CHAPTER 2

Literature Review

2.1 Overview

The term "climate change" is used to describe a global phenomenon of climate transformation defined by changes in the average climate of the planet (in terms of precipitation, temperature, and evapotranspiration) primarily caused due to anthropogenic activities. Uncontrolled weather on the earth jeopardizes the survival of the planet's ecosystems, humanity's future, and the global economy's stability. Understanding the statistical analysis of climate extremes and identifying trend patterns is required to comprehend the changing behavior of climate and its consequences. Drought is a widely occurring climate extreme that causes more severe negative impacts in the continuation of changing climate. The following sections show the literature connected to the study of the research area. This chapter conducts a thorough literature review related to the present study, including the impact of climate change, climate extremes, downscaling of climatic variables, trend assessment, and drought characterization based on drought indices under both observed and future climate scenarios.

2.2 Impact of Climate Change

The Intergovernmental Panel on Climate Change (IPCC) defines climate change as “Climate change refers to a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer.

Climate change occurs due to natural internal processes or external forcings such as modulations of the solar cycles, volcanic eruptions, and persistent anthropogenic changes in the composition of the atmosphere or land use". Thousands of studies conducted all over the world have documented the negative impact of climate change on natural and human systems, while the intensity of the effects varies by region (IPCC, 2014). Rising sea levels and an increase in the frequency of climate extreme events such as tropical cyclones, heavy rainfall, heat waves, droughts, and floods are all consequences of a changing climate. The increase in atmospheric greenhouse gas concentrations is attributable to human activity which modifies the climate system (IPCC, 2014). In many parts of the world, rainfall variability and drought intensity will likely grow (Kusangaya et al., 2014; Mosley, 2015). Drought frequency will most likely rise as a result of decreased rainfall and higher evaporation, which is primarily related to rising temperatures (Sheffield et al., 2012).

There has been a fundamental concern about how climate change will affect water resources (Vörösmarty et al., 2000). According to a linear trend, the global average land and ocean surface temperature rose by 0.85°C between 1880 and 2012. The average temperature varied by 0.78°C from 1850 to 1900 to 2003 to 2012 (IPCC, 2013). The World Meteorological Organization (WMO) and the United Nations Environment Program (UNEP) founded the IPCC to give scientific, technological, and socioeconomic data to comprehend the climate change process. For policy and decision-making purposes, the IPCC delivers scientific information to the research community in terms of potential future climate change scenarios. The IPCC has generated long-term emission scenarios based on radiative forcing, and demographic, technical, and socio-economic data, which are used by policymakers, scientists, and other specialists as a standard reference (Wilby et al., 2004). The researchers were able to conduct climate change analysis, modeling, impact assessment, adaptation, and mitigation studies using these emission scenarios. Based on Assessment Report 4 (AR4), IPCC has defined Special Report on Emission Scenarios (SRES) with four storylines: A1, B1, A2, and B2, which are driven by driving forces such as demographic development, socioeconomic development, and technology change with changes in CO_2 levels. The AR5 of the IPCC (IPCC, 2014) examines the scientific, technological, economic, and societal elements of climate change mitigation. According to the report, freshwater-related risks are expected to rise dramatically with rising levels of atmospheric greenhouse gas concentrations (IPCC, 2014). It adopted greenhouse gas concentration (not emissions) trajectories called Representative Concentration Pathways (RCPs), which succeeded special report on Emissions Scenarios (SRES) (Taylor et al., 2012; van Vuuren et al., 2011). The RCPs refer to time-dependent projections of greenhouse gas concentrations in the atmosphere and the RCPs denote time-dependent projection of atmospheric greenhouse gas concentrations, while the numbers 2.6, 6.0, 4.5, and 8.5 denote radiative forcing in Watts/m^2. The RCP 4.5 and RCP 6.0 are thought to represent stability routes, whereas the RCP 2.6 radiative forcing peaks around 3Watts/m^2 before 2100 and subsequently drops. RCP 8.5 is a high pathway scenario in which radiative forcing exceeds 8.5 watts/m^2 by 2100 and continues to increase. Integration of anticipated climatological variables under climate change scenarios with water resources decision and management models to examine the effect assessment over water quantitative and qualitative availability and demand has attracted a lot of interest in the scientific community (Ghosh & Mujumdar, 2008; Mishra et al., 2014; Raje & Mujumdar, 2010). Global climate models (GCM) are used in climate change studies to anticipate future climate scenarios. Climate models are based on well-known physical principles and simulate various climate processes and interactions in the atmosphere, oceans, land, ice, and the surface These models have been globally utilized to deduce past climate conditions and to forecast future climates using various scenarios (Taylor et al., 2012). The GCM is a type of climate model that mathematically models the overall circulation of a planet's atmosphere or ocean. GCMs are frequently used to investigate the impact of anthropogenic activities on the climate, make climate predictions, and to better understand the climate. The Fourth Assessment Report (AR4) of the IPCC is based on Atmospheric Ocean General Circulation Models (AOGCMs) that combine the atmosphere, ocean, and land and sea-ice components of climate systems. Over the AOGCMs, the Earth System Models (ESMs) include representations of multiple biochemical cycles on the Earth (Flato et al., 2013). The atmosphere, ocean, sea, ice, land surface and vegetation on land, and ocean biogeochemistry are all included in these models.

The climate change study necessitates a thorough examination of the variability and trend of meteorological data. During the 1950s, significant climatic change was documented, with the emission of greenhouse gases (GHG) generated by anthropogenic activity being blamed for the change (Pachauri et al. 2014). According to Fifth Assessment Report (AR5) (IPCC 2014), the global average temperature is anticipated to rise by 4°C by 2100. The climate change impact on hydrology has received a great deal of attention. Moderate to severe water shortages have been reported in several places in the world. Researchers utilized climate models and a large-scale hydrological model to predict that by 2050, a major part of the global population would be severely affected by water scarcity. Around one-third of the world population was estimated to be experiencing mild to high water stress (Arnell 1999). Rising CO_2 and other greenhouse gas concentrations will have a considerable impact on the hydrological cycle (IPCC, 2013). An increasing amount of data now exists to support the assumption that anthropogenic actions, namely the production of greenhouse gases, are to blame for global climate change (McMichael et al., 2004). However, the rise in precipitation has also been disproportionately high. The frequency of heavy precipitation events is changing (Sillmann & Roeckner, 2008). An increase in evaporation and rainfall is expected as a result of the intensification of the hydrological cycle; however, it is expected that the additional precipitation will not be equally distributed, resulting in changes in extreme occurrences including storms, floods, and droughts (Déry et al., 2009; Huntington, 2006). According to Chou et al. (2013), an unequal rise in precipitation was to blame for an increase in the annual range of precipitation over the world. Reduced rainfall or a shift in the timing of the rainy and dry seasons are both possible outcomes for some regions of the planet in the future. The percentage of precipitation that falls as snow decreases as the temperature rises (Arnell, 1999). The extent of snow cover in the northern hemisphere is expected to decrease (Mudryk et al., 2017). Marty (2008) observed that the rise in the mean winter temperature was associated with a significant drop in the amount of snowfall in Switzerland over the winter. Over the past few decades trend of warming in India has been identical to those of global warming (Datta & Das, 2019). As the temperature rises, long-term precipitation patterns change, which affects the availability of surface and subsurface water. The water cycle and streamflow, as well as the water demand in different sectors, have been significantly affected by changes in precipitation, temperature, and evapotranspiration. Singh et al. (2014) showed statistically significant decreases in peak-season precipitation and statistically significant increases in the frequency and intensity of wet and dry spells during the South Asian monsoon season from 1951 to 2011.

