Application of Geoinformatics for Modelling Drought Dynamics in Odisha State, India

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STATEMENT OF ORIGINALITY

I, Samadrita Mukherjee, registered on 08 July 2015, do hereby declare that this thesis entitled "Application of Geoinformatics for Modelling Drought Dynamics in Odisha State, India" contains reviews of literature and original research work carried out by the undersigned candidate for the partial fulfillment of the doctoral research.

All information in this thesis has been obtained and presented in accordance with existing academic rules and ethical conduct. I declare that as required by these rules and conduct, I have fully cited and provided reference to all materials and results that are not original to this work.

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CERTIFICATE FROM THE SUPERVISOR

This is to certify that the thesis entitled "**Application of Geoinformatics for Modelling Drought Dynamics in Odisha State, India**" submitted by **Ms. Samadrita Mukherjee** who got her name registered on **08 July 2015** for the award of **Ph.D. (ISLM)** degree of **Jadavpur University**, is absolutely based upon her own work under the supervision of **Prof.Sugata Hazra** and that neither this thesis nor any part of it has been submitted for either any degree/diploma or any other academic award anywhere before.

(Signature of the Supervisor with Date and Official Seal)

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Samadrita Mukherjee

Abstract

Drought generally occurs when a region consistently receives less precipitation. It is a most devastating natural hazards which impact on the agriculture and economy of a state. In this research, various climatic and space based remote sensing datasets are utilized to delineate the drought dynamics, its cause, future prediction and technique for field scale soil moisture and drought mapping. Analysis of physical and cultural settings of Odisha clearly brings out that southwest monsoon has large impact and control on the agriculture of Odisha state. Mapping of drought dynamics of Odisha state over two decades using SPI and SPEI depicts that 2000, 2002, 2004, 2009, 2010, 2013 and 2015 are predominantly drought affected years , while the mild to moderate droughts are seen in Odisha in most of the years. The spatial distribution and mapping of drought characteristics i.e., drought frequency, drought severity and drought event shows that in most of the districts drought frequency is high though Odisha has experienced severe drought various occasions. Monsoon drought is most significant as it affects the Kharif crop, however, post monsoon droughts are also seen in Odisha. The drought pattern in Odisha is random, but few districts like Nuapada, Kalahandi, Bolangir, Rayagada, Ganjam, Bargarh, Malkangiri and Phulbani are chronically affected by droughts. The major climatic factors affecting drought in Odisha are precipitation, temperature, soil moisture, evapotranspiration, ground water storage, El Nino/ La Nina and IOD. The main reason of drought over Odisha state is variability of the onset of south west monsoon and the quantum of rainfall affecting the kharif crop resulting in severe droughts. Positive anomaly of the land surface temperature (LST) is observed which results in the increase of evapotranspiration ,decrease in soil moisture and ground water storage. The combined effect is severe agricultural drought. ENSO and IOD is the controlling factor of air circulation over Indian Ocean significantly impacting on the south west monsoon which in turn, affects the drought situation of Odisha.. Odisha as coastal state gets highly influence by the rainfall variability.

Short and long-term drought scenario prediction, using NorESM2-MM CMIP6 GCM model predicted precipitation and temperature datasets, suggests that in the year of 2023, 2027, 2029, 2031, 2036, 2040, 2048 and 2050, more than 50% of area under the state of Odisha will be under drought. The analysis also indicates that predicted minimum and maximum temperature may increase approximately 2°C and 1.5°C respectively in this period (2023 to 2050). Temperature anomaly is also positive after 2040. In the predicted drought map, the pattern is random and the state may suffer severe droughts in the

future. Enhancement of agricultural drought and soil moisture mapping by downscaling the spatial resolution of LST from coarse to medium/ finer resolution (250 m) with the help of NDVI is attempted and to derive VHI and TVDI for mapping of soil moisture and drought. . The downscaled 250 m resolution LST depicts higher spatial details compared to 1000 m resolution LST. Similar pattern with higher details is observed in the fine resolution VHI and TVDI. Entropy function is used to validate the generated VHI and TVDI maps of 250 m resolution. Larger intra-pixel variability is seen which suggests that high-resolution maps are useful for drought and soil moisture mapping and monitoring over the study area. Due to the daily availability of MODIS VNIR and thermal data, this technique may improve the probability of daily or weekly field/ regional drought and soil moisture mapping. The high frequency spatio-temporal pattern of drought/ soil moisture will certainly help the state authority for drought management and policy formation. Delineation of agricultural drought affected areas has been carried out with the help of multi-temporal Sentinel 1 SAR and landsat optical datasets for the monsoon period based on correlation between NDVI and SAR backscatter as SAR data is weather independent and sensitive to dielectric property of the soil moisture. The result shows that it is feasible to delineate drought affected areas using SAR data. Therefore, in the coastal region where cloud affects the optical data, SAR could be a potential source of drought mapping. In Odisha only 20 % agricultural area is covered by canal irrigation, therefore better drought management, irrigation system development is required for drought mitigation. The entire study reveals that management and mitigation of drought is essentially required in Odisha state.

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ACRONYMS

CGWB	...	Central Ground Water Board
IMD	...	Indian Meteorological Department
MODIS	...	Moderate Resolution Imaging Spectroradiometer
ESA	...	European Space Agency
GRACE	...	Gravity Recovery and Climate Experiment
IPCC	...	Intergovernmental Panel on Climate Change
LST	...	Land Surface Temperature
ET	...	Evapotranspiration
NDVI	...	Normalized Difference Vegetation Index
IOD	...	Indion Ocean Dipole
SPI	...	Standardize Precipitation Index
SPEI	...	Standardize Precipitation Evapotranspiration Index
VHI	...	Vegetation Health Index
VCI	...	Vegetation Condition Index
TCI	...	Temperature Condition Index
SMOS	...	Soil Moisture and Ocean Salinity
AMSR-E	...	Advanced Microwave Scanning Radiometer for EOS
CMIP6	...	Coupled Model Intercomparison Project Phase 6
GCM	...	General Circulation Model
DisTrad	...	Dis-Aggregarion of Radiometric Temperature
TsHARP	...	Temperature Sharpening

!! I have dedicated this thesis to my beloved father, who has inspired me to carry out the PhD work !!

1 Introduction

The important thing is not to stop questioning. Curiosity has its own reason for existing.

- Albert Einstein, 1955

1.1 Background

A drought is a prolonged period, measured in months or years, during which an area suffers from a shortage of available water. When precipitation is regularly below average in a certain area, drought conditions may develop. It is one of the most consequential environmental and economic threats to nations throughout the world. The regions of drought cannot be tracked with just weather data. Though it's not easy to pin down, drought is characterised by a prolonged lack of precipitation, often throughout a season or more, which leads to a water deficit in areas like agriculture and the environment. A lengthy period of inadequate precipitation that causes widespread damage to crops and, ultimately, loss of output is known as a drought. Difficulties in detecting and preparing for drought are compounded by the lack of a universally accepted operational definition of the term, which hampers the efforts of resource planners, policymakers, and others.

Geoinformatics is the science and technology that uses information science infrastructure to counter the various problems related to geography, geosciences, mapping, and other branches of science and engineering. It comprises remote sensing, geographic information system, cartography, photogrammetry, surveying, computer programming and other branches of geospatial sciences. "Remote Sensing" is a method of gathering data about distant things without actually touching them(Lillesand, Kiefer, & Chipman, 2015). Data about Earth's surface is gathered using a variety of remote sensing equipment, some of which are satellite-based (in orbit) and others that are airborne. The capacity to continuously detect and observe surface materials and processes across several periods makes space-based sensing technology more valuable today. To track the state of Earth's resources on a global, regional, and even a microscale, this is an essential tool.

The information must flow from the item or phenomena of interest to the space-based observing sensor, and some mechanism must be in place to transport this information from one to the other. Carrier in remote sensing is the electromagnetic spectrum (EMS). Several EMS functions make use of remote sensing. The sensor creates a picture using radiation from the visible-near-infrared, thermal-infrared, and microwave ranges that have been reflected, emitted, or backscattered. Imagery includes DN (digital number) data representing ground signals picked up by the satellite-based sensor.The satellite imagery-based information along with weather-related data is very useful for monitoring drought. As the space-based satellite sensors continuously monitor the Earth-surface, therefore, monitoring of long-term drought phenomena and modelling of drought dynamics of a region is feasible through geoinformatics.

1.2 Problem Statement

India is one of the nations which is most prone to drought, and the peninsular regions of the country are particularly vulnerable. India has a total area of 3.28 million km2, however, roughly 1.07 million km2 of that have experienced water stress or drought to varying degrees. According to the World Bank's "4-degree study," the severity of droughts in southern Africa, the United States, Southern Europe, Brazil, and Southeast Asia may grow shortly as a result of an increase in dry spells, evapotranspiration, and the decline of arable land. An increase in food insecurity might be a result (World Bank, 2012). For decision-makers and planners to make educated choices about water conservation and drought response strategies, they must have access to accurate maps and conduct constant monitoring of drought and soil moisture status.

Once every two and a half years, India experiences a drought. Droughts that lasted for many years and affected large areas have also been documented in the previous five decades. It's impossible to anticipate where or when a drought may strike. There would be a correlation between the frequency, intensity, volume, and duration of the rainfall and the prevalence of drought in any given location. Droughts affect a large proportion of India's agricultural fields, and this problem may improve in the future. Successful management of an unforeseen drought scenarios requires constant monitoring of drought patterns, intensities, and probability.

Many researchers across the world have created techniques and indices for tracking agricultural drought by combining remote sensing and climate data (Palmer, 1965; Kogan .1990; Kogan F. , 2002; McKee, Doesken, & Kleist, 1993; Seiler, Kogan, & Sullivan, 1998; Peters, et al., 2002; Keyantash & Dracup, 200; Bhuiyan, Singh, & Kogan, 2006; Mishra & Singh, 2010; Rojas, Vrieling, & Rembold, 2011). For instance, the Vegetation Health Index

(VHI) is often used for drought detection and monitoring of drought severity and duration, and it is produced from remote sensing inputs (Kogan, 2001; Kogan F. , 2002; Bhuiyan, Singh, & Kogan, 2006; Mukherjee, Joshi, & Garg, 2014. Good agreement with the precipitation patterns is shown, and it is utilised to evaluate the geographical aspects of droughts. MODIS, among other sensors, has seen extensive usage in assessing agricultural drought on a regional scale (Wan, Wang, & Li, 2004; Mallick, Bhattacharya, & Patel, 2009; Rhee, Im, & Carbone, 2010; Son, Chen, Chen, Chang, & Minh, 2012; Du, et al., 2013; Wu, Zhou, Liu, Zhang, Leng, & Diao, 2013). Due to their capacity to gather information regardless of the weather, satellite-based microwave remote-sensing devices are also employed to keep tabs on drought conditions. LST and soil moisture data from the Advanced Microwave Scanning Radiometer (AMSR-E), as well as rainfall data from the Tropical Rainfall Measuring Mission (TRMM), are often utilised for drought monitoring (Du, et al., 2013; Son, Chen, Chen, Chang, & Minh, 2012). Soil moisture may be measured in a precise, spatial manner using remote sensing photography (Verstraeten, Veroustraete, van der Sande, Grootaers, & Feyen, 2006). Soil moisture estimate may benefit from thermal and microwave (passive and active) remote sensing because of the unique thermal and dielectric characteristics of water compared to those of other natural surfaces. Since their inception, the Scanning Multichannel Microwave Radiometer (SMMR), the Tropical Rainfall Measuring Mission Microwave Imager (TMI), the Advanced Spaceborne Thermal Emission and Reflection Radiometer (AMSR-E) for the Earth Observing System, the European Remote Sensing Satellites (ERS-1 and ERS-2), the European Space Agency's Meteorological Operation (MetOp-A), and the Soil Moisture Ocean Salinity (SMOS)(Rudiger, et al., 2009; Albergel, et al., 2013; De Jeu et al., 2003). Because of an irregular fluctuation of sea-surface temperatures known as the Indian Ocean Dipole (IOD), the western section of the Indian Ocean is cyclically warmer and then colder than the eastern part of the ocean. The IOD directly or indirectly control the onset of the Monsoon. The coastal states of the country suffer from drought due to irregular behaviour of the onset of the Monsoon. It is observed that drought occurs in East Africa and Australia due to IOD.

Odisha only experiences drought once every three years because of its coastal location. Odisha has conducted drought studies, but more accurate simulations of drought dynamics are needed for this province to fully comprehend the phenomenon of drought. It is also necessary to focus on long-term drought forecasting modelling. The association between IOD's location and the frequency of drought in India's east coast and Odisha must be studied.

1.3 Benefits of Drought Dynamics Mapping

- Delineate drought intensity, severity, and special diversity
- Communicate drought-related information,
- Depicts a Spatio-temporal pattern of drought to help the decision-makers and planners,
- Guide community water systems' Drought Management Plans,
- Encourage regional water resources and irrigation management planning,
- Provide technical assistance,
- Develop and implement data and information delivery systems for drought management,
- This will also support decision-making for drought mitigation measures.

1.4 Literature Review

Drought is seen as a fundamental hydrologic risk. However, the word "drought" has been misconstrued and is currently the least controllable phenomenon afflicting the planet. (Eslamian & Eslamian, 2017. Drought is sometimes referred to as a "creeping phenomenon" since it is incredibly difficult to forecast when it will begin or end (Wilhite & Glantz, , 1985). Though there is no universally acknowledged definition of drought, it can be outlined in both formative and reflective aspects. The conceptual definition of drought provides general and comparable terms (such as dry, long period), whereas the operational definitions imply the emergence, severity, revocation, presumption of possible ramifications, and comparing of evapotranspiration to daily precipitation values, determining soil moisture deficiency (Mishra & Singh, 2010; Tate & Gustard; Wilhite & Glantz, , 1985). Some conceptual definitions include (i) the World Meteorological Organization's (WMO) definition from 2014, which explains that "drought is a protracted dry phase in the climatological cycle that can develop almost anywhere on the planet." It is a sluggish phenomenon caused by a lack of rainfall"; (ii) drought, as defined by the Food and Agricultural Organization (FAO) in 1983, is "the percentage of years when crops struggle due to a lack of moisture"; and (iii) drought, as defined by the United Nations Convention to Combat Desertification

(UNCCD) in 1994, is "the natural occurrence that appears to exist when rainfall has been substantially below standard documented thresholds, causing severe hydrological systems"(Mishra & Singh, 2010). Drought is eventually observed in every climatic zone. At least once in both high and low precipitation regions, there is drought (Wilhite & Glantz, 1985). Drought, in principle, may be characterized as an absence of rainfall concerning normal circumstances for a long period (typically a season or more in the case of agriculture), resulting in a lack of water for specific activities, enterprises, the ecosystem, or society (Eslamian & Eslamian, 2017). Wind gusts, temperatures, length, duration, dispersion, and kind of rainfall, as well as low comparative moisture, are the primary forces behind the drought event (Mishra & Singh, 2010). Drought vulnerability is rising because of climate change, growing populations, and ever-increasing strain and demand on water supplies that exceed the availability of water utilized for human usage in various forms (Eslamian & Eslamian, 2017). The intensity is especially difficult to assess since it relies not only on the severity, length, and physical breadth of the drought but also on the demands for water sources by anthropogenic and flora in the territory throughout a specific drought occurrence (Wilhite & Glantz, 1985).

1.4.1 Types of Droughts

Droughts are divided into various forms. The conventional categorization of drought includes climatological drought (rainfall deficit), hydrological drought (groundwater, underground water, and storage insufficiency), agricultural drought (insufficiency in moisture in the soil), and socio-economic drought (reduction in agricultural yield and production of goods reliant on water affecting society), while the most recent categorization contains two additional kinds of drought as well as the conventional classification (drought affecting ecosystems) (AghaKouchak, Rad, Navari, & Sadegh, 2021). Droughts can be classified into the following categories: (i) Climatological or meteorological drought is defined as a lack of precipitation compared to typical circumstances during a particular period and the degree of dryness (Tate & Gustard, 2000; Wilhite & Glantz1985). As a result, meteorological drought may be described as a lack of precipitation accompanied by an increase in reference evapotranspiration that spreads over a large region beyond a long period. (Van & Anne, 2015). However, meteorological droughts are frequently defined by geographical area. For example, in the USA, drought pertains to precipitation less than 2.5 mm in forty-eight hours, in the United Kingdom, it pertains to less than 0.25 mm of precipitation in fifteen days, in Libya, it refers to 180 mm of yearly precipitation, in India, it corresponds to scarcity in normal rainfall by two times the mean deviation, and in Bali, it refers to six days of anhydrous condition. (Wilhite & Glantz, 1985). (ii) Hydrological drought pertains to the effects of dry circumstances on subterranean and subsurface conditions. Its intensity and recurrence determine the influence it has on river basins, such as lower groundwater and lake levels, decreased wetland area and reduced river flow (Van & Anne, 2015). Hydrological drought is caused by numerous atmospheric anomalies, such as rainfall and temperature abnormalities, that are frequently associated with the ocean and atmospheric phenomena such as ENSO, sea surface temperature, and NAO (Van & Anne, 2015). Furthermore, soil moisture loss is related to prior circumstances, evapotranspiration from plants, evaporation from uncovered soil layers, runoff to rivers and streams, and underground drains. (Van & Anne, 2015). (iii) Agricultural drought, also referred to as agrometeorological drought, is described as the effects on the agricultural output caused by a shortage of available water for agricultural uses; it is most commonly connected with crop failure caused by a reduction in soil moisture (Dalezios, Gobin, Alfonso, Tarquis, & Eslamian, 2017). The operational definition of agricultural drought, therefore, connects several meteorological drought factors with their potential effect on agricultural production, including a lack of precipitation, a departure from normal circumstances, or other climatic components like evapotranspiration. The operational definition also highlights the different susceptibilities of crops at different phases of growth, such as a shortage of moisture in the subsoil in the early stages of crop development. The study was conducted in 1985 by Wilhite and Glantz (Wilhite & Glantz, 1985).

Reduced soil moisture also leads to decreased availability of water in soil, reservoirs, and streams, which has many knock-on negative effects including, but not limited to, hunger, famine, population migration, a drop in agricultural income, and so on (Dalezios, Gobin, Alfonso, Tarquis, & Eslamian, 2017). (iv) Socioeconomic drought occurs when an area suffers from a lack of water, which has negative effects on the local economy, population, and ecosystem (Liu, Shi, & Sivakumar, 2020; Zhao & Dai, 2015). Socioeconomic drought is especially severe in arid and semi-arid nations due to rising water use caused by urbanization, industry, and population expansion, all of which are aggravated by climate variables and associated changes (Zhao & Dai, 2015). An ecological drought is defined as an extended period without precipitation or precipitation levels that exceed the threshold of ecosystem sensitivity, hence disrupting ecosystem functions and ecological feedback (Crausbay, et al., 2017). (vi) Anthropogenic drought is the lack of water that occurs when the water table drops when wetland and lake water is depleted, and when river flows are reduced as a consequence of human activities like overexploitation (AghaKouchak, et al., 2015). A major problem, anthropogenic drought occurs when human demands on water resources exceed those that can be met without negatively impacting the environment (AghaKouchak, et al., 2015).

1.4.2 Causes of Droughts

The main cause of drought should be a change or drop in the normal amount of rainfall. This has a big effect on farming, which depends on the moisture in the soil and water availability during the many stages of crop growth (Eslamian & Eslamian, 2017). Several natural and manmade factors contribute to the lowering of precipitation, particularly rainfall. Subsidence or the downward movement of air as a result of atmospheric circulation is one of the most important natural causes of drought. Also, it has been noticed that almost all places where droughts happen (often in the middle of continents) are in places where air movement is mostly downward (Zolotokrylin, 2010). Subsidence of the air mass has three effects on precipitation: (a) a decrease in the air's moisture content; (b) a decrease in the air's relative humidity and an increase in its moisture capacity; and (c) air currents that are unfavourable for the condensation of moisture, leading to fewer clouds, more solar radiation, more potential evaporation, and drier soil (Zolotokrylin, 2010). In high-pressure regions, where the air has been compressed to increase its pressure, air masses sink because the absolute water vapour content remains constant while the relative humidity drops because of a rise in moisture capacity. This has the effect of decreasing evaporation and cloud formation, leading to a decrease in precipitation and, eventually, a drought (Eslamian & Eslamian, 2017; Zolotokrylin, 2010). For instance, the 'dust layer' in the Sahara might block sunlight and cause the air mass in the tropics to heat, leading to more air mass stability and less cloud formation (Zolotokrylin, 2010). Droughts occur when the ocean and atmosphere interact in a way that causes global wave anomalies of westerlies to be observed in the equatorial, tropical, and temperate regions. This is because the westerlies depend on ocean surface temperature, which controls large-scale atmospheric circulation, ocean surface evaporation, transport of water vapour to the landmasses of different continents, and heat liberation during water vapour condensation (Zolotokrylin, 2010). Drought is mostly caused by changes in air circulation over the eastern Pacific Ocean, which may be triggered by the occurrence of climatic events like El Nino (Eslamian & Eslamian, 2017). However, "forced droughts" are widespread in tropical areas due to ocean surface temperature anomalies, but the natural causes of dryness in other latitudinal zones may be linked to meteorological dynamics and geographical isolation, making drought prediction more challenging (Zolotokrylin, 2010). Drought may be caused by both natural and human forces. Severe water scarcity may occur if the water demand greatly outpaced the supply, as could happen if the water quality declined. The likelihood of a drought is increased by the stress that human activities have on water resources (Eslamian and Eslamian, 2017). Drought conditions are caused by changes in land use, the elimination of vegetative cover, over-cultivation, over-grazing, soil degradation, industrialisation, and urbanisation, which all put more strain on already stressed water supplies. Further, a loss in plant cover might raise Earth's albedo, which in turn could cause air subsidence, decreased precipitation, and a decrease in soil moisture, ultimately altering the relationship between the atmosphere and the land surface (Zolotokrylin, 2010). Furthermore, the rise in global temperature caused by automobile and industrial emissions (particularly carbon dioxide) has resulted in climate change, which may lead to an abnormal temperature rise affecting the hydrological and meteorological systems and subsequently causing severe drought conditions (Zolotokrylin, 2010). Drought and prolonged dry spells are the inevitable results (Ummenhofer, D'Arrigo, Anchukaitis, Buckley, & Cook, 2013).

1.4.3 Impact of Drought on Human Life, Livelihood and Economy

Negative consequences of drought tend to be indirect and slow-moving, depending on the sensitivity and resilience of the people in the afflicted region, which may be affected by factors like poverty, poor health, and conflict (Stanke, Kerac, Prudhomme, Medlock, & Murray, 2013). In 2011, drought was estimated to have affected 35 million people in China, 17 million in Kenya, Ethiopia, Uganda, Somalia, Burundi, Niger, and Djibouti; to have cost $8 billion in Mexico and the United States, and $2.4 billion in China; and to have killed the most people between 1900 and 2012 in China and India (Stanke, Kerac, Prudhomme, Medlock, & Murray, 2013). The agriculture industry is the first to feel the consequences of drought due to decreasing soil moisture (Maia et al., 2015). Due to a prolonged decline in soil moisture, crops and pastures fail, resulting in a decrease in production and a lack of supplies, which in turn signals the advent of drought by the appearance of abandoned croplands, dried crops, and withered pastureland (Ding et al., 2011). Farmers don't shoulder the whole burden of the cost when crops fail because of drought; consumers pay a higher price for food as a result. Furthermore, food scarcity causes individuals to relocate, suffer from despair and hunger, engage in antisocial behaviour like thievery, and, in the worst-case scenario, starve to death (Ding, Hayes, & Widhalm, 2011; Gaike & Baisane, 2019). Drought conditions harm businesses and industries that use a lot of water, such as tourism, horticulture, navigation, public utilities, landscaping services, and others; public distribution of water is hampered by a lack of fresh water, and groundwater water levels decline due to over-extraction; and businesses and industries that rely on agricultural products, like the ethanol plant, suffer as a result (Ding, Hayes, & Widhalm, 2011; Gaike & Baisane, 2019). As a result, droughts have a devastating effect on tourism and leisure which depend significantly on water supplies. Multi-year drought would affect activities like boating and fishing by drying up reservoirs and lakes. This would have an influence on winter sports like skiing as well (Ding, Hayes, & Widhalm, 2011). Damage to nursery crops caused by a shortage of water has a significant economic impact on landscaping and nursery service providers, in addition to the negative consequences of depletion and drying of water resources on construction and navigational activities (Ding, Hayes, & Widhalm, 2011). Drought has far-reaching consequences for human life, including health consequences due to the spread of different diseases, population shifts, and the disappearance of essential resources. People lose their jobs and those who rely solely on agriculture are particularly vulnerable to drought; malnourishment in infants and children becomes common due to a lack of food and nutrition, making them susceptible to several diseases and mortality; and people suffer from several water-borne diseases due to a lack of water, so migration is necessary in cases of severe drought conditions to ensure a better standard of living (Gaike & Baisane, 2019). Indirectly, drought may cause malnutrition and mortality by reducing food availability (especially cattle and crops), which in turn lowers dietary quality and quantity, leaving people more vulnerable to sickness and death. Drought may have serious consequences, although the extent of such consequences varies widely according to economic circumstances (Stanke, Kerac, Prudhomme, Medlock, & Murray, 2013). Many studies have found that the failure of a major food crop and the subsequent lack of availability forces economically weaker sections of society to make drastic changes to their usual food intake, putting them at increased risk for a variety of diseases and health problems. These deficiencies have been linked to everything from anaemia due to iron scarcity to night blindness and scurvy. Consumption of mould-affected food due to severe drought conditions in India led to the outbreak of aflatoxicosis disease; inclusion of selenium in the food chain due to drought conditions in China caused skin lesions, nail and hair loss, and problems in the digestive tract in 22% of the population affected by drought in China during 1970-1972. (Stanke, Kerac, Prudhomme, Medlock, & Murray, 2013) Drought exacerbates the spread of water-borne illnesses such as paratyphoid, typhoid, shigellosis, schistosomiasis, salmonellosis, hepatitis A, diarrhoea, amoebiasis, and many more (Ole-MoiYoi, 2013; Stanke, Kerac, Prudhomme, Medlock, & Murray, 2013). Water contamination causes vector-borne diseases like dengue, malaria, Japanese encephalitis, Chikungunya, Tick-borne disease, St. Louis encephalitis virus, and West Nile Virus to spread during and after a drought; in addition to having negative effects on physical health, drought conditions also contribute to mental stress in people, especially cultivators, as a result of loss of financial stability (Stanke et al., 2013). In temperate climates, heat waves are often accompanied by dry spells, especially during the summer when anti-cyclonic winds dominate. Wildfires may also break out in dry areas due to the combination of low soil moisture and high surface temperature, as happened in western Europe in August 2003. The heat wave caused 30,000 deaths and the flames caused another 25,000; a similar number of deaths, 54, were reported in Russia in July and August of 2010 after a severe drought plagued the country in 2009. (Stanke, Kerac, Prudhomme, Medlock, & Murray, 2013; Zarafshani et al., 2016). The breakdown of the healthcare system due to an increase in patients, and the interruption of the power supply due to a drop in lake and reservoir levels, which hinders the generation of hydroelectricity and, in turn, impacts industrial production and other production processes, are two other indirect effects (Stanke, Kerac, Prudhomme, Medlock, & Murray, 2013). Droughts and dry spells are inevitable (Ummenhofer, D'Arrigo, Anchukaitis, Buckley, & Cook, 2013).

1.4.4 Remote Sensing of Drought

Before this, scientists mostly from the fields of agriculture and meteorology would use interpolated grids or ground measurements to study and track droughts. However, not all areas with agricultural output have sufficient instrumentation to collect and report necessary data on weather variables such as precipitation, wind speed, surface air temperature, relative humidity, water vapour content, and evaporation demand (AghaKouchak, et al., 2015)**.** The very first satellite devoted to weather observation was the Television Infrared Observation Satellite (TIROS -1). Landsat, Geostationary Operational Environmental Satellites (GOES), and Advanced Very High-Resolution Radiometers all owe their existence to their launch in 1960. (AVHRR). Normalized Difference Vegetation Index (NDVI) and other indices were used to track environmental problems and trends in the 1980s (Wardlow, Anderson, & Verdin, 2012)**.** Thermal infrared, microwave and multispectral data are used to monitor meteorological factors like precipitation, temperature, and evapotranspiration that contribute to the occurrence of drought; infrared (IR) and satellite visible (VIS) images are used to monitor droughts associated with ecosystems and their associated consequences (AghaKouchak, et al., 2015)**.** At some point, we'll go through all the variables that can be tracked by satellite to gauge drought severity. Satellites' visible (VIS) and infrared (IR) wavelengths reveal data on cloud depth, droplet size, cloud top temperature, cloud phase, and water vapour channels, while microwave data reveals data on cloud pattern, brightness, shape, area, shadow, texture, and movement, all of which can be used to estimate rainfall and precipitation (Eslamian & Eslamian, 2017). It has been hypothesised that by integrating the data acquired by MW and GEO sensors, a more precise estimate of precipitation may be achieved (AghaKouchak, et al., 2015)**.** The Cloud Indexing Technique (where the rate of precipitation is assigned to each type of cloud), the Bi-spectral Approach, Cloud Modelling, Active Microwave Remote Sensing, Rainfall Indicators like SPI (quantification of water scarcity based on precipitation data), Monthly Dryness Indicators, and Dekadal Dryness Indicators, are just a few of the many methods for monitoring precipitation (Eslamian & Eslamian, 2017)**.** Weather conditions are tracked by the National Oceanic and Atmospheric Administration (NOAA), IR sensors, INSAT, GOES, Meteosat, and Elektro-L in Russia (AghaKouchak, et al., 2015)). Soil moisture is another important indicator of drought severity. X band (wavelength 2.5 - 3.8 cm), C band (wavelength 3.8 - 7.5 cm), and L band (wavelength 15 - 30 cm) are the most effective bands in monitoring soil moisture and are therefore used for estimation of soil moisture in thermal remote sensing, which is used to interpret the thermal condition of the soil surface (AghaKouchak, et al., 2015)**;**(Eslamian & Eslamian, 2017)**.** The most reliable information in this respect comes from passive microwave (MW) sensors. The use of MW sensors in the 1-3 GHz range offers many advantages, including (a) direct sensitivity to soil moisture changes, (b) the ability to penetrate modest amounts of vegetation, and (c) little interference from cloud cover (Eslamian & Eslamian, 2017). Backscatter indicators are quantified using active microwave sensors like scatterometers and synthetic aperture radar (SAR) (Eslamian & Eslamian, 2017). Groundwater and terrestrial or land water storage are also vulnerable to the effects of drought, but the gravity Recovery and Climate Experiment (GRACE) mission launched in 2002 helps to evaluate these effects (TWS). GRACE aids in estimating the amount of precipitation (water) needed for drought recovery by providing quantification of anomalies in surface water, soil moisture, groundwater, moisture content in plants, etc. However, GRACE is restricted in its ability to monitor water since it only takes a single reading at a given time (AghaKouchak, et al., 2015). The SVI, VCI, TCI, and VHI are all components of the NDVI, or Normalized Differential Vegetation Index (VHI). Indicators such as the VCI and TCI point to terrestrial vegetation and moisture, while the VHI points to the health of the vegetation, and the SVI may identify short-term climatic impacts on near-ground vegetation (Eslamian & Eslamian, 2017; Wardlow, Anderson, & Verdin, 2012). Compared to the Normalized Difference Vegetation Index (NDVI), which also uses the MODIS 500m SWIR band, the Normalized Difference Water Index (NDWI) is a more accurate predictor of moisture content and mesophyll beneath dense plant canopies (Mishra & Singh, 2010). Droughts may also be tracked and identified with the use of a variety of evapotranspiration indexes. Crop Water Stress Index (CWSI), Water Deficiency Index (WDI), Evaporative Stress Index (ESI), Evaporative Drought Index (EDI), Drought Severity Index (DSI), and Reconnaissance Drought Index (RDI) are all examples of (AghaKouchak, et al., 2015). Land Surface Temperature (LST) is used to estimate biospheric stress owing to soil moisture shortage, and it may be measured in three different ways: (a) using a single infrared (IR) channel, (b) using a split window, and (c) using MODIS LST (Eslamian & Eslamian, 2017). Because of their low cost and quick turnaround, remote sensing techniques have been more useful in reducing the severity of drought's negative consequences (Wardlow et al., 2012).

1.4.5 Climate Change and Drought

There are strong correlations between drought frequency and severity and meteorological factors and outliers. Droughts are caused by temperature and precipitation extremes, both of which will become more often as the global climate changes (Mukherjee, Mishra, & Trenberth, 2018). Droughts have increased in frequency around the globe since the 1970s. This is because evaporation has increased but rainfall has not (Jehanzaib and Kim, 2020). In addition, slow-moving anticyclones that move over a region have an impact on its climate by disrupting the normal weather systems, which in turn affects the feedback processes between land and atmosphere by increasing the temperature, which in turn increases the moisture demand in the atmosphere, resulting in arid conditions and drought events(Mukherjee, Mishra, & Trenberth, 2018). Several analysts have predicted that the likelihood of drought in today's drought-prone areas would increase dramatically in the twenty-first century. Additionally, climate change and the associated changes in average seasonal precipitation and dry spells owing to different emissions are predicted to increase summer aridity in mid-latitudinal portions of the continents, notably in the Northern Hemisphere (automobile, industrial, etc.). As proven by research (Arnell, 2008). The Palmer Drought Severity Index (PDSI) and others have forecast a xeric trend that may worsen throughout the twenty-first century, with especially severe aridity expected across the United States, the Amazon Basin, southern Europe, eastern Asia, and northern Africa. Furthermore, it was predicted that both the proportion of land and the frequency with which severe droughts occurred would double by the end of the twenty-first century (Arnell, 2008). However, various indices anticipate different percentage changes in the area that would be negatively impacted by drought as a result of climate change. For instance, the Palmer Drought Severity Index (PDSI) predicts a rise from 25% to 80% in the proportion of the region experiencing drought severity, whereas indices evaluating the availability of soil moisture predict a range from 10% to 55%. Those findings may be seen in (Arnell, 2008). As a result of climate change, it is predicted that the return period of hydrological drought in south-eastern and southern Europe will decrease to ten years or less by the 2070s, from an average of one hundred years. Furthermore, it is predicted that between 670 and 1,500 million people living in drought-prone, water-stressed regions will experience a deficiency in water availability by the 2050s (Arnell, 2008). Drought and climate change tend to go hand in hand in certain ways, but in others, the connection is less clear and may be studied independently. To provide one concrete example, as a result of human-caused global warming, precipitation is expected to drop in the Mediterranean area in the future and has already reduced throughout the region over the 20th century. Warm temperatures since the turn of the century have reduced precipitation below average across much of North Western America, leading to the Pacific North Western drought of 2015; the Colorado River Basin experienced drought conditions in 2000 and 2012 due to a seven per cent decline in streamflow over the past thirty years as a result of riverine erosion (Cook, Mankin, & Anchukaitis, 2018). The term "flash drought" was used to describe droughts that emerge and deepen fast, with little or no previous warning, due to precipitation shortage and high evaporation demand; consequently, flash droughts are intimately related to climate change (AghaKouchak, Rad, Navari, & Sadegh, 2021; Cook, Mankin, & Anchukaitis, 2018).

1.4.6 Monsoon and Drought

Drought is linked to abnormalities in the monsoon. For example, a low or late monsoon could reduce the amount of rainfall, which would cause a meteorological drought, Hydrological drought would worsen if rainfall was not sufficient to replenish terrestrial water storage (TWS) (Jiang et al., 2017). There are seven areas where the monsoon prevails: The agricultural civilization of Asia relies heavily on the monsoon rains that occur during the I East Asian monsoon, the II South Asian monsoon, the III Southern and Northern African monsoon, the IV South American monsoon, the V Southwest U.S. and Mexican monsoon, and the VI Australian monsoon (Chang, 2011). D'Arrigo et al. , 2006 found that El Nino Southern Oscillation and the Indian Ocean Dipole (IOD) are mostly responsible for monsoon failure or weakening (ENSO). Changing sea surface temperatures and thus changes in rainfall patterns are triggered by the El Nino Southern Oscillation (ENSO). This is accomplished by an east-west shift in the Walker Circulation (Fan, Dong, Fang, Xue, Zheng, & Zhu, 2017). El Nino's poor monsoon circulation in Southeast Asia and the Indian subcontinent, along with subsidence irregularities that cause moisture loss, ultimately leads to a long dry spell, that has affected most of Southeast Asia, Indonesia, and India. Weak monsoons in South Asia, subsidence and diverging anomalies in Indonesia, and a decrease in precipitation are all outcomes of the interaction between El Nino and the Indian Ocean Dipole (Ummenhofer, D'Arrigo, Anchukaitis, Buckley, & Cook, 2013). El Nino Southern Oscillation (ENSO), decadal timeframes, interannual timeline variability of the Pacific Ocean, the Pacific Decadal Oscillation (PDO), and the Interdecadal Pacific Oscillation have all been related to shifts in the location and intensity of the monsoon system (IPO). In addition, the Palmer Drought Severity Index (PDSI) attributes the worst droughts in Asia to El Nino Southern Oscillation (Fan, Dong, Fang, Xue, Zheng,

& Zhu, 2017; Ummenhofer, D'Arrigo, Anchukaitis, Buckley, & Cook, 2013). In addition, the sea surface temperatures (SST) of the Indian and Pacific Oceans, the melting of snow cover in the Eurasian region, and the availability of soil moisture all contribute to fluctuations in the monsoon, which in turn affect the hydrological system and influence the amount of precipitation, leading to dry spells and drought in Asia (Ummenhofer, D'Arrigo, Anchukaitis, Buckley, & Cook, 2013).

1.4.7 Droughts in India

Around fifty per cent of the world's most populated areas are at risk of drought, and many of those areas contain important agricultural fields. (USDA Report, 1994).The economy of our country is predominantly agricultural. This industry directly employs over sixty-five per cent of the Indian population and accounts for sixteen per cent of the country's GDP. Since the middle of the twentieth century, India has experienced widespread and prolonged droughts in successive years, and this trend is causing great concern. This is especially true given India's reputation as one of the most drought-prone countries in Asia and the world at large (Mishra and Singh, 2010). The majority of India's drought-prone regions are concentrated in the country's peninsular regions. India has a total geographical area of 3.28 million km2, of which around 1.07 million km2 of land experiences varying degrees of water stress and drought intensity. Previously, India experienced 24 megadroughts in the years 1891, 1896, 1899, 1905, 1911, 1915, 1918, 1920, 1941, 1951, 1965, 1966, 1972, 1974, 1979, 1982, 1986, 1987,1988, 1999, 2000, 2002, 2009, and 2012, with speeding up regularity between 1891 and 1920, 1965 and 1990, and 1999 and 2012, with the latter period experiencing fourteen drought events, resulting in an economic loss of 2441 US million dollars and negatively (Ray, Sesha, & Chattopadhyay, 2015).Meteorological drought in India is defined by the Indian Meteorological Department (IMD) as a condition in which rainfall deficiency in a sub-division is twenty-five per cent or higher concerning the LTA or long-term average for that specific period in that sub-division. Twenty-six per cent to fifty per cent deficit conditions are considered "moderate," and more than fifty per cent deficiency is considered "severe."Agricultural drought in India, besides, refers to a period of concomitant decrease in precipitation accounting for a percentage greater than fifty per cent of LTA (long-term average) or less than 5 mm per week during the Kharif season, i.e., from mid-May to mid-October for four consecutive weeks when eighty per cent of India's total agricultural crop is sown, or such six consecutive weeks for the rest of the months of the year (Ray, Sesha, & Chattopadhyay, 2015). Drought in India is mainly caused by weak or failed monsoon rainfall, which can be related to changes in climate or meteorological volatility such as El Nino Southern Oscillation (ENSO), with eleven out of twenty-one droughts occurring during El Nino years between 1871 and 1988 (Shah & Mishra, 2020). Drought impacts around fifty million Indians each year, accounting for approximately eighteen per cent of the total land area in India (Shah & Mishra, 2020). It is possible to discuss the incidence and possibility of drought in various parts of India in the following ways - In the north western part of India, there is a one in five chance of a moderate drought and a one in twenty chance of a severe drought; in the west-central part of India, there is a five in twenty-six chance of moderate drought and a one in eight chance of a severe drought; and in the peninsular part of India, there is a three in twenty-five chance of moderate drought and a one in eight chance of a severe drought. It is estimated that (iv) in the central northeast region of India, moderate drought has a sir per cent to thirty-seven per cent chance of occurring and severe drought has a one per cent to ten per cent chance, (v) in the northeast region of India, moderate drought has one per cent to twenty-six percentage chance of occurring and severe drought has one per cent to three percentage chance, and (vi) in the hilly region of India, moderate drought has a nine per cent to fifteen per cent chance of occurring (Ray, Sesha, & Chattopadhyay, 2015). As can be seen in the table below, the frequency of precipitation deficits varies across India and is not constant.

Table 1.1: The Rainfall Deficiency Frequency in Different Locations in India

Regions	Frequency of Rainfall Deficiency (75% or less)
Assam	Extremely rare, once in every 15 years
West Bengal, Odisha, Bihar, Madhya Pradesh and Konkan	Once every 5 years
South Interior, Vidarbha, Eastern Uttar Pradesh and Karnataka	Once every 4 years
Gujarat, Western Uttar Pradesh and Eastern Rajasthan	Once every 3 years

Tamil Nadu, Telangana and Jammu and Kashmir	Once every 2.5 years
West Rajasthan	Once every 2 years

Source: Ray et al., 2015

Prolonged arid conditions and the total number of dry days in India have increased by 5.6 2.38% and 3.7 1.92%, respectively, while prolonged arid conditions in the western and north-eastern portion of India have increased by 6.2 3.17% and 7.8 4.30%, respectively, also, the proneness to severe drought in India is increasing, especially in the western and north-eastern portions of the country (Mishra & Liu, 2014) addition, numerous studies have shown that, between 1951 and 2010, the average number of dry days in India rose by about 24.42 per cent, the average number of dry days rose by about 36.26 per cent, and the average number of dry days rose by about 39.22 per cent in the western region and 51.06 per cent in the north-eastern region. Additionally, the likelihood that India will experience severe drought conditions rose by about 54.76 per cent (Mishra & Liu, 2014). More than 50 peacocks died in Morena district, Madhya Pradesh in 2013 and 16, respectively, from the effects of drought; deaths of amphibians and avifauna were also reported as a result of the summer drought; migration motivated by drought was also observed, with, for instance, 600 out of 800 residents of Damoh district, Madhya Pradesh moving to Jabalpur because of water shortages (Kala, 2017). Drought in India may be prevented via activities such as water harvesting, river interlinking, and efficient water storage (Kala, 2017). It's impossible to anticipate where or when a drought may strike. There would be a correlation between the frequency, intensity, volume, and duration of the rainfall and the prevalence of drought in any given location. Droughts affect a significant proportion of India's farmland, however, this trend is expected to reverse over time. Successful management of unforeseen drought scenario requires constant monitoring of drought patterns, intensities, and probability.

1.4.8 Droughts of Odisha

According to (Ray-Bennett & Nibedita, 2009), the districts of Nuapada, Koraput, Kalahandi, and Bolangir in Odisha are particularly susceptible to drought because of the state's location and the climatic variations that it experiences. Drought is one of the most prominent natural disasters that the state experiences overall. It has been documented that the state of Odisha had periods of drought in the years 1841-42, 1942-43, 1849-50, 1850-51, 1954-55, 1965, 1966, 1967, 1979, 1984, 2000, 2002, and 2003 (Sarangi & Penthoi, 2012). The dry spell lasted for 89 days as a result of which 99 blocks and 29 blocks out of 314 blocks encountered a deficit in rainfall between 50% to 75% and 50% respectively which consequently led to soil and atmospheric moisture stress. In 2010, a deficiency in mean rainfall was recorded during June, July, August, and September; the deficit accounted for 30.6%, 14.4%, 20.2%, and 1.7% respectively throughout the four months; and the dry spell lasted for (Annual Report on Natural Calamities, Government of Odisha , 2010-2011). In the year 2010, the state government of Odisha declared that 17 districts, including Angul, Balasore, Bargarh, Bhadrak, Bolangir, Boudh, Deogarh, Dhenkanal, Jaipur, Jharsuguda, Kendrapara, Keonjhar, Mayurbhanj, Puri, Sambalpur, Subarnapur, and Sundargarh, along with 10,674 villages, were affected by drought and had suffered a loss (Annual Report on Natural Calamities, Government of Orissa, , 2010-2011). In 2011, during June, July, and up to the 16th of August, 15 districts comprising 31 blocks received less than 50% of rainfall. This resulted in a condition of moisture stress in the paddy cultivation, and there was no probability of crop revival in these blocks. In addition, 15 districts received more than 50% of rainfall(Annual Report on Natural Calamities, Government of Orissa, 2011-2012). In 2011, the state government of Odisha declared 21 districts to be affected by drought. These districts included Angul, Bargarh, Bhadrak, Bolangir, Boudh, Cuttack, Dhenkanal, Gajapati, Ganjam, Jharsuguda, Kalahandi, Khordha, Koraput, Malkanagiri, Nabarangapur, Nayagarh, Nuapada, Rayagada, Sambalpur, Subarna(Annual Report on Natural Calamities, Government of Orissa , 2011–2012). Above 59% deficit in rainfall was observed in 25 blocks, rainfall deficit varied between 40% and 59% in 63 blocks, and rainfall deficit varied between 20% and 39% in 83 blocks, thus a rainfall deficit of 26.1% was observed in Odisha in 2012. The scarcity accounted for 18.7% up to the 15th of July, and the total reduction in rainfall for the months of June and July accounted for 22.8%. In addition, 21 districts in Odisha experienced either a severe deficit or a deficit of rainfall(Annual Report on Natural Calamities, Government of Orissa , 2012-2013). Although the rainfall deficit decreased slightly after the 16th of July, it was still observed that on the 31st of July, a deficit of more than 19% of rainfall was observed in 171 blocks, among which above 59% deficit in rainfall was observed in 13 blocks, rainfall deficit varied between 40% and 59% in 13 blocks, rainfall deficit varied between 20% and 39% in 43 blocks, and therefore a total of 128 blocks spanning over 27 districts experienced above 19% rainfall deficit for the months of

June and July in the state of Uttar(Annual Report on Natural Calamities, Government of Orissa , 2012-2013). In the most recent drought year, 2015-16, conditions of drought were present in 26 of Odisha's 30 districts (Patel, 2018). It has also been observed that the majority of droughts in Odisha occurred during pre and post-monsoon periods and that droughts with a duration of above six months within a year took place at a frequency of 13.6%, 27.2%, and 43.1% in Koraput, Kalahandi, and Bolangir district respectively during the period of more than four decades (1960-2003). Both of these observations were made in Odisha(Kar, Chandra, & James, 2007). In addition to this, the number of drought years was three (6.8%), six (13.6%), and eighteen (40.9%) for the districts of Koraput, Kalahandi, and Bolangir, respectively (Kar, Chandra, & James, 2007). As an agrarian economy, Odisha is primarily dependent on rainfall for the production of agriculture; nevertheless, a lack of rainfall and circumstances of drought are rendering Odisha's agricultural output a setback, which in turn leads to social and economic instability (Patel, 2018). The lack of water resources has harmed the yield of pulses, vegetables, and most importantly paddy, which has resulted in economic hardship for the cultivators due to a decline in productivity. Additionally, the small, marginal, and poor cultivators have in some cases failed to cater to the necessities of food, nutrition, health, and education, which has made the people economically vulnerable. For example, in 2009, as a result of drought conditions, the sowing area of Kharif crops was reduced by approximately (Annual Report on Natural Calamities, Government of Orissa , 2009-2010); (Patel, 2018). The population of Odisha, in particular the tribals and economically weaker sections, are more susceptible to the occurrence of drought. For example, the droughts that occurred in 2009, 2010, and 2012 affected more than one million people residing in fifteen districts of Odisha. This population primarily consisted of tribal people (mostly belonging to Scheduled Tribes and Scheduled Castes) who lived in the western part of the state. In addition, due to crop failure and consequent unemployment, more than one million people lost their jobs(Annual Report on Natural Calamities, Government of Orissa, 2009-2010). The population of Odisha that was impacted by the drought also suffered from a variety of illnesses that were brought on by the lack of available water, including dysentery, diarrhoea, starvation, anaemia, scabies, jaundice, renal failure, blood cancer, and other conditions (Annual Report on Natural Calamities, Government of Orissa, 2009-2010; Patel, 2018). Food was distributed at a reduced cost through the public distribution system (PDS), examination and school fees were waived for students living in drought-stricken areas, and subsidies were offered on agricultural inputs. These are just some of the measures that the government of Odisha took to combat the numerous challenges that were faced during the drought. Other measures included providing subsidies on agricultural inputs; (ii) converting loans with short terms to loans with medium terms during the Kharif season in drought-stricken regions; (Annual Report on Natural Calamities, Government of Orissa, 2012-2013). Additionally, management strategies such as crop replacement by drought-tolerant and resistant crops, soil nutrient management in an integrated manner by using inorganic and organic fertilisers, rainwater harvesting and mixed cropping, cover cropping, and intercropping might be adopted to reduce the severe consequences of drought on the social, economic, and environmental aspects of Odisha (Kar, Chandra, & James, 2007).

Drought means acute water shortage which results from the failure of rain. The coming of the Monsoon is uncertain in Odisha. So, most of the year, Odisha suffers from drought ravage. In 1866 a terrible drought took place all over Odisha. It caused the death of one-third of people. So, the Government made a canal system in Odisha. From that time the ravage of drought does not seize the whole of this land. But the parts outside the canal facilities are hit hard by drought when it breaks out. These parts of Odisha are generally the districts of Mayurbhanj, Kalahandi, Bolangir, Boud, Phulbani, Sundargarh and Sambalpur.

The drought-affected year is identified from news, government report, and annual report of agricultural and disaster management agencies. The major drought-affected years (between 2001-2020) are listed below:

2002, 2009, 2010, 2013, 2015, 2020

In 2002, Odisha state received 60% less rainfall compared to normal in the month of July which is the lowest rainfall in the last 40 years. The Kharif crop production was highly affected and 68% damage to the paddy crop happened. 4.2 million hectares of agricultural land were affected due to drought in 2002.

A severe drought hit the state in 2009 as a result of the monsoons' unpredictable behaviour, which showed up as spotty and insufficient precipitation. Around June 10 is when the monsoon typically begins in Odisha. Although the India Meteorological Department had predicted a near typical South-west monsoon season for 2009, it failed to materialise until late June or early July, causing a protracted heat wave. There was a 60.6% shortfall in June precipitation in the State. After a disappointing June, the Southwest monsoon returned in July 2009, but its spatial distribution over the state was far from ideal.

July 2009 had a 77.3% increase in rainfall than normal. Precipitation was 93% over average until July 21st, then 63% below average beginning with the 22nd. The pattern of below-average precipitation, which began on the 22nd of July, persisted through August and September. About 20.3% less rain fell than normal in August 2009. Not everything in the state was on the monsoon's axis in September. Due to the influence of low pressure over the North-West Bay of Bengal, five districts, including Cuttack, Jajpur, Kendrapada, Balasore, and Bhadrak, had more precipitation compared to the average. A total of 24.5% less precipitation than average fell throughout the state, with the remaining districts seeing even larger decreases (Sate Annual Report).

Due to low rainfall, drought hit 15 districts of Odisha in 2010. In response to farmers' crop losses, the government paid them compensation. Up till the end of September 2013, it was determined that 10,440 villages across 15 districts in Odisha were impacted by the drought. More than half of the paddy crop was destroyed because of the lack of rain. Odisha's agriculture-based economy suffered greatly as a result of the drought.

From the beginning of the monsoons to the end of September, Odisha got a total of 1,120 mm of rain. However, the weather takes a drastic turn in October, with the state receiving at least 220 mm of rainfall compared to the typical rainfall of 74 mm, a tremendous 195 per cent extra rainfall. For the first three weeks of August 2013, the state experienced insufficient and little precipitation. According to the state's hydrology statistics compiled by the Indian Meteorological Department (IMD), the deficit increased to 68% by the end of August (Source: DownToEarth).

Drought conditions and a crop loss of almost 33 per cent on over-cultivated land of 5.23 lakh hectares resulted from a 14% shortfall in rainfall in the state in 2015. According to historical data, the state typically gets rainfall of 1,120 mm during the monsoon season (June–September), however this year, the actual precipitation was just 1,031 mm. The greatest percentage of rain shortfall, at 21.

Unreliable precipitation in different regions led to the drought. All districts except Balangir, Boudh, Balasore, Bargarh, Deogarh, Kalahandi, Koraput, Gajpati, Ganjam, Malkangiri, Nabrangpur, Rayagada, Nuapada, Subernapur, and Sambalpur began to have insufficient rainfall in June. There was a lack of precipitation in most of the state in July.

The only exceptions were the districts of Bhadrak, Deogarh, Balasore, Dhenkanal, Jagatsinghpur, Jharsuguda, Kendrapara, Jajpur, Mayurbhanj, and Sunderghar.

In 2020, 26 districts out of 30 districts in the Odisha state barring Koraput, Khordha, Jagatsinghpur and Malkangiri recorded deficient rainfall of 20% or more. Jajpur district was the worst affected which received 54% less rainfall. The paddy crop was highly affected due to the prolonged dry period.

1.5 Identification of Research Gap

Attempts have been made to model the drought dynamics using the Geoinformatics technique by various researchers using different methodologies. But it has been found that the applicability of Geoinformatics to model the drought dynamics in the coastal states, particularly in Odisha is need to be analysed further. The robustness of the methodology for different cropping seasons has to be analysed holistically. Most of the previous research has tried to detect the drought using optical satellite data, but in the coastal area, due to frequent cloud conditions, it is required to test the applicability of SAR data for the detection of drought-affected areas. The effect of EL Nino and IOD on the coastal drought of Odisha also needs to be studied further. For regional scale drought analysis, researchers have used coarse-resolution satellite data / spectral indices, however, studies need to be carried out to downscale the drought map for regional/local scale drought mapping. Another important aspect is drought modelling and predictive analysis. There is a large scope to carry out long-term drought modelling and predictive analysis. The research will be helpful to use the remotely sensed routinely available open source data for local/ regional scale drought modelling and monitoring.

1.6 Expected Outcome

- A methodology for mapping drought dynamics.
- Map of drought-affected areas
- Estimation of drought intensity, severity and spatial pattern
- Mapping of drought frequency
- Relationship and trend between drought and the climatic parameters
- Downscaled drought map for deriving field-scale agricultural drought information
- A modelling framework for the prediction of a future drought situation

- A micro-level study for detecting drought using SAR data

1.7 Overall Methodology

The entire methodology of the study is divided into three parts; data collection and pre-processing, drought modelling using geoinformatics and predictive model development. The study is carried out using various types of satellite and climatic datasets. Pre-processing includes calibration, correction, calculation of spectral indices and resolution matching etc. The process data is used for modelling of drought dynamics of Odisha state, building the relationship with climatic parameters, carrying out the Spatio-temporal modelling, downscaling the drought map and finally developing predictive modelling.

The overall methodology/flow of the study is given in Figure 1.1.

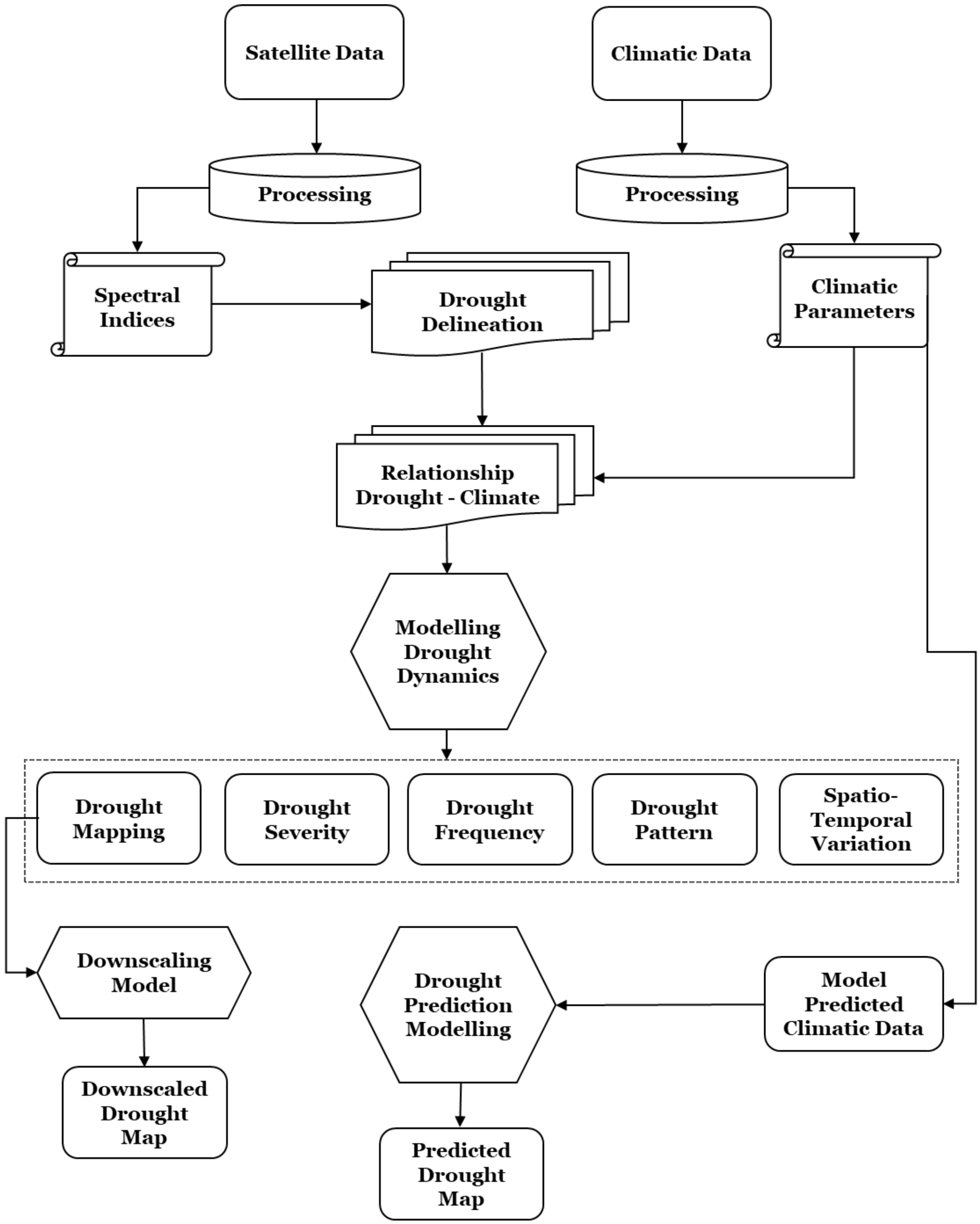


Figure 1.1: Flowchart of the overall methodology

1.8 Structure of the Thesis

This thesis is organized into nine chapters which are Introduction, Objectives, Study area and datasets, Drought dynamics in Odisha, Cause of drought in Odisha, Downscaling of drought map, Modelling of draught dynamics and future drought scenario prediction, Micro level drought assessment technique using SAR data, and Conclusion and recommendation.

Chapter one discusses the background of the research. It reviews the present drought scenario, concisely covers the requirements of drought dynamic modelling, and briefly reviews the existing literature on this subject. The chapter also describes the research problem in detail, research gaps and justification for the research. It also briefly gives an overview of the overall methodology and a gist of the thesis structure.

The second chapter describes the specific objectives of the research. It also includes the research questions behind these objectives.

The third chapter describes the details of the study area and its physical and cultural settings. The chapter also describes the overview of the economy of the state. In this chapter details about the datasets used in the study are also described.

Chapter four covers drought scenarios and modelling of drought dynamics it includes spatial pattern, frequency etc. The chapters also describe the Spatio-temporal analysis of drought.

The fifth chapter covers the cause of drought in Odisha state, it highlights the agricultural drought scenario due to rainfall and temperature variability, EL-Nino and IOD situation etc.

The sixth chapter describes the methodology of downscaling drought maps and their utility for regional-scale drought mapping.

The seventh chapter presents the modelling of draught dynamics and future drought scenario prediction, as short-term and long-term drought prediction.

Eight chapter covers micro-level drought assessment using SAR data. It describes the methodology of detecting drought from SAR data.

The ninth chapter: The thesis's findings and recommendations are presented in Chapter 9, along with suggestions for how and where the line of inquiry may be explored scientifically in the future. Furthermore, the report details the study's aims and the constraints that were encountered throughout its execution. Finally, suggestions for further study are provided.

2 Objectives

To raise new questions, new possibilities, to regard old questions from a new angle, requires creative imagination and marks real advances in science.

- *Albert Einstein*

2.1 Introduction

Drought is generally considered as an effect of less than normal rainfall, it can also be related to soil moisture, groundwater level, evapotranspiration and vegetation health. Droughts could potentially lead to scarcity of water, hampering agricultural growth and output, and extremities like famine. Drought could have an adverse effect on agricultural, socioeconomic and financial sectors, especially in developing countries like India, where almost 68% population are dependent on agriculture. In the era of climate change, an increase in surface temperature (IPCC, 2001) and modification in the hydrological cycle will increase extreme events like floods and droughts which may hit a country or state economy negatively.

Severe drought events hit India many times such as 10 drought years between 1950 and 1990, and 6 drought years between 2002 and 2016. In India drought happened due to variation of decreased monsoonal rainfall resulting from climatic variability, along with El Niño events and high sea surface temperature in the Indian Ocean. Moreover, changes in climatic parameters associated with changes in global precipitation pattern, increasing evaporation rates resulting from high land surface temperature and decrease in weak precipitation days might increase the frequency of drought events in India. Approximately 68% of agricultural land in India are vulnerable to drought. The drought frequency of Odisha state is once in three years. Despite of coastal location, Odisha state affected by drought severely in many times. To identify the agricultural drought dynamics, its pattern, spatio-temporal variations and cause, long term analysis of drought with the help of remote sensing and climatic data is essential. It will help the decision makers and planners to take the appropriate measures and implement the policy for the state. This will also help in applicability of open-source Earth Observation Satellite data for regional – field scale drought and soil moisture mapping and related applications.

2.2 Research Questions

Q1) Can we map the agricultural drought dynamics using geoinformatics?

Q2) How the Odisha state can be divided as per drought severity? Is it possible to detect the agricultural drought through spatio-temporal analysis?

Q3) Can we identify district wise pre-monsoon, post-monsoon and winter agricultural drought affected areas in Odisha state?

Q4) What are the cause of drought in Odisha state?

Q5) Can we downscaling of satellite data for deriving of regional to field scale drought and soil moisture map?

Q6) What is the optimal resolution to downscale the drought and soil moisture map for regional to field scale drought and soil moisture mapping?

Q7) Can we predict the future drought scenario through geospatial modelling?

Q8) Is it possible to detect the agricultural drought affected area using SAR data?

The objective is multi-fold with modelling of drought dynamics, identify the cause of drought and predictive analysis.

2.3 Objectives

The objectives of the study are following:

The objective is multi-fold with mapping and assessment of drought dynamics, its relationship with climate extremity and modelling.

(i) Mapping of drought dynamics using Geoinformatics in Odisha state.

- Divide the state according to drought vulnerability based on last 20 years data analysis with the help of Remote Sensing and GIS. Mapping of drought distribution/ pattern analysis i.e., spatial and temporal distribution of drought.

- Classification and estimation of drought prone area, drought frequency/ severity mapping and identification major agricultural drought affected districts.
- Analysis of pre-monsoon, post-monsoon and winter agricultural drought pattern and identification of affected crop types.

(ii) Identification of cause of drought and relationship with climate extremities.

- Rainfall and temperature pattern analysis for last two decades and establish the relationship between drought severity with climatic factors.
- Mapping of soil moisture condition for drought severity assessment.
- Analysis of other local physical phenomena for drought assessment.

(iii) Downscaling of satellite data for deriving of field scale drought and soil moisture related information from open-source coarse resolution satellite data.

(iv) Modelling of drought for predicting future drought scenario.

(v) Micro level drought assessment using SAR data

3 Study Area and Datasets

"The world as we have created it is a process of our thinking. It cannot be changed without changing our thinking."

- Albert Einstein

3.1 Introduction

As per geographical perspective, study area referrers to the area under observation under any research which is mapped and sampled with quantitative methods to meet inferences. In this research, Odisha state is taken as study area. The state of Odisha is geographically located between 17.31°North to 22.31°North latitude and from 81.31°East to 87.29°East longitude (figure 3.1).

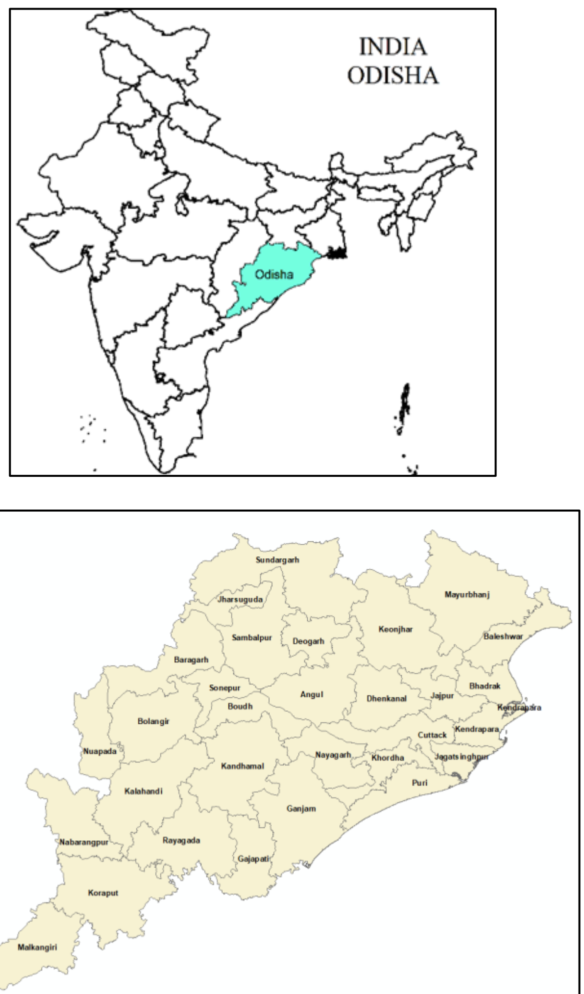


Figure 3.2: Study Area

3.2 Administrative setup

Odisha, a state in eastern India, is home to several beautiful beaches, and it is divided into thirty administrative units/ districts. These districts are under the jurisdiction of three revenue divisions to exert the state governance on them. Each District is divided into sub-divisions which are further divided into Tehsils. Odisha has three revenue divisions, thirty districts, fifty-eight sub-divisions, three hundred and seventeen tehsils and three hundred and fourteen blocks (Source: Govt. of Odisha information portal).

The state spans a total of 1,55,707 square kilometres, or roughly 800 kilometres from north to south and 500 kilometres from east to west. Odisha has a coastline on the Bay of Bengal that is about 480 kilometres in length. It occupies 4.7% of India's total land area, making it the country's ninth-largest state. Some of the most populous districts and cities in the state include Cuttack, Ganjam, Bhubaneswar, Puri, Mayurbhanj, Balasore, Sundargarh, Khordha, and Jajpur. The city of Bhubaneswar serves as the capital of the state (Source: Odisha Profile 2018, Govt. of Odisha).

3.3 History

In 1936, it was the first state that was created on a linguistic basis. Earlier, it was the part of previous Bihar. On 1st April in 1936, ultimately the Orissa state became a separate province. The Indian state of Orissa came into existence on April 1, 1936, around a decade before India acquired independence from the British colonization rule. Orissa territorial map with thirteen districts published in 1950 immediately few years later after achievement of independence with the formation of the state. Orissa was then renamed Odisha by the Parliament of Indian Republican Government on 9th November in 2010 (figure 3.2). The Oriya language was also simultaneously renamed Odia. (Source: Odisha review 1936-2011).

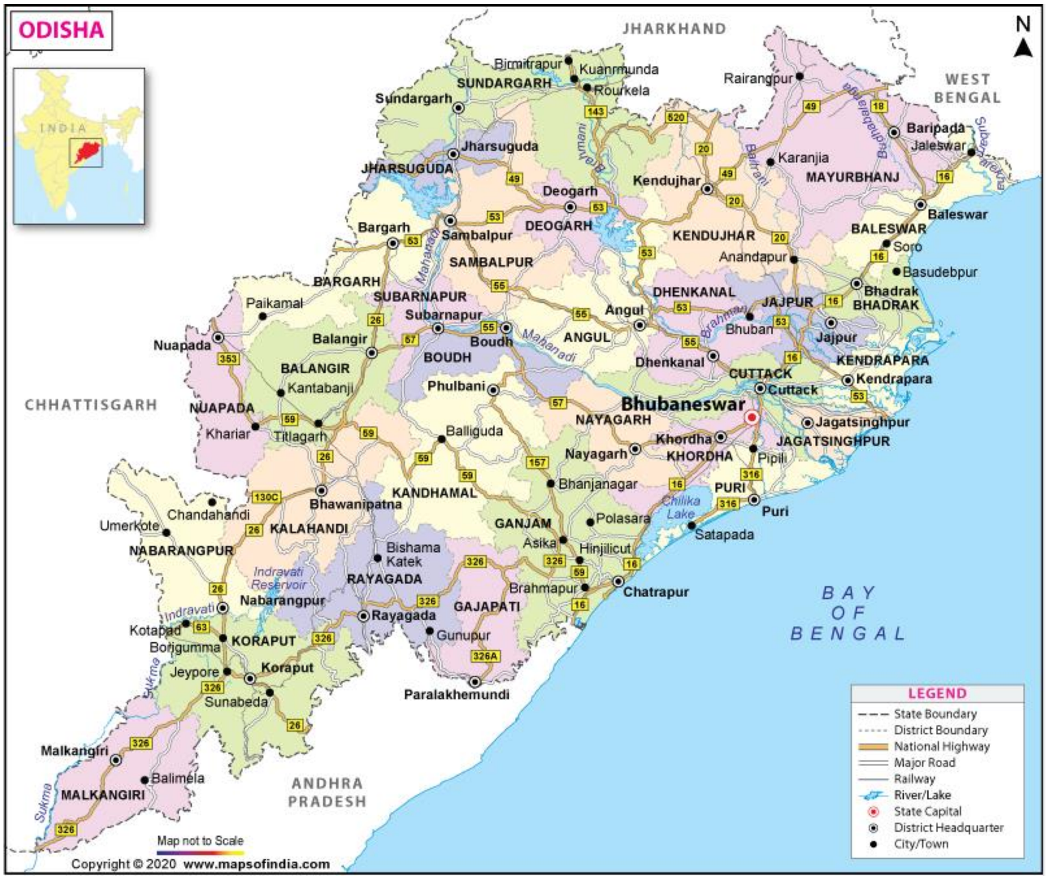


Figure 3.3: State of Odisha (Source: Maps of India)

3.4 Geological settings

The state is located on the geologically significant Indian Peninsula, an old piece of Gondwanaland. Odisha is located on the eastern edge of the peninsular India, and around 73% of the land is inhabited by Precambrian metamorphic rocks (Archaean and Proterozoic age), which contain most of the minerals. It is estimated that just around 8 percent of the region is located on the Gondwana strata, which has the coal reserves. The remainder of the region is comprised of Tertiary and Quaternary rock layers (figure 3.3), which act as conduits for heavy metals and aluminous laterites. About three-quarters of Odisha is covered by the state's mountainous and hilly terrain (Source: Odisha Profile 2018).

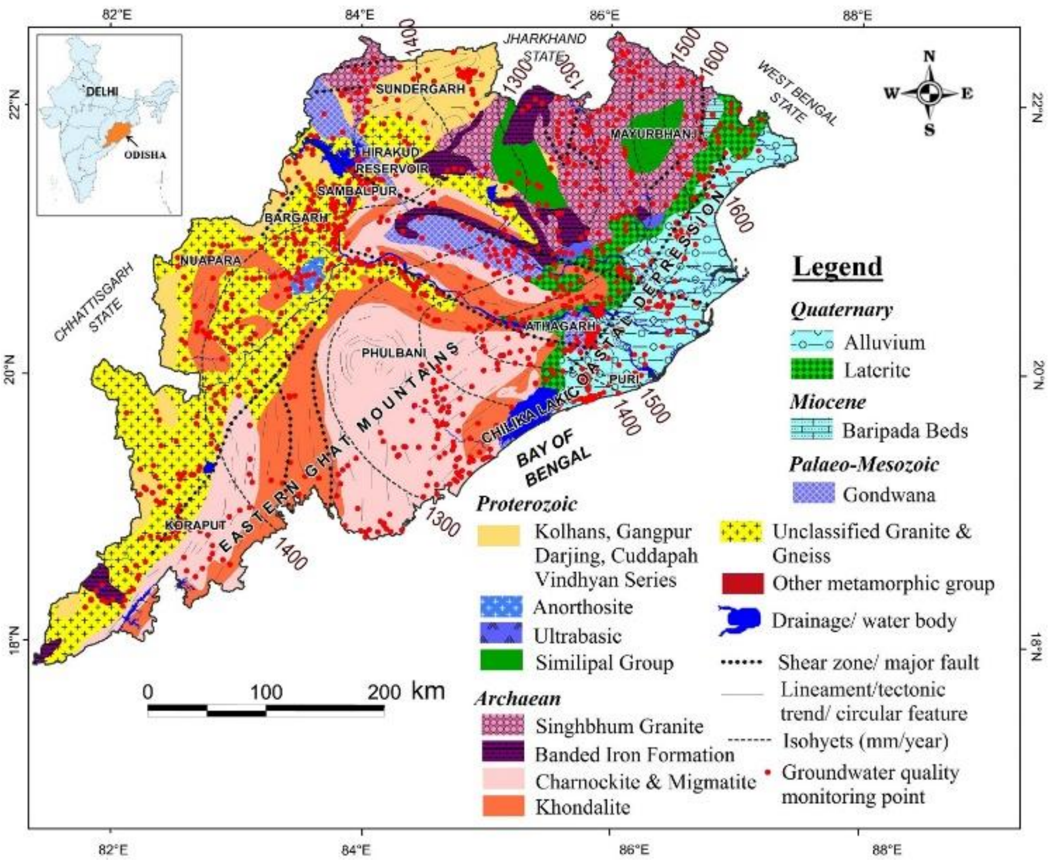


Figure 3.4: Geological formations of Odisha (Source: CGWB 2021)

3.5 Geological formations

According to the age of geological formations of rock strata as well as their typesare divided into three major types i.e. Proterozoic, Archaean and Quaternary. In the Proterozoic system, the major rock series are Cudapah-Vindyan series, anorthosite, ultrabasic and simplipalgroup. The Archaean system cinsists of singbhumgranite, banded iron formation, charnockite, khondaliteandmagmatite. In the Quaternary system, there are alluvial and laterites, baripda beds of miocene epoch and Gondwana seam of paleo-mesozoic era. Besides a large part of western part of Odisha consists of unclassified granite and gneiss.

3.6 Mineral resources

Because it is located on the peninsular plateau, the state is rich in natural resources. The state has abundant supplies of coal, iron ore, chromite, dolomite, bauxite, limestone, fireclay, manganese, graphite, china-clay, nickel, gemstones, and quartz. The State

Directorate of Geology has made a recent discovery of diamond deposit in the Nuapada district's Dharambandha region.

The state's mineral processing sector has made it a centre for manufacturing. Because to its advantageous geological configuration, the state has an abundant mineral endowment. The majority of Orissa's minerals are preserved in the Precambrian metamorphic rocks that cover around 72.5% of the state.

Iron, manganese, and gold are concentrated in the bands of metasedimentary rocks within the Archaean strata found in northern Odisha. Plutonic rocks such the granite, gneisses, migmatite, and mafic/ultramafic intrusive of the Singhbhum, Bonai, and Mayurbhanj regions are also included here. The majority of the state's coal is found in the Mesozoic rocks of the Gondwana main group. Alluvial sediments, ash beds, and low-level laterites, all of which date back to the Cenozoic Era, may be found in the eastern coastal plains, opening up pathways for the occurrence of minerals and construction materials in the sands of the beach. The oil and gas deposit is located in deltaic fans that extend into offshore areas.

3.7 Hydrogeology

The hydro-geological classification of the state may be broken down into consolidated, semi-consolidated, and unconsolidated formations due to the wide variety of rock ages present underneath the state. Semi-consolidated formations contain worn and friable Gondwana sedimentary rocks and weakly cemented baripada beds, whereas consolidated formations are made up of hard crystallines and compact sedimentary rocks. Laterites and recent alluvium are preserved in the unconsolidated strata. The yields of tubewells tapping into granite and gneiss are between 10 and 35 m3/hr, whereas the yields of tubewells tapping into other consolidated formations are between 5 and 18 m3/hr. Semi-consolidated formation tubewells typically produce between 20 and 115 m3/h. (Source: CGWB, 2021).

3.8 Climate

High temperatures, a moderate to high quantity of rainfall, high humidity, and brief, mild winters are all hallmarks of the state's tropical climate. Many parts of Odisha have the tropical Savannah climate described by Koppen's AW climate category. As of July 1st, the whole state is often dominated by the south-west monsoon, which typically begins on the coastal plain between June 5th and June 10th. The south-west monsoon leaves the state entirely by October 15th. These are the typical dates, however they change from year to year because of the El Nino and La Nina Phenomena. Based on "Thornthwaite's classification," Odisha is classified as "Sub humid," which indicates that the state receives insufficient winter precipitation.

3.9 Rainfall

Odisha is a state in eastern India with a subtropical climate and the three seasons of summer, monsoon, and winter. Typically, the southwest monsoon will begin to rain around the middle of June and last until about the middle of October. Spring and early summer (late March to early June) are summer months, whereas late fall (late October to early February) and winter (late December to early February) are winter months. An annual average of 1482 mm of precipitation is typical for the state. The southwest monsoon is responsible for around 86 percent of the average yearly precipitation. Rainfall in the state tends to fall in odd places and never follows a pattern. Looking at the Isohyet map of average rainfall over a certain time period reveals that the northern half of the coastline tract receives more precipitation, between 1520 and 1697 mm, on average. As one travels west, precipitation decreases from 1487 millimetres to 1211 millimetres in the districts of Angul, Keonjhar, and Kandhamal, and from the south to roughly 1221 millimetres in the districts of Gopalpur and Ganjam. In the districts of Koraput, Bolangir, Kalahandi, Sundergarh, and Sambalpur, annual precipitation varies from 1331 millimetres (mm) to 1491 mm. Extreme summer heat is experienced throughout the state, with temperatures reaching as high as 50 °C in the west and 45 °C in the east. The mornings and evenings throughout the winter months are very chilly. However, the average monthly low during the winter months varies from 18°C to 22°C throughout the state. However, the average summer monthly temperature ranges from 37°C in the west to 28°C in the south. The state often has a total humidity anywhere between 70% and 100%. The relative humidity in the eastern sections of the state stays relatively high during the monsoon season, whereas it drops in the western parts of the state throughout the summer. According to CGWB 2021 climate issues in Odisha experiences some notable issues from the perspective of climatic conditions as follows:

- Droughts and dry periods occur around once every two years in Western Odisha, while a serious drought occurs once every five or six years due to the state's highly variable rainfall.
- Some devastating inundation during rainy season.
- Excessive heat waves with scorching heat in peak summer season.
- Intense coastal inundation with cyclones and storm surge.

