Spatio-temporal Assessment of Agricultural Performance and its Drought Vulnerability using Long-term Satellite and Climate data

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by

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Declaration

Centre for Earth, Ocean and Atmospheric Sciences
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I hereby declare that, this thesis entitled "**Spatio-temporal Assessment of Agricultural Performance and its Drought Vulnerability using Long-term Satellite and Climate data**" is the result of investigation carried out by me in the Centre for Earth, Ocean and Atmospheric Sciences (School of Physics), University of Hyderabad, India under direct guidance and supervision of Drs. V. Chakravarthi and P.S. Roy, is a bonafide research work and free from plagiarism. I also declare that it has not been submitted previously, in part or in full to this University or any other University or Institute, for the award of any degree or diploma.

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1. *Bhavani, P, Chakravarthi V, PS Roy, PK Joshi, and Chandrasekar, K., 2017, Long-term agricultural performance and climate variability for drought assessment: a regional study from Telangana and Andhra Pradesh states, India. Geomatics, Natural Hazards and Risk 1-19. doi:http://10.1080/19475705.2016.1271831. ISSN Number 1947-5705 (Print), 1947-5713 (Online),*
   Chapter of dissertation where this publication appears (Delete if not applicable) *3 & 4*,
2. *Bhavani, P., P. S. Roy, V. Chakravarthi, Vijay P. Kanawade, 2017, Satellite Remote Sensing for Monitoring Agriculture Growth and Agricultural Drought Vulnerability Using Long-Term (1982–2015) Climate Variability and Socio-economic Dataset, Proc.Natl. Acad. Sci. India, Sect. A Phys. Sci. 87 (4), 733–750, doi: https://doi.org/10.1007/s40010-017-0445-7 ISSN Number 0369-8203 (print) 2250-1762 (Online),*
   Chapter of dissertation where this publication appears (Delete if not applicable) *3 & 4*

and has made presentations in the following conferences :

1. *Bhavani, P., Chakravarthi, V., Roy, P.S., Agriculture stress leading to drought and comparative analysis between GIMMS and MODIS NDVI, TROPMET 2016, National Symposium on Tropical Meteorology: Climate change and coastal vulnerability, IIT Bhubaneswar, India, 18-21 December, 2016. (National),*
2. *Bhavani, **P.**, Roy, **P.S.**, Chakravathi, V., Spatio –Temporal Analysis of Drought Using Decadal MODIS Dataset, APGEOS National Conference on spatial Technologies for Disaster Management, Indian National Centre for Ocean Information Sciences, Hyderabad, January 23-24, 2015, (National).*

Further, the student has passed the following courses towards fulfillment of the coursework requirement for Ph.D.

Sl No.	Course Code	Course Title	Credits	Pass/Fail
1	ES 801	Earth System Sciences	4	Pass
2	ES 805	Research Methodology	3	Pass
3	ES 806	Mathematics for Earth Sciences	4	Pass
4	ES 807	Interdisciplinary Course	3	Pass
5	AP 811 – 830	Special Paper on Specified Research Topic	2	Pass

Joint Supervisor **Supervisor**

Head of Department **Dean of School**

DEDICATED WITH EXTREME AFFECTION

AND GRATITUDE

To my beloved ones

My mother (P. Anuradha),

My sisters (Rupa Rani & Lavanya)

&

brother (P. Chandra shekar)

For their endless love, support, encouragement and prayers.

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CHAPTER ONE

Introduction

1.1 General

Agriculture is the art and science of conversion of the natural ecosystem into growing crops, raising livestock, cultivating the soil, production of food, fiber, and fuel (Chandrasekaran et al., 2010). About 37% of Earth's land area is occupied by agricultural practices (FAO, 2003). Agriculture is put into practice through farming, imposes costs upon the society through pesticides, nutrient runoff, excessive water consumption, loss of environment and assorted other problems. It supports 17% of world population from about 2.3% of its geographical area (Pandey, 2009). Agriculture is being practiced all over the world in different ways. In nomadic pastoralist, herds of livestock move from place to place in search of fodder, pasture, and water. This type of farming is being practiced in most of the arid and semi-arid regions of Central Asia, Sahara, and also in parts of India. In shifting cultivation, small area of forest cover is cleared and the land is subsequently used for growing the crops for some years. However, once the soil covering the land becomes infertile, it is abandoned and alternate patch of land is identified and the process is repeated. This kind of farming is practiced primarily in areas receiving ample amount of rainfall where the forest restores rapidly. This practice is used in Northeast India, Southeast Asia, and the Amazon Basin. Subsistence farming is practiced to sustain family or local needs alone, with a little left over for transport elsewhere. This kind of farming is intensively practiced in parts of South and Southeast Asia. In intensive type of farming, being practiced mainly in the developed countries, the crops are fostered mainly for commercial purpose i.e., for selling. The main purpose of the farmer is to make revenue, with a low fallow ratio and high use of inputs.

Crop cultivation systems

Cropping systems vary among farms depending on the availability of resources and constraints, geography and climate of the farm, policies of government, economic, social and political pressures, and the philosophy and culture of the farmer (Henkel, 2015). Further, industrialization has led to the use of monocultures when one cultivar is planted on a large acreage. Because of the low biodiversity, nutrient use is uniform and pests tend to build up, necessitating the greater use of pesticides and fertilizers (Henkel, 2015). Multiple cropping, in which several crops are grown sequentially in one year, and intercropping (Gallaher, 2009) when several crops are grown at the same time, are other kinds of annual cropping systems known as polycultures (Gliessman, 1985).

In subtropical and arid environments, the timing and extent of agriculture may be limited by rainfall, either not allowing multiple annual crops in a year or requiring irrigation. In all of these environments perennial crops are grown (coffee, chocolate) and systems are practiced such as agroforestry. In temperate environments, where ecosystems were predominantly grassland or prairie, productive annual farming is the dominant agricultural system.

India is identified as one of the mega-centers of biodiversity (Agrawal and Danai, 2017). It accounts for 2.4% of the global land, 11.2% of arable land, and 4.2 % of water and 8,000 km of coastline (Singh, 2017). Apart from this, the country coexists with tropical, temperate, semi-arid, wide range of soils conditions and landforms. Due to diversified agro-climatic conditions in the country, a large number of agricultural items are produced. Broadly, these can be classified into two groups - food grain crops and commercial crops (FAO). Indian agriculture is characterized by agro-ecological diversities in the soil, rainfall, temperature, and cropping system. (Pandey, 2009).

1.1.1 Agriculture in India

India is the 2nd largest agriculture producer in the world. 70% of the population of India is dependent on the agriculture sector (Ramprasad, 2011). The population of the country has been increased about 3.6 times since 1951 from 361.1 million to 1302 million in 2016. However, the production of food grains grew 5.36 times from 51 million tonnes (mt) in 1951 to 273 million tonnes in 2016 (Singh, 2017). India has shown immense progress towards the food security, particularly after the independence. Over the last century, agriculture endorses three distinct phases of growth. Subsistence agriculture is self-sufficiency farming till 1960's. This type of farming was mainly focused to cater the food needs of family and towards saving for other essential and social requirements. During late 1960‘s to 1990's, the increase in food grain per capita attained India's Green Revolution. During this second phase (Green Revolution), India has adopted new technology and major policy to improve the productivity of important crops, especially rice and wheat. The major sources adopted are high yield varieties (HYV), disease resistant wheat varieties in combination with better farming knowledge, an extension of irrigated area etc. During the third phase, the diversification of agriculture is emphasized for improving the household nutrition, farmers' income, sustainability and rural employment.

The cereal productivity (Kg/hectare) of developing countries for the period 1990 to 2015 is shown in Table 1.1. It can be observed from Table 1.1 that among all the developing countries India has experienced less productivity (Table 1.1).

India is endowed with diverse agro-climatic regions in terms of season, rainfall, temperature, soil and biological diversity. Based on the agro-climatic features the country is broadly categorized into fifteen agricultural regions namely, Western Himalayan division, Eastern Himalayan division, Lower Gangetic plain, Middle Gangetic plain, Upper Gangetic plain, Trans-Gangetic plain , Eastern plateau and hill region, Central plateau and hill region, Western plateau and hill region, Southern plateau and hill region, East coast plain and hill region, West coast plain and hill region, Gujarat plain and hill region, Western plain and hill region, Island region.

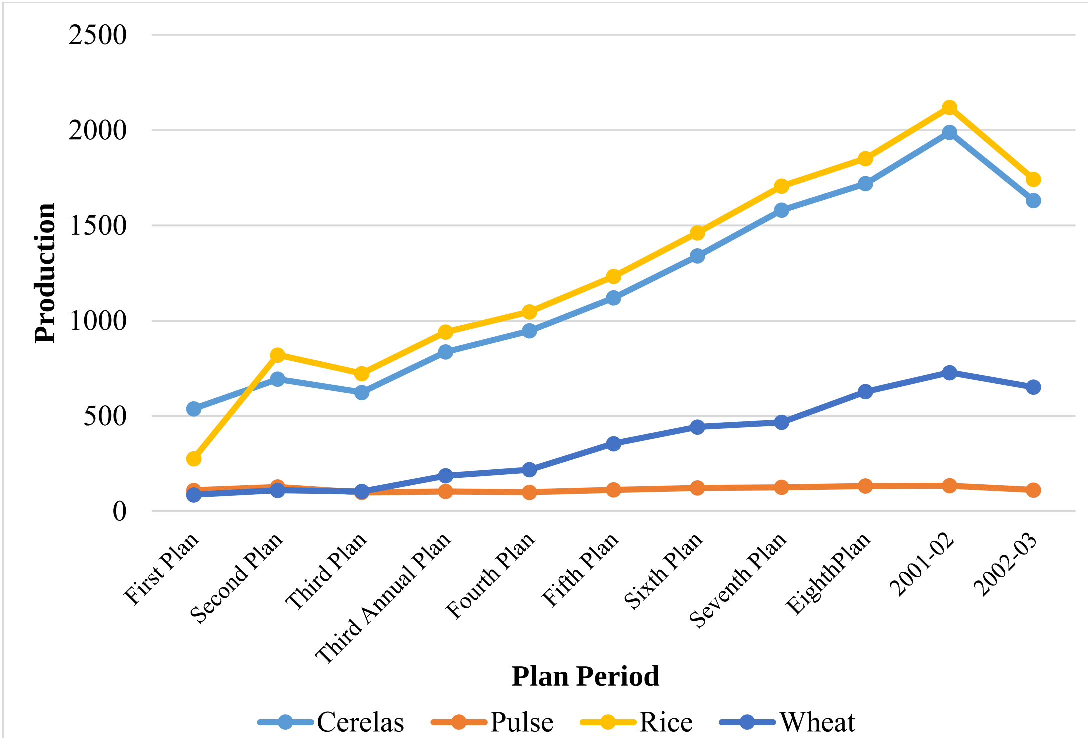
Table 1.1 Cereal productivity (metric tons) by developing countries

Country	1990	1995	2000	2005	2010	2015
Brazil	32490390	49641823	46527238	55670925	75160114	106029517
China	401934965	416113700	405224140	427760100	496343192	572045000
Egypt	13022243	16097252	20105573	22423470	19464743	23141051
Indonesia	51912780	57990042	61575000	66674990	84797028	95010276
India	193919312	210012500	234931192	239997492	267838308	284333000
Sri Lanka	2578860	2850089	2896040	3294530	4469740	4182606
Poland	28013511	25905314	22340612	26927924	27228098	28002726
Russian	NA	61901840	64242691	76192100	59616880	102450556
Thailand	21169497	26412970	30529251	34962740	40880882	32786514
Turkey	30201369	28168560	32240094	36464200	32764875	38632438
Vietnam	19896104	26140900	34537045	39621600	44614027	50393869

(*Source: World Bank website: https://data.worldbank.org/indicator/ AG.PRD. CREL. MT?name_desc=false)

1.1.2 Trend of agriculture in India

Figure 1.1 clearly reveals that the production of food-grains (lac in tones) in India in the first two five years' plans, was on the higher side. However, in the third five-year plan it had shown a declining trend. Further, in the course of three annual plans, the production of food-grains had shown a considerable increase. In the subsequent five year plans, the rate of growth of agricultural production has fluctuated.



(*Source:http://www.economicsdiscussion.net/agriculture/agricultural-production-trends-in-india-an-overview/13211)

Figure 1.1 Trends in production of food grains

Kannan and Sundaram (2011) have reported that the growth rate of crop production was increased by 1.42% in the 1980s when compared to 1970s. However, this growth rate was not sustained during the 1990s. The yields of almost all crops were decreased during 1990-91 and 1999-2000 (post-liberalization period/economic reform period). Consequently, the growth rate in food grain production has declined to 2.26% during the period of economic reforms when compared to 2.73% in the mature green revolution period. Singh (2017) has also reported that the period of the 1990s represents a lost decade for agriculture. This might have happened due to large-scale land degradation (approximately 120 million hectares) i.e., increase in urbanization, industrialization, and a shift in land use form.

However, there was a slight improvement in production and yield of some of the crops during 2000-01 to 2007-08. Further, growth in the food grain production was 2.06 %

against the annual population growth of 1.64% (Census, 2011). This reveals that the production of food grains needs to be increased to achieve the long-term food security in the country. However, it was evident from 10th Plan that agriculture and allied sector growth was 2.5%. It is of paramount interest to note that the growth rate of agriculture and allied sectors was 6% during 2005-06, 4% in 2006-07, 4.9% in 2007-08, 1.6% in 2008-09 and 2.5% during the 10th plan. GIAi (2016) has reported that the growth rate of agriculture sector (GRAS) in India has undergone considerable fluctuations during 1950-2011 (Fig. 1.2), whereas the contribution of agriculture sector to total Gross Domestic Product (GDP) showed a declining trend (Fig.1.3).

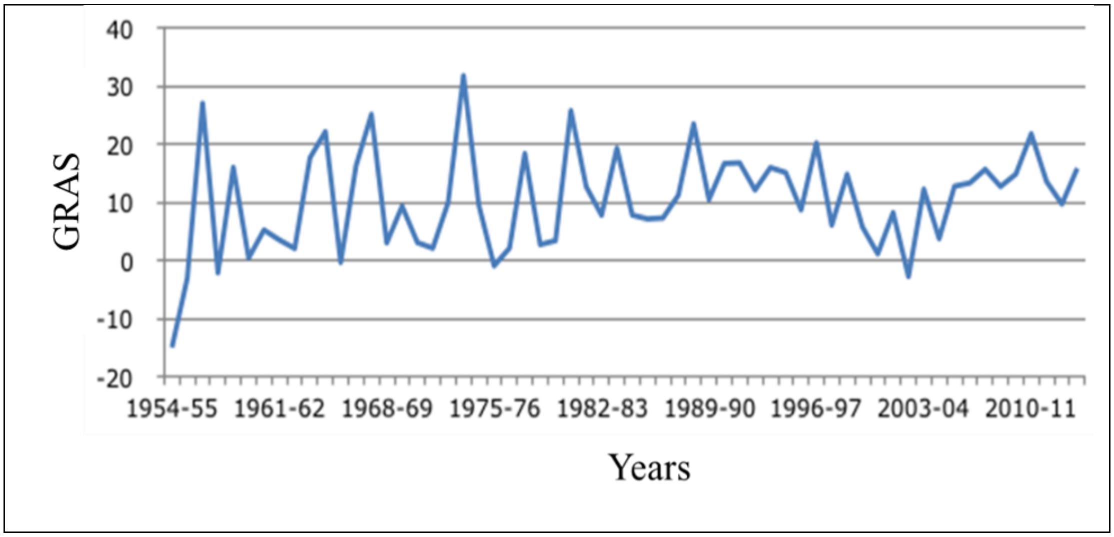


Figure 1.2 Growth rate of agriculture sector in India (1950 – 2013) (after GIAi, 2016)

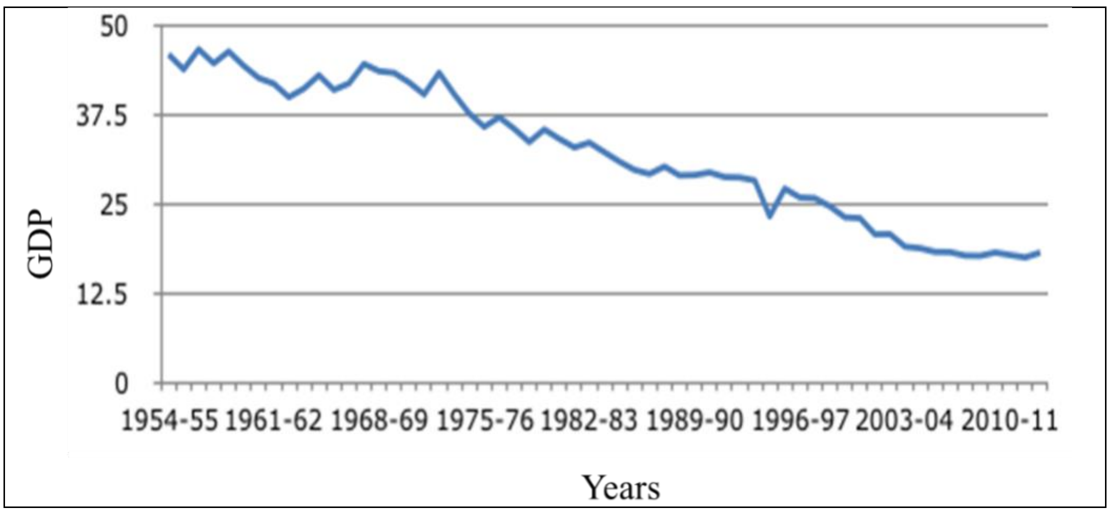


Figure 1.3 Contribution of agriculture sector to total GDP, India (1954- 2012) (after GIAi, 2016)

Such trends have resulted in fragmentation and decline in the size of landholdings which ultimately lead to agronomic inefficiency, a rise in unemployment, and a low volume of marketable surplus (Mall et al., 2006). These factors could contribute to increased vulnerability to global environmental variability (Aggarwal et al., 2004).

1.1.3 Water resources and agriculture

Water is the most important and critical resource for agriculture, plant growth, and gaining primacy even over the soil. India has only about 4 per cent of the world's freshwater resources (Tariq, 2014). In India, rainfall is highly variable, irregular and undependable with widespread variation among various meteorological sub-divisions in terms of distribution and amount. About 88% of water is being used in agriculture sector covering around 80 M ha area under irrigation.

Among the rain-fed agricultural countries of the world, India ranks first in terms of both extent and value of produce (Ashalatha et al., 2012). More than 60% of agriculture is rain-fed. It occupies 67% of the net sown area, 44% of food grains and supports 40% of the population (Venkateswarlu, 2011). The importance of rain-fed agriculture is obvious from the fact that 55% of rice, 91% of coarse grains, 90% of pulses, 85% of oilseeds and 65% of cotton are grown in rainfed areas.

Based on the adequacy of soil moisture during cropping season rain-fed farming has been classified into dry land and wetland farming. In India, the dry land farming is largely confined to the regions where the annual rainfall is less than 75 cm. Drought resistant crops such as ragi, bajra, moong, gram and guar (fodder crops) are being cultivated in these regions. In wetland farming, the rainfall is in excess of soil moisture requirement of plants during the rainy season. Such regions face flood and soil erosion hazards. Water intensive crops such as rice, jute, and sugarcane are being cultivated in these regions and at places practice aquaculture in the freshwater bodies.

Indian agrarian is a system of rain-fed agriculture and is largely dependent on the summer monsoon rains. Almost 53% of its gross cropped area (GCA) is rainfed and even the area that is irrigated through canals, tanks, watersheds, and groundwater gets impacted when rainfall is low, and the reservoir levels and groundwater levels dip (Ashok et al., 2013). Most of the Indian farmers rely on the monsoonal/ Kharif crop for their regular livelihood and source of income. Rainfall scarcity/crop failure is the major reason for mass farmer suicides across the country. Thus disturbance in the monsoon system would severely impact the economy. It is to note that more than 60% of the cropped area in India, is still dependent on the monsoon rainfall (Central Statistical Organization, 1998).

The cultivation in western parts of India is dominated by oilseed, grain, and cotton whereas in the east, rain-fed rice dominates. These crops will be prone to effect in case of a late or weak start of the rainy season and extended breaks in monsoon rains. If the southwest monsoon withdraws from a region earlier than expected, then late-planted crops may be damaged because of lack of moisture during grain filling. Conversely, a late withdrawal resulting in late-season rains can be detrimental to maturing crops, especially cotton (Krishna Kumar et al., 2004). The summer monsoon is vital for both Kharif and Rabi crop production in India. Irrigation refers to the process of supplying water through artificial means such as pipes, ditches, sprinklers etc. Such irrigation facility helps the farmers to have less dependency on rain-water for the purpose of agriculture.

Large-scale agriculture is being practiced on the banks of rivers since the times of ancient Indus-valley civilization. However, the Indus-valley civilization came to an end when the irrigation system had failed to sustain the crop production. Irrigation was gradually developed in the early second century, perennial irrigation began with the construction of the Grand Anicut by the Cholas in south India. In medieval India, rapid advances took place in the construction of canals. This has culminated in the rise of the water level to utilize for the fields.

In the 19th Century, the British government had developed three important irrigation facilities i.e. Western-Yamuna canal, Eastern-canal, and Cauvery Delta canal to improve the irrigation facilities. At the time of Independence, India had lost major canal systems, including the Sutlej and Indus systems due to the partition of countries (India and Pakistan).

After the independence, particularly during the Green Revolution phase major irrigation programmes had been initiated which resulted in the improvement of crop productivity.

Irrigation Development

The countries with the largest irrigated areas were India (39 million hectares), China (19 million), and the United States (17 million) as per 2010record (FAO). Survey of India has assessed the irrigation potential through major, medium and minor irrigation projects have increased from 22.6 million hectares (Mha) in 1951 to about 102.77 Mha at the end of 2006-07. The different sources of irrigation since 1950-51 to 2002-03 are shown in Table 1.2.

Table 1.2 Source wise development of Irrigated Area in India (Mha)

Year	Canal	Tank	Ground water	Others	Net Irrigated Area (NIA)	Gross Irrigated Area (GIA)
1950-51	8.30	3.61	5.98	2.97	20.58	22.56
1960-61	10.37	4.56	7.29	2.44	24.66	27.98
1970-71	12.84	4.11	11.89	2.27	31.10	38.20
1980-81	15.29	3.18	17.70	2.55	37.72	49.78
1990-91	17.45	2.94	24.70	2.93	48.02	63.20
2002-03	16.34	2.26	34.50	2.73	55.85	78.33

(*Source: ICRISAT VDSA)

1.1.4 Cropping seasons

Cropping season is defined as "the crops sustain to grow i.e. from time of sowing to time of harvesting, depending on particular weather condition during particular periods of time". India is the top producer of many crops in the world. Based on seasons, the crops in India are divided into three types namely Rabi, Kharif and Zaid.

Kharif Crops: The crops in this season sown during June-July when rains first begin (Monsoon crop). These crops are harvested during September-October. Crops in this period requires large quantities of water and also warm weather to grow. Examples: Sugarcane, Jowar, Bajra, Rice, Turmeric, Maize, Cotton, Jute, Groundnut, Pulses (like Urad Dal) etc.

Rabi Crops: These are sown in October-November and harvested in April-May. The crops in this category requires warm climate for germination of seeds and maturation and cold climate for growth. Example: Wheat, Gram, Pea, Barley, Tomato, Potato, Onion, Oil seeds (like Rapeseed, Sunflower, Sesame, Mustard) etc.

Zaid Crops: These early maturing crops are grown between March-June between Rabi and Kharif crop seasons. Example: Cucumber, Bitter Gourd, Pumpkin, Watermelon, Muskmelon, Moong Dal etc.

1.1.5 Climate Variability

According to Intergovernmental Panel on climate variability (IPCC), climate variability refers to a variability in the state of climate that can be identified (e.g. using statistical tests) by variability's in the mean and/or the variability of its properties, and that it persists for an extended period, typically decades or longer. It is caused by factors such as biotic processes, variations in solar radiation received by Earth, plate tectonics, and volcanic eruptions. The primary causes of ongoing climate variability are often due to human activities and it is referred to as global warming or anthropogenic climate variability (America’s Climate Choices, 2010; Thornton et al., 2014). Climate variability has a serious impact on the available earth natural resources especially water, which sustains life on this planet (Kundzewicz and Doll 2009; Anil, 2014). Variability in the biosphere, biodiversity and natural resources are adversely affecting human health and quality of life. Throughout the 21st century, India is projected to experience warming above global level (Kumar and Gautam, 2014). In present conditions, climate variability is a serious concern for all the countries over the world. In India, climate variability and impacts are likely to vary substantially across the geographical regions and populations. Impacts of climate variability are likely to vary in different parts of the country. Parts of western Rajasthan, Southern Gujarat, Madhya Pradesh, Maharashtra, Northern Karnataka, Northern Andhra Pradesh, and Southern Bihar are likely to be more vulnerable in terms of extreme events

(Mall et al. 2006a). The climatic phenomena lead to extreme weather events such as floods, droughts, cyclones, extreme temperatures, disease outbreak, the emergence of new pests and diseases etc. Agriculture is extremely vulnerable to climate variability.

Impacts of climate variability on agriculture

Droughts are damaging because of the long-term lack of water available to the plants. Droughts have been responsible for some of the more serious famines in the world, although sociological factors are also important. Heat waves can cause extreme heat stress in crops, which can limit yields if they occur during certain times of the plant's life-cycle (pollination, pod or fruit set). Also, heat waves can result in wilted plants (due to elevated transpiration rates) which can cause yield loss if not counteracted by irrigation. Strong winds can cause leaf and limb damage, as well as "sandblasting" of the soil against the foliage. Heavy rains that often result in flooding can also be detrimental to crops and to soil structure. Most plants cannot survive in prolonged waterlogged conditions because the roots need to breathe. In addition, flooding can erode topsoil from prime growing areas, resulting in irreversible habitat damage. Heavy winds combined with rain (from events such as hurricanes and tornadoes) can down large trees, and damage houses, barns and other structures involved in production agriculture. Climate variability will have an impact on agriculture and food security, forest, water resources, coastal areas, species and natural areas and human health (IPCC, 2007). The climate sensitivity of agriculture is uncertain, as there is regional variation in rainfall, temperature, crops and cropping systems, soils and management practices. Agriculture is not only sensitive to climate variability but is also one of the major drivers of climate variability (Ved et al., 2017). The crop productivity in rain-fed regions is likely to be affected more on account of variation in climatic factors like rainfall, wet-day frequency and temperature as compared to that in irrigated regions (Shalander et al., 2011).

Rao et al. (2011) have observed a decline in total food production and productivity during El Nino years in the AP and TS regions. Adilabad, Nizamabad, Karimnagar, Medak, Nalgonda and Mahbubnagar districts of TS; and Prakasam, Ananthapur, Y.S.R Kadapa, Chittoor, Srikakulam, Vizianagaram and Visakhapatnam districts of AP are severely affected by the El Nino event. Also, decrease/ and erratic rainfall in the monsoon season will severely affect the Rabi crop and temperature fluctuation will have an impact on the Rabi crop and crop production in Andhra Pradesh (Ramprasad, 2011).

1.1.6 Drought

Drought is the most important parameter of the weather-related natural disaster which seriously impacts the regional food production and socio-economic conditions. Its impacts are generally observable in agriculture. Drought varies with regard to the time of occurrence, duration, intensity, and frequency of the area affected. Drought starts with an extended period of reduced precipitation. It is related to time and the efficacy of rains.

Drought is the most significant global natural climatic hazard followed by tropical cyclones, regional floods, and earthquakes (Bryant, 2005). It is a slow and insidious onset environmental disaster. Drought is influenced by vegetation, land use, water resources, climate-related parameters like precipitation, temperature, and evapotranspiration, and socio-economic parameters (Kaushalya et al., 2013a).

Types of Drought

Drought is further classified into meteorological drought, agricultural drought, hydrological drought and socioeconomic drought, based on water deficiency in a specific part of the hydrologic cycle (Wilhite and Glantz1985). There is an element of connection between different droughts as drought in one stage can lead to a drought in another stage. Meteorological drought occurs when the precipitation is less than the normal amount of precipitation over a region. Agricultural drought occurs when the soil water content is low and not sufficient to support plant growth. Hydrological drought occurs when there is a depletion of water in surface water bodies including irrigation tanks, streams, reservoirs, lakes and also a depletion of the groundwater level. Hydrological drought is further classified into stream-flow drought and groundwater drought.

Meteorological drought is related to the deficiency of rainfall compared to long-term average amounts on monthly, seasonal or annual timescales. The India Meteorological

Department (IMD) uses a meteorological definition of drought based on rainfall deficiency from normal of the mean annual, mean summer monsoon, mean monthly and mean weekly rainfall. This classification covers special scales from meteorological sub-divisions of India as a whole. As per IMD, meteorological drought is defined as the event occurring when the seasonal rainfall received over an area is less than 75% of its long-term average value. It is further classified as moderate drought if the rainfall deficit is 26-50% and severe drought when the deficit exceeds 50% of normal. A year is considered to be a drought year for the country if the area affected by the drought is more than 20% of the total area of the country.

Hydrological drought is associated with the effects of periods of precipitation shortfalls on surface or subsurface water supply (e.g., streamflow, reservoir and lake levels, and groundwater). The frequency and severity of hydrological drought are often defined on a watershed or river basin scale. Hydrological droughts are usually out of phase with the occurrence of meteorological droughts. Water in hydrologic storage systems (e.g., reservoirs, rivers) is often used for multiple and competing purposes (e.g., flood control, irrigation, recreation, hydropower), which further complicates the sequence and quantification of impacts. Although the climate is the primary contributor to hydrological drought, other factors such as variabilities in deforestation, land degradation and the construction of dams also affect the hydrological system of a basin.

Agricultural drought links various characteristics of meteorological and hydrological droughts to agricultural impacts. It is related to precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits etc. Plant water requirements depend on prevailing weather conditions, biological characteristics of the specific plant, its stage of growth, and the physical and biological properties of the soil. Agricultural drought should be able to account for the variable susceptibility of crops during different stages of crop development, from emergence to maturity. Deficient topsoil moisture at planting may hinder germination, leading to low plant populations per hectare and a reduction of final yield. Based on its time of incidence, such rainless periods/ agricultural drought may be designated as early season drought, mid-season drought, and terminal drought.

Early-season drought arises because of delayed onset of monsoon or prolonged dry spell soon after the start of the rainy season. This may result in poor crop stand as well as sprout growth. Further, the period of water availability for crop growth also gets reduced and the crops suffer from severe shortage of water during generative stage.

Mid-season drought occurs due to inadequate soil moisture availability between two successive rainfall events during the crop growth period. Its effect varies with the crop growth stage and intensity and duration of the dry spell. Stunted growth takes place if it occurs at the vegetative phase and in case it occurs at flowering or early reproductive stage it will have an adverse effect on crop yield. Late season or terminal drought occurs as a result of an early cessation of monsoon rains and can be anticipated to occur with greater certainty during the years with late commencement or weak monsoon activity.

Terminal droughts are more critical as the final grain yield is strongly related to water availability during the reproductive stage. These conditions are often associated with an increase in ambient temperatures leading to forced maturity. The probability of getting affected by drought at the terminal stage of the crop is high in the regions of northern, western and central India (Sarma et al., 2008).

Socio-economic drought is associated with the supply and demand of economic goods such as water, forage, food grains, fish, hydroelectric power etc.

1.1.7 Historical account of major droughts

Indian agriculture is usually seen as a gamble on summer monsoon rainfall (Chopra, 2006). Summer monsoon rains not only supports the country's agriculture and food security but also contribute to irrigation, power generation (Das, 2000). India has experienced many drought events and it is one of the most vulnerable and drought-prone countries in the world (Mishra and Singh, 2010).

Drought occurrence is a gradual process with long-lasting effects, which are distinct from other natural disasters such as earthquakes, floods, and cyclones. On an average, 28% of the geographical area is vulnerable to droughts in India (Samra, 2004). Over the last 110 years, India has experienced 26 major drought events during 1901, 1904, 1905, 1907,1911, 1918, 1920, 1939, 1941, 1951, 1965, 1966, 1971,1972, 1974, 1978,1979, 1982, 1985, 1987, 1988,1992 (Gupta et al., 2011) 2002,2009, 2014, and 2015 (Department of Agriculture, 2015-2016).

Droughts in Andhra Pradesh (AP) and Telangana (TS)

Former Andhra Pradesh (undivided) is historically the third most severe drought-prone state in India (South Asia Environment and Social Development Department World Bank Report, 2005). The districts of Anantapur, YSR Kadapa, Chittoor, Kurnool, and Prakasam are chronically drought-prone regions out of 13 districts of the AP state. Table 1.3, shows the number of mandals affected by drought during the period 1995-2015 in AP (out of 664 total mandals) and TS (out of 464 total mandals).

1.2 Literature Review

1.2.1 Assessment and monitoring of drought

Drought assessment involves analysis of spatial and temporal water-related data. Several methods were developed to assess the drought quantitatively. Basically, droughts are assessed with reference to nature of water deficit, averaging period, and truncation level and regionalization (Dracup et al., 1980). Drought events are normally characterized by drought indices because the phenomenon is very complicated and the time, development process, and scope of influence are difficult to observe directly (Heim et al., 2002; Solomon et al., 2007; Dai, 2011). The important parameters that may be influencing drought are rainfall, groundwater levels, stream flows, soils, soil moisture, sowing/crop conditions, land use etc (Moreland, 1993; Descroix et al., 2015).

Conventional Method

Post-independence India evolved the administrative mechanism at grass root level. The "Patwaris" are used to collect the information on the date of sowing, crop type, and the information on growth stages, qualitative precipitation, and total yield estimate. The village wise information is collected in administrative hierarchy up to the district level and finally collated at the state level. At the end of monsoon season, the national meet coordinated by agriculture operation and statistics are used to finalize the national figures. With the developments in information technology states have taken initiatives to computerize these field data. In recent years, a few states have also automatized the data collection and management by using GPS and automatic weather stations.

Table 1.3 Number of mandals declared as drought affected in Andhra Pradesh and Telangana regions (1995-96 to 2014-15)

Year	No. of Mandals affected in AP	No. of Mandals affected in TS
1995-1996	198	15
1996-1997	13	17
1997-1998	487	433
1998-1999	0	0
1999-2000	444	245
2000-2001	112	30
2001-2002	589	406
2002-2003	641	446
2003-2004	302	151
2004-2005	408	383
2005-2006	0	0
2006-2007	195	103
2007-2008	0	0
2008-2009	0	0
2009-2010	626	442
2010-2011	0	6
2011-2012	460	418
2012-2013	218	N/A
2013-2014	123	N/A
2014-2015	230	N/A

(*Source: Memorandum on drought in Andhra Pradesh – 2014, Annexure – 1 and State Action Plan on Climate Variability for Telangana State. N/A: Not available).

Using network base communication, some of the advanced states are centralizing the data in real-time. The processed information is being sent back to farmers using mobile technologies in the different administrative hierarchy. Since the process is still humanly managed; there exists sufficient amount of subjectivity, discontinuity or gaps in the national context. Also, the impacts of weather and management practices are not captured spatially. In these circumstances, remote sensing and mobile technologies have significantly improved the drought assessment and forecasting. The present research uses satellite remote sensing data having a high temporal resolution to capture the spatial crop growth patterns and signatures of stress.

Based on the data received from a network of automatic weather stations spread across the country, Indian Meteorological Department (IMD) is using a large number of indices to characterize drought. It monitors the incidence, spread, intensification, and cessation of drought (near real-time basis) on a weekly time scale over the country based on Aridity Anomaly Index. Weekly Aridity Anomaly Reports and maps for the Southwest Monsoon Season for the entire country and for the Northeast Monsoon Season for the five meteorological sub-divisions viz., coastal Andhra Pradesh, Rayalaseema, South Interior Karnataka, Tamil Nadu and Pondicherry and Kerala, are prepared and sent to various agricultural authorities and Research Institutes on operational basis for their use in Agricultural Planning. These Aridity Anomaly maps/reports help to assess the moisture stress experienced by growing plants and also to monitor agricultural drought situation in the country. The aridity index (AI) is calculated by

$$AI = \frac{PE - AE}{PE} * 100, \tag{1.1}$$

where, PE denotes the water need of the plants (potential evapotranspiration), AE denotes the actual evapotranspiration. ($PE - AE$) denotes the water deficit. PE is computed by Penman's equation. AE is obtained from the water balance procedure which takes into account the water holding capacity of the soil at the place. Aridity Anomaly Map gives the information about the moisture stress experienced by growing plant. In addition, other indicators such as Standardized Precipitation Index (SPI), Meteorological Drought Severity Index (MDSI) and occurrence of Dry Spells are also recommended. SPI is used as an indicator of deviation of rainfall from the normal and can serve as a more robust statistical indicator under certain conditions as compared to simple rainfall deviations. The dry spell, in contrast, is an indicator of anomalies in the distribution of rainfall.

Standardized Precipitation Index (SPI)

It expresses the actual rainfall as a standardized departure with respect to the rainfall probability distribution function. The computation of SPI requires long-term data on precipitation to determine the probability distribution function (gamma distribution), which is then transformed to a normal distribution with zero mean and standard deviation of one. The longer the reference period to calculate the distribution parameters, the greater the likelihood of obtaining more accurate results (for e.g. 50 years' data will be better than that for 30 years). Thus, the values of SPI are expressed in standard deviations (positive SPI indicates more than median precipitation and negative values indicate less than median precipitation).

Meteorological Drought Severity Index (MDSI)

This index is calculated based on the frequency analysis as to the number of times the precipitation has deviated in a given period of time from historically established normal or mean rainfall.

Remote Sensing techniques

Remote sensing is the science and art of obtaining information about an object through the analysis of data acquired by a device that is not in contact with the object (Lillesand and Keifer, 1994; Sivakumar et al., 2004). The term remote sensing is frequently constrained to the methods that employ electromagnetic energy (such as light, heat and radio waves) as the means of detecting and measuring target characteristics (Sabins,1986). Consistent and systematic observation from a vantage point through satellite remote sensing system helps in monitoring the dynamics of vegetation, characterization of vegetation structure and estimation of gross primary production (Potter et al., 1993; Liu and Kogan, 2002; Xiaoyang et al., 2003; Atzberger, 2013). Remote Sensing provides spatial coverage of the land surface across a wide range of wavebands, from the ultra-violet (UV), visible (VIS), near-infrared (NIR), shortwave infrared (SWIR), mid-infrared (MIR), thermal infrared (TIR), and microwave regions of the electromagnetic spectrum. In general, the possible tools of remote sensing technique can be grouped into three main categories namely, satellite, radar, and near-to-surface instruments. The platform for remote sensing can be fixed or moving, terrestrial or operating from different altitudes, and be either manned or unmanned. Sensors can be differentiated into two main groups viz., passive sensors (without their own source of radiation), and active sensors (built in source of radiation).

The reflective portion of the Electromagnetic Spectrum (EMS) ranges nominally from 400nm to 3750 nm. Light shorter than 400 nm wavelength is termed as ultraviolet (UV). The reflective portion of the EMS can be further subdivided into the visible (400-700 nm), near-infrared (NIR) (700-1100 nm) and shortwave infrared (SWIR) (1100-3750 nm). Remote sensing converts an analog photon flux to digital images, where the number of quantization levels is a function of the number of bits used to represent the photon flux. The number of quantization levels equals two to the power of the number of bits. That is, 7-bit data provide 128 (27) levels of quantization, 8-bit data 256 (28), 10-bit data 1024 (210) and 12-bit data 4096 (212). The ability of remote sensing measurements to distinguish different properties of the Earth's surface in the EMS is partly determined by the level of quantization. Remote sensing data acquired by various sensors like TM, ETM+, MODIS, ASTER, AMSR-E, AVHRR, SMOS, AWiFS, LISS-III, etc. serve as input for the purpose of identification, location and also to estimate the severity of agricultural drought. Precipitation related satellite i.e. TRM M was also evolved for the assessment of drought.

Moreover, observation from space provides permanent data archive, extra visual information, and enables one to have a regular and repetitive view of nearly the earth's entire surface (Kogan, 1997) as well as the region. This technique makes it possible to acquire information rapidly over large areas by means of sensors operating in several spectral bands mounted on satellites. Satellite-sensor data is continuously available and can be used to detect the onset of a drought, its duration, and magnitude (Thiruvengadachari, 1993).

Even though weather satellites such as NOAA (National Oceanic and Atmospheric Administration) .were first designed to help weather forecasts, they are found useful for addressing vegetation status in the earth surface (FEWS-NET). According to Kogan (1997), since the late 1980s, they have also been used for drought detection, monitoring and impact assessment in agriculture. Satellite-derived rainfall/vegetation products can be used to assess meteorological or agricultural drought at spatial scales in different time periods (daily, weekly and fortnightly).

1.2.2 Methods to assess drought

Agriculture is one of the most sensitive and vulnerable to climate variability among all the sectors (IPCC, 2007). Agricultural drought, caused by reduced rainfall, soil moisture availability to crops, leads to considerable economic loss worldwide. Several scientific approaches i.e. satellite based indices, meteorology based indices, and hybrid indices have been developed for monitoring agricultural drought (Thiruvengadachari et al., 1993; Wood, 1997; Kogan, 1997; Vogt and Niemeyer, 1998; Murthy et al., 2010; Sharmistha et al., 2011; Gao et al., 2014; Farahmand et al., 2015; Yagci et al., 2015). The impacts of agricultural drought are the result of the interactions of agro-socio-economic factors with the meteorological drought phenomenon (Bohle, 2001; Bantilan and Keatinge, 2007; Birkmann, 2008).

Normalized Difference Vegetation Index (NDVI)

Many remote sensing instruments have channels situated in the red and NIR wavelength of the spectrum. These two reflective bands are often combined to produce vegetation indices. The most common linear combinations are the simple ratio (NIR/red) and Normalized Difference Vegetation Index (NDVI). The Normalized Difference Vegetation Index (NDVI) is defined by Tucker (1979) as

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}, \quad (1.2)$$

where, NIR and Red represent the percentage reflected radiation in the near infrared and red portion of the spectrum respectively. The red portion of the EMS is absorbed by the chlorophyll and hence for a healthy crop, there is the least reflectance from this region. On the contrary, radiation is scattered by the internal spongy mesophyll leaf structure, which leads to higher values in the NIR region of EMS. An index like the NDVI from the spectral measurements reduces the two spectral data to a single number that is related to physical characteristics of vegetation (e.g. leaf area, biomass, productivity, photosynthetic activity, or percent cover) (Perry and Lautenschlager, 1984; Huete, 1988; Payero et al., 2004). This also helps in minimizing the effect of internal (e.g. canopy geometry, leaf and soil properties) and external factors (e.g. sun-target-sensor angles, and atmospheric conditions at the time of image acquisition) on the spectral data (Richardson and Wiegland, 1977; Slater and Jackson, 1982; Huete et al., 1985; Huete, 1987; Liu and Kogan, 1996; Van Niel and McVicar, 2003). Vegetation Indices (VIs) were developed in an attempt to obtain this objective from remote sensors by taking advantage of the differences in the reflective responses of vegetation in the red and NIR wavelengths. Although VIs are often hampered by limitations in dealing with the complex nature of real-life vegetation canopy interactions (Huete et al., 1985; Qi et al., 1993), they have gained widespread popularity due to the benefits of remote sensing high spatial density and extent and the value added to generic, rather coarse-scale vegetation modeling.

NDVI has become the primary tool for the description of vegetation variability and interpretation of the impact of environmental phenomena (Kogan, 1990). NDVI is also effectively used for monitoring rainfall and drought, estimating net primary production (NPP) of vegetation and crop yields, detecting weather impacts and other events important for agriculture, ecology and economics (Tucker et al., 1985; Prince and Tucker, 1986; Hielkema et al., 1986; Kogan, 1987 a,b and 1990). NPP derived from SPOT-VEGETATION 10-day NDVI product has shown that India with 1.45% of world's landmass accounts for approximately 2.7%-5.5% of global NPP estimates (Chhabra and Dadhwal, 2003). The fPAR derived from NOAA AVHRR (Advanced Very High Resolution Radiometer) data has shown a decadal increase in vegetation activity of 2-3% from 1981-2001 (Pandya et al., 2004). It is a known fact that NDVI lags rainfall by one to two fortnights. The relation between rainfall and the NDVI in southern parts of Africa was studied and the results show that monthly NDVI follows monthly rainfall with a lag of one to two months and are best correlated with the bimonthly antecedent rainfall (Richard and Poccard, 1998). Similarly, in the state of Andhra Pradesh, the NOAA AVHRR NDVI lags rainfall by one to two months in most of its districts and the initial three-month monsoon rainfall correlates well with the seasonal cumulative NDVI (Chandrasekar et al., 2006).

Since 1989, NDVI derived from NOAA AVHRR data has been used operationally in India for district-level agricultural drought assessment and monitoring for 10 important states of the country through a project called NADAMS (National Agricultural Drought Assessment and Monitoring System) (Thiruvengadachari, 1990).

Vegetation Condition Index (VCI)

Kogan (1990) suggested the Vegetation Condition Index (VCI) as a parameter for drought detection and tracking. It identifies the drought events and determine the onset, severity and frequency of vegetation condition using historical (Gutman, 1990; Nicholson and Farrar, 1994; Kogan, 1995; Unganai and Kogan, 1998; Seiler et al., 2000; Wang et al., 2001; Anyamba et al., 2001; Ji and Peters, 2003).

$$VCI = \frac{\left(X_{ij} - Max(X_{ij})\right)}{\left(Min\ (X_{ij}) + Max(X_{ij})\right)}, \tag{1.3}$$

where, X_{ij} is NDVI of a particular year, $Max(X_{ij})$ is long-term maximum of NDVI, and $Min(X_{ij})$ is long-term minimum of NDVI.

Kogan (1997) found that the VCI was strongly correlated with agricultural production in South America, Africa, Asia, North America, and Europe, particularly during the critical periods of crop growth. The suitability of the NDVI and VCI for monitoring drought has been evaluated in a variety of regions around the world.

Meteorological drought assessment

Standardized Precipitation Index (SPI)

The SPI is a normalized index representing the probability of occurrence of the observed rainfall at a certain geographical location compared with the rainfall at that location over a long-term reference period. Negative SPI values represent the deficit in rainfall, whereas positive values indicate surplus rainfall. The seasonal rainfall data were used to derive the SPI using the equation (McKee et al., 1993)

$$SPI = \frac{X_i - X_m}{\sigma}, \tag{1.4}$$

where, X_i represents yearly/monthly rainfall, X_m is historic long-term mean rainfall of the particular year/month.

The SPI is calculated by standardizing the probability of observed precipitation for any duration of interest (e.g., weeks, months, or years). Duration of weeks or months can be used to apply the SPI for agricultural or meteorological purposes, and longer durations of years can be used to apply it for hydrological and water management purposes (Guttman, 1999). The SPI requires a long-term precipitation record because it fits a probability density function to the observed data and then transforms it using an inverse normal (Gaussian) function (Guttman, 1999). This ensures that the mean SPI value for any given location (and duration) is zero and the variance is one. Positive values of the SPI indicate greater than median precipitation, while negative values indicate less than median precipitation. The 1-,2-, 3-, 6-, 9-, 12-, and 24-month SPI was calculated for each county (World Meteorological Organization, 2012).

Various studies have examined the temporal linear relationship between NDVI and climate (rainfall and temperature) (Wang et al., 2001; Ji and Peters, 2003; Sarma et al., 2008). Bora and Goswami (2016) have also determined a strong linear relationship between the vegetation indices and rainfall over land use land cover. Kawabatan et al. (2001) have analyzed the annual and seasonal relationship of NDVI with rainfall and temperature at the global level. These studies have found a 3-month lag time period between the occurrence of precipitation and vegetation response (Ji and Peters, 2003). NDVI is a useful variable to monitor vegetation conditions and their relationship with climate on the seasonal timing and variations in vegetation and soil type. However, the enlisted studies did not focus on the response of summer monsoon rainfall on respective cropping season (Kharif), winter/Rabi and summer/ Zaid crop. The monsoonal rainfall not only affect the respective crop but also the soil moisture condition and irrigation system which will, in turn, have an impact on other cropping periods. Thus the studies focus on multiple regression relationships of agricultural NDVI with precipitation and water resources.

1.2.3 Assessment of long-term satellite data

Time-series NDVI is known to capture vital features of seasonal and inter-annual vegetation variability. It has been adopted by many researchers to extract numerical observations linked to vegetation dynamics (Tucker and Sellers, 1986; Pettorelli et al., 2005). Long-term satellite datasets are significant to determine the cropland productivity response to climate variability and management practices (Tottrup et al., 2004; Rembold et al., 2013). NDVI can provide a suitable index of vegetation variability on seasonal and inter-annual time-scales, and that long-term monitoring of NDVI explains the relationships between fluctuations of vegetation and climate (Ramachandra et al., 2016). Time series vegetation data can provide valuable information about global warming (Pettorelli et al., 2005), phenological variability (White et al., 2009), crop status (Tottrup et al., 2004), land degradation (Metternicht et al., 2010) and desertification (Symeonakis and Drake, 2004). It can also serve as a proxy for detecting variabilities in vegetation activity, e.g., greening (NDVI increase) and browning (NDVI decrease) trends (Alcaraz et al., 2010). NDVI along with climate and soil moisture time-series are needed over long time spans to analyze agricultural phenophase derived length of the growing period and their relationship.

NDVI is strongly linked to rainfall fluctuations with index values generally increasing with the amount of precipitation (Tucker et al., 1991). This close connection helps one to employ NDVI as a substitute to monitor the agriculture response to rainfall variation. By and large, the positive trend in NDVI is taken as a response to an overall increase in precipitation (Nicholson et al., 1990; Hickler et al., 2005), although several theories exist attributing the rainfall variability to global sea surface temperature (Caminade and Terray, 2010). Irrespective of whether or not the climate/human activity is responsible for rainfall variability, the greening trend becomes a subject of discussion leading to ongoing research (Huber et al., 2011). Seaquist (2008) has performed regression of NDVI record on the precipitation data (satellite-measured) and NDVI residual time-series was examined for important trends for the period ranging from 1982–2003. The observed trends in residuals show thereby that portion of the measured NDVI was not explained by the measured rainfall. Yet, Herrmann et al. (2005) used all the months of a year, including the long dry season in their study. NDVI residual time-series has also been used extensively for identifying long-term trends in vegetation greenness induced by factors other than water availability (Huber et al., 2011). The mechanisms of the response of vegetation to climate variability is still a subjective question (Wang et al., 2003). Most of the studies have related NDVI to climate factors during the growing season or examined their spatial variability (Yang et al., 1997; Potter and Brooks, 1998; Suzuki et al., 2007, Hou et al., 2015). Some studies have explored the relationships between NDVI variability and climate parameters in different seasons to decipher their spatial patterns (Jobbagy et al., 2002; Zhou et al., 2003; Piao et al., 2004; Kumar et al., 2013; Kaushalya et al., 2013). Precipitation and temperature directly influence the water balance, thereby causing variability in the soil moisture which, in turn, influence the agricultural condition (Wang et al., 2003).

Crop phenophase

Crop phenology is the study of crop life cycle. To understand the timing of periodic events in the life cycle of a crop is relevant for various activities, such as irrigation scheduling, fertilizer management, evaluating crop productivity, and analyzing seasonal ecosystem carbon dioxide (CO_2) variabilities (Sakamoto et al., 2005). The information of crop phenology and its particular variability in the greenness (start) and browning (end) of the crop growing season, is important for the study of the impact of variability on crop (Xingzhi You et al., 2013). Phenological data are useful for assessing crop conditions, drought severity, and wildfire risk as well as tracking invasive species, infectious diseases, and insect pests. Because phenological events are sensitive to climate variation, these data also represent a powerful tool for documenting phenological trends over time and detecting the impacts of climate variability on ecosystems at multiple scales (USGS). Variabilities in the phenological period and length of the growing season may be caused by climate variability (Brown and de Beurs, 2008; Linderholm, 2006; Reed et al., 1994). Vegetation phenology is an effective indicator of intra as well as inter-annual variability in vegetation caused by climatic changes (van Vliet and Schwartz, 2002). Vegetation phenology has been performed using three possible ways viz., in situ observation, bioclimatic models and remote sensing techniques (Schaber and Badeck, 2003; Jeremy et al., 2007). Remote sensing is a feasible tool for delineating spatiotemporal patterns of vegetation phenology (Xin et al., 2002; Sakamoto et al., 2006; Mingwei et al., 2008; Wu et al., 2010; Liang et al., 2011).

However, time series satellite data are affected by clouds and aerosols, which add noise to the signal sensor (Bruno and Marcelo, 2016). Many methods are developed viz., Fourier or harmonic analysis (Leinenkugel et al., 2013), wavelet decomposition (Zhao et al., 2012), the Whitakker smoother (Atzberger and Eilers, 2011), double logistic (DL) function (Beck et al., 2006; Liu et al., 2013), the asymmetric Gaussian (AG) function fitting (Jonsson and Eklundh, 2002), Savitzky–Golay (SG) filters (Tan et al., 2011, Sehgal, 2011) to estimate phenology and production metrics based on NDVI time-series to overcome the problems associated with the noise.

Phenological events such as the start and end of the season (Jeong et al., 2011) are based on certain rules. Few studies estimated phenological events to derive the LGP using a time-series NDVI threshold values (Lloyd, 1990; Delbart et al., 2006; Karlsen, 2008; Jeong et al., 2011; Kaushalya et al., 2014). Phenological events differ for different crops according to the crop growing periods (Pan et al., 2012). The use of just one threshold value for a research area, in most threshold studies, ignores the differences among crop types and physical environments. Not only crop type but also planting patterns and climatic conditions can affect crop phenological events within a region. Therefore, it is critical to choose the "right" method for the "right" place (Cong et al., 2012) and for threshold methods to choose the "right" threshold for the "right" place. A number of studies have been conducted to monitor vegetation and crop phenology at regional to global scales from satellite-based vegetation indices (e.g., NDVI and EVI) using the double logistic algorithm over the past decade (Zhang et al., 2003; Beck et al., 2006; Wardlow et al., 2006; Julien and Sobrino, 2009; Zhao et al., 2012).

Time series analysis

Several studies have used NDVI to monitor the temporal response of vegetation to climatic fluctuations around the world (Anyamba et al., 2002; Wang et al., 2003; Chang et al., 2014; Hawinkel et al., 2016). However, only a few studies have examined spatial patterns of NDVI-rainfall associations (Tucker et al., 1985; Anyamba et al., 2002; Lakshmi Kumar et al., 2013). Multi-temporal satellite-derived NDVI analyses have been demonstrated in literature for deriving various vegetation phenology metrics at an aggregated level (Xiaoyang et al., 2003). Long-term satellite datasets are significant to determine the cropland productivity response to climate variability and management practices (Rembold et al., 2013) and also agricultural drought vulnerability assessment.

1.2.4 Importance of drought vulnerability assessment

Globally climate variability has impacted agriculture and it will inevitably have a huge impact on agricultural production in the future. Rainfall variability, soil type, land topography, groundwater availability and utilization, irrigation coverage, economic strength and institutional support system are some of the key factors that determine the nature and extent of drought vulnerability in a region (Swaina and Swain, 2011). It is also influenced by the coping capacity of inhabitants characterized by their resource endowments and entitlements. Some exogenous factors like climate variability do influence the level of risk and vulnerability of different livelihood groups in a region (Blaikie et al., 1994).

To face the challenges of drought events, decision-makers need to be better informed so that they can decide on the allocation of resources (Fontain et al., 2009). Risk management can improve farmers' ability to cope with the impact of drought by establishing a comprehensive system of early warning systems (Rahmanian, 2001). Hence, assessment of agriculture vulnerability to drought is essential to develop appropriate coping strategies at various levels, from the central government to the individual households.

The impact of disasters resulting from natural hazards depends not only on the magnitude and frequency of the event but also on the vulnerability of the affected area or social group (Bohle, 2001; Birkmann, 2008). The vulnerability is a key link between hazard and risk and forms an important component of disaster risk reduction strategies. Joseph (2013) conceptualizes vulnerability as the asymmetric response of disaster occurrences to hazardous events. Agricultural drought, caused by reduced soil moisture availability to crops, leads to considerable economic loss worldwide. In the developing countries, long-term/mitigation programmes of drought management are given low priority, and hence, successive droughts are causing serious environmental problems such as land degradation, loss of topsoil and overgrazing of grasslands (Bryant, 2005).

Three widely used approaches are in vogue to assess the vulnerability (a) socio-economic, (b) biophysical and (c) integrated. The limitation of the socio-economic approach is that it focuses only on assessment of socio-economic and political status. The biophysical approach is based on the physical impact of climate variability variables. The integrated assessment approach overcomes the drawbacks associated with the other approaches (Singh et al., 2014).

The integrated assessment approach combines both the socio-economic and the biophysical attributes in vulnerability analysis (Fussel, 2007). In this approach, the vulnerability analysis conceptualizes vulnerability as a function of adaptive capacity, sensitivity, and exposure to events such as drought (Brooks et al., 2005). In the IPCC framework, exposure has an external dimension, whereas both sensitivity and adaptive capacity have an internal dimension, which is implicitly assumed in the integrated vulnerability assessment framework (Singh et al., 2014). The vulnerability is important as it enables the identification of areas or resources at risk, and the loss of such resources that could threaten future adaptation and sustainable development (Berry et al., 2006). It enables to identify the role, extent, and level of vulnerabilities and coping capacities to disaster and enables the government and policymakers to enlarge the adaptation, mitigation and sustainable capacities of extreme agriculture vulnerable areas. Metrics derived from time series Normalized Difference Vegetation Index (NDVI) has used to map drought vulnerability in India (Murthy et al., 2010).

The climate variability is expected to influence the drought condition, which in turn has an impact on agriculture (IPCC, 2001; Shukla et al., 2015). In India, many studies have been carried out to assess the drought vulnerability. For example, Chandrasekar et al. (2009) have adopted Multi-Criteria Analysis (MCA) for assessing agricultural drought vulnerability in Tamil Nadu region; Kaushalya (2013a) computed the vulnerability considering satellite and climatic data in Agro-ecological sub-division (ASER) of India; and Murthy et al. (2015) adopted IPCC composite index approach using remote sensing data during peak Kharif crop (August-October) in various states. A few studies were also carried out without spatial data, considering bio-physical and socio-economic parameters with climate variability during Kharif season in Indo-Gangetic plains using integrated approaches (Sehgal et al., 2013). It can be observed from the literature that most of the studies have ignored the impact of monsoon rains on winter/rabi and summer/zaid cropping season.

1.3 Aim and Scope

Agriculture is one of the major sources of Indian economy. It also provides employment to 60% of the population. Major agriculture production is achieved during monsoon period when the rainfed areas are also cultivated. The agriculture performance depends on weather/climate, soil and its properties and management practices. Total crop production and productivity of India computed from three cropping seasons, which plays a vital role in Indian economy. Hence, other two cropping seasons (Rabi and Zaid) performance is essential to consider. A necessity exists to monitor and assess the agriculture performance in three cropping seasons. Failure or delay or unusual break of monsoon, extreme climate events, and climatic anomalies will have an impact on agriculture. The crop growth pattern, agriculture stress, production, and yield are all related to the long-term anomaly of climate.

Remote Sensing is one of the important methods to assess and monitor agriculture and the agriculture performance. The indices are derived using National Oceanic and Atmospheric Administration (NOAA) Global Inventory Modeling and Mapping Studies (GIMMS) Advanced Very High-Resolution Radiometer (AVHRR), MODIS (MODerate Resolution Imaging Spectroradiometer) and Advanced Microwave Scanning Radiometer for Earth Observing System (EOS) (AMSRE) datasets to capture the crop performance, agriculture stress along with climate parameters and their anomalies.

The research questions addressed in the thesis are as follows:

1. Will the three seasonal precipitations have an impact on the total agricultural performance?
2. Is it possible to develop an understanding of long-term trend between climate/soil-moisture variables with NDVI/VCI and length of the growing periods? and
3. Do long-term multi-criteria viz., climate, remote sensing, and socio-economic data provide information on agriculture drought vulnerability?

CHAPTER TWO

Study Area

General

The erstwhile undivided state of Andhra Pradesh, comprising Telangana (TS) and Andhra Pradesh (AP) regions, forms the study area. The undivided Andhra Pradesh is one of the south Indian states positioned in the coastal area towards the southeastern part of the country. The then undivided state comprised of three regions viz., Coastal Andhra, Telangana and Rayalaseema was formed on 1st November 1956.

The northern side of the Deccan plateau comes under Telangana region, while the southern side is known as the Rayalaseema region. The river Krishna separates these two regions from each other. The coastal area of the state is mostly formed by the deltas of the rivers flowing through the Sate. The undivided state was comprised of 23 districts namely Hyderabad, Adilabad, Ananthapur, Chittoor, Y.S.R Kadapa, East Godavari, Guntur, Krishna, Karimnagar, Khammam, Kurnool, Mahbubnagar, Medak, Nalgonda, S.P. S.R Nellore, Nizamabad, Prakasam, Rangareddy, Srikakulam, Vizianagaram, Visakhapatnam, West Godavari, and Warangal (Fig. 2.1). Ananthapur is the largest district covering an area of 19130 sq km , followed by Mahbubnagar (18432 sq km), Kurnool (17600 sq km), Prakasam (17140 sq km), Adilabad (16105 sq km), Khammam (16029 sq km), YSR Kadapa (15380 sq km), Chittoor (14990 sq km), Nalgonda (14240 sq km), SPS Nellore (13160 sq km), Warangal (12846 sq km), Karimnagar (11823 sq km), Visakhapatnam (11340 sq km), Guntur (11330 sq km), East Godavari (10820 sq km), Medak (9699 sq km), Krishna (8800 sq km), West Godavari (7800 sq km), Nizamabad (7956 sq km), Rangareddy (7493 sq km), Vizianagaram (6300 sq km), Srikakulam (5840 sq km), and Hyderabad (217 sq km).

The main source of income of the state is from agriculture and livestock. Among the two, agriculture has been the chief source of income for 70% of the population in the state. Andhra Pradesh was one among a few states in the country, which was influenced by the Green Revolution phase in rice cultivation during the 1970s. Rice is the major food crop and staple food of the state (Adusumilli and Bhagya Laxmi, 2011).

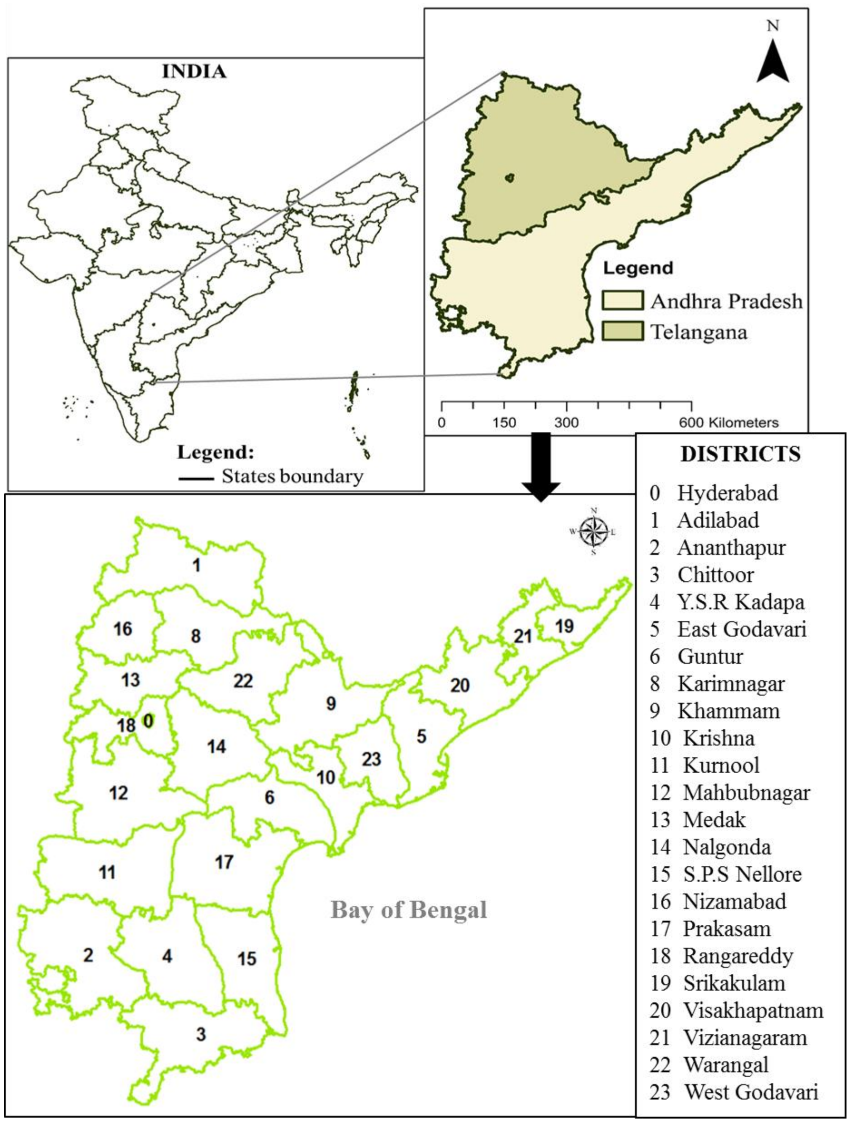


Figure 2.1 Location map of the study area

2.1 Geography

The then undivided AP state lies in the tropical region between 12°14' and 19°54' North latitudes and 76°46' and 85°40' East longitudes. Because of its unique position in the merging area of the Deccan plateau and the coastal plains, the state has diversified physical features. The State spread over an area of 2, 75, 045 sq. km shares its borders with Chhattisgarh, Maharashtra and Orissa states towards the north, Tamil Nadu in its south, Karnataka towards its west, and bordered by the Bay of Bengal on the east. The important rivers flow in the state are Godavari, Krishna, Pennar, Nagavali, and Vamsadhara. These rivers carry large quantities of water during the monsoon period and low currents in summer. In summer some of the rivers even dry.

The Godavari River and its tributaries pass through the states of Maharashtra, Karnataka, Madhya Pradesh, Orissa and Andhra Pradesh. Within the state, the Godavari flows through the districts of Nizamabad, Adilabad, Karimnagar, Warangal, Khammam, East Godavari and West Godavari. River Godavari enters the Andhra Pradesh state in Basar Village of Adilabad District after flowing through over a length of 692 km from Trimbak in Maharashtra state. The river then flows through the EGs (Eastern Ghats) and finally emerges into the plains near Polavaram. The Godavari branches out into Gautami and Vasishta rivers near Dhawaleswaram and the fertile Godavari Central Delta lies between these two branches. Godavari River receives most of its water from the lower reaches when compared to the Western Ghats. Important tributaries of river Godavari are Kinnerasani, Pranahita, Sabari, Manjira, Indravati, and Penganga. The Manjira contributes 6% water to the river Godavari, whereas Pranahita contributes 40%, Indravati 20%, and Sabari 10% respectively. The river flows into the Bay of Bengal after traversing nearly 1446 km.

The Krishna River originates near Mahabaleshwar in Maharastra State and flows about 780 km before it enters the State of Andhra Pradesh near Tangadi Village of Mahaboobnagar district. Unlike the Godavari River, it gets most of its water from the WGs (Western Ghats). The Krishna River drains through Kurnool, Nalgonda, Guntur and Krishna districts before it joins Bay of Bengal. Bhima, Koyna, Mallaprabha, Ghataprabha, Yerla,Tungabhadra, Dindi, Warna, Dudhganga, and Musi are the main tributaries of the Krishna River.

The origin of river Pennar is the Nandidurg hills of Mysore. After traversing a length of 40 km in Mysore State, the river enters Anantapur district of Andhra Pradesh. It flows through Cuddapah and Nellore districts before enters the Bay of Bengal in Nellore District. Jayamangali, Chitravati, Pennar, Papagni, Kunderu, Cheyyeru, Sagileru are the important tributaries of this river.

The Nagavali River originates in the state of Odhisa. It drains through the districts of Vijayanagaram and Srikakulam, before meets the Bay of Bengal in the Srikakulam district. The Swarnamukhi, its chief tributary, also originates from Odhisa.

The river Vamsadhara originates from Jayapur hills of the Eastern Ghats and enters Andhra Pradesh at Patapatnam village and merges into the Bay of Bengal at Kalingapatnam.

2.2 Major features of the study area

2.2.1 Population

According to Census 2011, the State of Andhra Pradesh has recorded a total population of 84,665,533 against 76,210,007 in 2001. It forms 7% of the Indian population in 2011. Out of the total population of 84,665,533, the male population is recorded as 42,509,881 and female 42,155,652 respectively. The Sex Ratio is increased from 978 as recorded in census 2001 to 992 in 2011 for each 1000 male. The child sex ratio is 943 per 1000 males in the census 2011 as compared to 896 in the 2001 census. The Literacy rate has risen and is 67.66%, with male literacy at 75.56% and female literacy at 59.74%. Among all the all the districts in Andhra Pradesh, Mahabubnagar (89.41%) is having highest rural population followed by Srikakulam (89%) and Nalgonda (86.74%). It is obvious that more pressure shall be exerted on the land for natural resources and economic activities once the population in the rural areas increased.

2.2.2 Land Utilization and Agriculture Profile

The state enjoys a position of supremacy in respect of production of food grains and accordingly earned the distinction of being called the "Rice Bowl" of South India. It is a surplus state in Rice Production and significantly contributes a major share of food grains to the central pool. Nearly 71% of the State population is dependent on Agriculture and allied sectors contributing to more than 60% of the state's income till 1973-74. Since then its contribution to State Domestic Product has declined to 42% in 1984-85 and 37.52% in 1996-97. Significant diversification in the economy is evident from the structural shifts in the State Domestic Product.

Based on the rainfall and cropping patterns, the state is divided into nine agro-climatic zones. They are i) High altitude and Tribal Zone, ii) Krishna Zone, iii) Godavari zone, iv) North coastal zone, v) Northern Telangana zone, vi) Central Telangana Zone, vii) Scarce rainfall zone, viii) Southern Telangana zone and ix) Southern zone.

Out of the total geographical area of the state, forest cover is 22.6%, fallow land is 9.8%, area under non-agricultural use is 9.6%, and barren and uncultivable land is 7.5% respectively. The net area sown during the year 2006-07 was 102.39 lakh ha. During 2007-08, the net area sown was increased by 5.9% (102.39 lakh ha) because of the existence of favorable seasonal conditions. In addition to paddy, other major crops grown in the State are sugarcane, beans, oilseeds, and pulses. Cultivation is performed in the state in three cropping seasons namely, Kharif, rabi, and summer. The decadal land utilization and agricultural profile of erstwhile Andhra Pradesh is given in Table 2.1. Although significant cultivable area and water resources are prevailed, the state is experiencing stressful conditions due to drought. In some areas of the state water is available in surplus, whereas in some other parts water is hardly available even to cater the needs for drinking.

Table 2.1 Utilization and agricultural profile of erstwhile Andhra Pradesh

S.No.	Category	1966-1967	1976-1977	1986-1987	1996-1997	2005-2006	2010-2011	2011-2012	% Total geographical area
1	Total Geographical Area (lakhs Ha)	274.4	274.4	274.4	274.4	274.4	275.0	275.0	100
2	Forest	61.17	63.82	58.35	62.45	61.99	62.3	62.3	22.7
3	Barren & Un-cultural land	274.4	274.4	274.4	274.4	274.4	275	275	100
4	Land Put to Non-Agrl. Uses	274.4	274.4	274.4	274.4	274.4	275	275	100
5	Land Put to Non-Agrl. Uses	13.74	9.56	8.64	7.22	6.92	6.26	6.14	2.2
6	Permanent pastures	11.57	9.72	8.81	7.63	6.76	5.54	5.52	2
7	Land under Miscellaneous	3.05	2.73	2.64	2.47	2.78	2.9	2.89	1
8	Other fallow lands	8.66	12.16	14.96	15.47	16.23	14.9	15.59	5.7
9	Current fallow lands	21.74	26.47	35.23	24.43	24.34	22.29	22.73	8.3
10	Net Area sown (CROPS)	113.4	106	100.5	108.3	107.5	111.9	110.5	40

(*Source: Directorate of Economics and Statistics)

2.2.3 Irrigation

Irrigation plays an important role in agriculture performance of a country/state. The available statistics reveals that the area under irrigation and the cropping intensity in the state have shown increasing trends during the 1980s and 1990s, although the net sown area remained more or less the same at 11 million hectares (ha) from 1955-56 onwards. The cropping intensity which was 110% in 1960-61 rose to 123% in 1999-2000. The Gross Irrigated Area (GIA) in AP during 2015-16 from all the sources is 35.47 lakh Hectares. This is accounted for 47.10% of the gross cropped area against 50.53% during the previous. In Telangana, GIA is 20.25 lakh Hectares, which is accounted for 41.44% of the gross cropped area against the previous year (47.58%).

Canal irrigation is the major source of irrigation in the state. Vasant (2011) has reported that irrigation by groundwater system is increased since 1970's, whereas the canal and tank irrigation decreased. Till the early 1970s, tanks were the dominant sources of irrigation in the Telangana and Rayalaseema regions, whereas canals are the main sources in Coastal Andhra. After the 1970s, the traditional tank irrigation was replaced by well irrigation in many parts of Telangana and Rayalaseema. The well irrigation in the state has increased from 27% in 1963 to 40% in 2008.

From 2005 to 2007, fluctuation in NIA was noticed with a major decline during 2008-09 and 2009-10. The occurrence of drought in the state during 2002-2003, 2004-2005 and 2009-10 was due to the decline of NIA.

2.2.4 Climate

The state experiences a tropical climate with moderate to subtropical weather. Humid to semi humid conditions prevail in the coastal areas while arid to semi-arid conditions in the interior parts of the state. The summer season generally starts in the month of March and extends up to June. Overall, the coastal areas experience high temperatures in the summer when compared to other parts of the state. The average temperature within the state ranges from 20° C to 44.8° C.

The state receives the rainfall from both South-West and North-East monsoons. The normal annual rainfall of the State is 940 mm. The South-West Monsoon (June-Sept) contributes 68.5% rainfall to the state whereas the North-East Monsoon (Oct-Dec) 22.3%. The remaining 9.2% rainfall is received during the months of winter and summer. The South-West Monsoon contributes 714 mm rainfall to Telangana, 620 mm to Coastal Andhra and

407 mm to Rayalaseema regions. On the other hand, North-East Monsoon contributes 324 mm rainfall in Coastal Andhra, 238 mm in Rayalaseema and 129 mm in Telangana, respectively.

There are no significant differences in the distribution of rainfall during winter and hot weather periods among the three regions. The rainfall in the State is highly variable resulting in frequent droughts. The State is highly vulnerable to climate change and adverse climate events. Due to the change in rainfall and temperature patterns, the river basins and coastal areas are being affected considerably (State Action Plan on Climate Change for Andhra Pradesh (SAPCCAP, 2011)).

Figures 2.2 and 2.3 show the long-term trend of climatic parameters at national and state (undivided AP) levels. One can notice from Figs. 2.2a to 2.2c and 2.2a to 2.2c that the rainfall portrays large fluctuations over a long-term period in all the three seasons, whereas the minimum and maximum temperatures show increasing trends (Figs. 2.2d to 2.2i and 2.3d to 2.3i).

2.2.5 Soil types

The characteristics of the soils are influenced by bedrock composition, altitude of the area and also by other factors like rainfall, excessive heat etc. About 65% of the area in the state is covered by red soils, followed by 25% area by black soils. About 10% of area is occupied by fertile alluvial soils. Rayalaseema and Telangana regions of the state are dominated with red soils having low nutrient values. The upland regions of the coastal districts are primarily dominated with red loamy soils associated with sands, whereas black cotton soils cover nearly 25% of the cultivated area. By and large, the alluvial loamy soils are restricted to Krishna and Godavari deltas covering about 5% of the cultivated area. Lateritic soils cover about 2% area in certain pockets of the state.

2.2.6 Droughts

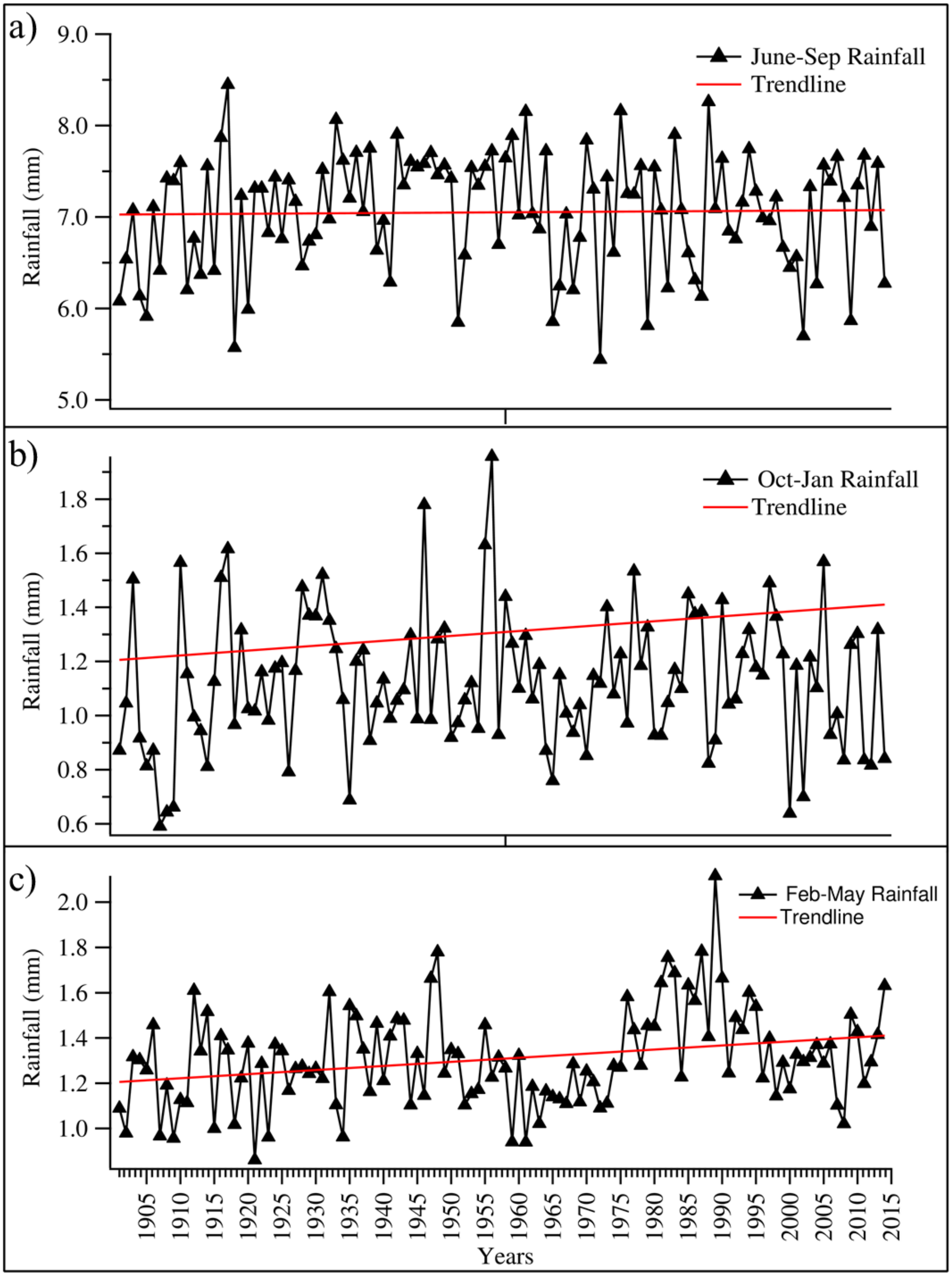
Andhra Pradesh state ranks third in terms of drought-prone after Rajasthan and Karnataka in India. Rayalaseema and Telangana regions of Andhra Pradesh state are historically drought-prone when compared to the coastal region. During the period from 1921 to 1952, a total of 12 drought events were reported in the state. Droughts have been occurred continuously for three to four years, during different periods for example, from 1921 to 1924; 1933 to 1935; 1941 to 43, and 1950 to 52. During these periods more than one-third taluks of Rayalaseema region have been severely affected; the extensive damages caused to the agricultural production was a testimony to the severity of such droughts. During the 1980s five consecutive drought events occurred i.e. 1981-82, 1983-84, 1985-86, 1986-87 and 1987-88. The drought during 1981-82 had significantly affected the crops like jowar,bajra, pulses and groundnut (Memorandum on Drought, 1981). During 1984-85, considerable areas have been left fallow under both rainfed crops and paddy crops. Major historic drought events occurred in the state are given in Table 2.2.

