CHAPTER 1
INTRODUCTION

1.1 Background

The global climate has been continuously changing throughout Earth's history, but the rate of change has accelerated to unprecedented levels in recent times (Huangpeng et al., 2021). Natural factors such as volcanic eruptions, variations in solar radiation, and natural climatic cycles have historically driven climate variability. However, the current rate of change is unparalleled, primarily due to rapid industrialization and other human activities (S. Zhang et al., 2023). Since the onset of the Industrial revolution, a wealth of independent research has consistently shown that human activities have profoundly altered the Earth's climate (Tong et al., 2022). This evidence has led to a global consensus on the urgent need to address climate change, now recognized as one of the most critical challenges of the twenty-first century (Malhi et al., 2020), posing severe risks to both natural ecosystems and human society. Climate change refers to long-term alterations in the average state or variability of climate properties persisting over extended periods (Barros et al., 2012). It encompasses alterations in climate conditions that can be attributed, either directly or indirectly, to human activities altering the composition of the Earth's atmosphere (UNFCCC, 2011; Pillay, 2013). These changes are distinguishable from natural climate variability observed over similar time spans, which includes shifts in global and regional climates. Such shifts influence atmospheric conditions over timescales ranging from several decades to centuries and beyond. Observable evidence includes shifts in global temperatures, changes in rainfall patterns, and variations in the frequency and intensity of extreme weather events. Fundamental variables such as rainfall and temperature are widely used as indicators of global climate change, due to the extensive availability of long-term data worldwide (Irwandi et al., 2023). These variables are crucial for understanding climatic shifts, providing clear and measurable evidence of changes in the Earth's climate system over extended periods (Chadwick et al., 2016). Variations in rainfall and temperature profoundly impact society by affecting water availability, agricultural productivity, ecosystem health, and infrastructure resilience (Chettri et al., 2019). These changes can lead to droughts, floods, altered growing seasons, heat-related illnesses, and strained energy resources.

Therefore, one of the primary goals of climate studies has always been to comprehend the variability of rainfall and temperature across diverse geographical and temporal scales. This entails exploring the intricate factors that influence these changes, ranging from local microclimates to the global climate system. By delving into these complexities, researchers aim to gain insights into current climate patterns and accurately forecast future trends. This approach not only helps in understanding the natural variability and underlying mechanisms driving climate dynamics but also in identifying and predicting extreme weather events such as floods, droughts, and heatwaves (Easterling et al., 2000). Together, these efforts create a robust framework for assessing climate change, providing valuable information for policymakers, and communities, and utilizing it as an effective decision-support tool (WMO, 2012).

1.1.1 Global Temperature: Critical Trends

The global climate is changing rapidly, exceeding the natural variations observed throughout Earth’s history (NOAA, 2023). Since 1880, the Earth's temperature has increased by 0.08°C per decade. However, since 1981, this rate of warming has accelerated to 0.18°C per decade (Malakouti, 2023), more than twice the rate observed in earlier decades. Figure 1.1 shows global annual average temperature anomalies spanning from 1880 to 2023, from the baseline period of 1951-1980. Since the records began in 1880, 2023 is marked as the warmest year on record, with temperatures about 1.2°C higher than the baseline average (Kuhlbrodt et al., 2024).

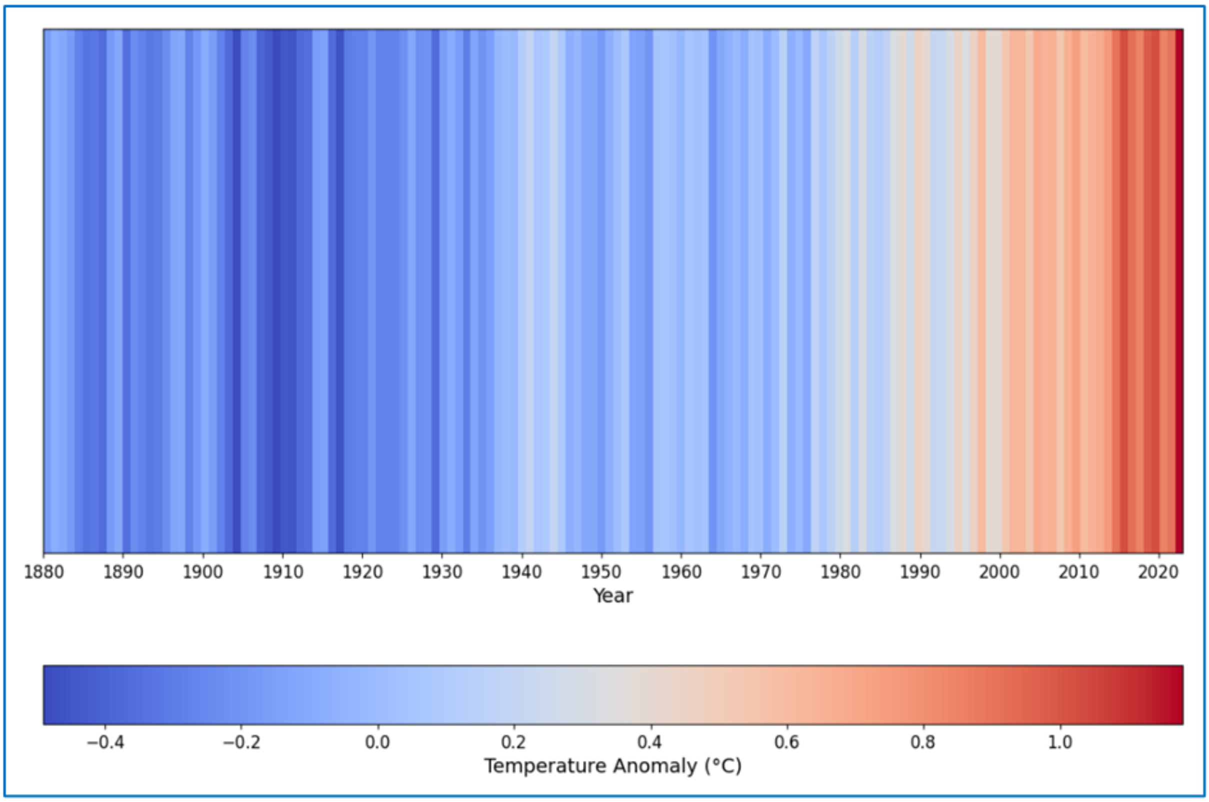

Figure 1.1 Global Annual Average Temperature Trends, 1880-2023, Baseline 1951-1980.