Some regions of Odisha state may experience heavy rainfall and flood threats, while other portions may experience less rainfall and lengthy droughts as a result of climate change. The geographical distribution of rainfall changes, favouring already flood-prone coastal zones (figure 3.4) while already water-deficient regions become much more so, worsening drought and agricultural unproductively. (ENVIS Centre of Odisha's State of Environment).

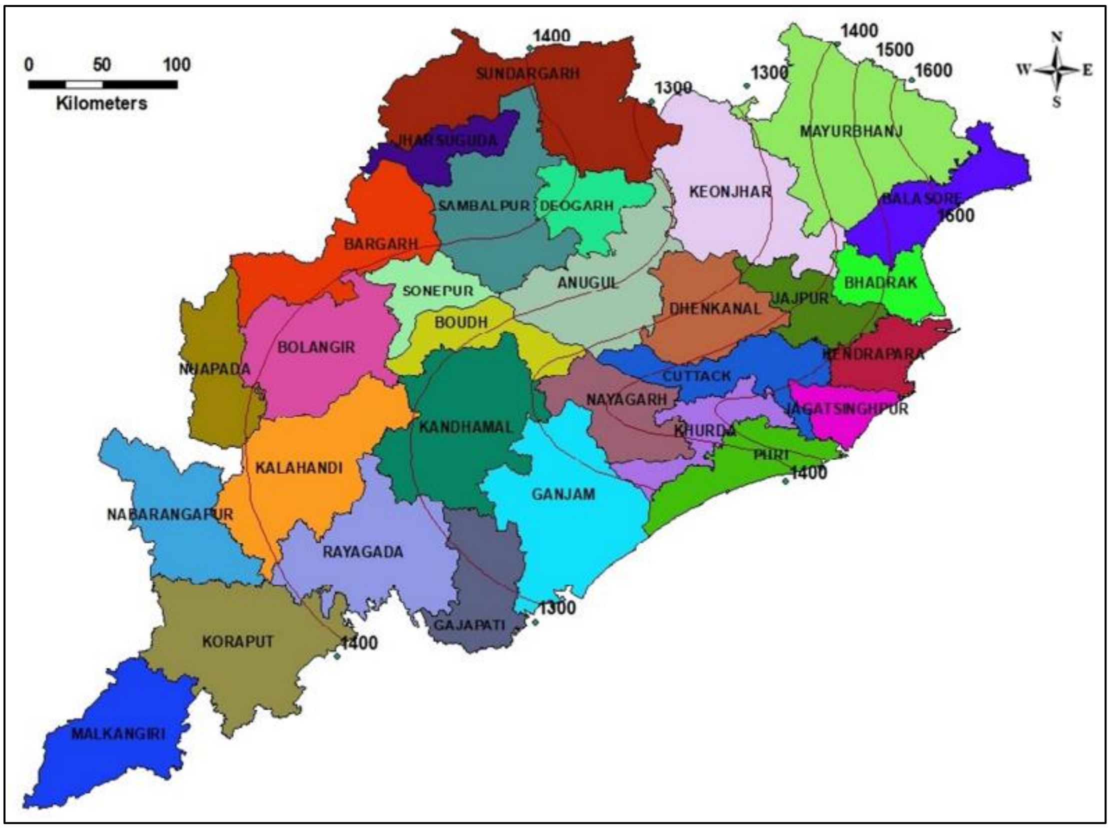


Figure 3.5: Isohyet map of Odisha (Source: CGWB 2021)

3.10 Water resources

Odisha mainly depends on the monsoon rain for its water resources. Out of 230 billion cubic metre of precipitated water a large amount is lost from evapotranspiration, a part goes to groundwaterreserve and the rest comes s surface water resources in the form of surface run off. The surface run off and the groundwater together forms the water resources of the state (figure 3.5).

3.11 Surface water resources

Odisha is home to a vast river and stream system. According to a 2001 evaluation, the state has access to an average of 82.84 billion cubic metres of surface water per year (Table 3.1). In light of the area's geology and topography, it has been determined that 65.68 BCM of surface water resources are exploitable (Source: Water Resources Overview-Odisha, 2018-19).

While not every river in Odisha is a permanent water source, those that are essential to the state's economy. Odisha's rivers are divided into four categories based on where they originate:

(i)Rivers that originate outside of the state, such the Subarnarekha, Brahmani, and Mahanadi, but ultimately empty into the Bay of Bengal (figure. 3.6).

(ii)Budhabalanga, Baitarini, Salandi, and Rushikulya are all rivers that originate inside their respective states.

(iii) The Bahuda, the Vansadhara, and the Nagavali all begin their journeys via other states before returning to their respective states' interiors as rivers.

(iv) Rivers like the Machhkund, Sileru, Kolab, and Indravati that have their origins in Odisha but ultimately feed into rivers that run through other states (Odisha Profile 2018).Table-1: Basin wise water resources, Source: Department of Water Resources of Odisha (Orissa State Water Plan – 2004).

Table 3.2: River basis statistics of Odisha

Sl. No.	Name of the River Basin	Catchment Area (Sq. Km)	Water Resources (MCum)

		Total Area	Within Odisha	% Geographical Area of State	75% Dependable	Average
1	Mahanadi	141134	65628	42.15	48732	59155
2	Brahmani	39116	22516	14.46	14011	18577
3	Baitarani	14218	13482	8.66	5434	7568
4	Kolab	20427	10300	6.61	8885	11089
5	Rushikulya	8963	8963	5.76	2782	3949
6	Vansadhara	11377	8960	5.75	3881	5083
7	Indravati	41700	7400	4.75	4451	6265
8	Burhabalanga& Jambhira	6691	6354	4.08	2521	3111
9	Nagavali	9275	4500	2.89	2322	2853
10	Subernarekha	19277	2983	1.92	2308	2308
11	Bahuda	1118	890	0.57	213	438
Draining into Sea			3731	2.4		
Total				**100**	**95540**	**120397**

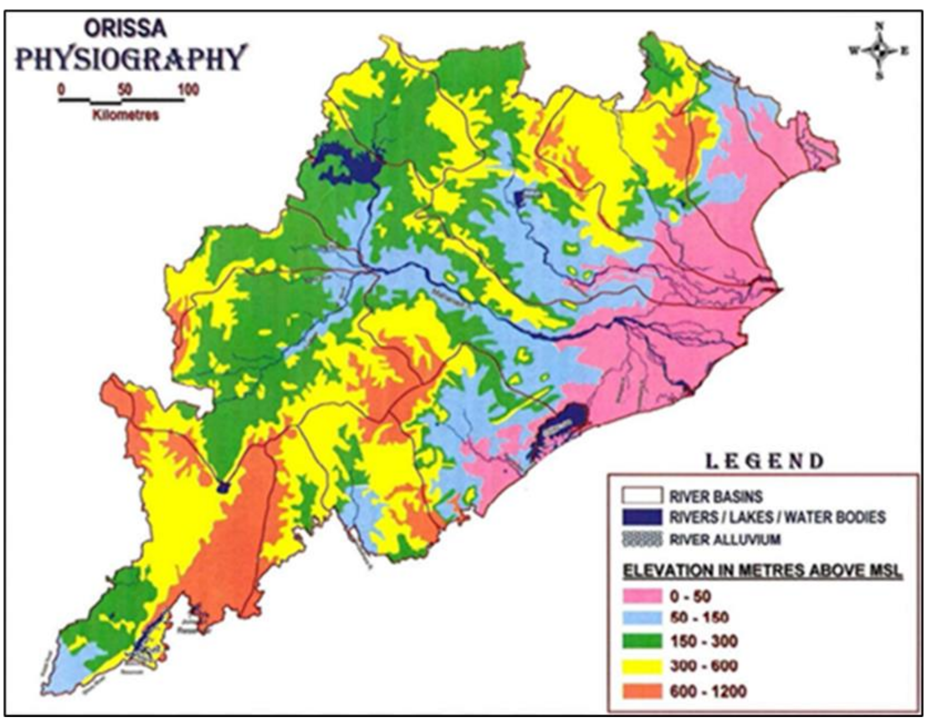


Figure 3.6: Physiography map of Odisha (Source: CGWB 2021)

3.12 Ground water resources

Majority of groundwater reserve takes place from the percolation of rain events underneath the ground. The quantum of groundwater that may be drafted every year depends on the groundwater potential. As per the assessment made by Groundwater Estimation Committee of Govt. of India, the state of Odisha has net dynamic groundwater resources of 16.69 lakh ha m (BCM).

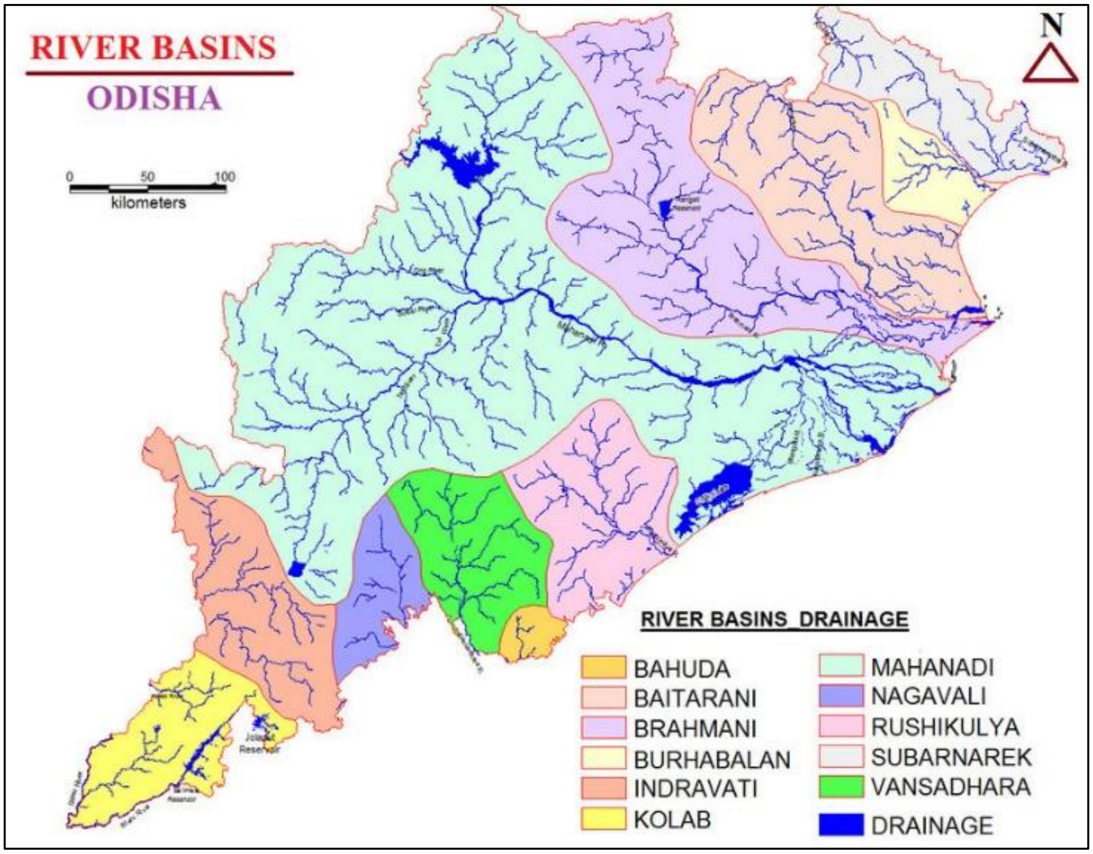


Figure 3.7: The map of Odisha showing various river basins in the state (Source: CGWB 2021)

3.13 Forest resources

The state of Odisha has extensive, diverse, and well-protected forest resources. Champion and Seth's (1968) classification of forest types categorises Odisha's forests into four broad categories, each of which is further broken into nineteen minor categories. This state has a total of around 61,204 square kilometres of forest, with a reserve area of about 36,049 square kilometres. Another 25,133 square kilometres of forest are also recorded (figure 3.7). km of woodland is designated as protected, and another 22 sq. Between 2015 and

2019, 4,968 hectares of forest in Odisha were cleared for use in other industries, in violation of the state's Forest Conservation Act of 1980. Despite this, 6,30,896 acres of plantations were cultivated in the preceding two years. The state's network of protected areas consists of two National Parks and nineteen Wildlife Sanctuaries, and together they comprise around 5.19 percent of the state's total landmass.

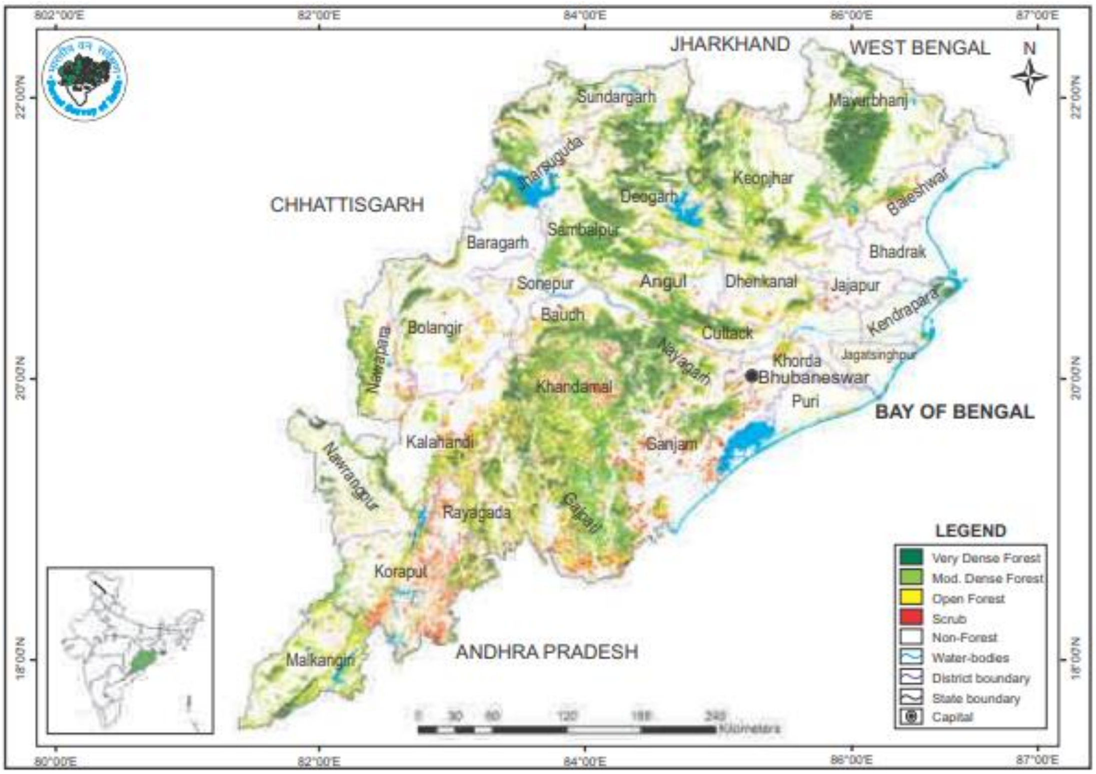


Figure 3.8: Forest cover map of Odisha (Source: India State of Forest Report-ISFR 2019)

The IRS Resourcesat-2 LISS III satellite data for 2017 and 2018 indicate that the State's Forest Cover was 51,618.51 sq km, or 33.15 percent of the State's total area. Based on forest canopy density classifications, 6,969 square kilometres of the state are covered by extremely thick forest, 21,551 square kilometres are occupied by moderately dense forest, and 23,096 square kilometres are enclosed by open forest. In the last review report published in ISFR 2017, forest cover in the state was found to have grown by 273 square kilometres (Table 3.2)as compared to the previous evaluation published in ISFR 2017.

Table 3.3:Forest Cover statistics of Odisha state (in sq. km)

Class	Area	% of Ground Area
Very Dense Forest	6,969.71	4.48
Medium Dense Forest	21,551.93	13.84
Open Forest	23,096.87	14.83

Total	51,618.51	33.15
Scrub	4,326.91	2.78

Trees outside Forests (TOF) refer to tree resources that exists outside the forests as defined in the Government records. FSI maps the forest cover of the state using satellite data and assesses tree cover outside forests also using sampling-based method. Forest cover outside the recorded forest area is derived assessing the boundaries of recorded forest areas or green wash (Table 3.3). Extent of TOF might, therefore, be estimated as the sum of extent of forest cover outside the recorded forest areas and tree cover of the area (Source: ISFR 2018).

Table 3.4: Coverage of TOF in Odisha (Square kilometers)

Forest Cover outside the RFA	**Tree Cover**	**Extent of TOF**
18,810	4,648	23,458

3.14 Soil

Odisha's soils are divided into eight major types (Fig. 3.8). There are eight major classes of soil, each of which is further divided into eighteen subgroups based on their position in one of four taxonomic orders and ten suborders. Agricultural output is limited by the unique characteristics and gaps that come with each of the major soil groups. Since these traits have been recognised, they are receiving extra focus in an effort to boost agricultural output. Below, we'll go through the characteristics of the various soil types (Source: Soil of Odisha and Its Management et.al Sahu and Mishra).

The districts of Koraput, Nawrangpur, Rayagada, Keonjhar, Kalahandi, Malkanagiri, Ganjam, Bolangir, Nuapada, Dhenkanal, and Mayurbhanj all have red soil, making up around 7.14 million hectares (ha) of the state's total land area. The soil's red hue is preserved by the presence of iron-oxides in excess. Soils in the first four districts are more heavy textured, while those in the remaining districts are more light textured. Soils continue to exhibit an angular to sub-angular blockiness. Iolites and kaolins keep the soils' clay content stable. A broad variety of crops, including rice, minor millets, potato, finger millet, brinjal, and fruit trees like mango, guava, jack fruit, papaya, etc., are cultivated in these soils.

3.14.1 Red and Yellow soil

Lands with an area of 5.5m hectares include these soils, making them the second most extensive. Sambalpur, Deogarh, Bargarh, and Sundargarh are all located in districts with these soil types. Catenary associations of undulating and rolling physiography give rise to mixed red and yellow soils that range in texture, depth, and colour. There is a moderate lack of depth, and the soils are poor in texture. Soils in the uplands are thinner and less dense than those in the lowlands. The presence of ferruginous elements and groundwater level fluctuations cause the soil to be a mottled reddish-yellow. Soil in the uplands is somewhat more acidic than soil in the lowlands. Roughly speaking, highland soils are best for growing things like rice, sugarcane, finger millet, brinjal, potato, pointed guard, and tomato. Paddy is grown as a pyra crop in the lowlands after pulses. Guava trees, mango trees, and banana trees all flourish on these grounds.

3.14.2 Black Soil

is uncommon since it only develops in certain areas. These soils occur randomly across an area of 0.96 million hectares in the districts of Puri, Malkangiri, Ganjam, Nuapada, Kalahandi, Bolangir, Boudh, Sonepur, Sambalpur, Angul, and Bargarh. Titaniferous magnetite, bitumins, and humins, generated mostly from the weathering of basic rocks in low places, give the soil its characteristic black colour. You may successfully cultivate these crops in this soil: rice, bengal gramme, jowar, bajra, maize, sunflower, cotton, and mustard.

The soils of Odisha have been classified into eight broad soil categories (Fig. 3.8). These eight broad groups of soil come under four taxonomic orders, ten suborders and further reclassified into eighteen sub-groups. Each main soil group is associated with specific characters and lacunae having constraints for agricultural productivity. As these characters have been identified, thus, special attentions are made to raise the agricultural productivity. The natures of each soil group are discussed below (Source: Soil of Odisha and Its Management).

3.14.3 Red Soil

Red soils is the largest coverage of among the soil groups of the state which covers about 7.14m ha of lands and seen in the districts of Koraput, Nawrangpur, Rayagada, Keonjhar, Kalahandi, Ganjam, Bolangir, Malkanagiri,Nuapada, Dhenkanal and Mayurbhanj. Presence of excessive iron-oxides retains the red colours to the soil. The soils of the previous four districts are with heavier texture and the rest of the districts have light textured. The soils persist of angular to sub angular blocky structure. The clay part of these soils is maintained by iolites and kaolinites. Crops like rice, minor millets, potato, finger millet, brinjal and fruit trees such as mango, guava, jack fruit, papaya etc. are grown widely in these soils.

3.14.3 Mixed red and Yellow Soil

Thus type of soil resides in 5.5m ha of area having and covers the second largest in area. These particular soils are seen in the district of Sambalpur, Bargarh, Deogarh, and Sundargarh. This type of soil is formed as a catenary association of slightly hilly to undulating and rolling physiography which varies in depth, texture, and colour. The soils are shallow in depth and the texture is coarse. The soils of upland are shallower and lighter in texture than the low land. Presence of ferruginous materials and water table fluctuation provides the mixed red and yellow colour to the soil. The soils of uplands are moderately acidic whereas soils of lowlands are slightly acidic. The soils of uplands are suitable for crops like rice, sugarcane, finger millet, brinjal, potato, pointed guard and tomato. The soils of lowlands are suitable for paddy following pulse as pyra crops. Fruit trees like guava, mango and banana grow well in these soils.

3.14.3 Black Soil

Black soils forms in isolated locations. These soils forms sporadically in the districts of Malkangiri, Ganjam,Puri, Nuapada, Kalahandi, Bolangir, Boudh, Sonepur, Sambalpur, Angul and Bargarh covering an area of 0.96 m. ha. of geographical area (figure 3.8). The colour of the soil is black and it formed due to the presence of bitumins, titaniferous magnetite, and humins which are mainly formed due to weathering process of basic rocks of the depressed areas. The soil is suitable for growing rice, bengal gram, jowar, bajra, maize, sunflower, cotton and mustard.

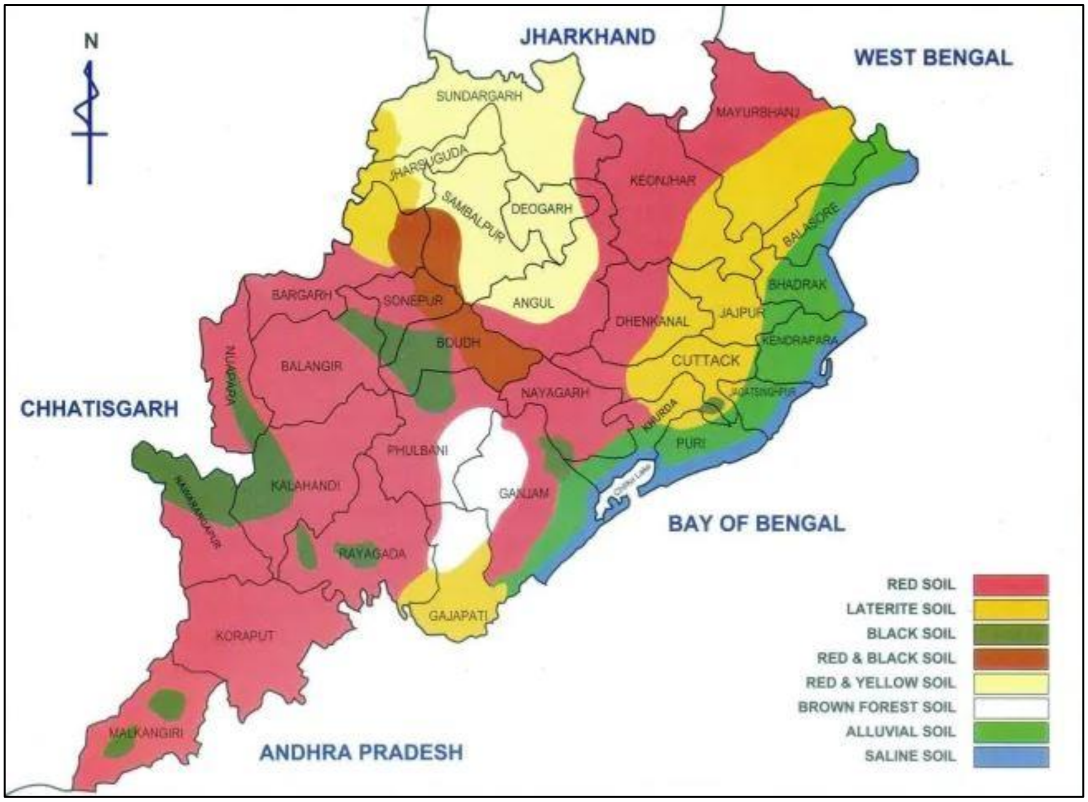


Figure 3.9: Soil map Odisha State (Source: Cereal Systems Initiative for South Asia – CSISA)

3.14.4 Laterite Soil

Lands with laterite soil may be found in the districts of Puri, Nayagarh, Keonjhar, Khurda, Dhenkanal, Cuttack, Mayurbhanja, and Sambalpur, totaling over 0.70 million hectares (ha). Lateritic soils have a compact structure and are high in iron and aluminium oxides with trace levels of titanium, manganese, and quartz. Honeycomb-shaped, degraded laterites produced in the Cuttack and Khurda areas. The top of these soils is loamy or sandy, while the subsurface is hard pan. Because of the high levels of exchangeable aluminium and manganese, the pH of this material is somewhat acidic, falling between 4.5 and 5.8. Fruits including mango, jack fruit, guava, banana, and sapota thrive in this soil along with rice, miner millets, finger millet, and sesamum.

3.14.5 Deltaic alluvial soil

These soils can be found in the districts of Balasore, Kendrapara, Bhadrak, Jajpur, Cuttack, Puri, Jagatsinghpur, Gajapati, and Ganjam, and they cover an area of 0.67m. ha. These soils are located in the deltaic portions of rivers like the Mahanadi, Baitarani, Brahamani, Subarnarekha, and Rushikullya. Depending on the geomorphology of the wet regions and the kind of alluvium, this soil's texture may range from coarse sand to clay. The soil is perfect for growing black gramme, groundnut, and green gram.

3.14.5 Coastal Saline and Alluvial Soil

Soluble salt-rich alluvial soils are listed here. Littoral deposits of estuarine incursion of brackish tidal water via streams cause the salinity. The districts of Balasore, Jagatsinghpur, Bhadrak, Puri, Kendrapara, Khurda, and Ganjam have a combined saline soil area of around 0.254 million hectares. Saline soils, like the lacustrine deposits of Lake Chilika, are high in soluble salts of sulphate and chloride in conjugation with magnesium and sodium. Subsoil salinity develops in low-lying areas during the monsoon because of an increase in ground water. Safflower, barley, mustard, linseed, sugar beet, chilli spinach, tomato, and various cucurbits are all rabi crops that thrive in these conditions. Cotton, if properly cared for, may thrive on salty soil.

3.14.6 Brown Forest Soil

About 0.17 million hectares of land is covered by the forest-associated soils found in the Rayagada, Phulbani, Kandhamal, Nayagarh, and Ganjam districts. This soil has a light texture and an acidic response, and its colour ranges from a brownish grey. The soils have an average to high amount of organic matter and nitrogen. The levels of potash and phosphate are around average. Erosion from the slope causes the soil in the affected areas to become barren and unsuitable for farming. Here, erratic cropping patterns are common and contribute to soil depletion. Mangoes, guavas, jackfruits, and citrus trees are just few of the many horticultural crops that thrive in these conditions.

3.14.7 Mixed red and black soil

The formation of these soils is linked to the presence of both red and black dirt. So thoroughly mingled are red and black soils that only the higher margins may be reliably identified as being mostly red or black. Sambalpur, Sonepur, Bolangir, and Bargarh are four western districts where one may find the soil. To put it simply, the pH of the soils is neutral and the texture ranges from fine to medium. Medium fertility characterises the deep soils. This kind of soil is common in lowlands, where zinc is in little supply. These soils are ideal for growing rice, sugarcane, ragi, maize, sesamum, groundnut, and a wide variety of vegetables. (Source: Soil of Odisha and Its Management *et.al*Sahu and Mishra).

3.15 Landuse

The definition and categorization of landuse varies amongst government agencies. It has therefore been challenging to consolidate the facts discussed by several divisions into a coherent whole. The Ministry of Agriculture in India uses a nine-fold categorization system to organise the many uses of the land at its disposal (Source: Statistical Year Book of India 2017).The land cover classes of Odisha state are shown in the table 3.4.

Table 3.5:Landuse pattern, Source: Odisha State Land Use (Planning) Policy-2019, Planning and Convergence Department (P&C), Odisha.

Land use classes	Area (in thousands ha)	Percentage
Total geographical area	15570.70	NA
Reporting area for land utilization	15466.62	100.00
Forests	5813.55	37.59
Not available for cultivation	2332	15.08
Permanent pastures and other grazing lands	524	3.39
Land under misc. tree crops and groves	216	1.40
Culturable wasteland	575	3.72
Fallow lands other than current fallows	634	4.10
Current fallows	877	5.67
Net area sown	4495.07	29.06

3.15.1 Land use pattern

Estimates place the amount of unusable land at 8.28%, with vacant lots and fields making up 6.82% and buildings, roads, and bodies of water making up the remaining 0.28%. (15.08 percent). Over the last several decades, urbanisation, industrialisation, and mining have significantly altered Odisha's land use pattern. The ecological transformation of a region's landscape is inextricably linked to changes in the pattern of land use. With just 0.37 ha of land available per person and 0.11 ha of net planted area per person, Odisha has a very limited supply of agricultural space. ISFR, or the India State of Forest Report (2017), estimates that 41.87 percent of Odisha is covered by forests and trees, with another 2.56 percent covered by trees in non-forest areas. It is believed that 4.47 percent of Odisha is made up of wetland.

3.16 Urbanisation and Spatial Growth Dimension

For India as a whole, Odisha has one of the lowest rates of urbanisation. Khordha (with 800 people per sq. km.) is the highest dense, the second one is Jagatsinghapur (682 people/ km^2) discerned in 2001 and 2011 Censuses, which together define the threshold between a sparsely populated rural area and one with a low degree of urbanisation (16.69%). Kandhamal district had the lowest population density (91 people per square kilometre) throughout both censuses.

Population growth is most fast in Odisha's southern and central regions, but most people live in the state's northern and coastal regions (Census of India 2011). There is a large disparity in the population's dispersal throughout Odisha. The districts of Ganjam (2.76 million), Baleshwar (2.06 m), Mayurbhanj (2.32 m), Cuttack (1.89 m), Jajpur (1.69 m), and Kendujhar, Balangir, Kalahandi,and Puri (each with 1.69 m) have the biggest rural populations in the state (approximately 1.5 million each).

The districts of Khorda (48.49%), Sundargarh (35.26%), Jharsuguda (39.89%), Sambalpur (29.59%), Ganjam (27.55%) and Cuttack (27.55%) have the highest rates of urbanisation (21.62 percent). While 16.66% of the state's population lives in urban areas as per the 2011 Census, the other districts have a lower rate of urbanisation (Source: Odisha State Land Use Planning and Policy2019).

3.17 Agriculture

The agricultural sector of Odisha's economy is very important. Agricultural production is the backbone of Odisha's economy. Seventy-six percent of Odisha's labour force is either in agriculture or an agriculturally-based industry. Nearly half of Odisha's landmass is suitable for farming. Odisha's most fertile farmland may be found in its coastal districts, which include Cuttack, Bhadrak, Jagatasinghpur, Khurda, Balasore, Ganjam, Kendrapara, Jajpur, Nayagarh, Puri, and many more.

3.17.1 Crops cultivated in Odisha

Odisha state is a major rice producing states in India. The production of rice is almost $1/10^{th}$ of the country. The main crops cultivated by the farmers in the state are rice, oil seeds, jute, mesta, coconut, pulses, sugarcane, sesame, gram, mustard, ragi, maize, rubber, tea, cotton, potato, and soybean etc. The Crop rotation system is followed in different parts of the state to meet the domestic needs (Fig. 3.9).

The crops cultivated in Kharif season are paddy, ragi, rrhar, maize, mung, groundnut, cotton, small millets, cowpea, biri, til, turmeric and mesta. Marketable vegetables like brinjal, tomato, sweet potato, and cauliflower are also produced in Kharif season.

Crops like gram, mung, potato, sunflower, onion, coriander, garlic,mustard, biri, niger and various other type of vegetables are cultivated in Rabi Season.

3.17.2 Main agricultural hubs in Odisha

Sambalpur, Baleshwar, Cuttack, Puri, Ganjam, Kendujhar, Koraput and Kalahandi districts are famous for rice production. Major agro-economic zones (figure 3.9) of the state are shown inTable 3.5. Koraput, Cuttack, Kalahandi, Puri, Dhenkanal, Sambalpur and Balangir are famous for pulses production. Sambalpur, Cuttack, Balangir, Puri and Kalahandi districts are the main producer of the Cash crops in the state of Odisha.

Table 3.6: Agro-climatic zones of Odisha (Source: Agriodisha.nic.in)

Name of the Agro-climatic zone	Name of the districts
North – Western Plateau	Sundargarh, Deogarh
North Central Plateau	Mayurbhanj, Keonjhar
North-Eastern Coastal Plain	Balasore, Bhadrak, Jajpur
East and South-eastern Coastal Plain	Cuttack, Jagatsingpur, Kendrapada, Puri, Khurdha, Nayagarh
North Eastern Ghat	Ganjam, Gajapati, Rayagada, Phulbani
Eastern Ghat High Land	Koraput, Nowragpur
South Eastern Ghat	Malkangiri
Western Undulating Zone	Kalahandi, Nuapada
Western Central Table Land	Bolangir, Sonepur, Boudh, Sambalpur, Baragarh, Jharsuguda
Mid Central Table Land	Dhenkanal, Angul

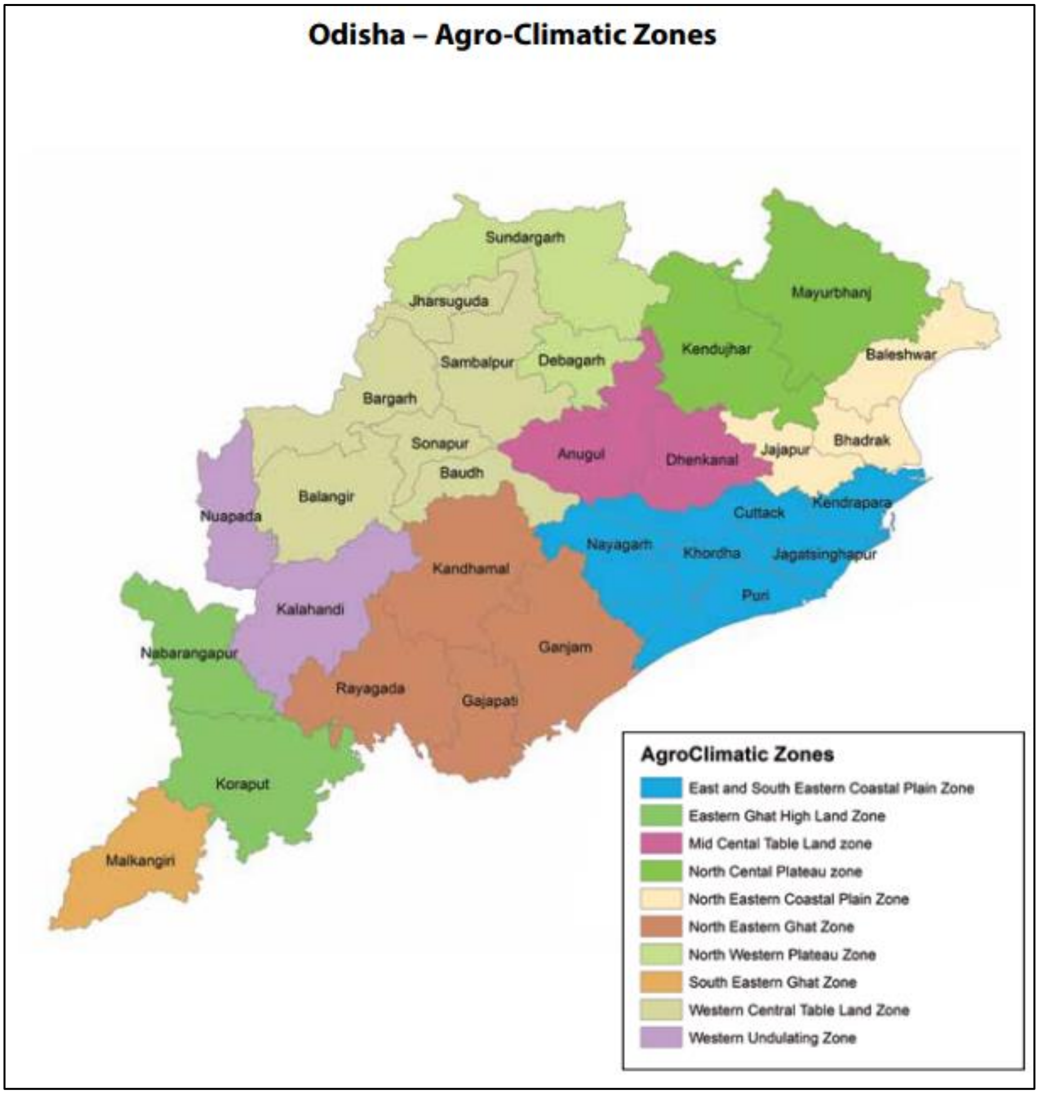


Figure 3.10: Agro-climatic region of Odisha, (Source: Dairying in Odisha - A Statistical Profile 2016)

3.18 **Population/** Demographics

As a result of its size and population, Odisha is among India's most important states. There are as many people living in this state as live in the whole country of Bhutan (figure 3.10 to 3.15). In addition to other demographic data, the literacy rate in Odisha has increased dramatically, increasing by 10 percent between the 2001 and 2011 censuses (Table 3.6 to 3.9).

Table 3.7: Census Population 2011 (Source: Office of the Registrar General & Census Commissioner, India)

District	Population	Increase (%)	Sex Ratio/1000	Literacy (%)	Density/Sq. Km
Ganjam	3,529,031	11.66%	983	71.09%	430
Cuttack	2,624,470	12.10%	940	85.50%	667
Mayurbhanj	2,519,738	13.33%	1006	63.17%	242
Baleshwar	2,320,529	14.62%	957	79.79%	610
Khordha	2,251,673	19.94%	929	86.88%	800
Sundargarh	2,093,437	14.35%	973	73.34%	216
Jajapur	1,827,192	12.49%	973	80.13%	630
Kendujhar	1,801,733	15.35%	988	68.24%	217
Puri	1,698,730	13.05%	963	84.67%	488
Balangir	1,648,997	23.32%	987	64.72%	251
Kalahandi	1,576,869	18.07%	1003	59.22%	199
Bhadrak	1,506,337	12.94%	981	82.78%	601
Bargarh	1,481,255	10.02%	977	74.62%	254
Kendrapara	1,440,361	10.63%	1007	85.15%	545
Koraput	1,379,647	16.86%	1032	49.21%	157
Anugul	1,273,821	11.74%	943	77.53%	200
Nabarangapur	1,220,946	19.03%	1019	46.43%	231
Dhenkanal	1,192,811	11.80%	947	78.76%	268
Jagatsinghapur	1,136,971	7.50%	968	86.59%	682
Sambalpur	1,041,099	11.27%	976	76.22%	157
Rayagada	967,911	16.46%	1051	49.76%	137
Nayagarh	962,789	11.37%	915	80.42%	248
Kandhamal	733,110	13.10%	1037	64.13%	91
Malkangiri	613,192	21.62%	1020	48.54%	106
Nuapada	610,382	15.02%	1021	57.35%	158
Subarnapur	610,183	12.61%	960	74.42%	261
Jharsuguda	579,505	13.69%	953	78.86%	274
Gajapati	577,817	11.37%	1043	53.49%	134
Baudh	441,162	18.16%	991	71.61%	142
Debagarh	312,520	14.01%	975	72.57%	106

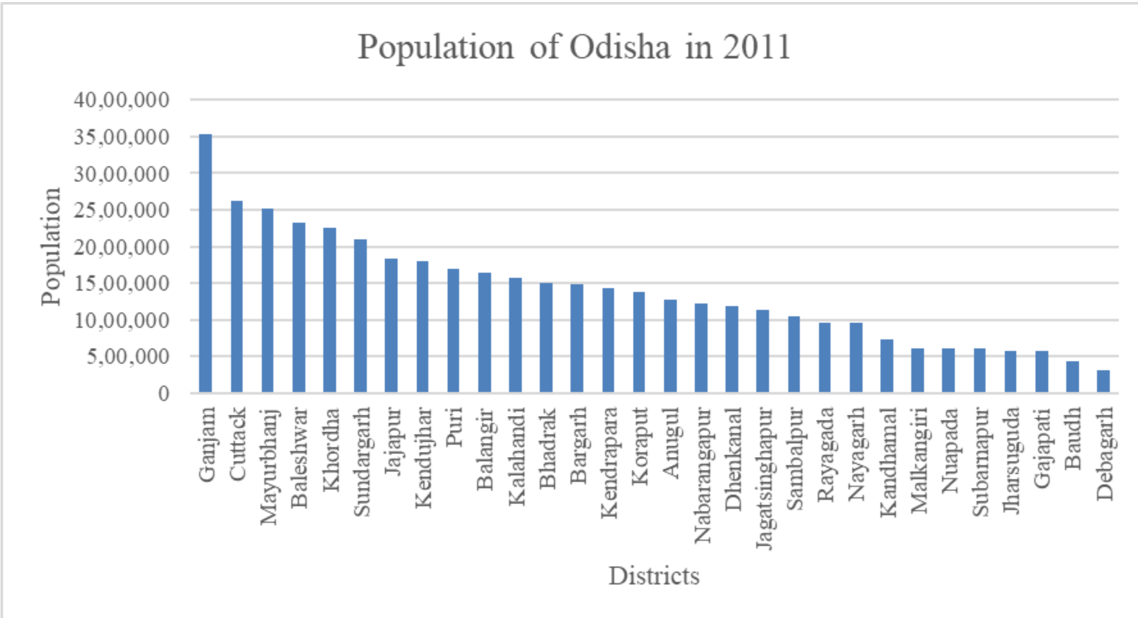


Figure 3.11: Total Population (Census 2011)

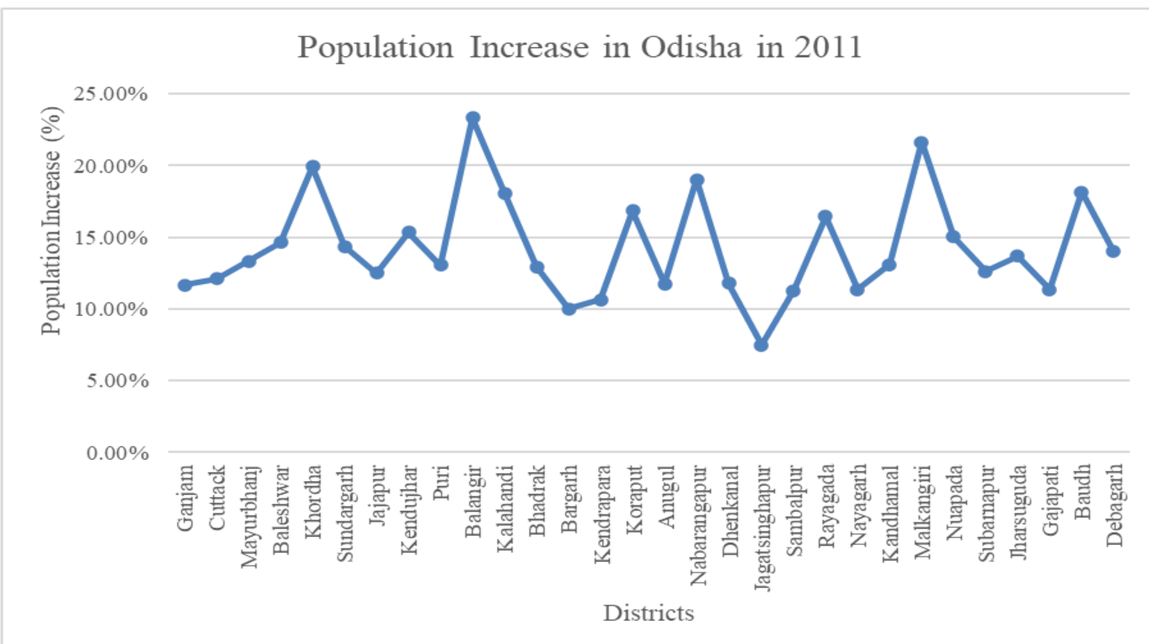


Figure 3.12: Population Increase (Census 2011)

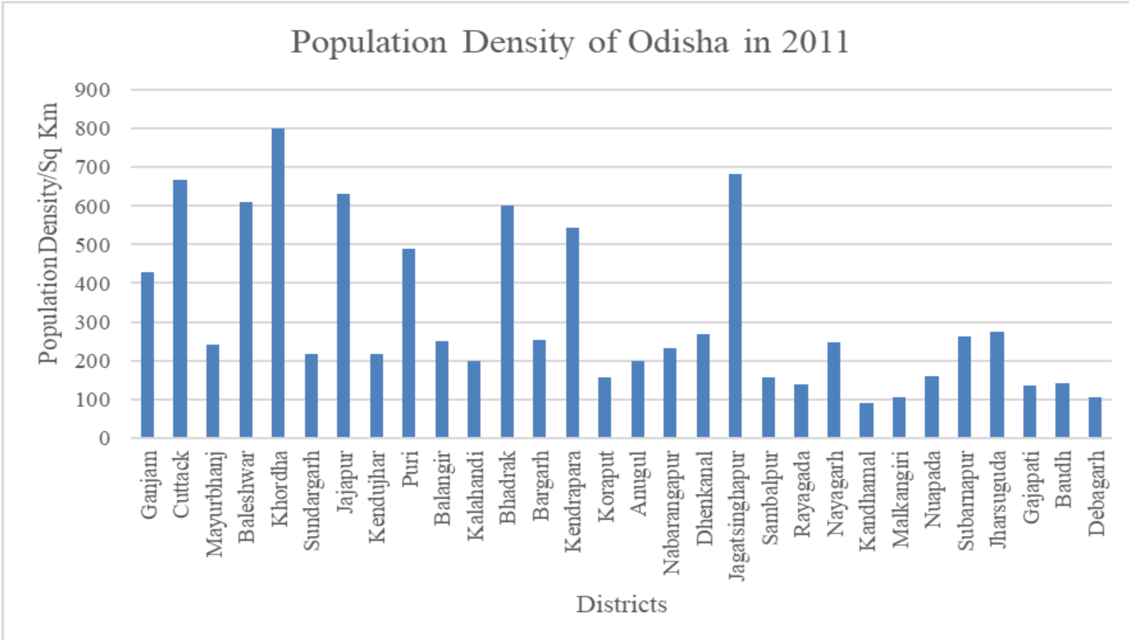


Figure 3.13: Population Density (Census 2011)

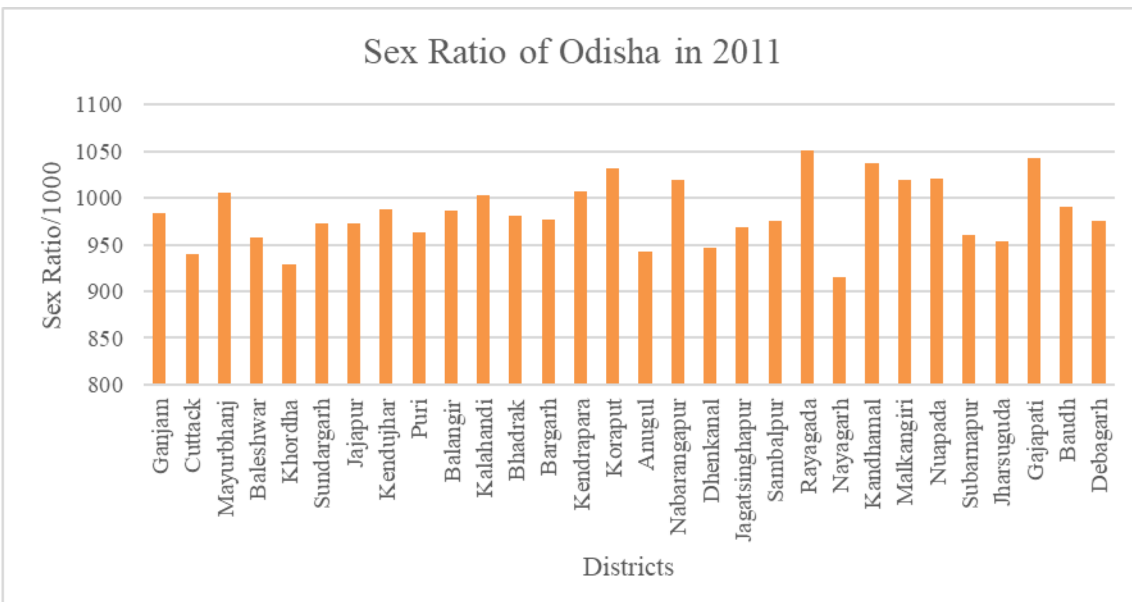


Figure 3.14: Population Density (Census 2011)

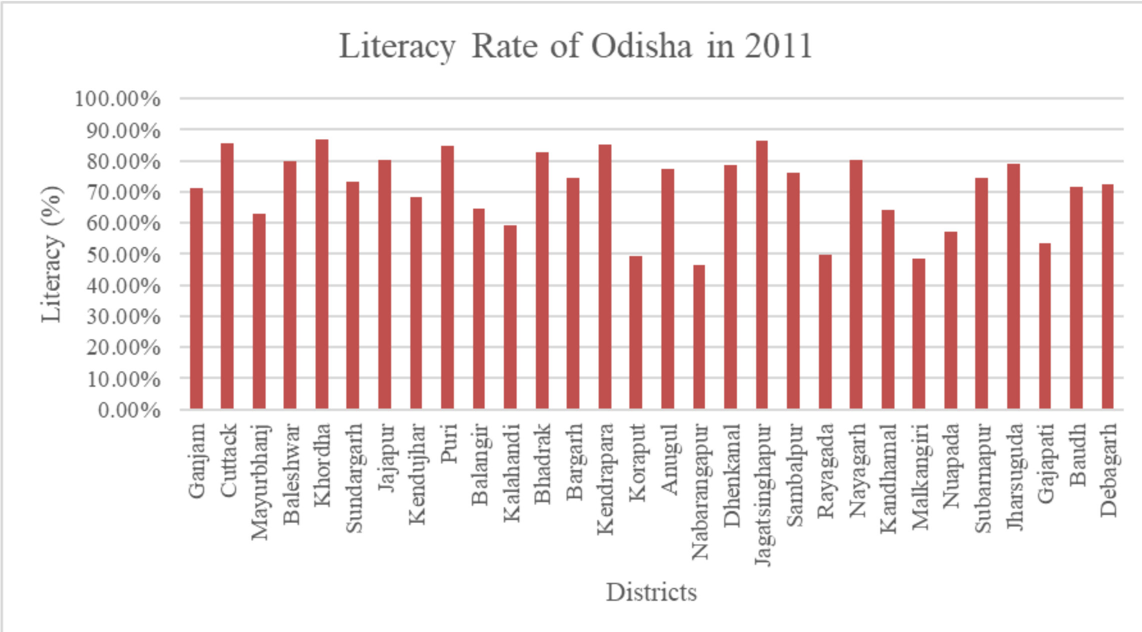


Figure 3.15: Literacy Rate (Census 2011)

Table 3.8: Highly populated districts

Sl. No.	District	Population Growth
1	Balangir	23.32%
2	Malkangiri	21.62%
3	Khordha	19.94%
4	Nabarangapur	19.03%
5	Baudh	18.16%

Table 3.9: Districts with higher literacy rate

Sl. No.	District	Literacy Rate
1	Khordha	86.88%
2	Jagatsinghapur	86.59%
3	Cuttack	85.50%
4	Kendrapara	85.15%
5	Puri	84.67%

Table 3.10: Age-sex composition 2011, Source: Statistics Times

Age group	Male	Female	Total		M per 100 F
			Persons	Share (%)	
00-04	1,878,127	1,774,902	3,653,029	8.7	105.816
05-09	2,085,339	1,989,429	4,074,768	9.71	104.821
10-14	2,203,535	2,145,090	4,348,625	10.36	102.725
15-19	1,972,684	1,952,714	3,925,398	9.35	101.023
20-24	1,870,939	1,912,588	3,783,527	9.01	97.822
25-29	1,772,876	1,801,161	3,574,037	8.51	98.43
30-34	1,542,233	1,560,758	3,102,991	7.39	98.813
35-39	1,528,685	1,522,503	3,051,188	7.27	100.406
40-44	1,387,920	1,303,554	2,691,474	6.41	106.472
45-49	1,212,366	1,121,664	2,334,030	5.56	108.086
50-54	957,524	890,288	1,847,812	4.4	107.552
55-59	744,291	739,429	1,483,720	3.53	100.658
60-64	737,635	736,426	1,474,061	3.51	100.164
65-69	487,849	491,676	979,525	2.33	99.222
70-74	380,635	387,435	768,070	1.83	98.245
75-79	183,294	181,506	364,800	0.87	100.985
80-84	121,629	115,184	236,813	0.56	105.595
85-89	43,817	37,635	81,452	0.19	116.426
90-94	22,234	22,842	45,076	0.11	97.338
95-99	9,256	9,106	18,362	0.04	101.647
100+	7,921	8,368	16,289	0.04	94.658
Age not stated	61,347	57,824	119,171	0.28	106.093
Total	**21,212,136**	**20,762,082**	**41,974,218**		**102.168**

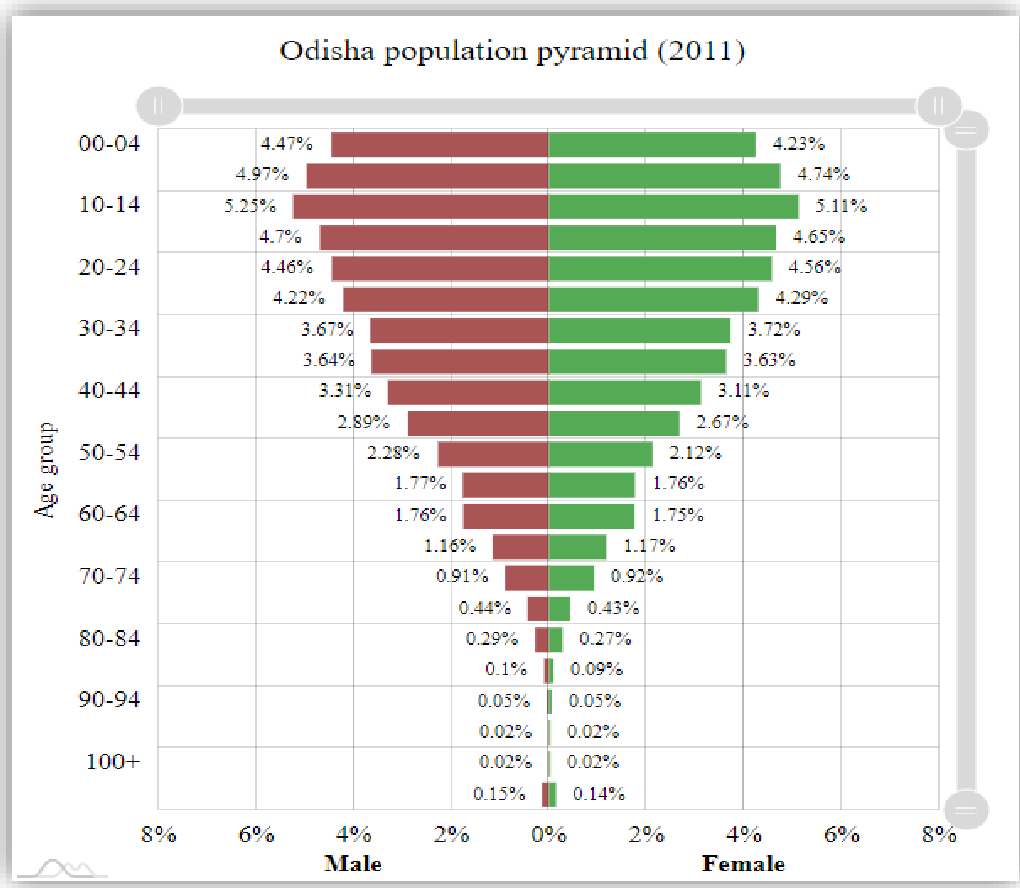


Figure 3.16: Age-sex composition, Population Pyramid (Census 2011)

3.18.1 Population Analysis 2011

- According to the analysis of Census 2011, the population of Odisha has grown by 14.05% in the decade (2001-2011) compared to the previous decade (1991-2001). Over the last decade, Odisha state's population has averaged 316 people per square kilometre. Following are some 2011 population estimates for the Indian state of Odisha.Total population of Odisha was approximately 4.2 crores.
- The density of population is 316 persons per sq.km.
- Amongst all the districtsBalangir, Malkangiri, Nabarangapur,Khordhaand andBaudh experiences higher population growth.

- From the age-sex pyramid it is found that the dependency rate of old age population was very less and there was an existence of growing young age population for proceeding decade.
- Khordha, Jagatsinghapur, Cuttack, Kendrapara and Puri experiences higher Literacy rate among all districts.

3.18.2 Current population of Orissa in 2021

In the year of 2021, Odisha state is having 48 million population. It is India's one of the densely populated states. Current population of Odisha is approx. 48,126,658 while the last year record was 47,439,243 (Source: India Census.net).

3.19 Economy

3.19.1 GDP status

In the viewpoint of economics, gross value added is the measure of the value of goods and services produced in part, industry, or the sector of an economy. Ministry of Statistics and Programme Implementation releases the sector wise GDP in terms of GVS in Odisha in 2021 (Table 3.10).

Table 3.11: Sector wise GDP of Odisha in 2021, Source: Ministry of Statistics and Programme Implementation, 28 Mar 2021

Sector	GVA (Rs. in Lakh) at current prices		GVA (Rs. in Lakh) at 2011-12 prices	
	2020-21	**% Share**	**2020-21**	**% Share**
Primary Sector	13,487,442	30.25	8,908,711	26.24
Agriculture, forestry &fishing	9,484,561	21.27	4,942,823	14.56
Crops	6,084,836	13.65	2,971,648	8.75
Livestock	1,111,523	2.49	538,879	1.59
Forestry & logging	1,206,627	2.71	780,724	2.3
Fishing and aquaculture	1,081,575	2.43	651,572	1.92
Mining & quarrying	4,002,881	8.98	3,965,888	11.68
Secondary Sector	12,165,013	27.28	10,825,045	31.88

Manufacturing	7,825,778	17.55	7,271,090	21.42
Electricity, gas, water supply & other utility services	1,369,792	3.07	1,196,342	3.52
Construction	2,969,443	6.66	2,357,613	6.94
Tertiary Sector	18,933,578	42.47	14,219,031	41.88
Trade, repair, hotels, and restaurants	4,168,322	9.35	3,412,963	10.05
Trade & repair services	4,004,275	8.98	3,277,797	9.65
Hotels & restaurants	164,047	0.37	135,167	0.4
Transport, storage, communication & services related to broadcasting	2,716,890	6.09	1,926,499	5.67
Railways	380,730	0.85	269,080	0.79
Road transport	1,257,972	2.82	886,756	2.61
Water transport	106,684	0.24	77,360	0.23
Air transport	4,808	0.01	3,389	0.01
Services incidental to transport	176,657	0.4	124,527	0.37
Storage	26,075	0.06	23,031	0.07
Communication & services related to broadcasting	763,963	1.71	542,356	1.6
Financial services	1,886,592	4.23	1,512,703	4.46
Real estate, ownership of dwelling & professional services	2,813,722	6.31	2,346,835	6.91
Public administration & defence	2,854,941	6.4	2,347,834	6.91
Other services	4,493,111	10.08	2,672,197	7.87
GVA at basic prices	44,586,033		33,952,787	

The GVS statistics shows that the Tertiary sector is overwhelming all other sector followed by Primary and Secondary Sectors in the state economy. The outstanding growth of

Tertiary Sector in this state, indicates a trend to arrive at the developed economic state with respect to the other progressive states of the country.

3.19.2 Economy of the State

Odisha's average yearly growth rate has shown a favourable differential trend when compared to the growth results of the other states of India from 2012-13 to 2019-20. It shows that Odisha's GDP increased by 7.1% on average between 2012-13 and 2019-20, which is higher compared to India's nationwide average of 6.6% and the rates of advancement in 13 other states. (Odisha Economic Survey 2020-21, Govt. of Odisha).

3.19.3 Per Capita Income (PCI)

In 2019-20 (RE), the per capita income of Odisha was INR 10,4566, up from INR 4,8998 in 2011-12. This is an increase of 115.60 percent. PCI-India increased during this time by 111.51 percent, from INR.63462 to INR.134226. Insights from this study reveal that Odisha's PCI has outpaced India's PCI in the space of a decade. PCI-Odisha, which represented around 76.42 percent of the national PCI in 2011–12, skyrocketed to 80.46 percent in 2020–21. Current prices show that Odisha's PCI for 2019-20 (1st RE) is more than that of Bihar, Uttar Pradesh, Madhya Pradesh, Jharkhand, Meghalaya, and Chhattisgarh. (Source: Odisha Economic Survey 2020-21, Govt. of Odisha).

3.20 Datasets

The present research concentrates on mapping of drought dynamics using Geoinformatics, therefore, various types of remote sensing datasets are taken for analysis. In addition to satellite/ remote sensing data, present study has taken the climatic data to carry out the analysis of climatic factor responsible for drought. All datasets used in this study, their source/ sensor / gateway, product type, vintage, resolution and other characteristics are given in the Table 3.11.

Table 3.12: Datasets used in this research

Sl. No	Source/ Sensor	Product	Vintage	Cell Size	Remarks
1.	**IMD**	Rainfall	1975 – 2019	25 km	SPI calculation, Rainfall analysis
2.	**IMD**	Temperature	1975 – 2019	25 km	Temperature analysis

3.	**MODIS**	MCD12Q1	2001, 2009, 2019	500 m	Landcover classification for agricultural area delineation
4.	**MODIS**	LST	2000-2020	1000 m	LST assessment
5.	**MODIS**	ET	2000-2020	500 m	Heat stress assessment
6.	**ESA**	Soil Moisture	2000-2020	25 km	Assessment of soil moisture content
7.	**ESA**	Sentinel 1A SAR	2020-2021	10 m	Drought estimation using SAR data
8.	**Earth Explorer**	Landsat 8	2020-2021	30 m	Drought estimation
9.	**Earth Explorer**	MODIS- NDVI	2000-2020	250m / 1000 m	Drought estimation/ downscaling
10.	**NOAA**	Vegetation Health Index (VHI)	2000-2020	4 km	Agricultural drought assessment
11.	**NOAA**	EL-NINO & IOD	2000-2020	--	Identifying EL-NINO year
12.	**Grace**	Ground water storage	2002-2020	300 km	Ground water stress assessment
13.	**IPCC**	GCM data	2023-2050	25 km	Drought prediction
14.	**NASA**	SPEI	1975-2018	50 km	Drought assessment

4 Modelling of Drought Dynamics

Knowledge is limited. Imagination encircles the world.

- *Albert Einstein1929*

4.1 Introduction

Drought is generally considered to be the most devastating and unpredictable natural hazard in the world. In the world, India is considered one of the most drought-prone countries. Most of the drought-prone areas in India are located in peninsular parts. There are four types of droughts such as meteorological, hydrological, agricultural, and socio-economic drought. Agricultural drought is very significant because it affects the country's food security. The major challenge for any drought-related study is to define the beginning and end of drought events/ occurrence as it continues and declines gradually and stays over a variable time period, often months to years (Mishra and Singh 2010).

Drought frequency in India is high, drought is reported every three years in our country in the last five decades. Odisha is a coastal state, but the drought frequency of this state is once in three years. Studies have been carried out related to drought in Odisha, but holistically drought dynamics modelling is required for this state to understand the drought pattern in detail. It is also required to work on predictive modelling of drought considering the long-term trend. The relationship between the IOD position and the occurrence of drought on the east coast of India / Odisha also needs to be studied.

Mapping drought dynamics means the analysis of various drought-related characteristics of any region. It involves mapping/ analysis of various characteristics of drought such as drought intensity, drought severity, drought event and drought frequency of meteorological, hydrological, and agricultural drought. It also deals with Spatio-temporal mapping of drought distribution of a region/ state or country. Efforts have been made over the last decade to understand the dynamics of the intensity, severity, and frequency of droughts in India.

Remote sensing plays a vital role in delineating the drought dynamics of any region. Satellite data provides continuous raster data of the Earth's surface of environmental and atmospheric variables which is required for mapping drought dynamics. Another advantage of remote sensing is it provides succinct, systematic repeated coverage, in a consistent manner (AghaKouchak et al., 2015). Various space-based visible and near-infrared, thermal infrared and microwave sensors have been used for drought assessment(Wardlow et al., 2012). Researchers have generated various spectral indices to monitor the different types of droughts(Mishra and Singh, 2010). Space-based and observed (station-based) climatic data like precipitation, temperature, El Nino and IOD index etc. are also used by researchers for mapping drought dynamics.

The present research is concentrated to map the drought dynamics of Odisha state for the last two decades (2000-2022). The major focus of the study is on mapping agricultural drought dynamics as 60% people of the state are dependent on agriculture. Satellite data and climatic data from Indian Meteorological Department have been used and map the characteristics of drought dynamics using geoinformatics techniques.

4.2 Methodology

The methodology adopted in this research is described as sequential manner.

4.2.1 Landcover classification

Terra MODIS landcover data product MCD12Q1 of 500 m resolution for the vintage of 2001, 2009 and 2019 are taken for this research. The data products are downloaded and processed to delineate the 16 landcover classes over the Odisha state. The area under each class is estimated for the year 2001, 2009 and 2019 and carries out change detection. The area under the agricultural land is demarcated from this data product.

4.2.2 Standardized Precipitation Index

The standardized Precipitation Index (SPI) is used in this research to identify meteorological droughts (McKee et. al., 1993; Mondal and Lakshmi, 2021). It is a dimensionless index which is based on the precipitation probability distribution. SPI can be calculated for drought assessments of various time scales like monthly, seasonal, and annual basis, or long-term (one to two years or more). In this research, a three-month time scale is selected for estimating seasonal drought which represents the cumulative surplus/ deficits of precipitation/ rainfall for every three consecutive months.

SPI is calculated with the help of IMD gridded rainfall data of 25 km x 25 km grid size. The Gamma probability distribution was fitted for each IMD data grid to characterize the cumulative probability distribution function (CDF) of the precipitation as described by previous studies (Mishra et. al., 2010; Sohn et al. 2012).

To assess SPI it is necessary to fit a gamma probability density function to the total precipitation. The gamma probability density distribution function ($\Gamma(\alpha)$) is fitted to the precipitation dataset (raster data is converted into ascii files) which consists of a shape factor and a scale factor, termed as α and β, respectively, it consists of estimation for each month and time scale. To do this, the maximum likelihood functions are applied. The total of precipitation is characterized by x, the cumulative probability (G(x)), can be represented by

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^{\alpha}\Gamma(\alpha)}\int_0^x x^{\alpha-1}\, e^{-x/\beta}dx \qquad (4.1)$$

Where x equal to zero. Gamma function is remains indeterminate and the precipitation distribution may contain zeros (Mckee et al. 1993).

The cumulative probability (H(x)) become (Mondal and Lakshmi, 2021):

$$H(x) = q + (1-q)G(x) \qquad (4.2)$$

Here, q denotes the probability of a zero. The cumulative probability is therefore changed to standard normal random variable Z, with mean equal to zero and variance equal to one. It represents the SPI value.

SPI is classified to delineate the drought. The classification scheme used is describe as SPI less than -2.0 is extreme drought, SPI from -1.6 to -1.9 severe drought, SPI between -1.0 to -1.5 moderate drought, SPI -0.5 to -0.99 mild drought and SPI >-0.5 no drought.

4.2.3 Standardized Precipitation Evapotranspiration Index (SPEI)

The standardized Precipitation Evapotranspiration Index (SPEI) has been used in this research (Vicente-Serrano et al., 2010). SPEI is calculated based on precipitation and potential evapotranspiration. Monthly potential evapotranspiration (PET) is calculated from monthly min-max temperature and the extra-terrestrial solar radiation data using the method proposed by Hargraves-Samani (Hargreaves 1982).

SPEI is calculated by fitting the present difference of precipitation (P) value and PET value to the gamma distribution. SPEI is used by many researchers for drought-related studies (Mondal and Lakshmi, 2021; Tiwari and Mishra 2019; Vicente-Serrano et al., 2010; Shah and Mishra 2014). With a value for PET, the difference between precipitation and PET for every month i is calculated using

$$D_i = P_i - PET_i \tag{4.3}$$

In the above equation, P_i represents precipitation (mm), and PETi stands for potential evapotranspiration (mm).

The water balance sequence of different time scales is executed as

$$D_n^k = \sum_{i=0}^{k-1}(P_{n-i} - PET_{n-i}), n \geq k \tag{4.4}$$

Here, k is the time scale in month, and n shows the computation times.

Log-logistic probability density function is applied to fit the recognized series with 03 parameters as under:

$$f(x) = \frac{\beta}{\alpha}(\frac{x-\gamma}{\alpha})^{\beta-1}\left[1 + (\frac{x-\gamma}{\alpha})^{\beta}\right]^{-2} \tag{4.5}$$

Where, β is equal to shape parameter, α is scale parameter and γ is the original parameter. The parameter estimation has been carried out by the method known as L-torque. In a given time scale the cumulative probability can be considered as under

$$F(x) = \left[1 + (\frac{\alpha}{x-\gamma})^{\beta}\right]^{-1} \tag{4.6}$$

After using the standard normal distribution method, SPEI can be calculated as

$$SPEI = W - \frac{C_0+C_1W+C_2W^2}{1+d_1W+d_2W^2+d_3W^3}, W = -2\ln(P) \tag{4.7}$$

Where, P ≤ 0.5,

P = 1 - F(x); where P > 0.5, P = 1 - P,

The symbol of the SPEI is reversed.

The constants are C_0 = 2.515517, C_1 = 0.802853, C_2 = 0.010328, d_1 = 1.432788, d_2 = 0.189269, and d_3 = 0.001308 as per Vicente-Serrano et al. 2010; Wang et al. 2015.

In this research SPEI time scales of 03 months are used.

SPEI is classified to delineate the droughts. The classification scheme is SPEI less than -2.0 is extreme drought, SPEI from -1.6 to -1.9 severe drought, SPEI between -1.0 to -1.5 moderate drought, SPEI -0.5 to -0.99 mild drought and SPEI >-0.5 no drought.

4.2.4 Mapping of agricultural drought

Agricultural drought mapping is carried out using the Normalized Difference Vegetation Index (NDVI) and Vegetation Health Index (VHI) (Karnieli et al., 2006). NDVI datasets are taken from the Earth Explorer data gateway. MODIS satellite data-derived NDVI product of 250 m resolution of 2000 to 2020 is taken into consideration for drought assessment. Only agricultural area is taken out from the NDVI images of Odisha state and an NDVI value less than 0.2 over the agricultural area within the growing season is considered a drought-affected area. Vegetation Health Index is a combination of the Vegetation Condition Index (VCI) and Temperature Condition Index (TCI). Weekly VHI datasets are taken from NOAA sensors of 4 km x 4 km grid size for the period of 2000 to 2020 for drought mapping. The classification scheme for drought mapping using VHI is used as VHI <= 10 is extreme drought, VHI >10 to <= 20 is severe drought, VHI >20 to <=30 is moderate drought, VHI >30 to <= 40 is mild drought and VHI > 40 is no drought. The study area is divided into different drought categories using this classification scheme.

4.2.5 Mapping of drought characteristics

The drought characteristics are mapped using SPEI/ VHI values and calculated spatial distribution of drought frequency, severity, and event/intensity. A single drought event over a region may happen in a single month/year as well as consecutive multiple months/years(Mondal and Lakshmi, 2021). Drought severity estimation (DSe) provides the absolute value of the sum of all VHI/ SPEI during a drought event (Mondal and Lakshmi, 2021; Tan et al. 2015).

$$DS_e = \left|\sum_{j=i}^{m} Index_j\right|_e \tag{4.8}$$

Drought intensity (DI_e) of any drought event can be refers to drought severity divided by the drought duration.

$$DI_e = \frac{S_e}{m} \tag{4.9}$$

In the above equation, subscript e represents to any drought event. Subscript j refers a drought month.

Index j represents the VHI/ SPEI value in month j while m refers duration of any drought event (e).

The drought frequency (DF) is calculated as under

$$DF_S = \frac{n_s}{N_s} \times 100\% \qquad (4.10)$$

Where n_s represents the no. of drought events, N_s refers to the total number of years consider for this research and s is a station.

For example, to calculate the spatial drought frequency using VHI for any month from the year 2000 to 2020, drought and no drought areas are delineated for every raster. All the drought-non-drought raster datasets (21 datasets) are stacked, a vertical counting of each pixel is checked for drought or non-drought, and then the total number of drought counts is divided by the number of years and expressed in percentage.

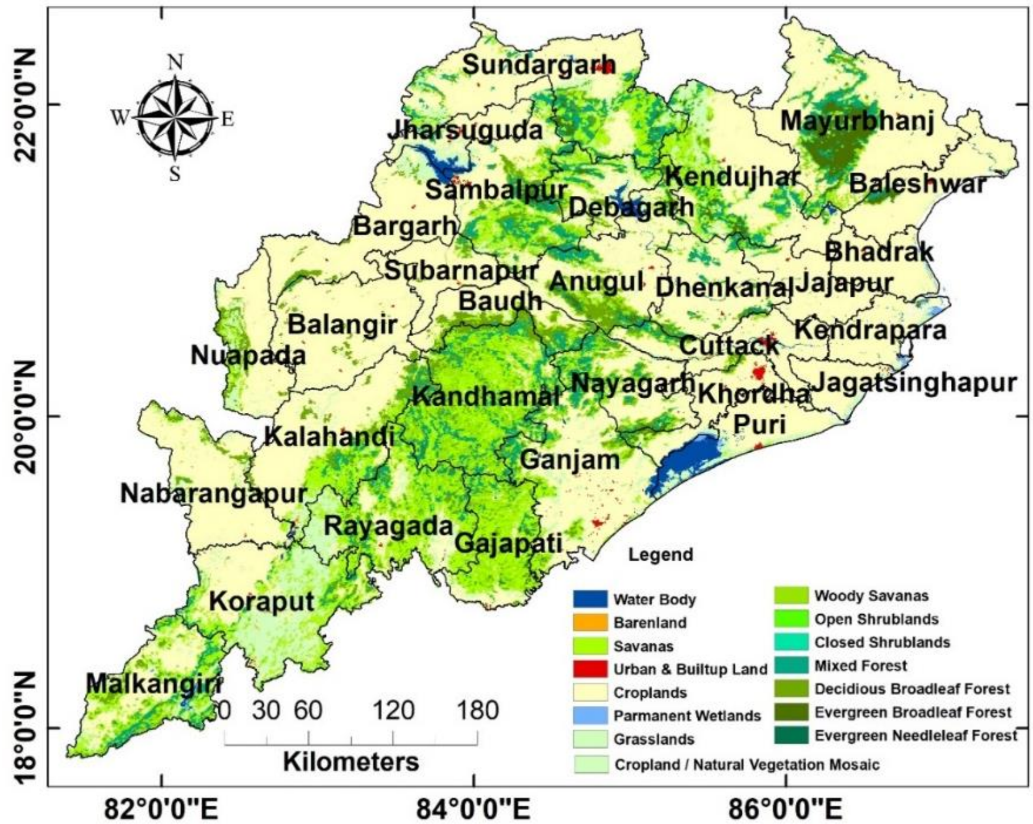
4.3 Results

Results generated using the above methodology are discussed in this section in a sequential manner.

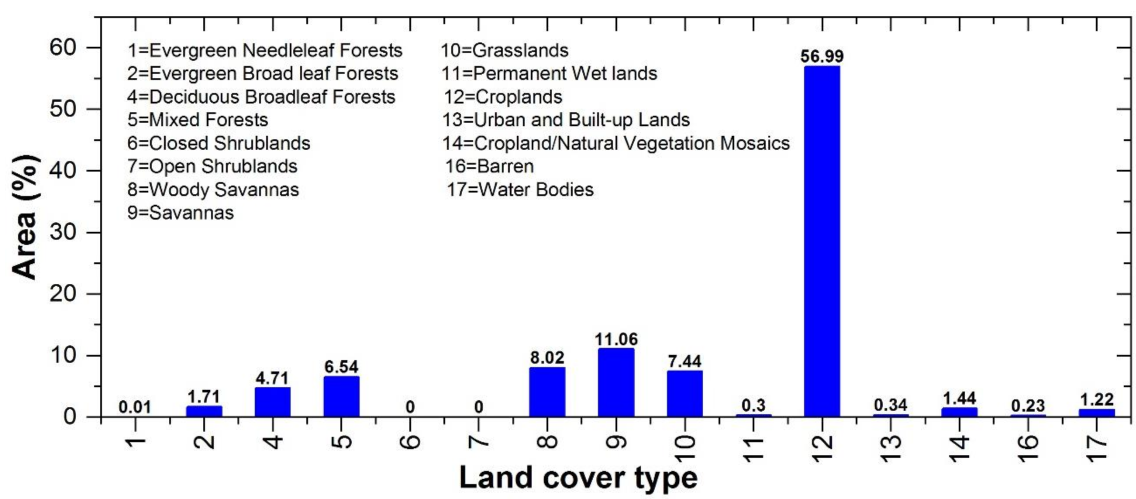
4.3.1 Landcover mapping of Odisha district

Landcover mapping using 500 m spatial resolution MODIS data products for the year 2001, 2009 and 2019 are shown in the figure 4.1. The landcover classes are waterbody, barenlands, savannas, urban and built-up lands, croplands, permanent wetlands, grasslands, cropland/ natural vegetation mosaic, woody savannas, open shrublands, closed shrublands, mixed forest, deciduous broadleaf forest, evergreen broadleaf forest, evergreen needleleaf forest.