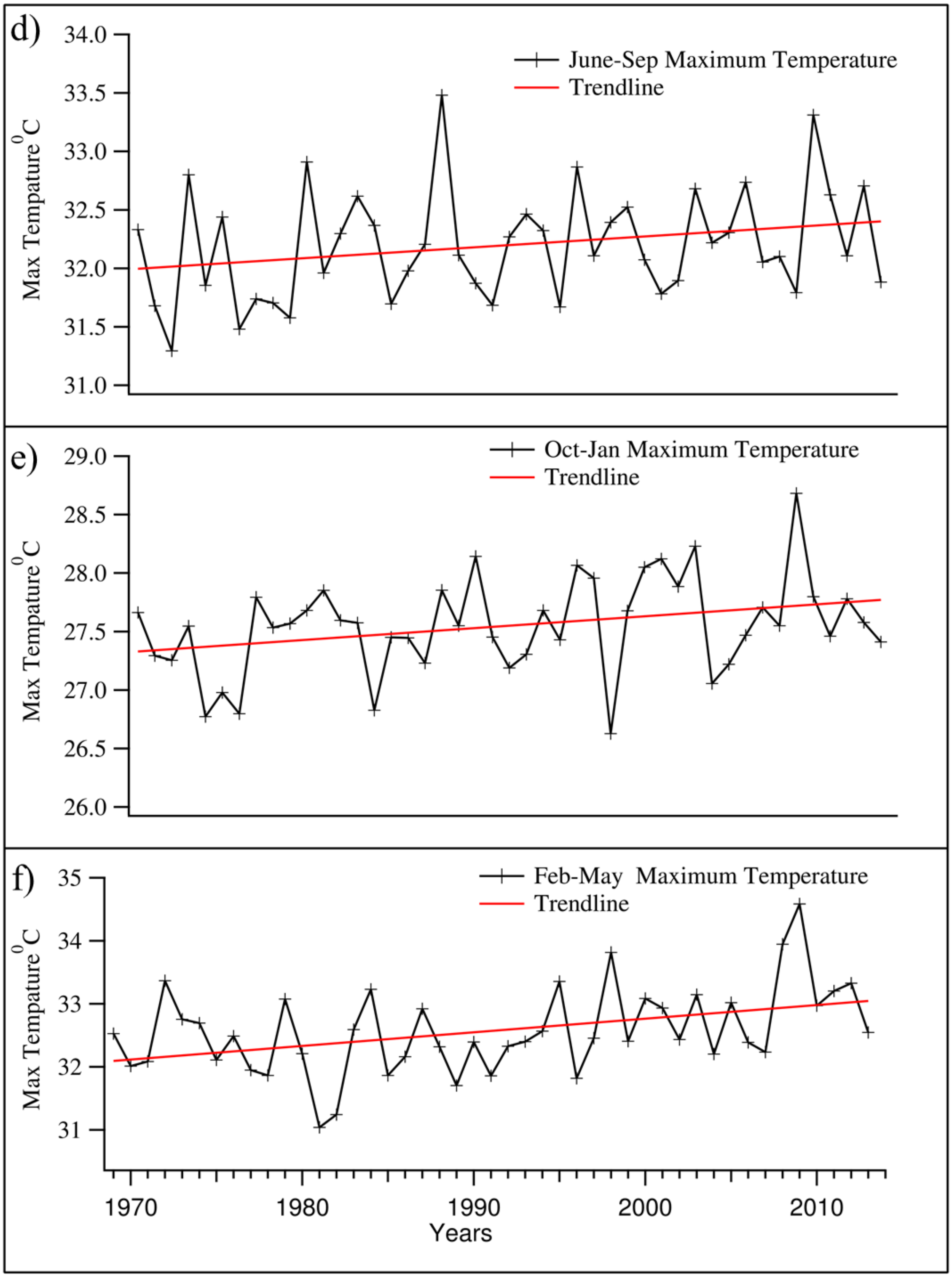
Table 2.2 Major historic drought events in Andhra Pradesh.

Year	Number of Districts affected	Factors affected by drought
1981-82	14	• Jowar, Bajra, pulses and groundnut
1983-84	20	• Both Kharif and Rabi crops • water scarcity
1984-85	19	• Groundnut • Rain-fed crop area left fallow
1985-86	19	• 25% of laborers were affected • Out of a total population of 29, 56,798 vulnerable to drought, 10, 01,518 were affected by drought.
1986-87	14	• Out of a population of 90, 51,631 vulnerable to drought 31, 27,005 were affected by drought.
1987-88	14	• 42% of the area was left as fallow; 25.03 lakh of agricultural laborers, small and marginal farmers affected; and • A total population of 76,61,676 were vulnerable to drought out of which 25,03,050 persons were affected by the drought.
1992-93	7	A decline in crop yield.

(*Source: Govt, of A.P., Memorandum on Drought 1981-82 to 1992-93)

There was a decline in the growth rate of black gram, chickpea, groundnut, and sunflower crops during 1991-2005. The average annual index of total factor productivity during 1995-2000 period was 5% less than that during the 1980s in the state (Rama Rao et al., 2008). As per the report of irrigation department (1972), Ananthapur district was identified as severely affected drought-prone area. Other drought-prone districts of the state are Chittoor, Y.S.R. Kadapa, Kurnool, Mahbubnagar, Nalgonda, Rangareddy and Prakasam (rain-shadow) (Manual for Drought Management, 2009). The impact of drought severity varies across location and crops. According to South Asia Environment and Social Development Department World Bank's report (2005), the rice yield was reduced to 62 % in the Kurnool district due to severe drought. The state has been bifurcated into two independent states namely, Telangana (TS) and Andhra Pradesh (AP). The new state of Telangana was formed on 2 June 2014. The APcomprises of 13 districts of Coastal Andhra and Rayalaseema regions, whereas TS comprises of 10 districts. The present study performs the long-term agricultural performance and stress/ drought and assessment of agricultural drought vulnerability for all 23 districts of undivided Andhra Pradesh. Hyderabad district is excluded in the present study because it does not contain significant agricultural area according to the statistics report of the state (Vamsi, 2004).


a)
June-Sep Rainfall
Trendline
Rainfall (mm)
b)
Oct-Jan Rainfall
Trendline
Rainfall (mm)
c)
Feb-May Rainfall
Trendline
Rainfall (mm)
Years


d)
June-Sep Maximum Temperature
Trendline
Max Tempature ^{0}C
34.0
33.5
33.0
32.5
32.0
31.5
31.0
e)
Oct-Jan Maximum Temperature
Trendline
Max Tempature ^{0}C
29.0
28.5
28.0
27.5
27.0
26.5
26.0
f)
Feb-May Maximum Temperature
Trendline
Max Tempature ^{0}C
35
34
33
32
31
1970
1980
1990
2000
2010
Years

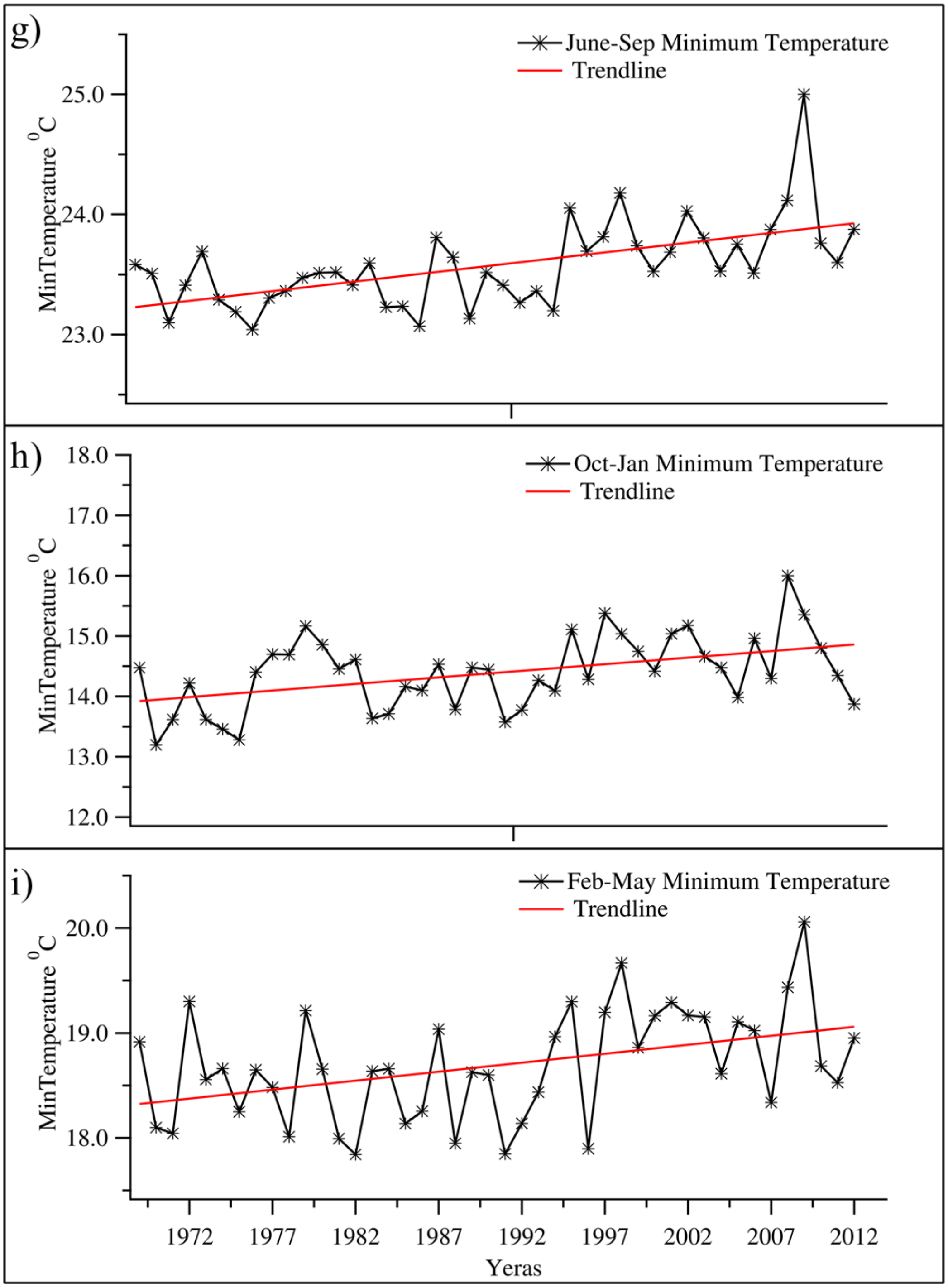
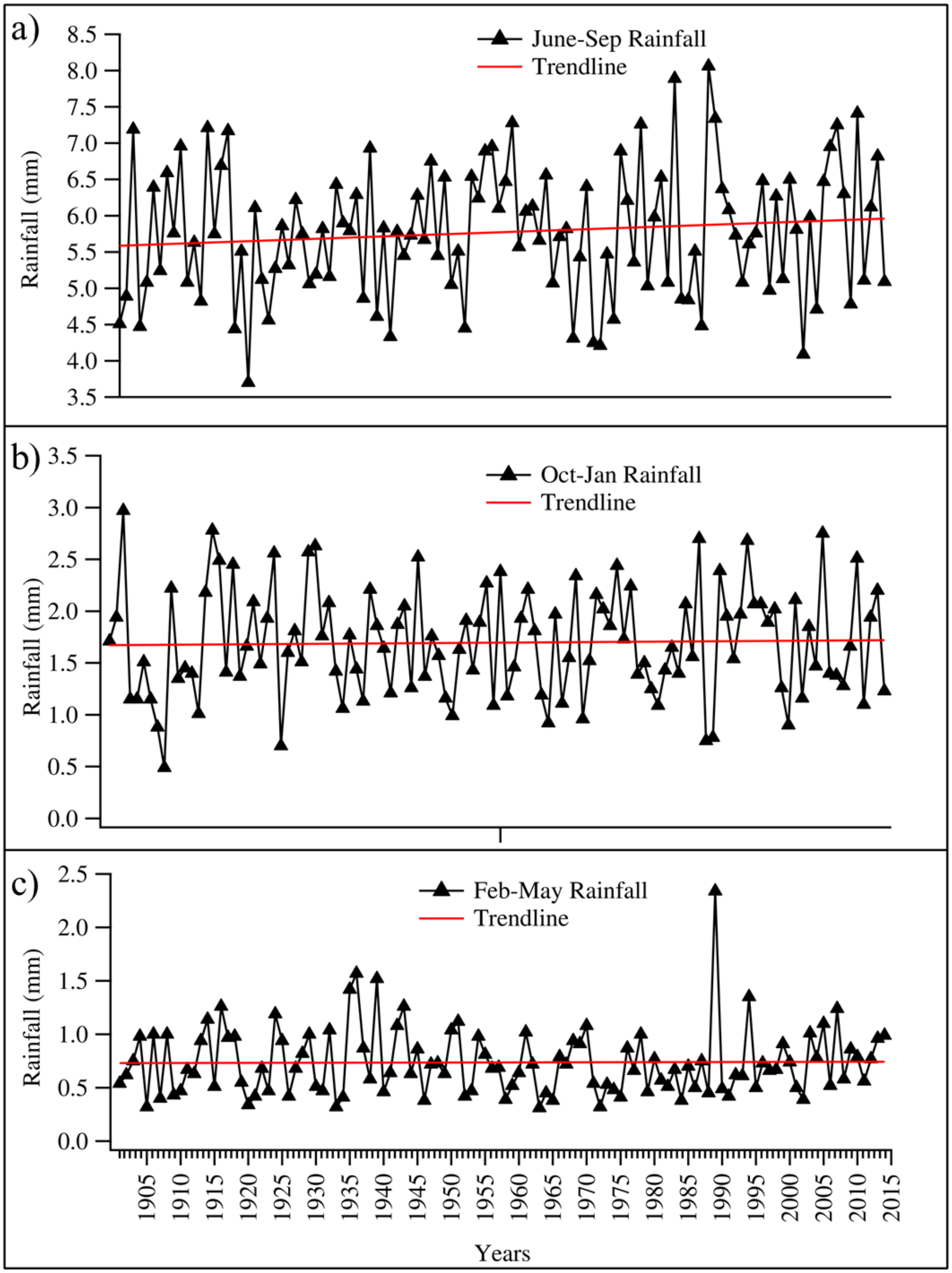
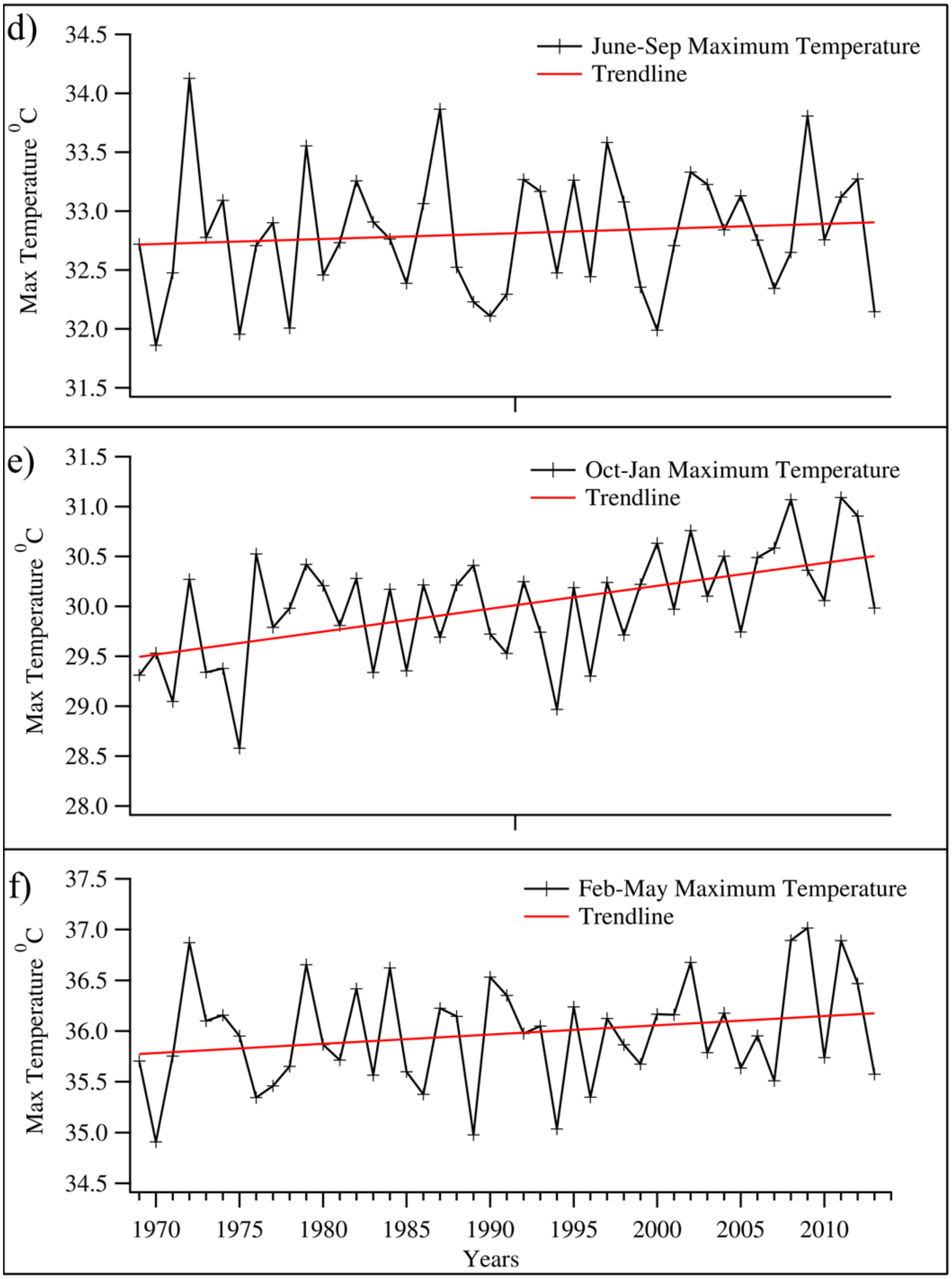


Figure 2.2 Long-term trend of rainfall (1901-2015), Maximum and Minimum temperatures (1969-2013) at the national level a) Summer monsoon rainfall; b)Winter rainfall; c)Summer rainfall; d) Summer monsoon maximum temperature; e) Winter maximum temperature; f) Summer maximum temperature; g) Summer monsoon minimum temperature; h)Winter minimum temperature; and i) Summer minimum temperature.


a)
June-Sep Rainfall
Trendline
Rainfall (mm)
b)
Oct-Jan Rainfall
Trendline
Rainfall (mm)
c)
Feb-May Rainfall
Trendline
Rainfall (mm)
Years


d)
June-Sep Maximum Temperature
Trendline
Max Temperature 0C
34.5
34.0
33.5
33.0
32.5
32.0
31.5
e)
Oct-Jan Maximum Temperature
Trendline
Max Temperature 0C
31.5
31.0
30.5
30.0
29.5
29.0
28.5
28.0
f)
Feb-May Maximum Temperature
Trendline
Max Temperature 0C
37.5
37.0
36.5
36.0
35.5
35.0
34.5
1970
1975
1980
1985
1990
1995
2000
2005
2010
Years

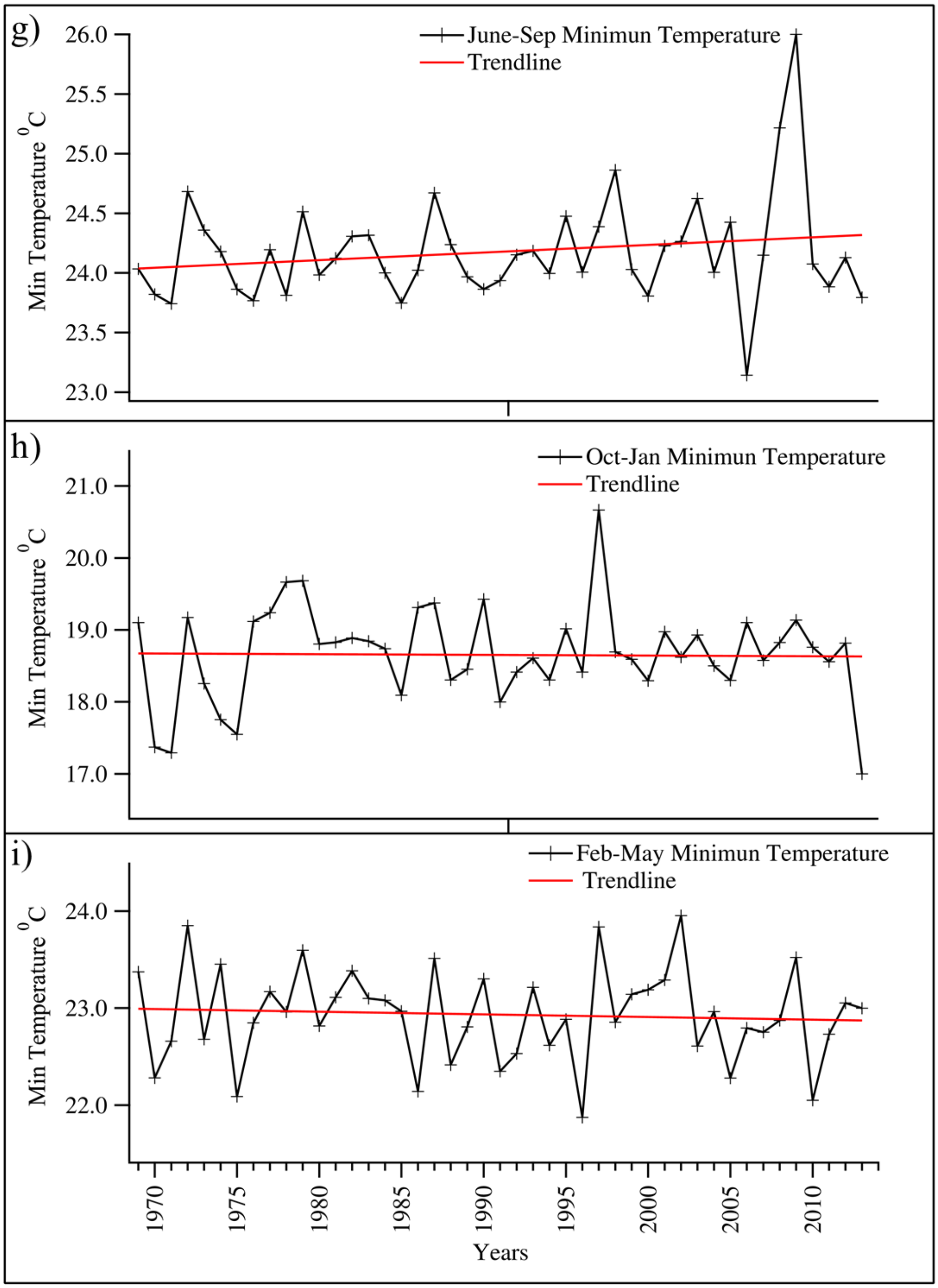


Figure 2.3 Long-term trend of rainfall (1901-2015), Maximum and Minimum temperatures (1969-2013) at the state level (undivided AP) a) Summer monsoon rainfall; b)Winter rainfall; c)Summer rainfall; d) Summer monsoon maximum temperature; e) Winter maximum temperature; f) Summer maximum temperature; g) Summer monsoon minimum temperature; h)Winter minimum temperature; and i) Summer minimum temperature

CHAPTER THREE

Materials and Methods

3.1 Objectives

The objectives of the study are to

i) capture the agriculture stress and drought condition using satellite-derived NDVI and climate (rainfall) derived indices,

ii) perform time series analysis between the derived length of the growing period (LGP) with climate and soil moisture during 1982-2015, and to project 2050 agricultural NDVI for IPCC AR5 2050 RCP 2.5 climate scenario,

iii) compute and assess the agricultural drought vulnerability in undivided state of Andhra Pradesh (both Telangana and Andhra Pradesh regions) at meso-level (district level) using GIMMS and MODIS satellite data (1982-2015) and at micro-level (tehsil level) using MODIS satellite data (2000-2015), and the future vulnerability in three cropping seasons (only at district level) for the projected climate scenarios developed using four Representation Concentration Pathways.

3.2 Material used

The present study uses the satellite data sets namely, bimonthly NOAA AVHRR GIMMS (Global Inventory Modelling and Mapping Studies) NDVI (Normalized Differential Vegetation Index), Terra MODIS (MODerate-resolution Imaging Spectroradiometer) fortnightly NDVI product, Landsat images, climate datasets i.e. precipitation, maximum and minimum temperatures, projected AR5 (Fifth Assessment Report) climate data, Land use land cover (LULC) maps, socio-economic and agriculture field and water resources data to assess the agricultural performance and its drought vulnerability.

3.2.1 Satellite data

3.2.1.1 NOAA AVHRR GIMMS NDVI

NOAA AVHRR GIMMS NDVI 3g.v1 (third generation version 1) bimonthly products with a spatial resolution of 8km × 8 km were downloaded from https://ecocast.arc.nasa.gov /data/pub/gimms/3g.v1/00FILE-LIST.txt. The data is derived from imagery obtained from the Advanced Very High Resolution Radiometer (AVHRR) instrument onboard the NOAA satellite series 7, 9, 11, 14, 16 and 17. These NDVI datasets have been corrected for calibration, view geometry, volcanic aerosols and other effects that are not related to vegetation change prior to analysis. The data contain global geographical projections (Geographic, WGS 1984). The GIMMS NDVI product is an 8-km resolution, 15-day maximum value composite (MVC) bimonthly global NDVI product generated from AVHRR data (daac.ornl.gov). The GIMMS NDVI raster data are in GEO TIFF format. The products are downloaded during 1982-2000 period for assessing agricultural stress. The continuous GIMMS NDVI 3g.v1 data available for the period 1982-2015 is used to assess the long-term time series trend of agriculture growth/stress and to compute Length of the Growing Period (LGP).

3.2.1.2 Terra MODIS

Terra MODIS fortnightly NDVI products [MOD13A2] were downloaded from LP DAAC (https://lpdaac.usgs.gov) for the period 2000-2015. The product is at a 1km*1km resolution as a gridded level-3 product in the Sinusoidal projection. The 16-day composite vegetation indices (VI) is generated using an algorithm to ingest the two 8-day composite products that overlap the 16 days and employs a weighted temporal average if data is cloud free or a maximum value in case of clouds. The Terra MODIS NDVI products are in HDF format.

Landsat: Three seasons' Landsat satellite data for every five years (2000, 2010 and 2015) have been downloaded from GLCF (Global Land Cover Facility) to prepare land use land cover maps.

3.2.1.3 Land Use Land Cover (LULC) maps

The LULC map of the study area for the year 2005 has been downloaded from the Bhuvan (http://bhuvan.nrsc.gov.in/gis/thematic/index.php). This map has been used as a reference to prepare LULC maps of the years 2000, 2010 and 2015 following the procedure described by Roy et al. (2015).

3.2.1.4 Soil Moisture

Soil moisture plays an significant role in agriculture process, drought, and runoff generation. It is influenced by climate variations, thereby, shed an impact on the agriculture condition. Essential Climate Variable (ECA) global soil moisture data is generated using active and passive microwave space borne instruments.

The soil moisture data has been downloaded from European Space Agency (ESA) Climate Change Initiative (CCI) daily merged passive and active sensor data sets soil moisture at (0.25° × 0.25°) during 1982-2013 (ESA CCI SM v02.x) (http://esa-soilmoisture-cci.org/node/139). The layer depth soil moisture available is 0.5-2cm. The datasets are available in NetCDF (.nc) format and expressed in volumetric soil moisture units (m^3m^{-3}).

3.2.2 Soil Maps

Soil maps are downloaded from National Bureau of Soil Survey and Land Use Planning (NBSSandLUP), an Institute of Indian Council of Agricultural Research (ICAR). These maps consist of surface form, soil depth, parent material, particle size class, mineralogy, calcareousness, soil temperature regime, soil reaction (pH), slope, soil drainage, erosion, surface texture, salinity, sodicity, organic carbon (OC), surface stoniness, Cation-Exchange Capacity (CEC), and flooding. In the present study, soil depth, soil texture, and soil erosion parameters have been used to generate the available water holding capacity.

3.2.3 Climate data

3.2.3.1 Current data

Rainfall and Temperature (Maximum and Minimum Temperature):

The daily rainfall and temperature (maximum and minimum) datasets available at 0.25° × 0.25° and 0.5° × 0.5° from the India Meteorological Department (IMD) have been used in the present study (Pai et al., 2014).The rainfall data pertains to the period 1982–2014 whereas temperature data 1982 2013.

3.2.3.2 Future projected AR5 climate data

Rainfall and Temperature (Maximum and Minimum Temperature):

AR5 climate parameters are used as one of the indicators to project /assess future agricultural drought vulnerability (Bhavani et al., 2017b).

Future projected data available are the IPPC AR5 climate projections from global climate models (GCMs) for four representative concentration pathways (RCPs). The four RCPs are based on the emission of greenhouse gas concentration. The four RCPs viz., RCP2.6, RCP4.5, RCP6, and RCP8.5 are named after a possible range of radiative forcing values in the year 2100 relative to pre-industrial values. RCP2.6 assumes that global annual GHG emissions would be high during 2010-2020 and then declines noticeably thereafter. Emissions in RCP 4.5 will be very high around 2040, and then decline. In RCP 6, emissions reach high around 2080, then decline. In RCP 8.5, emissions continue to increase all through the 21st century. The GCM output was downscaled and calibrated (bias corrected) using World Clim 1.4 as baseline 'current' climate.

AR5 global gridded climate data with a spatial resolution of 30 seconds (1km*1km) have been downloaded from WorldClim- Global Climate data (http://www.worldclim.org/). The file format is GeoTiff. The monthly climate data i.e. minimum and maximum temperature, precipitation generated from Hadley Centre Global Environment Model version 2-Earth

System (HadGEM-ES) available for the periods 2050 and 2070 have been used in the study.

3.2.4 Socio-economic data

Socio-economic data sets are used as indicators of vulnerability. The available past datasets from 1966 to 2011 viz., population density, literacy rate, and livestock are downloaded from International Crop Research Institute for Semi-Arid Tropics (ICRISAT) Village Dynamics in South Asia (VDSA) (http://vdsa.icrisat.ac.in/) to generate/project the socioeconomic parameters for the year 2030. Socio-economic datasets of 2011 comprising of population density, literacy rate, migrant rural persons, and livestock are downloaded from Census of India.

3.2.5 Agricultural field data

The historic datasets from the 1960s pertaining to total agricultural labors, agriculture wages, and gross irrigated data are downloaded from Agricultural statistics. The present (2011) available field data i.e. agricultural labors (main and marginal), agriculture wages and agriculture consumption are downloaded from Census of India, ICRISAT VDSA and Commissioner -, Relief. The Gross Irrigated Area (GIA), Extent of Gross Irrigated Area (Ex. GIA), Surface Water (SW), Ground Water (GW) and the Net Irrigated Area (NIA) statistics of the state for the period 2000-2011 was downloaded from the ICRISAT VDSA and for the period 2012-2015 from the Agricultural Statistics of the groundwater planning department of AP (DACNET). Other field datasets ie, soil erosion and soil texture maps available for the year 2005 are downloaded from NBSSLUP and DAB (1960). Available crop production area during 2000-2012 downloaded from ICRISAT VSDA is also considered in the present study.

3.2.6 Institutional data

The Institutional data available for the year 2011 pertaining to agricultural credit society, commercial banks, agricultural marketing society and road networks are downloaded from Census of India at Tehsil level

3.3 Methodology

3.3.1 Agriculture performance and stress assessment

3.3.1.1 Pre-processing

Preparation of agriculture mask from LULC maps:

The LULC map of the year 2005 was overlaid on the LANDSAT data of the years 2000, 2010 and 2015 to derive the respective LULC maps by appropriately modifying the theme polygon wherever the changes are observed (Bhavani et al., 2017a). The LULC maps of 2000, 2005, 2010 and 2015 are used to identify the agricultural area (cropped and currently fallow) using the maximum area under agriculture during 2000–2015.

3.3.1.1.1 NOAA GIMMS NDVI processing

The downloaded NOAA AVHRR GIMMS NDVI data were multiplied by a scale factor of 0.004 (ftp://gimms.gsfc.nasa.gov/MODIS/README.txt) and subset the study area. The bimonthly NDVI products from 1982 to 2000 were stacked in sequence for the three cropping seasons, namely Kharif/summer monsoon (June–September), rabi/winter (October–February) and zaid/summer (February–May). The stacked seasonal NDVI files are then masked out for the non-agricultural areas using the LULC mask prepared from the LANDSAT data. The seasonal agriculture NDVI files (1982–2000) are used to generate NDVI anomalies using the equation.

$$NDVI_{Dev} = X_i - X_m \,, \tag{3.1}$$

where, $NDVI_{Dev}$ represents NDVI anomaly, X_i is seasonal NDVI and X_m is historic long-term mean NDVI of a particular season.

3.3.1.1.2 MODIS NDVI processing

The Terra MODIS fortnightly NDVI products downloaded from the LP DAAC data pool are projected onto the geographic coordinates with the WSG84 datum. The fortnightly NDVI layer was further refined by removing the cloud-covered and other unreliable pixels using the quality flag provided with the NDVI product. The fortnightly NDVI products from 2000 to 2015 are stacked in sequence for the three cropping seasons, namely Kharif/summer monsoon (June–September), rabi/winter (October–February) and zaid/summer (February–May). Following the procedure described in the above section, the non-agricultural areas are masked out to prepare the MODIS agricultural NDVI files. The agricultural area includes the cropped area and the currently fallow land.

3.3.1.2 Processing of data

3.3.1.2.1 Extraction of agricultural/cropped area

The masked agriculture NDVI was considered as potentially cultivable area. However, due to lack or insufficient rainfall and other reasons the potential cultivable area may not fully sow every year. Hence, the percentage of cropped and fallow land varies each year. In order to extract the cropped area of each season (during 2000–2015), NDVI thresholds were determined on the basis of sampled ground data. The thresholds are then used for hierarchical image classification (Bikash, 2006; Brian et al., 2008) (Fig.3.1). Ananthapur, Kurnool and YSR Kadapa districts (summer monsoon); Adilabad, Ananthapur, Mahbubnagar, Medak, Nizamabad, and Rangareddy districts (winter) are given different thresholds (Table 3.1) according to ground truth and varied cropping practices (Table 3.2) (Bhavani et al., 2017a).

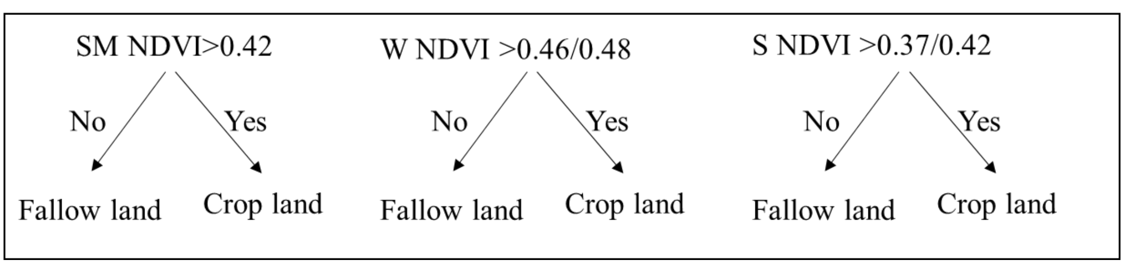


Figure 3.1 NDVI threshold for each season for cropped land.
SM: summer monsoon, W: winter, S: summer season.

Table 3.1 NDVI threshold for districts having different cropping pattern for the cropland (Bhavani et al., 2017a)

Districts / Season	1	2	3	4	5	6	7
SM	NDVI >0.327	NDV I > 0.366	NDVI > 0.37	-	-	-	-
W	NDVI >0.347	-	-	NDVI > 0.38	NDVI > 0.44	NDVI > 0.40	NDVI >0.407

1: Ananthapur; 2: YSR Kadapa; 3: Kurnool; 4: Mahbubnagar; 5: Medak; 6: Nizamabad; 7: Rangareddy

The percentage crop areas (CA%) in different cropping seasons during the period 2000–2015 are generated using the equation (Bhavani et al., 2017a)

$$CA\% = \frac{\text{No. of cropped pixels}}{\text{Total no. of agriculture pixels}} * 100, \tag{3.2}$$

The ratio of the cropped area (RC) to the potential cultivable area in each district is calculated by (Bhavani et al., 2017a)

$$RC = \frac{\text{Cropped Area}}{\text{Agricultural land}}, \tag{3.3}$$

The ratio of crop area (%) fluctuation is (RCF) calculated using the following equation to capture the sensitivity of crop stress due to the variability in rainfall.

$$RCF = \frac{\text{Xmax}}{\text{Xmin}}, \tag{3.4}$$

where, Xmax and Xmin are the long-term maximum and long-term minimum of the crop area (%).

Table 3.2 Details of crop cultivation in undivided Andhra Pradesh (Bhavani et al., 2017a)

Seasons / Districts	Kharif		Rabi			Zaid
	Rainfed	Irrigation	Rainfed	Irrigation	Vegetable Rainfed	Irrigation
Adilabad	Cotton, Pigeon pea, Soybean	Rice	Sorghum, Chickpea, Cowpea		Chilies, Tomatoes, Bhendi, Coriander, Brinjal	
Ananthapur	Groundnut, Pigeon pea, Sorghum	Rice, Groundnut	Sorghum, Chickpea, Sunflower	Rice, Groundnut	Chilies	
Chittoor	Groundnut, Pigeon pea	Rice, Groundnut		Rice, Groundnut, Sugarcane, Sunflower	Chilies	
YSR Kadapa	Groundnut, Sunflower, Cotton	Rice	Sunflower, Chickpea	Rice, Groundnut	Chilies	
East Godavari		Rice, Sugar cane		Rice	Chilies, Gourds, Bhendi, Brinjal	Green gram, Black gram
Guntur		Rice, Cotton	Black gram, Tobacco	Rice, Maize	Chilies, Gourds, Bhendi	
Karimnagar	Cotton, Pigeon pea, Green gram	Rice, Maize, Cotton.	Cowpea	Rice, Maize	Chilies	
Khammam	Cotton, Maize, Green gram, Pigeon pea	Rice, Maize, Cotton	Maize, Green gram, Cowpea	Rice, Maize	Chilies, Tomatoes	
Krishna		Rice, Cotton, Maize	Black gram, Tobacco	Rice, Maize, Sugarcane, Tobacco	Chilies, Bhendi	

Kurnool	Groundnut, Sunflower, Pigeon pea, Sorghum	Rice	Chickpea, Sorghum	Rice, Groundnut, Sunflower, Sorghum	Chilies	
Mahbubnagar	Maize, Castor, Rice, Sorghum, Pigeon pea, Groundnut	Rice	Sorghum, Horse gram	Groundnut, Maize, Rice	Chilies, Tomatoes	
Medak	Maize, Sorghum, Green gram, Cotton, Black gram	Rice	Sorghum, Chickpea, safflower	Maize, Rice, Groundnut, Sunflower	Chilies	
Nalgonda	Cotton, Castor, Groundnut, Pigeon pea	Rice	Horse gram, Cowpea, Pigeon pea	Groundnut, Rice	Potato	
SPSR Nellore		Rice, Sunflower Groundnut	Black gram, Green gram, Sunflower, Chickpea	Rice, Sugarcane, Groundnut	Chilies	Cotton
Nizamabad	Cotton, Pigeon pea, Green gram, soybean, Black gram, Rice	Rice, Maize, Sugarcane	Chickpea, Sunflower	Rice, Maize	Tomatoes	
Rangareddy	Cotton, Maize, Pigeon pea, Sorghum	Rice	Maize, Sorghum, Chickpea	Maize	Tomatoes	
Prakasam	Pearl millet	Rice, Cotton, Pearl millet	Tobacco, Sunflower	Rice, Chickpea, Groundnut, Sunflower	Chilies, tomato	
Srikakulam	Mesta, Sesame	Rice, Sugar cane	Green gram, Horse gram	Rice, Groundnut	Chilies	

Visakhapatnam	Rice, Finger millet	Rice	Horse gram	Rice, Sugarcane, Groundnut	Chilies, gourds, tomato, beans, brinjal	
Vizianagaram	Mesta, Sesame	Rice	Black gram, Green gram, Maize, Groundnut, Rice, Horse gram	Rice	Chilies	
Warangal	Cotton, Maize, Pigeon pea, Green gram, Groundnut, Rice	Rice, Maize, Cotton, Sugarcane, Sunflower	Pigeon pea, Sorghum, Chickpea, Pearl millet, Rice, Cowpea	Rice, Maize Groundnut	Chilies	
West Godavari		Rice, Sugar cane, Maize, Sesame	Black gram	Rice, Maize, Tobacco, Groundnut, Sunflower, Black gram	Chilies	

NDVI anomaly ($NDVI_{Dev}$) and Vegetation Condition Index (VCI)

The vegetation indicators, namely the NDVI anomaly and VCI, provide alternative measures of the relative health of the vegetation. These indices can be used to monitor the areas where vegetation may be stressed, as a proxy to detect potential drought. The difference between the average NDVI for a particular fortnight of a given year and the average NDVI for the same fortnight over the last 15 years (MODIS NDVI 2000–2015) is called the NDVI anomaly (Tucker, 1979).

In most of the agro-ecosystems, the growth of vegetation is controlled by the quantity of water available, so the relative density of the vegetation becomes a good indicator of agricultural drought. The VCI compares the current NDVI with the range of values observed in the same period in previous years and can be expressed as in equation 1.3 (Kogan, 1995 and1997).

The VCI (expressed in %) gives an idea where the observed value is located in the range between the extreme values (minimum and maximum) of the previous years. Lower and higher values indicate bad and good vegetation conditions, respectively. The deviation of NDVI ($NDVI_{Dev}$) and VCI were used to assess the vegetation stress and vegetation growth conditions.

The percent NDVI deviation (1982-2000 and 2000-2015) was derived from the following equation for the agricultural area to assess the frequency of stress at the state and district levels (Bhavani et al., 2017a).

$$NDVI_{Dev}\,\% = \frac{(\text{No. of Negative } NDVI_{Dev} \text{ pixels})}{(\text{Total no. of pixels})} * 100, \qquad (3.5)$$

$$FrequencyNDVI_{Dev}\,\% = No.of\,\frac{years}{districts}\,NDVI_{Dev}\,\% > 50\%, \qquad (3.6)$$

The temporal and spatial extremities of agricultural performance were measured by aggregating the frequency of CAF and the frequency of $NDVI_{Dev}$ (percentage).

3.3.1.2.2 Standardized Precipitation Index (SPI)

The daily gridded data are converted into seasonal data for the three cropping seasons using the GrADS and ERDAS software. The seasonal rainfall data were used to derive the SPI using equation (1.4). The main advantage of SPI is that it can be compared across regions in different climatic zones. The gridded daily rainfall data of the IMD (0.25° × 0.25°) for the period from 1982 to 2015 (>30 years) are used to derive the SPI of the study area (Bhavani et al., 2017a). The NDVI, VCI, and $NDVI_{Dev}$ at the state and district levels are statically analyzed using R statistical package (http://openwetware.org/wiki/R_Statistics). The relation between the mean NDVI and the rainfall, surface water, groundwater and NIA is determined for the period 2000-2015 using simple and multiple linear regressions, and confidence level (p and t values). The overall approach is shown in Fig. 3.2.

3.3.2 Phenophase* and *Time series analysis

For continuous time series analysis of agriculture NDVI, phenol-phase matrices, its relation with climate (precipitation and maximum temperature) and soil moisture, and projection of agriculture NDVI for 2050 IPCC AR5 RCP 2.6 scenario, GIMMS NDVI 3g.v1 bimonthly pre-processed data have been used in addition to statistically computed data at the state level (TS and AP) . For grid wise projection of agriculture NDVI at three cropping seasons, raster bimonthly agriculture NDVI is converted to seasonal data for the period 1982-2015. The daily rainfall, temperature and soil moisture datasets have been converted to mean bimonthly, similar to that of the satellite GIMMS NDVI 3g.v1 and then subset the area of interest (AOI).

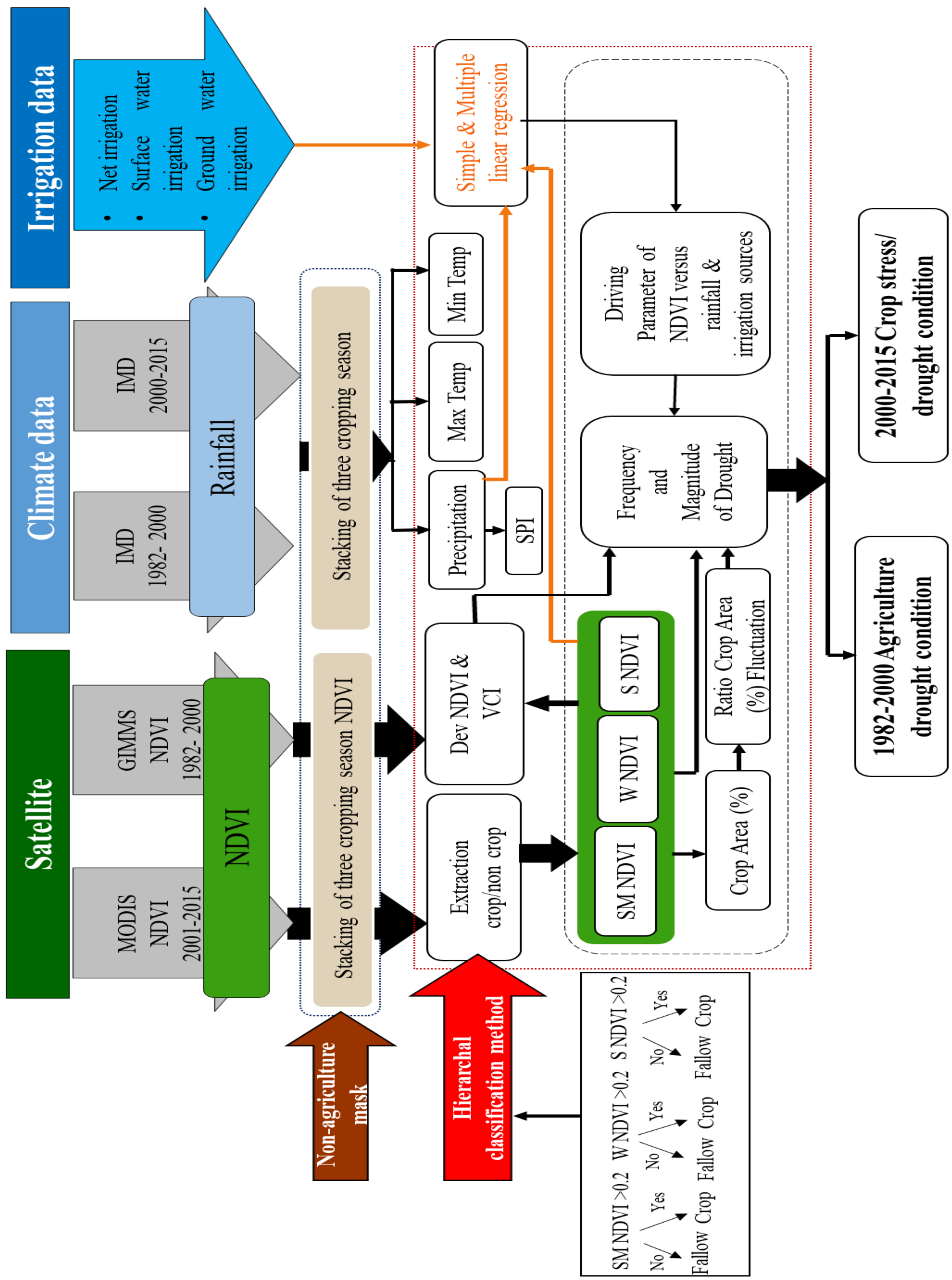


Figure 3.2 Schematic flow chart describing the methodology of assessing agriculture performance and stress.

3.3.2.1 Computing the length of growing period from phenophase events

The bimonthly agriculture NDVI data starting from June to January each year (1982- 2015) is considered, as June to January period (summer monsoon and winter cropping seasons) covers both kharif and rabi cropping seasons. Double logistic model (Klosterman et al., 2014) is fitted to time series agricultural NDVI to extract the phonological events i.e. start of the season (SOS), the peak of the season (POS) and end of the season (EOS) based on pheno first derivatives. SOS and EOS are the points where the NDVI profile crosses the threshold value in upward and downward directions respectively. The extracted pheno events for each year are mentioned in Table 3.3 (Bhavani et al., 2017b). The performance of fitting DL model, smoothing, and extraction of phenol-phase are done in R language phenoix package. LGP is computed from aggregated days from SOS to EOS events using the equation (3.7) (Bhavani et al., 2017b),

$$LGP = \sum SOS\ to\ EOS, \tag{3.7}$$

A similar procedure is repeated for each year during 1982-2015. Summation of bimonthly rainfall and soil moisture statistic datasets have also been done with similar NDVI pheno events i.e SOS to EOS, whereas for maximum temperature, the mean value is generated.

Table 3.3 Crop phenophase matrices during 1982-2015 for Telangana (TS) and Andhra Pradesh (AP)

	TS			**AP**		
Year	***SOS***	***POS***	***EOS***	***SOS***	***POS***	***EOS***
1982-1983	16-Jun	16-Oct	16-Jan	1-Sep	16-Nov	1-Jan
1983-1984	1-Oct	16-Oct	1-Dec	1-Oct	16-Oct	16-Nov
1984-1985	16-Jun	1-Oct	16-Jan	1-Sep	16-Oct	1-Dec
1985-1986	16-Jul	16-Oct	16-Nov	1-Oct	16-Oct	1-Dec
1986-1987	16-Jul	1-Oct	16-Nov	1-Oct	16-Oct	16-Nov
1987-1988	1-Aug	1-Nov	16-Jan	1-Oct	16-Oct	16-Dec

1988-1989	16-Sep	1-Oct	16-Nov	16-Aug	16-Oct	16-Nov
1989-1990	16-Sep	1-Oct	16-Nov	16-Sep	16-Oct	16-Nov
1990-1991	1-Jul	1-Oct	1-Nov	1-Sep	1-Nov	16-Dec
1991-1992	1-Sep	16-Oct	1-Dec	16-Sep	16-Oct	16-Dec
1992-1993	16-Aug	16-Oct	16-Dec	1-Sep	16-Oct	1-Dec
1993-1994	16-Aug	1-Oct	16-Dec	1-Sep	1-Nov	1-Dec
1994-1995	1-Sep	1-Oct	16-Nov	1-Aug	16-Oct	16-Nov
1995-1996	1-Sep	16-Oct	1-Dec	16-Aug	16-Oct	1-Dec
1996-1997	16-Aug	16-Oct	16-Dec	1-Sep	16-Nov	1-Dec
1997-1998	1-Aug	1-Oct	1-Dec	1-Sep	16-Oct	1-Dec
1998-1999	1-Jul	16-Oct	16-Jan	16-Jul	1-Nov	16-Jan
1999-2000	16-Sep	1-Oct	1-Nov	1-Sep	16-Oct	16-Dec
2000-2001	1-Sep	16-Sep	16-Jan	16-Aug	1-Dec	1-Jan
2001-2002	1-Sep	16-Oct	1-Dec	1-Sep	1-Nov	16-Dec
2002-2003	16-Aug	16-Oct	16-Dec	1-Sep	16-Nov	1-Jan
2003-2004	16-Jun	16-Oct	1-Nov	16-Sep	1-Nov	1-Jan
2004-2005	1-Sep	16-Oct	1-Dec	16-Sep	1-Oct	16-Dec
2005-2006	1-Sep	16-Nov	16-Dec	1-Sep	16-Nov	1-Dec
2006-2007	16-Sep	1-Oct	16-Jan	16-Sep	1-Oct	16-Jan
2007-2008	16-Sep	16-Oct	1-Dec	1-Sep	1-Nov	1-Dec
2008-2009	16-Aug	1-Oct	16-Nov	16-Aug	16-Oct	16-Nov
2009-2010	1-Aug	1-Oct	16-Nov	16-Aug	1-Oct	1-Mar
2010-2011	1-Sep	1-Oct	16-Jan	1-Sep	1-Oct	16-Jan
2011-2012	1-Sep	1-Oct	1-Nov	1-Sep	16-Oct	1-Dec

2012-2013	1-Sep	1-Oct	1-Feb	16-Aug	16-Nov	16-Dec
2013-2014	1-Sep	1-Oct	1-Jan	16-Aug	16-Sep	1-Jan
2014-2015	1-Jul	1-Aug	1-Oct	1-Sep	16-Oct	16-Nov

(SOS: Start Of Season; POS: Peak Of Season; EOS: End Of Season)

3.3.2.2 Long-term trend of Agriculture NDVI to the climate and soil moisture

The pre-processed agriculture NDVI of GIMMS and temperature data sets have been rescaled to 0.25 degree, to make them consistent with the rainfall gridded dataset of IMD. The converted bimonthly rainfall, maximum temperature, soil moisture and agriculture NDVI extracted at the state level during 1982-2015, starting from June 1982 to May 2015. To these datasets, applied decompose function using R statistical software. A decompose function is applied to these data sets using R software to obtain trend component, the seasonal component, and irregular component (Annexure 3.1 a-c). The relation of agriculture NDVI with climate variables and soil moisture is then studied for the study area using the graphical plots of time series trends (Bhavani et al., 2017b).

3.3.2.3 Projection of agriculture NDVI for AR5 2050RCP 2.6 Scenario

Grid wise projection of agriculture NDVI has been carried out predicted using multiple linear regression models based on the relationship of recent-past long-term (1982-2015) multiple variables i.e agricultural NDVI and climate data (rainfall and maximum temperature). Bimonthly multiple datasets have been converted into three seasons during the study period. Three raster datasets i.e., seasonal agricultural NDVI, rainfall and maximum temperature per year stacked, which consists of 32 raster layers each. Multiple linear regression has been performed using R programming script (Sahel studies, 2014). The parameters i.e slope, intercept, the coefficient of determination (R^2) and significance level (p-values) are extracted at grid level and plotted. R^2 values are used to examine the relationship between agricultural NDVI and climate datasets. Fig 3.3 shows the schematic flow chart describing the methodology.

The estimated parameters i.e slope and intercept from regression model along with IPCC projected AR5 climate data (i.e. rainfall and maximum temperature) for the year 2050 have been used to predict the 2050 seasonal agricultural NDVI at pixel level using the equation (3.8) (Bhavani et al., 2017b),

$$Y = a + b_1\beta_1 + b_2\beta_2, \tag{3.8}$$

Here, Y is predicted agriculture NDVI at grid wise, a is intercept value on Y; b_1 and b_2 are slopes of two independent variables (rainfall and maximum temperature) and $\beta_1 and\ \beta_2$ are observed/projected AR5 independent climate variables (rainfall and maximum temperature).

3.3.3 Agricultural drought vulnerability assessment

The agriculture drought vulnerability index (ADVI) is calculated using IPCC framework (2007). IPCC defines vulnerability (V) as the composite index of exposure (E), sensitivity (S) and adaptive index (AC). In the context of climate change, exposure is defined as "the nature and degree to which a system is exposed to significant climatic variation" (IPCC, 2001), sensitivity of the system to climate change is defined as "degree to which a system is affected, either adversely or beneficially, by climate variability or change" (IPCC, 2007), and adaptive capacity is defined as "the ability (or potential) of a system to adjust successfully to climate change" (IPCC, 2007). The study uses ADVI at both district and tehsil levels during three cropping seasons. Table 3.4 summarizes the description of data used in ADVI assessment.

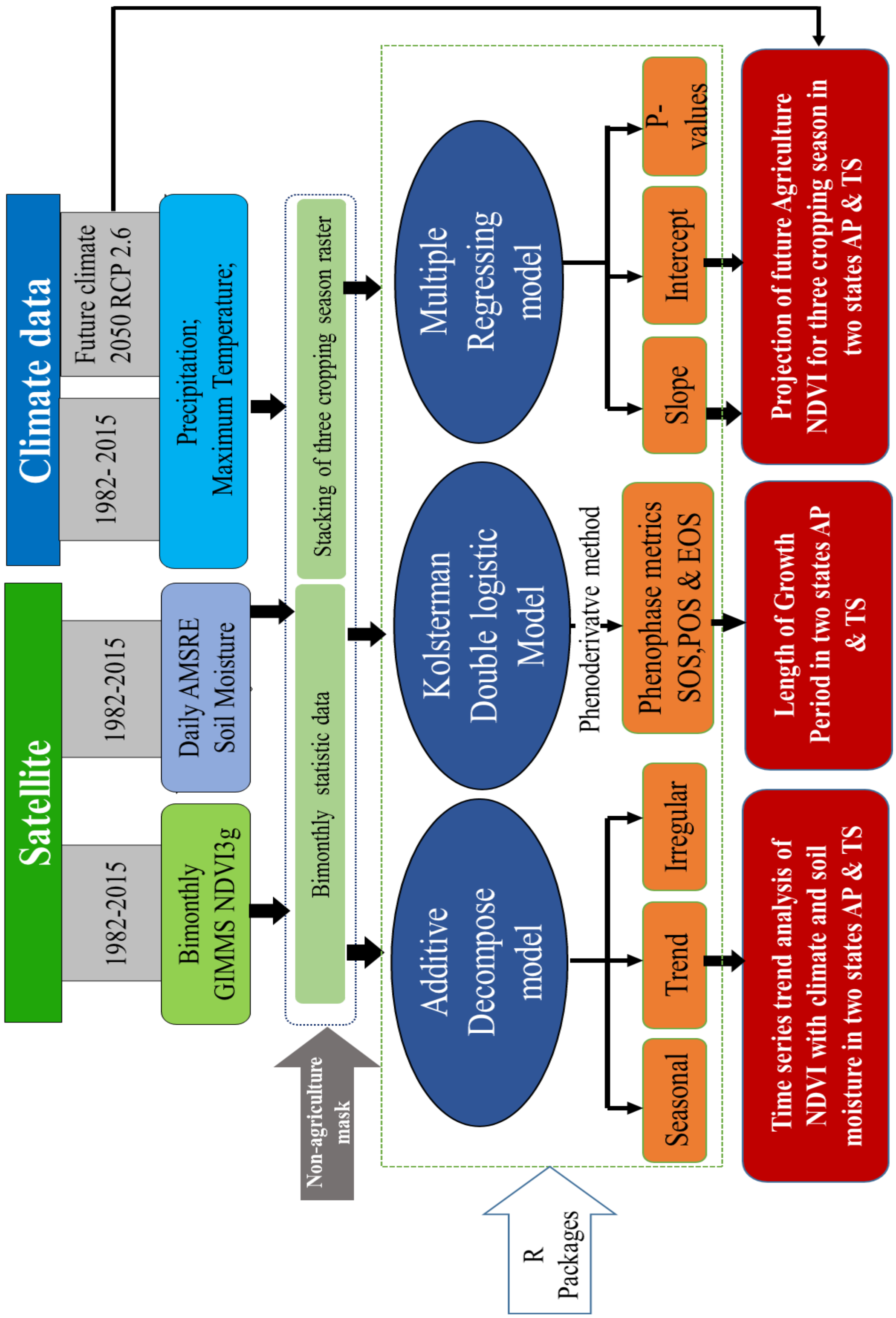


Figure 3.3 Schematic flow chart describing the methodology of phenophase and time series analysis.

Table 3.4 Description of data used in the study (Bhavani et al., 2017b)

Variables		**Measurements**	**Sources**
Satellite (1982-2015 & 2000-2015)			
GIMMS & MODIS NDVI	Drought Frequency (June-September, October-January and February-May)	It is generated from frequency of deviation of NDVI. It is used to assess the drought prone level. $DevNDVI = (NDVIi - NDVImean)$	LP DAAC http://reverb.echo.nasa.gov/reverb
	VCI (June-September, October-January and February-May)	It can estimate the status of vegetation according to best and worst vigour over a time period. It is derived from NDVI time series product. It has a negative relation with vulnerability. $\frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$	Kogan (1997)
MODIS NDVI	% Ratio of crop fluctuation (June-September, October-January and February-May)	It is used to capture the percentage crop variation during 15 years period.	
Climate data (1982-2014 & 2000-2014)			
Rainfall	Present (June-September, October-January and February-May)	15 years annual and two separate cropping calendar (January-May & June-December) mean Rainfall. Good monsoon controls the effect of drought.	IMD

		Thus it is negatively related to vulnerability.	
	Future (June-September, October-January and February-May)	AR5 RCP 2.6 & 4 Scenarios	WorldClim data
Temperature	Maximum Minimum	15 years (Annual, January-May &June-December) monthly max and mean temperature. Temperature has an impact on agriculture It is negatively related to vulnerability.	IMD
	Future (Maximum and Min temperature)	AR5 RCP (2.6, 4.5, 6 & 8.5) Scenarios	WorldClim data
Socio-Economic	% Migrants Rural Persons	It is the percentage of the migrant rural population to that of total migrant's population. It has a positive relationship with vulnerability.	Census of India
	Total Agriculture Rural Labours	The sum of main and marginal agriculture labor. It has a positive relation with vulnerability.	
	Population Density	It is the ratio of total population to that of total geographical area. Population density is positively related to vulnerability.	

	% Total Literacy	It is the percentage of total literacy person to that of total population person. It is negatively related to vulnerability, more the literate results more awareness to adapt about the climate change and agriculture vulnerability.	
	% Rural Literacy	It is the percentage of total rural literacy person to that of total rural population person. It is negatively related to vulnerability, more the literate results more awareness to adapt about the climate change and agriculture vulnerability.	
	Live Stock	It supports agriculture through animal power and manure and also to farmers' alternate source of income. Thus, it has a negative relation with vulnerability.	ICRISAT
	%Net cropped Areas	Total area sown at least once in particular year. It has a positive relation with vulnerability.	Agricultural Statistic Glance;
	% Gross Cropped Area	Total area sown more than one time in particular year. It also has a positive relation with vulnerability.	
	Extent of Gross Irrigated Areas	Total area irrigated only once in a year. Irrigation facility is adapted to overcome moisture stress require for the crop productions. Have a negative relation.	

	Gross Irrigated Areas; Total Irrigated Land area	Total area irrigated more than once in a year. Irrigation facility is adapted to overcome moisture stress require for the crop productions. It is negatively related to vulnerability.	Census of India (http://censusindia.gov.in/)
	Agriculture Power Consumption	It has a impact on various dimension i,e. improvement of education, health, standard living, demand Irrigation is adopted by supply of electricity. It is negatively related with vulnerability.	
Filed	Soil Erosion	Soil degradation leads to the reduction in soil fertility which impacts on agriculture. Positive relation with vulnerability	National Bureau of Soil Survey and Land Use Planning (NBSSLUP)
	% Non-Cropped Area	The total % of Barren & Un-cultivable land area and% of the Cultivable wasteland area.	Census data
	Available Water Holding Capacity	It is computed using soil texture with standard water holding capacity values for particular textures. Negative relation with vulnerability.	NBSSLUP, Department of Agriculture Bulletin (DAB) (1960)
Institutional Data	Agriculture Credit Society	Enable the farmers to adopt modern technology and improve agricultural practices for increasing agricultural production and productivity. Thus, has a negative impact on vulnerability.	Census of India
	Commercial Banks		

	Road Networks	Agrarian communities are highly dependent on a reliable transport system. Thus has a negative relation with vulnerability.	
	Agriculture Marketing Society	These societies provide marketing facilities and make arrangements for the supply of agricultural necessities and consumer articles in the rural area. Thus has a negative relation with vulnerability.	

ADVI is calculated based on four steps i.e identification of indicators, normalization, ranking, the weighting of indicators using Analytical Hierarchy Process (AHP).

- **Identification of indicators**

Parameters of each indicator (E, S, and AC) for vulnerability analysis is identified based on the previous studies (Singh et al., 2014; Murthy et al., 2014 and 2015). Redundancy analysis is carried out to finalize the list of indicators to improve the vulnerability analysis at district and tehsil levels. This has helped to reduce the dimensionality of parameters for vulnerability assessment.

Climate data sets namely precipitation, maximum and minimum temperatures have been considered to determine the exposure indicator for present ADVI. The long-term time series (1982-2014), average seasonal precipitation, maximum and minimum temperatures have been computed. The computed seasonal average of the three climate parameters has been extracted at district and tehsil level.

Projected AR5 2050 and 2070 monthly climate data (precipitation, maximum and minimum temperature) at 1km spatial resolution has been converted into three cropping seasons and the values are extracted at the district level.

Sensitivity indicator

Sensitivity is the degree to which the crops are influenced by the climate change. The increase in population, migration, agriculture labor are also sensitive to agriculture. Sensitivity indicators used in the study are the crop, moisture, soil conditions and socio related.

Agriculture Drought is the primary issue of agriculture drought vulnerability. Time series satellite data are essential to measure determine the response of vegetation to meteorological factor. Murthy et al. (2015) have demonstrated that crop/drought events and moisture condition can be well captured using the satellite-based data. Satellite-derived indices (GIMMS and NDVI), a few socio-economic parameters and agricultural field datasets have been used to determine the sensitivity indicator. The integrated satellite GIMMS and MODIS NDVI data sets have been used to generate the Vegetation Condition Index (VCI) and Number of drought frequency (No. DF) using equations 1.5 and 1.7. The long-term time series (1982-2015), average seasonal VCI have been computed. % RCF computed at the district level (section 3.3.1) has been used. The satellite and seasonal derived parameters have been extracted at the district and tehsil levels.

Apart from satellite-derived parameters, a few socio-economic parameters viz., population density (Pop. D), (ratio of population to that of total geographical area; percentage of migrated population (% MgR) (percentage ratio of total population to that of migrated population) and percentage of total agriculture labors (% T-AgL) (sum of main and marginal labors to that of total population) are also estimated and organized at the district and tehsil levels.

Agriculture field parameters i.e. soil erosion and soil texture maps (2005) have been obtained at district and tehsil levels. Using the ID of the extracted soil texture maps and the water holding capacity values (Department of Agriculture Bulletin, 462, 1960), the Available Water Holding Capacity (AWHC) has been computed.

Some of the agricultural field and socio-economic parameters i.e population and agriculture labors are projected using the available past datasets. The projections of parameters (population and agricultural labors) are the aggregation of decadal growth rate. The population of Andhra Pradesh and Telangana (TS) regions is considered to be stabilized by the year 2030. Hence, the projection of parameters is computed for the year 2030.

Adaptive Capacity: The indicators of Adaptive Capacity are related to crop and farms economy coping facilities. The increase in literacy levels will improve the ability of people to retrieve the information and manage the adversities, resulting in reduced vulnerability (Leichenko and O'Brien, 2002). The agriculture power consumption helps the agriculture/crop area with well irrigation. The credit and bank facility enables the farmers to adopt modern technologies to improve the agricultural practices for increasing agricultural production and productivity. Therefore, the parameters used from the available field and socio-economic practices are the gross irrigated area (GIA), agriculture power consumption (AgP), agriculture wages (AgW), number of total and rural literates and livestock at the district level. All these parameters have been organized at the district and tehsils levels. Additional available institutional data i.e. agriculture credit society, agriculture marketing society, commercial bank and road networks data are considered and organized at tehsil level.

Similar to sensitivity indicator, total and rural literacy rate, livestock, agriculture wages and gross irrigated area (GIA) are projected using past available data. The projections of parameters are the aggregation of decadal growth rate at district level only. The finalized parameters in each indicator are given in Table 3.5 and the approach of ADVI calculation in Table 3.6.

The sensitive and exposure indicators i.e., satellite-derived indices and climate parameters vary seasonally, hence, these parameters are changed during the assessment of ADVI in three seasons.

Normalization

Because of the fact that the selected parameters of each indicator have different units and scales normalization was carried out using the equations (Bhavani et al., 2017a)

$$Y_{ij} = \frac{X_{ij} - MIN(X_{ij})}{MAX(X_{ij}) - MIN(X_{ij})}, \tag{3.9}$$

$$Y_{ij} = \frac{MAX(X_{ij}) - X_{ij}}{MAX(X_{ij}) - MIN(X_{ij})}, \tag{3.10}$$

Here, X_{ij} represents the actual value of the indicator i for the district j, where i and j can vary from i=1,2, 3.., n; j =1,2,3…, m. $MIN(X_{ij})$ and $MAX(X_{ij})$ are the minimum and maximum values of the indicator i. If the indicator has a positive relationship with vulnerability, equation (3.9) is used for normalization; else equation (3.10) is used.

After normalization, weights for each component of indicators are determined using the Analytical Hierarchy Process (AHP) method (Saaty, 1980) adapted from Cheng et al. (2010) and Miura (2013) for vulnerability analysis.

Weights/Ranks

Each normalized parameter is categorized into 5 ranks during three cropping seasons. Higher the normalized value in each parameter of each indicator higher is the rank. Rank listed for each indicator of three components district wise is shown in Tables 3.7 to 3.9.

AHP: The following steps are adapted to assign weights to each indicator of the parameters using AHP. Before doing the pairwise comparison, each indicator is scaled between 1 to 9 based on the priority of agriculture drought vulnerability (Table 3.10). The important indicator is assigned a value of 9 and least important indictor as 1 (Table 3.10). AHP is used to determine the pairwise comparison matrix for assigning relative weights to the indicators of two components i.e. sensitivity and adaptive capacity as shown in Table 3.11 to 3.13.

Table 3.5 Recent-past and future indicators finalized in each component (Bhavani et al., 2017b)

Indicators	**Parameter**	**District wise**			**Tehsils Level**	**Source**
		Present Period		**Future**		
		1982-2015	**2000-2015**			
Sensitivity	GCA	2011	2011	≈	N/D	Census of India
	DF	Generated from GIMMS and MODIS Deviation of NDVI	Generated from MODIS Deviation of NDVI	≈	N/D	Bhavani et al., (2017a)
	VCI	Derived from NDVI 1982-2015	N/D	≈	E*	Kogan (1997)
	% RCF	N/D	Generated from % cropped area	≈	E*	Bhavani et al., (2017a)
	S.Er	Vector Soil map available 2005	Vector Soil map available 2005	≈	E*	NBSSLUP
	AWHC	Generated using soil texture	Generated using soil texture	≈	E*	NBSSLUP & DAB (1960)
	Pop. D	2011	2011	**	2011	Census of India
	% T-AgL	2011	2011	**	2011	Census of India
	% MgR	2011	2011	≈	N/D	Census of India
	% NCA	N/D		N/D	2011	Census of India
	% NSA	N/D		N/D	2011	Census of India
	% LiT	2011	2011	**	-	Census of India
	% LiR	2011	2011	**	2011	Census of India
Adaptive Capacity	AgP	2011	2011	≈	2011	Agricultural Statistical glance & Census of India
	AgW	2011	2011	**	N/D	Census of India
	L/S	2011	2011	**	N/D	ICRISAT VDSA

	ExGIA		2011	2011	≈	N/D	Agricultural Statistical glance
	GIA		2011	2011	**	2011	ICRISAT VDSA
	TIA		N/D		N/D	2011	Census of India
	Ag-CrSo		N/D		N/D	2011	Census of India
	CoB		N/D		N/D	2011	Census of India
	RN		N/D		N/D	2011	Census of India
	Ag-Mr-So		N/D		N/D	2011	Census of India
Exposure	RF		1982-2014	2000-2014 ($0.25^{\circ}\times0.25^{\circ}$)	AR5, RCP Scenarios	E*	India Meteorology Department & World Climate
	Temp	Max Temp	1982-2013	2000-2013 ($0.25^{\circ}\times0.25^{\circ}$)		E*	
		Min Temp					

DF: No. of drought frequency; %RCF: Percentage ratio of Crop Fluctuation; VCI: Vegetation Condition Index; GCA: Gross Cropped Area; S. Er: Soil Erosion; AWHC: Available water holding Capacity; Pop. D: Population Density; T-AgL: Total Agriculture Labour; % MgR: Percentage of Migrants Rural; % NCA: % Non cropped area; %NSA: Percentage of Net Sown Area; %LiT: Percentage of Total Literacy; %LiR: Percentage of Rural Literacy; AgP: Agriculture Power Consumption; AgW: Agriculture Wages; L/S: Live Stock; ExGIA: Extent of Gross Irrigated Area; GIA: Gross Irrigated Area; TIA: Total Irrigated Land area; Ag-CrSo: Agriculture Credit Society; CoB: Commercial Banks; RN: Road Networks; Ag-MrSo: Agriculture Marketing Society; RF:Rainfall; Temp:Temperature; Min Temp: Minimum Temperature; Max Temp: Maximum Temperature; RCP: Representative Concentration Pathway; ≈: Same (1982-2015 or 2000-2015) present data; **: Generated 2030 using past 50 years data;
E*: Extracted data for Tehsils study area; and N/D: No Data.

Table 3.6 Approach for Agricultural Drought Vulnerability Index (ADVI) in Present and Future climate (after Shukla et al., 2015, Bhavani et al., 2017b)

Parameters used for agricultural drought vulnerability analysis							
Exposure			**Sensitivity**			**Adaptive Capacity**	
Current	**Future (2050 & 2070)**		**District**		**Tehsils**	**District**	**Tehsils**
			1982-2015	**2000-2015**			
• Long-term mean RF • Long-term mean Max Temp • Long-term mean Min Temp	RCP 2.5 RCP 4.5 RCP 6.0 RCP 8.5	• Annual Max Temp and Min Temp • Annual Mean Rainfall	• GCA • DF • VCI • S.Er • AWHC • Pop.D • % T-AgL • % MgR	• GCA • DF • % RCF • S.Er • AWHC • Pop.D • % T-AgL • %MgR	• % NSA • % RCF • VCI • % NCA • S.Er • AWHC • Pop.D • T AgL	• GIA • Ex GIA • AgW • AgP • L/S • % LiR • % LiT	• TIA • AgP • Ag-CrSo • CoB • %LiT • RN • Ag-MrSo
Analysis		Extraction of pre-processing Indicators					
		Normalisation of Indicators					
		Weights of indicators using AHP method					
GIS Analysis		Agricultural Drought Vulnerability index for all climate scenarios ADVI= ([E+S]-AC)					
		Overlay of district boundary to find the highest vulnerable zones					
		Generate vulnerability map					

(*Abbreviations are mentioned below Table 3.5)

Table 3.7 Ranks of each parameter of Sensitivity of vulnerability.

