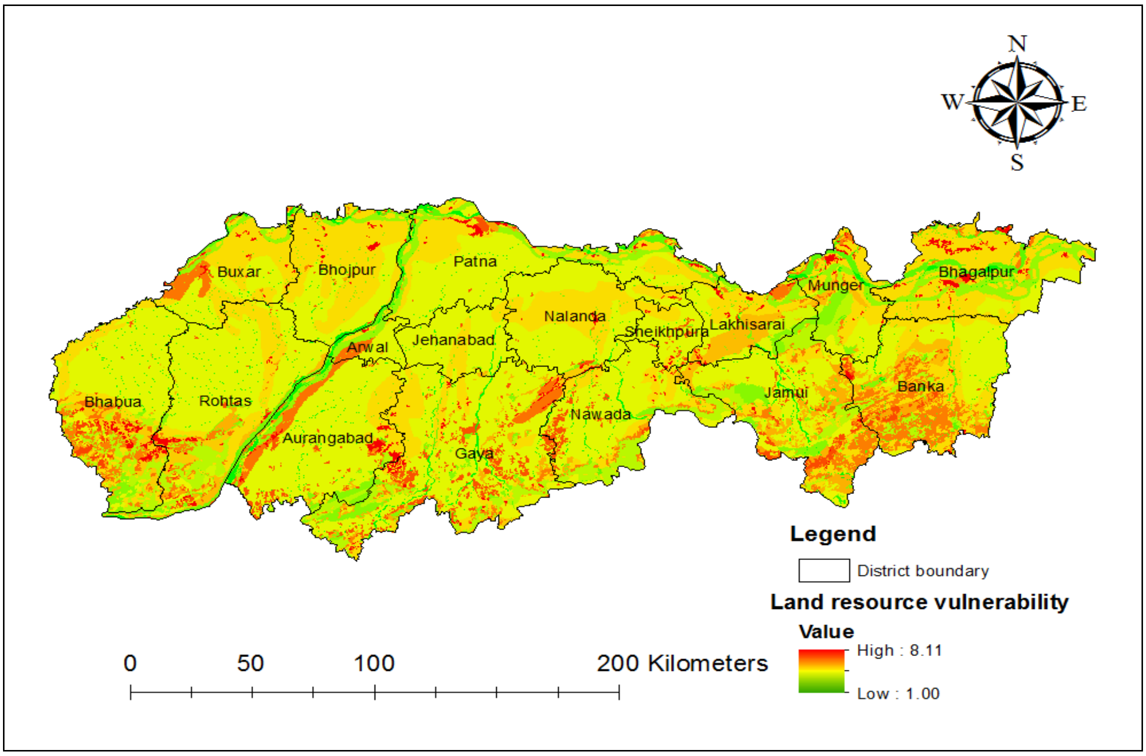

Figure 4.40 Land resource vulnerability map (2015)

The hydro-meteorological vulnerability indicates the unfavorable environment of hydrological (rainfall and its attributes) and meteorological (temperature) conditions. This vulnerability is continuously increasing from 1995 to 2015 as can be seen in Figures from 4.41 to 4.43. This is due the increasing demand of water due to the increasing population, population density and socio-economic demand. The reducing nature of rainfall and number of rainy days in the decades are also contributing significantly in making the situation more vulnerable. This vulnerability is mainly concentrated to Gaya, Jamui and Bhabhua districts in the decades.

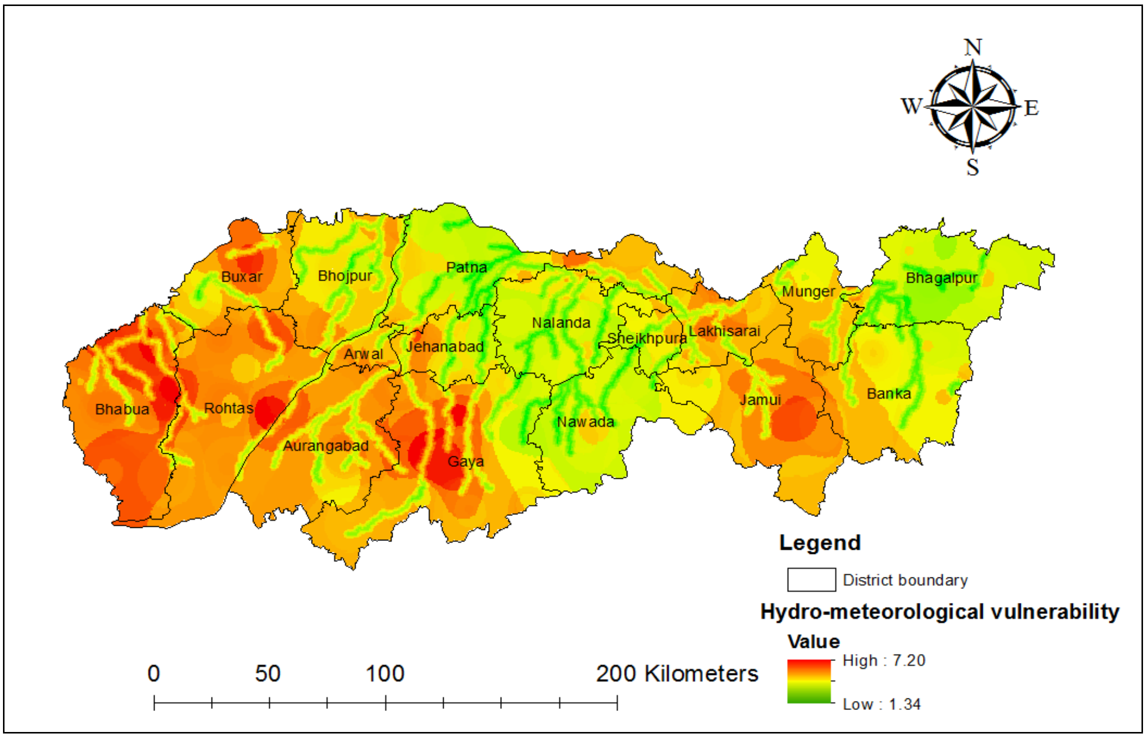

Figure 4.41 Hydro-meteorological vulnerability map (1995)

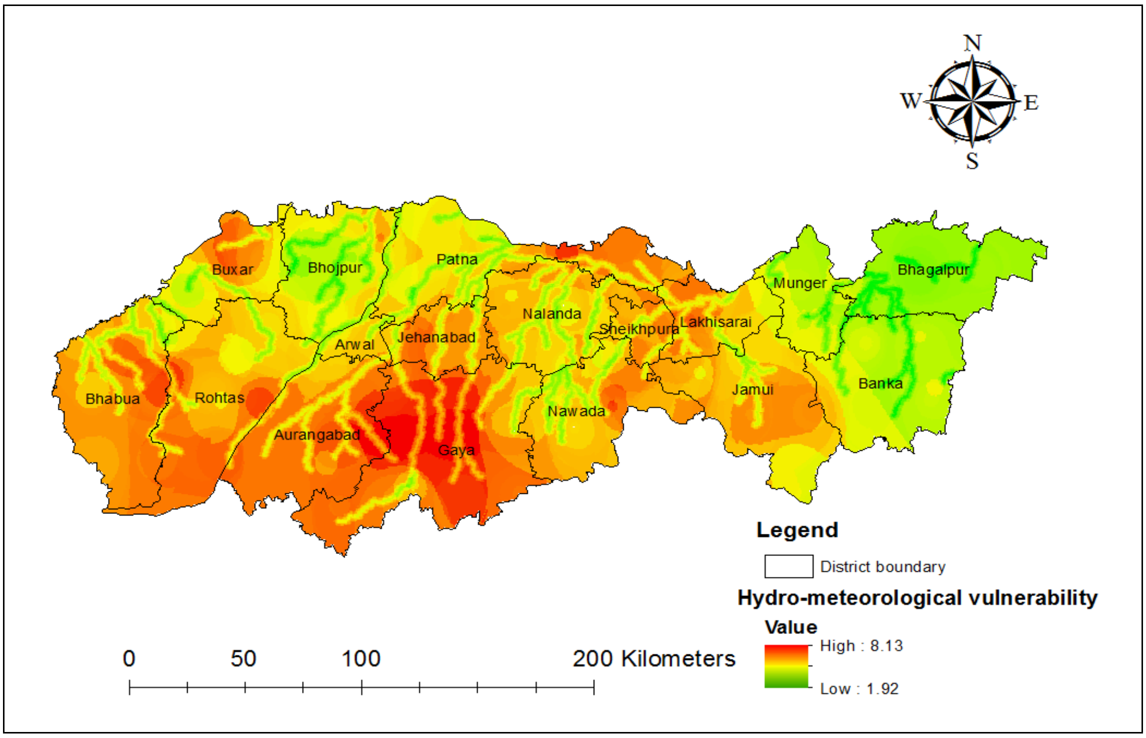

Figure 4.42 Hydro-meteorological vulnerability map (2005)

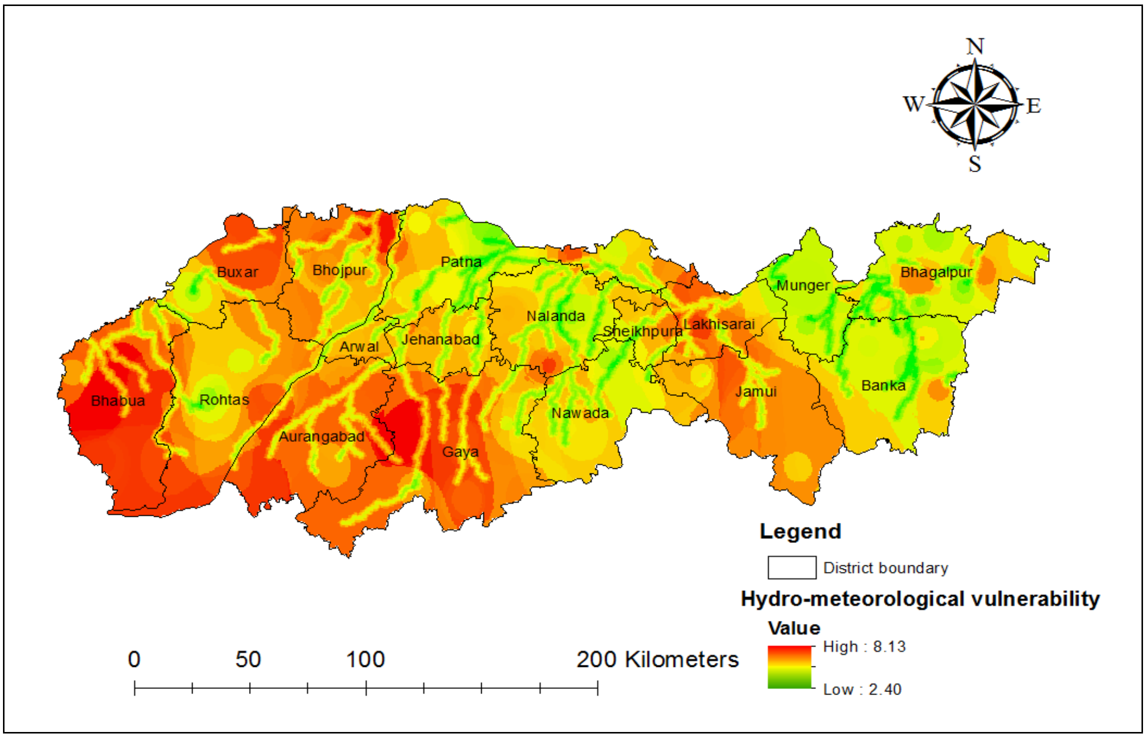

Figure 4.43 Hydro-meteorological vulnerability map (2015)

The socio-economic vulnerability map has been shown from Figure 4.44 to Figure 4.46 for decadal years of 1995, 2005 and 2015 respectively. In 1995 the Bhabhua district is highly vulnerable; however the vulnerability shifts fastly, from the western region to eastern region in the study area as can be seen in the Figures 4.46, 4.47 and 4.48. This shifting is only in the southern region of the study area. This is due to the increase in literacy rate, literacy gender gap in the western region which has its boundary with present developed Varanasi city with good education hub due to the presence of central Banaras Hindu University and other science and engineering colleges.

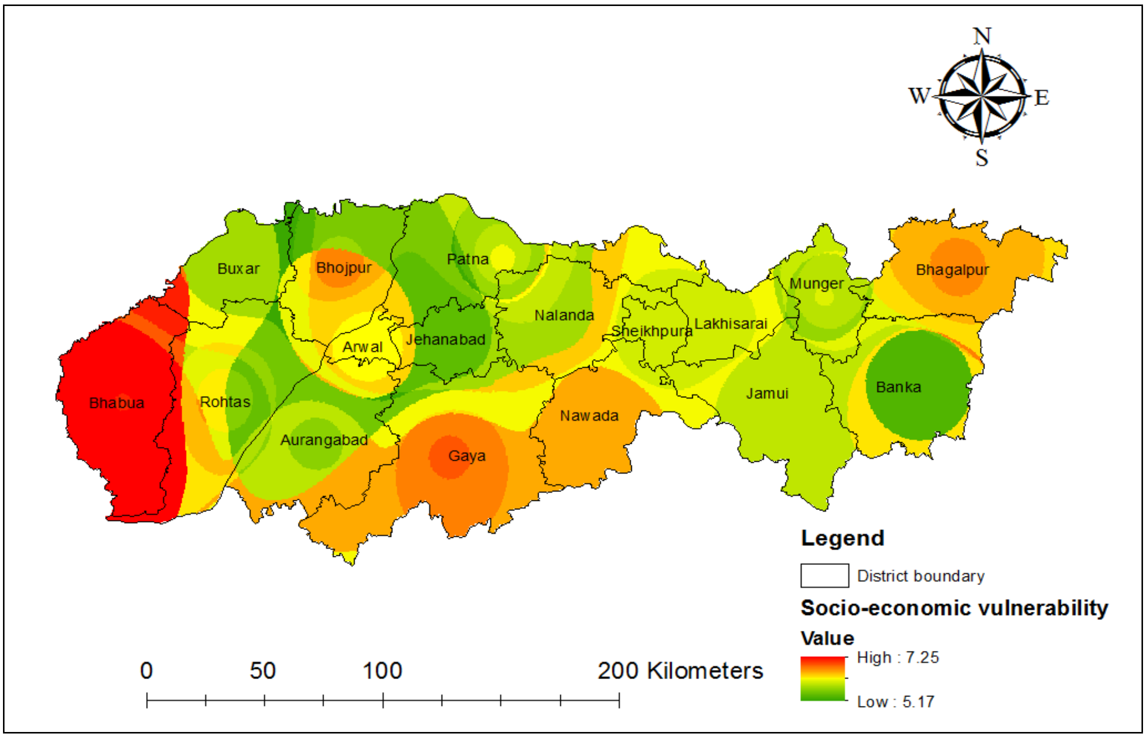

Figure 4.44 Socio-economic vulnerability map (1995)

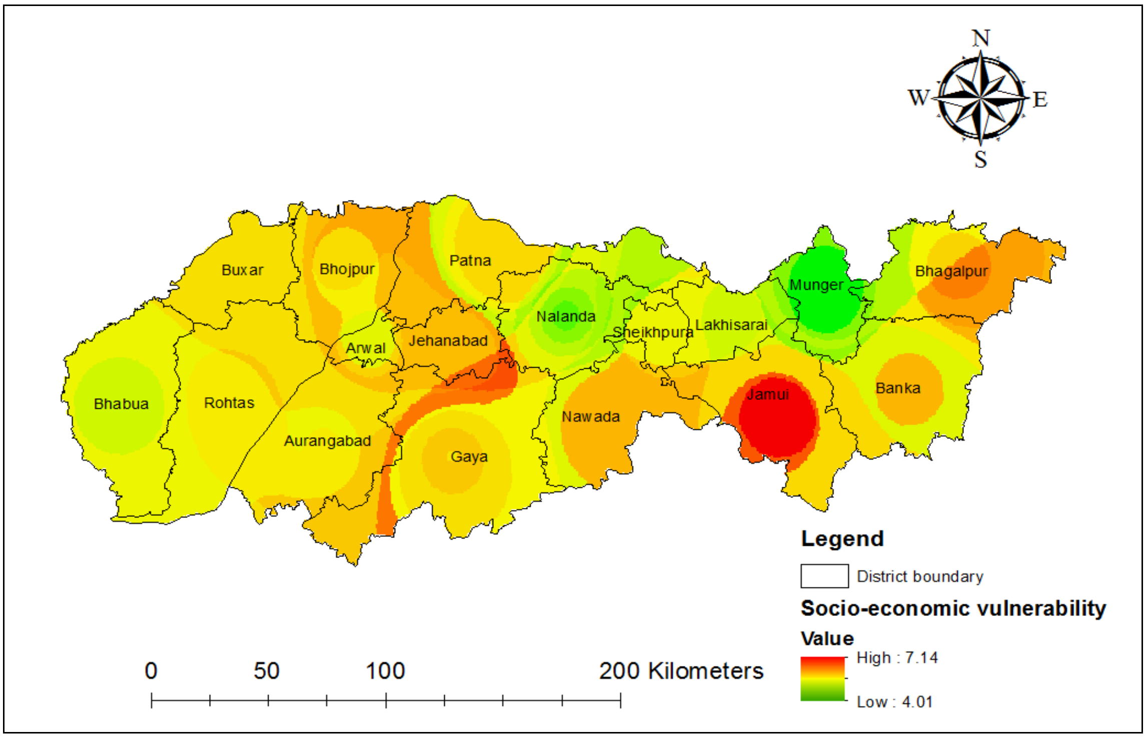

Figure 4.45 Socio-economic vulnerability map (2005)

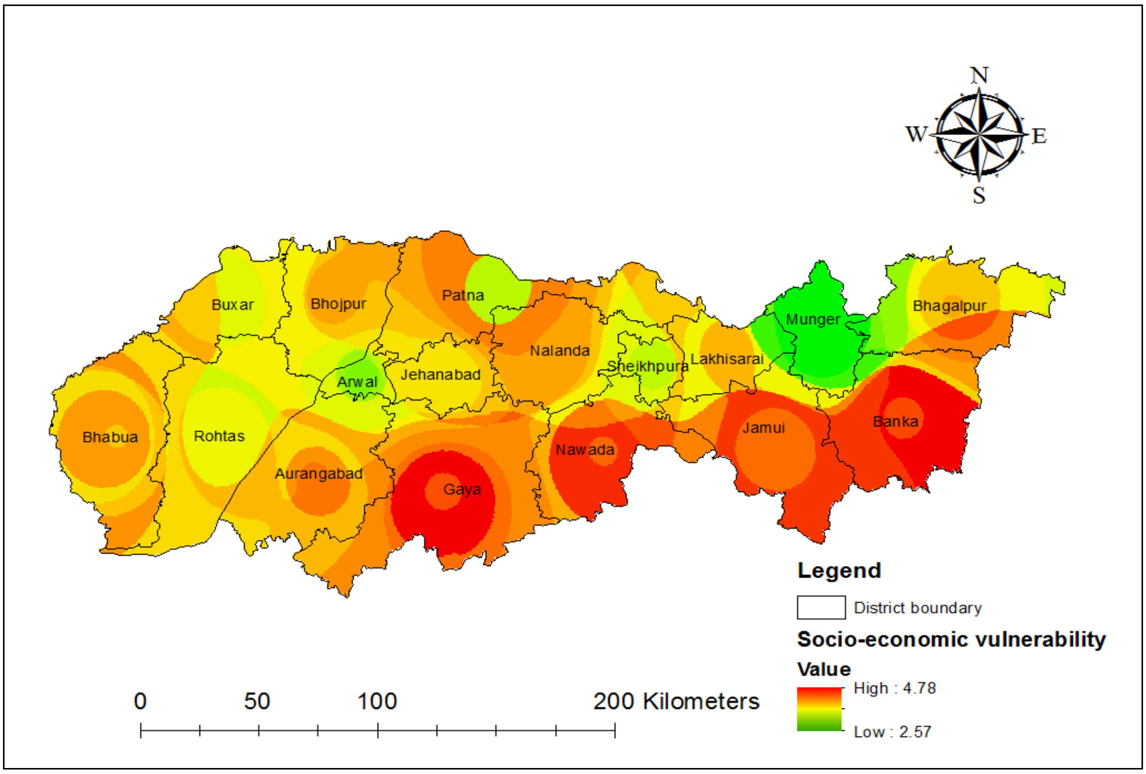

Figure 4.46 Socio-economic vulnerability map (2015)

4.2.3 Eco-environmental vulnerability evaluation using AHP

To perform the assessment of eco-environmental vulnerability index (EVI) using the analytical hierarchy process (AHP), the so created group indicator maps have been integrated in raster calculator based on their priority vector as determined from their pair-wise comparison matrix analysis. The final EVI map is created for three different decadal times of 1995, 2005 and 2015 and classified in different grades following Table 4.6, as shown in Figure 4.47, 4.48 and 4.49 respectively.

The analysis of vulnerability map of the year 1995 (based on AHP), indicates that maximum area (about 45%) is under light level of vulnerability followed by slight vulnerability class (about 24%). This is due to the moderate development of education, high literacy gender gap and improper management of water resources at that time in the study area. In other words the socio-economic vulnerability is high at that time.

The vulnerability is mainly concentrated in the southernmost region of the study area. It shows a sharp upward move from 1995 to 2005 and then maintains an increasing trend in the period of 2005 to 2015. The trend of the vulnerability in the period of 1995 to 2005 is due to slow reduction in the socioeconomic vulnerability with slow increase in literacy and reduction in literacy gender gap in the mean time. Since 1995 the hydro-meteorological vulnerability has increased and counter-balances the positive effect of reduction in socio-economical vulnerability till the year 2005. From the year 2005 onwards the hydro-meteorological vulnerability dominates in the region and causes the overall eco-environmental vulnerability to increase.

Table 4.6 Classification range of EVI level for different grades

Evaluation level	Grade	EVI Value
Potential vulnerability	I	**<4**
Slight vulnerability	II	**4 to 4.5**
Light vulnerability	III	**4.5 to 5**
Medial vulnerability	IV	**5 to 5.5**
Heavy vulnerability	V	**> 5.5**

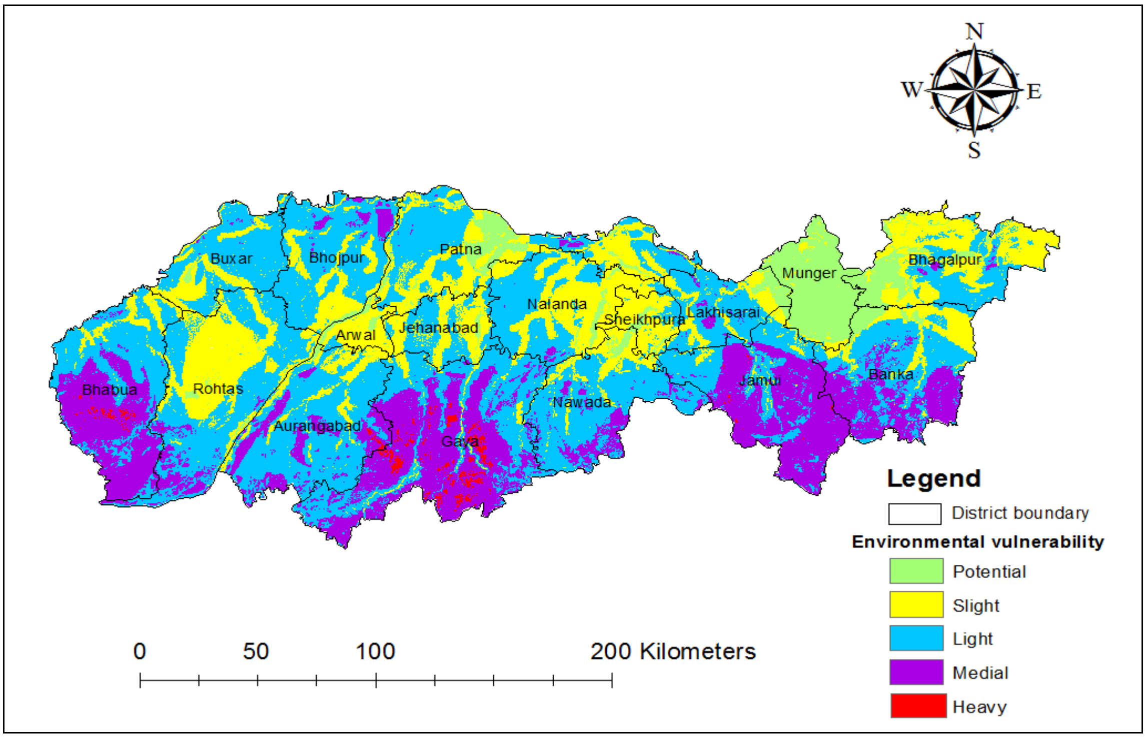

Figure 4.47 Eco-environmental vulnerability map (AHP, 1995)

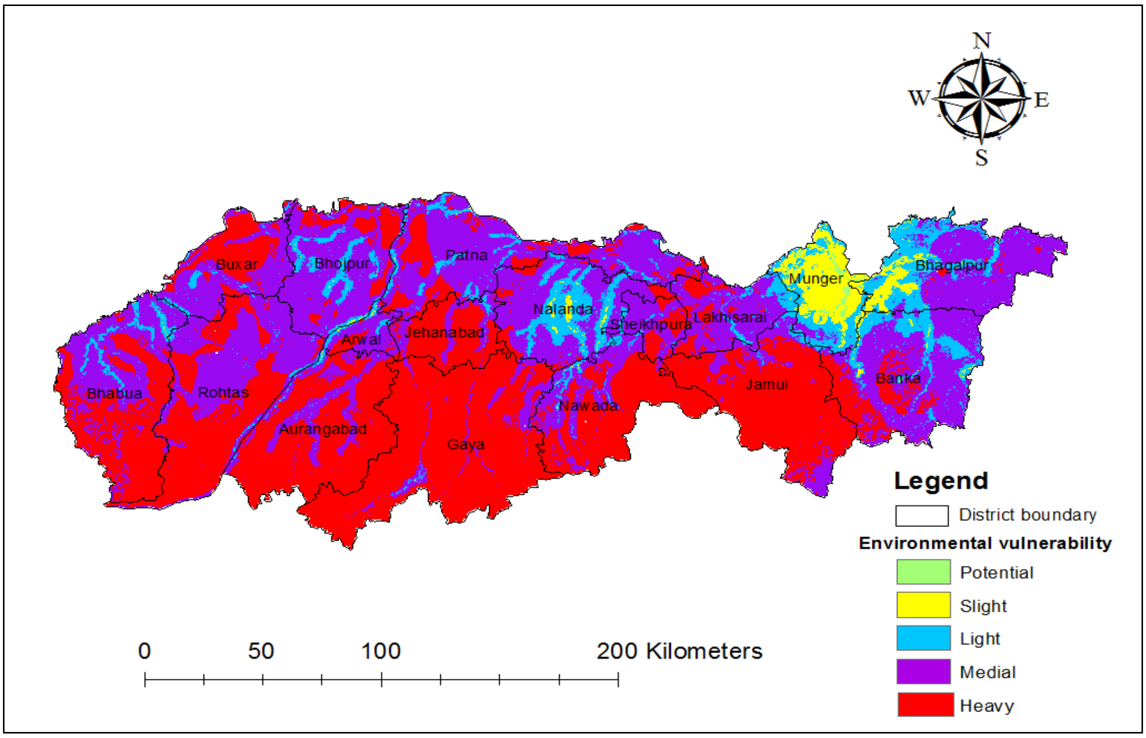

Figure 4.48 Eco-environmental vulnerability map (AHP,2005)

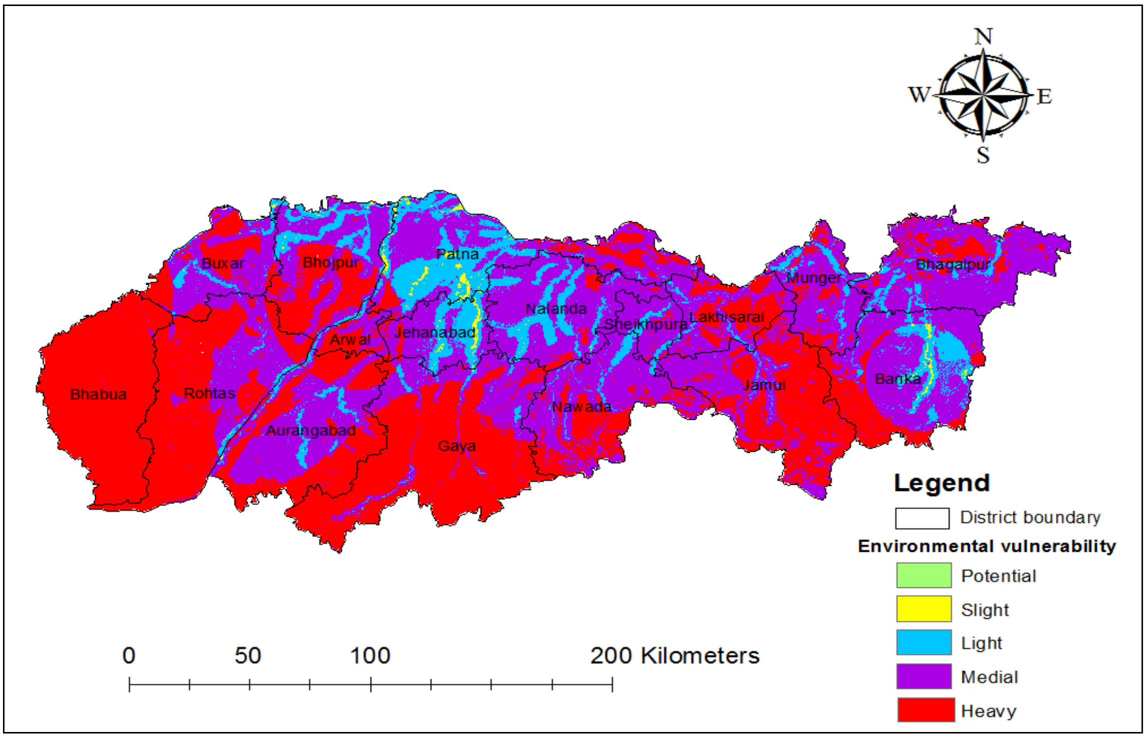

Figure 4.49 Eco-environmental vulnerability map (AHP, 2015)

4.2.4 Eco-environmental vulnerability evaluation using SPCA

The assessment of eco-environmental vulnerability index (EVI) using the spatial principal component analysis has been performed in ARC GIS 10.1 environment using the PCA tool. For the accomplishment of the work, the four group indicator maps of topographical, land resource, hydro-meteorological and socio-economic have been considered as input variables and output principal components is set out to four. The results of SPCA for the four principal components have been shown in Table 4.7. Finally algebra computation has been performed on principal components based on their contribution ratios to develop the final EVI map for the years 1995, 2005 and 2015 as shown in Figures 4.50, 4.51 and 4.52 respectively. The detailed method has been depicted in section 3.3.2.4 of chapter 3.