Integration of anticipated climatological variables under climate change scenarios with water resources decision and management models to examine the effect assessment over water quantitative and qualitative availability and demand has attracted a lot of interest in the scientific community (Ghosh & Mujumdar, 2008; Mishra et al., 2014; Raje & Mujumdar, 2010). For an accurate assessment of the effects of climate change on water resources, accurate projections of multiple hydroclimate variables are required, which necessitate downscaling climate projections to hydrological variables. It is becoming increasingly important to generate accurate hydrometeorological projections using climate model outputs from General Circulation Models (GCMs) and Regional Circulation Models (RCMs), which can then be statistically or dynamically downscaled (Fowler et al., 2007). Downscaling models have been developed to obtain future projections of hydrometeorological variables (precipitation, runoff, temperature, etc.) at regional scales based on large-scale climate simulations (mean sea level pressure, wind speed, humidity, etc.) acquired from GCM (Hewitson & Crane, 1992; Tripathi et al., 2006). The coarse resolution of GCM climate projections of the order of 2.5°-3.5° (about 200km-500km) makes this data inefficient for meteorological and hydrological research. Downscaling is a technique for re-estimating coarse resolution inputs to a finer resolution of 0.25° (or) 0.5° (25-50km) (Spatial Downscaling) at monthly or smaller (weekly, daily) timescales (Temporal Downscaling). Downscaling techniques are broadly classified into dynamic and statistical downscaling models.

2.3 Downscaling

GCM divides the earth's surface into many grid cells, with a horizontal resolution of 250 to 600 km and 10 to 20 vertical layers in the atmosphere, and 10 to 30 layers in the oceans. Their spatial resolution is so low that they can't account for processes at finer scales. The downscaling technique is predicated on the assumption that large-scale and fine-scale climatic factors interact with one another. The method for downscaling large-scale to fine-scale climate can be applied to temporal and spatial features of climate projections. Spatial downscaling is the method of obtaining finer spatial resolution climate information from coarser spatial resolution GCM output (e.g., 20 km resolution from 500 km grid cell GCM output). Temporal downscaling is a method of obtaining fine-scale temporal data from coarser-scale temporal GCM output data. Downscaling techniques are broadly classified into dynamic and statistical downscaling models, as described in subsequent sub-sections.

2.3.1 Dynamic downscaling

Dynamic downscaling is based on RCM, generating finer resolution output based on atmospheric physics over a region using GCM fields as boundary conditions in dynamical downscaling (Giorgi & Mearns, 1991). The procedure involves nesting a regional climate model (RCM) with coarse GCM data as boundary conditions. The main advantage of RCMs is their ability to describe smaller-scale atmospheric processes in order to generate realistic climate information at a spatial resolution of approximately 20-50 km. The divergence between the RCMs and their driving GCMs is controlled by the domain size chosen by each individual (Jones et al., 1997). The use of dynamically downscaled RCM output can resolve smaller-scale atmospheric processes of orographic precipitation than the GCM host (Pharasi, 2006). However, as with GCMs, the main drawback of RCM techniques is their high computational cost. This is because RCMs require the explicit solution of atmospheric system dynamics using fundamental conservation laws of mass, energy, and momentum. Furthermore, RCM outputs are prone to systematic errors and cannot correct discrepancies in the nesting GCM variables used at the boundaries; as a result, bias correction or further downscaling to a higher resolution is required. RCMs are that the driving GCM can leave significant biases in the simulation of mean precipitation on large scales (Durman et al., 2001). According to (Frei et al., 2006), inter-model differences are related to model biases. Christensen et al. (2008) suggest that GCM biases may not be linear and that biases may not be eliminated by simply taking differences between control and future scenarios. RCMs are afflicted by imperfect modeling and numerical stability (Lenderink & van Meijgaard, 2008; Maraun et al., 2010). Despite their rapid development, RCMs continue to have issues with parameterization schemes because physical processes are modeled at a scale that cannot be explicitly resolved (Maraun et al., 2010). The numerical method and parameters continue to influence the RCM precipitation outputs (Bachner et al., 2008; Fowler et al., 2000). Disparities between average areal values and site-specific data are likely to persist (Chen & Knutson, 2008). A few studies have been conducted on the impact of climate change on temperature trends in the upcoming decade using downscaling approach (Goyal & Ojha, 2012; Whan et al., 2014).

2.3.2 Statistical downscaling

Statistical downscaling techniques are found on the principle that the local climate is the function of the large-scale atmospheric state. Reviews of downscaling methods are widely available (Maurer, 2007). To downscale a local-scale climate variable (e.g., daily precipitation) from a larger-scale climate predictor variable (e.g., atmospheric circulation indices), the statistical relationship or transfer function is defined as R=F(L) where R denotes the local scale predictand climatic variable (e.g., daily precipitation) to be downscaled and L represents the set of large-scale climatic variables (e.g., large scale atmospheric circulation indices). Time-independent training and validation techniques using observations (such as stations and reanalysis) are utilized to establish the function. (Amorim, 2015). This downscaling approach applies the information from GCMs to the region using a series of equations that relate global climate differences to local climate variations. RCMs are computationally limited to a spatial resolution of 20-50 km; hence statistical downscaling can create site-specific climate estimates that RCMs cannot (Trzaska & Schnarr, 2014). These methods demand less computational effort than dynamic downscaling since they test scenarios over longer timescales (decades or centuries) rather than the brief (shorter timeframes) of the downscaling method. This enables users to create a huge number of distinct climatic simulations and, as a result, explore the statistical properties of downscaled variables. Furthermore, statistical downscaling approaches allow for the use of weather data available at the study site. Nonetheless, this strategy relies on the crucial assumption that the link between the present large-scale atmospheric circulation and the local climate will remain valid under the varied forcing circumstances of possible future climates. The statistical downscaling approach is broadly classified into three categories, i.e., weather typing approach, stochastic weather generators, and regression-based method (Pharasi, 2006).