Districts	Common for all seasons						Summer Monsoon			Winter season			Summer season		
	GCA	S.Er	AWHC	Pop. D	% T-Ag.L	% MgR	DF 1982-15	VCI 1982-15	% RCF 2000-15	DF 1982-15	VCI 1982-15	% RCF 2000-15	DF 1982-15	VCI 1982-15	% RCF 2000-15
Adilabad	3	5	1	1	4	4	4	3	1	3	2	3	2	3	3
Ananthapur	4	1	5	1	4	4	5	5	3	5	5	2	2	4	1
Chittoor	2	1	5	1	4	4	1	3	1	3	1	2	2	1	1
YSR Kadapa	2	5	4	1	2	4	4	5	1	3	3	3	3	2	1
East Godavari	3	5	1	3	3	4	1	1	1	3	1	2	1	1	1
Guntur	4	1	2	4	2	4	4	3	1	3	1	2	2	2	1
Karimnagar	3	5	3	1	5	4	2	2	1	2	2	2	2	1	3
Khammam	2	5	4	1	5	4	2	2	1	2	1	1	1	2	2
Krishna	4	1	1	3	2	4	1	3	1	1	1	1	1	1	1
Kurnool	5	1	2	1	3	4	4	3	1	5	4	1	4	3	2
Mahbubnagar	5	5	3	1	5	5	5	3	5	5	5	5	3	5	5
Medak	2	1	3	1	5	5	3	1	1	4	3	3	3	3	5
Nalgonda	3	5	3	1	5	5	3	2	2	4	4	4	3	3	5
SPSR Nellore	2	5	1	1	4	4	4	4	1	3	2	2	1	1	1
Nizamabad	2	5	2	1	4	5	1	2	1	2	1	4	2	2	3
Prakasam	3	1	3	1	4	4	4	5	2	2	2	2	2	2	1
Rangareddy	1	5	1	5	1	2	3	3	1	5	4	4	3	5	2
Srikakulam	2	5	1	5	4	5	2	1	1	1	1	1	2	1	1
Visakhapatnam	2	5	1	3	3	3	1	1	1	2	1	1	1	2	1
Vizianagaram	2	5	1	2	4	4	2	1	1	1	1	2	2	1	1
Warangal	3	5	2	1	3	5	1	1	1	1	3	2	1	2	4
West Godavari	3	5	1	3	3	4	1	1	1	2	1	1	2	1	1

Table 3.8 Ranks of each parameter of Exposure of vulnerability

District	Summer Monsoon			Winter season			Summer season		
	RF	Max Temp	Min Temp	RF	Max Temp	Min Temp	RF	Max Temp	Min. Temp
Adilabad	1	2	2	5	4	1	5	5	1
Ananthapur	5	0	0	4	2	2	1	3	1
Chittoor	4	3	2	2	1	3	0	2	1
YSR Kadapa	5	3	2	3	2	3	3	3	2
East Godavari	3	0	4	2	1	4	3	0	3
Guntur	4	3	4	3	4	4	3	3	4
Karimnagar	2	1	3	5	3	1	4	4	2
Khammam	2	2	3	4	4	3	3	4	2
Krishna	3	1	4	3	2	4	3	3	3
Kurnool	5	2	2	4	2	3	3	2	3
Mahbubnagar	4	3	1	5	5	2	4	5	2
Medak	3	1	1	5	3	1	4	4	1
Nalgonda	1	1	3	2	3	3	1	4	3
SPSR Nellore	5	2	4	1	4	5	3	4	4
Nizamabad	2	5	1	5	3	0	4	3	1
Prakasam	5	1	5	2	3	5	3	4	5
Rangareddy	3	5	1	5	5	1	3	4	2
Srikakulam	3	1	3	3	3	1	1	4	1
Visakhapatnam	2	1	3	2	1	2	1	1	2
Vizianagaram	2	0	3	3	1	1	0	1	0
Warangal	2	0	3	5	1	2	4	0	3
West Godavari	3	2	5	3	4	5	3	4	5

Table 3.9 Ranks of each parameter of Adaptive Capacity of vulnerability

Districts	% LiT	% LiR	L/S	AgP	AgW	ExGIA	GIA
Adilabad	1	1	2	1	2	1	1
Ananthapur	2	2	5	3	1	1	1
Chittoor	5	5	2	3	2	1	1
YSR Kadapa	1	1	1	3	1	1	1
East Godavari	2	2	2	1	4	4	3
Guntur	1	1	1	1	3	5	4
Karimnagar	2	2	2	2	5	2	5
Khammam	2	2	1	1	1	1	1
Krishna	3	2	2	1	1	3	3
Kurnool	1	1	5	2	1	2	2
Mahbubnagar	1	1	2	5	1	1	2
Medak	1	1	3	4	1	1	1
Nalgonda	2	2	2	5	2	1	3
SPSR Nellore	1	1	2	2	2	2	3
Nizamabad	1	1	2	3	2	1	2
Prakasam	2	2	1	2	2	1	1
Rangareddy	3	2	1	2	1	1	1
Srikakulam	1	1	1	1	2	2	1
Visakhapatnam	1	1	1	1	1	1	1
Vizianagaram	1	1	3	1	1	1	1
Warangal	2	2	1	3	1	1	3
West Godavari	3	3	2	3	5	4	5

Table 3.10 District and Tehsil level scales/priority of indicators for each component

District						Tehsils					
Adaptive Capacity		**Sensitivity**		**Exposure**		**Adaptive Capacity**		**Sensitivity**		**Exposure**	
Indicators	Scale	Indicators	Scale	Indicators	Scale	Indicators	Scale	Indicators	Scale	Indicators	Scale
% LiT	1	% MgR	1	Min Temp	1	Ag-MrSo	1	T-AgL	1	Min Temp	1
% LiR	2	% T-AgL	2	Max Temp	3	RN	2	Pop.D	2	Max Temp	3
L/S	3	Pop.D	3	RF	9	% LiT	3	AWHC	3	RF	9
AgW	5	AWHC	4			CoB	5	S.Er	4		
AgP	6	S.Er	5			Ag-CrSo	6	% NCA	5		
ExGIA	7	% RCF,VCI	6			AgP	7	VCI	6		
GIA	9	DF	8			TIA	9	% RCF	7		
		GCA	9					% NSA	8		

(*Abbreviations as mentioned in Table 3.5)

Table 3.11 Pairwise comparison of different indicators of adaptive capacity and sensitivity

Item Number	**Item Number**	1.00	2.00	3.00	4.00	5.00	6.00	7.00
	Item Description	% LiT	% LiR	L/S	AgW	AgP	ExGIA	GIA
1.00	% LiT	1.00	1/2	1/3	1/5	1/6	1/7	1/9
2.00	% LiR		1.00	1/2	1/3	1/5	1/6	1/7
3.00	L/S			1.00	1/2	1/3	1/5	1/6
4.00	AgW				1.00	1/2	1/3	1/5
5.00	AgP					1.00	1/2	1/3
6.00	ExGIA						1.00	1/2
7.00	GIA							1.00

Table 3.12 Pairwise comparison of different indicators of sensitivity

Item Number	**Item Number**	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00
	Item Description	% MgR	T-AgL	Pop.D	AWHC	S.Er	VCI, % RCF	DF	GCA
1	% MgR	1.00	1/2	1/3	1/4	1/5	1/6	1/8	1/9
2	T-AgL		1.00	1/2	1/3	1/4	1/5	1/6	1/8
3	Pop.D			1.00	1/2	1/3	1/4	1/5	1/6
4	AWHC				1.00	1/2	1/3	1/4	1/5
5	S.Er					1.00	1/2	1/3	1/4
6	VCI, % RCF						1.00	1/2	1/3
7	DF							1.00	1/2
8	GCA								1.00

Table 3.13 Pairwise comparison of different indicators of exposure

Item Number	**Item Number**	1.00	2.00	3.00
	Item Description	Min Temp	Max Temp	RF
1	Min Temp	1.00	1/3	1/9
2	Max Temp		1.00	1/3
3	RF			1.00

Calculation of the priority vector

Each value of the element in the pairwise comparison of the matrix is divided by the sum of values in that column. The resultant matrix is called as normalized/synthesized pairwise comparison matrix (Sehgal et al., 2013). The priority vector is computed by row averaging of the resultant normalized/synthesized pairwise comparison matrix.

Consistency Ratio (CR)

The following steps are used to calculate the Consistency Ratio (CR)

i) Multiply the assigned weights and the respective values of the pairwise comparison matrix followed by the summation of each row values. The resultant yields the weighted sum matrix.
ii) Divide all the elements of the weighted sum matrix with their respective priority vector elements.
iii) Averages values to compute λ_{max} using the equation

$$\lambda_{max} = \frac{Sum\ of values}{n}, \qquad (3.11)$$

where n is the number of indicators in each component

iv) Then consistency index (C.I) is computed by

$$C.I = \frac{\lambda_{max} - n}{n - 1}, \qquad (3.12)$$

v) Select appropriate random consistency index (CIr) (Saaty, 1980) based on the size of the indicators/matrix (Table 3.14). CIr represents the randomly generated pairwise comparison of the matrix which depends on the size of the matrix (Sehgal et al., 2013).

vi) Then generate the consistency ratio, CR, using the equation.

$$CR = \frac{C.I}{CIr}, \qquad (3.13)$$

Higher the value of CR, lower the consistency in assigning priority of the indicator. Pairwise comparison of matrix with level of consistency of components' adaptive capacity, sensitivity and exposure are shown in Tables 3.15a to 3.15c.

Table 3.14 CIr values for matrices (Saaty, 1980)

Size of Matrix	Random Consistency (CIr)
1	0
2	0
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

Once the CR is acceptable, the priority vector of indicators of each component (adaptive capacity and sensitivity) shown in Table 3.16 is multiplied by the priority weights relative to each criterion shown in Table 3.11 to 3.13 in order get overall priority vector/weights for adaptive capacity and sensitivity components of each district.

Finally, Agriculture Drought Vulnerability Index (ADVI) is calculated By (Bhavani et al., 2017b)

$$ADVI = f\big((E + S) - AC\big), \tag{3.14}$$

Where, E is obtained from weights of exposure, S is taken from overall priority vector of sensitivity and AC is taken from overall priority vector of adaptive capacity.

The similar procedure is adopted for tehsil level and for future ADVI at the district level. Spatial distribution of exposure, sensitivity, adaptive capacity and vulnerability maps are prepared using ARC GIS. Categorization of the level of vulnerability on a scale of 1-5 based on ADVI is shown in Table 3.17. The quantitative assessment of vulnerability which is referred as "degree of vulnerability" is assessed at the district level as

$$\text{Degree of Vulnerability} = \frac{\text{Number of mandals with 3} - \text{5 level of vulnerable}}{Total\ number\ of\ mandals}, \tag{3.15}$$

Table 3.15a APH logic for pairwise comparison of the matrix of Adaptive Capacity

Indicators	Step 1							Step 2								Step 3								
	1	2	3	4	5	6	7	1	2	3	4	5	6	7	Pr. V	1	2	3	4	5	6	7	S	S/W
1	1	1/2	1/3	1/5	1/6	1/7	1/9	0.03	0.02	0.02	0.02	0.02	0.03	0.04	0.03	0.03	0.02	0.02	0.02	0.03	0.03	0.04	0.19	7.09
2	2	1	1/2	1/3	1/5	1/6	1/7	0.06	0.04	0.03	0.03	0.03	0.04	0.06	0.04	0.05	0.04	0.03	0.03	0.03	0.04	0.05	0.29	7.04
3	3	2	1	1/2	1/3	1/5	1/6	0.09	0.08	0.06	0.05	0.05	0.06	0.08	0.07	0.08	0.08	0.07	0.05	0.05	0.06	0.07	0.47	7.06
4	5	3	2	1	1/2	1/3	1/5	0.15	0.12	0.13	0.09	0.07	0.08	0.10	0.10	0.14	0.12	0.13	0.10	0.08	0.08	0.09	0.75	7.11
5	6	5	3	2	1	1/2	1/3	0.18	0.20	0.19	0.18	0.14	0.11	0.13	0.16	0.16	0.20	0.20	0.21	0.16	0.12	0.12	1.18	7.22
6	7	6	5	3	2	1	1/2	0.21	0.24	0.25	0.27	0.28	0.23	0.20	0.24	0.19	0.24	0.26	0.31	0.33	0.24	0.18	1.76	7.31
7	9	7	6	5	3	2	1	0.27	0.29	0.32	0.36	0.42	0.46	0.39	0.27	0.24	0.29	0.33	0.42	0.49	0.48	0.36	2.61	7.29
Average																								7.16
λ max																								7.16
CR																								0.02

(Pr.Vec: Priority Vector/Weights, S: Weighted sum matrix, S/W: Sum/Weights, CR: Consistency Ratio)

Table 3.15b APH logic for pairwise comparison of matrix of Sensitivity

Indicator	Step 1								Step 2								
	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	Pr. V
1	1	1/2	1/3	1/4	1/5	1/6	1/8	1/9	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.04	0.023
2	2	1	1/2	1/3	1/4	1/5	1/7	1/8	0.05	0.04	0.02	0.02	0.02	0.03	0.04	0.05	0.034
3	3	2	1	1/2	1/3	1/4	1/5	1/7	0.08	0.07	0.05	0.03	0.03	0.03	0.04	0.06	0.049
4	4	3	2	1	1/2	1/3	1/4	1/5	0.11	0.11	0.09	0.06	0.04	0.04	0.05	0.07	0.073
5	5	4	3	2	1	1/2	1/3	1/4	0.13	0.14	0.14	0.12	0.09	0.07	0.07	0.09	0.107
6	6	5	4	3	2	1	1/2	1/3	0.16	0.18	0.18	0.19	0.18	0.13	0.11	0.12	0.156
7	7	6	5	4	3	2	1	1/2	0.21	0.21	0.23	0.25	0.27	0.27	0.22	0.18	0.230
8	8	7	6	5	4	3	2	1	0.24	0.25	0.27	0.31	0.35	0.40	0.44	0.37	0.329

Step 3											
	1	2	3	4	5	6	7	8	9	S	S/W
1	0.02	0.01	0.01	0.01	0.02	0.02	0.02	0.03	0.03	0.17	9.22
2	0.04	0.03	0.02	0.02	0.02	0.02	0.03	0.03	0.04	0.24	9.10
3	0.06	0.05	0.04	0.03	0.03	0.03	0.03	0.04	0.04	0.34	9.08
4	0.08	0.08	0.07	0.05	0.04	0.04	0.04	0.04	0.12	0.56	10.44
5	0.09	0.10	0.11	0.11	0.08	0.05	0.05	0.05	0.06	0.71	9.34
6	0.11	0.13	0.15	0.16	0.15	0.11	0.08	0.07	0.08	1.04	9.55
7	0.13	0.16	0.19	0.21	0.23	0.22	0.15	0.11	0.10	1.50	9.72
8	0.15	0.18	0.22	0.27	0.31	0.33	0.31	0.22	0.15	2.13	9.78
9	0.17	0.21	0.26	0.32	0.38	0.44	0.46	0.44	0.31	2.98	9.71
λ max											9.55
C.R											0.05

(Pr.Vec: Priority Vector/Weights, S: Weighted sum matrix**,** S/W: Sum/Weights, CR: Consistency Ratio)

Table 3.15c APH logic for pair wise comparison of the matrix of exposure

Indicators	Step 1			Step 2				Step 3				
	1	2	3	1	2	3	Pr. V	1	2	3	S	S/W
1	1	1/3	1/9	0.08	0.08	0.08	0.077	0.08	0.08	0.08	0.23	3.00
2	2	1	1/3	0.23	0.23	0.23	0.231	0.23	0.23	0.23	0.69	3.00
3	3	2	1	0.69	0.69	0.69	0.692	0.69	0.69	0.69	2.08	3.00
Average												3
λ max												3
CR												0.00

Table 3.16 Pairwise priority weights of indicators of components sensitivity, adaptive capacity, and exposure (Bhavani et al., 2017b)

Indicators	Parameter	District wise	Tehsils Level
Sensitivity	% MgR	0.023	N/D
	% T-AgL	0.034	0.019
	Pop. D	0.049	0.026
	AWHC	0.073	0.037
	S. Er	0.107	0.053
	% NCA	N/D	0.076
	% RCF	0.156	0.109
	VCI	0.230	0.154
	GCA	0.329	0.218
	NSA	N/D	0.307
Adaptive Capacity	Ag-MrSo	N/D	0.027
	RN	N/D	0.041
	% LiT	0.027	0.066
	% LiR	0.041	N/D
	L/S	0.066	N/D
	CoB	N/D	0.105
	Ag-CrSo	N/D	0.163
	AgP	0.105	0.241
	AgW	0.163	N/D
	TIA	N/A	0.358
	ExGIA	0.241	N/D
	GIA	0.358	N/D
Exposure	RF	0.597	0.597
	Temp Max Temp	0.276	0.276
	Min Temp	0.128	0.128

Abbreviations as mentioned in Table 3.5, N/D: No Data

Table 3.17 Categorization of the level of vulnerability

ADVI values	Scale of vulnerability	Labels
<0	1	Very less
1-2	2	Less
3-4	3	Vulnerable
5-6	4	High vulnerable
<7	5	Very high vulnerable

3.4 Software

In the present study software such as image processing (ERDAS and Arc GIS), statistical computing (R package), data visualization (IDL) and scientific graphing (IGOR) are used.

3.4.1 Image processing software

ERDAS is a raster-based software designed to extract information from satellite imagery. It includes a complete set of tools to create precise base imagery for inclusion into a GIS and ESRI geodatabase. Supplemented with a variety of tools such as geometric correction, radiometric correction, GIS integration, image ortho-rectification, mosaicking, re-projection, sub-setting, model making, classification, map production and interpretation the software allows the user to analyze image data and present it in different formats.

ERDAS tools that are extensively used in the present study are layer stack, subset, re-project, and spatial modeler. Layer stack tool is used to combine more than one raster image into single raster image with multiple layers. Subset tool allows one to extract a small area of interest from a larger scene. The re-project tool allows to change/transform the raster image data from one projection to another. Spatial Modeler enables the user to create and run models for image processing and GIS analysis.

3.4.2 Geospatial Analysis

ARC GIS software, developed by Environmental Systems Research Institute (ESRI), consists of three modules viz., Arc Map, Arc Catalog and Arc Toolbox. ArcMap is used to display, edit, analyze, create GIS data and allows to create maps. Arc Catalog is a data management application of spatial data. It presents the information in a tree-based view and allows the user to select a GIS item, view its properties, and to access the tools to operate on the selected item(s). Arc Toolbox provides a reference to the toolboxes to facilitate the user interface in ArcGIS for accessing and organizing a collection of geo-processing tools, models, and scripts.

ArcGIS software tools used in the study are spatial analyst tool, data view and layout view. Data view provides a geographic window to explore, display, and query the data on a map. Layout view allows to work with the map layout elements. The spatial map can be created in layout view.

3.4.3 Programming Language - Statistical computing

3.4.3.1 R

R is a programming language for statistical computing and graphics. It allows data manipulation, calculation and displays graphics.

Interactive Data Language (IDL) is a programming language for data analysis. In the present study, IDL is used to handle and process large amount of climate data.

3.4.3.2 Igor Pro

Igor Pro is an interactive software for carrying out tests with scientific and engineering data and to create high quality graphs and page layouts.

CHAPTER

Four

Results and Discussion

4.1 General

Soil, water, nutrition values and proper management practices are the primary requirements for agriculture. The proportions of these inputs often vary depending upon the amount of precipitation a region receives besides the availability of irrigation facilities, the management of the nutrition and other cultural practices (FAO, 2003). Socio-economic factors are one of the drivers of changes in agriculture, land use practices and climate change (IPCC, 2014). The present study uses the normalized difference vegetation index (NDVI), climate, anomalies associated with them namely deviation of NDVI and Standard Precipitation Index ($NDVI_{Dev}$ and SPI), soil moisture, irrigation, and socio-economic data. The precipitation and irrigation sources (surface water and groundwater), their influence on the agricultural crops have been found to be one of the most important drivers (Bhavani et al., 2017a). The analysis also revealed that the strong negative anomaly is an indicator of drought. During the cropping seasons, frequency of negative anomalies and degree of variability of anomaly show the magnitude and strength of the drought both spatially and temporally. The failure of summer monsoon has a direct bearing on the winter and zaid seasonal crops. Based on three decades' "satellite and climate continuous data (1982-2015)" and trend analysis, the influences of climate and soil moisture on the agriculture and LGP are estimated. The data from three decades has been used to project the "agricultural NDVI for IPCC AR5 RCP 2.6 scenario". Finally, agriculture drought vulnerability is realized using IPCC framework for present and future.

4.2 Assessment of agricultural performance and stress/drought condition

4.2.1 Deviation of NDVI

4.2.1.1 Temporal pattern of $NDVI_{Dev}$ at state level

NOAA GIMMS NDVI

The $NDVI_{Dev}$ varies both temporally and/spatially and captures the crop stress (Bhavani et al., 2017a). The pattern of $NDVI_{Dev}$ of the undivided state for the period 1982 to 2000 is shown in Fig. 4.1a. One can clearly see from Fig. 4.1a that agricultural performance was poor in all the three cropping seasons (summer monsoon, winter, and summer) during the period 1982-87 except during the summer monsoon/Kharif season of 1983-84. , where a marginal rise in the agriculture performance was noticed due to the monsoonal rains. Fluctuations in the agricultural growth conditions have been observed in the subsequent years also from 1987 to 1994. Due to the deficit in rainfall during August–September 1994, the Kharif season agricultural performance during 1994-95 was reflected with negative $NDVI_{Dev}$. Due to the shift in the cropping pattern (Madhusudana, 2013), maximum positive deviation of NDVI is observed during 1998-99.

MODIS NDVI

The variation of $NDVI_{Dev}$ over the period 2000-2015 is shown in Fig. 4.1b. Poor agricultural performance, reflected by large negative deviations of NDVI (Fig. 4.1 b), was observed during the years 2002-03, 2008-09 and 2009-10 due to prevailing drought conditions. Due to the delayed or deficit monsoonal rainfall during 2000-01 and 2011-12, the rabi and zaid cropping had been affected. Good amount and widespread precipitation during 2010-11 had resulted in a positive influence on agricultural NDVI in all the three cropping seasons.

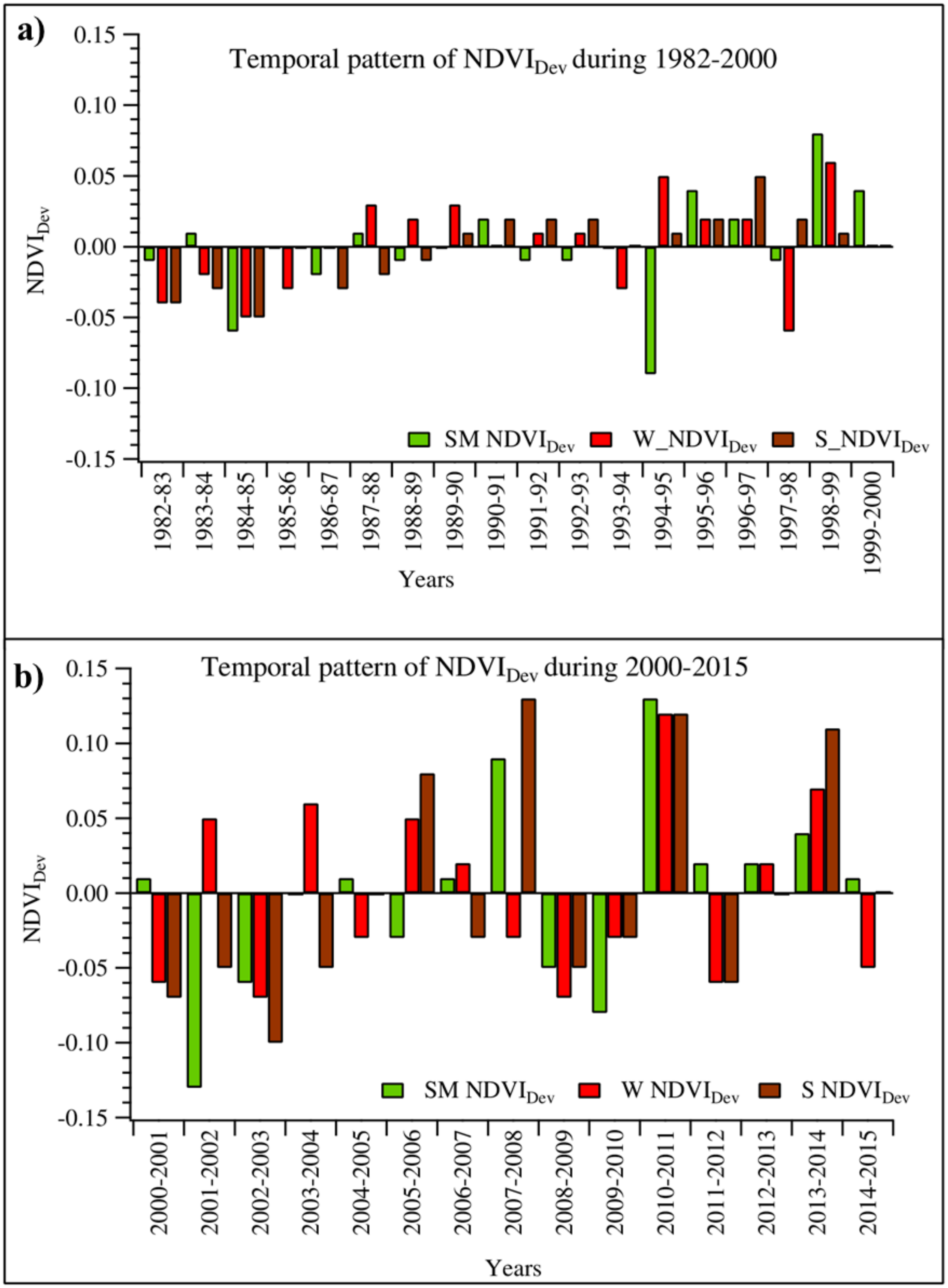


Figure 4.1 Temporal pattern of the deviation of NDVI, undivided Andhra Pradesh during a) 1982-2000 (NOAA GIMMS); and b) 2000-2015 (MODIS)

4.2.1.2 Temporal pattern of $NDVI_{Dev}$ at District level

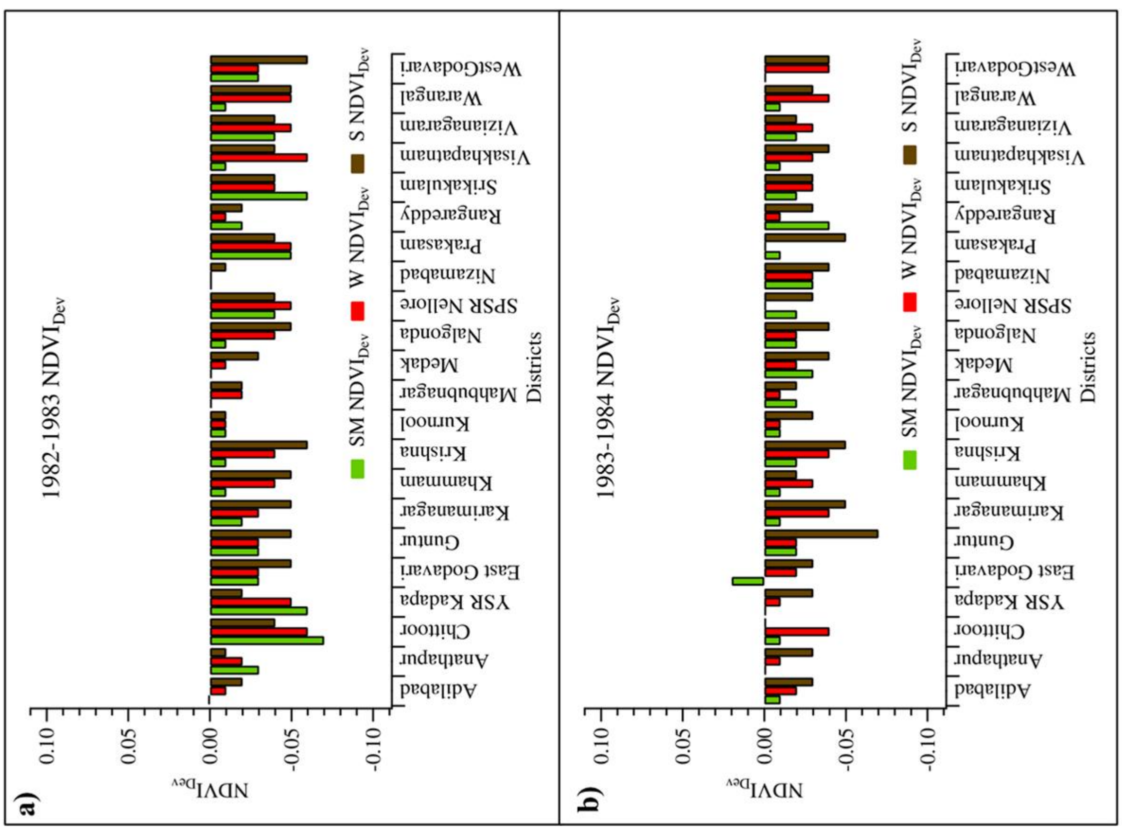
GIMMS NDVI

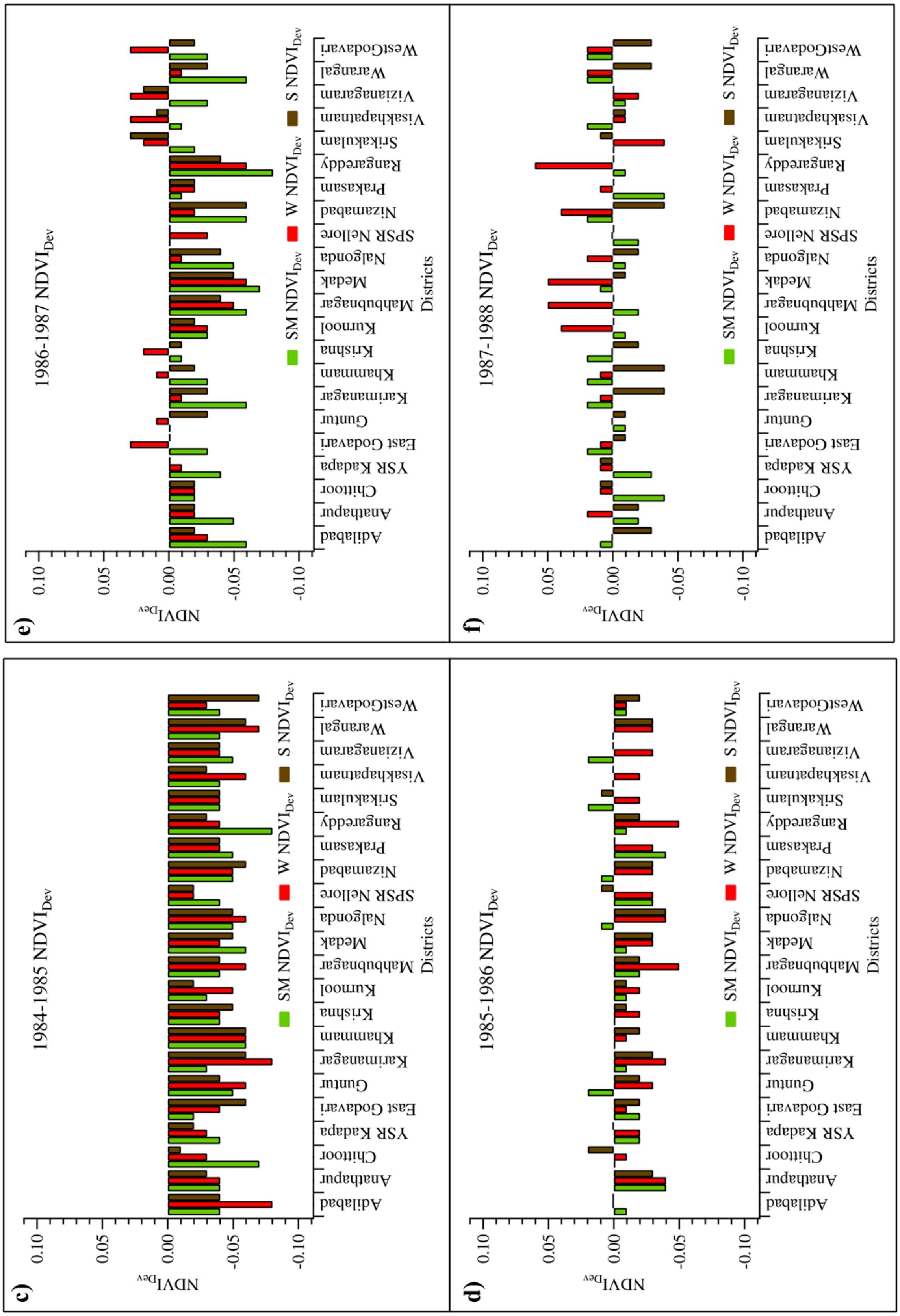
Drought stresses inferred from the deviation of NDVI in 23 districts of undivided AP for the period 1982-2015 are illustrated in Fig. 4.2. By and large, four consecutive years of the early 1980s, i.e. 1982-83, 1983-84, 1984-85, and 1985-86 are observed as bad agricultural years as they are reflected with a negative deviation of NDVI in all 23 districts (Figs. 4.2a to 4.2r). During 1986-87, except the coastal districts (Srikakulam, Visakhapatnam, and Vizianagaram), all other districts of the state have shown agricultural stress in three cropping seasons (Fig. 4.2e). In 1987-88, Mahbubnagar, Medak, Nizamabad, Kurnool, and Rangareddy districts of the state have received significant rainfall during the winter season which is responsible for good rabi agricultural growth. This has been well captured by positive $NDVI_{Dev}$ (Fig. 4.2f). Also, the State had received heavy rainfall due to a cyclonic storm in the months of November 1989 and May 1990, which enhanced the agricultural growth condition of rabi season and zaid season of 1989-90. $NDVI_{Dev}$ is shown in Fig. 4.2h for all the districts has clearly picked up the good agricultural growth condition. The positive deviation of NDVI in almost all the districts of the State in the Kharif season during 1990-91 (Fig. 4.2i) proves the fact that residual soil moisture would also have played an important role in agriculture growth /stress conditions. On the other hand, due to unseasonal rains during August-September, 1994-95 agricultural stress conditions prevailed in all the districts of AP which were captured as negative deviations of NDVI in the Kharif season. The features of $NDVI_{Dev}$ in all the cropping seasons during the period 1995-96 to 1999-2000 indicate good agricultural performance in all the districts (Figs. 4.2n to 4.2r). It is pertinent to mention here that the shift in the cropping pattern (Kensuke Kobo, 2005) and widespread rainfall received in most of the districts in the state during the above period have paved the way for good agricultural performance.

MODIS

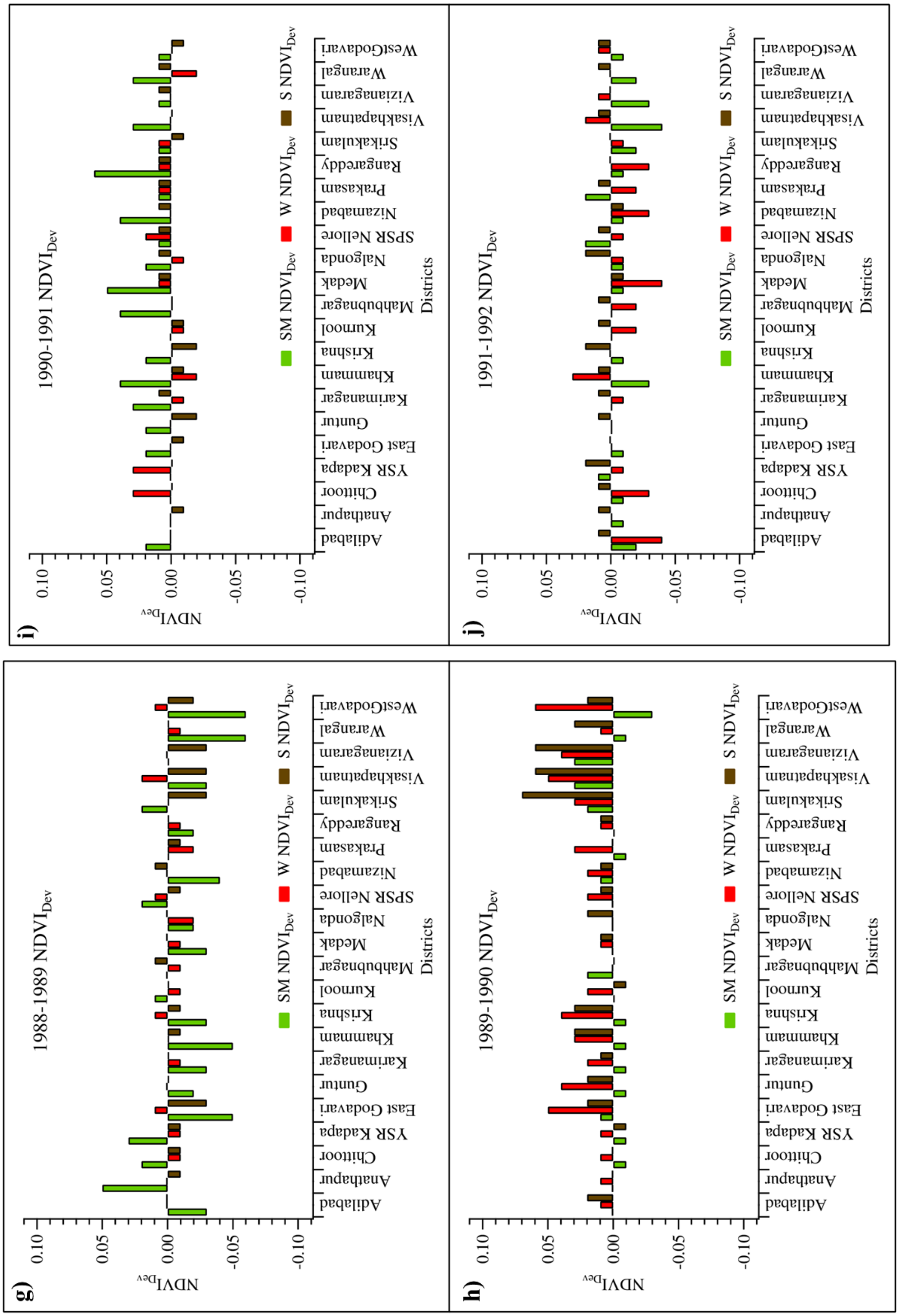
On the contrary, a negative deviation of NDVI observed in almost all the districts of the state in all the three seasons during 2002-03, 2008-09 and 2009-10 (Figs. 4.3c, 4.3i and 4.3j) have revealed poor agricultural growth. The similar agricultural performance was repeated in all the districts even during 2011-12 (Fig. 4.3l) with the exception of Chittoor and SPS Nellore (shown a positive deviation of NDVI in all the three cropping seasons). All the districts have shown a positive deviation of NDVI in all the three seasons during 2010-11 indicating a good agricultural year (Fig. 4.3k). The Anantapur district has exhibited a negative deviation of NDVI in all the three cropping seasons during 2012-13, 2013.-14, and 2014-15 (Figs. 4.3m, 4.3n and 4.3o) indicating poor agricultural performance. YSR Kadapa district was also reflected by negative deviation of NDVI in all the three cropping seasons during 2014-15 (Fig. 4.3o).

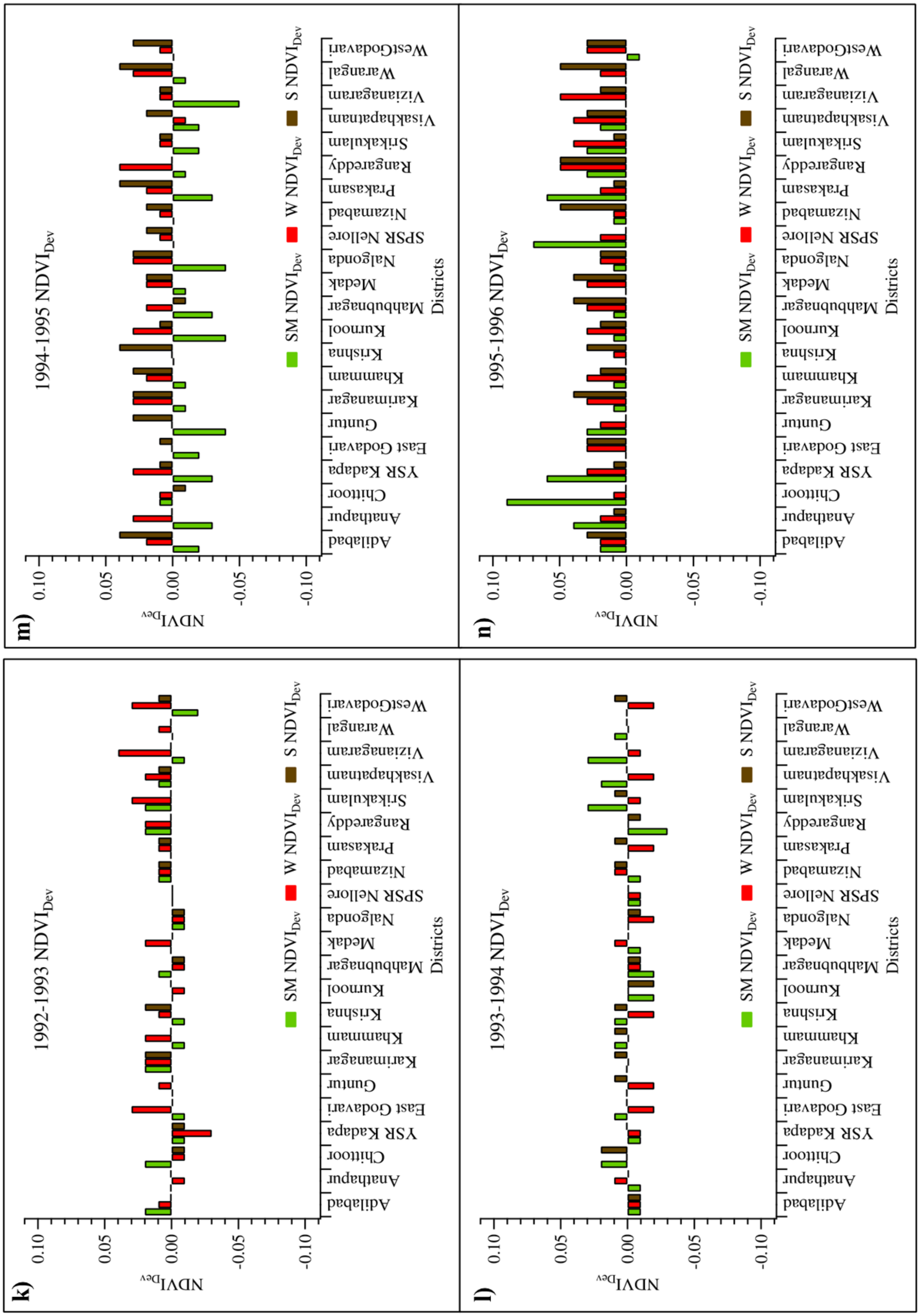
In short, it is demonstrated that long-term variability of agriculture performance can be captured at different scales using NDVI analysis.

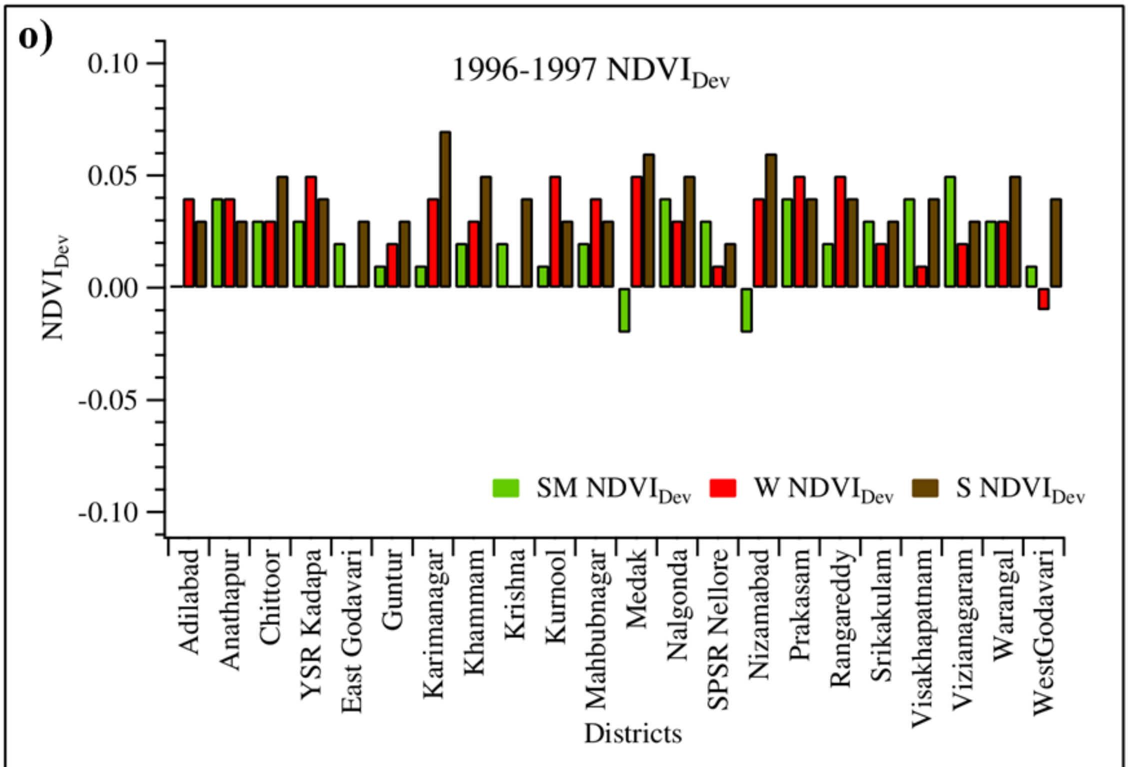


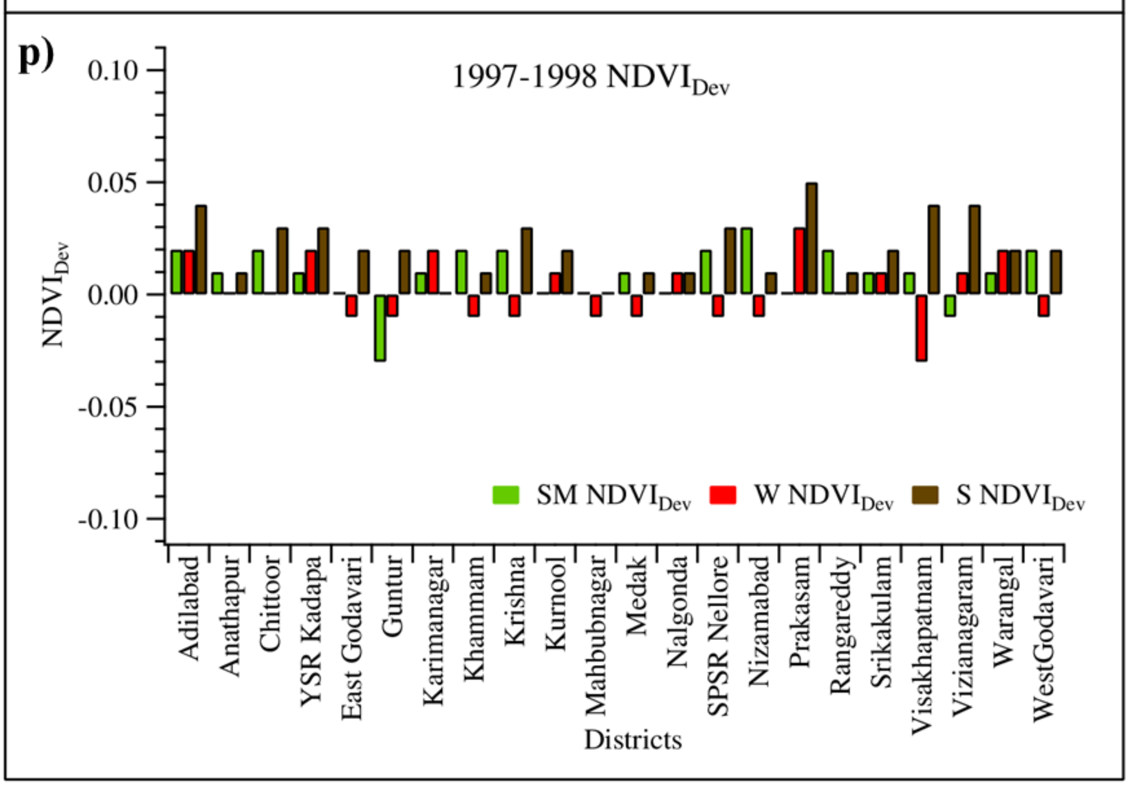


c)
1984-1985 NDVI$_{Dev}$
d)
1985-1986 NDVI$_{Dev}$
e)
1986-1987 NDVI$_{Dev}$
f)
1987-1988 NDVI$_{Dev}$
NDVI$_{Dev}$
0.10
0.05
0.00
-0.05
-0.10
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimnagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts
SM NDVI$_{Dev}$
W NDVI$_{Dev}$
S NDVI$_{Dev}$


g)
1988-1989 NDVI$_{Dev}$
h)
1989-1990 NDVI$_{Dev}$
i)
1990-1991 NDVI$_{Dev}$
j)
1991-1992 NDVI$_{Dev}$
SM NDVI$_{Dev}$
W NDVI$_{Dev}$
S NDVI$_{Dev}$
NDVI$_{Dev}$
Districts
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari


k)
1992-1993 NDVIDev
l)
1993-1994 NDVIDev
m)
1994-1995 NDVIDev
n)
1995-1996 NDVIDev
NDVIDev
Districts
SM NDVIDev
W NDVIDev
S NDVIDev
0.10
0.05
0.00
-0.05
-0.10
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimnagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari


o)
1996-1997 $NDVI_{Dev}$
$NDVI_{Dev}$
0.10
0.05
0.00
-0.05
-0.10
SM $NDVI_{Dev}$
W $NDVI_{Dev}$
S $NDVI_{Dev}$
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts


p)
1997-1998 $NDVI_{Dev}$
$NDVI_{Dev}$
0.10
0.05
0.00
-0.05
-0.10
SM $NDVI_{Dev}$
W $NDVI_{Dev}$
S $NDVI_{Dev}$
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts

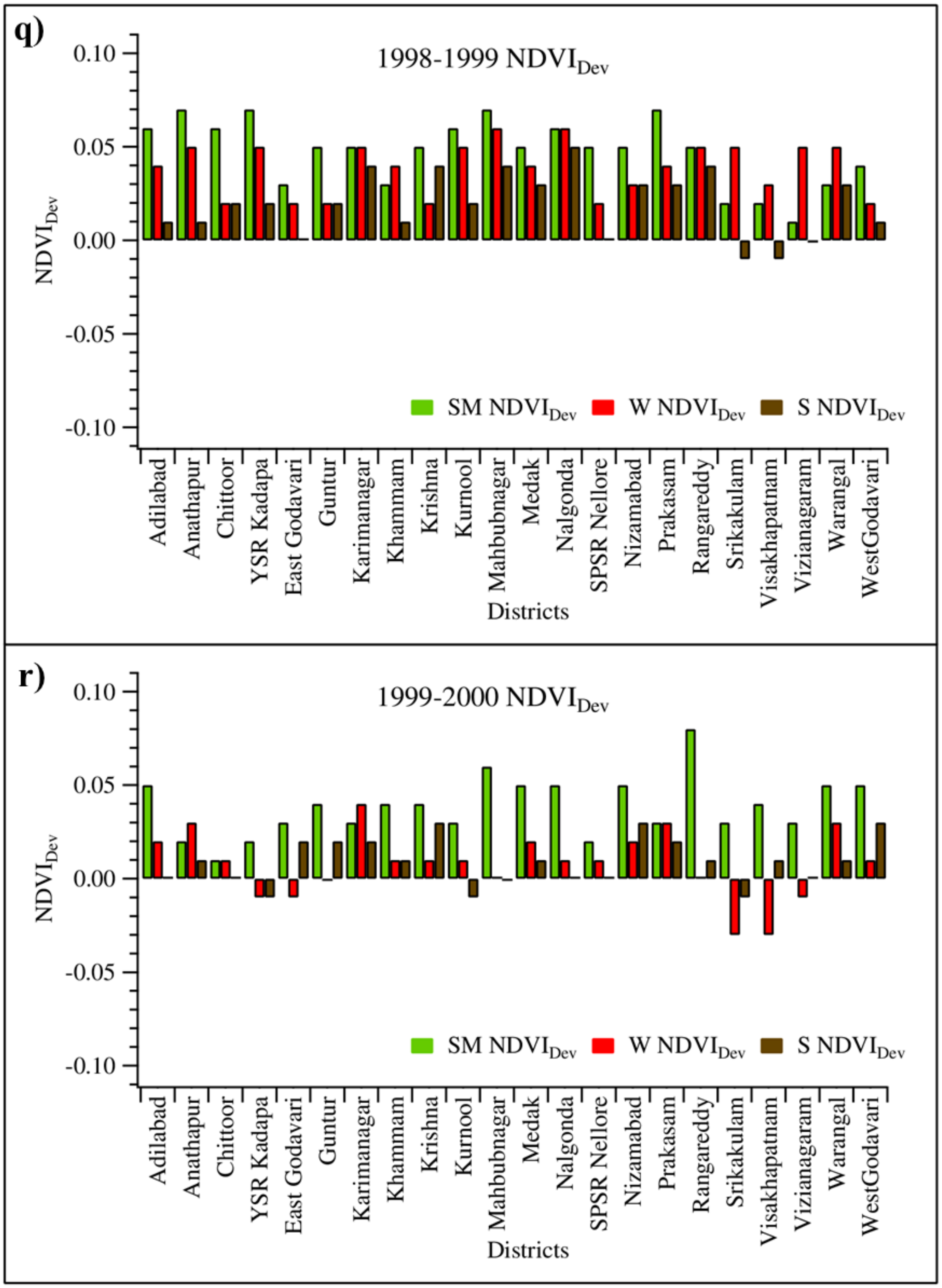
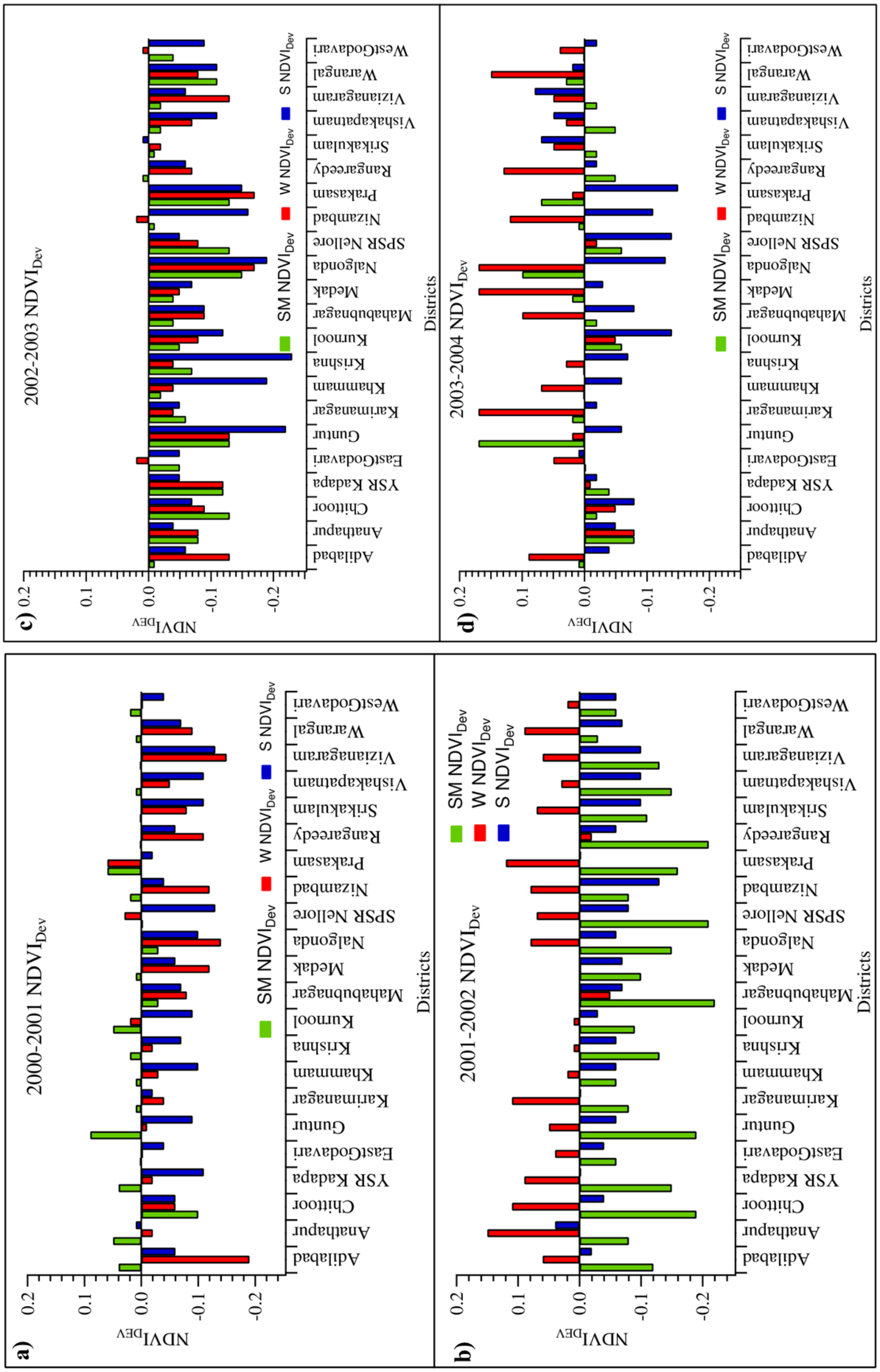
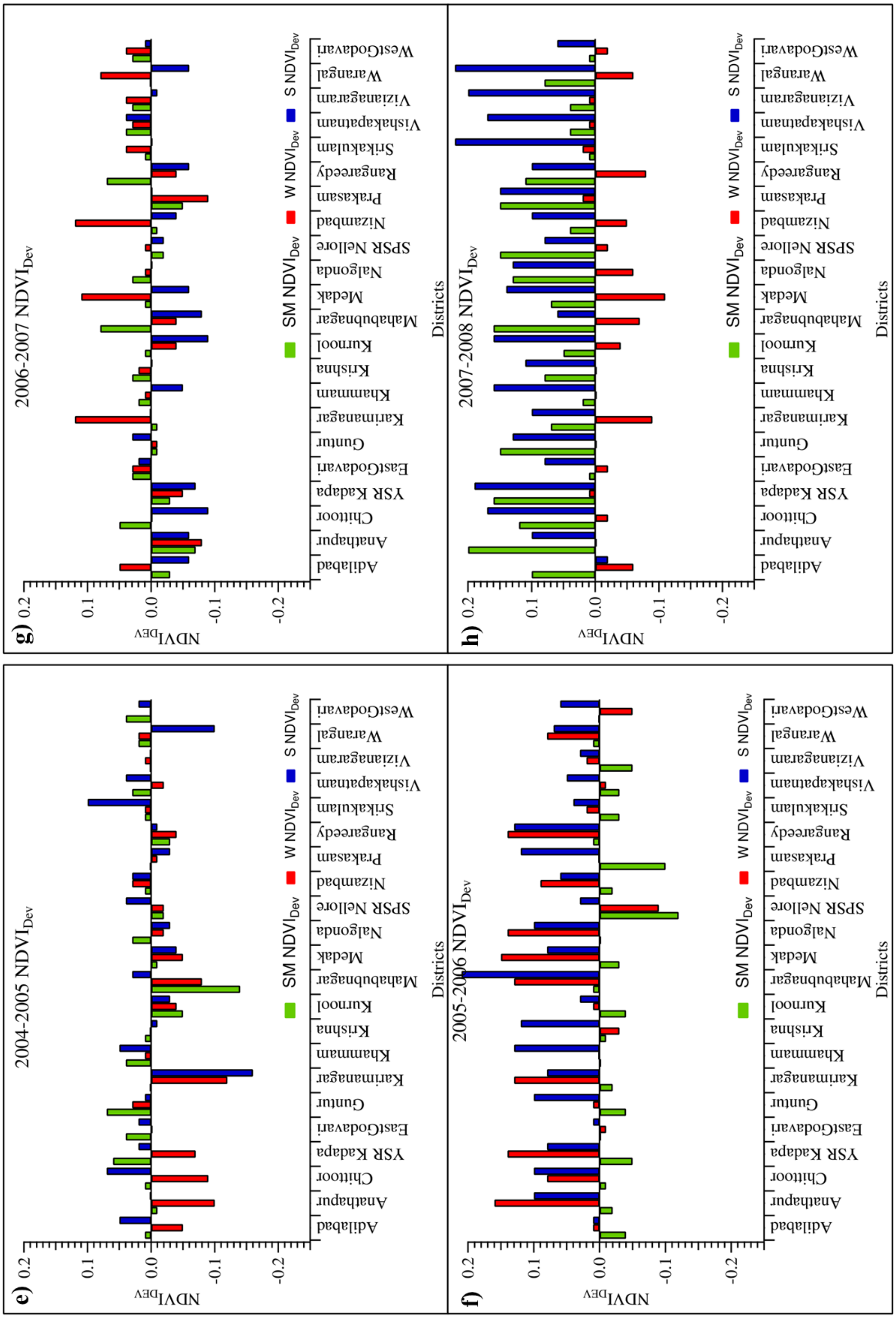


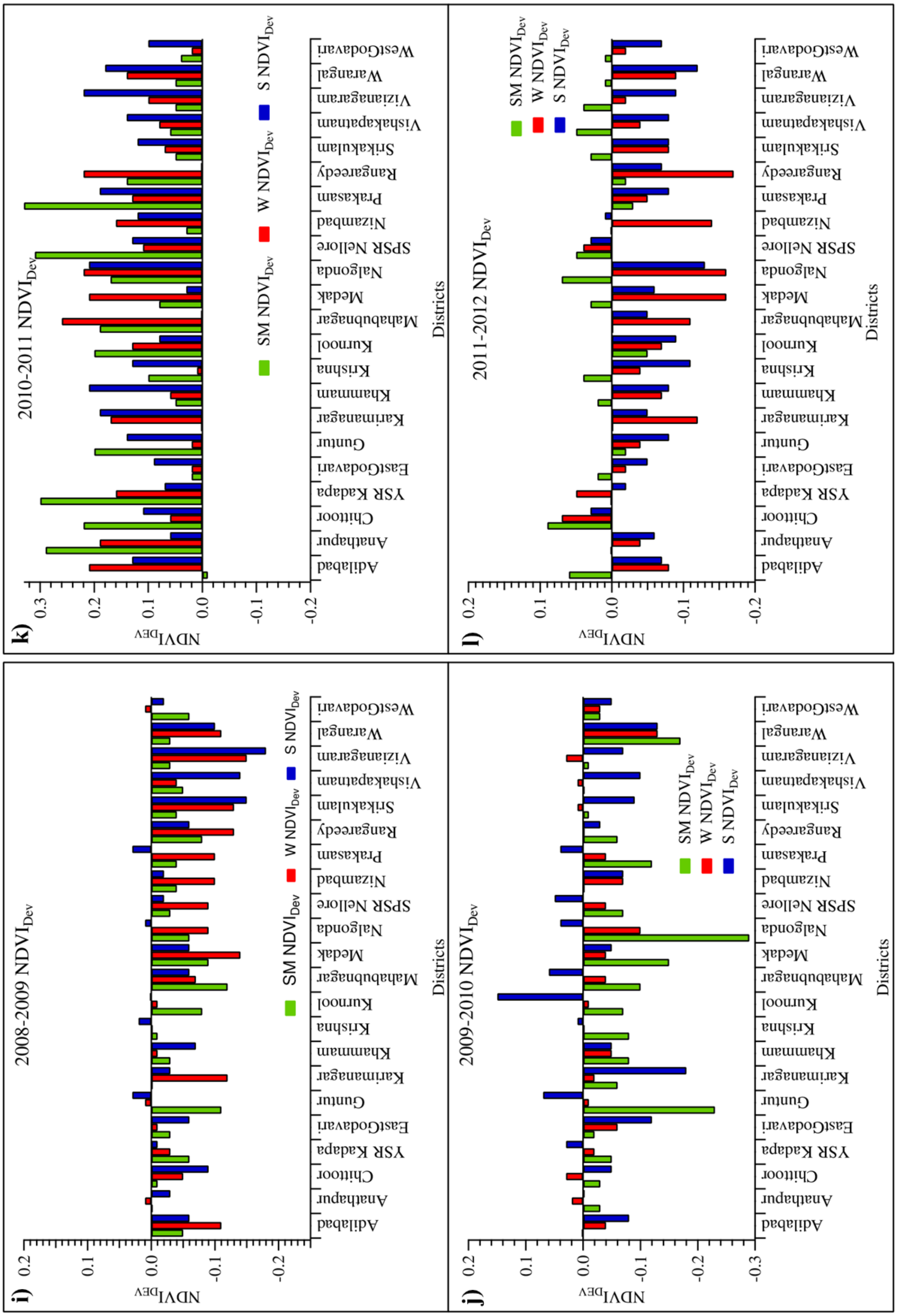
Figure 4.2 District wise seaonal pattern of NDVI$_{Dev}$ derived from GIMMS NDVI in undivided Andhra Pradesh a) 1982-83; b) 1983-84; c) 1984-85; d)1 985-86; e) 1986-87; f) 1987-88; g) 1988-89; h) 1989-90; i) 1990-91; j) 1991-92; k) 1992-93; l) 1993-94; m) 1994-95; n) 1995-96; o) 1996-97; p)1997-98; q)1998-99; and r)1999-2000.

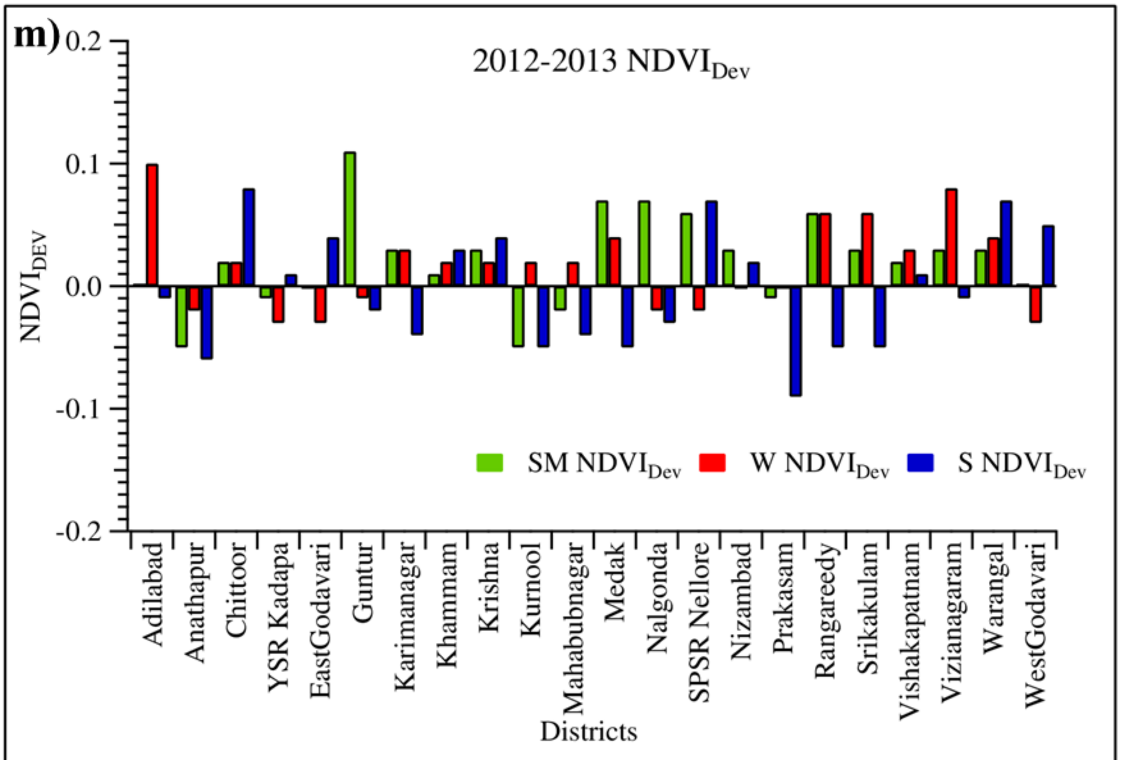


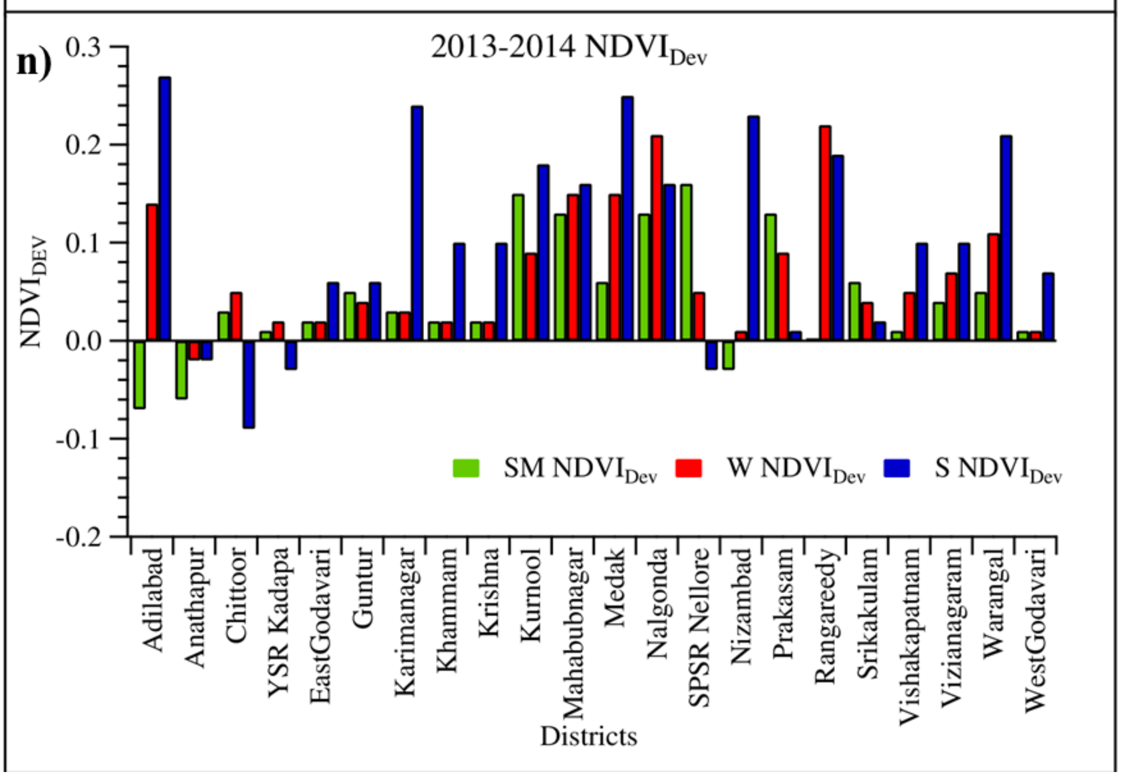
a)
2000-2001 NDVI_Dev
b)
2001-2002 NDVI_Dev
c)
2002-2003 NDVI_Dev
d)
2003-2004 NDVI_Dev
SM NDVI_Dev
W NDVI_Dev
S NDVI_Dev
NDVI_DEV
Districts
0.2
0.1
0.0
-0.1
-0.2
Adilabad
Anathapur
Chittoor
YSR Kadapa
EastGodavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahabubnagar
Medak
Nalgonda
SPSR Nellore
Nizambad
Prakasam
Rangareedy
Srikakulam
Vishakapatnam
Vizianagaram
Warangal
WestGodavari



e) 2004-2005 NDVI_Dev
f) 2005-2006 NDVI_Dev
g) 2006-2007 NDVI_Dev
h) 2007-2008 NDVI_Dev
NDVI_DEV
Districts
SM NDVI_Dev
W NDVI_Dev
S NDVI_Dev
Adilabad
Anathapur
Chittoor
YSR Kadapa
EastGodavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahabubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareedy
Srikakulam
Vishakapatnam
Vizianagaram
Warangal
WestGodavari


i)
2008-2009 NDVI$_{Dev}$
j)
2009-2010 NDVI$_{Dev}$
k)
2010-2011 NDVI$_{Dev}$
l)
2011-2012 NDVI$_{Dev}$
NDVI$_{DEV}$
SM NDVI$_{Dev}$
W NDVI$_{Dev}$
S NDVI$_{Dev}$
Districts
Adilabad
Anathapur
Chittoor
YSR Kadapa
EastGodavari
Guntur
Karimnagar
Khammam
Krishna
Kurnool
Mahabubnagar
Medak
Nalgonda
SPSR Nellore
Nizambad
Prakasam
Rangareedy
Srikakulam
Vishakapatnam
Vizianagaram
Warangal
WestGodavari


m)
2012-2013 NDVI$_{Dev}$
NDVI$_{DEV}$
0.2
0.1
0.0
-0.1
-0.2
SM NDVI$_{Dev}$
W NDVI$_{Dev}$
S NDVI$_{Dev}$
Adilabad
Anathapur
Chittoor
YSR Kadapa
EastGodavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahabubnagar
Medak
Nalgonda
SPSR Nellore
Nizambad
Prakasam
Rangareedy
Srikakulam
Vishakapatnam
Vizianagaram
Warangal
WestGodavari
Districts


n)
2013-2014 NDVI$_{Dev}$
NDVI$_{DEV}$
0.3
0.2
0.1
0.0
-0.1
-0.2
SM NDVI$_{Dev}$
W NDVI$_{Dev}$
S NDVI$_{Dev}$
Adilabad
Anathapur
Chittoor
YSR Kadapa
EastGodavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahabubnagar
Medak
Nalgonda
SPSR Nellore
Nizambad
Prakasam
Rangareedy
Srikakulam
Vishakapatnam
Vizianagaram
Warangal
WestGodavari
Districts

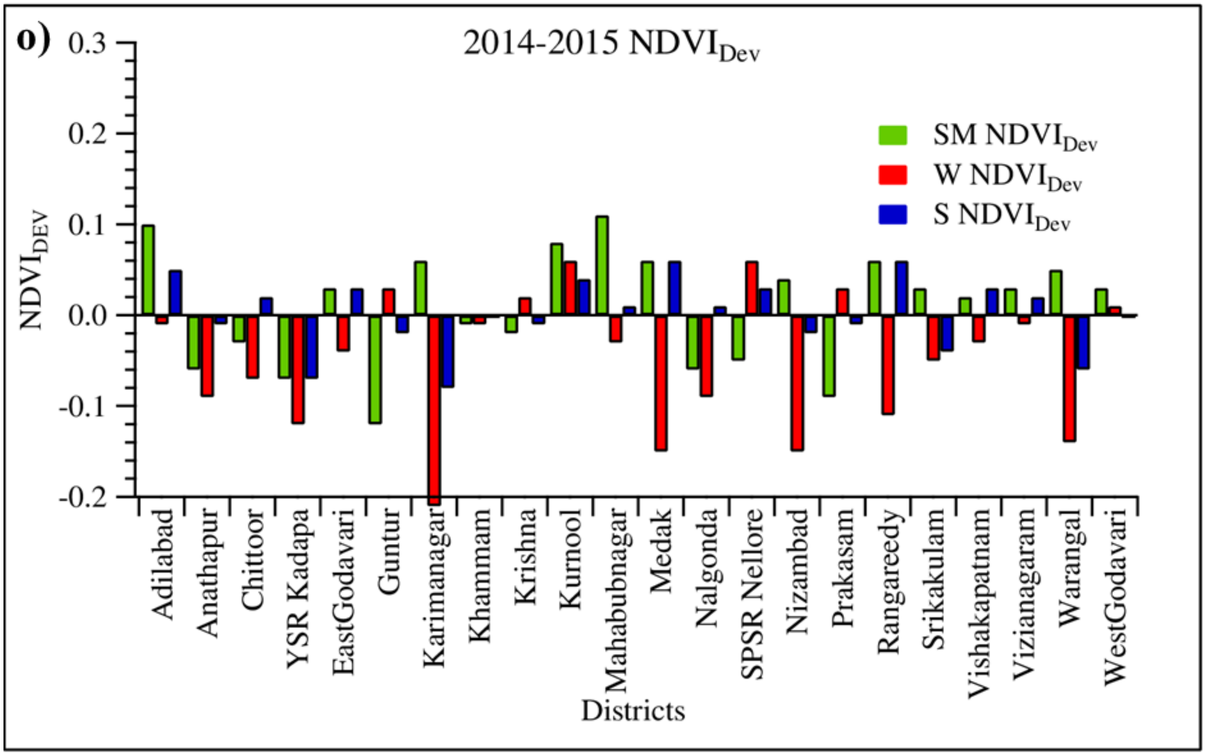


Figure 4.3 District wise seasonal pattern of $NDVI_{Dev}$ derived from MODIS data a) 2000-01; b) 2001-02; c)2002-03; d) 2003-04; e) 2004-05; f) 2005-06; g) 2006-07; h) 2007-08; i) 2008-09; j) 2009-10; k) 2010-11; l) 2011-12; m)2012-13; n) 2013-14; and o) 2014-15

4.2.2 Vegetation Condition Index (VCI)

4.2.2.1 State Level

NOAA GIMMS and MODIS

The temporal variation of NDVI derived indices (deviation of NDVI and VCI) corresponding to three cropping seasons (summer monsoon, winter, and summer) of the period 1980-2000 and 2000-2015 are shown in Fig. 4.4 and 4.5, respectively. Although both the NDVI derived indices (deviation of NDVI and VCI) show more or less similar patterns (Figs. 4.4 and 4.5) the range of differentiation was better in NDVI anomaly, hence it was used in the subsequent analysis.

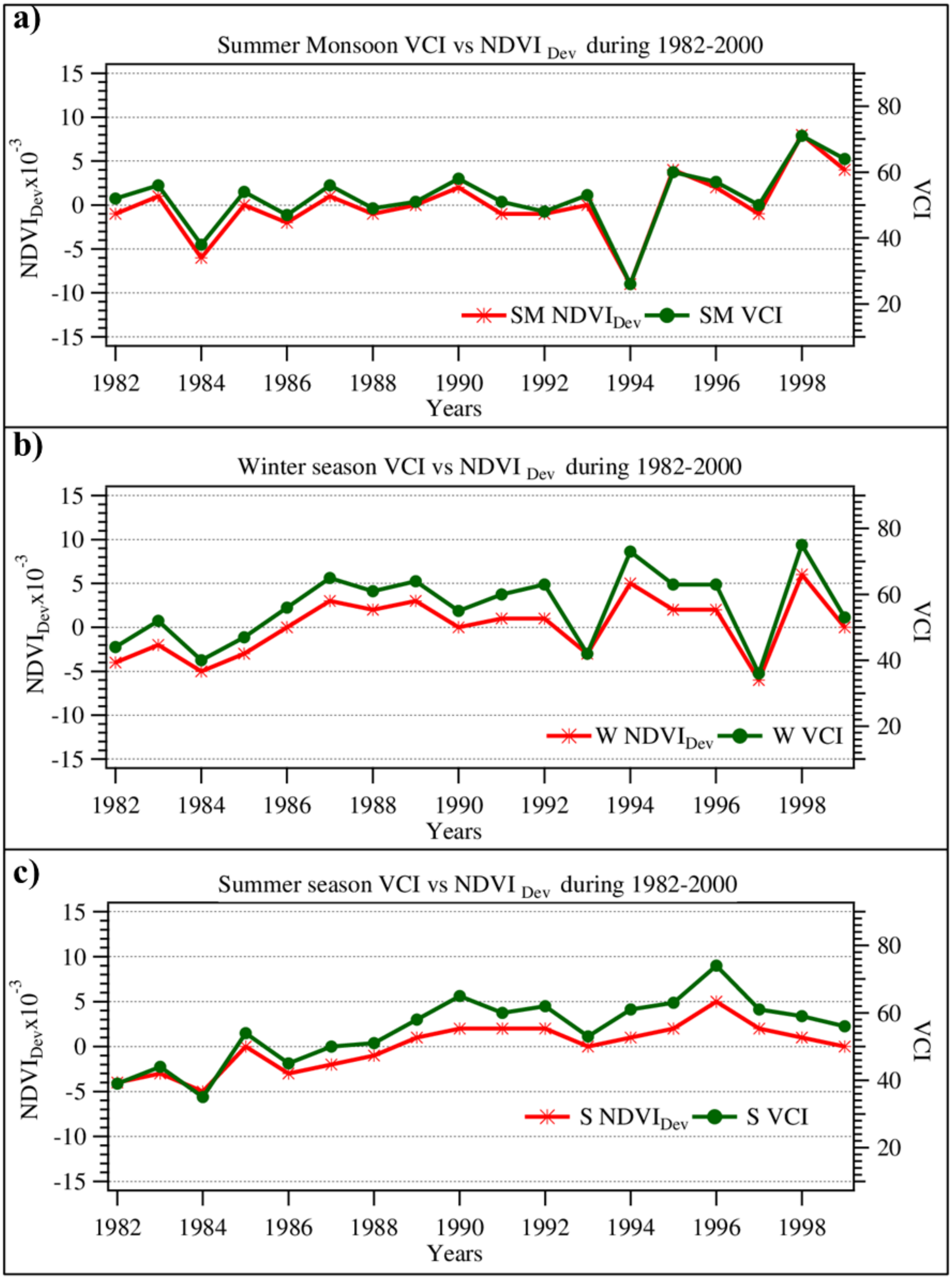


Figure 4.4 Seasonal comparison of VCI and $NDVI_{Dev}$ during 1982-2015 a) summer monsoon; b) winter; and c) summer season.