Table 4.7 Results of spatial principal component analysis in the study area

S. No.	Year	Parameters	Selected Principal Components			
			I	II	III	IV
1	1995	Eigen-value	0.562	0.411	0.367	0.096
		Contribution ratios (%)	39.137	28.601	25.547	6.714
		Cumulative contribution (%)	39.137	67.738	93.286	100
2	2005	Eigen-value	0.860	0.467	0.3913	0.108
		Contribution ratios (%)	47.068	25.567	21.408	5.956
		Cumulative contribution (%)	47.068	72.635	94.044	100
3	2015	Eigen-value	0.596	0.381	0.337	0.086
		Contribution ratios (%)	42.599	27.159	24.089	6.153
		Cumulative contribution (%)	42.599	69.758	93.847	100

The results of SPCA show the similar trend in the vulnerability as concluded from the AHP method as can be seen from Figure 4.50 to Figure 4.52. Firstly, the environment vulnerability increases sharply in the period of 1995 to 2005 and then maintains a positive turn from 2005 to 2015. However SPCA method indicates quite high increase in the overall environmental vulnerability level as compared to that of AHP for the decades from 1995 to 2015. This is due the fact that the PCA is based on dimensional reduction and so ignores a lot of information.

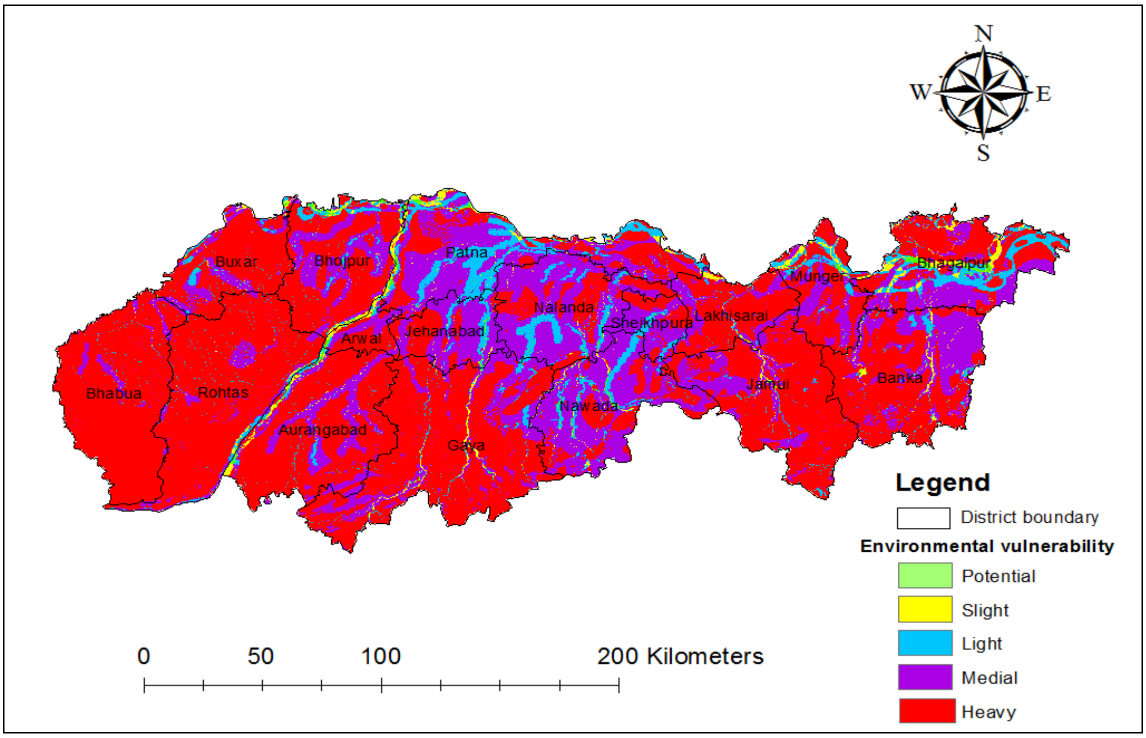

Figure 4.50 Eco-environmental vulnerability map (PCA, 1995)

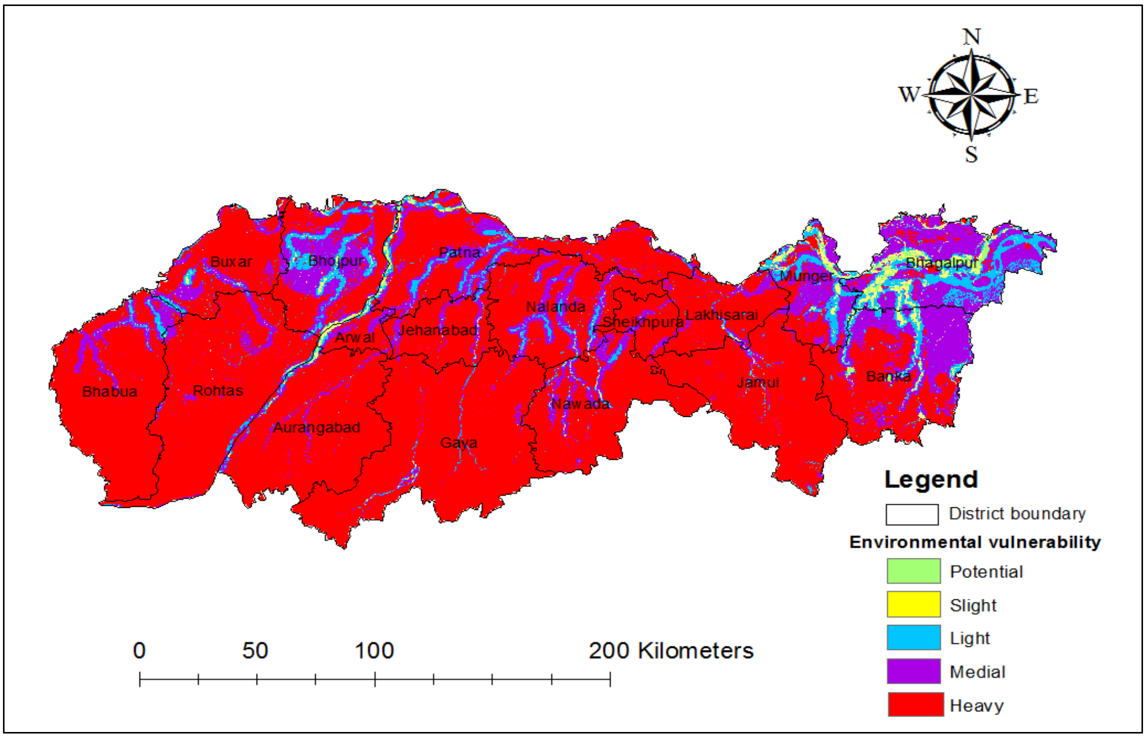

Figure 4.51 Eco-environmental vulnerability map (PCA, 2005)

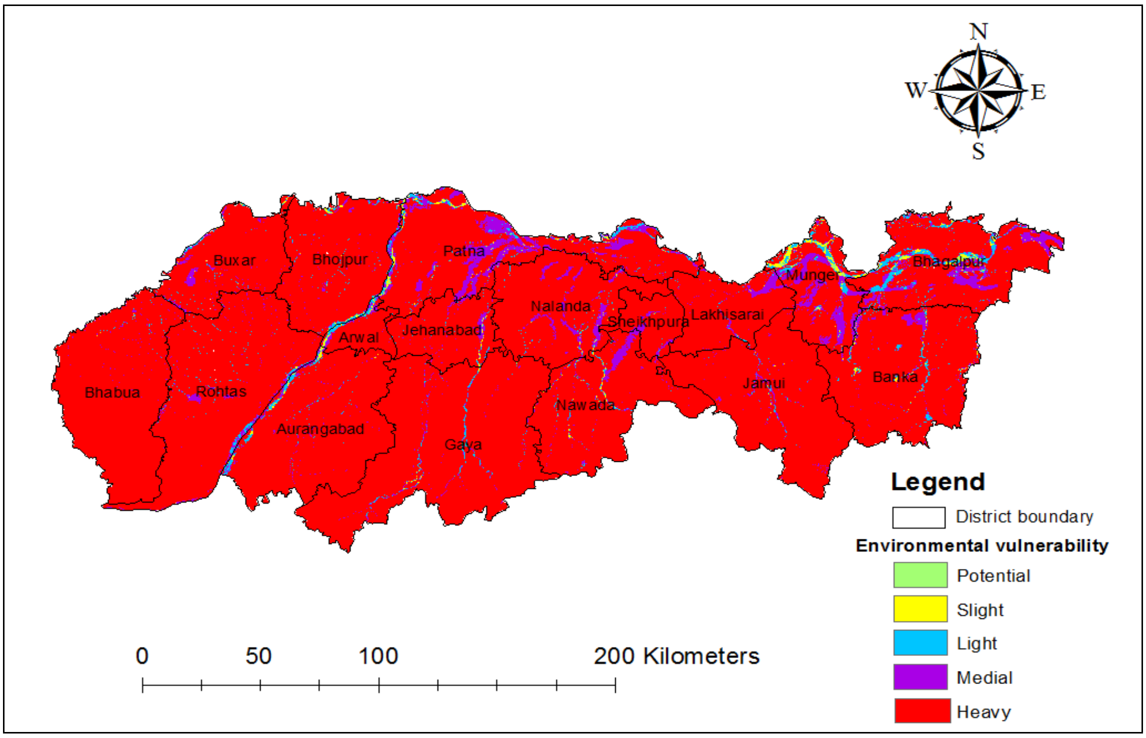

Figure 4.52 Eco-environmental vulnerability map (PCA, 2015)

4.3 Analysis for decadal change in eco-environmental vulnerability level:

The spatiotemporal decadal change in the vulnerability level of group indicators and final EVI are analyzed for the periods of 1995-2005, 2005-2015 and 1995-2015.

The topographical vulnerability doesn't vary for the period very significantly and so has been computed for once only. It shows that more that 40 % area are potential vulnerable and only about 11% area are heavy vulnerable as shown in Figure 4.53.

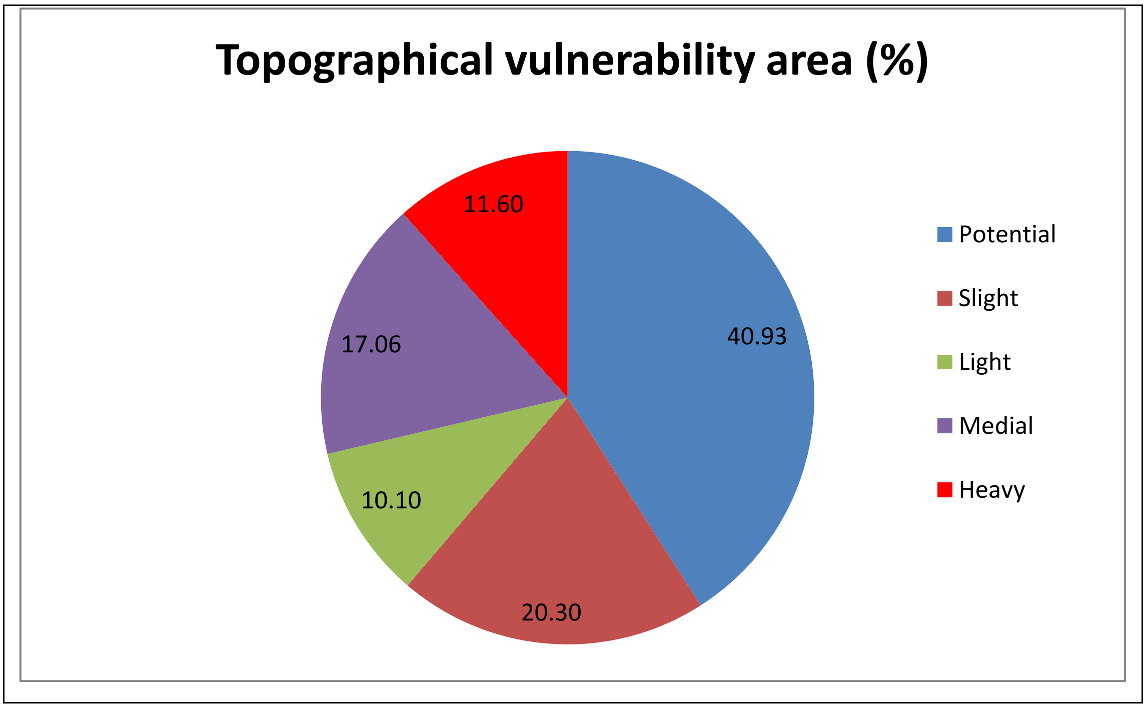

Figure 4.53 Topographical vulnerability

The land resource vulnerability varies slightly over the decades as shown in Figure 4.54, as LULC is considered to be the only variable factor out of the three (LULC, Soil texture and soil depth) in defining the vulnerability. The area under heavy vulnerability has increased quietly from 9.26 % to 9.78% over the study period. The maximum area about 45 % remains under slight vulnerability level with nearly 0.5% fall from 1995 to 2015. This shows that there is not any large industrial development and other urban built-up in the study area in the period of study. The same is the reason for the high migration of labour class from Bihar to different states throughout the India for job.

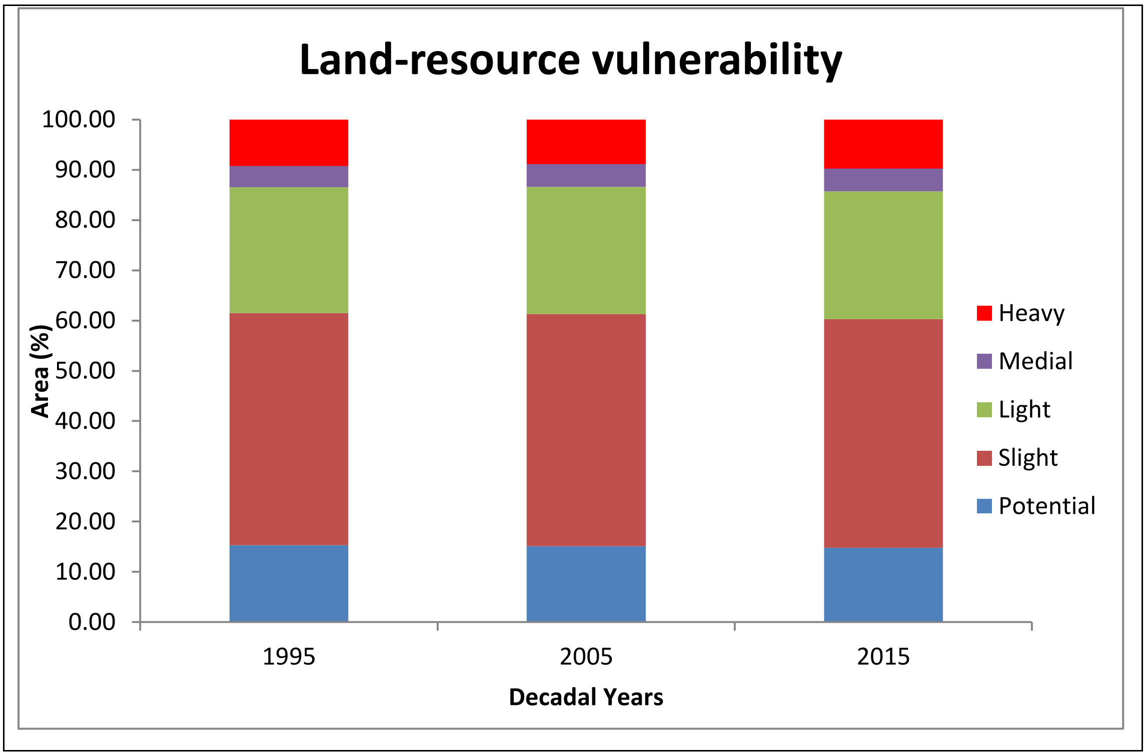

Figure 4.54 Decadal variations in land resource vulnerability

The hydro-meteorological vulnerability has increased sharply from 1995 to 2015 as shown in Figure 4.55. The area under high level of this vulnerability in 1995 is about 18 % which goes up to about 77 % in 2015. This shows that area is under severe drought prone. The same has been concluded from the drought severity assessment in the study area as discussed in section 4.1 of this chapter.

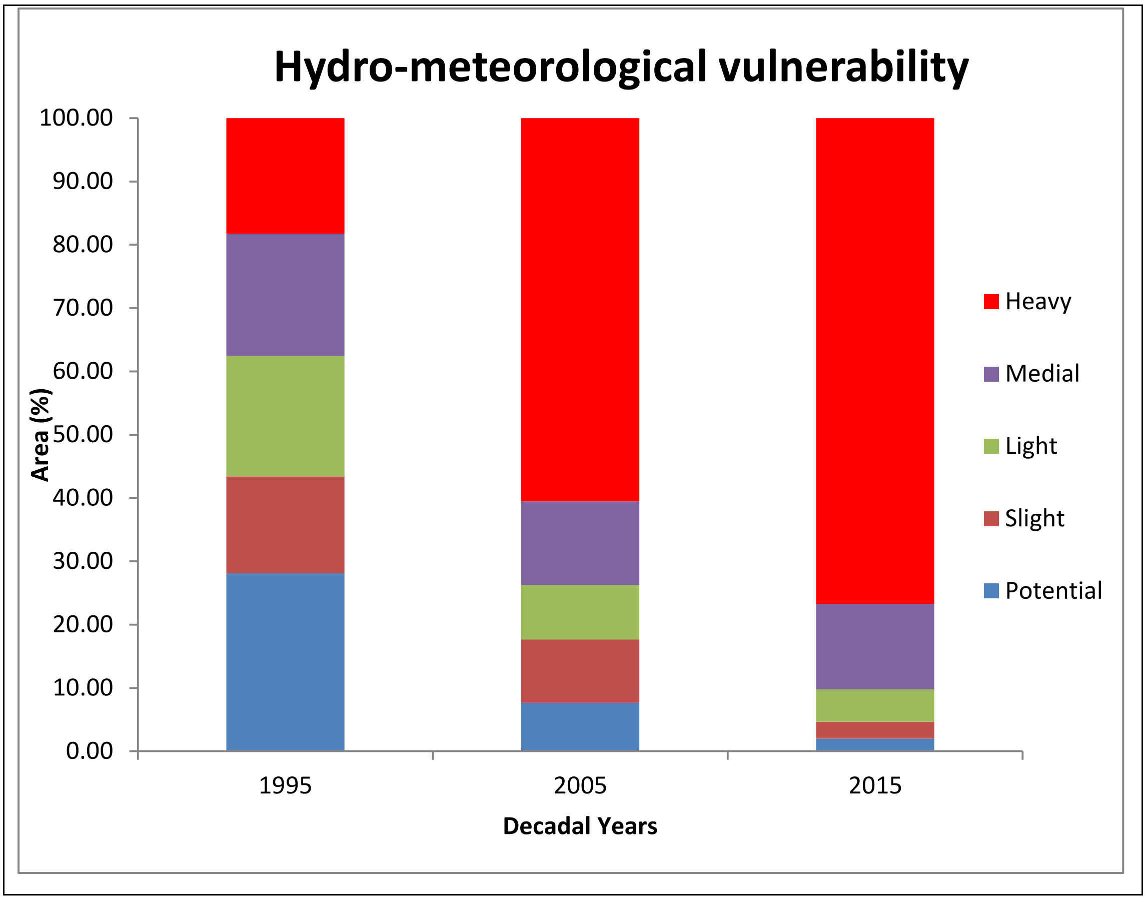

Figure 4.55 Decadal variations in hydro-meteorological vulnerability

The socio-economic vulnerability has reduced sharply in the period of study as can be seen in Figure 4.56. This is due to the government sincere steps towards education development by ensuring proper functioning of middle-schools in villages and other backward areas like Banka and Jamui districts

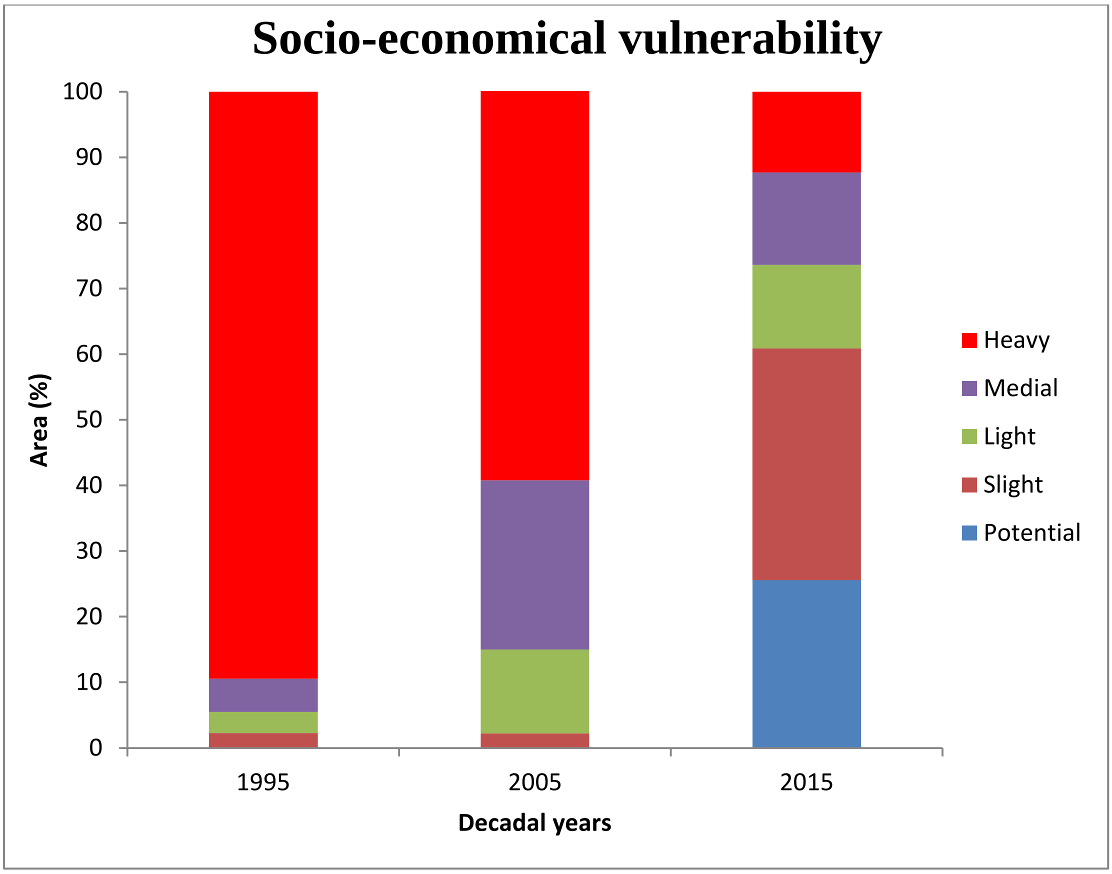

Figure 4.56 Decadal variations in socio-economic vulnerability

For the analysis of the decadal environmental vulnerability change district wise, the results of AHP method has been adopted, since the results of PCA are not very interpretable and also reduces the dimension of information. To accomplish the work an integrated index "EVSI" (Eco-Environmental Vulnerability Integrated Index) is computed using the Equation 4.1.

$$EVSI_j = \sum_{i=1}^{n} (P_i) * \frac{A_i}{S_j} \qquad (4.1)$$

In this formula, n is the number of valuation grade, EVSIj is the EVSI in unit j, Ai the occupied area of grade i in analysis unit j, Sj is the total area of analysis unit j, and Pi is the rating value of grade i.

The district wise results concluded for the decadal environment vulnerability change has been tabulated in Table 4.8. It shows that the vulnerability increases in most of the districts abruptly in the first phase from 1995 to 2005. However in the second phase of study from 2005 to 2015, the vulnerability takes an upward turn with quite positive increment. The reason is that the socio-economic development in the first phase reduces the effect of all other vulnerability, while in the second phase the hydro-meteorological vulnerability dominates over it and hence increases the overall vulnerability. The same can be ensured from the drought severity assessment of the study area.

The highest increment in vulnerability is in Arwal district (108%) followed by Jehanabad district (92.24%).