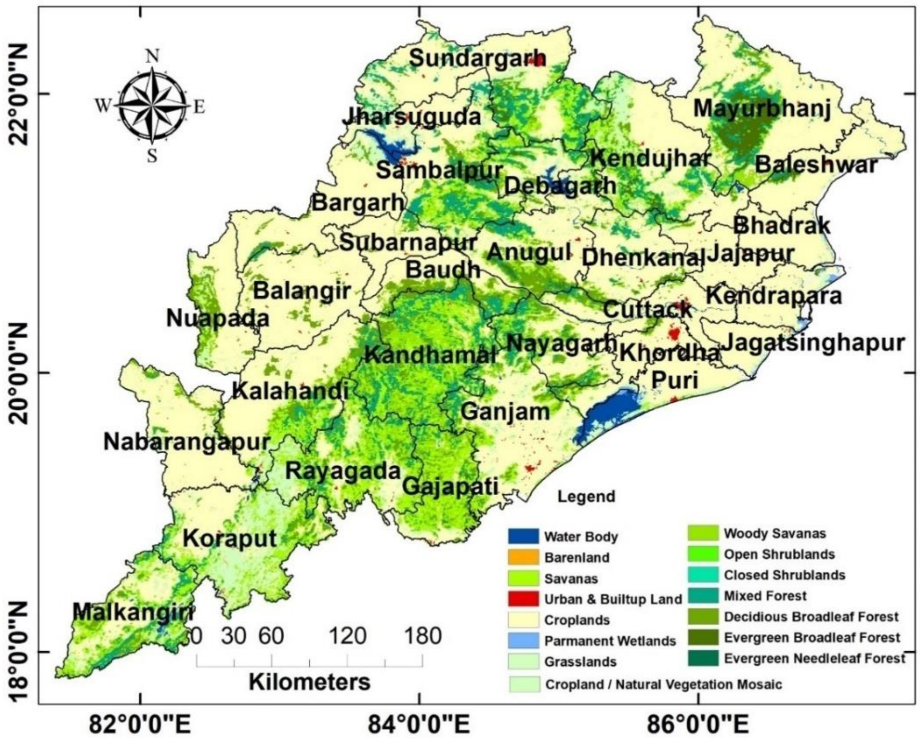
Landcover 2001



Land Cover Area Statistics (%)

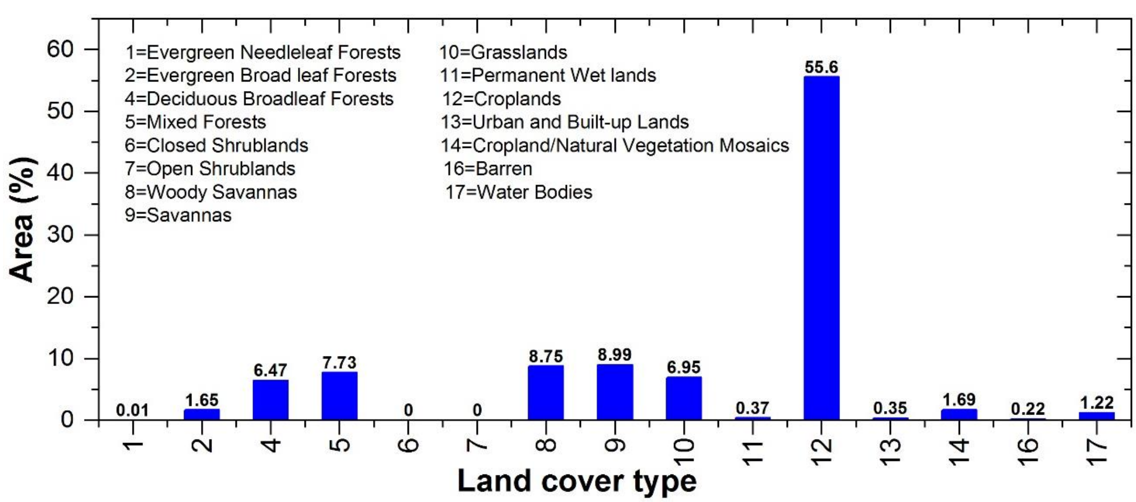


Landcover 2009

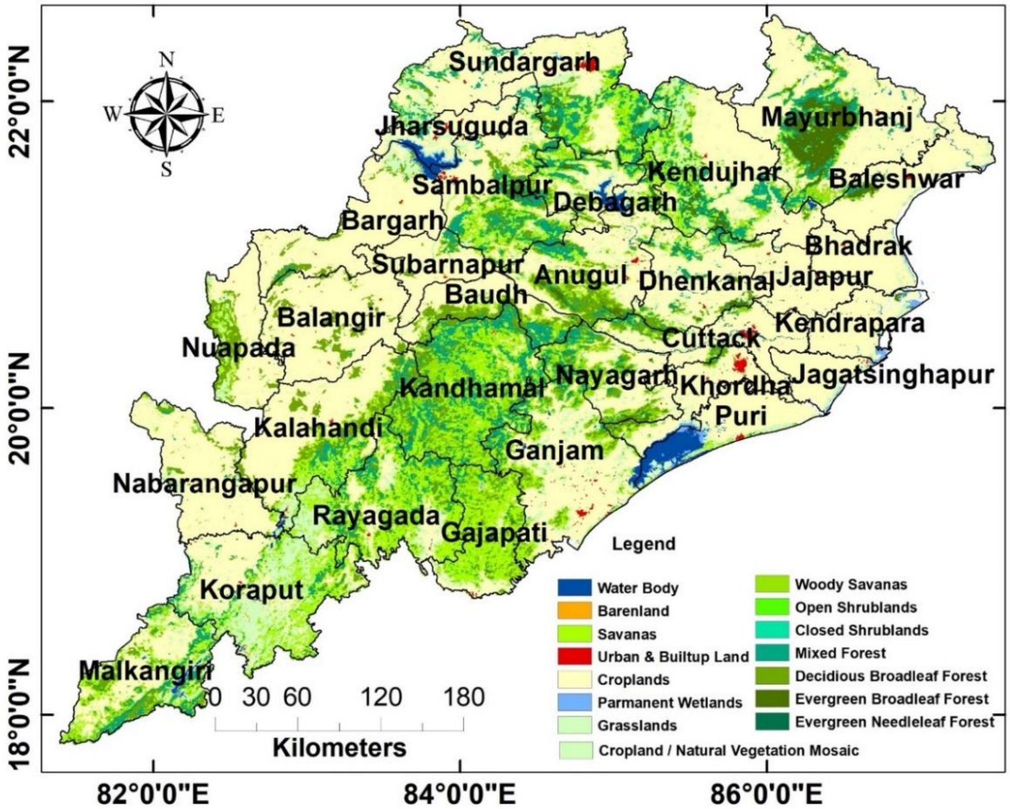


The landcover statistics (year wise) are estimated and plotted for all three years. It is observed that the central part is occupied with forest and major parts are occupied by cropland. Cropland area was 56.99% in 2001 which is reduced to 54.57% in 2019.

Land Cover Area Statistics (%)



Landcover 2019



Land Cover Area Statistics (%)

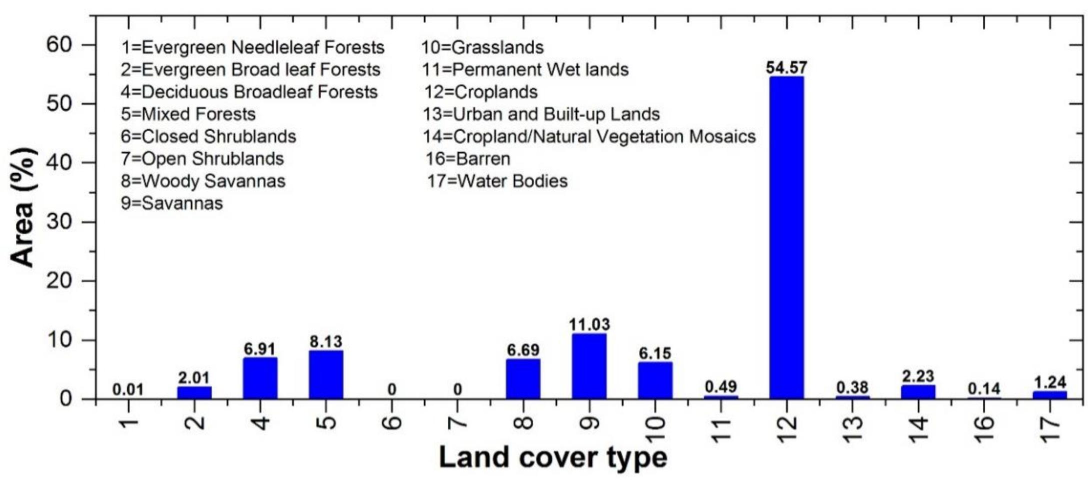


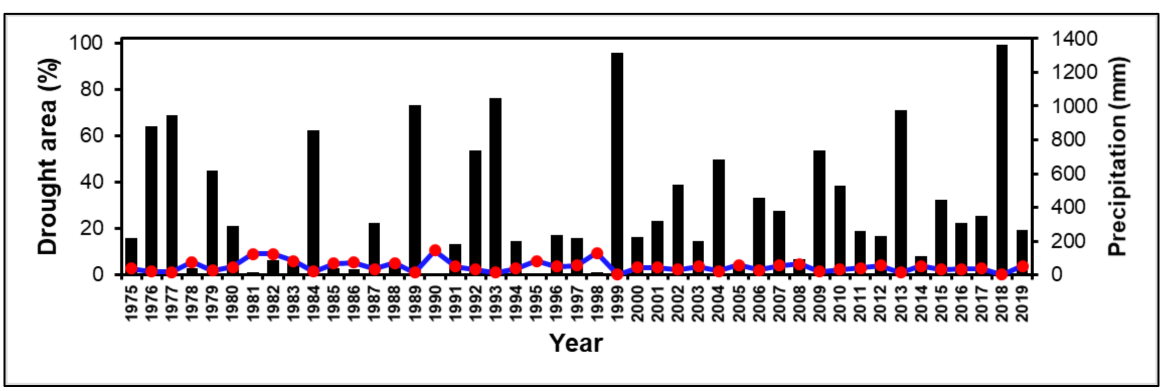
Figure 4. 17: MODIS Land cover map of Odisha state of 2001, 2009 and 2019. Landcover statistics are also shown here. The total agricultural area in 2019 was 54.57% of the total area of the state.

4.3.2 Identification of meteorological drought using SPI

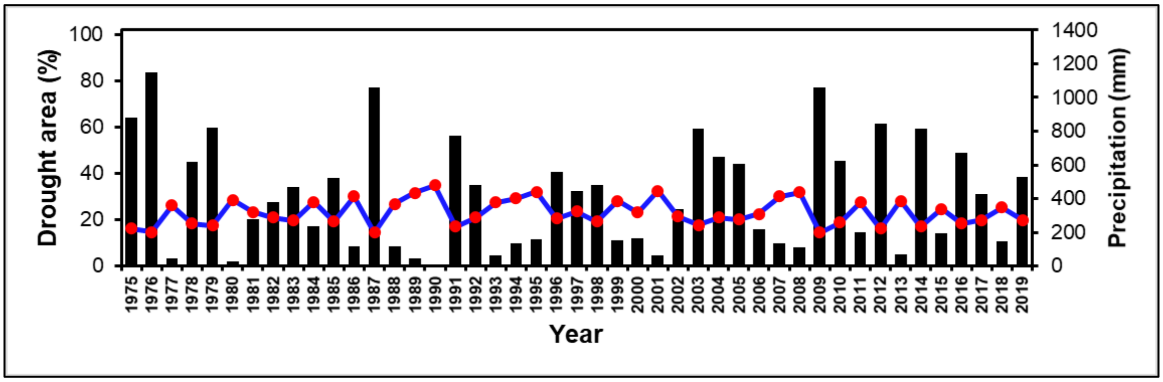
Try-monthly SPI calculated from IMD precipitation datasets from 1975 to 2019. The raster data is divided into drought and non-drought areas, percentage of area under drought to the total area of the state calculated as per the given classification scheme above is shown in figure 4.2. The amount of precipitation is superimposed on the SPI plot. It is found that the amount of rainfall is less in the month of Jan-Feb-Mar and Apr-May-Jun, therefore, more % of the area is shown under the drought category. However, Ravi and Zaid crops are cultivated in these seasons and the moisture/crop water requirement of these crops is very less.

Monsoon season is more important for the assessment of meteorological drought as the Kharif crop, especially paddy is grown in this season and water requirement is very high. The % of the area under the drought category is calculated from the try-monthly SPI of July-Aug-Sep and it is used for drought assessment. If more than 50 % area is falling under the category of drought for any year that is designated as a drought year. It is observed that the years 1979, 1982, 1987, 1996, 1998, 2002, 2004, 2009, 2010, 2013 and 2015 can be designated as major drought years in Odisha state. As the focus of the study is drought assessment of the last two decades, therefore, further analysis of drought characteristics has been carried out for 2002, 2004, 2009, 2010, 2013 and 2015 drought situations. The plot of Oct-Nov-Dec is also shown the number of post-monsoon drought years, but again in Odisha as well as in India monsoon drought is considered as most important.

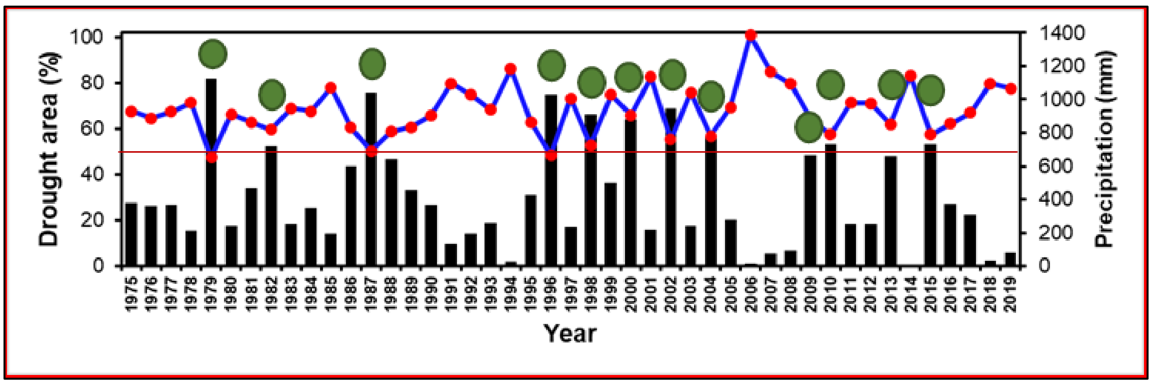
Jan-Feb-Mar



Apr-May-Jun



Jul-Aug-Sep



Oct-Nov-Dec

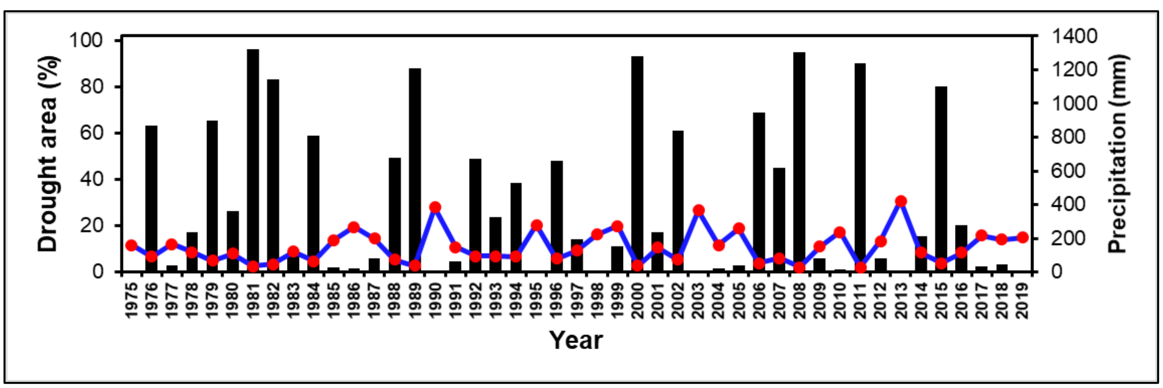
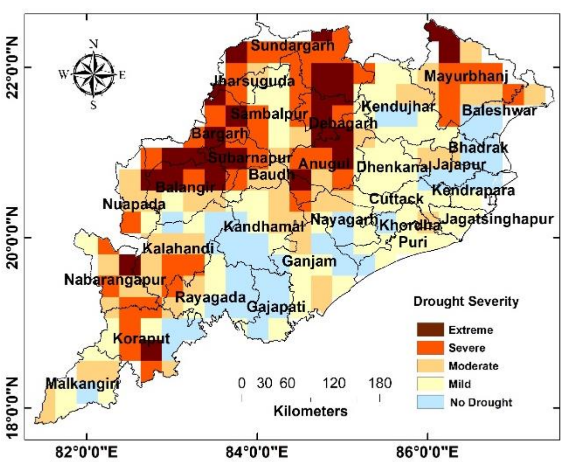


Figure 4.18: Percentage of area under meteorological drought against each year calculated based on SPI.

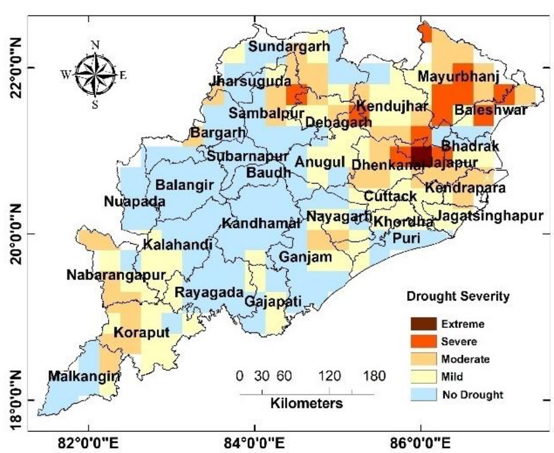
Spatio-temporal distribution of SPI (classified) of the identified drought years (1979, 1982, 1987, 1996, 1998, 2002, 2004, 2009, 2010, 2013 and 2015) are shown in the figure 4.3. In the year of 1979, northern, central, western, and southern part of the Odisha are highly affected by the extreme and severe drought. Eastern part of the state is affected by the moderate and mild drought. In 1982, north-eastern part of the state is affected by the drought. In 1987, southern, eastern and central part of the state are affected by the extreme and severe drought. In 1996, major part of the Odisha is affected by the extreme drought situation. In 1998, northern and western part of the Odisha was affected by the drought. In the year 2000, major part of the Odisha was affected by the extreme and severe drought.

In 2002, northern, central and southern part of the Odisha state was experienced by the severe drought. In 2004, the eastern coast of the Odisha was hit by the extreme and severe drought, southern part of the state was also experienced drought during the monsoon period. In 2010, mainly, all the districts located in the northern part of the Odisha state are experienced extreme and severe drought. No drought was seen in the southern part of the state. In 2015, north-eastern, western and central part of the state were affected by the drought and the intensity of the drought was slightly less compared to 2010. From the above-mentioned analysis it can be concluded that the drought pattern of the Odisha state is random, there is no define pattern observed for drought occurrence. The intensity of the drought also varies every year as per the climatic regime.

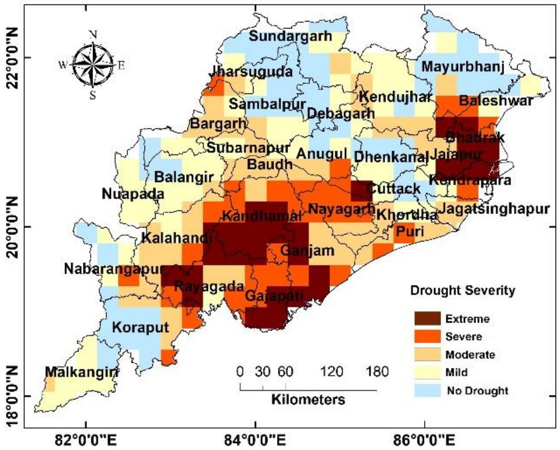
Jul-Aug-Sep 1979



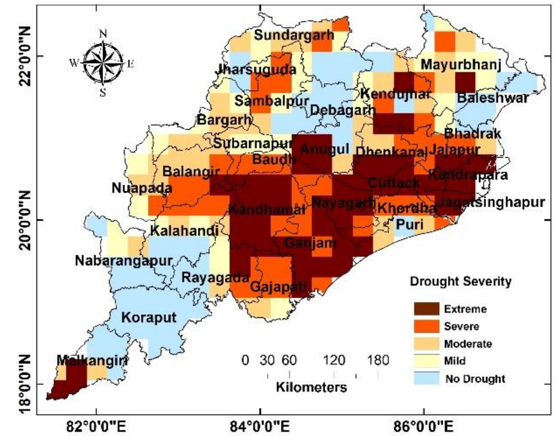
Jul-Aug-Sep 1982



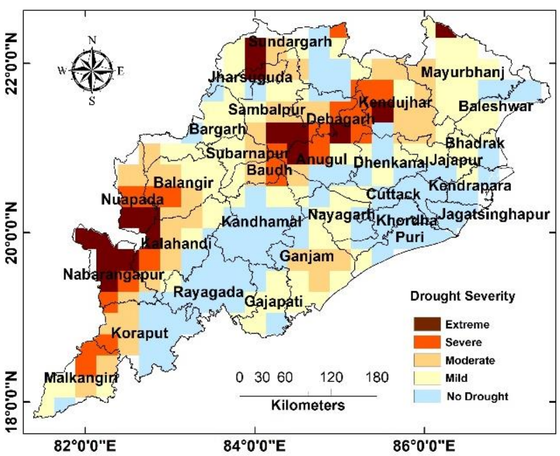
Jul-Aug-Sep 1987



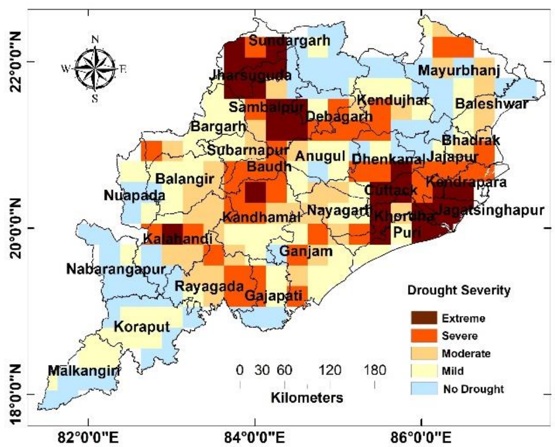
Jul-Aug-Sep 1996



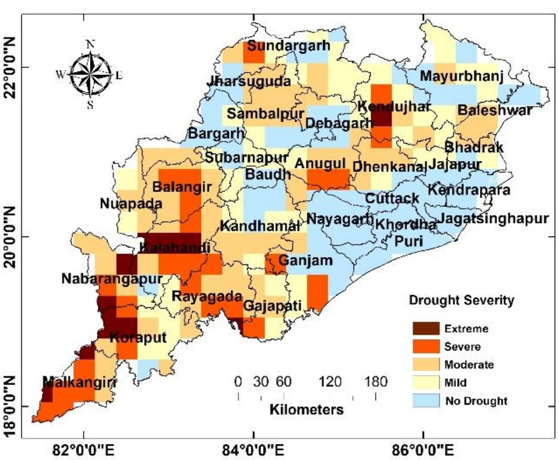
Jul-Aug-Sep 1998



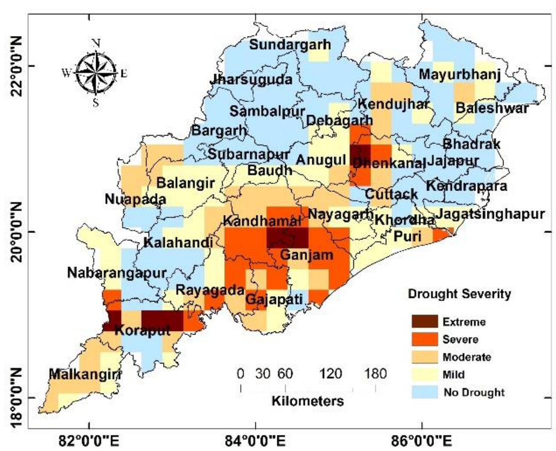
Jul-Aug-Sep 2000



Jul-Aug-Sep 2002



Jul-Aug-Sep 2004



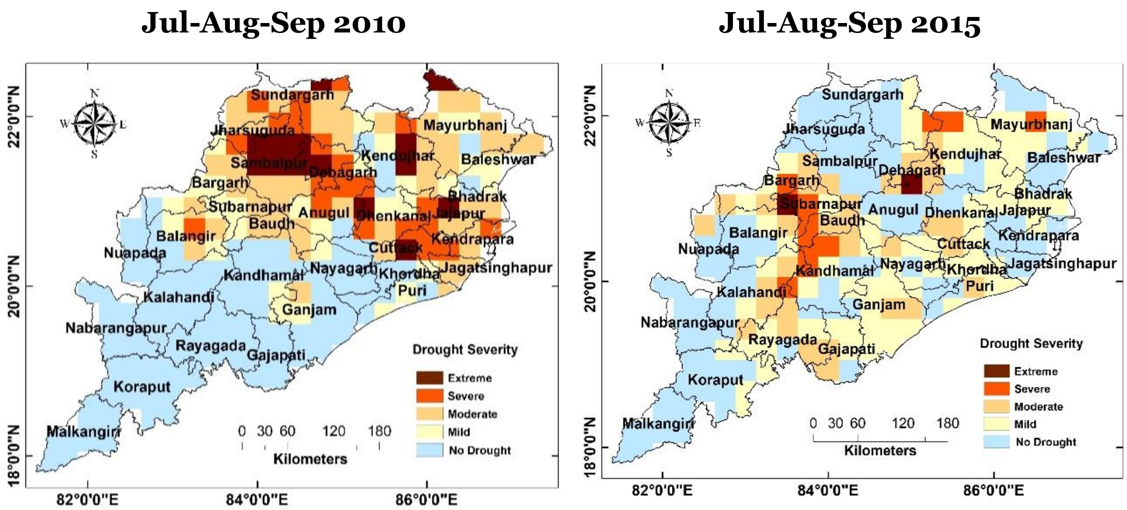
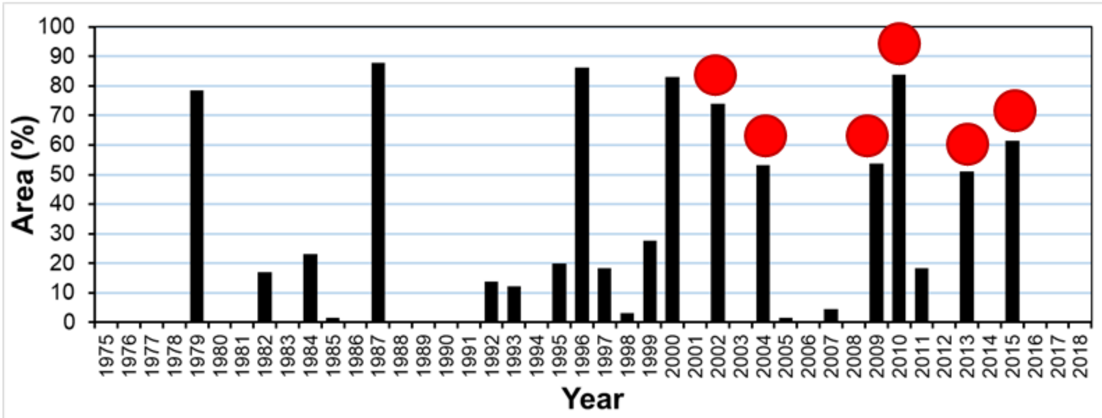


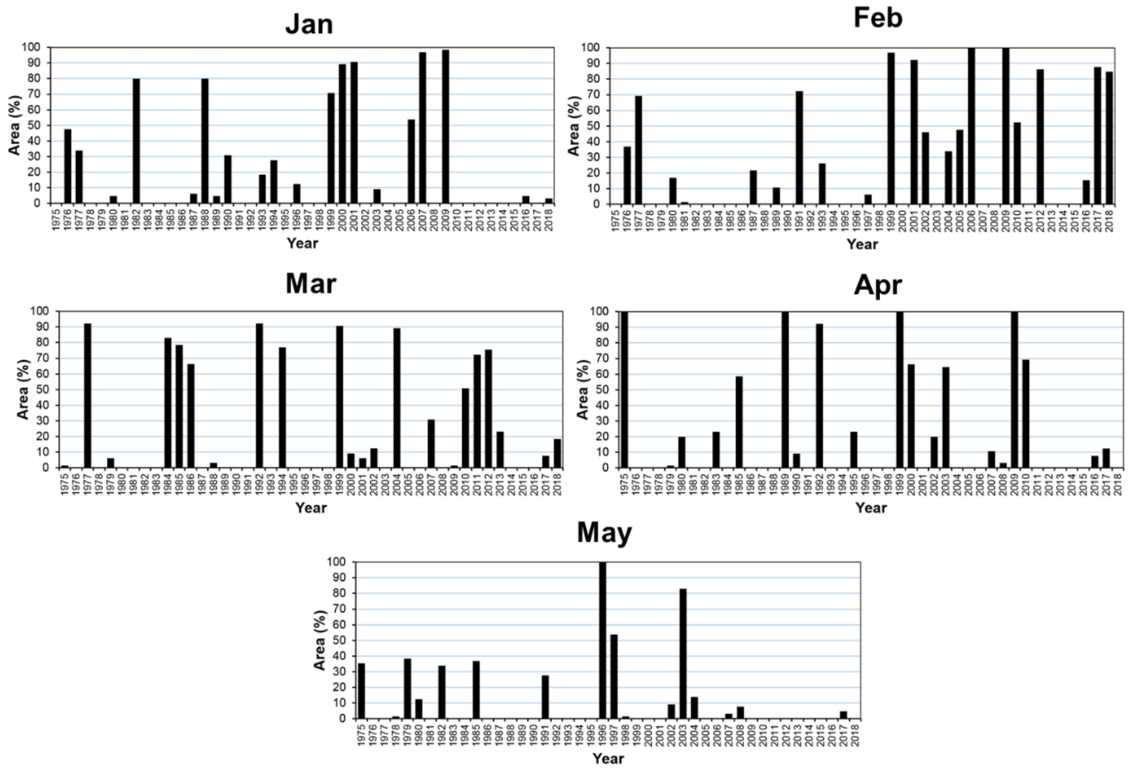
Figure 4.19: Spatial distribution of SPI over Odisha state for selected year.

4.3.3 Identification of meteorological drought using SPEI

Assessment of meteorological drought has also been carried out using SPEI. Figure 4.4 is showing the annual and monthly SPEI from 1975 to 2018. The annual SPEI plot indicates that from 2000 to 2018, the year 2000, 2002, 2004, 2009, 2010, 2013 and 2015 experienced meteorological droughts and more than 50% area is covered under drought. The % of drought area calculated based on monthly SPEI is also plotted in figure 4.4. The plot of January to May months showing the variation in SPEI value, but the most significant is June to September months as this is the monsoon season. The analysis suggests that 2000, 2002, 2004, 2009, 2010, 2013 and 2015 were the predominant drought years as more than 50% area of the state was under drought. The monsoon drought is the most severe in Odisha. Post-monsoon drought was also seen in the plot of October, November and December, however, the crop water requirement is very less during this time. Crop water requirement is high during the Kharif crop period which is grown during the monsoon month, therefore, meteorological drought during the monsoon period affects the Kharif crop growth and agricultural drought occurs. The observation matched with the analysis carried out based on SPI in the previous section.

2002/ 2004/ 2009/ 2010/ 2013/ 2015





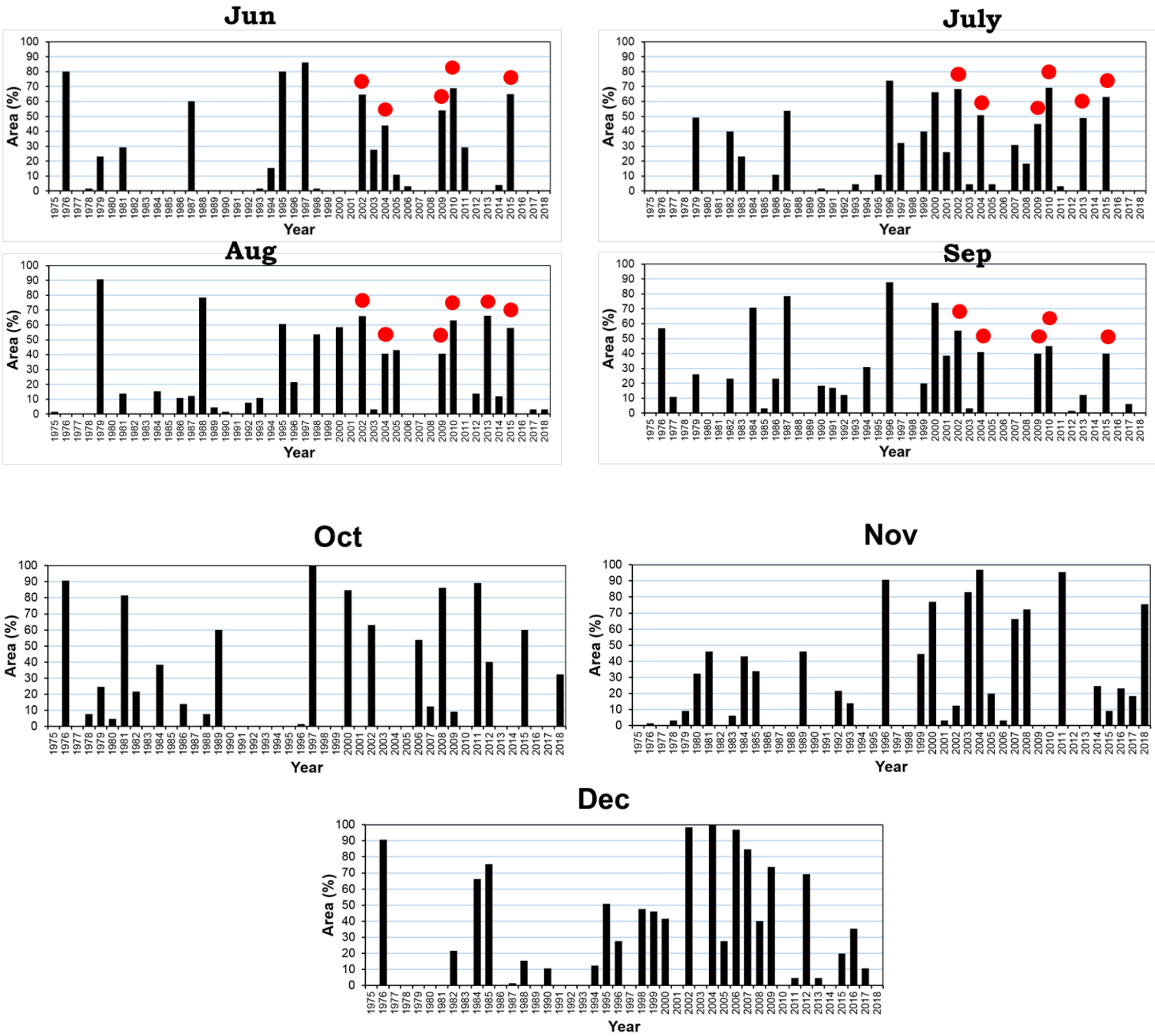
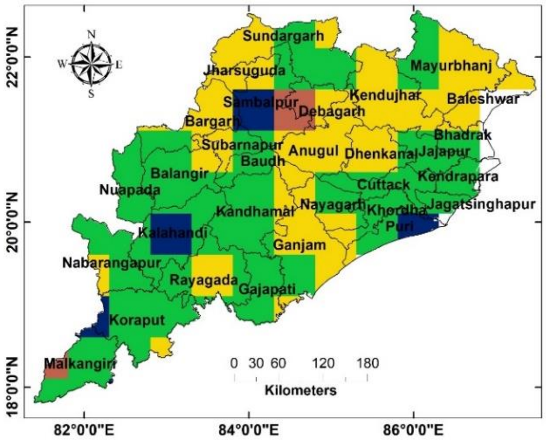


Figure 4.20: Percentage of area under meteorological drought against each year calculated based on SPEI.

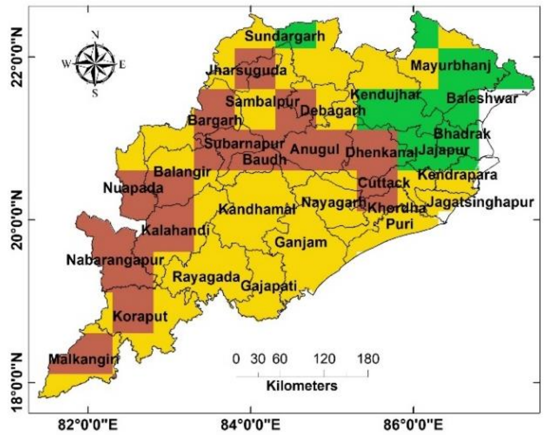
4.3.4 Analysis of drought characteristics – Drought Frequency using SPEI

Drought frequency analysis is carried out using SPEI. Spatial frequency (%) of drought in Odisha state is mapped using SPEI data of 1975 to 2018 in each month is calculated and shown in the figure 4.5 using different colour coding. The analysis suggests that northern and south western part of Odisha state is showing higher drought frequency in monsoon period. It is also observed that drought frequency is higher in the pre and post monsoon months. The major reason of this is because of less amount of rainfall in the pre and post monsoon season. In the monsoon season, drought frequency is significantly higher in the Odisha state which affects the agriculture as well as economy of the state. Mayurbhanj, Kendujhar, Sundargarh, Kalahandi, Bhadrak, Koraput, Malkangiri, Nuapada, Balangir districts are highly drought prone. No define pattern is seen in the drought frequency map.

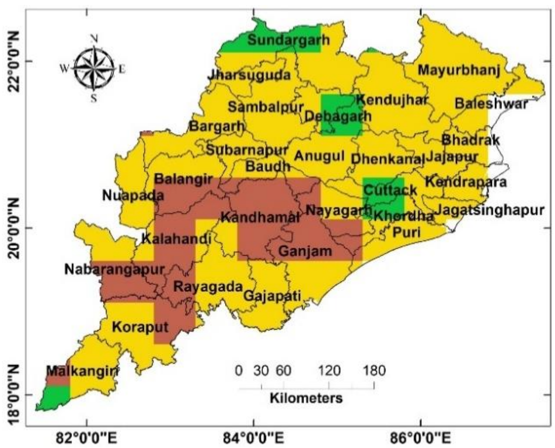
January



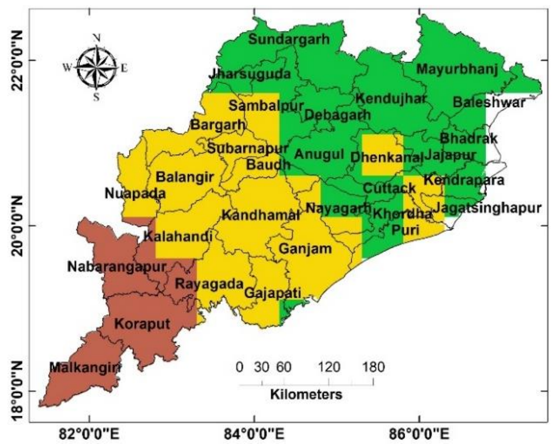
February



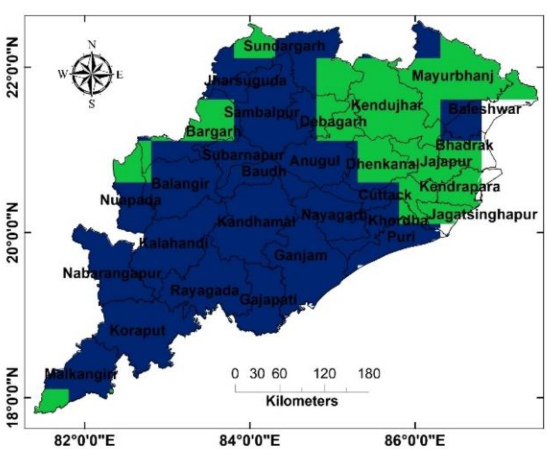
March



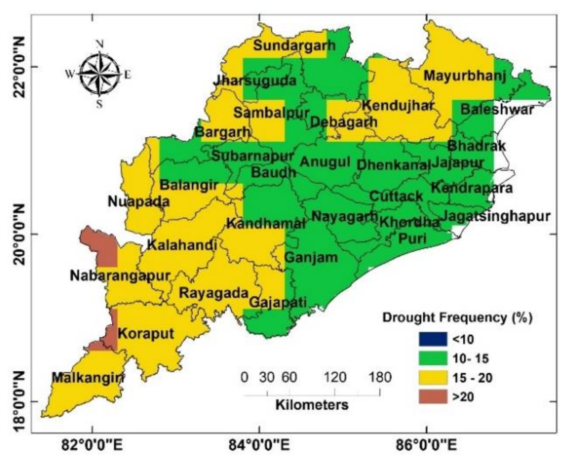
April



May



June



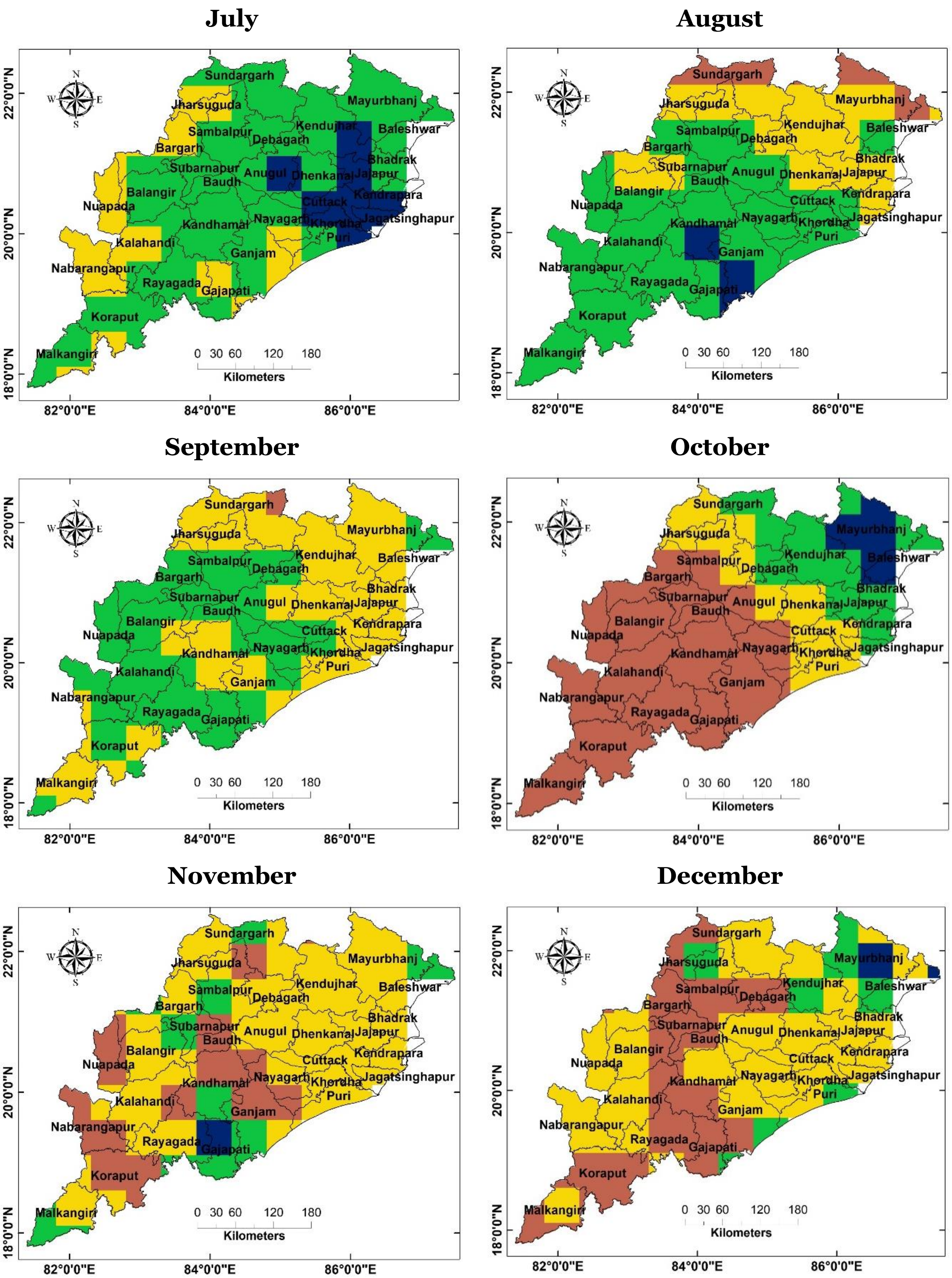
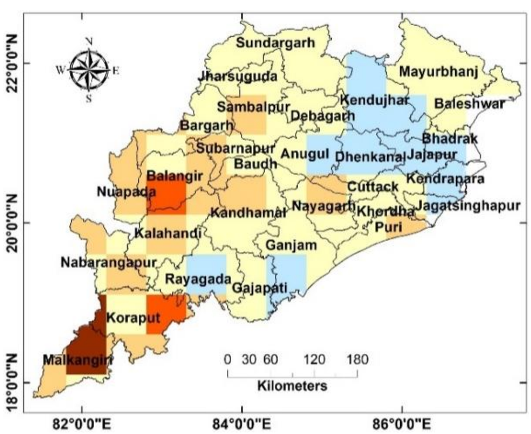


Figure 4.21: Spatial drought frequency map of Odisha calculated based on SPEI.

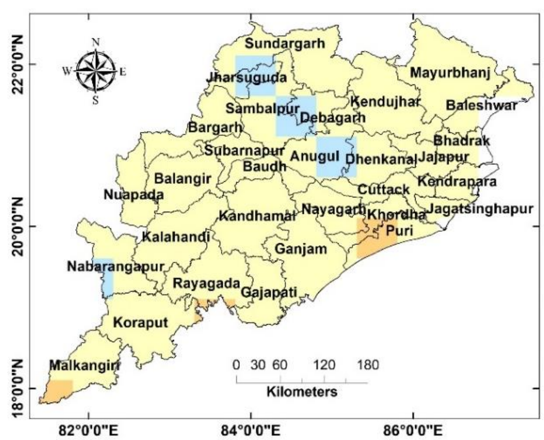
4.3.6 Analysis of drought characteristics – Drought severity using SPEI

Drought severity analysis is carried out for each month based on 1975 to 2018 SPEI datasets. Figure 4.6 shows the spatial distribution of drought severity over Odisha state. The classification scheme followed in this research is SPEI less than -2.0 is considered as extreme drought, SPEI from -1.6 to -1.9 is severe drought, SPEI between -1.0 to -1.5 is moderate drought, SPEI -0.5 to -0.99 is mild drought and SPEI >-0.5 is consider as no drought. It is found from the drought severity map that in the pre-monsoon season, drought severity is very low in Odisha. However, in monsoon season i.e., June, July, August and September months, drought severity is high, especially in the northern part of the state. It is also observed that in September, drought severity is very high. Drought severity is higher in most monsoon seasons which suggests that post-monsoon drought occurs in Odisha, however, the crop water requirement in the Ravi crop is less and therefore the meteorological drought does not affect agriculture significantly. Monsoon drought highly affects agriculture as the crop water requirement of paddy (Kharif) is very high compared to Ravi and Zaid crops.

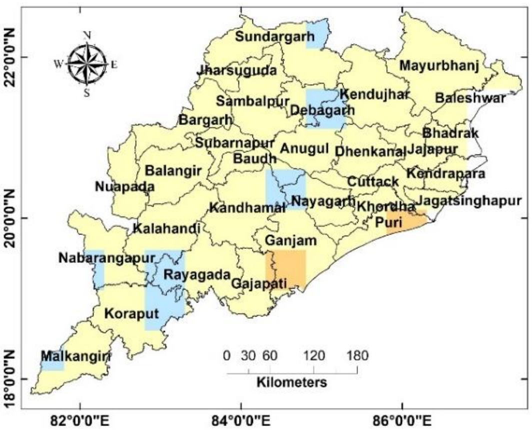
January



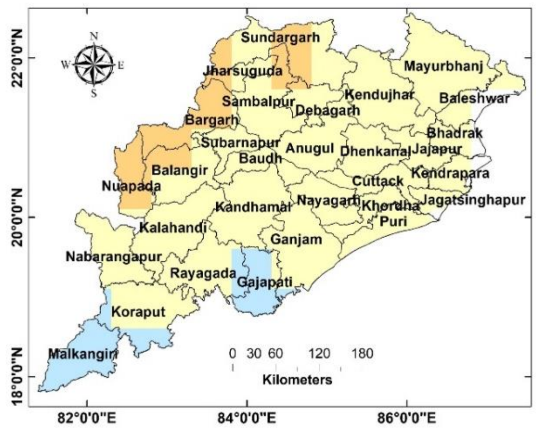
February



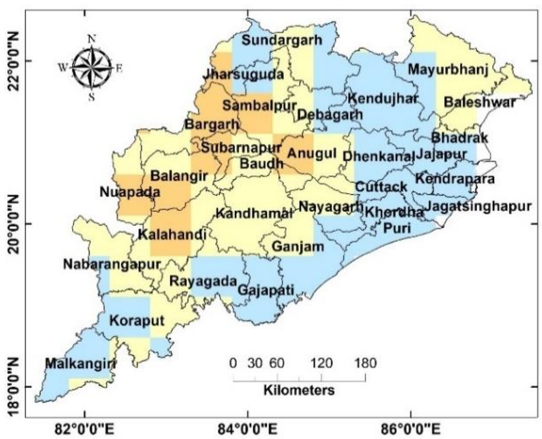
March



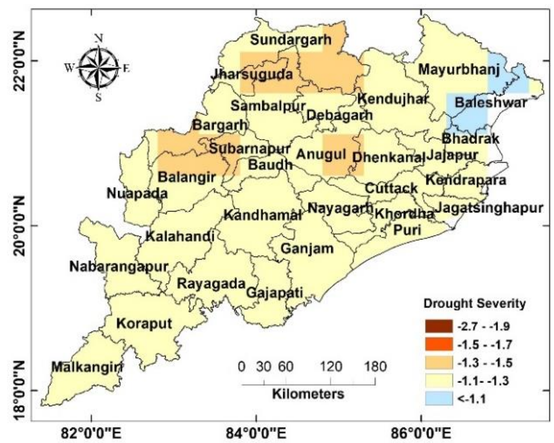
April



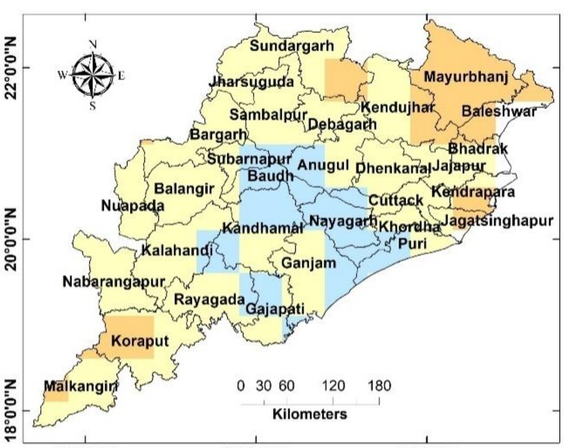
May



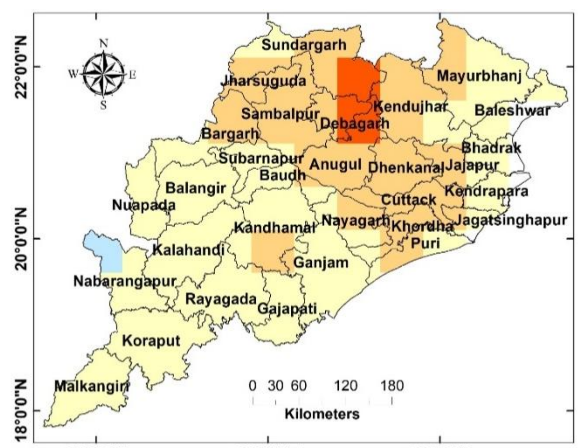
June



July



August



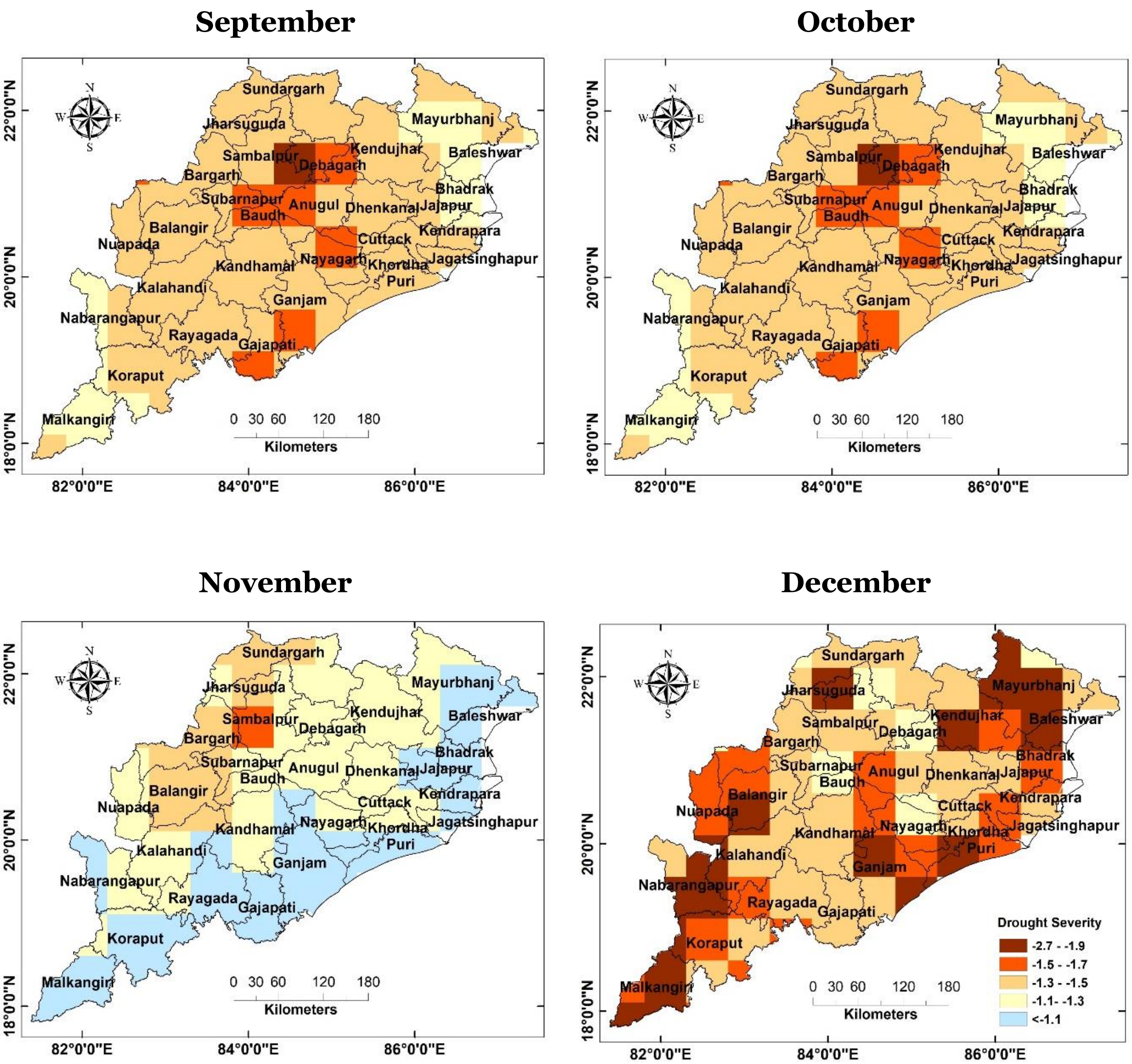
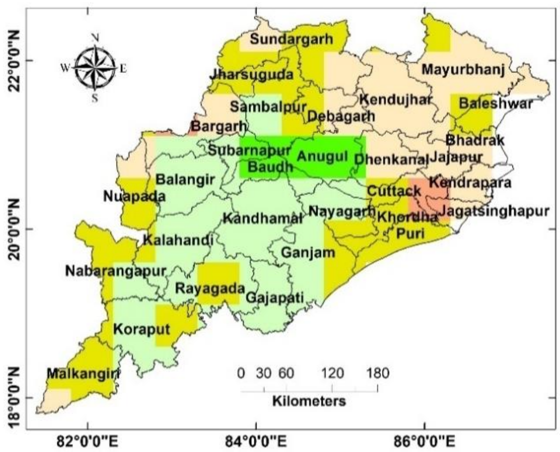


Figure 4.22: Spatial drought severity map of Odisha calculated based on SPEI.

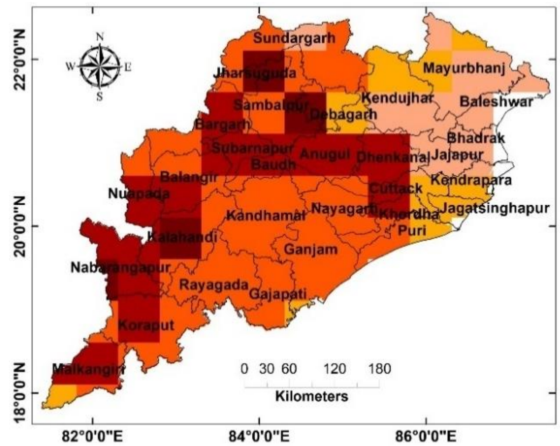
4.3.7 Analysis of drought characteristics – Drought intensity/ event using SPEI

Month wise meteorological drought intensity / event is calculated using SPEI of 1975 to 2018 datasets. It represents the continuous drought event occur in this month within the stipulated time frame. The spatial distribution of drought event of Odisha is shown in the figure 4.7. The result indicates that drought intensity/ event is higher in Odisha state. Considering the three-cropping season (Ravi, Kharif and Zaid), drought event is higher in all seasons. In the monsoon season, drought event/ intensity is high in the month of June, July, August and September. Almost entire state is hit by higher drought event and there is no pattern is observed. In the post-monsoon months also drought intensity is high which signifies that in Odisha drought occur in the post monsoon season.

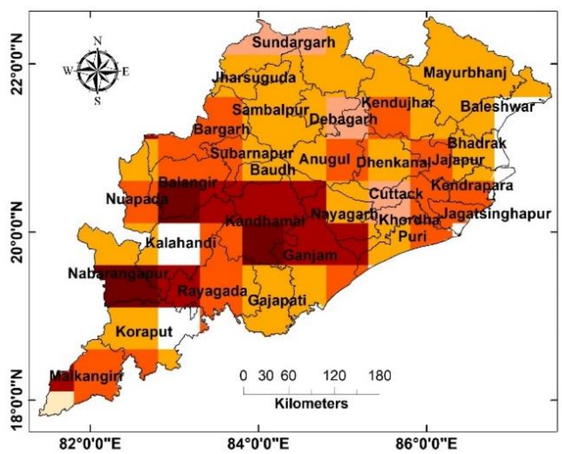
January



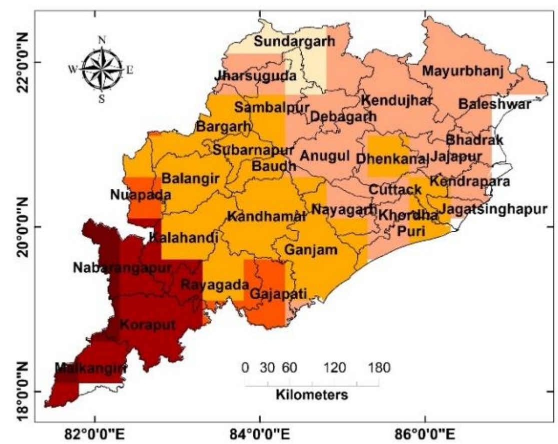
February



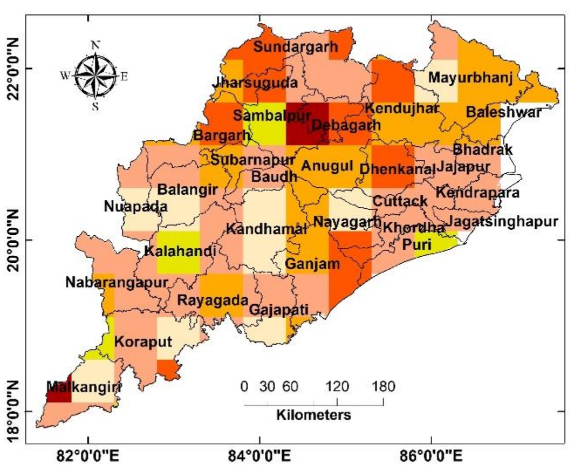
March



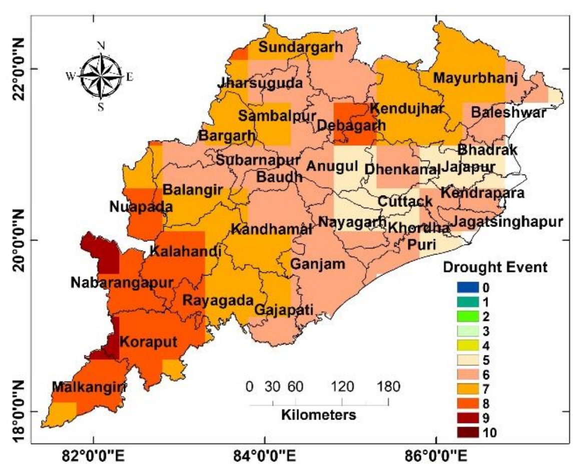
April



May



June



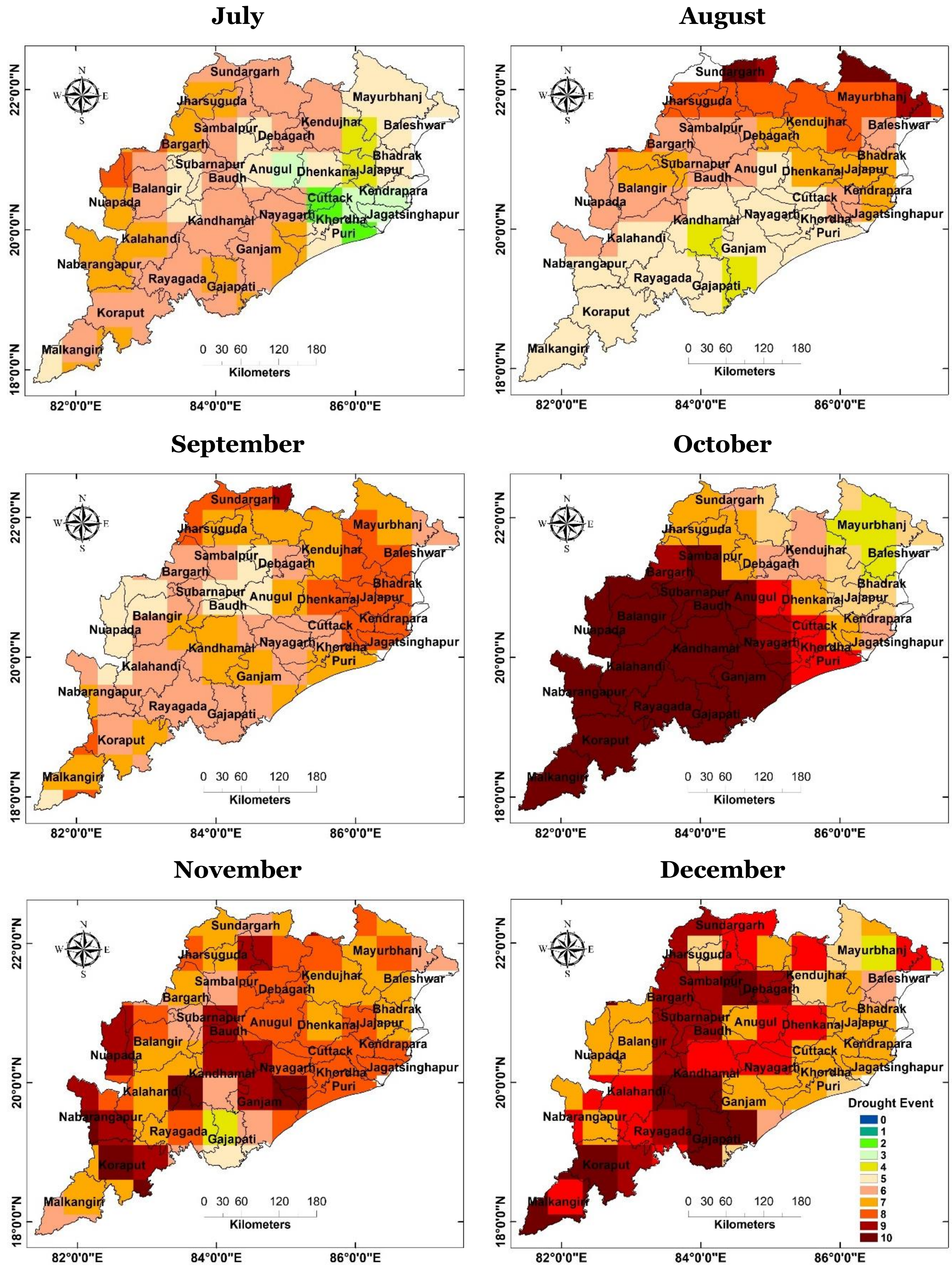


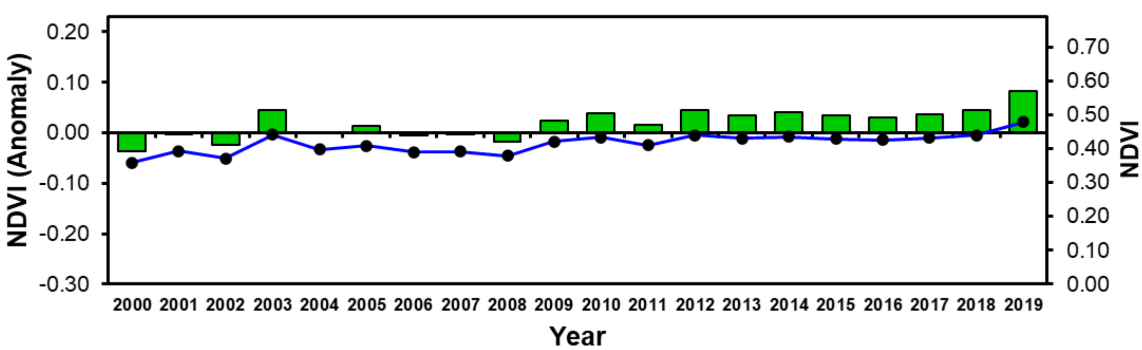
Figure 4.23: Spatial distribution of drought intensity/ event map of Odisha calculated based on SPEI.

4.3.8 Analysis of agricultural drought characteristics using NDVI

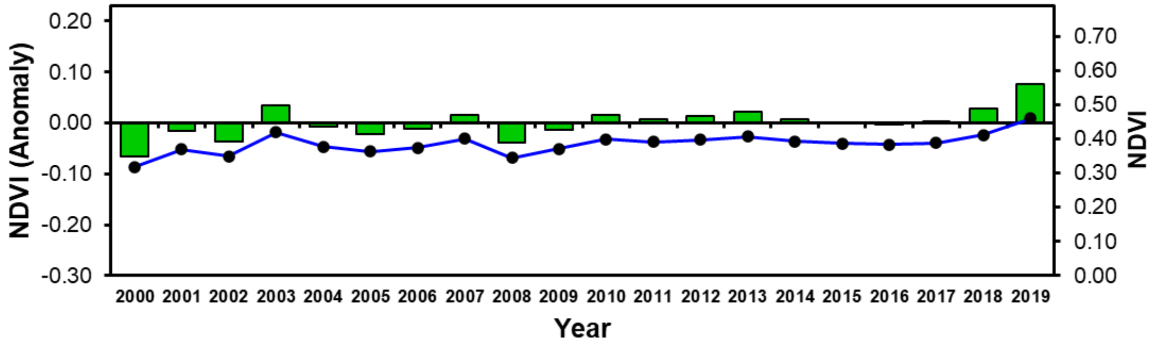
Normalized difference vegetation index (NDVI) is one of the important parameters for assessment of agricultural drought. NDVI indicates the vegetation/ agricultural growth. High vegetation growth indicates vegetation vigour and lower growth signifies drought situation. NDVI varies from +1 to -1, if the NDVI value of any agricultural field is higher than 0.4 or 0.5 in the growing season means the agricultural growth is good and if the NDVI value is less than 0.2, indicates poor growth of vegetation. When the drought occurs over an agricultural area, then agricultural growth of the area is affected and NDVI goes down to 0.2 or less which signifies agricultural drought. Month wise mean NDVI values of agricultural area and anomaly calculated from 2000 to 2020 satellite data is plotted and shown in the figure 4.8.

Results indicates that during the year 2002, 2004, 2009, 2010, 2013 and 2015 mean NDVI of the agricultural area of Odisha is low and NDVI anomaly is negative during the monsoon months i.e., June, July, August and September. It signifies thatagricultural drought occurred during the Kharif season of the year 2002, 2004, 2009, 2010, 2013 and 2015. It is also seen in the previous sections as well as chapter 5 that all climatic parameters were in the favour of drought in these years. The secondary data also suggests the same.

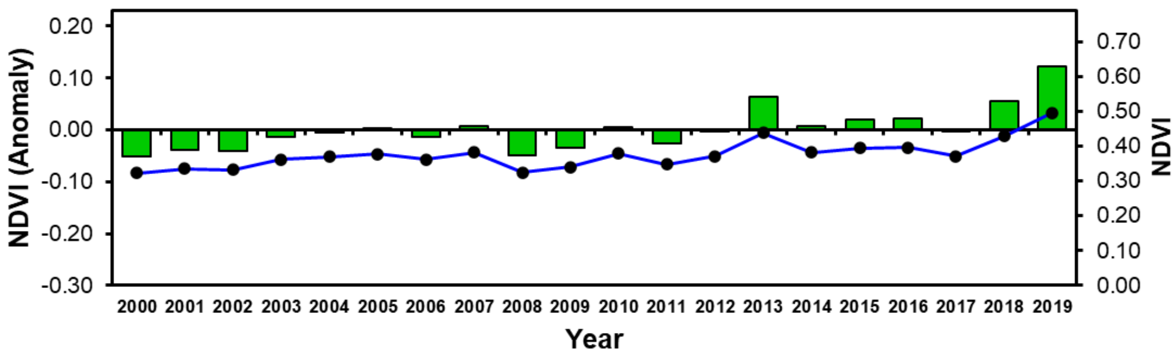
January



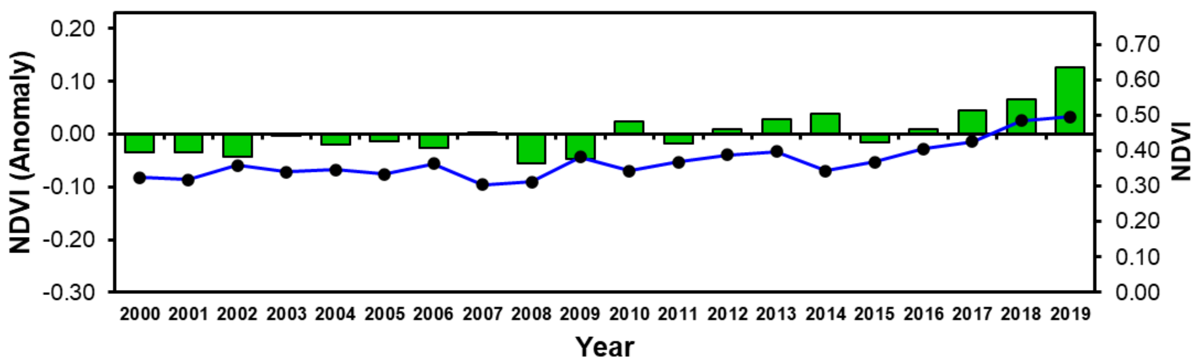
February



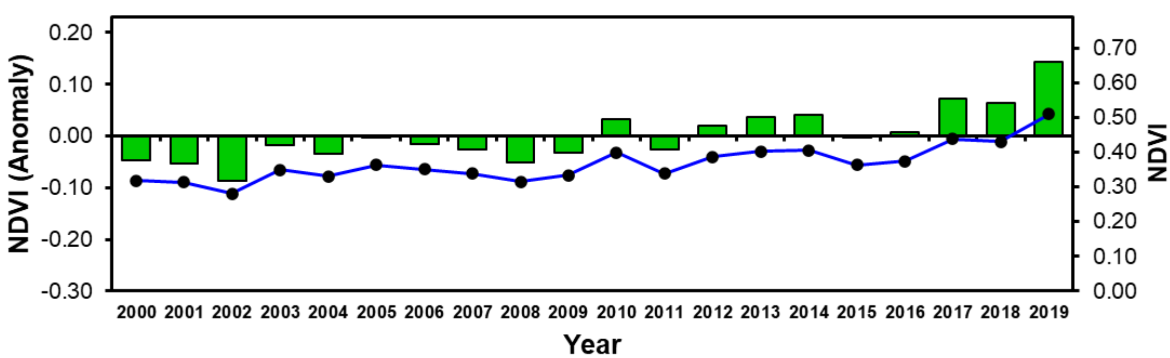
March



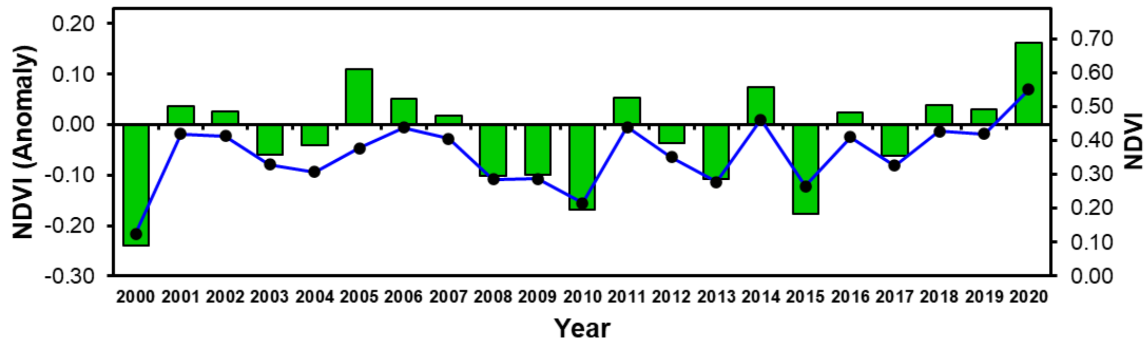
April



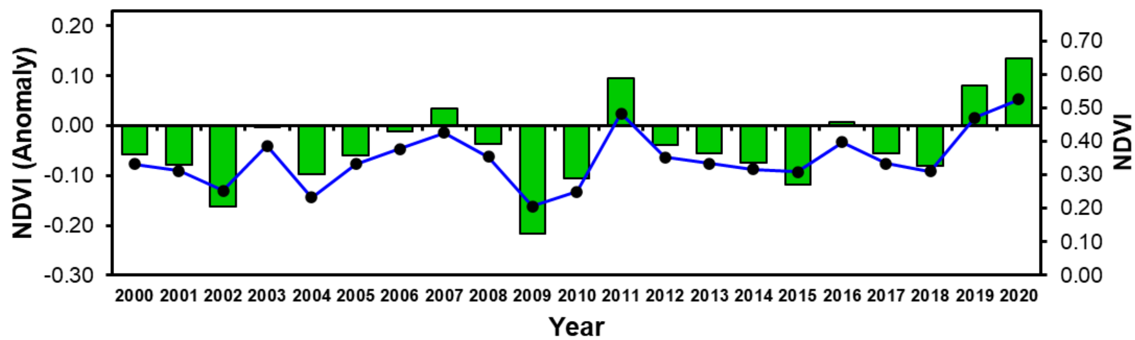
May



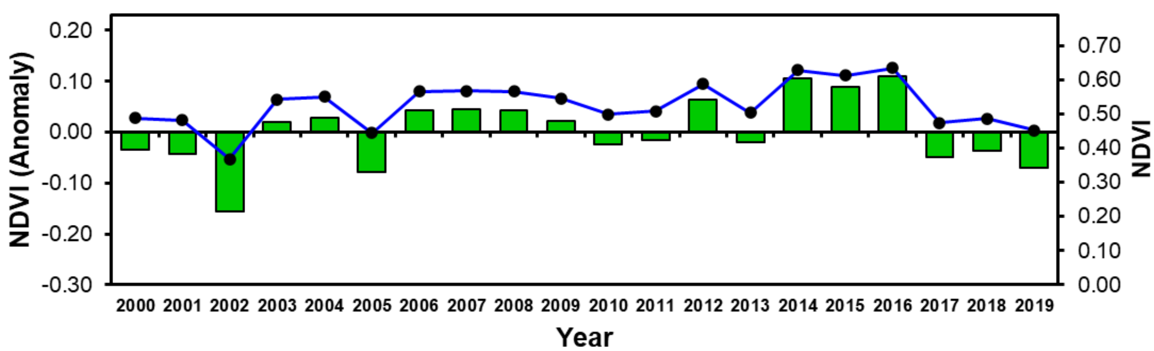
June



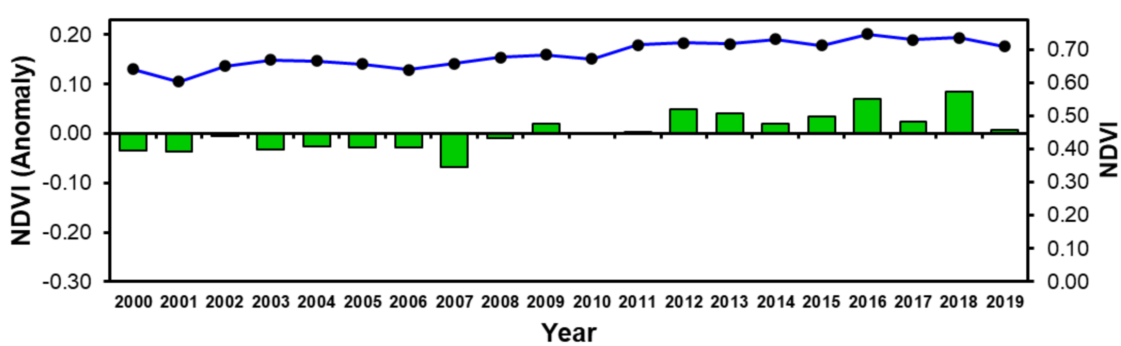
July



August



September



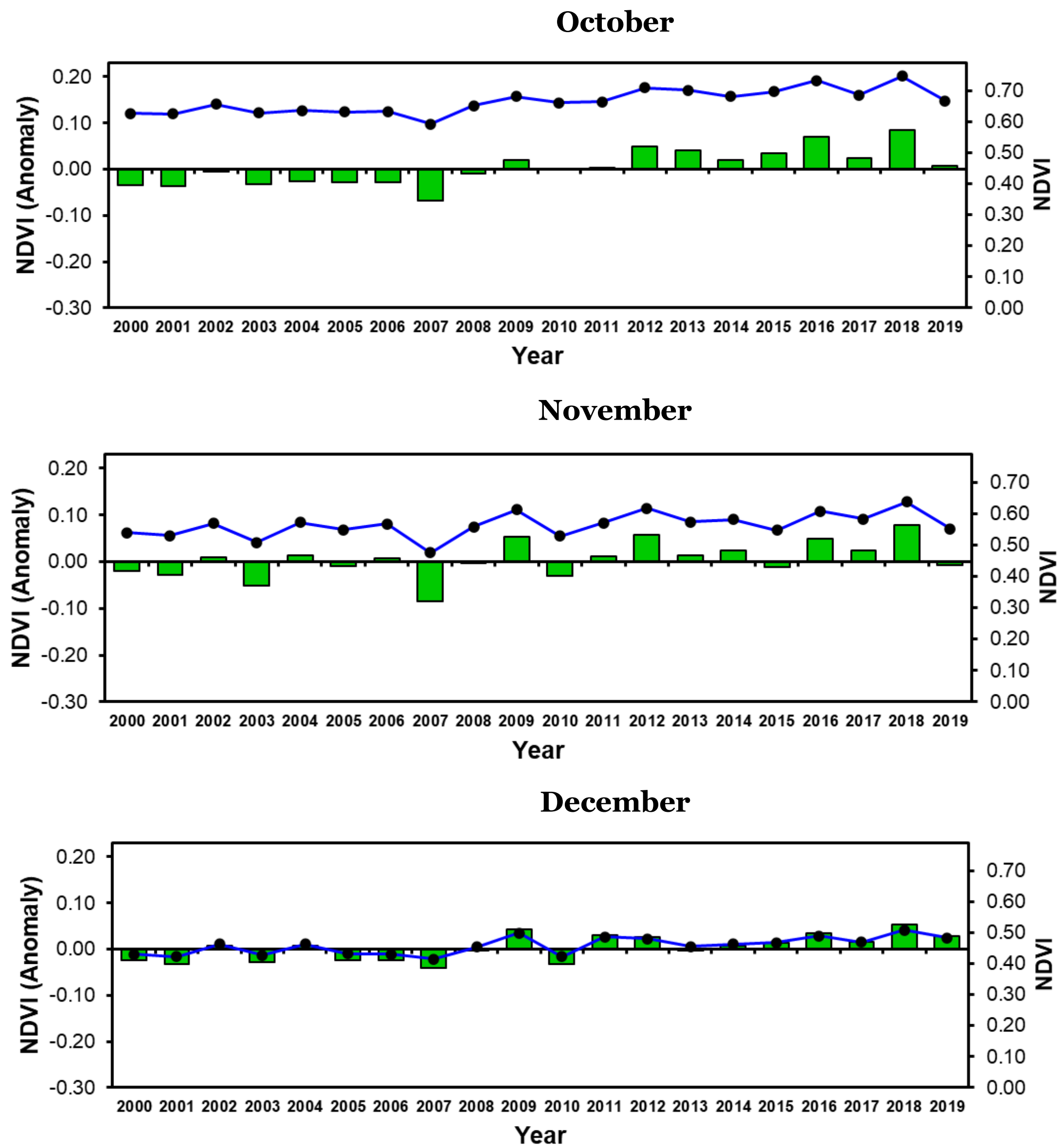


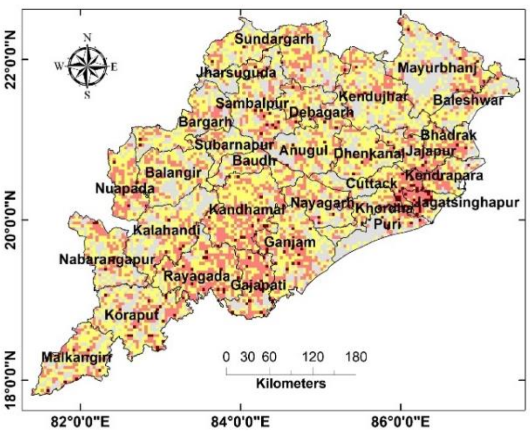
Figure 4.24: Assessment of drought using NDVI over Odisha state from 2000-2020 datasets.