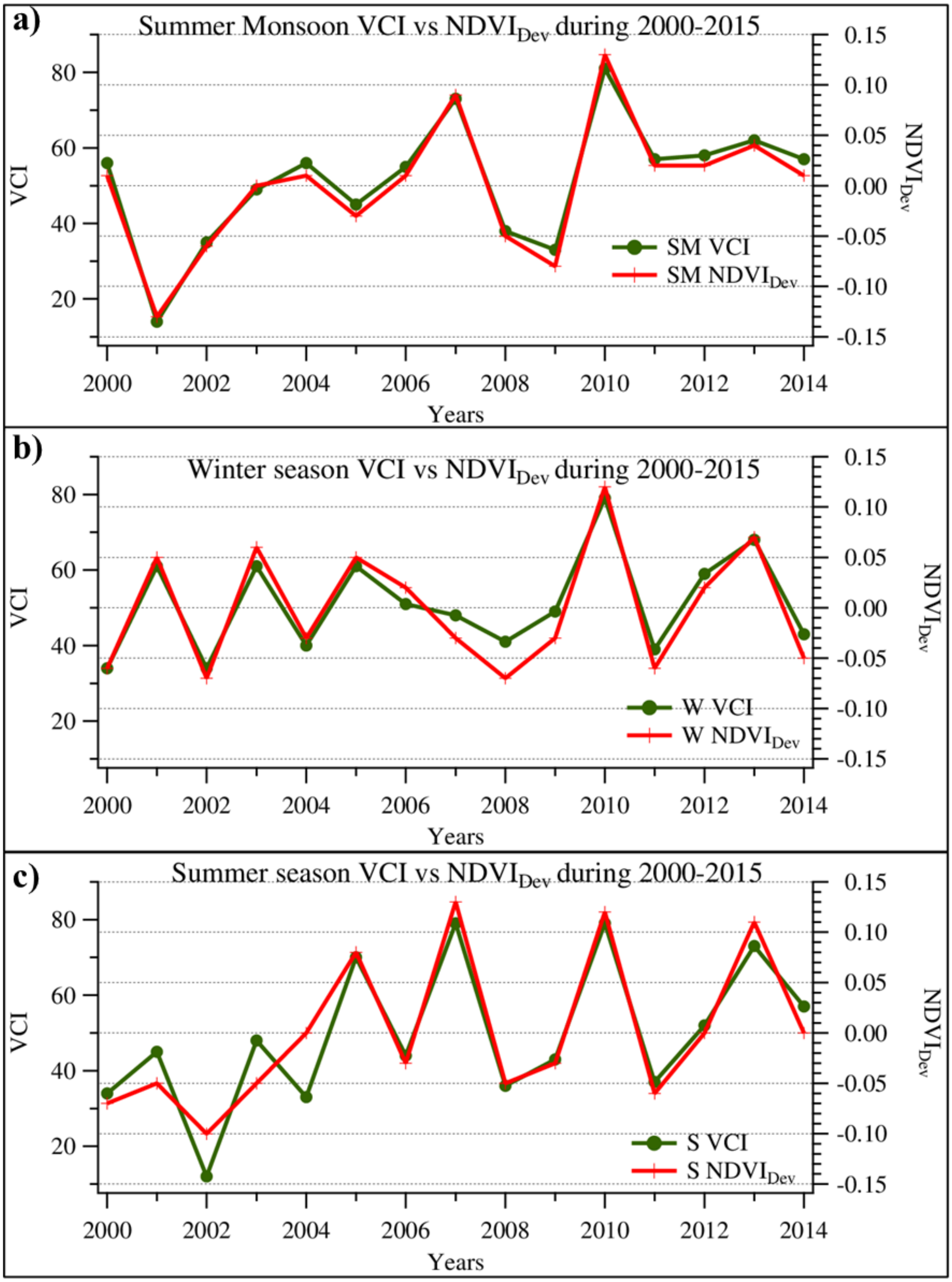


Figure 4.5 Seasonal comparison of VCI and $NDVI_{Dev}$ during 2000-2015 a) summer monsoon; b) winter; and c) summer season.

NOAA GIMMS

A significant drop in VCI (< 30%) was observed in the state during the summer monsoon of 1994-95 and 1984-85 (Fig. 4.6a). During the winter season, VCI has attained its low (<40%) during 1997-98, followed by 1993-94 (~40%) indicating poor winter/rabi crop condition. Low VCI observed consistently during the summer monsoon, winter and summer seasons of 1984-85 reveals poor vegetation conditions in all three cropping seasons (Fig. 4.6a).

MODIS

The temporal variation of VCI from 2000-2015 clearly shows that the crop conditions during the summer monsoon of 2001-2002 and 2009-2010 years were poor (Fig. 4.6b). The increase of VCI from less than 14% to ~55% during the Kharif season of 2001-2002 and 2004-2005 years indicate better vegetation condition above the normal. Poor vegetation conditions also prevailed during the winter seasons of 2002-03 (lowest VCI), 2011-12 and 2008-09 years. Similarly, during the summer season, 2002-2003 has the lowest VCI, indicating poor vegetation condition (Fig. 4.6b).

4.2.2.2 District level

NOAA GIMMS

The spatial pattern of VCI for the period from 1982-83 to 1999-2000 in three cropping seasons under consideration is shown in Fig. 4.7. During the 1980s, by and large, the Ananthapur district had shown low VCI (below 50%) (Fig. 4.7a to 4.7h) indicating the prevalence of poor vegetation conditions in all the three cropping seasons. On the other hand, the study clearly captures the improved vegetation condition in the district during the late 1990s, which was happened due to the shift in cropping pattern.

MODIS

The pattern of VCI (derived from MODIS data) for the period 2000-2001 to 2014-2015 are shown in Fig. 4.8. During the year 2002-03, all the districts in the State were reflected with low VCI (below 50%) (Fig. 4.8c), indicating low vegetation growth during the year.

Similar trends in VCI (low values) were repeated in the year 2008-09 (Fig. 4.8i), where the majority of the districts in the state have shown poor vegetation growth. During 2009-2010all 22 districts, except Visakhapatnam, have observed low VCI in the summer season. The Warangal district has shown poor vegetation condition in all the three cropping seasons of the year 2009-2010. During 2010-2011, except Adilabad and Karimnagar, all other districts have shown VCI above 50%, indicating good agricultural performance year.

From the above analysis, it can be concluded that VCI is able to capture the peak stress but unable to identify short duration or minor stress both temporally and spatially. Hence NDVI (of NOAA-AVHRR and MODIS) anomaly is a better indicator of stress/ drought conditions. This is in contrary to many research observations (Dutta et al., 2015, Yan et al. 2016).

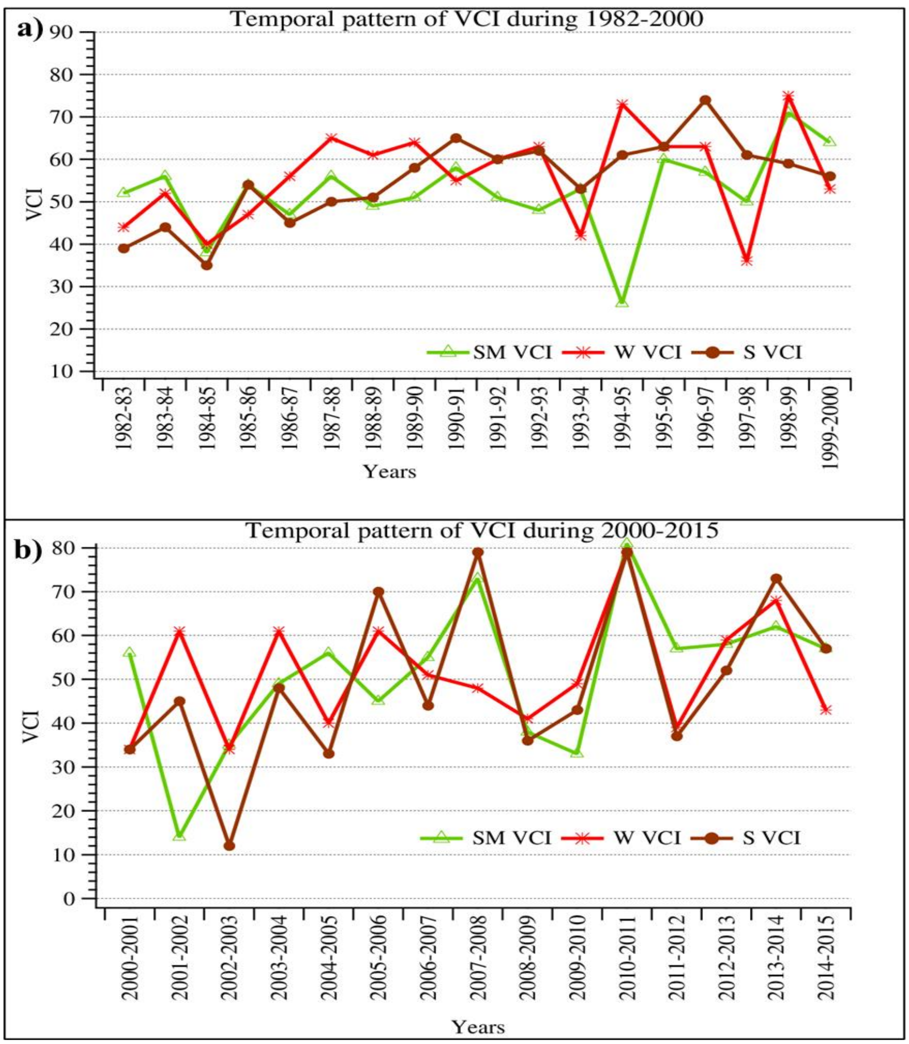
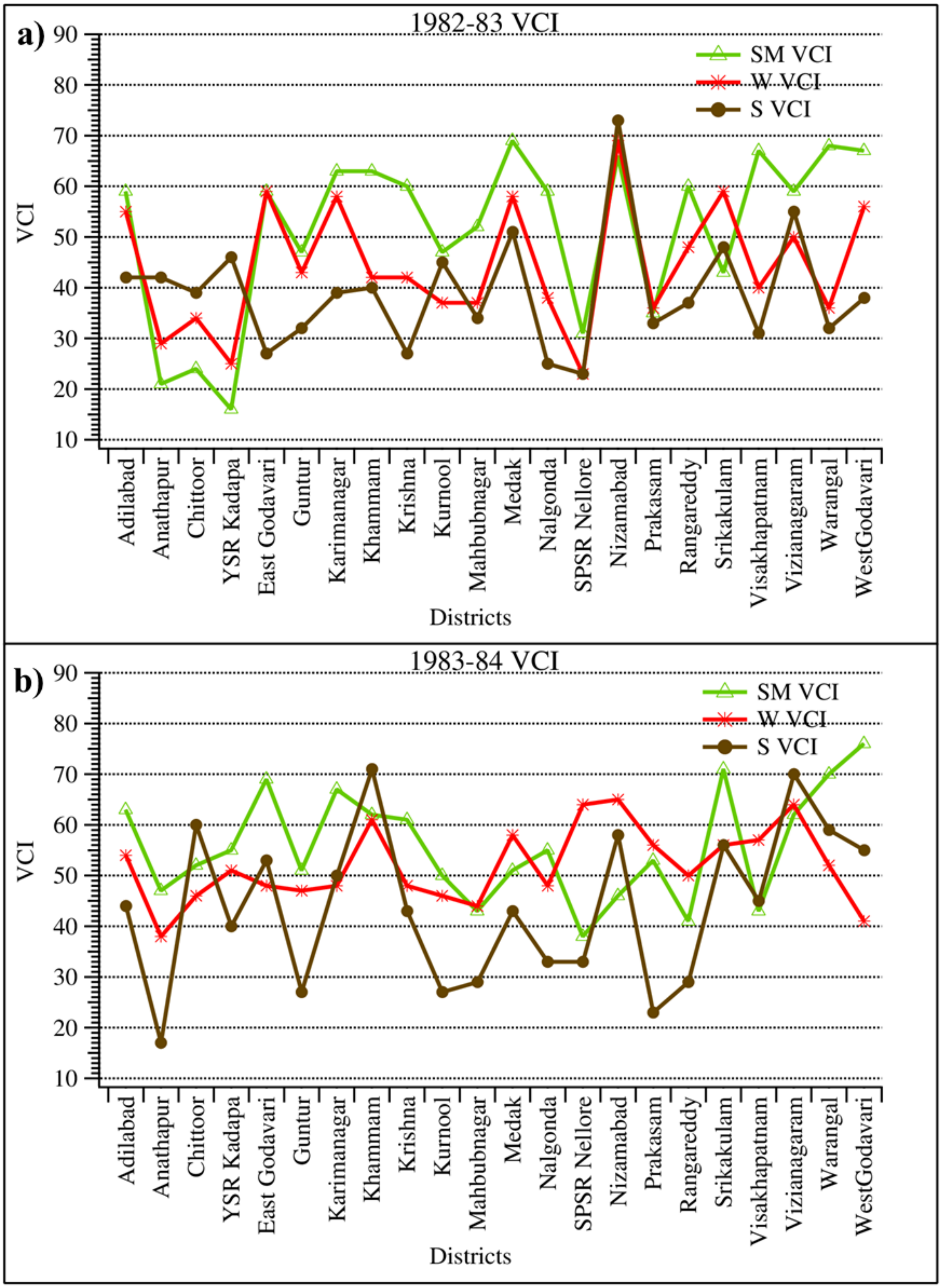
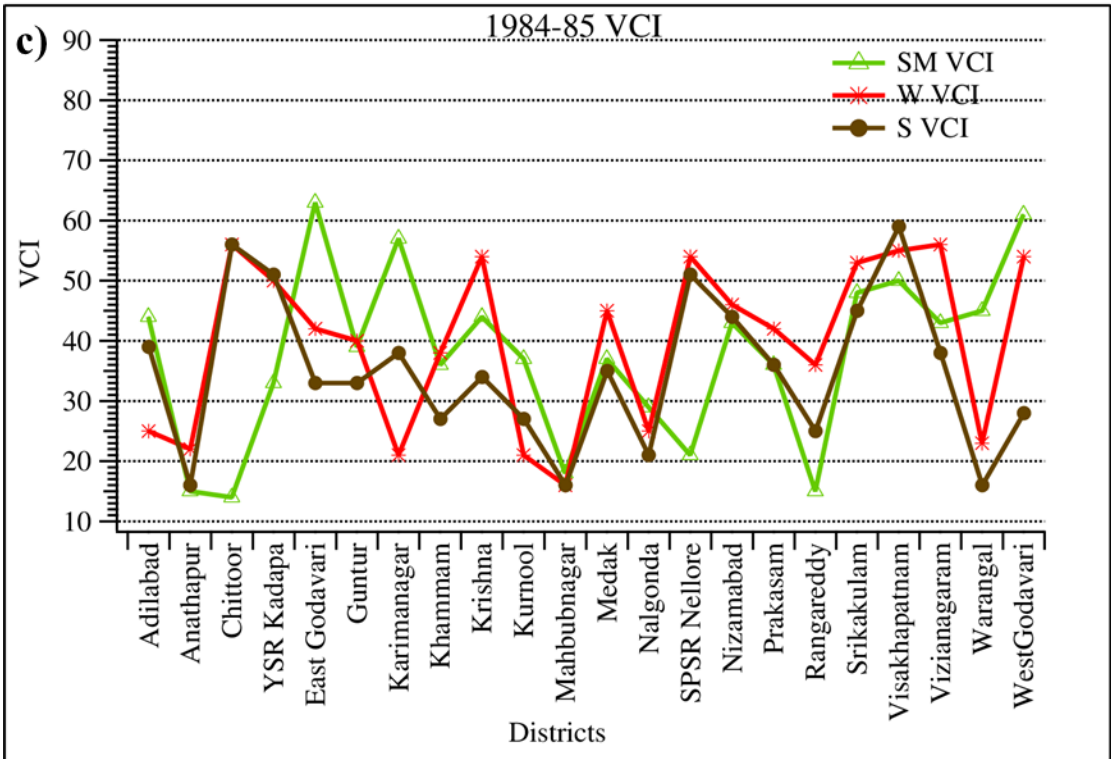
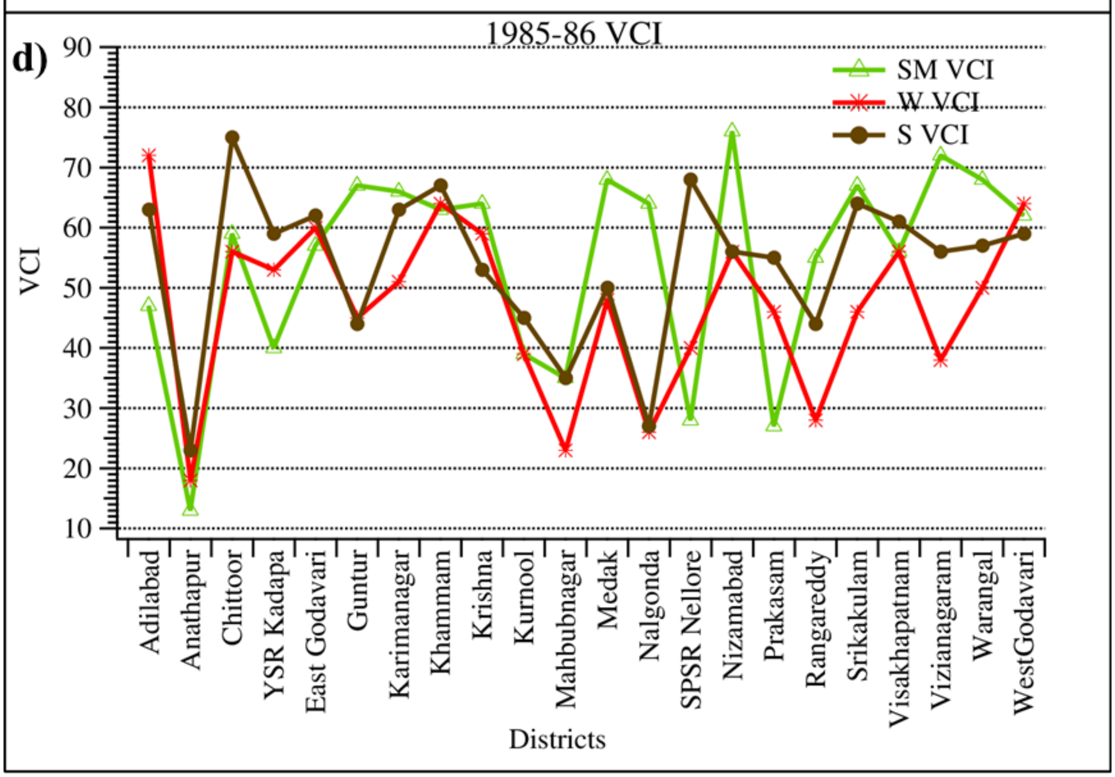
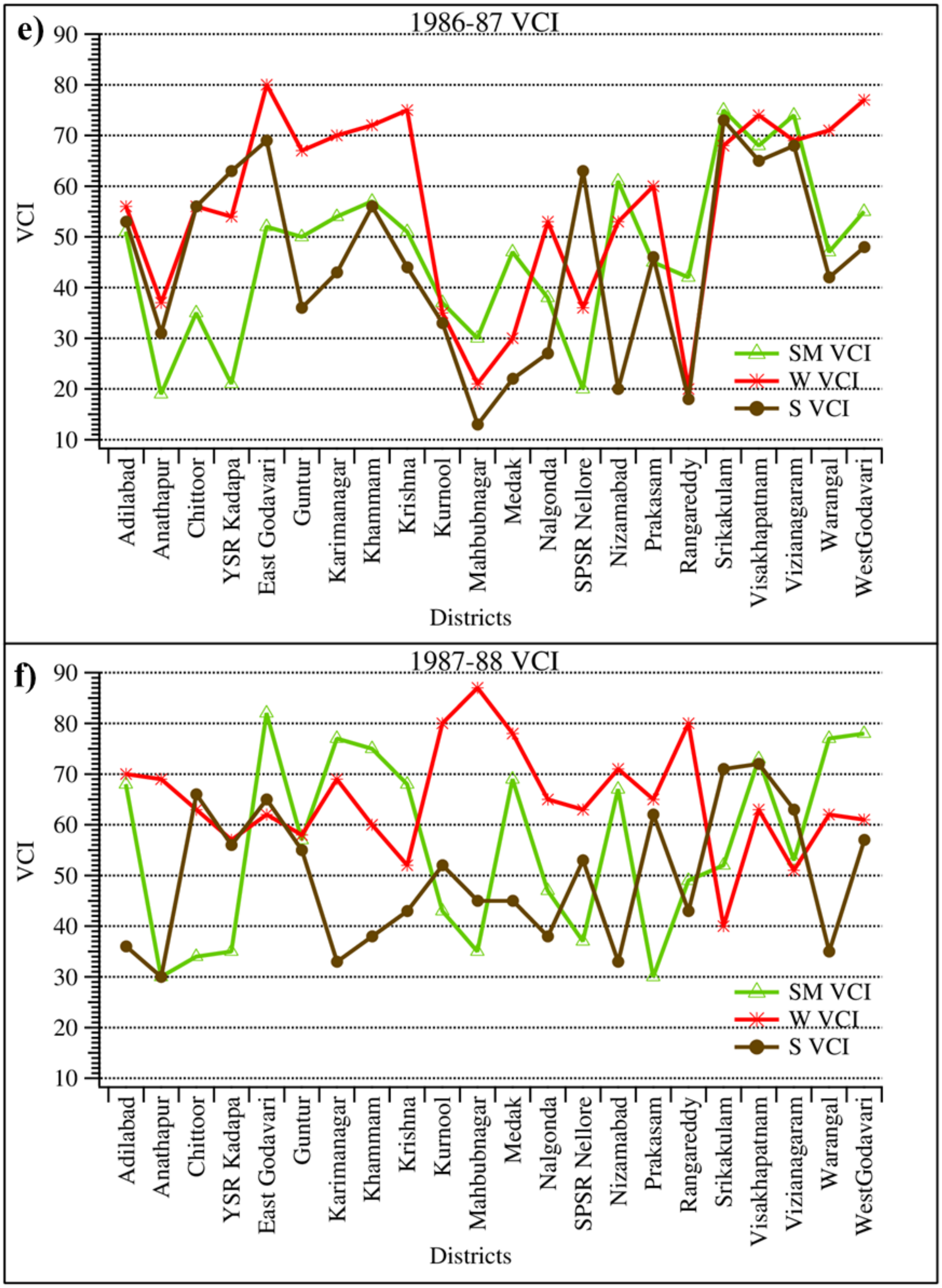


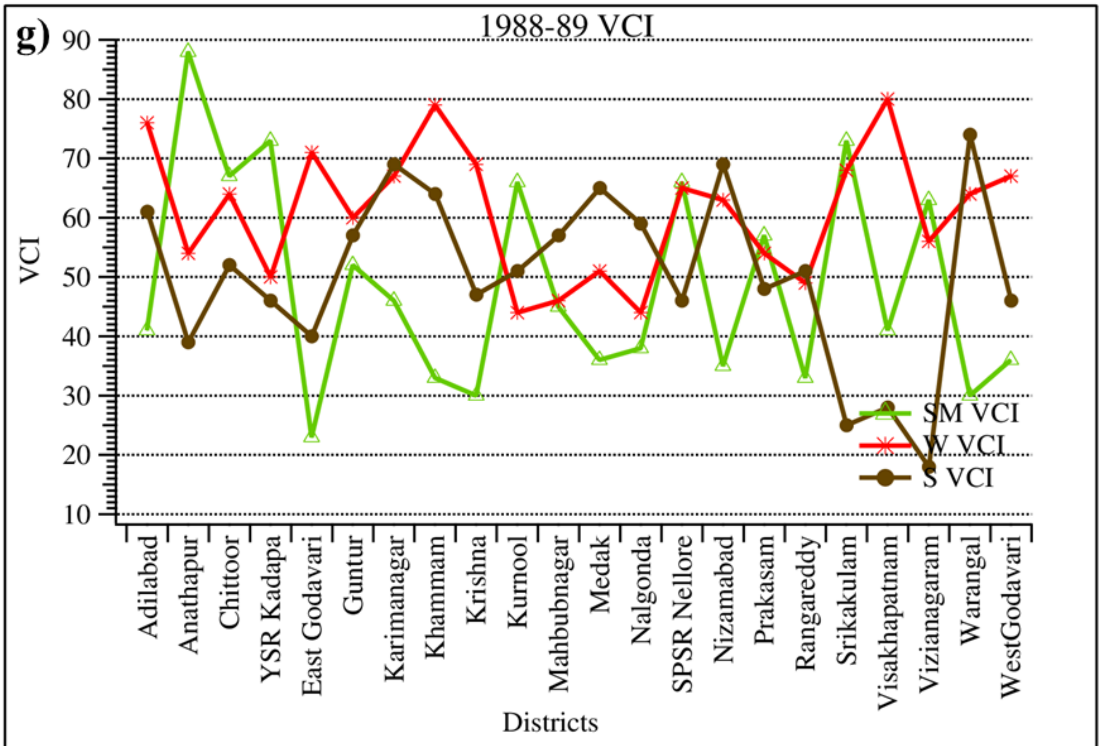
Figure 4.6 Seasonal pattern of VCI at state level during (a) 1982-2000; and (b) 2000-2015.


a)
1982-83 VCI
SM VCI
W VCI
S VCI
VCI
Districts
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
b)
1983-84 VCI
SM VCI
W VCI
S VCI
VCI
Districts

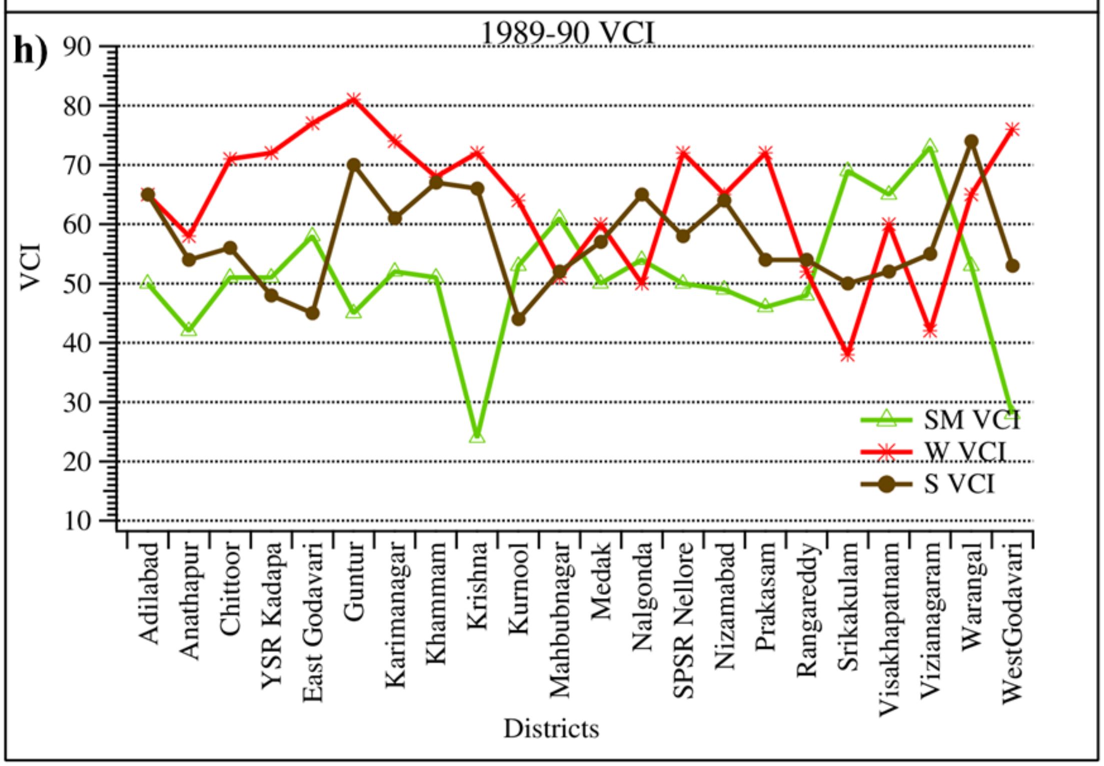

c)
1984-85 VCI
SM VCI
W VCI
S VCI
VCI
90
80
70
60
50
40
30
20
10
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts


d)
1985-86 VCI
SM VCI
W VCI
S VCI
VCI
90
80
70
60
50
40
30
20
10
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts

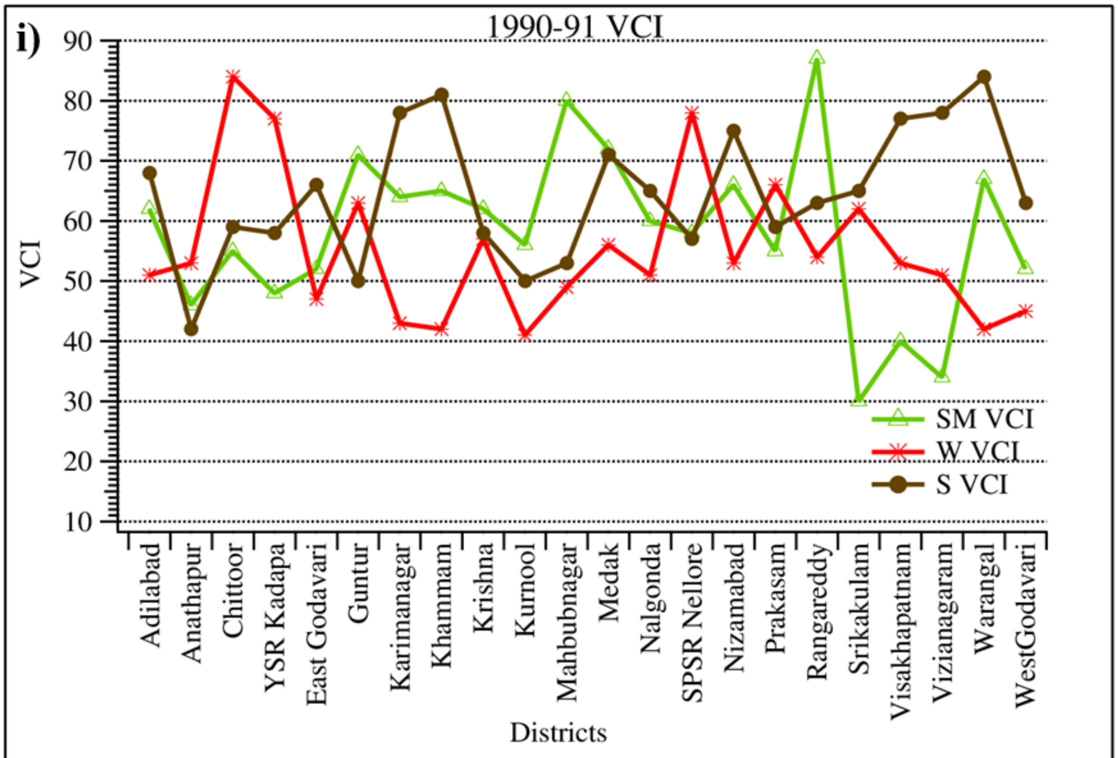

e)
1986-87 VCI
VCI
90
80
70
60
50
40
30
20
10
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts
f)
1987-88 VCI
VCI
90
80
70
60
50
40
30
20
10
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts



g)
1988-89 VCI
VCI
Districts
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari



h)
1989-90 VCI
VCI
Districts
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari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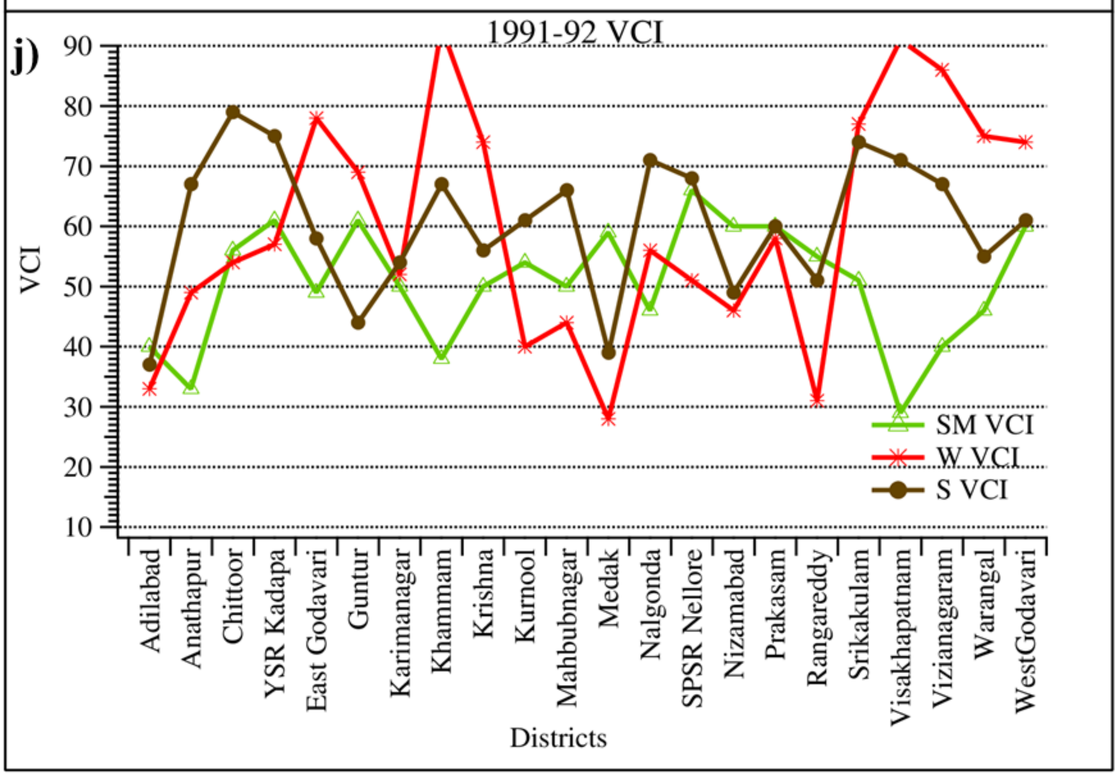
1990-91 VCI
VCI
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts


j)
1991-92 VCI
VCI
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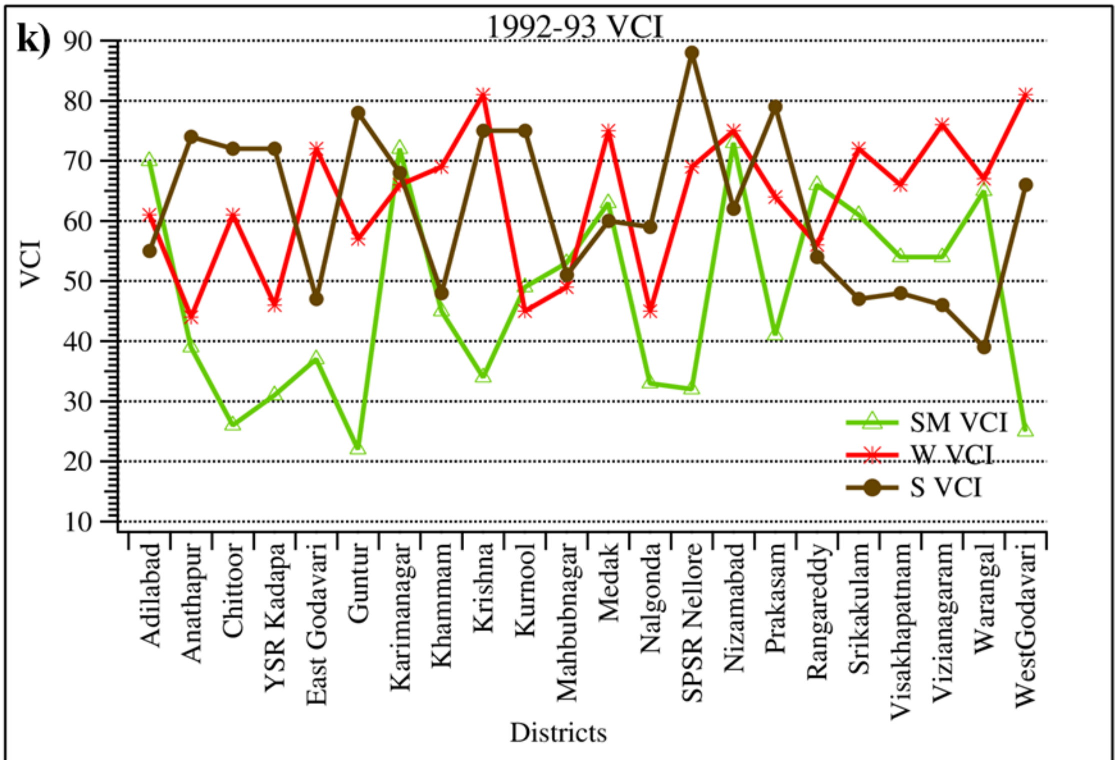
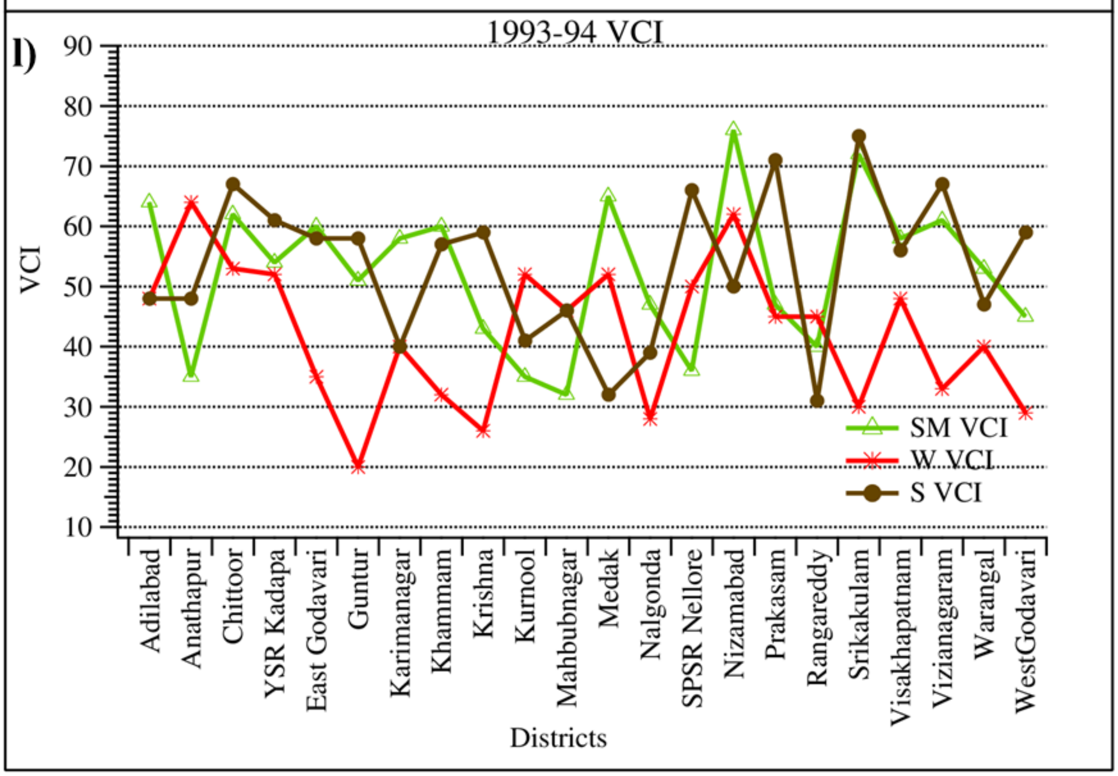
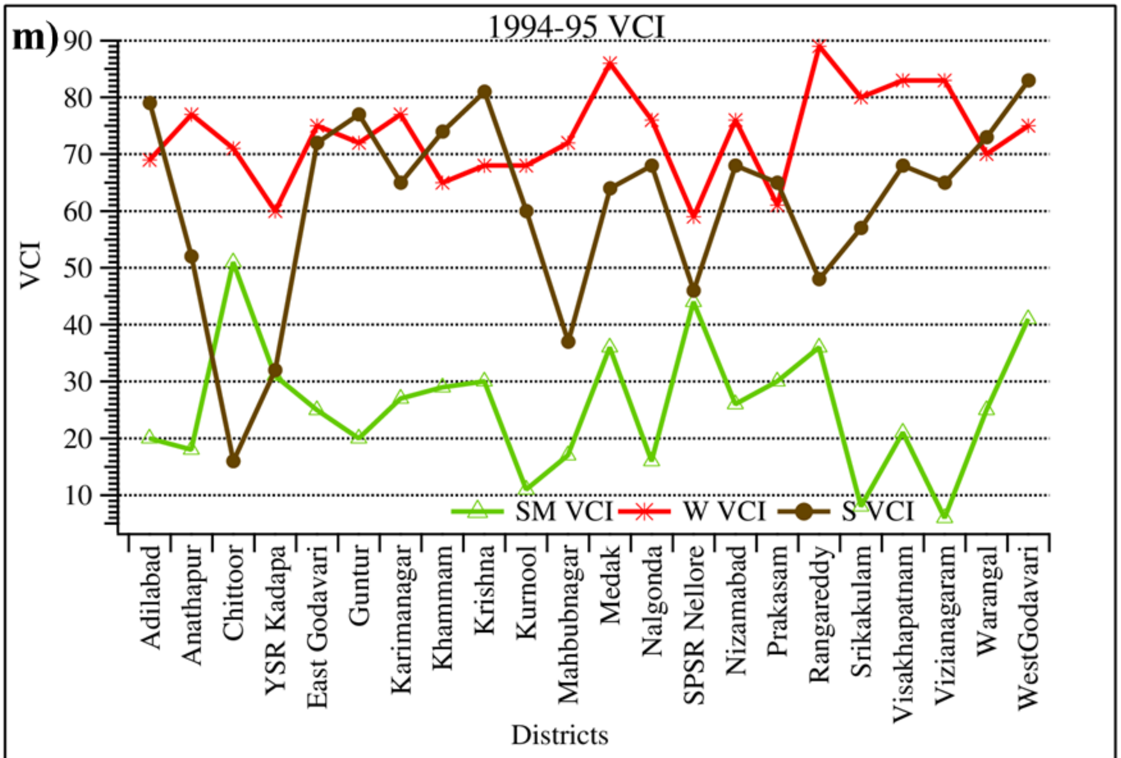
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts


k)
1992-93 VCI
VCI
90
80
70
60
50
40
30
20
10
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts


l)
1993-94 VCI
VCI
90
80
70
60
50
40
30
20
10
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts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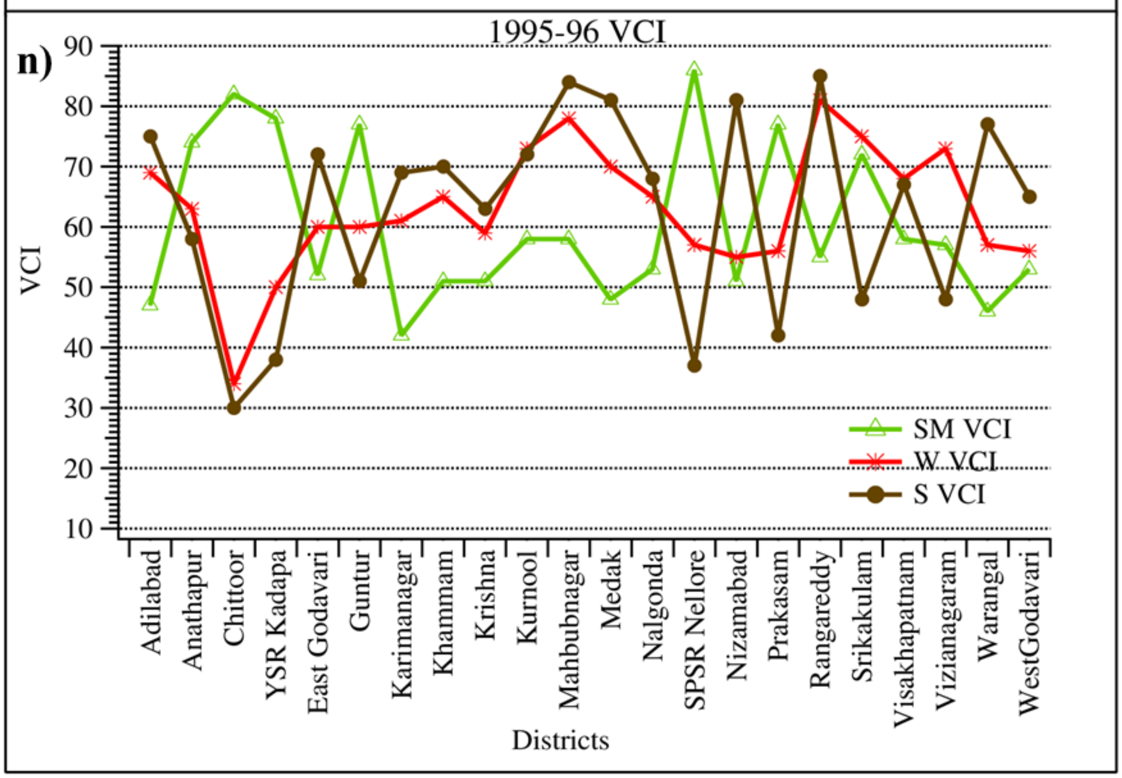
1994-95 VCI
VCI
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts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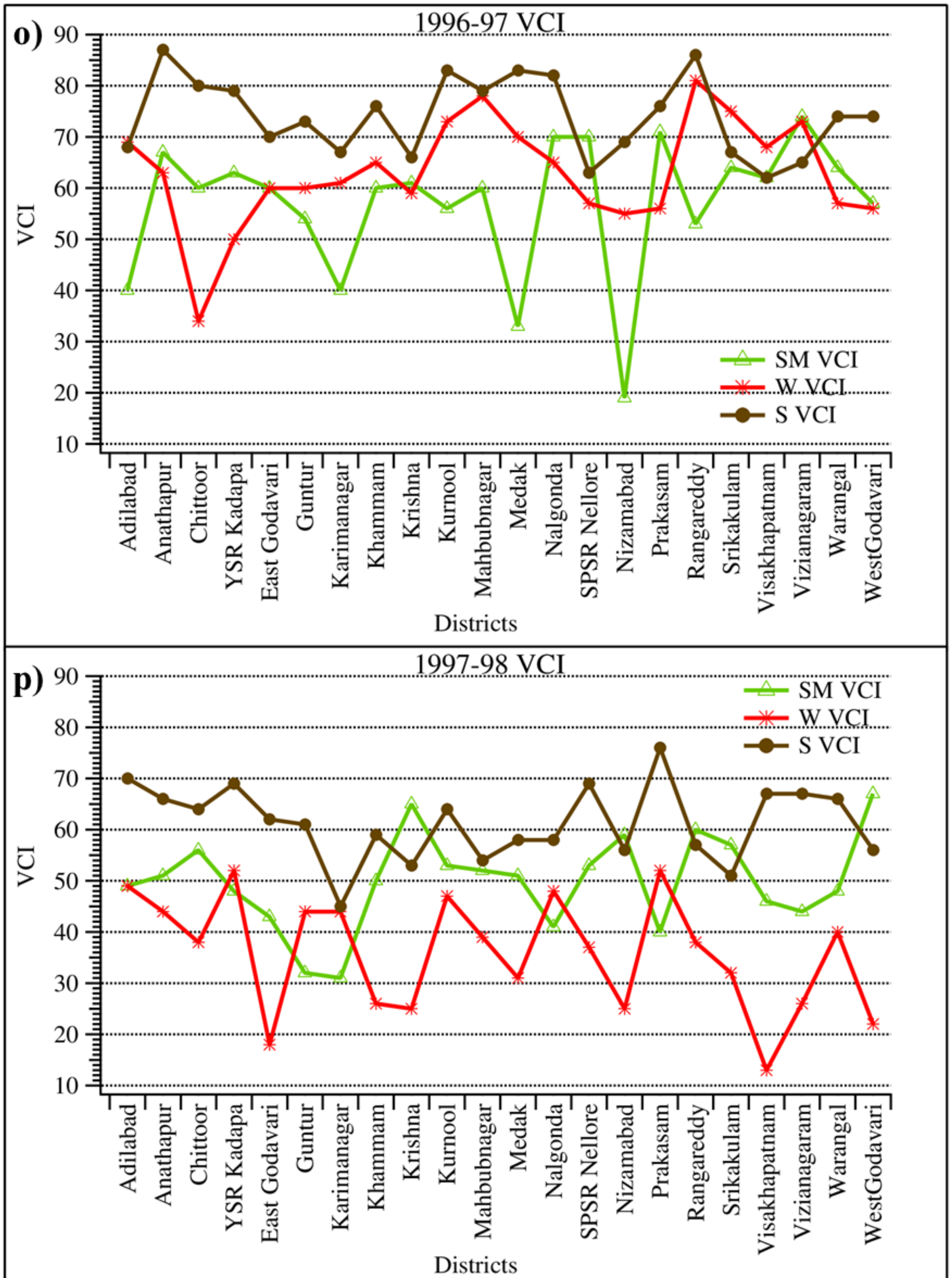
1995-96 VCI
VCI
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts


o)
1996-97 VCI
VCI
90
80
70
60
50
40
30
20
10
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts
p)
1997-98 VCI
VCI
90
80
70
60
50
40
30
20
10
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts

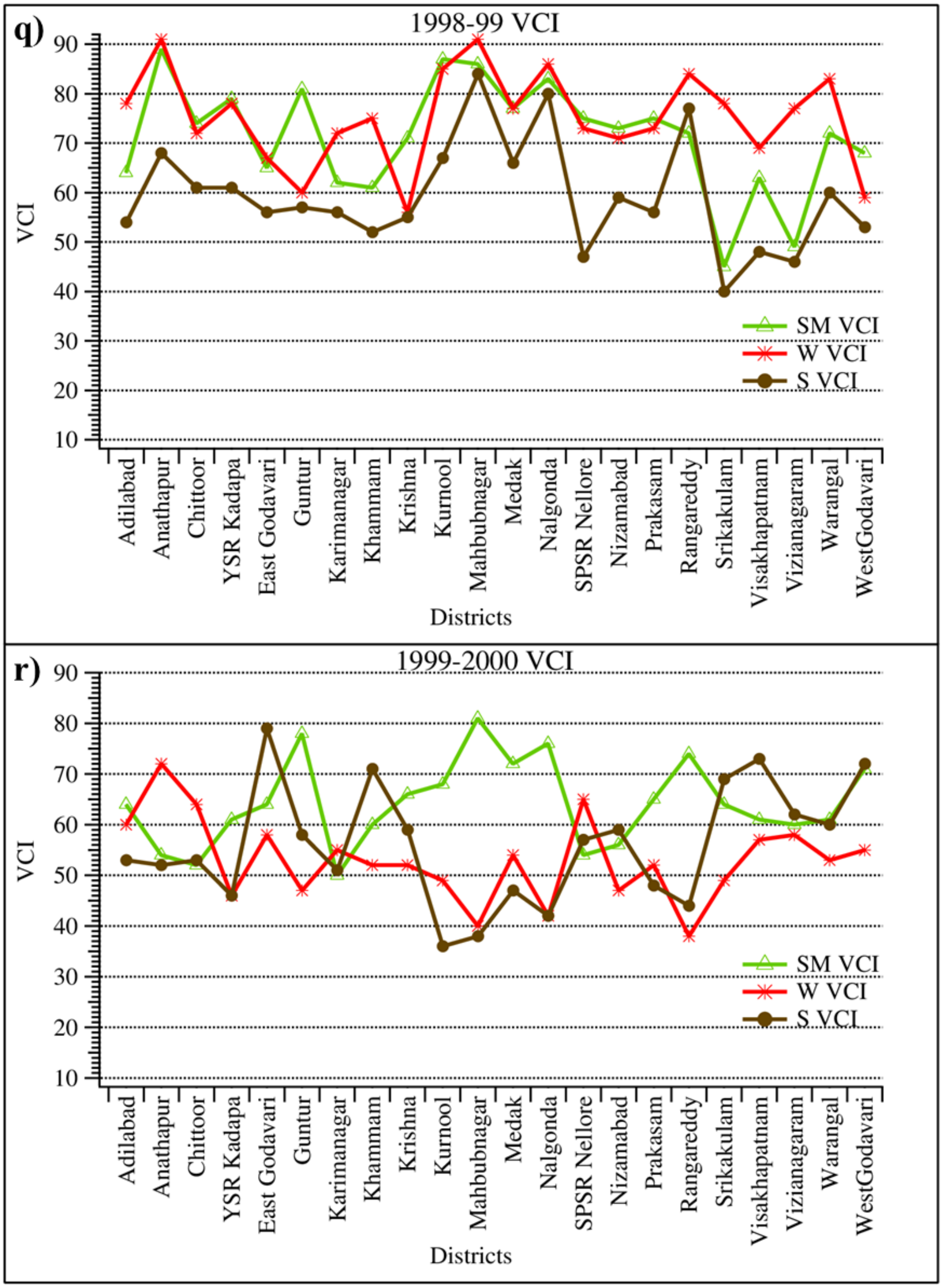
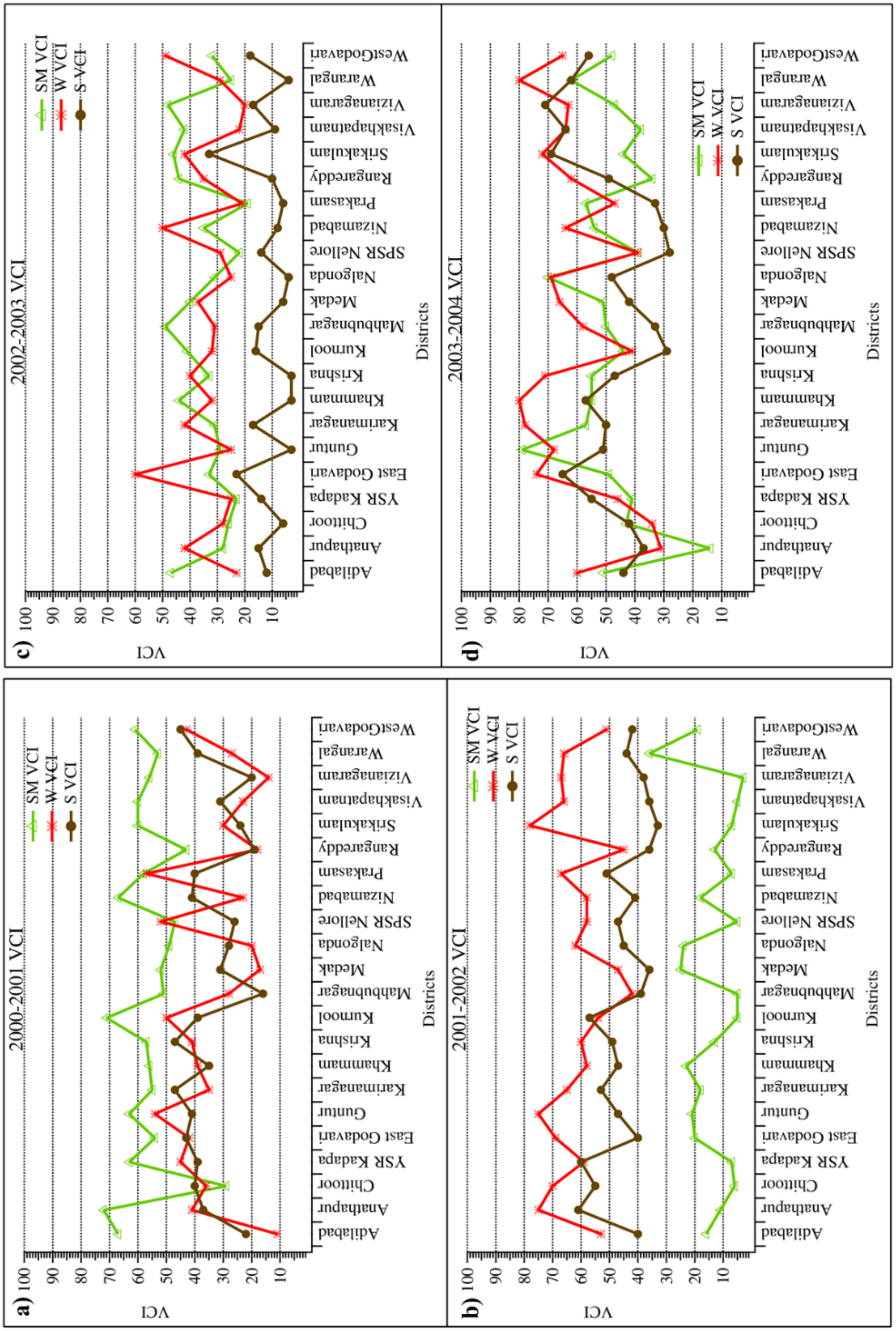
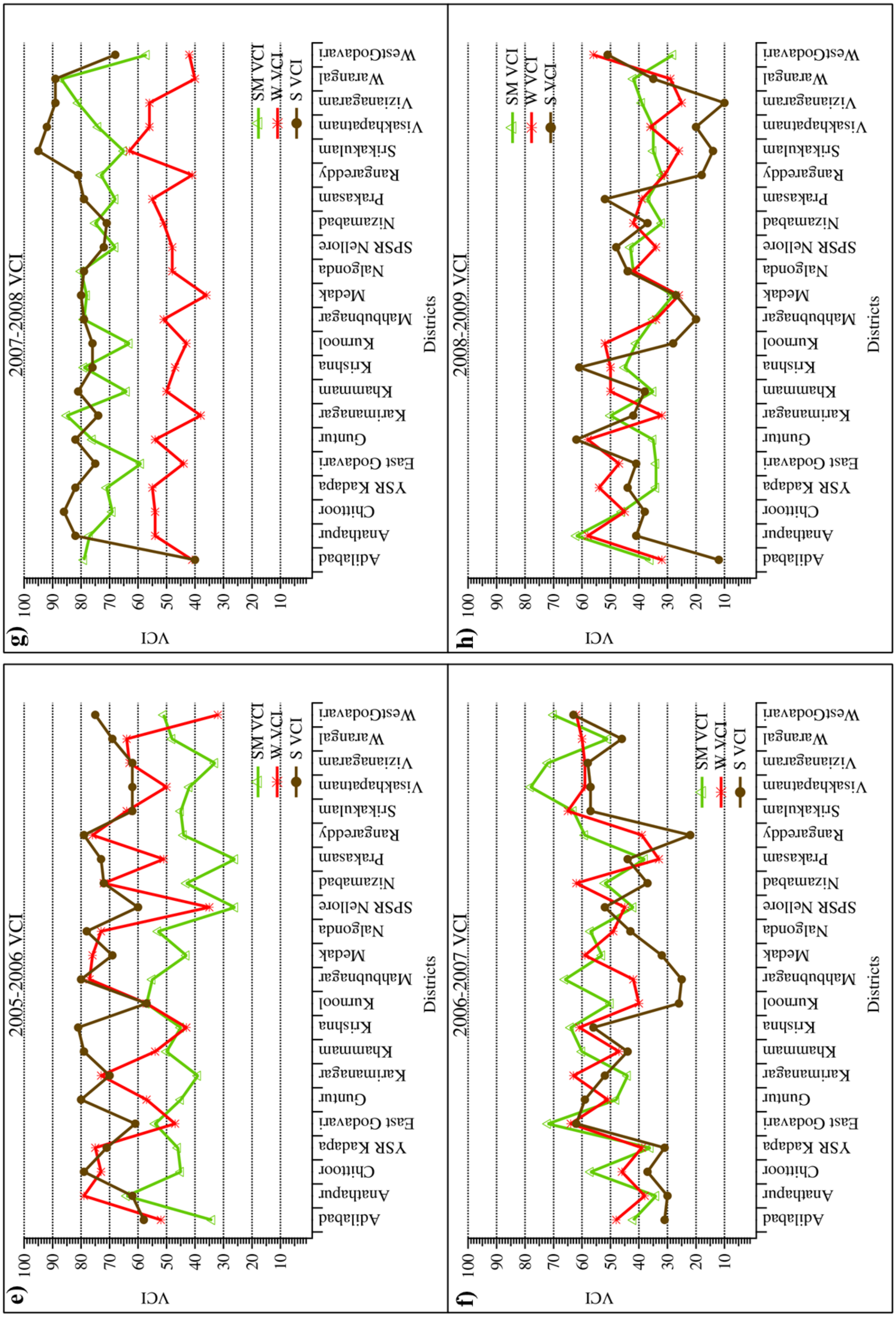
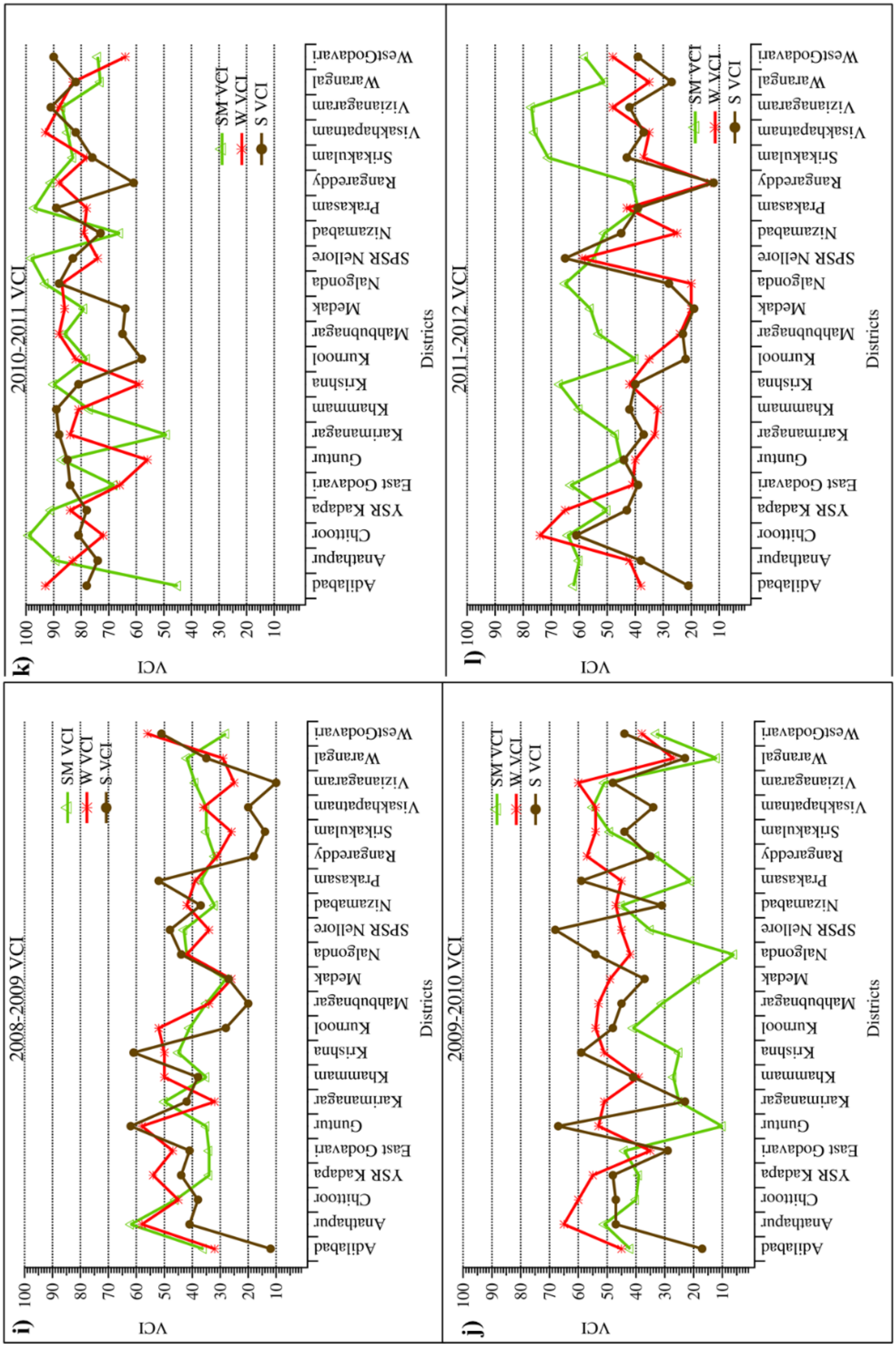
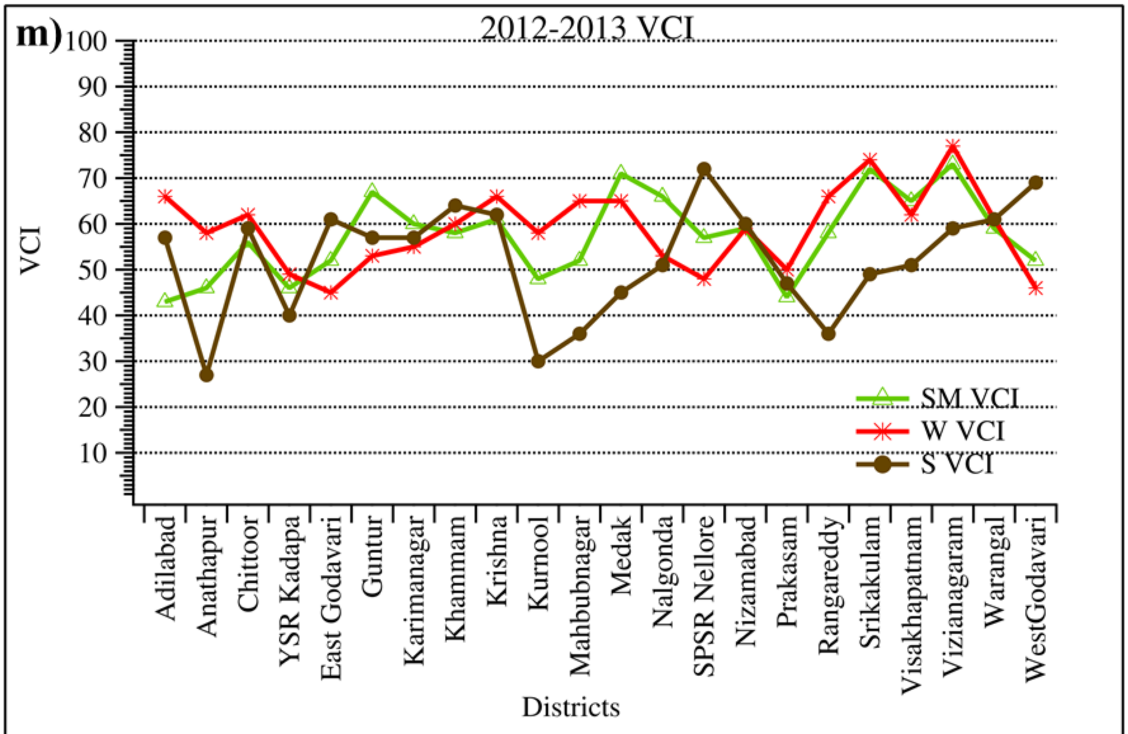


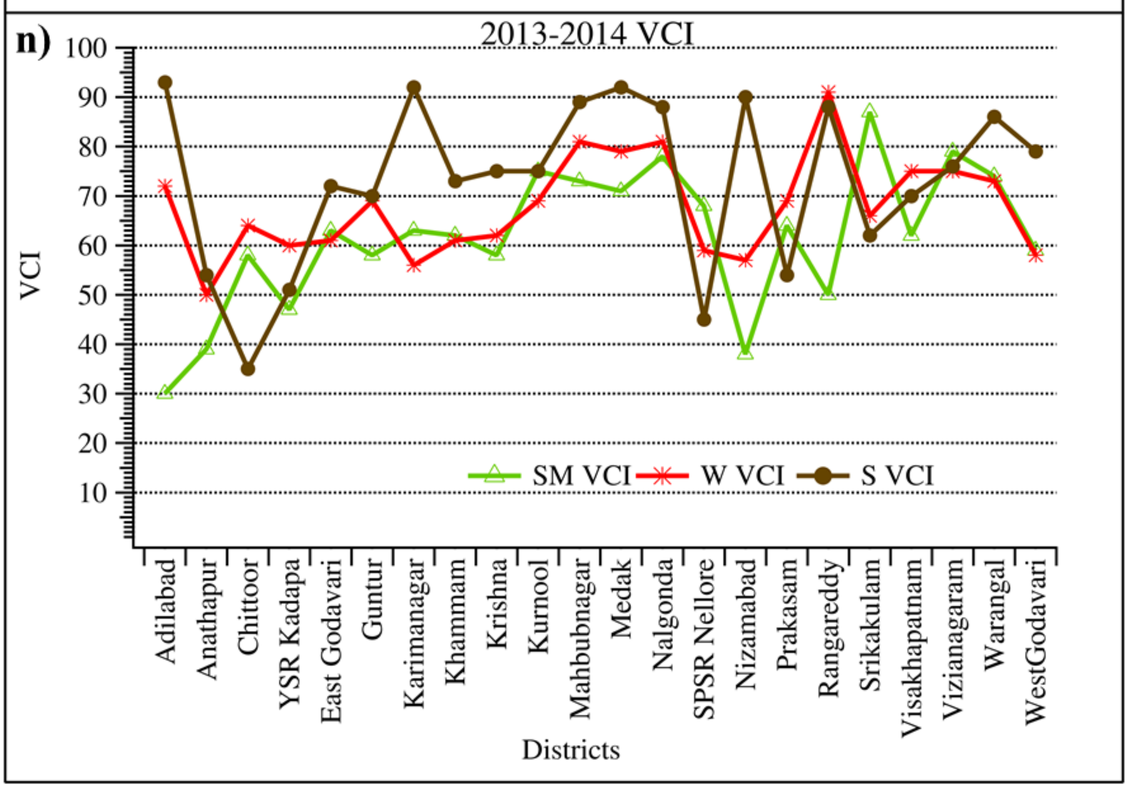
Figure 4.7 District wise seasonal pattern of VCI derived from NOAA GIMMS data a) 1982-83; b) 1983-84; c) 1984-85; d)1 985-86; e) 1986-87; f) 1987-88; g) 1988-89; h) 1989-90; i) 1990-91; j) 1991-92; k) 1992-93; l) 1993-94; m) 1994-95; n) 1995-96; o) 1996-97; p)1997-98; q)1998-99; and r)1999-2000.


a) 2000-2001 VCI
b) 2001-2002 VCI
c) 2002-2003 VCI
d) 2003-2004 VCI
SM VCI
W VCI
S VCI
VCI
Districts
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimnagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari


e)
2005-2006 VCI
f)
2006-2007 VCI
g)
2007-2008 VCI
h)
2008-2009 VCI
VCI
Districts
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari


i)
2008-2009 VCI
j)
2009-2010 VCI
k)
2010-2011 VCI
l)
2011-2012 VCI
VCI
Districts
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari


m)
2012-2013 VCI
VCI
100
90
80
70
60
50
40
30
20
10
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts


n)
2013-2014 VCI
VCI
100
90
80
70
60
50
40
30
20
10
SM VCI
W VCI
S VCI
Adilabad
Anathapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
WestGodavari
Districts

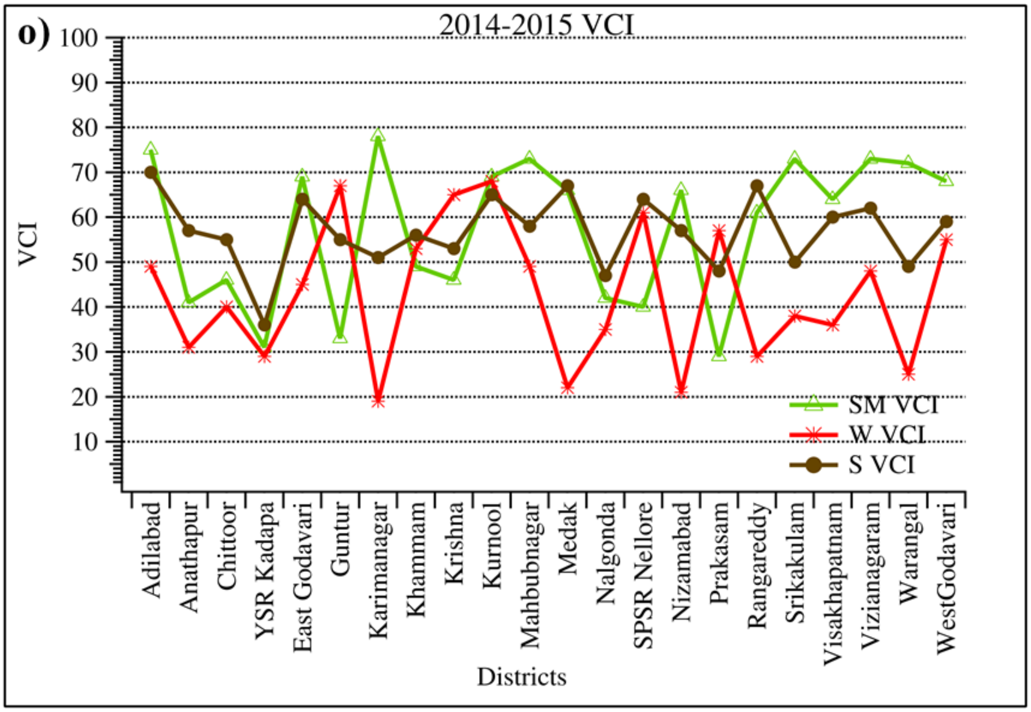


Figure 4.8 District wise seasonal pattern of VCI derived from MODIS data a) 2000-01; b) 2001-02; c)2002-03; d) 2003-04; e) 2004-05; f) 2005-06; g) 2006-07; h) 2007-08; i) 2008-09; j) 2009-10; k) 2010-11; l) 2011-12; m)2012-13; n) 2013-14; and o) 2014-15.

4.2.3 Standardized Precipitation Index

4.2.3.1 State Level

NOAA GIMMS

The temporal variation of SPI in the state for the period 1982-83 to 1999-2000 is shown in Fig. 4.9 (a). Significant negative SPI, indicative of less rainfall/break in rainfall, is observed during the summer monsoon of 1987-88, 1997-98; winter monsoon of 1988-89, 1989-90; and summer season of 1985-86 and 1992-93. Significant positive SPI, indicating good rainfall is observed during the summer monsoon of the year 1983-84, 1988-89 and 1989-90; winter season of 1986-87, 1995-96, and 1997-98; and summer season of 1990-91.

MODIS

The temporal pattern of SPI for the period from 2000-2001 to 2014-2015 is shown in the Fig. 4.9b. It is clearly evident from Fig. 4.9b that significant negative SPI is observed in all the three seasons of 2002-03, 2011-12 and 2014-15, again indicating low rainfall. A significant deficit of rainfall is also well reflected by negative SPI during the summer monsoon of 2009-2010 and winter season of 2000-2001 (Fig. 4.9b).