Data Source: Lenssen et al., 2019; GISTEMP Team, 2024: GISS Surface Temperature Analysis (GISTEMP), version 4. NASA Goddard Institute for Space Studies. Dataset accessed 2024-05-20 at https://data.giss.nasa.gov/gistemp/.

The period from 2014 to 2023 is marked as the warmest decade on record, spanning the 144-year historical climate record (Bardan, 2024). In 2023, global temperatures reached an unprecedented level of 14.9°C, marking a substantial increase of 0.169°C from the previous record set in 2016 (Lopez, 2024). This temperature exceeded the average for the period from 1991 to 2020 by 0.60°C, indicating a significant departure from recent historical norms. Additionally, the 2023 temperature reading was 1.48°C higher than pre-industrial levels, highlighting the persistent warming trend observed since the onset of industrialization (Bardan, 2024). The year 2023 also surpassed previous records from June to October, with other months ranking among the top seven highest recorded temperatures for their respective periods (Laimighofer & Formayer, 2024). This trend highlights a pronounced warming pattern observed on a global scale. Earlier recorded warmest years, such as 2005, initially set new benchmarks but have since been surpassed by subsequent years like 2010, now ranked 11th, with 2005 following as 12th. Between 2014 and 2023, global surface temperatures increased by about 1.1°C compared to the baseline period, 1951-1980, reflecting the acceleration of climate change (Bardan, 2024). These temperature trends show the persistent impact of human-induced greenhouse gas emissions, driving global warming and its associated consequences, including intensified heatwaves, altered rainfall patterns, and rising sea levels (Shivanna, 2022). These emissions are projected to increase the frequency and severity of extreme events and contribute to emerging challenges ahead. Understanding and responding to these temperature increases are crucial for shaping effective policies, implementing adaptation measures, and fostering international cooperation to safeguard the planet for future generations (Calvin et al., 2023). The IPCC is gradually acknowledging the threat that increased temperature poses to future growth, human well-being, and ecological health (IPCC, 2007).

However, the trend highlights the differential impacts across various geographical domains. In general, land surface temperatures have been observed to increase at a faster rate and to higher levels than sea or ocean surface temperatures when compared to the baseline period (Lenssen et al., 2019). This distinction shows the varying responses of different parts of the Earth's surface to global warming. In 2023, land areas experienced a temperature increase of 1.71°C, surpassing the 0.85°C increase observed in ocean regions compared to the baseline period. Figure 1.2 shows the temperature anomalies observed over land and ocean from 1880 to 2023, using the period from 1951 to 1980 as the baseline. This graph highlights how temperatures have deviated from the average during the baseline period, showing the trends and differences in warming between land and ocean regions over the extended historical record.

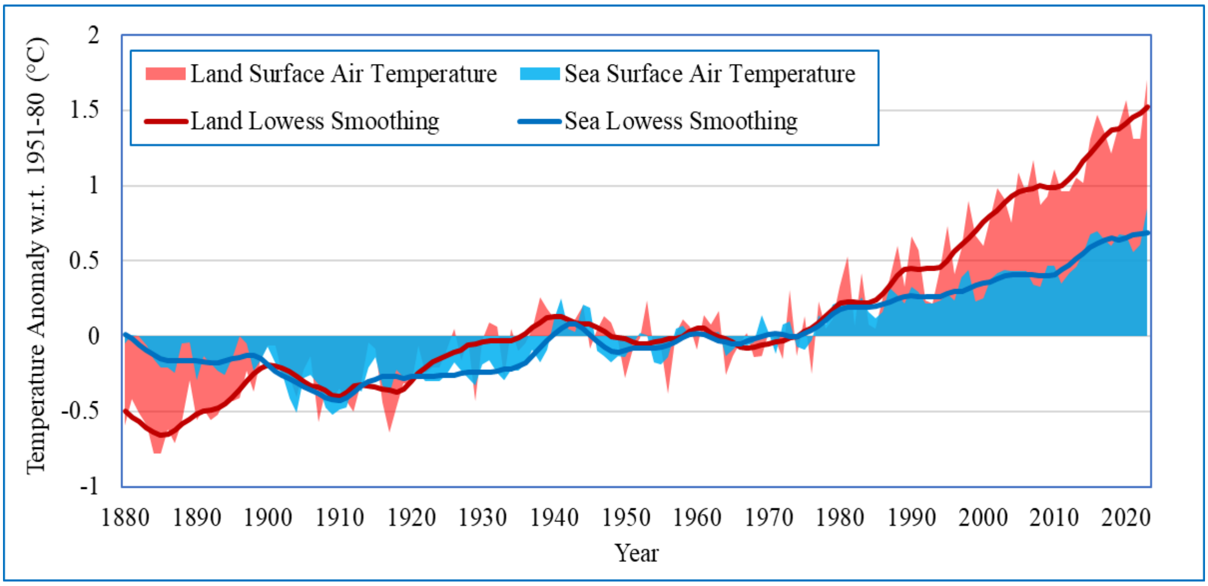

Figure 1.2 Temperature Anomalies over Land and Ocean, 1880-2023, Baseline 1951-1980.

Data Source: Lenssen et al., 2019; GISTEMP Team, 2024: GISS Surface Temperature Analysis (GISTEMP), version 4. NASA Goddard Institute for Space Studies. Dataset accessed 2024-05-20 at https://data.giss.nasa.gov/gistemp/.

