CHAPTER 3
LITERATURE REVIEW

Reviewing existing literature aids in identifying knowledge gaps and research areas that have not been explored thoroughly. Understanding what has been studied previously allows for identifying unanswered questions and setting research objectives that add to the existing body of knowledge. Additionally, it provides researchers with a comprehensive overview of the theoretical frameworks, methodologies, and findings used in previous studies, providing valuable insights into the evolution of ideas within the field. It also helps in identifying patterns, trends, and viewpoints, promoting critical thinking and detailed understanding. Incorporating historical works into research broadens and deepens scholarly investigations. It enables the integration of key findings and themes from multiple studies. Currently, researchers can readily explore a wide range of studies from around the globe, presenting an unprecedented opportunity. Many resources, including historical literature, scholarly articles, journal publications, conference proceedings, Government reports, and other paid or complimentary data, can be conveniently accessed through digital libraries, public databases, and academic search engines. These tools help researchers find relevant research, browse the literature, and keep up with the recent advancements in their fields. Ultimately, a well-executed literature review serves as the cornerstone of rigorous academic inquiry, guiding researchers toward informed and impactful contributions to their respective disciplines.

This review explores various approaches and models used to study temperature and rainfall variations across different geographical scales, highlighting their strengths and weaknesses. It will highlight gaps in current knowledge and areas that require additional research to understand this complex relationship. It attempts to identify the key trends, drivers, and impacts associated with these changes by synthesizing the findings from a vast scholarly source. In accordance, the review of literature has been structured to explore the issues faced by changing climate on global temperature and rainfall in five sub-heads:

- Global Climate Dynamics: Temperature and Rainfall Trends.
- Climate Profile of India: Influences and Associated Impacts.
- Climate Profile of Gujarat: Exploring Distinct Regions.
- Assessing Trends and Weather Extremes.
- Time Series Forecasting Models.

3.1 Global Climate Dynamics: Temperature and Rainfall Trends

Global climate change is inducing profound alterations in environmental conditions, affecting all life forms worldwide (Bernatchez et al., 2024). Several studies globally have extensively examined climate change, its underlying causes, and its far-reaching consequences. Climate change generally refers to prolonged shifts in weather patterns, often influenced by natural factors such as changes in solar activity, along with anthropogenic factors (Trenberth, 2018). Climate change, caused by human activities, entails prolonged alterations in temperature and weather patterns at different scales. Throughout history, lifeforms and weather have coexisted in a subtle harmony crucial for sustaining all lives on Earth (Shivanna, 2022). However, since the Industrial Revolution, this equilibrium has been gradually disrupted, becoming more evident in late 20th century (Ahmed et al., 2022). Now, it poses a significant threat to society. The recent climatic changes, largely driven by human activity, are having widespread and rapid detrimental effects than they had predicted less than a decade ago (Lenton et al., 2023). The consensus is that human activities, particularly fossil fuel combustion and greenhouse gas emissions, are the primary drivers of the current global warming trend (Fakana, 2020).

Besides human activities, the current warming trends are influenced by several other factors. One of the most significant signs of climate change is the alteration of global temperature and rainfall patterns (Viloria et al., 2023). The Earth's climate is influenced by various phenomena, including the El Niño–Southern Oscillation (ENSO) cycle, marked by warm El Niño and cold La Niña events originating in the tropical Pacific Ocean (Chen et al., 2024). The phenomenon is responsible for variations in atmospheric temperature, circulation patterns, and rainfall levels across the tropics and subtropics (Bhatla et al., 2020). Its effects reverberate worldwide, affecting both the environment and socioeconomic factors, even though it originates in the Pacific Ocean (Geng et al., 2023). The ENSO cycles stand as the foremost and impactful climate phenomena globally, holding profound implications for long-term forecasting (G. G. Wang et al., 2023). Other factors, such as the Indian Ocean Dipole (IOD), resemble the El Niño phenomenon but occur in the Indian Ocean (Z. Huang et al., 2022). Distinguished by SST anomalies between its western and eastern parts, the IOD exerts a substantial impact on regional weather patterns (K. Huang et al., 2024; Y. Jiang et al., 2021; S.-K. Kim et al., 2024). It influences rainfall distribution across the Indian subcontinent, Australia, and eastern Africa, making it a pivotal factor in the climate dynamics of these regions (Marchant et al., 2007). Additionally, the Madden-Julian Oscillation (MJO) is a significant tropical phenomenon lasting 30–90 days (Utari et al., 2022), characterized by eastward-moving clusters of clouds and rain systems along the equator, influencing intense tropical rainstorms and extreme weather in middle to high latitudes (X. Jiang et al., 2020). Together, these phenomena show how various climatic elements shape global weather patterns, emphasizing the complexity of climate change and its impacts at different geographical scales (Z. Huang et al., 2022). Understanding and monitoring these phenomena is essential for adapting and mitigating the adverse effects of climate change on ecosystems, economies, and societies worldwide.

The period from 2014 to 2023 marks the warmest decade in the 144-year record (Bardan, 2024). In 2023, global temperatures surpassed previous records from June to October, while other months also ranked among the top seven highest recorded temperatures for their respective months (Laimighofer & Formayer, 2024). Although 2005 initially set a new global temperature record, it is now ranked 12th, while 2010, which surpassed it initially, is now ranked 11th (Bardan, 2024). Between 2011 and 2020, the global surface temperature increased by 1.09°C compared to the pre-industrial period (1850-1900) (Soon et al., 2023), with land areas experiencing a larger temperature increase (1.59°C) than ocean regions (0.88°C). Over the first two decades of the 21st century (2001–2020), temperatures were 0.99°C higher than in 1850–1900 (Calvin et al., 2023a). In 2023, the global average temperature soared to 14.9°C, marking a 0.16°C increase from the previous highest annual reading in 2016. It stood at 0.60°C above the 1991-2020 average and 1.48°C higher than the pre-industrial levels of 1850-1900 (Lopez, 2024).

Table 3.1 Overview of IPCC Assessment Reports: Climate Predictions and Key Findings

Assessment Reports	Models	Predictions/ Key Points
IPCC FAR, 1990	CGCM	Global mean temperatures are projected to increase by about 0.3°C per decade in the 21st century. Human activities are increasing greenhouse gas concentrations in the atmosphere, leading to a rise in global temperatures.
IPCC SAR, 1995	CGCM	Global mean temperatures are expected to rise by 0.4-1.1°C (1990-2025) and 0.8-2.6°C (1990-2050).