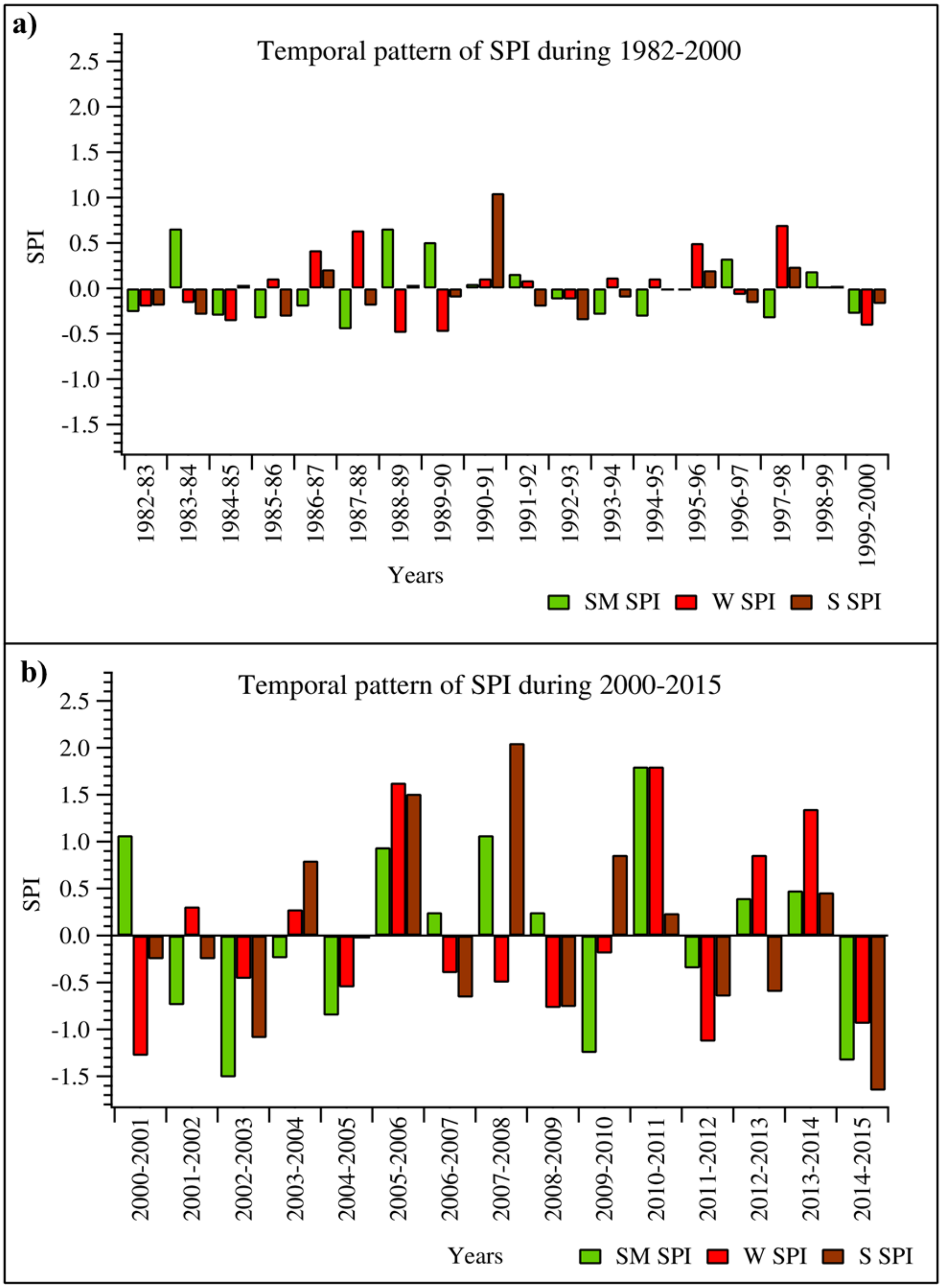
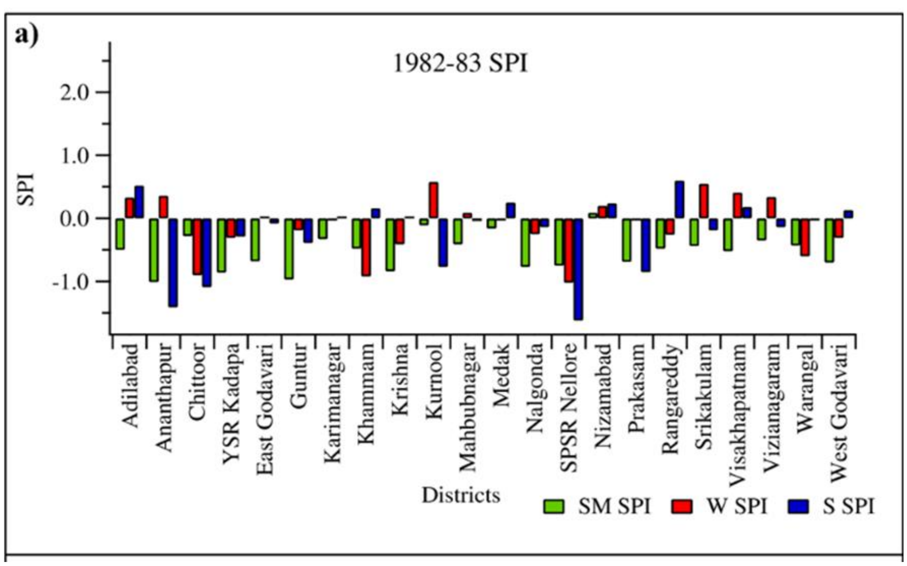


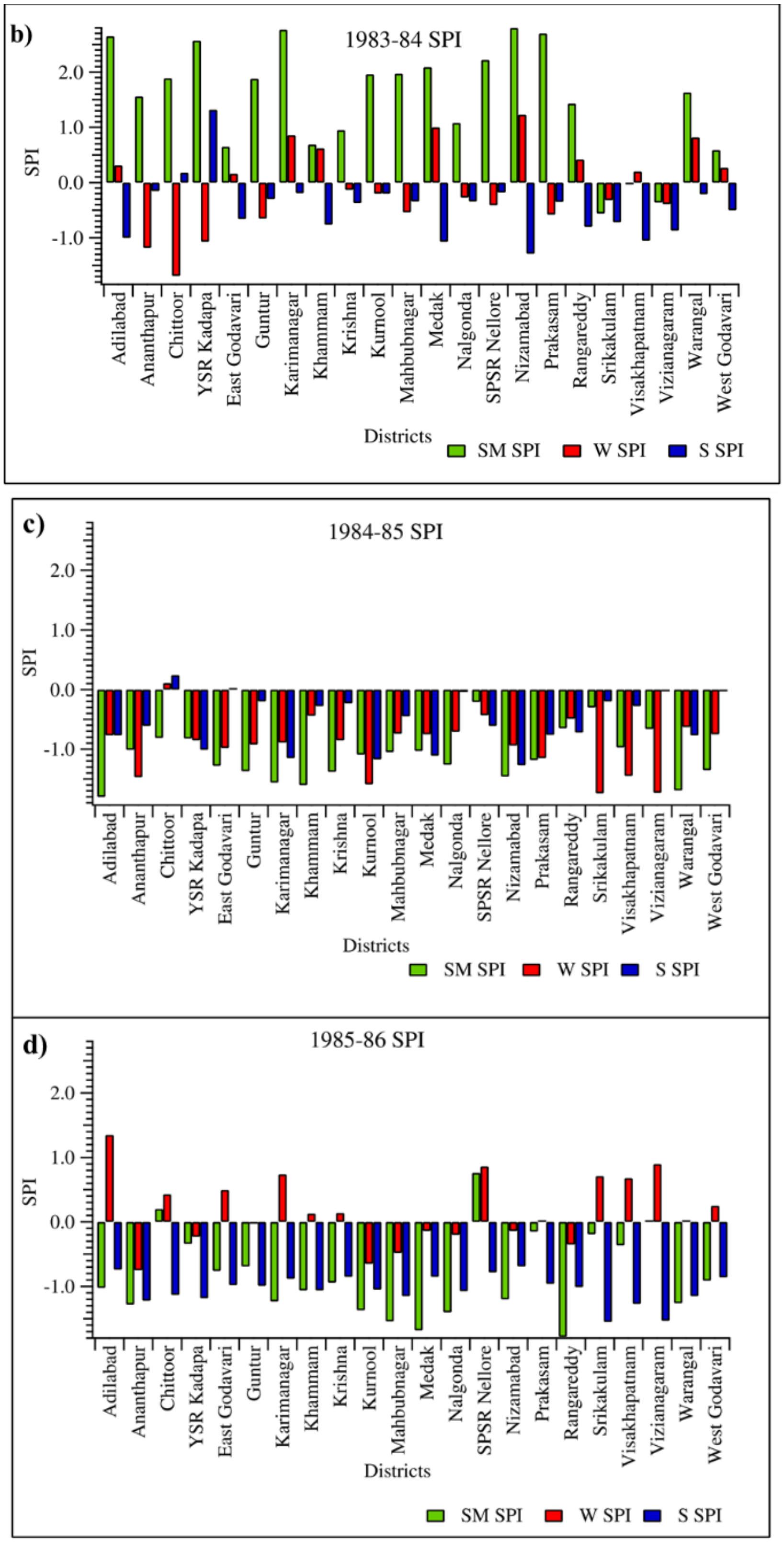
Figure 4.9 Seasonal pattern of SPI at state level a) 1982-2000; and b) 2000-2015.

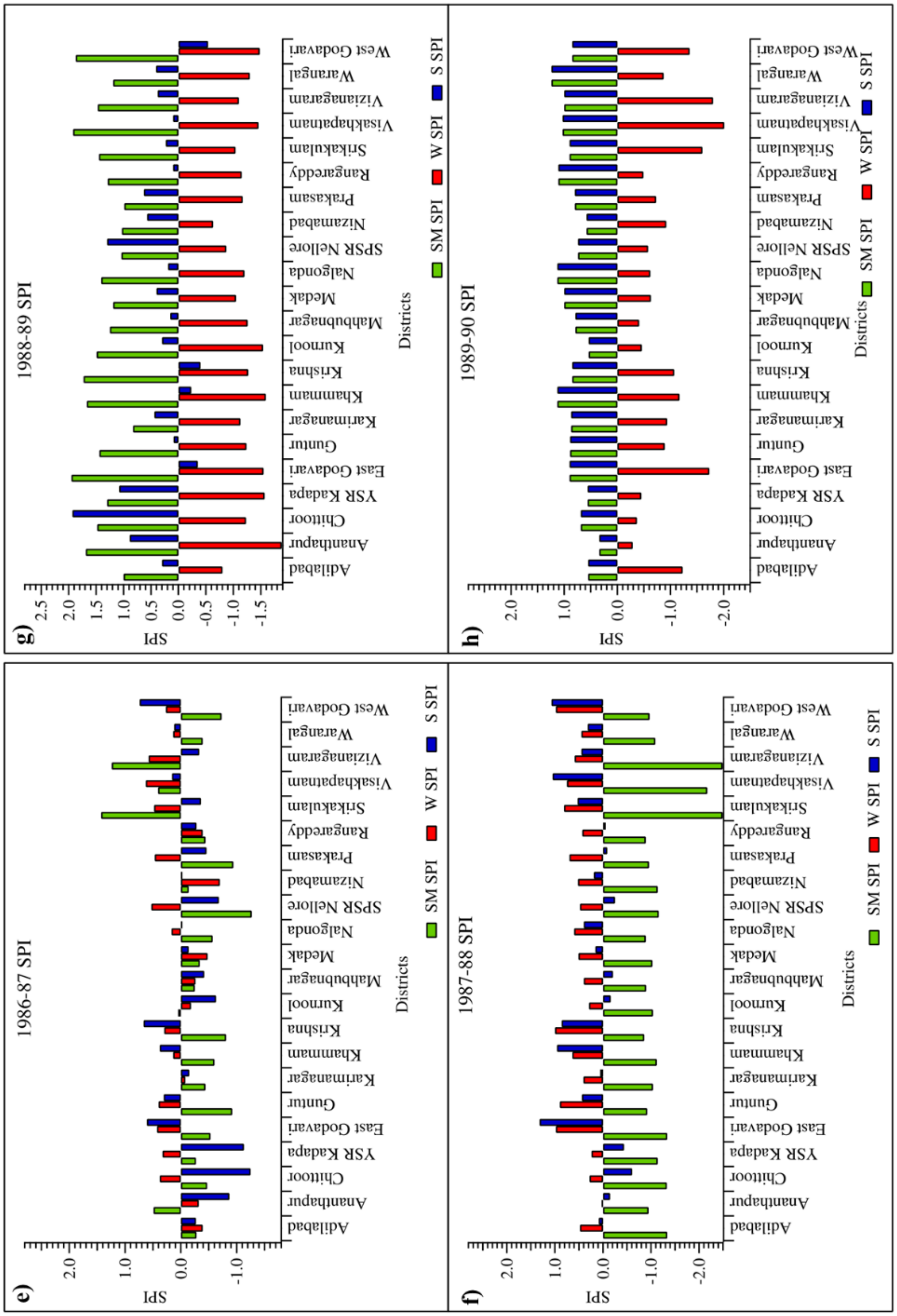
4.2.3.2 District level

NOAA GIMMS

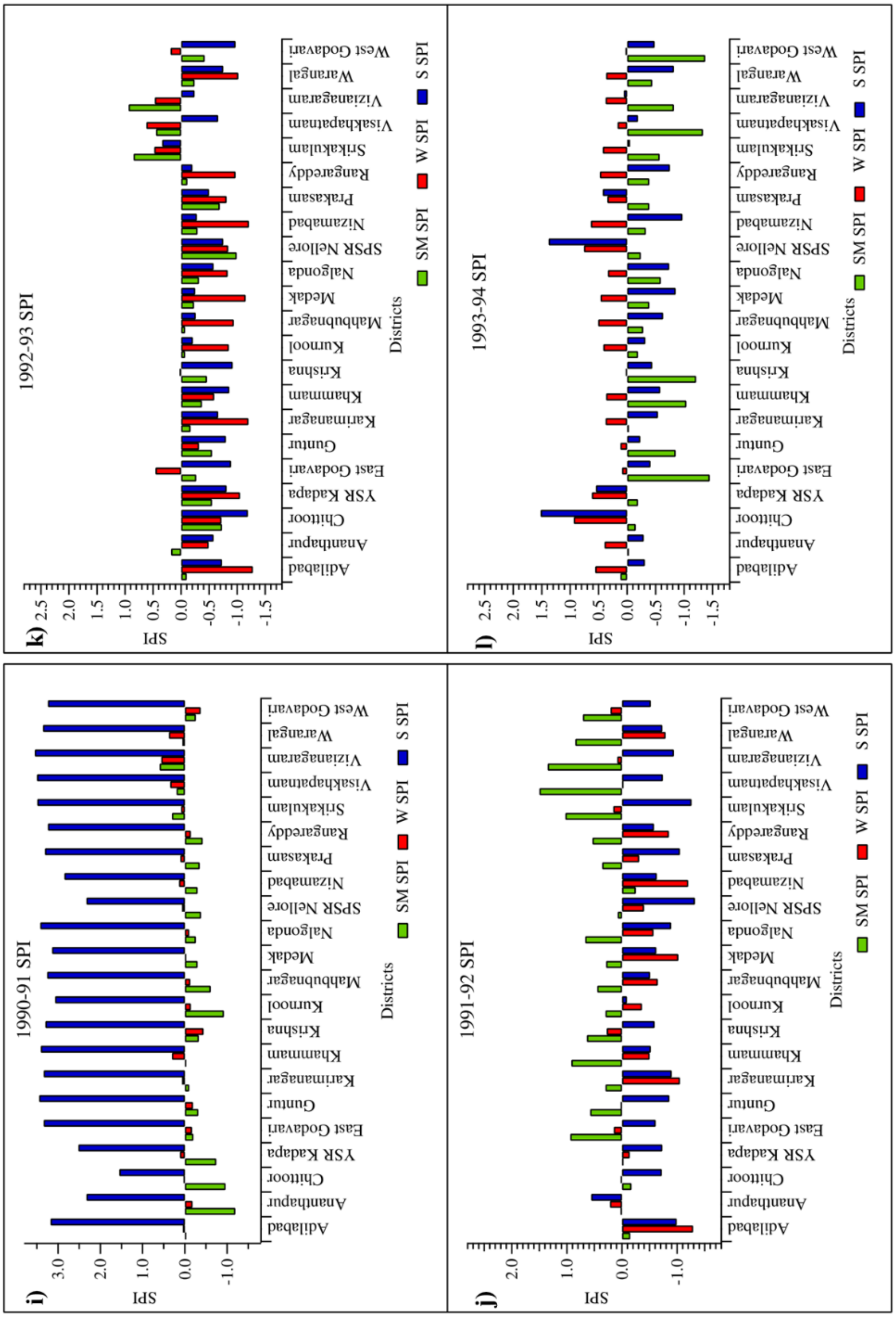
District wise seasonal patterns of SPI for the period 1982-83 to 1999-2000 are shown in Fig. 4.10. From 1982-83 to 1985-86 negative SPI is observed in a majority of the districts, indicating that the state has received low monsoonal rainfall (Figs. 4.10a to 4.10d) except during the summer monsoon of 1983-84, where a positive SPI was observed (Fig. 4.10b). The observation indicates that the period of the early 1980s was meteorologically drought year. It is also evident from Fig. 4.10f that during 1987-88, all the districts have shown negative SPI during the summer monsoon season (Fig. 4.10f) indicating that the state has experienced bad south-west monsoon during that year. On the other hand, the state has received good summer monsoon (South-West) during 1988-89 and 1989-90 (positive SPI), and short of NE monsoon /winter rainfall (negative SPI) (Figs. 4.10g and 4.10h). During 1990-91, the only summer season has experienced good rainfall which is indicated by positive SPI in all the districts compared to other two monsoonal seasons (Fig. 4.10i). This is attributed to the serve cyclonic storm occurred during the month of May 1990. During 1994-95 and 1997-98, positive SPI is observed in most of the districts in the winter season, due to severe cyclonic storm in the month of October 1994 and September 1997. Deficiency in summer monsoon and winter season rains during 1999-2000, which had caused meteorological drought in the state, have been well captured by negative SPI (Fig. 4.10r).



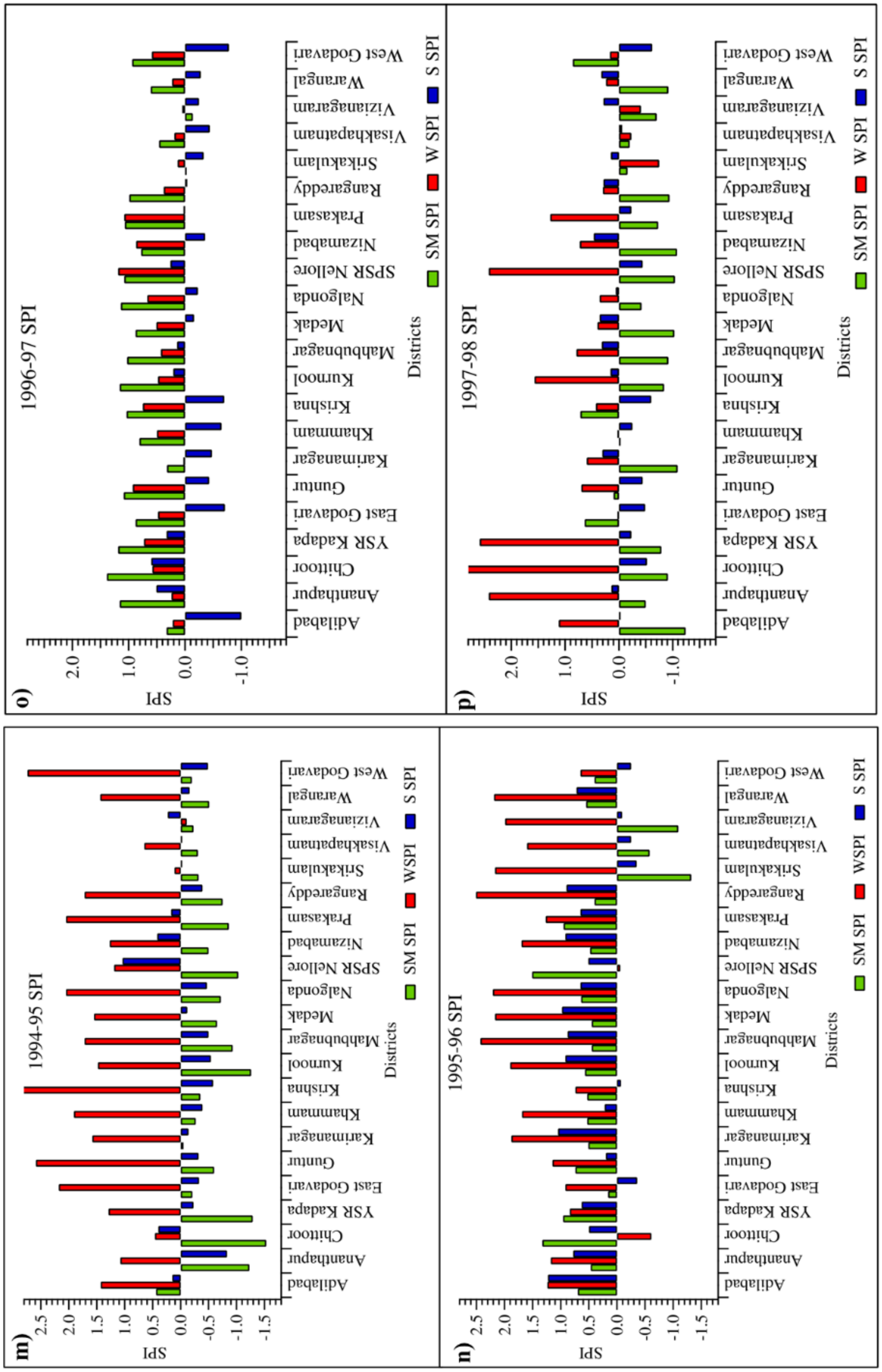

b)
1983-84 SPI
c)
1984-85 SPI
d)
1985-86 SPI
SPI
2.0
1.0
0.0
-1.0
Adilabad
Ananthapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
West Godavari
Districts
SM SPI
W SPI
S SPI



e) 1986-87 SPI
f) 1987-88 SPI
g) 1988-89 SPI
h) 1989-90 SPI
SPI
Districts
SM SPI
W SPI
S SPI
Adilabad
Ananthapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
West Godavari



i)
1990-91 SPI
j)
1991-92 SPI
k)
1992-93 SPI
l)
1993-94 SPI
SPI
Districts
Adilabad
Ananthapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
West Godavari
SM SPI
W SPI
S SPI



m)
1994-95 SPI
n)
1995-96 SPI
o)
1996-97 SPI
p)
1997-98 SPI
SPI
Districts
Adilabad
Ananthapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimnagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
West Godavari
SM SPI
WSPI
W SPI
S SPI

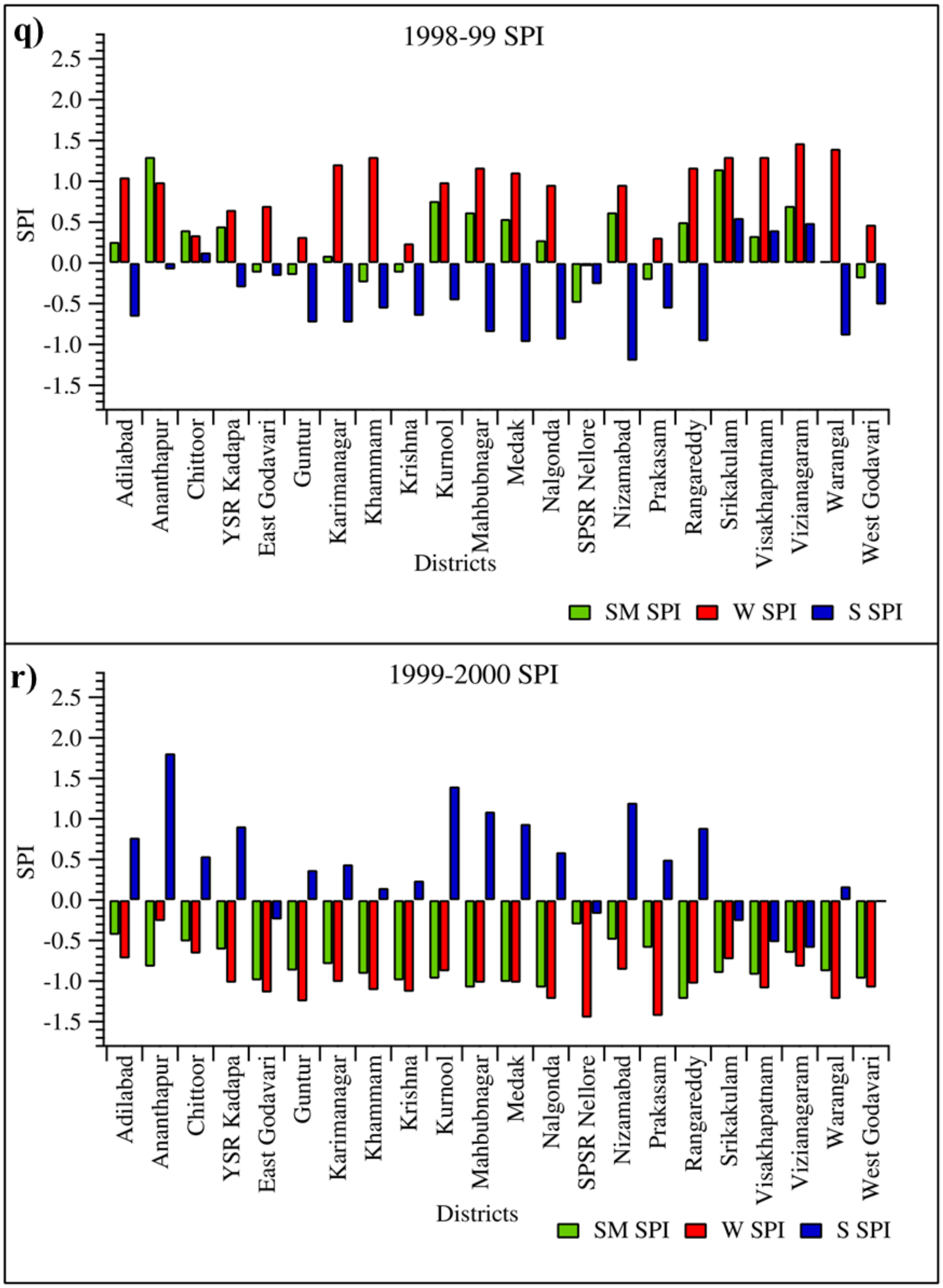
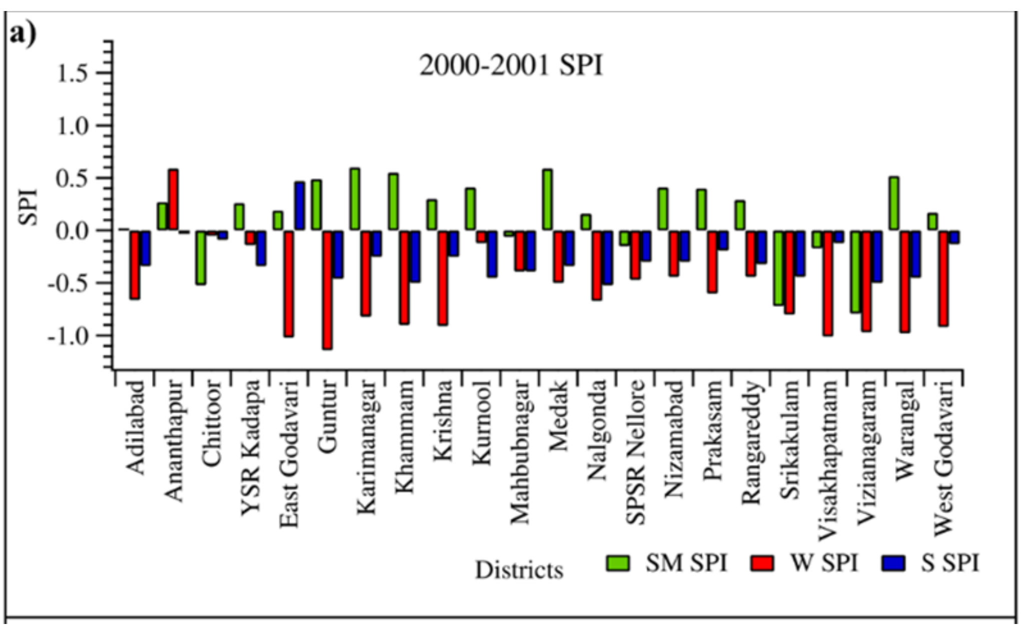


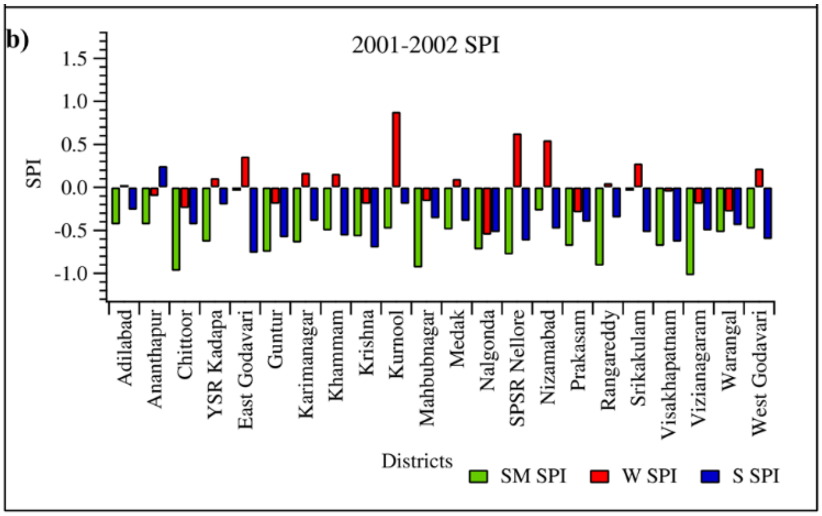
Figure 4.10 District wise seasonal pattern of SPI derived from NOAA GIMMS data a) 1982-83; b) 1983-84; c) 1984-85; d)1 985-86; e) 1986-87; f) 1987-88; g) 1988-89; h) 1989-90; i) 1990-91; j) 1991-92; k) 1992-93; l) 1993-94; m) 1994-95; n) 1995-96; o) 1996-97; p)1997-98; q)1998-99; and r)1999-2000.

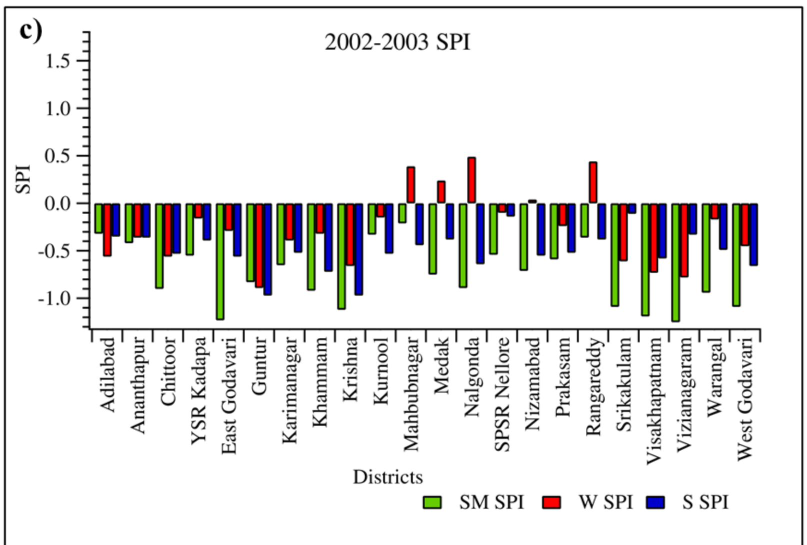
MODIS

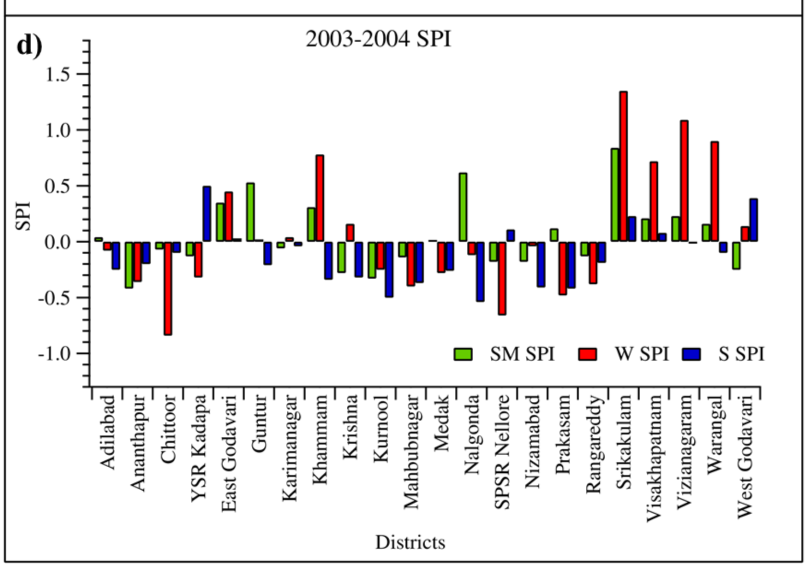
Spatial patterns of SPI in the state for the period 2000-2001 to 2014-2015 are shown in Fig.4.11. During 2002-2003, negative SPI is observed more or less in all the districts (Fig. 4.11c), indicating poor or unseasonal rainfall. In case of the year 2004-2005, both summer monsoon and winter seasons are reflected with negative SPI in all the districts (Fig. 4.11e), again indicating low rainfall events. The year 2007-2008 had experienced good and widespread rainfall in both summer monsoon and summer season in all the districts, which is captured well by positive SPI (Fig. 4.11h). During the period 2008-09 (Fig. 4.11i) and 2011-12 (Fig. 4.11l) negative SPI is observed in all the districts in all most all seasons due to reduced and poor rainfall, whereas positive SPI indicating good rainfall in 2010-2011. During 2013-2014, except three districts of Rayalaseema region namely Ananthpur, Chittoor, YSR Kadapa and one coastal district SPSR Nellore all other districts had experienced good rainfall throughout the year, which is effectively captured by positive SPI (Fig. 4.11n).

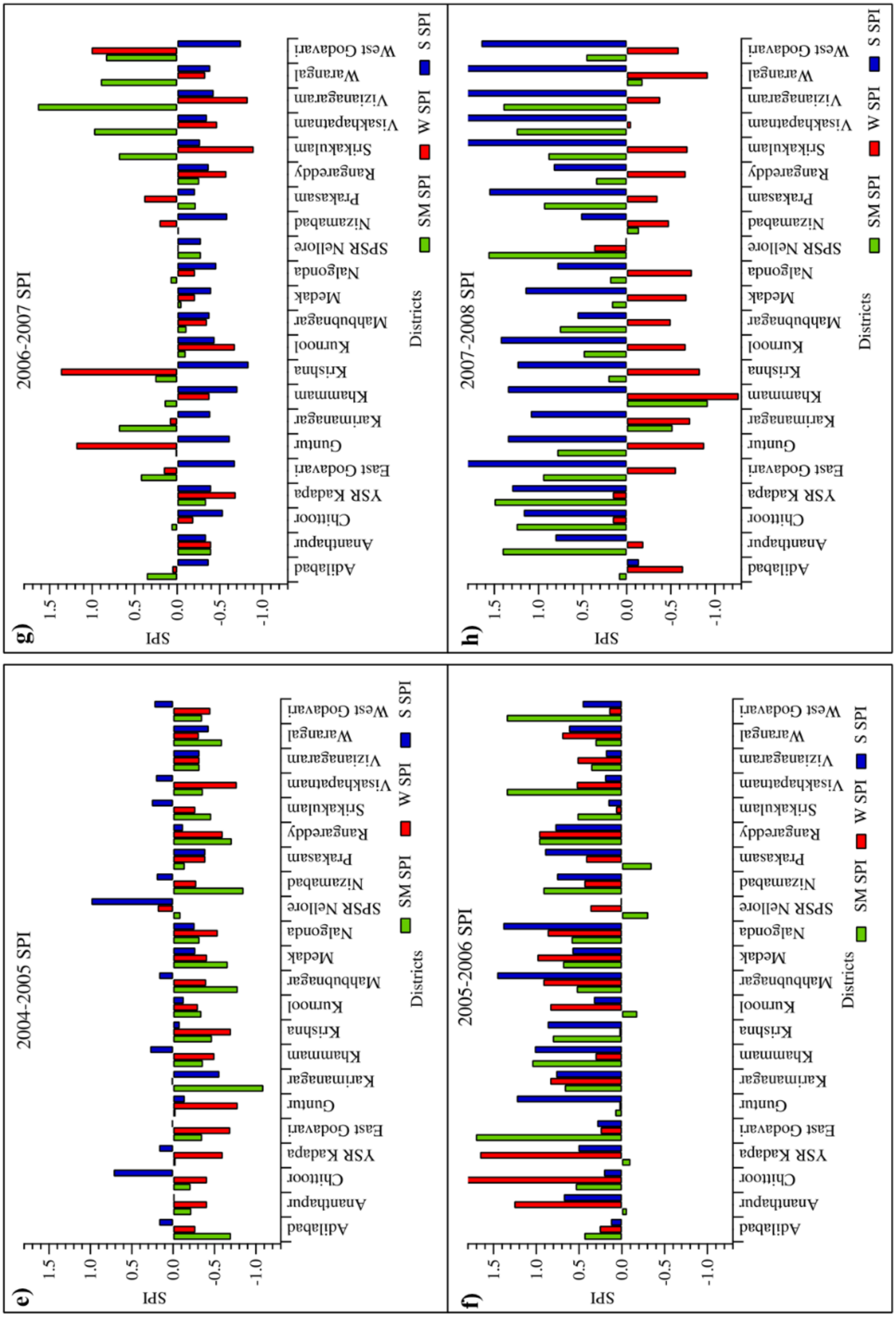
The enlisted observations clearly demonstrate that rainfall variability can be effectively captured by SPI.

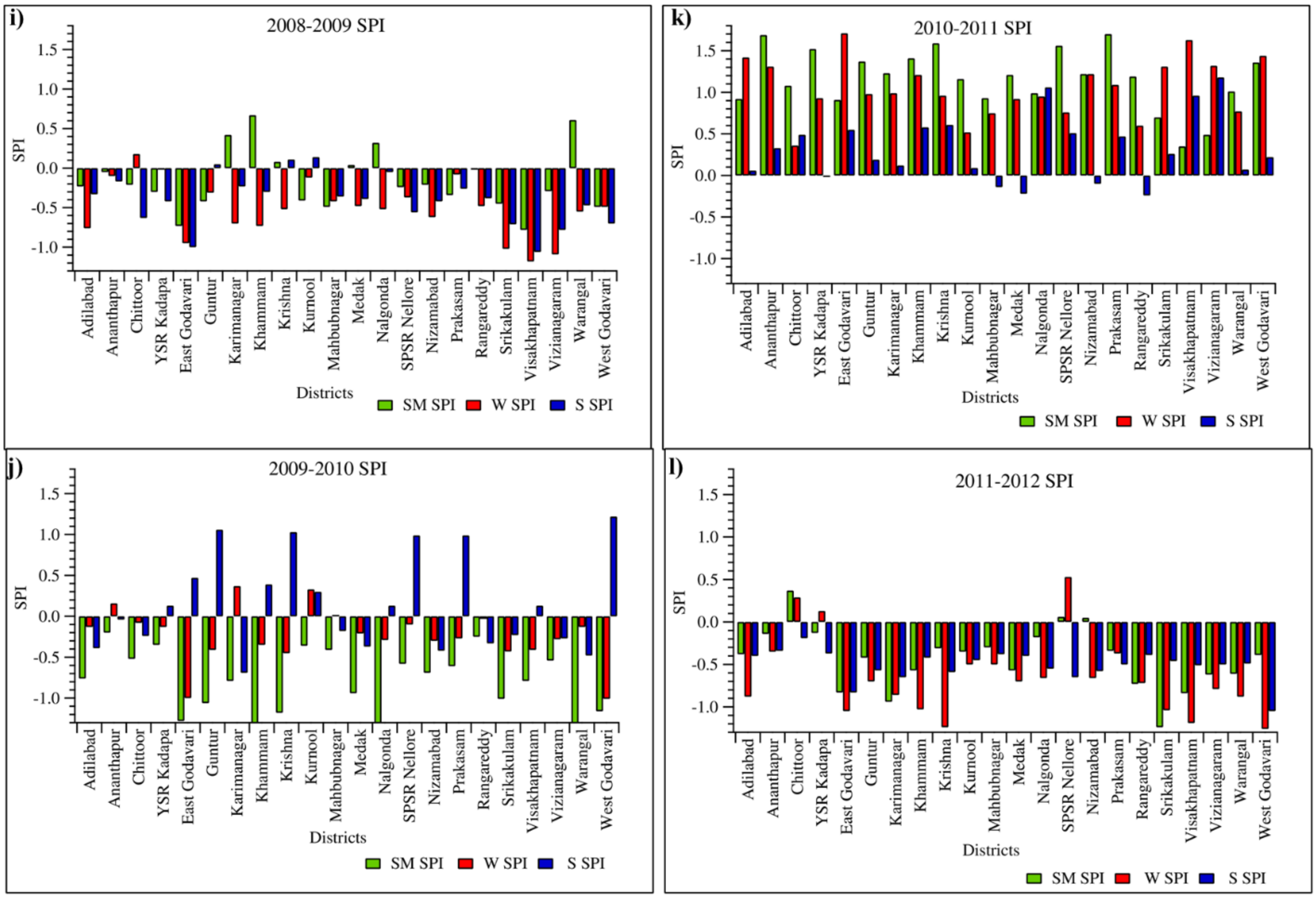



b)
2001-2002 SPI
SPI
1.5
1.0
0.5
0.0
-0.5
-1.0
Adilabad
Ananthapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
West Godavari
Districts
SM SPI
W SPI
S SPI


c)
2002-2003 SPI
SPI
1.5
1.0
0.5
0.0
-0.5
-1.0
Adilabad
Ananthapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
West Godavari
Districts
SM SPI
W SPI
S SPI


d)
2003-2004 SPI
SPI
1.5
1.0
0.5
0.0
-0.5
-1.0
SM SPI
W SPI
S SPI
Adilabad
Ananthapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
West Godavari
Districts


e)
2004-2005 SPI
f)
2005-2006 SPI
g)
2006-2007 SPI
h)
2007-2008 SPI
SPI
Districts
SM SPI
W SPI
S SPI
Adilabad
Ananthapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimnagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
West Godavari


i)
2008-2009 SPI
k)
2010-2011 SPI
j)
2009-2010 SPI
l)
2011-2012 SPI
SPI
1.5
1.0
0.5
0.0
-0.5
-1.0
Adilabad
Ananthapur
Chittoor
YSR Kadapa
East Godavari
Guntur
Karimanagar
Khammam
Krishna
Kurnool
Mahbubnagar
Medak
Nalgonda
SPSR Nellore
Nizamabad
Prakasam
Rangareddy
Srikakulam
Visakhapatnam
Vizianagaram
Warangal
West Godavari
Districts
SM SPI
W SPI
S SPI

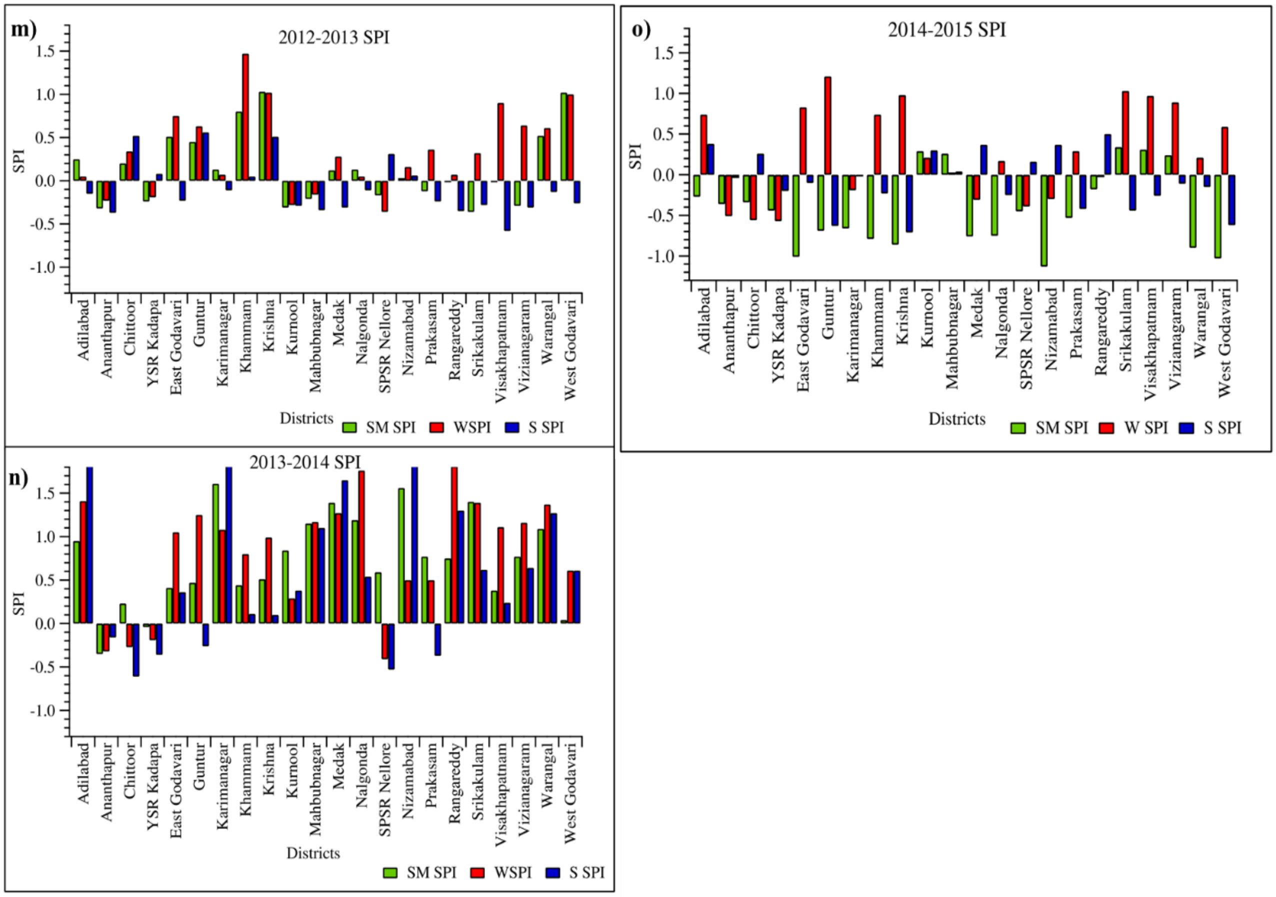


Figure 4.11 District wise seasonal pattern of SPI derived from MODIS data a) 2000-01; b) 2001-02; c)2002-03; d) 2003-04; e) 2004-05; f) 2005-06; g) 2006-07; h) 2007-08; i) 2008-09; j) 2009-10; k) 2010-11; l) 2011-12; m)2012-13; n) 2013-14; and o) 2014-15.

4.2.4 Seasonal pattern of NDVI anomaly and SPI

4.2.4.1 NOAA AVHRR GIMMS (1982-2000)

Figure 4.12a shows the seasonal patterns of “GIMMS NDVI anomaly and SPI during 1982–2000” in the state. Except for the period 1999-2000, the deviation of NDVI during the summer monsoon more or less follows the pattern of corresponding SPI (Fig. 4.12a). A sharp rise in NDVI is observed during August to September (Figure 4.12b) due to the impact of heavy rainfall. A similar correlation between $NDVI_{Dev}$ and monsoon SPI is repeated for winter and summer seasons (Fig. 4.12a).

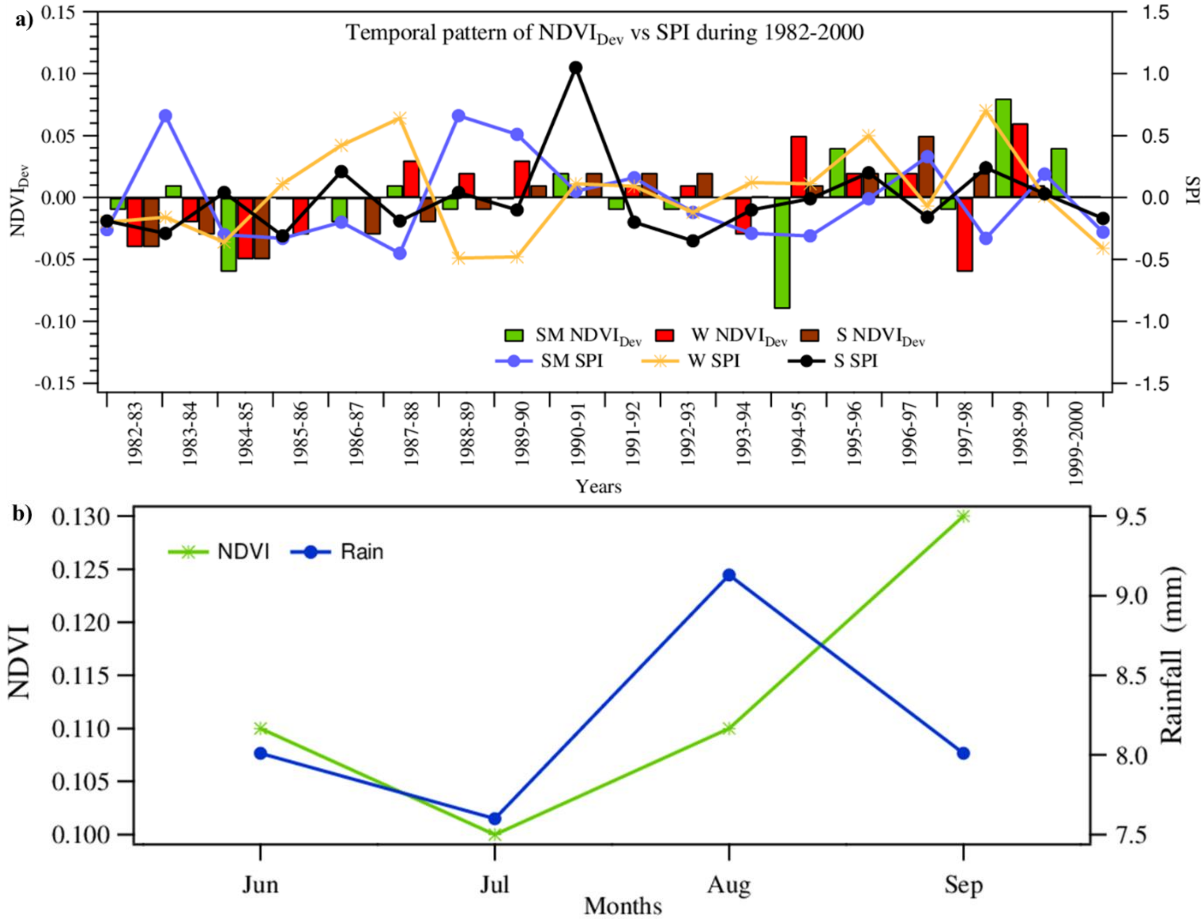


Figure 4.12 a) Seasonal pattern of $NDVI_{Dev}$ and SPI during 1982–2000 years (SPI is based on 30 years rainfall data-set); and b) June–September monthly profile of NDVI and rainfall during 1999–2000.

4.2.4.2 MODIS (2000-2015)

Figure 4.13a shows the seasonal patterns in the deviation of NDVI and SPI for the period 2000-2001 to 2014-2015. The patterns of deviation of NDVI and SPI are, by and large, similar to each other with an exception during 2001–2002. Although the summer monsoon was failed during the year 2001-2002 the state had received a normal winter monsoon resulting a normal winter crop. This observation clearly demonstrates that the "summer monsoon and the resulting residual soil moisture" play vital roles in the winter and summer cropping seasons (Bhavani et al., 2017).

Figure 4.13b shows the variation of NDVI of a good monsoon year (2010–2011), two stress years (2001–2002 and 2002–2003), and the average of NDVI over a period of 15 years (2000–2015). One can notice from Fig. 4.13b that the NDVI has attained its maximum during September to October of 2010-11summer cropping season. On the other hand, during the summer monsoon of the year 2001–2002 the NDVI was below the average. Similarly low NDVI was observed during the winter season of 2002-2003. For the year 2010–2011, the NDVI is above the average during all three seasons. Similar relation is observed with VCI and SPI (Annexure 4.1 a-c).

It is concluded that SPI and NDVI are synchronous to each other and highly correlated with SPI variability (r value greater than 0.5 in all the three season).

4.2.5 Crop area and proportions

Figure 4.14 shows the crop area percentages during all the cropping seasons of the period 2000–2001 to 2014–2015. Minimum percentages of cropped area were observed during the summer monsoon and winter cropping seasons of 2001–2002, winter monsoon of 2008–2009 and summer monsoon of 2009–2010. High percentage of cropped area was noticed during 2010–2011 in all the cropping seasons. A correlation is observed between the fluctuation (increase or decrease) of cropped area and the amount of rainfall received from the southwest monsoon in that year. It is well known that large proportions of potential agricultural area will be cultivated during a good monsoon year and a large proportion left fallow in case of poor monsoon. The proportions of cropped and fallow land areas are calculated (district-wise) to understand the impacts of southwest monsoon and the resulting residual soil moisture.

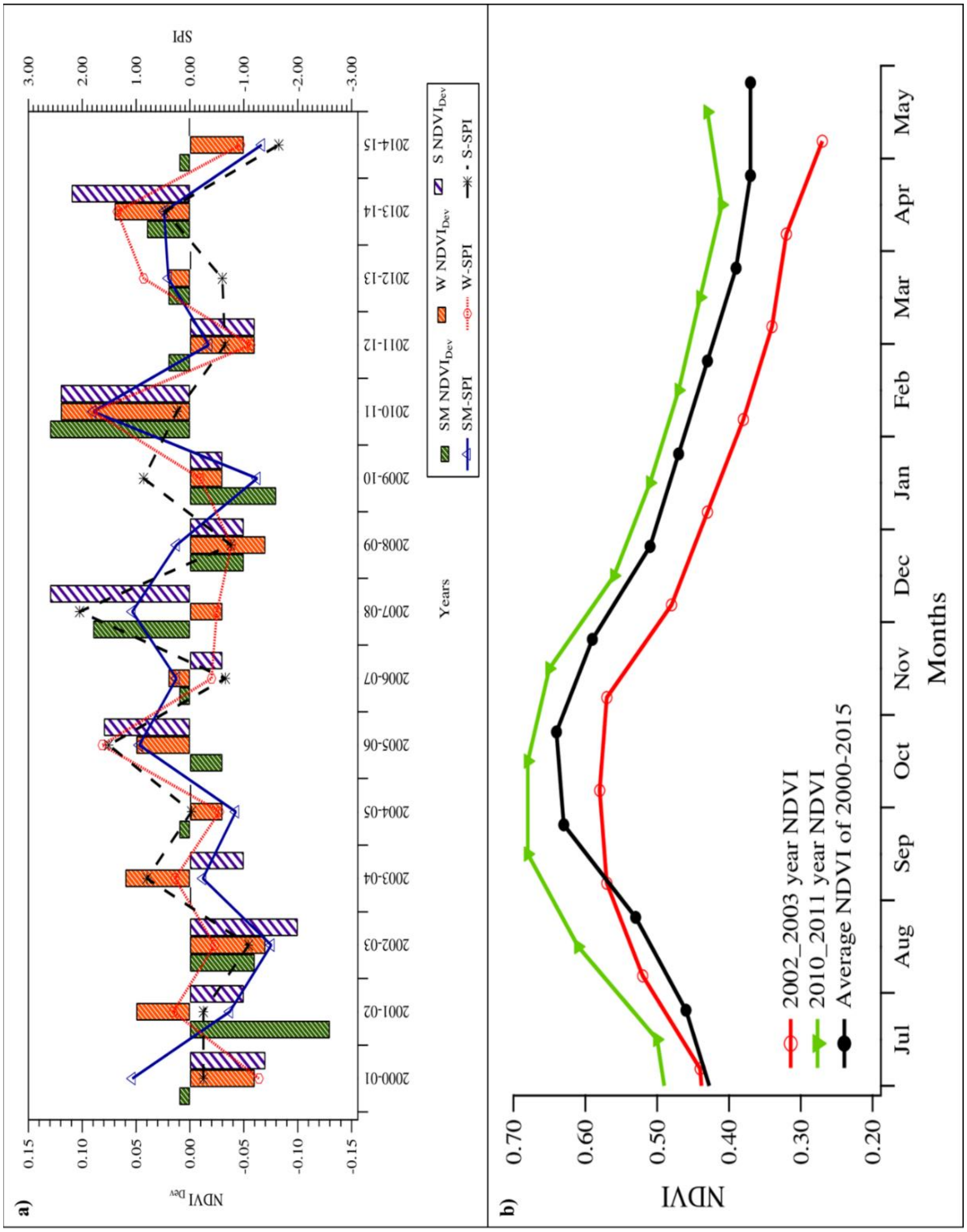


Figure 4.13 a) Seasonal pattern of $NDVI_{Dev}$ and SPI during 2000-2015 years (SPI based on 30 years rainfall data-sets); and b) Monthly pattern of NDVI of extremely dry and wet years (2002–2003 and 2010–2011) and long-term average of 2000–2015

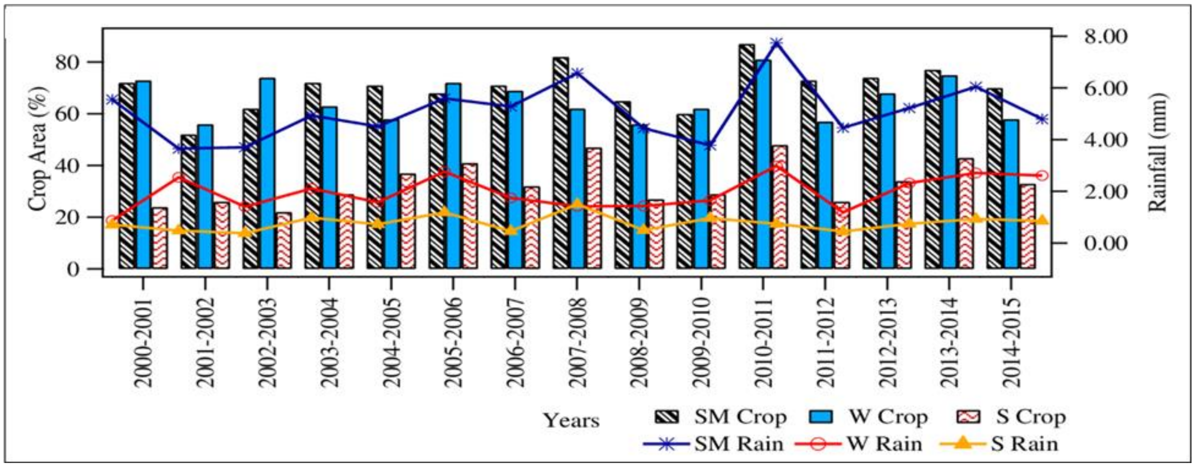


Figure 4.14 Seasonal pattern of crop area (%) and rainfall during 2000–2015.

Figure 4.15 shows the ratios of the cropped area (season wise) to the total agricultural area at the district level. It is observed that the proportion of long-term mean of cropped area to fallow land was minimum in Kurnool and Prakasam districts during the summer monsoon cropping season. On the other hand, high crop area proportions were observed in Srikakulam, Visakhapatnam, Vizianagaram, and East Godavari districts (Fig. 4.15a). During the winter cropping season, Prakasam district again had shown low proportion of long-term average of cropped area, where as Khammam and Warangal districts showed maximum proportions (Fig. 4.15b). Ananthapur, Rangareddy and Mahbubnagar, districts have shown low crop proportions during the summer cropping season. The West Godavari had shown high proportions of cropped area in all the three cropping seasons of the study period (Bhavani et al., 2017a).

The maximum fluctuation in the cropped area observed at the state level is 35% during the summer monsoon, 26% in summer, and 25% in winter season. The variation in rainfall and the availability of soil moisture (Komuscu et al., 1999; Kang et al., 2009; Alam et al., 2011) are primarily responsible for the observed fluctuations. The correlation analysis and multiple regression (Table 4.1) also support the enlisted observations. Further, the fluctuation in cropped area also vary from district to district due to change in the rainfall, available soil moisture, cropping system and market scenario. Maximum fluctuations in the cropped area was observed in SPS Nellore and Prakasam districts during the summer monsoon. In winter, maximum fluctuations are noticed in the districts of Mahbubnagar,

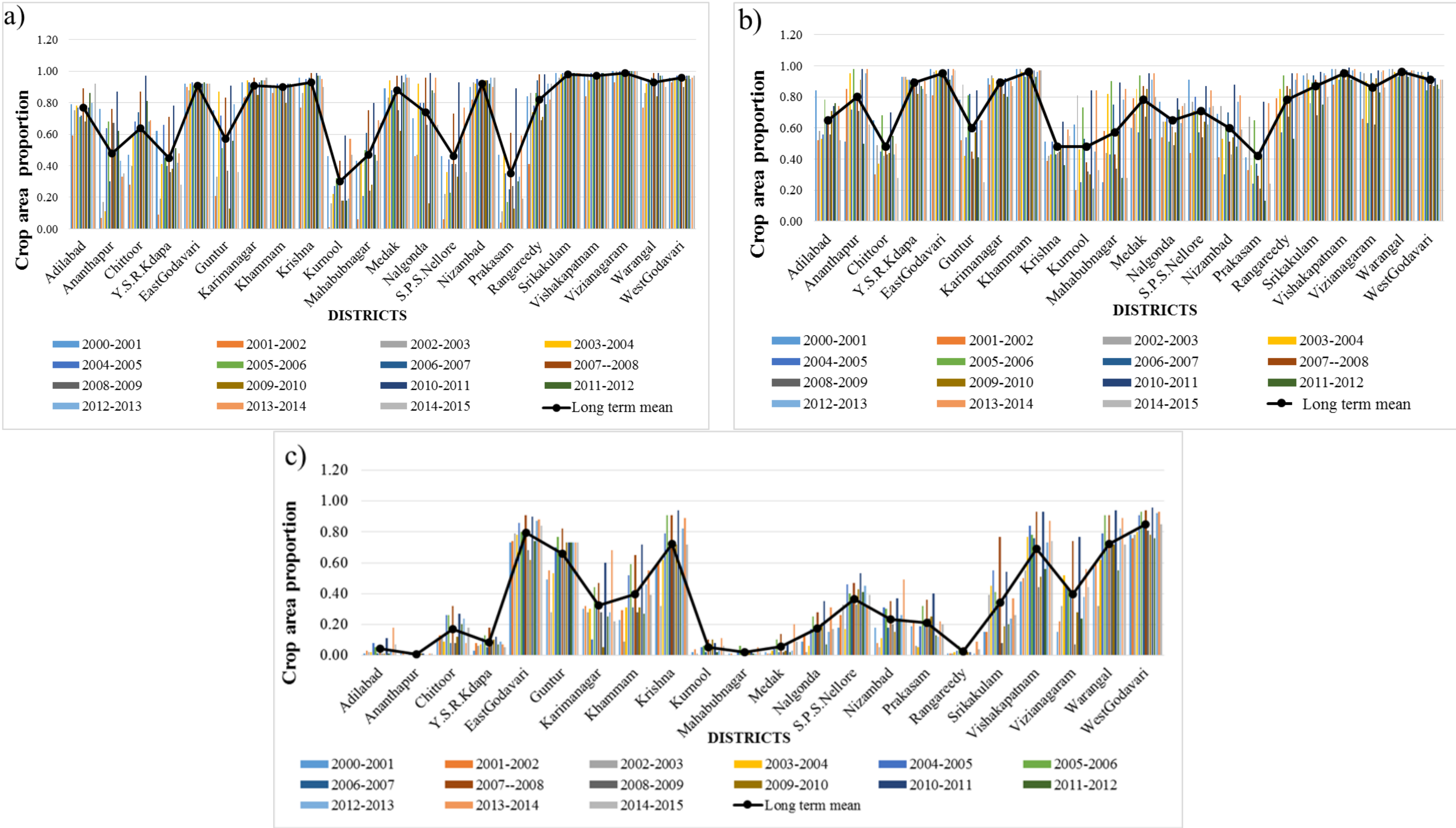


Figure 4.15 Crop area proportion (%) and its long-term mean at district-wise during 2000–2015 a) summer monsoon; b) winter; and c) summer season (Bhavani et al., 2017a)

Kurnool, Prakasam followed by Karimnagar. Maximum fluctuation was observed in Vizianagaram district during the summer (Figure 4.16) season.

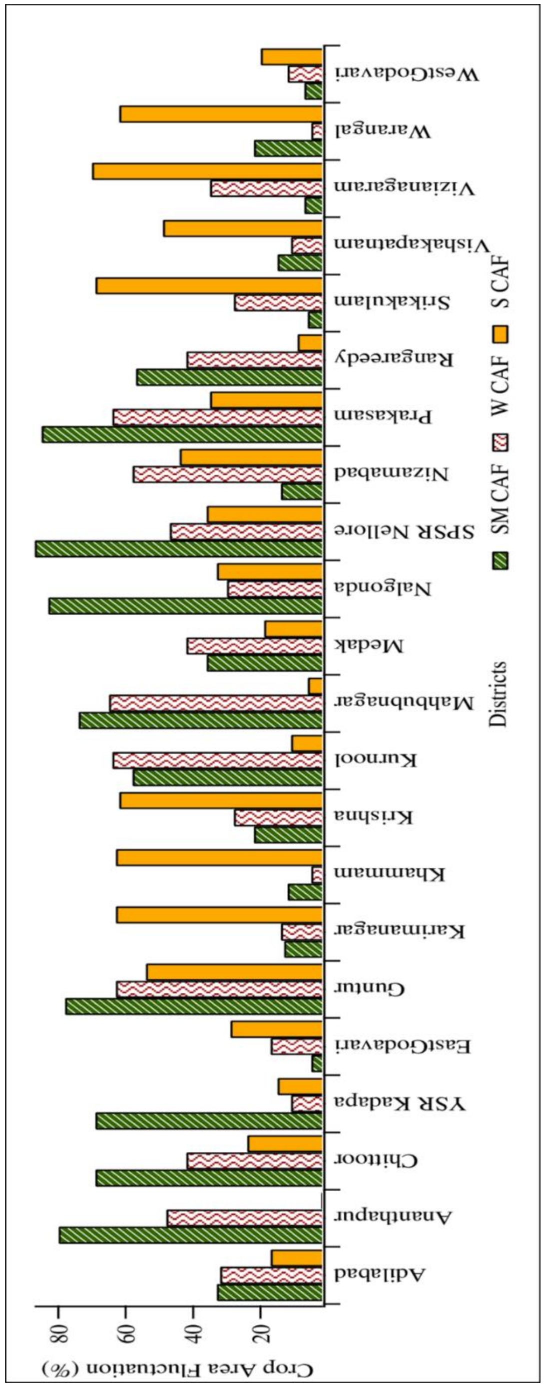


Figure 4.16 Seasonal crop area (%) fluctuation at district level during 2000–2015.

4.2.6 Relation between NDVI, precipitation and water resources

4.2.6.1 State level

It is clear from Figure 4.13a that there exists a significant correlation between the summer monsoon SPI and the summer monsoon cropping season $NDVI_{Dev}$, whereas the winter crop $NDVI_{Dev}$ was more related to the summer monsoon SPI and the resulting residual soil moisture. Regression analyses (simple and multiple linear) were performed between the seasonal NDVI and the monsoon rainfall, surface water and groundwater, NIA to substantiate this hypothesis. The coefficient of determination (r^2) of the relation between the NDVI and rainfall, surface water and groundwater, and NIA for the state is shown in Table 4.1. The state NDVI has shown 95% ($p<0.05$) significant relation with the summer monsoon rainfall in most of the years during the monsoon period, except the year 2001–02 (extreme dry year). A strong relation was observed during 2003–04 and 2006–07, whereas no substantial relation was noticed during 2010–11 because of surplus rainfall during 2010. It is well-known that the NDVI gets saturated after certain amount of precipitation, beyond which no significant change in NDVI is observed (Duffaut et al., 2017; Bhavani et al., 2017).

Regression analysis was also performed between the winter cropping season NDVI and water sources such as the monsoon rainfall, winter rainfall, surface water and groundwater, NIA. Significant relations between the winter crops NDVI, monsoonal rainfall and winter rainfall are observed. A strong relation is noted during the years 2012–13 and 2006–07. During the drought years i.e. 2002–03, 2008–09 and 2011–12, the NDVI relations with the monsoon, winter rainfall and surface water were significant. During summer, the NDVI shows significant relations with the total annual rainfall and NIA due to the assured irrigation and residual soil moisture. It is clear from the analysis that the performances of the winter and summer crops largely depend on the summer monsoon rainfall, because it improves the residual soil moisture, surface and groundwater resources. The significant correlations (R^2, with $p<0.05$) are as follows: (1) during the summer monsoon high R^2 value (0.70) was observed in the year 2006–07 and a low (0.19) during 2008–09; (2) during the winter season high R^2 value (0.75) was observed in 2012–13 and the low (0.23) in 2000–01; and (3) during summer, the annual total rainfall and NIA show large R^2 value (0.85) in 2012–13 and a low (0.40) in 2001–02 (Bhavani et al., 2017).

Table 4.1 Seasonal Relation of NDVI (yearly) with Rainfall and water resources

Years	R^2 Monsoon Rain	Remarks	Winter R^2	Remarks Multiple Regression	Summer R^2	Remarks Multiple Regression
2000-2001	0.23*	MNDVI vs MR	0.23*	WNDVI vs MR and WR	0.50*	SNDVI vs Annual Total Rain and NIA
2001-2002	0.16**	MNDVI vs MR and NIA	0.26*		0.40*	
2002-2003	0.49*	MNDVI vs MR	0.37*	WNDVI vs MR and WR and SW	0.46*	
2003-2004	0.65*		0.65*	WNDVI vs MR and WR	0.81*	
2004-2005	0.47*		0.34*		0.64*	
2005-2006	0.42*		0.41*		0.54*	
2006-2007	0.70*		0.73*		0.82*	
2007-2008	0.27*		0.32*		0.56*	
2008-2009	0.19*		0.27*	WNDVI vs MR and WR and SW	0.49*	
2009-2010	0.49*		0.23**	WNDVI vs MR and WR	0.49*	
2010-2011	-	-	0.32*		0.49*	
2011-2012	0.56*	MNDVI vs MR	0.43*	WNDVI vs MR and WR and SW	0.57*	
2012-2013	0.51*		0.75*	WNDVI vs MR and WR	0.85*	
2013-2014	0.45*		0.55*		0.54*	
2014-2015	0.33*		0.46*			

(* : 95 % confidence level ($p<0.05$), **: 90 confidence level ($p<0.10$); MNDVI: Monsoon NDVI; WNDVI :Winter NDVI; SNDVI: Summer NDVI; MR: Monsoon Rain; WR; Winter Rain; SW: Surface Water NIA: Net Irrigated Area)

4.2.6.2 District level

The state is experiencing varied spatial and temporal rainfall distribution. It is to note that a different cropping system may not reflect the actual relation of NDVI with the rainfall and other water resources. Therefore, simple and multiple linear regressions of the NDVI on the rainfall and other water resources were performed for the periods from 2000–2001 to 2014–2015. Table 4.2 shows the relation of NDVI with the rainfall and other water resources, district-wise. A significant relation (with $p<0.05$) was observed between the

NDVI and rainfall during the summer monsoon cropping season. A strong relation is noticed in the West Godavari district (R^2=0.87), and an insignificant relation in the Medak district (R^2=0.25) respectively. Further, it is observed that during the summer cropping season significant relation was observed only with the summer rainfall. In the winter cropping season, a significant relationship between the NDVI, monsoon and winter rainfall is observed in many districts except Guntur, SPS Nellore, Karimnagar, Warangal, Nizamabad, and West Godavari (significant relations may exist if surface water sources are included). A strong relation is observed in Karimnagar district (R^2=0.86), whereas insignificant relations in Prakasam and East Godavari (R^2 = 0.32) districts. So also, during the summer season substantial relations ($p<0.05$) were observed with the annual rainfall and NIA, with a significant R^2 value (0.91) noticed in the East Godavari district.

In short, the analysis highlights that the cropping performances during winter and summer seasons (both at state and district levels) in all the years had a direct bearing on the summer monsoon rainfall, residual soil moisture resulting from it and the winter/summer precipitation during respective seasons, including the available water resources (NIA and SW) (Krishna Kumar et al., 2004, Bhavani et al., 2017a).

4.2.7 Frequency and magnitude of crop stress/drought analysis

4.2.7.1 State level

NOAA GIMMS

The frequency assessment of drought stress is shown in Table 4.3a for the period 1982-83 to 1999-2000. The occurrence of negative percentages of $NDVI_{Dev}$ was maximum in the year 1984-85, followed by 1982-83 and 1994-95 in summer monsoon. During the winter season, the frequency of negative percentages of $NDVI_{Dev}$ was maximum in 1984-85, followed by 1982-83 and 1984-85. In the summer season, the year 1984-85 has experienced significant occurrences of negative $NDVI_{Dev}$, followed by 1982-83 and 1983-84. In terms of annual frequency of the occurrence of negative $NDVI_{Dev}$, 1984-85 is inferred as an extremely drought-affected year, followed by 1989-90 and 1988-89.

Table 4.2 Relation of NDVI vs Rainfall and water resources (Bhavani et al., 2017a)

<table>
<tr><th>Districts</th><th>Monsoon R^2</th><th>Remarks</th><th>Winter R^2</th><th>Remarks Multiple Regression</th><th>Summer R^2</th><th>Remarks Multiple Regression</th></tr>
<tr><td>Adilabad</td><td>0.32*</td><td rowspan="22">MNDVI VS MR</td><td>0.51*</td><td rowspan="5">WNDVI vs MR and WR.</td><td>0.53*</td><td rowspan="22">SNDVI vs Annual Total Rain and NIA</td></tr>
<tr><td>Ananthapur</td><td>0.49*</td><td>0.75*</td><td>0.53*</td></tr>
<tr><td>Chittoor</td><td>0.72*</td><td>0.41*</td><td>0.73*</td></tr>
<tr><td>Y.S.R. Kadapa</td><td>0.58*</td><td>0.63*</td><td>0.73*</td></tr>
<tr><td>EastGodavari</td><td>0.33*</td><td>0.32*</td><td>0.91*</td></tr>
<tr><td>Guntur</td><td>0.41*</td><td>0.52*</td><td rowspan="2">WNDVI vs MR, WR and SW</td><td>0.60*</td></tr>
<tr><td>Karimnagar</td><td>0.33*</td><td>0.86*</td><td>0.71*</td></tr>
<tr><td>Khammam</td><td>0.76*</td><td>0.63*</td><td rowspan="6">WNDVI vs MR and WR</td><td>0.64*</td></tr>
<tr><td>Krishna</td><td>0.38 *</td><td>0.51*</td><td>0.52*</td></tr>
<tr><td>Kurnool</td><td>0.43*</td><td>0.44*</td><td>0.64*</td></tr>
<tr><td>Mahbubnagar</td><td>0.33*</td><td>0.68*</td><td>0.69*</td></tr>
<tr><td>Medak</td><td>0.25*</td><td>0.55*</td><td>0.71*</td></tr>
<tr><td>Nalgonda</td><td>0.69*</td><td>0.64*</td><td>0.69*</td></tr>
<tr><td>S.P.S.RNellore</td><td>0.71*</td><td>0.55*</td><td rowspan="2">WNDVI vs MR, WR and SW</td><td>0.57*</td></tr>
<tr><td>Nizamabad</td><td>0.56*</td><td>0.69*</td><td>0.51*</td></tr>
<tr><td>Prakasam</td><td>0.51*</td><td>0.32*</td><td>WNDVI vs MR and WR</td><td>0.71*</td></tr>
<tr><td>Rangareddy</td><td>0.26*</td><td>0.68*</td><td rowspan="5">WNDVI vs MR and WR WNDVI vs MR, WR and SW</td><td>0.55*</td></tr>
<tr><td>Srikakulam</td><td>0.53*</td><td>0.43*</td><td>0.50*</td></tr>
<tr><td>Visakhapatnam</td><td>0.72*</td><td>0.55*</td><td>0.83*</td></tr>
<tr><td>Vizianagaram</td><td>0.65*</td><td>0.61*</td><td>0.82*</td></tr>
<tr><td>Warangal</td><td>0.71*</td><td>0.75*</td><td>0.86*</td></tr>
<tr><td>West Godavari</td><td>0.87*</td><td>0.64*</td><td>WNDVI vs MR, WR and SW</td><td>0.64*</td></tr>
</table>

(* : 95 % confidence level ($p<0.05$), **: 90 confidence level ($p<0.10$),MNDVI: Monsoon NDVI, WNDVI :Winter NDVI, SNDVI: Summer NDVI,MR: Monsoon Rain, WR; Winter Rain, SW: Surface Water NIA: Net Irrigated Area)

MODIS

Table 4.3b shows the estimated frequency of drought stress during the period 2000-2001 to 2014-15. Maximum frequency of negative percentages of $NDVI_{Dev}$ observed during the summer monsoon period of the years 2001–02, 2002–03, 2008–09 followed by 2009–10 indicates severe drought stress. The impact of low precipitation during the summer monsoon on the following winter crops is clearly observable in the years 2000–01, 2002–03, 2011–2012, followed by 2004–05 and 2008–09. In case of summer season, maximum frequency of negative $NDVI_{Dev}$ is observed during 2000–01 and 2004–05, followed by 2002–03 and 2011–12. In terms of annual frequency of negative $NDVI_{Dev}$, the years 2002-2003 and 2008-2009 are estimated as severely affected by drought. The two parameters namely total crop area fluctuation (%) and annual $NDVI_{Dev}$ are aggregated to assess the extremities of drought during the study period 2000–2015. The results reveal that 2002–03 was the extreme drought year, followed by 2008–2009 (Table 4.3b).

Table 4.3a Frequency percentage of negative $NDVI_{Dev}$ during 1982-2000

1982-2000 period				
Years	SM	W	S	Annual
1982-1983	18	21	22	13
1983-1984	18	20	21	9
1984-1985	22	22	22	17
1985-1986	12	21	14	8
1986-1987	20	14	16	12
1987-1988	11	3	13	8
1988-1989	13	10	12	15
1989-1990	9	0	2	14
1990-1991	0	5	8	9
1991-1992	15	13	2	13
1992-1993	7	6	4	11
1993-1994	9	13	5	13
1994-1995	17	1	2	13
1995-1996	1	0	0	8
1996-1997	2	1	0	5
1997-1998	2	10	0	6
1998-1999	0	0	2	4
1999-2000	0	5	3	6

Extreme Severe High

Table 4.3b Frequency percentage of negative $NDVI_{Dev}$ (>50%) from total agricultural area during 2000-2015.

Years	SM>50%	W>50%	S>50%	Annual	CAF	Sum $NDVI_{Dev}$ and CAF
2000-2001	5	20	22	47	1	48
2001-2002	22	3	15	40	3	43
2002-2003	22	20	21	63	2	65
2003-2004	13	6	14	33	1	34
2004-2005	6	18	22	46	1	47
2005-2006	17	6	1	24	1	25
2006-2007	8	11	13	32	1	33
2007-2008	1	13	0	14	1	15
2008-2009	21	18	17	56	3	59
2009-2010	20	12	13	45	3	48
2010-2011	0	2	0	2	0	2
2011-2012	5	20	19	44	2	46
2012-2013	3	4	9	16	0	16
2013-2014	3	2	2	7	0	7
2014-2015	11	13	6	30	1	31

Extreme Severe High

SM: Summer Monsoon; W: Winter; S: Summer; and CAF: Crop Area Fluctuation.

The magnitude of NDVI anomaly is shown in Figure 4.13a. Large negative $NDVI_{Dev}$ is observed during the monsoon season of 2001–02 and 2009–10 and winter season of 2002–03, followed by 2011–12. The results highlight the fact that the drought not only influences the cropped area but also the magnitude of the $NDVI_{Dev}$, indicating stress.

4.2.7.2 District level

NOAA GIMMS

Table 4.4a shows the frequency of negative $NDVI_{Dev}$ in each district for the period 1982-83 to 1999-2000. It can be clearly seen from the annual frequency that the districts of YSR Kadapa, Kurnool, Mahbubnagar and Nalgonda are frequently influenced by drought stress.

MODIS

For the period 2000-2015 the frequency of negative $NDVI_{Dev}$ in all the cropping seasons including the annual Crop Area Fluctuation (CAF) is shown in Table 4.4b (district-wise). One can notice that the districts were drought affected in different cropping seasons (Table 4.4b). For e.g., Adilabad, SPS Nellore and Rangareddy districts have experienced frequent occurrences of negative percentages of $NDVI_{Dev}$ during the summer season. Similarly, in the winter crop there are frequent occurrences of negative $NDVI_{Dev}$ in Adilabad District, and during the summer crop in Nalgonda District. Overall, the extreme drought-prone districts are YSR Kadapa, Nalgonda, SPS Nellore and Rangareddy (Table 4.4b). Spatial and temporal distribution of extreme and severely dry; normal and extremely good crop area years during 2000-2015 in three cropping seasons are illustrated in Fig. 4.17 (a-c) (Bhavani et al., 2017a).

The study concludes that in addition to precipitation, irrigation facilities and residual soil moisture, the socio-economic and market factors are also needed to be considered as important factors for vulnerability and risk analysis.