In recent reports, WMO, 2022, and IPCC AR6 (IPCC Working Group II, 2022) have highlighted critical findings regarding global temperature trends. 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 and irreversible impacts. Additionally, Climate projections indicate that by the year 2100, global surface temperatures may increase by an alarming range of 1.3°C to 8.0°C (Scafetta, 2024). This wide range reflects the uncertainty in future climate policies and actions. These projections highlight the critical need for immediate and sustained action to enhance resilience and prevent the most severe consequences of global warming. Adapting to these changes and implementing effective mitigation strategies are essential to protect ecosystems, human health, and infrastructure from the escalating threats posed by extreme weather events and long-term climate shifts.

1.1.2 Global Rainfall Patterns: Alarming Changes

The global climate has shown substantial variability in recent decades and is expected to continue this trend in the future (Praveen et al., 2020). Rainfall being one of the most common weather events and a climatic variable that varies from year to year and across decades (Y. Zhang & Wang, 2023). Global annual land mean rainfall exhibited a slight, yet uncertain, increase throughout the 20th century, averaging about 1.1 mm per decade (IPCC, 2007;

Hersbach et al., 2015). This overall trend, however, obscures significant fluctuations between decades, reflecting the inherent variability in rainfall patterns, and from 1950 onward, there has been a non-significant decline in global annual land mean rainfall trends (IPCC, 2007), suggesting a complex relation of factors influencing rainfall distribution. However, the trend shifts after late 1990s (Adler et al., 2017). This variability highlights the difficulty of understanding long-term rainfall patterns and highlights the challenges in predicting future trends. Figure 1.3 shows the 30-year running average of annual global rainfall from 1960 to 1990. The distribution of rainfall across the globe varies substantially, reflecting diverse influences from a range of factors, whether they are local conditions specific to certain regions or broader global phenomena impacting weather patterns. These factors include local geography, atmospheric circulation patterns, ocean currents, and global climate drivers such as El Niño and La Niña events. Together, they contribute to the complex and varied patterns of rainfall observed across different parts of the world.

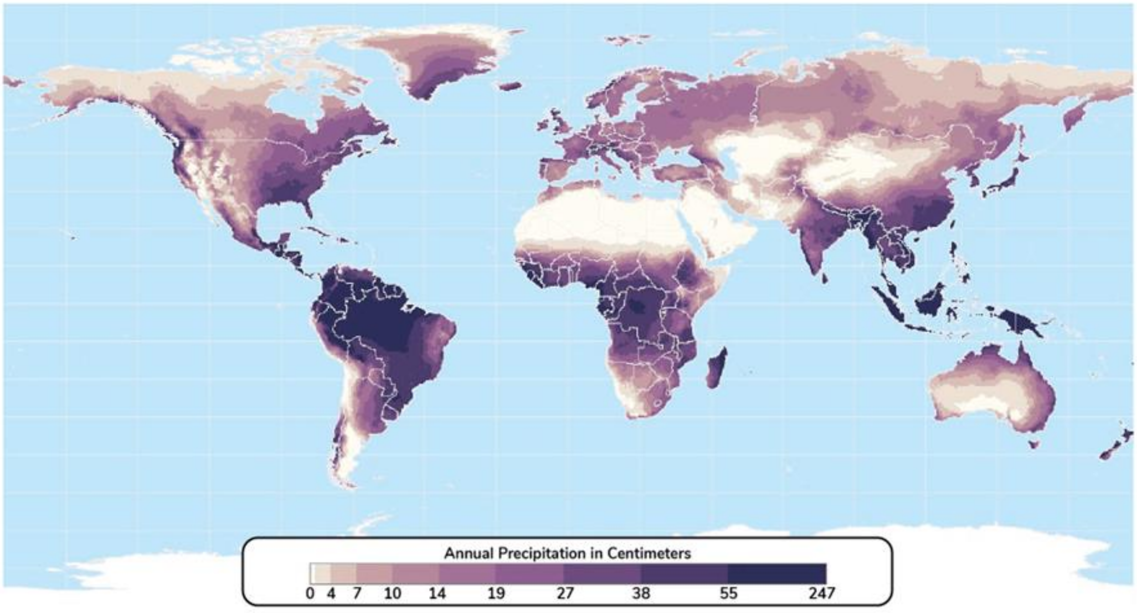

Figure 1.3 Global Annual Rainfall: 30-Year Running Average from 1960 to 1990.

Data Source: CRU 0.5 Degree Dataset, (New et al., 1999); Visual: Atlas of the Biosphere, Center for Sustainability and the Global Environment, University of Wisconsin–Madison.

Due to the continued rise in temperatures, extreme rainfall events are projected to intensify and occur more frequently in numerous regions worldwide (Wang et al., 2017). As temperatures rise, the atmosphere can hold more moisture, following the Clausius-Clapeyron relationship (Tabari, 2020), which states that for every degree Celsius of warming, water vapor capacity increases by approximately 6-7% (Tabari, 2020). This escalation is expected to increase evaporation rates from both oceans and land surfaces. While this increased evaporation may result in more frequent and intense rainfall in some regions, it also poses a simultaneous threat of exacerbating dry conditions in others. These dual impacts of increased rainfall variability present substantial risks to global ecosystems, agriculture, and water security. The changing rainfall trends due to increasing temperatures have become significant concerns worldwide in recent decades (Kharin et al., 2018), with far-reaching effects on the environment, and agricultural and food security (Praveen et al., 2020).