Weather Typing Approach downscaling method involves relating the observed local-scale metrological data to a subjectively or objectively derived weather classification scheme (Choux, 2005). Local or regional climate frequency distributions are determined by weighting the local climate states with the relative frequencies of the weather classes. Then, regional climate projections are determined by analyzing the frequency distribution of simulated weather classes. In contrast, the approach is insufficient for simulating extreme occurrences and, like all statistical models, is fully dependent on stationary connections (IPCC 2007). Furthermore, systematic studies evaluating GCM performance in reproducing weather patterns are lacking, and in certain circumstances, changes in the frequency of observed weather patterns are compatible with GCM simulations (Amorim, 2015). The fundamental benefit of weather typing is that large-scale atmospheric patterns are likely to maintain their influence on local climate while the climate evolves and fluctuates.

Stochastic Weather Generation is comparable in many features to the circulation-based downscale techniques but differs in how they are applied to future climate circumstances. Instead of being conditioned by circulation patterns, stochastic models mimic all surface weather variables, such as precipitations conditional on the precipitation occurrence. The fundamental benefit of stochastic weather generation is that it can accurately reproduce several observable climate statistics, including mean, median, and interquartile range. However, accurate links to the host GCMs are impossible since these models do not include secondary variables like humidity and air circulation in the calibration phase. Furthermore, stochastic generators simulate precipitation extremes poorly and have persistent issues with modeling variability and outliers (Pharasi, 2006).

Regression Based Method Regression model is performed by drawing a linear or non-linear relationship between global and local scale predictor variables (Wilby et al., 1998). Multiple regression methods including the SDSM (Wilby et al., 2002), artificial neural network (Hewitson & Crane, 2002), and canonical correlation analysis (CCA) (Von Storch et al., 1993) are frequently employed. The predictor-predictand relationship can characterize using different functions (Choux, 2005). The cheap computing power and relative ease of implementation of regression-based downscaling are significant benefits of this method (Wilby et al., 2002). This technique is only applicable locally, where accurate predictor-predictand relationships can be identified. Because of the limited predictability of local precipitation based on global sale forcing, regression-based techniques are known to underestimate precipitation (Bürger, 1996).

2.3.2.1 Statistical Downscaling Model (SDSM)

The Statistical Downscaling Model (SDSM), which was developed by Robert L. Wilby and Christian W. Dawson, is a statistical method for estimating future climate change (Wilby & Dawson, 2007). SDSM based on a transfer function and a stochastic weather generator, is one of the most extensively used statistical downscaling methods (Wilby et al., 2002). SDSM performance was determined to be superior than that of conventional weather generators (Hashmi et al., 2011). SDSM enables the rapid and cost-effective creation of multiple single-site forecasts of daily surface climatic variables under current and future climate forcing. More precisely, predictors are linked to the local predictand by linear relationships that minimize root mean square error.

Additionally, the variance of the downscaled daily data is stochastically adjusted to more accurately reproduce the observed time series (Wilby & Dawson, 2007). The detailed methodology of SDSM is described in section 4.6 of this thesis. Furthermore, when compared to other statistical downscaling models, SDSM excels in capturing rainfall features as well as maximum and minimum temperatures (Hashmi et al., 2011; Hassan et al., 2014; Wilby et al., 2002). Hassan et al. (2014) used Long Ashton research station weather generators (LARS-WG) and SDSM for downscaling the rainfall and temperature. Both models are used for quantifying the effect of climate change conditions on a local scale. As a result, it is found that SDSM yields better performance as compared to LARS-WG. The statistical downscaling model gives a relatively greater change in annual rainfall as compared to Long Ashton research station weather generators.

Along with the impact of SDSM, selecting a predictor has been identified as a crucial component influencing downscaling results (Kidson & Thompson, 1998). Other researchers discovered that predictor performance is affected by the season and region and that a combination of predictor factors beats single variable forecasters (Hessami et al., 2008). Furthermore, as documented in some publications, the downscaled outcomes and the number of predictors are connected (Meher & Das, 2020; Timbal et al., 2003). At the moment, the most popular predictor selection approaches are correlation analysis (CA), partial correlation analysis (PCA), p-value, and stepwise regression analysis (SRA) (Huang et al., 2011; Mahmood & Babel, 2013). However, it is still unknown how different strategies for predictor selection affect predictor combination downscaled results and the process of predictor combination itself (Goyal & Ojha, 2012).

2.4 Trend Characterization of Meteorological Variable and Climatic Extreme

Understanding climate variability, trend, and predictions is fundamental for improved water resource management and planning in a basin. A comprehensive description of temperature and precipitation trend and variability is required for the study linked to hydrology, climatology, and agriculture. A long-term trend study of temperature and precipitation is crucial for rainfed agricultural and irrigated regions, where both temperature and precipitation can affect the irrigation schedule (Feng et al., 2016). The regional climate can be accurately assessed through the use of trend analysis of climate variables, which provides an overall picture of how climate variables change over time. Consequently, understanding temperature and precipitation trend is necessary for better water management in a basin, water demand and supply, agricultural water usage and control, and regional planning (Mahmood & Jia, 2017). Long-term trend analysis includes the relevance of trend monotonicity as well as essential statistical parameters. To investigate a trend, techniques such as parametric tests or non-parametric tests might be applied (Shahid & Khairulmaini, 2009). The assumptions of parametric tests (i.e., normally distributed datasets, zero autocorrelation, and stationarity) are violated by climatological data. Therefore, non-parametric tests, particularly the Mann-Kendall (Kendall 1975; Mann 1945), have been widely accepted among the climatological community for analyzing hydrologic time series data. Non-parametric trend tests are extensively used for trend assessment of climatic variables and climatic extremes (Huth & Pokorná, 2005; van Belle & Hughes, 1984). To reduce trend persistence, data pre-whitening and variance correction approaches are applied (Kumar et al., 2017). The time and spatial scales usually suffer from restriction because of the unavailability of accurate data. For example, in a recent study by (Zaifoğlu. et al., 2017) quality control test was carried out to identify the errors due to missing data in daily precipitation data series. The following sections provide a thorough assessment of the literature that is now available with pertinent contributions to the trend analysis of precipitation and temperature that has been conducted worldwide. Farhangi et al. (2016) analysed eight subbasins in western Iran for rainfall trends. Six out of ten sub-basins showed a declining trend in annual average rainfall. According to the IPCC, the global averaged temperature could rise by 1.4–5.8°C over the next 100 years, whereas in South Asia, it is expected to rise by 1.0–1.4°C and 2.23–2.87°C by 2020 and 2050, respectively (IPCC, 2001). In recent decades, some countries in the tropical Asia region have witnessed rising surface temperatures. An examination of seasonal and annual surface air temperatures over India revealed a substantial warming trend of 0.57 ^{o}C/Century (Pant & Kumar, 1997). The post-monsoon and winter seasons are the primary contributors to global warming. The monsoon temperatures do not exhibit a notable trend in any major region of the country, except for Northwest India, where they exhibit a large negative trend. Also, statistics assessed in terms of daytime and nighttime temperatures indicate that the warming was primarily attributable to an increase in maximum temperatures, but minimum temperatures have stayed virtually unchanged over the last century. Another study spanning the years 1901-1987 indicated that the mean maximum temperature has risen by 0.60 ^{o}C while the mean minimum temperature has reduced by 0.10 ^{o}C (Kumar et al., 1994). A significant warming trend has been detected along the west coast, in central India, the interior peninsula, and over north-eastern India, while a significant cooling trend has been observed in northwest India and a pocket in southern India. Singh & Sontakke