Table 4.4a District wise percentage frequency of negative $NDVI_{Dev}$ (>50%) from total agricultural area during 1982-2000

	1982-2000			
Districts	SM	W	S	Annual
Adilabad	8	6	6	20
Ananthapur	8	6	8	22
Chittoor	7	8	6	21
Y.S.R. Kadapa	9	10	7	26
EastGodavari	8	7	7	22
Guntur	8	6	7	21
Karimnagar	8	8	6	22
Khammam	9	6	8	23
Krishna	8	6	8	22
Kurnool	8	9	9	26
Mahbubnagar	7	10	8	25
Medak	9	8	7	24
Nalgonda	9	10	8	27
S.P.S.R. Nellore	6	7	4	17
Nizamabad	7	6	7	20
Prakasam	8	7	5	20
Rangareddy	10	7	6	23
Srikakulam	6	8	7	21
Visakhapatnam	7	9	6	22
Vizianagaram	9	7	4	20
Warangal	8	7	6	21
West Godavari	9	7	8	24

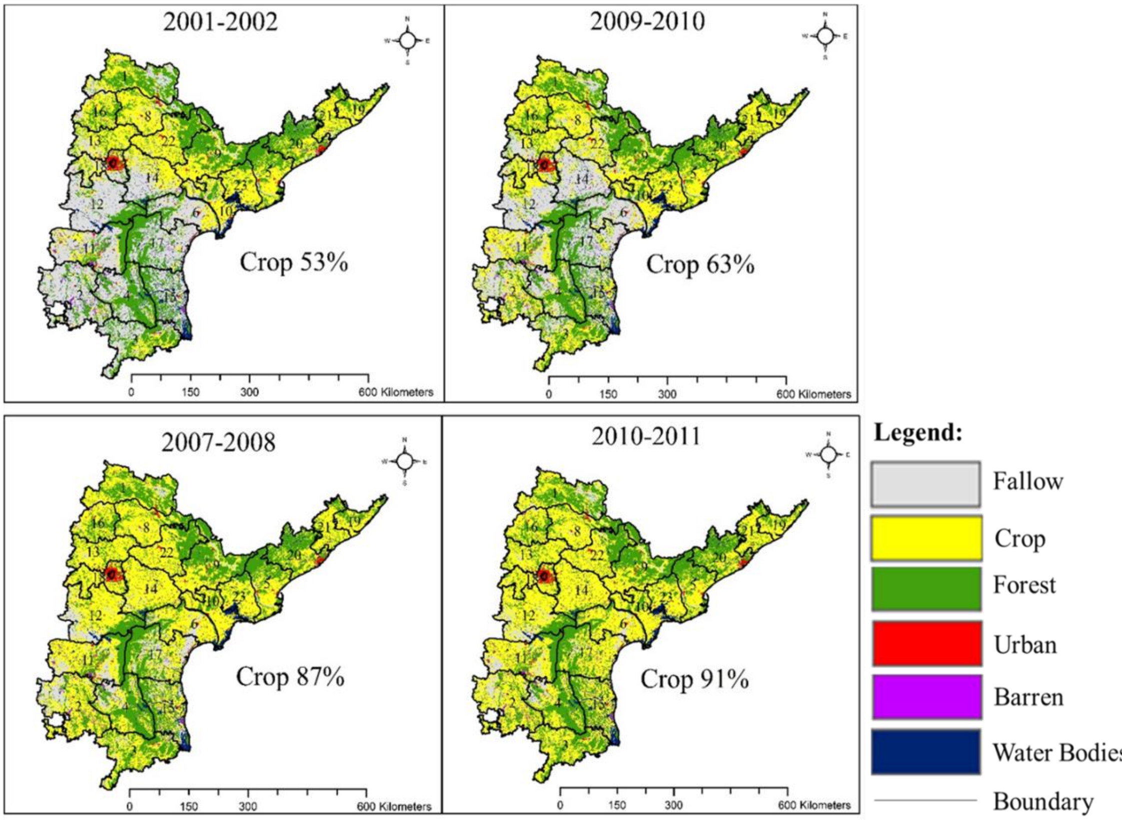
Extreme Severe High

Table 4.4b District wise percentage frequency of negative $NDVI_{Dev}$ (>50%) from total agricultural area during 2000-2015

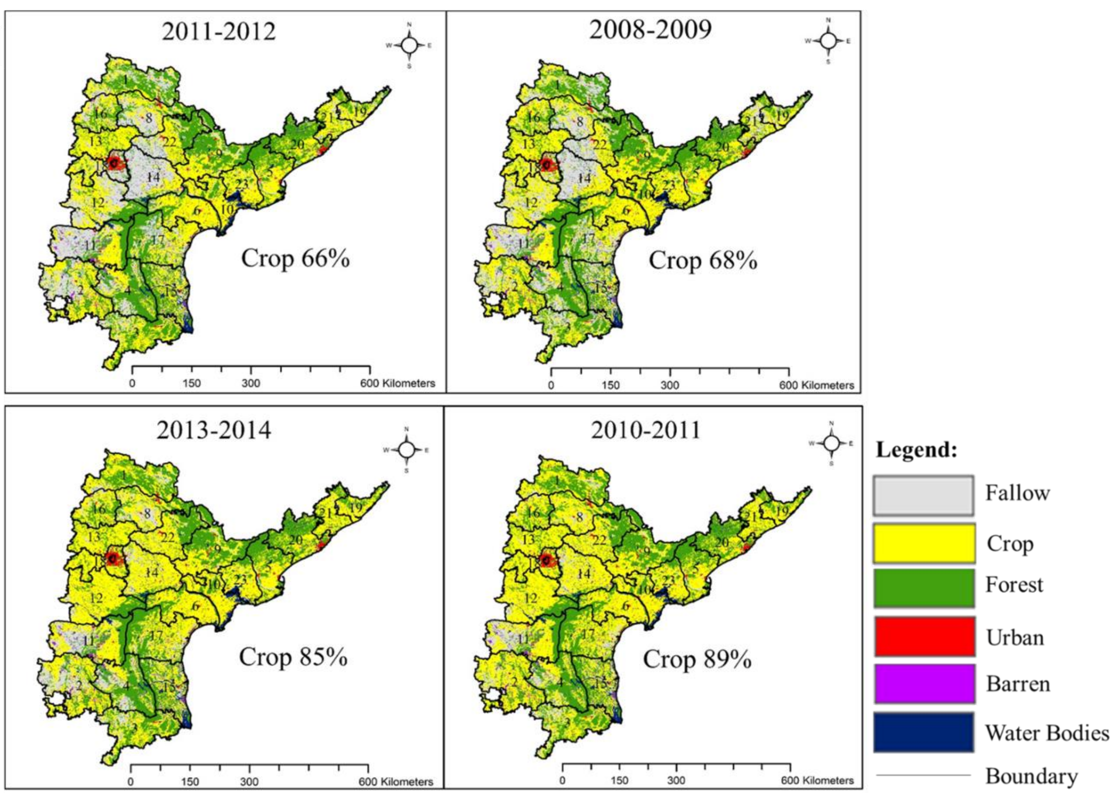
District	SM>50%	W>50%	S>50%	Annual	Annual CAF >60%	Sum of CAF and $NDVI_{Dev}$
Adilabad	9	12	5	26	0	26
Ananthapur	7	8	8	23	1	24
Chittoor	8	7	8	23	1	24
Y.S.R. Kadapa	8	9	9	26	1	27
EastGodavari	5	9	7	21	0	21
Guntur	8	8	8	24	2	26
Karimnagar	8	7	7	22	1	23
Khammam	6	8	8	22	1	23
Krishna	6	8	7	21	1	22
Kurnool	8	7	8	23	1	24
Mahbubnagar	7	7	9	23	2	25
Medak	6	8	9	23	0	23
Nalgonda	7	9	10	26	1	27
S.P.S.R. Nellore	9	9	8	26	1	27
Nizamabad	6	7	9	22	0	22
Prakasam	8	7	8	23	2	25
Rangareddy	9	9	9	27	0	27
Srikakulam	6	6	8	20	1	21
Visakhapatnam	6	6	7	19	0	19
Vizianagaram	8	6	7	21	1	22
Warangal	6	8	7	21	1	22
West Godavari	6	9	8	23	0	23

Extreme Severe High

(SM: Summer Monsoon; W: Winter; S: Summer; and CAF: Crop Area Fluctuation) a)


2001-2002
Crop 53%
2009-2010
Crop 63%
2007-2008
Crop 87%
2010-2011
Crop 91%
0 150 300 600 Kilometers
Legend:
Fallow
Crop
Forest
Urban
Barren
Water Bodies
Boundary

b)


2011-2012
Crop 66%
2008-2009
Crop 68%
2013-2014
Crop 85%
2010-2011
Crop 89%
0 150 300 600 Kilometers
Legend:
Fallow
Crop
Forest
Urban
Barren
Water Bodies
Boundary

c)

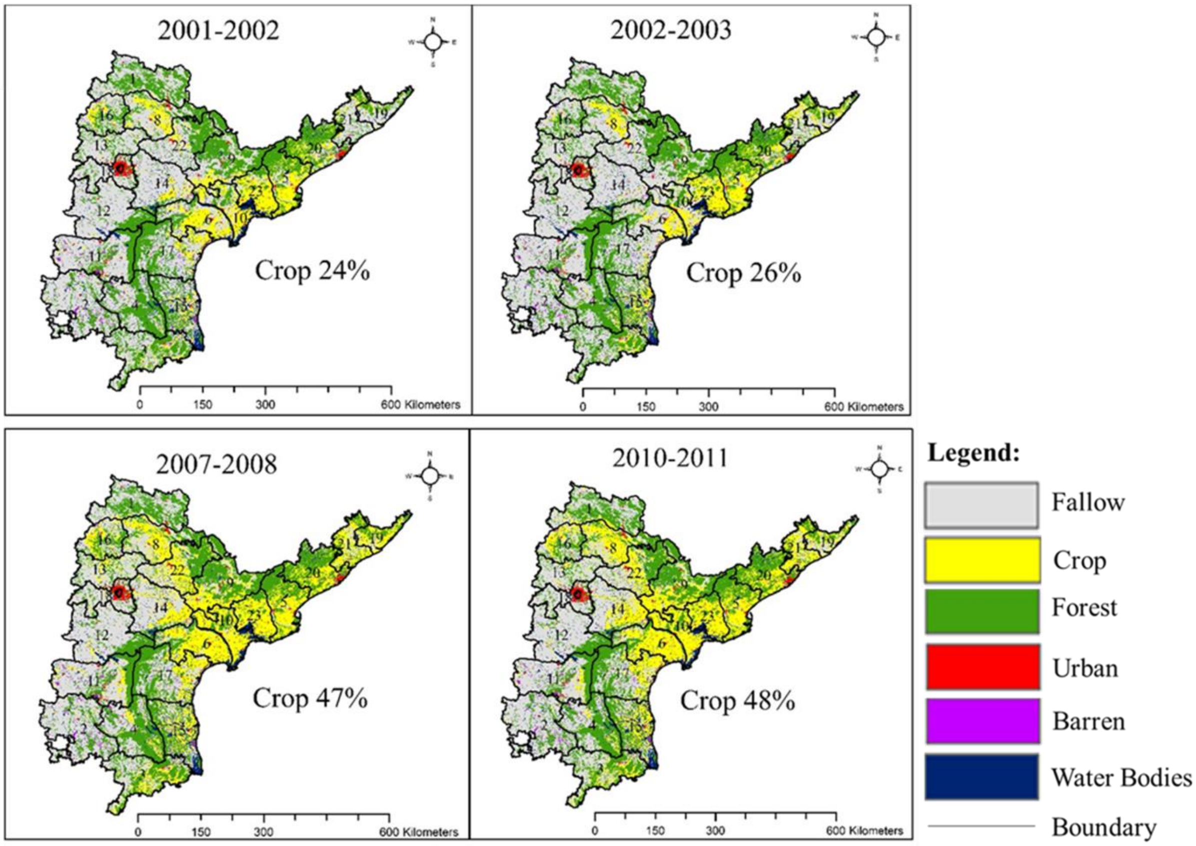


Figure 4.17 Spatial and temporal distribution of extreme and severely dry; normal and extremely good crop area years during 2000–2015 a) summer monsoon; b) winter and c) summer season (Bhavani et al., 2017a)

4.2.8 Discussion

The agricultural condition related to stress and drought situation during the summer monsoon has been monitored by remote sensing technology (Jeyaseelan, 2003; Friedl et al., 2010; Zambrano et al., 2017). The present study, however, looks at GIMMS/MODIS NDVI of three different cropping seasons and their influence on each other due to rainfall and residual moisture. Agricultural drought condition and stress have been determined using NDVI indices i.e., deviation of NDVI and VCI (Rouse et al., 1974; Kogan et al., 2012; Francisco et al., 2016, Bhavani et al., 2017a). The $NDVI_{Dev}$ and VCI have followed more or less similar patterns both temporally and spatially. The $NDVI_{Dev}$ varies considerably and captures the stress in cropped areas, whereas VCI captures only the severe drought-affected years. SPI has been used to monitor meteorological drought (McKee et al., (1993, 1995); Patel et al., 2007; Kumar et al., 2009; Belayneh et al., 2014; Jiang et al., 2017). Results from the present study revealed that GIMMS/MODIS can provide the information on long-term stress and drought conditions both at the state (erstwhile Andhra Pradesh) and district levels. So far, the crop stress and agricultural performance have been assessed only in a specific agricultural growing season (Murthy et al., 2011; Gizachew and Suryabhagavan, 2014; Chandrasekar and Sesha Sai, 2015; Dutta et al., 2015). It is pertinent to mention here that the agricultural drought assessed by National Agricultural Drought Assessment and Monitoring System (NADAMS Technical report, 2017) in fourteen agricultural drought-prone states of India also considered the Kharif season alone in the analysis, which may be inconclusive. It is established from the present study that the analysis of long-term data can only provide conclusive information on drought severity The annual picture indicates that the monsoonal rainfall not only has an impact on the agricultural growing season but also on the total crop calendar. The study clearly shows that the failure of monsoon has an impact on winter/Rabi and summer/Zaid cropping periods apart from summer monsoon/Kharif crop season. Summer monsoon along with winter rains have a significant impact on Adilabad, Ananthapur, Chittoor, and YSR Kadapa districts on winter/Rabi crop. Total rainfall and residual moisture/irrigation system showed an impact on summer crops in all the 23 districts of erstwhile AP. The interlinking of meteorological drought to agricultural drought is clearly evident in the agricultural growing seasons (Dutta et al., 2015; U Ma'rufah et al., 2017; Zambrano et al., 2017, Bhavani et al., 2017a).

No studies have been carried out in erstwhile Andhra Pradesh for the assessment of agricultural drought over a long-term period (1982-2015) in three cropping seasons. The present study indicates that the spatial extremity of drought stress varies as a function of the long-term time period and also due to different satellite sensor and its resolutions. With NOAA GIMMS data Nalgonda, YSR Kadapa, and Kurnool districts have been noticed as extremely drought-prone areas, whereas with continuous long-term NOAA GIMMS latest version, Adilabad, Mahbubnagar, and Vizianagaram are observed as extremely drought-prone districts, followed by Ananthapur, Prakasam, and Rangareddy (Annexure 4.2 a-b). The severity of drought area over a long-term period varies the drought impact (Anil and Indira, 2007; Parmeshwar et al., 2014). The results of drought frequency reveal the fact that the districts of Adilabad, Mahbubnagar, and Vizianagaram are often susceptible to agricultural stress due to the frequent occurrence of drought over a long period. The results highlight that 12 months long-term analysis can refine the assessment of drought in both state and district levels in varying cropping season. To quantify the drought area based on acreage MODIS fine resolution data has been used. YSR Kadapa, Nalgonda, SPSR Nellore, and Rangareddy are noticed as extremely drought-prone districts based on the aggregation of drought frequency and crop area fluctuations. Overall, the study clearly captured the rain shadow regions (Ananthapur, YSR Kadapa, Chittoor, Kurnool, Mahbubnagar, Nalgonda, Rangareddy and Prakasam districts) of the state (Bhavani et al., 2017a).

4.3 Phenophase and Time series analysis

4.3.1 Relationship of length of the growing period with climate and soil moisture

Phenophase determines the length of crop growth cycle. The period of agriculture crop growth (SOS to EOS events) is dependent upon many weather parameters, including soil moisture and irrigation sources. This time is referred to as Length of Growing Period (LGP) (Kaushalya et al., 2014; Aleixandre et al., 2016). This parameter (LGP) is important to understand the variation of vegetation/plant growth, start, and end of the crop events in each year, and also to study the impact of rainfall and temperature variability on the crop. The present study considers two cropping seasons, namely, Kharif/summer monsoon and Rabi/winter in the analysis. The trend of LGP against the rainfall, maximum temperature, and soil moisture during the period from 1982 to 2015 for both AP and TS regions are illustrated in Figure 4.18 (Bhavani et al., 2017). LGP shows an increasing trend against the rainfall and soil moisture, whereas a decreasing trend against the temperature. Therefore, decision making in sowing, growth pattern, cropping pattern, crop calendar, and all crop husbandry practices should make use of such analysis over a long-term data. A good coefficient of determination (R^2=0.67 for TS and R^2=0.57 for AP) was observed between LGP and rainfall.

4.3.2 Long-term response of NDVI to the climate and soil moisture

To understand the climatic and biophysical influence on the agriculture NDVI, long-term response of NDVI with climate and soil moisture is studied. It is known that crop growth pattern/change in NDVI are influenced by climate and bio-physical distribution (Propastin and

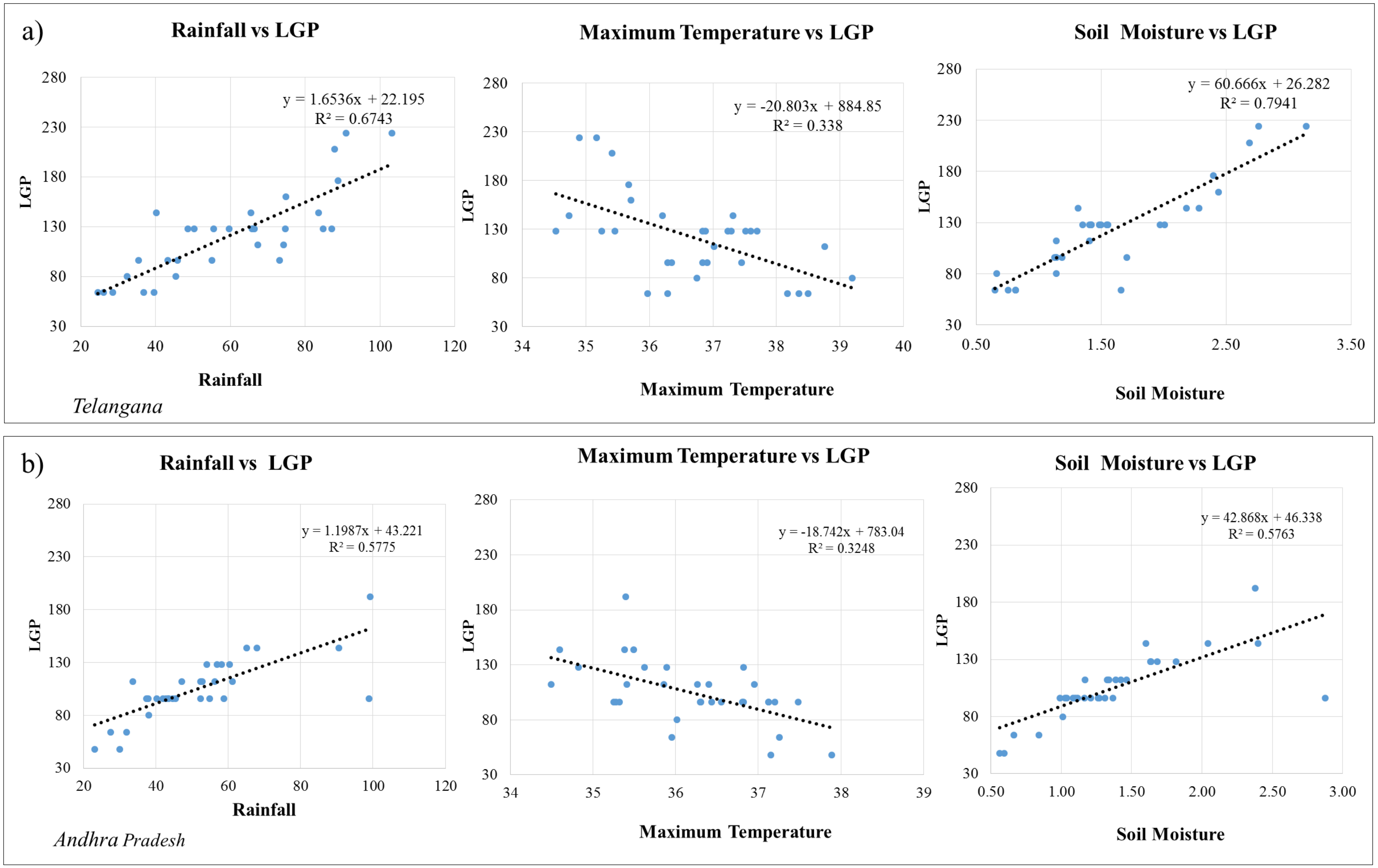
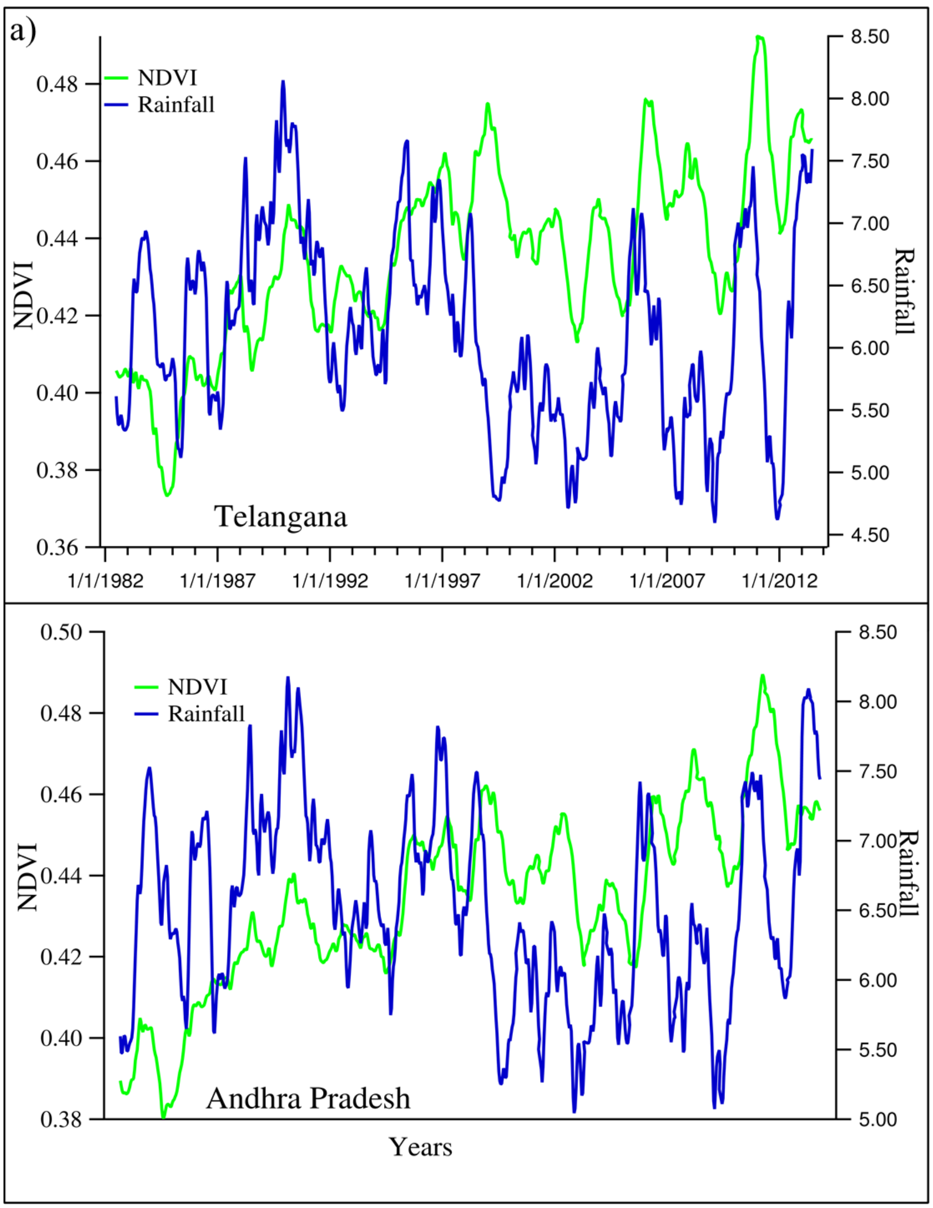
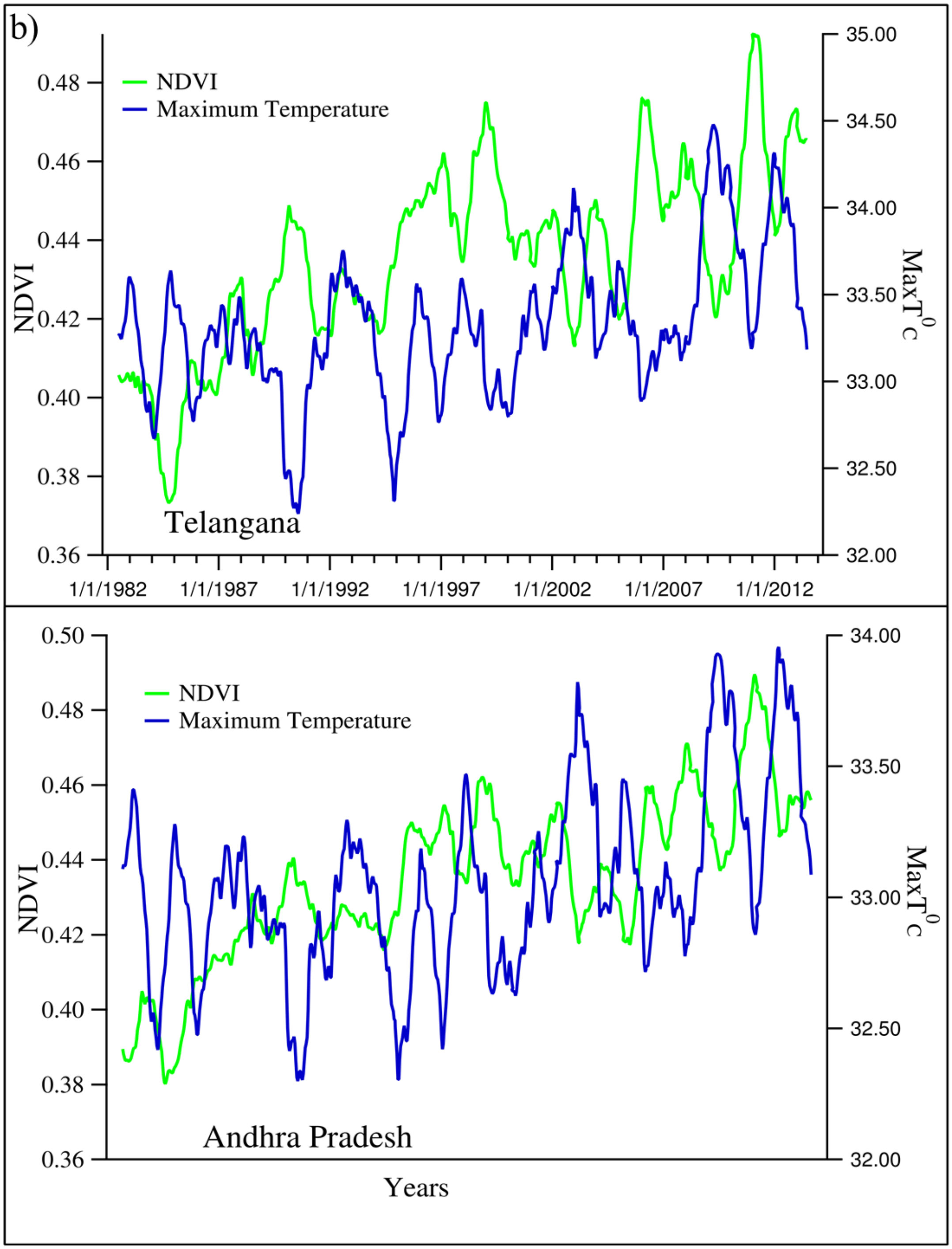


Figure 4.18 Long-term trend of climate and soil moisture parameters with LGP a) Telangana ; and b) Andhra Pradesh regions.

Kappas, 2008; Liu et al., 2015). Due to large inter-annual variability, spatial patterns of NDVI and their driving parameters vary significantly in different areas when different study periods are selected (Liu et al., 2015). Thus, long-term fortnightly NDVI and rainfall time series data shall provide a basis to understand the crop progression during different years of study. The impact of climate and soil moisture on agricultural NDVI during 1982-2015 for AP and TS are illustrated in Fig. 4.19 (Bhavani et al., 2017b). It can be observed that with the increase in rainfall and soil moisture, the agriculture NDVI also increases and vice versa. However, an inverse relationship between the NDVI and the maximum temperature is observed in both the regions under study.




b)
NDVI
Maximum Temperature
Telangana
NDVI
MaxT^{0}C
0.48
0.46
0.44
0.42
0.40
0.38
0.36
35.00
34.50
34.00
33.50
33.00
32.50
32.00
1/1/1982
1/1/1987
1/1/1992
1/1/1997
1/1/2002
1/1/2007
1/1/2012
NDVI
Maximum Temperature
Andhra Pradesh
NDVI
MaxT^{0}C
0.50
0.48
0.46
0.44
0.42
0.40
0.38
0.36
34.00
33.50
33.00
32.50
32.00
Years

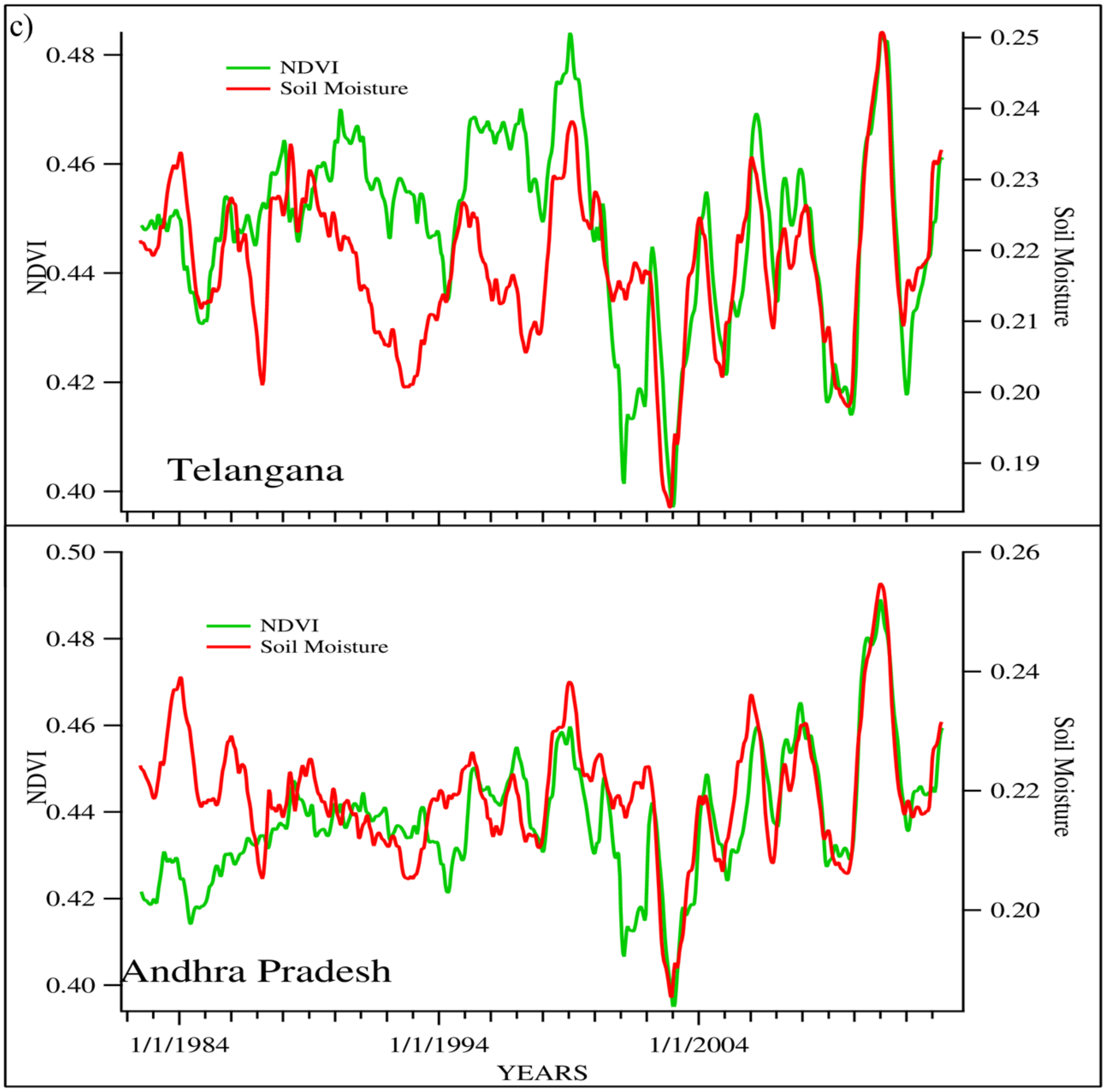


Figure 4.19 Long-term trend pattern of climate and soil moisture parameters with NDVI in Andhra Pradesh (AP) and Telangana (TS) regions a) Rainfall with NDVI; b) Maximum Temperature with NDVI and c) Soil Moisture with NDVI (Bhavani et al., 2017b)

4.3.3 Projection of agriculture NDVI using satellite and climate datasets (> 3 decades)

It is evident from section 4.3.1 that long-term trend of agriculture NDVI and LGP have been influenced strongly by climate and its variables over the last 3 decades. With this evidence, the future agricultural NDVI spatial pattern is simulated over the study region using the coefficients estimated from the model and IPCC projected climate for RCP 2.6 scenario. The model significance ($p < 0.05$) at grid wise is illustrated in Fig. 4.20 (Bhavani et al., 2017b).

The spatial distribution of seasonal projected 2050 agriculture NDVI along with extreme stress, normal and best agricultural NDVI years during the last 15 years (2000-2015) are presented in Fig. 4.21. The projected agricultural NDVI is quite similar to the normal agricultural years during all seasons. However, a decline in projected agricultural NDVI has been observed during the summer monsoon and winter season, particularly in the coastal areas of AP. Further studies are needed to assess the magnitude and spatial variability of agricultural NDVI under drought/ agriculture stress conditions in combination with other additional environmental and climatic parameters in projected climatic conditions.

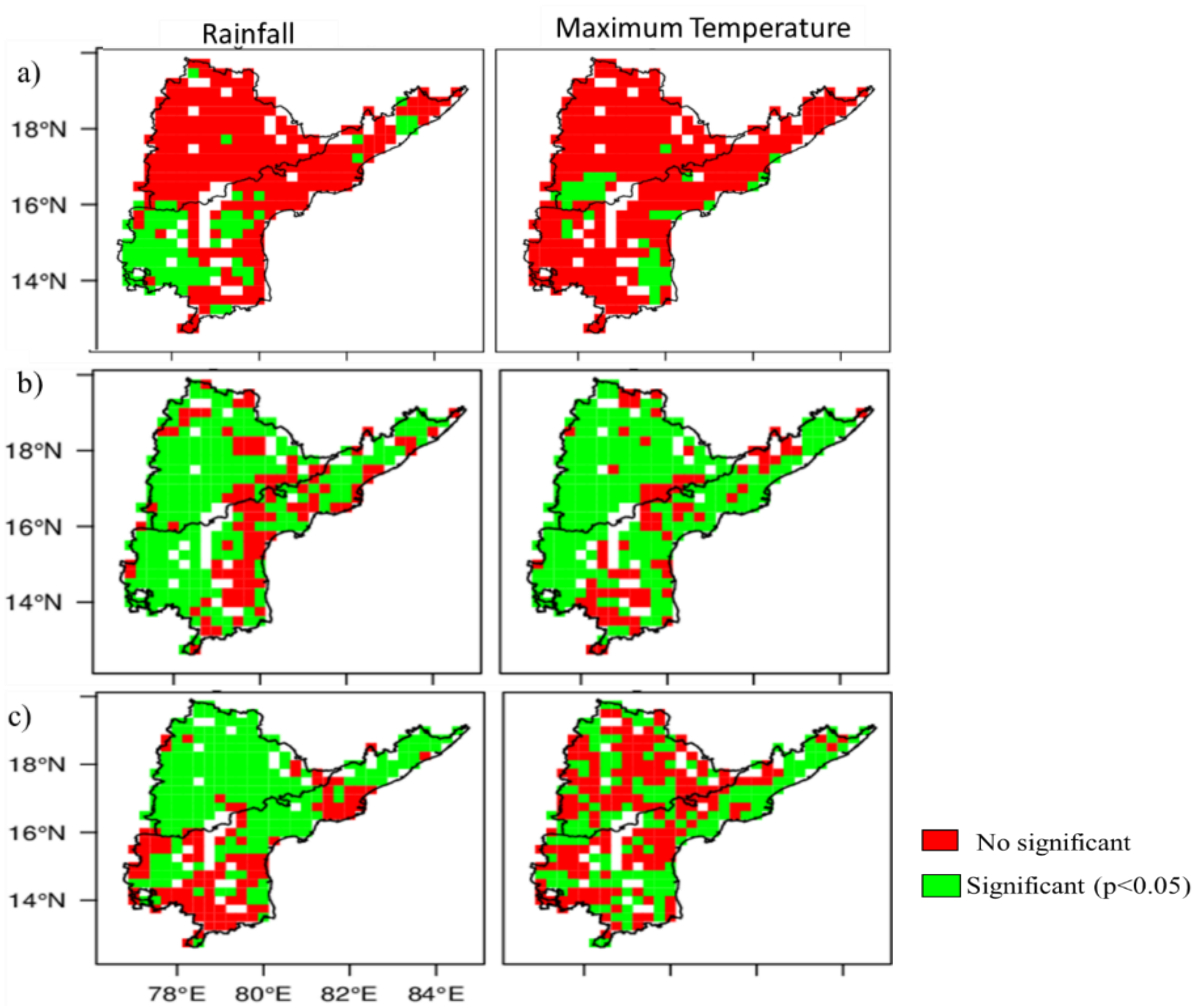


Figure 4.20 Significance level of pixels for rainfall and maximum temperature (p<0.05) using multiple regression model a) summer monsoon/Kharif, b) winter/Rabi, and c)summer season/Zaid (Bhavani et al., 2017b)

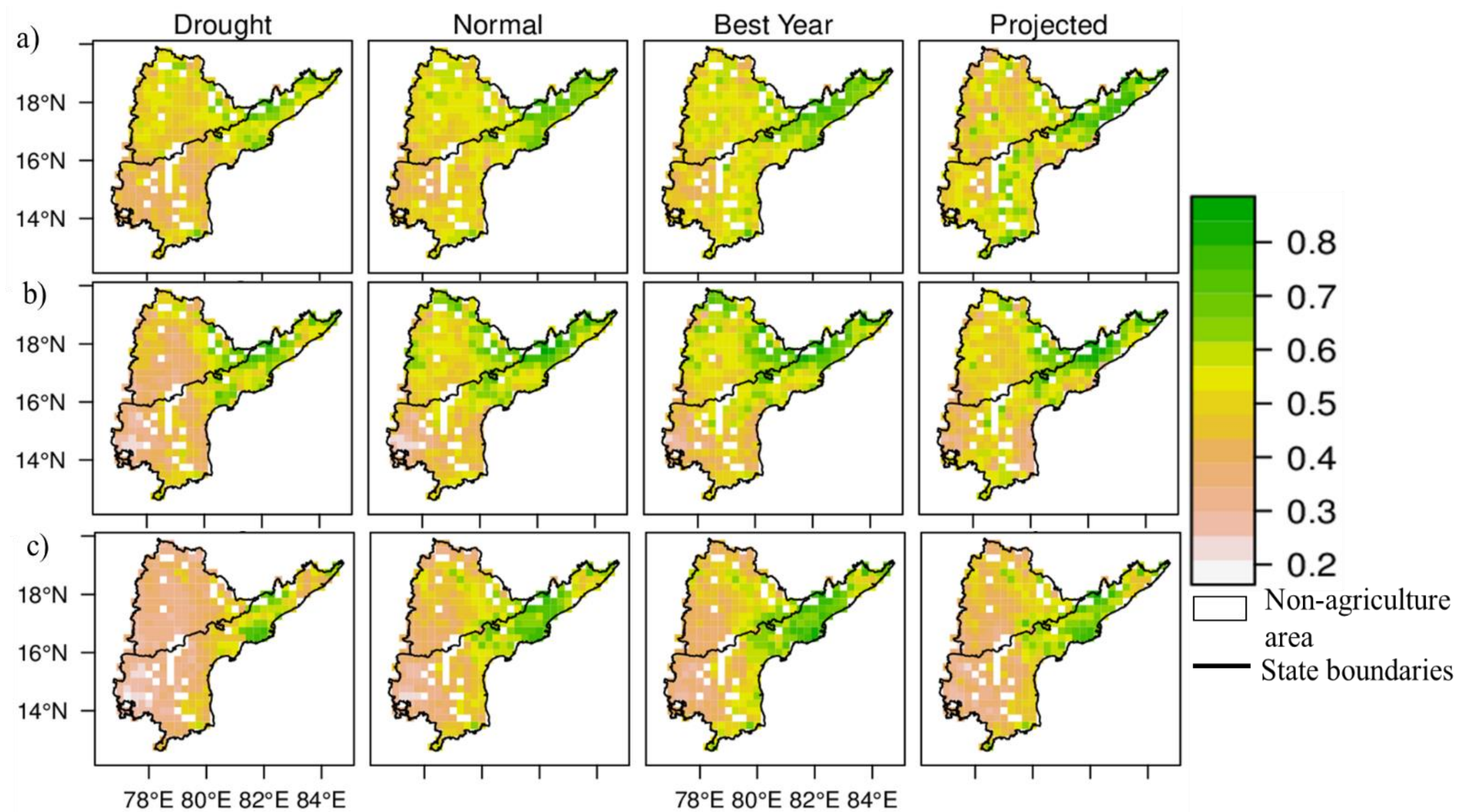


Figure 4.21 Spatial distribution of agriculture NDVI for drought, normal, best years of 2000-2015 and projected agriculture NDVI for 2050 RCP 2.6 scenario for three seasons a) summer monsoon/Kharif; b) winter/Rabi; and c) summer season/Zaid (Bhavani et al., 2017b)

4.3.4 Discussion

To meet the future demand for agricultural commodities, it is important to know about the past and future agriculture in addition to climatic trends. Time series satellite data products help in examining the impact of weather aberrations and climate change on the bio-physical cover like vegetation, land use, water resource and soils (Murthy et al., 2011). Failure of monsoon, continuous reduction in rainfall/ break in monsoon will severely affect the crop growth (Farooq et al., 2012) and leads to agriculture drought. Phenology is influenced by temperature and rainfall variations (Thakur et al., 2008; Julien and Sobrino, 2009). Several studies described the change in phenology is due to climate change (Badeck et al., 2004; Bernal et al., 2011; Swidrak et al., 2013). The present study uses time-series NDVI data to capture the annual crop cycle growth and decay. It generates LGP to capture the response with climate and weather events i.e. the number of rainy days. The study observed that change in climate has a strong significant impact on LGP derived from crop-phenophase (R^2 value 0.67 and 0.57 with rainfall vs LGP in TS and AP and R^2 value 0.33 and 0.32 with maximum temperature vs LGP in TS and AP). Thus, the analysis of the NDVI time-series through time permits the extraction of appropriate metrics, allowing a better monitoring and understanding of change in crop phenology with climate change and weather conditions. Information about crop calendar is essential for proper management of agriculture, hence the crop growth cycle is estimated for the complete growing period. The study has observed that length of the growing period has a significant relation to the number of rainy days in Andhra Pradesh (r= 0.34) and less significant in Telangana region (r=0.14) due to the availability of irrigation supplement (Annexure 4.3 a-b). There is considerable change in the start of season and end of season in both TS and AP regions (Merugu et al., 2015), because the LGP depends not only on the rainfall distribution but also on the type and depth of soil, its release characteristics and water retention capacity, daylight hours and air temperatures.

de Jong et al. (2012) have studied global greening and browning trends based on GIMMS NDVI and highlighted the importance of trend changes (breakpoints; change between greening and browning) in long-term analysis. Similar studies are carried out by many researchers focusing on land cover change (Clark et al., 2012; Aide et al., 2013; Bonilla et al., 2013; Waylen et al., 2014; Ramachandra et al., 2016). Trends were analyzed for fortnightly rainfall, temperature, and soil moisture data to assess possible relations to agricultural NDVI trends and LGP for the 1982-2015 period. Vegetation greenness strongly related to the seasonal precipitation cycle (Erasmi et al., 2009; Schucknecht et al., 2013) is also visible in the present study. The study also found a significant trend of temperature and soil moisture with agricultural NDVI and LGP trends for the 1982-2015 period. Also, based on the time series agriculture NDVI for IPCC AR5 scenario is predicted to assess the future agricultural condition in both regions for early agriculture warning.

4.4 Agricultural drought vulnerability

The Agriculture Drought Vulnerability Index (ADVI) is computed using integrated datasets i.e. satellite-derived indices, climate and socio-economic data for (1982–2015) at district as well as at Tehsil levels for 2000–2015.

4.4.1 Parameter analysis

Parameter analysis has been carried out for Adaptive capacity (AC), Sensitivity (S) and Exposure (E).

4.4.1.1 Adaptive capacity

The parameters/variables used to generate AC for two periods i.e.1982-2015 and 2000-2015 remain the same. The seven variables of socio-economic data namely Percentage of total literacy(% LiT), Percentage of rural literacy(% LiR), Livestock (L/S), Agriculture power consumption (AgP), Agriculture wages (AgW), Extent of gross irrigated area (ExGIA), and Gross irrigated area (GIA) are used to compute the adaptive capacity. Fig. 4.22 illustrates the proportionality of each parameter in the districts of the state.

- **Percentage of total literacy (% LiT)**: The total literate population in Andhra Pradesh region is higher than the Telangana region (38%) (Fig. 4.22a). Within the AP region, Chittoor district has shown highest % LiT (13%) followed by Krishna and West Godavari districts (8% each); whereas, in TS, Rangareddy district has shown a high percentage of literacy (8%).
- **Percentage of rural literacy (% LiR)**: As in the case of % LiT, AP region has shown a high proportion of %LiT when compared to TS (Fig. 4.22b). Again Chittoor district has shown a high percentage of rural literacy with 14% followed by West

Godavari with 8%. Thus, AP has one of the highest capacity to sustain the agriculture vulnerability compared to TS.

- **Live stock (L/S):** In line with %LiT and %LiR, the AP region has shown a high proportion of L/S than TS (Fig. 4.22c). Within the AP region, Anantapur and Kurnool districts have shown a higher proportion of L/S. In TS region, Medak district has shown a higher proportion of L/S.
- **Agriculture power consumption (AgP)**: TS has shown a high proportion of AgP (52%) than AP (48%) (Fig. 4.22d). Within TS, Mahbubnagar and Nalgonda districts consume high agriculture power consumption with 10% each.
- **Agriculture wages (AgW)**: AP Region has shown a high proportion of AgW than TS (38%). West Godavari district with 12% followed by East Godavari with 10% in AP and Karimnagar with 12% in TS have shown a high proportion of AgW (Fig. 4.22e).
- **Extent of gross irrigated area (ExGIA)**: Less proportion of ExGIA is available in TS (26%) compared to AP. Guntur district (13%) followed by East and West Godavari (11% each) have shown high ExGIA in AP region. In TS, Karimnagar district with 5% showed a high proportion of ExGIA (Fig. 4.22f).
- **Gross irrigated area (GIA)**: Compared to AP region TS has less proportion of GIA (41%), out of which Karimnagar has shown 11%.

Adaptive Capacitive Index (AC)

Based on the level of priority and weights of parameters, AC is generated for each region under study and shown in Fig 4.22h. The TS region comprises 36% proportion of AC compared to AP region. Except for the districts of Karimnagar (12%), Nalgonda (5%) and Warangal (5%) TS region have shown at least AC. Whereas in AP, Ananthapur, Chittoor, Prakasam, Srikakulam, Visakhapatnam, and Vizianagaram (Coastal) districts showed less AC than other districts. The districts with less AC in both regions will have a positive impact on vulnerability.

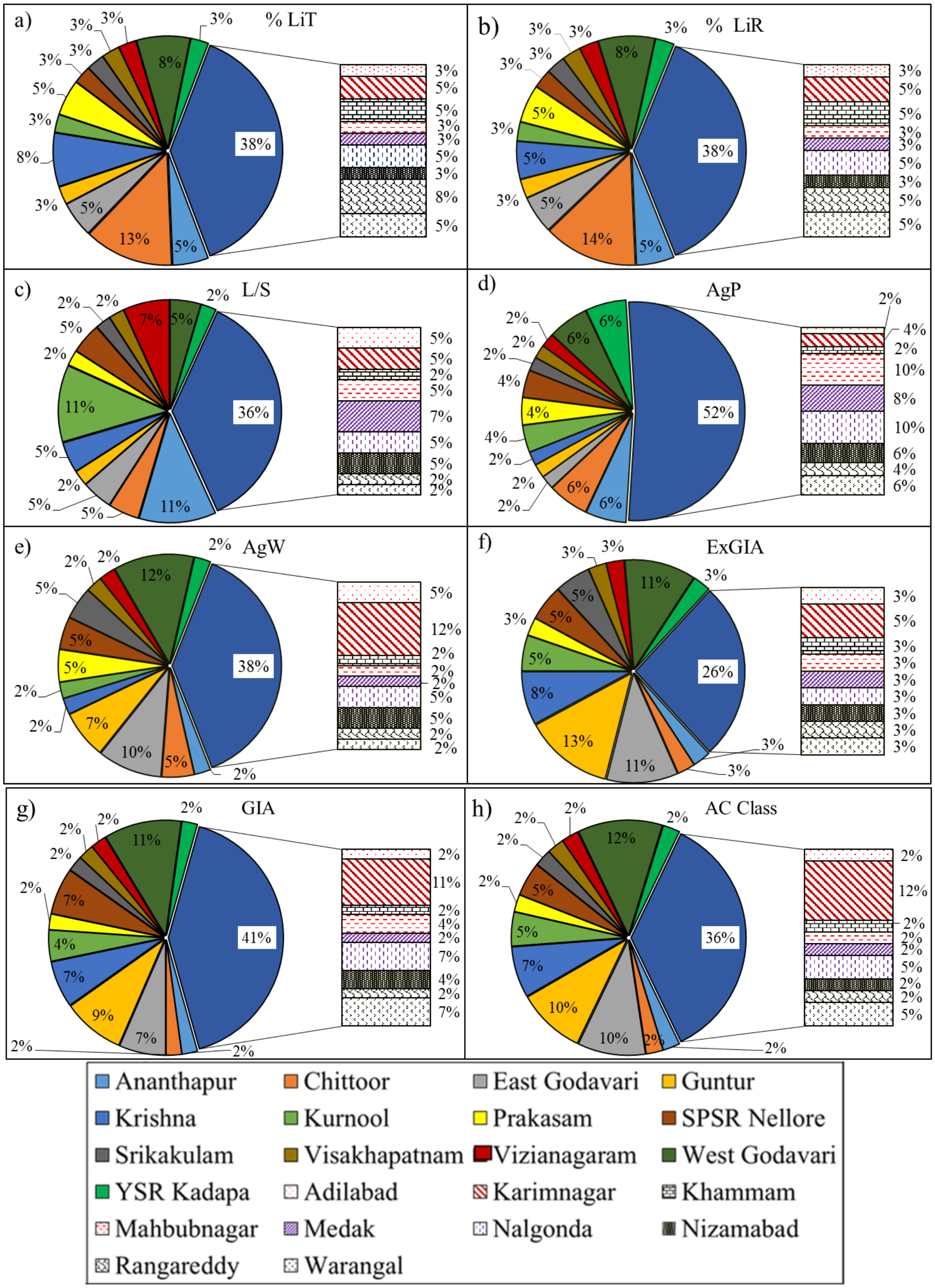


Figure 4.22 Adaptive Capacity generated parameters proportional to all districts a) Percentage of Total Literacy (% LiT); b) Percentage of Rural Literacy (%LiR); c) Live Stock (L/S); d) Agriculture Power Consumption (AgP); e) Agriculture Wages (AgW); f) Extent of Gross Irrigated Area (ExGIA); g) Gross Irrigated Area (GIA); h) Adaptive capacity index (AC)

4.4.1.2 Sensitivity

Except for remote sensing parameters the other parameters/variables used to generate the sensitivity in both AP and TS regions for two periods 1982-2015 and 2000-2015 remain the same. The proportionality of sensitivity parameters for AP and TS regions are shown in Fig. 4.23.

- **Percentage of Migrants Rural (% MgR)**: The proportion of % MgR in AP region is more than TS (43%). Except for Visakhapatnam and Rangareddy districts, all other districts have shown a high proportion of % MgR (Fig. 4.23a). A high proportion of sensitive parameters of districts will have a positive impact on the vulnerability.

- **Percentage of Total Agriculture Labour (% T- AgL)**: A high proportion of % T-AgL was found in the AP region when compared to TS (Fig. 4.23b). Within AP, Guntur, Krishna, and YSR Kadapa showed least T-AgL, whereas, in TS, Rangareddy showed 1% of T- AgL.

- **Population Density (Pop.D)**: Compared to TS (31%), AP region has shown a high proportion of Pop.D (Fig. 4.23c) Within AP, a high proportion of population density is found in the district of Srikakulam (12%) followed by Guntur (10%). In TS region, Rangareddy district (12%) has dominated the other districts in terms of Pop.D.
- **Available Water Holding Capacity (AWHC)**: TS has shown less proportion of AWHC with 44% when compared to the AP region (Fig. 4.23d). Within AP, Ananthapur and Chittoor districts have shown a maximum proportion of AWHC with 10%each, whereas, in TS, Khammam has shown high proportion with 8% (Fig. 4.23d). The above observation indicates that the enlisted districts of AP and TS appear to be more sensitive to agriculture vulnerability.
- **Soil Erosion (S.Er)**: Both states have shown constant proportion (50%) of S.Er. In addition, 16 out of 23 districts have shown a maximum proportion of S.Er at 6% each (Fig. 4.23e).
- **Gross Cropped Area (GCA):** TS has shown 39 % proportion of GCA compared to 61% by AP region (Fig. 4.23f). Thus AP seems to be more sensitive to vulnerable based on GCA parameter. Kurnool and Mahbubnagar districts have shown high proportion (8%) of GCA

among all the districts of the state (Fig. 4.23f). Therefore, these districts have high possibility to be more vulnerable.

- **Number of drought frequency and VCI (DF and VCI)**: The number of drought frequency and VCI are generated from satellite data in three seasons using NOAA GIMMS and MODIS data.

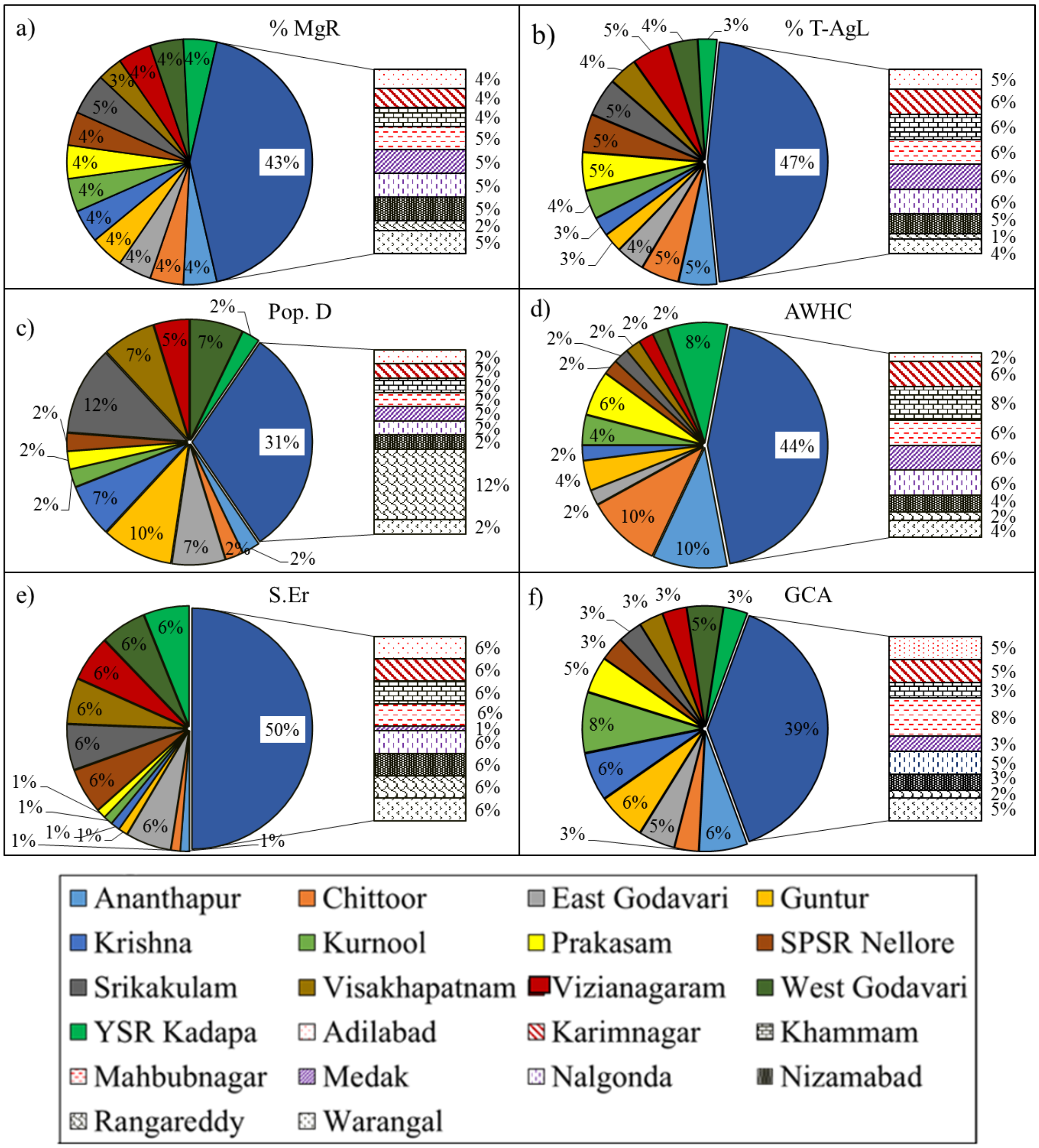


Figure 4.23 Sensitivity generated parameters proportional of all districts a) Percentage of Migrants Rural (% MgR); b) Percentage of Total Agriculture Labour (% T-AgL); c) Population Density (Pop. D); d) Available water holding Capacity (AWHC); e) Soil Erosion (S.Er); f) Gross Cropped Area (GCA)

NOAA GIMMS

Drought frequency in Summer Monsoon (DF SM): Drought frequency in Summer Monsoon (DFSM):- It can be seen from Fig. 4.24a that AP region has shown maximum proportion (59%) of drought frequency (DFSM) compared to TS (41%). Ananthapur district of AP and Mahbubnagar district of TS showed a high proportion of DF SM (9%) among the districts.

Drought frequency in winter season (DF W): In line with DFSM AP region has shown more proportion of drought frequency (55%) in winter season than TS region (45%) (Fig. 4.24c). Also, the drought frequency in TS region is more (3%) during the winter season when compared to the drought frequency in summer monsoon. On the other hand, in AP the DFSM is more than DFW. Ananthapur and Kurnool districts of AP; Mahbubnagar and Rangareddy districts of TS have shown high proportion (8%) of drought frequency in the winter season (Fig. 4.24c).

Drought frequency in summer season (DF SS): Similar to the drought frequency in summer monsoon and winter season, the summer season has also experienced considerable proportion of drought frequency particularly in Coastal and Rayalaseema regions of AP (Fig 4.24e). The drought frequency proportions of different districts are shown graphically in Fig. 4.24e. The Kurnool district of AP has shown a high proportion of DF SS (9%) and in case of TS, Mahbubnagar, Medak and Rangareddy districts have shown high proportions.

VCI: Figs. 4.25b, 4.25d, and 4.25e show the proportionality of VCI during the summer monsoon, winter and summer seasons during the period 1982-2015. Among the two regions, AP is found to be more sensitive as it showed 65% of the proportion of VCI during the summer monsoon. However, during the winter and summer seasons, TS is more sensitive as it recorded 51% and 54% proportion of VCI.

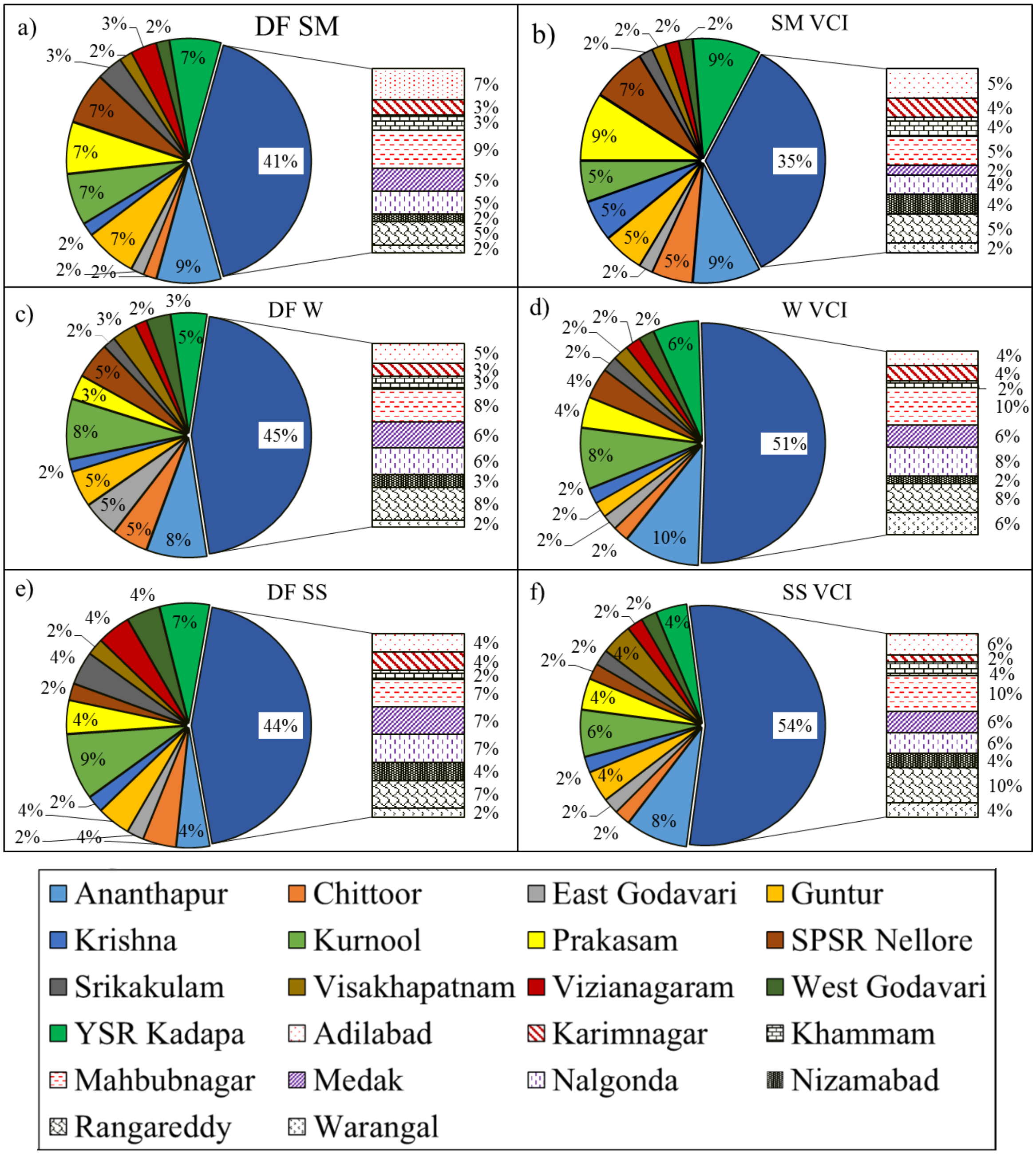


Figure 4.24 Proportionality of sensitivity parameters derived indicator generated from satellite derived indices during 1982-2015 period in three seasons a) drought frequency in summer monsoon (DF SM); b) summer monsoon VCI; c) drought frequency in winter season (DF W); d) winter season VCI; e) drought frequency in summer season (DF SS); and f) summer season VCI

Sensitivity index: Based on above parameter priority and weights, sensitivity is determined (as explained in section 3.3.3) for all the districts of AP and TS regions during the three cropping seasons for the period 1982-2015 and shown in Fig. 4.25a-c.

In all the three seasons AP has shown a high proportion of sensitiveness to agriculture drought vulnerability compared to TS. During the winter and summer seasons, an increase in sensitivity proportion is noticed in TS. Within TS, Mahbubnagar has shown a high proportion of sensitiveness in all three seasons and in AP, Ananthapur, and Kurnool have shown high sensitivity.

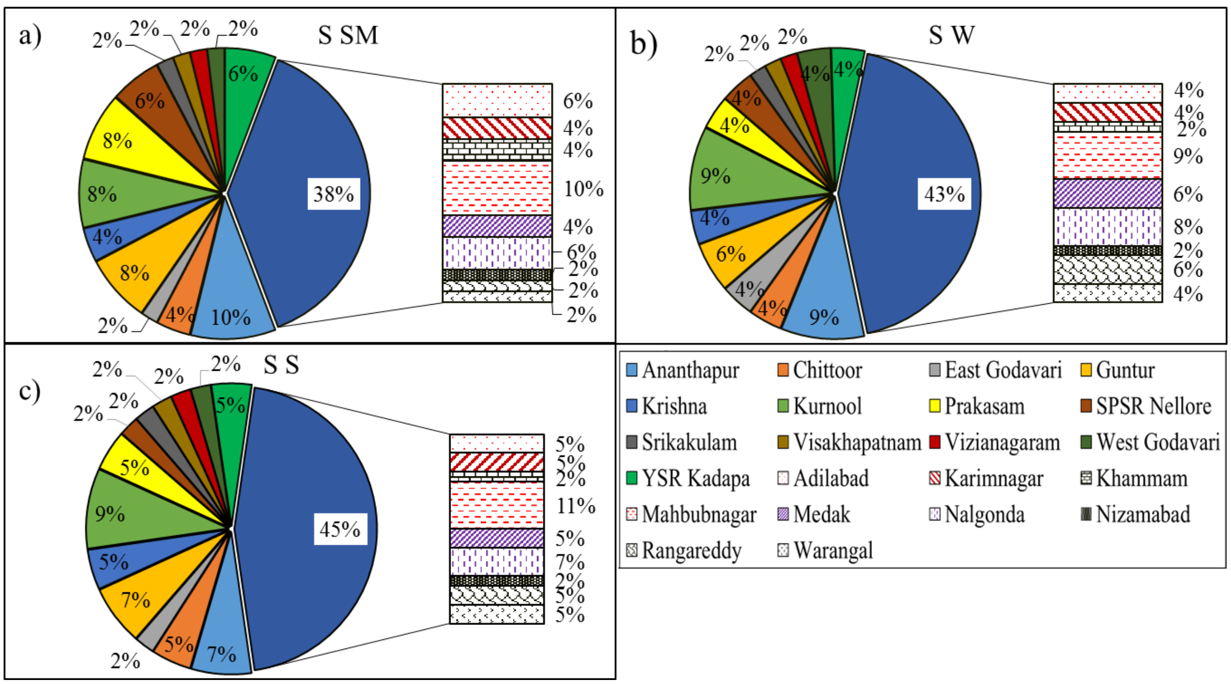


Figure 4.25 Proportionality of Sensitivity index indicator during 1982-2015 in three seasons a) sensitivity in summer monsoon; b) sensitivity in winter season; and c) sensitivity in summer season.

MODIS

The proportionality of sensitivity parameters obtained from satellite-derived indices during the period 2000-2015 in three seasons is shown in Fig. 4.26.

Drought frequency: In all the three seasons AP has shown high proportions (>50%) of drought frequency than TS, similar to the period 1982-2015, indicating it's sensitiveness to drought vulnerability.

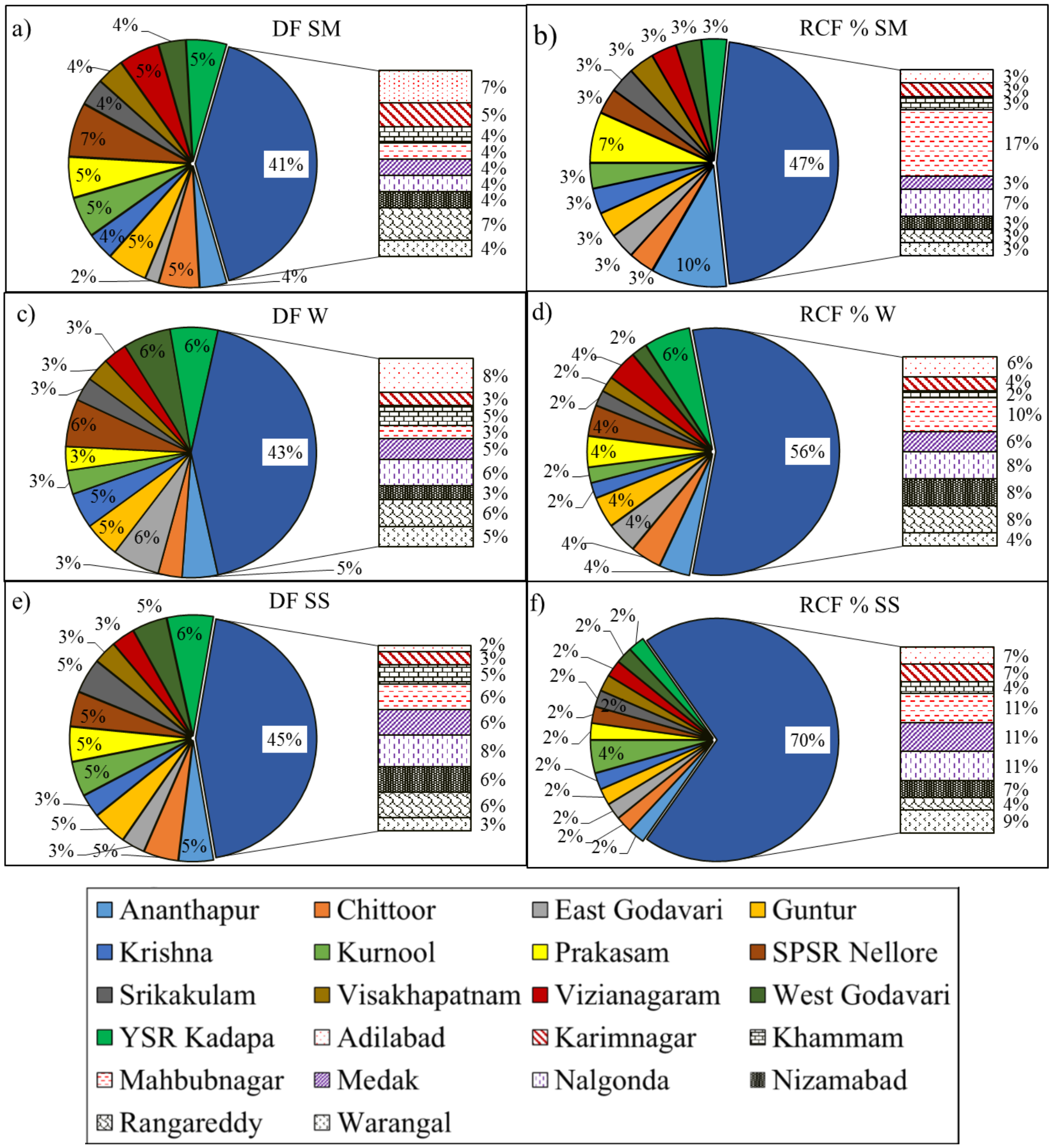


Figure 4.26 Proportionality of sensitivity parameters obtained from satellite derived indices during 2000-2015 in three seasons a) drought frequency in summer monsoon (DFSM); b) ratio of crop area fluctuation in summer monsoon (RCF % SM); c) drought frequency winter season (DF W); d) crop area fluctuation in winter season (RCF % W); e) drought frequency in summer season (DF SS); and f) ratio of crop area fluctuation in summer season (RCF % SS).

Ratio of crop area fluctuation (RCF %): High proportions of RCF observed in TS during the winter and summer seasons (56% and 70%) indicate that it was more sensitive to vulnerability during the winter and summer seasons. On the other hand, a relatively high proportion of RCF is noticed in AP during the summer monsoon (53%). It is to note that the Mahbubnagar district in TS has shown maximum proportions of RCF in all the seasons when compared to other districts (Fig. 4.26b, d, f). Also, Medak and Nalgonda districts of TS have reflected with high proportions in the summer season (Fig. 4.26f).

Sensitivity index: Following the similar procedure to generate AVHRR GIMMS sensitivity, MODIS data has been used to generate the sensitivity for all the districts of AP and TS regions for the period 2000-2015 and shown in Fig. 4.27 a-c. The maximum proportion of sensitivity is observed in AP than in TS during three seasons.

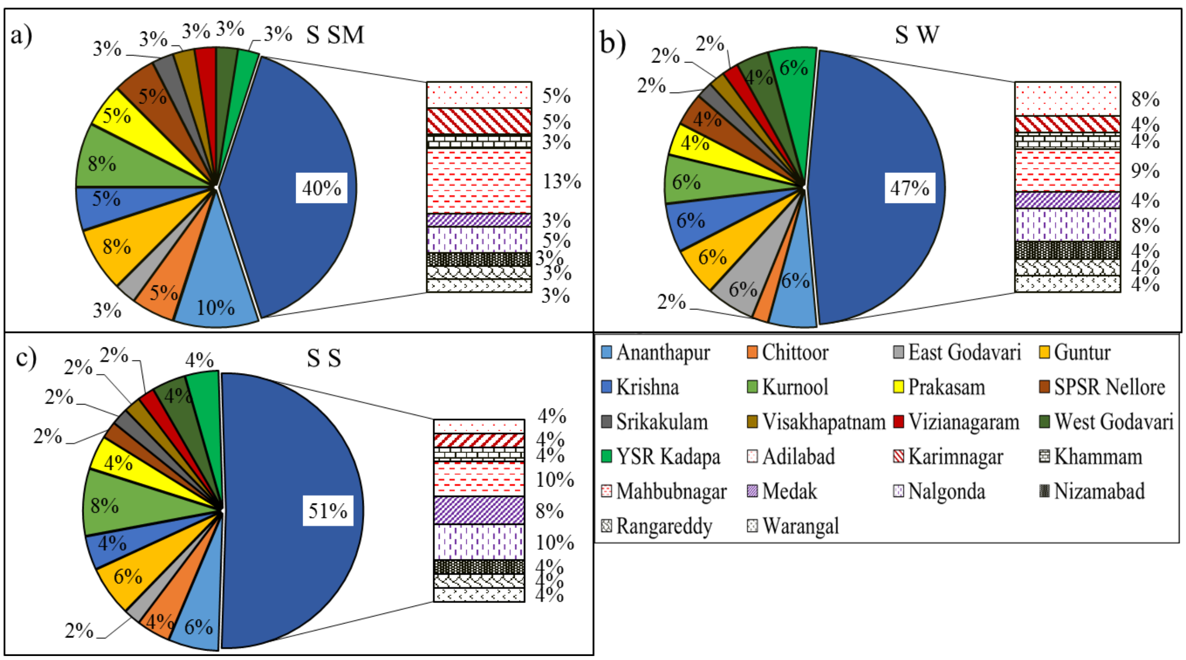


Figure 4.27. Proportionality of Sensitivity indicator during 2000-2015 in three seasons a) sensitivity in summer monsoon; b) sensitivity in winter season; and c) sensitivity in summer season

4.4.1.3 Exposure

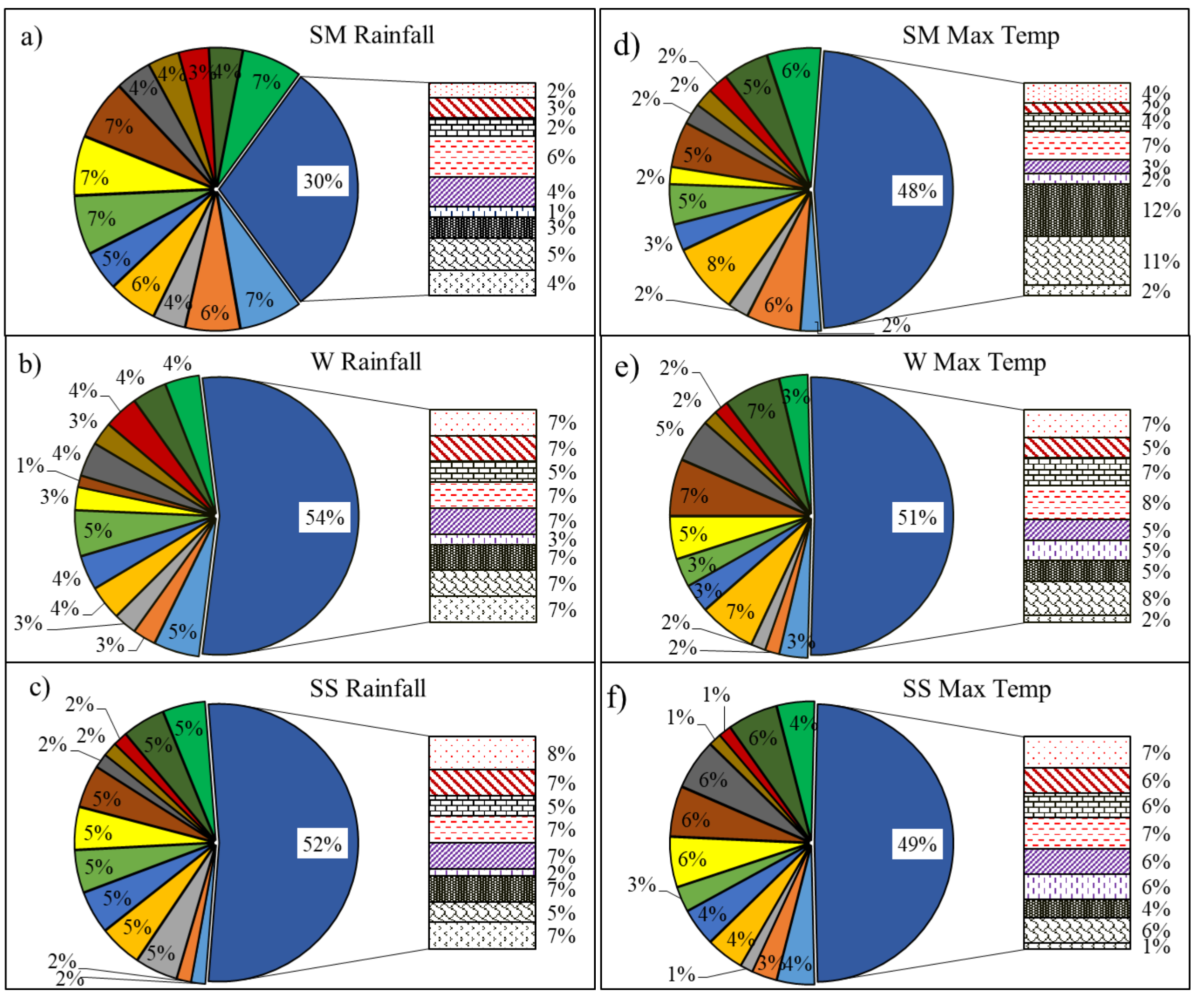
NOAA GIMMS

The proportionality of exposure generated parameters derived from climate data during the period 1982-2015 in three seasons are shown in Fig. 4.28.