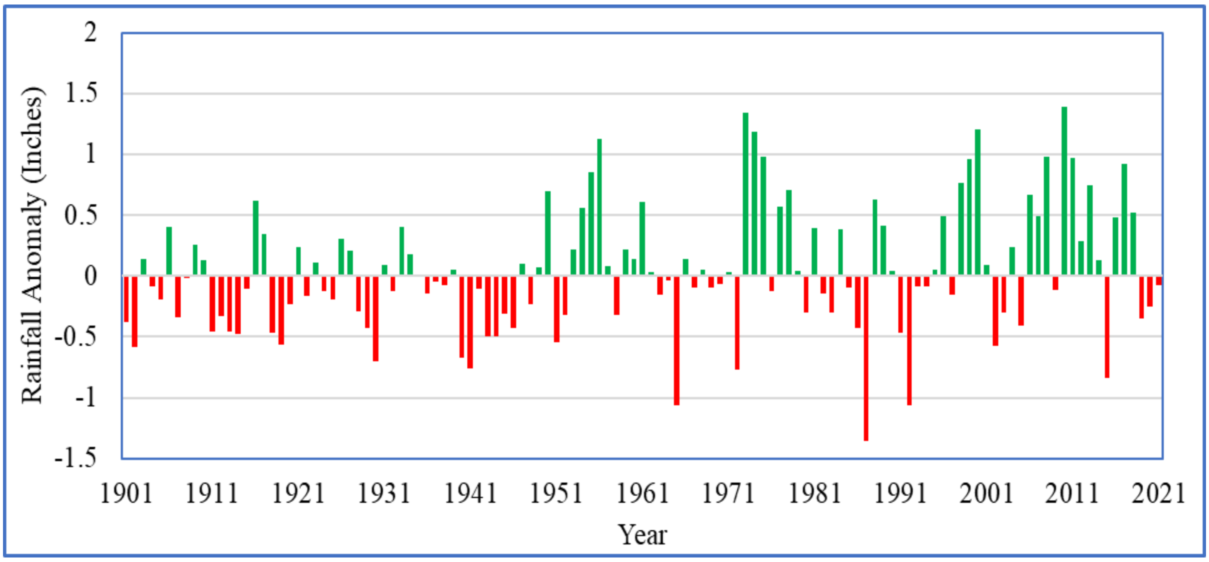

Figure 1.4 Annual Rainfall Anomaly Over Land Worldwide (Baseline: 1901-2000)
Data Source: Blunden & Boyer, 2021 [NOAA, 2022. Extended version of GPCC dataset]

Figure 1.4 exhibits the fluctuating yet concerning trend of global rainfall anomalies from 1901 to 2021. Over this period, there have been noticeable deviations from the average rainfall levels of the baseline years (1901-2000). The data reveals a pattern of variability with both positive and negative anomalies. In the earlier years of the dataset, such as the early 20th century and mid-20th century, periods of below-average rainfall were prevalent, indicating potential drought conditions in various regions. However, the latter half of the 20th century and the beginning of the 21st century have witnessed more frequent occurrences of above-average rainfall anomalies, suggesting increased rainfall variability and potential flooding risks in certain regions. Particularly, the years with significant positive anomalies, such as 1973, 1974, and 1975, indicate periods of exceptionally high rainfall globally. Conversely, the negative anomalies observed in recent years, mainly in 2015, highlight the unpredictability and potential impact of climate variability on global rainfall patterns. This trend of increased variability in rainfall anomalies stress the importance of robust monitoring and adaptation strategies to address the potential impacts of climate change on global water resources and ecosystems. In recent decades, regions once characterized by predictable rainfall patterns are experiencing intensified variability and intensity in rainfall events. Studies across various regions of the world (Kanellopoulou, 2002; Rose, 2009; Shahid, 2011; Feng et al., 2013; Asarian & Walker, 2016; Kundu et al., 2017; Mahlalela et al., 2020; Tabari, 2020 Alves et al., 2021; McKay et al., 2023) witnessed substantial shifts in rainfall trends. These shifts emphasise the urgent need for proactive measures and enhance forecasting accuracy, especially since 40% of the world's population directly relies on agriculture and related sectors.

1.2 Climate of India: Modulating Factors IOD and ENSO

India's climatic diversity spans from tropical climates in the south to temperate and alpine climates in the north, resulting in varied temperatures, rainfall patterns, and weather phenomena across regions (Attri & Tyagi, 2010). The country experiences four distinct seasons as categorized by the IMD: Winter (January-February), Pre-Monsoon (March-May), Southwest Monsoon (June-September), and Post-Monsoon (October-December). Each season significantly influences weather patterns, agricultural cycles, and socio-economic activities, exhibiting India's climatic richness and the profound impact of seasonal variability. Additionally, India exhibits substantial variability in rainfall, ranging from 160 to 1800 mm annually, varying spatially and temporally (V. Kumar et al., 2010). The nation experiences two distinct monsoon seasons: the Southwest Monsoon (SWM) and the Northeast Monsoon (NEM). While the SWM contributes significantly with 70-85% of India’s annual rainfall, the NEM provides 9-12%, highlighting contrasting seasonal patterns (Narayana Rao et al., 2009). Over time, significant variations in the SWM have been observed across different temporal and spatial scales, impacting crucial aspects of India's water resources, power generation, agriculture, and economy. Agriculture, which sustains a large portion of India's population, relies heavily on SWM rainfall. Any deviation from normal SWM patterns can have profound consequences. Even slight changes in the timing, intensity, or distribution of SWM rainfall can result in crop failures, water shortages for irrigation, reduced agricultural productivity, and economic hardships for farmers. This dependency highlights the importance of SWM rainfall for ensuring food security, stable rural incomes, and overall economic stability in India. However, the SWM is mainly influenced by two key climate phenomena: the Indian Ocean Dipole (IOD) and the El Niño-Southern Oscillation (ENSO) (Ratna et al., 2024). The IOD is defined as the difference in SST between the Western Tropical Indian Ocean (WTIO) and the Southeast Tropical Indian Ocean (SETIO). It significantly influences the SWM by altering atmospheric circulation patterns and moisture transport. During positive IOD years such as 1961, 1963, 1972, and others, where SSTs in the WTIO are warmer than in the SETIO, it enhances convection and rainfall over the Indian subcontinent, typically resulting in above-normal monsoon rainfall (Jiang et al., 2021). Conversely, in negative IOD years like 1960, 1964, 1974, and others, characterized by cooler SSTs in the WTIO relative to the SETIO, the monsoon can weaken, leading to below-normal rainfall (Jiang et al., 2021). However, the abundance or scarcity of rainfall further depends on the intensity of these phases and their interaction with other local or global phenomena. While, the ENSO cycle, involving periodic variations in SST and atmospheric pressure in the equatorial Pacific Ocean, also plays a crucial role in modulating the SWM. During El Niño years, warming of the central and eastern Pacific Ocean disrupts global weather patterns, including the SWM in India (Athira et al., 2023), often resulting in reduced SWM rainfall, droughts, and adverse agricultural impacts. Conversely, La Niña events, marked by cooler SST in the eastern Pacific, enhance monsoon rainfall by altering atmospheric circulation to increase moisture transport to India (Geng et al., 2023). The impacts of ENSO phases extend beyond the SWM to influence temperature patterns significantly. El Niño and La Niña events can lead to significant temperature anomalies, triggering various climatic extremes (Revadekar et al., 2009). El Niño phases often coincide with increased temperatures, exacerbating the frequency and intensity of heatwaves and severe weather events. These conditions can severely affect agriculture, water resources, and public health. Conversely, La Niña phases typically bring cooler temperatures but can still contribute to extreme weather occurrences, showing the broad and intricate influence of ENSO on regional climate dynamics. These temperature variations profoundly impact weather patterns, agricultural productivity, and broader climate trends. According to IMD data spanning 122 years, India has experienced 22 El Niño events since 1901. Of these, 16 have resulted in drought-like conditions due to below-normal SWM rainfall. Particularly severe El Niño years such as 1911-12, 1918-19, 1972-73, 1997-98, and 2015-16 witnessed significant rainfall deficiencies and severe droughts across many parts of India (Velivelli et al., 2024). During La Niña events (1903-04, 1908-09, 1955-56, 1970-71, 2010-11, and others), India often benefits from favourable agricultural conditions. However, during periods of high intensity, La Niña can cause floods and posing challenges for agricultural management.