(2002) reported that the annual surface air temperature in the Indo-Gangetic Plains (IGP) of India increased (0.53 °C/100 years, at 0.1 significance level) during 1875 to 1958, but decreased (–0.93 °C/100 years, significant at the 0.05 significance level) between 1958 to 1997. According to a study of decadal trend, the most recent two decades (1971–1980 and 1981–1990) have shown greater warming rates than the preceding decades (Srivastava et al., 1992). Kothyari & Jain (1997) reported a diminishing trend in precipitation across India since1965. In addition, when the annual maximum temperature in the Ganges basin increases, the amount of monsoon precipitation and the number of wet days during the monsoon season decreases. Parthasarathy et al. (1994) and Srivastava et al. (1992) reported the change in annual and seasonal precipitation at various locations and scales over India. According to the majority of these studies, despite decadal and inter-annual fluctuation, the Indian summer monsoon rainfall (ISMR) has exhibited remarkable stability over time. The long-term series of ISMR shows no significant trend but there has been decadal fluctuation from the long-term average for three decades (Kothyari & Singh, 1996). Summer seasonal rainfall across India varies annually; however, the Mann-Kendall rank statistic shows no notable long-term trend (Kripalani et al., 2003). Dash et al. (2009) examined the Indian rainfall time series from 1871 to 2002 and found a declining monsoon trend and an increasing pre- and post-monsoon trend. Linear trend analysis of monthly rainfall conducted by Rajeevan et al. (2008) used observations from 1476 rain gauge stations spread across 36 meteorological sub-divisions in India and reported significantly decreasing monsoon rainfall over Jharkhand, Chhattisgarh, and Kerala sub-divisions between 1901 and 2003. Only three sub-divisions, namely Haryana, Punjab, and Coastal Karnataka, exhibited a statistically significant increase in annual rainfall. Sathyasan et al. (2018) evaluated the trend using the Mann-Kendall test of long-term seasonal and annual precipitation data of Chennai city and found a non-significant increase in precipitation, whereas winter rainfall exhibited a significant decreasing trend over the study period. A study of long-term variations in precipitation and evapotranspiration over the Narmada River in India revealed a significant downward trend in precipitation and an upward trend in evapotranspiration due to changes in temperature (Pandey & Khare, 2018). Several studies have been conducted in this context to assess the impact of climatic variability on annual and seasonal rainfall and intensity trend, the number of rainy days in various parts of India, and temperature (Kothawale et al., 2010; Ramesh & Goswami, 2007). Changes in climatic variables have also had a significant impact on the country's inclusive economy, water resource management, and agricultural sector (Gosain et al., 2006; Sonali & Nagesh Kumar, 2013). As a result, extensive research is being done on long-term trend analysis for hydrologic variables using climatic data to study the effects of climate variability on the hydrological cycle. Here are a few examples of this type of work: Suryavanshi et al. (2014) discovered a considerable rise in the greatest temperature over Jharkhand, resulting in a change in the growth stage of the wheat crop. According to their findings of the study of Arora et al.(2005) and Kishore et al. (2016) temperature increases have the greatest impact on years with below-average rainfall, erratic distribution, and extended dry spells.

Trend assessment of drought assist in identifying the future vulnerability of expected drought event and facilitate discerning the variability and pattern of drought characteristics over s region (Mallya et al., 2016). Mann-Kendall (MK) test has been used extensively to determine the monotonic change in long-term time series data.

Several authors focused on the trend of changing behavior of meteorological variables and drought to anticipate future changes. In the Upper Krishna basin, Maharashtra, a trend analysis of SPI was conducted (Mahajan & Dodamani, 2015) and found a significant increase in the magnitude of SPI trend over the studied area. Guhathakurta et al. (2017) assessed the SPI trend at the district level across India and found that trend was declining in 132 districts across central and northeastern India. Thomas et al. (2015) reported the declining trend of SPI time series at a shorter timescale over the Bundelkhand region of central India. By examining the trend of historical drought episodes, it is possible to anticipate future patterns of potential drought episodes in a region. The spatiotemporal trend of meteorological drought over various timescales will aid in determining long-term historical and prospective future fluctuations of a drought characteristic of a region (Pathak & Dodamani, 2020).

2.5 Climate Extremes

Climate extreme events, for example, droughts, snowmelts, and floods can be long-term or short-term. They generate a complicated network of direct and indirect effects on numerous aspects of life (for example, economic, environmental, and social). Globally, the average annual number of persons affected by drought and flood events in recent decades is estimated to be 55 million and 1.4 billion, respectively (Sreeparvathy & Srinivas, 2022). South Asia is predicted to experience more intense and frequent heat waves and humid heat stress during the twenty-first century, while both annual and summer monsoon precipitation will increase, with increased inter-annual variability, according to climate change projections for the Asian continent in the IPCC's sixth Assessment Report (AR6) (Arias et al., 2022). The concurrent occurrence of floods and droughts, or wet and dry hydrological extremes more generally, has been the subject of a great deal of research for both historical and projected climates at both the local and regional scales. Hydro-climatic variability may increase as a result of climate change because both dry and wet events are linked and influenced by the same underlying hydrological processes and atmospheric dynamics. A number of recent rapid wet-dry events have recognized the importance of wet and dry event sequences. It results from the intensification of the hydrologic cycle and the spatiotemporal variability of air circulation patterns caused by climate change. Therefore, in the context of a changing environment, it is crucial to conduct a quantitative assessment of the trends of dry and wet event characteristics in order to manage regional water security and water-related disasters better. The precipitation and temperature variability are the main factors that directly affect the trend of dry and wet events (Alexander et al., 2006). In particular, temperature changes can modify the patterns of potential evapotranspiration (PET), which in turn affects the hydrological cycle. Thus, uncertainty in regional drought and flood events estimation increases. Several studies used indices to estimate the drought and wet features (Huang et al., 2017; Malik et al., 2020; Ojha et al., 2013). In most of the studies, dry and wet events quantified using PDSI and SPI neglected the impact of temperature. SPEI is considered more effective in measuring the multiscalar characteristics of the extreme dry and wet occurrences, considering the relative effectiveness of multiple indices. It quantifies the severity of the events while considering the relative contributions of temperature and precipitation as antecedent conditions (Nath et al., 2017). These events are anticipated to intensify regionally and increase in frequency within the context of global warming, highlighting the significance of collaborative study on wet-dry extreme weather event.