Table 4.8 District wise decadal change analysis in EVI level using AHP method

Sr. No.	Districts	1995 (EVSI)	2005 (EVSI)	2015 (EVSI)	1995-2005 % change	2005-2015 % change	1995-2015 % change
1	Sheikhpura	2.50	3.92	4.00	56.85	2.01	60.00
2	Gaya	3.59	4.72	4.91	31.62	3.96	36.84
3	Jamui	3.57	4.61	4.80	29.23	4.20	34.66
4	Buxar	2.72	4.28	4.36	57.21	1.80	60.04
5	Rohtas	2.67	4.66	4.51	74.71	-3.16	69.20
6	Bhojpur	2.80	4.18	4.03	49.24	-3.65	43.80
7	Patna	2.35	3.71	4.12	57.73	11.18	**75.37**
8	Bhagalpur	2.13	4.07	3.52	90.95	-13.51	65.15
9	Nawada	2.93	4.27	4.64	45.97	8.58	58.49
10	Bhabhua	3.42	5.00	4.45	45.92	-10.95	29.93
11	Nalanda	2.45	3.81	3.73	55.57	-2.04	52.39
12	Banka	3.08	4.01	4.00	30.33	-0.27	29.98
13	Munger	2.60	4.06	4.00	56.00	-1.38	53.85
14	Aurangabad	3.04	4.39	4.77	44.19	8.66	56.68
15	Lakhisarai	2.58	4.37	4.06	69.22	-7.13	57.15
16	Arwal	1.94	4.43	4.05	127.89	-8.38	**108.78**
17	Jehanabad	2.46	3.60	4.72	46.51	31.21	**92.24**

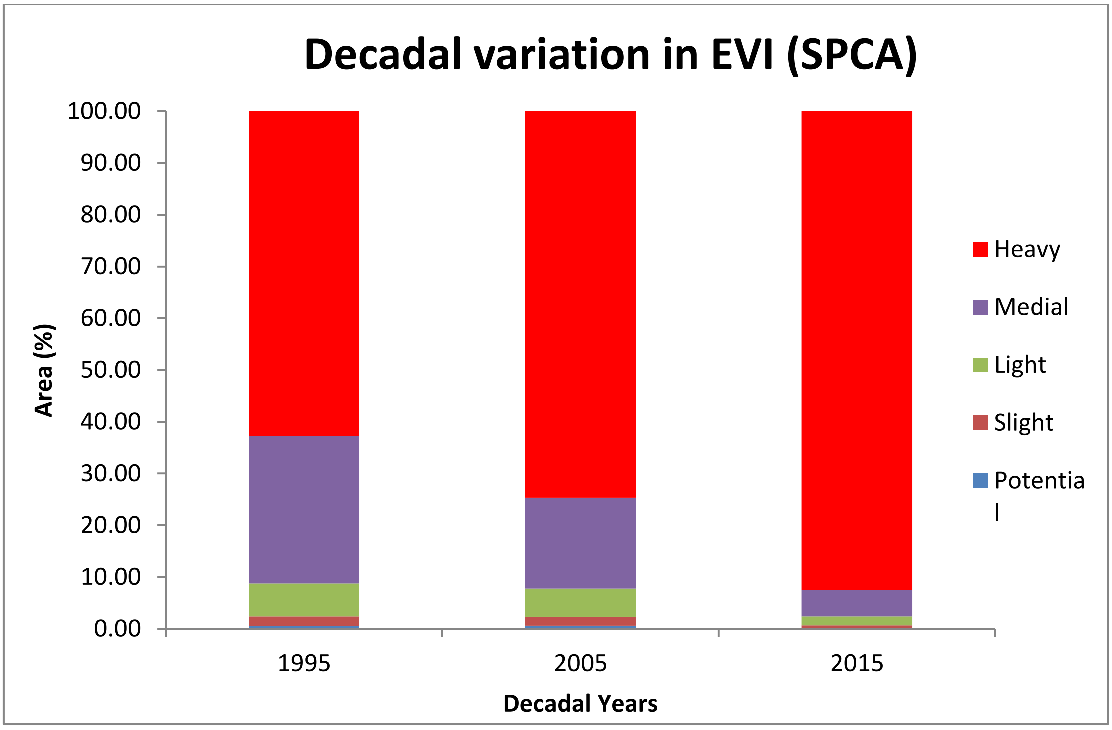

Figure 4.57 Decadal variations in eco-environmental vulnerability (SPCA)

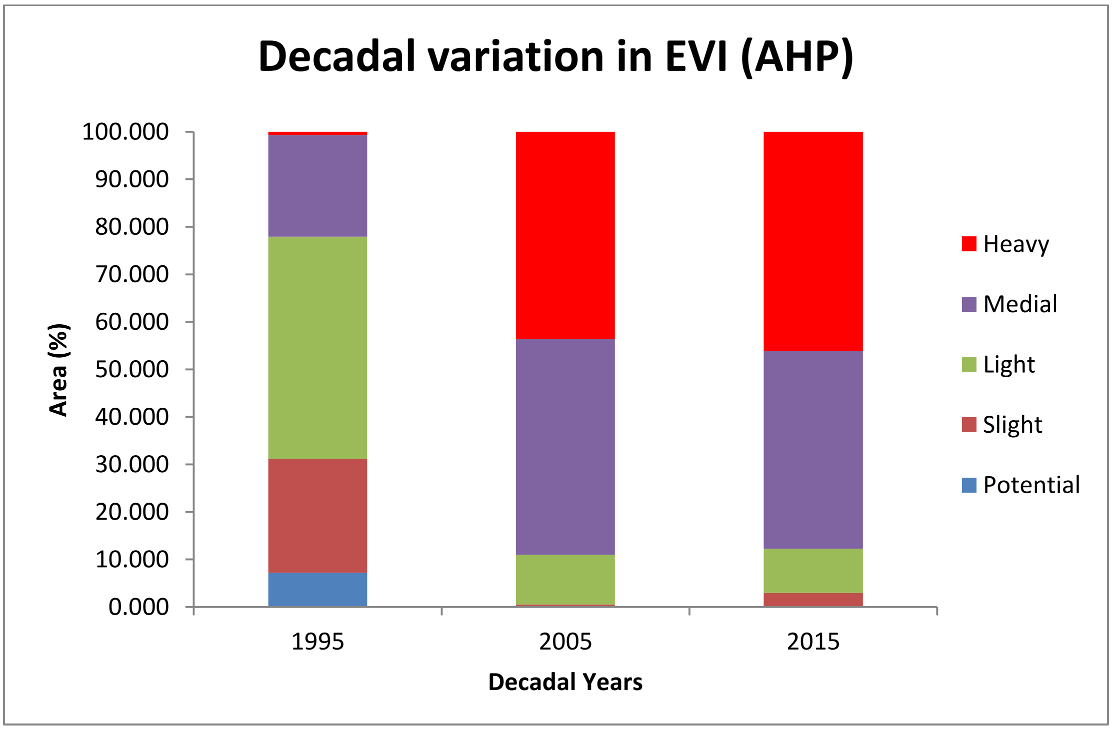

Figure 4.58 Decadal variations in eco-environmental vulnerability (AHP)

4.3 Rebuilding planning to mitigate the vulnerability:

The rebuilding planning is a very comprehensive work. It involves a detailed description of the plan to reduce the impact of the vulnerable situation. The first step in the rebuilding process is to identify the problem by analyzing the results of the research work conducted in the study area. Secondly, finding the cause for the vulnerable situation and then lastly, designing the mitigation plan to reduce its impact on the agricultural and socio-economic activities.

The present research work performed in the agro-climatic zone - III of Bihar region during the study period from 1901 to 2016, finds the prevailing problems as: drought severity and hydro-meteorological vulnerability is increasing in the southern and eastern districts of the study area, socio-economic vulnerability is quite decreasing, but the increasing population and population density and their increasing demands are alarming the situation, which requires proper and careful monitoring and overall eco-environmental vulnerability is increasing throughout the study area during the period of study.

Since 1995 the hydro-meteorological and overall vulnerability is increasing and as a result drought occurrence has increased in the study area. This evolved situation is causing heavy loss, directly to the agriculture production and indirectly to the related socio-economic activities. The delayed and erratic nature of rainfall, high runoff, slow ground-water recharge and improper management of water resources are the primary causes for the vulnerable situation. The so-produced adverse situation ensures the necessity of the implementation of proper mitigation plan to normalize the impact of the vulnerability. The ultimate solution for the problems requires both short term as well as long term treatment plan.

The short term measures proposed are as:

- Mulching and zero-tillage in the crop field to reduce the loss of water as evaporation,
- Proper selection of drought resistant crops for Kharif and Rabi season,

- Nutrient management to enhance the drought resistant ability of the crops,
- Application of life-saving supplemental irrigation at critical stages of crop to avoid complete crop failure,
- Introduction of the micro-irrigation system (sprinkler and drip irrigation system) to increase the water use efficiency.
- Contour farming and establishing fishing zone near streams

The main concept behind the implementation of the short term measures is to reduce the impact of the adverse situation at its onset, at low cost. It has been reported that around 30–60% of total applied water get lost as evaporation and remains unproductive, which is required to be utilized. The evaporation is more dominant in the high temperature regions which lies in the south-western districts of the study area, as can be seen from the spatial variation map of the maximum temperature during the summer monsoon season in Figure 27 of Appendix-I. So it is highly suggested to introduce the concept of mulching and zero-tillage particularly in the cropping area of the districts of Gaya, Bhabhua, Rohtas and Arwal, preferably during the summer-monsoon season from June to September. The mulching improves water-use efficiency by 10–20% (Ossom et al. 2001; Rama krishna et al. 2006; Kazemia and Safaria 2018; Waraich et al. 2011) by enhancing the infiltration rate (Ahmad et al. 2015) and reducing evaporation loss (Ramakrishna et al. 2006) and temperature fluctuation (Ranjan et al. 2017). Conservation tillage is the method of soil tilling in which at least 30% of soil surface is covered by residue (Ali et al. 2016). The crop residue insulates the soil from solar energy and reduces evaporation. It helps in reducing soil compaction and crusting and adds considerable amount of organic matter in soil which increases infiltration rate and water-holding capacity of soil (Wallander et al. 2013).

The selection of proper crop varieties also plays an important role in avoiding the complete crop failure during drought periods. Crops varieties that need shorter duration to mature and demand less water, are requires to be encouraged in the drought-prone districts. Crops such as pear millet, sorghum, gram, barley, mustard, cotton, sunflower, and castor are more droughts tolerant and so must be adopted by the farmers of Banka, Bhabhua, Arwal and other water scarce districts, as represented by the hydro-meteorological vulnerability map of the study area.

Maintenance of adequate potassium nutrition to plants has also been found effective in mitigating drought stress (Khan et al. 2018) and so the advantages of nutrient management in agriculture field are required to be acknowledged to the farmers of the vulnerable districts, particularly in the southern districts with low literacy rate. Potassium improves many physiological processes by the regulation of turgor pressure, photosynthesis, translocation of assimilates to various organs and enzymes activation and thus improves drought tolerance ability of plants (Raja et al. 2017). Hussain et al. (2017) recorded higher yield and profit when maize crop was sprayed with potassium fertilizer. Similarly, Dewangan et al. (2017) recorded higher yield of pearl millet with the foliar spray of 2% KCl + 0.4% sodium selenite under drought condition.

The fishing must be promoted to the farmers of nearby streams, particularly in the districts of Buxar, Bhojpur, Patna, Munger and Bhagalpur where the Ganga River passes through. This will create an additional income source to maintain livelihood, during the complete failure of crops during drought period.

Application of water at critical growth stages of crop during prolong dry spell to save crops from total failure is known as life-saving irrigation or supplemental irrigation. Every crop is more sensitive at specific growth stages for drought, and lack of moisture at these stages (critical crop stages) may cause total crop failure.

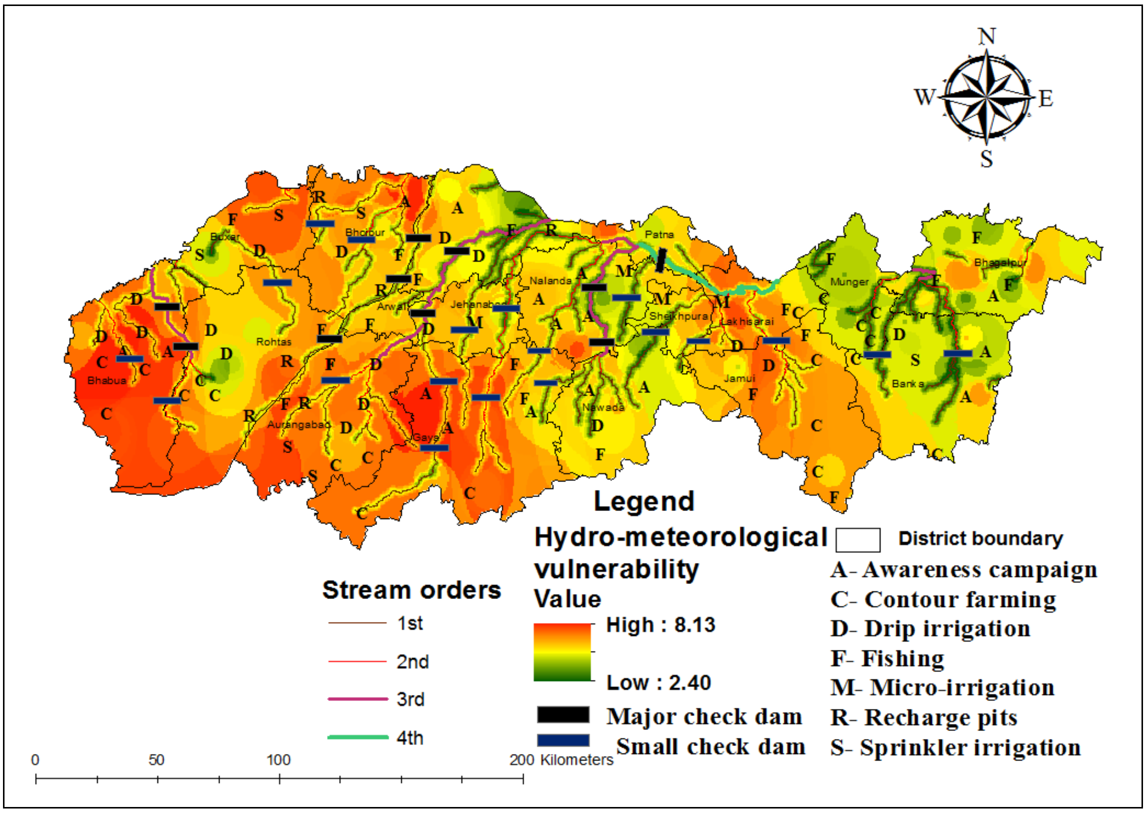

Fig. 4.59 Rebuilding planning map

Under drought and high temperature conditions, crops can be profitably raised with one or two need-based life-saving irrigations, applied according to their need during its specific critical growth stages for the best achievable yield under the given set of conditions (Oweis and Hachum 2006; Praharaj et al. 2017).

It is very effective to apply limited amount of water during critical growth stages through the application of micro-irrigation system either drip or sprinkler irrigation, depending on the soil and topographical conditions. The sprinkler system is proposed for cropping area with sandy soil having high infiltration rate and particularly in the undulating conditions of southern districts. The drip system is suggested for the agricultural area of the vulnerable districts with clayey texture soil in the plain region of northern districts. The complete plan for the application of micro-irrigation system (drip system or sprinkler system) considering the hydro-meteorological vulnerability spatial variation, soil texture and topography have been proposed as shown in Figure 4.59.

The long term measures are planned for very effective mitigation, which requires high cost. It includes runoff collection using surface and underground structures (small and large check dams, recharge pits etc.), exploration of additional water resources through inter-basin linking and launching awareness campaigns for different government schemes in the low literacy regions, for reducing the risk and vulnerability to agriculture and environment.

The proposed long term mitigation plan includes:

- Organizing awareness campaigns in the low literacy regions of Banka, Lakhisarai and Sheikhpura districts,
- Establishing recharge pits at the suitable sites in alluvial plain, nearby effluent streams,
- The 1^{st} and 2^{nd} order streams are proposed for the contour bunding and sunken pits,
- The small check dams are proposed for 3^{rd} order streams and
- Major check dams are suggested to be constructed on the 4^{th} order streams.

The detailed rebuilding plan for short term as well as long term measures have been shown in Figure 4.59. The awareness programs in low literacy regions of hydro-meteorological vulnerable districts will aware the farmers regarding the crop insurance scheme, drought relief fund (NDRF and SDRF) scheme provided by state and central government, soil health card scheme, importance of micro-irrigation system in increasing water use efficiency, rain-water harvesting techniques and other livelihood activities like fishing, small agriculture and dairy processing units, that will balance their livelihood during drought and other adverse environmental conditions. The smaller check dams have been proposed for 1^{st} and 2^{nd} order streams, while major check dams have been proposed for 3^{rd} and 4^{th} order streams. The check dams and recharge pits will allow the water to infiltrate and get stored as ground water during the monsoon season, which will ensure the availability of water throughout the year. This will reduce the risk of crop failure and related socio-economic activities. The measures will enhance the topographical, land resource, hydro-meteorological and socio-economical conditions of the study area and thus will make the environmental conditions more favorable and sustainable for the peoples of the agro-climatic zone of the Bihar region.

Chapter V

SUMMARY AND CONCLUSION

The present research work has been carried out in the south Bihar region, comprising of seventeen districts with an area of 40.9 thousand square kilometer. The work has focused on the evaluation of drought severity conditions, assessment of eco-environmental vulnerability level, detection of decadal change in the vulnerability level and has finally proposed a mitigation plan to reduce the negative impact of the so-produced vulnerability.

Summary and conclusions of major results of this work and recommendations for future work have been discussed in this chapter.

5.1 Summary for the research work

5.1.1 Drought condition analysis

The rainfall departure, rainfall probability and Standardized Precipitation Index (SPI) have been computed for the identification of drought years, drought prone zones and drought severity assessment and monitoring respectively, in the period of study of 116 years from 1901 to 2016, at fifty-five grids with 0.25 degree resolution, covering the whole study area. The results of rainfall departure analysis have been categorized in four classes of mild, moderate, severe and extreme drought conditions at all the fifty-five grids. The results of probability analysis has classified the region into two classes either normal or drought prone based on the variation of the 75% dependable rainfall at different grids.

The Standardized Precipitation Index (SPI) has been computed for four different timescales of 1-month, 3-months, 6-months and 12-months for the analysis of meteorological, agricultural, hydrological and groundwater drought conditions respectively. The results has been further analyzed into three category of (i) drought prevailing for one month, (ii) drought prevailing for two months and (iii) for drought events prevailing continuously for three or more than three months respectively. The results of SPI-3 and SPI-6 have been processed for the monitoring of agricultural and hydrological drought conditions.

For rainfall departure

- The maximum annual rainfall departure of -82.99% (deficit rainfall) was observed during the year 1978-79 (with mean annual rainfall as 1137.74 mm) for the grid-32 (Banka district). The second most rainfall departure of -80.35% is observed during the year 1948-49 (with mean annual rainfall as 932.53 mm) for the grid 52 (Patna district).
- The minimum rainfall departure of -39.76 % has been observed for the grid 28 (Lakhisarai district) during 1953-54 (with mean annual rainfall as 1096.31 mm).
- The grid forty-seven (Bhagalpur district) faces a maximum number of sixty-two drought (in 116 years of the study period) events with the drought frequency of at least once in 1.9 years while the grid 2 (Gaya district) faces the second highest of fifty-two (52) drought events during the study period.
- The grid 11 (Gaya district) and grid 24 (Jehanabad district) is at lowest position with the occurrence of only 35 drought events.
- At the district level, on an average, Arwal district is the one that faces a maximum number of forty-nine (49) drought events and Bhagalpur district is at second position with forty-eight (48) drought events, while Buxar district is at the lowest position with only thirty-six to thirty-seven (36.5) drought events in the study area.
- More than fifty percent of the area faces drought in the range of 40-45 years in the study period of 116 years.
- The occurrence of drought greater than sixty years are mainly concentrated in Bhagalpur district, this indicates the severity of the Bhagalpur district and nearby area.
- More than 70% of the study area is under drought frequency of 2.5 to 3 years.

For rainfall Probability

- There is a considerable variation in the 75% dependable rainfall values from a maximum of 1101.67 mm at grid 48 (Bhagalpur district) to a minimum of 726.14 mm at grid 52.
- Most part of the zone-III (B) shows the dependable rainfall in the range of 900-1000 mm while most part of zone-III (A) shows the dependable rainfall to vary from 800-900 mm. This indicates that the western portion of the study area can survive even with the low amount of rainfall, while the eastern portion requires relatively higher amount of rainfall to fulfill the water needs and thus is more vulnerable to drought.
- It is indicative of the fact that the areas influenced by grids 37, 42, 45 and 47 are drought-prone (probability of 75% mean rainfall being less than 80%) and faces water scarcity and droughts.

For SPI-1(Meteorological Drought)

- The results show that grid 32(Banka district) faces maximum times extreme drought with total duration of 27 months.
- The grid 47 (Bhagalpur district) suffers highest number of total drought periods of 366 months and also faces maximum drought events of grade-III of 33 events with total of 230 drought events.
- The grid 16 faces maximum number of 252 drought events with 20 events of grade-III.

For SPI-3 (Agricultural Drought)

- The results show that grid 32 face maximum number of extreme drought duration of 41 months.
- The grid 47 of Bhagalpur district suffers highest number of total drought periods of 438 months with 18 as extreme months.
- The grid 25 faces maximum of 73 drought events of grade-iii with total drought events of 168.

For SPI-6 (Hydrological Drought)

- The SPI-6 results show that grid 11 and grid 54 faces highest number of extreme drought condition for 51 months.
- The grid 14 faces maximum of 429 drought months.
- The grid 2 suffers highest number of 58 extreme drought events.
- The grid 19 faces maximum drought events of 133 with 48 as extreme events.

For SPI-12 (Groundwater Drought)

- The SPI-12 results show that grid 11 faces maximum number of extreme drought condition for 60 months while the grid 2 faces maximum of 499 drought months.
- The grid 22 (Aurangabad district) suffers highest number of 39 of grade-iii drought events with total number of fifty-seven (57) events and four hundred thirty-two (432) drought months where forty-one (41) are under extreme period.
- The grid 46 faces maximum of 67 drought events with 36 as grade-iii events and duration of 389 months with 43 as extreme months.

5.1.2 Eco-environmental vulnerability level

The total of twenty-one (21) sub-indicators classified into four (4) group indicators as topographical, land resource, hydro-meteorological and socio-economic has been computed to evaluate the eco-environmental vulnerability index (EVI) in the Bihar region, using the spatial principal component analysis (SPCA) and analytical hierarchy process (AHP) techniques. The eco-environmental vulnerability integrated index (EVSI) has been computed for detecting the spatio-temporal decadal change in the vulnerability level for the three selected periods of 1995 to 2005, 2005 to 2015 and 1995 to 2015 in the study area.

- The topographical vulnerability is prevailing more in the southern region of the study area due to the presence of eroded and dissected hills.
- The land resource vulnerability is high in the districts of Bhabhua and Banka and shows a quite change in the study period (1995-2015).
- The hydro-meteorological vulnerability is more pronounced in the districts of Bhabhua, Aurangabad, Gaya Jamui and Lakhisarai. This vulnerability shows a sharp increase in the period of 1995-2015 due to the delayed and non-uniform nature of the south-west monsoon.
- The socio-economic vulnerability is quite decreasing in the study period, due to the continuously increasing and decreasing nature of literacy rate and literacy gender gap respectively. But the increasing pressure of population and population density is alarming the situation which needs careful monitoring of the socio-economic situation.
- The overall eco-environmental vulnerability is found to be continuously increasing since 1995 to 2015. The vulnerability level is more pronounced in the Arwal, Patna and Jehenabad districts. These districts must be kept in priority for the implementation of the mitigation plan.
- Out of the three above mentioned districts the situation of Patna is more vulnerable as its population and its density is very high, that will cause more people to be affected due to the so-increasing vulnerable situation.

5.2 Conclusions

- The work indicates that the southern and eastern region of the study area, particularly the districts of Banka, Gaya, Bhabhua and Bhagalpur are more vulnerable to drought.
- The probability of occurrence of agriculture drought (SPI-3) is found to be high as compared to the other types of droughts with an average return period of 1.9 year.

- The topographical vulnerability results indicate that more that 40 % area are potential vulnerable and about 11% area are heavy vulnerable.
- The area under high level of hydro-meteorological vulnerability in 1995 is about 18 % which goes up to about 77 % in 2015. This shows that area is under severe drought prone.
- The environmental vulnerability increases in most of the districts abruptly in the first phase from 1995 to 2005. However in the second phase of study from 2005 to 2015, the vulnerability takes an upward turn with quite positive increment. The reason is that the socio-economic development in the first phase reduces the effect of all other vulnerability, while in the second phase the hydro-meteorological vulnerability dominates over it and hence increases the overall vulnerability.
- The highest increment in vulnerability is in Arwal district (108%) followed by Jehanabad district (92.24%).

5.3 Scope of future work

Few limitations in the study work which can be overcome in future are listed below:

1. The drought severity assessment can be done more effectively using crop yield data and ground-validation.
2. The other drought indices like Palmer drought severity index (PDSI), normalized differential vegetation index (NDVI), vegetation condition index (VCI), temperature condition index (TCI) can be computed along with SPI to validate the results.
3. The work can be accomplished for basin, using hydrological models like SWAT, VIC, MODFLOW, WEAP etc.

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APPENDICES

Appendix I: Drought Results Tables

Table 1 Drought results based on SPI-1

	Drought durations (months)					No. of Drought Events with durations			
Grids	**Extreme**	**Severe**	**Moderate**	**Mild**	**Total**	**1 month**	**2 months**	**≥ 3 months**	**Total**
1	13	19	74	202	313	160	45	19	224
2	13	20	59	184	277	154	47	9	210
3	13	35	92	206	352	175	50	22	247
4	11	46	65	227	355	172	50	25	247
5	13	17	77	241	349	170	42	26	238
6	10	17	98	227	356	180	47	23	250
7	14	17	71	177	280	160	39	11	210
8	11	13	67	180	273	160	41	9	210
9	10	26	94	232	363	172	44	31	247
10	12	21	116	198	349	171	47	26	244
11	17	22	93	201	334	165	48	22	235
12	14	23	85	185	309	174	39	18	231
13	15	24	49	151	241	148	23	13	184
14	19	22	82	219	346	170	46	26	242
15	15	31	64	238	350	177	43	26	246
16	15	31	75	237	363	175	57	20	252
17	18	24	76	231	354	169	54	21	244
18	12	15	49	208	287	160	42	14	216
19	13	20	52	195	284	155	43	12	210
20	13	14	94	190	316	172	44	16	232
21	12	18	71	246	354	171	37	30	238
22	11	17	101	230	364	163	49	30	242
23	10	15	106	216	352	163	44	30	237
24	19	14	71	216	323	170	52	14	236
25	16	21	69	226	334	159	47	23	229
26	17	32	53	194	300	174	38	15	227

	Drought durations (months)					No. of Drought Events with durations			
Grids	**Extreme**	**Severe**	**Moderate**	**Mild**	**Total**	**1 month**	**2 months**	**≥ 3 months**	**Total**
27	12	36	54	170	275	141	42	15	198
28	8	33	62	204	311	162	44	18	224
29	13	34	58	233	340	166	40	27	233
30	13	29	54	262	363	163	44	31	238
31	15	27	86	221	349	168	48	23	239
32	27	22	61	179	293	148	29	23	200
33	13	24	67	174	280	160	42	10	212
34	12	12	97	223	345	175	41	25	241
35	15	16	91	188	311	168	38	20	226
36	19	15	70	202	307	169	33	21	223
37	13	15	80	209	319	167	35	24	226
38	12	17	78	170	281	148	47	11	206
39	10	22	70	178	282	156	41	12	209
40	16	15	72	181	287	156	42	13	211
41	13	35	55	177	282	144	45	15	204
42	12	31	56	214	318	147	49	21	217
43	15	27	59	240	345	171	39	28	238
44	17	28	57	245	349	180	43	22	245
45	16	35	50	239	345	161	47	25	233
46	9	36	87	208	343	188	38	21	247
47	13	26	102	225	366	157	40	33	230
48	15	28	67	193	306	142	47	20	209
49	15	26	58	188	290	161	38	15	214
50	16	18	73	169	279	152	39	14	205
51	12	19	74	174	281	154	40	14	208
52	14	22	72	160	268	158	37	10	205
53	14	16	74	217	323	164	53	15	232
54	11	35	70	206	322	174	49	15	238
55	10	38	57	237	343	152	42	29	223

Table 2 Drought results based on SPI-3

	Drought durations (months)					No. of Drought Events with durations			
Grids	**Extreme**	**Severe**	**Moderate**	**Mild**	**Total**	**1 month**	**2 months**	**≥ 3 months**	**Total**
1	17	70	132	178	403	87	30	56	173
2	16	49	165	168	403	81	38	55	174
3	35	64	117	178	401	83	33	59	175
4	40	62	116	172	391	97	32	55	184
5	18	78	119	190	411	67	33	61	161
6	19	80	111	201	419	80	32	60	172
7	19	71	120	200	417	77	38	59	174
8	20	61	128	210	425	76	32	60	168
9	26	72	117	179	403	77	38	53	168
10	35	65	112	185	404	77	41	53	171
11	27	78	125	162	396	91	22	61	174
12	20	62	149	160	393	83	28	56	167
13	20	44	152	174	394	86	20	63	169
14	22	50	134	214	427	82	32	61	175
15	20	63	157	185	426	68	34	63	165
16	20	52	156	170	400	67	38	56	161
17	20	62	141	187	416	72	33	60	165
18	19	56	133	223	436	72	31	62	165
19	17	60	140	209	433	74	32	67	173
20	21	79	118	182	410	82	33	61	176
21	19	72	127	182	403	82	31	61	174
22	25	70	113	188	403	83	36	61	180
23	21	81	100	203	410	93	38	56	187
24	25	53	140	208	432	78	28	63	169
25	20	63	127	205	418	71	24	73	168
26	24	57	131	188	404	65	33	59	157
27	25	41	142	175	391	74	28	51	153
28	30	54	118	204	411	76	35	59	170
29	23	57	123	202	414	70	35	60	165
30	25	50	144	204	430	70	25	67	162