Rainfall*:* AP region has witnessed high proportion of rainfall during the summer monsoon (Fig. 4.28a), whereas in winter and summer seasons TS has shown the maximum proportion of rainfall (Fig. 4.28b-c). Therefore, TS appears to be more sensitive to agriculture during winter and summer seasons and AP during the summer monsoon.

Maximum Temperature (Max Temp): During summer monsoon and summer season, AP has shown a high proportion of maximum temperature than TS (Fig. 4.28 d and f). Of all the districts of AP and TS, Nizamabad and RangaReddy districts result in maximum proportion during the summer monsoon.

Minimum Temperature (Min Temp): In all the three seasons, AP has shown a high proportion of minimum temperature than TS. Overall, Prakasam and Nellore districts have maximum proportions, which indicate that these districts appear to be more sensitive to agriculture during the said cropping seasons.



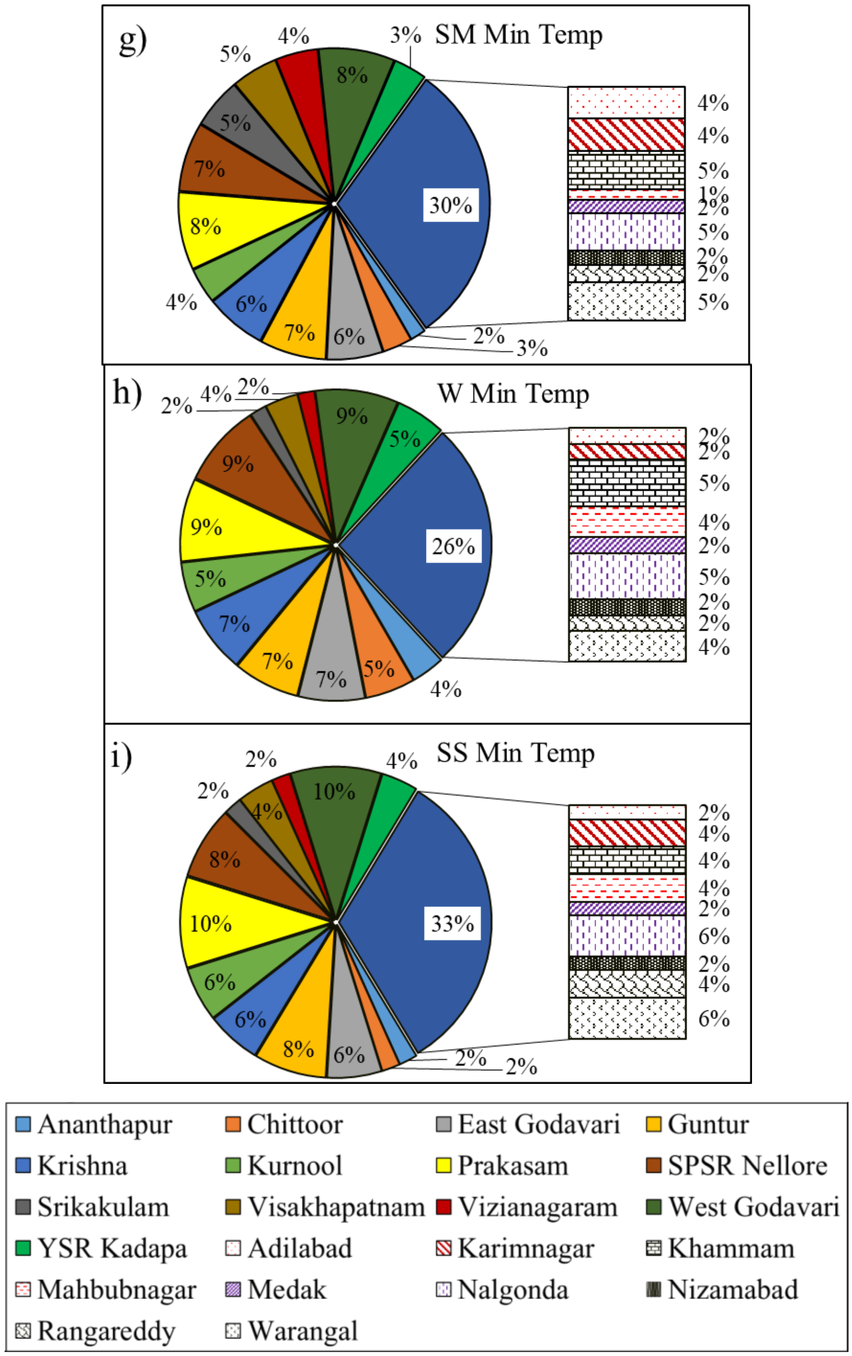


Figure 4.28 Proportionality of exposure generated parameters derived from climate data during 1982-2015 period in three seasons a) summer monsoon rainfall; b) winter rainfall; c) summer season rainfall; d) summer monsoon maximum temperature; e) winter maximum temperature; f) summer season maximum temperature; g) summer monsoon minimum temperature; h) winter minimum temperature; and i) summer season minimum temperature.

Exposure index

Using three climatic parameters (rainfall, maximum temperature, and minimum temperature) exposure components are generated in three seasons during the period 1982-2015 period and shown in Fig. 4.29. During the monsoon seasons, the proportionality of exposure is high in AP region. During summer season TS has shown a maximum proportion of exposure.

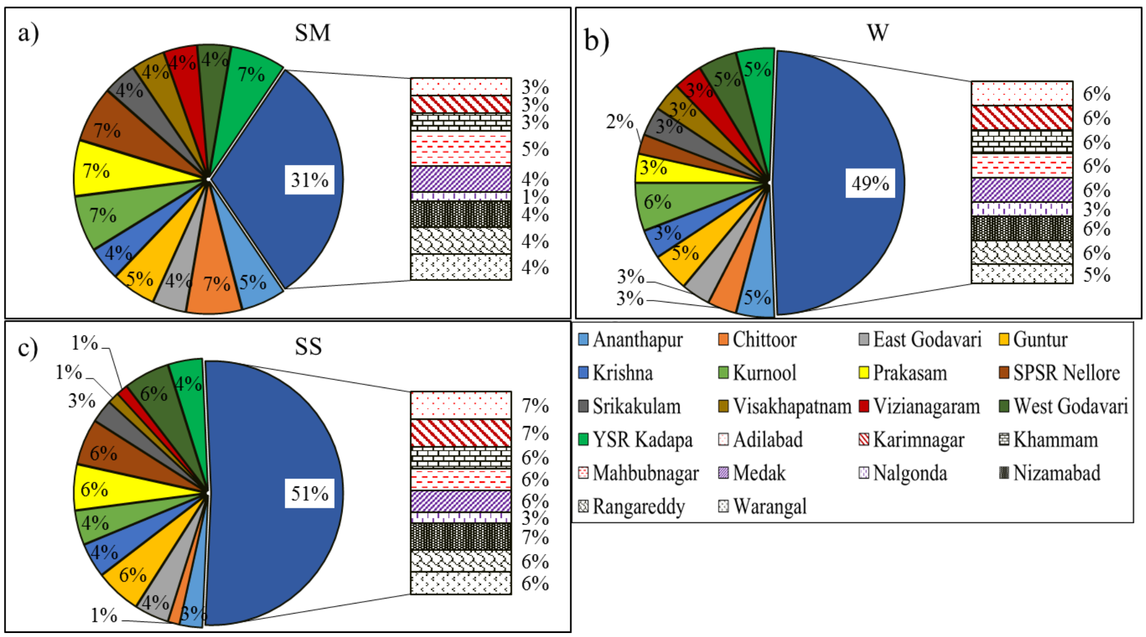


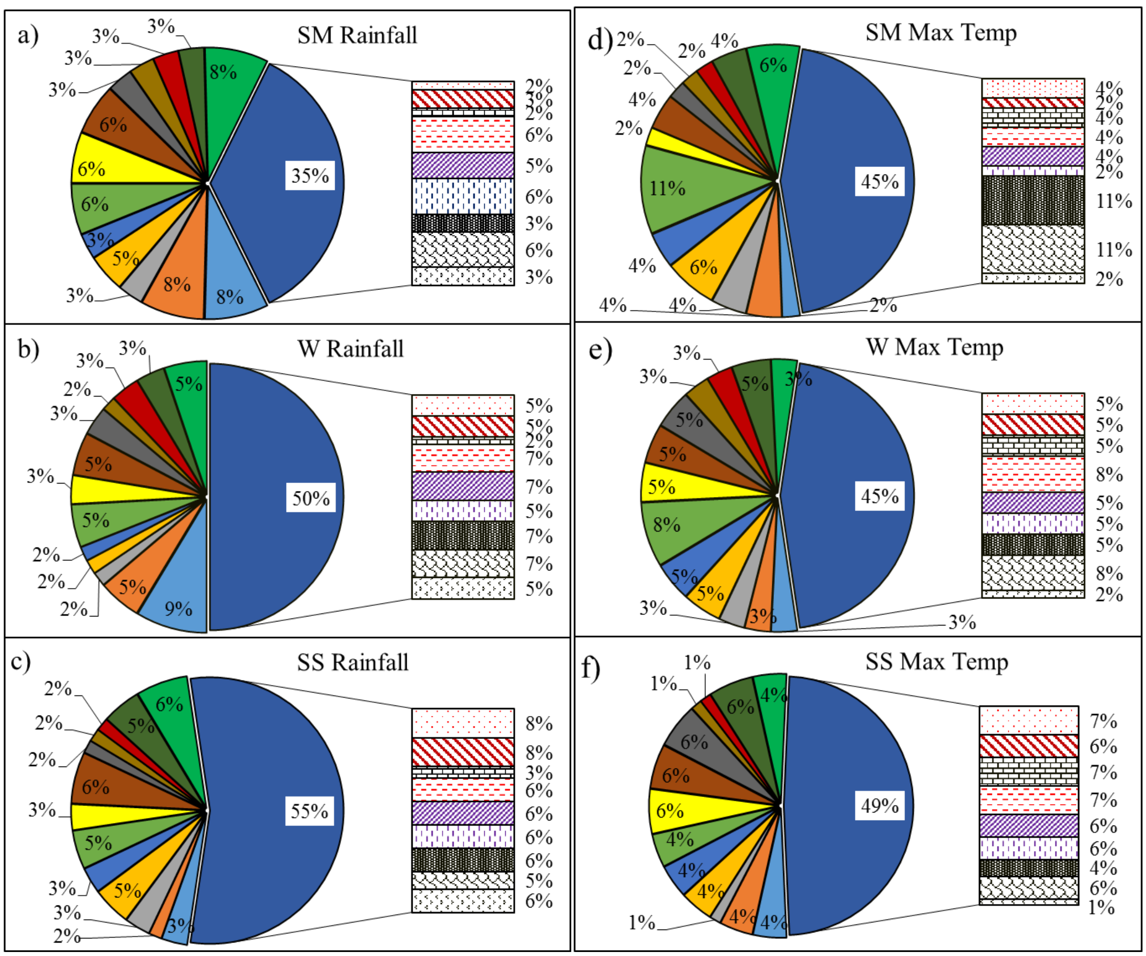
Figure 4.29 Proportionality of Exposure indicator during 1982-2015 in three seasons a) exposure in summer monsoon; b) exposure in winter season; and c) exposure in summer season

MODIS

The proportionality of exposure generated parameters derived from climate data during the 2000-2015 period in three seasons is shown in Fig. 4.30.

Rainfall: During the period 2000-2015, the proportion of summer monsoon rainfall to exposure is found the maximum in AP (65%) than in TS (35%) (Fig. 4.30a). During the winter season, both states have shown equal rainfall proportions (50%). Similar to the period 1982-2015 (Fig. 4.28c), TS has shown maximum rainfall proportion during the summer season for the period 2000-2015 (Fig. 4.30c). Ananthapur, Chittoor and YSR districts have contributed maximum proportions of summer monsoon rainfall among all other districts of AP and TS (Fig. 4.30a).

Maximum Temperature (Max Temp): During three seasons, AP has shown a high proportion of Max Temp exposure. Among all others, the districts of Kurnool, Nizamabad, and Rangareddy have shown high proportions of Max Temp during the summer monsoon (11%) and winter season (8%).In the summer season, Adilabad, Khammam, and Mahbubnagar districts have shown large proportion (7%) of Max Temp of all the districts (Fig. 4.30f).



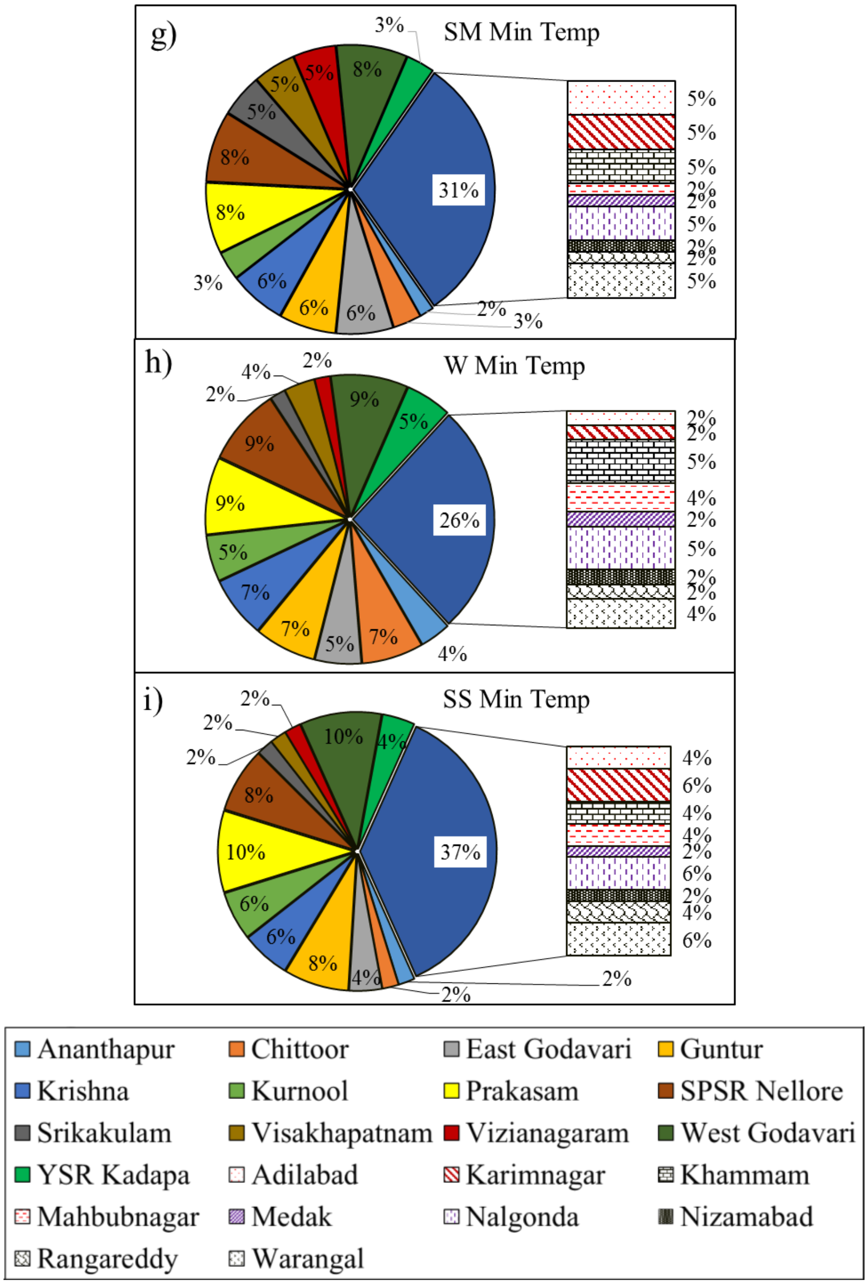


Figure 4.30 Proportionality of exposure generated parameters derived from climate data during 2000-2015 period in three seasons a) summer monsoon rainfall; b) winter rainfall; c) summer season rainfall; d) summer monsoon maximum temperature; e) winter maximum temperature; f) summer season maximum temperature; g) summer monsoon minimum temperature; h) winter minimum temperature; and i) summer season minimum temperature.

Minimum Temperature (Min Temp): More or less similar results observed for the period 1982-2015 are repeated in the present case also, however, with an increase in proportionality of 1 % and 4 % in TS during the summer monsoon and summer season.

Exposure index: Exposure component for the period 2000-2015 in three seasons are shown in Fig. 4.31. It can be noticed that all districts of AP and TS have shown more or less similar proportions of exposure to that of the 1982-2015 period.

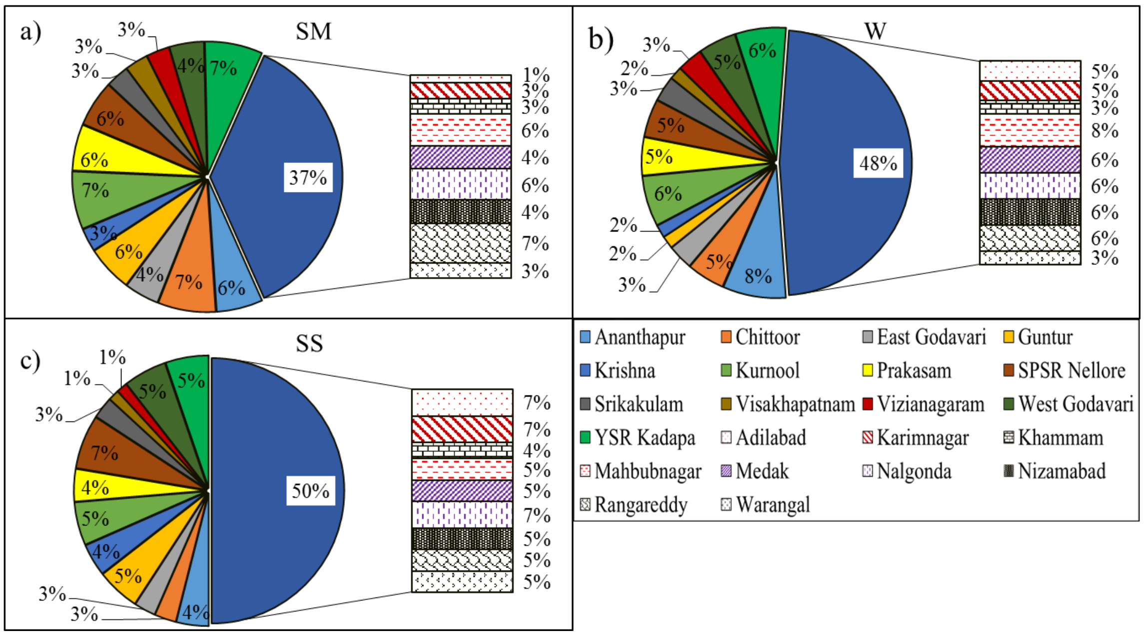


Figure 4.31 Proportionality of Exposure indicator during 2000-2015 in three seasons a) exposure in summer monsoon; b) exposure in winter season; and c) exposure in summer season.

4.4.2 ADVI

4.4.2.1 ADVI during 1982-2015

4.4.2.1.1 District level

Time series datasets to assess the spatial pattern and radar chart of sensitivity (S,) adaptive capacity (AC), exposure (E) and resultant V are shown in Fig. 4.32 and 4.33. Among 22 districts, 13 districts (covering 59% of the total geographical area of united AP) have very low AC. Karimnagar (covering 10% of the total geographical area of TS) and West Godavari (covering 5% of the total geographical area of AP) are the only districts, which showed high AC due to a large irrigated area. In three cropping seasons, Mahbubnagar district is found to be highly vulnerable due to less adaptive capacity and high sensitivity. Ananthapur and Kurnool districts are highly vulnerable during the first two cropping periods (summer monsoon and winter), as vegetation indices are highly sensitive to climate change and exposed to frequent climate variability. Y.S.R.Kadapa and Prakasam districts (covering ~20 % of the total geographical area of AP) have shown high vulnerability during the summer monsoon. During summer/zaid season, out of eight districts considered from TS, 5 districts (covering ~77% of the total geographical area of TS) have shown high to extreme vulnerability. In AP, approximately 44% of the total geographical area is vulnerable (medium to high) to agriculture drought (Bhavani et al., 2017b).

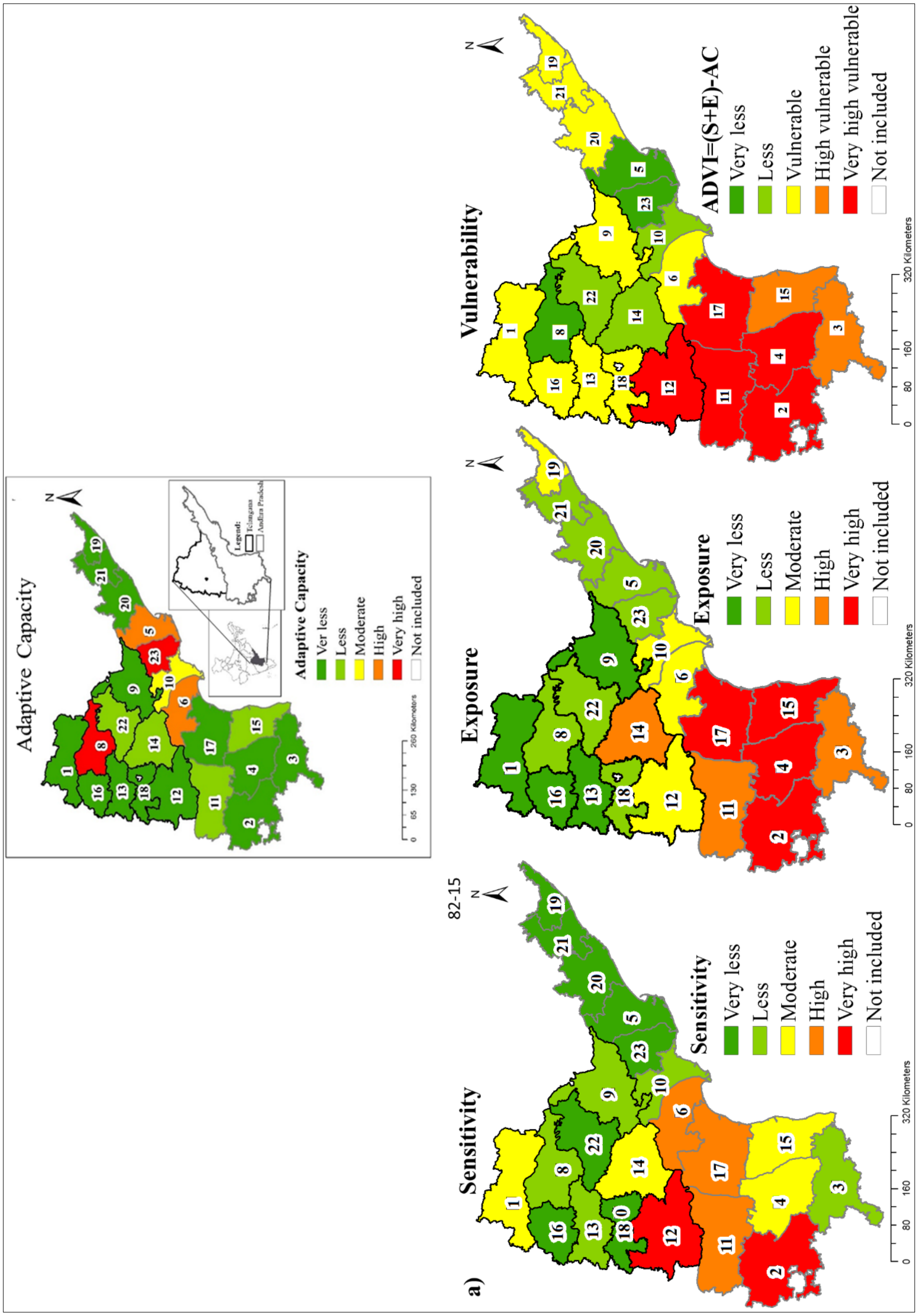
Figure 4.34 illustrates the current and projected/future vulnerability in Telangana and AP regions during the three cropping seasons. The extent of vulnerability decreases in TS and AP is due to increase in adaptive coping parameters (AgW and GIA) and climate variation (increase in rainfall) during June-September. It is observed that in winter and summer, TS is more vulnerable in recent-past and in future, whereas during the summer monsoon AP is more vulnerable.

4.4.2.2 ADVI during 2000-2015

4.4.2.2.1 District level

ADVI is also computed using MODIS NDVI data for the period 2000-2015. The distribution of S, E, AC, and V represented in radar charts for three seasons are shown in Fig. 4.35. Similar to the 1982-2015 period, Mahbubnagar district has shown extreme vulnerability in three cropping seasons due to less adaptive capacity and high sensitivity.

.Ananthapur and Kurnool districts have shown high vulnerability during the first two cropping periods (summer monsoon and winter), as vegetation indices are highly sensitive to climate change and exposed to frequent climate variability. Chittoor, Y.S.R.Kadapa, Prakasam districts (covering 30 % of the total geographical area of AP) have shown high vulnerability during the summer monsoon.


a)
82-15
Sensitivity
Sensitivity
Very less
Less
Moderate
High
Very high
Not included
Exposure
Exposure
Very less
Less
Moderate
High
Very high
Not included
Vulnerability
ADVI=(S+E)-AC
Very less
Less
Vulnerable
High vulnerable
Very high vulnerable
Not included
Adaptive Capacity
Adaptive Capacity
Ver less
Less
Moderate
High
Very high
Not included
Legend:
Telangana
Andhra Pradesh
320 Kilometers
260 Kilometers

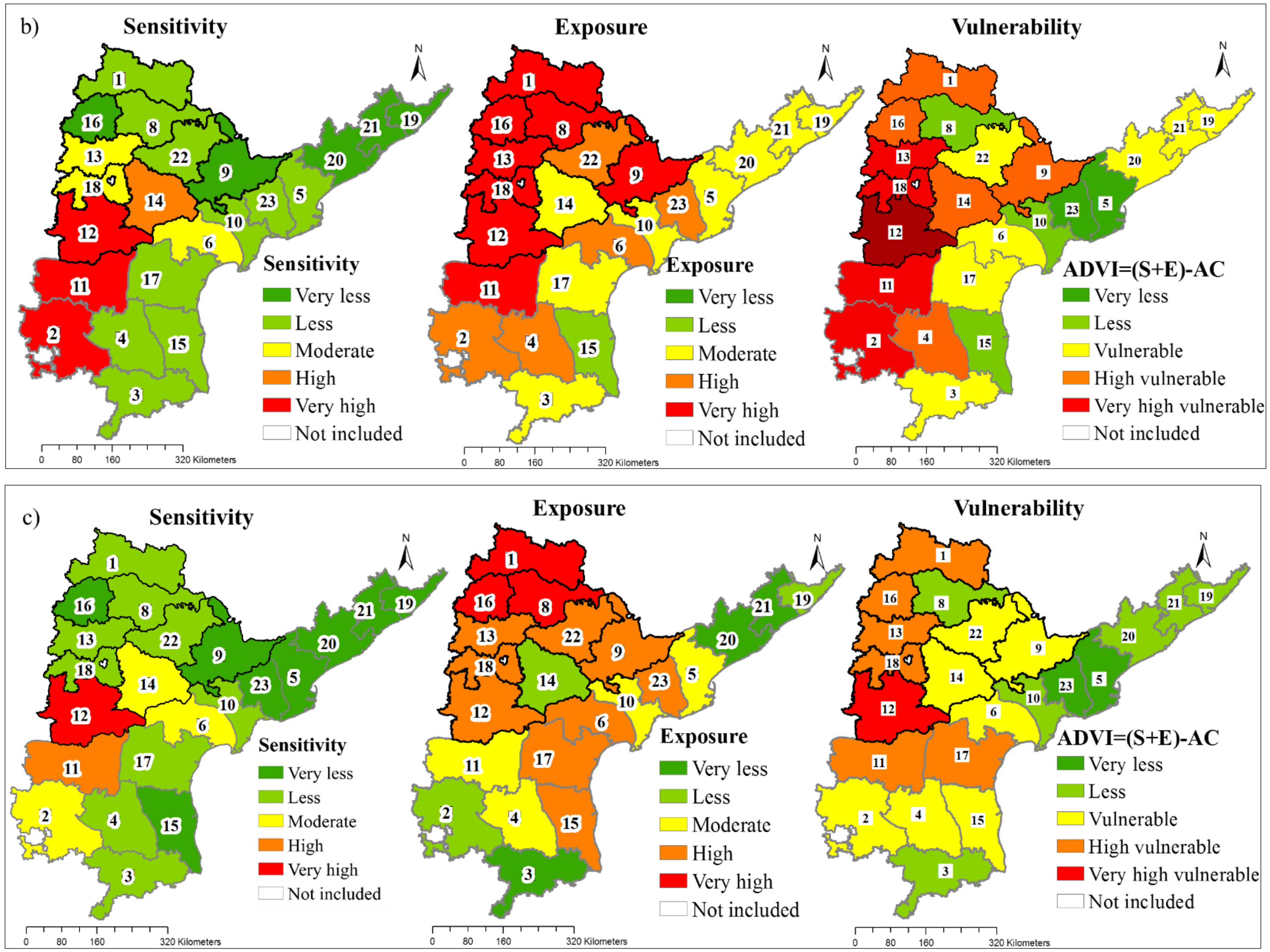


Figure 4.32 Spatial distribution of adaptive capacity; sensitivity, exposure and ADVI during the period 1982-2015 a) summer monsoon; b) winter season; and c) summer season (Bhavani et al., 2017b)

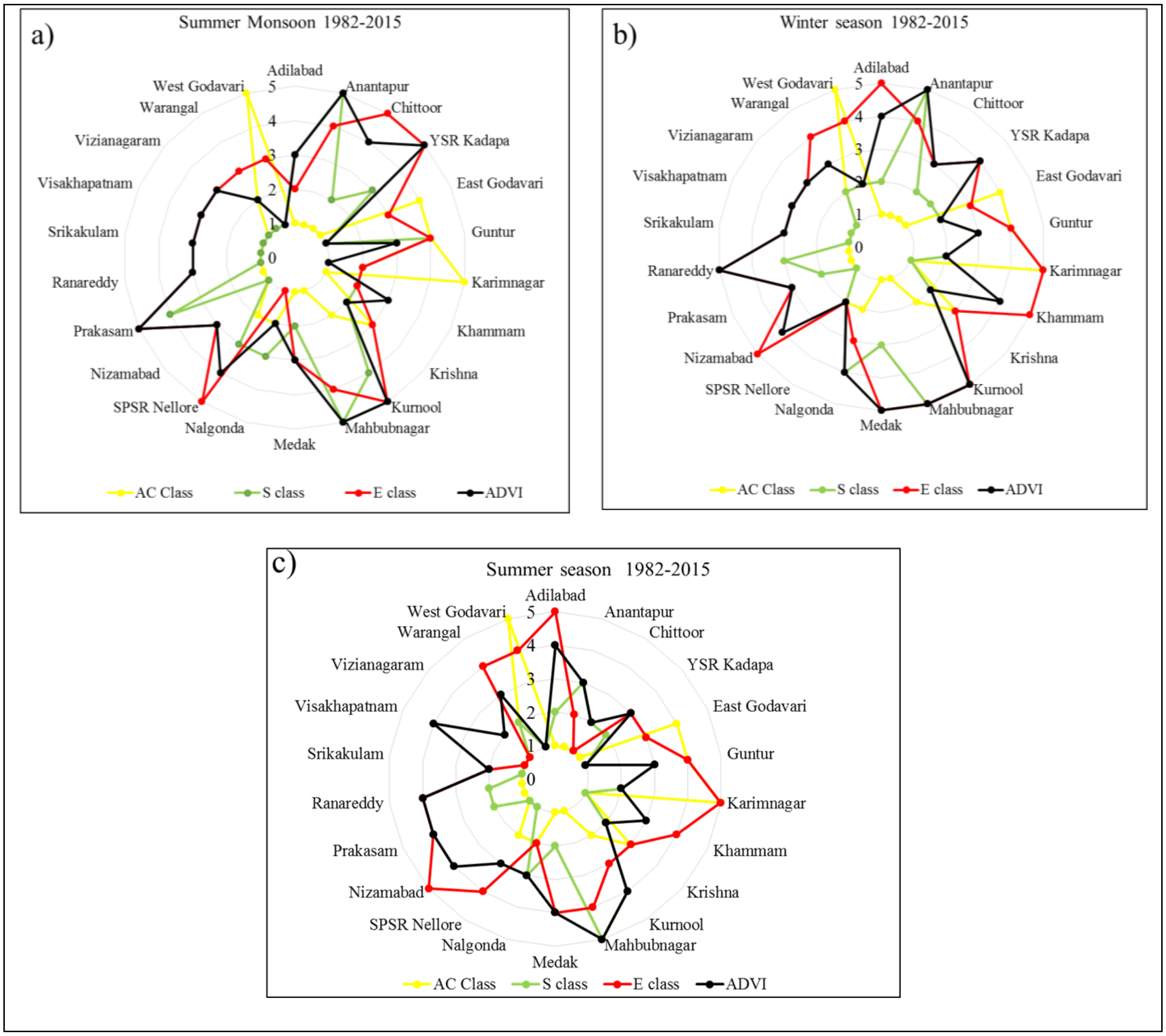


Figure 4.33 Representation of adaptive capacity; sensitivity, exposure and ADVI during the period 1982-2015 a) summer monsoon; b) winter season; and c) summer season

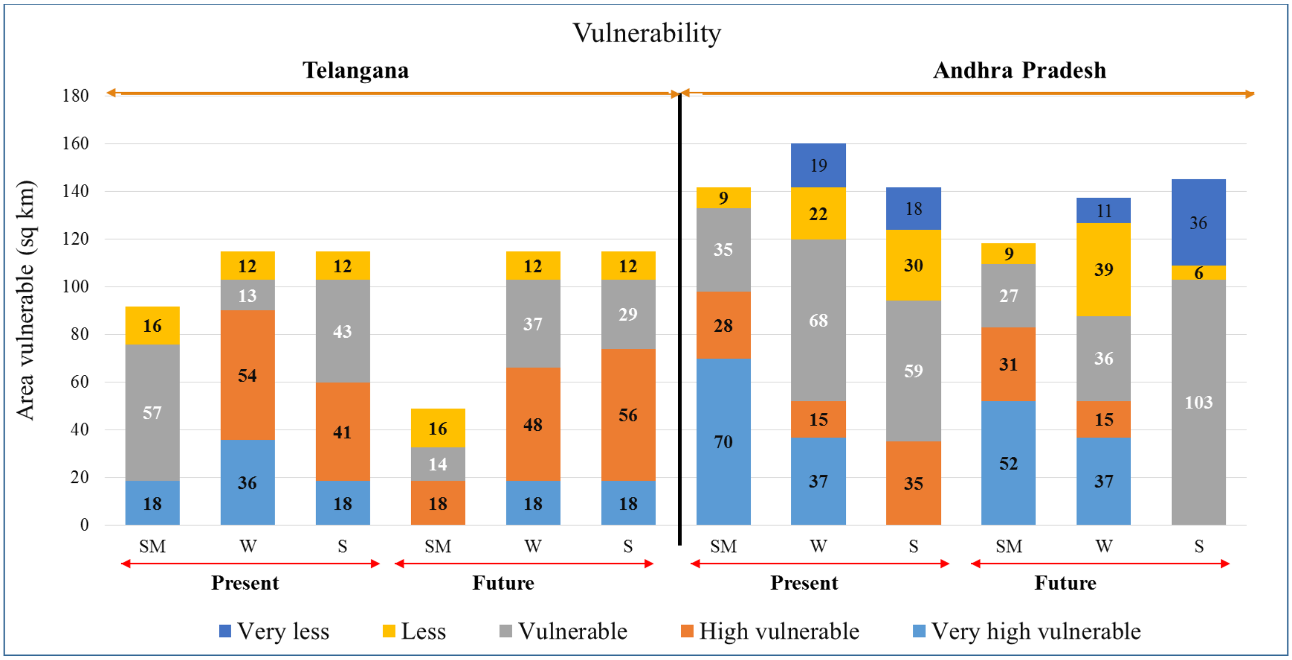
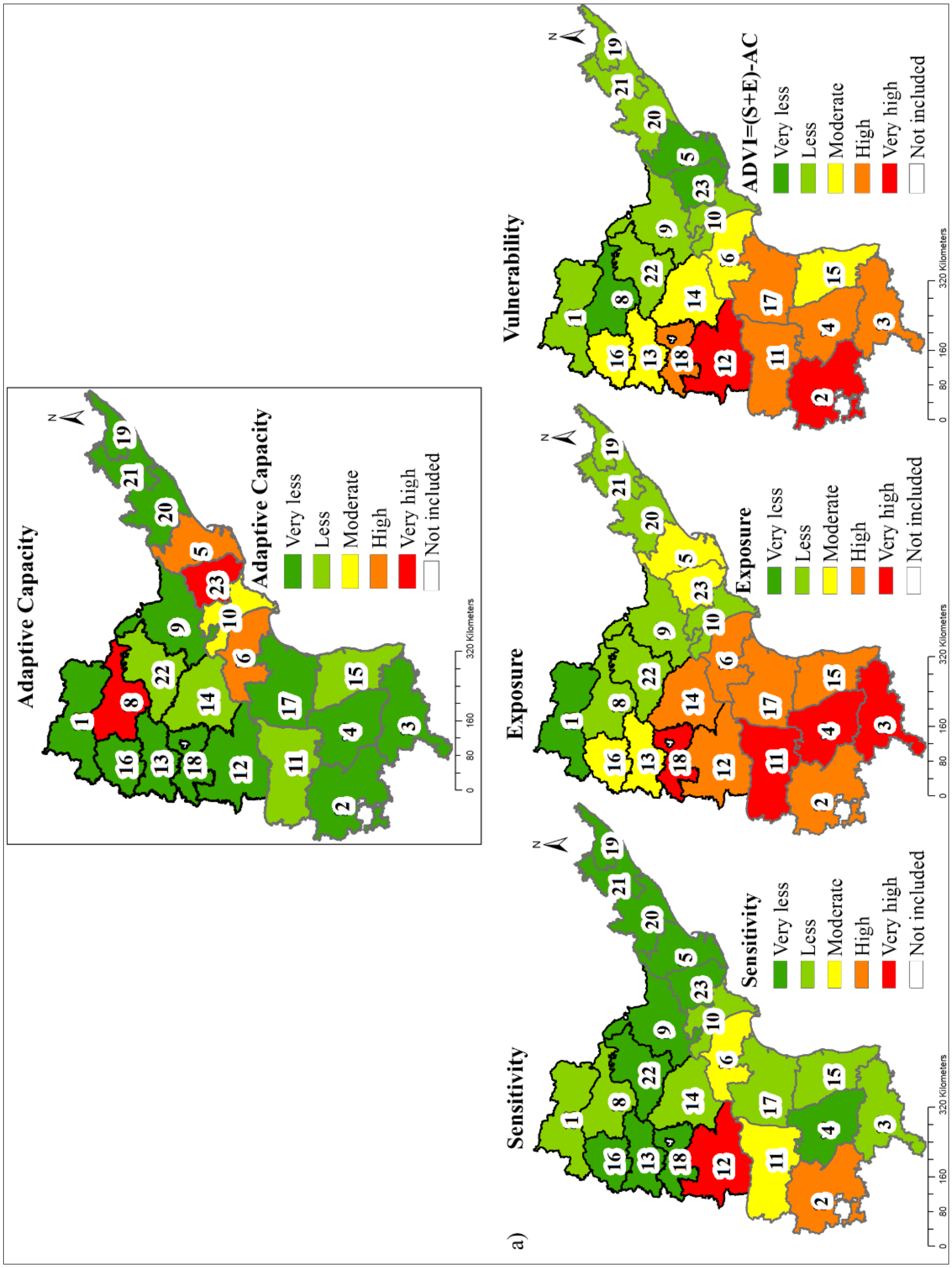


Figure 4.34 Comparison of present and projected vulnerability at state level during three cropping seasons (Bhavani et al., 2017b).

4.4.2.2.2 Tehsils level

The spatial patterns of AC, E, S, and V at Tehsil levels of TS and AP regions are shown in Figure 4.36. It is noticed that less than 20 % of tehsils come under Adilabad, Ananthapur, Chittoor, and Mahbubnagar districts have shown moderate to high AC (Top panel of Fig. 4.36)   More than 50% of tehsils fall under the Nalgonda district have showed moderate to very high sensitivity during the summer monsoon (Fig.4.36a), because the ratio of crop fluctuation percent is more due to climate change and also due to the fact that the district is largely covered by red soil (85%) whose water holding capacity is less. More than 90% tehsils in Adilabad and Krishna districts are exposed to climate during the summer monsoon, and during the winter season large number of tehsils (more than 90%) in Kurnool, Krishna, Prakasam, Mahbubnagar, Warangal, West Godavari and Adilabad districts are exposed to climate. More than 50% of tehsils in Warangal and Khammam districts have shown high to very high sensitivity during the summer season. Moderate to high exposure is noticed in the districts of Guntur and Warangal (more than 80% of tehsils), followed by Mahbubnagar (Bhavani et al., 2017b).



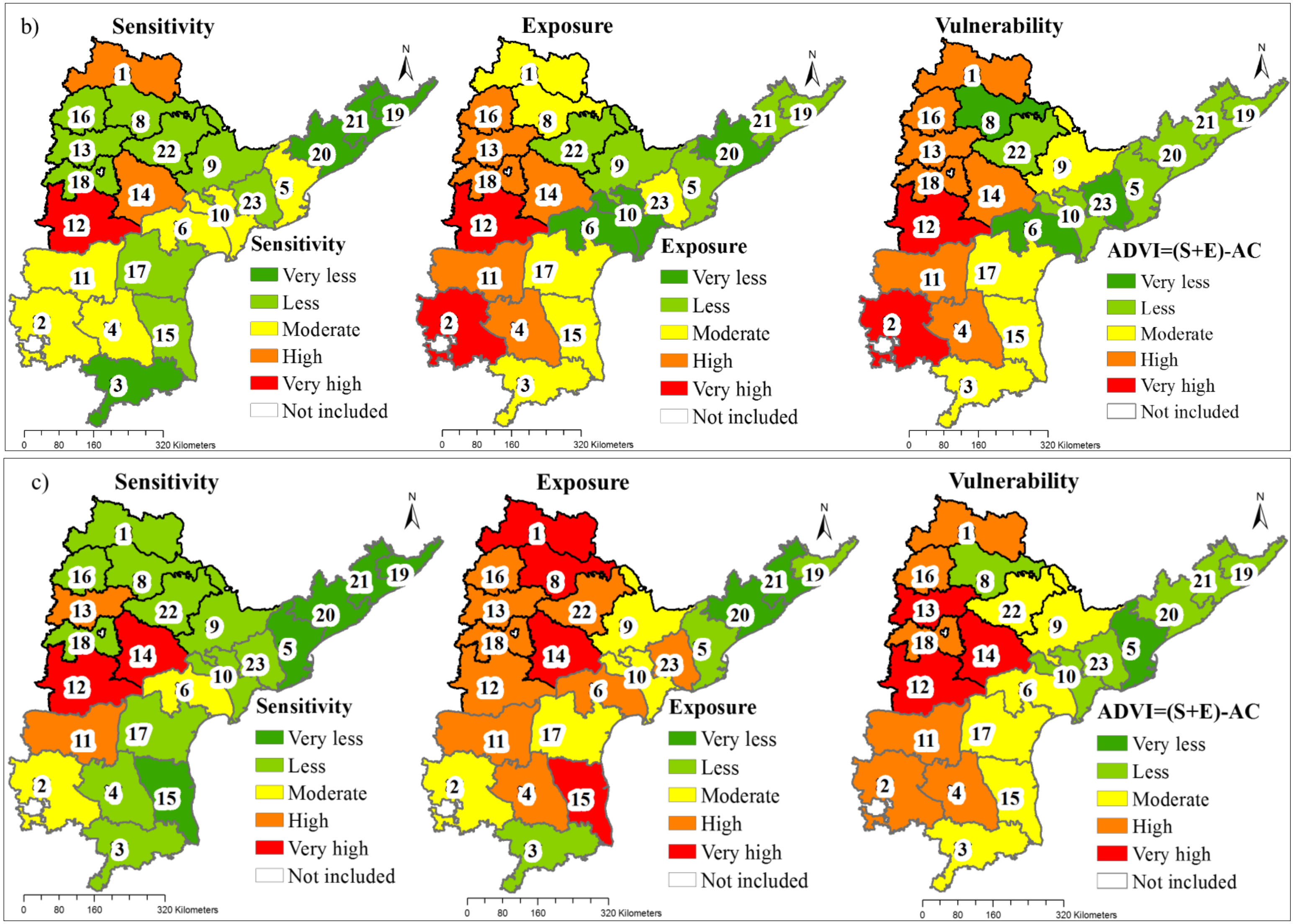
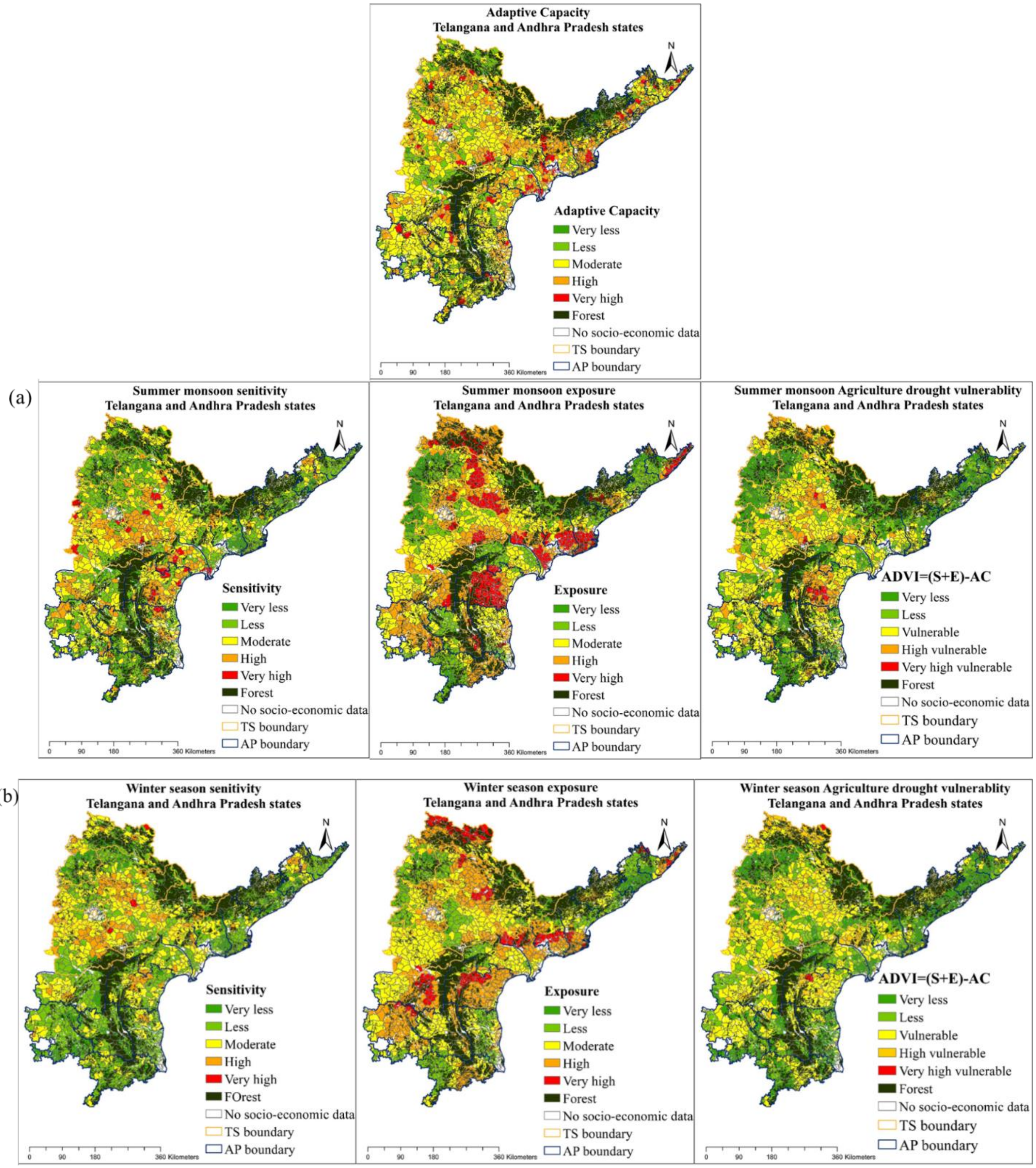


Figure 4.35 Spatial distribution of adaptive capacity; sensitivity, exposure and ADVI at districts wise during 2000-2015 period for three seasons a) summer monsoon; b) winter season; and c) summer season


Adaptive Capacity
Telangana and Andhra Pradesh states
N
Adaptive Capacity
Very less
Less
Moderate
High
Very high
Forest
No socio-economic data
TS boundary
AP boundary
0 90 180 360 Kilometers
(a)
Summer monsoon senitivity
Telangana and Andhra Pradesh states
Sensitivity
Very less
Less
Moderate
High
Very high
Forest
No socio-economic data
TS boundary
AP boundary
Summer monsoon exposure
Telangana and Andhra Pradesh states
Exposure
Very less
Less
Moderate
High
Very high
Forest
No socio-economic data
TS boundary
AP boundary
Summer monsoon Agriculture drought vulnerablity
Telangana and Andhra Pradesh states
ADVI=(S+E)-AC
Very less
Less
Vulnerable
High vulnerable
Very high vulnerable
Forest
No socio-economic data
TS boundary
AP boundary
(b)
Winter season senitivity
Telangana and Andhra Pradesh states
Sensitivity
Very less
Less
Moderate
High
Very high
FOrest
No socio-economic data
TS boundary
AP boundary
Winter season exposure
Telangana and Andhra Pradesh states
Exposure
Very less
Less
Moderate
High
Very high
Forest
No socio-economic data
TS boundary
AP boundary
Winter season Agriculture drought vulnerablity
Telangana and Andhra Pradesh states
ADVI=(S+E)-AC
Very less
Less
Vulnerable
High vulnerable
Very high vulnerable
Forest
No socio-economic data
TS boundary
AP boundary

(c)

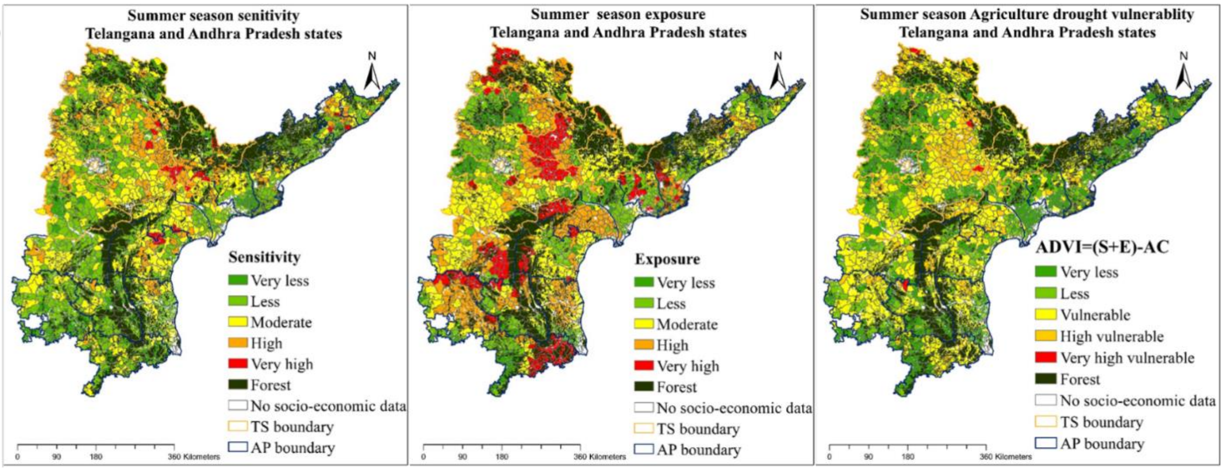


Figure 4.36 Spatial distribution of adaptive capacity (AC), sensitivity (S), exposure (E) and Vulnerability (V) at tehsil level during 2000-2015 a) summer monsoon; b) winter season; and c) summer season.

4.4.2.3 Future status

The estimated ADVI for summer monsoon, winter and summer seasons for the projected year for 2070 behaves almost similar to 2050 RCP 2.6 scenario (Fig. 4.37). Hence, the spatial distribution of E indicator and projected S and AC indicators for the year 2050 are explained briefly as follows.

District level

The future agricultural drought vulnerability has been assessed using AR5 RCPs for climate, as an E indicator and projected S and AC indicators for the years 2050 and 2070 (Fig. 4.38 and 4.39). Majority of the districts show a similar distribution of E and vulnerability during three cropping periods. The AC index (top panel of Fig. 4.38) shows high values in Karimnagar and Khammam districts, followed by West Godavari district (5%). Among 22 districts, 5 districts show low AC (21%). The predicted annual ADVI for 2050 and 2070 (all four RCP's) show a similar pattern in most of the districts of AP and TS except Ananthapur, Chittoor, East Godavari, Guntur, Nalgonda, and Krishna. Also, the districts of Ananthapur, Y.S.R.Kadapa, Nellore, and Prakasam show very high E, followed by Kurnool, Chittoor, and Guntur. In a nutshell, it is concluded that the districts falling in AP region namely Ananthapur, Prakasam, Chittoor, and Nellore (representing ~ 41% geographical area) exhibit high to very high vulnerability when compared to TS (16%).

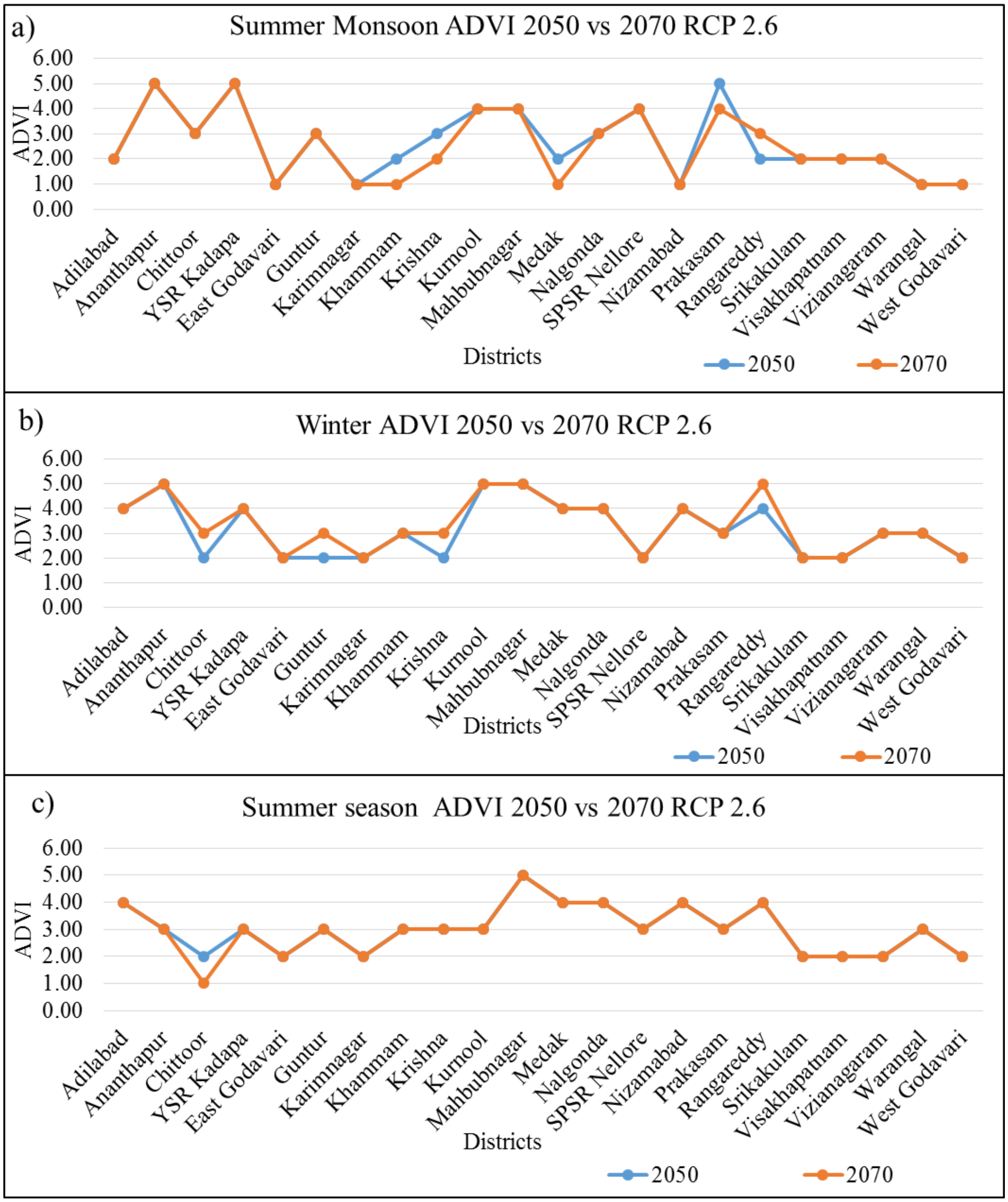
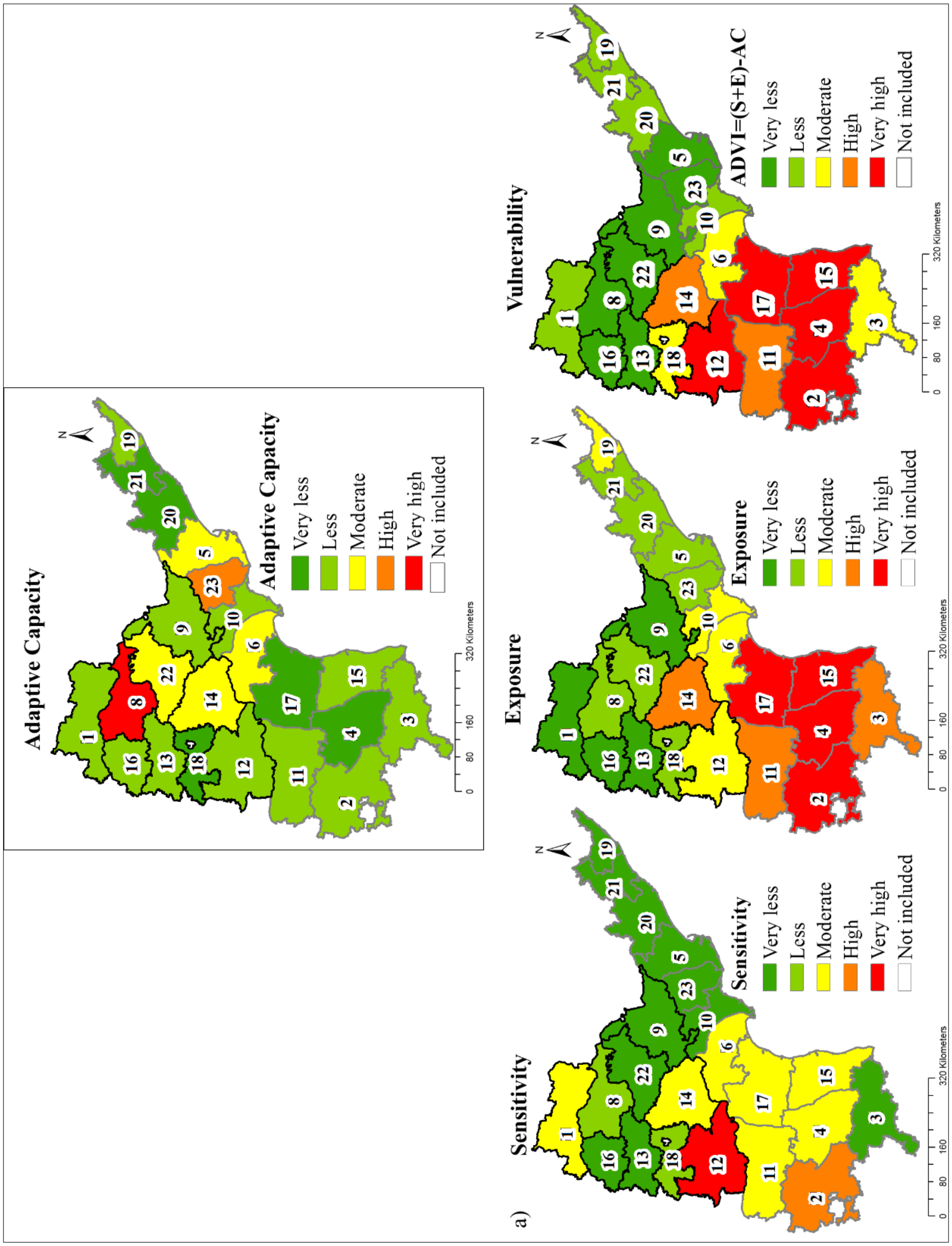


Figure 4.37 Comparison of projected ADVI for IPCC AR5 2050 and 2070 2.6 scenario at district level a) summer monsoon; b) winter season; and c) summer season (Bhavani et al., 2017b)


a)
Sensitivity
Sensitivity
Very less
Less
Moderate
High
Very high
Not included
Adaptive Capacity
Adaptive Capacity
Very less
Less
Moderate
High
Very high
Not included
Exposure
Exposure
Very less
Less
Moderate
High
Very high
Not included
Vulnerability
ADVI=(S+E)-AC
Very less
Less
Moderate
High
Very high
Not included
0 80 160 320 Kilometers
N

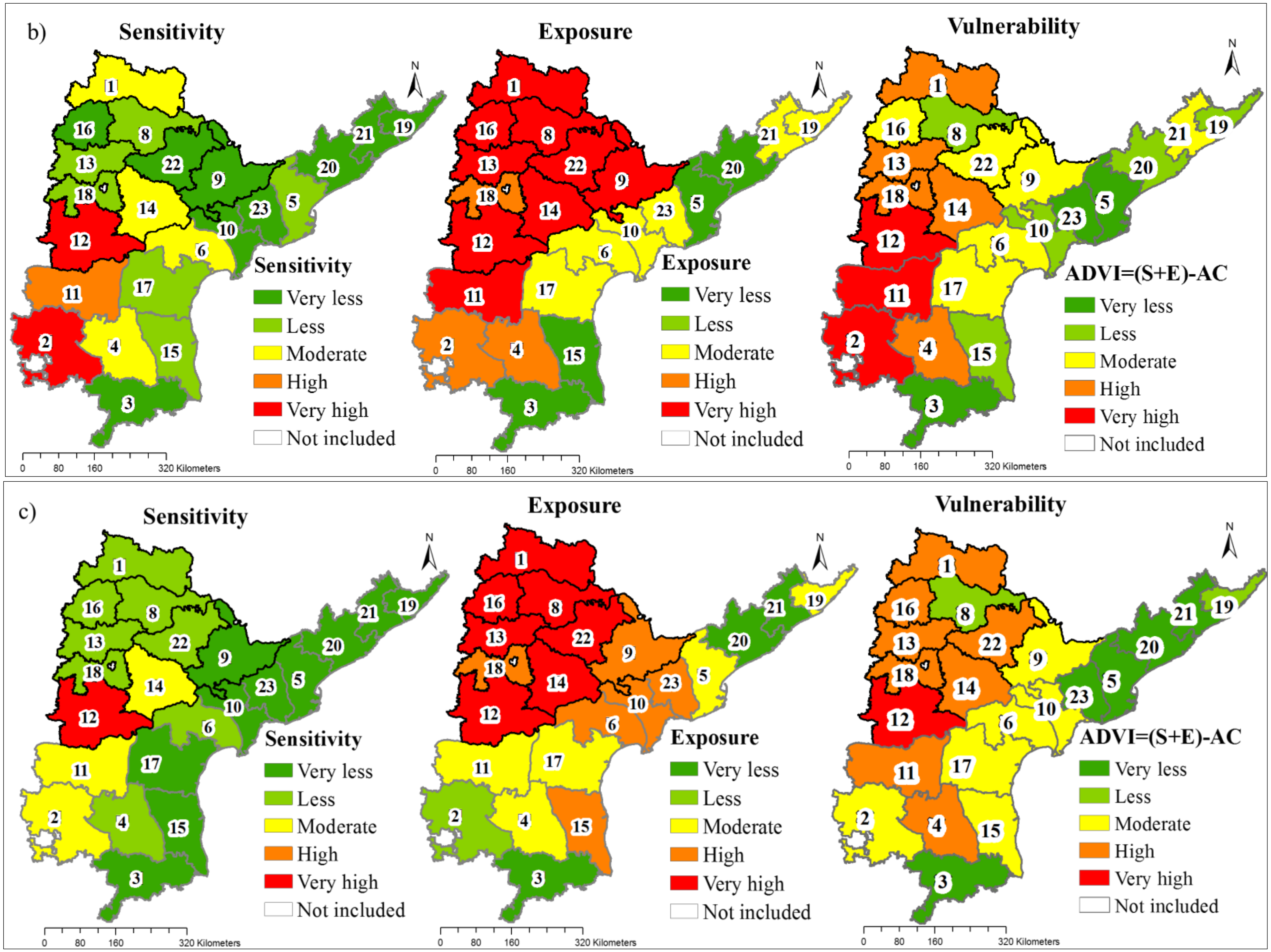


Figure 4.38 Spatial distribution of adaptive capacity (AC), sensitivity (S), exposure (E), and Vulnerability (V) for 2050 RCP 2.6 scenario at district level a) summer monsoon; b) winter season; and c) summer season (Bhavani et al., 2017b)

The vulnerability is found to be very high - high in Ananthapur, Kurnool and Mahbubnagar districts during October-January (Fig. 4.39b). Almost all (9) districts of TS are found to be high exposure in all scenarios. Whereas, in AP the Kurnool, Ananthapur and Y.S.R. Kadapa districts show very high to high exposure. Mahbubnagar district was found to be highly vulnerable due to high sensitivity (driven parameters are GCA, %RCF, % TAg.L, %Mig.R) during the summer season (Fig. 4.39c). Nalgonda district shows the highest rise in intensity/degree of vulnerability in future ADVI during summer monsoon and summer season due to the influence of climate variability (decrease in rainfall).

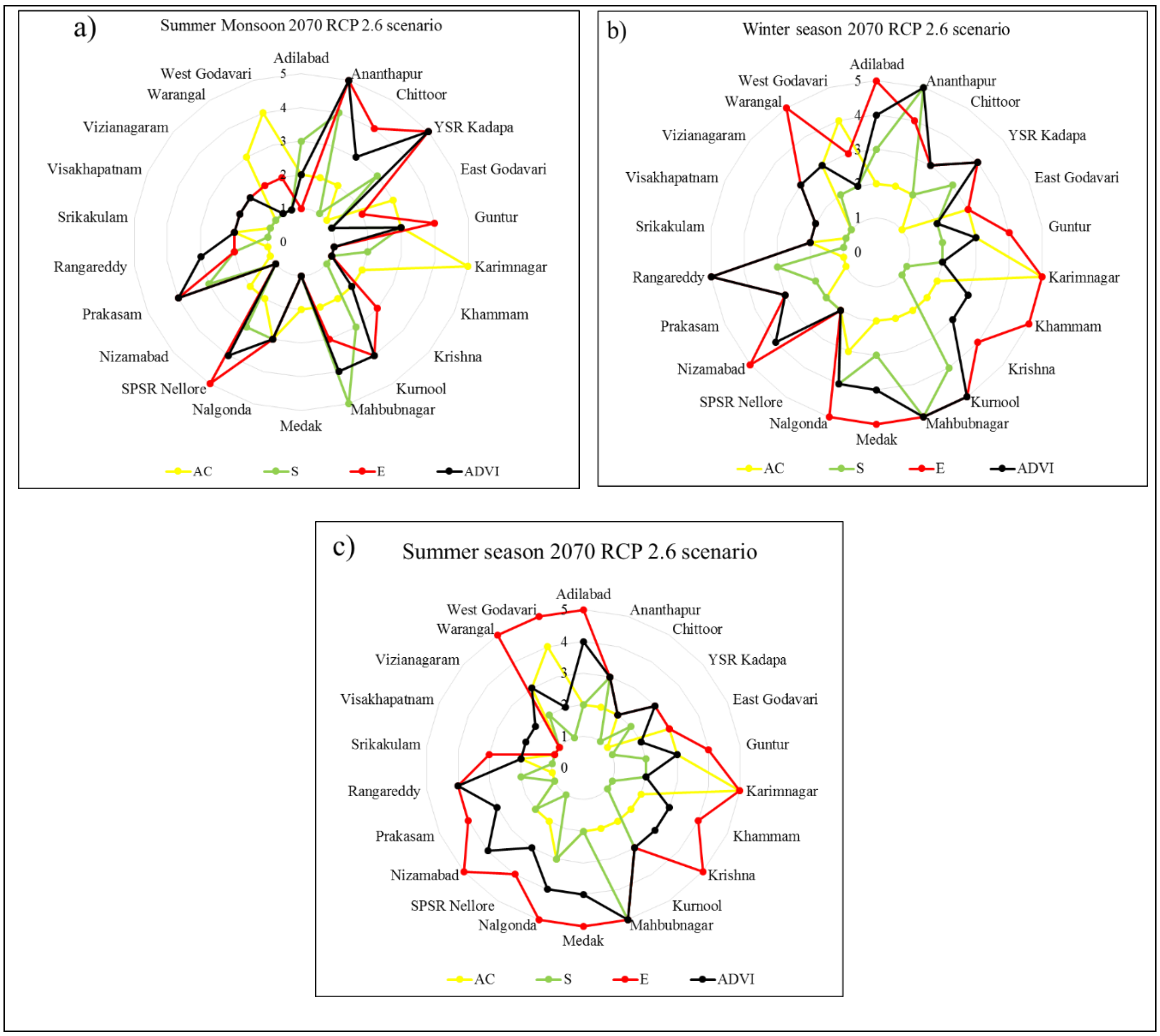


Figure 4.39 Radar chart representation of adaptive capacity (AC), sensitivity (S), exposure (E), and Vulnerability (V) for 2070 RCP 2.6 scenario at district level a) summer monsoon; b) winter season; and c) summer season

From the above analysis, it is concluded that the estimation of present and projected vulnerability in three periods, independently, has resulted in capturing the vulnerability of districts in respective cropping season (Bhavani et al., 2017b).

4.4.2.4 Sensitivity analysis

Drought vulnerability analysis was carried out for all three cropping periods (June to September, October to January, and February to May) and shown in Fig. 4.40. It can be observed from Fig.4.40 that the districts of Ananthapur, Kurnool, and Mahbubnagar are showing high vulnerability in all three cropping periods, whereas, East Godavari, Karimnagar, and West Godavari showed low vulnerability. Nellore and Prakasam districts are found to be highly vulnerable during the summer monsoon as they are largely dependent on the northeast monsoon.

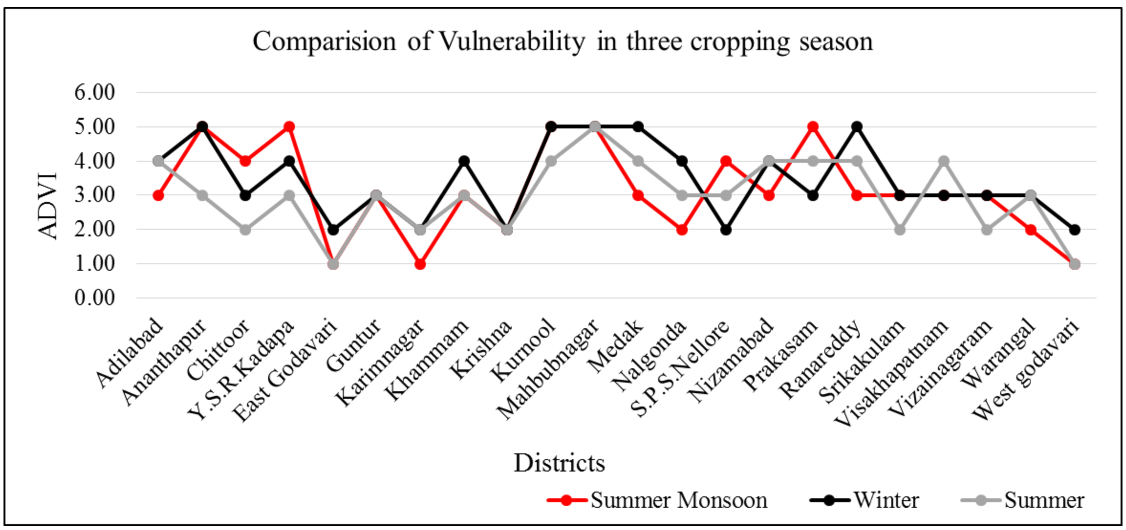


Figure 4.40 Comparisons of vulnerability during (a) summer monsoon; (b) winter season; and (c) summer season

Sensitivity analysis is also carried out on the drought vulnerability to assess the influence of remote sensing component (Fig. 4.41). The vulnerability is largely controlled by E and AC. However, in those districts which have a large extent of agricultural area (input coming from remote sensing), the sensitivity plays an important role. The study deals with the vulnerability of drought in TS and AP at district and tehsil levels in the present and only at the district level for future climate scenarios. The previous studies conceptualized vulnerability based on the socio-economic, biophysical and monsoon period satellite indices (which integrate specifically the Kharif period) in present and projected climate change scenarios (O'Brien et al., 2004; IPCC, 2007; Fussel, 2007; Murthy et al., 2014). However, the present study reveals that season wise (12-month satellite data) analysis would provide a better assessment of drought (Bhavani et al., 2017b). The present study indicates that future vulnerability (with projected climate AR5 RCP scenarios) will increase during February-May (summer cropping season) compared to June-September (summer monsoon cropping season) because of high exposure values (particularly due to increases in minimum temperature).

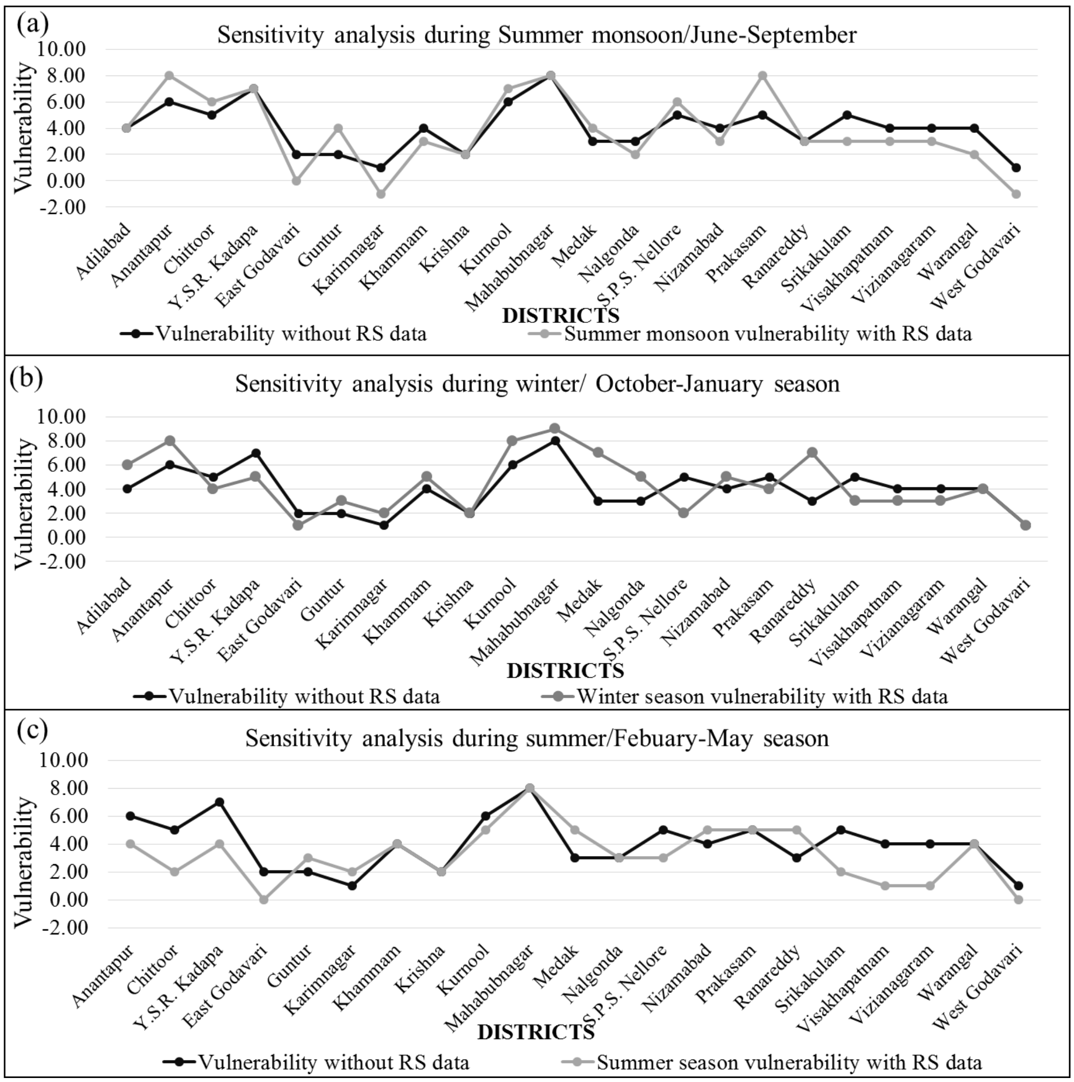


Figure 4.41 Comparison of vulnerability at district level with and without remote sensing data (a) summer monsoon; b) winter season; and (c) summer season.