2.6 Drought and its Classification

Droughts are defined as the duration of low precipitation, soil moisture, and insufficient water supplies to support and supply a region's socioeconomic activity. It impacts millions of people worldwide, devastatingly affecting economies, the environment, and property (Omonijo & Okogbue, 2014). Drought is becoming more common and severe all across the world. Drought characteristics and consequences differ significantly from place to place (Wilhite, 1997). The extent to which a drought falls below a threshold level over time (Morid et al., 2007) indicate the severity of the drought. Due to the wide range of sectors affected by drought, its diverse geographical and temporal distribution, and the demand placed on water supply by human-use systems, there is no common definition of drought. Wilhite & Glantz (1985) provided over 150 definitions, each of which might potentially create a collection of relevant indicators. According to Yevjevich (1969), one of the major impediments to drought assessment is the widely disparate interpretations of drought definitions. Any scientific subject of study, including drought research, requires a precise definition. As the effects of drought accrue over a long period of time, determining the commencement and conclusion of a drought is a challenging process. Hence, drought is frequently referred to as a "creeping phenomenon" (Tannehill, 1947). Drought definitions can be divided into conceptual and operational types (Wilhite & Glantz, 1985). Conceptual definitions are dictionary-style definitions that generally define the bounds of the concept of drought and are thus generic in their description of the phenomena (e.g., a drought is a long and dry period). Drought operational definitions aim to pinpoint the exact qualities and thresholds that determine the commencement, continuance, and termination of drought occurrences, as well as their severity. These definitions lay the groundwork for a successful early warning system (Wilhite, 2000). They can examine drought frequency, severity, and duration for a given historical period. Drought can be viewed from a variety of disciplinary perspectives. Different disciplines use a variety of physical, biological, and socioeconomic criteria to define drought. As a result of the different and differing disciplinary perspectives, there is sometimes substantial ambiguity on what really constitutes a drought (Glantz & Katz, 1977). The following are some of the most prevalent definitions: It is defined by the World Meteorological Organization (WMO, 1986) as a long-term lack of precipitation. According to the United Nations Convention to Combat Drought and Desertification, drought is the naturally occurring phenomenon that exists when precipitation has been significantly below normal recorded levels, resulting in serious hydrological imbalances that adversely affect land resource production systems' (UN Secretary-General, 1994). The United Nations Food and Agriculture Organization (FAO, 1983) defines a drought hazard as "the proportion of years when crops fail due to a lack of rainfall." The Encyclopedia of climate and weather defines a drought as 'an extended period, a season, a year, or many years with inadequate rainfall relative to the statistical multi-year mean for a region' 'Drought' was defined by Palmer (1965) as a severe divergence from the typical hydrologic conditions of an area. There are many different ways to define drought, each with its own unique set of characteristics. Droughts are classified as meteorological, hydrological, agricultural, and socioeconomic droughts (Wilhite & Glantz, 1985).

Meteorological drought is commonly described as the degree of dryness (in comparison to some "average" or "normal" quantity) and the duration of the dry spell. The atmospheric circumstances that lead to precipitation deficits are largely region-specific; therefore, definitions of meteorological drought must take this into consideration. Since there are so many distinct meteorological definitions in different countries, a single definition of drought cannot be used across the world. According to the India Meteorological Department (IMD), a meteorological drought affects an area when seasonal rainfall falls below 75% of the area's long-term average. If the rainfall deficit is between 20% and 50%, it is considered a "moderate drought," and if it is greater than 50%, it is defined as a "severe drought." Meteorological drought is defined in the United States as less than 2.5 mm of rain in 48 hours, but in Great Britain (BRO, 1936), drought is defined as fifteen days of daily precipitation less than 0.25 mm. In Libya, on the other hand, a meteorological drought is declared when the annual rainfall drops below 180 millimeters. Six days without rain on Bali, Indonesia's tropical Indonesian island, is considered a meteorological drought (Heim, 2002). Meteorological drought can be assessed using daily rainfall data, temperature, humidity, wind velocity and pressure, and evaporation.

Agricultural drought refers to a period of diminishing soil moisture and resulting crop failure, with no mention of surface water supplies. It impacts the greatest number of people with all types of droughts. Meteorological drought is linked to agricultural impacts by focusing on several features such as precipitation shortages, discrepancies between actual and potential evapotranspiration, soil water deficits, and lower groundwater or reservoir levels. Demand for water from plants is affected by various factors, including local weather conditions, a plant's biological traits, its current stage of development, and the soil's physical and biological qualities. A good definition of agricultural drought should consider crop susceptibility at various phases in the growth of crops. Low plant populations per hectare and lower yields can result from insufficient moisture in the topsoil at the time of planting. Soil texture, fertility, soil moisture, crop type and region, crop water requirements, pests, and climate are all essential factors to consider while evaluating an agricultural drought.

Hydrological drought refers to a period in which there are insufficient surface and subsurface water resources for the established water uses of a specific water resources management system. Streamflow data are commonly used for hydrologic drought studies (Clausen & Pearson, 1995; Dracup et al., 1980; Mohan & Rangacharya, 1991; Zekai, 1980). The term "hydrological drought" refers to a long-term decline in stream and reservoir water levels, which can endure for months or even years. Human activities have the potential to intensify a natural phenomenon like a hydrological drought. Hydrological droughts are often associated with meteorological droughts, and the recurrence interval of hydrological droughts varies with the frequency of meteorological droughts. The severity and frequency of hydrological droughts can be influenced by changes in land use and degradation. Surface water area and volume, surface runoff, stream flow measurements, infiltration, water-table changes, and aquifer parameters are some data sets needed to assess a hydrological drought.