4.3.9 Analysis of agricultural drought characteristics using VHI – Drought frequency mapping

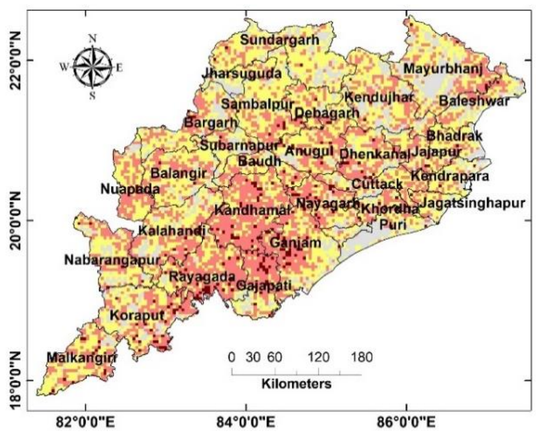
Assessment of agricultural drought is carried out using vegetation health index (VHI). Weekly basis 4 km resolution VHI data is taken and converted to monthly average VHI for 2000 to 2020 and drought characteristics has been assessed. Drought frequency map of agricultural drought for January to December is generated and shown in the figure 4.9.

The results indicate that drought frequency is low in the pre-monsoon season i.e., January to April, only Ganjam, Gajapati, Kalahandi and Rayagada district drought frequency is found more. In the month of May, drought frequency is found higher, but it is harvesting season therefore crop water requirement is very low this time. It is observed that in the monsoon season i.e., June, July, August and September agricultural drought frequency are higher all over the state compared to pre-monsoon season. It affects the Kharif crop growth of the Odisha state and agricultural productivity is affected. In the post monsoon season, agricultural drought frequency is also found to be higher over the Odisha state. However, post monsoon season drought does not the affect the agriculture. The results again signify the monsoon drought situation of Odisha.

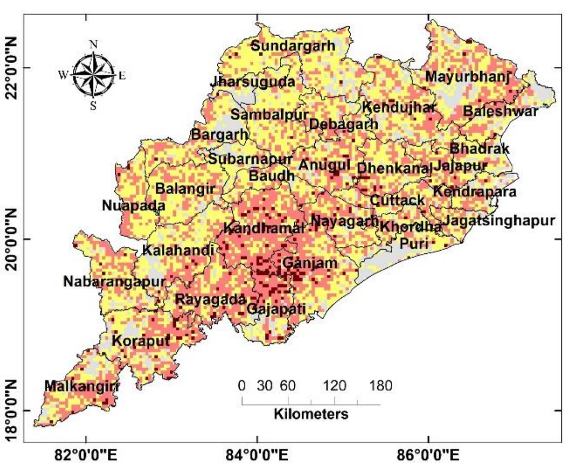
January



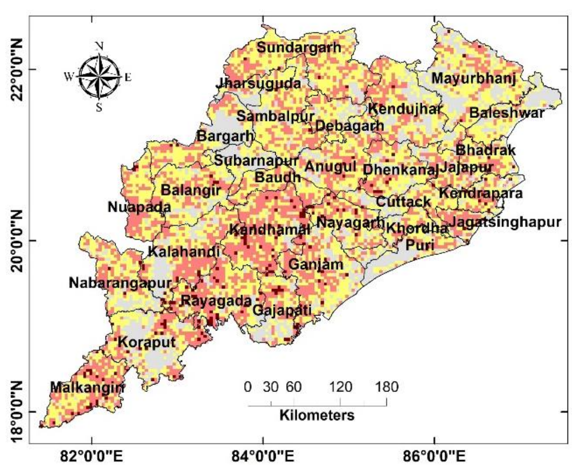
February

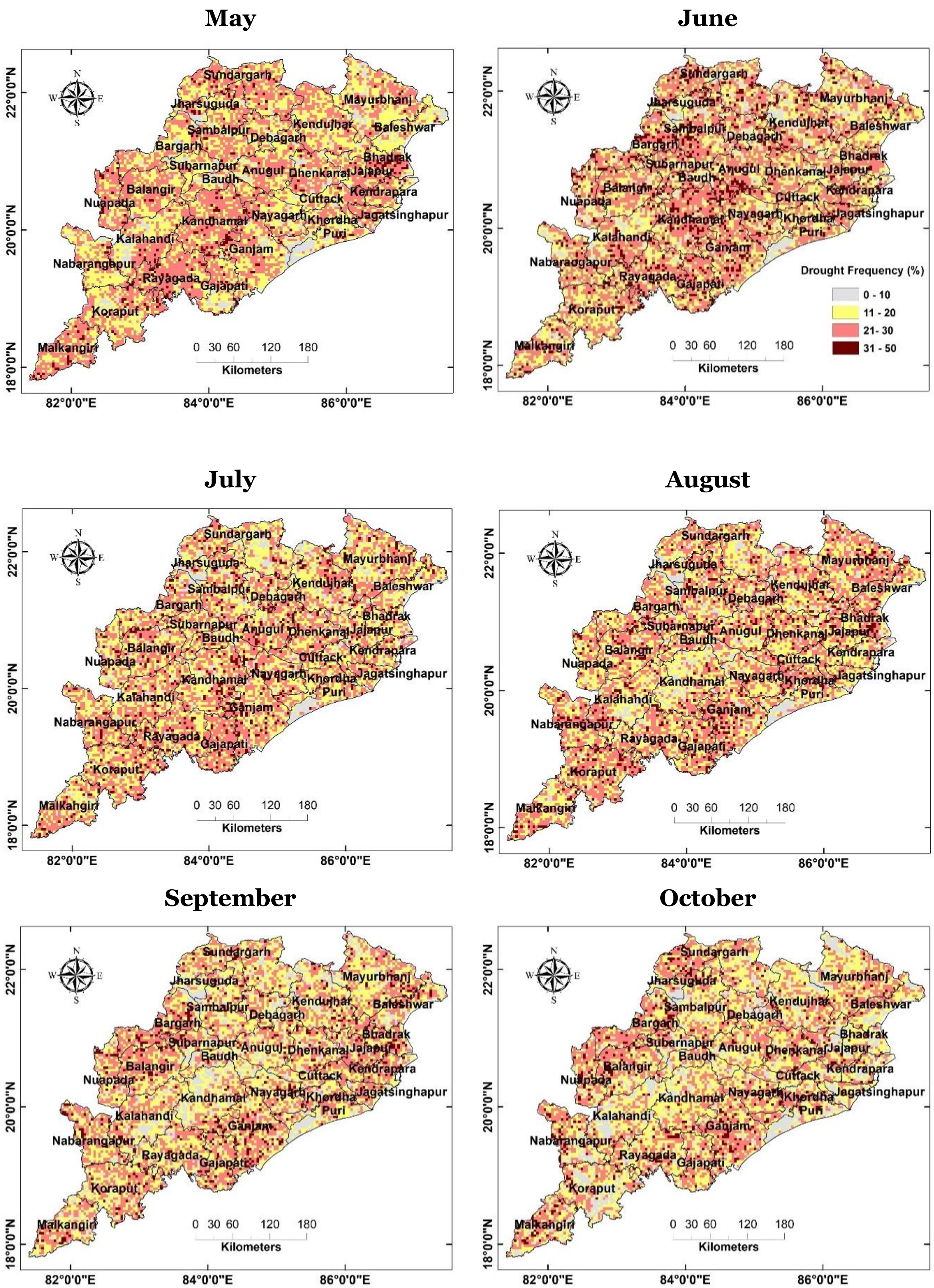


March



April





May
June
July
August
September
October
Drought Frequency (%)
0 - 10
11 - 20
21- 30
31 - 50
Sundargarh
Jharsuguda
Mayurbhanj
Sambalpur
Kendujhar
Baleshwar
Debagarh
Bargarh
Bhadrak
Subarnapur
Anugul
Dhenkanal
Jajapur
Baudh
Balangir
Kendrapara
Cuttack
Nuapada
Kandhamal
Nayagarh
Khordha
Jagatsinghapur
Puri
Kalahandi
Ganjam
Nabarangapur
Rayagada
Gajapati
Koraput
Malkangiri
0 30 60 120 180
Kilometers
N
S
E
W
22°0'0"N
20°0'0"N
18°0'0"N
82°0'0"E
84°0'0"E
86°0'0"E

November **December**

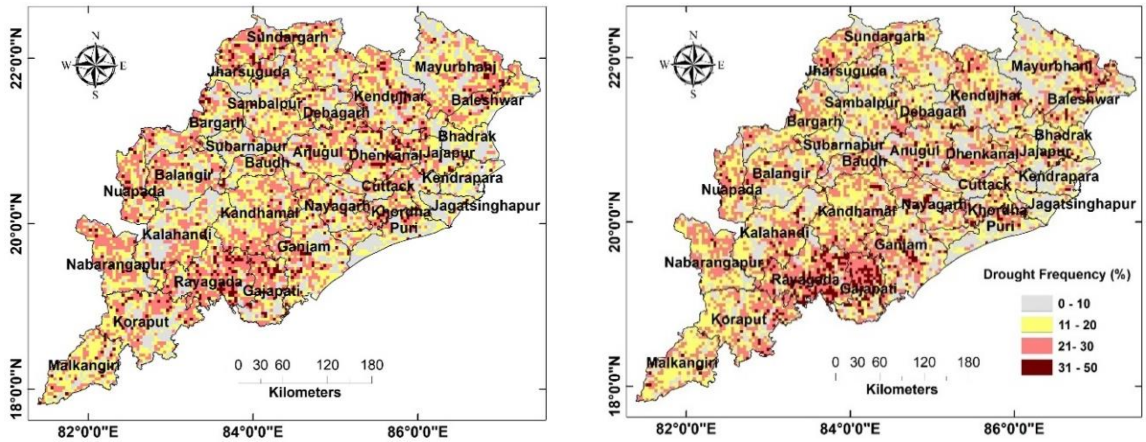
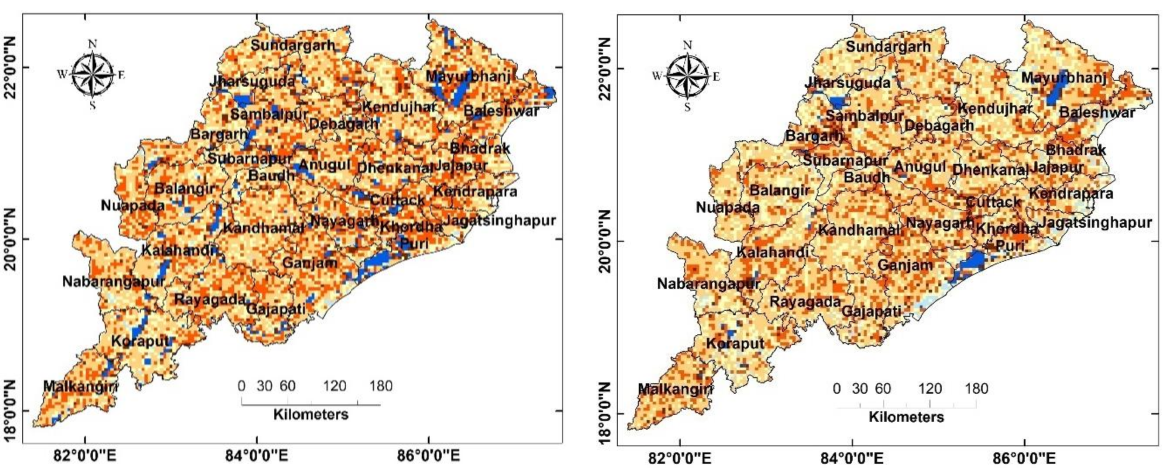


Figure 4. 25: Spatial distribution of agricultural drought frequency over Odisha using VHI data of 2000-2020.

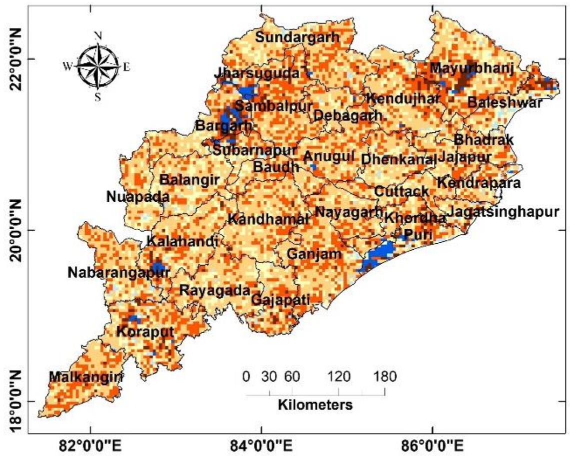
4.3.10 Analysis of agricultural drought characteristics using VHI – Drought severity mapping

Drought severity analysis for agricultural drought is carried out using VHI data and results are shown in the figure 4.10. The spatial distribution of agricultural drought severity depicts that severe drought occurred over Odisha state in all agricultural seasons i.e., Ravi, Kharif and Zaid. Generally, severe to moderate drought is seen in the monsoon season. The pattern of drought severity is random in nature.

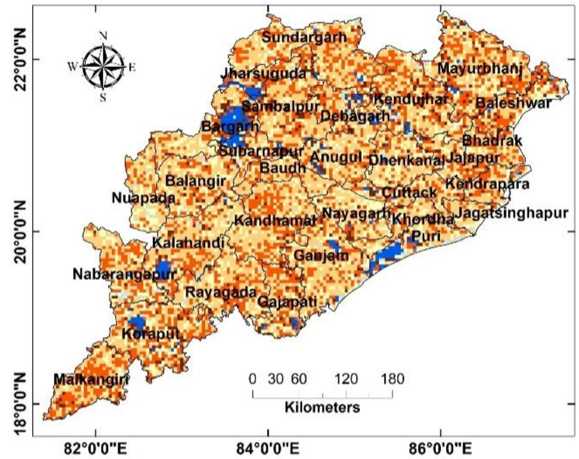
January **February**



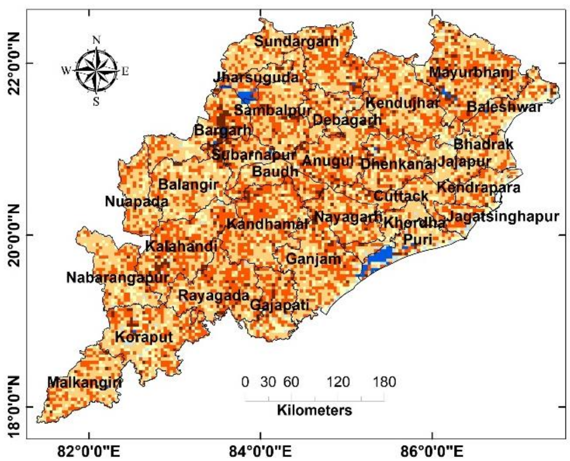
March



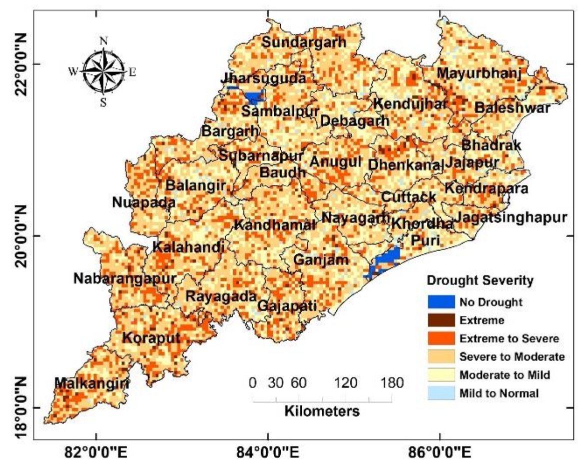
April



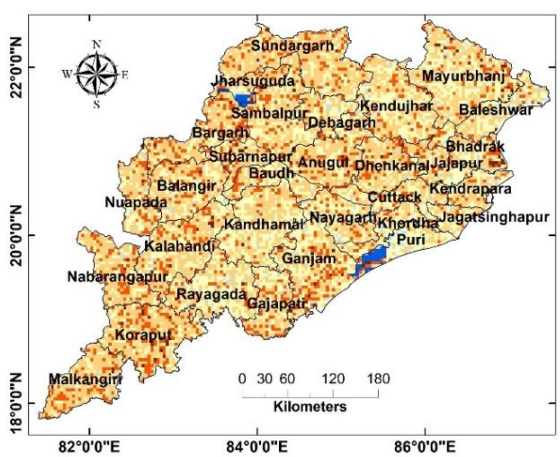
May



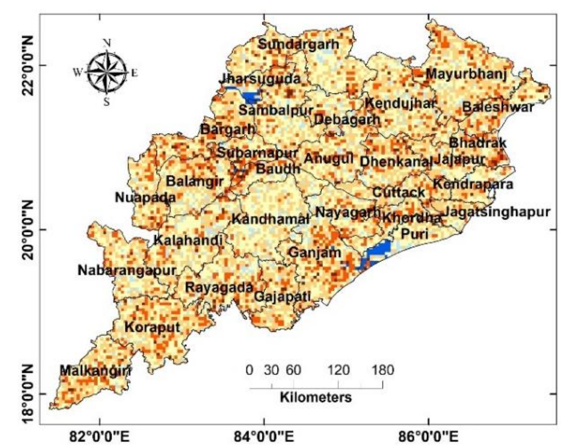
June



July



August



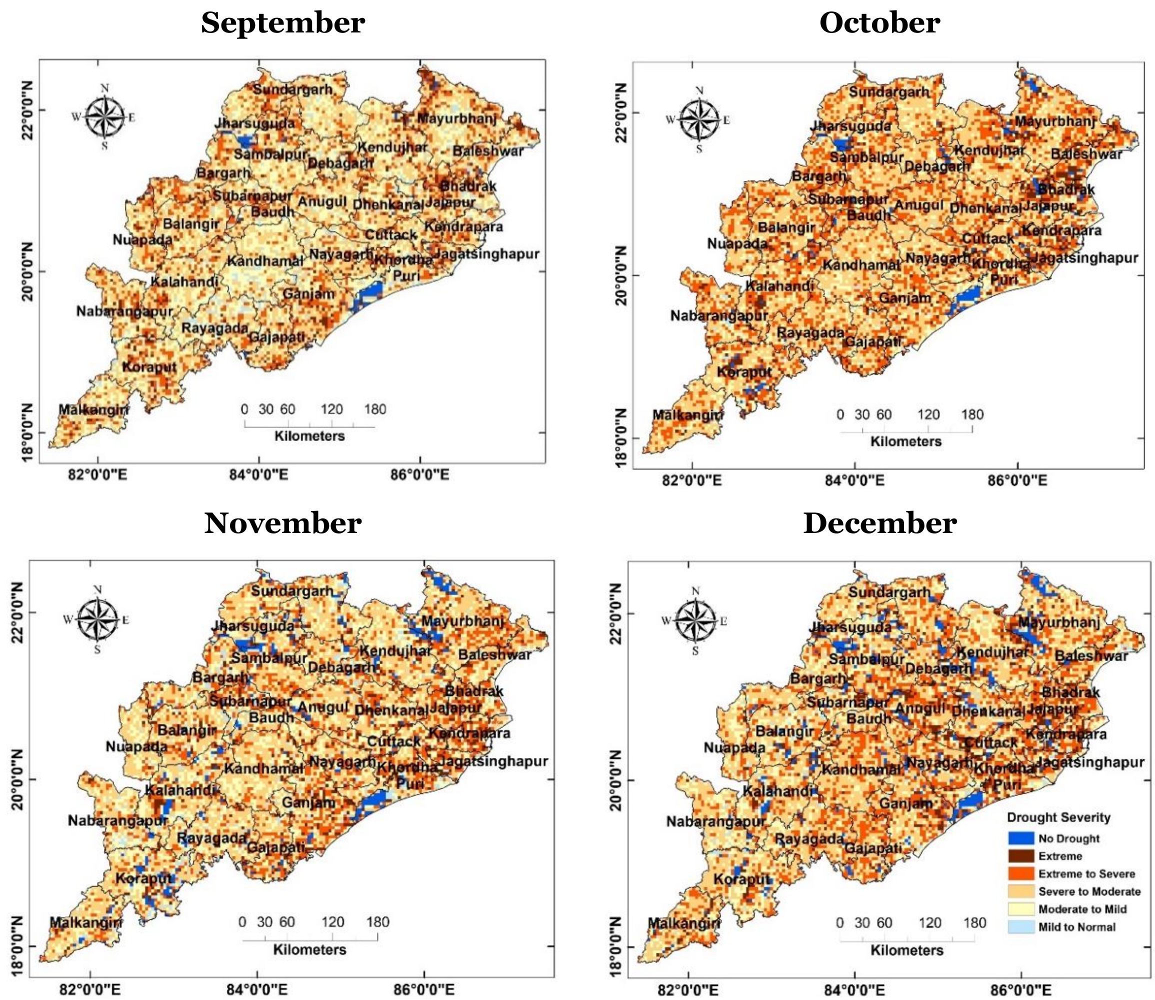
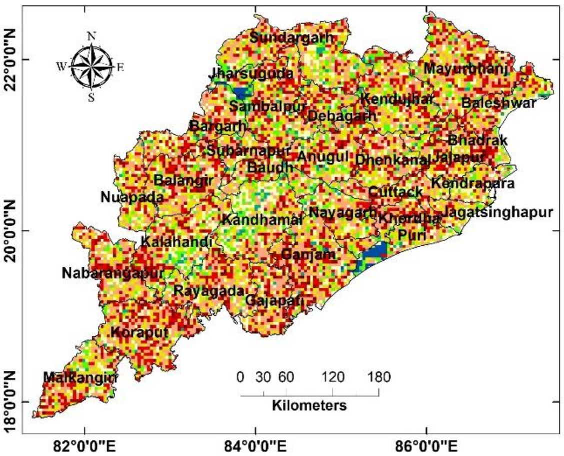


Figure 4.26: Spatial distribution of agricultural drought severity over Odisha using VHI data of 2000-2020.

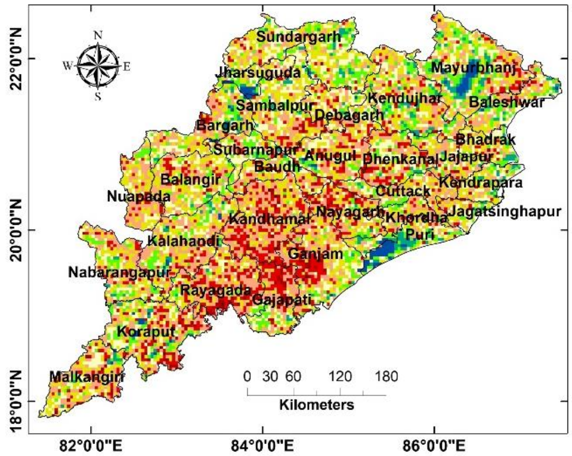
4.3.11 Analysis of agricultural drought characteristics using VHI – Drought intensity/ event mapping

Agricultural drought intensity /event is mapped using VHI data of 2000 to 2020. The spatial distribution of drought intensity /event are shown in the figure 4.11. The results show higher drought event in the monsoon months compared to pre-monsoon and post monsoon seasons. In the pre-monsoon months it is observed that southern part of the state is having more drought event, but in the monsoon and post monsoon months the pattern is random.

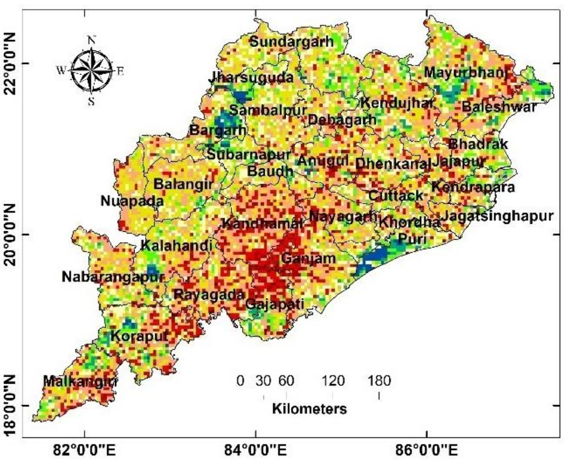
January



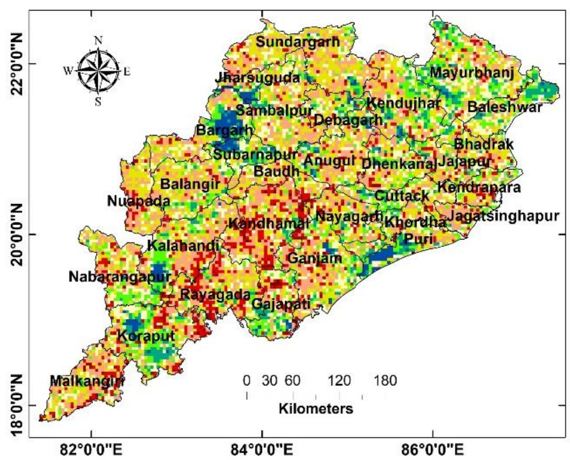
February



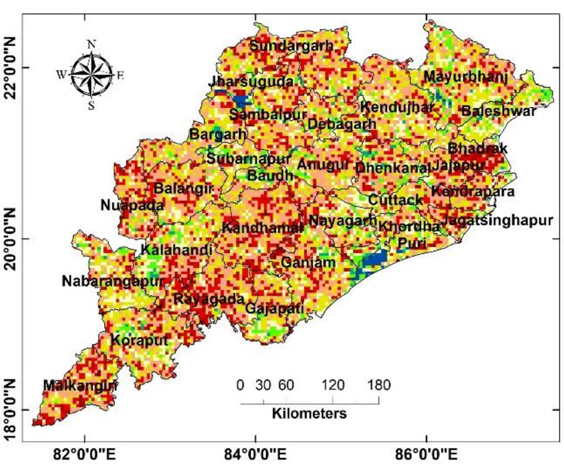
March



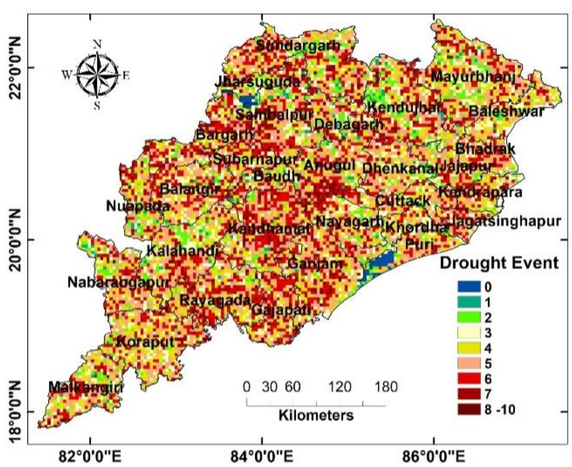
April



May



June



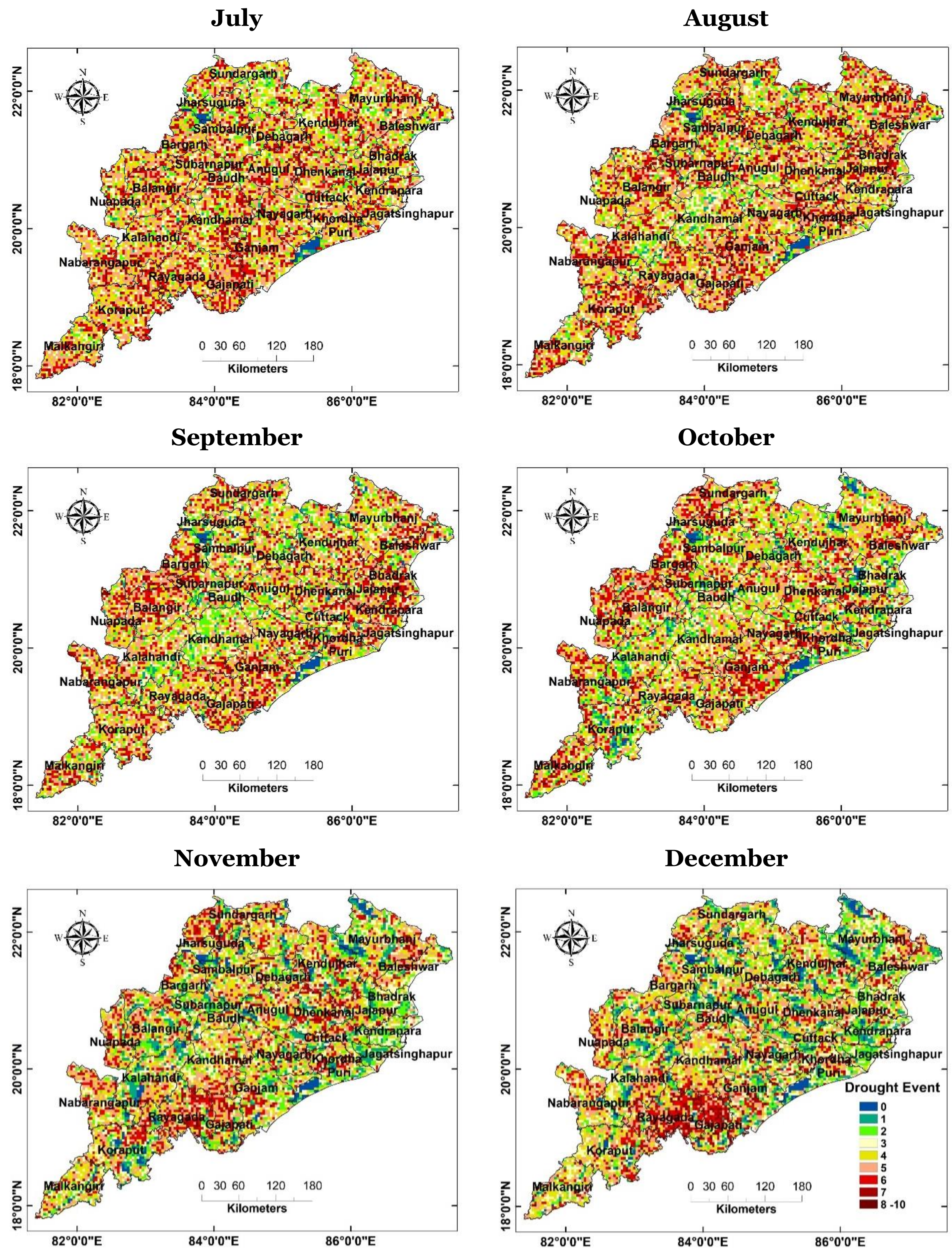


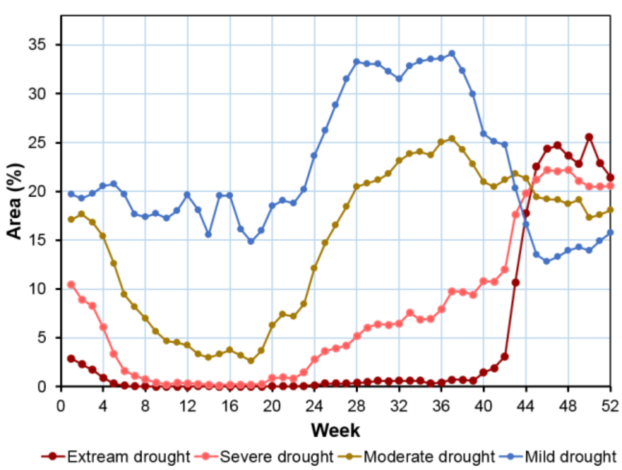
Figure 4.27: Spatial distribution of agricultural drought frequency over Odisha using VHI data of 2000-2020.

4.3.12 Analysis of weekly agricultural drought characteristics using VHI over two decades

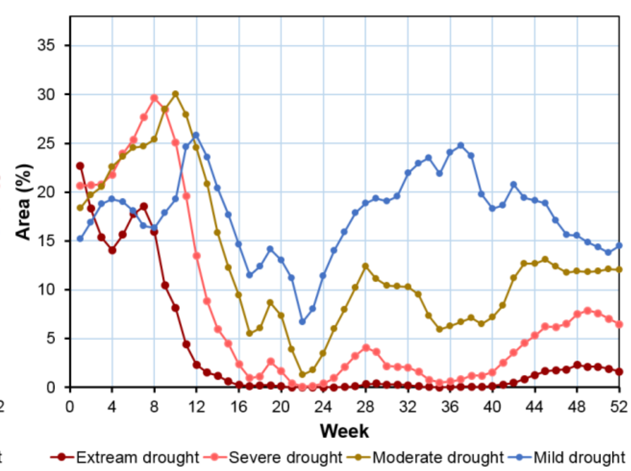
Drought assessment and monitoring is carried out in every week using VHI datasets of 2000 to 2020. Total 1092 raster datasets were processed to generate the vegetation health/ drought characteristics of Odisha state of last two decades. The VHI ranges from 0-100 which is classified as per classification scheme given by Kogan (2001) as mentioned in the methodology section. Percentage of drought affected area under various drought class such as extreme drought, severe drought, moderate drought, mild drought and no drought is estimated and plotted with respect to weeks of 2000 to 2020 and shown in the figure 4.12. There is some anomaly is seen in the 2005 plot due to data problem.

The result shows that there is a major pick in 24thto 32ndweeks, which indicates that in most of the year severe drought occurred in the month of June and July. The observation again signifies the monsoon drought in Odisha state which is also seen in the earlier analysis. Another pick is also discerned after 44th week which continues upto 8th week which is post-monsoon season. The graph also reveals that in the identified drought year i.e., 2002, 2004, 2009, 2010, 2013 and 2015 severe drought occurred in the 24th to 36th week, signifies drought in the monsoon period.

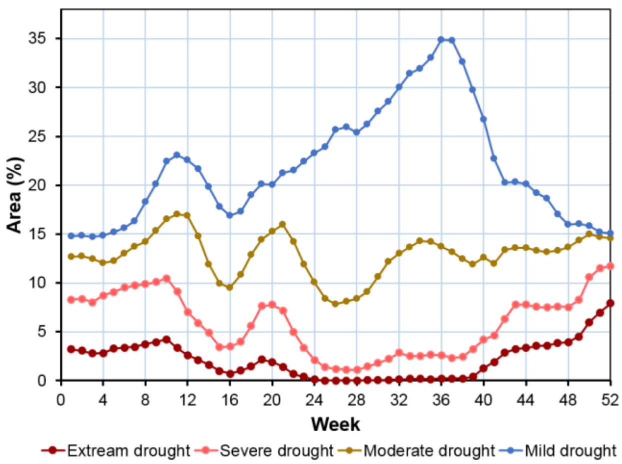
2000



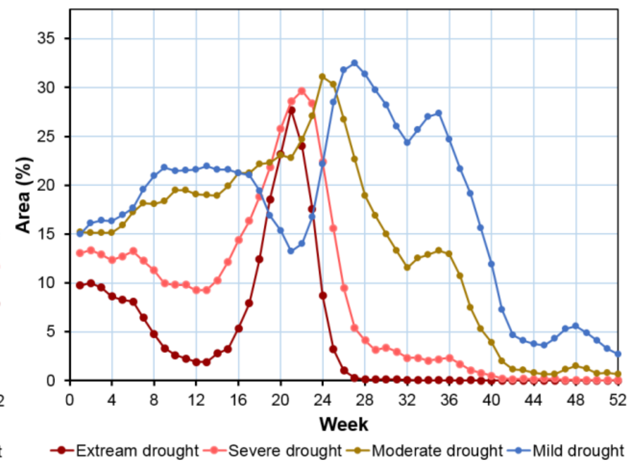
2001



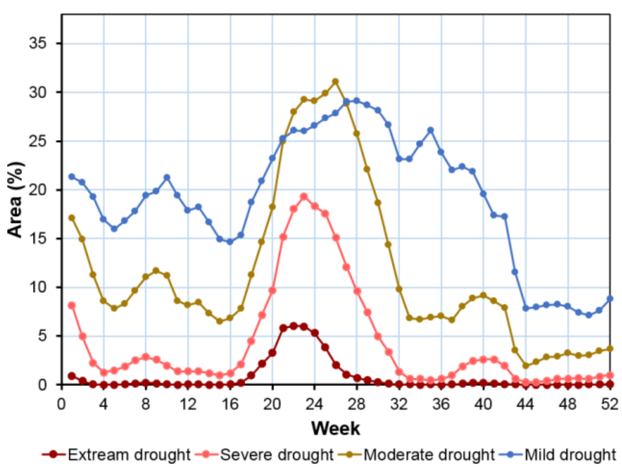
2002



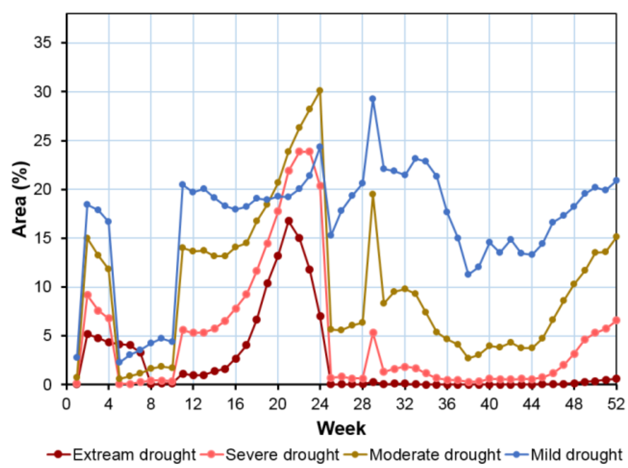
2003



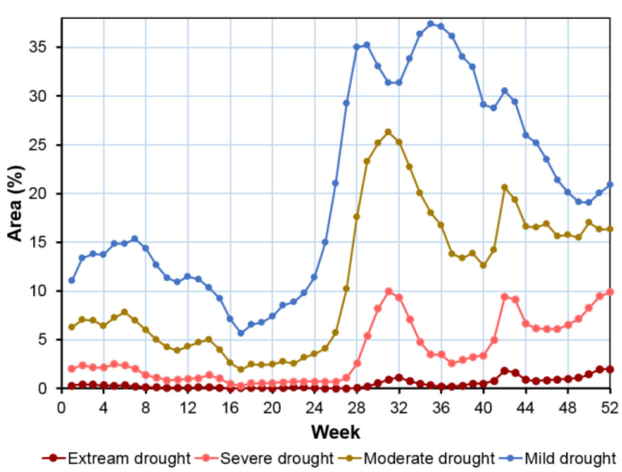
2004



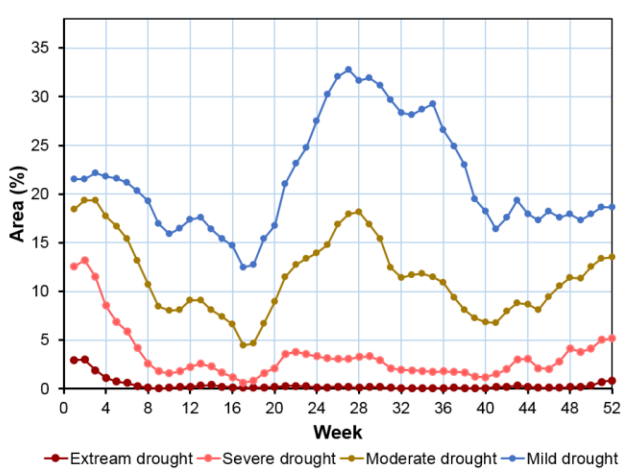
2005

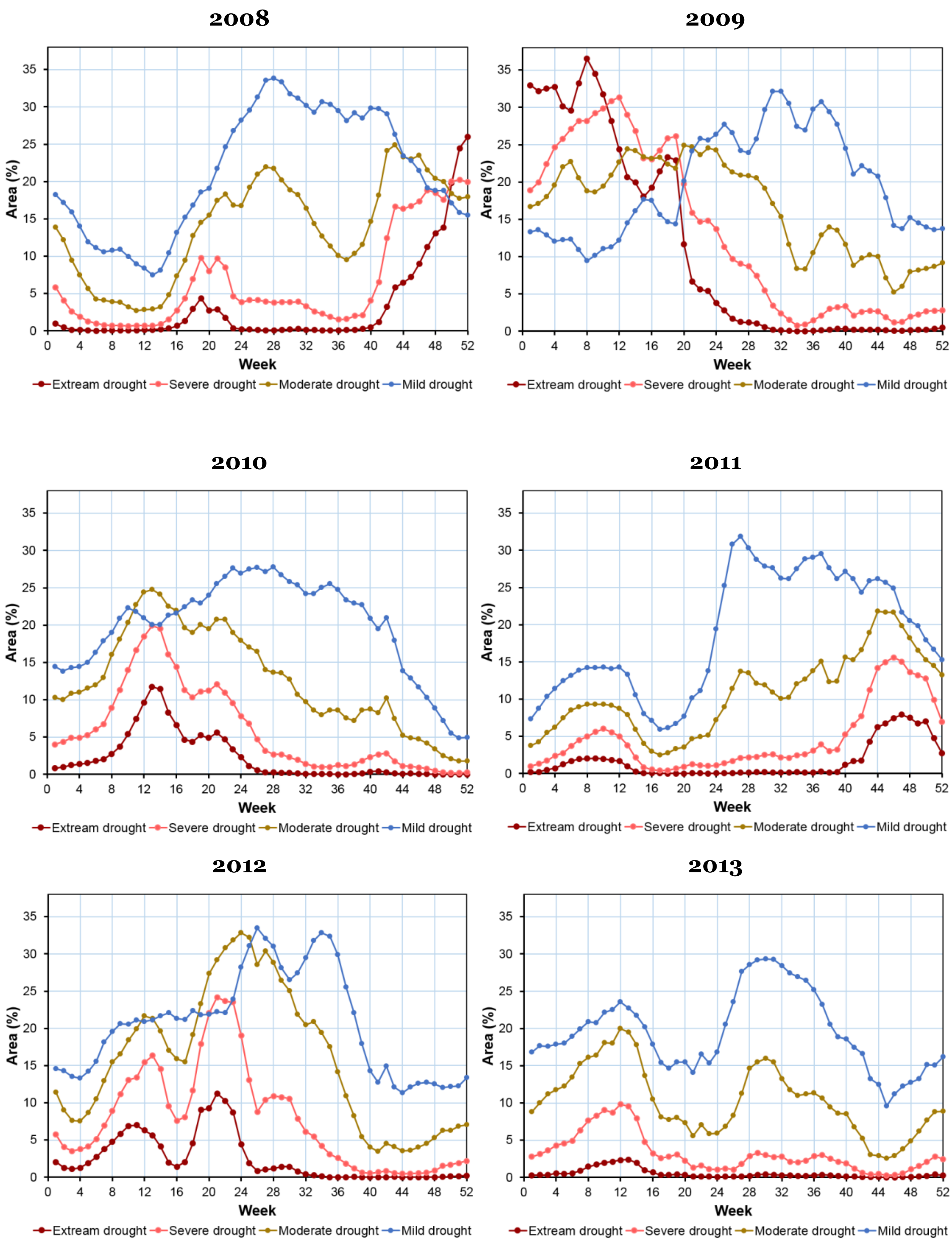


2006

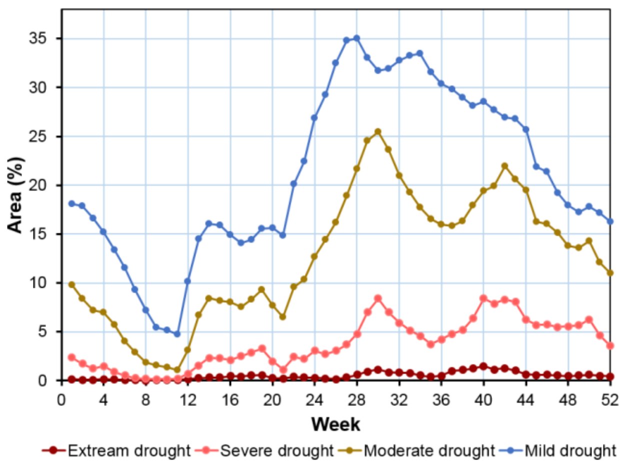


2007

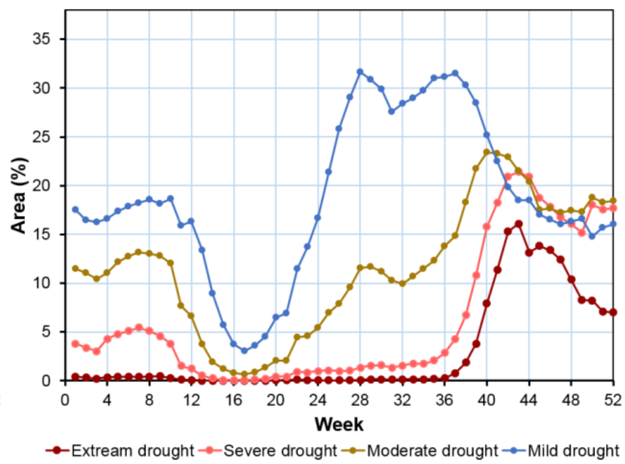



2008
2009
2010
2011
2012
2013
Area (%)
Week
Extream drought
Severe drought
Moderate drought
Mild drought

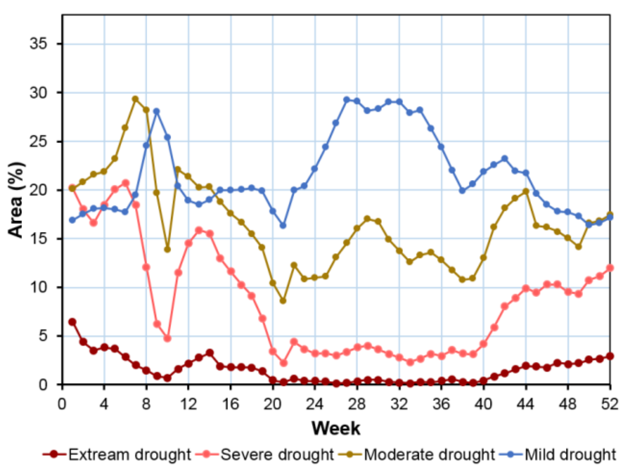
2014



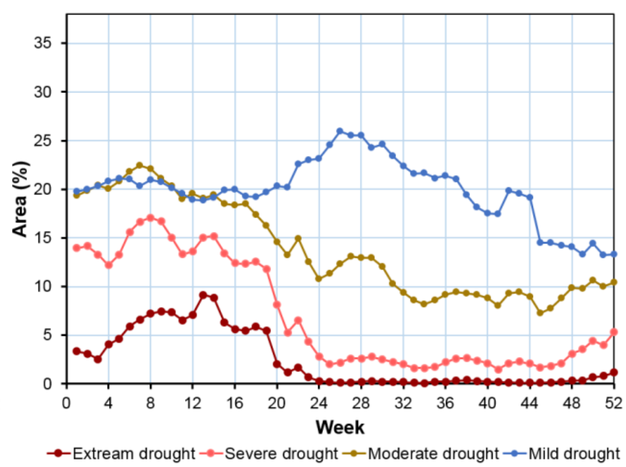
2015



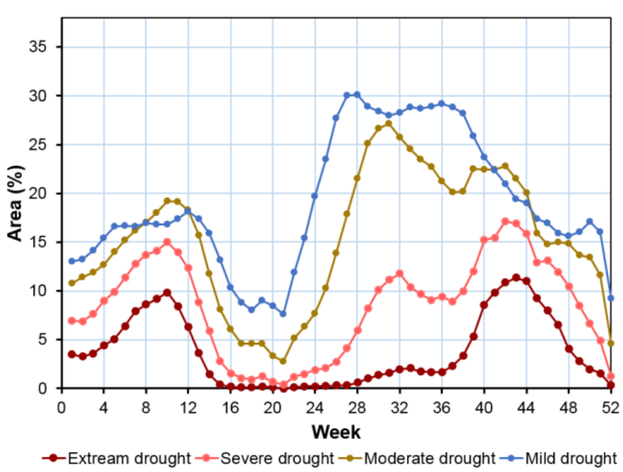
2016



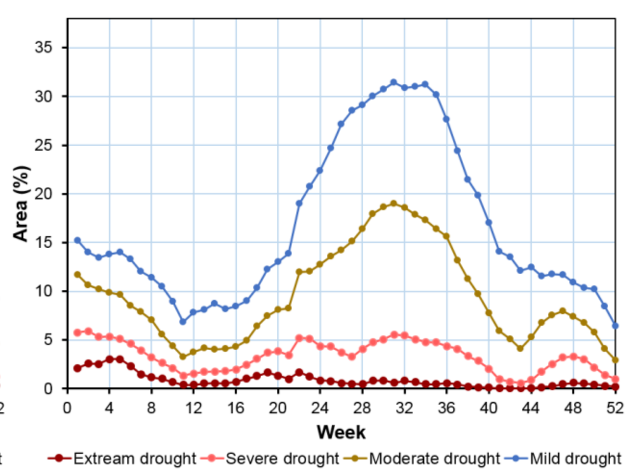
2017



2018



2019



2020

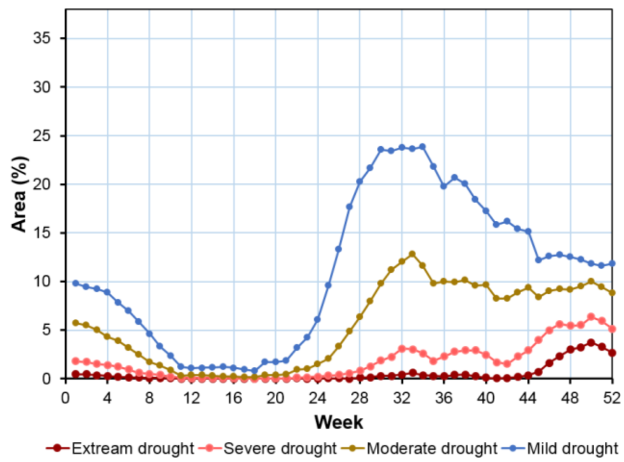
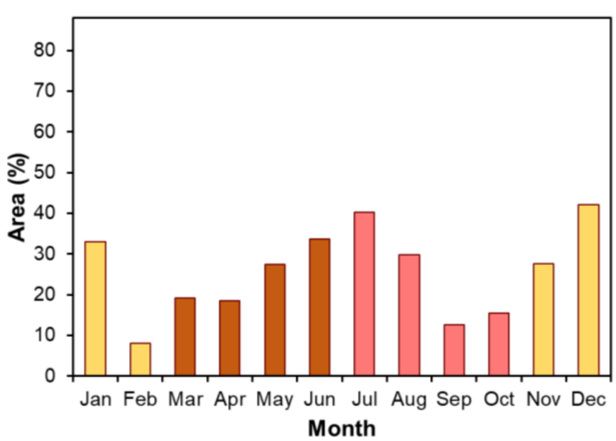


Figure 4.28: Weekly drought assessment and monitoring using VHI data of 2000-2020.

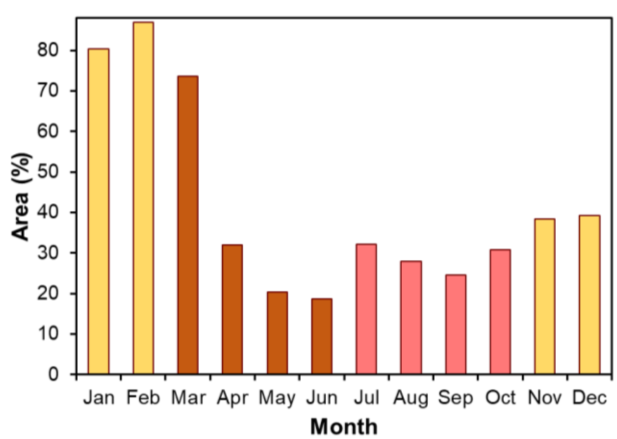
4.3.13 Month wise estimation of Agricultural drought area using VHI

Agricultural area is extracted from the MODIS land cover map. Using the agricultural land cover class only drought affected agricultural area is estimated and % of drought area with respect to total area is plotted(figure 4.13) with respect to each month. Different colour code is used to indicate the Kharif, Ravi and Zaid cropping season. The result shows that in the identified drought year i.e., 2002, 2004, 2009, 2010, 2013 and 2015more than 50% agricultural area was affected by the drought. The results again correlated with the analysis of previous section and cause of drought analysis given in chapter 5.

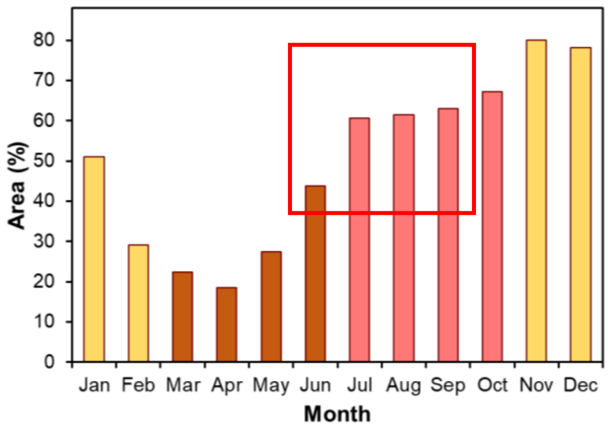
2000



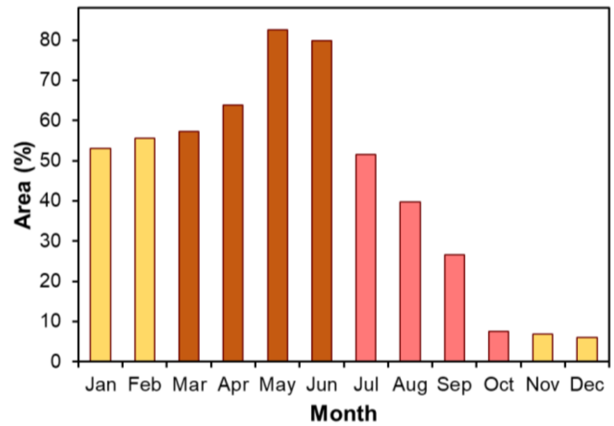
2001



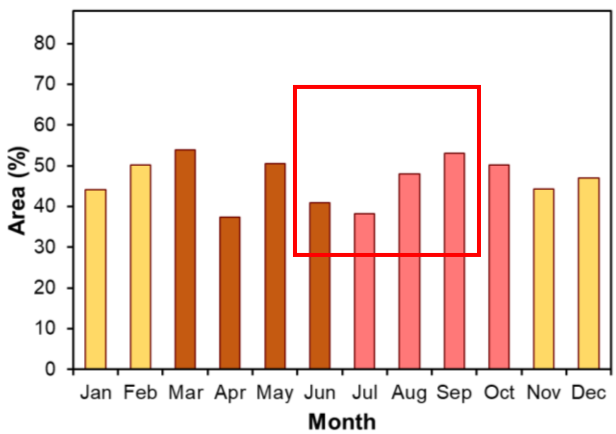
2002



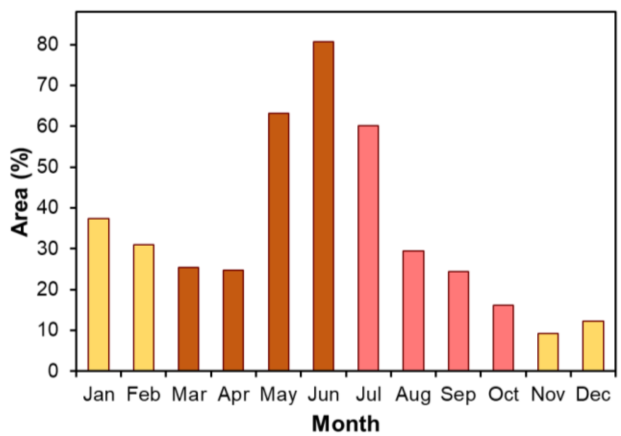
2003



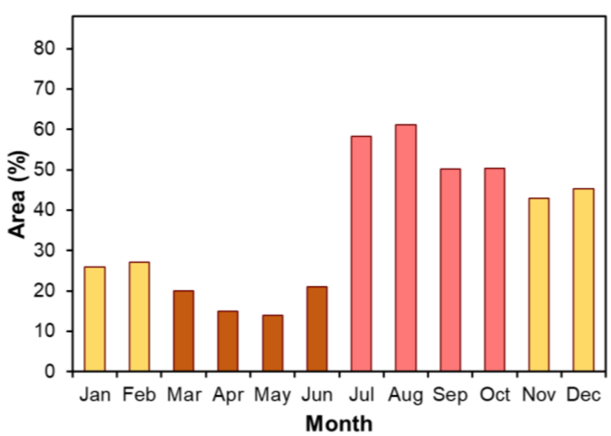
2004



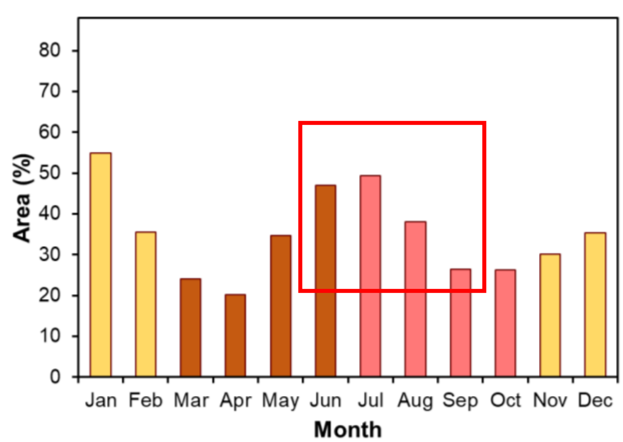
2005



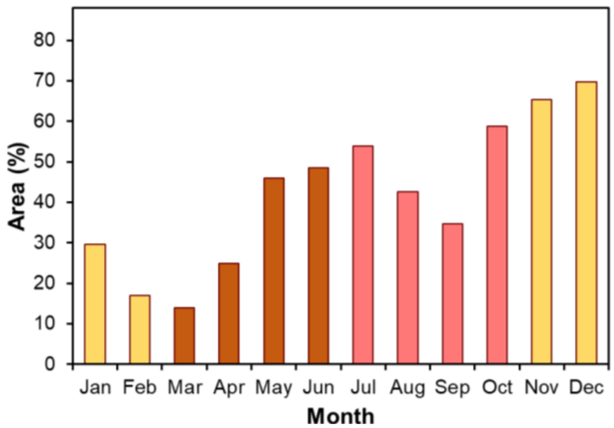
2006



2007



2008



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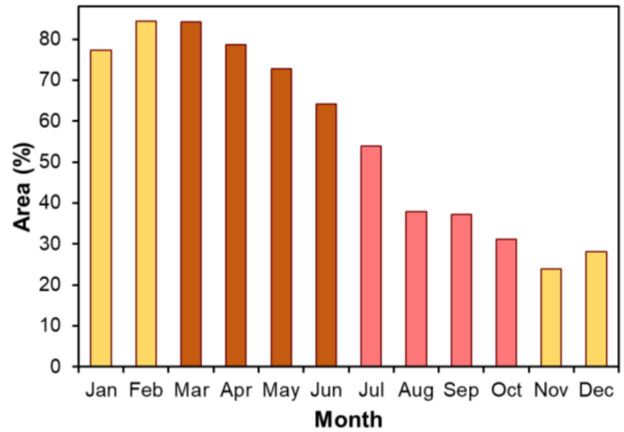

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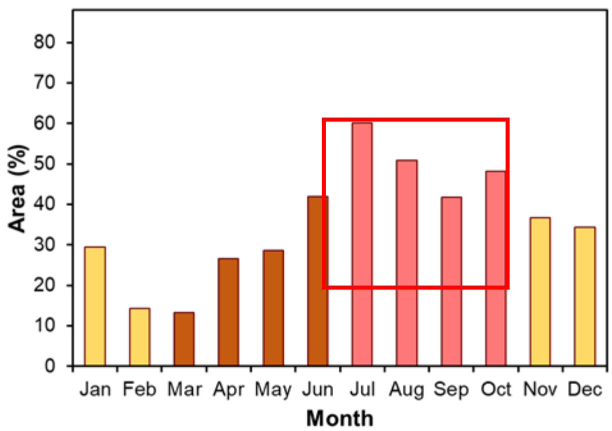

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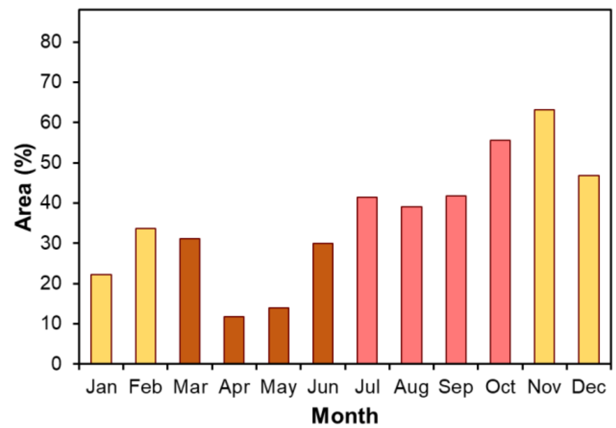

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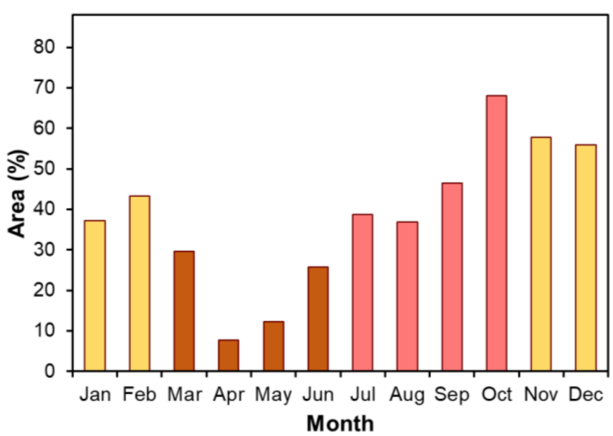

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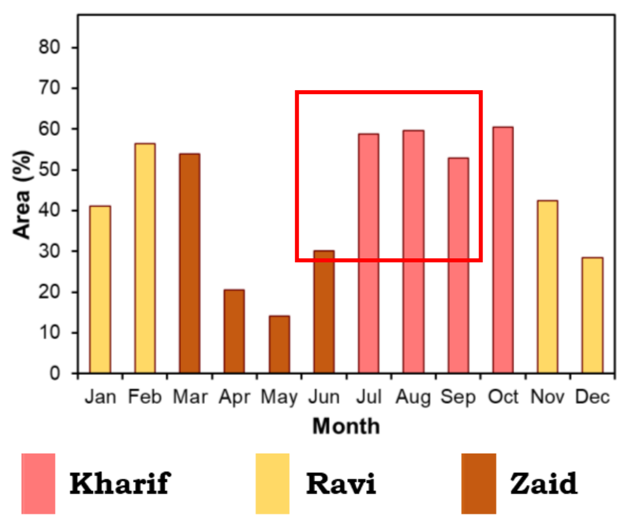

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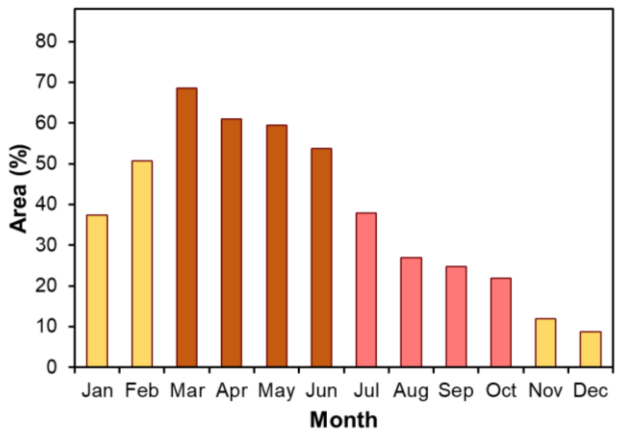
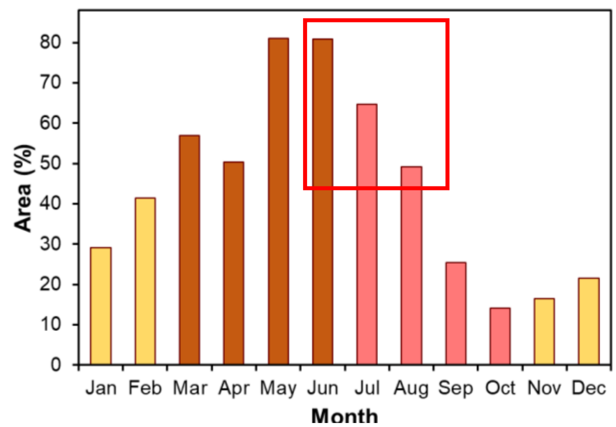
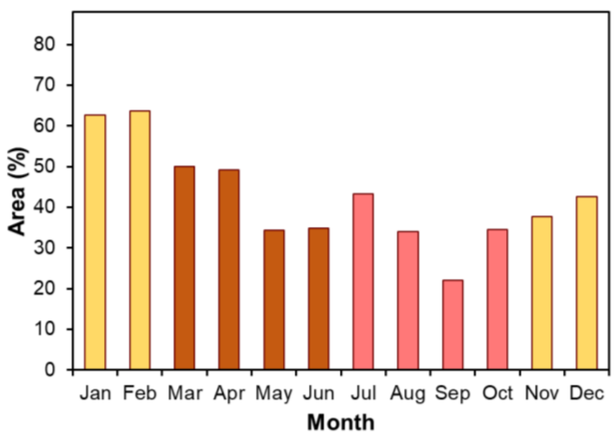
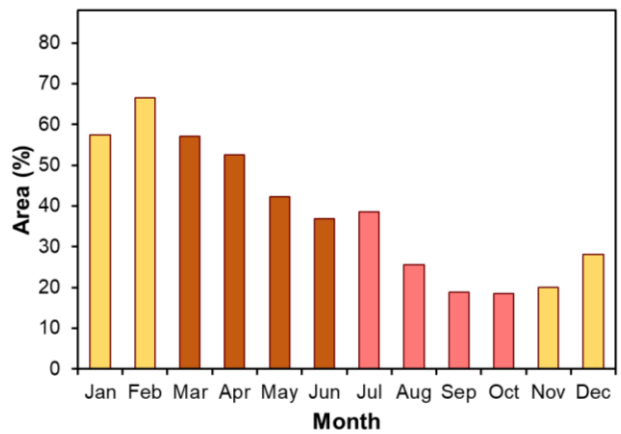


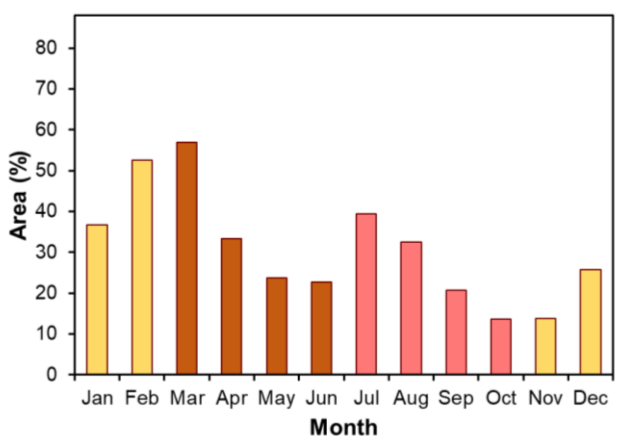


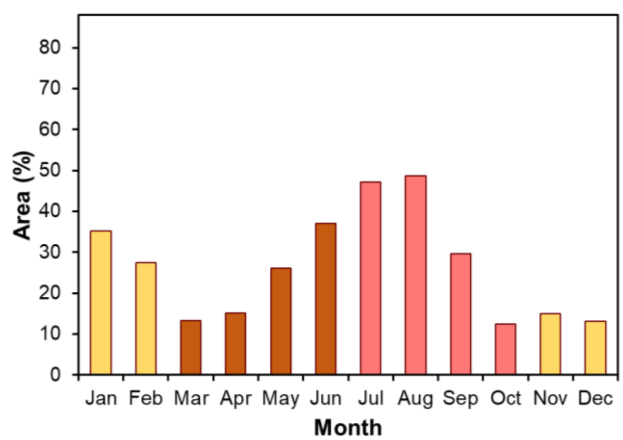
2016 **2017**





2018 **2019**





2020

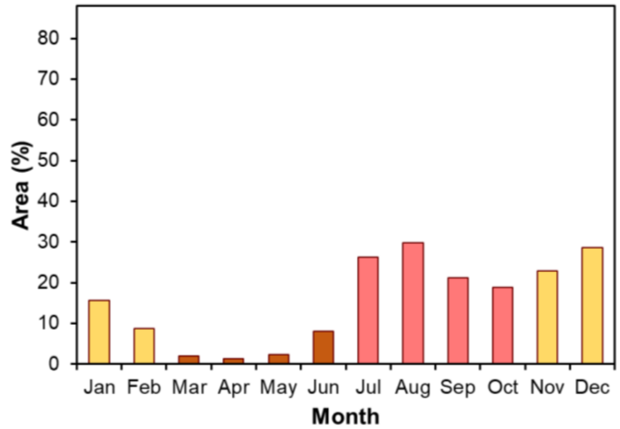


Figure 4.29: Month wise estimation of Agricultural drought area using VHI.

4.4 Discussion

In this chapter drought dynamics of Odisha state for the last two decades have been analysed. It is observed that within the last two decades 2002, 2004, 2009, 2010, 2013 and 2015 are major drought years, although the intensity and severity of drought varies within this period. It is also found that moderate to mild drought occurred in most of the year in Odisha, however, in the above-mentioned years extreme to severe drought occurred in the Odisha state. The analysis reveals that meteorological drought due to variability of rainfall is the major reason for the groundwater drought and both affect the agricultural drought. Assessment of drought using SPI and SPEI both are showing similar results regarding the identification of meteorological drought. Previous studies (Saha et. al., 2021; Santos et. al., 2021; Patel et. al., 2019) also support the above-mentioned observations. Assessment of drought characteristics is very important and has been carried out in terms of spatial drought frequency, severity and drought event. No pattern has been identified in the drought in Odisha, however, the study of Saha et. al., 2021 found a clear pattern of drought vulnerability from high to low from the west to eastern part of Odisha.

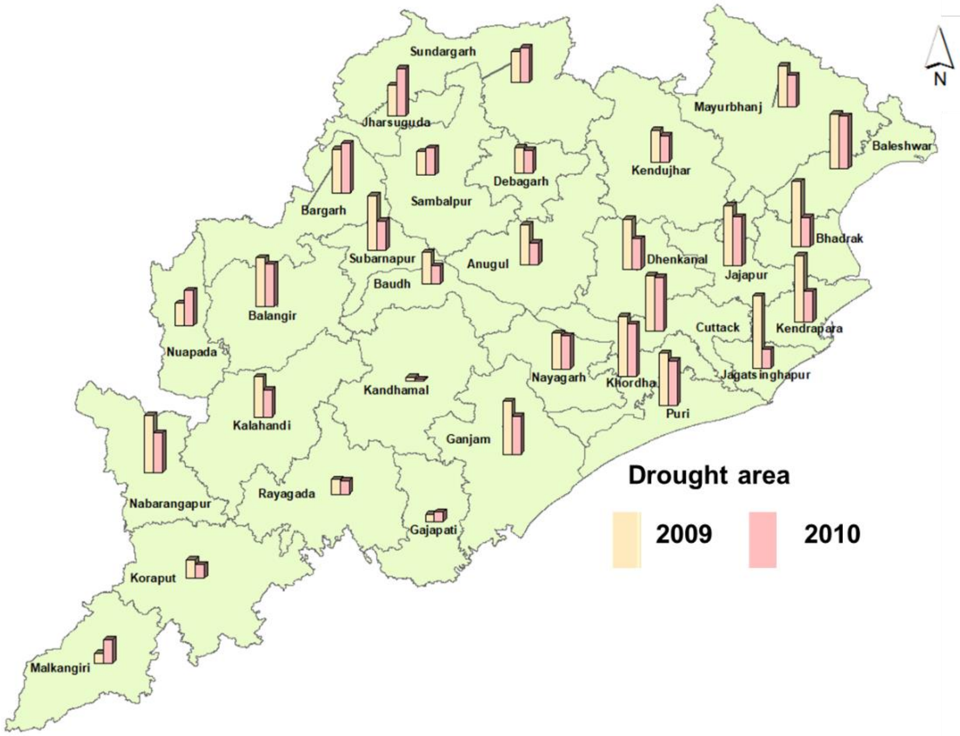


Figure 4.30: Spatial distribution of drought affected area based on 2009 and 2010.

The spatial distribution of drought-affected areas during the monsoon drought of 2009 and 2010 is shown in figure 4.14. It is observed that drought impact is slightly low in the central part of the state. This is because the central part of Odisha state falls under the Mahanadi basin and canal-based irrigation is high in this area. As per the state irrigation department report, 20% of the agricultural area of Odisha is covered under irrigation and the rest of the area depends on monsoon rain only, therefore drought in the monsoon season affects agriculture significantly. Another important aspect of this study is the assessment of drought characteristics weekly basis based on VHI data. It has been found that a major drought occurred within the 24th to 36th week which again signifies a monsoon drought over Odisha state. Kharif crops highly suffer due to drought in Odisha. It is also observed that Odisha also suffer from post-monsoon drought. However, the effect is not very significant as the crop water requirement of the Ravi crop is less compared to the Kharif crop.

4.5 Conclusion

The present research concentrates on mapping of drought dynamics of Odisha state over the last two decades using satellite-based remote sensing data with the help of geoinformatics techniques. The study aims to delineate the drought-affected area, drought characteristics and spatial distribution/ pattern of drought over Odisha state from 2000 to 2020. Assessment of meteorological drought has been carried out using SPI and SPEI and identify the major drought-affected years and observed that 2000, 2002, 2004, 2009, 2010, 2013 and 2015 are the prominent year in which extreme to severe drought occurred over Odisha, however, the state was hit by mid to moderate drought on most of the year. The mapping of drought characteristics i.e., drought frequency, drought severity and drought event signify that in most of the district drought frequency is high as well as Odisha is experienced severe drought on various occasions. The drought pattern in Odisha is random, however, a few districts like Nuapada, Kalahandi, Bolangir, Rayagada, Ganjam, Bargarh, Malkangiri and Phulbani are highly affected by the drought. Agricultural drought assessment has been carried out using NDVI and VHI data and delineating the drought characteristics. Monsoon drought is the most significant in Odisha which affects the Kharif crop, mainly paddy cultivation. Post-monsoon drought is also seen in Odisha, but the intensity and effect are less compared to monsoon drought. Overall, although it is a coastal state highly affected by drought and remote sensing data and geoinformatics were found to be very suitable to delineate the drought characteristics and spatial pattern of drought over Odisha state.

5 Cause of Drought

The true sign of intelligence is not knowledge but imagination.

\- *Albert Einstein*

5.1 Introduction

Drought is considered as a natural hydrological hazard. Drought is least controllable event affecting the world presently. It is one of the most devastating natural hazards in Odisha state as well as in India. In the last five decades, 19 times droughts occurred in Odisha. The drought frequency in Odisha is high, approximately once in three years. Extreme to Severe drought was observed in Odisha state in the recent past. Approx. 20% of the agricultural area of Odisha is covered under irrigation which is a major reason for the drought. The most important reason behind the occurrence of drought is deficient rainfall than its usual amount. The decrease in rainfall highly affects the state's agriculture as the agriculture practice depends on soil moisture and water obtainability throughout different growing stages of crops. Drought generally occurs during the Kharif cropping season and mainly the paddy crops get affected In Odisha. The drought pattern of the Odisha state is random, however, Bolangir, Bargarh, Nuapada, Phulbani and Kalahandi comprising 47 administrative blocks have been identified as highly drought-prone areas of Odisha as per the state drought monitoring cell report. The major reason identified for drought in the Kharif cropping season in this area is deficient rainfall due to variations in the onset of monsoon.

There are several causes of drought comprising both natural and anthropogenic that result in the reduction of rainfall. One of the major causes of drought is subsidence or downward movement of air due to atmospheric circulation. The world's utmost prominent drought-prone regions are situated in the prevailing zone of subsiding air motion. The air mass subsidence disturbs rainfall/ precipitation in three ways (a) the moisture content in the air reduces, (b) the heating of air result to a decline in relative humidity and increase in moisture holding capacity and (c) concentrates the air unsuitable for moisture condensation, cloud formation decreases due to all this reason, solar radiation increases, potential evapotranspiration increases and soil moisture decreases(Zolotokrylin, 2010). Aerosol sources also perform a significant role in the occurrence of drought situation by enhancing the air mass stability and resulting in a slower rate of cloud formation over any region.