IPCC TAR, 2001	AOGCM	Projected temperature increases: 0.4-1.1°C (1990-2025), 0.8-2.6°C (1990-2050), 1.4-5.8°C (1990-2100). Earth's surface is warming, attributed to human activities. Global mean temperature is expected to rise in the future. Sea levels will rise, impacting vulnerable regions.
IPCC AR4, 2007	CMIP3	The global average surface temperature has increased by about 0.74°C between 1906 and 2005 and continues to rise at about 0.13°C per decade. Warming has been greater over land than over oceans, particularly since the 1970s. Limiting warming to 1.5°C is crucial to mitigate adverse effects.
IPCC AR5, 2014	CMIP5	Predicted changes include temperature increases of 1-3-7°C and sea level rise of 0.40-0.63m by 2081-2100 compared to 1986-2005.
IPCC AR6, 2023	CMIP6	A global temperature rise of 3.3–5.7°C (5.9–10.3°F) by 2100 is projected if emissions remain high. Climate changes will intensify globally, leading to increased heat waves, glacier melt, and water scarcity.

Source: (Calvin et al., 2023)

AR- Assessment Report, GCM- General Circulation Model, CMIP- Coupled Model Intercomparison Project, FAR- First Assessment Report, SAR- Second Assessment Report, TAR- Third Assessment Report, AOGCM- Atmosphere-Ocean General Circulation Model, and CGCM- Coupled Global Climate Model.

In recent reports, IPCC AR6 have highlighted critical findings regarding global temperature trends and carbon dioxide emissions. The WMO's report highlights a concerning projection, indicating a 66% likelihood that the annual average near-surface global temperature between 2023 and 2027 will surpass 1.5°C above pre-industrial levels for at least one year (WMO, 2022). This alarming forecast signals the urgency of addressing climate change to mitigate its potentially devastating impacts. Similarly, the IPCC's AR6 emphasizes the importance of stringent carbon dioxide emission reductions. It suggests that the world can emit only 500 gigatonnes more of carbon dioxide, measured from the beginning of 2020, to maintain a 50% chance of limiting global warming to below 1.5 degrees Celsius (Calvin et al., 2023). These reports serve as critical reminders of the pressing need for ambitious climate action to safeguard our planet and future generations. According to NOAA's 2023 Annual Climate Report, the average rate of global warming has increased significantly since 1850, reaching 0.20°C per decade in recent decades (NOAA, 2023).

The world witnessed an array of extreme events in 2023, ranging from heatwaves and floods to droughts and wildfires, occurring across the globe (Cartwright, 2024). Although warming varies across the globe, the overall upward trend in the global average temperature indicates that more regions are experiencing warming rather than cooling. The warming El Niño event in 2023, which started in spring and intensified during the summer, is projected to further increase temperatures in 2024 (Cartwright, 2024), amplifying the severity and frequency of extreme events. The strong correlation between El Niño and global surface temperature changes has reignited interest among researchers. The increasing temperature exerts diverse impacts, profoundly influencing rainfall patterns, their intensity, and global distribution (Yun et al., 2021). Additionally, alterations in rainfall patterns can influence water availability, soil moisture, and ecosystem productivity and composition (Weiskopf et al., 2020). Intense rainfall exacerbates the impact of hydrometeorological disasters like floods, landslides, and mudslides. In July 2021, Henan Province, China, experienced 201.9 mm of rainfall within an hour, resulting in 302 deaths, displacing 1.47 million people, and affecting over 13 million (Z. Wang et al., 2024). Europe faced similar devastation within the same month, with record-breaking rainfall causing floods, power outages for 0.2 million properties, and $12 billion in damages (Kreienkamp et al., 2021). Recent Floods and Heavy Rainfall Disrupting Daily Life in Middle Eastern and Asian Countries (Francis et al., 2024), further exemplify the far-reaching consequences of extreme rainfall events, which caused $329 billion in global economic losses in 2021 alone, and this figure is expected to rise due to increasing frequency and severity.

The potential impacts and risks of future climate change are closely linked to the extent of global warming throughout the 21st century. Climate projections indicate that by the year 2100, global surface temperatures may surge by an alarming range of 1.3°C to 8.0°C (Scafetta, 2024). This concerning variability suggests that the consequences of climate change could pose a significantly greater threat to both societies and the environment throughout the century, potentially leading to widespread devastation and irreversible damage (S. K. Kim et al., 2022). The IPCC is gradually acknowledging the threat that climate change poses to future growth, human well-being, and ecological health (IPCC, 2007). Although global temperatures have increased by about 1.48°C in 2023 compared to the period from 1850-1900, it's important to understand that climate change encompasses a wider array of changes and impacts, and extends beyond alterations in temperature and rainfall alone (Bardan, 2024). It includes irregular weather patterns and the melting of ice sheets, leading to rising sea levels. In 2023, global sea levels attained a new peak since satellite records began in 1993 (Guérou et al., 2023), indicating ongoing ocean warming and ice melting. Over the past decade (2013-22), sea levels increased twice as rapidly as in the preceding decade (1993-02) (WMO, 2023). The repercussions of rising sea levels can lead to significant outcomes. These include the displacement of coastal populations, increasing vulnerability to natural disasters, disruptions to agriculture and water resources, as well as economic losses (FAO, 2017).

Climate change also exerts a huge impact on agricultural output and forest environments, thereby affecting socioeconomic conditions worldwide (WMO, 2022) and already exceeding the tolerance thresholds of plants and animals, causing catastrophic loss of species such as trees and corals (IPCC, 2022). Climate change is projected to increase the frequency and intensity of current hazards, increase the likelihood of extreme events, and spur the emergence of upcoming challenges (Ebi et al., 2020). The frequency and severity of extreme weather events will rise with every tenth of a degree as global temperatures rise further (Myhre et al., 2019). With increasing global temperatures, heat waves are projected to become more frequent, and more intense (Rohini et al., 2019). Heatwaves can have severe impacts on human health, leading to heat-related illnesses and even mortality, especially among vulnerable populations. Additionally, higher temperatures contribute to increased evaporation, which can lead to more moisture in the atmosphere (Tabari, 2020). This, in turn, can result in more intense rainfall events and an increased risk of floods. Additionally, it has the potential to accelerate the erosion processes, resulting in the loss of topsoil and the deposition of sediment in water bodies (Wei et al., 2024). Increasing temperatures can also worsen the occurrence and severity of droughts in certain regions. When temperatures rise, the rate of evaporation from soils and water bodies increases, leading to greater moisture loss (Qiao et al., 2023). This, combined with reduced rainfall, intensifies drought conditions. These prolonged and severe droughts can have far-reaching impacts on ecosystems, agriculture, water resources, and human populations. Reduced crop yields, livestock losses, water scarcity, and increased competition for limited resources can affect livelihoods, food security, and economic stability. With prolonged dry spells, soil moisture levels decrease, and water availability becomes limited (Hunt et al., 2009). Overall monitoring global temperature and rainfall patterns is essential for understanding climate change and developing effective mitigation and adaptation strategies.