Socioeconomic Drought definitions of drought include components of meteorological, hydrological, and agricultural drought in their descriptions of the phenomenon. Supply and demand factors influence the occurrences of this type of drought, unlike other types of droughts. Weather influences water, pasture, food grains, fish, and hydroelectric power. Climate change affects the amount of water available to people and the environment. Water shortages can cause socioeconomic drought when demand exceeds supply. Demand for economic items rises as the population and economy grow. Socioeconomic drought worsens when water demand exceeds its availability. Socioeconomic drought is determined by human and animal population and growth, water and feed needs, crop failure severity, industry type and water need.

The sequence of impacts associated with meteorological, agricultural, and hydrological drought further emphasizes their differences. Due to its reliance on stored soil water, agriculture is frequently the first to suffer from drought. Extended droughts drain soil water quickly. People relying on other water sources will feel the scarcity if precipitation shortages continue. Those who rely on reservoirs, lakes, and groundwater are usually the last to be affected. Depending on the hydrologic system and water use requirements, a 3 to 6-month drought may have little influence on these sectors. When precipitation returns to normal, and drought conditions end, surface and underground water resources recover. First, soil water is supplied, then streamflow, reservoirs, and lakes. Drought effects may fade quickly in agriculture, which relies on soil water, but last months or years in other sectors. Groundwater consumers, who are generally last to be affected by drought, maybe last to see normal water levels. The length of the recovery period depends on the drought's intensity, duration, and ending precipitation.

2.6.1 Drought indices

The most often used drought assessment technique is a drought index, which is more valuable than raw data in decision-making when assessing drought conditions around the world. Drought indices are numerical representations of drought severity based on hydrometeorological indicators. Drought indicators are climatic or hydrometeorological variables or factors that are used to describe the state of the drought. For example, precipitation, evapotranspiration streamflow, snowpack, and other water supply-related indicators, into a single number that is far more useful than the raw data for decision making (Hayes et al., 2007). Such variables or indicators are utilized in combination to produce a drought index using various models (e.g., water balance and hydrological models). These indicators can be meteorological, hydrological, or water supply and demand indicators. Some indicators, such as precipitation, potential evapotranspiration, and soil and vegetation cover characteristics, have had broader practical applications and influences. (Tsakiris & Vangelis, 2005). Around 150 different drought indices have been created (Niemeyer 2008), and more indices have been presented lately (Cai et al., 2011; Mohammad et al., 2009; Rhee et al., 2010; Vasiliades et al., 2011; Vicente-Serrano et al., 2010). Several different drought indices have been developed to quantify a drought, and each one has its own set of advantages and disadvantages. A comprehensive analysis of drought, including its benefits and drawbacks, stated by Mishra & Singh (2010) and Zargar et al. (2011). This section describes several meteorological drought indices that are frequently used in forecasting, monitoring, and planning operations. Because of their prevalence, they warranted a longer description.

Palmer drought severity index (PDSI) was the first drought index developed in the United States, and it is still one of the most extensively used and accessible indexes today. It is used as a meteorological drought index because it monitors the moisture supply deviation from normal. To measure the supply and demand of moisture in a two-layer soil model, Palmer (1965) developed indices, which is now known as the Palmer drought index (PDI), by combining rainfall and temperature measurements. This was the first time a region's total moisture condition had been evaluated in such a comprehensive way. Since its foundation, PDSI has undergone a few changes. A modified version is known as the Palmer hydrological drought index (PHDI can be used to monitor water supplies (Karl & Young, 1987). For example, Karl & Koscielny (1982) have used the index to illustrate the areal extent of various drought episodes and investigate the spatial and temporal characteristics of drought. Numerous studies have taken into account the limitations of PDSI in assessing drought (Alley, 1984; Karl, 1986). Assumptions that all precipitation is rain make PDSI values problematic during winter and at high elevations, making the model more suitable for agricultural impacts than hydrologic droughts. Running off occurs only when all soil layers are saturated, which means that PDSI underestimates runoff, and PDSI is slow to respond to developing and lessening droughts (Hayes et al., 1999). While PDSI has limitations, it also has advantages. It has a lengthy history of use and has been thoroughly tested and proven over a wide range of situations. Temperature and soil properties are taken into account, and the data is standardized to allow for comparisons between climatic zones. Self-Calibrating Palmer Drought Severity Index (sc-PDSI) is a modified PDSI developed by Wells et al.(2004). It considerably enhanced PDSI spatial comparability and made it more appropriate for monitoring extreme wet and dry episodes over diverse climatological regions**.** It is a measure of soil moisture availability based on water balance equation supply and demand assumptions. It is estimated on a monthly time frame (or other timescales) depending on temperature, precipitation, and the soil's available water content (Palmer, 1965; Wells et al., 2004). The absence of multiscalar features like SPI and SPEI is a major drawback of PDSI (Dai et al., 2004; Wells et al., 2004) and its autoregressive structure, which limits its usefulness spatially. The sc-PDSI is best suited as a mid- and long-timescale drought monitoring indicator and can be used to monitor changes in river runoff streamflow and groundwater level, according to these two findings (Wang et al., 2017; Zhao et al., 2017)

Standardized precipitation index (SPI) is a multiscalar drought index developed by McKee et al. (1993), which requires only precipitation records for drought assessment. SPI is used to calculate precipitation deficits at different timescales. Its main advantage is that it can be calculated over multiple timescales. This long-term data is fitted to a probability distribution, then transformed to a normal distribution, resulting in a mean SPI of zero for the specified region and desired time period (Edwards & McKee, 1997). SPI at different timescales is employed to reflect changes in different water characteristics because of the slow and variable effects of long-term precipitation deficits (e.g., streamflow, groundwater, and snowpack). Droughts can also be easily identified and monitored for the duration of the drought, thanks to the ability to examine different timescales. SPI requires a 30-year of precipitation data, but it is advised to use 50 years of precipitation data (Guttman, 1998). The advantages and limitations of adopting the SPI to characterize drought severity are discussed by Hayes et al.(1999). The SPI has several significant advantages over other drought indexes. The first and most obvious advantage is its simplicity of calculation. Unlike the Palmer Drought Severity Index (PDSI), which requires 68 computational terms to explain, the SPI is fully based on rainfall and requires only the computation of two parameters. Because it is not affected by soil moisture levels, the SPI can be utilized effectively in both summer and winter. Topography does not affect the calculation of SPI; hence it can be used for probabilistic analysis. The SPI can be defined over different timescales, allowing it to characterize drought conditions relevant to various meteorological, agricultural, and hydrological applications. This temporal adaptability is also helpful in analyzing drought dynamics, particularly for determining the commencement and end of droughts, which has historically been difficult to follow with other indices. The other advantages are its standardization, which assures that the frequency of extreme events is consistent across all locations and timescales. The SPI predicts drought months ahead of the Palmer Index.