El Nino/ La Nina plays a significant role in drought events as it leads to the shifting of air circulation particularly over the eastern Pacific Ocean, resulting in dry periods and making wet regions dry (Eslamian and Eslamian, 2017). Indian Ocean Dipole plays a vital role in the onset of South-West monsoon and therefore, influences the variation of timing of the monsoon rainfall which significantly affects the drought in the coastal area of the Indian peninsular region.

However, natural factors are not the sole contributors to the occurrence of drought, a decline in water quality also creates stress upon available water resources due to which the water demand exceeds its supply and acute water shortage might be encountered. The changes in land use, reduction of vegetation cover, over-cultivation, overgrazing, land degradation, industrialization, and urbanisation not only leads to overexploitation of water resources but also increase the pressure on available freshwater supply due to increased demand, resulting in drought conditions. The greenhouse effect leads to global warming due to burning of fossil fuel, industrial emissions etc. which have increased atmospheric temperature ensuing in climate change which might lead to hydrological and meteorological drought and finally agricultural drought.

5.2 Methodology

In this research cause of drought has been assessed based on various climatic factors like precipitation, land surface temperature, soil moisture, evapotranspiration, groundwater reserve, impact of El Nino/ La Nina and Indian Ocean Dipole etc. All datasets related to these climatic factors are collected from various sources as mentioned in Chapter 3, Table 3.11. The processing methodology of all data sets and the derivation of outputs are discussed below.

5.2.1 Precipitation

Daily precipitation data from Indian Meteorological Department (IMD) has been taken for this research. Grided rainfall raster data of 25 km x 25 km cell size of 45 years (1975 to 2019) is used. From the daily total precipitation raster data, monthly total precipitation of the entire Odisha state is calculated. The mean of the total precipitation of the month of the state is estimated and plotted. Precipitation/ rainfall anomaly is calculated concerning the long-term average rainfall of the same month.

5.2.2 Land Surface Temperature (LST)

Satellite imagery-based land surface temperature derived from Terra MODIS sensor from 2000 - 2020 is used in this research. The spatial resolution of the MODIS LST data is 1000 metres and daily LST data is taken into consideration. The monthly average LST is calculated from the daily LST by taking the average of daily LST raster datasets and the mean temperature is estimated and plotted. Temperature anomaly is calculated by taking the deviation from the long-term LST of the same month.

IMD-derived ambient temperature is also calculated from daily grided temperature raster datasets of 25 km x 25 km. With the help of the daily temperature raster monthly temperature raster is computed and the mean temperature value of the monthly average raster is plotted. Temperature anomaly is calculated based on the deviation of mean monthly temperature concerning long-term mean temperature.

5.2.3 Soil Moisture

Grided soil moisture data downloaded from European Space Agency (ESA) is used in this research. This soil moisture product is a combination of various satellite-based soil moisture sensors like SMOS, AMSR-E etc. This dataset is available since 1987 and its spatial resolution is 25 km x 25 km. This is volumetric soil moisture which is the content of liquid water present in a surface soil layer at a depth of 2-5 cm and expressed as meter^3 water / meter^3 soil. This soil moisture is estimated from the passive microwave sensor. In this research, monthly soil moisture raster datasets of the 2000 to 2020 vintage are used. The average soil moisture value of the state of the respective month is calculated and graphical plot is generated. Soil moisture anomaly is estimated by taking the deviation of mean soil moisture from the long-term mean.

5.2.4 Evapotranspiration

MODIS satellite data-derived evapotranspiration product of 500 metres spatial resolution is used in this research for heat stress assessment. This data product is available as 8-day composite which is utilized to derive the monthly composite by taking the spatial average of four raster datasets. The monthly total evapotranspiration is computed and the mean of the raster of Odisha state of the respective month is plotted for analysis. The anomaly of the evapotranspiration is calculated concerning the deviation from the long-term mean evapotranspiration of the individual month.

5.2.5 Groundwater storage/ reserve estimation

Groundwater reserve is estimated from Gravity Recovery and Climate Experiments (GRACE) study mission data. It is a joint mission of NASA and ESA and data is available since the year 2002. GRACE data provides a detailed measurement of the gravity field of Earth and improve investigations on Earth's water reservation over the land surface. In this research monthly basis, GRACE data from 2002 to 2020 is taken for estimation of groundwater storage. The grid size of the GRACE data is 300 km x 300 km and the mean monthly value is used for analysis. The anomaly of groundwater storage is calculated by taking the difference between individual observation and the long-term mean.

5.2.6 Impact of El Nino and Indian Ocean Dipole

It is observed that in Odisha state major droughts are experienced during the El Nino year. Therefore, El Nino is considered one of the most important factors for drought in Odisha state. It is a climate pattern which depicts the unusual warming of ocean surface waters in the eastern tropical Pacific Ocean. The warm phase is called El Nino and La Nina is the cool phase. El Nino and La Nina determine the surface temperature of the ocean and therefore control the air pressure, hence, it affects the rainfall in coastal states such as Odisha. El Nino index is taken from the NOAA site and analysed to build an empirical relation with drought.

Another important phenomenon is Indian Ocean Dipole (IOD).IOD is characterized by the sea surface temperature variance between two areas western Indian Ocean (Arabian Sea), a western pole and the eastern Indian Ocean (south of Indonesia)i.e., an eastern pole. IOD is a significant contributor to rainfall variation. It significantly changes the temperature gradients across the Indian Ocean and therefore, affects changes in the preferred regions of descending and rising moisture and air. It is observed that in most cases IOD is linked with El Nino and La Nina. The positive IOD is associated with El Nino and the negative IOD is associated with La Nina. IOD and El Nino / La Nina significantly influence the air circulation over the Indian Ocean and thus effects the rainfall variation as well as monsoon drought.

5.2.7 Analysis of other secondary datasets

Various secondary datasets/ information such as irrigation, physiography, soil types, river, geology, hydrography, and datasets from state disaster management authorities etc. are taken into consideration for the analysis of drought.

5.2.8 Test of significance of climatic variables

To test the long-term trend, Mann–Kendall test was applied for monotonic trend analysis, which is considered as better than the parametric tests (Xu et al. 2003; Mondal et al. 2018). The MK (Mann-Kendall) test was performed for all datasets to determine the trends and their significance levels (Z-statistic). Trend magnitude was determined by the Theil-Sen's estimator (Sen, 1968).

5.3 Results

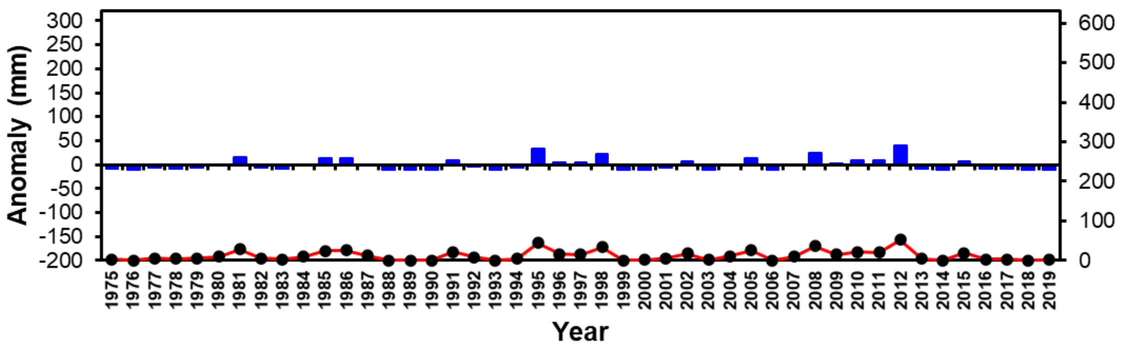
All possible factors which are responsible for drought are analysed in this section. The major natural factors identified which are responsible for drought are precipitation, temperature, soil moisture, evapotranspiration, groundwater storage, El Nino, La Nina and IOD. This research focus on agricultural drought for the period of 2000 to 2020, therefore, the analysis is carried out concerning that period. The datasets collected from IMD and satellite-based sources are graphically plotted and analysed. The results are discussed below.

5.3.1 Precipitation

Month-wise (Jan - Dec) graphical plot of precipitation from 1975 to 2019 vintage is shown in figure 5.1. It is seen from the plot that precipitation is very low in the month of Jan, Feb, Mar, April, and May, as the precipitation of the study area is mainly governed by the southwest monsoon. In the study area, the monsoon generally comes during the month of June. Kharif is the main crop of this region, and the major crop type is paddy. Kharif crop (paddy) mainly depends on monsoon rainfall. Any fluctuation in the onset of monsoon affects the showing and growing season of the Kharif crop. In this region, the crop grows in the Zaid season i.e., the pre-monsoon period, doesn't require much water due to its nature. Therefore, the major rainfall requirement lies for the Kharif crop which is grown in the monsoon season i.e., June to September.

The precipitation plot for June, July, August, and September shows that between 2000 to 2019, rainfall less than the long-term average is observed in a few years such as 2002, 2004, 2009, 2010, 2013 and 2015. It is also seen in Chapter 4 during the analysis that these years are identified as meteorological drought years in Odisha state. The total amount of precipitation/rainfall is deficient compared to other calendar year as well a negative precipitation anomaly is also seen. It is observed that before the year 2000, severe drought occurred in Odisha in 1976, 1973, 1995, and 1998. These observations are also matching with the Odisha state disaster management authority reports, newspaper reports and rainfall data available in the various reports.

January



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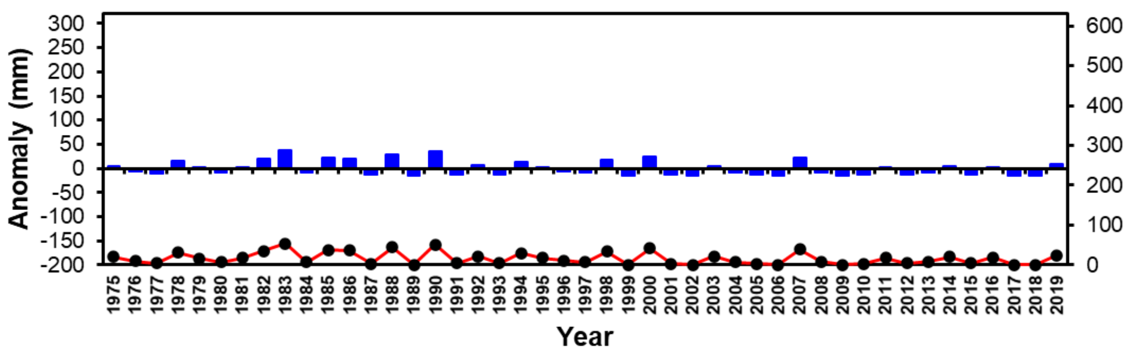

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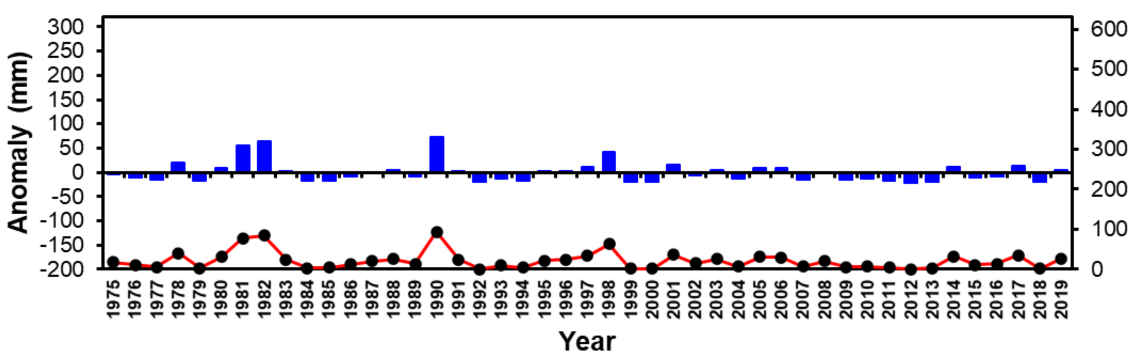

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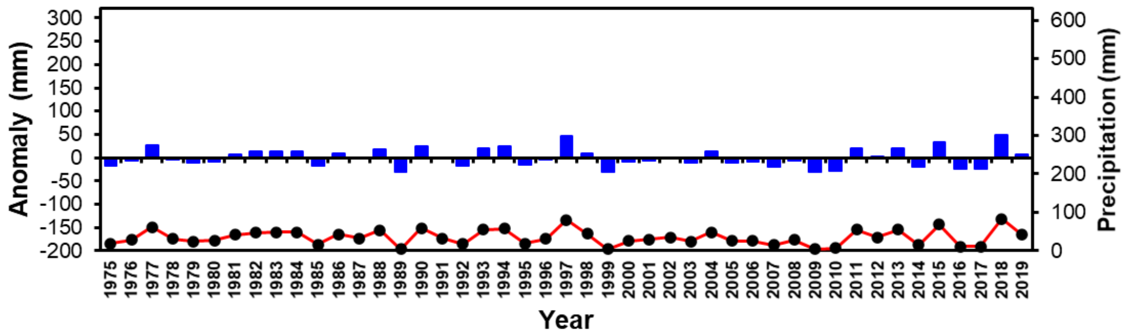
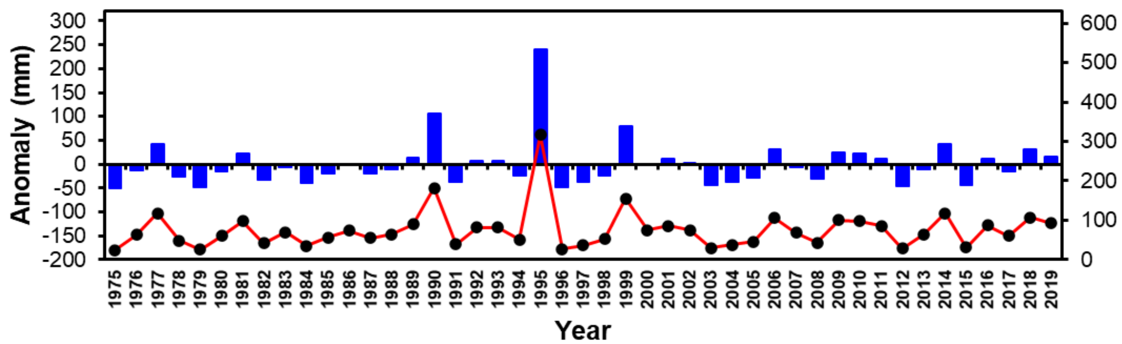
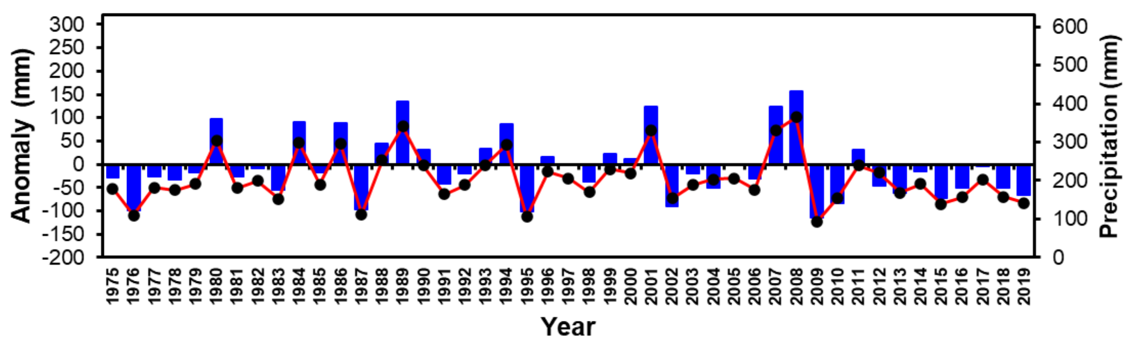


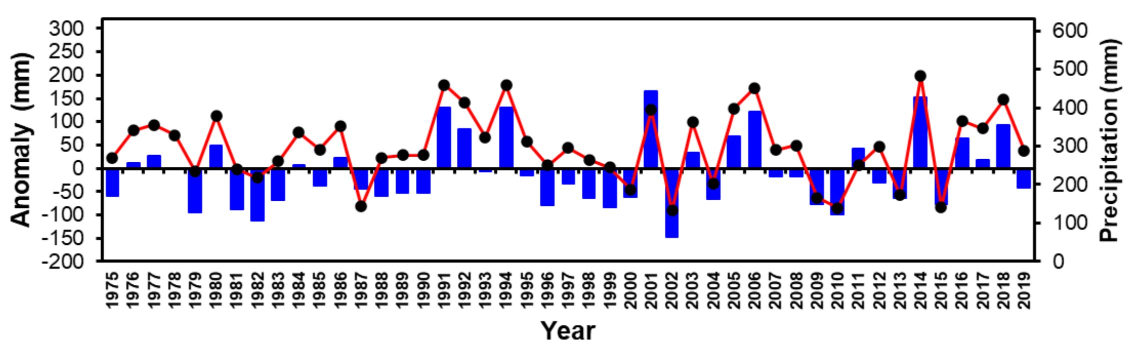
May



June



July



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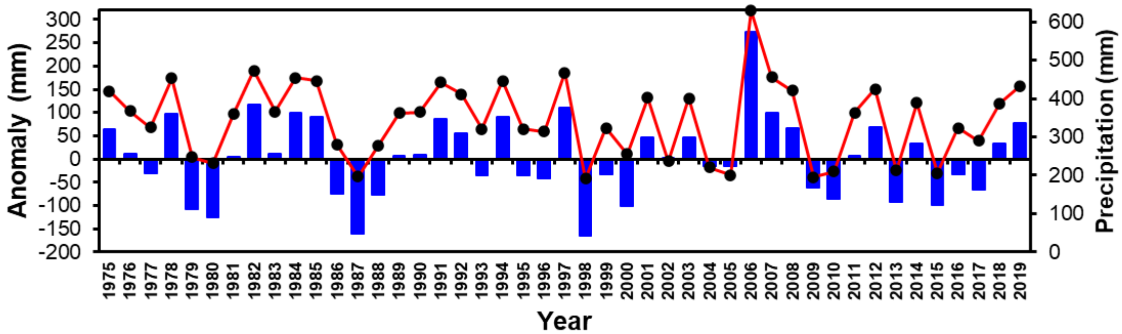
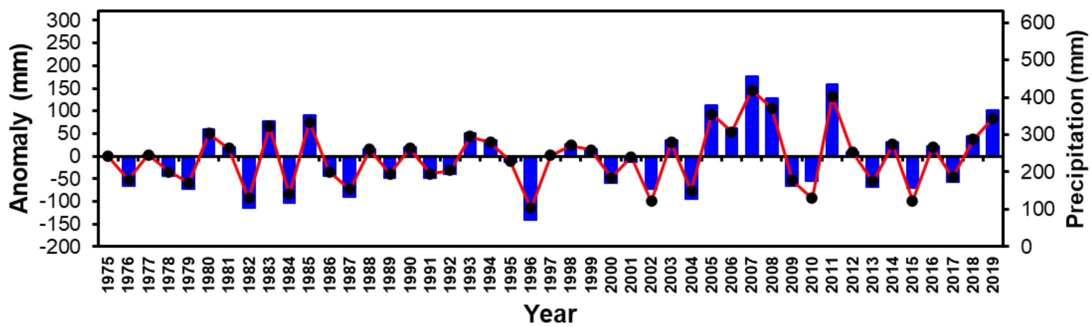
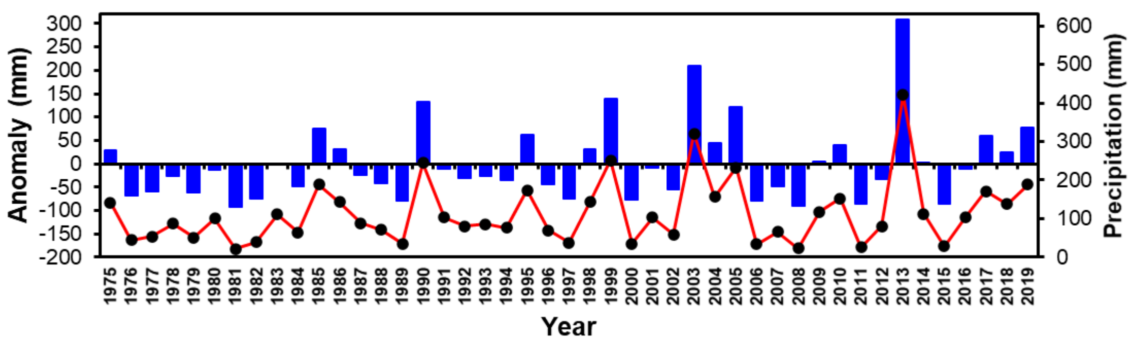


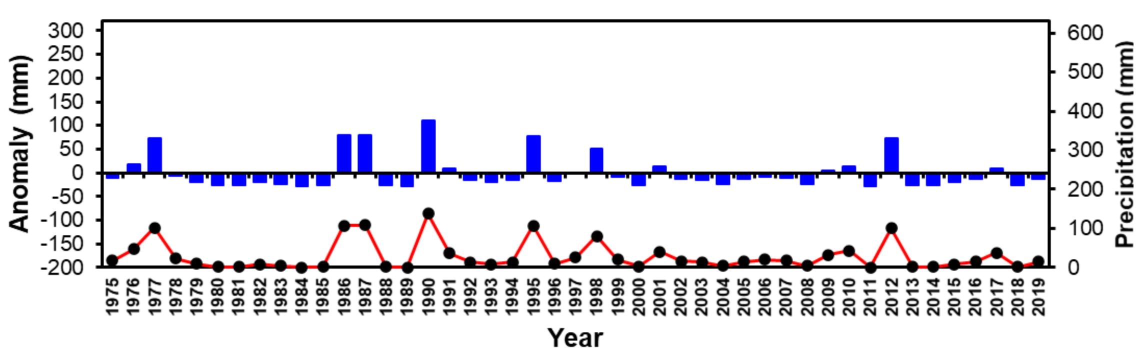
September



October



November



December

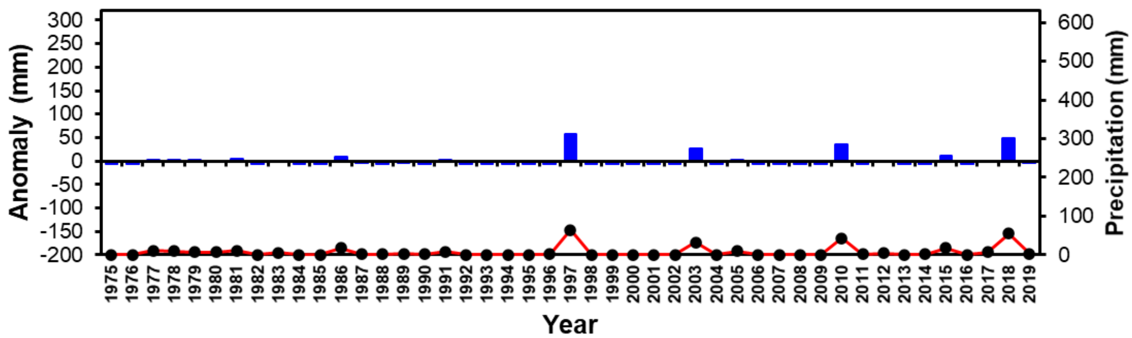


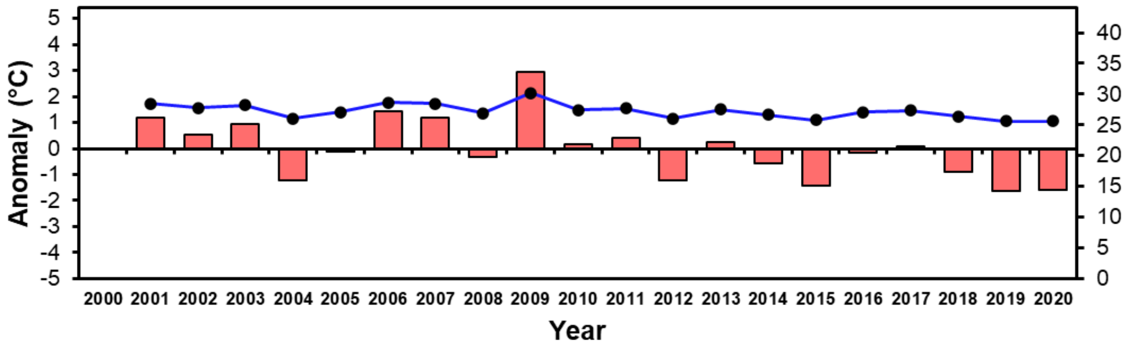
Figure 5.31: Month-wise total precipitation over Odisha and precipitation anomaly

5.3.2 Temperature

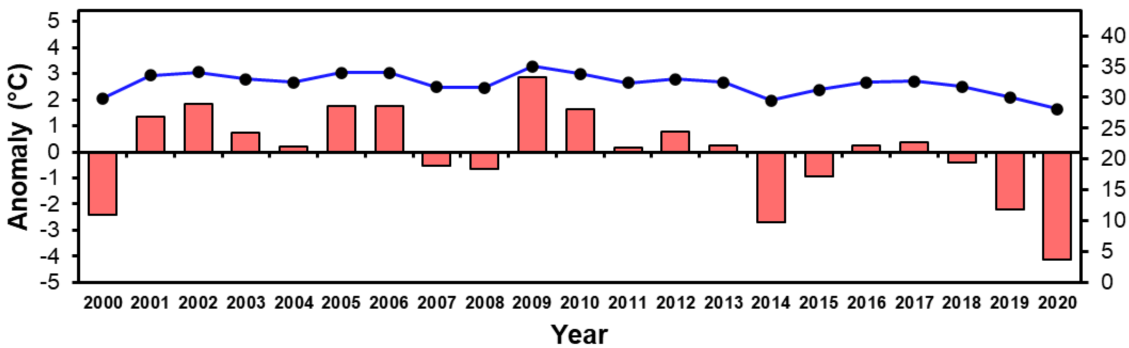
Odisha state is located in a tropical climate which is mainly characterized by high temperature and humidity, moderate to high rainfall, and mild and short winters. As per climatic classifications of Koppen major portion of the state comes under the 'AW' climatic type which is a Tropical Savannah type of climate. Temperature is one of the most important factors which is responsible for drought. Satellite-based monthly mean land surface temperature is analysed and shown in figure 5.2. The plot shows that the temperature variation of the last 21 years over each month. Temperature is low in the month of January, and February and starts increasing from March onward, reaching the highest in the month of April – May - Jun and then slowly start decreasing.

LST impact on evapotranspiration and soil moisture. Evapotranspiration increases due to high LST, the level of soil moisture decreases and the plant does not get an adequate amount of capillary water and began to wilt which causes agricultural drought. In the previous chapter, it is identified that drought occur in Odisha during the monsoon period in the years 2002, 2004, 2009, 2010, 2013 and 2015which affects the Kharif crops. The temperature plot for the month of June, July, August, and September shows that during the drought year LST was higher compared to the long-term average temperature. Warmer LST/ air temperatures enhance the evaporation rate and reduce surface water/ moisture and due to this reason soils and vegetation dry out which results in severe drought.

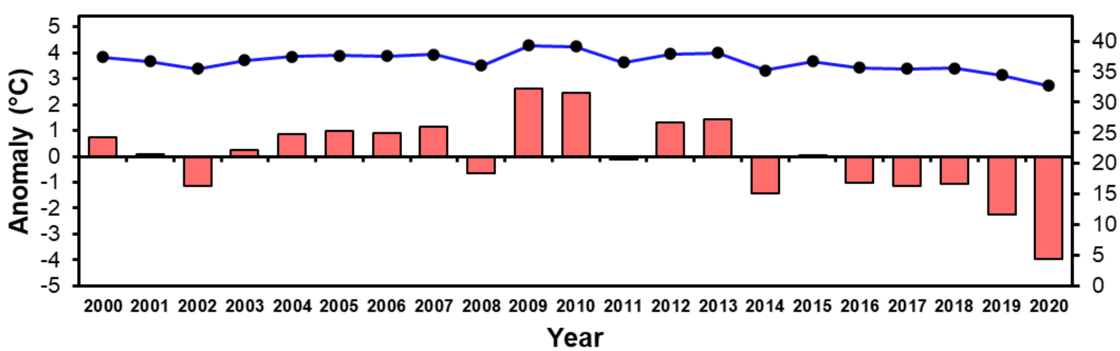
January



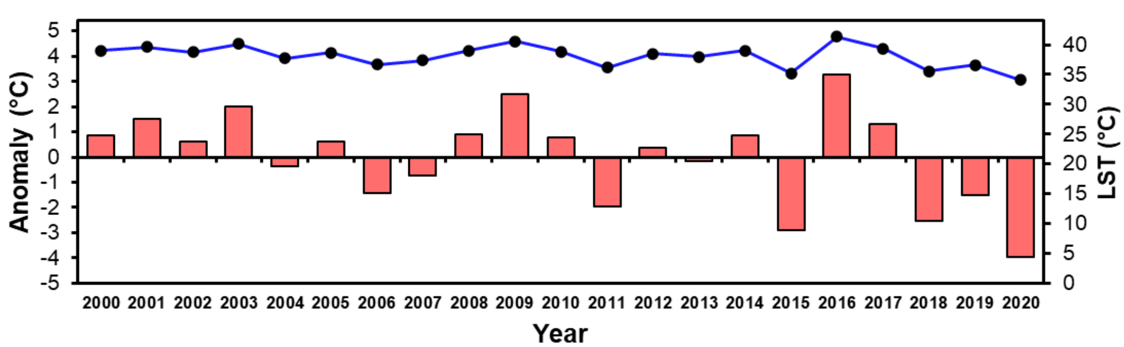
February



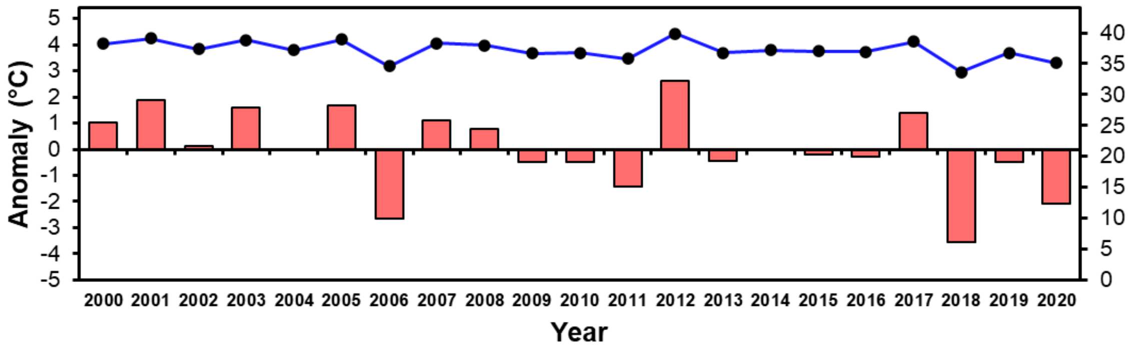
March



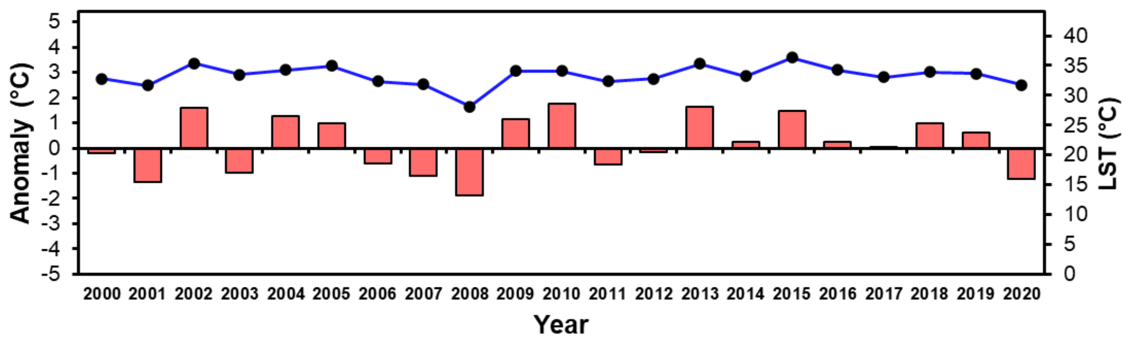
April



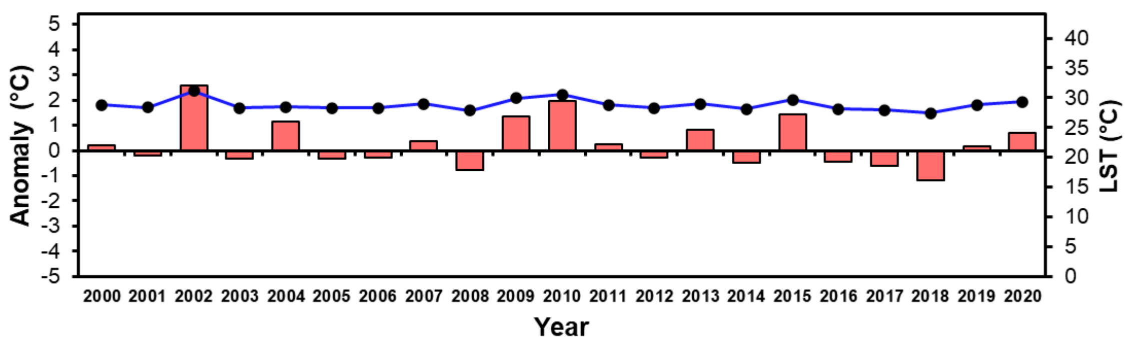
May



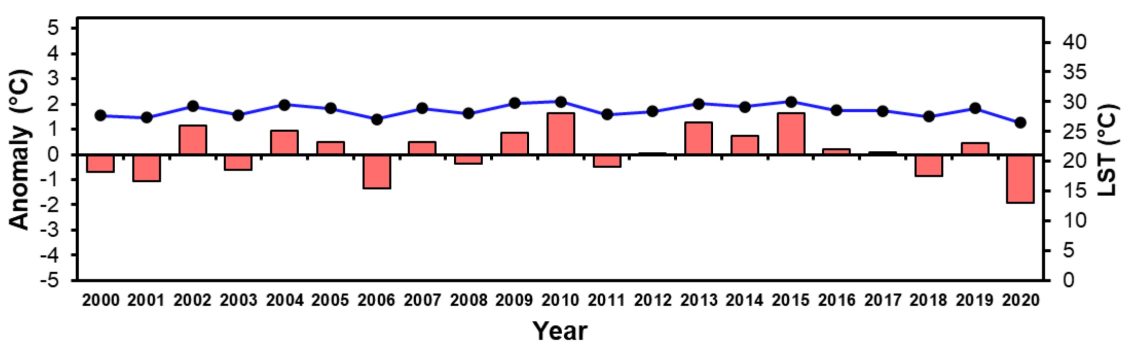
June



July



August



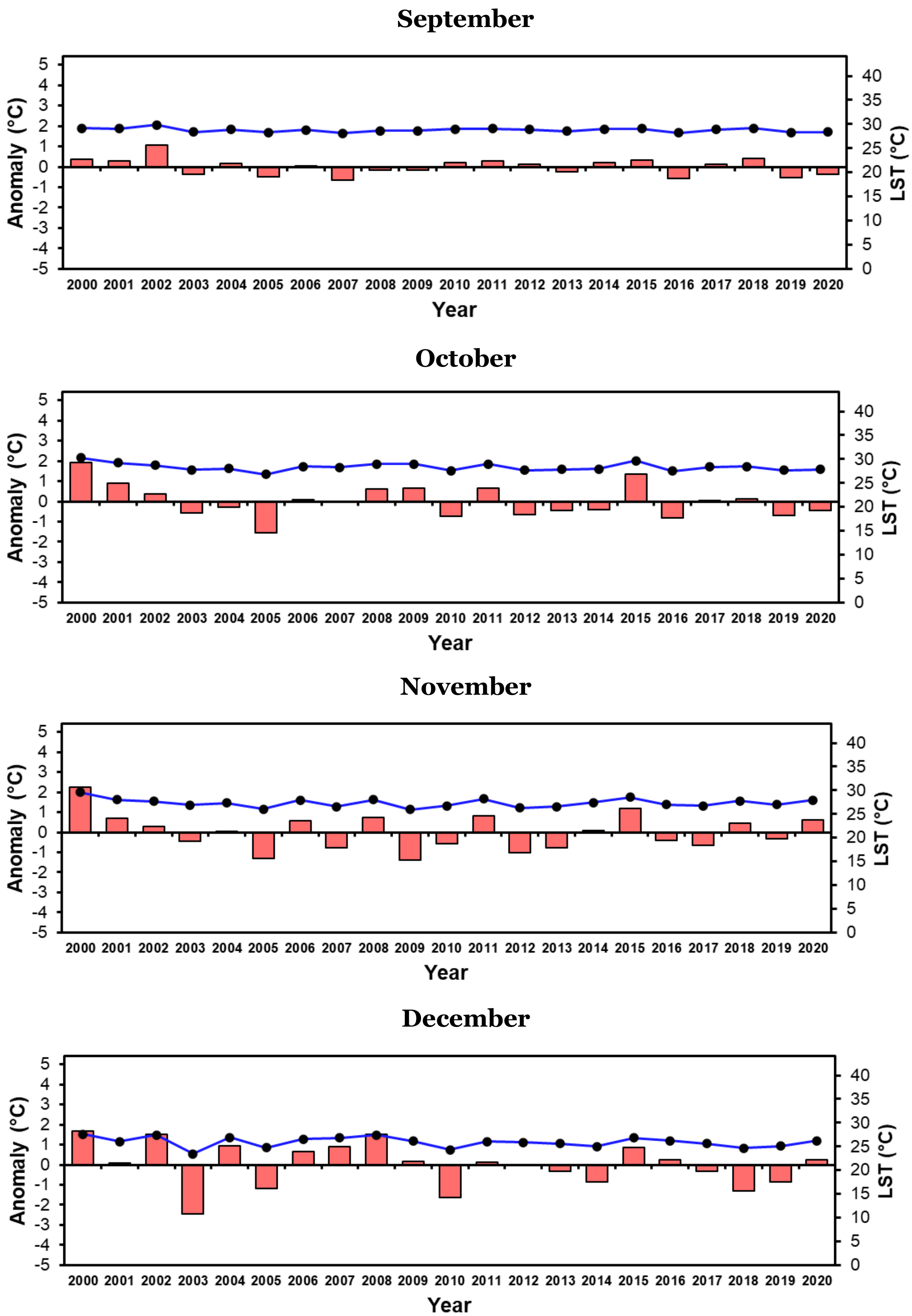


Figure 5.32: Month-wise land surface temperature for the period of 2000- 2020 over Odisha.

Ambient/ air temperature recorded at IMD is also analysed in this research. The maximum temperature from 1975 to 2019 is processed and analysed, shown in figure 5.3. The minimum temperature from 1975 to 2019 is estimated and analysed shown in figure 5.4. Trend analysis was also carried out based on 45 years of temperature and trend lines are fitted on the data shown in figures 5.3 and 5.4. Trend analysis shows there is a positive trend in the maximum temperature and the slope of the trend line is slightly higher. The minimum temperature plot shows a slightly negative to stable trend.

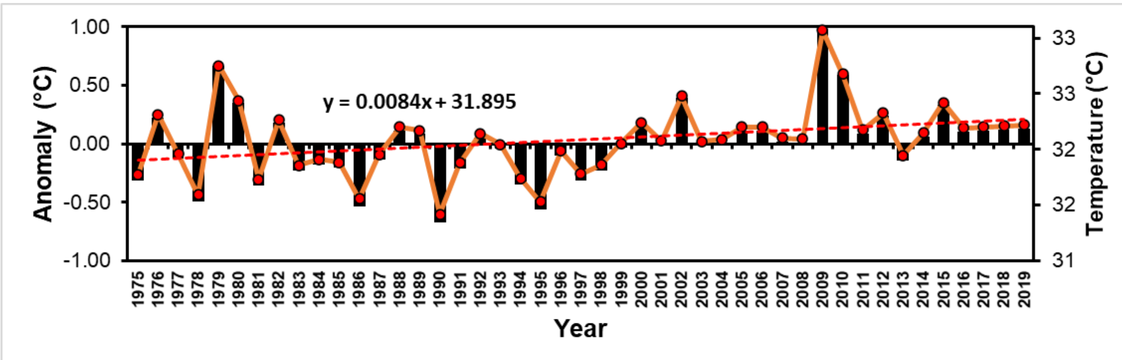


Figure 5.33: T_{Max} estimated from IMD temperature data of 1975 to 2019

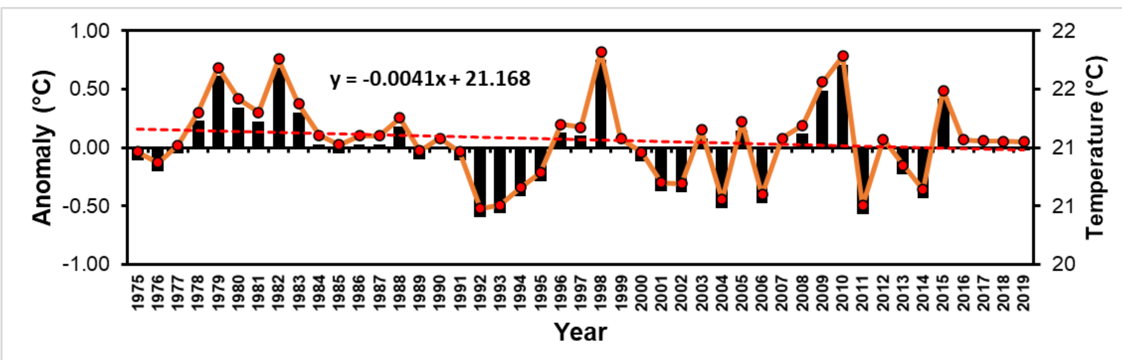


Figure 5.34: T_{Min} estimated from IMD temperature data from 1975 to 2019

5.3.3 Soil Moisture

Month-wise soil moisture conditions of Odisha state for the period of 2000 to 2020 are shown in figure 5.5. It is observed that generally soil moisture condition is low in Odisha state in the month of January to May. Soil moisture start increasing in the month of June due to the arrival of the monsoon and moisture condition are high till the month of October and thereafter again decline in November/ December.

It is one of the major factors governing the agricultural drought. Agricultural drought occurs due to a deficiency in water in the soil and resulting in water stress to plants, reducing biomass and impacting crop growth. Soil health is important for agriculture and it affects due to lack of nutrient uptake by crops because water is the key medium for moving nutrients to the plants. In the study area drought mainly occurs during the monsoon, if the soil moisture level reduces during this period, then drought occurs. In Odisha, severe agricultural drought was discerned in monsoon period of 2002, 2004, 2009, 2010, 2013 and 2015. It can be observed that soil moisture level was less during the monsoon period for this drought years.

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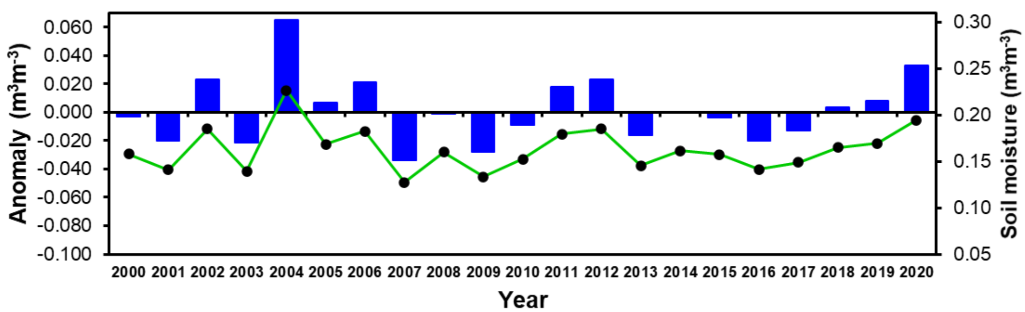

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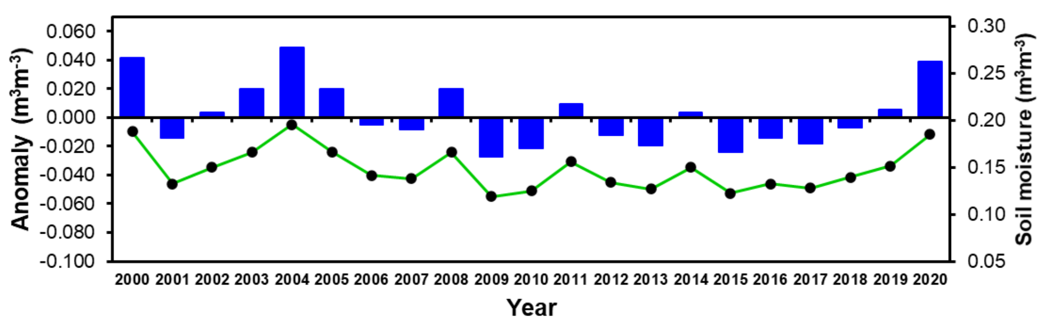

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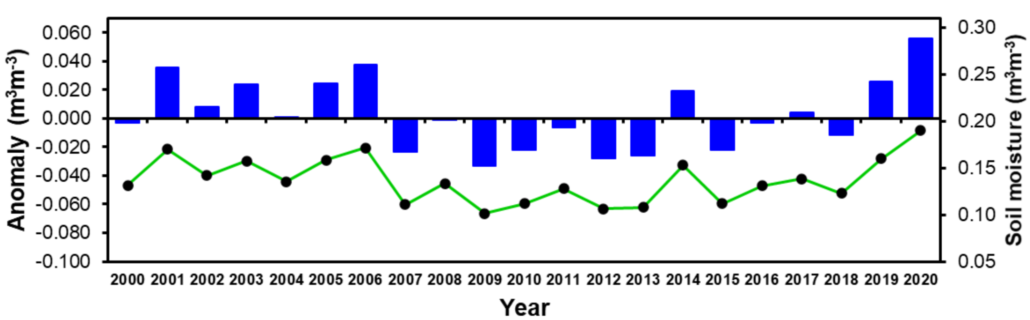

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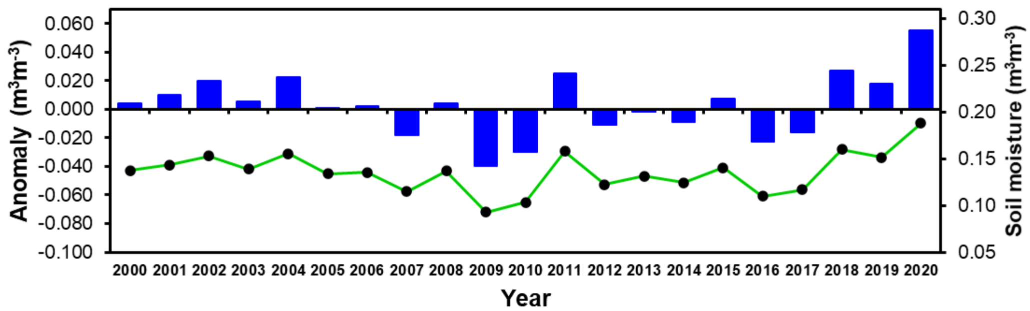

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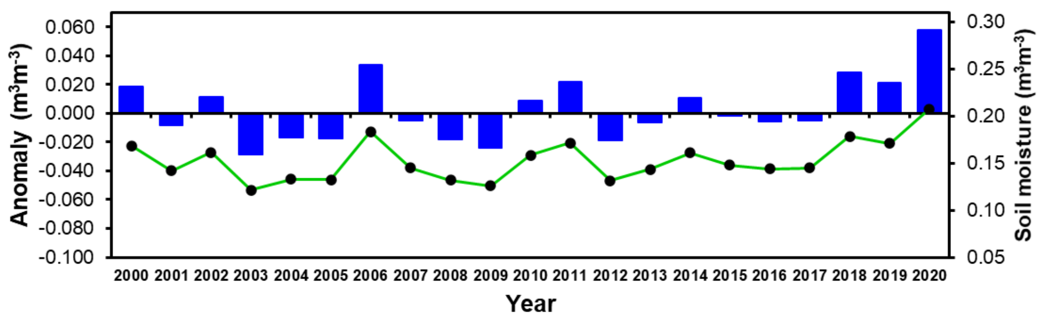

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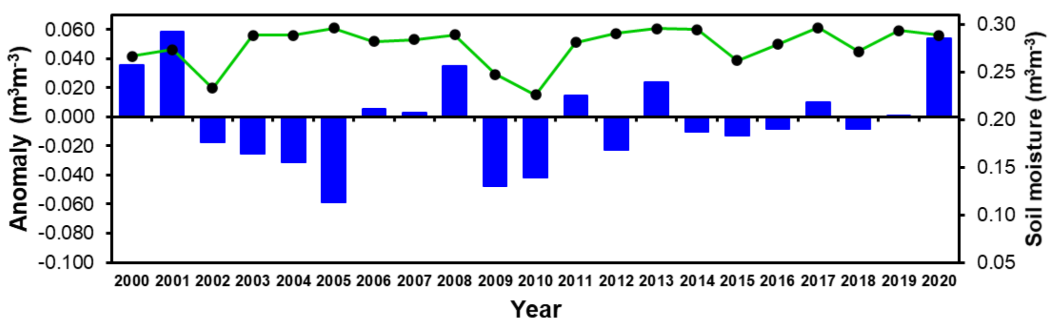

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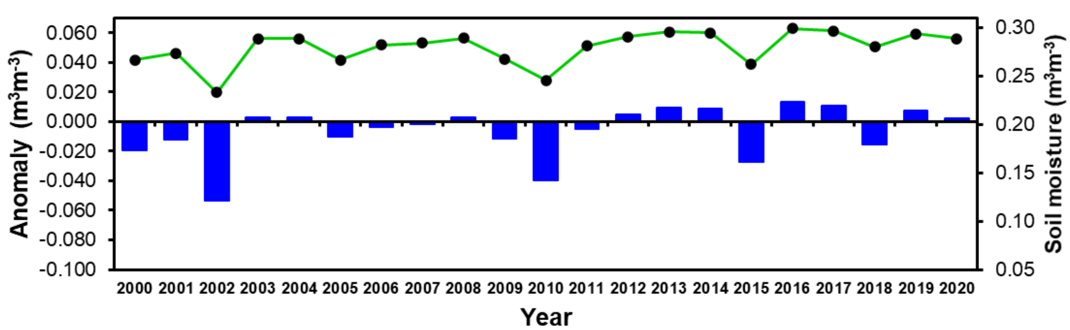

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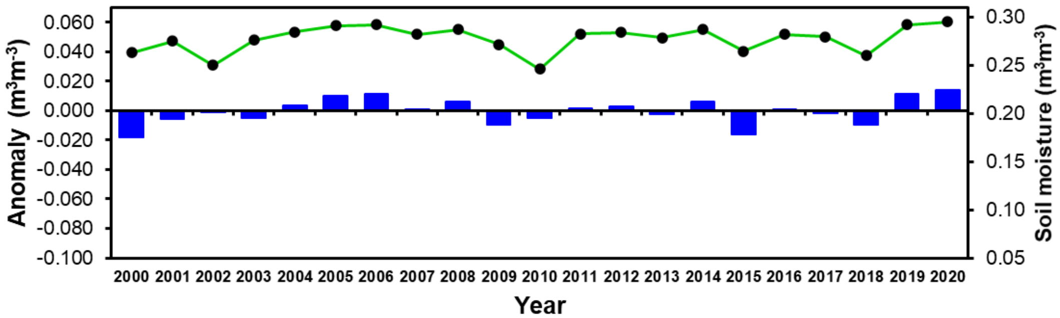

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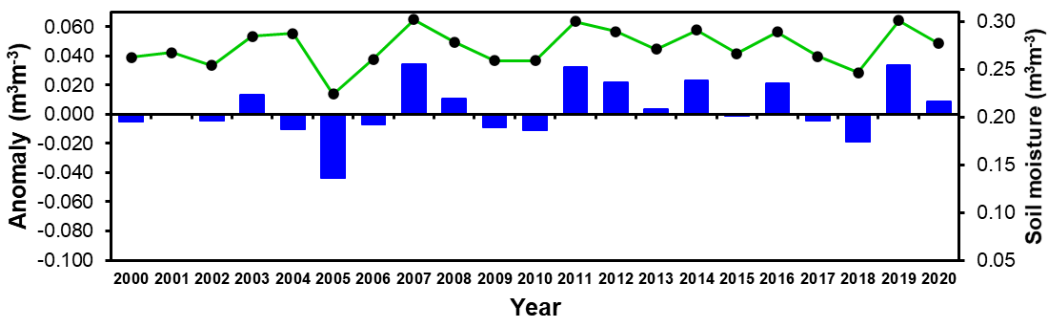

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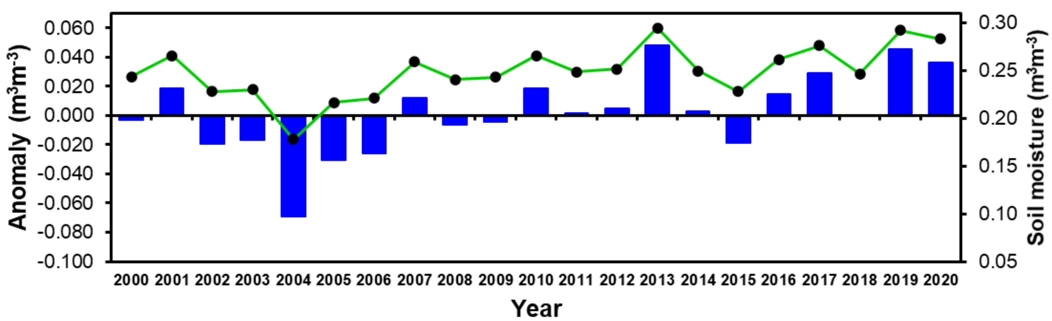

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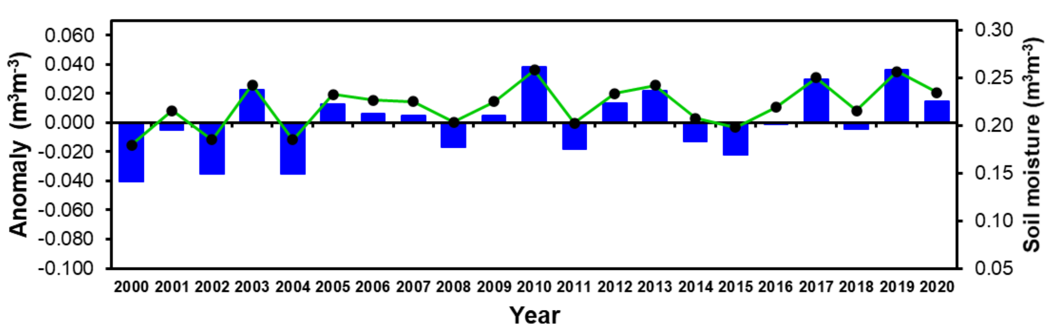


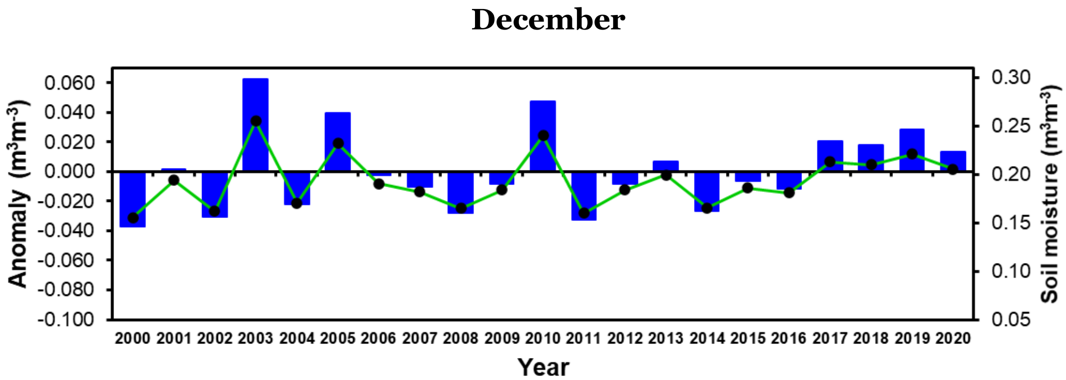


Figure 5. 35: Month-wise soil moisture level over Odisha state during 2000-2020.

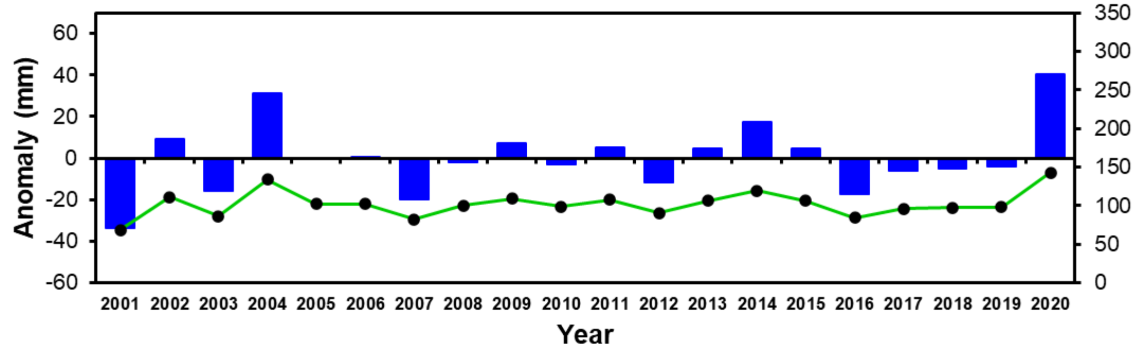
5.3.4 Evapotranspiration (ET)

Evapotranspiration consists of both the process of soil evaporation and transpiration. It is an essential soil water balance element and is acting a major role in controlling the potential yields in agriculture. Inadequate water distributions affect crop growth, harvest and finally food scarcity. ET provides the highest loss of water in any agricultural area.

Figure 5.6 shows the month-wise variation of ET estimated from MODIS data for the period 2001 to 2020 over the study area. The plot shows that from the month of January to May ET is low over the study area and thereafter it increases till October and again decreases from November onwards. A similar trend is also seen in LST,as ET and LST are highly correlated. During the drought, weather conditions generally show very less cloud cover and high temperature. The humidity is high and the wind speed is above normal. This type of climatic condition leads to an increase in the rate of evaporation from the soil if moisture is available.

In the monsoon period of the identified drought year i.e., 2002, 2004, 2009, 2010, 2013 and 2015, ET values in the month of June, July and August were observed to be higher (high positive anomaly) than the long-term average ET rate. This is because of low rainfall, high temperature and low soil moisture as discussed in the previous sections. Therefore, the cumulative effect of all these factors results in severe drought in Odisha state.

January



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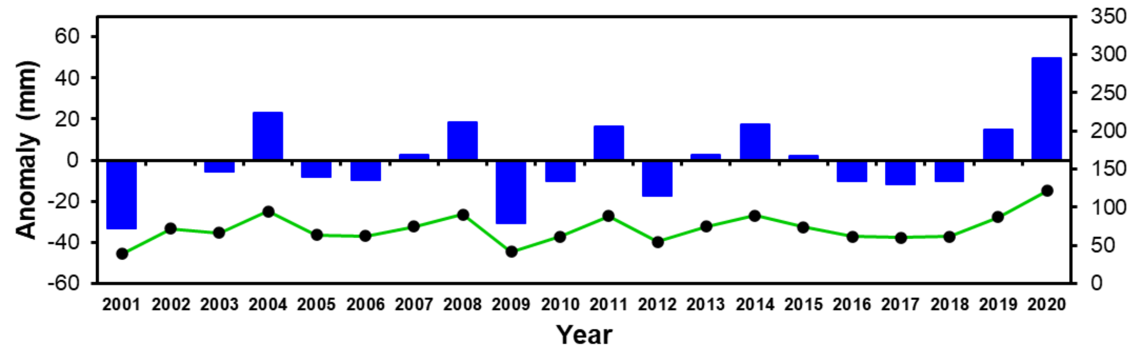

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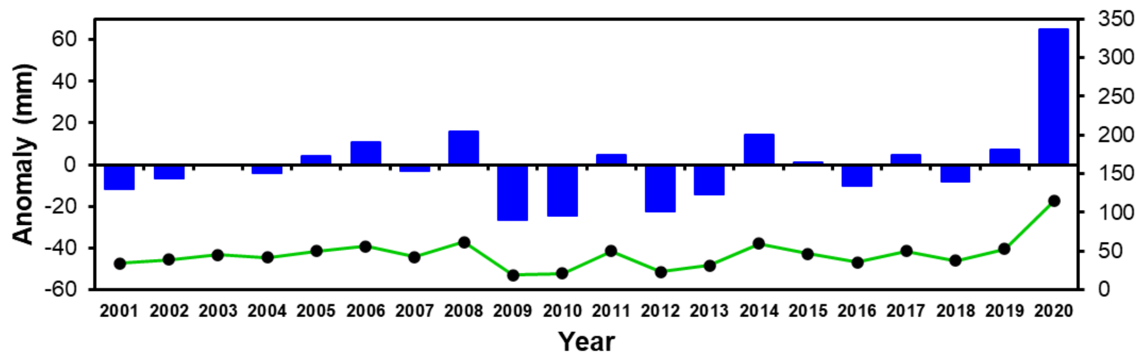

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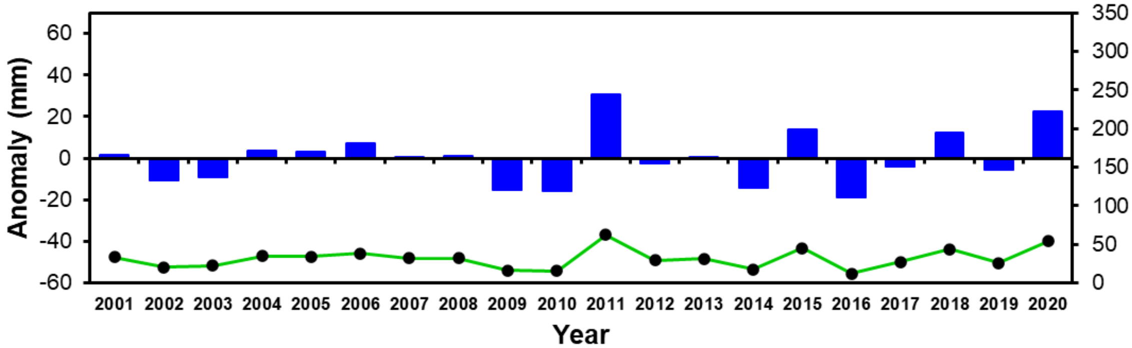

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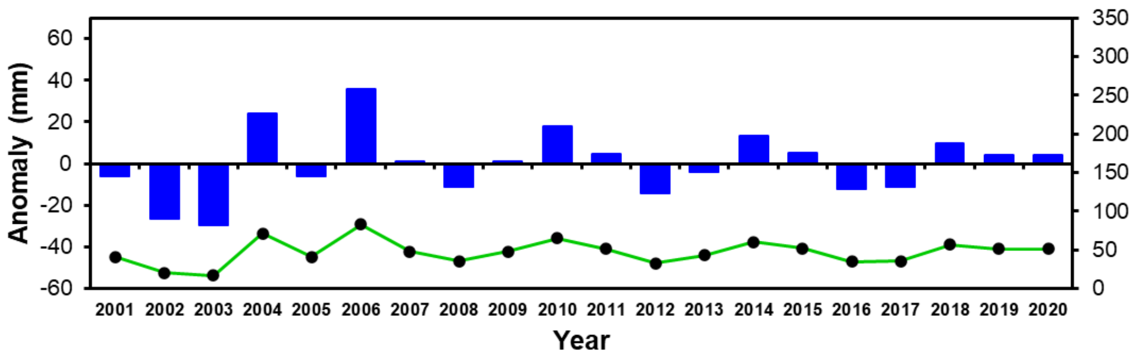

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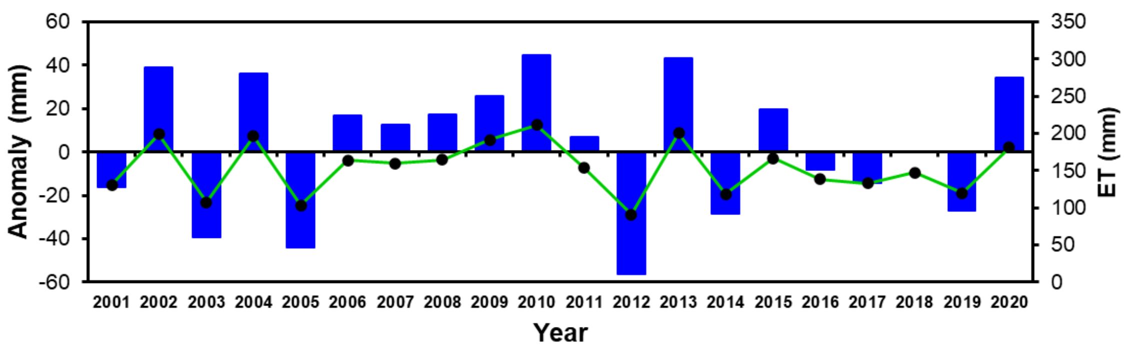

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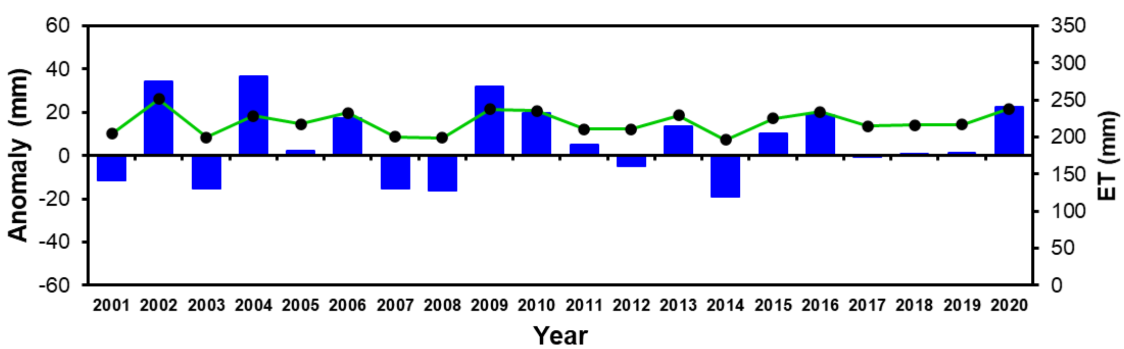

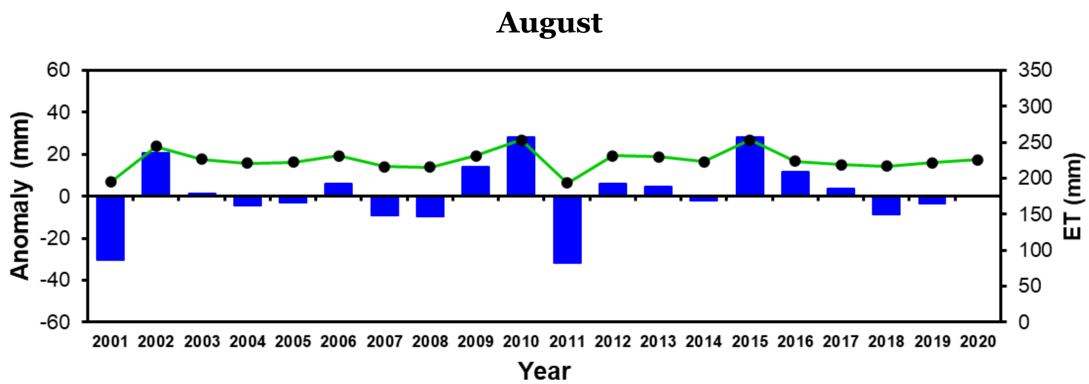
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Anomaly (mm)
ET (mm)
Year
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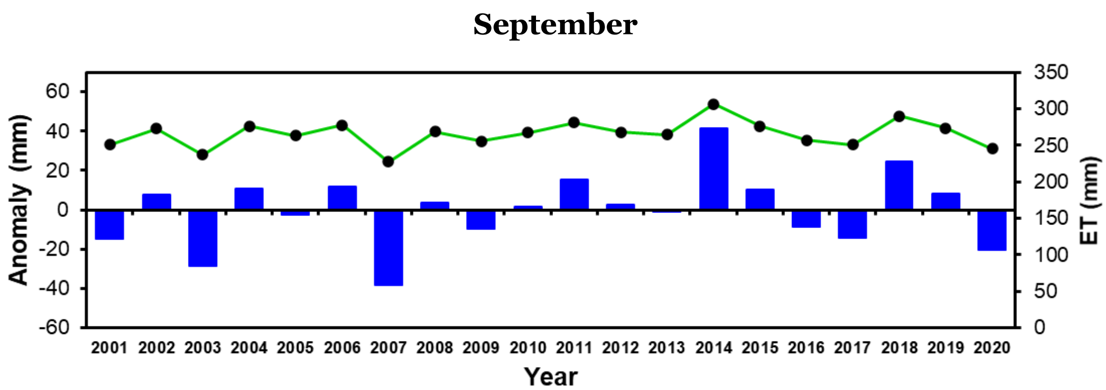
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Anomaly (mm)
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Year
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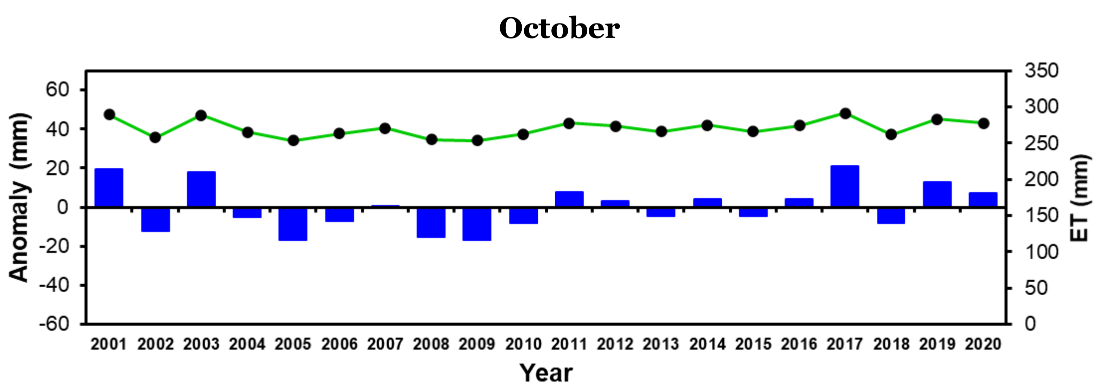
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Anomaly (mm)
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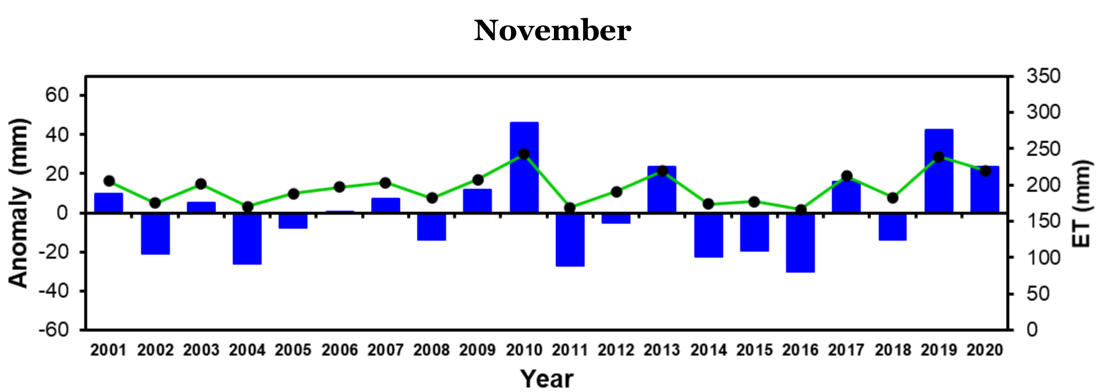
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Anomaly (mm)
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2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020

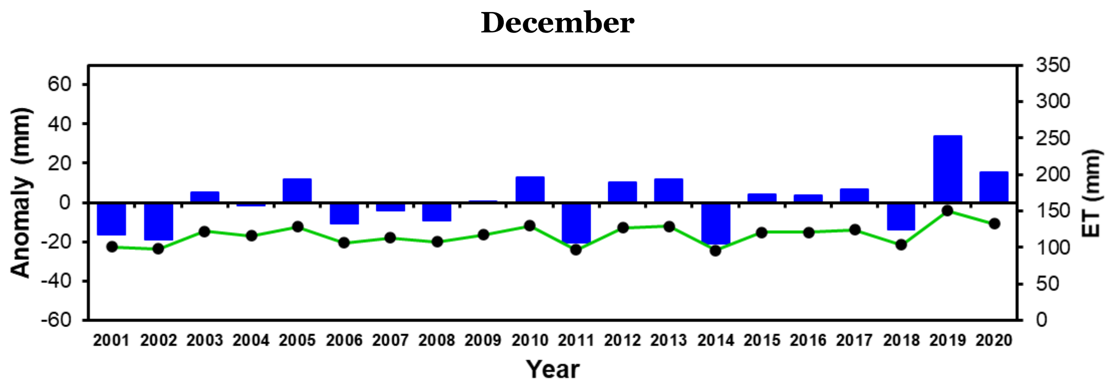

Figure 5.36: Month-wise evapotranspiration level over Odisha state during 2001 – 2020.

5.3.5 Groundwater storage (GRACE)

Groundwater is an important marker of climatic variability. Researchers have used a combination of hydrological modelling and GRACE data to examine dynamic changes in groundwater levels over large areas. The gravity differences studied carried out by GRACE have been used to determine land surface groundwater reserve/ storage estimation. Researchers prepare the groundwater anomaly map by comparing present data (average over time) and previous data to identify groundwater storage depletion or increased over any region. This quantity/ anomaly is often utilized to delineate the hydrological / groundwater drought.

GRACE data has been used for monthly drought indicators by various agencies. It is being used for hydrological drought assessment, and characterization, across various spatio-temporal scales. GRACE mission gives monthly combined water storage variations and subsurface water balance estimation of the surface which was not available previously. GRACE data measures water storage variability in total over a region, therefore time series analysis can be carried out to characterize the groundwater storage variability and depletions from long-term measurements. The variation provides a quantitative estimation of essential water requirements to bring the storage into normal condition to improve from a drought event.

Figure 5.7 shows the long-term monthly water storage variations over Odisha state. Water storage anomaly is also estimated and shown in the same graph. Temporal variation of groundwater storage is seen over Odisha. Water storage is seen generally in the winter months and continues a similar situation till month of June. From July onwards, it increases and continues till November- December. The variation of groundwater storage is also seen in each month within the long-term period. It can be observed that during the identified drought years i.e., 2002, 2004, 2009, 2010, 2013 and 2015, groundwater storage was low compared to the long-term average as well as the groundwater storage anomaly was negative. The demand for water for Kharif crops (mainly paddy) is generally high, and hence drought situations happened. The results also correlate with the previous analysis of rainfall, soil moisture, ET etc. Therefore, an extreme to severe drought occurred in the monsoon period of 2002, 2004, 2009, 2010, 2013 and 2015.