3.2 Climate Profile of India: Influences and Associated Impacts

The climatic conditions across India vary significantly, ranging from tropical climates prevalent in the southern regions to temperate and alpine climates observed in the northern Himalayan territories, where higher altitudes experience sustained winter snowfall (Krishnan et al., 2020). Within the latitudinal range of 8° N and 37° N, India's geographical setting, characterized by its peninsular shape and proximity to the Bay of Bengal, Indian Ocean, and Arabian Sea, with a coastline spanning about 7,516.6 kilometers, profoundly impacts various meteorological phenomena (Subramanian et al., 2023). This influence extends to rainfall patterns, monsoon winds, air currents, and the formation of tropical cyclones. The Himalayas in the North prevents the cold Katabatic winds, which descend from Central Asia, from reaching the northern plains of India (Swain et al., 2022). These winds, characterized by their dry and cold nature, have the potential to cause extremely low temperatures in the regions they traverse. However, the Himalayas act as a barrier, hindering these cold winds from advancing further, thus contributing to a milder climate across much of the Indian subcontinent, particularly in the northern plains (Pai et al., 2017). The country experiences distinct seasonal transitions, including pre-monsoon (MAM), SWM (JJAS), post-monsoon (OND), and winter (JF), each characterized by unique temperature and rainfall patterns. During winter, the northern parts of India experience relatively cooler temperatures than the rest of the year and remaining India. The average mean temperature during winter is around 10°C in many regions of northern India, although it can be lower in the higher-altitude areas of the Himalayas (Nageswararao et al., 2016). In contrast, pre-monsoon brings hot and dry conditions across India, preceding the onset of the monsoon rainfall (Kothawale et al., 2010). The average mean temperatures during pre-monsoon can reach around 32°C and even higher in some parts of the country. Particularly in western areas like Rajasthan and Gujarat, temperatures can escalate beyond 45°C during the peak summer months (Jaswal et al., 2015). Following the pre-monsoon period, the SWM season arrives in India. The SWM season in India is a crucial climatic phenomenon characterized by the onset of heavy rainfall across the country. The SWM typically begins over the southern part of the Indian peninsula in early June and advances northward, covering approximately the entire country in the following weeks (Guhathakurta et al., 2015). The spatial and temporal variability of the monsoon across India is significant. Different regions experience the onset and duration of the monsoon at varying times and intensities. The amount of rainfall varies throughout the nation, ranging from 100 to 2000 mm/year, and constitutes about 75-80% of the annual mean rainfall of India. While SWM begins its retreat from September to early October, starting in the northwest and progressing south-eastward (Mausam, 2021). This withdrawal brings reduced rainfall and the return of dry weather conditions across India. The interannual fluctuations of the SWM represent about 9% of its average, yet they have considerable socio-economic impacts (Athira et al., 2023). Following the SWM, the Post-Monsoon season occurs, marking a transition to drier conditions. While some areas may experience sporadic rainfall, overall rainfall decreases gradually. This period is crucial for agricultural activities, serving as a bridge between the wet and dry seasons.

The country receives two seasons of rain: Southwest monsoon and Northeast monsoon (Rajeevan et al., 2012). In the winter, the Indian sub-continent is dominated commonly by dry, cold air advancing from northern latitudes in a north-easterly direction. Several regions in southeastern peninsular India, particularly areas including the states of Tamil Nadu and Andhra Pradesh, experience heavy rainfall from October to December with the arrival of the northeast monsoon (Krishnan et al., 2020). While a seasonal shift in the winds brings heavy rainfall over the Indian subcontinent during SWM (JJAS). This preeminent system not only affects India but also holds global significance, impacting approximately one-third of the world's population (Verma & Bhatla, 2021). The SWMR shows high spatial variability, resulting in regions experiencing either surplus or deficit rainfall across the country (Hrudya et al., 2021). The interannual variability of SWMR becomes more pronounced when considering the spatial variability of rainfall distribution (Athira et al., 2023). Over time, extensive temporal and spatial variations in the SWM have been observed, profoundly impacting the nation's water supplies, power production, agriculture, economy, and ecosystems (Attri & Tyagi, 2010). India's dependence on SWMR renders it susceptible to extreme weather events, with the unpredictable nature of the monsoon exacerbated by its interaction with various local and global factors, including El Niño, La Niña, the Indian Ocean Dipole (IOD), and Madden Julian

Oscillation (MJO) (Z. Huang et al., 2022). Several studies have rigorously examined how each of these climate drivers influences SWMR (Pai et al., 2011; Ratna et al., 2024). This interaction amplifies the country's vulnerability to EWE. The Rainfall patterns across the Indian subcontinent vary on a sub-seasonal scale in response to El Niño and La Niña events (Kiran Kumar & Singh, 2021). For instance, El Niño and La Niña years in India are typically linked with deficient and abundant SWMR, respectively (Chaturvedi & Dwivedi, 2024). Additionally, the ENSO phenomenon influences global heat distribution. Specifically, it impacts the climate across the Indian subcontinent, particularly during the development and decay of ENSO events (Velivelli et al., 2024). El Niño occurrences increase surface air temperatures during pre- and post-monsoon seasons, whereas La Niña leads to a decrease during monsoon and post-monsoon months over the Indian subcontinent (Revadekar et al., 2009). These temperature variations have a significant impact on weather patterns, agricultural productivity, and broader climate dynamics. According to IMD data spanning 122 years, India experienced 22 El Niño events since 1901. Of these, 16 have resulted in drought-like conditions due to below-normal SWMR. A few strong El Niño years- 1877-88, 1911-12, 1918-19, 1972-73, 1997-98, 2015-16, and 2023-24 witnessed significant rainfall deficiencies and severe droughts across many parts of India. While, there were a few moderate El Niño years as well- 1914-15, 1976-77, 2006-07, and 2009-10 during which the impact was relatively less severe. Similar to ENSO in the Pacific Ocean, the Indian Ocean Dipole (IOD) is an ocean-atmosphere phenomenon characterized by abnormal differences in SST between the western and eastern tropical Indian Ocean (Ratna et al., 2024). IOD typically emerges during boreal summer, reaching maturity in fall, and dissipating by winter, the IOD stands as a significant climate indicator in tropical oceanic systems, which often triggers widespread natural calamities along the Indian Ocean (Marchant et al., 2007). However, forecasting the IOD poses greater challenges compared to ENSO, mainly due to the intricate dynamics of air-sea interactions influenced by both local and remote factors, as well as the intense intraseasonal variability within the tropical Indian Ocean (K. Huang et al., 2024). During a positive IOD phase, the W-Indian Ocean (WIO) experiences unusually warm SST, while the EIO experiences relatively cool SST, with the opposite occurring during a negative IOD phase (Z. Huang et al., 2022). The positive phase of the IOD tends to enhance SWMR across the Indian subcontinent and reduce temperatures due to increased cloud cover and rainfall, potentially mitigating drought conditions. While, the negative phase often leads to suppressed SWMR, intensifying drought conditions and impacting agriculture and water resources (Ashok et al., 2004). These events disrupt oceanic and atmospheric circulation, leading to significant rainfall anomalies and effects rippling across countries bordering the Indian Ocean (S.-K. Kim et al., 2024). Following El Nino/ La Nina and IOD, MJO primarily drives intra-seasonal variability (lasting 30–90 days) across tropical regions (Utari et al., 2022). It initiates convective anomalies in the west equatorial Indian Ocean and traverses the Maritime Continent including SE Asian countries before fading away over the Pacific Ocean (Karlowska et al., 2024). The MJO consists of two distinct phases, often dividing the earth into two halves during periods of strong activity: one experiencing enhanced rainfall (convective) phase and the other undergoing suppressed rainfall phase (Kang et al., 2024). During the SWM season, when the MJO is positioned over the Indian Ocean, it generally leads to favourable rainfall across the Indian subcontinent (S. K. Mishra et al., 2017). Conversely, if the MJO cycle persists over the Pacific Ocean, it tends to suppress convection over the Indian subcontinent, which leads to reduced SWM rainfall over the Indian subcontinent (Sasikumar et al., 2022).