SPI has a few potential drawbacks that should be considered. The SPI does not account for evapotranspiration as a measure of water supply, which limits its ability to reflect the effect of rising temperatures (related to climate change) on moisture demand and availability. For calculating SPI, the length of the precipitation record and the type of probability distribution are critical. The SPI standardized nature limits its usefulness as extreme droughts (or any other drought threshold) defined by the SPI occur at the same frequency at all locations over a long period of time. As a result, the SPI is unable to identify areas that may be more susceptible to drought. If the SPI is employed on short timescales (1, 2, or 3 months) at the region with low seasonal precipitation values that are misleadingly large positive or negative can occur in these situations. Despite containing the least local contextual information, the SPI, a single-variable index, is still the most often employed in many climatic and geographic conditions (Kchouk et al., 2021).

The Standardized Precipitation Evapotranspiration Index (SPEI) is modified drought indices developed by Vicente-Serrano et al. (2010) which assessed the impact of global warming on drought (Beguería, 2014). Like the Palmer Drought Severity Index (PDSI), SPEI evaluates the effect of reference evapotranspiration on drought severity, but its multi-scale nature allows it to identify different drought types and their implications on diverse systems (Vicente-Serrano et al., 2012,2013). SPEI measures evapotranspiration demand with the sensitivity of the PDSI and is easy to calculate and multi-scalar, just like the Standardized Precipitation Index (SPI). Detailed computation of SPEI is explained in section 4.4.2 of this thesis. The climatic water balance (P- PET) is calculated at multiple timescales, and the resulting values are fitted to a probability distribution to convert the original values to standardized units that are similar in space and time and across different SPEI timescales.

SPEI's major limitations are its sensitivity to the method of estimating potential evapotranspiration and the need for more data for assessing drought severity, which restricts its usefulness in practice. Beguer et al. (2014) evaluated the suitability of using the evapotranspiration method. They reported PET to be suitable for use in SPEI for humid and arid regions, generating accurate estimates of drought severity. Even though PET and AET have been debated for their potential to predict drought variability in the SPEI throughout India, multiple research has already been conducted to test this hypothesis (Alam et al., 2017; Das et al., 2016; Mallya et al., 2015; Nath et al., 2017; Niranjan Kumar et al., 2013). PET can be estimated using the Thornthwaite approach if only minimal variables, such as temperature and precipitation, are available (Gond et al., 2019). This simple technique ignores factors that could affect PET, such as wind speed, surface humidity, and solar radiation. An expanded technique for calculating PET is sometimes used to account for drought fluctuations more accurately when extra data is available. These additional variables, on the other hand, can pose significant uncertainty. Multiple studies reported the SPEI to have a greater correlation with hydrological and ecological variables than any other drought index. Despite its recent development, SPEI has been extensively utilized in studies on drought variability (Potop, 2011; Sohn et al., 2013; Spinoni et al., 2013), drought reconstruction (Allen et al., 2010), drought atmospheric mechanisms (Deng & Chen, 2011; Liu et al., 2021;

Polong et al., 2019; Suroso et al., 2021; Tirivarombo et al., 2018; Tomas-Burguera et al., 2020; Vicente-Serrano et al., 2011; Wang et al., 2021).

2.6.2 Drought characterization

The characteristics of the drought indicate the nature of the drought and its importance to the water resources sector. There are several methods for determining the characteristic of drought; however, the use of drought indices is the most common (Tsakiris et al., 2007). Frequency, duration, severity, and spatial extent are the parameters used to characterize drought impact over the study region. The implications of drought classification are beneficial to the basin. For example, frequent droughts of short duration will have the most impact on agriculture, whereas droughts of high severity and short duration will have the greatest impact on reservoir hydropower output (Mishra et al., 2009). Severity is the degree to which an index deviates from the norm. An intensity threshold can be established to define when a drought begins and ends as well as the impacted area. The commencement and cessation dates are used to determine the timing and duration of the drought event. The impact is defined by the interaction of the hazard occurrence and the exposed components (people, agricultural areas, reservoirs, and water sources), as well as the vulnerability of these elements to droughts. Previous drought events may have exacerbated vulnerabilities, forcing the sale of productive assets to fulfil immediate requirements. The timing of droughts may be just as significant as their intensity in terms of factors that affect them. Short-term, low-intensity intra-season droughts can have a greater influence on crop yield than longer-term, higher-intensity droughts that occur at a less vital point in the agricultural cycle. This gives users an idea of the likelihood of droughts of varying severity occurring. However, it is important to note that historical trend will begin to shift as a result of climate change. It is important to know the local climate and drought climatology before using indicators and indices in planning and designing (Svoboda & Fuchs, 2016). The approach presented by Yevjevich (1967) for identifying drought parameters and examining their statistical properties is (a) duration, (b) severity, and (c) intensity. The truncation or threshold level, a constant or a function of time, is the most basic factor for determining these values. The threshold approach is based on run theory and has been frequently used since its inception for the assessment of drought characteristics (Dracup et al., 1980; Loaiciga & Leipnik, 1996). The threshold can be either a set threshold that remains constant throughout the simulation period or a variable threshold that changes over the year for each season, month, or day (Fleig et al., 2006).