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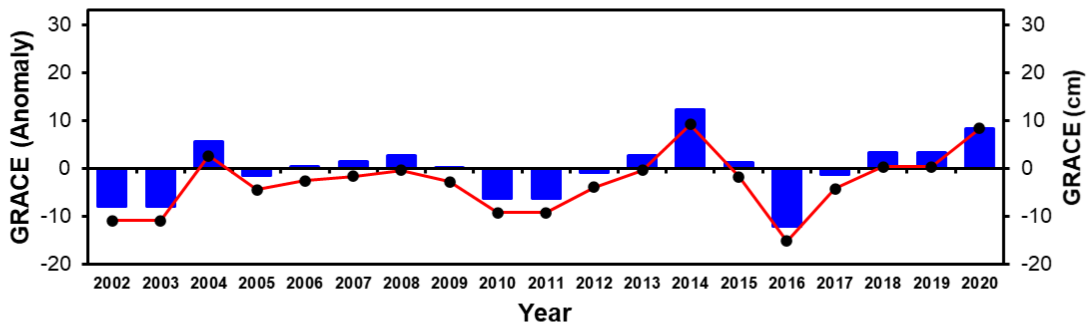

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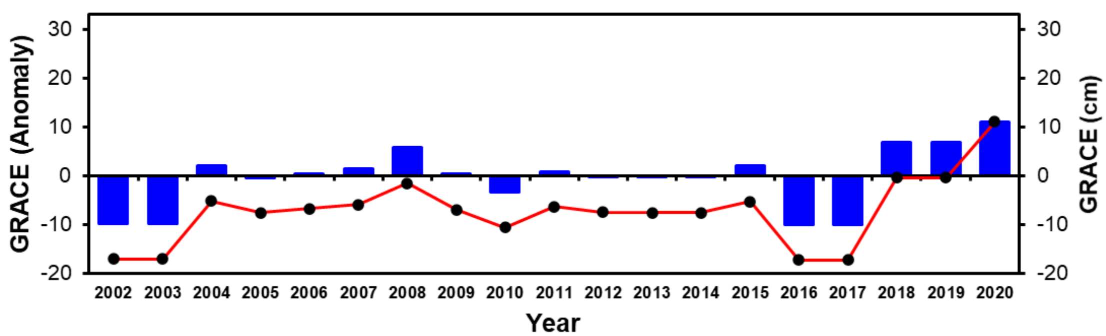

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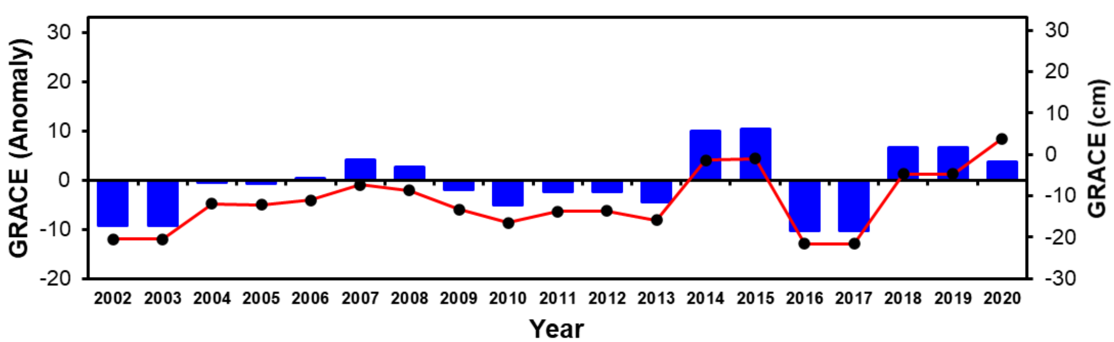

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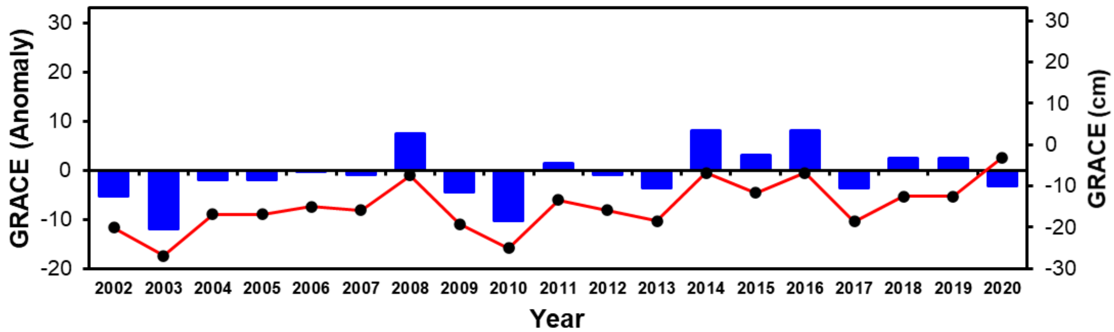

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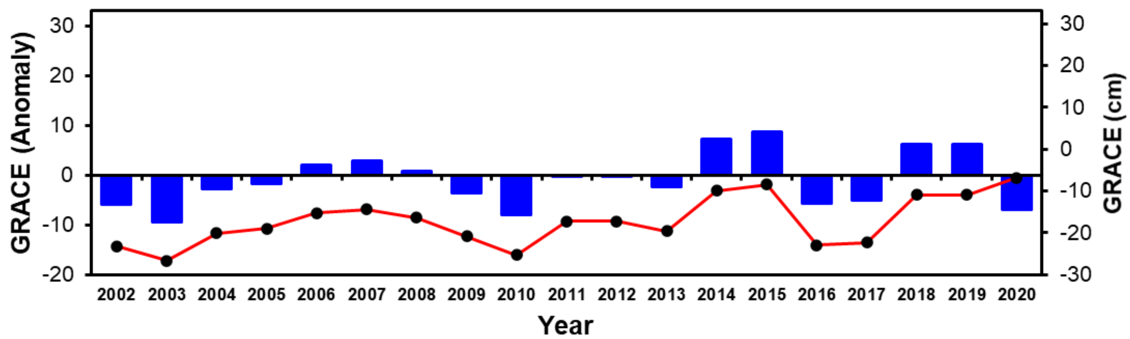

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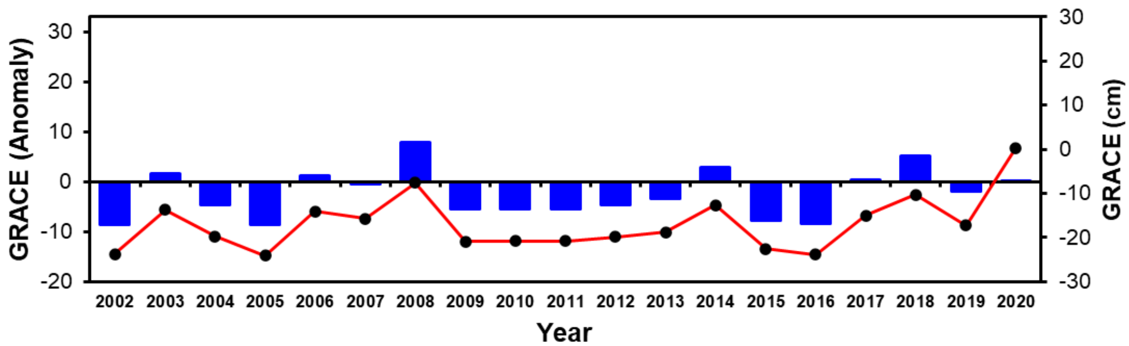

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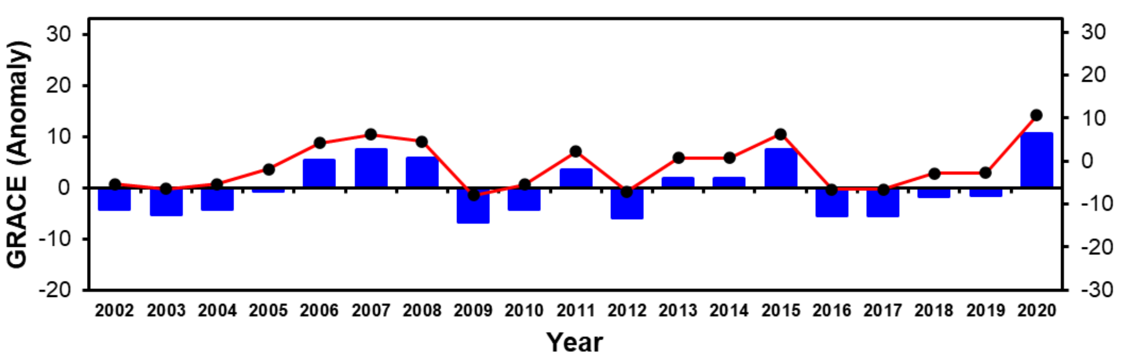

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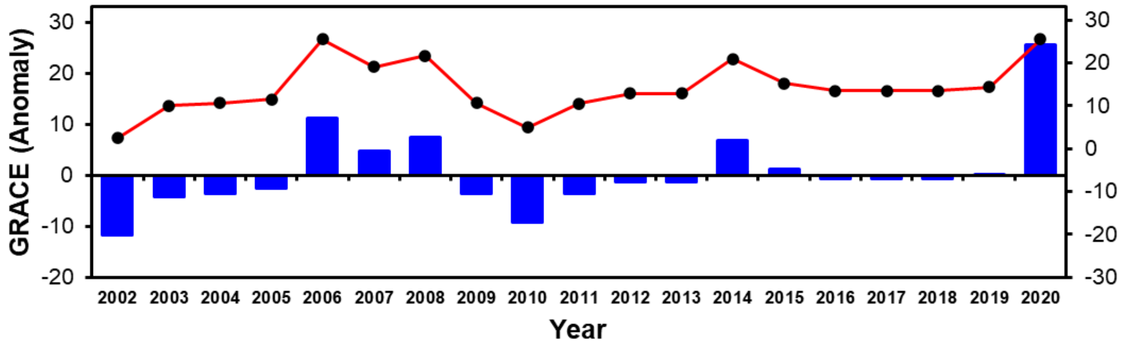

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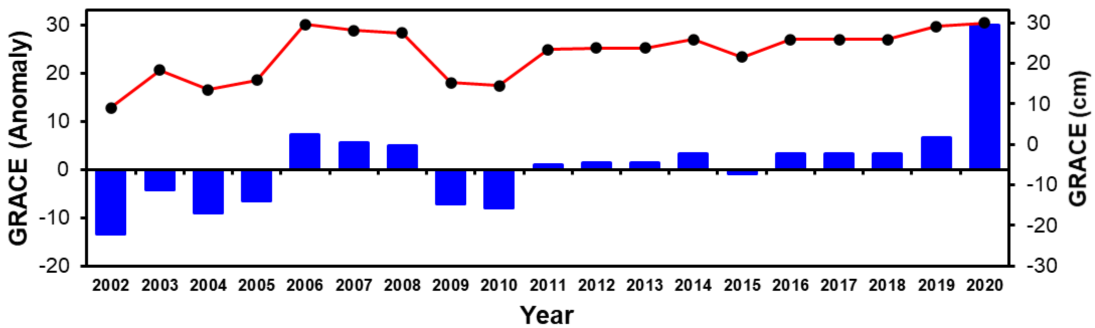

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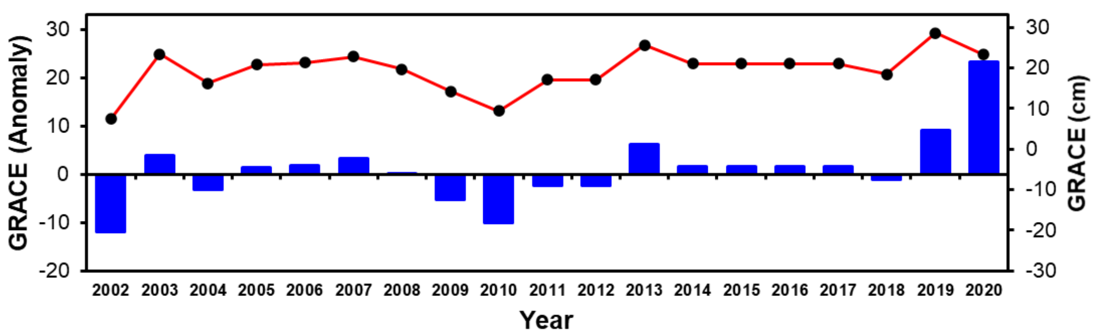

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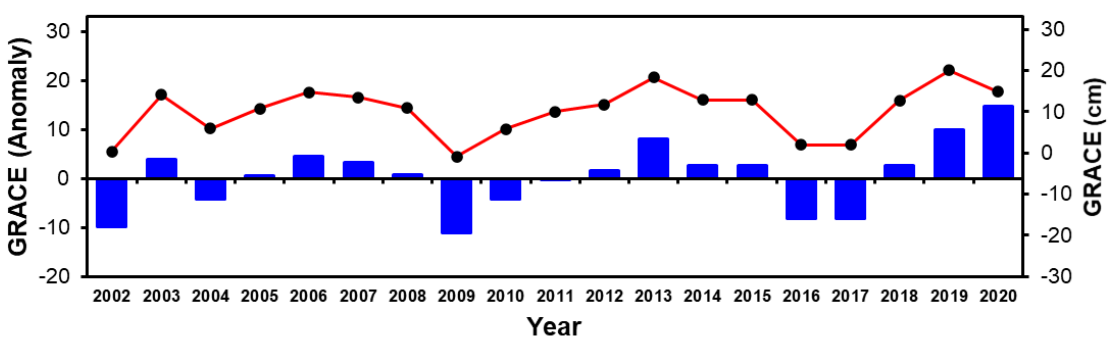

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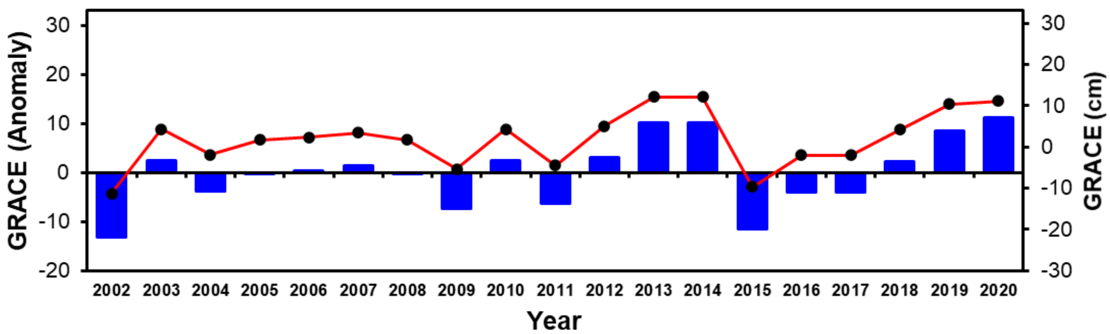


Figure 5.37: Month-wise groundwater storage estimated from GRACE data over Odisha.

5.3.6 El Nino and IOD

It has been observed over long time that El Nino and La Nina influence the rainfall variability and therefore responsible for drought events. Odisha is located in the coastal region and therefore highly influenced by the rainfall variability due to the El Nino effect. The Oceanic Nino Index from 2000 to 2020 is shown in figure 5.8. The positive Oceanic Nino Index is shown in brown colour and the negative index is shown in blue colour. Positive Oceanic Nino Index is known as El Nino and the negative Oceanic Nino Index is known as La Nina. All the identified drought years are plotted in the same graph to correlate the Oceanic Nino index and drought events. It is observed that 4 out of 6 drought years (2002, 2004, 2010 and 2015) coincided with the El Nino phase and the other 2 which coincided with the La Nina phase were either followed by an El Nino phase (2009) or just after an El Nino phase (2013). During the El Nino episodes, the normal patterns of precipitation/rainfall and atmospheric circulation in the tropical region become disrupted triggering extreme climate events such as drought. The relationship observed during the above-mentioned analysis signifies that there is a strong influence of El Nino events on drought over Odisha.

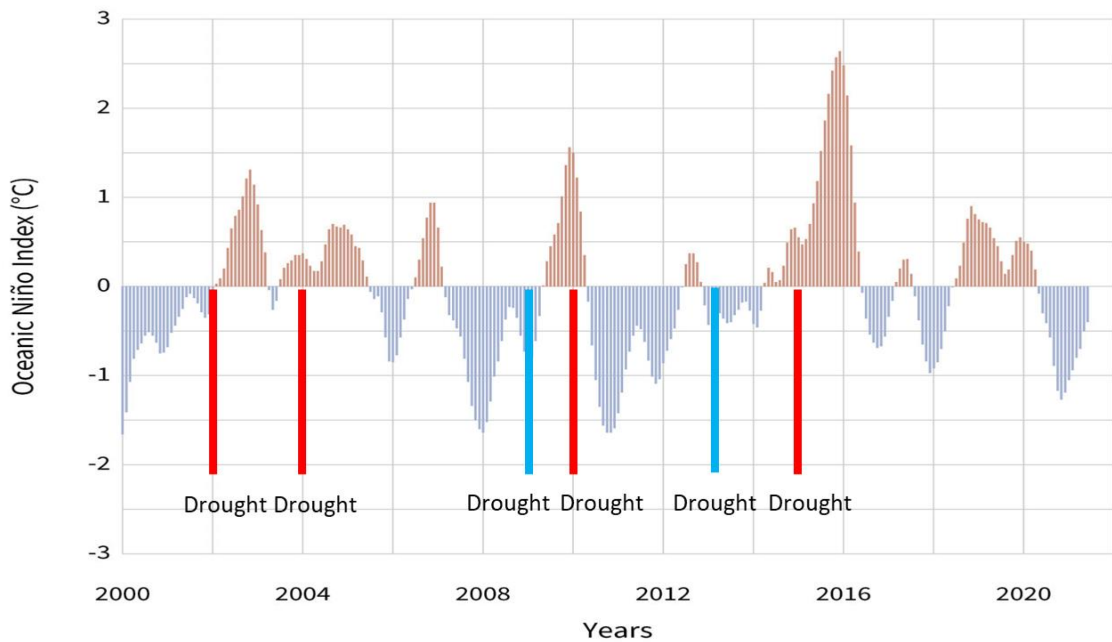
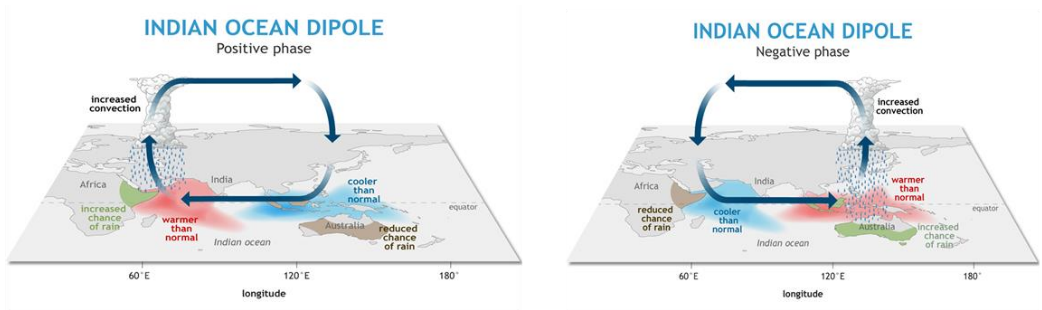


Figure 5.38: Oceanic Nino Index and drought over Odisha from 2000 to 2020. Source: NOAA Climate.gov.

IOD is another important factor which is also responsible for the drought. The Block diagram of the Indian Ocean Dipole concept along with relationship between IODMI and drought years of Odisha is shown in figure 5.9. The Indian Ocean Dipole affects the climate of the various countries surrounding the Indian Ocean basin and especially in Australia. It is a significant contributor variability of rainfall. The positive IOD often linked with El Nino and the negative IOD events are associated with La Nina. When the IOD and ENSO are active, the effects of El Nino and La Nina events become most severe over various countries of the Indian Ocean region. However, when IOD and ENSO are inactive (out of phase) the effects of El Nino and La Nina actions is weakened. It has also been noticed that during the period of positive IOD events, the Indian summer monsoon rainfall is considerably high in comparison with the negative IOD period. It is obvious from figure 5.8 that all the severe drought years (2002, 2004, 2009, 2010, 2013 and 2015) in Odisha almost coincided with the peak negative phase of IODMI, i.e., warmer east Indian Ocean and cooler west Indian ocean scenario.



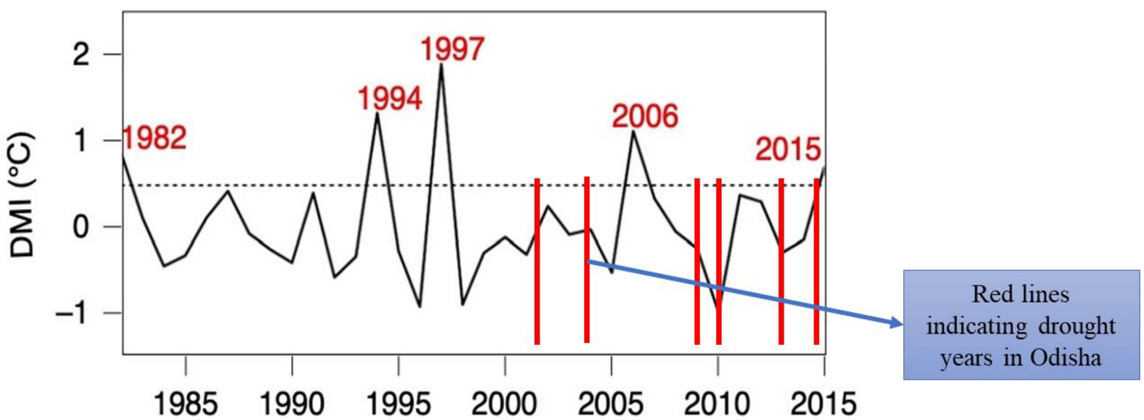


Figure 5.39: IODMI vis-a-vis drought years are plotted for 1982 to 2015. Source: NOAA Climate.gov.

5.3.7 Test of significance of variables

Sen's slope and z-value calculated using The MK (Mann-Kendall) test for major climatic parameters are shown in the Table 5.1. Sen's slope indicate the rate of change of that variables respect to per unit time and Z-value indicates the level of significance. The positive trend (non-significance level at 0.05, but significant at 80% level) of precipitation is observed (3.98 mm year^{-1}). The positive (significance level at 0.05) of maximum temperature and negative trend (non-significance level at 0.05, significant at 80% level) of minimum temperature were found (0.009 °C year^{-1} and -0.004 °C year^{-1}) from 1975 to 2019 in the study area. LST, ET and soil moisture are significant at 95% level as the Z-value is >1.96 or -1.96. The GRACE data is non-significant at 95% level and significant at 90% level as the Z-value is >1.645. The test results suggest that all parameters used in this research are valid at 90 to 95% significance level.

Table 5.13: Sen's slope and Z-vale of Mann-Kendall test

Variables/ Parameter	Sen Slop	Z-value

Precipitation	3.981	1.418
T_{max}	0.009	2.905
T_{min}	-0.004	-1.379
LST	-0.12	-2.89
ET	9.45	2.11
GRACE	0.37	1.89
Soil Moisture	0.001	2.14

5.4 Discussion

The present research has tried to identify the cause of drought in Odisha state from 2000 to 2020. Various factors have been identified such as rainfall, temperature, soil moisture, evapotranspiration, groundwater storage, El Nino and IOD etc. All these factors control the climatic conditions of the Odisha state and cumulatively affects the drought situation. The effects of all factors responsible for drought in Odisha are summarized in Table 5.1.

Table 5. 14: Analysis of various factors affecting and drought scenario in Odisha (2000 - 2020).

Year	PCP.	LST	SM.	ET	GWS.	The affected area (lakh hac.)	Crop loss	Remarks
2002	Deficit (< 60%)	High	Low	High	Low	28.46 in 30 districts.	68%	Extreme Drought
2004	Deficit (< 47%)	High	Low	High	Low	17.2 in 28 districts.	50%	Severe Drought
2009	Deficit (< 21%)	High	Low	High	Low	15.25 in 15 districts.	33%	Moderate Drought
2010	Deficit (< 47%)	High	Low	High	Low	21.6 in 15 districts.	50%	Severe Drought
2013	Deficit (< 39%)	High	Low	High	Low	50% in 259 blocks	33%	Severe Drought
2015	Deficit (< 25%)	High	Low	High	Low	23.2 in 26 districts.	33%	Moderate Drought

Table 5.1 shows that the drought year identified in the Odisha state has a high degree of precipitation deficit, LST was higher than normal, soil moisture was low, ET was high and groundwater storage was less. These all conditions are favourable to drought. However, analysis of this research, previous research (Kar et al., 2007; Sarangi and Penthoi, 2012)

as well as available reports, data and publications of state disaster management department and other state authorities (Annual Report on Natural Calamities, Government of Orissa, 2011-2012) also revels the similar facts.

Secondary data of affected districts and crop loss is collected from the state disaster management department published reports. The data also shows that in 2002, the rainfall deficit was 60 % compared to normal. Generally, the state receives 564.80 mm of rainfall, but in 2002 only 306.94 mm of rainfall was received and due to this reason 28.46 lakh hectare area of Odisha was affected by drought and the total crop loss was 68%. In a similar way years 2004, 2009, 2010 2013 and 2015 (Sate Annual Report; DownToEarth; Annual Report on Natural Calamities, Government of Orissa, 2009-2010; Patel, 2018)were affected by drought. The % of crop loss was 50%, 33%, 50%, 33% and 33% respectively. The results clearly indicates that drought hit Odisha state severely due to variability of the above-mentioned factors including El Nino and IOD. Moreover, the irrigation system helps a bit to cope up with the situation. Irrigation is the major support system of Agriculture. It decreases the vulnerability of the farmers to the vagaries of monsoon. But only 20% of the total agricultural area is covered under canal-based irrigation, therefore, farmers are still depending on monsoon rainfall for agriculture.

5.5 Conclusion

In this chapter causes of drought in Odisha state are analysed in detail. The major affecting factors for drought are identified from the literature, State Government reports, published news etc. All datasets related to the rainfall, temperature, soil moisture, evapotranspiration, groundwater storage, El Nino and la Nina, IOD, and secondary datasets related to crop loss, precipitation deficit, and drought-affected areas are taken into consideration. Precipitation and air temperature data from 1975-2019 (45 years) and 2000-2020 other datasets are processed and analysed. The detailed analysis signifies that the major reason for drought in Odisha state is variability of monsoon rainfall. The total amount of rainfall is not the basic cause of drought but the timing of rainfall due to the onset of the southwest monsoon which affects the Kharif crop and results in severe drought. The analysis also suggests that positive anomaly of LST increases evapotranspiration and therefore decreases soil moisture and because of this reason groundwater storage decreases. All these factors cumulatively affect the agricultural practice negatively and drought occurs in Odisha state. The study also analysed the ENSO and IOD effects on drought. These two phenomena are the main controlling factor of air circulation over the Indian Ocean and therefore significantly impact the southwest monsoon. It influences the variability of rainfall. Odisha as a coastal state gets highly influenced by rainfall variability. Irrigation is the lifeline for agricultural activity, but only 20 % area of Odisha is covered by canal irrigation in Odisha. However, better drought management and irrigation system development are required for drought mitigation in Odisha state.

6 Drought Prediction

Logic will take you from A to B. Imagination will take you anywhere.

- *Albert Einstein*

6.1 Introduction

Drought is one of the devastating natural hazards in India as well as in Odisha. The drought frequency in India is high, approximately once in three years. India has faced severe drought in recent decades and a post-drought water scarcity scenario. Hence, in Odisha state, drought frequency is higher, and most districts are drought prone. The state has 48 million population and it is one of the most densely populated states in India, therefore, agricultural activity is very important for this state. The state Government has implemented policies for irrigation and agriculture, however, monitoring agricultural drought is important. Drought monitoring is also necessary for the food and water security of the state.

The occurrence and severity of drought are significantly associated with climatic variables and anomalies, hence, a change in the global climate would aggravate the occurrence of drought due to anomalies in temperature and precipitation (Mukherjee, Mishra, & Trenberth, 2018)**.**In most regions across the world, the occurrence of drought has remarkably increased since 1970 owing to a rise in evapotranspiration while no significant increase in precipitation was observed (Jehanzaib & Kim, 2020). Researchers have found that changing climate scenarios and global warming issues impacted enhanced and prolonged drought situations. It results in soil moisture deficit, high evapotranspiration, reduction of groundwater and increase drought frequency and severity. Warming climate increases the drought intensity due to the land-water-atmosphere interaction which results in loss of crop productivity.

To ensure food security, it is important to understand the future drought of the state and therefore, modelling/ prediction of drought is a necessity. This will also provide an estimate to evaluate the impact of climate change on drought frequency/intensity/severity etc. Previous studies (Turner & Annamalai, 2012; Sharmila, Joseph, Sahai, Abhilash, & Chattopadhyay, 2015; Huang, Yu, Guan, Wang, & Guo, 2016; Liu, et al., 2018) have studied the water scarcity/availability and drought risk with respect to climate change in future.

Various researchers have used CMIP5 (Coupled Model Intercomparison Project Phase 5) models(Taylor, Stouffer, & Meehl, 2012) for predicting the future climate. It is observed that CMIP5-GCMs give considerable uncertainty while predicting the summer monsoon precipitation (Chen & Zhou, 2015; Dai & Zhao, 2017).GCMs showed a limited capability to characterize the long-term changes of summer monsoon precipitation in monsoon regions(Jin & Wang, 2017). In addition, many CMIP5-GCMs fail to capture the precipitation of the monsoon season, its onset, and scale variability in the summer monsoon of the future climate(Sabeerali, Rao, Dhakate, Salunke, & Goswami, 2015). Studies have also been carried out to identify the projected change in the drought frequency of agricultural, meteorological, and hydrological droughts in the future climate over the Indian subcontinent using the CMIP6-GCMs.Aadharand Mishra**,** (Aadhar & Mishra, 2020)studied the prediction of drought in South Asia using CMIP6-GCMs and compared various climatic models to check their suitability. However, the present research has carried out short-term and long-term drought predictions over Odisha state to analyse the future drought scenario.

6.2 Methodology

In this research future drought assessment has been carried out based on the model-predicted rainfall and temperature datasets. Aadhar and Mishra, 2020 has compared the 16 CMIP6-GCMs climatic data and observed that the NorESM2-MM CMIP6 GCM model is suitable for South Asia. Therefore, the predicted temperature of precipitation and temperature of NorESM2-MM CMIP6 GCM have been taken in this study. Bias-corrected predicted precipitation and rainfall of 2023 to 2050 vintage data, available from the web portal of IIT Gandhinagar, have been downloaded and processed for short-term (2023-2030) and long-term (2031-2050) drought prediction. All the datasets were available in the text file format which has been converted to grid format after geocoding with the required projection system.

The model predicted daily temperature has been converted to minimum and maximum monthly temperature and from that tri-monthly minimum and maximum temperature (Jan-Feb-Mar/ Apr-May-Jun/ Jul-Aug-Sep/ Oct-Nov-Dec) has been estimated. Using the tri-monthly temperature, annual minimum, and maximum temperature. Temperature anomaly has been calculated and trend analysis has been carried out.

Similarly, using the model predicted precipitation tri-monthly SPI has been generated and classified as per the classification scheme defined in Chapter 4 for estimation of drought severity and estimated the percentage of the drought-prone area against each class. Tri-monthly total precipitation, anomaly and percentage of drought have been plotted for analysis. Classified SPI i.e., drought severity map has been generated to analyse the spatial distribution of predicted drought during the vintage of 2023-2050.

6.3 Results

6.3.1 Temperature analysis

A predicted maximum temperature plot is generated and shown in figure 6.1. The plot shows that there is a steady increase in the maximum temperature during the period of analysis. It is observed from the graph that approx. 2°C increase in the maximum temperature between 2023 to 2050. The temperature anomaly shows that higher positive anomaly after 2040. The trend analysis also shows a positive increasing trend in temperature that signifies a high possibility of an increase in temperature over the Odisha state that may cause a warmer climate and result in higher drought frequency and severity.

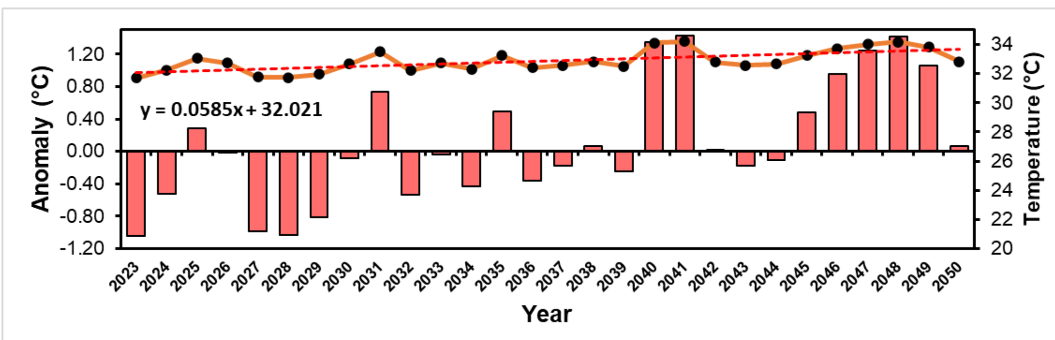


Figure 6.40: Predicted Maximum Temperature (Tmax)

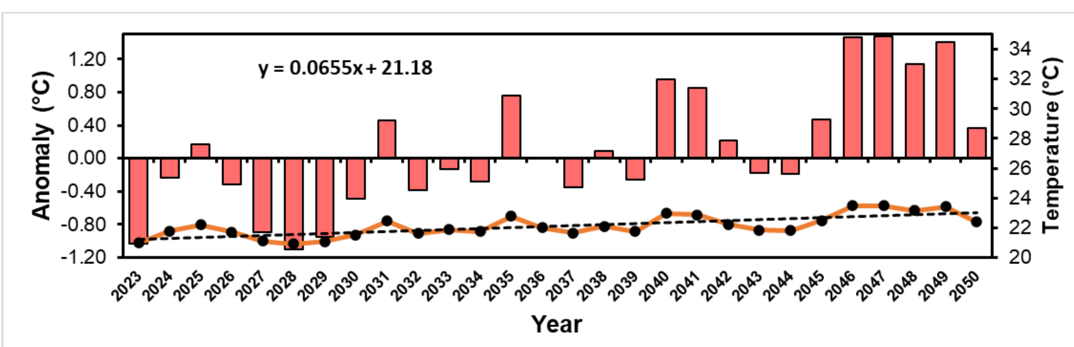


Figure 6.41: Predicted Minimum Temperature (Tmin)

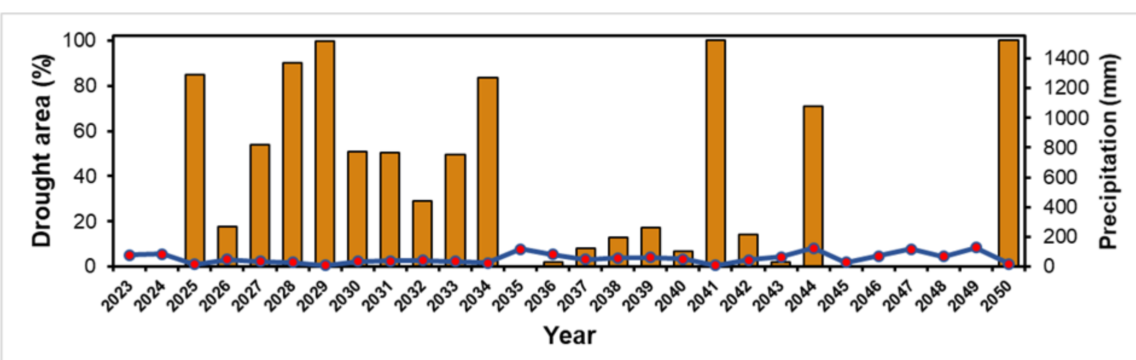
The predicted minimum temperature graph is shown in figure 6.2. The minimum temperature plot shows that there is an increasing trend in the minimum temperature during the period of analysis. It is observed from the plot that approx. 1.5°C increase in minimum temperature during the analysis period (2023 to 2050). Temperature anomaly also shows a positive anomaly after 2040. The positive increasing trend is seen in the trend analysis which indicates that higher probability of increasing the temperature over the study area. It again signifies that higher temperature in the future, lead to high evapotranspiration and loss of soil moisture which may result in more severe drought.

6.3.2 Precipitation and drought scenario analysis

NorESM2-MM CMIP6 GCM model predicted tri-monthly total precipitation is plotted and analysed. SPI is derived tri-monthly basis and classified the drought and non-drought areas. The percentage of drought area of Odisha state for 2023-2050 based on Jan-Feb-Mar/ Apr-May-Jun/ Jul-Aug-Sep and Oct-Nov-Dec are shown in figure 6.3. In the month of Jan-Feb-Mar of the year 2025, 2027, 2028, 2029,2034,2042,2055 and 2050 more than 50% area will be drought affected as per predicted precipitation, but this may not be very significant because in India rainfall is very less in the winter season, therefore, the major area is showing meteorological drought. However, the crop cultivated this time does not require much rainfall, hence, a drought at this time may not be very relevant.

Similarly, for Apr-May-Jun is the pre-monsoon period, the year 2025, 2026, 2031, 2035, 2040, 4041, and 2047-49 shows more than 50% area under drought. The study area will receive very less rainfall at this time. This is the Zaid crop growing season which requires warm dry weather condition during the major growth period as well as longer day stretch for flowering, therefore, less rainfall/ meteorological drought does not affect the agriculture/crop growth very significantly.

Jan-Feb-Mar



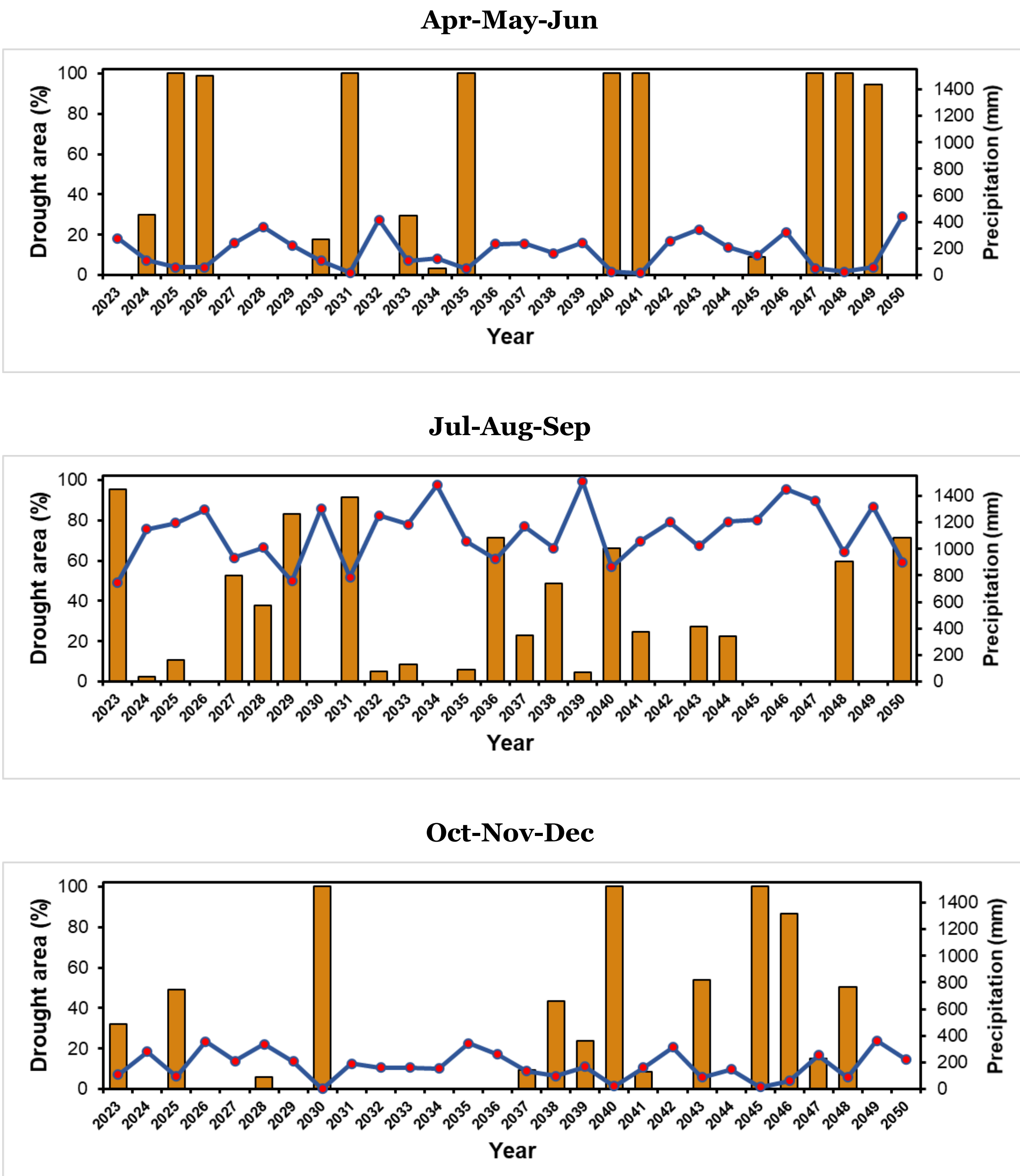


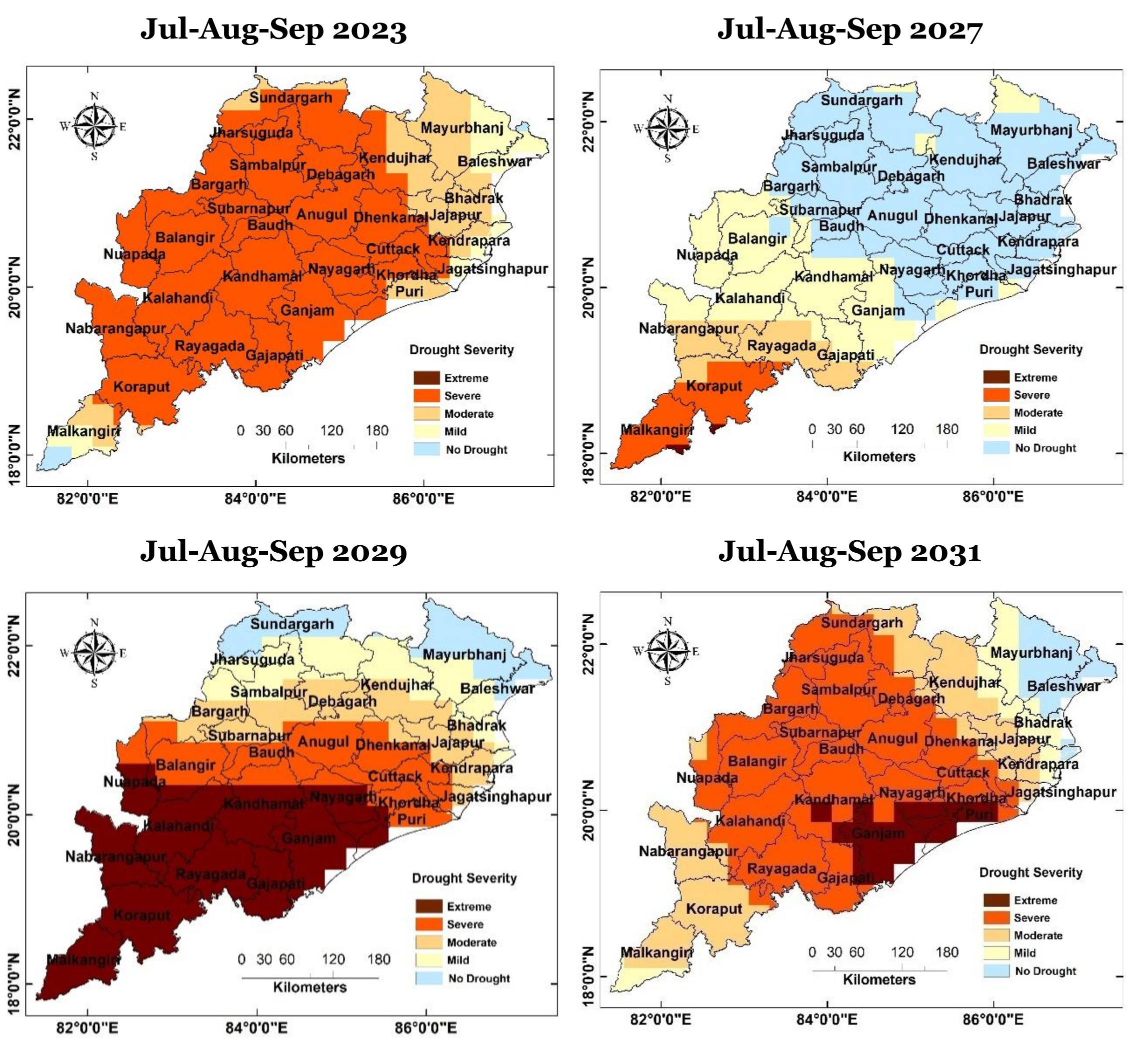
Figure 6.42: Predicted precipitation and percentage of drought area plot. It is a tri-monthly drought estimation: Jan-Feb-Mar/ Apr-May-Jun/ Jul-Aug-Sep/ Oct-Nov-Dec.

The most significant time is the monsoon period i.e., Jul-Aug-Sep. The plot shows that there is a relationship between precipitation and drought. In the years 2023, 2027, 2029, 2031, 2036, 2040, 2048, and 2050 more than 50 % of the state area is showing will be under drought. It can be observed that in the same year precipitation is less compared to other years' monsoon periods. This is the Kharif crop growing season which required rainfall/soil moisture, therefore, if a meteorological drought occurs during the monsoon period, it will lead to agricultural drought and the crop will be affected.

During the post-monsoon, Ravi crop sowing and growing period (Oct-Nov-Dec), less drought is showing in the predicted rainfall and drought area plot. The only year 2030, 2040, 2045 and 2046 will be the probable drought affected, however, the Ravi crop does not require much rainfall, hence this drought may not affect agriculture much.

6.3.3 Spatial distribution of future drought scenario

Figure 6.4 shows the predicted future drought map in Odisha state.



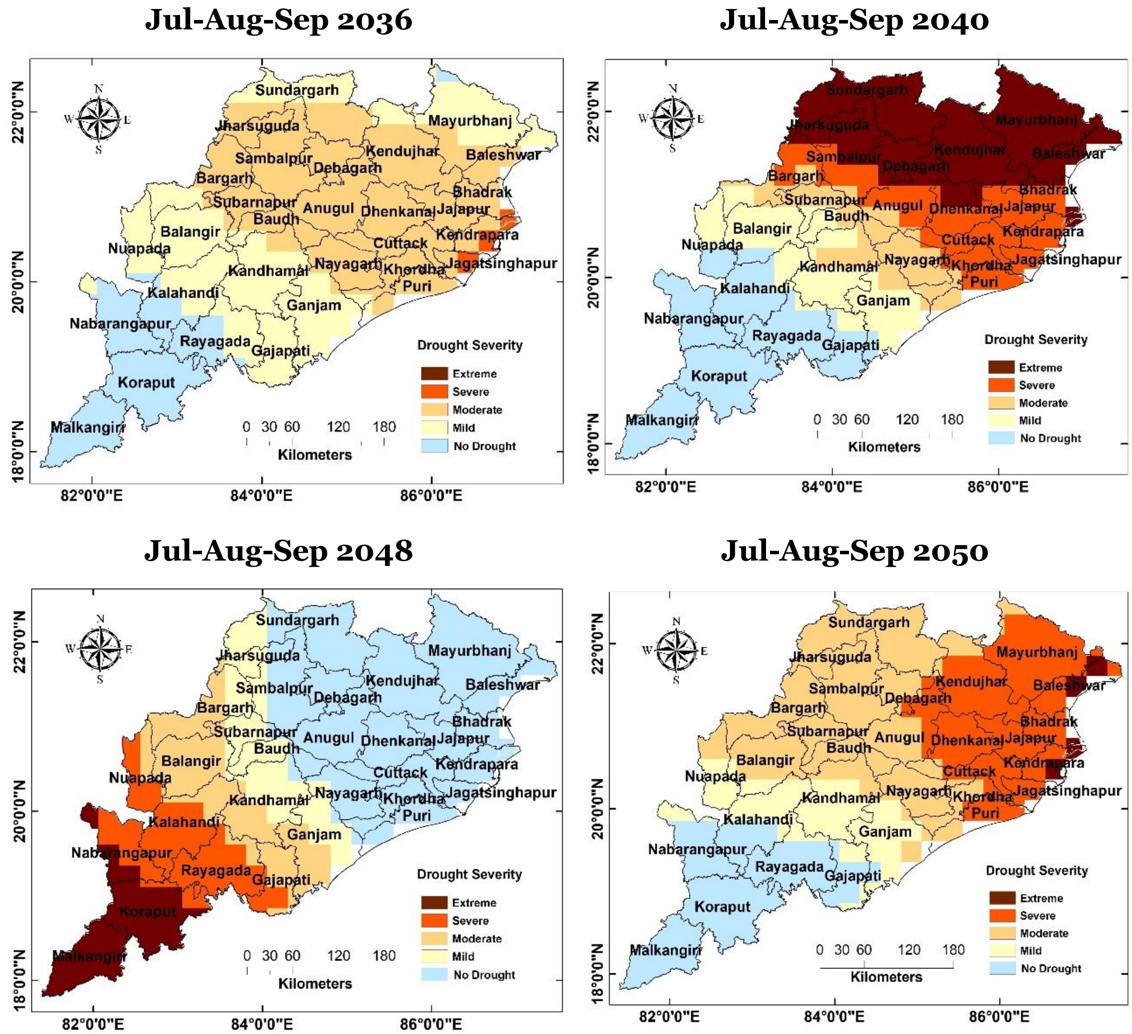


Figure 6. 43: Spatial distribution of predicted drought of Odisha for the year of 2023/ 2027/ 2029/ 2031/ 2036/ 2040/ 2048/ 2050. This is a classified SPI map which is depicting meteorological drought.

Based on the precipitation analysis it is obvious that drought in the monsoon period is significant in the study area. Hence, the spatial distribution of predicted drought patterns in the monsoon period i.e., Jul-Aug-Sep for the identified drought years 2023, 2027, 2029, 2031, 2036, 2040, 2048, and 2050 is shown in figure 6.4.

The predicted drought map of 2023 indicates that a major part of Odisha will be facing severe drought. The north-eastern and southern parts of the state will be facing moderate drought. In 2027, the central, southern-eastern, and southern parts of the state will be facing mild, moderate and severe drought respectively. In 2029, a major part of Odisha will be under drought. In the central part, moderate and severe drought will prevail, but in the southern and south-eastern parts, extreme drought will be seen. In 2031, a major part of the state will be facing severe drought, but in the coastal part, extreme drought will be seen. In the other parts of the state, moderate drought will be discerned.

In 2036, Odisha will face drought, but the severity will not be high. A major part of the state will face moderate and mild drought. No drought will be seen in the south-eastern part of the state. However, in 2040, drought severity will be high in Odisha state. The northern part of the state will face extreme and severe drought. The central part of the state will face moderate and mild drought, and no drought will be seen in the south and south-eastern part of the state. In 2048, no drought is showing in the northern part of the state, although the west, south, and south-eastern part of the state will be facing moderate, severe and extreme drought. In 2050, the central, western, and eastern parts of the state will face moderate and extreme drought. The result indicates that there will be no fixed pattern of drought in Odisha state in future.

The statistical test of significance has been carried out to check the validity of the results. The Mann-Kendall test were performed as mentioned in the chapter 5 to determine the trends using Theil-Sen's estimator and their significance levels (Z-statistic). The results are shown in the Table 6.1. The positive trend (non-significance level at 0.05, but significant at 80% level) of precipitation is observed (5.706 mm year^{-1}). The positive (significance level at 0.05) of maximum and minimum temperature were found (0.058 °C year^{-1} and -0.063 °C year^{-1}) from 1923 to 2050 in the study area.

Table 6.15: Sen's slope and Z-vale of Mann-Kendall test

Variables/ Parameter	**Sen Slop**	**Z-value**
Drought area from SPI	-0.287	-0.92
Precipitation	5.706	1.29
Tmax	0.058	3.54
Tmin	0.063	3.97

6.4 Discussion

The present research has tried to estimate the future drought scenario in Odisha state with the help of model-predicted rainfall and temperature data. NorESM2-MM CMIP6 GCM model predicted bias-corrected data has been used in this research. 16 CMIP6-GCMs climatic data have been compared by Aadhar and Mishra, (Aadhar & Mishra, 2020)and concluded that the NorESM2-MM CMIP6 GCM model is most suitable for South Asia, therefore, the model predicted data of NorESM2-MM CMIP6 GCM model has been taken for this study. Researchers have carried out studies on drought assessment over Odisha like, such spatial assessment of drought vulnerability has been carried out by Saha et. al., 2021, perception of climate change, rainfall trends and perceived barriers to adaptation in a drought has been studied by Architesh Panda (Panda, 2016). Studies have also been carried out for forecasting rainfall using ARIMA / other predictive models (Swain, Nandi, & Patel, 2018)over India/ Odisha (Swain, Nandi, & Patel, 2018; Shrivastava, Kar, Sahai, & Sharma, 2018; Santos, et al., 2021;Mishra & Desai, 2005), but it is difficult to find out the studies particularly related to short and long-term drought prediction and its spatial distribution over Odisha state. This research worked on predictive drought analysis particularly over Odisha, its spatial pattern of distribution, intensity, and severity.

6.5 Conclusion

In this research predictive analysis of future drought scenarios (short and long term) has been carried out over Odisha state using NorESM2-MM CMIP6 GCM model predicted precipitation and temperature datasets. Tri-monthly SPI is generated with the help of model-predicted precipitation and predicted spatial distribution of meteorological drought map has been generated. The drought scenario in the monsoon period i.e., Jul-Aug-Sep month is analysed and it is observed that 50% of the area will be under drought in the years 2023, 2027, 2029, 2031, 2036, 2040, 2048 and 2050. The predicted minimum and maximum temperature show approx. 2°C and 1.5°C increase respectively during the analysis period (2023 to 2050). Temperature anomaly also shows a positive anomaly after 2040. The predicted drought map indicates that the drought pattern in Odisha is random and a major part of the state will face severe drought in the future. The analysis signifies a warm climate in the future, less precipitation and more severe drought in the future due to the climate change effect.

7 Downscaling of Drought and Soil Moisture Map

"Reality is merely an illusion, albeit a very persistent one"

- *Albert Einstein*

7.1 Introduction

One example of a crucial biophysical metric generated by satellites is the land surface temperature (Morrow & Friedl, 1998); (LST) (Agam, Kustas, Anderson, Li, & Neale, 2007) It has many scientific and environment-related uses, such as drought mapping in agriculture (Sobrino, Gomez, Jimenez-Munoz, & Olioso, 2007; Karnieli, et al., 2010) and determining the moisture content of soil (Yang & Wang, 2011; Chakraborty, Kant, & Mitra, 2015; Hulley, Hook, & Baldridge, 2010).

When a drought hits an area, it can be very difficult for the environment, agriculture, and economy of an area (Riebsame, 1991; Wilhite, p. 2000; Wu, Zhou, Liu, Zhang, Leng, & Diao, 2013). Drought can be broken down into four primary categories: (a) weather-related, (b) agricultural, (c) hydrological, and (d) social and economic. Among these, remote sensing data can be used to create maps of agricultural drought. The term "agricultural drought" is used to describe a situation in which there hasn't been enough rain for a long time, causing the soil to dry out and crops to suffer a lot of damage (Mishra & Singh, 2010). Scientists from all over the world have come up with many drought indices (Palmer, 1965; Kogan F. N1999,Kogan F., 2002; McKee, Doesken, & Kleist, 1993; Seiler, Kogan, & Sullivan, 1998; Peters, et al., 2002; Keyantash & Dracup, 2004;Bhuiyan, Singh, & Kogan, 2006); Mishra & Singh, 2010;Rojas, Vrieling, & Rembold, 2011) to keep track of agricultural droughts. As an illustration, the Vegetation Health Index (VHI) is commonly used for drought identification, monitoring of drought severity and duration, and so on (Kogan F. , 2002; Kogan F. N., 2001; Bhuiyan, Singh, & Kogan, 2006; Karnieli, Bayasgalan, Bayarjargal, Agam, Khudulmur, & Tucker, 2006; Mukherjee, Joshi, & Garg, 2014). This index combines the Vegetation Condition Index (VCI) and the Temperature Condition Index (TCI) to describe changes in humidity and temperature caused by weather. NOAA Global Vegetation Index provides weekly VHI calculated from AVHRR sensor data for drought monitoring at 4 km spatial resolution(http://www.star.nesdis.noaa.gov). The MODIS satellite has been routinely used to measure agricultural dryness across large regions (Rhee, Im, & Carbone, 2010;

Son, Chen, Chen, Chang, & Minh, 2012; Du, et al., 2013; Wu, Zhou, Liu, Zhang, Leng, & Diao, 2013; Wan, Wang, & Li, 2004; Mallick, Bhattacharya, & Patel, 2009).

Soil moisture is important for many different reasons, including but not limited to crop growth and crop water management (Finn et al., 2011; Chen et al., 2011; Wang et al., 2016), weather and climate prediction, agriculture and water resource management, climate-sensitive socio-economic activities, and drought assessment (Choi and Hur, 2012; Patel et al., 2009;Verstraeten et al., 2006; Patel et al., 2009) have shown that satellite pictures taken with remote sensing can be used to measure soil moisture very accurately. The European Space Agency's (ESA) Soil Moisture Ocean Salinity (SMOS) satellite and the Advanced Microwave Scanning Radiometer for the Earth (AMSR-E) have both been used to provide regional to global scale mean surface soil moisture data (De Jeu et al., 2003; Rudiger et al., 2009; Brocca et al., 2010; Albergel et al., 2013; Dorigo et al., 2010). Using a spatial resolution of 25–50 kilometres and a temporal frequency of 3 days, these passive microwave devices can quantify soil moisture on Earth. The Temperature Vegetation Dryness Measure (TVDI) is a simplistic index created by Sandholt et al. (2002) that is helpful for the qualitative investigation of surface soil moisture. In the dry region, the TVDI value is high, whereas, in the wet region, it is low (Patel et al., 2009). Researchers have used TVDI from satellite data to track soil moisture on a global and regional scale (Sandholt et al., 2002; Patel et al., 2009; Wan et al., 2004; Sun et al., 2008; Xin et al., 2006; Chen et al., 2011), among other things.

Long return periods (16 days) between consecutive satellite overheads (Hong et al., 2011), narrow swath/coverage (185 kilometres) (Hong et al., 2011), and periodic cloud cover all pose significant challenges to continuous monitoring of drought and soil moisture using high-resolution satellite imaging (Moran et al., 1996). In contrast, MODIS imagery with a coarse spatial resolution (1000 m) and a large swath (2330 kilometres) that is consistently accessible (frequency 1-2 days) is particularly helpful for monitoring. MODIS thermal and VNIR (visible and near-infrared) images have a 1000-meter and 250-meter spatial resolution, respectively. Therefore, MODIS imagery can be used to monitor drought and soil moisture at a 1000 m spatial resolution (Wardlow and Callahan, 2014; Chen et al., 2011), though this may not be practical in developing countries where agricultural land holdings are much smaller than the spatial resolution of available open-source thermal images like MODIS/ AVHRR. Consequently, several methods for reducing the size of thermal images have been developed. These methods may be used to reduce the spatial resolution of a thermal picture from 1000 metres to 250 metres, which is necessary for producing the remote sensing-based indices necessary for drought and soil moisture mapping. The goal of this study was to use LST data from the MODIS sensor to measure soil moisture and agricultural drought in Odisha, a state with a lot of different types of farmlands. Two remote sensing indices, TVDI and VHI, were used in the study to map soil moisture and agricultural drought. The MODIS-derived LST imagery is downscaled to a moderate to fine spatial resolution (250 meters) using the downscaling process and then used to create VHI and TVDI at that resolution for field/regional scale drought and moisture in the soil mapping.

7.2 Data used

Drought mapping made use of Terra MODIS surface temperature 8-day composite product of 1000 meter spatial resolution (MOD11A2) and surface reflectance of VNIR bands at 250 meter spatial resolution (MOD09Q1). The NDVI was calculated using the surface reflectance of VNIR bands from the MODIS sensor. Drought downscaling data was collected during the pre-monsoon drought phase of the second week of May 2015. The VHI was calculated using the average LST during the second week of May 2015 (9-16). For this purpose, we compared maps using AVHRR's VHI product (Muriithi et al., 2016), which has a spatial resolution of 4 kilometres. The 2009 MODIS landcover map was used to demarcate farmland.

Soil moisture mapping was performed using the Terra MODIS daily LST product (product code - MOD11A1) at 1000 m resolution and the Terra MODIS daily surface reflectance (product code - MOD09GQ) at 250-meter resolution. On May 9, 2015, we mapped the soil moisture condition by calculating LST and NDVI and then used that data to create TVDI.

We utilised the atmospherically adjusted and radiometrically calibrated MODIS data packages. The original Sinusoidal projection data were reprojected to a Universal Transverse Mercator (UTM) projection using zone 45.

7.3 Methodology

The methodology adopted in this study has been divided into four parts; LST downscaling, VHI generation for mapping of agricultural drought, generation of TVDI for mapping of soil moisture and validation using statistical models.

7.3.1 LST downscaling model

Downscaling in case of LST refers to an increasing information content in the thermal imagery by enhancing the spatial resolution of satellite-based thermal imagery(Atkinson, 2013). Attempts were made to downscale thermal imagery (Anderson et al., 2004; Agam et al., 2007a, 2007b; Bindhu et al., 2013; Ha et al., 2011; Jeganathan et al., 2011; Kustas et al., 2003; Merlin et al., 2010; Yang et al., 2010a; Yang et al., 2010b; Rodriguez-Galiano et al., 2012; Zhu et al., 2013) using different techniques (Zhan et al., 2013). LST (day time) at 1000 m spatial resolution and NDVI at 250 m resolution are derived from MODIS sensor data. The LST downscaling model is established based on LST and NDVI relationship (Mukherjee et al., 2014a; Black and Stephen, 2014; Kustas et al., 2003; Rhee et al., 2014). The basis of the LST downscaling model is the strong inverse correlation / relationship between LST and NDVI (Agam et al., 2007a; Mukherjee et al., 2014a;Kustas et al., 2003; Karnieli et al., 2006).Previous studies observed that LST-NDVI relationship is site specific, therefore, the function of downscaling model is derived from the extent of the study area. Initially the model is developed at 1000 m resolution data (equation 7.1), derived the residual LST at 1000 m resolution by taking the difference between actual LST and model derived predicted LST (equation 7.2), applied the model to NDVI of 250 m resolution (equation 7.3) and the residual LST derived at 1000 m resolution is added back (equation 7.4).

$$L\hat{S}T_{1000} = a + b \times NDVI_{1000} \tag{7.1}$$

$$\Delta L\hat{S}T_{1000} = LST_{1000} - L\hat{S}T_{1000} \tag{7.2}$$

$$L\hat{S}T_{250} = a + b \times NDVI_{250} \tag{7.3}$$

$$L\hat{S}T_{250Fin} = L\hat{S}T_{250} + \Delta L\hat{S}T_{1000} \tag{7.4}$$

A schematic representation of the LST downscaling model is shown in the figure 7.1.

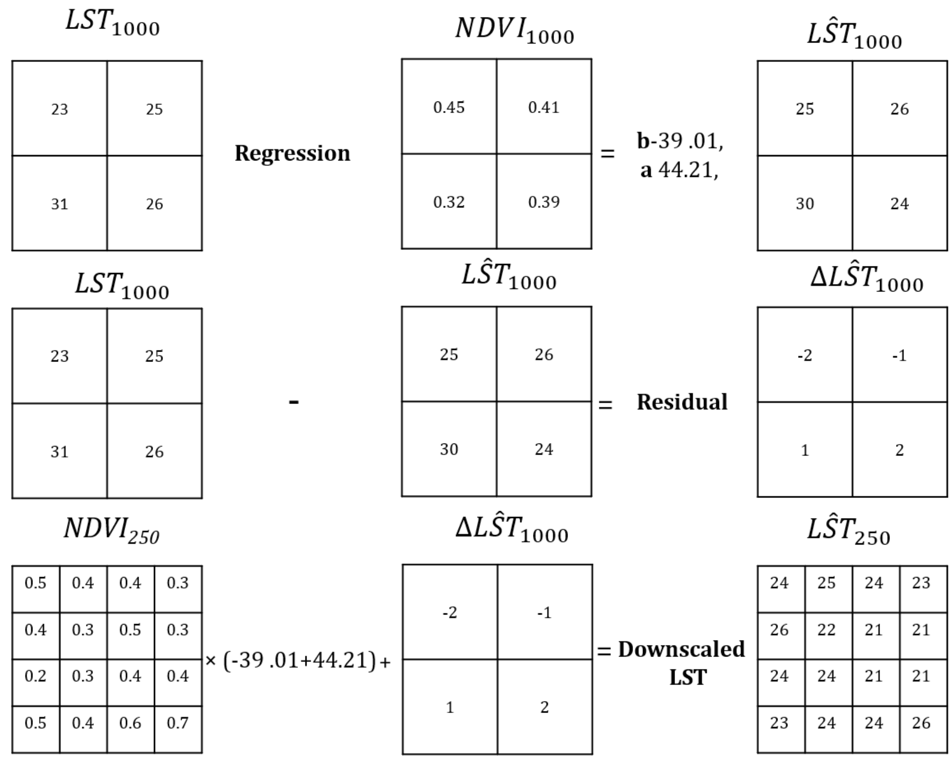


Figure 7.44: Schematic representation of downscaling model of LST

Due to the existence of varied terrain across the research region, a Least Median Square (LMS) regression-based model is utilised for LST downscaling in this work (Mukherjee et al., 2014a). The downscaling model was constructed using the NDVI and LST data. The model makes use of a robust regression function that is less vulnerable to the effects of extreme data points, Ordinary Least Square (OLS) regression, as demonstrated by Equation 7.5, was used to estimate model parameters like slope and intercept in prior downscaling models like DisTrad and TsHARP etc.

$$MinSSR = \sum_{i=1}^{n} (LST_i - (a + b \times NDVI_i))^2 \tag{7.5}$$

However, OLS regression is not as robust as other models since it is susceptible to outliers (Rousseeuw, 1984). Regression parameter estimations in the presence of outliers in a landscape with a diverse set of plant and animal species. Previous studies have used sub-pixel variability-based systematic sampling (CV ≤ 25%) to prevent the outliers effect (Kustas et al. 2003; Agam et al. 2007a), but in a diverse environment, it is challenging to eliminate the outliers in the sampling process while estimating model parameters.

In the large area outliers is unavoidable and to address this problem, a robust regression method i.e., Lease Median Square based downscaling method was used. In the downscaling model given above (equation 7.1 to 7.4) OLS regression function has been replaced with LMS regression and followed the same methodology. As an alternative approach to minimising the sum of square residuals, the parameters of the downscaling model were determined in the LMS regression model to provide the least median of the square residual. According to measures of central tendency, the median is a rank statistic that is less susceptible to outliers than other measures of central tendency (Mukherjee et al., 2014a; Rousseeuw, 1984; Rousseeuw and Leroy, 1987). This is the formula:

$$MinMedSR = Median\{(LST_1 - (a + b \times NDVI_1))^2, (LST_2 - (a + b \times NDVI_2))^2 \ldots\ldots. (LST_n - (a + b \times NDVI_n))^2\} \quad (7.6)$$

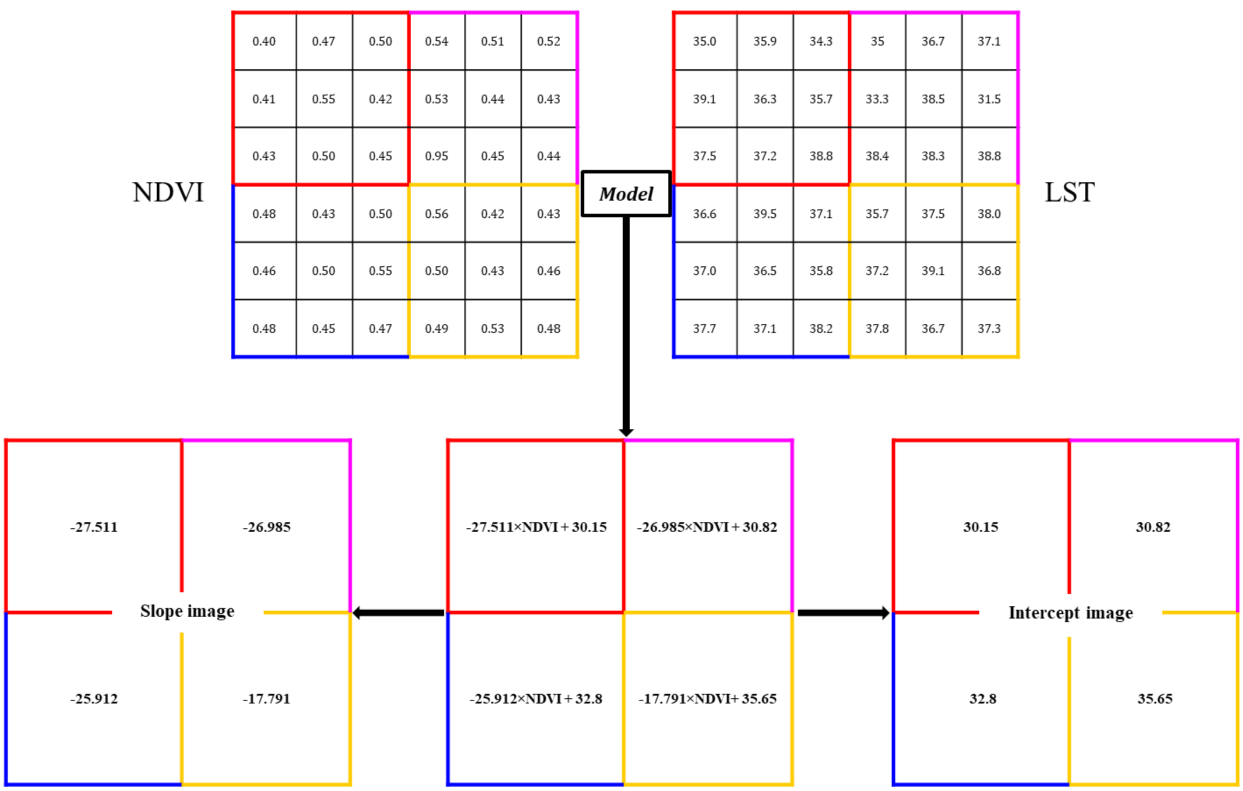


Figure 7.45: A schematic representation of window based local regression model

The present study has been carried over entire Odisha state, therefore, to avoid outliers effect and considering the local land cover types / climatic condition a local window based LMS regression model is adopted. A convolution process of 5x5 window size has been applied to apply the model for parameter estimation LST downscaling. A schematic representation of window based local regression model is shown at figure 7.2.

7.3.2 Drought mapping using VHI

The agricultural land cover based on the MODIS land cover map data of 2009is considered for agricultural drought assessment. Area other than agriculture has been masked out before generating VHI (Kogan, 2001; Singh and Kogan, 2002). In MODIS sensor, band 1 and 2 provides red and near infrared data which are used to compute the NDVI (Rouse et al., 1973).

Each pixel's Vegetation Condition Index (VCI) is proportional to the difference between its long-term lowest and highest absolute NDVI for the week. MODIS weekly composite NDVI is used to determine these long-term multi-year absolute minimum and maximum values (2001-2014). Short-term NDVI fluctuations due to weather and long-term ecosystem shifts are represented by a VCI value anywhere from 0 to 100. (Bhuiyan et al., 2006; Kogan, 1990). Vegetation vitality is represented by a VCI value over zero, whereas vegetation stress is represented by a VCI value below zero. The value of VCI is determined by solving Equation 7.7.

$$VCI = 100 \times \frac{NDVI_{Max} - NDVI}{NDVI_{Max} - NDVI_{Min}} \quad 7.7$$

Where, $NDVI$, $NDVI_{Min}$, and $NDVI_{Max}$ are the seasonal average NDVI, its multi-year absolute minimum and maximum, respectively.

The TCI measures the rate of change from average long-term temperatures (LST) throughout a region. The MODIS weekly composite thermal imaging product for the years 2001–2014 is the source for this absolute multi-year lowest and maximum LST values. Compared to normal and rainy years, dry years have a lower VCI value and a higher TCI value, both of which are favourable to drought situations. You can figure out your TCI with some simple math using equation 7.8.

$$TCI = 100 \times \frac{T_{Max} - T}{T_{Max} - T_{Min}} \quad 7.8$$

In this equation, T represents the average seasonal LST for a given week, T_{Min} represents the absolute lowest, and T_{Max} represents the highest possible LST for that week.

VHI is derived from the combination of VCI and TCI and the vale ranges from 0 to 100. The research of Kogan (2001) provided a classification scheme of VHI for measurement of drought severity; (a) extreme drought (< 10), (b) severe drought (< 20), (c) moderate drought (< 30), (d) mild drought (<40) and (e) no drought (> 40). VHI is calculated using equation 7.9.

$$VHI = 0.5(VCI) + 0.5(TCI) \tag{7.9}$$

The present research used NDVI derived from corrected surface reflectance MODIS sensor product. Surface reflectance at 250 meters resolution is aggregated to 1000 meters and computed NDVI from the relevant resolution. Using the methodology described in the section 4.1, LST data (1000 meters resolution) is downscaled to 250 meters resolution and calculate TCI. With the help of NDVI and downscaled LST, the VHI are calculated at 1000 meters and 250 meters resolution.

7.3.3 TVDI mapping of soil moisture

The TVDI are used to qualitatively assess soil moisture. It's a product of the NDVI-LST triangle space. NDVI-LST For the region of full-range soil moisture and plant cover, the scatter plot often demonstrates an inverse connection, resulting in the NDVI-LST triangle space (Wan et al., 2004). Various degrees of evapotranspiration and soil moisture status is represented by the picture pixels that fall inside the NDVI-LST triangle space. Sandholt et al. (2002)'s method, implemented in equation 7.10, is used to determine TVDI.

$$TVDI = \frac{LST - LST_{Min}}{LST_{Max} - LST_{Min}} \tag{7.10}$$

Wet and dry edges are defined by the minimum and maximum temperatures in the NDVI-LST triangle, respectively (where LST is the surface temperature of each pixel and LST_{Min} and LST_{Max} are the minimum and maximum temperatures, respectively). Linear regression of the dry edge (LST_{Max} = a1 + b1 NDVI) is used to get the LST_{Max}, which is then used to determine the maximum LST for the same NDVI. In this investigation, the wet edge is additionally linearly regressed (LST_{Min} = a2 + b2 NDVI), taking into account the findings of Moran et al. (1994) and Patel et al. (2009) on the NDVI-LST trapezoid.

Extremely wet conditions (0–0.2), wet conditions (0.2–0.4), normal conditions (0.4–0.6), dry conditions (0.6–0.8), and very dry conditions (0.8) may be described qualitatively using the TVDI (Han et al., 2010; Chen et al., 2011). (0.8 - 1.0).

To get NDVI, the surface reflectance output from the MODIS sensor at a resolution of 250 m is averaged to 1000 m. To calculate TVDI at both the 1000 m and 250 m resolutions, the LST from the MODIS thermal data is downscaled from 1000 m using the methods described in section 4.1.

7.3.4 Map comparison/ validation

Downscaled Land Surface Temperature is evaluated for similarity/quality using the mean and standard deviation of the dataset. The theory is that if LST is upscaled from a fine resolution to a coarse resolution by averaging across a large region, the two values should be quite close to one another (Mukherjee et al., 2014a; Wald et al., 1997; Wald, 1999). The similarity is determined by re-aggregating downscaled LST to its original coarse resolution and calculating statistics such as the mean bias, standard deviation, image quality index (equation 7.11)(Rodriguez-Galiano et al., 2012) and correlation coefficient. Q-index represents the degree to which two monochrome raster data are correlated, have distorted contrast, and have had their brightness distorted (Mukherjee et al., 2014a; Wang and Bovik, 2002). Estimates of Q are averaged across moving 8x8 and 16x16 windows (Rodriguez-Galiano et al., 2012).

$$Q = \frac{4\sigma_{xy}\bar{x}\bar{y}}{\left(\sigma_x^2 + \sigma_x^2\right)\left[\left(\bar{x}\right)^2 + \left(\bar{y}\right)^2\right]} \qquad (7.11)$$

Entropy(Shannon, 1948) statistics are also used for validation as information content measures to compare VHI and TVDI maps of different resolution (Bjorke 1996; Knopfli 1983; Li and Huang, 2002). Various studies (Vieux and Farajalla, 1994; Vieux, 1993;) have used entropy statistics for measuring of information content from Digital Elevation Model. When geographic data is aggregated or smoothed, a loss of information and, by extension, entropy, occurs as a consequence of the underlying change in resolution/grid size (Wise, 2012). This study uses entropy statistics to compare the amount of information in VHI and TVDI maps with different grid sizes. Wise (2012) proposes a technique for computing entropy/information statistics. This approach involves rounding the VHI and TVDI values to the closest integer, estimating the entropy in each bin, and summing the results (equation 7.12).

$$I = -\sum_{i=1}^{n} p_i, \log(p_i) \qquad (7.12)$$

Where, I is entropy statistics, n is number of bins in the TVDI/ VHI data and p_i is the proportion i^{th} bin of a TVDI or TVDI. Log to base 10 is used(Wise, 2012) and therefore the units for entropy are Hartleys.

7.4 Results

The entire results section is divided into two parts: (i) downscaling of LST (ii) mapping of agricultural drought and (iii) mapping of soil moisture.

7.4.1 Downscaling of LST

In 250 m resolution NDVI, it is observed that range of NDVI varies from -0.02 to 0.99, with a mean of 0.48. High value of mean NDVI indicates good crop growth conditions over the study area (figure 7.3). Temperature range of 1000 m resolution LST data varies from27.45to46.74 °C and mean temperature is 37.31 °C, indicating high land surface temperature prevailing over the study area (figure 7.4).

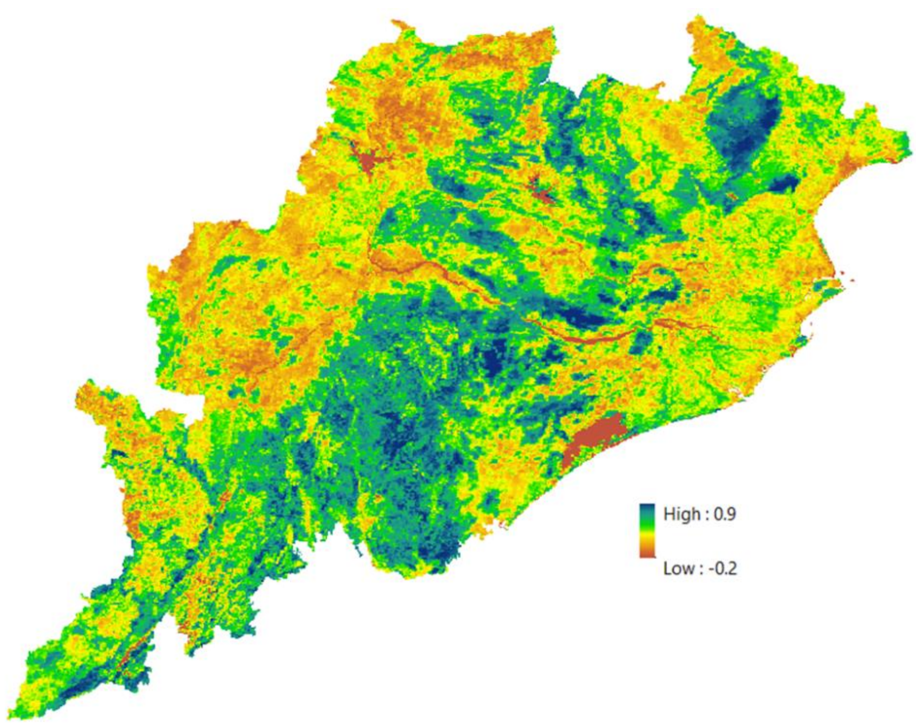


Figure 7.46: NDVI of 250 m resolution of entire Odisha state.

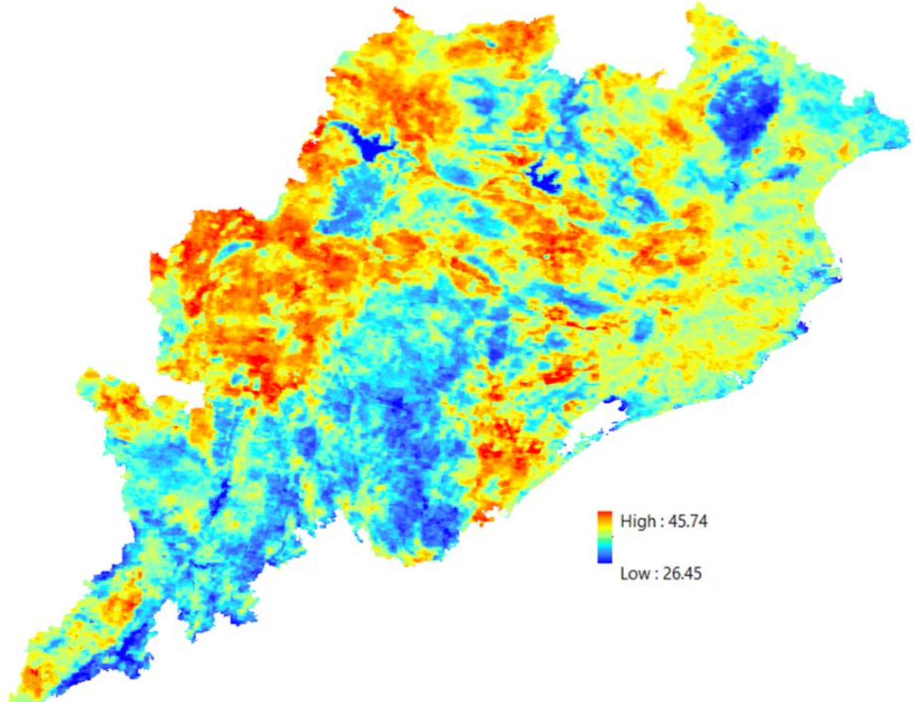


Figure 7.47: LST of 1000 m resolution of entire Odisha state.

Land Surface Temperature data of 1000 meter resolution is downscaled to 250 meter resolution using the downscaling procedure mentioned in the section 4.1 and shown in figure 7.5. Temperature range of 250 m resolution model predicted LST varies from15.06to49.85 °C and mean temperature is 36.53 °C, indicating lower range of temperature has decrease and upper range of temperature has increase along with the almost similar mean. This is because of increasing the sub pixel variability within the data in the higher resolution.