Understanding the effects of both phenomena is crucial for developing strategies to mitigate their adverse impacts. As climate change continues to alter global weather patterns, studying these phenomena becomes increasingly important for forecasting and preparing for future extremes. Their combined influence on India's climate highlights the need for comprehensive research and strategic planning to ensure resilience against these complex factors.

1.2.1 Impacts of Concurrent Phases of IOD and ENSO

The impacts of concurrent phases of the IOD and ENSO can be profound and complex, varying substantially depending on the intensity of their occurrences. When both phenomena align, their combined influence can amplify or mitigate each other's effects on the Indian climate patterns (Ratna et al., 2024). The variability and unpredictability of rainfall and temperature patterns during concurrent phases further compound these risks (Z. Huang et al., 2022). Agricultural sectors face economic losses due to fluctuating rainfall, which affects crop yields and water availability, while disruptions in supply chains impact livelihoods and food security. For example, periods characterized by a negative IOD and La Niña (such as 1964, 1974, 1989) often result in enhanced moisture availability, potentially increasing rainfall and benefiting agricultural conditions in affected regions, but the extent of these effects can vary widely. Conversely, a negative IOD paired with El Niño (observed in 2016 during studied period) may exacerbate dry conditions, leading to reduced rainfall and negatively impacting agricultural productivity. Similarly, positive IOD phases combined with El Niño events (1963, 1972, 1982) can lead to complex atmospheric circulation patterns, intensifying droughts or altering rainfall distribution across different regions, with varying degrees of severity. Understanding these interactions and their intensity is crucial for effectively managing the diverse impacts of climate variability on socio-economic sectors, including agriculture, water resources, and public health.

Concurrent phases often intensify extreme weather events such as heatwaves, intense rainfall, and droughts (K. Huang et al., 2024). This increased intensity poses risks to vulnerable communities and infrastructure, exacerbating existing vulnerabilities. Water shortages, disruptions in supply chains, and impacts on public health due to changes in disease patterns and waterborne illnesses are significant concerns. Vulnerable populations, particularly in rural and coastal areas, disproportionately bear the socio-economic inequalities exacerbated by these shifts. Effective climate monitoring and implementation of adaptive strategies are essential for reducing impacts, enhancing resilience, and improving preparedness in affected regions.

1.2.2 Impact and Intensification of Extreme Weather Events

Extreme weather events (EWE) encompass a broad spectrum of phenomena that profoundly impact both natural environments and human societies (Sillmann et al., 2017). These events include intense heatwaves, severe storms, prolonged droughts, heavy rainfall leading to floods, and other disruptive weather patterns. These events have increasingly become more hazardous in recent decades (Kalyan et al., 2021), exacerbated by climate change. Each of these EWE presents unique challenges, from immediate threats to infrastructure and safety to long-term impacts on agriculture, ecosystems, and public health. For instance, heatwaves can result in severe heat-related illnesses and fatalities, strain energy resources, and worsen urban heat island effects (Dubey et al., 2021). The IPCC's global report on EWE indicates a high likelihood of increased occurrences of warm days and warm nights (Barros et al., 2012). It projects that extreme heat events will increase in frequency, intensity, and duration over the 21st century (McPhillips et al., 2018). Beyond heat-related impacts, severe storms often result in widespread infrastructure damage and population displacement, while heavy rainfall events trigger devastating floods that disrupt communities and economies. Prolonged droughts threaten agricultural productivity, water availability, and food security, often leading to economic hardship and social instability in affected regions. The impact of these EWE is multifaceted, affecting infrastructure, livelihoods, economy and exacerbating environmental degradation. The continued increase in temperatures also escalate evaporation rates, increasing atmospheric moisture and intensifying rainfall events. Studies (Sillmann et al., 2017; Wang et al., 2017; Yin et al., 2022) indicate that extreme rainfall events are becoming more frequent and intense, a trend expected to worsen. This increased rainfall can result in flash floods and infrastructure damage, highlighting the profound impact of extreme rainfall events.

In India, where agriculture and rural economies heavily rely on predictable weather patterns, EWE can inflict damage on infrastructure, including roads and bridges, and disrupt critical transportation networks crucial for commerce and daily life. The country faces a broad spectrum of EWE: Heatwaves trigger health crises and increased energy demands, particularly affecting North and Northwest India during the Pre-Monsoon season (Nori-Sarma et al., 2019), with their frequency and intensity increasing in recent decades; Intense rainfall and floods devastate low-lying regions and urban centers (Rafiq et al., 2016), leading to loss of life, displacement, and damage to property and crops; droughts severely impact agriculture and water resources, resulting in crop failures, water shortages, and economic loss (Niranjan Kumar et al., 2013; UNICEF, 2016); Coldwaves pose health risks, especially in northern India during winters (Malik et al., 2020); Landslides and cloud bursts predominantly affect hilly and mountainous regions, endangering lives, settlements, and transport routes (Sharma, 2020); while Wildfires, although less frequent in earlier decades, now occur frequently in northern hilly and mountainous regions, ravaging forested areas and threatening biodiversity, air quality, and nearby communities (Kale et al., 2022). These diverse events collectively weaken ecosystem stability and economic sustainability across vulnerable areas nationwide.