These climatic drivers contribute to significant variations in rainfall and temperature patterns across the Indian subcontinent. These variations have far-reaching consequences that extend beyond immediate weather impacts (Ashok et al., 2004). With the current trend of increasing temperatures (IPCC, 2021) and extreme rainfall events, the challenges posed by the SWM are further exacerbated. Projections suggest that India's average temperature is expected to increase by 1.5°C to 4.5°C by the end of the 21st century compared to pre-industrial levels (Maurya et al., 2023). In addition, Climate change can exacerbate water scarcity issues in India, particularly in arid and semi-arid regions (Martin & Martin., 2010). Changes in rainfall patterns, increased evaporation rates, and shrinking glaciers can impact water availability for agriculture, industry, and domestic use. Apart, rising sea levels, projected to increase to 1 meter by 2100 (Kay et al., 2015), pose risks to the extensive coastline of India, including increased erosion, saltwater intrusion, mangroves, and vulnerability to storm surges (Roy et al., 2023). Addressing these challenges requires robust monitoring, forecasting, and adaptation strategies to mitigate impacts and build resilience for sustainable development in a changing climate.

3.3 Climate Profile of Gujarat: Exploring Distinct Regions

Among all the mainland states of India, Gujarat has the longest coastline. Despite its proximity to the Arabian Sea, Gujarat has a predominantly dry, arid to semi-arid climate in most areas, owing to its proximity to the Thar Desert in the north (Ray et al., 2008). The state experiences high spatio-temporal variability in the distribution of rainfall and temperature (Bandyopadhyay et al., 2016). This variability stems from the state's diverse physiography, encompassing an assortment of distinct landforms including alluvial plains, hilly terrain, highlands, desert expanses, and coastal areas. These varying geographical features contribute to a complex spectrum of climatic conditions across the state (N. Kumar et al., 2015). The state has a subtropical climate, with sub-humid conditions in southern Gujarat, moderately humid conditions in central Gujarat, hot and humid conditions along the coast, dry conditions in parts of central Gujarat, and arid and semi-arid conditions in northern Gujarat and Kutch (Dasgupta et al., 2021). The vast majority of Gujarat is located in climatically arid and semi-arid regions, characterized by irregular rainfall patterns. Droughts typically occur in the Indian Subcontinent due to the delayed arrival and early departure of the SWM and/or insufficient rainfall (Bandyopadhyay et al., 2016). According to IMD (2015), the state faced fifteen major droughts in the past three decades between 1981 and 2010, affecting large portions of its land area, with some instances covering up to 80% of the total area, with heat waves and high temperatures observed in most of these affected years, particularly in Kutch and North Gujarat (Bandyopadhyay et al., 2020). The state experiences drought frequently, with two or three events occurring every five years, and a severe event striking every decade. The state's agriculture sector, engaging over half of the state's rural workforce, faces instability in drought-prone regions, which worsens the impact on rural communities (Bhukya et al., 2023). This recurring drought pattern leads to substantial financial losses and drives significant migration from affected areas. All drought years in the state coincide with El Nino events, but not all El Nino years result in drought conditions (Power et al., 2020). Observations indicate an increase in frequency and intensity of droughts in the state over time, resulting in severe water scarcity.

Besides, Gujarat faces a significant risk of waterlogging resulting from flooding due to rising sea levels, excessive rainfall, and cyclones. Almost all the parts of Gujarat are prone to floods with the last two decades have been particularly severe (Waghwala & Agnihotri, 2019), with seven flooding events occurring in 2003, 2004, 2005, 2006, 2013, 2015, and 2019 in different parts of the state. Floods occur approximately every two years in various parts of Saurashtra, Kutch, and Northern Gujarat (Singh et al., 2022). Additionally, the state is vulnerable to various extreme events, including cyclones and heatwaves, which have been occurring more frequently and with increasing intensity in recent decades (Suthinkumar et al., 2023). Projections indicate a further intensification and increase in the frequency of these events. In the past decade, the state has experienced growing impacts of heat waves attributed to rising temperatures and urbanization (Gujarat State Disaster Management Authority, 2020). Heat-related fatalities have increased annually since 2010, with projections indicating a continuing rise in casualties (Bandyopadhyay et al., 2016). The urban heat island effect also exacerbates the event by intensifying temperatures in urban areas and with the increasing SST of the Arabian Sea, the frequency of cyclones surged by nearly 50% between 2001 and 2020 compared to the previous two decades (Baburaj et al., 2022).

The state is categorized into five distinct physiographic regions: Central Gujarat, Kutch, North Gujarat, Saurashtra, and South Gujarat (State of Environment Reports Gujarat 2012, http://gujenvis.nic.in/PDF/soe-land.pdf; Srivastava et al., 2023). Climatic conditions exhibit significant variations across distinct regions. The annual rainfall varies across the state, ranging from about 400mm in the Kutch to over 1500mm in South Gujarat (Ray et al., 2008). Typically, South Gujarat receives abundant and reliable rainfall, while Central Gujarat experiences moderate rainfall. On the other hand, the Kutch region experiences scarce and unpredictable rainfall patterns (Dave & James, 2017). The state experiences a large spectrum in the spatial distribution of SWMR, which gradually decreases from South Gujarat to the Kutch (Dasgupta et al., 2021), along with the number of rainy days. The frequency of rainy days varies across Gujarat, with an average of 35 days per year (according to IMD's criteria of a rainy day as one with daily rainfall exceeding 2.5mm). The usual rainfall period in the state extends from June 15 to September 30, with observed variability ranging from 20% to more than 50% across distinct regions (Nath et al., 2023). Additionally, the temperature in Gujarat exhibits considerable variation throughout the year. During the pre-monsoon period, the average temperature ranges from 30 to 35°C. In certain regions, the maximum temperature may occasionally soar to 45°C, particularly during heatwaves (Ray et al., 2013). A heatwave is defined by a minimum maximum temperature of 40°C in plains and 30°C in hilly regions (Pai et al., 2017). However, relief comes with the arrival of the SWM season, with temperatures ranging between 27 and 32°C. The delayed withdrawal of the SWM can cause rainfall during the post-monsoon months, leading to erratic weather patterns. Despite being in the post-monsoon phase, temperatures in Gujarat can still be relatively high, with warm and humid daytime conditions, occasionally reaching uncomfortable levels (Shahfahad et al., 2022). Meanwhile, winter in Gujarat is relatively mild, with temperatures ranging from 10 to 22°C (Bandyopadhyay et al., 2016). Despite variations in the spatial distribution of rainfall and temperature, there is a consistent trend of overall decreasing rainfall and increasing temperature from South Gujarat to the Kutch. Consequently, the Kutch faces an increased risk of aridity and drought. About 51% of the area of Kutch is occupied by high saline and unproductive land (https://kachchh.nic.in/about-district/), covering 11.9% of the total area of Gujarat, exhibits challenges for sustainable development and resource management in the region.