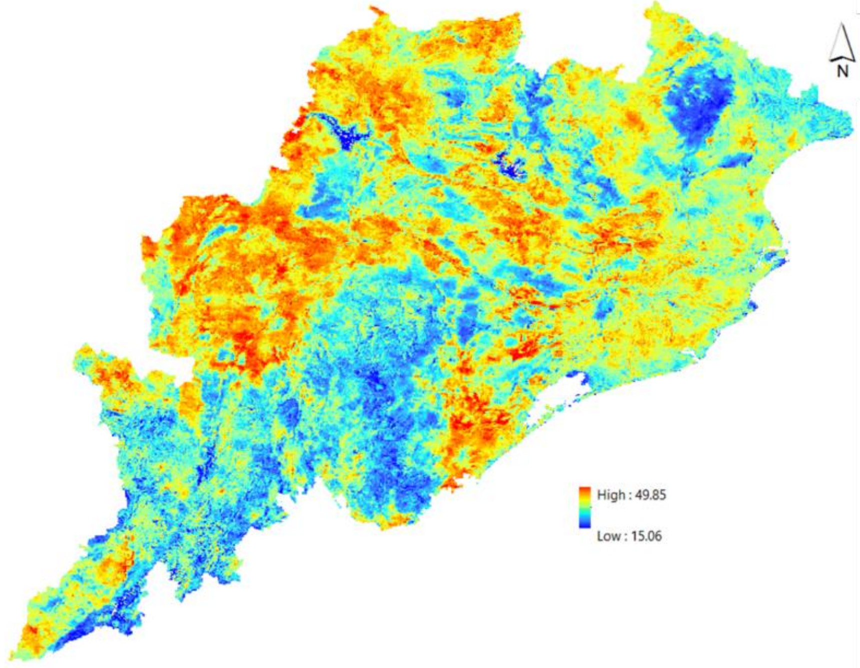
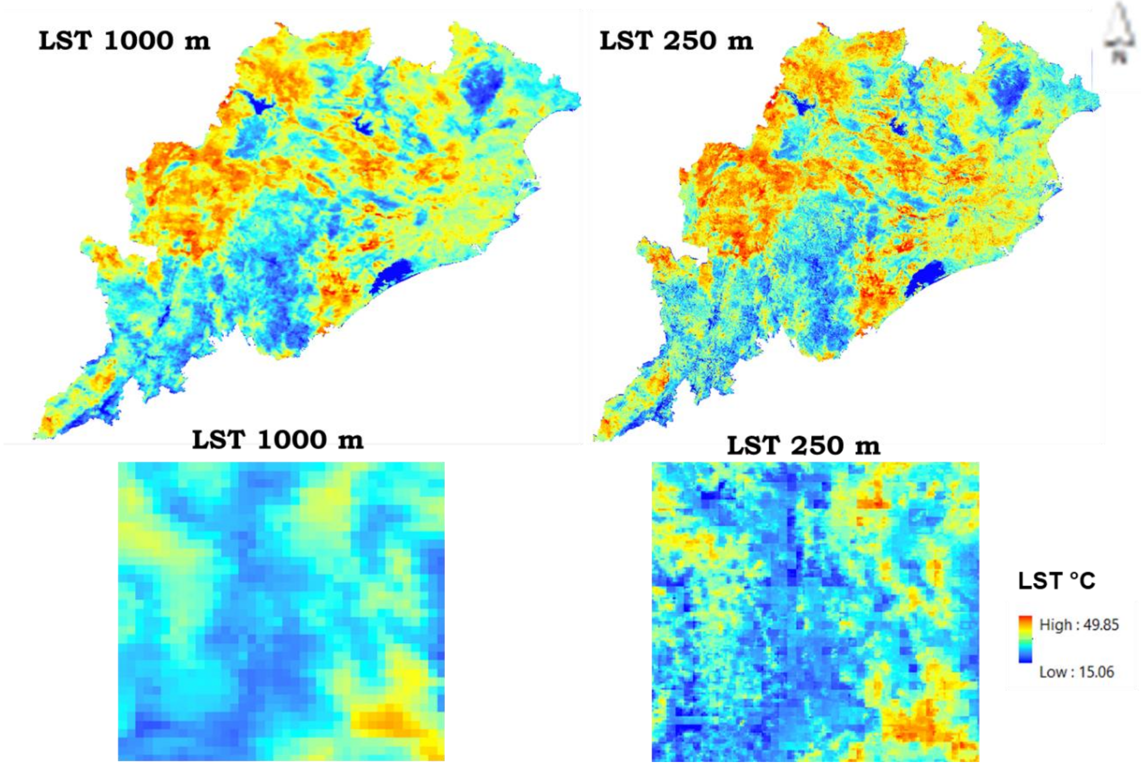


Figure 7.48: LST of 250 m resolution of entire Odisha state.

Details of two small areas are shown in figure 7.6. Higher information content is seen in the $L\hat{S}T_{250}$, however, patterns of LST_{1000} and $L\hat{S}T_{250}$both surfaces are similar. Figure 7.5 displays LST_{250} data, which greatly outperforms LST_{1000}in terms of visual information for evaluating spatial variability of temperature. As a result of signal mixing, separating temperature variation between landcover classes in LST_{1000} data is challenging, however, this is possible in LST_{250}. In Table 7.1, we provide some LST data statistics. The comparison of mean LST between LST 1000 and LS T 250 is quite close. The dispersion in the $LST_{1000}$and LST $_{250}$ maps is 2.16 and 2.67, respectively. Higher resolution results in a larger LST $_{250}$ standard deviation, suggesting more variation on a sub-pixel scale. The surface detail representation is averaged inside a coarse-resolution pixel, leading to a more generic LST representation. It can be seen from the similarity evaluation findings that the discrepancies between the $LST_{1000}$and the downgraded LST_{250} in terms of bias and standard deviation are small, showing that the model performs well while downscaling (Wald et al., 1997). The Q-index and correlation (R2) between LST $_{1000}$ and LST $_{250}$ are both 0.82, indicating an excellent degree of agreement.


LST 1000 m
LST 250 m
LST 1000 m
LST 250 m
LST °C
High : 49.85
Low : 15.06

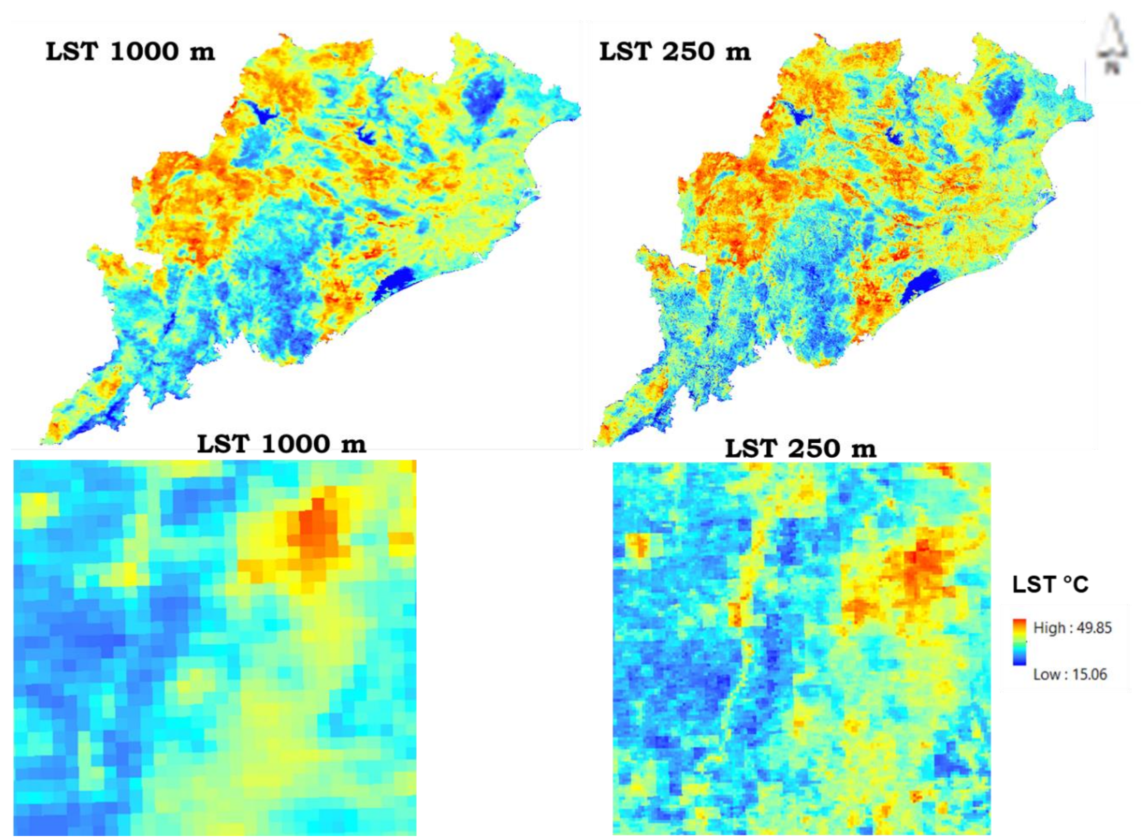

LST 1000 m
LST 250 m
LST 1000 m
LST 250 m
LST °C
High : 49.85
Low : 15.06

Figure 7.49: Detail of LST representation in two small areas in 1000 and 250 m resolution.

7.4.2 Mapping of agriculture drought

The 1000-meter and 250-meter resolution VHI maps are classed according to drought severity. The 250-meter resolution drought maps show a similar trend with a greater informational density. Table 7.1 provides a summary of the drought maps' statistical information.

Table 7.16: Vegetation Health Index statistics are presented. The higher entropy value indicates more detailed information content is represented in the downscaled VHI image.

VHI (m)	**VHI Statistics**				
	Min	**Max**	**μ**	**σ**	**Entropy**
VHI_{1000}	0.72	87.14	37.39	15.75	1.21
VHI_{250}	0	100	38.39	21.12	1.65

The average value of the VHI/drought map goes up a little bit, but the standard deviation has gone up a lot in the 250 meters resolution VHI. The standard deviation of data at 1000-meter resolution is 15.75, whereas it jumps to 21.12 for VHI data at 250-meter resolution. Standard deviation reveals that the 250-meter resolution drought map has a greater degree of inherent variability. This result demonstrates the well-established fact that the downscaling of temperature image increases intra-pixel variability in 250 m data (Atkinson et al., 2007; Garrigues et al., 2006). 1000 m and 250 m drought maps had entropy values of 1.21 and 1.65, respectively. Entropy statistics indicate a constant rise in data with a resolution of 250 meters, indicating an increase in informational detail. Figure 7.7 displays drought maps of varying resolutions for two small regions (areas 'A' and 'B') to assist visual quality assessment and qualitative evaluation. There are significant differences between real and downscaled drought/VHI maps. Therefore, it is evident that the 250-meter resolution drought/classified VHI map contains much more drought-related data than the 1000-meter resolution drought map. The downscaled agricultural drought map facilitates the delineation of field-scale drought severity.

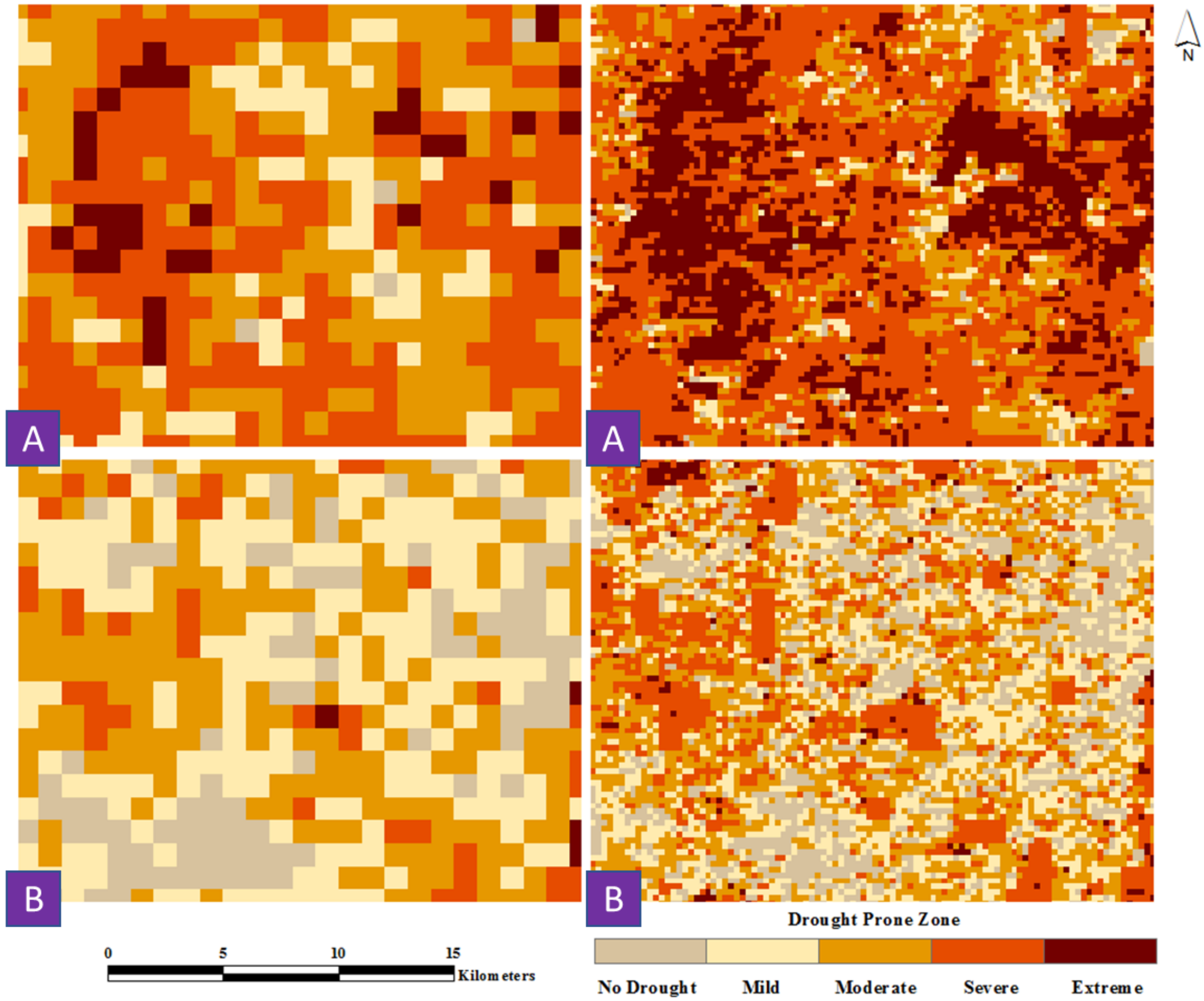


Figure 7.50: Various resolution drought maps of two small areas (area 'A' and 'B')

To evaluate the severity of the drought, the area that falls under each drought class has been assessed and displayed in figure 7.8. It is calculated how much of a difference there is between the different drought severity classifications for the region that is affected by drought. As the geographical resolution of the drought maps becomes higher, a greater proportion of the landmass is falling into the categories of 'extreme drought,''severe drought,' and 'no drought.'

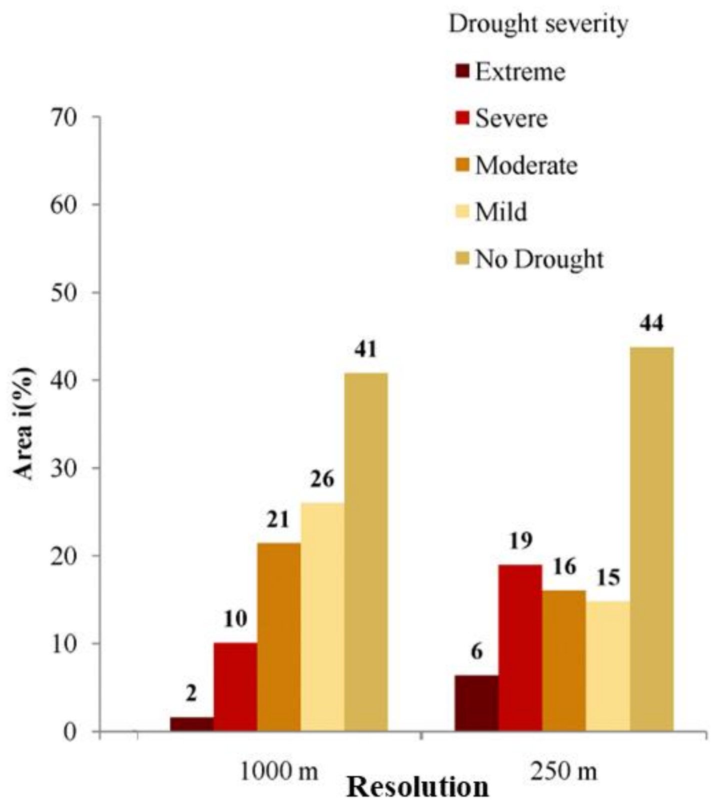


Figure 7.51: Distribution of area under various drought prone zones is estimated from different resolution drought maps

7.4.3 Soil moisture mapping

TVDI is used for soil moisture mapping. TVDI is derived at 1000 mand 250 m resolution using actual $LST_{1000}$and downscaled $L\hat{S}T_{250}$for soil moisture mapping/ measurement. Some missing values appears in the TVDI images which represent cloud pixels, are masked out. TVDI statistics are calculated and summarized in Table 7.2.

Table 7.17: Statistics of 1000 m and 250 m resolution TVDI represent more detail soil moisture related information in the high-resolution downscaled data.

TVDI at various resolution (m)	**TVDI Statistics**		
	μ	**σ**	**Entropy**
$TVDI_{1000}$	0.63	0.16	0.97
$TVDI_{250}$	0.66	0.24	1.39

Resolutions of 250 and 1000 meters TVDI provide standard deviations value of 0.16 and 0.24, respectively. High intra-pixel variability as measured at a 250-meter resolution is indicated by an increased standard deviation. The high level of information detail in the 250-meter TVDI data is shown by the entropy value of 0.97, which is much lower than that of the 1000-meter TVDI data. Classified TDVI pictures at 1000-meter and 250-meter resolutions across a portion of the research region are shown in Figure 7.9. Figure 7.9 shows how the TVDI picture with a resolution of 200 meters provides more detail than the TVDI image with a resolution of 1000 meters. The high-resolution TVDI image faithfully reproduces a great deal of spatial information compared to a TVDI raster with a resolution of 1000 metres. Soil moisture fluctuation in a 250-meter resolution TVDI raster shows a similar pattern, but with more extensive moisture-related data.

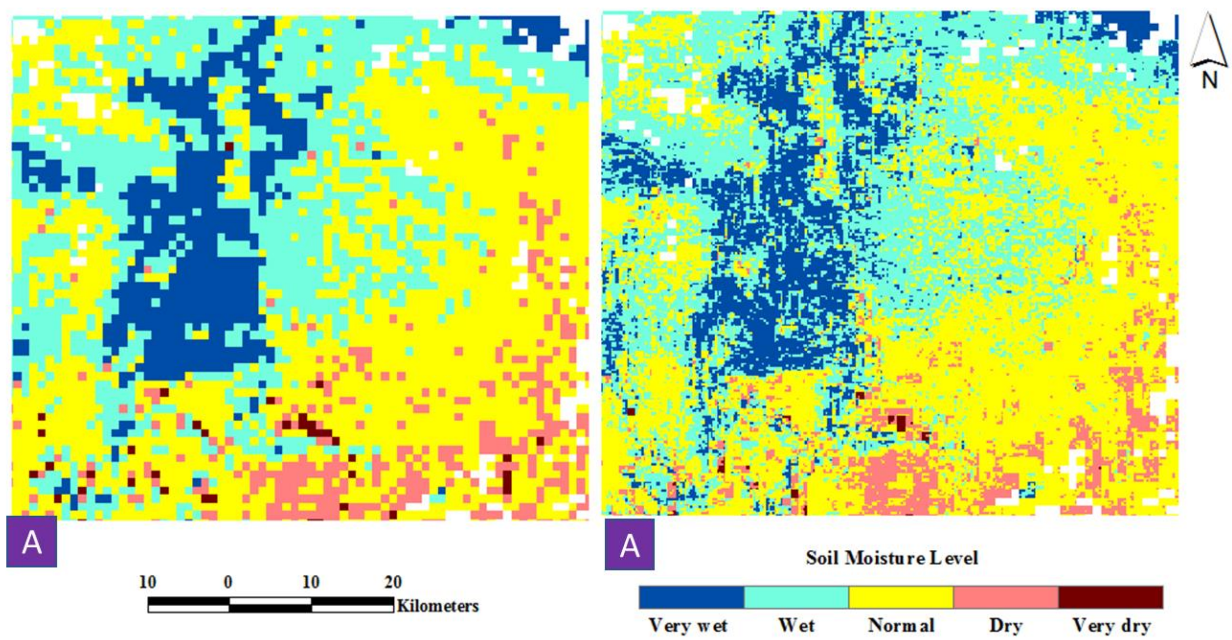


Figure 7.52: Classified TVDI of a subset of the areas at (a) 1000 m and (b) 250 m

Large degree of soil moisture level variation is observed over the study area. The northern and western parts of the study area showing more drought prone area compared to eastern part of the state which is the coastal region. The 250 m resolution drought and soil moisture maps show larger details and it indicates that coarse resolution imagery might lead one to overlook and miss out areas that are suffering from drought.

7.5 Discussion

Several studies have confirmed that the LST downscaling methodology has been confirmed to have a good degree of accuracy across nations. According to Jeganathan et al. (2011), the accuracy of the downscaled MODIS LST at a resolution of 250 metres is within 2 kelvins (RMSE), which makes the model is applicable in India's diverse agricultural environment. Bindhu et al. (2013) finds a downscaling RMSE = 0.96 K for the southern state/part of India. As a result, this finding validates the use of high-resolution downscaled LST for investigations involving drought and soil moisture mapping across India's geography.

For drought mapping, scientists have previously used VHI data generated from NOAA-AVHRR sensors on a weekly timescale (Mukherjee et al., 2014b; Choi et al., 2013; Karnieli et al., 2010; Bhuiyan et al., 2006). In developing countries like India, where agricultural firm size is smaller, a 4 x 4 km grid size drought map may not be suitable for field level drought mapping due to its depiction of lower drought intensity due to generalization/pixelated effects. However, such a map can be useful for mapping drought intensity on a country/ global scale. Drought evaluation and monitoring using MODIS-derived 1000 m resolution VHI has also been employed by several studies (Chen et al., 2011). Since the resolution of LST is 1000 m, we can create TCI at a resolution of 1000 m, while using MODIS data we can derive VCI at a resolution of 250 m. To carry out resolution matching (Chen et al., 2011) and compute VHI at 1000 m, it is the usual practice among researchers to resample the VNIR band (250 m) to the corresponding resolution of the TIR band (1000 m). Drought classes of varying intensities are present in each 1000 m VHI pixel, making them difficult to discern. Agricultural field size drought features may be defined in the VHI-generated 250 m resolution drought intensity map (Figure 7.7). Greater percentages of land are classified as extreme, severe, or no drought on the downscaled LST-derived 250 m grid size map than on coarser resolution drought maps (Figure 7.8). These results demonstrate the generalisation effect in low-resolution LST data. The thermal mixing effect, caused by mixed signals from different land cover classes inside a pixel (Zhan et al., 2013), causes the coarse resolution LST to indicate a lower surface temperature value, leading to a higher VHI and a lesser degree of drought severity.

Chen et al. (2011) and Patel et al. (2009) created the TVDI for measuring soil moisture using 1000 m resolution MODIS images and discussed the need to resample VNIR data to LST comparable resolution. However, studies focusing on the downscaling of soil moisture across the Indian terrain or TVDI at 250 m grid size using satellite-based open-source data were not found. It has been shown, however, that TVDI maps created at a resolution of 250 metres give far more comprehensive soil moisture details than 1000 metres of TDVI (Figure 7.9). Although the TVDI with a 250 m resolution may not be sufficient to distinguish between individual agricultural fields across the varied terrain of the research region, the borders of agricultural fields are more visible and sub-class soil moisture variability is replicated well.

7.6 Consequences for drought prevention, management, planning, and policy

The impact of a drought is more compared to flood. Any droughts phenomena cause negative impacts on the socio-economic condition of a country. As there is no live/ property losses involve, therefore, drought gets slightly less importance. However, the impact of droughts is more in totality compared to floods. Drought management and mitigation policies include many things such as (a) the consideration of water needs/irrigation within an agro-climatic zone, (b) agricultural planning and methods, and so on. Currently, the scientific and policymaking communities are largely concerned with agricultural land management (Pandey and Seto, 2015). There are two ways to lessen the effects of drought: (a) making plans for the future, such as making rules and other measures, and (b) responding when a drought starts. Authorities and policymakers have made an effort to sustain dry land agriculture by expanding ways for planting contingent crops in rain-fed agricultural regions. The current research will be crucial in elucidating the daily and weekly nuances of regional drought and soil moisture patterns. The drought and soil moisture downscaling methodology presented in this research can be implemented to a sequential automated/ semi-automated process model to convert satellite data derived inputs into drought and soil moisture mapping. This automated process can provide near real-time info and avoid data processing delays for preparation of drought/ soil moisture maps. The rear-real time drought and soil moisture info about area can be conveyed to the decision makers which will enhance the decision making process for management, planning and policy formation.

The present study has one more aspect i.e., its correlation with NASA Synergy programme. Synergy programme of NASA identifies six major areas such as (a) Agriculture, (b) water resource management, (c) disaster management, (d)climate, (e) urban planning and (f) human health are most important issues. The purpose of this initiative is to use data collected by Earth Observation Satellites (EOS) to develop space-based applications for use in environmental and disaster management. The goal of the initiative is to share this information with researchers and government agencies so that they can make better decisions in this area (Kalluri et al., 2003). Through this study, the geographical and temporal resolution trade-off of MODIS satellite data will be improved, making it more useful for field/regional scale soil moisture and drought severity mapping. Developing a method for frequent monitoring of drought and soil moisture and developing a management action plan will be of great assistance to decision-makers.

7.7 Conclusion

Using a greater geographic resolution of LST, this study aims to improve agricultural drought and soil moisture mapping. The study focuses on the state of Odisha in India and makes use of data collected by the MODIS satellite. Medium-to-fine resolution VHI and TVDI are produced by downscaling the 1000-meter spatial resolution LST using NDVI. Statistical parameters and entropy are used to evaluate the information content of high-resolution VHI and TVDI vs low-resolution data. Downscaled MODIS LST at 250-meter resolution shows more spatial information than LST at 1000 m resolution, it has been found. The patterns of VHI and TVDI at coarse and fine resolutions are relatively similar. However, higher-resolution maps reveal more information. Intra-pixel variability is greater in the VHI/TVDI data at a resolution of 250 metres. When comparing fine-resolution VHI with TVDI, the greater entropy value indicates better information density. Based on the results of the investigation, it seems that these detailed maps help trace the evolution of dryness and soil moisture across the study region from before the monsoons until after they have passed.

The lack of ground samples made it hard to verify the MODIS LST downscaling results in this study. The study has not been validated in the field, however, this is something that may be addressed in future studies. This technique will improve the probability of daily or weekly basis field / regional drought and soil moisture mapping due to the availability of MODIS VNIR data (250 metres) and thermal data (1000 meters) at a one-day frequency. The high-frequency Spatio-temporal pattern of drought/ soil moisture will certainly help with drought management and policy formation at the state or country level. This method would be a significant improvement in drought and soil moisture monitoring and would be useful in the planning and management of agricultural techniques at the national level. Since the majority of Indian states have a mixed cropping pattern, and the country's economy is heavily dependent on agriculture, this method would be useful in planning and managing agricultural techniques at the national level.

8 Drought Delineation Using SAR Data

"Anyone who has never made a mistake has never tried anything new."

- Albert Einstein

8.1 Introduction

Drought is primarily considered as an effect of less than normal rainfall, the definition is highly complex and controversial as it can also be related to soil moisture, groundwater level, evapotranspiration and vegetation health (Shewale & Kumar, 2005;Wilhite & Glantz, 1985; Lloyd-Hughes, 2014; Mishra & Singh, 2010). Droughts could potentially lead to scarcity of drinking water, hampering agricultural output, and extremities like famine(Mishra, et al., 2019; Dutta, Kundu, & Patel, 2013). Drought could have an adverse effect on agricultural, socioeconomic and financial sectors, especially in developing countries like India(Shah & Mishra, 2020), where almost 68% population are dependent on agriculture. In the era of climate change, an increase in surface temperature (IPPC, 2001) and modification in the hydrological cycle (Allen & Ingram, 2002) will increase extreme events like floods and droughts.

India has a prolonged history of drought events with 10 drought years between 1950 and 1990, and 6 drought years between 2002 and 2016 (Kala, 2017). The droughts in India are primarily due to decreased monsoonal rainfall resulting from climatic variability (Roxy, Ritika, Terray, Murtugudde, Ashok, & Goswami, 2015;Mishra, Smoliak, Lettenmaier, & Wallace, 2012), along with El Niño events (Kumar, Rajagopalan, Hoerling, Bates, & Cane, 2006; Gadgil, Vinayachandran, & Francis, 2003) and high sea surface temperature in the Indian Ocean (Kumar, Rajagopalan, Hoerling, Bates, & Cane, 2006; Roxy, Ritika, Terray, Murtugudde, Ashok, & Goswami, 2015). Moreover, changes in climatic parameters associated with changes in global precipitation pattern (Trenberth, Dai, Rasmussen, & Parsons, 2003), increasing evaporation rates resulting from high land surface temperature and decrease in weak precipitation(Dash, Nair, Kulkarni, & Mohanty, 2011) days might increase the frequency of drought events in India (Kulkarni, Gadgil, & Patwardhan, 2016). Approximately 68% of agricultural land in India are vulnerable to drought with large irregularities in terms of breaks, late arrival and early withdrawal of monsoon rainfall(Prabhakar & Shaw, 2008) (NDMA, 2010). In the most recent drought that occurred in 2016, almost 330 million people from 10 states were affected (Kala, 2017).

Wide varieties of indices are used for drought assessment in literature mainly based on rainfall data, like Standardized Precipitation Index (McKee, 1995), Drought Severity Index (Palmer, 1965), Soil Moisture Deficit Index (Narasimhan & Srinivasan, 2005), Standardized Evapotranspiration Deficit Index(Kim & Rhee, 2016) etc. Other meteorological drought indices include Reconnaissance Drought Index (Tsakiris, 2005), Effective Drought Index (Byun & Wilhite, 1999), Streamflow Drought Index (Nalbantis, 2008) etc. Several attempts were made to understand the causes and effects of droughts in India, by implementing different models and indices. Standardized Precipitation Index (SPI) and Standardized Runoff Index (SRI) was used for the reconstruction of historical droughts (Mishra V. 2020, Long-term (1870-2018) drought reconstruction in India), new indices like the Integrated Drought Index (Shah & Mishra, 2020), has been developed for better understanding. Percent of Normal Precipitation method was applied to identify probable drought areas (Guhathakurta, 2003; Mahajan & Dodamani). Vegetation Health Index (VHI) is widely used for assessment of agricultural drought. Currently, crop growth and agricultural output are estimated in India by the Ministry of Agriculture through a scheme launched in 2006 known as FASAL (Forecasting Agricultural output using Space, Agro-meteorology and Land-based observations).

The use of remote sensing in drought monitoring opened a new paradigm in this line of research and the Standardized Precipitation Evapotranspiration Index (Vicente-Serrano & Beguer, 2010) was utilized to determine frequent drought-prone regions in India (Aadhar & Mishra, 2018). Drought indices like Temperature Vegetation Dryness Index (TVDI), derived from MODIS data, and Standardized Water Level Index (Bhuiyan, Saha, Bandyopadhyay, & Kogan, 2017) are formulated using remote sensing datasets. In recent years, remote sensing became a crucial technology for estimating and monitoring agricultural crop yield and subsequent drought stages (Kogan, Powell, & Fedorov, 2011;Kogan F. a., 2012). Keeping in mind that reduced crop yield due to climate change will be a common phenomenon in future, (Bhuiyan, Saha, Bandyopadhyay, & Kogan, 2017) tried an integrated approach using Vegetation Health Index (VHI), Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) to monitor agricultural drought. A fusion approach involving drought indices and remote sensing data is a field of growing interest in the scientific community (Dutta, Kundu, & Patel, 2013; Prabhakar & Shaw, 2008). Although there are abundant studies on drought assessment using multispectral remote sensing (Gao, 2011); (Ozelkan, Chen, & Ustundag, 2016; Singh, Roy, & Kogan, 2003;Arekhi, Saglam, & Ozkan, 2020; Orhan, Ekercin, & Dadaser-Celik, 2014;

Ringrose & Matheson, 1991;Sholihah, et al., 2016; Nguyen, Baez, Oscar, Bui, Nguyen, & Ribbe, 2020, Synthetic Aperture Radar (SAR) based drought estimation is relatively scarce. (Chandna & Mondal, 2020) used soil moisture data along with Landsat-8 and Sentinel-1 data for analysis of rice yield in Odisha. Drought and surface moisture monitoring in South Africa by several multispectral and SAR images were accomplished by (Urban, et al., 2018) and (Abdel-Hamid, Dubovyk, Graw, & Greve, 2020). Large scale, as well as local scale drought assessment (Ghazaryan, Dubovyk, Graw, Kussul, & Schellberg, 2020; Lopez, Al, Biancamaria, Guntner, & Jaggi, 2020; Lee, Kim, Lee, Lee, & Kim, 2018) using SAR and multispectral remote sensing data is also tried by few researchers. Most of these studies are based on a specific crop yield estimation and the subsequent drought effect on that particular crop.

Odisha is a coastal state located in the eastern coast of India and drought frequency of this state is once in three years. Due to the coastal location, availability of cloud free wide swath electro-optical satellite data is difficult. For example, in the kharif season of 2020 and 2021 very few clouds free Landsat scenes are available in the coastal part of Odisha state, therefore, SAR due to it all-weather day-night capability and sensitivity to soil-moisture condition could be an alternative option for drought assessment in the coastal states. In this paper, an attempt was made to assess and analyse drought over complete agricultural area of part of Odisha state, India employing multi-temporal Sentinel-1 SAR and Landsat-8 data. The main objective of the study is to explore a methodology to delineate the agricultural drought affected areas using SAR data.

8.2 Study Area

The study area selected was part of northeast Odisha (Figure 8.1). It located between 20° 43' N to 21° 13' N and 86° 6 ' E to 87° E encompassing 2505 km2 area (Panda, Mishra, Pradhan, & Mohanty, 2015). The study area is surrounded by Balasore in the north, Kendrapara in the east, Jajpur in the south and Koenjher in the west (Jaman, Dharanirajan, & Sharma, 2021). The major population of the study area is living in the villages and dependent on agriculture. Agricultural yield in this state is heavily dependent on monsoon rainfall and water from adjacent rivers like Baitarani, Kansbans, Mantei, Genguti, Gamei, Salandi, and Kapali. The climate is warm and humid with three distinct seasons namely summer (March to July), monsoon (August to October) and winter (November to February). In summer, the mean temperature ranges from 36.4° C to 24.6° C and in winter, the mean temperature range is 27° C to 14° C. The study area receives an average annual rainfall of approx. 1428 mm with the majority of its occurrences during the monsoon period. The area being situated near the Bay of Bengal coast is vulnerable to cyclonic storms and strong winds resulting in a loss of infrastructure, crops and population.

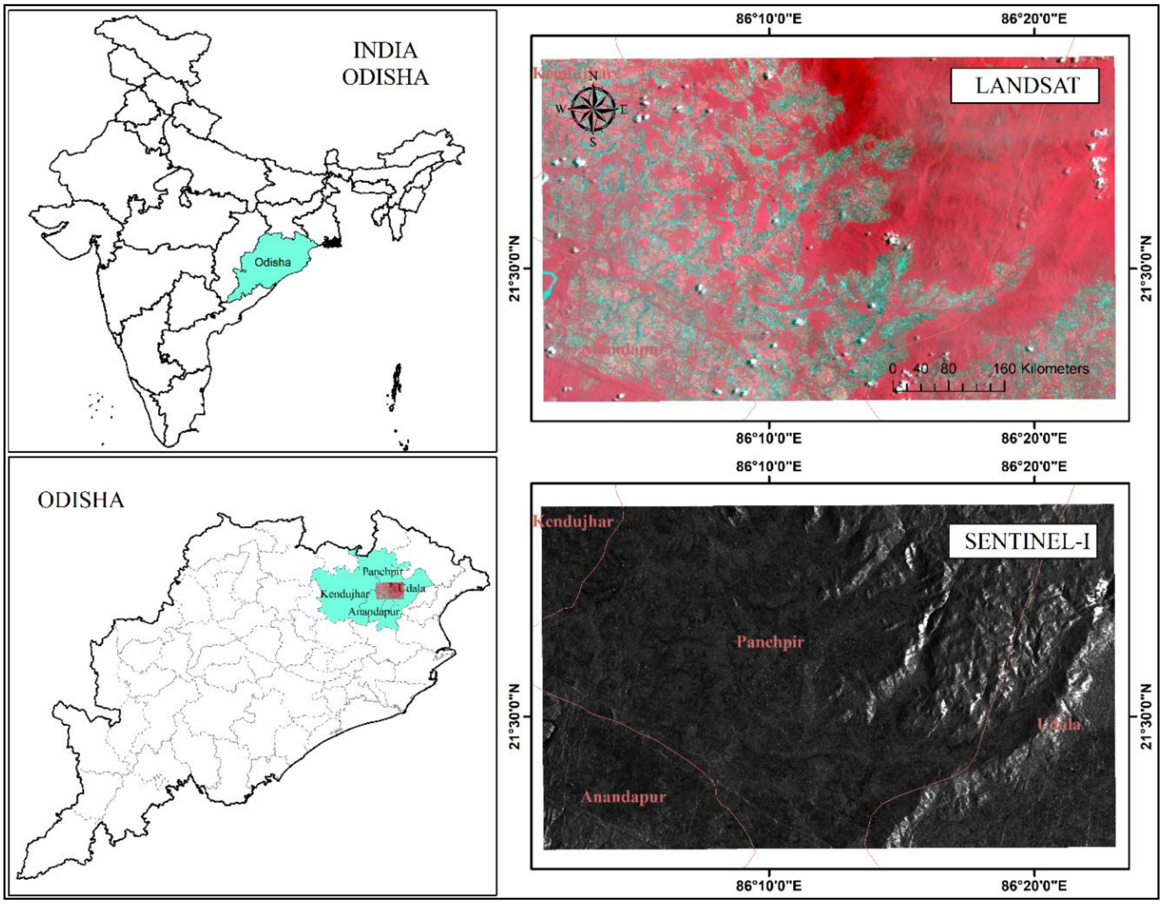


Figure 8.53: Study area depicting part of Odisha state, India. Figure 1(a) showing the general location, 1(b) showing the area taken for this study. Figure 1(c) and 1(d) showing the Landsat data depicting agricultural growth and Sentinel 1 SAR data.

8.3 Dataset

In this research, two different types of datasets, Sentinel-1 SAR data and Landsat-8 Operational Land Imager (OLI) data were used for drought analysis. Landsat-8 data, which was used for NDVI calculation, contains nine spectral bands with 30 m spatial resolution (except for the panchromatic band, which has a resolution of 15 m). The Landsat sensor could be characterized by push broom in nature with high signal to noise ratio, two extra added band (band 1 for coastal waters and band 9 for cirrus cloud detection) compared to its predecessor, Landsat 7 ETM+ sensor. Landsat data of pre-monsoon season of the study area were taken. The available cloud free data of 2020 and 2021 were of the pre-monsoon (kharif crop) of the study area was taken into consideration (Table 8.1).

Sentinel-1, which is a part of Copernicus mission, carries only C band SAR sensor with 5.405 GHz frequency. The Sentinel-1 data, obtained from Copernicus Sentinel Scientific Data Hub has dual degree polarisation (VH-vertical transmit, horizontal receive and VV-vertical transmit, vertical receive). The image was at level-1 GRD (ground range detected) and has a spatial resolution of 10 m. Three scenes of sentinel-1 SAR data of each year of 2020 and 2021 of pre-monsoon season were taken in this study.

MODIS sensor provides global land cover type product (MCD12Q1). These global maps of land cover are annual time steps and spatial resolution is 500 m. The data is available from 2001 till present. The land cover map of 2019 is taken in this study.

Table 8. 18: Datasets

Sensor	Date of acquisition	Spatial Resolution	Path and Row / Orbit number	Remarks
Landsat-8 OLI	02 July 2020 03 June 2021	30 m	Path 139 / Row 45	NDVI Calculation
Sentinel-1 SAR	26 July 2020 20 Jun 2020 08 Jun 2020 21 July 2021 09 July 2021 27 Jun 2021	10 m		Back scatter calculation
MODIS	2019	500 m	MCD12Q1	Landcover class for agricultural area delineation

8.4 Methodology

8.4.1 Landsat data processing

The Landsat images were georeferenced according to Universal Transverse Mercator (UTM) projection and a subset of the study area was selected for further pre-processing. Level-1 standard dataset DN values were converted to Top Of the Atmosphere (TOA) reflectance followed by atmospheric correction in ENVI using Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH). The reflectance data has been used to generate the Normalized Difference Vegetation Index (NDVI). NDVI is derived from reflectance of Near-infrared and Red band using the equation

$$NDVI = (NIR-R / NIR +R)$$

8.4.2 Sentinel-1 data processing

The Sentinel-1 data, obtained from Copernicus Sentinel Scientific Data Hub has dual degree polarization (VH-vertical transmit, horizontal receive and VV- vertical transmit, vertical receive). The sensor is operated in Interferometric Wide swath mode with a width of 250 km and carries only C band with 5.405 GHz frequency. The image was at level-1 GRD (ground range detected) and has a spatial resolution of 10m. The Sentinel -1 SAR data was processed in the Sentinel Application Platform (SNAP version 6.0).

In the first step before pre-processing, orbit file is applied as the Orbital State vectors stored in the metadata of the SAR image are often inaccurate. Applying orbit file enables SNAP software to download and update existing state orbit vectors in the metadata of each image. This results in accurate sensor location and velocity information. In the next step, thermal noise is removed from the Sentinel-1 GRD products. Thermal noise reduction, in particular, eliminates interference issues in the inter-sub-swath texture. The noise-removed product now need calibration in order to accurately represent different backscatter phenomena generated from different objects. It is a technique for processing SAR data such that the pixel values accurately depict the radar backscatter of the reflecting object. The Sentinel-1 GRD product contains all the information needed to apply the calibration equation. The calibration vector included in the programme makes converting product intensity measurements to σ0 (sigma nought) values simple. The calibration process necessarily alters the already implemented scaling factor in the time of level-1 data generation by implementing an offset and a boost which is dependent on the range. Finally, an absolute calibration constant is applied which is a common parameter for each pixel. The calibrated data is then checked for speckle filtering. The inherent salt and pepper in the SAR data, known as 'speckles,' degrade the image quality and make it more difficult to identify the objects. They are generated by the variation in the intensity of the backscatter radiation. 'Boxcar,' 'Median,' 'Frost,' 'Gamma Map,' 'Lee,' 'Refined Lee,' 'Lee Sigma,' 'IDAN' are some of the filters offered in the SNAP single product filter operator. In this study, “Lee Sigma” filter has been used. The filter assumes the noise level in the dataset to be distributed like a Gaussian curve and substitute the middle pixel of the running window with an average value within 2σ range. SAR data are often captured at angles greater than 0°, leading to geometric distortions in the image. Terrain corrections are performed to rectify the problems. The process in the SNAP downloads SRTM DEM (v.4) from the FTP Joint Research Centre. Then the image is ortho-rectified according to the elevation. In the last step, backscatter signals are converted to dB. The equation for the generation of backscatter images from Sentinel-1 is as follows:

$$\sigma^{\circ}[dB] = 10.\log_{10}(\sigma^{\circ})$$

Where σ° is the backscattering coefficient.

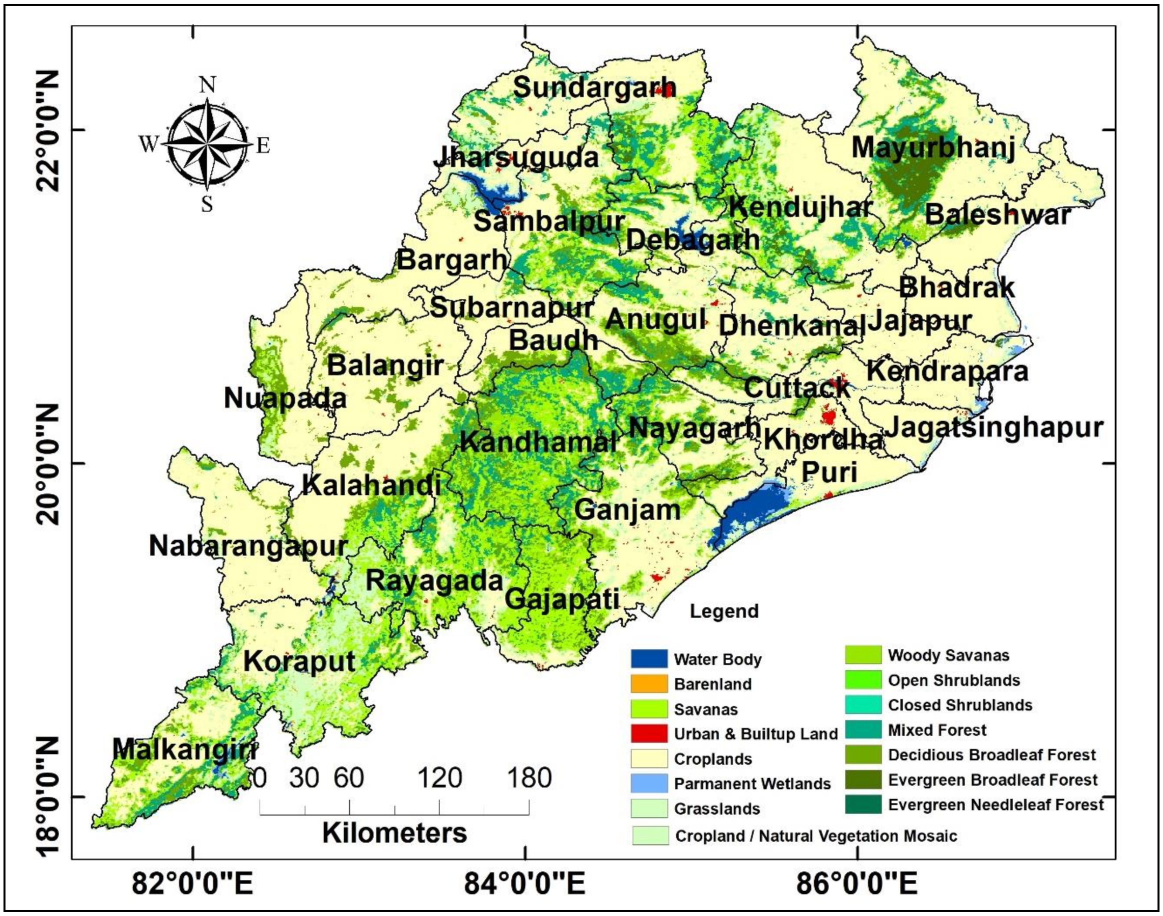
8.4.3 MODIS data processing

Agricultural land was extracted from the MODIS Landcover data. All the pixels representing cropland and small-scale agriculture is separated out in GIS. Samples of those pixels from NDVI and SAR data were taken to carry out the regression and correlation analysis. With the help of correlation analysis, the threshold value of SAR backscatter was estimated. Using the threshold value, the SAR scene were masked out and carry out the drought assessment.

8.5 Results and Discussions

8.5.1 Agricultural Area Extraction

Agricultural area has been classified and extracted for drought estimation from MODIS landcover data product of 2019. The land cover map of Odisha state of 2019 and land cover statistics are shown in the Figure 8.2. Only agricultural area related classes were taken for assessment of agricultural drought and the non-related classes like settlements, water bodies etc. was not considered because these classes do not provide the accurate picture of drought in the study area. Agricultural area has been identified by taking MODIS landcover product 500 m spatial resolution as a reference. MODIS full-resolution products are capable to provide regional assessment and combining with Landsat data provides the foundation for monitoring and modelling land use and land cover change, as well as other biophysical and biochemical observations (Justice, et al., 2002). The agricultural land within our selected study area has been shown in the Figure 8.3.



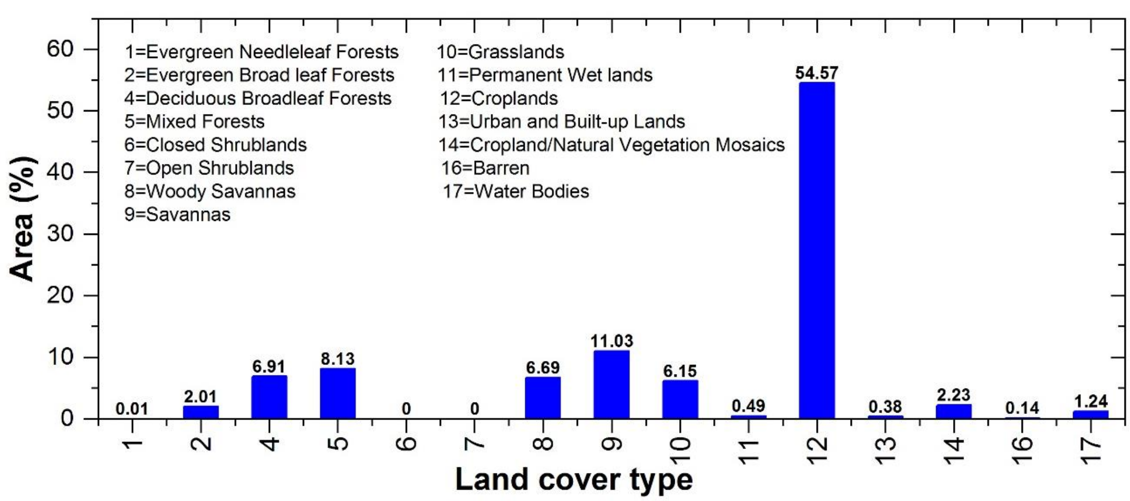


Figure 8.54. MODIS Land cover map of Odisha state of 2019 and land cover statistics. The state is having agricultural area of 54.57% of the total state area.

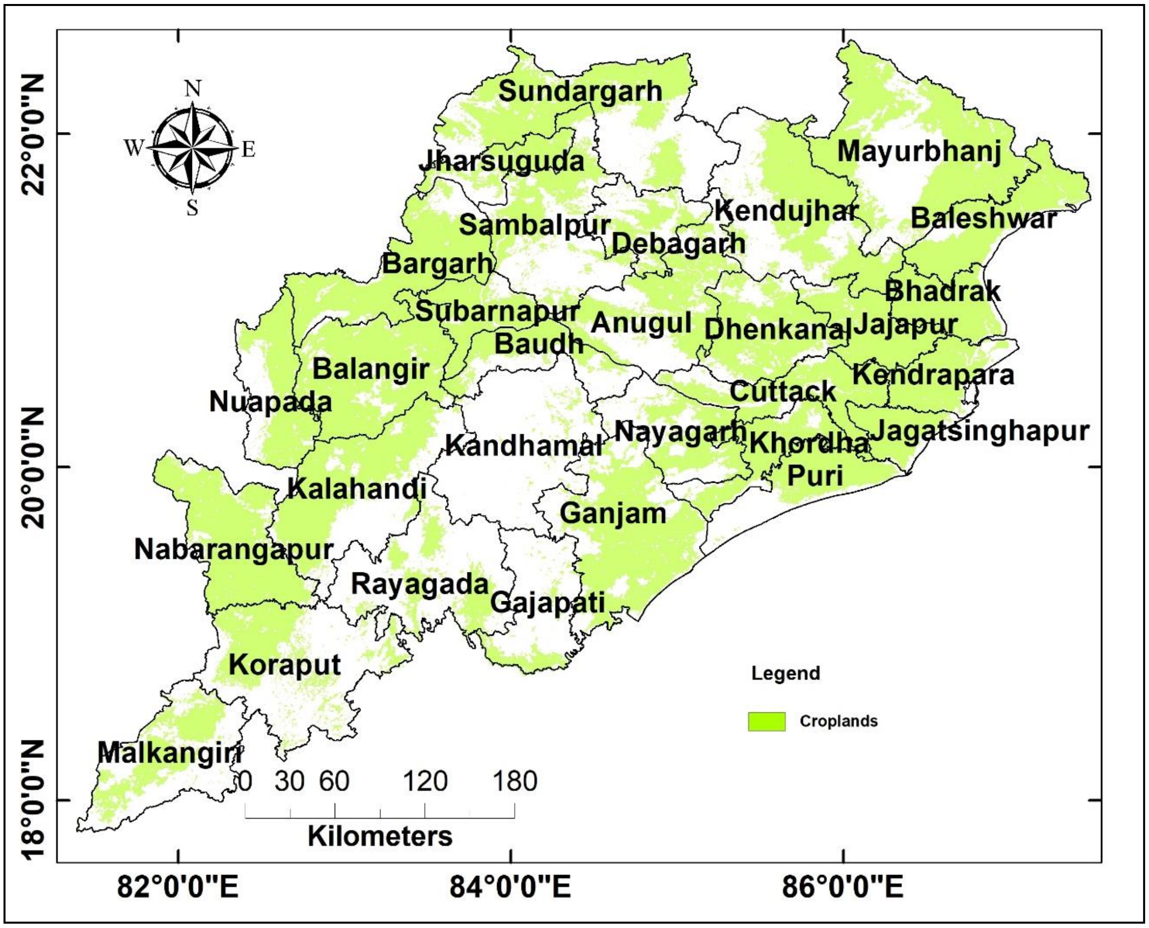


Figure 8.55: Agricultural area extracted from MODIS landcover data product of 2019.

8.5.2 Correlation between NDVI and SAR backscatter

The relationships between Sentinel-1 SAR data and LANDSAT derived NDVI were analysed and compared to check whether there is a possibility of estimating the drought characteristic. Few researchers have used similar type of datasets to delineate drought in the grassland / agricultural areas. Figure 8.4 represents the Sentinel SAR data of VV and VH polarization over agricultural area and the corresponding NDVI images of 2020 and 2021. Generally, in this study area kharif crop is cultivated in this season, and if the drought occurs during the sowing and initial phase of growing season, then the crop gets affected. Kharif crop sowing and growing period is generally month of June – July. Any crop area if gets drought affected, then the NDVI value comes down and it ranges from 0 to 0.2. Therefore, correlation between SAR and NDVI is carried out within the NDVI range of 0 to 0.2. A set of correlation operations were performed between backscatter coefficients and NDVI values extracted from the study area. Figure 8.5 represents the correlation between NDVI value range of 0 to 0.2 and the corresponding backscatter coefficients. As drought generally happens in this region during pre-monsoon, so only pre-monsoon dataset has been considered in this study.

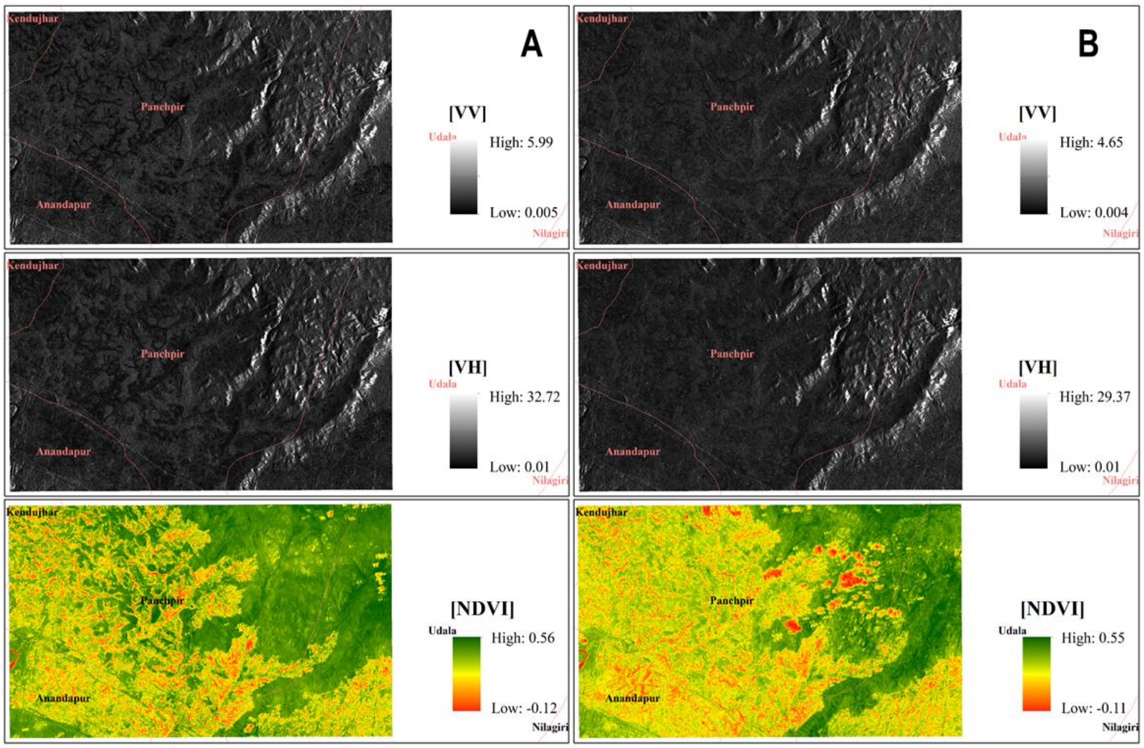


Figure 8.56: Backscatter images and NDVI derived from Sentinel-1 data and LANDSAT data respectively for (A) year 2020 and (B) year 2021.

From the correlation assessment it was also observed that VH backscattering with NDVI had higher R2 values than VV backscattering with NDVI during the drought seasons. The VH backscattering also tend to fluctuate in the presence of water layer on the leaves (Wang, Ge, & Li, 2013)**.** The backscattering coefficient consists of soil and the vegetation layer in low frequency (C-band), but in high frequency, the contribution of the vegetation layer is prominent in the total backscattering coefficient (Wang, Ge, & Li, 2013).

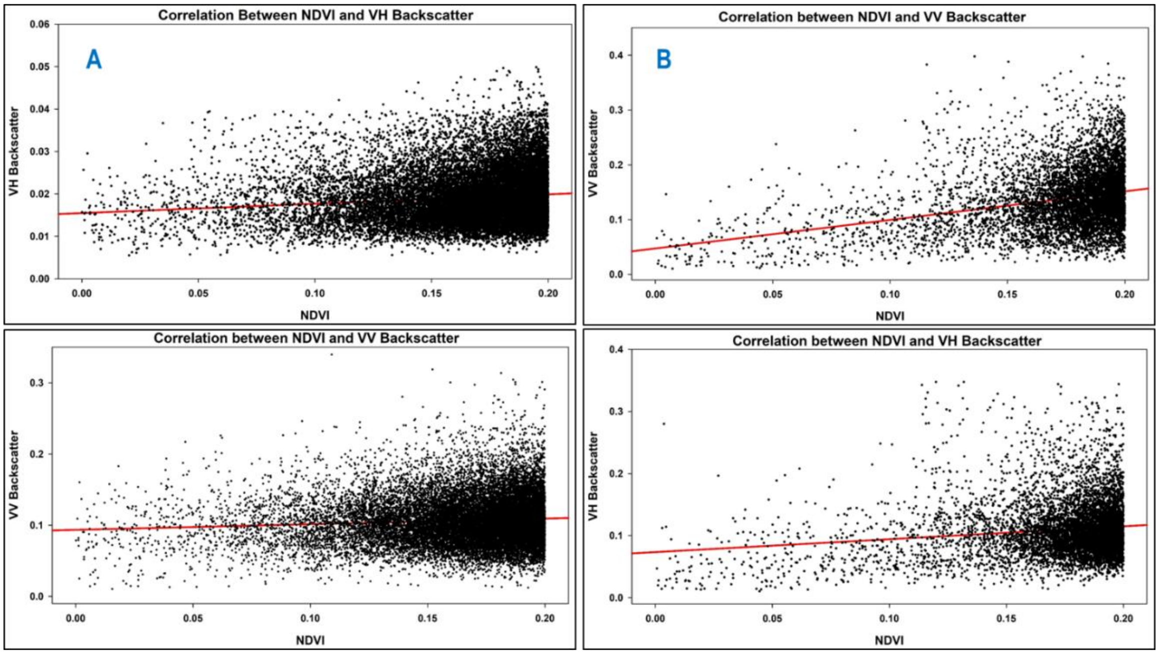


Figure 8. 57: Correlation plots between SAR backscatter values and NDVI for (A) 2020 and (B) 2021.

The correlation coefficient (R2) values obtained for the correlation between NDVI and VV for 2020 was 0.51, and between NDVI and VH for 2020 was 0.57. It is probably due to the enhanced ability of VH backscatter in determining vegetation characteristics than VV backscatter. The coefficient between NDVI and VV for 2021 was 0.54 and between NDVI and VH for 2021 was 0.59. Therefore, the year 2021 had overall better performance in correlation than 2021, which reflects the more prolonged drought event occurred in 2021. As per the online report of DownToEarth, severe drought happened in the study area in the month June – July in 2021. The study area received 49% deficiency in rainfall during month of June-July 2021 and resulted severe drought. Table 8.2 summarizes the coefficients and derivable obtained from the group of correlation estimations.

Generally, in the study area if the vegetation growth is high, the backscatter value increases. In the beginning of the agricultural season, the backscattering coefficient i.e., σ0 value is low in the agricultural fields because the fields are dry and incident radar signal is distributed. A small proportion of the energy is backscattered to the sensor. The backscatter of the dry agricultural field is very low in both polarizations. The σ0 of the agricultural fields again increases if the rainfall happen, moisture content in the fields increases at the beginning of the crop growing season. Therefore, SAR data is important and gives a very good indication of agricultural drought assessment. The coastal areas are affected by cloud cover, therefore, optical data is not effective for drought assessment, SAR data does not affected by any weather phenomena and useful for estimating the soil moisture due to its sensitivity to dry-electric constant, therefore suitable for agricultural drought assessment.

Table 8.19: Summary of NDVI and SAR backscatter correlation parameters

Year	Parameters for correlation	R^2 values	Equation
2020	VH vs NDVI	0.57	VH = 0.0222NDVI + 0.0155
	VV vs NDVI	0.51	VV = 0.1571NDVI + 0.0806
2021	VH vs NDVI	0.59	VH = 0.2079NDVI + 0.0734
	VV vs NDVI	0.54	VH = 0.5206NDVI + 0.0474

8.5.3 Identification of drought affected areas in SAR data

The agricultural drought areas generally fall within the NDVI values ranging from 0.0 to 0.2. Therefore, SAR backscatter data range is extracted within the NDVI range of 0 to 0.2 and a threshold value i.e., backscatter range rages for estimating the drought has been identified which is further used as potential backscatter value for delineating the drought areas in study area from the SAR images. SAR backscatter value ranged from 0.05 to 0.28 for VV and 0.01 to 0.33 for VH in the year 2020. For the year 2021, backscatter value ranged from 0.04 to 0.29 for VV and 0.01 to 0.34 for VH polarized SAR data.

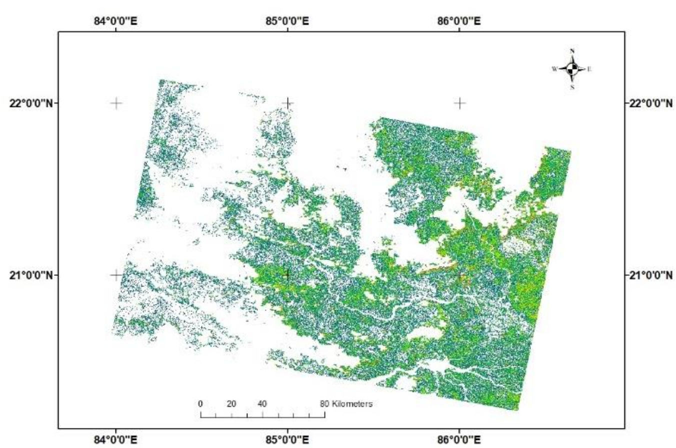
Once the methodology for the drought estimation had established in the agricultural zone under the study area, we expanded the same formula for drought assessment in the entire study area. According to this assessment, drought prone areas for 2020 under the agricultural zone and the total study area was 6.5 km2 and 12.97 km2 respectively. The drought prone areas of 2021 under the agricultural zone and study area were 18.07 km2 and 23.76 km2 respectively. These findings further support our precious results obtained from the correlation analysis.

Similar methodology has been adopted to delineate the drought areas from the full scene of the Sentinel-1 SAR data. First, agricultural land has been extracted from the SAR data with the help of landcover map derived from MODIS data, thereafter sampling has been carried out to derive the threshold value for delineation of drought areas from the SAR data. The threshold values and drought affected areas delineated from the SAR data has been shown in the Table 8.3. The drought affected agricultural areas of 2020 and 2021 extracted from VV polarized data are shown in the Figure 8.6 and Figure 8.7 respectively which shows that the study area was more drought affected in 2020 compared to 2021.

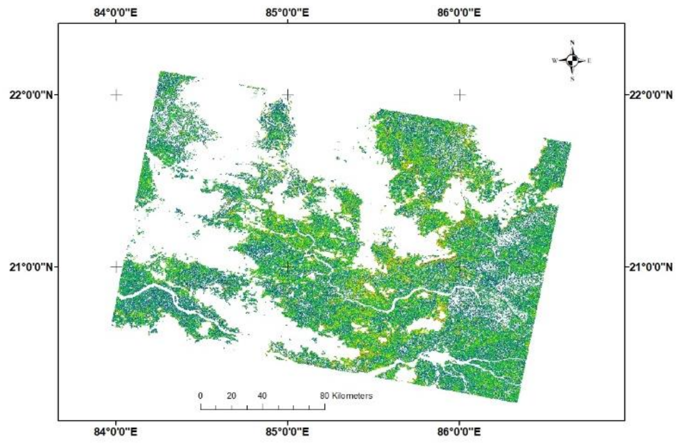
Table 8.20: Drought affected agricultural area (%) estimated from SAR VV and VH polarized data

Date	Backscatter threshold value	Drought affected area (%) in VV polarized data	Backscatter threshold value	Drought affected area (%) in VH polarized data
08-06-2020	0.025-0.2	67.27	0.026-0.21	65.21
20-06-2020	0.025-0.22	85.49	0.022-0.23	81.32
26-07-2020	0.023-0.18	68.18	0.024-0.19	66.28
09-07-2021	0.04-0.21	9.02	0.042-0.18	8.12
21-07-2021	0.023-0.20	28.72	0.021-0.22	26.77
27-06-2021	0.041-0.18	24.74	0.039-0.23	21.94

08 Jun 2020



20 Jun 2020



26 July 2020

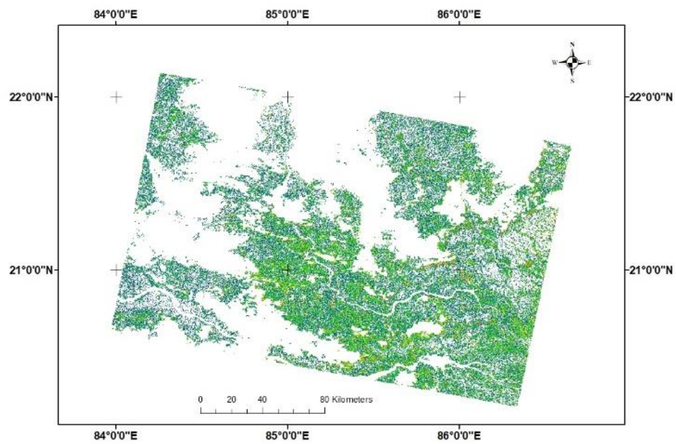
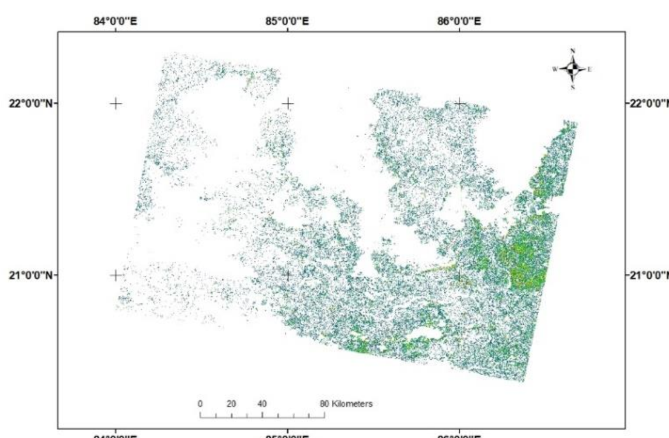
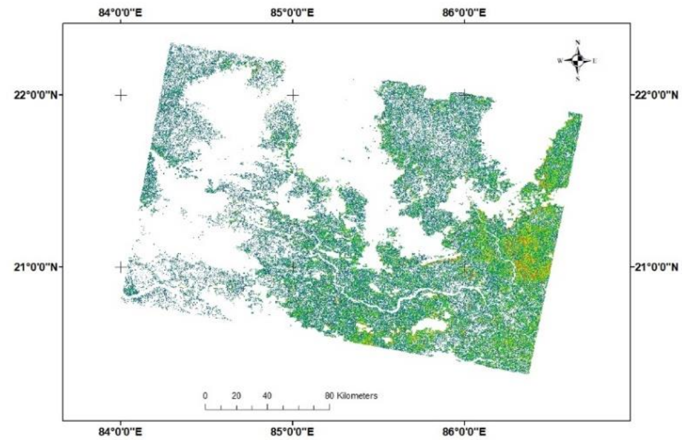


Figure 8.58: Draught affected agricultural zones as evident from Sentinel VV polarized data of 2020

27 Jun 2021



09 July 2021



21 July 2021

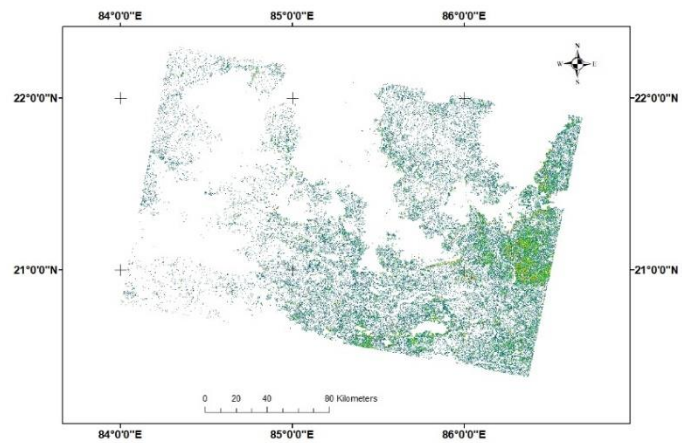


Figure 8.59: Draught affected agricultural zones as evident from Sentinel VV polarized data of 2021.

The spatial extent of the identified potential drought zone is similar to the finding of a SPI derived drought assessment by (Liansangpuii, Panigrahi, & Paul, 2019)**.** Moreover, (Ward n & Makhija, 2018) also denoted the study area taken in this study as potential drought prone area. Extreme drought scenario in the study area is also not uncommon, as reported by Swain (Swain, Mishra, Pandey, & Dayal, 2021) utilizing the percent departure from mean precipitation (PDM) method. In this study, it is observed that in comparison to optical data, SAR applications for agricultural drought monitoring have been far fewer due to restricted availability and complex data structures and processing in comparison to optical data. The scenario completely changed after the availability of Sentinel-1 SAR dataset (Torres, et al., 2012)**,** which offered a high spatial resolution and temporal coverage. This helped the scientific community to address the pressing issues like potential effects of climate change on agricultural drought analysis and agricultural / vegetation dynamics (Jiang, Bao, Guo, & Ndayisaba, 2017; Liu, Zhu, Pan, Li, Liu, & Ma, 2016).

8.6 Conclusion

The present study has tried to identify the agricultural drought affected areas with the help of multi-temporal Sentinel 1 SAR and Landsat optical datasets in coastal area of Odisha state. The land cover of the above-mentioned study area is basically cropland and vintage is month of June – July in 2020 and 2021. Initially correlation between NDVI and SAR backscatter was established to prove that there is a good correlation between drought affected agricultural area and its SAR backscattering values. Thereafter, the backscattering vale range has been identified as the threshold value to delineate the agricultural drought affected areas from other SAR images of various dates. In this study, it is observed that although the area is drought affected, received less rainfall, but due to location in coastal region this area is mostly under cloud cover, therefore, it is very difficult assess the agricultural drought using optical remote sensing data. As the SAR data does not affect by the cloud, it is very convenient to assess the agricultural drought using these datasets. SAR data also has the very high potential to estimate the soil moisture conditions due to its sensitivity to dielectric constant property, therefore, SAR data with its high its availability, could be of potential source for drought monitoring, especially in the coastal region. However, the present study faced certain limitations, like use of more number of datasets during the crop growing seasons, field verification, other methods of establishing the correlation of SAR and optical data, which can be addressed by the future study by the other researchers.

9 Conclusion

If can't explain it to a six-year-old, you don't understand it yourself.

- Albert Einstein

9.1 Introduction

In this chapter, conclusions and recommendations of the study are presented based on the findings of the research. It gives the research insight into the mapping of drought dynamics over the Odisha state using remote sensing datasets and geoinformatics techniques. For better understanding, the chapter is divided into five sections such as conclusion, scope, limitations, contribution, and recommendation for future research.

9.2 Conclusion

Drought generally occurs when a region consistently receives less precipitation. It is the most devastating natural hazard which impacts the agriculture and economy of a state. The economy of Odisha largely depends on agriculture. Despite the coastal location, the state is highly drought-prone and therefore, understanding the drought situation and its monitoring is very important. Remote sensing datasets and geoinformatics techniques are very much helpful for wide-area drought monitoring. In this research, various climatic and space-based remote sensing datasets are utilized to delineate the drought dynamics, its cause, future prediction and technique for field scale drought and soil moisture mapping. The findings of the research are summarized in this chapter.

In chapter 1 problem statement is given with a detailed literature survey. From the literature survey, the gaps in the knowledge is identified. Details of the drought situation in India as well as in the Odisha state are analysed to understand the reason for frequent droughts in Odisha state. Based on the literature survey and research gap analysis, the research questions and objectives of the study are formulated in chapter 2. In chapter 3, the physical and cultural settings of Odisha are analysed. Administrative setup, geology, soils, land cover, physiography, and climate all are very much necessary and are described in detail along with the spatial maps. The analysis brings out that the southwest monsoon has a large impact and control on the agriculture of Odisha state. Availability of groundwater resources, irrigation etc. are also analysed. The demographic and socio-economic status of the state is also important to understand which is analysed in this chapter. A total of approx. 34% of the Odisha state's GDP comes from the agricultural sector, therefore agricultural drought is important.

In chapter 4 mapping of drought dynamics of Odisha state over two decades has been carried out using SPI and SPEI. The drought-affected years are identified which are 2000, 2002, 2004, 2009, 2010, 2013 and 2015. The literature survey and report of Odisha state disaster management authority are also showing similar observations.

However, mild to moderate droughts are seen in Odisha in most of the years. The spatial distribution and mapping of drought characteristics i.e., drought frequency, drought severity and drought event signify that, in most of the districts, drought frequency is high as well as Odisha has experienced severe droughts on various occasions. Monsoon drought is most significant in the study area and it affects the Kharif crop. Post-monsoon drought is also seen in Odisha, but the intensity and effect are less compared to the monsoon droughts . The drought pattern in Odisha is random, however, a few districts like Nuapada, Kalahandi, Bolangir, Rayagada, Ganjam, Bargarh, Malkangiri and Phulbani are chronically affected by droughts.

In chapter 5 major climatic factors which are affecting droughts in Odisha are identified and analysed. The major factor responsible for drought is precipitation, temperature, soil moisture, evapotranspiration, groundwater storage, El Nino/ La Nina and IOD. The analysis identifies that the main reason for droughts in Odisha state is rainfall variability. The onset of the southwest monsoon affects the Kharif crop which results in severe droughts. The positive anomaly of LST is observed which results in the increase of evapotranspiration, decrease in soil moisture and therby decrease in groundwater storage. The combined effect is severe agricultural drought. It is found that ENSO and IOD are the controlling factor of air circulation over the Indian Ocean and therefore significantly impacts the southwest monsoon, affecting the drought situation of Odisha.. Odisha as a coastal state gets highly influenced by rainfall variability. In Odisha, only 20 % of the agricultural area is covered by canal irrigation, therefore better drought management, and irrigation system development is required for drought mitigation.

In chapter 6 short and long-term drought scenario prediction has been carried out for Odisha state using NorESM2-MM CMIP6 GCM model predicted precipitation and temperature datasets. The predictive analysis is based on tri-monthly SPI. As monsoon drought is found as a major concern in Odisha, therefore, drought scenario in the monsoon period i.e., Jul-Aug-Sep month is analysed which suggests that in the years 2023, 2027, 2029, 2031, 2036, 2040, 2048 and 2050, more than 50% of the area will be under drought. The analysis also indicates that the predicted minimum and maximum temperature will increase by approximately 2°C and 1.5°C respectively in this period (2023 to 2050). Temperature anomaly is also positive after 2040. In the predicted drought map, the pattern is random and the state may suffer severe drought in the future.

In chapter 7 enhancement of agricultural drought and soil, moisture mapping is carried out by downscaling the spatial resolution of LST from coarse to medium/ finer resolution. The 1 km spatial resolution temperature data is downscaled to 250 m resolution with the help of NDVI and to derive VHI and TVDI for mapping drought and soil moisture. The entropy function is used to validate the generated VHI and TVDI maps of 250 m resolution. The downscaled 250 m resolution LST depicts higher spatial details compared to the 1000 m resolution LST. A similar pattern with higher details is observed in the fine-resolution VHI and TVDI. Larger intra-pixel variability is seen which suggests that high-resolution maps are useful for drought and soil moisture mapping over the study area. Due to the availability of MODIS VNIR and thermal data in daily basis, this technique will improve the probability of daily or weekly field/ regional drought and soil moisture mapping and monitoring . The high-frequency Spatio-temporal pattern of drought/ soil moisture will certainly help the state authority for drought management and policy formation.

In chapter 8 delineation of agricultural drought-affected areas has been carried out with the help of multi-temporal Sentinel 1 SAR and Landsat optical datasets for the monsoon period as the validation of the concept based on the correlation between NDVI and SAR backscatter. It is observed that although the region received less precipitation and suffers monsoon droughts in spite of its coastal location it becomes sometimes difficult to assess the agricultural drought using optical remote sensing data as it remains mostly under cloud cover and. Due to cloud penetration capability in SAR data, it is very convenient for the assessment of agricultural droughts. Sentinel 1 SAR data is freely available and it also has a high potential to estimate the soil moisture conditions due to its sensitivity to dielectric property, therefore, could be of potential source for drought monitoring, especially in the coastal region.

9.3 Scope of the research

The objective of this research was the applicability of geoinformatics techniques for mapping of drought dynamics of Odisha state for the last two decades using climatic and satellite-based remote sensing datasets. Based on this research outcome remote sensing community and various researchers can assess the drought assessment and monitoring of the Odisha state. The spatial mapping of drought scenarios can be helpful for the understanding of drought characteristics which will help the state government departments with drought-related policy formulation. The methodology proposed in this study can also be useful for various environmental and natural resource monitoring and applications. The drought prediction will help the Odisha state disaster management department in future drought management.