1.3 Climate Risks and Extremes in Gujarat

Gujarat, characterized by its diverse landscape and extensive coastline along the Arabian Sea, faces a range of climate risks that threaten its environment, economy, and communities (Bandyopadhyay et al., 2016). This vulnerability is evident in the state's frequent encounters with cyclones, which unleash destructive winds, torrential rains, and storm surges. Recent events like Cyclone Vayu in 2019, Cyclone Tauktae in 2021, and Cyclone Biparjoy in 2023 have highlighted Gujarat's susceptibility to these EWE. Historically, cyclones formed in the Arabian Sea were rare, but with increasing SST, these storms now occur more frequently and with greater strength than in the past (Baburaj et al., 2022). This trend has resulted in widespread destruction of infrastructure, economic disruptions, and threats to livelihoods. Beyond cyclones, Gujarat also contends with multiple extreme events, such as heatwaves, particularly intensified during the pre-monsoon season. Once sporadic in certain parts of the state, these heatwaves have now become a more frequent and intense occurrence across Gujarat (Bandyopadhyay et al., 2016). Urban centers such as Ahmedabad and Vadodara are severely affected, enduring prolonged periods of high temperatures that pose significant health risks and increased energy demands. These heatwaves not only impact public health but also strain water resources and agricultural productivity. The state has experienced major flood events due to the expansive flat terrain through which its major rivers flow before reaching the sea. These low-lying areas in the lower river basins are particularly susceptible to flooding. Additionally, Urban floods, exacerbated by rapid urbanization and inadequate drainage systems, pose significant risks to infrastructure and public safety (Rafiq et al., 2016). In contrast, droughts, intensified by erratic rainfall patterns, significantly impact agriculture and water availability, with 22.3% of Gujarat's total geographical area designated as drought-prone (UNICEF, 2016). These climatic extremes have exhibited an increase in frequency and intensity in recent decades, further exacerbated by global phenomena (Seneviratne et al., 2012). This trend highlights the urgent need for detailed studies and robust management strategies to save lives, property, and the economy. Table 1.1 shows the seasonal occurrence of EWE in Gujarat.

Table 1.1 Seasonal Occurrence of Extreme Weather Events in Gujarat.

Events	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Cyclone	⬜	⬜	⬜	⬜	🟥	🟥	⬜	⬜	🟥	🟥	🟥	⬜
Drought	🟧	🟧	🟧	🟧	🟧	🟧	🟧	🟥	🟥	🟥	🟧	🟧
Flood	🟧	🟧	🟧	🟧	🟧	🟧	🟧	🟥	🟥	🟥	🟧	🟧
Heatwave	⬜	⬜	⬜	🟥	🟥	🟥	⬜	⬜	⬜	⬜	⬜	⬜

Legend 🟥 High Occurrence 🟧 Moderate Occurrence ⬜ Low Occurrence

Source: Volume 1, Gujarat State Disaster Management Plan, GSDMA (2020-21)

1.4 Study Area

Gujarat, situated on the western coast of India between latitudes 20°6' and 24°42'N and longitudes 68°10' and 74°28'E, features diverse geographical and climatic characteristics. Covering an area of 196,244 sq. km., Gujarat is the fifth-largest state in India, contributing about 5.96% to the country's total geographical area. The state has the longest coastline in mainland India, stretching 1,663 kilometres and encompassing varied habitats such as mangroves, salt marshes, and wetlands. Despite its coastal location adjacent to the Arabian Sea, most regions of Gujarat experience predominantly dry, arid to semi-arid climates, influenced by its proximity to the Thar Desert in the north. The state is geographically divided into five distinct physiographic regions: Central Gujarat, Kutch (Kachchh), North Gujarat, Saurashtra, and South Gujarat. These regions exhibit diverse climatic conditions. South Gujarat has a sub-humid climate, Central Gujarat is moderately humid, and the coastal areas experience muggy conditions. Interior Saurashtra has a dry climate, while Kutch and North Gujarat have semi-arid to arid climates (Ray et al., 2008). These climatic differences lead to significant variations in the spatial distribution of rainfall and temperature across Gujarat. Temperatures generally increase from the southwest to the northeast of the state, whereas rainfall patterns show an opposite trend, increasing from the northeast to the southwest (Guhathakurta et al., 2020). This disparity results in the northern region being mostly arid, characterized by dry conditions and sparse vegetation. The state receives the maximum rainfall during the SWM season, which shows substantial spatial heterogeneity. Maximum rainfall occurs in South Gujarat (approx. 1200 mm) and gradually decreases towards Kutch (approx. 450 mm), leading to varying levels of agricultural productivity and water availability across the state. July and August typically witness the highest rainy days, varying significantly across regions from about 24 days in Kutch to more than 82 days in South Gujarat (N. Kumar et al., 2015).

1.5 Objectives of the study

The objectives of the study encompass the following:

- To analyse the spatial and temporal patterns of rainfall and temperature across Gujarat state.
- To Identify spatial and temporal trends of temperature extremes in maximum and minimum temperatures and rainfall.
- To forecast spatial and temporal patterns of rainfall and temperature utilizing the Autoregressive Integrated Moving Average (ARIMA) model, and SARIMA.
- To propose water deficit and surplus regions based on the variability model.