Additionally, the state is divided into eight agro-climatic regions based on factors such as soil type, temperature, water resources, and rainfall patterns (Hiremath et al., 2016). Zone I and II, comprising a combined 9.86% of the state's total area falling under South Gujarat, experience annual rainfall ranging from moderate to heavy, between 1000-2000 mm. In Central Gujarat, Zone III covers 12.15% of the state's area, with annual rainfall varying between 800-1000mm. North Gujarat, in Zone IV, constitutes 12.53%, with average annual rainfall ranging from 600-850mm. Kutch, falling under Zone V and constituting 31.32% of the state's total area, receives annual rainfall ranging between 250-500mm. Saurashtra, covering 14.41% of the state's area in Zones VI and VII, experiences annual rainfall between 750-1000mm. Lastly, the coastal (Bhal) area, Zone VIII, covering 5.27% of the state's area, experiences annual rainfall between 625-1000mm (https://gec.gujarat.gov.in/files/2023/2/NL(Apr-Jun-2022).pdf).

3.4 Assessing Trends and Weather Extremes

3.4.1 Trend Assessment

Trend assessment involves the analysis of historical data to identify and understand patterns, shifts, and developments over time across various domains such as economics, finance, technology, climate studies, etc. Historical data serves as the foundation for trend assessment, providing insights into past trends, their drivers, and their impacts (Strandsbjerg Tristan Pedersen et al., 2021). This entails the aggregation of data from diverse sources, the discernment of significant trends, and the interpretation through analysis and forecasting techniques (Khashei et al., 2012). Globally, researchers across diverse disciplines have extensively employed a variety of trend assessment methods for multifold purposes. In its early stages, trend assessment predominantly utilized elementary statistical techniques like linear regression (Haan, 1977) and moving averages. While these methods offered fundamental insights into data trends, they struggled to capture intricate patterns effectively (Johnson & Berenson, 2019). However, the introduction of computers and statistical software ushered in a new era of trend analysis, facilitating the development of more sophisticated methodologies (Li et al., 2024). Among these advancements was the emergence of time series analysis, which empowered analysts to understand seasonality and long-term trends with high precision (Athiyarath et al., 2020). Additionally, the emergence of non-parametric approaches such as the Mann-Kendall (Mann, 1945; Kendall, 1975) test and Sen's slope (Sen, 1968) estimator presented robust alternatives for trend identification, especially while dealing with non-normal data distributions and outliers. In recent times, the widespread availability of big data and advancements in machine learning have transformed trend assessment and allowed the analysis of huge datasets of unprecedented complexity (Rodríguez-Mazahua et al., 2016). Techniques such as data mining, neural networks, and deep learning have empowered analysts to uncover subtle trends and patterns that were once imperceptible (Raschka et al., 2020). Furthermore, there is an increasing focus on interdisciplinary methodologies in trend assessment, integrating insights from disciplines such as econometrics, social sciences, and climatology (Mireles-Flores, 2018). This interdisciplinary approach enriches trend analysis by taking into account a wide range of factors influencing trends, including economic indicators (Dellink et al., 2017; Mireles-Flores, 2018), societal shifts (Harper, 2014), and climate variables (Caloiero et al., 2018; He et al., 2022; Kliengchuay et al., 2024; Song et al., 2023). Future developments could entail incorporating real-time data streams and refining predictive modeling capabilities.

In the realm of climate studies, trend assessment has garnered significant attention and exploration over the past six decades. Among recent shifts in climate variables, trends whether an upward or a downward shift have manifested in hydrometeorological records worldwide (Adler et al., 2017; Gu & Adler, 2023). Numerous researchers have focused on the comprehensive study of rainfall (S. K. Jain et al., 2013; N. Kumar et al., 2017; Caloiero, 2020) and temperature (Hingane et al., 1985; Jaswal et al., 2015; Kliengchuay et al., 2024; Kothawale et al., 2010; Stefanidis et al., 2022) trends, and aim to understand the broader implications of climate change at different geographical scales. Undoubtedly, the increasing temperature and rainfall trends and the intensification of variations highlight the need to employ rigorous trend analysis methodologies. Progressively gaining acclaim among nonparametric techniques, the Mann-Kendall (MK) test, has garnered recognition and earned the endorsement of the World Meteorological Organization (WMO, 2012) for analyzing trends in hydrometeorological time series. The test is non-parametric, implying that it does not demand the data to adhere to any specific distribution (Agbo et al., 2023), and is based on the ranks of the data, rather than the actual data values, making it robust against outliers. The MK trend test addresses the relationship between the observed ranking of values and their order (Pandey et al., 2024). The MK test has multiple advantages, including the handling of missing data, minimum dependency on assumptions, free from data distribution constraints, the unique ability to identify trends in time series without a predefined specification of linearity, and resistance to the impact of extremes (L. Jain & Bhatt, 2022), all contributing to its resilience to outliers, setting it apart from alternative analysis techniques. Additionally, (Theil, 1950) introduced the median of pairwise slopes as a robust estimator for the slope parameter in a basic linear model. (Sen, 1968) later expanded upon this method to accommodate tied observations, enhancing its applicability and accuracy. The Theil-Sen estimator is a robust method known for its resilience and effectiveness (Dang et al., 2009), offering reliability in various domains, and used to estimate the magnitude and direction of trends in time series or spatial data (Dabanlı et al., 2016). It calculates the median of all possible pairwise slopes between data points, providing a resistant measure of the trend's magnitude (Serinaldi et al., 2020). This method is useful when dealing with data that may contain outliers or have non-normal distributions because it takes into account the variability of the slopes to provide more reliable trend estimates (Ali et al., 2019). Traditional trend assessment methods offer numerous advantages, yet over time, innovative and sophisticated tests have emerged with advantages over these traditional approaches (Caloiero et al., 2018). Modified iterations of conventional tests are now frequently utilized, especially in the analysis of data series characterized by autocorrelation, wherein the non-randomness of the data is affected by serial correlation (Reddy & Henze, 2023).