9.4 Contribution

In the present research, a geoinformatics-based methodology is developed for mapping and assessment of drought dynamics of Odisha using climatic and satellite datasets for two decades which has not been systematically addressed by any other researcher. All important climatic factors which are responsible for drought have been identified, correlated, and analysed to generate a complete scenario and link it with the drought dynamics. The impact of El Nino and IOD on the drought of Odisha is clearly brought out by this research. Subsequently, this study developed a methodology to generate downscaled drought and soil moisture map for filed scale drought and soil moisture mapping and assessment. This methodology will help with daily/ weekly drought monitoring using open-source satellite data for the entire state. Predictive analysis of drought also has been carried out to understand the future drought scenario and the state department can prepare the management policy based on this input. Another important attempt has been carried out by this study to delineate the agricultural drought from SAR data. This methodology is very useful for monsoon drought mapping of the state which is located in the coastal region. Moreover, the present research open-up a new window for monitoring drought using open-source satellite and climatic data for any researcher or organisation.

9.5 Limitations

This research has the following limitations

Mapping of drought dynamics has been carried out using climatic and satellite-based remote sensing datasets. Field validation of the results has not been performed in this study.

Drought prediction is carried out using NorESM2-MM CMIP6 GCM model-predicted precipitation and temperature datasets. Bias correction of the model may be checked for more reliable prediction.

The study proposed a downscaling methodology to generate field scale drought and soil moisture maps, however, ground validation was a difficulty that the present research has faced for validating the downscaled MODIS LST result due to the non-availability of ground temperature samples.

A new methodology for agricultural drought mapping using SAR data is proposed in this research, however, the use of more number of datasets during the crop growing seasons, field verification, and other methods of establishing the correlation of SAR and optical data may be required.

9.6 Recommendations for further research

The present research has tried to generate a detailed drought scenario of Odisha state, but there are certain limitations as mentioned in the previous section. Therefore, this study recommends certain areas in which further research can be carried out.

Detailed analysis can be carried out on the impact of El Nino and IOD on the droughts of Odisha state.

Short and long-term drought prediction is carried out using NorESM2-MM CMIP6 GCM model predicted data, however, more models can be taken into consideration and results can be compared.

Ground validation of drought mapping may be carried out by future research. The downscaling result can also be validated using ground temperature samples. The downscaled LST can also be used for many other environment-related applications.

More number of SAR data may be taken into consideration for drought mapping along with other methods, and the result can be tested in various other areas to check the robustness.

Future studies can also be carried out to analyse the effect of drought on the socio-economy condition of the Odisha state.

Referrences

Aadhar, S., & Mishra, V. (2018). Impact of climate change on drought frequency over India. *Book Climate Change and Water Resources in India Publisher: Ministry of Environment, Forest and Climate Change (MoEF\&CC), Government of India* .

Aadhar, S., & Mishra, V. (2020). n the projected decline in droughts over South Asia in CMIP6 multimodel ensemble. *Journal of Geophysical Research: Atmospheres , 125* (20), e2020JD033587.

Aadhar, S., & Mishra, V. (2020). On the projected decline in droughts over South Asia in CMIP6 multimodel ensemble. *Journal of Geophysical Research: Atmospheres , 125* (20), e2020JD033587.

Abdel-Hamid, A., Dubovyk, O., Graw, V., & Greve, K. (2020). Assessing the impact of drought stress on grasslands using multi-temporal SAR data of Sentinel-1: A case study in Eastern Cape, South Africa. *European Journal of Remote Sensing , sup2* (53), 3--16.

Agam, N., Kustas, W. P., Anderson, M. C., Li, F., & Neale, C. M. (2007). A vegetation index based technique for spatial sharpening of thermal imagery. *Remote Sensing of Environment , 107* (4), 545--558.

AghaKouchak, A., Farahmand, A., Melton, F., Teixeira, J., Anderson, M., Wardlow, B. D., et al. (2015). Remote sensing of drought: Progress, challenges and opportunities. *Reviews of Geophysic , 52* (2), 452--480.

AghaKouchak, A., Rad, A. M., Navari, M., & Sadegh, M. (2021). Progress, Challenges, and Opportunities in Remote Sensing of Drought. *Global Drought and Flood: Observation, Modeling, and Prediction* , 1 -28.

Albergel, C., Dorigo, W., Balsamo, G., Munoz-Sabater, J., de, R., Pd Isaksen, L., et al. (2013). Monitoring multi-decadal satellite earth observation of soil moisture products through land surface reanalyses. *Remote Sensing of Environment , 138*, 77--89.

Allen, M. R., & Ingram, W. J. (2002). Constraints on future changes in climate and the hydrologic cycle. *Nature , 419* (6903), 228--232.

(2010-2011). *Annual Report on Natural Calamities, Government of Odisha* .

(2009-2010). *Annual Report on Natural Calamities, Government of Orissa* .

(2011–2012). *Annual Report on Natural Calamities, Government of Orissa* .

(2012-2013). *Annual Report on Natural Calamities, Government of Orissa* .

(2012-2013). *Annual Report on Natural Calamities, Government of Orissa* .

(2009-2010). *Annual Report on Natural Calamities, Government of Orissa*.

(2009-2010). *Annual Report on Natural Calamities, Government of Orissa*.

(2011-2012). *Annual Report on Natural Calamities, Government of Orissa*.

(2010-2011). *Annual Report on Natural Calamities, Government of Orissa,* .

Arekhi, M., Saglam, S., & Ozkan, U. Y. (2020). Drought monitoring and assessment using Landsat TM/OLI data in the agricultural lands of Bandar-e-Turkmen and Gomishan cities, Iran. *Environment, Development and Sustainability , 22* (7), 6691--6708.

Arnell, N. (2008). Climate change and drought. *Drought Management: Scientific and Technological Innovations, Options Mediterraneennes: Serie A. Seminaires Mediterraneens , 80*, 13--19.

Agam, N., Kustas, W.P., Anderson, M.C., Li, F., Colaizzi, P.D., 2007b. Utility of thermal sharpening over Texas high plains irrigated agricultural fields. J. Geophys. Res. 112, 1-10. DOI: 10.1029/2007JD008407

Agam, N., Kustas, W.P., Anderson, M.C., Li, F., Neale, C.M.U., 2007a. A vegetation index based technique for spatial sharpening of thermal imagery. Remote Sens. Environ. 107, 545-558. doi:10.1016/j.rse.2006.10.006

Albergel, C., Rüdiger, C., Carrer, D., Calvet, J.C., Fritz, N., Naeimi, V., Bartalis, Z., Hasenauer, S., 2009. An evaluation of ASCAT surface soil moisture products with in-situ observations in Southwestern France. Hydrol. Earth Syst. Sc. 13, 115–124.

Anderson, M.C., Neale, C.M.U., Li, F., Norman, J.M., Kustas, W.P., Jayanthi, H., Chavez, J. 2004. Upscaling ground observations of vegetation water content, canopy height, and leaf area index during SMEX02 using aircraft and Landsat imagery. Remote Sens. Environ. 92, 447-464. doi:10.1016/j.rse.2004.03.019

Anderson, M.C., Norman, J.M., Kustas, W.P., Houborg, J., Starks, P.J., Agam, N. 2008. A thermal-based remote sensing technique for routine mapping of land-surface carbon, water and energy fluxes from field to regional scales. Remote Sens. Environ. 112, 4227-4241. doi:10.1016/j.rse.2008.07.009

Atkinson, P. M., 2013. Downscaling in remote sensing. Int. J. Appl. Earth Obs. Geoinform. 22, 106-114. doi:10.1016/j.jag.2012.04.012

Atkinson, P.M., Sargent, I.M., Foody, G.M., Williams, J., 2007. Exploring the geostatistical method for estimating the signal-to-noise ratio of images. Photogram. Eng. Rem. Sens. 73, 1–10.

Agam, N., Kustas, W.P., Anderson, M.C., Li, F., Colaizzi, P.D., 2007b. Utility of thermal sharpening over Texas high plains irrigated agricultural fields. J. Geophys. Res. 112, 1-10. DOI: 10.1029/2007JD008407

Agam, N., Kustas, W.P., Anderson, M.C., Li, F., Neale, C.M.U., 2007a. A vegetation index based technique for spatial sharpening of thermal imagery. Remote Sens. Environ. 107, 545-558. doi:10.1016/j.rse.2006.10.006

Albergel, C., Rüdiger, C., Carrer, D., Calvet, J.C., Fritz, N., Naeimi, V., Bartalis, Z., Hasenauer, S., 2009. An evaluation of ASCAT surface soil moisture products with in-situ observations in Southwestern France. Hydrol. Earth Syst. Sc. 13, 115–124.

Anderson, M.C., Neale, C.M.U., Li, F., Norman, J.M., Kustas, W.P., Jayanthi, H., Chavez, J. 2004. Upscaling ground observations of vegetation water content, canopy height, and leaf area index during SMEX02 using aircraft and Landsat imagery. Remote Sens. Environ. 92, 447-464. doi:10.1016/j.rse.2004.03.019

Anderson, M.C., Norman, J.M., Kustas, W.P., Houborg, J., Starks, P.J., Agam, N. 2008. A thermal-based remote sensing technique for routine mapping of land-surface carbon, water and energy fluxes from field to regional scales. Remote Sens. Environ. 112, 4227-4241. doi:10.1016/j.rse.2008.07.009

Atkinson, P. M., 2013. Downscaling in remote sensing. Int. J. Appl. Earth Obs. Geoinform. 22, 106-114. doi:10.1016/j.jag.2012.04.012

Atkinson, P.M., Sargent, I.M., Foody, G.M., Williams, J., 2007. Exploring the geostatistical method for estimating the signal-to-noise ratio of images. Photogram. Eng. Rem. Sens. 73, 1–10.

Bhuiyan, C., Saha, A., Bandyopadhyay, N., & Kogan, F. (2017). Analyzing the impact of thermal stress on vegetation health and agricultural drought--a case study from Gujarat, India. *GIScience & Remote Sensing , 54* (5), 678--699.

Bhuiyan, C., Singh, R., & Kogan, F. (2006). Monitoring drought dynamics in the Aravalli region (India) using different indices based on ground and remote sensing data. *International Journal of Applied Earth Observation and Geoinformation , 8* (4), 289--302.

Byun, H.-R., & Wilhite, D. A. (1999). Objective quantification of drought severity and duration. *Journal of climate , 12* (9), 2747--2756.

Bindhu, V.M., Narasimhan, B., Sudheer, K.P., 2013. Development and verification of a non-linear disaggregation method (NL-DisTrad) to downscale MODIS land surface temperature to the spatial scale of Landsat thermal data to estimate evapotranspiration. Remote Sens. Environ. 135, 118-129. doi:10.1016/j.rse.2013.03.023

Bjorke, J.T., 1996. Framework for entropy-based map evaluation. Cartog. Geogr. Info. Sys. 23, 78-95. DOI: 10.1559/152304096782562136

Black, A. and Stephen, H., 2014. Relating temperature trends to the normalized difference vegetation index in Las Vegas. GIScience& Remote Sensing, 51(4), 468-482.

Boken, V.K., Hoogenboom, G., Kogan, F.N., Hook, J.E., Thomas, D.L., Harrison, K.A.. 2004. Potential of Using NOAA-AVHRR Data for Estimating Irrigated Area to Help Solve an Inter-State Water Dispute. Int. J. Remote Sens. 25, 2277–2286. DOI:10.1080/01431160310001618077

Brocca, L., Melone, F., Moramarco, T., Wagner, W., Hasenauer, S., 2010. ASCAT soil wetness index validation through in situ and modeled soil moisture data in central Italy. Remote Sens. Environ. 114, 2745–2755. doi:10.1016/j.rse.2010.06.009

Chen, C.F., Son, N.T., Chang, L.Y., Chen, C.C., 2011. Monitoring of soil moisture variability in relation to rice cropping systems in the Vietnamese Mekong Delta using MODIS data. Appl. Geogr. 31, 463–475. doi:10.1016/j.apgeog.2010.10.002

Choi, M., Hur, Y., 2012. A microwave-optical/infrared disaggregation for improving spatial representation of soil moisture using AMSR-E and MODIS products. Remote Sens. Environ. 124, 259–269. doi:10.1016/j.rse.2012.05.009

Choi, M., Jacobs, J.M., Anderson, M.C., Bosch, D.D., 2013. Evaluation of drought indices via remotely sensed data with hydrological variables. J. Hydro. 476, 265-273. doi:10.1016/j.jhydrol.2012.10.042

Chakraborty, S. D., Kant, Y., & Mitra, D. (2015). Assessment of land surface temperature and heat fluxes over Delhi using remote sensing data. *Journal of environmental management , 148*, 143--152.

Chandna, P. K., & Mondal, S. (2020). Analyzing multi-year rice-fallow dynamics in Odisha using multi-temporal Landsat-8 OLI and Sentinel-1 Data. *GIScience & Remote Sensing} , 57* (4), 431--449.

Chen, X., & Zhou, T. (2015). Distinct effects of global mean warming and regional sea surface warming pattern on projected uncertainty in the South Asian summer monsoon. *Geophysical Research Letters , 42* (21), 9433--9439.

Cook, B. I., Mankin, J. S., & Anchukaitis, K. J. (2018). Climate change and drought: From past to future. *Current Climate Change Reports , 4* (2), 164--179.

Crausbay, S. D., Ramirez, A. R., Carter, S. L., Cross, M. S., Hall, K. R., Bathke, D. J., et al. (2017). Defining ecological drought for the twenty-first century. *Bulletin of the American Meteorological Society} , 98* (12), 2543--2550.

Dai, A., & Zhao, T. (2017). Uncertainties in historical changes and future projections of drought. Part I: estimates of historical drought changes. *144* (3), 519--533.

Dalezios, N. R., Gobin, A., Alfonso, A. M., Tarquis, M., & Eslamian, S. (2017). *Agricultural drought indices: Combining crop, climate, and soil factors*. CRC Press.

Dash, S., Nair, A. A., Kulkarni, M. A., & Mohanty, U. (2011). Characteristic changes in the long and short spells of different rain intensities in India. *Theoretical and applied climatology , 105* (3), 563--570.

Ding, Y., Hayes, M. J., & Widhalm, M. (2011). Measuring economic impacts of drought: a review and discussion. *Disaster Prevention and Management: An International Journal*

De Jeu, R.A.M., Owe, M., 2003. Further validation of a new methodology for surface moisture and vegetation optical depth retrieval. Int. J. Remote Sens. 24, 4559–4578. DOI: 10.1080/0143116031000095934

Dickinson, R.E., Henderson-Sellers, A., Kennedy, P.J. and Wilson, M.F., 1986. Biosphere Atmosphere Transfer Scheme (BATS) for the NCAR Community Climate Model. NCAR Tech. Note, TN-275+STR, 69 pp. DOI: 10.5065/D6668B58

Dorigo, W.A., Scipal, K., Parinussa, R.M., Liu, Y.Y., Wagner, W., de Jeu, R. A. M., Naeimi, V., 2010. Error characterisation of global active and passive microwave soil moisture datasets. Hydrol. Earth Syst. Sc. 14, 2605–2616. doi:10.5194/hess-14-2605-2010

Du, L., Tian, Q., Yu, T., Meng, Q., Jancso, T., Udvardy, P., Huang, Y., 2013. A comprehensive drought monitoring method integrating MODIS and TRMM data. Int. J. Appl. Earth Obs. Geoinform. 23, 245-253. doi:10.1016/j.jag.2012.09.010

Du, L., Tian, Q., Yu, T., Meng, Q., Jancso, T., Udvardy, P., et al. (2013). A comprehensive drought monitoring method integrating MODIS and TRMM data. *International Journal of Applied Earth Observation and Geoinformation , 23*, 245--253.

Dutta, D., Kundu, A., & Patel, N. (2013). Predicting agricultural drought in eastern Rajasthan of India using NDVI and standardized precipitation index. *Geocarto International , 28* (3), 192--209.

Eslamian, S., & Eslamian, F. A. (2017). *Handbook of drought and water scarcity: environmental impacts and analysis of drought and water scarcity*. CRC Press.

Fan, F., Dong, X., Fang, X., Xue, F., Zheng, F., & Zhu, J. (2017). Revisiting the relationship between the South Asian summer monsoon drought and El Ni{\~n}o warming pattern. *Atmospheric Science Letters , 18* (4), 175--182.

Finn, M.P., Lewis, M., Bosch, D.D., Giraldo, M., Yamamoto, K., Sullivan, D.G., Kincaid, R., Luna, R., Allam, G.K., Kvien, C. and Williams, M.S., 2011. Remote sensing of soil moisture using airborne hyperspectral data.GIScience& Remote Sensing, 48(4), 522-540.

Gadgil, S., Vinayachandran, P., & Francis, P. (2003). Droughts of the Indian summer monsoon: Role of clouds over the Indian Ocean. *Current Science* , 1713--1719.

Gaike, A., & Baisane, V. (2019). Drought and It's Effect on Human life". *IJARIIE-ISSN(O)-2395-4396 , 5* (6), 481 - 484.

Gao, Z. a.-B. (2011). Integrating temperature vegetation dryness index (TVDI) and regional water stress index (RWSI) for drought assessment with the aid of LANDSAT TM/ETM+ images. *International Journal of Applied Earth Observation and Geoinformation , 13* (3), 495--503.

Ghazaryan, G., Dubovyk, O., Graw, V., Kussul, N., & Schellberg, J. (2020). Local-scale agricultural drought monitoring with satellite-based multi-sensor time-series. *GIScience & Remote Sensing , 57* (5), 704--718.

Gao, Z., Wang, Q., Cao, X. and 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), 1-16.

Garrigues, S., Allard, D., Baret, F., Weiss, M., 2006. Global and regional land cover characterisation from satellite data: an introduction to the special issue. Int. J. Remote Sens. 21, 1083-1092.

Gutiérrez, A.P.A., Engle, N.L., Nys, E.D., Molejón, C., Martins, S., 2014. Drought preparedness in Brazil. Weather Clim. Extr. 3, 95-106. doi:10.1016/j.wace.2013.12.001

Guhathakurta, P. (2003). Droughts in districts of India during the recent all India normal monsoon years and its probability of occurrence. *Mausam , 54* (2), 542--545.

http://www.star.nesdis.noaa.gov). . (n.d.). Retrieved from http://www.star.nesdis.noaa.gov). .

Huang, J., Yu, H., Guan, X., Wang, G., & Guo, R. (2016). Accelerated dryland expansion under climate change. *Nature climate change , 6* (2), 166--171.

Hulley, G. C., Hook, S. J., & Baldridge, A. M. (2010). Investigating the effects of soil moisture on thermal infrared land surface temperature and emissivity using satellite retrievals and laboratory measurements. *Remote Sensing of Environment , 114*, 1480--1493.

Ha, W., Gowda, P.H. and Howell, T.A., 2011. Downscaling of land surface temperature maps in the Texas high plains with the TsHARP method.GIScience& Remote Sensing, 48(4), 583-599.

Han, Y., Wang, Y., Zhao, Y., 2010. Estimating soil moisture conditions of the Greater Changbai Mountains by land surface temperature and NDVI. IEEE Trans. Geosci. Remote Sens. 48, 2509-2515. DOI: 10.1109/TGRS.2010.2040830

Hong, S., Hendrickx, J.M.H., Borchers, B., 2011. Down-scaling of SEBAL derived evapotranspiration maps from MODIS (250m) to Landsat (30m) scales. Int. J. Remote Sens. 32, 6457-6477. DOI:10.1080/01431161.2010.512929

Hulley, G.C., Hook, S.J., Baldridge, A.M., 2010. Investigating the effects of soil moisture on thermal infrared land surface temperature and emissivity using satellite retrievals and laboratory measurements. Remote Sens. Environ. 114, 1480-1493. doi:10.1016/j.rse.2010.02.002

Hargreaves, George H, and Zohrab A Samani. 1982. “Estimating Potential Evapotranspiration.” Journal of theIrrigation and Drainage Division 108 (3): 225–230.

IPPC. (2001). Climate change 2007: Impacts, adaptation and vulnerability.

Jaman, T., Dharanirajan, K., & Sharma, S. S. (2021). Assessment of impact of cyclone hazard on social vulnerability of Bhadrak District of Odisha State during Phailin Cyclone in 2013 and Titli Cyclone in 2018 using multi-criteria analysis and geospatial techniques. *International Journal of Disaster Risk Reduction , 53*, 101997.

Jehanzaib, M., & Kim, T.-W. (2020). Exploring the influence of climate change-induced drought propagation on wetlands. *Ecological Engineering , 149*, 105799.

Jiang, L., Bao, A., Guo, H., & Ndayisaba, F. (2017). Vegetation dynamics and responses to climate change and human activities in Central Asia. *Science of the Total Environment , 599*, 967--980.

Jin, Q., & Wang, C. (2017). A revival of Indian summer monsoon rainfall since 2002. *7* (8), 587--594.

Justice, C., Townshend, J., Vermote, E., Masuoka, E., Wolfe, R., Saleous, N., et al. (2002). An overview of MODIS Land data processing and product status. *Remote sensing of Environment , 83* (1-2), 3--15.

Jeganathan, C., Hamm, N.A.S., Mukherjee, S., Atkinson, P.M., Raju, P.L.N., Dadhwal, V.K., 2011. Evaluating a thermal image sharpening model over a mixed agricultural landscape in India. Int. J. Appl. Earth Obs. Geoinform. 13, 178-191. doi:10.1016/j.jag.2010.11.001

Kala, C. P. (2017). Environmental and socioeconomic impacts of drought in India: Lessons for drought management. *Applied Ecology and Environmental Sciences , 5* (2), 43--48.

Kala, C. P. (2017). Environmental and socioeconomic impacts of drought in India: Lessons for drought management. *Applied Ecology and Environmental Sciences , 5* (2), 43--48.

Kar, G., Chandra, D., & James, B. (2007). Drought characterization in western districts of Orissa. *Indian J, Softr Com , 35* (2), 97--102.

Karnieli, A., Agam, N., Pinker, R. T., Anderson, M., Imhoff, M. L., Gutman, G. G., et al. (2010). Use of NDVI and land surface temperature for drought assessment: Merits and limitations. *Journal of climate , 23* (3), 618--633.

Karnieli, A., Bayasgalan, M., Bayarjargal, Y., Agam, N., Khudulmur, S., & Tucker, C. (2006). Comments on the use of the vegetation health index over Mongolia. *International Journal of Remote Sensing , 27* (10), 2017--2024.

Keyantash, J. A., & Dracup, J. A. (2004). An aggregate drought index: Assessing drought severity based on fluctuations in the hydrologic cycle and surface water storage. *Water Resources Research , 40* (9).

Kim, D., & Rhee, J. (2016). A drought index based on actual evapotranspiration from the Bouchet hypothesis. *Geophysical Research Letters , 43* (19), 10--277.

Kogan, F. a. (2012). Forecasting crop production using satellite-based vegetation health indices in Kansas, USA. *International journal of remote sensing , 33* (9), 2798--2814.

Kogan, F. N. (2001). Operational space technology for global vegetation assessment. *Bulletin of the American meteorological society , 82* (9), 1949--1964.

Kogan, F. N. (1999). Remote sensing of weather impacts on vegetation in non-homogeneous areas. *International Journal of remote sensing , 11* (8), 1405--1419.

Kogan, F. N. (1999). Remote sensing of weather impacts on vegetation in non-homogeneous areas. *International Journal of remote sensing , 11* (8), 1405--1419.

Kogan, F. (2002). World droughts in the new millennium from AVHRR-based vegetation health indices. *Eos, Transactions American Geophysical Union , 83* (48), 557--563.

Kogan, F., Powell, A., & Fedorov, O. (2011). *Use of satellite and in-situ data to improve sustainability*. Springer.

Kulkarni, A., Gadgil, S., & Patwardhan, S. (2016). Monsoon variability, the 2015 Marathwada drought and rainfed agriculture. *Current Science , 111* (7), 1182--1193.

Kumar, K. K., Rajagopalan, B., Hoerling, M., Bates, G., & Cane, M. (2006). Unraveling the mystery of Indian monsoon failure during El Nino. *Science , 5796* (314), 115--119.

Kalluri, S., Gilruth, P., Bergman, R., 2003. The potential of remote sensing data for decision makers at the state, local and tribal level: experiences from NASA's Synergy program. Environ. Sci. Policy 6, 487-500. doi:10.1016/j.envsci.2003.08.002

Karnieli, A., Agam, N., Pinker, R.T., Anderson, M., Imhoff, M.L., Gutman, G.G., Panov, N., Goldberg, A., 2010. Use of NDVI and Land Surface Temperature for Drought Assessment: Merits and Limitations. J. Climate 23, 618–633. doi: http://dx.doi.org/10.1175/2009JCLI2900.1

Karnieli, A., Bayasgalan, M., Bayarjargal, Y., Agam, N., Khudulmur, S., Tucker, C.J., 2006. Comments on the use of the Vegetation Health Index over Mongolia. Int. J. Remote Sens. 27, 2017-2024. DOI: 10.1080/01431160500121727

Keyantash, J., Dracup, J.A., 2004. An aggregate drought index: assessing drought severity based on fluctuations in the hydrologic cycle and surface water storage. Water Resour. Res. 40, 1-13. doi:10.1029/2003WR002610

Knöpfli, R., 1983. Communication Theory and Generalization. In: Graphic Communication and Design in Contemporary Cartography, Taylor, D. R. F., (ed.), New York, John Wiley, 177

Kogan, F.N., 1990. Remote sensing of weather impacts on vegetation in non-homogeneous areas. Int. J. Remote Sens. 11, 1405-1419. DOI: 10.1080/01431169008955102

Kogan, F.N., 2001. Operational space technology for global vegetation assessment. B. Am. Meteorol. Soc. 82, 1949-1964. doi: http://dx.doi.org/10.1175/1520-0477

Kogan, F.N., 2002. World droughts in the new millennium from AVHRR-based Vegetation Health Indices. Eos, Trans. Amer. Geophys. Union 83(48), 562-563.

Kustas, W.P., Norman, J.M., Anderson, M.C., French, A.N., 2003. Estimating subpixel surface temperatures and energy fluxes from the vegetation index-radiometric temperature relationship. Remote Sens. Environ. 85, 429-440. doi:10.1016/S0034-4257(03)00036-1

Lee, D., Kim, J., Lee, M. H., Lee, S. B., & Kim, J. (2018). IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium. In *Application of Landsat- 8 and Sentinel-L Images for Drought Monitoring Over the Korean Peninsula* (pp. 7286--7288). IEEE.

Liansangpuii, F., Panigrahi, B., & Paul, J. (2019). Assessment of meteorological drought by standardized precipitation index for coastal agro-climatic zones of Odisha, India. *Indian Journal of Soil Conservation , 47* (3), 205--212.

Lillesand, T., Kiefer, R. W., & Chipman, J. (2015). *Remote sensing and image interpretation*. John Wiley & Sons.

Li, Z., Huang, P., 2002. Quantitative measures for spatial information of maps. Int. J. Geogr. Info. Sc., 16, 699-709.

Liu, S., Shi, H., & Sivakumar, B. (2020). Socioeconomic drought under growing population and changing climate: A new index considering the resilience of a regional water resources system. *Journal of Geophysical Research: Atmospheres , 125* (15), e2020JD033005.

Liu, W., Sun, F., Lim, W. H., Zhang, J., Wang, H., Shiogama, H., et al. (2018). Global drought and severe drought-affected populations in 1.5 and 2 C warmer worlds. *Earth System Dynamics , 9* (1), 267--283.

Liu, X., Zhu, X., Pan, Y., Li, S., Liu, Y., & Ma, Y. (2016). Agricultural drought monitoring: Progress, challenges, and prospects. *Journal of Geographical Sciences , 26* (6), 750--767.

Lloyd-Hughes, B. (2014). The impracticality of a universal drought definition. *Theoretical and Applied Climatology , 117* (3), 607--611.

Lopez, T., Al, B., Biancamaria, S., Guntner, A., & Jaggi, A. (2020). On the use of satellite remote sensing to detect floods and droughts at large scales. *Surveys in Geophysics , 41* (6), 1461--1487.

Mahajan, D. R., & Dodamani, B. M. Spatial and temporal drought analysis in the Krishna river basin of Maharashtra, India. *Cogent Engineering , 3* (1), 1185926.

Mondal, A. and Lakshmi, V., 2021. Estimation of total water storage changes in India. International Journal of Digital Earth, 14(10), pp.1294-1315.

Mallick, K., Bhattacharya, B. K., & Patel, N. (2009). Estimating volumetric surface moisture content for cropped soils using a soil wetness index based on surface temperature and NDVI. *Agricultural and Forest Meteorology , 149* (8), 1327--1342.

(1995). Drought monitoring with multiple time scales. In T. B. McKee, *Proceedings of 9th Conference on Applied Climatology, Boston, 1995.*

McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *Proceedings of the 8th Conference on Applied Climatology , 17* (22), 179--183.

Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *391* (1 -2), 202--216.

Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *Journal of hydrology , 391* (1-2), 202--216.

Mishra, A., & Desai, V. (2005). Drought forecasting using stochastic models. *Stochastic environmental research and risk assessment , 19* (5), 326--339.

Mishra, A., & Liu, S. C. (2014). Changes in precipitation pattern and risk of drought over India in the context of global warming. *Journal of Geophysical Research: Atmospheres , 119* (13), 7833--7841.

Mishra, V. (2020). Long-term (1870-2018) drought reconstruction in India. In *EGU General Assembly Conference Abstracts* (p. 12383).

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

Mishra, V., Tiwari, A. D., Aadhar, S., Shah, R., Xiao, M., Pai, D., et al. (2019). Drought and famine in India, 1870--2016. *Geophysical Research Letters , 46* (4), 2075--2083.

Morrow, N., & Friedl, M. (1998). Modeling biophysical controls on land surface temperature and reflectance in grasslands. *Agricultural and Forest Meteorology , 92* (3), 147--161.

Mukherjee, S., Joshi, P., & Garg, R. D. (2014). A comparison of different regression models for downscaling Landsat and MODIS land surface temperature images over heterogeneous landscape. *Advances in Space Research , 54* (4), 655--669.

Mukherjee, S., Mishra, A., & Trenberth, K. E. (2018). Climate change and drought: a perspective on drought indices. *Current Climate Change Reports , 4* (2), 145--163.

Mukherjee, S., Mishra, A., & Trenberth, K. E. (2018). Climate change and drought: a perspective on drought indices. *Current Climate Change Reports , 4* (2), 145--163.

Mallick, K., Bhattacharya, B. K., Patel, N. K., 2009. Estimating volumetric surface moisture content for cropped soils using a soil wetness index based on surface temperature and NDVI. Agr. Forest Meteorol. 149, 1327-1342. doi:10.1016/j.agrformet.2009.03.004

McKee, T.B., Doesken, N.J., Kleist, J., 1993. The relation of drought frequency and duration to time scales. Proceedings of the Eighth Conference on Applied Climatology. American Meteorological Society, Boston, 179–184.

Merlin, O., Duchemin, B., Hagolle, O., Jacob, F., Coudert, B., Chehbouni, G., Dedieu, G., Garatuza, J., Kerr, Y., 2010. Disaggregation of MODIS surface temperature over an agricultural area using a time series of Formosat-2 images. Remote Sens. Environ. 114, 2500-2512. doi:10.1016/j.rse.2010.05.025

Mishra, A.K., Desai, V.R., 2005. Spatial and temporal drought analysis in the Kansabati River Basin India. Int. J. River Basin Manag. 3, 31–41.

Mishra, A.K., Singh, V.P., 2010. A review of drought concepts. J. Hydro. 391, 202–216. doi:10.1016/j.jhydrol.2010.07.012

Moran, M.S., Clarke, T.R., Inoue, Y., Vidal, A., 1994. Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index. Remote Sens. Environ. 49(3), 246-263. doi:10.1016/0034-4257(94)90020-5

Moran, M.S., Rahman, A.F., Washburne, J.C., Kustas W.P., 1996. Combining the Penman-Monteith equation with measurements of surface temperature and reflectance to estimate evoparation rates of semiarid grassland. Agr. Forest Meteorol. 80, 87-109. doi:10.1016/0168-1923(95)02292-9

Morrow, N., Friedl, M.A., 1998. Modeling biophysical controls on land surface temperature reflectance in grasslands. Agr. Forest Meteorol. 92(3), 147-161. doi:10.1016/S0168-1923(98)00098-7

Mukherjee, S., Joshi, P.K., Garg, R.D., 2014a. A comparison of different regression models for downscaling Landsat and MODIS land surface temperature images over heterogeneous landscape. Adv. Space Res. 54, 655-669. doi:10.1016/j.asr.2014.04.013

Mukherjee, T., Mukherjee, S., Mukhopadhaya, A., Roy, A.K., Dutta., S., 2014b. Drought Monitoring of Chhattisgarh Using Different Indices Based on Remote Sensing Data. Climate Change and Biodiversity: Proceedings of IGU Rohtak Conference, Vol. 1, Advances in Geographical and Environmental Sciences, Springer Japan.

Muriithi, F.K., Yu, D. and Robila, S., 2016. Vegetation response to intensive commercial horticulture and environmental changes within watersheds in central highlands, Kenya, using AVHRR NDVI data. GIScience& Remote Sensing, 53(1), 1-21.

Nalbantis, I. (2008). Evaluation of a hydrological drought index. *European water , 23* (24), 67--77.

Narasimhan, B., & Srinivasan, R. (2005). Development and evaluation of Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) for agricultural drought monitoring. *forest meteorology , 133* (1-4), 69--88.

Nguyen, M. D., Baez, V., Oscar, M., Bui, D. D., Nguyen, P. T., & Ribbe, L. (2020). Harmonization of landsat and sentinel 2 for crop monitoring in drought prone areas: Case studies of Ninh Thuan (Vietnam) and Bekaa (Lebanon). *Remote Sensing , 12* (2), 281.

Orhan, O., Ekercin, S., & Dadaser-Celik, F. (2014). Use of landsat land surface temperature and vegetation indices for monitoring drought in the Salt Lake Basin Area, Turkey. *The Scientific World Journal , 2014.*

Ozelkan, E., Chen, G., & Ustundag, B. B. (2016). Multiscale object-based drought monitoring and comparison in rainfed and irrigated agriculture from Landsat 8 OLI imagery. *International Journal of Applied Earth Observation and Geoinformation , 44*, 59--170.

Palmer, W. C. (1965). *Meteorological drought* (Vol. 30). US Department of Commerce, Weather Bureau.

Palmer, W. C. (1965). *Meteorological drought* (Vol. 30). US Department of Commerce, Weather Bureau.

Panda, A. (2016). Exploring climate change perceptions, rainfall trends and perceived barriers to adaptation in a drought affected region in India. *84* (2), 777--796.

Panda, T., Mishra, N., Pradhan, B., & Mohanty, R. (2015). Diversity of leafy vegetables and its significance to rural households of Bhadrak district, Odisha, India. *Scientia agriculturae , 11* (3), 114--123.

Patel, S. K. (2018). Community-level assessment of droughts in Odisha: Effects, resilience, and implications.

Peters, A. J., Walter, S., Elizabeth, A., Ji, L., Vina, A., Hayes, M., et al. (2002). Drought monitoring with NDVI-based standardized vegetation index. *Photogrammetric engineering and remote sensing , 68* (1), 71--75.

Prabhakar, S., & Shaw, R. (2008). Climate change adaptation implications for drought risk mitigation: a perspective for India. *Climatic Change , 88* (2), 113--130.

Palmer, W.C., 1965. Meteorological drought. Research Paper No. 45, U.S. Department of Commerce Weather Bureau,Washington, DC.

Pandey, B., Seto, K.C., 2014. Urbanization and agricultural land loss in India: Comparing satellite estimates with census data. J. Environ. Manage. 148, 53-66. doi: 10.1016/j.jenvman.2014.05.014.

Patel, N.R., Anapashsha, R., Kumar, S., Saha, S.K., Dadhwal, V.K., 2009. Assessing potential of MODIS derived temperature/vegetation condition index (TVDI) to infer soil moisture status. Int. J. Remote Sens. 30, 23-29. DOI:10.1080/01431160802108497

Peters, A.J., Walter-Shea, E.A., Ji, L., Vina, A., Hayes, M., Svoboda, M.D., 2002. Drought monitoring with NDVI-based standardized vegetation index. Photogram. Eng. Rem. Sens. 68, 71–75.

Qin, Q., Ghulam, A., Zhu, L., Wang, L., Li, J., Nan, P., 2008. Evaluation of MODIS derived perpendicular drought index for estimation of surface dryness over northwestern China. Int. J. Remote Sens. 29, 1983–1995. DOI:10.1080/01431160701355264

Ray, S., Sesha, S., & Chattopadhyay, N. (2015). Agricultural drought assessment: Operational approaches in India with special emphasis on 2012. *High-impact weather events over the SAARC region* , 349--364.

Ray-Bennett, & Nibedita, S. (2009). Multiple disasters and policy responses in pre-and post-independence Orissa, India. *Disasters , 33* (2), 274--290.

Rhee, J., Im, J., & Carbone, G. J. (2010). Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data. *Remote Sensing of environment , 114* (12), 2875--2887.

Riebsame, W. E. (1991). Climate hazards, climatic change and development planning. *Land Use Policy , 8* (4), 288--296.

Ringrose, S., & Matheson, W. (1991). A Landsat analysis of range conditions in the Botswana Kalahari drought. *International Journal of Remote Sensing , 12* (5), 1023--1051.

Rojas, O., Vrieling, A., & Rembold, F. (2011). Assessing drought probability for agricultural areas in Africa with coarse resolution remote sensing imagery. *Remote sensing of Environment , 115* (2), 343--352.

Roxy, M. K., Ritika, K., Terray, P., Murtugudde, R., Ashok, K., & Goswami, B. (2015). Drying of Indian subcontinent by rapid Indian Ocean warming and a weakening land-sea thermal gradient. *Nature communications , 6* (1), 1--10.

Rudiger, C., Calvet, J.-C., Gruhier, C., Holmes, T. R., De, J., Richard, A., et al. (2009). An intercomparison of ERS-Scat and AMSR-E soil moisture observations with model simulations over France. *Journal of Hydrometeorology , 10* (2), 431--447.

Rhee, J., Im, J., Carbone, G. J., 2010. Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data. Remote Sens. Environ. 114, 2875-2887. doi:10.1016/j.rse.2010.07.005

Rhee, J., Park, S. and Lu, Z., 2014. Relationship between land cover patterns and surface temperature in urban areas. GIScience& Remote Sensing, 51(5), 521-536.

Riebsame, W.E., 1991. Climate hazards, climatic change and development planning. Land Use Policy 8, 288-296. doi:10.1016/0264-8377(91)90019-F

Rodriguez-Galiano, V., Pardo-Iguzquiza, E., Sanchez-Castillo, M., Chica-Olmo, M., Chica-Rivas, M., 2012. Downscaling Landsat 7 ETM+ thermal imagery using land surface temperature and NDVI images. Int. J. Appl. Earth Obs. Geoinform. 18, 515-527. doi:10.1016/j.jag.2011.10.002

Rojas, O., Vrieling, A., Rembold, F., 2011. Assessing drought probability for agricultural areas in Africa with coarse resolution remote sensing imagery. Remote Sens. Environ. 115, 343-352. doi:10.1016/j.rse.2010.09.006

Rousseeuw, P.J., 1984. Least Median of Squares Regression. J. Am. Stat. Assoc. 79, 871-880.

Rouse Jr., J.W., Haas R.H., Shell JA., Deering D.W. 1973. Monitoring vegetation systems in the Great Plains with ERTS. In: Third Earth Resources Technology Satellite-1 Symposium, 10-14 December 1973, Vol. 1, Washington D.C., 309-317.

Rudiger, C., Calvet, J.C., Gruhier, C., Holmes, T.R.H., de Jeu, R.A.M., Wagner, W., 2009. An intercomparison of ERS-Scat and AMSR-E soil moisture observations with model simulations over France. J. Hydrometeorology 10, 431–447. doi: http://dx.doi.org/10.1175/2008JHM997.1

Sandholt, I., Rasmussen, K., Andersen, J., 2002. A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status. Remote Sens. Environ. 79, 213-224. doi:10.1016/S0034-4257(01)00274-7

Seiler, R.A., Kogan, F., Sullivan, J., 1998. AVHRR-based vegetation and temperature condition indices for drought detection in Argentina. Adv. Space Res. 21, 481-484. doi:10.1016/S0273-1177(97)00884-3

Sellers, P.J., Mintz, Y., Sud, Y.C. and Dalcher, A., 1986. A simple biosphere model (SiB) for use within general circulation models. J. Atmos. Sci. 43, 505-531. doi: http://dx.doi.org/10.1175/1520-0469

Shannon, C.E., 1948. A mathematical theory of communication. Bell Sys. Tech. J. 27, 379-443.

Singh, R.P., Kogan, F.N., 2002. Monitoring vegetation condition from NOAA operational polar-orbiting satellites over Indian region. J. Indian Soc. of Remote Sens. 30, 117-118.

Sobrino, J.A., Gomez, M., Munoz, J.C.J., Olioso, A., 2007. Application of a simple algorithm to estimate daily evapotranspiration from NOAA-AVHRR images for the Iberian Peninsula. Remote Sens. Environ. 110, 139-148. doi:10.1016/j.rse.2007.02.017

Son, N. T., Chen, C. F., Chen, C. R., Chang, L. Y., Minh, V. Q., 2012. Monitoring agricultural drought in the Lower Mekong Basin using MODIS NDVI and land surface temperature data. Int. J. Appl. Earth Obs. Geoinform. 18, 417-427. doi:10.1016/j.jag.2012.03.014

Swain, S., Wardlow, B.D., Narumalani, S., Tadesse, T. and Callahan, K., 2011. Assessment of vegetation response to drought in Nebraska using Terra-MODIS land surface temperature and normalized difference vegetation index. GIScience& Remote Sensing, 48(3), 432-455.

Sun,W., Wang, P.X., Zhang, S.Y., Zhu, D.H., Liu, J.M., Chen, J.H., Yang, H.S., 2008. Using the vegetation temperature condition index for time series drought occurrence monitoring in the Guanzhong Plain, PR China. Int. J. Remote Sens. 29, 5133-5144. DOI: 10.1080/01431160802036557

USDA. 1994. Major world crop areas and climatic profiles. World Agricultural Outlook Board, US Department of Agriculture. Agricultural Handbook No. 664, 157–70.

Sabeerali, C., Rao, S. A., Dhakate, A., Salunke, K., & Goswami, B. (2015). Why ensemble mean projection of south Asian monsoon rainfall by CMIP5 models is not reliable? *Climate Dynamics , 45* (1), 161--174.

Saha, S., Kundu, B., Paul, G. C., Mukherjee, K., Pradhan, B., Dikshit, A., et al. (2021). Spatial assessment of drought vulnerability using fuzzy-analytical hierarchical process: a case study at the Indian state of Odisha. *Geomatics, Natural Hazards and Risk , 12* (1), 123--153.

Santos, C., Augusto, G., Neto, R., Moura, B., do, N., Thiago, V. M., et al. (2021). Geospatial drought severity analysis based on PERSIANN-CDR-estimated rainfall data for Odisha state in India (1983--2018). *Science of the Total Environment , 750*, 141258.

Sarangi, P., & Penthoi, G. (2012). Economic Implications of Natural Disasters in, Orissa: A Retrospective View. *Orissa Review* .

Seiler, R., Kogan, F., & Sullivan, J. (1998). AVHRR-based vegetation and temperature condition indices for drought detection in Argentina. *Advances in Space Research , 21* (3), 481--484.

Shah, D., & Mishra, V. (2020). Integrated Drought Index (IDI) for drought monitoring and assessment in India. *Water Resources Research , 56* (2), e2019WR026284.

Shah, D., & Mishra, V. (2020). Integrated Drought Index (IDI) for drought monitoring and assessment in India. *Water Resources Research , 56* (2), e2019WR026284.

Sharmila, s., Joseph, S., Sahai, A., Abhilash, S., & Chattopadhyay, R. (2015). Future projection of Indian summer monsoon variability under climate change scenario: An assessment from CMIP5 climate models. *Global and Planetary Change , 124*, 62--78.

Shewale, M., & Kumar, S. (2005). Climatological features of drought incidences in India. *Meteorological Monograph (Climatology 21/2005). National Climate Centre, Indian Meteorological Department* .

Sholihah, R. I., Trisasongko, B. H., Shiddiq, D., La Ode, S., Iman, S., Kusdaryanto, S., et al. (2016). Identification of agricultural drought extent based on vegetation health indices of landsat data: case of Subang and Karawang, Indonesia. *Procedia Environmental Sciences , 33*, 14--20.

Shrivastava, S., Kar, S. C., Sahai, A., & Sharma, A. R. (2018). Identification of drought occurrences using ensemble predictions up to 20-days in advance. *Water resources management , 32* (6), 2113--2130.

Singh, R. P., Roy, S., & Kogan, F. (2003). Vegetation and temperature condition indices from NOAA AVHRR data for drought monitoring over India. *International journal of remote sensing , 24* (22), 4393--4402.

Sobrino, J., Gomez, M., Jimenez-Munoz, J., & Olioso, A. (2007). Application of a simple algorithm to estimate daily evapotranspiration from NOAA--AVHRR images for the Iberian Peninsula. *Remote sensing of Environment , 110* (2), 139--148.

Son, N. T., Chen, C., Chen, C., Chang, L., & Minh, V. Q. (2012). Monitoring agricultural drought in the Lower Mekong Basin using MODIS NDVI and land surface temperature data. *International Journal of Applied Earth Observation and Geoinformation , 18*, 417--427.

Stanke, C., Kerac, M., Prudhomme, C., Medlock, J., & Murray, V. (2013). Health effects of drought: a systematic review of the evidence. *PLoS currents , 5*.

(2021). Identification of meteorological extreme years over central division of Odisha using an index-based approach. In S. Swain, S. Mishra, A. Pandey, & D. Dayal, *Hydrological Extremes* (pp. 161--174). Springer.

Swain, S., Nandi, S., & Patel, P. (2018). Development of an ARIMA model for monthly rainfall forecasting over Khordha district, Odisha, India. In *Recent Findings in Intelligent Computing Techniques* (pp. 325--331). Springer.

Swain, S., Nandi, S., & Patel, P. (2018). Development of an ARIMA model for monthly rainfall forecasting over Khordha district, Odisha, India. In *Recent Findings in Intelligent Computing Techniques* (pp. 325--331). Springer.

Saha, S., Kundu, B., Paul, G.C., Mukherjee, K., Pradhan, B., Dikshit, A., Abdul Maulud, K.N. and Alamri, A.M., 2021. Spatial assessment of drought vulnerability using fuzzy-analytical hierarchical process: a case study at the Indian state of Odisha. Geomatics, Natural Hazards and Risk, 12(1), pp.123-153.

Santos, C.A.G., Neto, R.M.B., do Nascimento, T.V.M., da Silva, R.M., Mishra, M. and Frade, T.G., 2021. Geospatial drought severity analysis based on PERSIANN-CDR-estimated rainfall data for Odisha state in India (1983–2018). Science of the Total Environment, 750, p.141258.

Tate, E., & Gustard, A. Drought definition: a hydrological perspective. In D. a. Europe, *2000* (pp. 23--48). Springer.

Taylor, K., Stouffer, R., & Meehl, G. (2012). An overview of CMIP5 and the experiment design, B. Am. Meteorol. Soc. *93*, 485--498.

Torres, R., Snoeij, P., Geudtner, D., Bibby, D., Davidson, M., Attema, E., et al. (2012). GMES Sentinel-1 mission. *Remote sensing of environment , 120*, 9--24.

Tiwari, A.D. and Mishra, V., 2019. Prediction of reservoir storage anomalies in India. Journal of Geophysical Research: Atmospheres, 124(7), pp.3822-3838.

Trenberth, K. E., Dai, A., Rasmussen, R. M., & Parsons, D. B. (2003). The changing character of precipitation. *Bulletin of the American Meteorological Society , 84* (9), 1205--1218.

Tsakiris, G. a. (2005). Establishing a drought index incorporating evapotranspiration. *European water , 9* (10), 3--11.

Turner, A. G., & Annamalai, H. (2012). Climate change and the South Asian summer monsoon. *Nature Climate Change , 2* (8), 587--595.

Ummenhofer, C., D'Arrigo, R. D., Anchukaitis, K. J., Buckley, B. M., & Cook, E. R. (2013). Links between Indo-Pacific climate variability and drought in the Monsoon Asia Drought Atlas. *Climate dynamics , 40* (5), 1319--1334.

Urban, M., Berger, C., Mudau, T. E., Heckel, K., Truckenbrodt, J., Onyango, O., et al. (2018). Surface moisture and vegetation cover analysis for drought monitoring in the southern Kruger National Park using Sentinel-1, Sentinel-2, and Landsat-8. *Remote Sensing , 10* (9), 1482.

Van, L., & Anne, F. (2015). Hydrological drought explained. *Wiley Interdisciplinary Reviews: Water , 2* (4), 359--392.

Verstraeten, W. W., Veroustraete, F., van der Sande, C. J., Grootaers, I., & Feyen, J. (2006). Soil moisture retrieval using thermal inertia, determined with visible and thermal spaceborne data, validated for European forests. *Remote Sensing of Environment , 101* (3), 299--314.

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

Vicente-Serrano, S. M., & Beguer, S. (2010). A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *Journal of climate , 23* (7), 1696--1718.

Vadrevu, K., Lasko, K., 2014. Fire regimes and potential bioenergy loss from agricultural lands in the Indo-Gangetic Plains. J. Environ. Manage. 148, 10-20. doi:10.1016/j.jenvman.2013.12.026

Verstraeten, W.W., Veroustraete, F., Sande, C.J.V.D., Grootaers, I., Feyen, J., 2006. Soil moisture retrieval using thermal inertia, determined with visible and thermal spaceborne data, validated for European forests. Remote Sens. Environ. 101, 299-314. doi:10.1016/j.rse.2005.12.016

Vieux, B.E., 1993. DEM aggregation and smoothing effect on surface run-off modeling. J. Comput Civil Eng. 7, 310-338. DOI: 10.1061/(ASCE)0887-3801

Vieux, B.E. Farajalla, N.S., 1994. Capturing the essential spatial variability in distributed hydrological modelling: hydraulic roughness. Hydrol. Processes 8, 221-26. DOI: 10.1002/hyp.3360080304

Wald, L., 1999. Some terms of reference in data fusion. IEEE Trans. Geosci. Remote Sens. 37, 1190-1193.

Wald, L., Ranchin, T., Mangolini, M., 1997. Fusion of satellite images of different spatial resolutions: assessing the quality of resulting images. Photogram. Eng. Rem. Sens. 63, 691-699.

Wan, Z., Wang, P., Li, X., 2004. Using MODIS land surface temperature and Normalized Difference Vegetation Index products for monitoring drought in the southern Great Plains, USA. Int. J. Remote Sens. 25, 61-72. DOI:10.1080/0143116031000115328

Wardlow, B.D. and Callahan, K., 2014. A multi-scale accuracy assessment of the MODIS irrigated agriculture data-set (MIrAD) for the state of Nebraska, USA. GIScience& Remote Sensing, 51(5), 575-592.

Wang, X., Chen, N., Chen, Z., Yang, X. and Li, J., 2016. Earth observation metadata ontology model for spatiotemporal-spectral semantic-enhanced satellite observation discovery: a case study of soil moisture monitoring.GIScience& Remote Sensing, 53(1), 22-44.

Wilhite, D.A., 2000. Drought as a natural hazard: concepts and definitions. In: Wilhite, D.A. (Ed.), Drought: A Global Assessment, vol. 1. Routledge, New York, 1–18.

Wilhite, D.A., 2003. Drought. Encyclopedia of Atmospheric Sciences, 650-658.

Wise, S., 2012. Information entropy as a measure of DEM quality. ComputGeosci. 48, 102-110. doi:10.1016/j.cageo.2012.05.011

World Bank. 2012. Turn down the Heat: Why a 4 °C Warmer World Must Be Avoided: World Bank Group, Washington DC.

Wu, J., Zhou, L., Liu, M., Zhang, J., Leng, S., Diao, C., 2013. Establishing and assessing the Integrated Surface Drought Index (ISDI) for agricultural drought monitoring in mid-eastern China. Int. J. Appl. Earth Obs. Geoinform. 23, 397-410. doi:10.1016/j.jag.2012.11.003

Wylie, B.K., Meyer, D.J., Tieszen, L.L. and Mannel, S., 2002. Satellite mapping of surface biophysical parameters at the biome scale over the North American grasslands – a case study. Remote Sens. Environ. 79, 266-278. doi:10.1016/S0034-4257(01)00278-4

Wan, Z., Wang, P., & Li, X. (2004). Using MODIS land surface temperature and normalized difference vegetation index products for monitoring drought in the southern Great Plains, USA. *International journal of remote sensing , 25* (1), 61--72.

Wang, X., Ge, L., & Li, X. (2013). Pasture monitoring using sar with cosmo-skymed, envisat asar, and alos palsar in otway, australia. *Remote Sensing , 5* (7), 3611--3636.

Ward n, P. S., & Makhija, S. (2018). New modalities for managing drought risk in rainfed agriculture: Evidence from a discrete choice experiment in Odisha, India. *World Development* , 163--175.

Wardlow, B. D., Anderson, M. C., & Verdin, J. P. (2012). *Remote sensing of drought: Innovative monitoring approaches*. CRC Press.

Wilhite, D. A. (2000). Drought as a natural hazard: concepts and definitions.

Wilhite, D. A., & Glantz, M. H. (1985). Understanding: the drought phenomenon: the role of definitions. *Water international , 3* (10), 111--120.

Wilhite, D. A., & Glantz, M. H. (1985). Understanding: the drought phenomenon: the role of definitions. *Water international , 10* (3), 111--120.

Wilhite, D., Drought, ,. A., Holton, J., Pyle, C., & Curry, J. (2003). Encyclopedia of Atmospheric Science.

Wu, J., Zhou, L., Liu, M., Zhang, J., Leng, S., & Diao, C. (2013). Establishing and assessing the Integrated Surface Drought Index (ISDI) for agricultural drought monitoring in mid-eastern China. *International Journal of Applied Earth Observation and Geoinformation , 23*, 397--410.

Wang, K.Y., Li, Q.F., Yang, Y., Zeng, M., Li, P.C. and Zhang, J.X., 2015. Analysis of spatio-temporal evolution of droughts in Luanhe River Basin using different drought indices. Water Science and Engineering, 8(4), pp.282-290

Xin, F., Tian, G., Liu, Q., Chen, L., 2006. Combining vegetation index and remotely sensed temperature for estimation of soil moisture in China. Int. J. Remote Sens. 27, 2071-2075. DOI:10.1080/01431160500497549

Yang, J., & Wang, Y. (2011). Estimating evapotranspiration fraction by modeling two-dimensional space of NDVI/albedo and day--night land surface temperature difference: A comparative study. *Advances in Water Resources , 34* (4), 512--518.

Yagci, A.L., Di, L. and Deng, M., 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(3), 290-314.

Yang, G., Pu, R., Zhao, C., Huang, W., Wang, J., 2010a. Estimation of subpixel land surface temperature using an endmember index based technique: A case examination on ASTER and MODIS temperature products over a heterogeneous area. Remote Sens. Environ. 115, 1202-1219. doi:10.1016/j.rse.2011.01.004

Yang, H., Cong, Z., Liu, Z., Lei, Z., 2010b. Estimating sub-pixel temperatures using the triangle algorithm. Int. J. Remote Sens. 3123, 6047-6060. DOI: 10.1080/01431160903376373

Yang, J., Wang, Y., 2011.Estimating evapotranspiration fraction by modeling two-dimensional space of NDVI/albedo and day–night land surface temperature difference: A comparative study. Adv. Water Resour. 34, 512-518. doi:10.1016/j.advwatres.2011.01.006

Yang, L., 2000. Integration of a numerical model and remotely sensed data to study urban/rural land surface climate processes. ComputGeosci. 26, 451-468. doi:10.1016/S0098-3004(99)00124-7

Zhao, T., & Dai, A. (2015). The magnitude and causes of global drought changes in the twenty-first century under a low--moderate emissions scenario. *Journal of climate , 28* (11), 4490--4512.

Zolotokrylin, A. (2010). Droughts: causes, distribution and consequences. *Natural Disasters , 1*, 239.

Zhan, W., Chen, Y., Zhou, J., Wang, J., Liu, W., Voogt, J., Zhu, X., Quan, J., Li. J., 2013. Disaggregation of remotely sensed land surface temperature: Literature survey, taxonomy, issues, and caveats. Remote Sens. Environ. 131, 119-139. doi:10.1016/j.rse.2012.12.014

Zhu, S., Guan, H., Millington, A. C., Zhang, G., 2013. Disaggregation of land surface temperature over a heterogeneous urban and surrounding suburban area: a case study in Shanghai, China. Int. J. Remote Sens. 34, 1707-1723. DOI:10.1080/01431161.2012.725957

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44 Leinenkugel, Patrick, Michel L. Wolters, Natascha Oppelt, and Claudia Kuenzer. "Tree cover and forest cover dynamics in the Mekong Basin from 2001 to 2011", Remote Sensing of Environment, 2015.
Crossref
25 words — < 1%

45 N. Singh, M. Yunus, K. Srivastava, S. N. Singh, V. Pandey, J. Misra, K. J. Ahmad. "Monitoring of auto exhaust pollution by roadside plants", Environmental Monitoring and Assessment, 1995
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25 words — < 1%

46 orissa.news.in
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47 "Data Assimilation for Atmospheric, Oceanic and Hydrologic Applications (Vol. IV)", Springer Science and Business Media LLC, 2022
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48 Jinlong Huang, Sanjit Kumar Mondal, Jianqing Zhai, Thomas Fischer et al. "Intensity-area-duration-based drought analysis under 1.5°C–4.0°C warming using CMIP6 over a climate hotspot in South Asia", Journal of Cleaner Production, 2022
Crossref
24 words — < 1%

49 ir.msu.ac.zw:8080
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51 C. Bhuiyan. "Monsoon variation and vegetative drought patterns in the Luni Basin in the rain-shadow zone", International Journal of Remote Sensing, 04/2010
Crossref
22 words — < 1%

52 Federico Filipponi. "Sentinel-1 GRD Preprocessing Workflow", 3rd International Electronic Conference on Remote Sensing, 2019
Crossref
22 words — < 1%

53 Mohammad Sadegh Abbasian, Mohammad Reza Najafi, Ahmad Abrishamchi. "Increasing risk of meteorological drought in the Lake Urmia basin under climate change: Introducing the precipitation–temperature deciles index", Journal of Hydrology, 2021
Crossref
22 words — < 1%

54 Niloy Pramanick, Rituparna Acharyya, Sandip Mukherjee, Sudipta Mukherjee, Indrajit Pal, Debashis Mitra, Anirban Mukhopadhyay. "SAR based flood risk analysis: a case study Kerala Flood 2018", Advances in Space Research, 2021
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59 Luminda Niroshana Gunawardhana, So Kazama, Saeki Kawagoe. "Impact of Urbanization and Climate Change on Aquifer Thermal Regimes", Water Resources Management, 2011
Crossref
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60 Rupali S. Ahire, Vikrant Nikam. "Analysis of Changes in Rainfall Magnitude over Haridwar District, India", World Environmental and Water Resources Congress 2020, 2020
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61 etd.aau.edu.et
Internet
20 words — < 1%

62 Ana Paula M. A. Cunha, Marcelo Zeri, Karinne Deusdará Leal, Lidiane Costa et al. "Extreme Drought Events over Brazil from 2011 to 2019", Atmosphere, 2019
Crossref
19 words — < 1%

63 Saran Aadhar, Vimal Mishra. "On the Projected Decline in Droughts Over South Asia in CMIP6 Multimodel Ensemble", Journal of Geophysical Research: Atmospheres, 2020
Crossref
19 words — < 1%

64 archive.org
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65 C. T. Sabeerali, Suryachandra A. Rao, R. S. Ajayamohan, Raghu Murtugudde. "On the relationship between Indian summer monsoon withdrawal and Indo-Pacific SST anomalies before and after 1976/1977 climate shift", Climate Dynamics, 2011
Crossref
18 words — < 1%

66 Hung Manh Le, Gerald Corzo, Vicente Medina, Vitali Diaz, Bang Luong Nguyen, Dimitri P. Solomatine. "A Comparison of Spatial–Temporal Scale Between Multiscalar Drought Indices in the South Central Region of Vietnam", Elsevier BV, 2019 — 18 words — < 1%
Crossref

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71 Deep Shah, Harsh L. Shah, Hari Manish Dave, Vimal Mishra. "Contrasting influence of human activities on agricultural and hydrological droughts in India", Science of The Total Environment, 2021 — 17 words — < 1%
Crossref

72 Grekousis, George, Marinos Kavouras, and Giorgos Mountrakis. "Land cover dynamics and accounts for European Union 2001-2011", Third International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2015), 2015. — 17 words — < 1%
Crossref

73 K.L. Chong, Y.F. Huang, C.H. Koo, Ali Najah Ahmed, Ahmed El-Shafie. "Spatiotemporal Variability Analysis of Standardized Precipitation Indexed Droughts Using Wavelet Transform", Journal of Hydrology, 2021 — 17 words — < 1%

Crossref

74 Monica Ionita, Silvia Chelcea. "chapter 2 Spatio-Temporal Variability of Seasonal Drought over the Dobrogea Region", IGI Global, 2015 — 17 words — < 1%
Crossref

75 Semra Kocaaslan, Nebiye Musaoglu, Saeid Karamzadeh. "Evaluating Drought Events by Time-Frequency Analysis: A case study in Aegean Region of Turkey", IEEE Access, 2021 — 17 words — < 1%
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Crossref 16 words — < 1%

87 J. Rajbanshi, S. Das. "The variability and teleconnections of meteorological drought in the Indian summer monsoon season: Implications for staple crop production", Journal of Hydrology, 2021
Crossref 16 words — < 1%

88 Most.Shahana Sultana, Yousuf Gazi, Bodruddoza Mia. "Multiple indices based agricultural drought assessment in the northwestern part of Bangladesh using geospatial techniques.", Environmental Challenges, 2021
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Crossref 16 words — < 1%

90 Pervez, M. S., and G. M. Henebry. "Spatial and seasonal responses of precipitation in the Ganges and Brahmaputra river basins to ENSO and Indian Ocean dipole modes: implications for flooding and drought", Natural Hazards and Earth System Science, 2015.
Crossref 16 words — < 1%

91 Pooja Verma, Amrita Biswas, Swastika Chakraborty. "Statistical analysis of an orographic rainfall for Eight North-East region of India with special focus over Sikkim", International Journal of Informatics and Communication Technology (IJ-ICT), 2022
Crossref
16 words — < 1%

92 Shamsuddin Shahid. "Drought risk assessment in the western part of Bangladesh", Natural Hazards, 09/2008
Crossref
16 words — < 1%

93 Zengchao Hao, Xing Yuan, Youlong Xia, Fanghua Hao, Vijay P. Singh. "An Overview of Drought Monitoring and Prediction Systems at Regional and Global Scales", Bulletin of the American Meteorological Society, 2017
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96 Arika Bridhikitti, Pajanun Ruamchalerm, Mathawut Keereesuwannakul, Thayukorn Prabamroong, Gaohuan Liu, Chong Huang. "Magnitude and factors influencing soil loss and sedimentation in the Mun River Basin, Thailand", CATENA, 2022
Crossref
14 words — < 1%

97 Arun Mondal, Venkat Lakshmi, Hossein Hashemi. "Intercomparison of trend analysis of Multisatellite Monthly Precipitation Products and Gauge Measurements for River Basins of India", Journal of Hydrology, 2018
Crossref
14 words — < 1%

98 Remote Sensing and Digital Image Processing, 2011.
Crossref
14 words — < 1%

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105 Lei Fan, Qinyu Liu, Chunzai Wang, Feiyan Guo. "Indian Ocean Dipole Modes Associated with Different Types of ENSO Development", Journal of Climate, 2017
Crossref
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ProQuest
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Change and Food Security: The Impact of Some Key Variables on Wheat Yield in Kazakhstan", Sustainability, 2021
Crossref

108 Abdelaziz Elfadaly, Nicodemo Abate, Nicola Masini, Rosa Lasaponara. "SAR Sentinel 1 Imaging and Detection of Palaeo-Landscape Features in the Mediterranean Area", Remote Sensing, 2020 — 12 words — < 1%
Crossref

109 Feng Liu, David G. Rossiter, Xiaodong Song, Gan‐Lin Zhang, Huayong Wu, Yuguo Zhao. "An approach for broad‐scale predictive soil properties mapping in low‐relief areas based on responses to solar radiation", Soil Science Society of America Journal, 2020 — 12 words — < 1%
Crossref

110 Knapp, Alan K., David L. Hoover, Kevin R. Wilcox, Meghan L. Avolio, Sally E. Koerner, Kimberly J. La Pierre, Michael E. Loik, Yiqi Luo, Osvaldo E. Sala, and Melinda D. Smith. "Characterizing differences in precipitation regimes of extreme wet and dry years: Implications for climate change experiments", Global Change Biology, 2015. — 12 words — < 1%
Crossref

111 S. K. Jain, R. Keshri, A. Goswami, A. Sarkar, A. Chaudhry. "Identification of drought‐vulnerable areas using NOAA AVHRR data", International Journal of Remote Sensing, 2009 — 12 words — < 1%
Crossref

112 Scaini, Anna, Nilda Sánchez, Sergio M. Vicente-Serrano, and José Martínez-Fernández. "SMOS-derived soil moisture anomalies and drought indices: a comparative analysis using in situ measurements : A COMPARATIVE ANALYSIS: SMOS-DERIVED SOIL MOISTURE AND DROUGHT INDICES", Hydrological Processes, 2014. — 12 words — < 1%

Crossref

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Internet
12 words — < 1%

115 www.planum.net
Internet
12 words — < 1%

116 Li, Chunqiang, Hongjun Li, and Susan L. Ustin. "<title>Study on winter wheat drought monitoring by TVDI in Hebei Province</title>", Remote Sensing and Modeling of Ecosystems for Sustainability III, 2006.
Crossref
11 words — < 1%

117 Pirjo Huovinen, Jaime Ramírez, Mauricio Palacios, Iván Gómez. "Satellite-derived mapping of kelp distribution and water optics in the glacier impacted Yendegaia Fjord (Beagle Channel, Southern Chilean Patagonia)", Science of The Total Environment, 2020
Crossref
11 words — < 1%

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122 www.hydrol-earth-syst-sci.net
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123 www.unoosa.org
Internet
11 words — < 1%

124 "Proceedings of the Eighth International Conference on Management Science and Engineering Management", Springer Science and Business Media LLC, 2014
Crossref
10 words — < 1%

125 Alok Kumar Samantaray, Gurjeet Singh, Meenu Ramadas, Rabindra Kumar Panda. "Drought hotspot analysis and risk assessment using probabilistic drought monitoring and severity–duration–frequency analysis", Hydrological Processes, 2018
Crossref
10 words — < 1%

126 Bayisa Negasa Wolteji, Sintayehu Teka Bedhadha, Sintayehu Legese Gebre, Esayas Alemayehu, Dessalegn Obsi Gemeda. "Multiple Indices Based Agricultural Drought Assessment in the Rift Valley Region of Ethiopia", Environmental Challenges, 2022
Crossref
10 words — < 1%

127 C. Cacciamani. "Monitoring and Forecasting Drought on a Regional Scale: Emilia-Romagna Region", Water Science and Technology Library, 2007
Crossref
10 words — < 1%

128 N. N. V. Sudha Rani, A. N. V. Satyanarayana, Prasad Kumar Bhaskaran. "Assessment of Climatological Trends of Sea Level over the Indian Coast Using Artificial Neural Network and Wavelet Techniques", Pure and Applied Geophysics, 2017
Crossref
10 words — < 1%

129	Pratima Singh, S. K. Mahna. "Symbiosis in nitrogen - fixing fabales trees of dry regions of Rajasthan: A review", Arid Soil Research and Rehabilitation, 1998 Crossref	10 words — < 1%
130	Xuejun Zhang, Hui Liu. "Chapter 4 Analysis of Drought Character in the Mekong River Basin", Springer Science and Business Media LLC, 2020 Crossref	10 words — < 1%
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10 words — < 1%

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143 Al-Faraj, Furat Ahmed Mahmood. "Sustainable Management of Transboundary River Basins in a Changing Climate and Human-Induced Interventions Upstream.", University of Salford (United Kingdom), 2021
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9 words — < 1%

144 Ch. Srinivasa Rao, K.A. Gopinath, J.V.N.S. Prasad, Prasannakumar, A.K. Singh. "Climate Resilient Villages for Sustainable Food Security in Tropical India: Concept, Process, Technologies, Institutions, and Impacts", Elsevier BV, 2016
Crossref
9 words — < 1%

145 Ellingwood, Kevin. "Flexible Design and Operation of Hybrid Concentrated Solar Power Plants to Enhance Solar Energy Generation and Levelized Cost", The University of Utah, 2022
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9 words — < 1%

147 Jun Li, Zhaoli Wang, Xushu Wu, Chong-Yu Xu, Shenglian Guo, Xiaohong Chen. "Toward Monitoring Short-Term Droughts Using a Novel Daily-Scale,
9 words — < 1%

Standardized Antecedent Precipitation Evapotranspiration Index", Journal of Hydrometeorology, 2020
Crossref

148 Ran Dong, Yuanhong Guan, Wen Zhou, Xianghua Wu, Chenguang Guo. "The Southern Indian Ocean Dipole and its effects on Precipitation in China", Research Square Platform LLC, 2022 — 9 words — < 1%
Crossref Posted Content

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Crossref

152 Vimal Mishra, Saran Aadhar, Shanti Shwarup Mahto. "Anthropogenic warming and intraseasonal summer monsoon variability amplify the risk of future flash droughts in India", npj Climate and Atmospheric Science, 2021 — 9 words — < 1%
Crossref

153 Wendy M Milne. " Evaluation of the establishment of Haliday (Hymenoptera: Braconidae) in lucerne aphid populations in New South Wales ", Australian Journal of Entomology, 2002 — 9 words — < 1%
Crossref

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155	edoc.ub.uni-muenchen.de Internet	9 words — < 1%
156	research.wri.org Internet	9 words — < 1%
157	"Full Issue in PDF / Numéro complet enform PDF", Canadian Journal of Remote Sensing, 2014 Crossref	8 words — < 1%
158	ANTHONY LEBOISSETIER, NORA OKONG'O, JOSETTE BELLAN. "Consistent large-eddy simulation of a temporal mixing layer laden with evaporating drops. Part 2. A posteriori modelling", Journal of Fluid Mechanics, 2005 Crossref	8 words — < 1%
159	Aly Kounta, Ahmad El-Aboudi, Macoumba Loum, Dieng El-Hadj Mamadou Ngom, ML Diongue Djim, Ismaguil Hanadé Houmma. "Agro-meteorological drought risk assessment in the groundnut basin of Senegal: the case of the municipalities of Djilor, Diossong, Keur Samba Gueye and Toubacouta", Geocarto International, 2022 Crossref	8 words — < 1%
160	Aniket Chakravorty, Bhagu Ram Chahar, Om Prakash Sharma, C.T. Dhanya. "A regional scale performance evaluation of SMOS and ESA-CCI soil moisture products over India with simulated soil moisture from MERRA-Land", Remote Sensing of Environment, 2016 Crossref	8 words — < 1%
161	Brahim Benzougagh, Pierre-Louis Frison, Sarita Gajbhiye Meshram, Larbi Boudad et al. "Flood	8 words — < 1%

Mapping Using Multi-temporal Sentinel-1 SAR Images: A Case Study—Inaouene Watershed from Northeast of Morocco", Iranian Journal of Science and Technology, Transactions of Civil Engineering, 2021
Crossref

162 Hailei Liu, Lisheng Xu, Jilie Ding, Xiaobo Deng. "A New Angle-Based Spectral Index and Its Application in Drought Monitoring", 2010 Symposium on Photonics and Optoelectronics, 2010 — 8 words — < 1%
Crossref

163 Hongshuo Wang, Hui Lin, Desheng Liu. "Remotely sensed drought index and its responses to meteorological drought in Southwest China", Remote Sensing Letters, 2014 — 8 words — < 1%
Crossref

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165 Israel R. Orimoloye, Johanes A. Belle, Adeyemi Olusola, Olusola O. Ololade. "Chapter 138-1 Space-Based Drought Disaster Risk and Climate Change Assessments: Strategies for Environmental Conservation", Springer Science and Business Media LLC, 2021 — 8 words — < 1%
Crossref

166 Jeongeun Won, Jeonghyeon Choi, Okjeong Lee, Sangdan Kim. "Copula-based Joint Drought Index using SPI and EDDI and its application to climate change", Science of The Total Environment, 2020 — 8 words — < 1%
Crossref

167 Jingcai Wang, Hui Lin, Jinbai Huang, Chenjuan Jiang, Yangyang Xie, Mingyao Zhou. "Variations of Drought Tendency, Frequency, and Characteristics and Their Responses to Climate Change under CMIP5 RCP Scenarios in Huai River Basin, China", Water, 2019
Crossref
8 words — < 1%

168 Meijian Yang, Denghua Yan, Yingdong Yu, Zhiyong Yang. "SPEI-Based Spatiotemporal Analysis of Drought in Haihe River Basin from 1961 to 2010", Advances in Meteorology, 2016
Crossref
8 words — < 1%

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8 words — < 1%

170 Muhammad Abrar Faiz, Yongqiang Zhang, Ning Ma, Faisal Baig, Farah Naz, Yasir Niaz. "Drought indices: aggregation is necessary or is it only the researcher's choice?", Water Supply, 2021
Crossref
8 words — < 1%

171 Navalgund, Ranganath R., Ranganath R. Navalgund, and Yoshifumi Yasuoka. "<title>Indian Earth Observation Programme towards societal benefits: a GEOSS perspective</title>", GEOSS and Next-Generation Sensors and Missions, 2006.
Crossref
8 words — < 1%

172 Nur'utami, Murni Ngestu, and Rahmat Hidayat. "Influences of IOD and ENSO to Indonesian Rainfall Variability: Role of Atmosphere-ocean Interaction in the Indo-pacific Sector", Procedia Environmental Sciences, 2016.
Crossref
8 words — < 1%

173 Prasanth A. Pillai. "Individual and combined influence of El Niño-Southern Oscillation and Indian Ocean Dipole on the Tropospheric Biennial Oscillation", Quarterly Journal of the Royal Meteorological Society, 2010 — 8 words — < 1%
Crossref

174 Richa Ojha. "Assessing seasonal variation of near surface air temperature lapse rate across India", International Journal of Climatology, 2017 — 8 words — < 1%
Crossref

175 Shamsuddin Shahid. "Spatial and temporal characteristics of droughts in the western part of Bangladesh", Hydrological Processes, 06/30/2008 — 8 words — < 1%
Crossref

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177 Tang, Mingliang. "Advances in Heap Leach Pad Surface Moisture Mapping Using Unmanned Aerial Vehicle Technology and Aerial Remote Sensing Imagery", University of Toronto (Canada), 2020 — 8 words — < 1%
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178 Tonini, F.. "Mapping return levels of absolute NDVI variations for the assessment of drought risk in Ethiopia", International Journal of Applied Earth Observations and Geoinformation, 201208 — 8 words — < 1%
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Influence Hydrological Drought Development and Recovery", Wageningen University and Research, 2021
ProQuest

180 Wang Yongqian, Shi Jiancheng, Liu Zhihong, Liu Wenjuan. "Application of Microwave Vegetation Index (MVI) to monitoring drought in Sichuan province of China", 2012 First International Conference on Agro-Geoinformatics (Agro-Geoinformatics), 2012 — 8 words — < 1%
Crossref

181 Xiaojing Shen, Xu Wu, Xinmin Xie, Zhenzhen Ma, Meijian Yang. "Spatiotemporal Analysis of Drought Characteristics in Song-Liao River Basin in China", Advances in Meteorology, 2017 — 8 words — < 1%
Crossref

182 Xingjun Hong, Shenglian Guo, Yanlai Zhou, Lihua Xiong. "Uncertainties in assessing hydrological drought using streamflow drought index for the upper Yangtze River basin", Stochastic Environmental Research and Risk Assessment, 2014 — 8 words — < 1%
Crossref

183 Zemede M. Nigatu, Dongming Fan, Wei You, Assefa M. Melesse, Lun Pu, Xinchun Yang, Xiangyu Wan, Zhongshan Jiang. "Crop production response to soil moisture and groundwater depletion in the Nile Basin based on multi-source data", Science of The Total Environment, 2022 — 8 words — < 1%
Crossref

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8 words — < 1%

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Crossref

7 words — < 1%

206 Boren, Erik James. "An Examination of Satellite-Based Cropland Canopy Water Content Maps for Yield Ratio Prediction", University of Idaho, 2022
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7 words — < 1%

207 Daniel Wyss, Kaleb Negussie, Antonia Staacke, Amadé Karnagel, Malin Engelhardt, Martin Kappas. "A comparative analysis of MODIS-derived drought indices for

7 words — < 1%

Northern and Central Namibia", African Journal of Environmental Science and Technology, 2022
Crossref

208 Engel, Valentina. "Cosmogenic 35S Behavior During “Double-Dip” La Niña Southern Oscillation and at Solar Minimum with an Application of Long-Term Monitoring for Anthropogenic 35S", University of California, San Diego, 2022 — 7 words — < 1%
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209 Garg, Ankit, and Charles Wang Wai Ng. "Investigation of soil density effect on suction induced due to root water uptake by Schefflera heptaphylla", Journal of Plant Nutrition and Soil Science, 2015. — 7 words — < 1%
Crossref

210 Hossein Bari Abarghouei, Mohammad Amin Asadi Zarch, Mohammad Taghi Dastorani, Mohammad Reza Kousari, Mehdi Safari Zarch. "The survey of climatic drought trend in Iran", Stochastic Environmental Research and Risk Assessment, 2011 — 7 words — < 1%
Crossref

211 Praveen Kalura, Ashish Pandey, V. M. Chowdary, P. V. Raju. "Assessment of Hydrological Drought Vulnerability using Geospatial Techniques in the Tons River Basin, India", Journal of the Indian Society of Remote Sensing, 2021 — 7 words — < 1%
Crossref

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214 "Protected Areas in Northern Tanzania", Springer Science and Business Media LLC, 2020 — 6 words — < 1%
Crossref

215 AghaKouchak, A., A. Farahmand, F.S. Melton, J. Teixeira, M.C. Anderson, B.D. Wardlow, and C.R. Hain. "Remote sensing of drought: progress, challenges and opportunities : REMOTE SENSING OF DROUGHT", Reviews of Geophysics, 2015. — 6 words — < 1%
Crossref

216 Arun Mondal, Deepak Khare, Sananda Kundu. "Spatial and temporal analysis of rainfall and temperature trend of India", Theoretical and Applied Climatology, 2014 — 6 words — < 1%
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Crossref

218 Hao Sun, Xiang Zhao, Yunhao Chen, Adu Gong, Jing Yang. "A new agricultural drought monitoring index combining MODIS NDWI and day–night land surface temperatures: a case study in China", International Journal of Remote Sensing, 2013 — 6 words — < 1%
Crossref

219 J. Heiskanen. "Evaluation of global land cover data sets over the tundra-taiga transition zone in northernmost Finland", International Journal of Remote Sensing, 2008 — 6 words — < 1%

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