	Drought durations (months)					No. of Drought Events with durations			
Grids	**Extreme**	**Severe**	**Moderate**	**Mild**	**Total**	**1 month**	**2 months**	**≥ 3 months**	**Total**
31	29	54	137	195	419	68	35	63	166
32	41	35	117	197	395	78	24	55	157
33	26	66	106	207	409	83	35	55	173
34	21	58	135	214	433	74	34	64	172
35	22	74	111	190	401	78	27	56	161
36	25	67	130	194	418	68	40	56	164
37	23	66	110	238	437	65	30	64	159
38	20	58	140	173	398	69	36	58	163
39	26	57	128	185	403	82	26	59	167
40	23	57	146	181	415	64	35	57	156
41	13	60	148	176	401	63	19	65	147
42	31	62	122	204	425	56	30	66	152
43	24	54	134	196	413	78	22	64	164
44	27	68	114	206	416	80	28	59	167
45	33	61	118	183	398	69	27	60	156
46	33	48	119	222	425	83	29	63	175
47	18	47	147	218	438	72	20	65	157
48	26	59	123	206	418	74	36	59	169
49	26	73	122	180	408	83	28	58	169
50	22	54	133	220	432	72	33	62	167
51	19	69	140	181	410	67	29	66	162
52	26	75	112	176	395	66	30	54	150
53	27	79	109	174	393	68	25	63	156
54	28	61	118	202	414	67	34	60	161
55	30	64	136	158	394	51	22	65	138

Table 3 Drought Results based on SPI-6

	Drought durations (months)					No. of Drought Events with durations			
Grids	**Extreme**	**Severe**	**Moderate**	**Mild**	**Total**	**1 month**	**2 months**	**≥ 3 months**	**Total**
1	44	45	100	195	389	43	24	43	110
2	37	48	133	207	428	42	15	58	115
3	41	51	120	193	411	38	30	54	122
4	39	49	130	190	416	50	22	53	125
5	42	54	102	186	387	44	18	47	109
6	42	56	97	213	413	47	27	48	122
7	37	58	103	193	398	55	19	47	121
8	37	65	98	195	398	44	20	51	115
9	32	75	115	172	400	56	23	44	123
10	38	62	118	183	407	50	19	52	121
11	51	57	102	184	399	54	16	51	121
12	38	62	119	195	414	51	23	51	125
13	39	41	121	183	390	53	27	47	127
14	31	52	136	206	429	49	23	51	123
15	35	55	126	203	424	45	23	51	119
16	28	54	119	197	408	57	17	50	124
17	34	62	124	188	415	51	15	49	115
18	32	57	112	211	421	46	20	49	115
19	38	51	124	195	410	57	28	48	133
20	35	55	126	201	425	44	19	52	115
21	26	63	129	190	412	52	21	50	123
22	40	44	135	200	420	53	21	53	127
23	33	54	136	192	420	55	21	53	129
24	38	60	121	184	406	58	15	51	124
25	23	54	134	199	416	44	12	53	109
26	40	55	107	195	402	38	16	50	104
27	37	68	95	189	394	41	28	41	110
28	28	71	119	176	397	56	18	48	122
29	36	61	96	216	415	55	31	40	126
30	40	43	123	202	413	45	20	52	117

	Drought durations (months)					No. of Drought Events with durations			
Grids	**Extreme**	**Severe**	**Moderate**	**Mild**	**Total**	**1 month**	**2 months**	**≥ 3 months**	**Total**
31	31	68	107	214	426	44	23	56	123
32	49	35	88	185	360	47	16	43	106
33	35	51	122	175	389	51	19	49	119
34	36	55	128	203	425	40	19	51	110
35	43	51	121	169	387	56	22	43	121
36	36	58	120	188	409	41	22	48	111
37	34	44	117	223	422	47	17	50	114
38	29	52	129	205	421	51	24	56	131
39	41	44	135	170	399	49	18	46	113
40	40	73	102	164	389	48	18	48	114
41	25	66	136	192	426	46	15	57	118
42	33	69	140	179	423	33	17	50	100
43	28	73	114	196	415	42	18	53	113
44	40	51	113	168	375	46	23	38	107
45	41	46	109	199	404	45	19	45	109
46	39	41	107	207	399	57	24	47	128
47	13	54	126	244	447	37	14	53	104
48	37	60	120	178	402	47	17	48	112
49	41	60	112	159	378	46	18	46	110
50	39	38	136	204	421	43	15	52	110
51	29	52	114	220	424	46	23	52	121
52	46	44	98	180	370	46	21	39	106
53	47	46	109	209	414	45	19	51	115
54	51	49	107	192	403	41	25	49	115
55	46	45	106	207	420	37	15	47	99

Table 4 Drought results based on SPI-12

	Drought durations (months)					No. of Drought Events with duration			
Grids	**Extreme**	**Severe**	**Moderate**	**Mild**	**Total**	**1 month**	**2 months**	**≥ 3 months**	**Total**
1	47	33	80	213	375	17	3	25	45
2	27	37	133	294	499	19	6	32	57
3	50	31	121	214	419	23	10	33	66
4	33	50	147	191	423	15	9	28	52
5	43	57	79	170	353	12	7	29	48
6	50	41	112	203	412	11	6	33	50
7	47	45	112	192	399	16	1	31	48
8	53	48	99	179	385	11	3	32	46
9	32	89	102	177	403	28	5	30	63
10	45	48	116	211	425	13	9	29	51
11	60	47	117	151	378	13	6	28	47
12	38	46	142	195	426	14	4	33	51
13	40	31	119	206	402	14	3	30	47
14	26	48	120	239	449	20	5	33	58
15	39	60	100	192	398	13	6	27	46
16	27	48	120	204	405	19	5	31	55
17	41	57	125	186	414	19	4	31	54
18	26	63	110	201	405	14	6	34	54
19	38	68	92	193	393	17	3	29	49
20	33	70	93	230	429	10	3	29	42
21	21	87	106	166	384	12	6	29	47
22	41	49	140	189	432	13	5	39	57
23	38	45	119	211	423	17	4	35	56
24	47	63	113	170	399	14	3	32	49
25	30	53	108	241	436	20	3	30	53
26	45	57	112	139	359	17	4	27	48
27	41	87	84	162	375	11	1	31	43
28	9	98	107	223	444	19	3	37	59
29	43	50	105	181	384	21	5	31	57
30	49	27	129	172	381	20	5	27	52

	Drought durations (months)					No. of Drought Events with duration			
Grids	**Extreme**	**Severe**	**Moderate**	**Mild**	**Total**	**1 month**	**2 months**	**≥ 3 months**	**Total**
31	33	63	114	210	429	14	5	33	52
32	47	18	68	168	305	15	7	23	45
33	45	36	122	169	377	16	8	32	56
34	28	75	129	169	406	11	5	30	46
35	41	64	107	149	366	12	8	28	48
36	40	65	92	211	415	12	8	29	49
37	38	31	106	202	383	15	4	28	47
38	25	40	151	245	464	12	6	35	53
39	34	50	147	157	397	24	1	29	54
40	40	83	89	165	384	13	1	32	46
41	34	69	138	170	419	8	4	31	43
42	33	85	136	153	418	4	6	26	36
43	31	55	134	215	441	12	1	33	46
44	56	35	113	140	347	18	5	28	51
45	35	56	109	204	410	7	4	33	44
46	43	38	92	213	389	20	11	36	67
47	1	40	157	279	483	9	5	35	49
48	33	77	117	187	416	13	4	35	52
49	43	68	99	159	372	20	7	20	47
50	38	36	114	173	366	18	5	29	52
51	40	49	98	193	391	13	7	30	50
52	43	45	78	209	377	14	4	20	38
53	41	29	139	212	425	13	6	31	50
54	44	50	122	181	403	13	5	33	51
55	45	44	130	222	445	10	2	28	40

Table 5 Drought events by different SPI scales with all durations (≥ 1 months)

SPI-1		SPI-3		SPI-6		SPI-12	
Durations	**Events**	**Durations**	**Events**	**Durations**	**Events**	**Durations**	**Events**
313	224	403	173	389	110	375	45
277	210	403	174	428	115	499	57
352	247	401	175	411	122	419	66
355	247	391	184	416	125	423	52
349	238	411	161	387	109	353	48
356	250	419	172	413	122	412	50
280	210	417	174	398	121	399	48
273	210	425	168	398	115	385	46
363	247	403	168	400	123	403	63
349	244	404	171	407	121	425	51
334	235	396	174	399	121	378	47
309	231	393	167	414	125	426	51
241	184	394	169	390	127	402	47
346	242	427	175	429	123	449	58
350	246	426	165	424	119	398	46
363	252	400	161	408	124	405	55
354	244	416	165	415	115	414	54
287	216	436	165	421	115	405	54
284	210	433	173	410	133	393	49
316	232	410	176	425	115	429	42
354	238	403	174	412	123	384	47
364	242	403	180	420	127	432	57
352	237	410	187	420	129	423	56
323	236	432	169	406	124	399	49
334	229	418	168	416	109	436	53
300	227	404	157	402	104	359	48
275	198	391	153	394	110	375	43

311	224	411	170	397	122	444	59
340	233	414	165	415	126	384	57
363	238	430	162	413	117	381	52
349	239	419	166	426	123	429	52
293	200	395	157	360	106	305	45
280	212	409	173	389	119	377	56
345	241	433	172	425	110	406	46
311	226	401	161	387	121	366	48
307	223	418	164	409	111	415	49
319	226	437	159	422	114	383	47
281	206	398	163	421	131	464	53
282	209	403	167	399	113	397	54
287	211	415	156	389	114	384	46
282	204	401	147	426	118	419	43
318	217	425	152	423	100	418	36
345	238	413	164	415	113	441	46
349	245	416	167	375	107	347	51
345	233	398	156	404	109	410	44
343	247	425	175	399	128	389	67
366	230	438	157	447	104	483	49
306	209	418	169	402	112	416	52
290	214	408	169	378	110	372	47
279	205	432	167	421	110	366	52
281	208	410	162	424	121	391	50
268	205	395	150	370	106	377	38
323	232	393	156	414	115	425	50
322	238	414	161	403	115	403	51
343	223	394	138	420	99	445	40

Appendix II: Vulnerability indicator maps

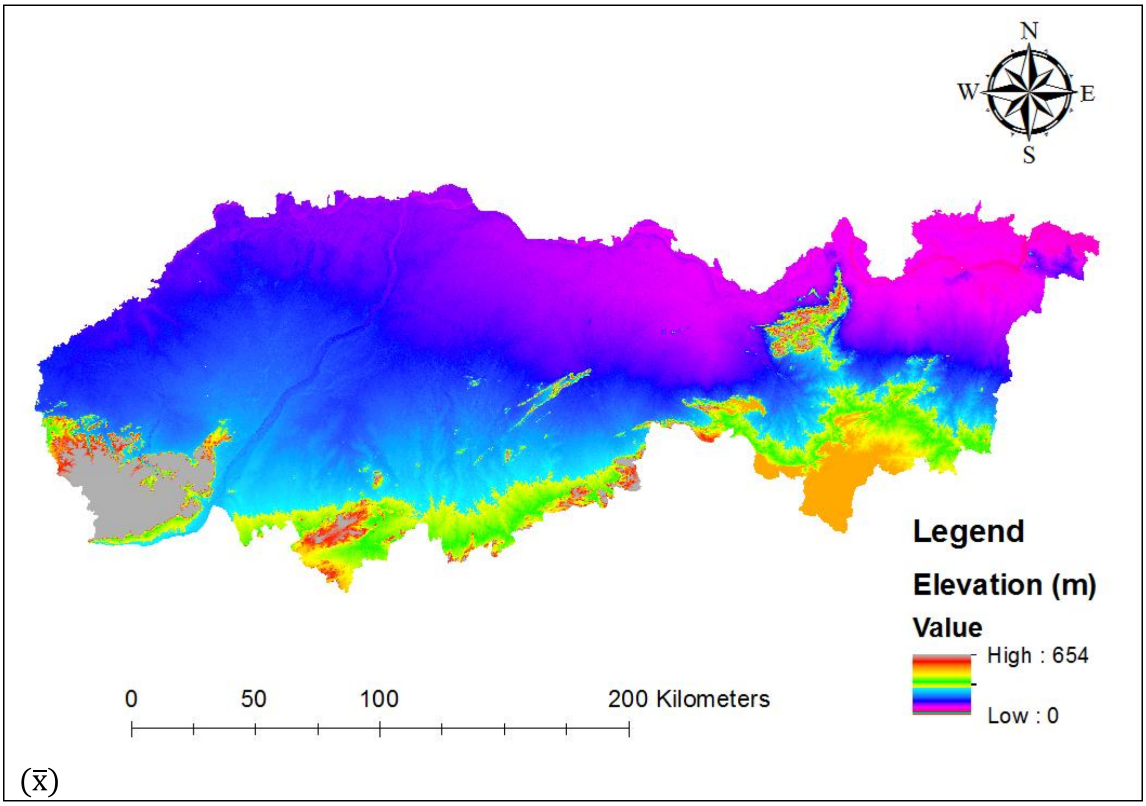

Figure 1 Elevation map

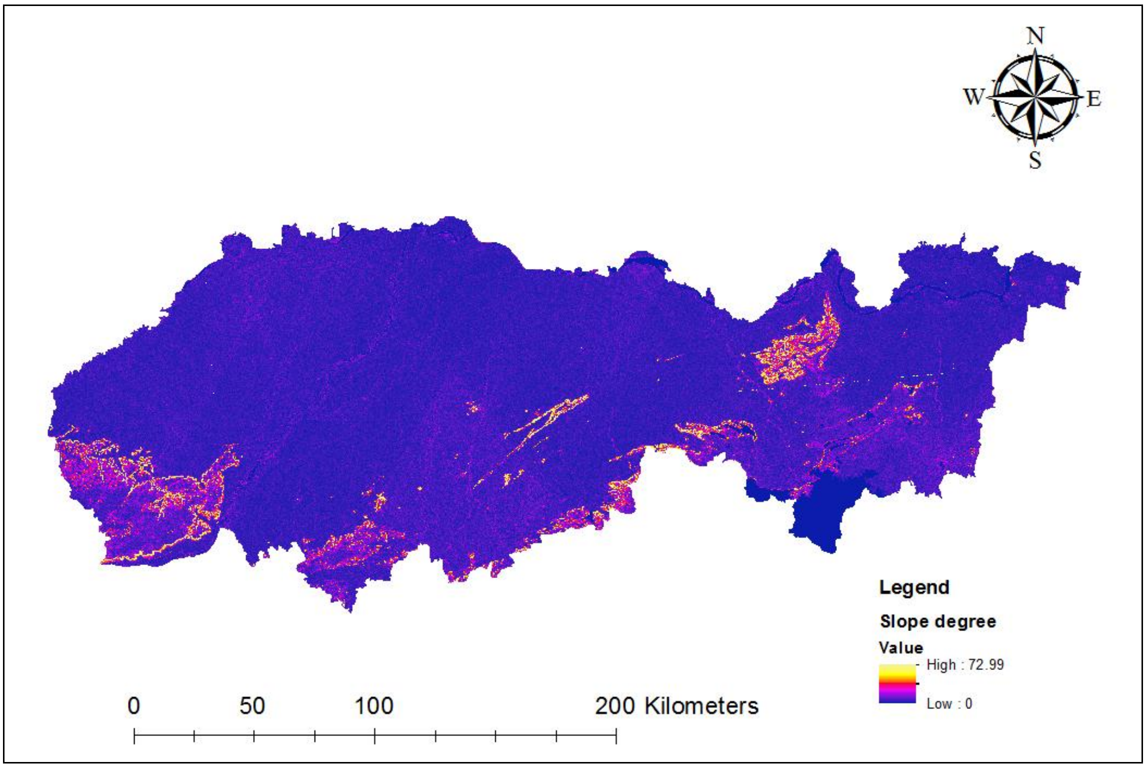

Figure 2 Slope map

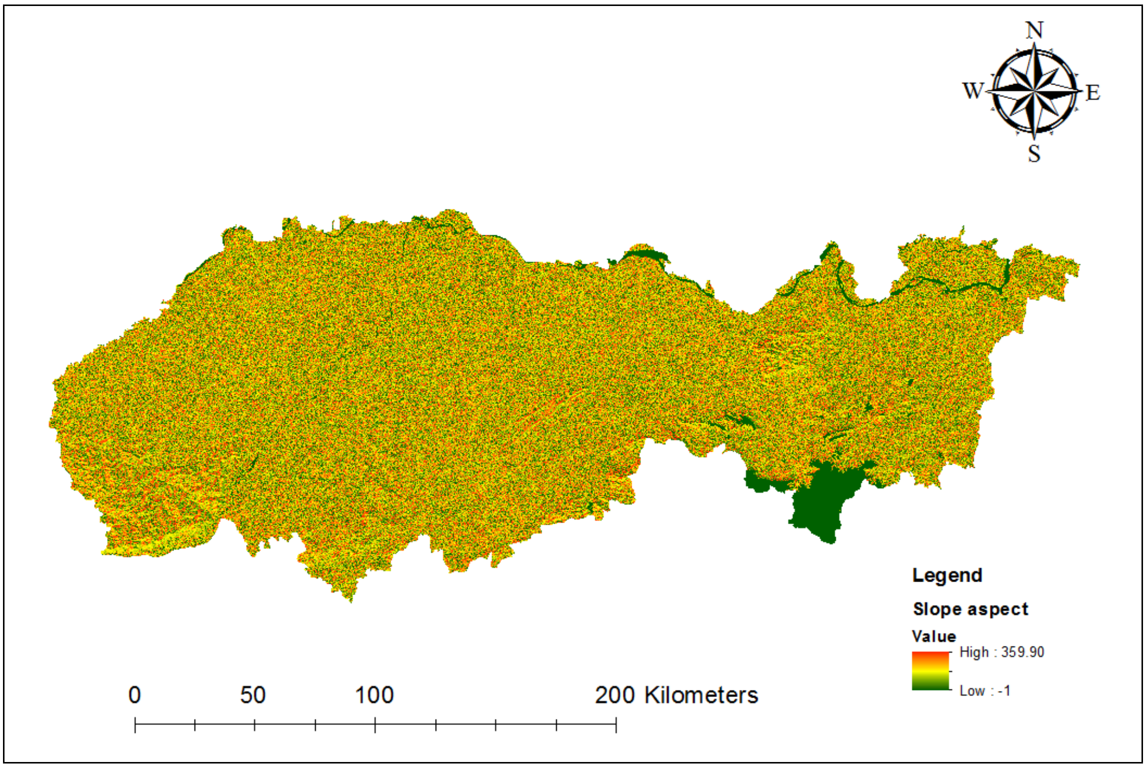

Figure 3 Slope aspect map

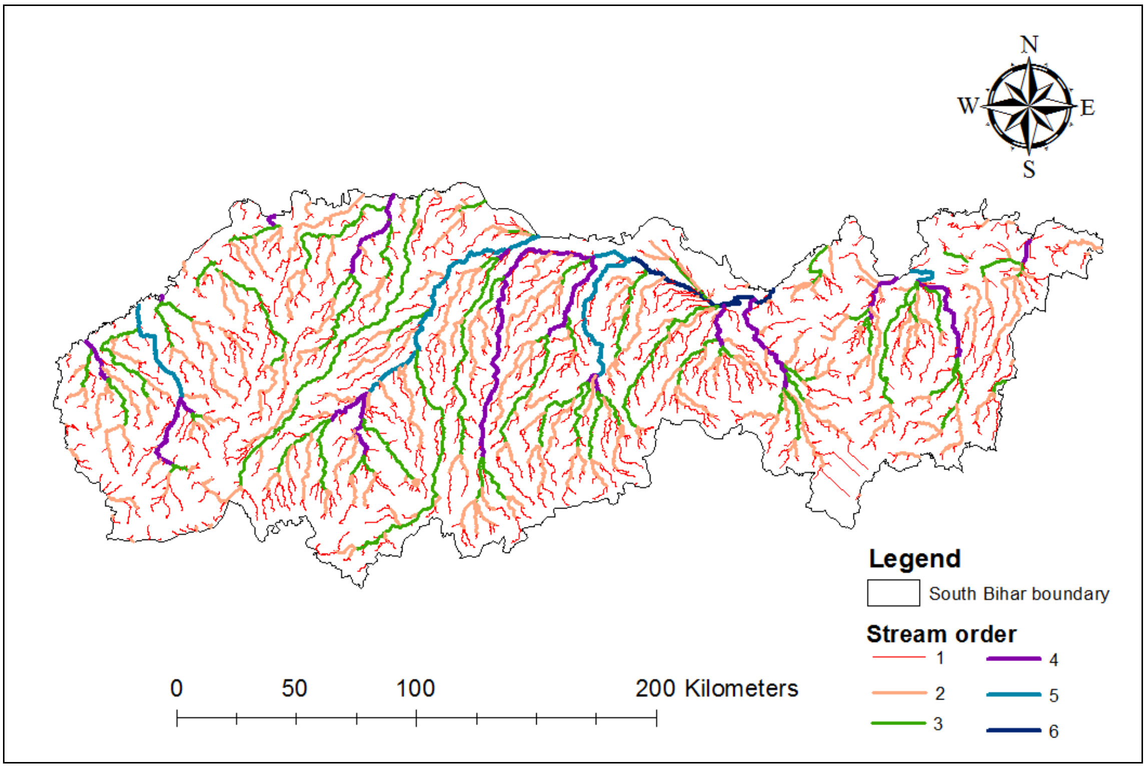

Figure 4 Drainage network map

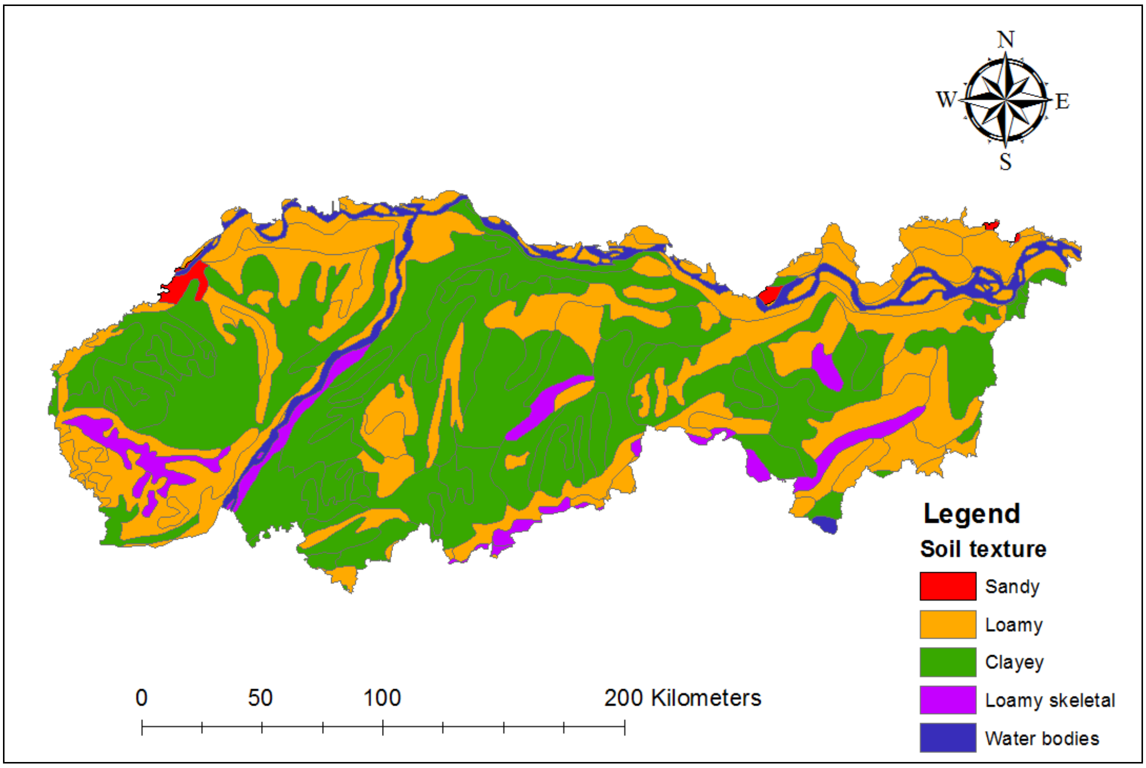

Figure 5 Soil texture map

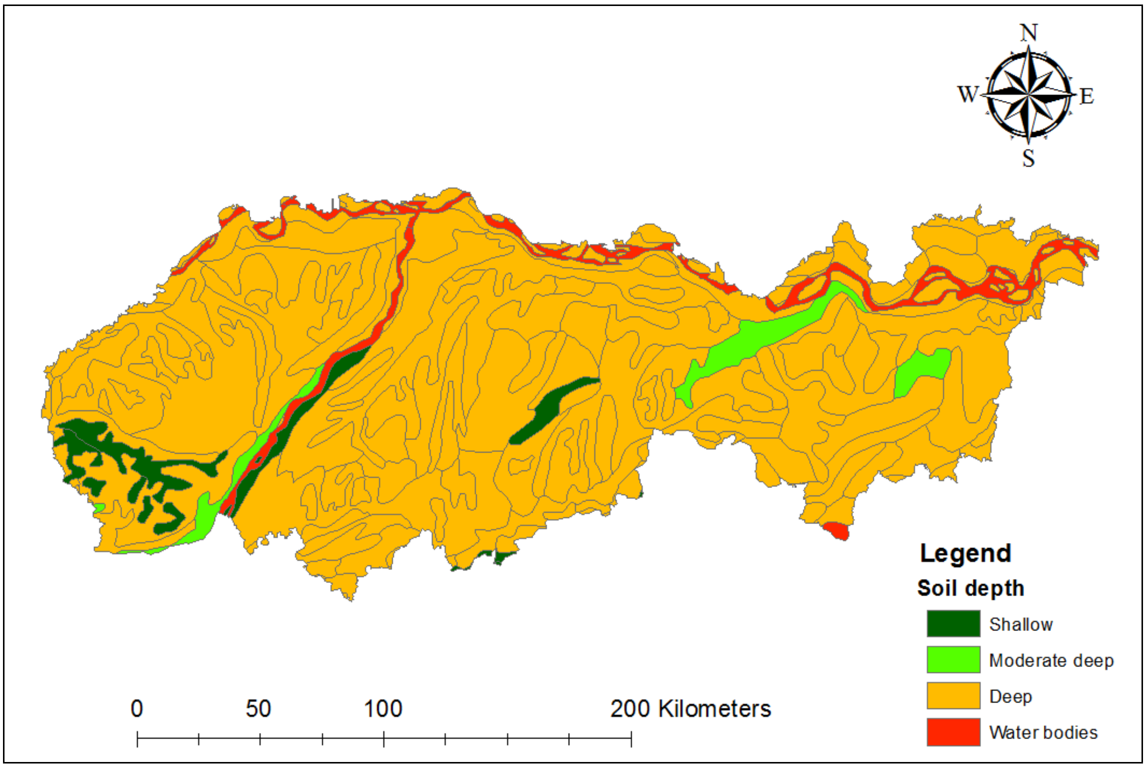

Figure 6 Soil depth

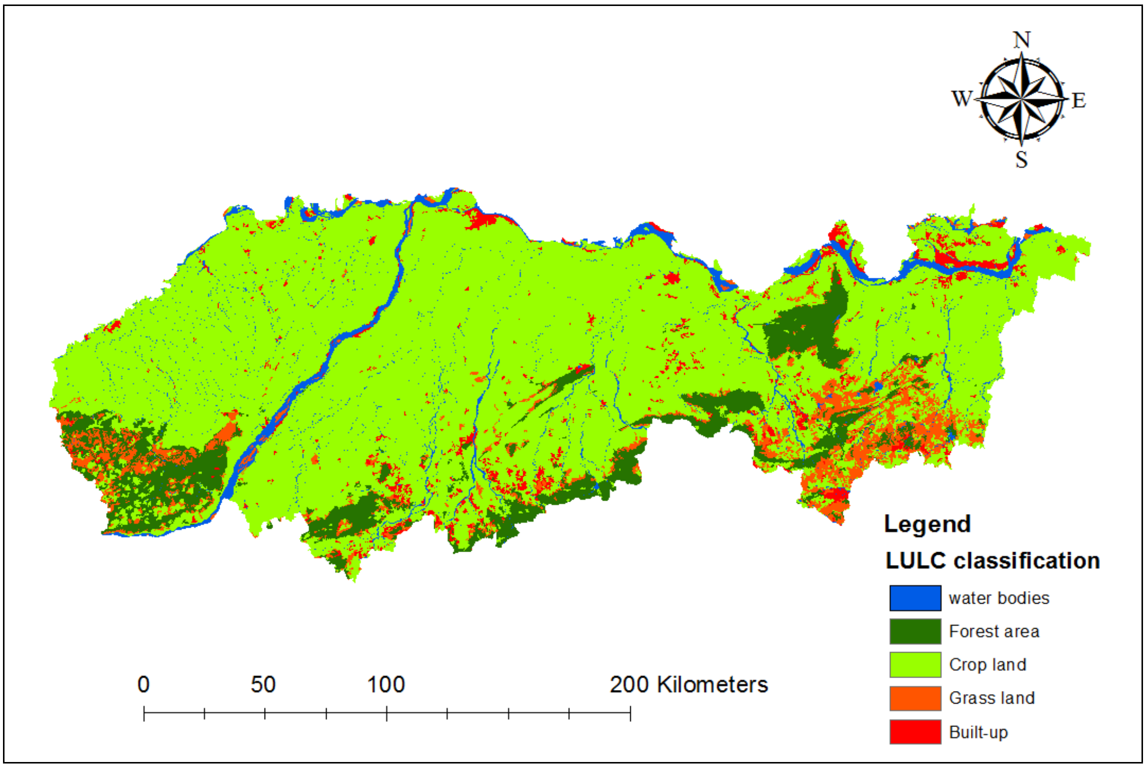

Figure 7 LULC (1995)