4.4.2.5 Discussion

Many studies have been reported on climate change vulnerability to understand its impact (Carney, 1998; Fischer et al., 2002; Turner et al., 2003a, b; Brinkmann, 2006; Parry et al., 2007; Edwards et al., 2007; UNDP, 2010; USAID, 2013, de Sherbinin et al., 2014). Social vulnerability in the context of climate change is also important (Beaumont et al., 2011) because populations may have less capacity to combat climate-related hazards (Lynn et al., 2011). However, the constraint of the socio-economic approach is that it emphases only on the assessment of socio-economic and political status. Wu et al. (2017) have used the rainfall, ecological sensitivity and social condition to assess ADVI in China. But the study did not consider temperature and other biophysical parameters and irrigation which also play important roles in agriculture. The present study, however, includes these important parameters for the assessment of ADVI. In India, agricultural drought vulnerability studies have been carried out using NDVI, SPI and LGP (Kaushalya et al., 2013b). Again, these studies did not use the socio-economic data. Sehgal et al. (2013) have adopted IPCC framework (like the present study does) to describe the agricultural drought vulnerability by integrating the climate, biophysical and socio-economic datasets in Indo-Gangetic plains. A similar approach was also followed by Rama Rao et al. (2016) to estimate the vulnerability at the district level. This approach is based on estimating only ADVI for the summer monsoon. In addition, these studies did not make use of satellite-derived NDVI products which are sensitive to climate. On the other hand, Murthy et al. (2015) have used exposure, sensitivity component, and adaptive capacity to describe the drought vulnerability in India. Although these studies have improved the comprehensive assessment of drought vulnerability, they have failed to assess the crop calendar agricultural drought vulnerability.

The present study measures and maps agricultural drought vulnerability with response to climate and socio-economic parameters to understand its impact to strategize adaptation and mitigation measures. The spatial vulnerability varies seasonally based on biophysical variables and climate conditions. During summer monsoon, exposure has shown an interesting pattern decreasing from south to north with an exception of the southernmost district. The districts falling in the middle part of the state are highly sensitive due to the presence of both irrigated and rainfed croplands. As the northern parts of the state are rich in soil fertility and having higher rainfall, most of the districts are categorized as less vulnerable to drought. During the winter season, east and North-East districts of the state have very high exposure because these districts are under rain-shadow regions. Coastal districts, particularly falling in the Krishna and Godavari deltas, are less vulnerable during winter seasons as the crops are cultivated by irrigation facilities. During the summer monsoon, the exposure is high to very high in north Telangana region. These regions witness dry weather conditions for long period of time, which leads to increase the day and night temperatures.

The present study has projected the future agricultural drought vulnerability for IPCC AR5 scenarios. YSR Kadapa, Nellore and Prakasam districts of AP are found to be vulnerable during the winter season. Adilabad, Mahbubnagar, Medak, Nalgonda, Nizamabad, Rangareddy and Warangal districts of TS region and YSR Kadapa, Krishna, and Kurnool of AP are found to be vulnerable during the summer season (Fig. 4.42).

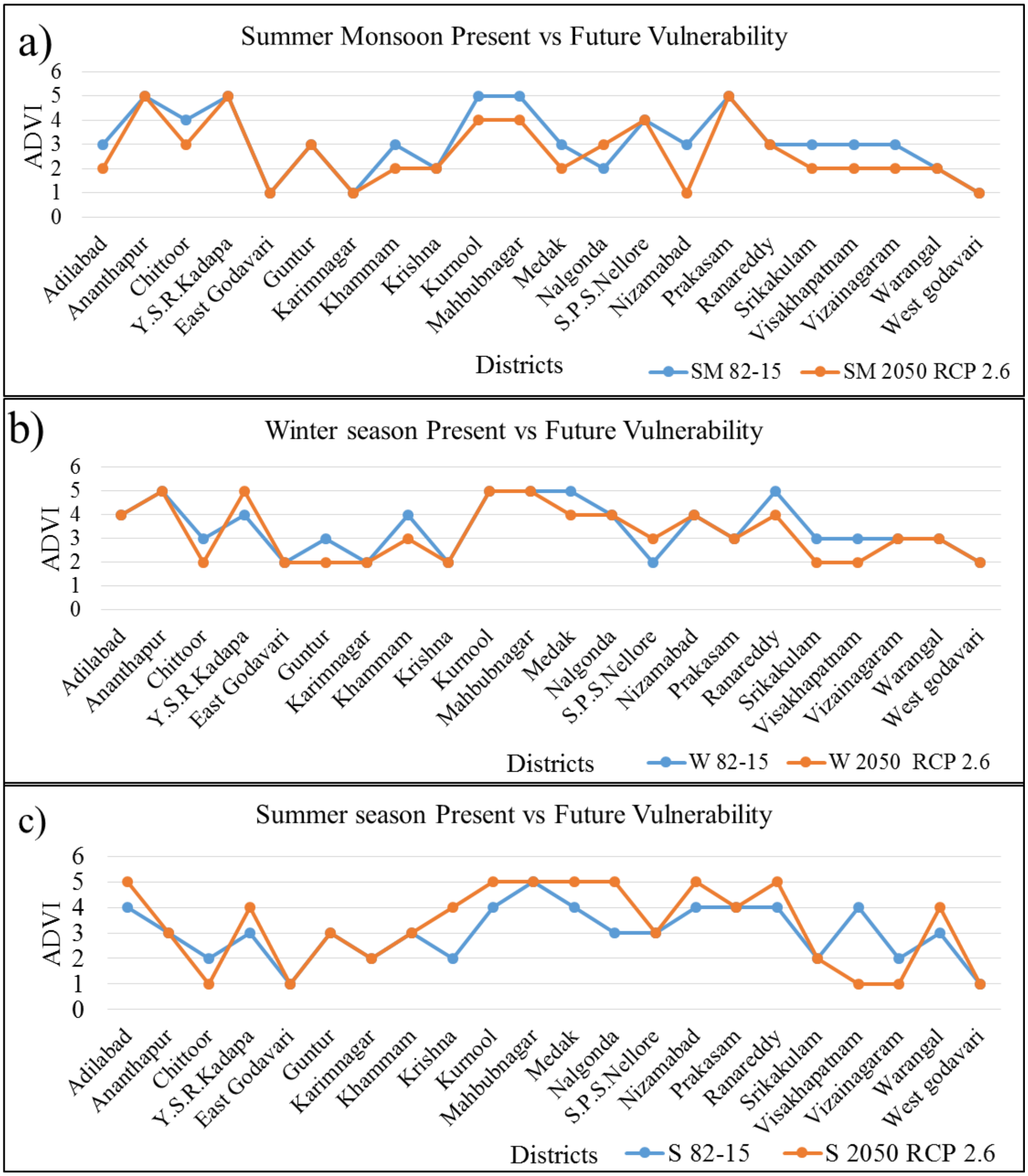


Figure 4.42 Comparison of present (1982-2015) and future (2050 AR5 RCP 2.6) agricultural drought vulnerability scenarios a) summer monsoon; b) winter season; and c) summer season at district level

CHAPTER

FIVE

Conclusions

The thesis consists of five chapters. The novel features and important conclusions originate from the research work presented in Chapters II, III, and IV are mainly on the following lines.

1. Telangana and Andhra Pradesh regions (undivided Andhra Pradesh), being the major contributors of agricultural production in India, are experiencing frequent crop failure due to drought or drought-like conditions. Climate variability studies during the last 30 years reveal that both regions are experiencing increasing temperatures (maximum and minimum) and decreasing rainfall.

2. The present study uses long-term climate and satellite-derived information for different crop growing seasons throughout the year, to understand the process of crop growth, recovery pattern, stress buildup and its relation with climate variables. In addition, socioeconomic data, soil moisture, irrigation pattern, and institutional data have been used to estimate the drought vulnerability during the present and future (IPCC AR5) climate scenario. The study highlights the long-term inter-annual variation in the agricultural stress using NDVIDev, SPI using NOAA GIMMS/MODIS and cropped performance using 1km*1km resolution data during 2000–2015 period (MODIS).

3. Drought assessment varies in different cropping seasons of Indian crop growth cycle. Compared to VCI, the range of differentiation is better in NDVI anomaly. Hence, NDVI anomaly is used in the analysis.

4. During the summer monsoon period except the year 2010, SPI has shown a significant relationship with crop growth and drought conditions. The high SPI observed during the monsoon period has shown positive influence on the winter and Zaid crops. Spatially, the districts of Adilabad, Nalgonda, SPSR Nellore, Ananthapur, Mahbubnagar, Kurnool, and Rangareddy have identified as extreme drought affected areas.
5. Drought stress has shown an impact on the cropped area. During the summer season, only 53% area was under cultivation in the year 2001-2002 followed by 63% in 2009-2010. During the winter season, least cropped areas were observed in the years 2011-12 (66%) and 2008-09 (68%). During the summer season, the years 2001-02 and 2002-03 showed least cropped areas (24% and 26%). The cropped area and magnitude of NDVI anomaly matches with drought and its severity. The present study is able to capture the severity of the drought in different seasons.
6. The long-term time series analysis indicates that there is a significant impact on agriculture performance with respect to change in climate and soil moisture. The study confirms that crop shifting (change in cropping systems specifically in Ananthapur district) has played an important role on the agriculture performance in spite of normal or below normal rainfall during 1998-90.
7. It was found that the future agricultural NDVI for IPCC AR5 2050 RCP 2.6 climate scenario would behave similarly to that of a normal year. A major decline in agricultural performance is observed during summer and winter cropping seasons, particularly in coastal regions of AP. This information is of vital significance while addressing climate change for framing improved adaptive capacity, mitigation leading to sustainable development. The agriculture in Adilabad and Warangal districts is likely to become more sensitive to climate change.
8. Increase in future agricultural vulnerability is noticed in the districts of YSR Kadapa, Nellore and Prakasam during the winter season. So also increase in future vulnerability is observed in Adilabad, Mahbubnagar, Medak, Nalgonda, Nizamabad, Rangareddy and Warangal districts of Telangana and YSR Kadapa, Krishna, and Kurnool of Andhra Pradesh during the summer season.

5.1 Scope for future work

- Fine resolution satellite data is needed to mask out the agricultural areas more precisely. In the present study 1km*1km satellite NDVI data has been used to commensurate with the available 0.25°*0.25°/0.5°*0.5° climate data (precipitation and temperature). Future research may be focused to assess the agriculture performance and drought stress with 250m fine resolution satellite NDVI and better-downscaled climate datasets.
- A comprehensive work plan, as illustrated in Fig. 5.1, is finally recommended to track the agriculture performance in a more lucid way.

Framework for monitoring life cycle of agriculture using multi-level information system

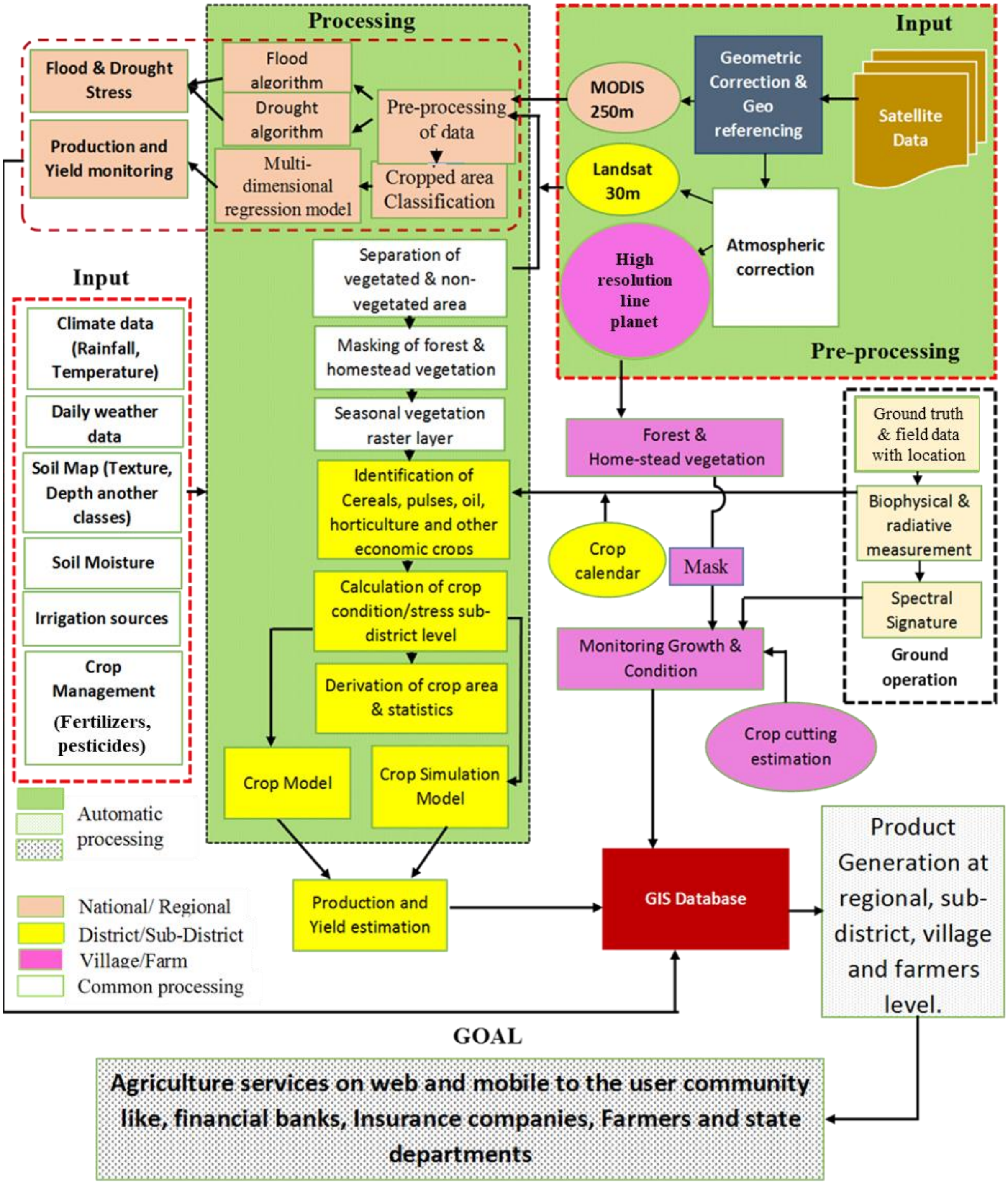


Figure 5.1 Recommended framework for monitoring life cycle of agriculture using multi-level information system.

References

Adusumilli, R., Bhagya Laxmi, S., 2011, Potential of the system of rice intensification for systemic improvement in rice production and water use: the case of Andhra Pradesh, India,: Paddy and Water, 9, 89:97

Aggarwal, P.K., Joshi, P.K., Ingram, Gupta, 2004, Adapting food systems of the Indo-Gangetic plain to global environmental change: Key information needs to improve policy formulation Environmental Sciences & Policy, 7,487-498.

Agrawal, T., Danai, P., 2017, Biodiversity Evaluation: International Journal of Current Research and Academic Review, 5, 86-92.

Aide, T.M., Clark, M.L., Grau, H.R., Lopez-Carr, D., Levy, M., Redo, D.J., Bonilla-Moheno, M., Riner, G., Andrade Núñez, M.J., Muñiz, M., 2013, The deforestation and reforestation of Latin America and the Caribbean (2001-2010): Biotopica, 45, 262-271.

Alam, M.M., bin Toriman, M.E., Siwar, C., Talib, B., 2011, Rainfall variation and changing pattern of agricultural cycle: American Journal of Environmental Sciences, 7, 82–89.

Alcaraz-Segura, D., Chuvieco, E., Epstein, H.E., Kasischke, E.S., Trishchenko, A., 2010, Debating the greening vs. browning of the North American boreal forest: differences between satellite datasets: Global Change Biology, 16,760–770.

Aleixandre Verger, Iolanda Filella, Frédéric Baret, Josep Peñuelas, 2016, Vegetation baseline phenology from kilometric global LAI satellite products: Remote Sensing of Environment, 178, 1-14.

America's Climate Choices, 2010, Panel on Advancing the Science of Climate Change; National Research Council, Advancing the Science of Climate Change. Washington, D.C.: The National Academies Press, ISBN 0-309-14588-0, Archived from the original on 29 May 2014.

Anil Kumar Roy, Indira Hirway, 2007, Multiple Impacts of Droughts and Assessment of Drought Policy in Major Drought Prone States in India: Centre for Development Alternatives, Gujarat, India.

Anil, K.M., 2014, Climate change and challenges of water and food security: International Journal of Sustainable Built Environment, 3,153-165.

Anyamba, A., Tucker, C.J., Eastman, J.R., 2001, NDVI anomaly patterns over Africa during the 1997/98 ENSO warm event: International Journal of Remote Sensing, 22, 1847-1859.

Anyamba A., Tucker, C.J,, Mahoney, R., 2002, From El Niño to La Niña: vegetation response patterns over east and Southern Africa during the 1997–2000 period: Journal of Climate 15, 3096-3103.

Ashalatha, K.V., Munisamy Gopinath, Bhat, A.R.S., 2012, Impact of Climate Change on Rainfed Agriculture in India:A Case Study of Dharwad: International Journal of Environmental Science and Development, 3, 368-371.

Ashok, G., Anwarul Hoda, 2013, India's quest for Keeping Food Prices Low, Chapter 2, Raj Kapila and Uma Kapila (ed) Economic Developments in India: Academic Foundation, New Delhi, India.

Atzberger, C., 2013, Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs: Remote Sensing, 5,949.

Badeck, F.W., Bondeau, A., Böttcher, K., Doktor, D., Lucht, W., Schaber, J., Sitch, S., 2004, Responses of spring phenology to climate change: New Phytologist, 162, 295–309.

Bantilan, M.C.S., Keatinge, J.D.H., 2007, Considerations for Determining Research Priorities: Learning Cycles and Impact Pathways. In: Loebenstein G, Thottappilly G (eds) Agricultural Research Management. Springer Netherlands, Dordrecht, 37-64.

Beaumont, L.J., Pitman, A., Perkins, S., Zimmermann, N.E., Yoccoz, N.G., Thuiller, W., 2011, Impacts of climate change on the world's most exceptional ecoregions: Proceedings of the National Academy of Sciences of the United States of America,108, 2306–2311.

Beck, P.S.A., Atzberger, C., Høgda, K.A., Johansen, B., Skidmore, A.K., 2006, Improved monitoring of vegetation dynamics at very high latitudes: A new method using MODIS NDVI: Remote Sensing of Environment, 100, 321-334.

Belayneh, A., Adamowski, J., Khalil, B., Ozga-Zielinski, B., 2014, Long-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet neural network and wavelet support vector regression models: Journal of Hydrology, 508, 418-429.

Bernal, M., Estiarte, M., Penuelas, J., 2011, Drought advances spring growth phenology of the Mediterranean shrub Erica multiflora: Plant Biology, 13, 252–257.

Berry, P.M., Rounsevell, M.D.A., Harrison, P.A., Audsley, E., 2006, Assessing the vulnerability of agricultural land use and species to climate change and the role of policy in facilitating adaptation: Environmental Science & Policy, 9, 189-204.

Bhavani, P., Chakravarthi, V., Roy, P.S., Joshi, P.K., Chandrasekar, K., 2017a, Long-term agricultural performance and climate variability for drought assessment: a regional study from Telangana and Andhra Pradesh states, India: Geomatics, Natural Hazards and Risk, 1-19.

Bhavani, P, Roy, P.S., Chakravarthi, V., Vijay, P.K., 2017b, Satellite Remote Sensing for Monitoring Agriculture Growth and Agricultural Drought Vulnerability Using Long-Term (1982–2015) Climate Variability and Socio-economic Data set: Proceedings of National Academy of Sciences, India Section, A Physical Sciences, 733–750.

Bikash, R.P., 2006, Analysing the effect of severity and duration of agricultural drought on crop performance using Terra/MODIS Satellite data and Meteorological Data [thesis]. The Netherlands: ITC, University of Twente. Available from: http://www.itc.nl/ library/ papers_ 2006/msc/iirs/bikash.pdf.

Birkmann, J., 2008, Assessing vulnerability before, during and after a natural disaster in fragile regions, case study of the 2004 Indian Ocean Tsunami in Sri Lanka and Indonesia: Research paper / UNU-WIDER, No. 2008.50, http://hdl. handle.net/10419/45110.

Blaikie, P., Cannon, T., Davis, I., Wisner, B., 1994, At Risk: Natural hazards, people's vulnerability, and disasters,: London, Routledge, 2.

Bohle, H.G., 2001, Vulnerability and criticality: perspectives from social geography, IHDP Update 2/2001. Newsletter of the International Human Dimensions Programme on Global Environmental Change : Bonn, Germany, 3–5.

Bonilla-Moheno, M., Redo, D.J., Aide, T.M., Clark, M.L., Grau, H.R., 2013, Vegetation change and land tenure in Mexico: A country-wide analysis: Land Use Policy, 30, 355–364.

Bora, M., Goswami, D.C., 2016, A Study on Relationship between NDVI and Precipitation over Kolong River Basin, Assam, India: IOSR Journal of Agriculture and Veterinary Science, 9,36-41.

Brian, D.W., Egbert, S.L., 2008, Large-area crop mapping using time-series MODIS 250m NDVI data: an assessment for the U.S. Central Great Plains: Remote Sensing Environment, 112,1096–1116.

Brinkmann, J., 20006, Measuring vulnerability to natural hazards: Towards disaster resilient societies. TERI, UNU, ISBN 817993-1226, 1-524.

Brooks, N., Neil, Adger, W., Mick Kelly, P., 2005, The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation: Global Environmental Change, 15,151-163.

Brown, M.E., de Beurs, K.M., 2008, Evaluation of multi-sensor semi-arid crop season parameters based on NDVI and rainfall: Remote Sensing of Environment, 112, 2261–2271.

Bruno Lara, Marcelo Gandini, 2016, Assessing the performance of smoothing functions to estimate land surface phenology on temperate grassland: International Journal of Remote Sensing, 37, 1801-1813.

Bryant, E., 2005, Drought as a hazard: In Natural Hazards,103-119.

Caminade, C., Terray, L., 2010, Twentieth century sahel rainfall variability as simulated by the ARPEGE AGCM, and future changes: Climate Dynamics, 35, 75–94.

Carney, D., 1998, Sustainable rural livelihoods: What contribution can we make? In: Carney, D. (Eds.), Department for international development’s natural resources advisers conference. London: DFID.

Central Statistical Organization, 1998, Compendium of Environment Statistics: Central Statistical Organization, Department of Statistics, Ministry of Planning and Programme Implementation, Government of India: New Delhi.

Chandrasekaran, B., Annadurai, K., Somasundaram, E., 2010, A Textbook of Agronomy, Chapter 1: An Introduction to Agriculture and Agronomy: New Age International, 2.

Chandrasekar, K., Sesha Sai, M.V.R., Jeyaseelan, A.T., Dwivedi, R.S., Roy, P.S., 2006, Vegetation response to rainfall as monitored by NOAA-AVHRR: Current Science, 91, 1626–1633.

Chandrasekar, K., Sesha Sai, M.V.R., Roy, P.S., Jayaraman, V., Krishnamurthy, R.R., 2009, Identification of Agricultural Drought Vulnerable Areas of Tamil Nadu, India-Using GIS Based Multi Criteria Analysis: Asian Journal of Environment and Disaster Management 1, 40-61

Chandrasekar K., Sesha Sai, M.V.R., 2015, Monitoring of late-season agricultural drought in cotton-growing districts of Andhra Pradesh state, India, using vegetation, water and soil moisture indices: Natural Hazards, 75, 1023-1046.

Chang, C.T., Wang, S.F., Vadeboncoeur, M.A., Lin, T.C., 2014, Relating Vegetation Dynamics to Temperature and Precipitation at Monthly and Annual Time Scales in

Taiwan Using MODIS Vegetation Indices: International Journal of Remote Sensing, 35,598–620.

Cheng, J., Tao, J.P., 2010, Fuzzy Comprehensive Evaluation of Drought Vulnerability Based on the Analytic Hierarchy Process: Agriculture and Agricultural Science Procedia, 1, 126-135.

Chhabra, A., Dadhwal, V.K., 2003, Estimating terrestrial net primary productivity over India using satellite data: Current Science, 86, 269–271.

Chopra, P., 2006, Drought Risk Assessment using Remote Sensing and GIS: A Case study of Gujarat [Thesis], https://www.itc.nl/library/papers_2006/msc/iirs/chopra.pdf, Accessed on August 2015.

Clark, M.L., Aide, T.M., Riner, G., 2012, Land change for all municipalities in Latin America and the Caribbean assessed from 250-m MODIS imagery (2001–2010): Remote Sensing Environment, 126,84–103.

Cong, N., Piao, S, L., Chen, A, P., et al., 2012, Spring vegetation green-up date in China inferred from SPOT NDVI data: A multiple model analysis: Agricultural and Forest Meteorology, 165, 104–113.

Dai, A., 2011, Drought under global warming: a review: WIREs Climate Change, 2, 45–65.

Das, H.P., 2000, Monitoring of Incidence of Large Scale Drought in India. Drought: A Global Assessment: WDA Routledge, 1,181-195.

de Jong, R., Verbesselt, J., Schaepman, M. E., de Bruin, S., 2012, Trend changes in global greening and browning: Contribution of short-term trends to longer-term change: Global Change Biology, 18, 642–655.

de Sherbinin, A., 2014, Spatial Climate Change Vulnerability Assessments: A Review of Data, Methods and Issues: Technical Paper for the USAID African and Latin American Resilience to Climate Change (ARCC) project. Washington, DC: USAID.

Delbart, N., Le Toan, T., Kergoat, L., Fedotova, V., 2006, Remote sensing of spring phenology in boreal regions: A free of snow-effect method using NOAA-AVHRR and SPOT-VGT data (1982–2004): Remote Sensing Environment, 101, 52–62

Descroix, L., Genthon, P., Peugeot, C., Mahé, G., Abdou, M.M., Vandervaere, J.P., Mamadou, I., Tanimoun, B., Amadou, I., Galle, S., et al., 2015, Paradoxes et contrastes en Afrique de l'Ouest: Impacts climatiques et anthropiques sur les écoulements. Géologues 187:47–51.

Dracup, J., Lee, K., E, Paulson, 1980, On The Definition of Droughts: Water Resources Research, 16, 297-302.

Duffaut Espinosa, L.A., Posadas, A.N., Carbajal, M., Quiroz, R.. 2017, Multifractal Downscaling of Rainfall Using Normalized Difference Vegetation Index (NDVI) in the Andes Plateau: PLoS ONE, 12.

Dutta, D., Kundu, A., Patel, N.R., Saha, S.K., Siddiqui, A.R., 2015, Assessment of agricultural drought in Rajasthan (India) using remote sensing derived vegetation condition index (VCI) and standardized precipitation index (SPI): Egypt J Remote Sensing Space Sciences, 18,53–63.

Edwards, J., Gustafsson, M., Naslund-Landenmark, B., 2007, Handbook for vulnerability mapping, EU and International affairs department of the Swedish rescue services agency.http://www.nsc.org.in/ANNEXES/3.2.4%20Risk%20assessments%20and%20 vulnerability%20maps/Handbook%20for %20vulnerbaility%20mapping.pdf

Erasmi, S., Maurer, F., Petta, R.A., Gerold, G., Barbosa, M.P., 2009, - Inter-annual variability of the Normalized Difference Vegetation Index over Northeast Brazil and its relation to rainfall and El Niño Southern Oscillation: Geo-Öko, 30,185-206.

FAO, 2003, Food and agriculture organization of the United Nations: http:// www.fao. org/ about/en/, Accessed on 18 January 2016.

FAO, http://vitalsigns.worldwatch.org/vs-trend/area-equipped-irrigation-record-levels-expan sion -s.

Farahmand, A., AghaKouchak, A., Teixeira, J., 2015, A Vantage from Space Can Detect Earlier Drought Onset: An Approach Using Relative Humidity: Scientific Reports, 5, 8553.

Farooq, M., Hussain, M., Abdul Wahid, Siddique, K.H.M., 2012, Drought Stress in Plants: An Overview. R. Aroca (ed.): Plant Responses to Drought.

Fischer, G., Shah, M., Van Velthuizen, H., 2002, Climate change and agricultural vulnerability: A special report prepared by the international institute for applied systems analysis under United Nations institutional contract agreement no. 1113 Climate Change and Agricultural Vulnerability as a contribution to the World Summit on Sustainable Development. 1-152 http://www.accc.gv.at/pdf/JB-Report.pdf.

Fontain, R., Gramain, A., Wittwer, J., 2009, Providing Care for an elderly parent: Interactions among siblings? : Health Economics, 18, 1011–1029.

Francisco, Z., Mario, L.S., Koen, V., Octavio, L., 2016, Sixteen years of agricultural drought assessment of the BioBıo region in Chile using a 250m resolution vegetation condition index (VCI): Remote Sensing, 8, 530.

Friedl, M.A., Sulla-Menashe, D., Tan, B., Schneider, A, Ramankutty, N., et al., 2010, MODIS collection 5 global land cover: Algorithm refinements and characterization of new datasets, Remote Sensing Environment, 114, 168-182.

Fussel, H.M., 2007, Vulnerability: A generally applicable conceptual framework for climate change research, Global Environmental Change, 17, 155-167.

Gallaher, R.N., 2009, Multiple Cropping Systems in Management of Agricultural, Forestry, and Fisheries Enterprises:Encyclopedia of Life Support Systems, 1,254–265.

Gao, Z., Wang, Q., Cao, X., Gao, W., 2014, The responses of vegetation water content (EWT) and assessment of drought monitoring along a coastal region using remote sensing, GIScience & Remote Sensing, 51, 1-16.

Gautam, R.C., 2014, Drought in India: its impact and mitigation strategies – a review: Indian Journal of Agronomy, 59, 179–190.

Giri, I., 2016, Overview of the agriculture sector in India since independence. https://www.projectguru.in/publications/agriculture-sector-india/

Gizachew, L., Suryabhagavan, K.V., 2014, Remote sensing and GIS based agricultural drought assessment in East Shewa Zone Ethiopia: Tropical Ecology, 55, 349-363.

Gliessman, S.R., 1985, Multiple cropping systems: A basis for developing an alternative agriculture: In Innovative biological technologies for lesser developed countries—workshop proceedings, OTA, Washington, DC, 69–83

Gupta, K., Tyagi, P., Sehgal, V.K., 2011, Drought disaster challenges and mitigation in India: strategic appraisal. Current Science, 100:1795-1806.

Gutman, G.G., 1990, Towards monitoring droughts from space: Journal of Climatology, 3,282:295.

Guttman, G.B., 1999, Accepting the "Standardized Precipitation Index": A calculation algorithm Index: Journal of the American Water Resources, 35, 311-322.

Hawinkel, P., Thiery, W., Lhermitte, S., Swinnen, E., Verbist, B., Van Orshoven, J., Muys, B., 2016, Vegetation response to precipitation variability in East Africa controlled by biogeographical factors, Journal of Geophysical Research-Biogeosciences, 121, 2422–2444.

Heim, R.R., 2002, A Review of Twentieth-Century Drought Indices Used in the United States: Bulletin American Meteorological Society, 83,1149–1165.

Henkel, M., 2015, 21st Century Homestead: Sustainable Agriculture I, Chapter 2, Agrarianism, 27.

Herrmann, S.M., Anyamba, A., Tucker, C.J., 2005, Recent Trends in Vegetation Dynamics in the African Sahel and their Relationship to Climate: Global Environmental Change, 15, 394-404.

Hickler, T., Eklundh, L., Seaquist, J.W., Smith, B., Ardo, J., Olsson, L., Sykes, M. T, Sjostrom, M., 2005, Precipitation controls Sahel greening trend: Geophysical Research Letters, 32, 1-4.

Hielkema, J.U., Roffey, J., Tucker,C.J., 1986, Assessment of ecological conditions associated with the 1980/1981 desert locust plague upsurge in West Africa using environmental satellite data: International Journal of Remote Sensing, 7, 1609-1622.

Hou, W., Gao, J., Wu, S., Dai, E., 2015, Interannual Variations in Growing-Season NDVI and Its Correlation with Climate Variables in the Southwestern Karst Region of China: Remote Sensing, 7, 11105-11124

Huber, S., Fensholt, S., Rasmussen, K., 2011, Water availability as the driver of vegetation dynamics in the African Sahel from 1982 to 2007: Global and Planetary Change, 76,186–195.

Huete, A.R., Jackson, R.D., Post, D.F., 1985, Spectral response of a plant canopy with different soil backgrounds: Remote Sensing of Environment, 17, 37–53.

Huete, A.R., Jackson, R.D., 1987, The suitability of spectral indices for evaluating vegetation characteristics on arid rangelands: Remote Sensing of Environment, 23, 213 – 232.

Huete, A.R., 1988, A soil−adjusted vegetation index (SAVI): Remote Sensing of Environment, 25, 295−309.

IPCC, 2001, Climate Change 2001: Impacts, Adaptation & Vulnerability: Contribution of Working Group II to the Third Assessment Report of the IPCC. Cambridge University Press, Cambridge, UK: Cambridge University Press.

IPCC, 2007,Climate Change 2007: Impacts, Adaptation and Vulnerability, Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on

Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds., 976.

IPCC, 2014, Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Barros, V.R., C.B. Field, D.J. Dokken, M.D. Mastrandrea, K.J. Mach, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 688.

Jeong, S. J., Ho, CH., Brown, M.E., Kug, J.S., Piao, S., 2011, Browning in desert boundaries in Asia in recent decades: Journal of Geophysics Research, 116, D02103.

Jeremy, I., Fisher, John, Mustard, F., 2007, Cross-scalar satellite phenology from ground, Landsat, and MODIS data: Remote Sensing of Environment, 109, 261-273

Jeyaseelan, A.T., 2003, Droughts & floods assessment and monitoring using remote sensing 0.nd GIS. In: Sivakumar MVK, Roy PS, Harmsen K, Saha SK, editors, Satellite remote sensing and GIS applications in agricultural meteorology, AGM-8, WMO/TD-No. 1182, 291–313.

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

Jiang, S., Ren, L., Zhou, M., Yong, B., Zhang, Y., Ma, M., 2017, Drought monitoring and reliability evaluation of the latest TMPA precipitation data in the Weihe River Basin, Northwest China:Journal of Arid Land, 9, 256-269.

Jobbagy, E.G., Sala, O.E., Paruelo, J.M., 2002, Patterns and controls of primary production in the Patagonian steppe: a remote sensing approach: Ecology, 83, 307–319.

Jonsson, P., Eklundh, L., 2002, Seasonality Extraction by Function-Fitting to Time Series of Satellite Sensor Data: Geoscience and Remote Sensing, 40, 1824–1832.

Joseph, J., 2013, Measuring Vulnerability to Natural Hazards: A Macro Framework: Disasters, 37, 185–200.

Julien, Y., Sobrino, J.A., 2009, Global land surface phenology trends from GIMMS database: International Journal of Remote Sensing, 30, 3495–3513.

Kang, Y., Khan, S., Ma, X., 2009, Climate change impacts on crop yield, crop water productivity and food security – a review: Progress in Natural Science, 19,1665–1674.

Kannan, E., Sundaram, S., 2011, Analysis of trends in India's agricultural growth: The Institute for Social and Economic Change, Bangalore, India, Working paper 276.

Karlsen Stein Rune, Anne Tolvanen, Eero Kubin, Jarmo Poikolainen, Kjell Arild Høgda, Bernt Johansen, Fiona S. Danks , Paul Aspholm, Frans Emil Wielgolaski, Olga Makarova, 2008, MODIS-NDVI-based mapping of the length of the growing season in northern Fennoscandia: International Journal of Applied Earth Observation and Geoinformation, 10, 253–266.

Kaushalya, R., Venkateshwarlu, B., Ramarao, C., Rao, V., Raju, B., Rao, A., Saikia, U., Thilagavathi, N., Gayatri, M., Satish, J., 2013a, Assessment of vulnerability of Indian agriculture to rainfall variability- Use of NOAA-AVHRR (8 km) and MODIS (250 m) time-series NDVI data products: Climate Change and Environmental Sustainability, 1, 37-52.

Kaushalya, R., Rama, C., Rao, B.M.K., Raju, M., Gayatri, V., Praveen Kumar, J., Satish, 2013b, Mapping Agricultural Vulnerability for India Employing Time series Satellite Data Products: Indian Cartographer, 33, 391-396.

Kaushalya, R., Gayatri, M., Praveen, V., Satish, J., 2014, Use of NDVI variations to analyse the length of growing period in Andhra Pradesh: Journal of Agrometeorology,16, 112-115.

Kawabatan, A., Ichii, K., Yamaguchi, Y., 2001, Global monitoring of interannual changes in vegetation activities using NDVI and its relationships to temperature and precipitation: International Journal of Remote Sensing, 22, 1377-1382.

Kensuke Kobo, 2005, Cropping Pattern Changes in Andhra Pradesh during the 1990s: Implications for Micro-level Studies," in Agricultural Production, Household Behavior, and Child Labor in Andhra Pradesh, ed., Seiro Ito, Wakaba, Japan: Institute for Developing Economies, 202-226.

Klosterman, S,T., Hufkens, K., Gray, J.M., Melaas, E., Sonnentag, O., Lavine, I., Mitchell, L., Norman, R., Friedl, M.A., Richardson, A.D., 2014, Evaluating remote sensing of deciduous forest phenology at multiple spatial scales using PhenoCam imagery: Biogeosciences, 11,4305–4320.

Kogan, F.N., 1987a, On using smoothed vegetation time-series for identifying near – optimal climate conditions: Proceeding 10th Conference on probability and statistics, AMS, Edmonton, Canada, 81-83.

Kogan, F.N. 1987b, Vegetation index for a real analysis of crop conditions: Proceedings 18th Conference Agricultural and Forest Meteorology, AMS, W Lafayette, Indiana, USA,103-106.

Kogan, F.N., 1990, Remote sensing of weather impacts on vegetation in non–homogenous areas: International Journal of Remote Sensing, 11, 1405-1419.

Kogan, F.N., 1995, Application of vegetation index and brightness temperature for drought detection: Advances in Space Research, 15, 91-100.

Kogan, F.N., 1997, Global Drought Watch from Space: Bulletin of the American Meteorological Society, 78, 621–636.

Kogan, F.N., Salazar, L., Roytman, L., 2012, Forecasting crop production using satellite-based vegetation health indices in kansas, USA: International Journal of Remote Sensing, 33, 2798-2814.10.

Komuscu, A.U., 1999, Using the SPI to analyze spatial and temporal patterns of drought in Turkey: Drought Network News (1994-2001), 11, 7–13.

Krishna Kumar, K., Rupa Kumar, K., Ashrit, R., Deshpande, N. R., Hansen, J. W., 2004, Climate impacts on Indian agriculture: International Journal of Climatology, 24,1375–1393.

Kumar, M.N., Murthy, C.S., Sesha Sai, M.V.R., Roy, P.S., 2009, On the use of Standardized Precipitation Index (SPI) for drought intensity assessment: Meteorological Applications, 16, 381-389.

Kumar, T., Rao, K., Barbosa, Humberto, Prabha Joth, E., 2013, Studies on spatial pattern of NDVI over India and its relationship with rainfall, air temperature, soil moisture adequacy and ENSO:Geofizika. 30,1-18.

Kumar, R., Gautam, H.R., 2014, Climate Change and its Impact on Agricultural Productivity in India: Journal of Climatology & Weather Forecasting, 2,109

Kundzewicz, Z.W., Doll, P., 2009, Will groundwater ease freshwater stress under climate change? : Hydrological Sciences Journal, 54,665-675.

Lakshmi Kumar, T.V., Koteswara Rao, K., Barbosa, H., Prabha Jothi, E., 2013, Studies on spatial pattern of NDVI over Indiaand its relationship with rainfall, air temperature, soil moisture adequacy and ENSO: Geofizika, 30,1-18.

Leichenko, R.M., O'Brien, K.L., 2002, The dynamics of rural vulnerability to global change: the case of southern Africa: Mitigation and Adaptation Strategies for Global Change, 7, 1-18.

Leinenkugel, P., Kuenzer, C., Oppelt, N., Dech, S., 2013, Characterisation of Land Surface Phenology and Land Cover Based on Moderate Resolution Satellite Data in Cloud Prone Areas — A Novel Product for the Mekong Basin: Remote Sensing of Environment, 136,180– 198.

Liang, L., Schwartz, M.D., Fei, S., 2011, Validating satellite phenology through intensive ground observation and landscape scaling in a mixed seasonal forest: Remote Sensing of Environment, 115,143–157.

Lillesand, T.M., Kiefer, R.W., 1994, Remote Sensing and Image Interpretation, 3rd ed. xvi + 750 pp. New York, Chichester, Brisbane, Toronto, Singapore: John Wiley & Sons: Geological Magazine,132, 248 - 249.

Linderholm, H.W., 2006, Growing season changes in the last century: Agricultural and Forest Meteorology, 137, 1–14.

Liu, W.T., Kogan, F.N., 1996, Monitoring regional drought using the Vegetation Condition Index: International Journal of Remote Sensing, 17, 2761-2782.

Liu, W.T., Kogan, F., 2002, Monitoring Brazilian soybean production using NOAA/AVHRR based vegetation condition indices: International Journal of Remote Sensing, 23, 1161-1179.

Liu, J., Yang, X., Liu, H., Qiao, Z., 2013, Algorithms and Applications in Grass Growth Monitoring: Abstract and Applied Analysis, 2013, 1-7.

Liu, Y., Li, Y., Li, S., Motesharrei, S., 2015, Spatial and Temporal Patterns of Global NDVI Trends: Correlations with Climate and Human Factors: Remote Sensing, 7, 13233

Lloyd, D., 1990, A phenological classification of terrestrial vegetation cover using shortwave vegetation index imagery: International Journal of Remote Sensing, 11, 2269-2279.

Lynn, K., MacKendrick, K., Donoghue, E.M., 2011, Social vulnerability and climate change: Synthesis of literature. Gen. Tech. Rep. PNW-GTR-838, U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland 67p.

Madhusudana, B., 2013, A Survey on Area, Production and Productivity of Groundnut Crop in India: Journal of Economics and Finance, 1, 1-7.

Mall, R.K., Gupta, A., Singh, R., Singh, R.S., Rathore, L.S, 2006a, Water resources and climate change: An Indian perspective: Current Science, 90, 1610–1626.

Mall, R.K., Singh, R., Gupta, A., Singh, R.S., Srinivasan, G., et al., 2006, Impact of climate change on Indian agriculture: A review: Climate Change, 78, 445-478.

Manual for Drought Management, 2009, Department of Agriculture Cooperation. Ministry of Agriculture Government of India New Delhi, http:// nidm.gov.in /pdf/manuals /drought_ manua.pdf

McKee, T.B., Doesken, N.J., Kliest, J., 1993, The relationship of drought frequency and duration to time scales. In: Proceedings of the 8th Conference on Applied Climatology, Anaheim, CA, American Meteorological Societey, Boston, 179–184.

McKee, T.B., N.J. Doesken, Kleist, J., 1995, Drought monitoring with multiple time scales. Ninth Conference on Applied Climatology: American Meteorological Society, 233-236.

Memorandum on Drought, 1981: Revenue Department, Government of Andhra Pradesh.

Ministry and Irrigation and Power, 1972, Report of the Irrigation Commission-1972:Government ofIndia, New Delhi, 1, 85.

Merugu Thirupathi, Shashikala, A.V., Mathyam Prabhakar, 2015, Variability study on the length of growing period (lgp) using ground and space based (MODIS) data for the selected mandals of Warangal district: International Journal of Advancement in Remote Sensing, GIS and Geography, 3, 48-58.

Metternicht, G.I., Zinck, J.A., Blanco, P.D., Del Valle, H.F., 2010, Remote sensing of land degradation: experiences from Latin America and the Caribbean: Journal of Environmental Quality, 39, 42–61.

Mingwei, Z., Qingbo, Z., Zhongxin, C., Jia, L., Yong, Z., Chongfa, C., 2008, Crop discrimination in Northern China with double cropping systems using Fourier analysis of time-series MODIS data: International Journal of Applied Earth Observations and Geoinformatics,10,476–485.

Mishra, A.K., Singh, V.P., 2010, A review of drought concepts: Journal of Hydrology, 391, 202-216.

Miura, A.B.S.F., 2013, Remote sensing, GIS, and AHP for Assessing Physical Vulnerability to Tsunami Hazard: International Journal of Environmental, Chemical, Ecological, Geological and Geophysical Engineering, 7, 670-679

Moreland, J.A., 1993, Drought: U.S. Geological Survey Water Fact Sheet, Open-File Report, 93-642.

Murthy, C.S., Sesha Sai, M.V.R., Prabir Kumar, D., Naresh Kumar, M., Abishek, C., Dwivedi, R.S., 2010, Assessing agricultural drought vulnerability using time series rainfall and NDVI: NNRMS Bulletin, 63–72.

Murthy, C.S., Chakraborty, A., Seshai Sai, M.V.R., Roy, P.S., 2011, Spatio-temporal analysis of the droughts of kharif 2009 and 2002: Current Science, 100, 1786–1788.

Murthy, C.S., Laxman, B., Sesha Sai, M.V.R., Diwakar, P.G., 2014, Analysing agricultural drought vulnerability at sub-district level through exposure, sensitivity and adaptive capacity based composite index: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 8, 65-70.

Murthy, C.S., Laxman, B., Sai, M.V.R.S., 2015, Geo-spatial analysis of agricultural drought vulnerability using a composite index based on exposure, sensitivity and adaptive capacity: International Journal of Disaster Risk Reduction, 12, 163–171.

Nicholson, S.E., Davenport, M.L., Malo, A.R., 1990, A comparison of the vegetation response to rainfall in the Sahel and east-Africa, using Normalized Difference Vegetation Index from NOAA AVHRR: Climatic Change, 17, 209–241.

Nicholson, E., Farrar, T.J., 1994, The influence of soil type on the relationships between NDVI, rainfall, and soil moisture in semiarid Botswana: I. NDVI response to rainfall: Remote Sensing of Environment, 50,107-120.

O'Brien, K., Leichenko, R., Kelkar, U., Venema, H., Aandahl, G., Tompkins, H., Javed, A., Bhadwal, S., Barg, S., Nygaard, L., West, J., 2004, Mapping vulnerability to multiple stressors: climate change and globalization in India: Global Environmental Change, 14, 303-313.

Pai, D.S., Latha, S., Rajeevan, M., Sreejith, O. P., Satbhai, N.S., Mukhopadhyay, B., 2014, Development of a new high spatial resolution (0.25° × 0.25°) long period (1901-2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region: Mausam,65, 1-18.

Pan, Y., Li, L., Zhang, J., Liang, S., Zhu, X., Sulla-Menashe, D., 2012, Winter wheat area estimation from MODIS-EVI time series data using the Crop Proportion Phenology Index: Remote Sensing of Environment, 119, 232–242.

Pandey, M.M., 2009, Indian Agriculture – An Introduction: Fourth Session of the Technical Committee of APCAEM 10-12 February 20 Chiang Rai, Thailand.

Pandya, M.R., Singh, R.P., Dadhwal, V.K., 2004, A signal of increased vegetation activity of India from 1981–2001 observed using satellite-derived fraction of absorbed photosynthetically active radiation, Current Science, 87, 1122–1126.

Parmeshwar Udmale, Yutaka Ichikawa, Sujata Manandhar, Hiroshi Ishidaira, Anthony, S., Kiem, 2014, Farmers′ perception of drought impacts, local adaptation and administrative mitigation measures in Maharashtra State, India: International Journal of Disaster Risk Reduction, 10, 250-269.

Parry, M.L, Canziani, O.F., Palutikof, JP., van der Linden, P.J., Hanson, C.E., 2007, Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L.Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds., 23-78.

Patel, N.R., Chopra, P., Dadhwal, V.K., 2007, Analyzing spatial patterns of meteorological drought using standardized precipitation index: Meteorological Applications, 14, 329-336.

Payero, J.O., Neale, C.M.U., Wright, J.L., 2004, Comparison of eleven vegetation indices for estimating plant height of alfalfa and Grass: American Society of Agricultural Engineers, 20, 385−393.

Perry, C.R., Lautenschlager, L.F., 1984, Functional equivalence of spectral vegetation indices: Remote Sensing of Environment, 14, 169−182.

Pettorelli, N., Vik, J.O., Mysterud, A, Gaillard, J.M., Tucker, C.J., Stenseth, N.C., 2005, Using the satellite-derived NDVI to assess ecological responses to environmental change: Trends in Ecology & Evolution, 20, 503-510.

Piao, S.L., Fang, J.Y., Ji, W., Guo, H., Ke, J.H., Tao, S., 2004, Variation in a satellite-based vegetation index in relation to climate in China: Journal of Vegetation Science, 15, 219-226,

Potter, C.S., Brooks, V., 1998, Global analysis of empirical relations between annual climate and seasonality of NDVI: International Journal of Remote Sensing, 19, 2921–2948.

Prince, S.D., Tucker, C.J., 1986, Satellite Remote Sensing of Rangelands in Botswana II: NOAA AVHRR and Herbaceous Vegetation: International Journal of Remote Sensing, **7**, 1555–1570.

Propastin, P., Kappas, M., 2008, Spatio-temporal drifts in AVHRR/NDVI-precipitation relationships and their linkage to land use change in central Kazakhstan: EARSeL eProceedings, 7, 30-45.

Qi, J., Huete, A.R., Moran, M.S., Chehbouni, A., Jackson, R.D., 1993, Interpretation of vegetation indices derived from multi-temporal SPOT images: Remote Sensing of Environment, 44, 89-101.

Rahmanian, D., 2001, Facing with drought: A failure without planning: Barzegar Magzine, 846, 50–53.

Rama Rao, C.A., Kareemulla, K., Sreenath Dixit, Y.S., Ramakrishna, Ravi Shankar, K., 2008, Performance of Agriculture in Andhra Pradesh – A spatial and temporal analysis: Central Research Institute for Dryland Agriculture (ICAR), Hyderabad Crida Publication, 1: 34

Rama Rao., C.A, Raju, B.M.K., Subba Rao, A.V.M., Rao, K.V., Rao, V.U.M., Kausalya, R., Venkateswarlu, B., Sikka, A.K., Srinivasa Rao, M., Maheswari, M., Srinivasa Rao, Ch., 2016, A district level assessment of vulnerability of Indian agriculture to climate change: Current Science, 110,1946.

Ramachandra, T.V., Uttam Kumar, Anindita, D., 2016, Time series MODISNDVI based Vegetation Change Analysis with Land surface temperature and Rainfall in Western Ghats, India:ENVIS technical report 100,Sahyadri Conversation Series 53, Energy and Wetlands Research Group, CES, Indian Institute of Science, Bangalore 560012.

Ramprasad, S., 2011, Current Agricultural Practices in Andhra Pradesh. Bharathi Integrated Rural Development Society (BIRDS): Strategic Pilot on Adaptation to Climate Change (SPACC) project.

Rao, V.U.M., Subba Rao, A.V.M., Bapuji Rao, B., Ramana Rao, B.V., Sravani, C., Venkateswarlu, B., 2011, El Niño Effect on Climatic Variability and Crop Production: A Case Study for Andhra Pradesh: Research Bulletin No. 2/2011, Central Research Institute for Dryland Agriculture, Santoshnagar, Hyderabad, Andhra Pradesh, India, 36.

Reed, B.C., Brown, J.F., VanderZee, D., Loveland, T. R., Merchant, J.W., Ohlen, D.O., 1994, Measuring phenological variability from satellite imagery: Journal of Vegetation Science, 5, 703–714.

Rembold, F., Atzberger, C., Savin, I., Rojas, O., 2013m Using low resolution satellite imagery for yield prediction and yield anomaly detection, Remote Sensing, 5,1704–1733.

Richard, Y., Poccard, I., 1998, A statistical study of NDVI sensitivity to seasonal and interannual rainfall variations in Southern Africa: International Journal of Remote Sensing, 15, 2907–2920.

Richardson AJ, and CL Wiegand (1977). Distinguishing vegetation from soil background information: Photogrammetric Engineering and Remote Sensing, 43:1541-1552.

Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W., 1974, Monitoring Vegetation Systems in the Great Plains with Erts: NASA Special Publication, 351, 309-317.9.

Saaty, T.L., 1980, Decision making with the analytic hierarchy process: International Journal of Services Sciences, 1,83–98.

Sabins, Jr, F.F., 1986, Remote Sensing. Principles and Interpretation, 2nd ed. xi + 449 pp, New York, Oxford: W. H. Freeman.

Sakamoto, T., Yokozawa, M., Toritani, H., Shibayama, M., Ishitsuka, N., Ohno, H., 2005, A crop phenology detection method using time-series MODIS data: Remote Sensing of Environment, 96, 366–374.

Sakamoto, T., Van Nguyen, N., Ohno, H., Ishitsuka, N., Yokozawa, M., 2006, Spatio–temporal distribution of rice phenology and cropping systems in the Mekong Delta with special reference to the seasonal water flow of the Mekongand Bassac rivers: Remote Sensing of Environment, 100, 1–16.

Samra, J.S., 2004, Review and analysis of drought monitoring, declaration and management in India, Working Paper 84: International Water Management Institute.

SAPCCAP, 2011, Submitted to Ministry of Environment and Forests, Government of India, New Delhi: Environment Protection Training and Research Institute (EPTRI), http://www.nicra-icar.in/nicrarevised/images/State%20Action%20Plan/AP-SAPCC.pdf

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

Schaber, J., Franz-W., Badeck, 2003, Physiology-based phenology models for forest tree species in Germany: International Journal of Biometeorology, 47,193-201.

Schucknecht, A., Stefan, E., Irmgard, N., Jörg, M., 2013, Assessing vegetation variability and trends in north-eastern Brazil using AVHRR and MODIS NDVI time series: European Journal of Remote Sensing, 46, 40-59.

Seaquist, J.W., Hickler, T., Eklundh, L., Ardo, J., Heumann, B., 2008, Disentangling the effects of climate and people on Sahel vegetation dynamics: Biogeosciences Discussions, 5,3045–3067.

Sehgal, V.K., Jain, S., Aggarwal, P.K., Jha, S., 2011, Deriving crop phenology metrics and their trends using times series NOAA-AVHRR NDVI Data: Journal of Indian Society Remote Sensing, 39-373–381.

Sehgal, V.K., Singh, M.R., Chaudhary, A., Jain, N., Pathak, H., 2013, Vulnerability of Agriculture to Climate Change: District Level Assessment in the Indo-Gangetic Plains: Indian Agricultural Research Institute, 74.

Seiler, R.A., Kogan, F.N., Wei, G., 2000, Monitoring weather impact and crop yield from NOAA AVHRR data in Argentina: Advances in Space Research, 26,1177-1185.

Sharmistha, S., Brian, D., Wardlow, Sunil, N., Tsegaye, T., Karin, Callahan., 2011, Assessment of Vegetation Response to Drought in Nebraska Using Terra-MODIS Land Surface Temperature and Normalized Difference Vegetation Index: GIScience & RemoteSensing, 48, 432-455.

Shalander, Kumar., Raju, B.M.K., Rama Rao, C.A., Kareemulla, K., Venkateswarlu, B., 2011, Sensitivity of Yields of Major Rainfed Crops to Climate in India: Indian Journal of Agricultural Economics, 66,340-352.

Shukla, R., Chakraborty, A., Joshi, P.K., 2017, Vulnerability of agro-ecological zones in India under the earth system climate model scenarios: Mitigation and Adaptation Strategies for Global Change 22, 399-425.

Singh, N.P., Bantilan, C., Byjesh, K., 2014, Vulnerability and policy relevance to drought in the semi-arid tropics of Asia – A retrospective analysis: Weather and Climate Extremes 3,54-61.

Singh, P., 2017, Reforms in Agricultural Research and Development: National Academy of Agricultural Sciences.

Sivakumar, M.V.K., Donald, E.H., 2004, Satellite remote sensing and GIS applications in agricultural meteorology and WMO satellite activities: Satellite remote sensing and GIS applications in Agricultural Meteorology, workshop Dehra Dun, India, 1-21.

Slater, P.N., Jackson, R.D., 1982, Atmospheric effect on radiation reflected from soil and vegetation as measured by orbiting sensors using various scanning directions: Applied Optics, 21, 3923-3931.

Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M., Miller H.L., 2007, IPCC 2007: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.

South Asia Environment and Social Development Department World Bank, 2005, Final Report. Drought in Andhra Pradesh: Long term impacts and adaptation strategies, Volume 1, http://www.indiawaterportal.org/sites/indiawaterportal.org/files/Drought%2C%20Andra%20Pradesh%20Vol-I.pdf.

Suzuki, R., Masuda, K., Dye, D.G., 2007, Interannual covariability between actual evapotranspiration and PAL and GIMMS NDVI of northern Asia: Remote Sensing of Environment, 106, 387–398.

Swaina, M., Swain, M., 2011, Vulnerability to Agricultural Drought in Western Orissa: A Case Study of Representative Blocks:Agricultural Economics Research Review, 24:47-56.

Swidrak, I., Schuster, R., Oberhuber, W., 2013, Comparing growth phenology of co-occurring deciduous and evergreen conifers exposed to drought: Flora- - Morphology, Distribution, Functional Ecology of Plants, 208, 609-617.

Symeonakis, E., Drake, N., 2004, Monitoring desertification and land degradation over sub-Saharan Africa: International Journal of Remote Sensing, 25,573–592.

Tan, B.J., Morisette, R., Wolfe, F., Gao, G., Ederer, J., Nightingale, Pedelty, J., 2011, An Enhanced TIMESAT Algorithm for Estimating Vegetation Phenology Metrics from

MODIS Data: Journal of Selected Topics in Applied Earth Observations and Remote Sensing 4, 361–371.

Tariq, A.B., 2014, An Analysis of Demand and Supply of Water in India: Journal of Environment and Earth Science, 4, 67-72.

Thakur, P.S., Dutt, V., Thakur, A., 2008, Impact of inter-annual climate variability on the phenology of eleven multipurpose tree species: Current Science, 94,1053-1058.

Thiruvengadachari, S., 1990, Satellite surveyed monitoring for improved continuous monitoring of agricultural drought conditions. Proceedings of the National Symposium of Remote Sensing for Agricultural Application, 389–407.

Thiruvengadachari, S., Gopalkrishna, H.R., 1993, An integrated PC environment for assessment of drought: International Journal of Remote Sensing, 14, 3201–3208.

Thornton, P.K., Ericksen, P.J., Herrero, M., Challinor A.J., 2014, Climate variability and vulnerability to climate change: a review: Global Change Biology, 20,33313-3328

Tottrup, C., Rasmussen, M., 2004, Mapping long-term changes in savannah crop productivity in Senegal through trend analysis of time series of remote sensing data: Agriculture, Ecosystems and Environment, 103,545–560.

Tucker, C.J., 1979, Red and photographic infrared linear combinations for monitoring vegetation: Remote Sensing of Environment, 8:127–150.

Tucker, C.J., Vanpraet, C.L., Sharman, M.J., Van Ittersum, G., 1985, Remote sensing of herbaceous biomass production in the Senegalese Sahel: 1980–1984: Remote Sensing of Environment, 17, 233 – 249.

Tucker, C.J., Sellers, P.J., 1986, Satellite remote Sensing of primary production: International Journal of Remote Sensing, 7, 1395-1416.

Tucker, C.J., Newcomb, W.W., Los, S.O., Prince, S.D., 1991, Mean and inter-year variation of growing-season Normalized Difference Vegetation Index for the Sahel 1981 – 1989: International Journal of Remote Sensing, 12, 1133–1135.

Turner II, B.L., Kasperson, R.E., Maston, P.A., McCarthy, J.J., Corell, R.W., Christensen, L., Eckley, N., Kasperson, J.X., Luers, A., Martello, M.L., Polsky, C., Pulsipher, A., Schiller, A., 2003a, A framework for vulnerability analysis in sustainability science: Proceedings of National Academy of Sciences,100, 8074-8079.

Turner II, B.L., Maston, P.A., McCarthy, J.J., Corell, R.W., Christensen, L., Eckley, N., Hovelsrud-Broda, G.K., Kasperson, J.X., Kasperson, R.E., Luers, A., Martello, M.L., Mathiesen, S., Naylor, R., Polsky, C., Pulsipher, A., Schiller, A., Selin, H., Tyler, N., 2003b, Illustrating the coupled human environment system for vulnerability analysis: three case studies: Proceedings of National Academy of Sciences, 100, 8080-8085.

U Ma'rufah, R., Hidayat, I., Prasasti, 2017, Analysis of relationship between meteorological and agricultural drought using standardized precipitation index and vegetation health index, IOP Conference Series: Earth and Environmental Science, 54.

UNDP, 2010, Mapping climate change vulnerability and impact scenarios: A guidebook for sub-national planners, 1-83.

Unganai, L.S., Kogan, F.N., 1998, Southern Africa's recent droughts from space: Advances in Space Research, 21,507-511

USAID, 2013, Uganda climate change vulnerability assessment report African and Latin: American resilience to climate change (ARCC) report.

Vamsi, V., 2004, Agricultural Growth and Irrigation in Telangana: A Review of Evidence: Economic and Political Weekly, 39, 1421-1426.

van Niel, T.G., McVicar, T.R., 2003, A simple method to improve field-level rice identification: toward operational monitoring with satellite remote sensing: Australian Journal of Experimental Agriculture ,43, 379 - 395.

van Vliet, A.J.H., Schwartz, M.D., 2002Phenology and climate: the timing of life cycle events as indicators of climatic variability and change: International Journal of Climatology, 22, 1713–1714.

Vasant, P., Gandhi, Vaibhav Bhamoriya, 2011, Groundwater Irrigation in India Growth, Challenges, and Risks: India Infrastructure Report, 7, 91-117.

Ved, P., Dwivedi, S.K., Santosh, K., Mishra, J.S., Rao, K.K., Singh, S.S., Bhatt, B.P., 2017, Effect of elevated CO2 and temperature on growth and yield of wheat grown in sub-humid climate of eastern Indo-Gangetic Plain (IGP): Mausam, 68,499-506.

Venkateswarlu, B., 2011, Rainfed agriculture in India: issues in technology development and transfer, Model training course on “impact of climate change in rainfed agriculture and adaptation strategies” November 22-29, CRIDA, Hyderabad, India

Vogt, J.V., Niemeyer, 1998, Towards monitoring drought conditions in sicily using an energy balance approach, In: Proceedings 7th International Conference, Florence, Italy.

Wang, J., Price, K.P., Rich, P.M., 2001, Spatial patterns of NDVI in response to precipitation and temperature in the central Great Plains: International Journal of Remote Sensing, 22, 3827-3844.

Wang, J., Rich, P.M., Price, K.P., 2003, Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA: International Journal of Remote Sensing, 24, 2345–2364.

Wardlow, B.D., Kastens, J.H., Egbert, S.L. 2006, Using USDA crop progress data for the evaluation of greenup onset date calculated from MODIS 250-meter data: Photogrammetric Engineering & Remote Sensing, 72, 1225-1234.

Waylen, P., Jane S., Cerian G., Huiping T., 2014, Time Series Analysis of Land Cover Change: Developing Statistical Tools to Determine Significance of Land Cover Changes in Persistence Analyses: Remote Sensing, 6,4473-4497.

White, M.A., de Beurs, K.M., Didan, K., Inouye, D.W., Richardson, A.D., Jensen, O.P., et al. 2009, Intercomparison, interpretation, and assessment of spring phenology in North America estimated from remote sensing for 1982–2006: Global Change Biology, 15, 2335–2359.

Wilhite, D.A., Glantz, M.H., 1985, Understanding the drought phenomenon: The role of definitions: Water International, 10,111–120.

Wood, E.F., 1997 Effects of soil moisture aggregation on surface evaporative fluxes: Journal of Hydrology, 190, 379–412.

World Meteorological Organization, 2012, Standardized Precipitation Index User Guide, 1090. Geneva: World Meteorological Organization. http://www.wamis.org/agm/pubs/SPI/WMO_1090_EN.pdf.

Wu, W., Yang, P., Tang, H., Zhou, Q., Chen, Z., Shibasaki, R., 2010, Characterizing spatial patterns of phenology in cropland of China based on remotely sensed data: Agricultural Sciences, 9,101–112

Wu, J., Lin, X., Wang, M., Peng, J., Yuanjie, Tu., 2017, Assessing Agricultural Drought Vulnerability by a VSD Model: A Case Study in Yunnan Province, China: Sustainability, 9.

Xiaoyang Z, Mark, A. F., Crystal, B., Schaaf, Alan H., Strahler, John, C.F., Hodges, Feng Gao, Bradley C. R., Huete A., 2003, Monitoring vegetation phenology using MODIS: Remote Sensing of Environment, 84, 471-475.

Xin. J., Yu, Z., van Leeuwen, L., Driessen, P.M., 2002, Mapping crop key phenological stages in the North China Plain using NOAA time series images: International Journal of Applied Earth Observations and Geoinformatics, 4,109–117.

Xingzhi You, Jihua Meng, Miao Zhang and Taifeng Dong (2013). Remote Sensing Based Detection of Crop Phenology for Agricultural Zones in China Using a New Threshold Method. Remote Sensing, 5(7), 3190-3211, doi:10.3390/rs5073190.

Yagci, A.L., Liping, Di., Meixia Deng, 2015, The effect of corn–soybean rotation on the NDVI-based drought indicators: a case study in Iowa, USA, using Vegetation Condition Index: GIScience & Remote Sensing, 52, 290-314.

Yan, N., Wu,B., Boken, V.K., Chang. S., Yang, L., 2016, A drought monitoring operational system for China using satellite data: design and evaluation: Geomatics, Natural Hazards and Risk 7, 264-277.

Yang,W., Yang, L., Merchant, W., 1997, An assessment of AVHRR/NDVI- ecoclimatological relations in Nebraska, USA: International Journal of Remote Sensing, 18, 2161-2180.

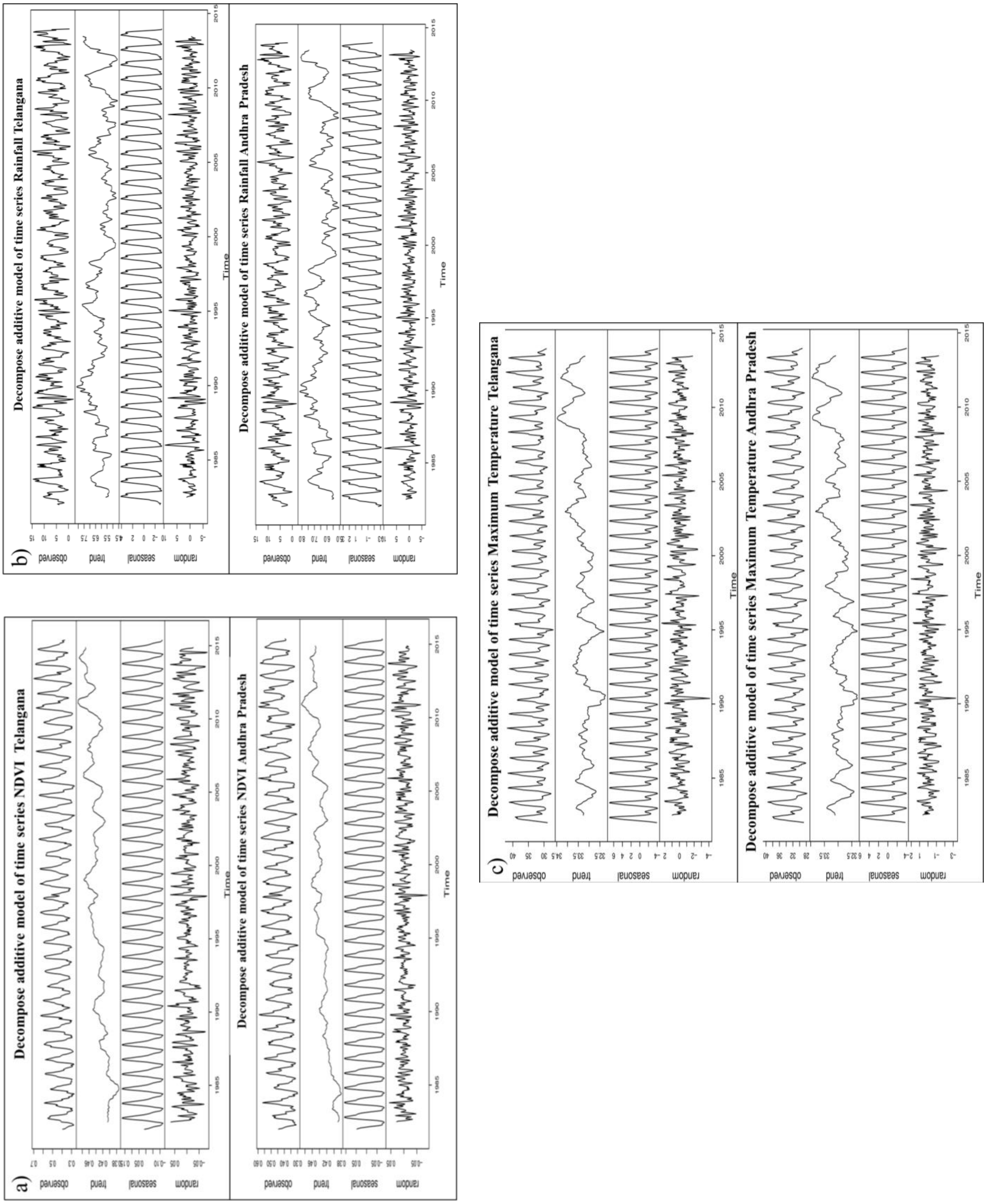
Zambrano, F., Wardlow, B., Tadesse, T., Lillo-Saavedra, M., Lagos, O., 2017, Evaluating satellite-derived long-term historical precipitation dataset for drought monitoring in chile: Atmospheric Research, 186: 26-42.15.

Zhang, X., Friedl, M.A., Schaaf, C.B., Strahler, A.H., Hodges, J.C.F., Gao, F., Reed, B.C., Huete, A., 2003, Monitoring vegetation phenology using MODIS: Remote Sensing of Environment, 84: 471-475

Zhao, H., Yang, Z., Di, L., Pei, Z., 2012, Evaluation of temporal resolution effect in remote sensing based crop phenology detection studies. In: Li D., Chen Y. (Eds.), Computer and Computing Technologies in Agriculture V. Springer Berlin Heidelberg, pp. 135150.

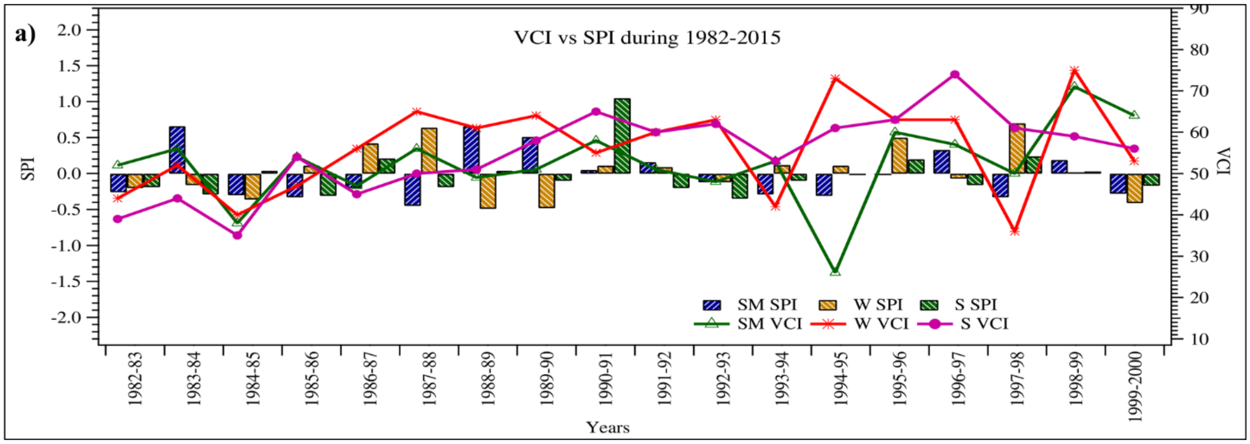
Zhou, L.M,, Kaufmann, R.K., Tian, Y., Myneni, R.B., Tucker., 2003. Relation between interannal variatio in satellite measures of vegettion greeenesss and climate between 1982 and 1999: Journal of Geophysics , 108 (D1).

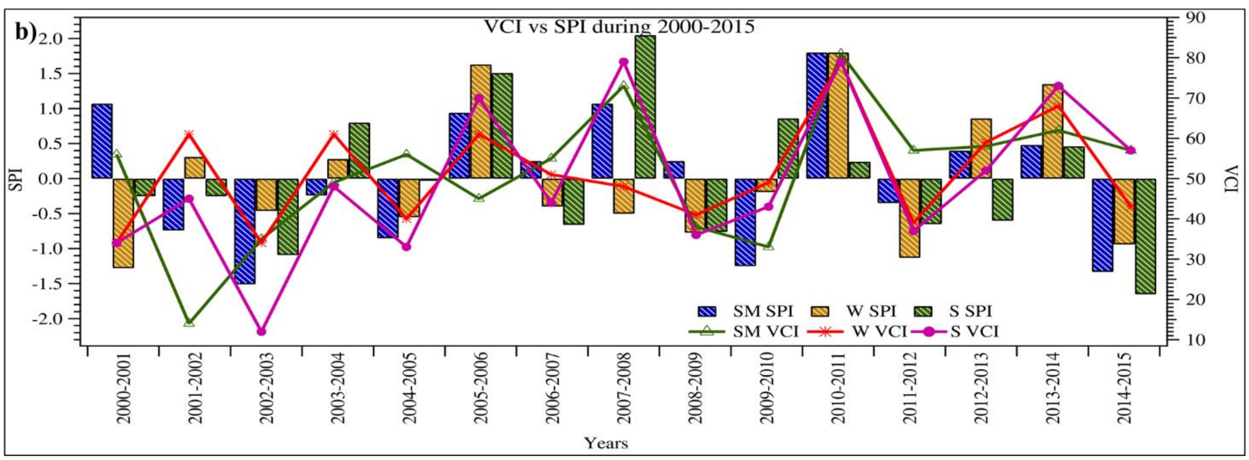
Annexure 3.1
Additive decompose model fits the time series data into linear trend, seasonal and irregular model
a) NDVI; b) Rainfall; and c) Maximum temperature

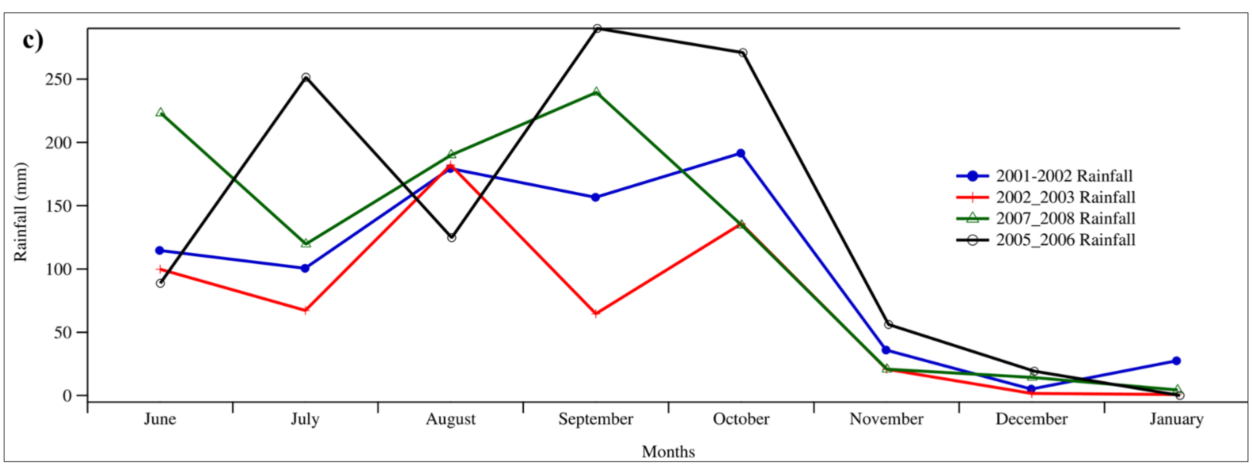


Annexure 4.1

Seasonal pattern of VCI vs SPI during a) 1982-2000; b) 2000-2015; and c) Monthly pattern of rainfall of dry (2001-2002 and 2002-2003), normal (2007-2008) and 2005-2006 years.







Annexure 4.2a

Frequency percentage of negative $NDVI_{Dev}$ during 1982-2015

	1982-2015 period			
Years	SM	W	S	Annual
1982-1983	22	22	22	22
1983-1984	20	22	22	21
1984-1985	22	22	22	22
1985-1986	15	22	20	19
1986-1987	22	15	21	19
1987-1988	13	9	19	14
1988-1989	16	17	17	17
1989-1990	14	7	5	9
1990-1991	6	18	12	12
1991-1992	19	18	8	15
1992-1993	13	11	15	13
1993-1994	12	19	14	15
1994-1995	21	6	6	11
1995-1996	3	0	4	2
1996-1997	3	4	0	2
1997-1998	9	14	2	8
1998-1999	0	0	5	2
1999-2000	2	9	10	7
2000-2001	7	9	4	7
2001-2002	13	0	3	5
2002-2003	9	14	20	14
2003-2004	11	1	12	8
2004-2005	6	10	19	12
2005-2006	16	1	0	6
2006-2007	2	4	8	5
2007-2008	0	0	0	1
2008-2009	0	8	12	7
2009-2010	9	8	8	8
2010-2011	1	0	0	0
2011-2012	0	10	2	4
2012-2013	2	0	2	1
2013-2014	4	0	1	2
2014-2015	4	4	2	3

Extreme Severe High

(SM: Summer Monsoon; W: Winter; and S: Summer)

Annexure 4.2b

District wise percentage frequency of negative $NDVI_{Dev}$ (>50%) from total agricultural area during 1982-2015 (NOAA GIMMS latest version)

	1982-2015			
Districts	SM	W	S	Annual
Adilabad	15	16	16	47
Ananthapur	17	16	13	46
Chittoor	14	12	14	40
Y.S.R. Kadapa	14	12	15	41
EastGodavari	12	13	15	40
Guntur	15	11	13	39
Karimnagar	13	14	11	38
Khammam	13	13	13	39
Krishna	18	12	12	42
Kurnool	15	15	14	44
Mahbubnagar	16	16	15	47
Medak	15	15	15	45
Nalgonda	15	15	14	44
S.P.S.R. Nellore	16	12	17	45
Nizamabad	12	15	13	40
Prakasam	17	15	14	46
Rangareddy	13	16	17	46
Srikakulam	11	14	16	41
Visakhapatnam	15	13	16	44
Vizianagaram	14	16	18	48
Warangal	12	13	15	40
West Godavari	14	10	11	35

Extreme Severe High

(SM: Summer Monsoon; W: Winter; and S: Summer)

Annexure 4.3

Relationship between number of rainy days vs Length of the Growing Period (LGP) a) Telangana; and b) Andhra Pradesh during 2000-2015.