However, the Innovative Trend Analysis (ITA), introduced by (Şen, 2012), has gained significant traction in recent times as it dissects time series data into various components, including long-term trends, seasonality, and random variations (Fattah et al., 2024). The widespread application of ITA in detecting trends within meteorological variables attests to its efficacy in effectively tackling the challenges associated with trend detection (Caloiero et al., 2018). The Conventional MK test remains robust regardless of the distribution of the data. However, the absence of trend categorization into high, medium, or low constitutes a limitation. Thus, the application of the contemporary method, ITA is advantageous, which utilizes graphic techniques to uncover trends within datasets, offering a means to detect hidden significant trends (Kliengchuay et al., 2024) and mitigate potential errors in trend detection. Additionally, it identifies trends even when these trends are non-monotonic; this is in contrast to the MK test which only identifies monotonic (increasing or decreasing) trends (Ali et al., 2019). The ITA utilizes a Cartesian coordinate system to plot the data (Hırca et al., 2022). Initially, the arranged (ascending) dataset is split into two equal parts, with the first half plotted on the x-axis and the second half on the y-axis. Trend interpretation is based on data scattering around a common line on the graph. Data above the line indicates an increasing trend, while data below implies a decreasing trend (Niazkar et al., 2024). ITA merges the benefits of both the MK and Sen's Slope tests by discerning the trend's nature based on the slope's sign and assessing the significance of the identified trend. (Swain et al., 2022). Numerous studies have compared conventional and contemporary methods across various fields (Ali et al., 2019; Seenu & Jayakumar, 2021; Gumus et al., 2022). These studies aim to assess their effectiveness, reliability, and applicability in addressing research questions and solving practical problems. By comparing outcomes, researchers identify strengths, weaknesses, and areas for improvement in existing methodologies. This comparative analysis contributes to the advancement of knowledge and informs decision-making processes by offering insights into the relative merits of different analytical techniques.

3.4.2 Extreme Events

The impact of climate change is exacerbating India's susceptibility to extreme events. Increasing temperatures, shifting rainfall patterns, rising sea levels, and glacier melting introduce additional risks and uncertainties, which impact agriculture, water resources, coastal regions, and ecosystems (Sharma, 2020). India's diverse geographical and climatic conditions make it susceptible to extreme weather events (USAID, 2018). The country has a large and unevenly distributed population, with many people residing in vulnerable areas such as coastal regions, river basins, and hilly terrains, increasing the exposure and risk to extreme climate events (A. Kumar et al., 2020). Key events include tropical cyclones, heatwaves, floods, droughts, etc. The coastal regions along the Bay of Bengal and the Arabian Sea are highly susceptible to cyclones due to their geographical positioning and the warm waters of these seas (Mohapatra, 2015). Heatwaves are a common occurrence in the arid, high-temperature climates of northwestern and central India, while flood is a recurring issue across various regions of the country, and droughts predominantly impact arid and semi-arid areas (Sharma, 2020).

3.4.2.1 Heatwaves

Heatwave refers to a period of unusually high temperatures surpassing the normal maximum in NW India during the pre-monsoon period (MAM), often extending till July (Pai et al., 2017). Heatwaves can have far-reaching impacts on both human health and the environment. Prolonged exposure to high temperatures can lead to heat-related illnesses such as heat exhaustion, heatstroke, and dehydration, particularly among vulnerable populations such as the elderly, young children, and those with pre-existing health conditions (Nori-Sarma et al., 2019). As per IMD guidelines, a heatwave is not deemed to occur until the maximum temperature of a station reaches at least 40°C in plains and at least 30°C in hilly regions (https://ndma.gov.in/ Natural-Hazards/Heat-Wave). Increasing global temperatures and heatwave intensity are increasingly common worldwide, attributed to climate change (Domeisen et al., 2023). India is not exempt from this trend, experiencing heightened occurrences of more intense heatwaves each year (Ravindra et al., 2024). These events have severe repercussions on human health, leading to a surge in heat-related casualties. India is expected to experience more frequent and intense heatwaves in the future (Z. Zhao et al., 2020). The duration of heatwaves may extend, with temperatures reaching higher thresholds, posing risks to agriculture and infrastructure. The effects of heatwaves on public health, especially among vulnerable populations, will become more pronounced (Nandi & Swain, 2022). In May 2015, India endured an intense and prolonged heatwave, affecting the states of Telangana and Andhra Pradesh, resulting in over 2,300 deaths and numerous severe heat-related illnesses (Rohini et al., 2016). In June 2019, Bihar, Uttar Pradesh, and adjoined states experienced a severe heatwave, leading to hundreds of fatalities (P. K. Das et al., 2020). Heatwaves are a recurring phenomenon in India and are expected to become more frequent and intense due to climate change (Rohini et al., 2019). The urban heat island effect will amplify in urban areas, exacerbating the impact of heat waves within cities. Additionally, heatwaves will negatively affect agriculture, resulting in diminished crop yields and impacting food security (Naveena et al., 2021).

Over the past decade, the impacts of heat waves have become increasingly evident in Gujarat (M. K. Goyal et al., 2023) due to rapid urbanization, industrialization, and rising temperature trends. Almost every year, the state experiences intense and frequent heatwave events. There has been an escalation in heat-related fatalities, with the number rising from 58 in 2015 to 775 in 2018. Projections suggest a continued upward trend in casualties (Nori-Sarma et al., 2019).

3.4.2.2 Drought

Drought is a persistent natural hazard in India, particularly impacting regions characterized by a semi-arid or arid climate (Mahto & Mishra, 2020). Around 68% of cultivable land in India is susceptible to drought including parts of Rajasthan, Gujarat, Maharashtra, Karnataka, Andhra Pradesh, Telangana, and others (Gangopadhyay et al., 2022). Droughts in India are frequently caused by irregular or inadequate SWMR, resulting in agricultural losses, water scarcity, and socioeconomic challenges (Saha et al., 2023). India has witnessed numerous severe drought events across its history, including the Great Indian Drought of 1876-1878, the drought of 1987, the 2002 drought, and the 2015-2016 drought (Chuphal et al., 2024). These periods of drought have resulted in extensive crop failures, shortages of food, water scarcity, and socioeconomic difficulties for the communities affected (V. Mishra et al., 2021). These instances highlight the vulnerability of the country to prolonged water scarcity and emphasize the necessity for effective drought mitigation strategies. Gujarat specifically has faced significant droughts throughout its history due to its vulnerability to aridity and water scarcity (UNICEF, 2016). These events, such as the droughts of are attributable to the region's semi-arid to arid climate, limited rainfall, and heavy reliance on uneven SWMR for agriculture. The droughts have caused extensive agricultural damage, water shortages, and economic challenges for farmers and rural society (Mwinjaka et al., 2010). The lack of rainfall and depletion of water sources has led to distress among the population, impacting not only humans but all life forms.