1.6 Data Source and Methodological Approach

1.6.1 Database

The study employed a robust methodology by integrating primary and secondary data sources to achieve its research objectives and conduct a thorough analysis. Primary data were collected to validate forecast results through ground truth checking. Secondary data were acquired from the IMDLIB (India Meteorological Department Library) and the Climate Prediction Center (CPC). IMDLIB, an open-source library developed for accessing and processing gridded meteorological observation datasets within India's geographic scope, allows for spatiotemporal analysis (Nandi et al., 2024), While the CPC is one of the distinct centers of NOAA's National Centers for Environmental Prediction (NCEP), National Weather Service, USA.

The study employed the key climate variables of rainfall and temperature. Daily rainfall levels and temperature (T_{max} and T_{min}) spanning 60 years (1961-2020) were collected from IMDLIB. For rainfall analysis, the study utilized the newly developed high spatial resolution IMD4 dataset, interpolated at consistent 0.25° x 0.25° spatial grid points across India (Pai et al., 2014). IMD4 gridded data, generated using Shepard's interpolation method, integrates daily rainfall data from 6995 observed stations nationwide, adhering to stringent quality control measures (Reddy et al., 2022). The unit of measurement is millimetres (mm). Analysis of rainfall data yielded crucial insights into geographical distribution, intensity, and frequency of rainfall events, essential for understanding regional climate dynamics. Temperature data at 1° x 1° resolution (Srivastava et al., 2009) facilitated identification of deviations and long-term trends in heat levels, aiding assessment of climate variability and change over time. IMD operates over 550 surface observatories nationwide for daily surface air temperature readings, with data undergoing digitalization, quality checks, and archival at the National Data Centre (Nandi et al., 2024). Temperature measurements are in degree Celsius (°C). Annual data files include 365 records for non-leap years and 366 for leap years. Comprehensive assessment of these variables aimed to understand their patterns, anomalies, and the overall climate system.

In addition to these variables, a set of indices was employed to analyse how different global phenomena, especially the changing SST influence the behaviour and patterns of climate variables. Specifically, the Oceanic Niño Index (ONI) and the Dipole Mode Index (DMI) were utilized to thoroughly assess these effects. The ONI represents a three-month average of Extended Reconstructed SST (v5) anomalies in the Niño 3.4 region (5°N-5°S, 120°-170°W) (Huang et al., 2017; Climate Prediction Center, 2023). Meanwhile, the Indian Ocean Dipole

Mode Index (DMI) is calculated as the difference in SST anomalies (in ºC) between the WTIO (Western Tropical Indian Ocean, 10°S to 10°N, 50°E to 70°E) and SETIO (Southeastern Tropical Indian Ocean, 10°S to 0°N, 90°E to 110°E) in Indian Ocean regions (Huang et al., 2017; Climate Prediction Center, 2022). The identification of IOD events relies on a data of positive and negative IOD phases provided by the Bureau of Meteorology, Australia (http://www.bom.gov.au/climate/iod/). The phases of the ENSO are determined using NOAA Climate Prediction Center's ONI (Cahyarini et al., 2021; Climate Prediction Center, 2023).

The research also utilizes secondary data sourced from various reputable institutions. This includes demographic information from the Census of India, digital products from Survey of India, and academic resources from the Smt. Hansa Mehta Library, The Maharaja Sayajirao University of Baroda. The study also draws on findings from peer-reviewed academic journals, geographical data from Bhukosh, and reports from various government and intergovernmental bodies and reputed agencies. These diverse sources provide a comprehensive foundation for the research, enriching the analysis with multiple perspectives and robust datasets. In addition to these data sources, various software tools were utilized to conduct the research. QGIS (v3.24.1), along with its Python console and plugins, was used for geographical data analysis, mapping, and extracting IMDLIB data. R-Studio facilitated statistical analysis, data visualization, and forecasting. XLSTAT provided advanced statistical functions integrated with MS Excel, which was used for data organization and basic analysis. MS Word was employed for documentation and report writing. These tools together enabled comprehensive data analysis and effective presentation of findings.

1.6.2 Methodological Approach

In pursuit of its objectives, the study has adopted a structured methodological framework organized into three interconnected phases. This approach ensures a systematic progression through each phase, facilitating not only clarity and organization but also enhancing the reliability and validity of the study's findings. The following methodologies were adopted and carried out in three phases:

- **Phase I**

Phase I involves data collection. Climate variables such as rainfall and temperature were extracted from IMDLIB using the Python Console. Verification of missing years and values is conducted through manual extraction of variable data via the Gridded Data Archive, Climate Data Service Portal (https://www.imdpune.gov.in/lrfindex.php). The extracted data are in a gridded file format, which is then converted to shapefile format (.shp) for further analysis using the IMD Data Conversion Toolbox. Overlapping features between the study area (input layer) and variables (overlaying layer) are extracted using the Intersection tool of QGIS. Different IMD criteria are applied to assess events such as heat waves, cold waves, rainfall intensity, and distribution patterns. Daily data are organized into different time scales including monthly and seasonal (based on IMD designated seasons: Winter, JF; Pre-Monsoon, MAM; Southwest Monsoon, JJAS; Post-Monsoon, OND), as well as annual scales for comprehensive analysis. In addition to climate variables, data on the 3-month running mean of ERSST.v5 SST anomalies in the Niño 3.4 region (ONI) and Indian Ocean DMI (WTIO-SETIO), which influence the studied climate variables, are sourced from NCEP's Climate Prediction Center spanning six decades. The extreme phases of these indices are identified by BOM (DMI) and CPC (ONI) and extracted using an ‘if’ conditional statement in Python. Phase I primarily focuses on collecting and preparing data, including organizing data across various geographical and time scales essential for the subsequent phases of analysis and forecasting.