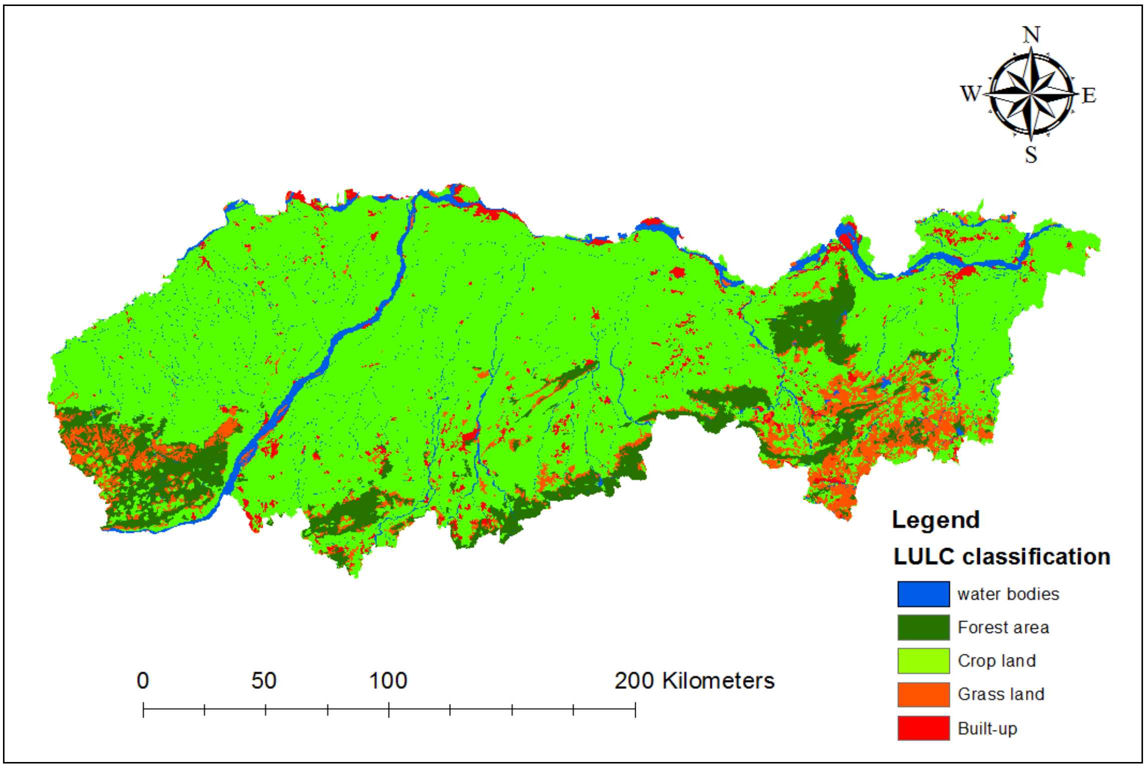

Figure 8 LULC (2005)

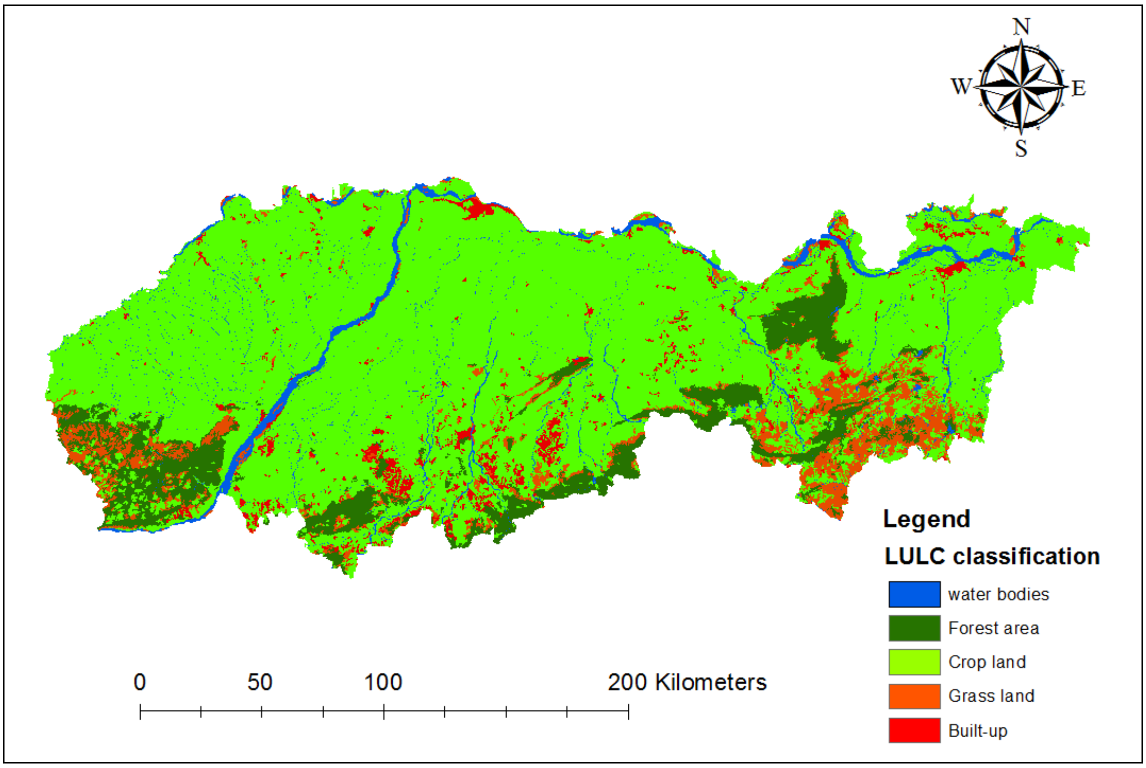

Figure 9 LULC (2015)

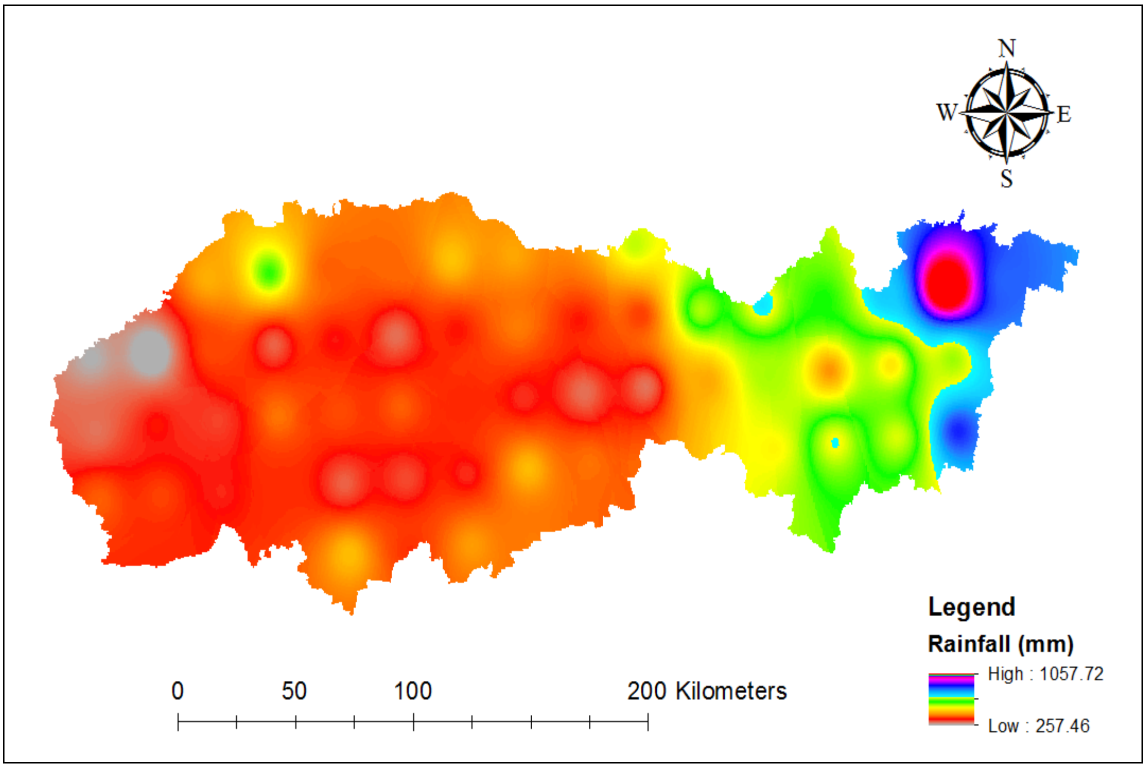

Figure 10 Rainfall map (1995)

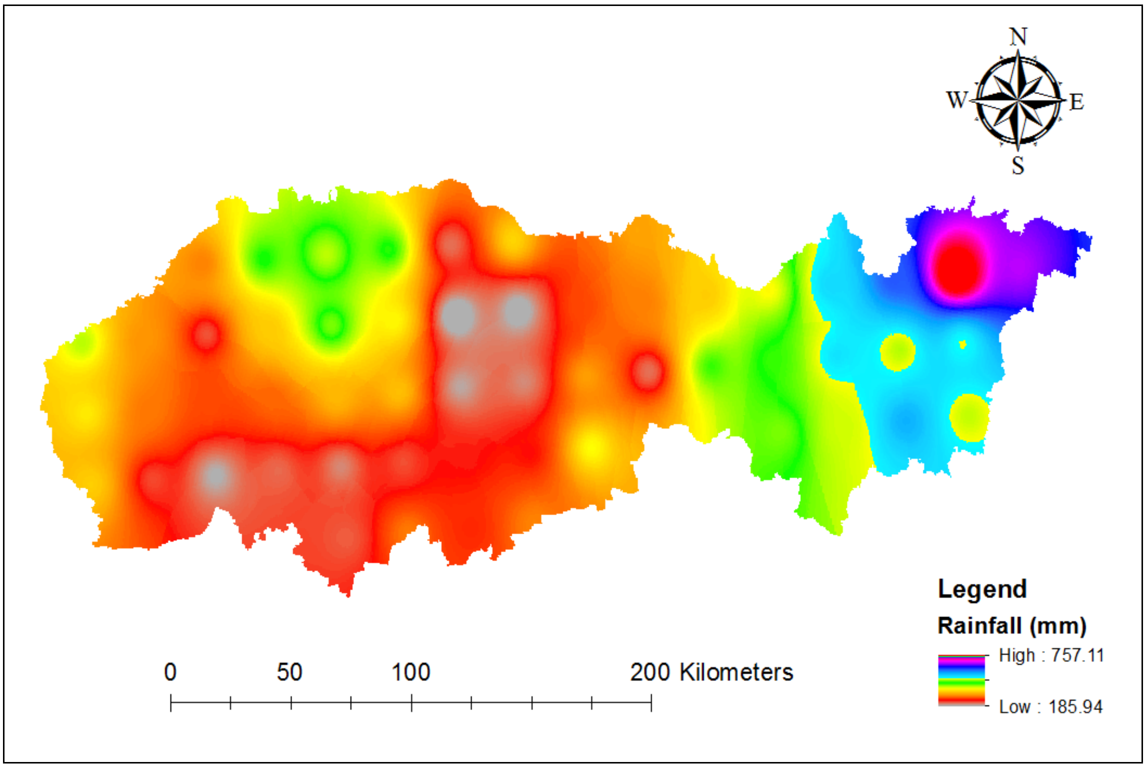

Figure 11 Rainfall map (2005)

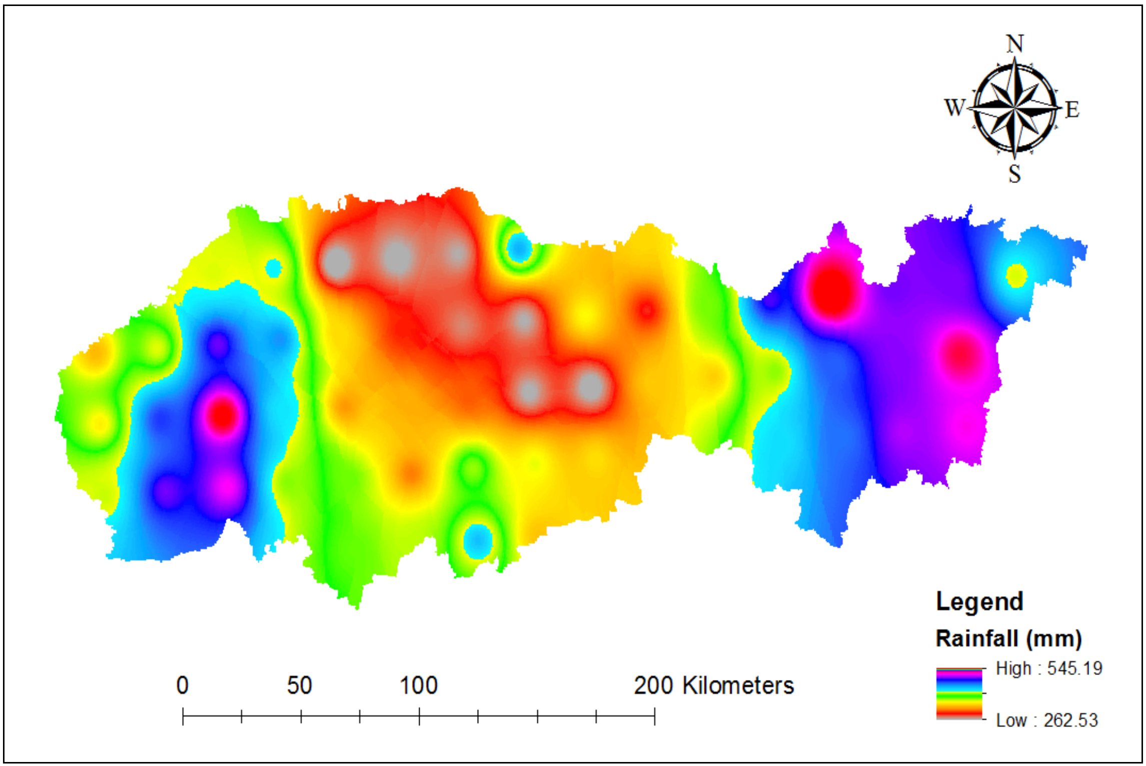

Figure 12 Rainfall map (2015)

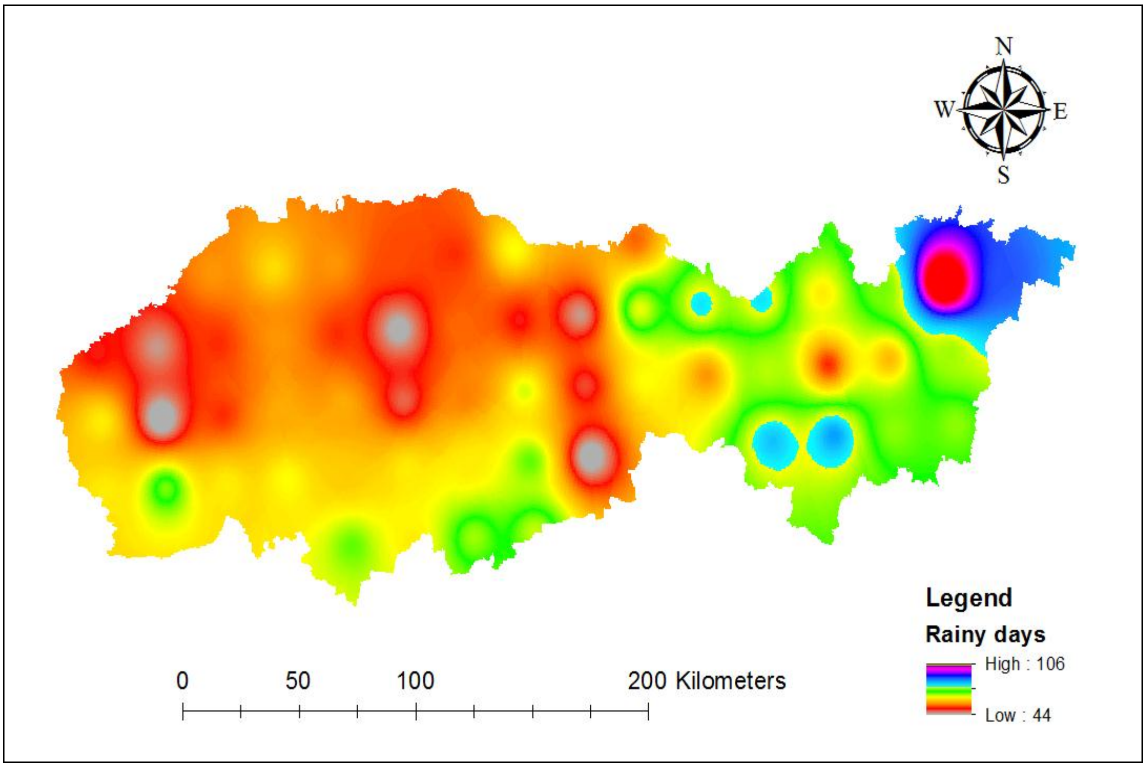

Figure 13 Rainy days map (1995)

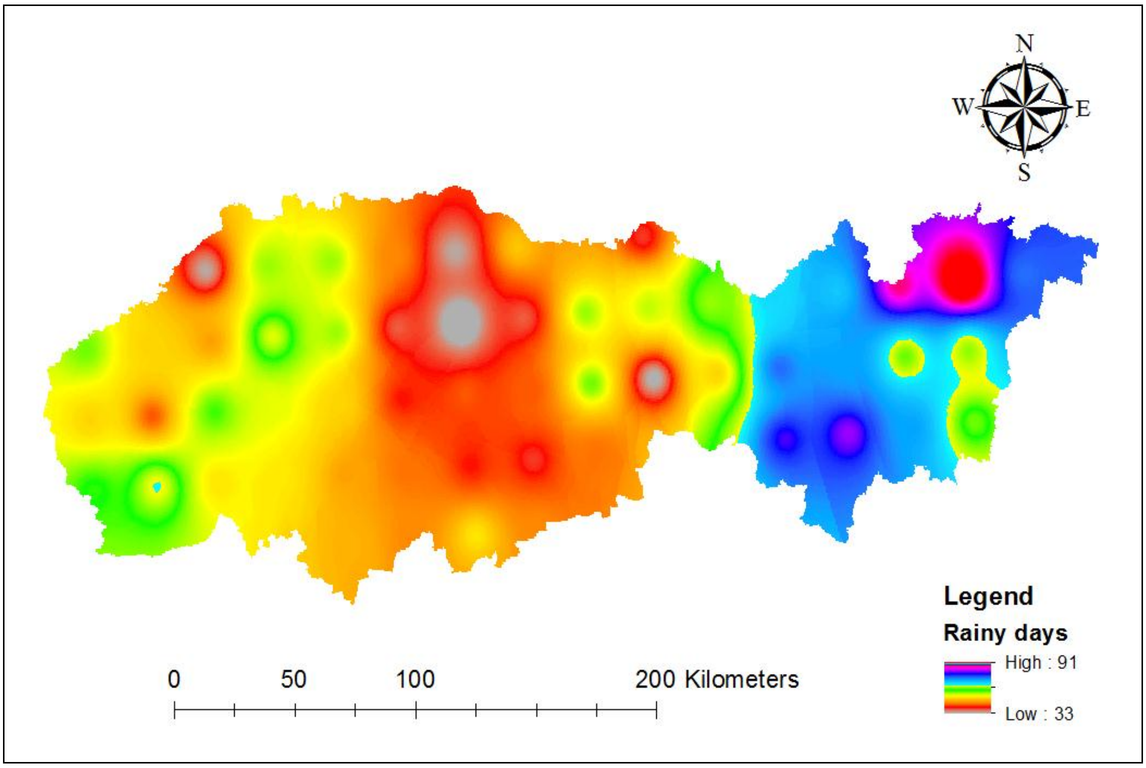

Figure 14 Rainy days (2005)

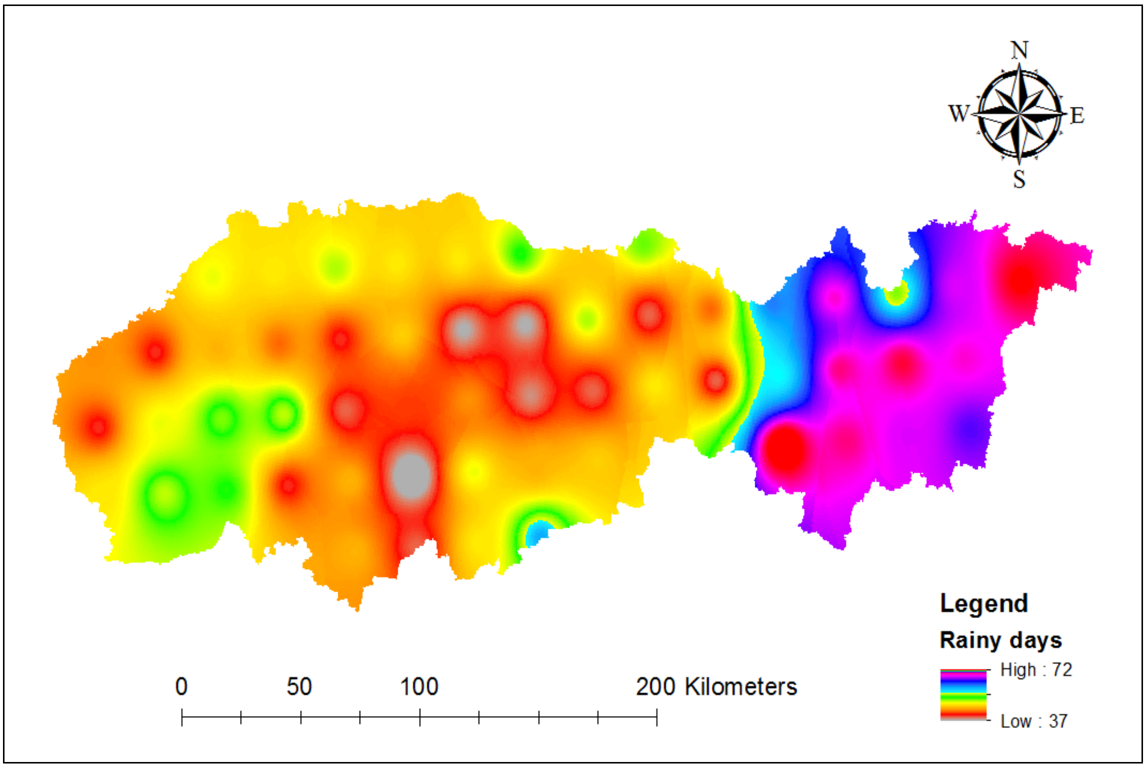

Figure 15 Rainy days (2015)

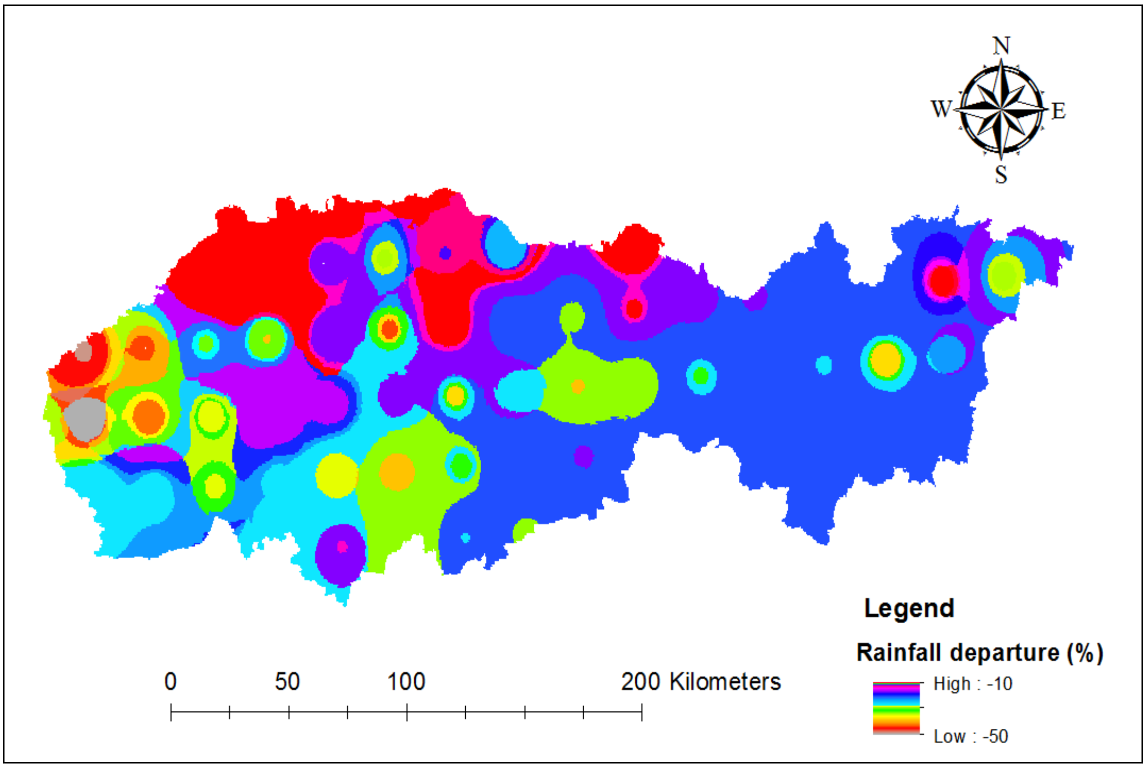

Figure 16 Rainfall departure map (1995)

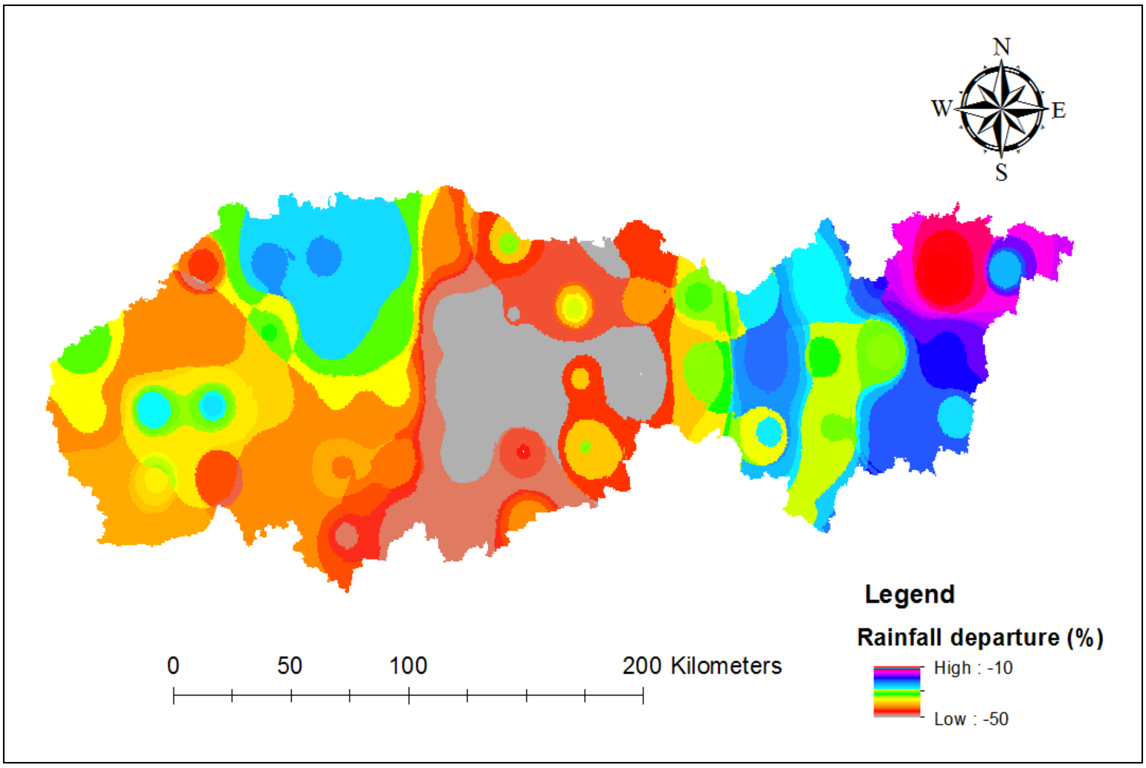

Figure 17 Rainfall departure map (2005)