3.4.2.3 Floods

Of India's total land area spanning 3.29 million sq. km, approximately 0.40 million sq. km are prone to flooding, constituting around 12% of the total area, which highlights its high susceptibility to floods (Mohanty et al., 2020). Floods are a recurring event and among the most prevalent disasters in India, impacting a large number of people, property, and infrastructure. The rising trend of flood-related damages is a matter of concern. Over the decade, from 1996 to 2005, the average annual flood damage was estimated to be INR 4,745 crores, higher than the previous 53-year average of ₹1,805 crores (https://ndma.gov.in/Natural-Hazards/Floods). Projections suggest that this upward trend is expected to persist, resulting in additional rises in flood-related damages. The surge in flood-related damages can be attributed to an increase in economic activities in flood-prone areas, growth in population, urbanization, and the effects of a continuous increase in warming worldwide, causing changes in rainfall patterns and influencing its distribution and intensity (Guhathakurta et al., 2011). India has experienced numerous severe flood events, including the Mumbai Floods in 2005, the Bihar Floods in 2008, the Uttarakhand Floods in 2013, the Kerala Floods in 2018, and the recurring floods in Assam almost every year or two. These floods have inflicted significant infrastructure damage, caused loss of life, and resulted in economic losses (Rajeev & Mishra, 2022). Gujarat is the seventh most affected state by floods in India, with 92 million people impacted and ₹5,612 crores in economic losses from 1953 to 2011 (Bahinipati et al., 2015). Gujarat has experienced frequent floods in recent years, causing widespread damage, displacement, and loss of life. Almost all parts of Gujarat are susceptible to floods. Urban areas such as Ahmedabad, Vadodara, Surat, and Rajkot experienced urban flooding due to intense rainfall and inadequate drainage systems (Waghwala & Agnihotri, 2019). The August 2019 floods were particularly severe, with record-breaking rainfall of 490mm within 24 Hours leading to overflowing rivers and waterlogging in low-lying areas of Vadodara city (Lobo, 2022). The floods of September 2013 and July 2017 also led to considerable waterlogging and disruption within the city (Patel et al., 2023). These urban flood events highlight the challenges of managing heavy rainfall and ensuring the efficiency of drainage systems within the city. Rapid urbanization often outpaces the capacity of existing infrastructure, leading to flooding.

3.4.2.4 Cyclone

India's history is marked by a series of devastating cyclones that have left a lasting impact on the country. Examples include the 1999 Odisha Super Cyclone, Cyclone Phailin in 2013, Hudhud in 2014, Titli in 2018, and Cyclone Fani in 2019 (T. Das et al., 2024). These cyclonic events have inflicted widespread destruction, causing loss of life and significant damage to infrastructure along the coastal regions of the country. The coastal states along the Bay of Bengal, including Odisha, Tamil Nadu, West Bengal, and Andhra Pradesh, as well as those along the Arabian Sea, such as Gujarat, Maharashtra, and Karnataka, are exceptionally vulnerable to cyclone events (G. K. Das, 2022). About 8% of the country's land is susceptible to cyclone-related disasters of varying degrees (https://nidm.gov.in/PDF/pubs/NDMA/4.pdf). Out of the coastline spanning 7,516.6 kilometers, approximately 5,700 kilometers are prone to cyclones. This susceptibility arises from their extensive coastlines, which render them directly exposed to the volatile weather conditions prevalent in these regions (Poulose et al., 2020). Cyclones such as Tauktae, a Severe Cyclonic Storm in 2021, and Cyclones Kyarr, Vayu, and Maha in 2019, along with Cyclone Nisarg in 2020 and Cyclone Biparjoy in 2023, have inflicted substantial damage upon Gujarat. The intensity of cyclones in Gujarat has increased due to the increased SST of the Arabian Sea (Mohapatra, 2015). Additionally, the number of cyclones in the Arabian Sea surged by almost 50% between 2001 and 2019 compared to the previous two decades (Albert et al., 2023). Coastal regions of Gujarat face increased risks of storm surges, floods, and wind damage. The increasing number of casualties and economic losses is concerning, especially with forecasts suggesting more intense cyclones (P. K. Goyal, 2024).

3.5 Time Series Forecasting Models

Time series forecasting (TSF) models serve as indispensable instruments for predicting future trends by analyzing patterns within historical data. In today's data-driven world, TSF is prevalent across a multitude of fields and applications (Zou et al., 2019). Their significance spans various domains including finance, economics, sales, weather forecasting, and others, where accurate prediction is paramount for informed decision-making. TSF is a quantitative methodology that entails gathering and analyzing historical data to construct suitable models (Utlaut, 2008). The process typically involves three fundamental steps: characterization, modeling, and forecasting (Kaur et al., 2023). Initially, the data is characterized to understand its underlying patterns and trends. Next, appropriate models are developed based on the identified characteristics. Finally, these models are utilized to forecast future values based on historical observations. In recent decades, TSF models have undergone substantial improvement and expansion (Hajirahimi & Khashei, 2023). These advancements have been fueled by developments in computational power, data availability, and advanced algorithms (Moraffah et al., 2021). As a result, these models have become more accurate, robust, and adaptable to a wider range of applications across various industries. Additionally, the integration of machine learning and deep learning techniques has further enhanced the capabilities of time-series forecasting (Kilimci et al., 2019), allowing for the identification of intricate patterns and the prediction of complex phenomena with greater precision (Parmezan et al., 2019). TSF models are typically categorized into two main groups: individual and hybrid models (J. J. Wang et al., 2012). Within individual models, there are two distinct types: statistical and intelligent models. Statistical models rely on historical data to forecast future values, utilizing techniques such as moving averages or exponential smoothing. Intelligent models, on the other hand, employ advanced computational algorithms, such as machine learning or neural networks, to analyse past data and generate predictions (Leverett et al., 2022; Petropoulos et al., 2022). Each model type possesses inherent strengths and weaknesses, rendering them suitable for distinct forecasting scenarios and data attributes. Utilizing the strengths of each model type and mitigating their weaknesses, researchers can tailor their approach to effectively address the unique attributes and requirements of the dataset, ultimately yielding more accurate and reliable forecasts (Moraffah et al., 2021).

TSF models are essential tools in climate studies for predicting future climate conditions and understanding climate variability (Yang et al., 2021), employing numerous mathematical and computational methodologies to simulate the intricate interactions among different components of the Earth's climate system. These models consolidate data from atmospheric, oceanic, and terrestrial sources, facilitating a comprehensive understanding of real-world conditions and enabling researchers to project future climate scenarios with greater accuracy and precision. In the realm of climate studies, a diverse array of forecast models is utilized (Mudelsee, 2010; Parnell, 2013), with each model tailored to meet distinct objectives and provide valuable insights spanning various spatio-temporal scales. These models serve as indispensable tools for understanding and predicting the complex dynamics of the Earth's climate system (Ye et al., 2013), encompassing a wide range of phenomena and variables. By employing a variety of model types, researchers can effectively address multiple challenges and explore climate dynamics across different timeframes and geographic regions. Commonly used comprehensive numerical models- GCM (General circulation models), which simulate the Earth's climate system on a global scale (Khan et al., 2018; Salman et al., 2020). These models represent the atmosphere, oceans, land surface, and sea ice, and their interactions (Hannah, 2022), following on a regional scale RCM (Regional circulation model), which provides higher resolution and more detailed information about climate patterns and processes within a specific region (Al-Hasani et al., 2023; Baigorria et al., 2008; Lloyd et al., 2021). Seasonal forecast models aim to predict climate conditions over a seasonal timeframe, typically spanning several months ahead. These models use historical climate data, observed oceanic and atmospheric conditions, and statistical techniques to estimate the likelihood of above-normal, normal, or below-normal conditions for a particular season (Mudelsee, 2019).