2.6.3 Drought characterization over India under observed and changing climate scenarios

In India, more than 70 percent of the population relies on agriculture for their livelihood. Water for agriculture is primarily derived from rainfall. Meteorological drought is used as a gauge of drought. It is well-known that irrigation provides a more consistent supply of water than rainfall. Almost 20% of the country's land is in the dry farming tract, where annual rainfall ranges from 40 to 100 cm without any irrigation support. Droughts have a significant and regular impact on farm revenue and food production, with drought affecting nearly one-sixth of the land area and 12% of the population. Agriculture, water availability, and socioeconomic conditions have all been negatively affected due to the increasing frequency of droughts (Mishra et al., 2016) and weaker summer monsoons during the last few decades (Roxy et al., 2015). In addition, India's food and water security would be further threatened in the future by an expanding population and decreasing water supply. Because of the 2002 extreme drought in India, more than 300 million people were affected (Bhat, 2006). For Indian agriculture, proper scientific assessment of drought spatiotemporal characterization is critical in framing the central government's policy of releasing financial support to state governments (Manual for Drought Management, 2016). About 20% of the land of India is in the dry farming tract, where annual rainfall ranges from 40 to 100 cm without any support from irrigation. It is estimated that about 70 million hectares of cultivable land will remain under rain-fed agriculture even after the country has fully exploited its irrigation potential. This includes parts of Haryana, Rajasthan, Uttar Pradesh, Maharashtra, Gujarat, Andhra Pradesh, and Tamil Nadu. Drought wreaks havoc on a farmer's livelihood. More than 68% of the country's net sown land is drought-prone, with 50% of that region experiencing severe drought. Every two to three years, the country is plagued by drought in one of its regions. The Gangetic region and Maharashtra underwent a 500-year return period drought in 2014 and 2015, resulting in severe water scarcity and affecting millions of people living in these areas (Mishra et al., 2016). This country has experienced regular and severe drought (once every three years) in the last few decades. Anthropogenic activity-induced increases in CO_2 emissions have prompted recent shifts in the global climate (Reichstein et al., 2013; Wang et al., 2015). Guhathakurta et al. (2017) and Swain et al. (2020) used the percent of normal index (PNI) to calculate the probability of drought at the district level during normal monsoon years in India. Lin et al. (2020) and Pai et al. (2011) analysed the southwest monsoon data by SPI between 1901 and 2003 for 458 districts of India and compared the results with PNI. The spatial pattern of SPI was evaluated using SPI using station data and assessed the effect of drought on food grain productivity using correlation analysis over Gujrat (India) (Patel et al., 2007). Mallya et al. (2016) analysed the trend of the SPI, the SPEI, the Gaussian mixture model-based drought index (GMM-DI), and the hidden Markov model-based drought index (HMM-DI) for the Indian region. Chanda & Rajib (2015) developed a new index, the standardized precipitation anomaly index (SPAI), and explored its advantages over the standard precipitation index (SPI). The variability of monsoon droughts across India has been discovered to be influenced strongly by tropical sea surface temperature anomalies. Niranjan Kumar et al. (2013) used Canonical Correlation Analysis (CCA) to demonstrate that the El Nino Southern Oscillation (ENSO) is responsible for the majority of the drought variability. In addressing the causes and predictability of meteorological dryness for any particular region of the globe, the large-scale drivers of precipitation deficits relevant to that area must be addressed. Several authors (Guhathakurta et al., 2015; Kucharski et al., 2006; Webster et al., 1998) have documented the influence of ENSO, the phenomenon of abnormal warming in the equatorial pacific sea surface temperature (SST), on the variability of the Indian monsoon. Naresh Kumar et al. (2012) reported an increase in the spatial extent of area experiencing moderate drought frequency in India. To emphasize the effects of the drought on wheat output, Zhang et al. (2017) recreated the drought in India's main wheat-growing regions from 1981 to 2013. In addition, they detected an increase in the severity of vegetation and meteorological droughts over subregions.

Drought risk in India has grown due to longer dry periods, more dry days overall, and fewer light precipitation days as a result of global warming (Mishra & Liu, 2014). Ojha et al. (2013) used SPI to assess the chance of a rise in drought episodes in west-central, central-northeast, and peninsular India, using bias-corrected monthly time series from 17 GCM. Recent studies imply that there are observed warming tendencies all across the world. These trends are projected to deteriorate due to rise in anthropogenic greenhouse gas emissions, contributing to global warming (Burke et al., 2006; Dai, 2013; Guhathakurta et al., 2017). The is uncertainty estimated in the estimation of drought trend for the future scenario, especially regarding these droughts will likely be caused by changes in precipitation or evaporation (Cook et al., 2014). The global mean precipitation is predicted to rise due to the intense hydrological cycle in warmer regions (Allen & Ingram, 2002; Huntington, 2006). Prediction of the nature and occurrence of droughts is essential during the regional water planning process (Hernandez & Uddameri, 2014). To acquire estimates of anticipated future changes in the climate variables, the GCMs and RCMs are utilized over the globe (Ojha et al., 2013).

2.7 Summary

There is significant scientific evidence to support the role of anthropogenic activities in climate. The intensification of the hydrological cycle due to the warming of the earth's atmosphere is leading to spatial heterogeneity in the distribution of precipitation. Climate extremes, such as droughts and floods, are becoming more intense and frequent in different parts of the world. In the previous few decades, India has experienced numerous hydroclimatic changes, and it is anticipated to continue to do so in the future. The intensity and frequency of climate extremes, such as dry and wet events, are changing and are getting worse in different parts. India has also faced many hydroclimatic changes in the last few decades and is expected to face many such changes in the future. Climate change could worsen hydroclimatic variability because dry and wet events are linked and affected by the same underlying hydrological processes and atmospheric dynamics. The current literature on drought in Uttar Pradesh, India, primarily focuses on evaluating drought based on a single index, resulting in an uncertain assessment of drought across the region's spatially varied climate. Previous studies have concentrated on drought evaluation based on trend assessment, drought severity, or duration while neglecting the regional variability of drought. There is also a lack of studies that provide a complete evaluation of drought characteristics, including intensity, duration, and frequency, considering all the evaluation parameters that measure drought characteristics. Although several studies have examined the impact of anticipated climatic changes on hydrological systems in various parts of the country, few studies have been conducted at the sub-regional level in Uttar Pradesh that specifically examine the effects of climate change on the characteristics of future droughts under varying climate scenarios. Furthermore, while extreme climatic events have increased in the region over the last few decades, there is a significant research gap in understanding wet-dry occurrences and their transitions and assessing hotspot regions of frequent transitions over the study region for the observed period. Therefore, there is a need for a comprehensive framework that evaluates drought in any study region, including spatially explicit analysis of drought characterization, with a particular emphasis on drought at the sub-regional scale as a foundation for any future climate change adaptation and resilience plans. An examination of the literature review indicate that numerous studies have been conducted in various sections of the country, emphasizing the negative effects of climate change on hydrology or water resources. The majority of the studies, on the other hand, concentrated on assessing trends in hydrometeorological variables such as precipitation, evapotranspiration, temperature, and so on, as well as drought. Compared to climate extreme events, gradual changes in climatic variables do not constitute a significant hazard to humans and natural systems. Number of recent rapid wet-dry events have shown how important it is to have a sequence of wet and dry events. As very few studies have been conducted that analyze the dry and wet event characteristics and their transition, considering this gap, this study focuses on the assessment of the concurrent evolution of characteristics of dry and wet events and their transition over the observed period. The SPI and SPEI are among the most commonly used drought assessment indices worldwide. SPI uses precipitation as its only input to assess drought. Unlike SPI, SPEI uses both precipitation and temperature, thereby considering the influence of global warming to some extent. Assessments of performance between SPI and SPEI are well addressed. However, no adequate literature was found on the assessment of drought characteristics using the SPI and SPEI at different timescales over Uttar Pradesh, India. This research focused on the evaluation of spatiotemporal characteristics of meteorological drought over northern India using different indices in observed and projected climate scenarios based on SPEI as drought assessment tools at 3-month, 6-month, 9-month and 12-month timescales. Therefore, there is a need for a comprehensive framework that evaluates drought in any study region, including spatially explicit analysis of drought characterization, with a particular emphasis on drought at the sub-regional scale as a foundation for any future climate change adaptation and resilience plans.