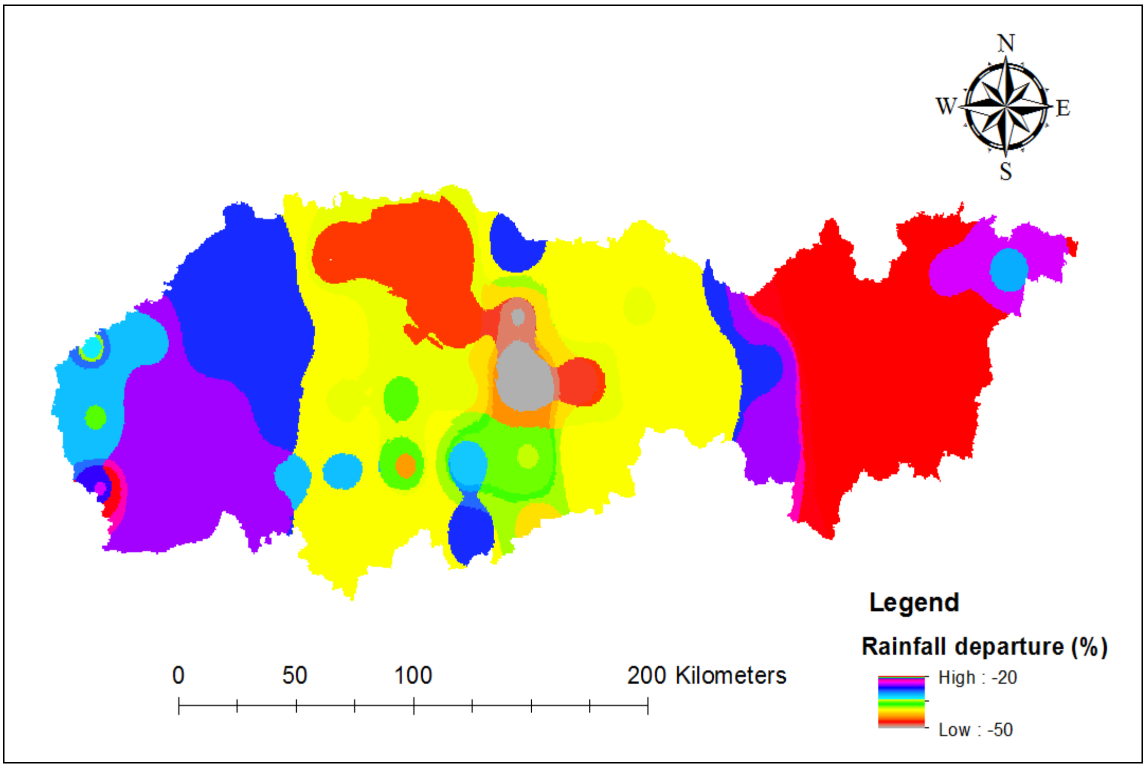

Figure 18 Rainfall departure map (2015)

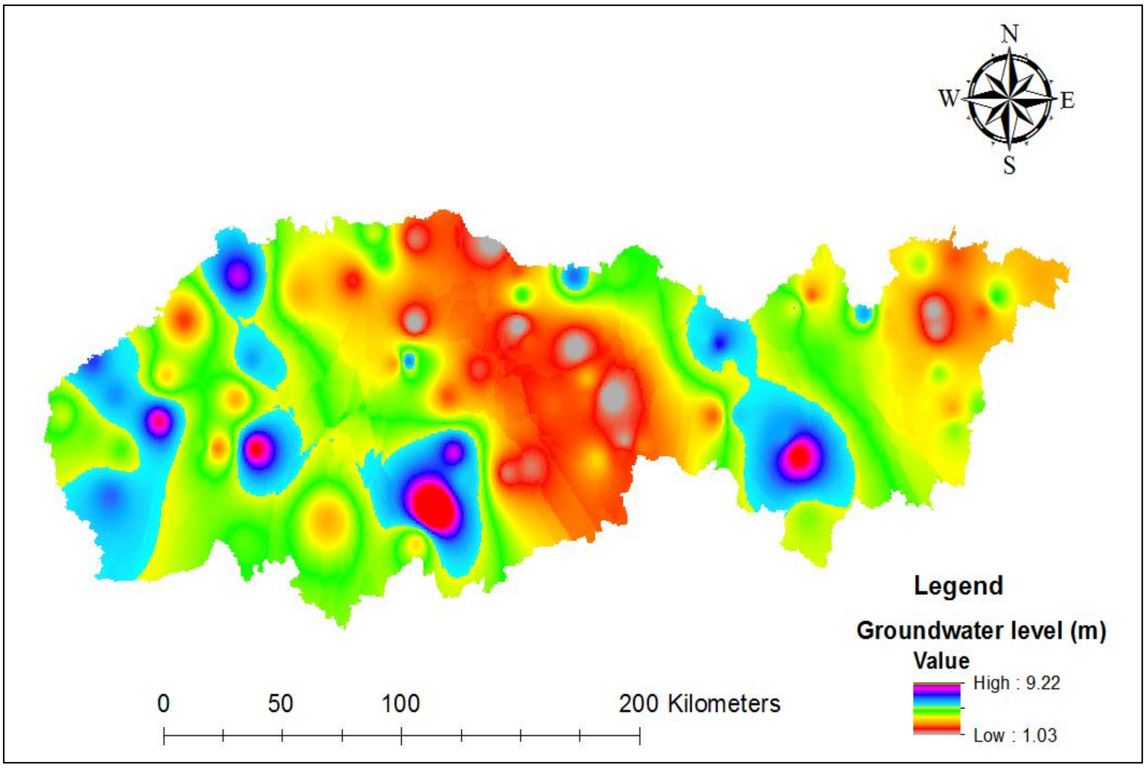

Figure 19 Groundwater availability map (1995)

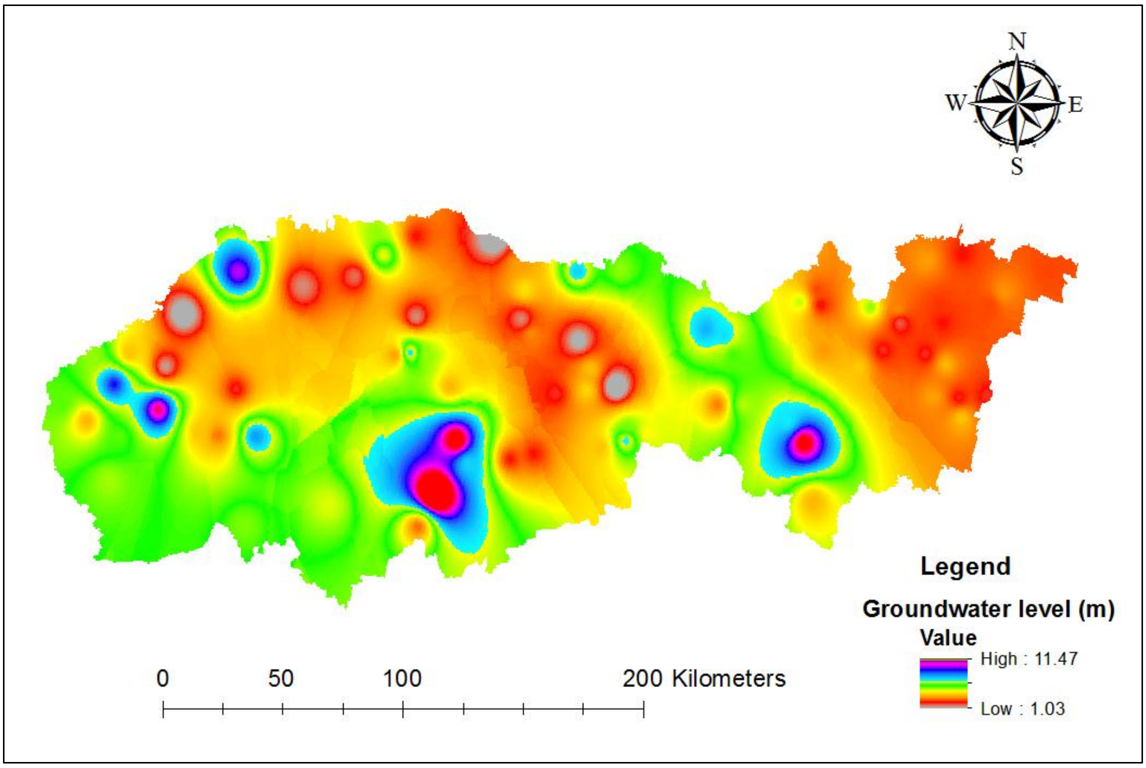

Figure 20 Groundwater availability map (2005)

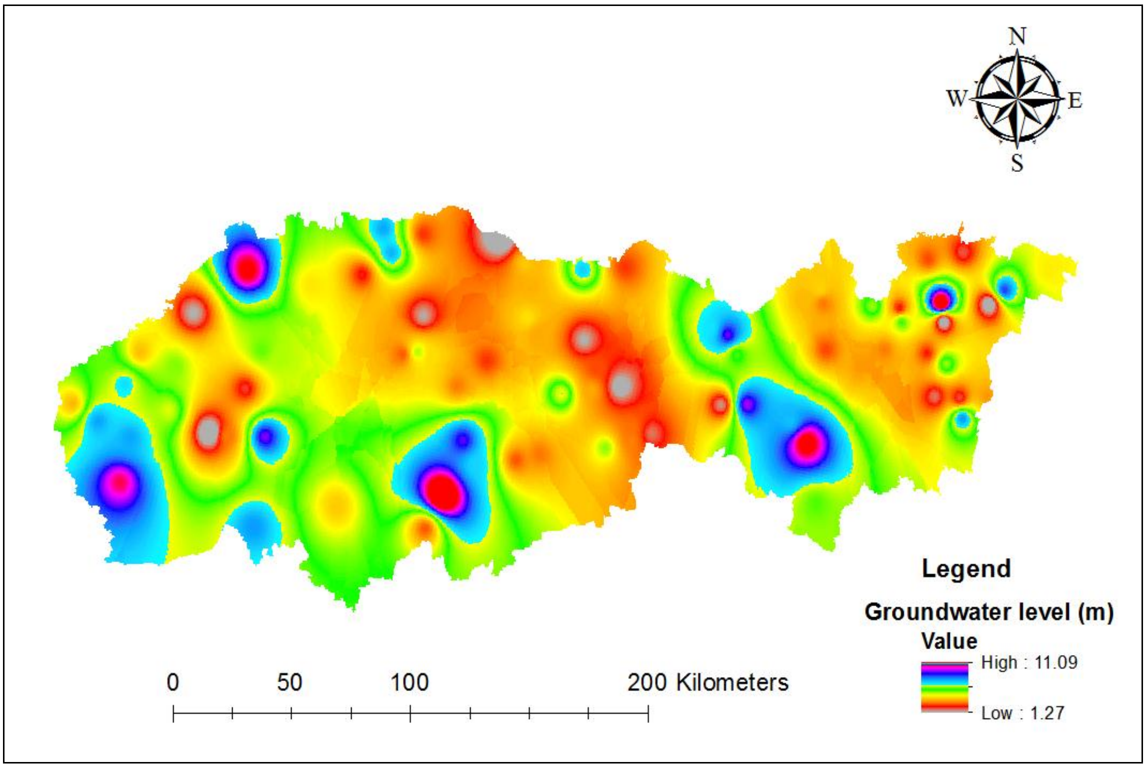

Figure 21 Groundwater availability map (2015)

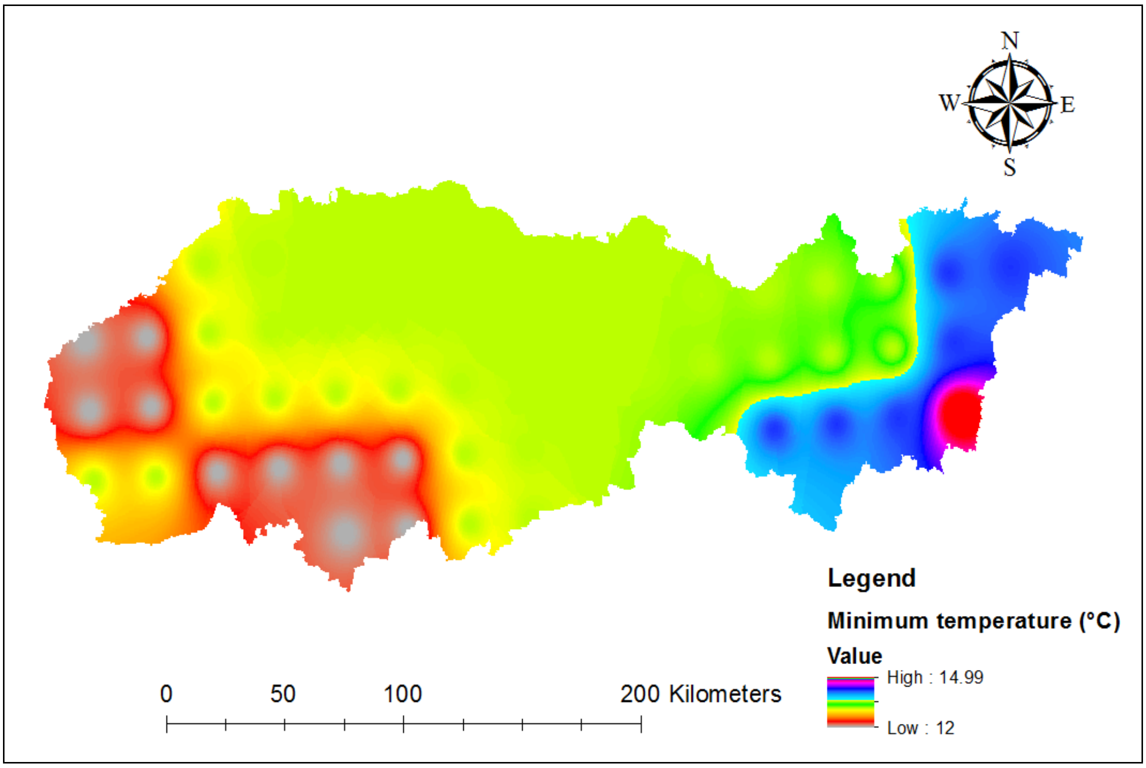

Figure 22 Minimum temperature map (1995)

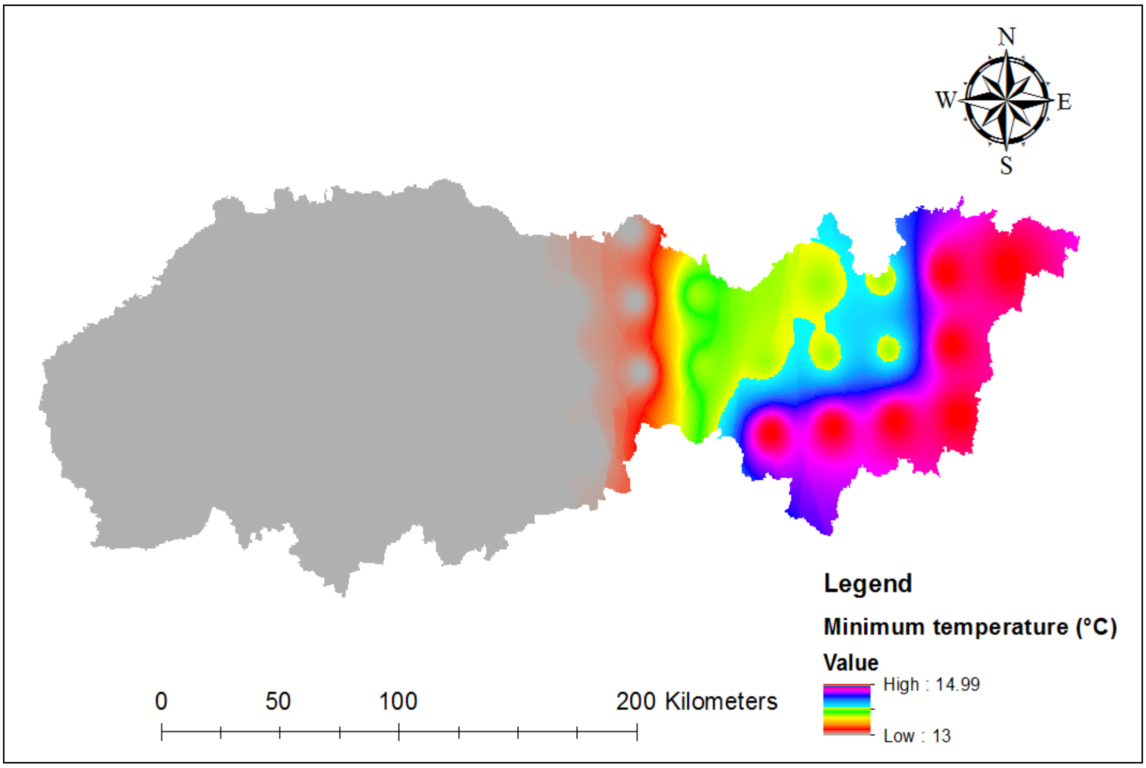

Figure 23 Minimum temperature map (2005)

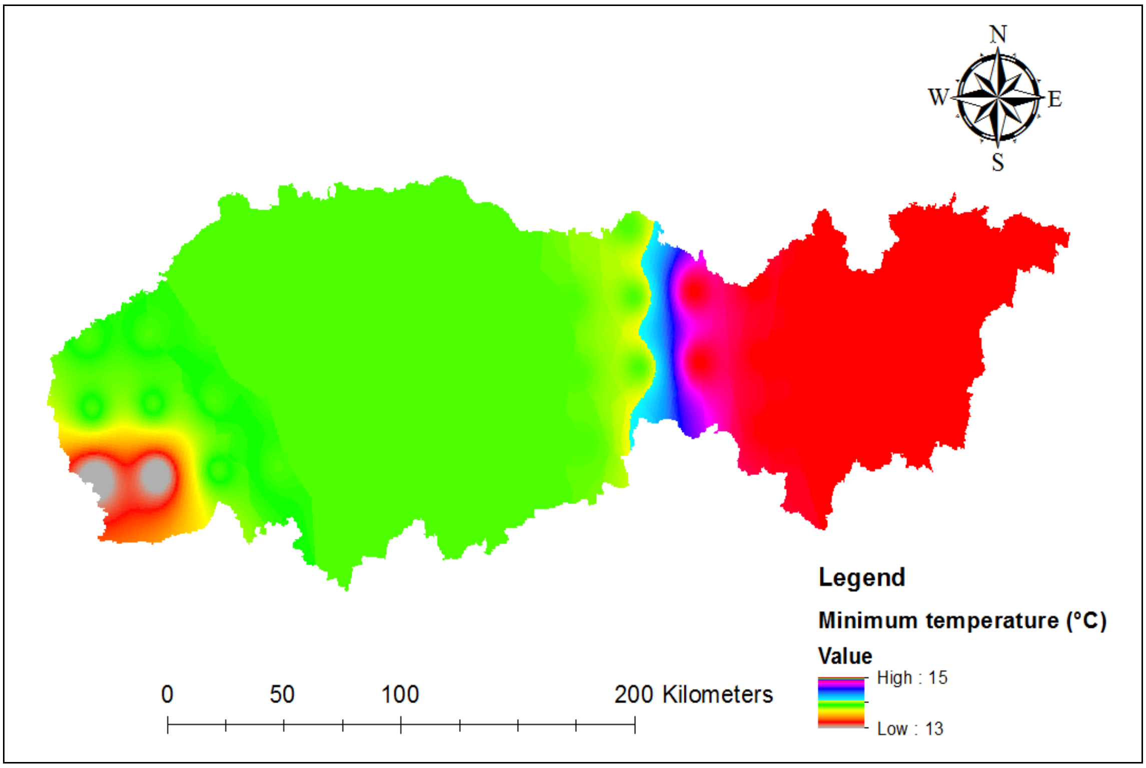

Figure 24 Minimum temperature map (2015)

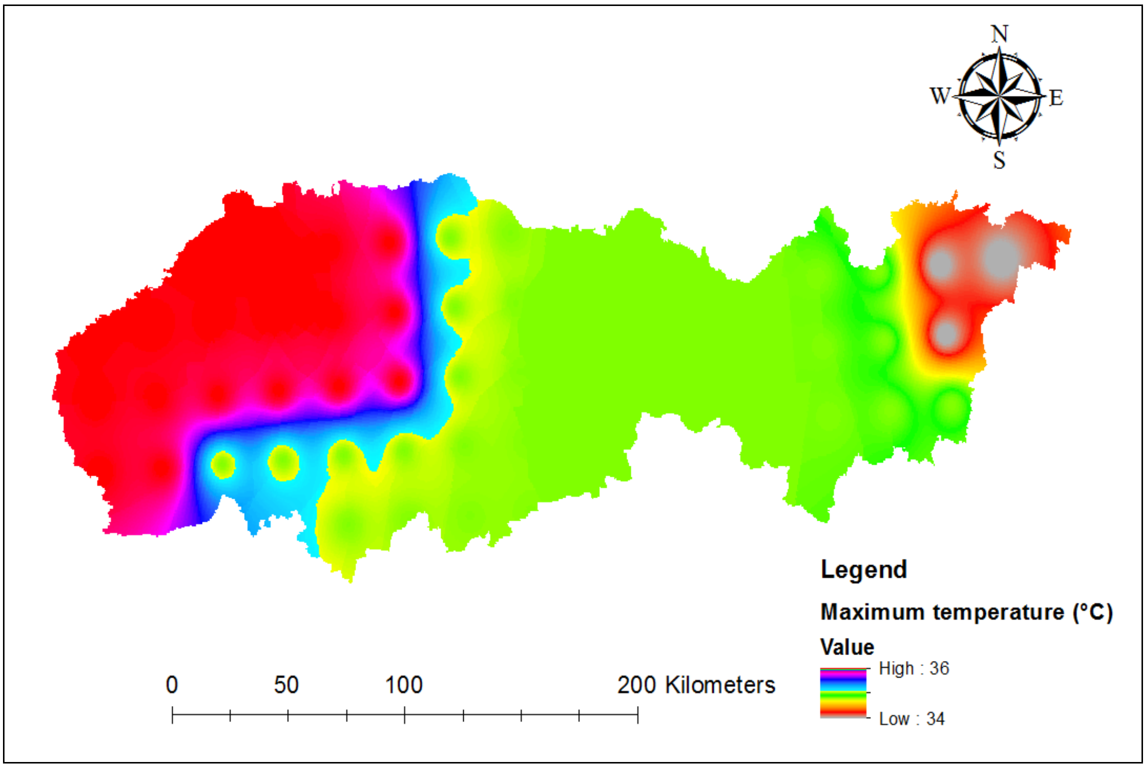

Figure 25 Maximum temperature map (1995)

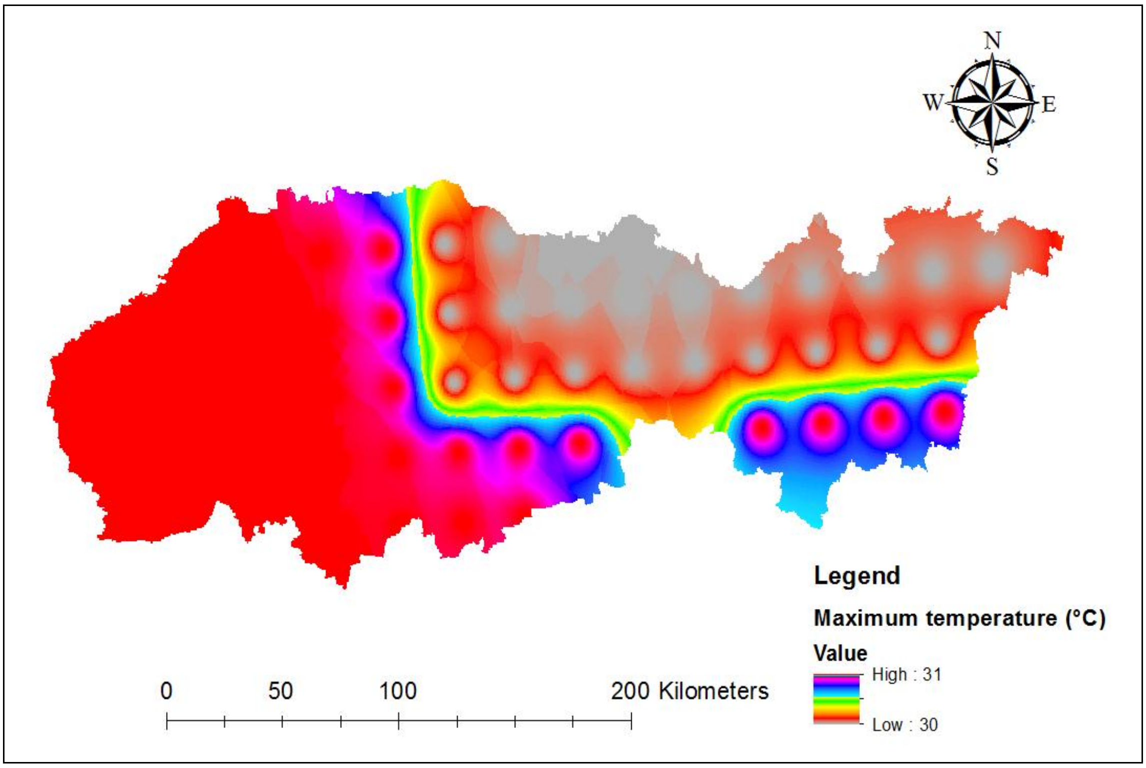

Figure 26 Maximum temperature map (2005)

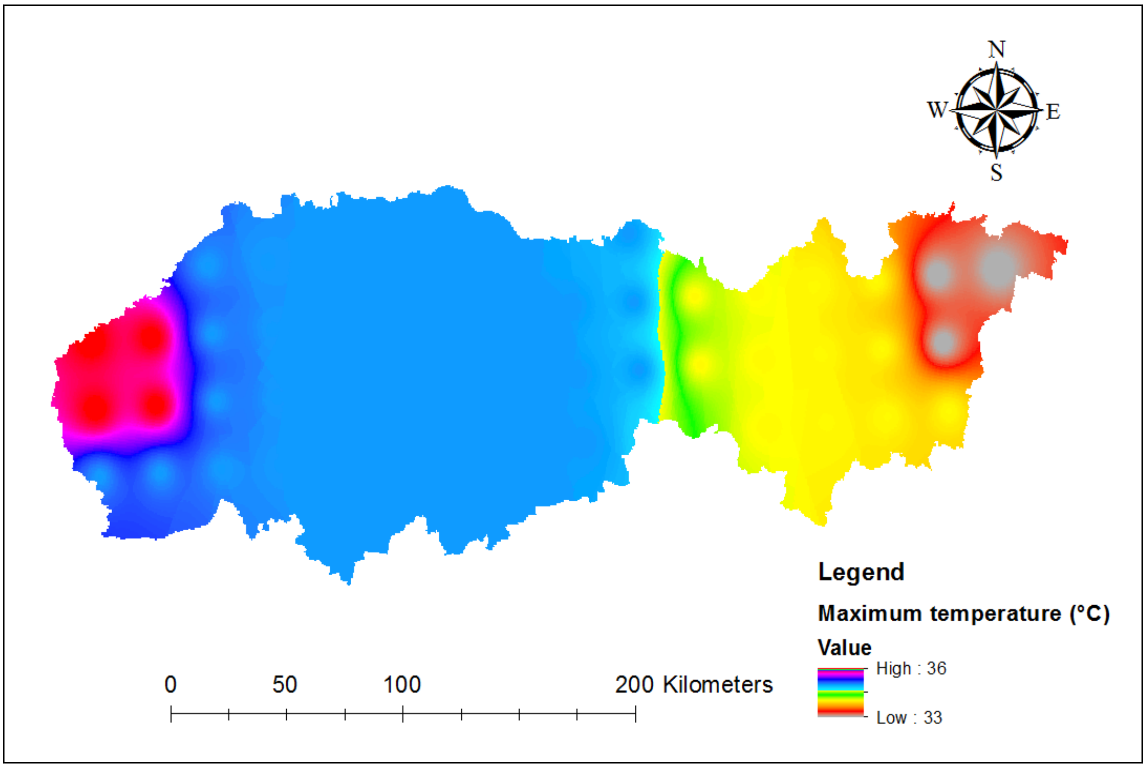

Figure 27 Maximum temperature map (2015)