Forecast models are continually improving due to advancements in computational capacity, data accessibility, and scientific knowledge, leading to more accurate and reliable climate predictions (Ziegel et al., 1995). One of these models is the ARIMA model, which has become a widely accepted and applied method for time series analysis and forecasting (Meyler et al., 1998). Its adaptability and simplicity make it suitable for a wide array of uses, spanning economics, finance, meteorology, and beyond (Rizeei et al., 2018). While the ARIMA model has its limitations, but it continues to be a valuable tool in the field of time series analysis (H. R. Wang et al., 2014). The ARIMA extends the ARMA model by incorporating differencing to make the time series stationary (Boyd et al., 2019). It consists of three components: autoregressive (AR), differencing (I), and moving average (MA). The order of the ARIMA model is denoted as ARIMA (p, d, q), where p represents the order of the AR component, d represents the degree of differencing, and q represents the order of the MA component (Siami-Namini et al., 2019). The ARIMA model offers advantages for forecasting rainfall and temperature data in climate studies. These advantages include the ability to capture temporal dependencies, handle non-stationarity through differencing, flexibility in model configuration, accuracy, interpretable model parameters, and availability of software and tools for implementation (Zhang & Wen, 2022). ARIMA models have shown reliable forecasting capabilities, particularly effective for predicting outcomes in the short to medium term (Kontopoulou et al., 2023). Complex climate phenomena and external factors may require additional model enhancements or alternative approaches to improve forecast accuracy. Rainfall data often exhibit distinct seasonal patterns, such as wet and dry seasons, annual cycles, or monthly variations. Seasonal ARIMA or SARIMA model is specifically designed to capture these seasonal patterns by including additional seasonal terms in the model formulation (Kabbilawsh et al., 2022). In contrast, ARIMA models are more suitable for data without significant seasonal variations (Adineh et al., 2021). By incorporating seasonal components, SARIMA models can provide more accurate and reliable forecasts for rainfall. The flexibility of SARIMA models allows for the inclusion of autoregressive (AR) and moving average (MA) components, both at the non-seasonal and seasonal levels (Sirisha et al., 2022). This enables the model to capture short-term dependencies and seasonal variations simultaneously, leading to more accurate forecasts. SARIMA models can also accommodate exogenous variables (SARIMAX), such as sea surface temperature or atmospheric indices, which may influence rainfall and temperature (Elshewey et al., 2023). Exogenous variables are external factors that may impact the time series but are not directly related to its past values. By integrating external influences, SARIMAX offer more thorough and precise forecasts, encompassing the impact of both seasonal patterns and external variables on the time series data (Elshewey et al., 2023).

Within the realm of rainfall and temperature forecasting, these models apply to historical data and allow for the estimation of future values. The selection of the appropriate model and its parameters (order) is based on statistical analysis, model diagnostics, and evaluation metrics such as the Akaike Information Criterion (AIC) (Akaike, 1974) or Bayesian Information Criterion (BIC) (de-Graft Acquah, 2010). When selecting the appropriate model, researchers generally assess various specifications and consider the one with the lowest AIC value (L. Zhao et al., 2022). This selection usually offers the optimal balance between model accuracy and simplicity. In addition to identifying suitable parameters for ARIMA models, ACF and PACF are utilized (Mestre et al., 2021). The ACF evaluates the correlation between observations at different time lags, providing insights into temporal dependencies within the data and assisting in determining the Moving Average (MA) component (q) in the ARIMA model (Mestre et al., 2021). Conversely, PACF calculates the correlation between observations at different lags while mitigating the effects of intermediate lags (Mulla et al., 2024). This aids in identifying direct relationships between observations, assisting in determining the Autoregressive (AR) component (p) of the ARIMA model. Furthermore, these models assume stationarity and may require data pre-processing techniques, such as detrending or seasonality removal, to satisfy this assumption. The Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979) test is a statistical test employed to evaluate the stationarity of a time series (L. Zhao et al., 2022). It holds particular significance in assessing the need for differencing to achieve stationarity (Sirisha et al., 2022). The confirmation of stationarity ensures analysts' confidence in their selected model's ability to accurately capture underlying data patterns and dynamics, thereby enhancing the reliability of subsequent statistical analyses and forecasts. The review highlights the diverse forecasting methods and models, demonstrating the integration of multiple data sources and predictive variables. This highlights the importance of flexibility and adaptability in addressing the unique challenges and complexities of forecasting in different domains (Chandran et al., 2023). Although numerous advancements have been achieved in enhancing forecasting accuracy, there remain areas that require attention and resolution (Liu et al., 2012). In the realm of future research endeavours, it is imperative to direct attention towards the refinement of cutting-edge models, harnessing the potential of emerging technologies, and the seamless integration of diverse datasets (Ben Ammar et al., 2024). This multifaceted approach has the potential to significantly enhance prediction capabilities and enable more accurate and insightful forecasts across various domains and applications (Cullen et al., 2023). Addressing these challenges through advancements in rainfall and temperature forecasting can significantly contribute to sustainable development, facilitate climate adaptation strategies, and streamline decision-making processes in the face of climate change.

3.6 Conclusion

Climate change exerts a profound influence on rainfall and temperature patterns across a spectrum of geographical and temporal scales, spanning from local to global levels. This phenomenon exhibits itself in various forms, including shifts in rainfall patterns, changes in the frequency and intensity of EWE, and alterations in temperature distribution across different regions. Through an analysis of various studies and reports, it is evident that climate variability poses significant challenges to regional climate dynamics, water resources, and ecosystem resilience. Additionally, it highlights the significance of comprehending spatio-temporal patterns in rainfall and temperature, emphasizing the necessity of identifying extremes through conventional and contemporary approaches aimed at enhancing analytical efficiency. This comparative analysis contributes to knowledge advancement and informs decision-making processes by offering insights into the relative advantages of different analytical techniques. It helps identifying strengths, weaknesses, and areas for improvement in existing methodologies, guiding decision-making. Despite numerous studies assessing trends across various geographical scales, conducting a regional assessment, forecasting future climate conditions, and identifying surplus and deficit regions remain crucial. Due to the high spatio-temporal variability of rainfall and temperature in Gujarat's diverse physiographic regions, assessing trends and forecasts is essential. The projected increase in temperature, rainfall variability, and the frequency and intensity of EWE in Gujarat highlights the importance of understanding these variables to effectively address their impact on the region's environment and communities.