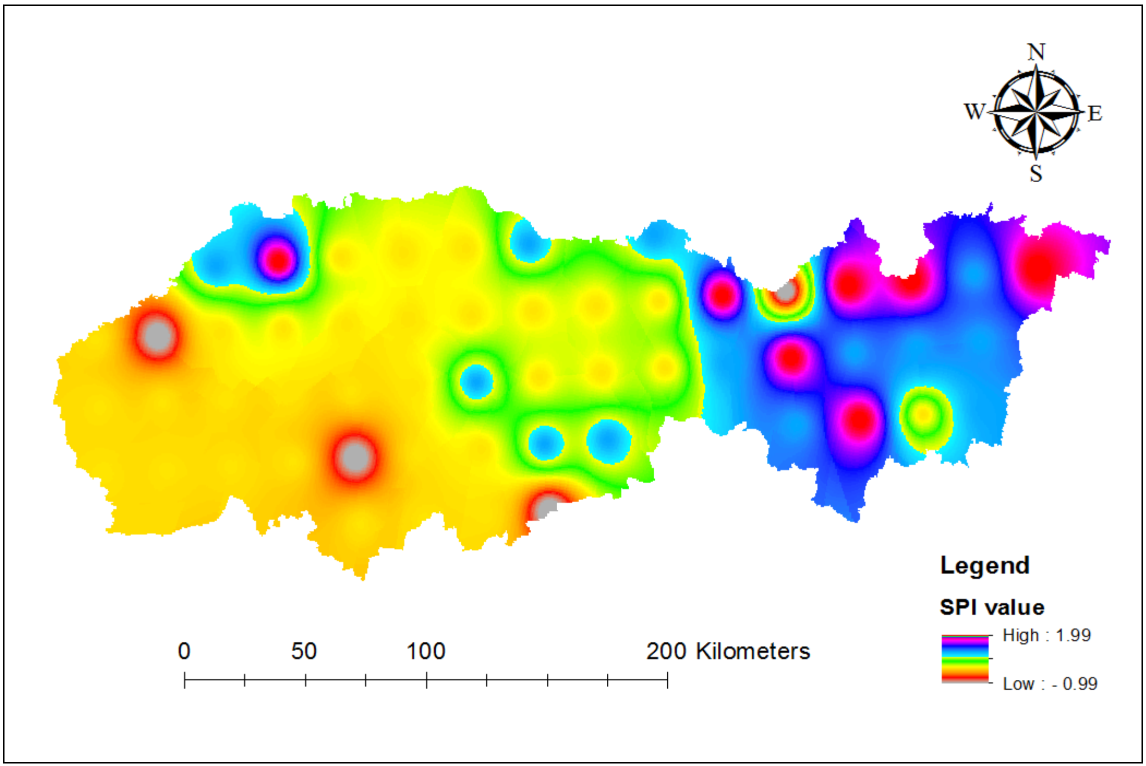

Figure 28 Soil moisture availability map (1995)

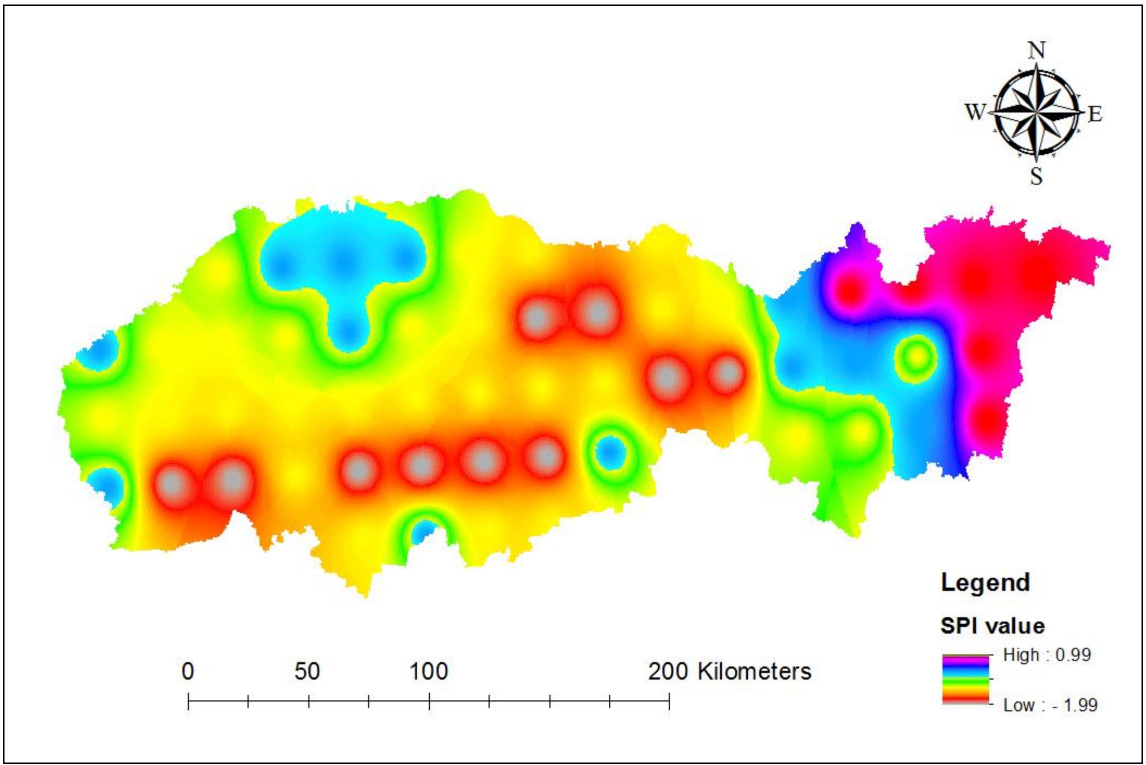

Figure 29 Soil moisture availability map (2005)

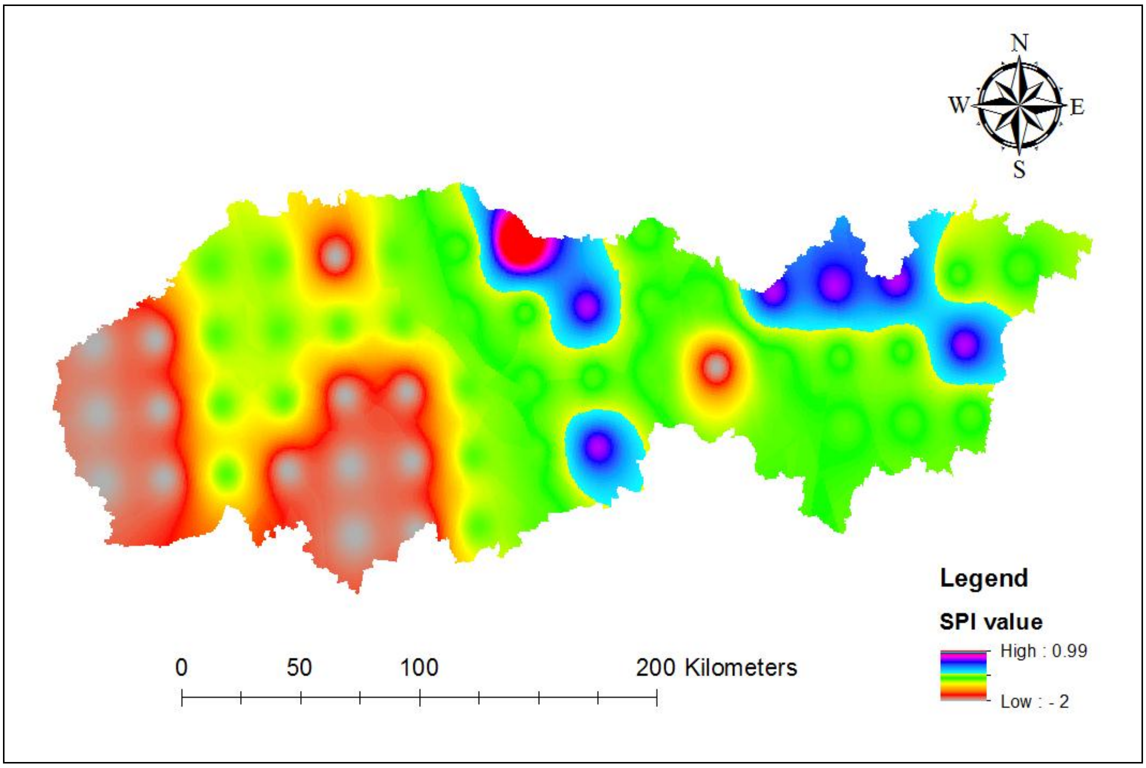

Figure 30 Soil moisture availability map (2015)

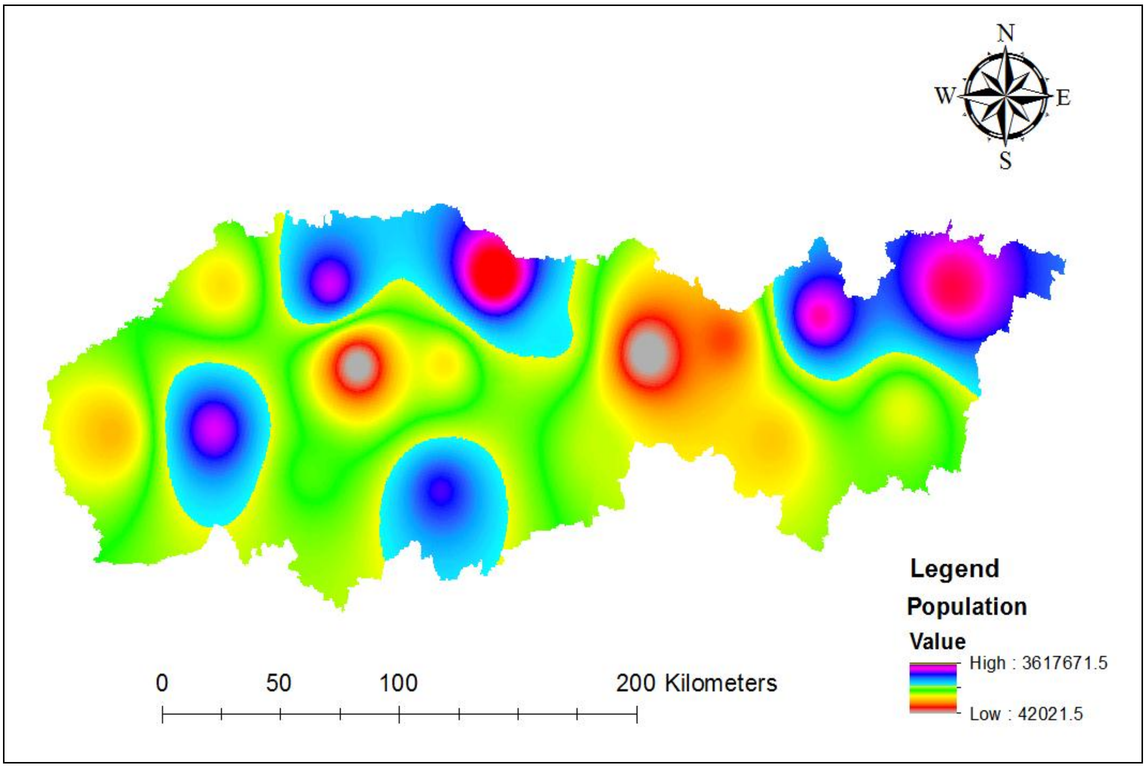

Figure 31 Population map (1995)

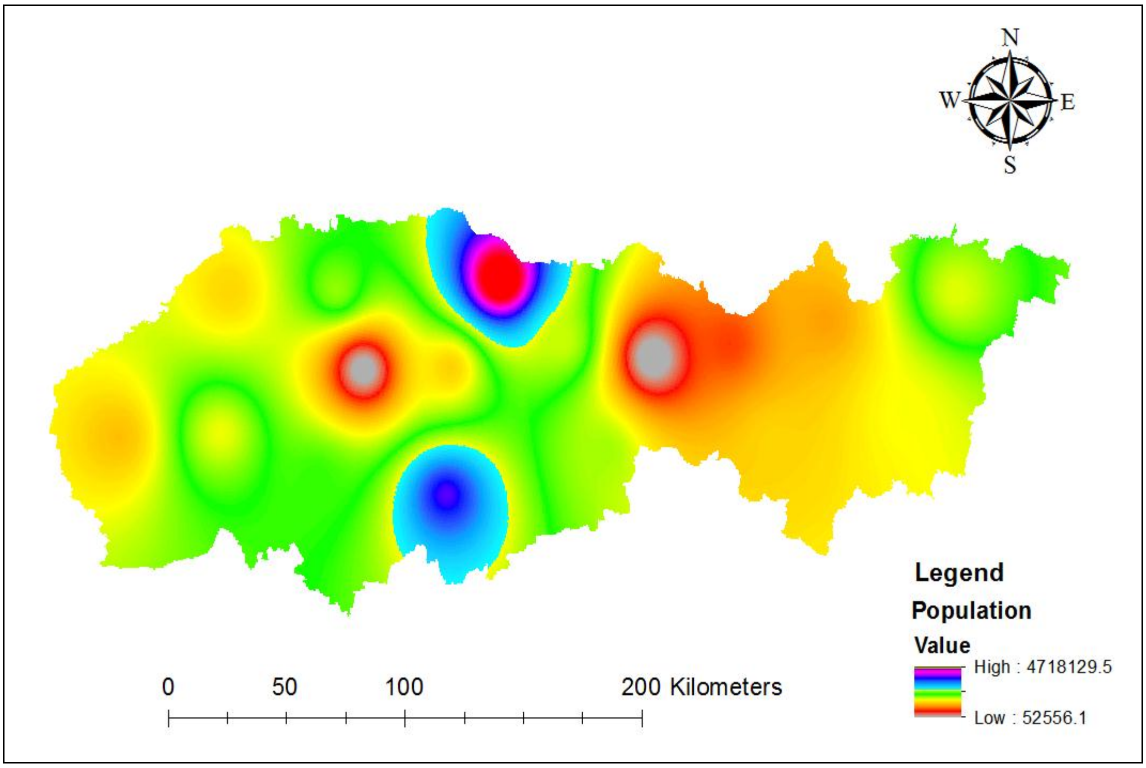

Figure 32 Population map (2005)

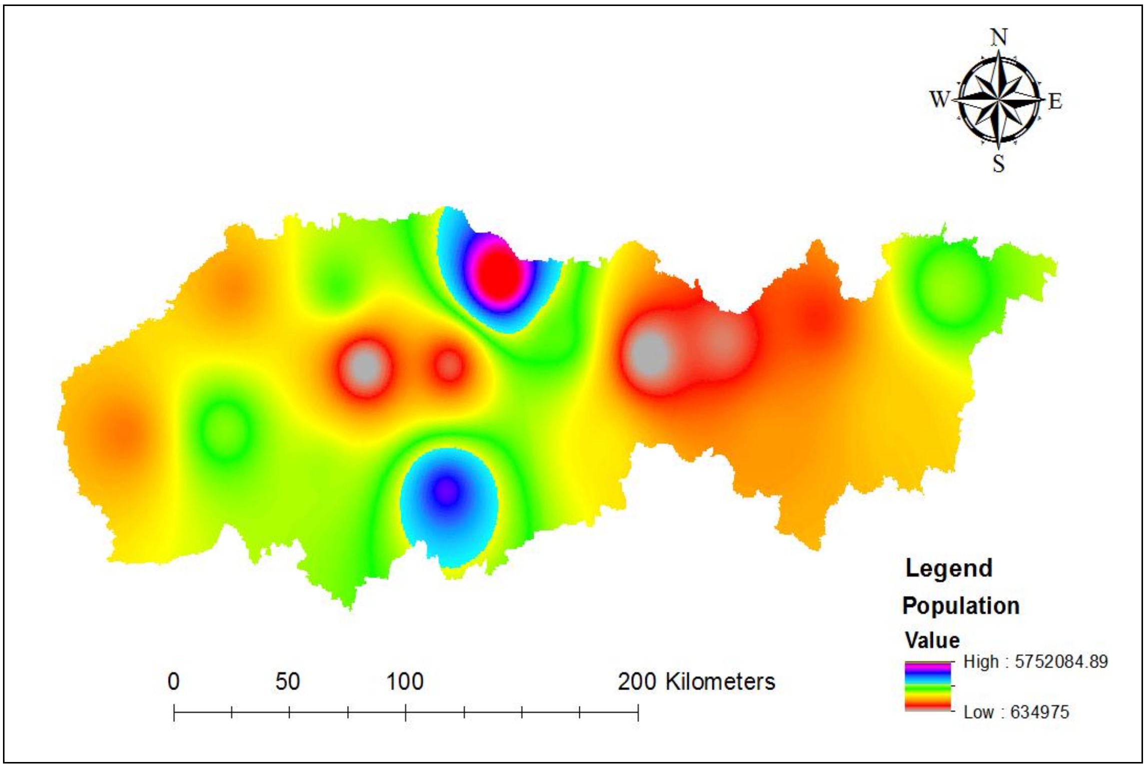

Figure 33 Population map (2015)

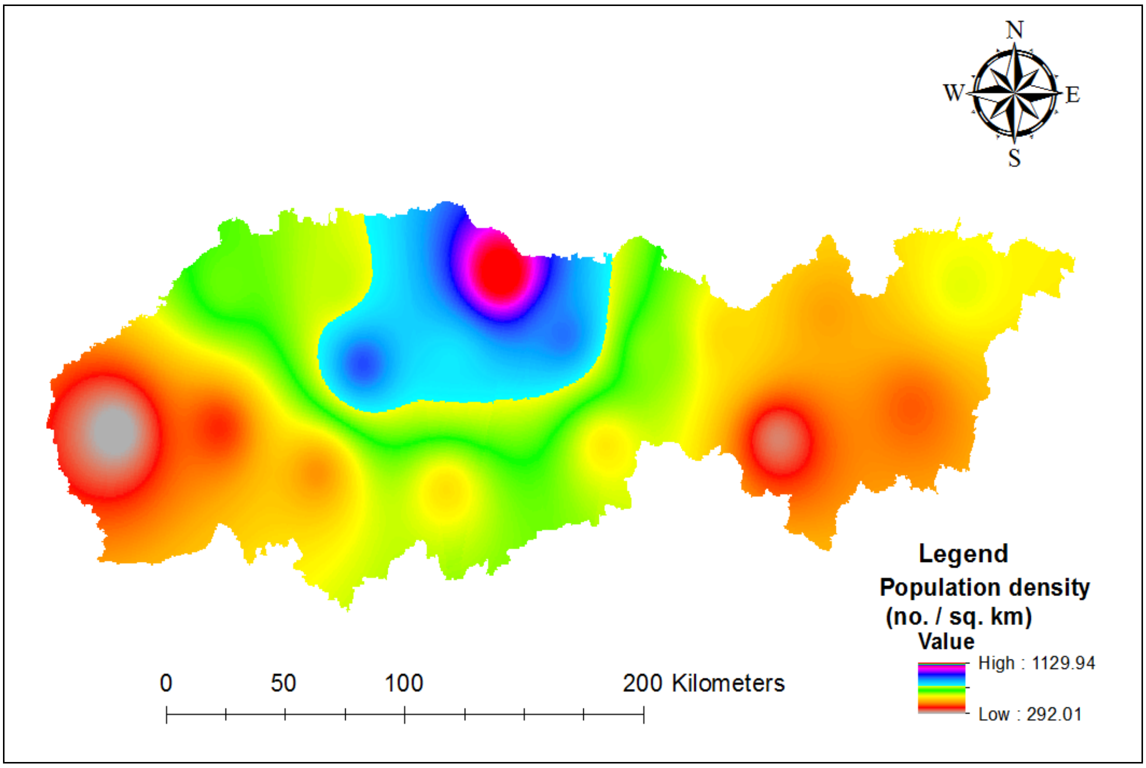

Figure 34 Population density map (1995)

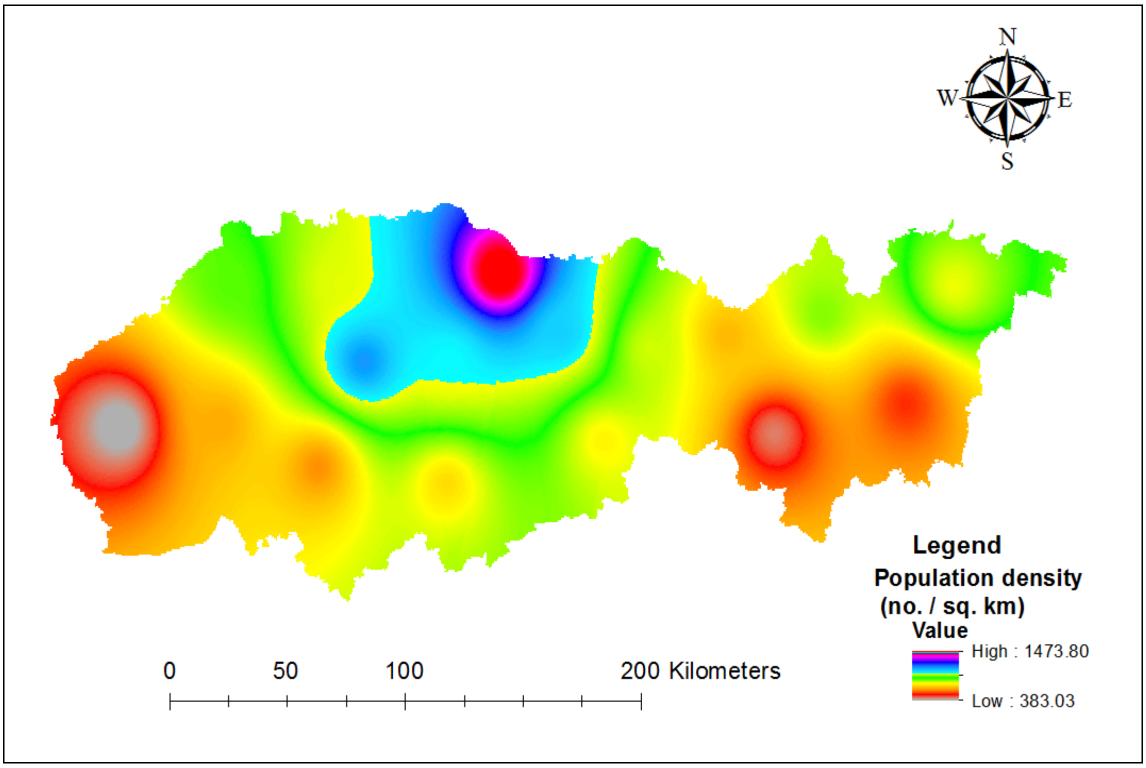

Figure 35 Population density map (2005)

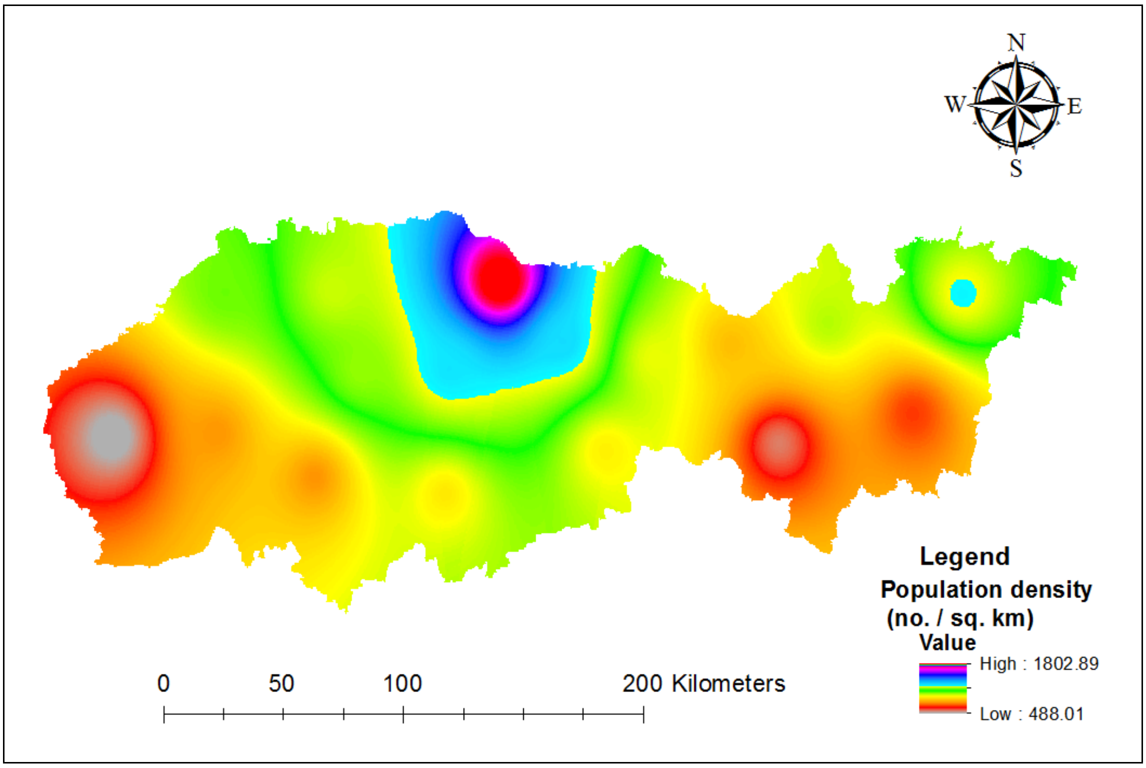

Figure 36 Population density map (2015)

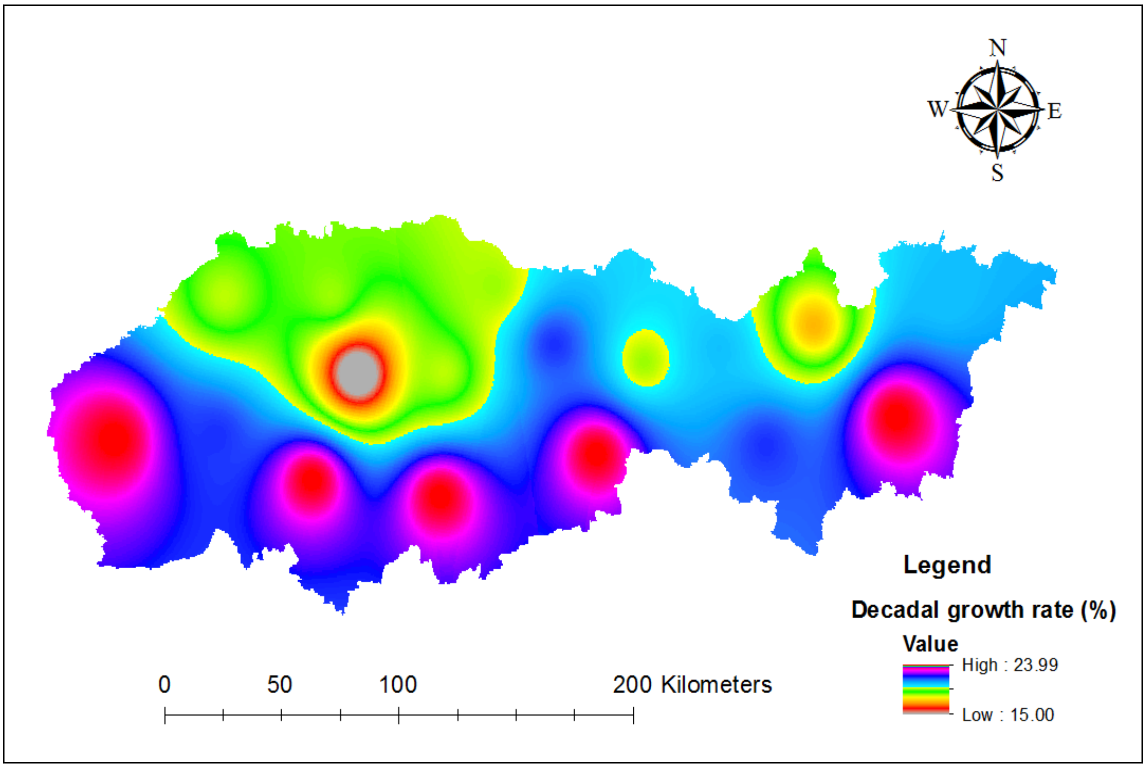

Figure 37 Decadal growth rate map (1981-1991)

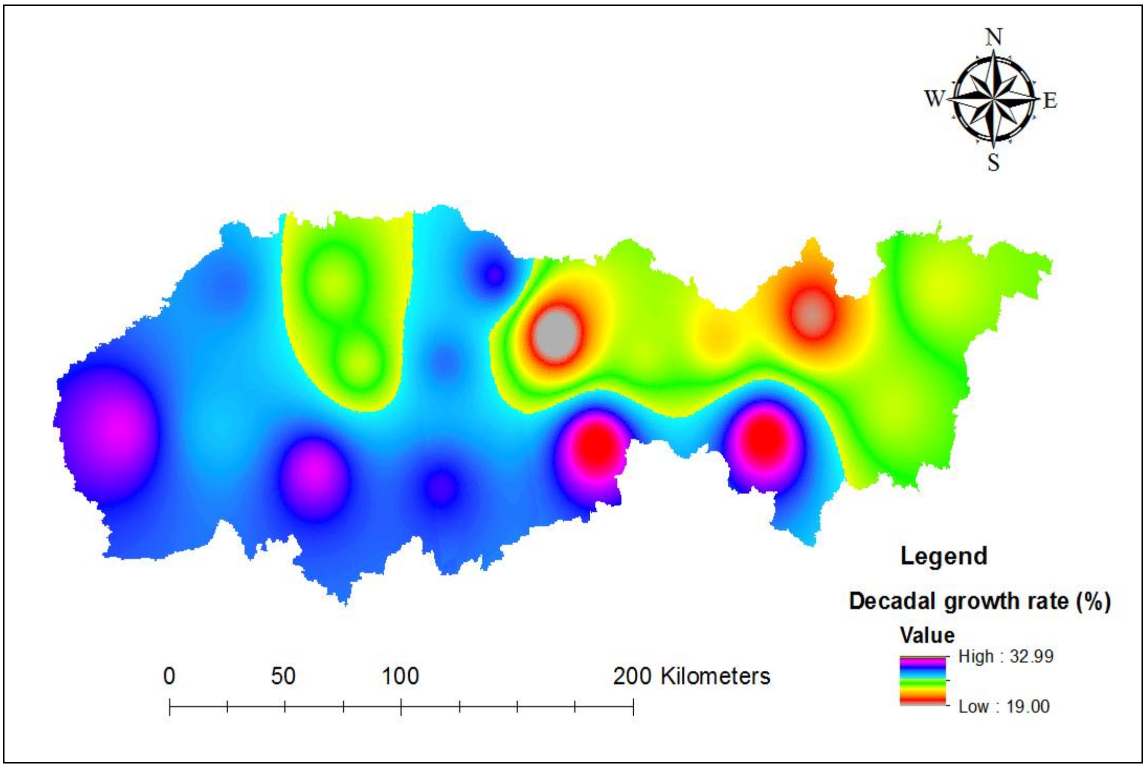

Figure 38 Decadal growth rate map (1991- 2001)

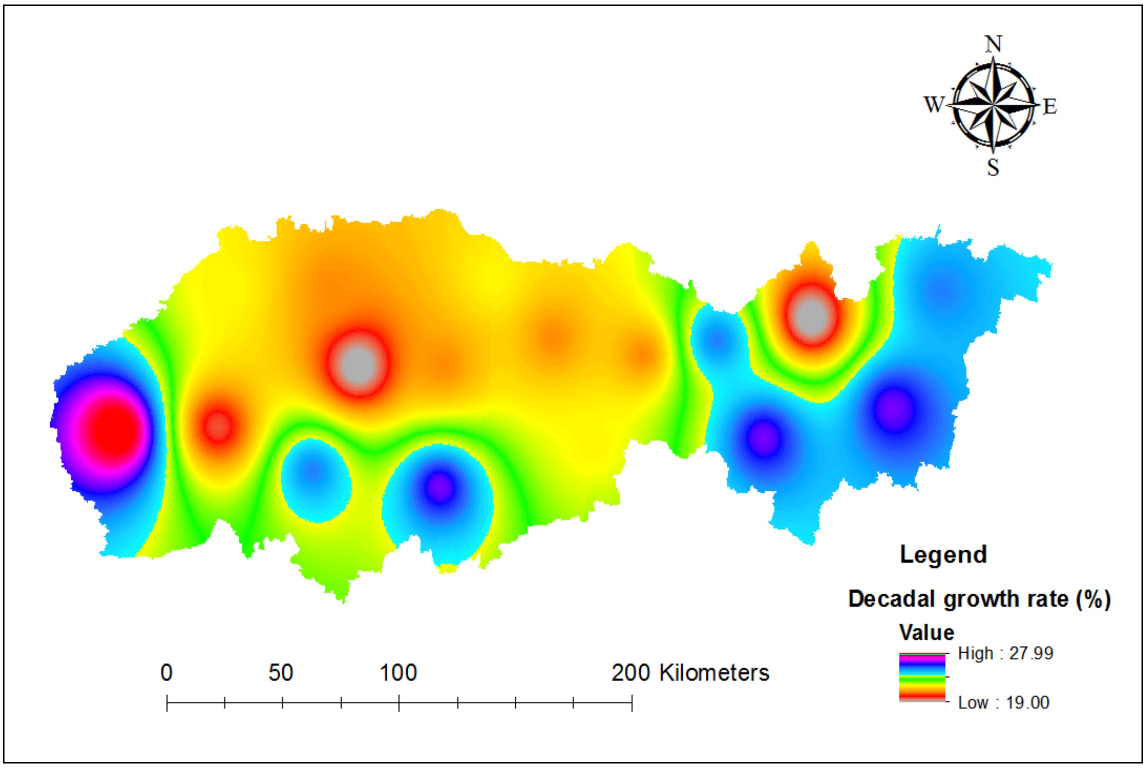

Figure 39 Decadal growth rate map (2001-2011)

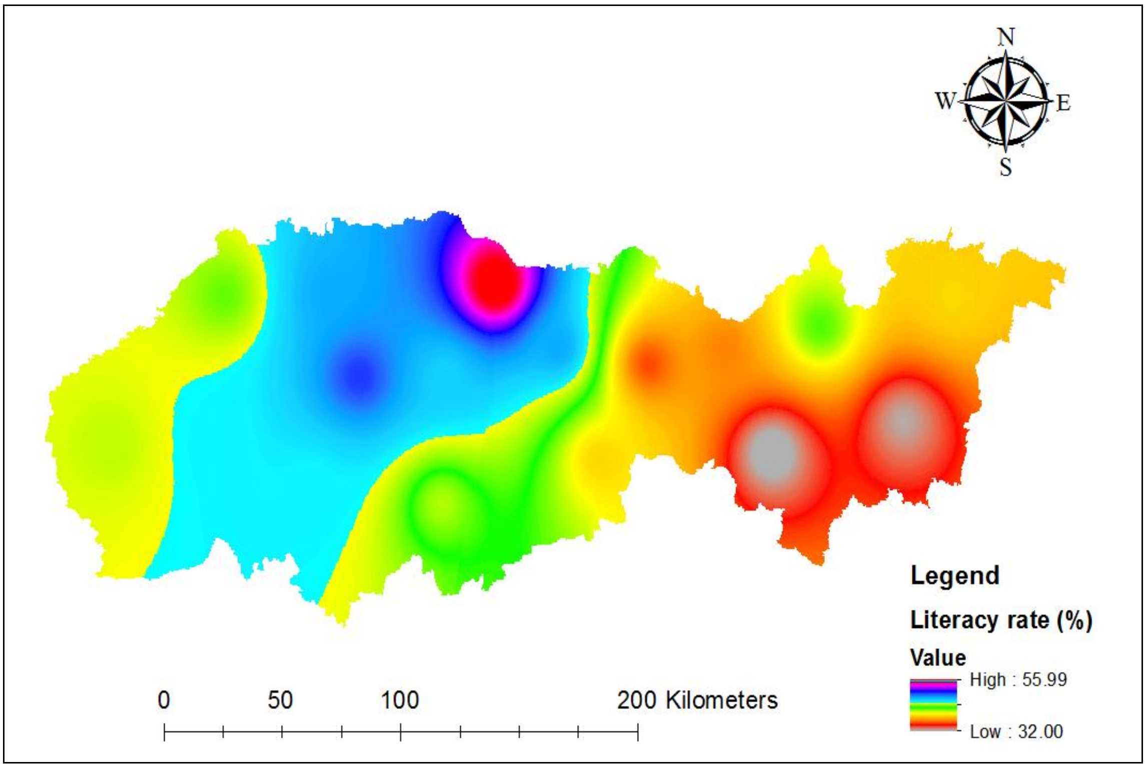

Figure 40 Literacy rate map (1991)

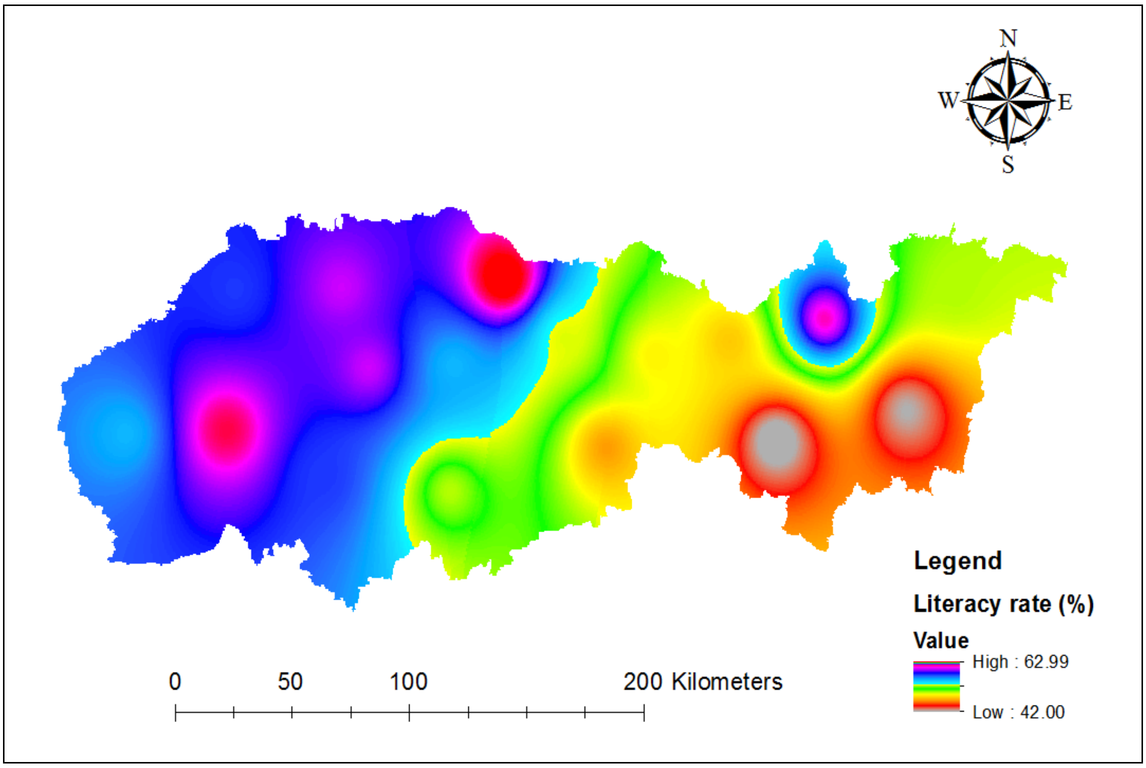

Figure 41 Literacy rate map (2001)

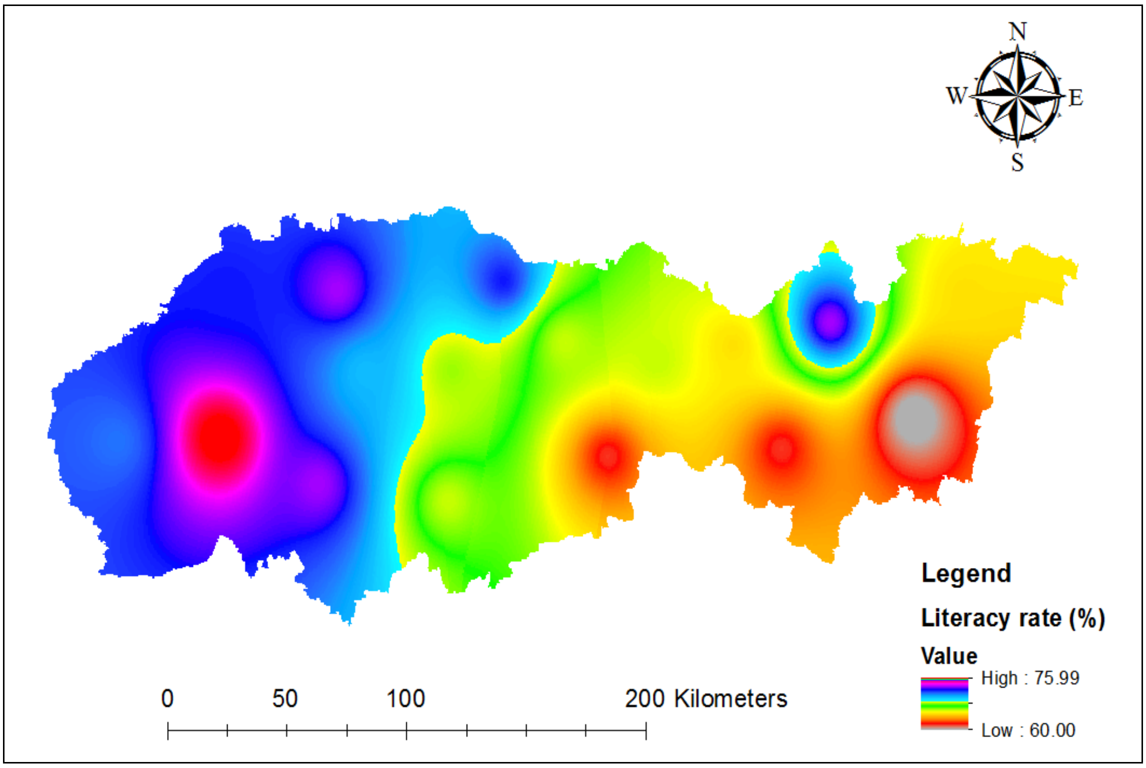

Figure 42 Literacy rate map (2011)

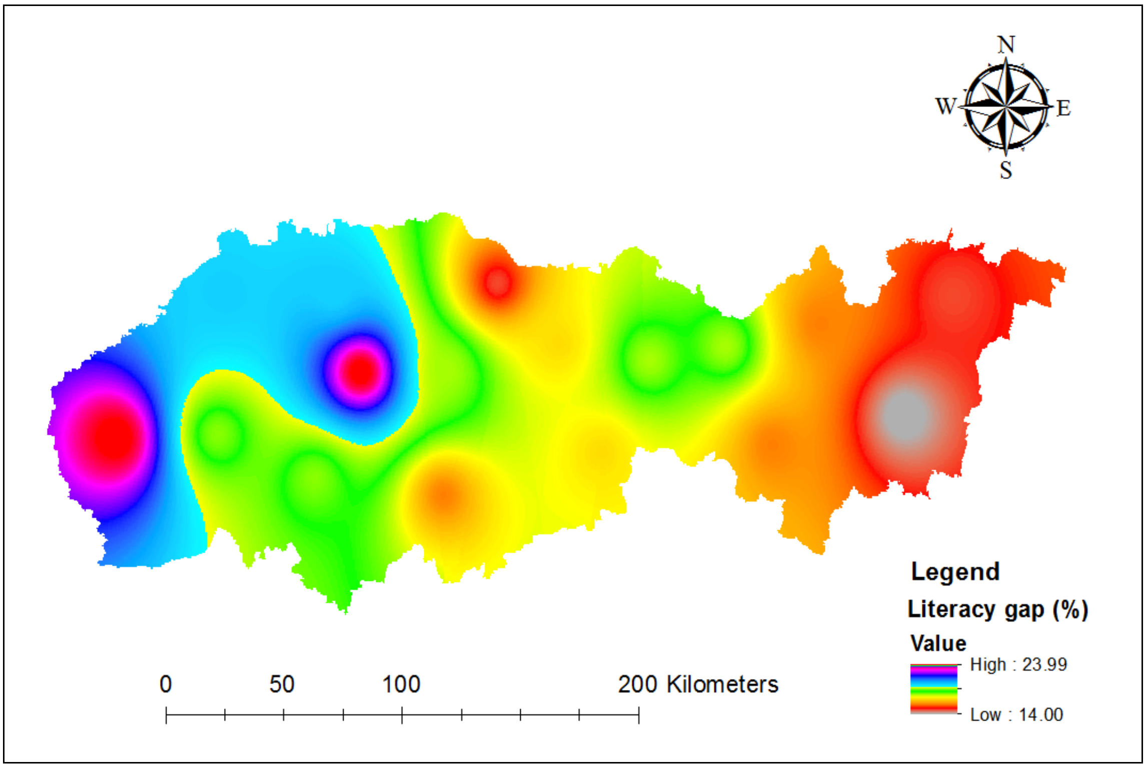

Figure 43 Literacy gap map (1991)

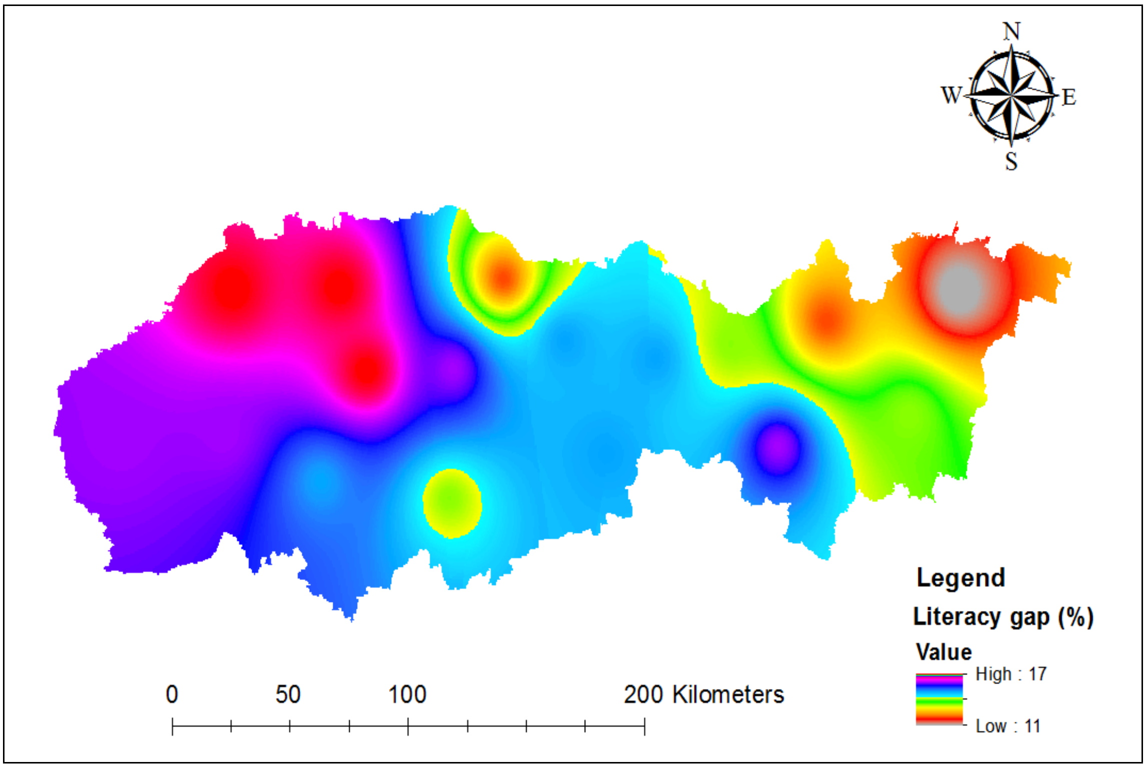

Figure 44 Literacy gap map (2001)

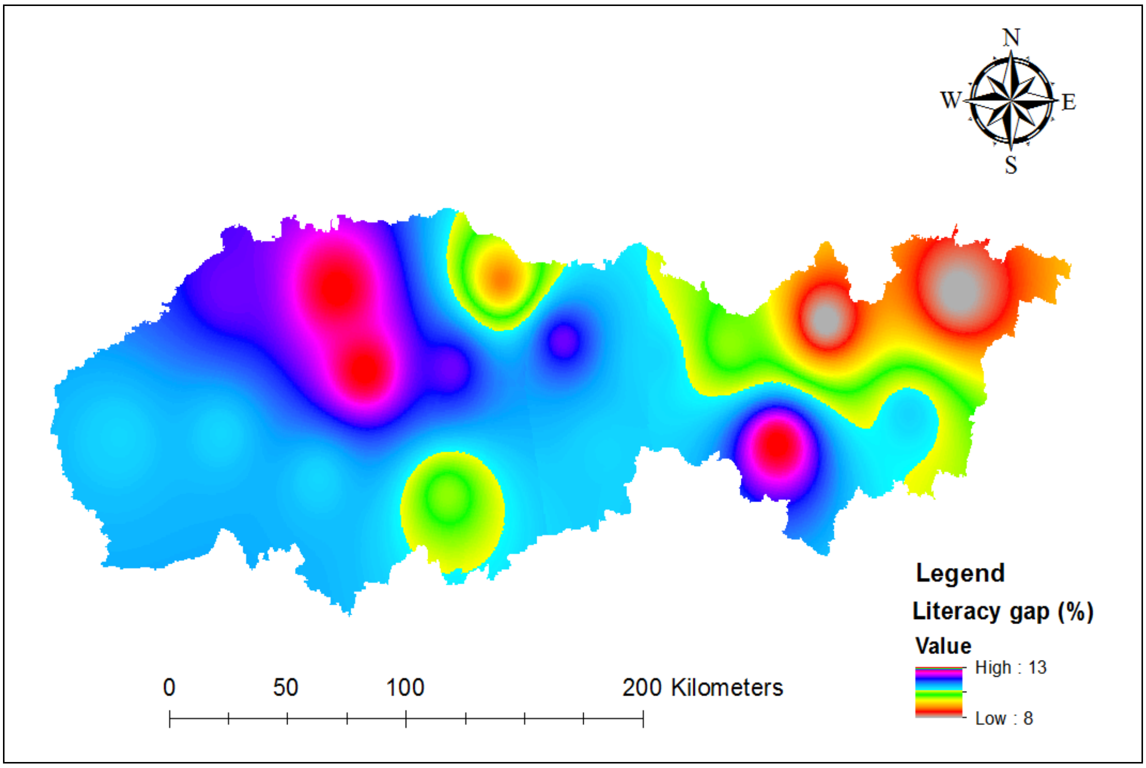

Figure 45 Literacy gap map (2011)

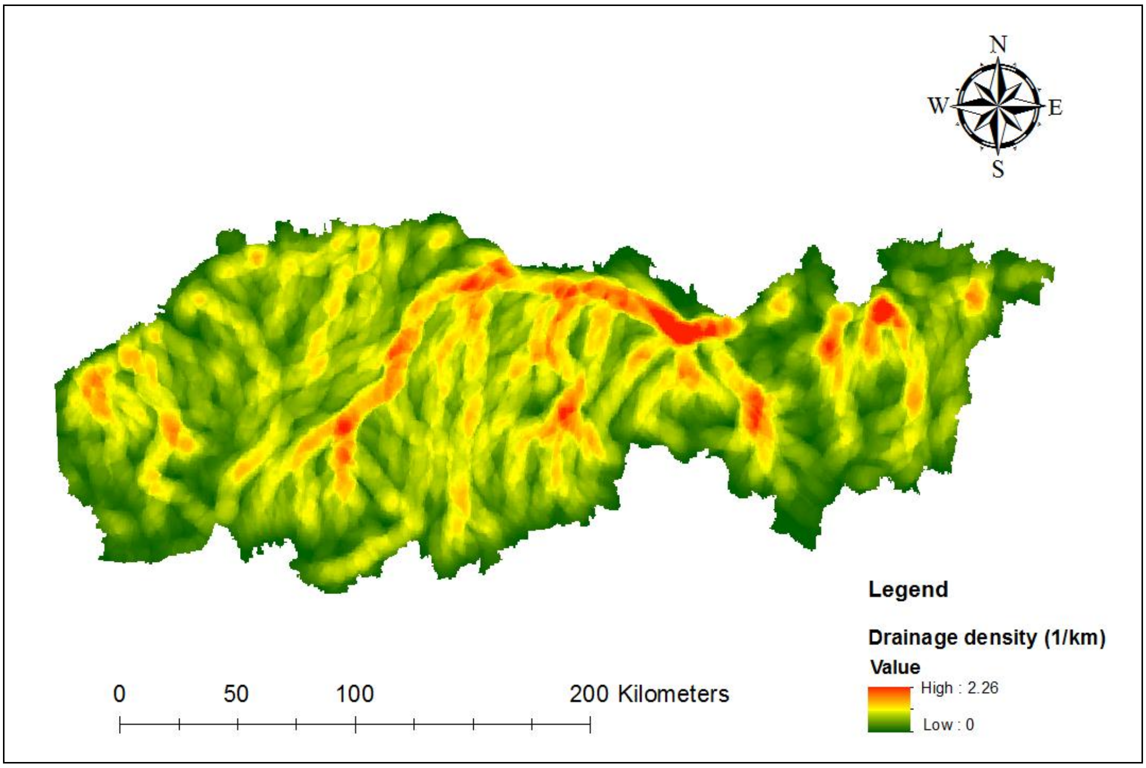

Figure 46 Drainage density map

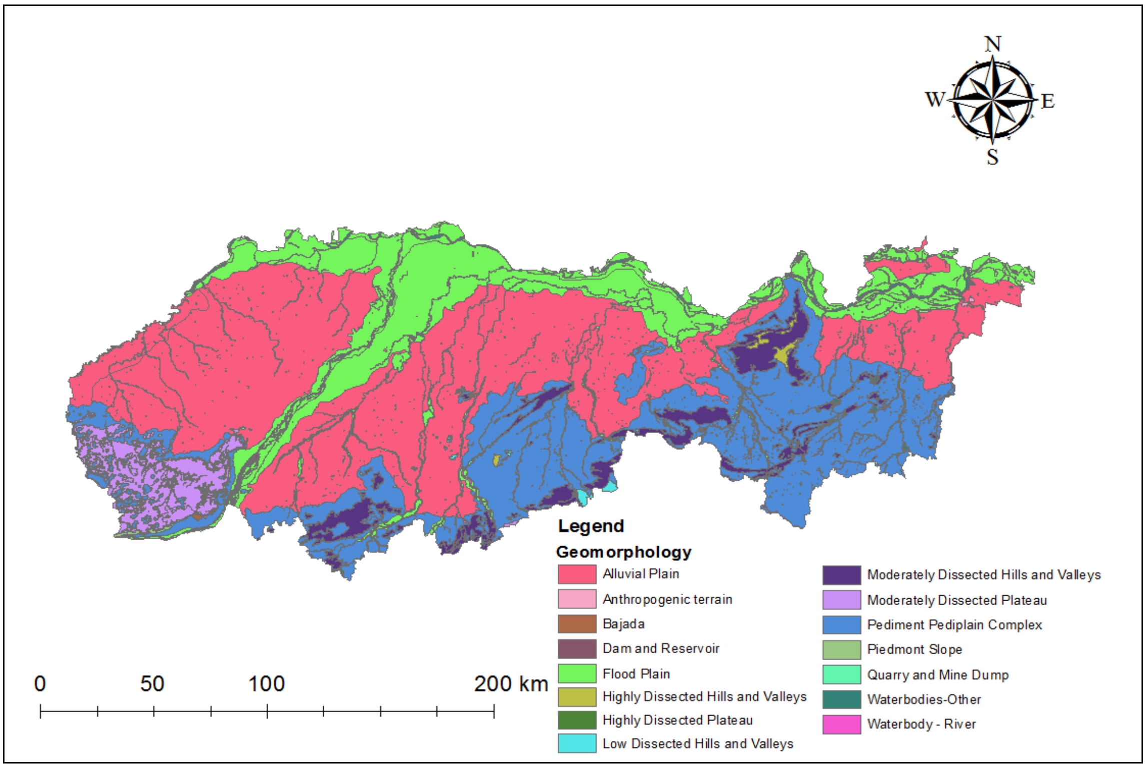

Figure 47 Geomorphology map