- **Phase II**

Phase II uses fundamental statistical methods, including the calculation of Mean, Standard Deviation (SD), and Coefficient of Variation (CV). Subsequent to this basic statistical analysis, the phase proceeds to analyse trends within variables and their extremes across diverse geographical and temporal scales. This is accomplished using both contemporary methods, such as Sen's Innovative Trend Analysis (ITA), and traditional methods, including the Mann-Kendall (MK) test and Sen’s Slope Estimation (SSE) test. Furthermore, the time series undergoes the Augmented Dickey-Fuller (ADF) test to assess stationarity. Stationarity is a prerequisite for accurate forecasting using the Auto Regressive Integrated Moving Average (ARIMA) and Seasonal ARIMA model. This comprehensive approach ensures that the data is thoroughly analyzed and adequately prepared for robust forecasting in the subsequent phases

- **Phase III**

Phase III focuses on forecasting climate variables. Utilizing the data prepared in the preceding phases, the SARIMA model is employed to generate forecasts. Before model application, the data undergoes rigorous pre-processing to ensure it meets all necessary assumptions. The optimal SARIMA model is selected based on the Akaike Information Criterion (AIC) and log-likelihood measures, while the model's parameters are adjusted to optimize accuracy and reliability. The selected model is validated through the Mean Absolute Error (MAE) and Root

Mean Squared Error (RMSE) before performing forecasts. Additionally, this phase includes the analysis of changes within the resultant forecast and observed mean, as well as the identification of water deficit and surplus regions. The insights gained from these forecasts provide valuable information for decision-makers, enabling them to develop more effective strategies for managing and mitigating the impacts of climate variability and extreme events. Phase III is crucial for transforming the analysis into actionable insights.

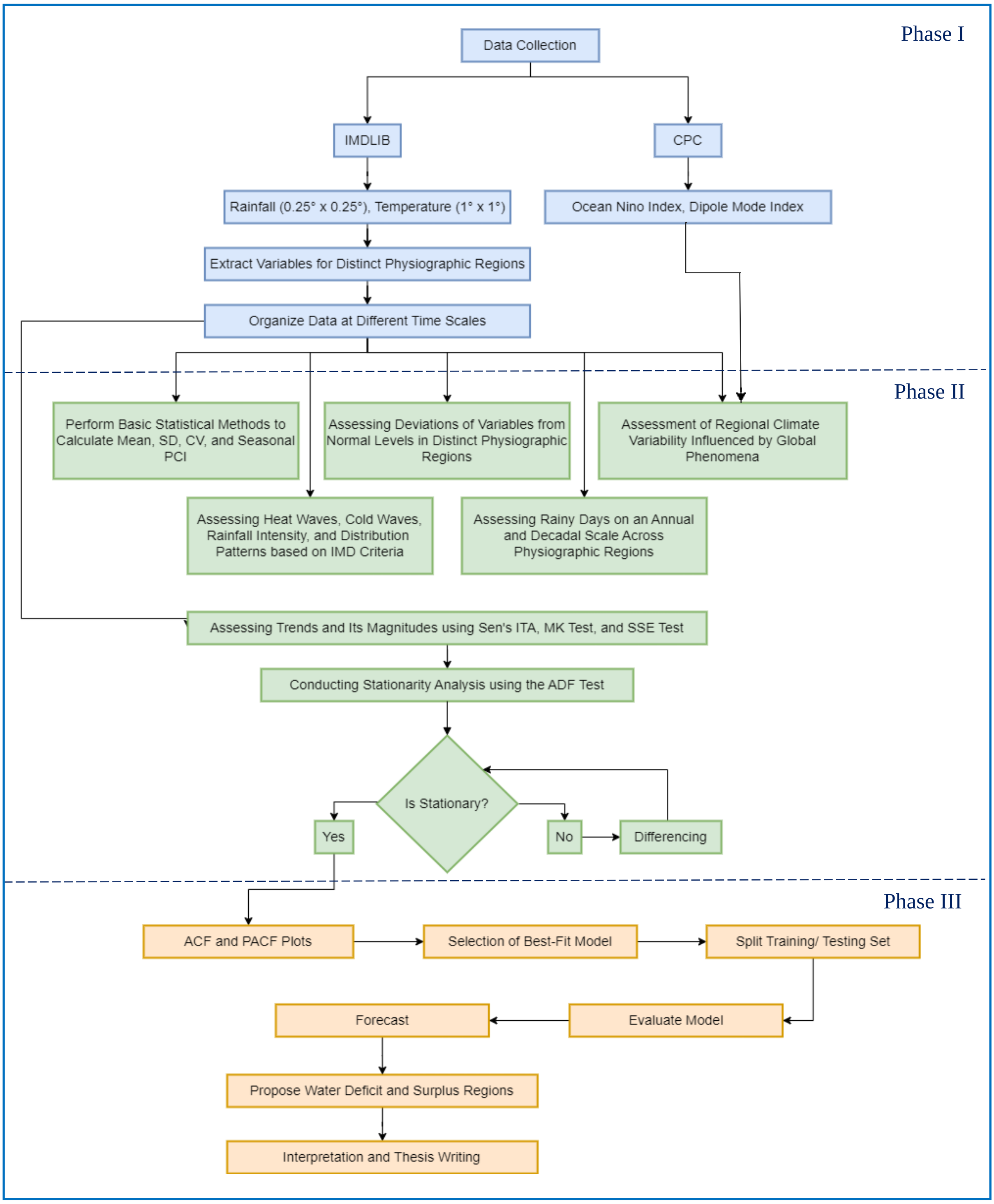

Figure 1.5 Flowchart of the Methodology Adopted.

1.7 Significance of the study

Despite extensive research and several studies aimed at understanding the complex behaviour of climate variables, a definitive conclusion has yet to be reached. The intricate and dynamic nature of climate systems, combined with the influence of various natural and anthropogenic factors, makes it challenging to draw conclusive insights about their patterns and future behaviour. This ongoing uncertainty highlights the need for continued investigation and more sophisticated analytical approaches. Over the past few decades, noticeable shifts in global climate patterns have been observed (Wang et al., 2017; Zhao et al., 2020; Mikhaylov et al., 2020; Abbass et al., 2022; Bernatchez et al., 2024). Erratic changes in rainfall and increasing temperatures, affecting both day and night, are clear signals of these transformations. The increasing intensity and frequency of EWE such as floods, droughts, and heat waves highlight the profound impact on the delicate balance of the world (Wang et al., 2017). This trend is particularly pronounced in regions like Gujarat, which is vulnerable due to its extensive coastline and susceptibility to climatic shifts (Poulose et al., 2020). Both temperature and rainfall have deviated substantially from their historical norms. To address these pressing issues, this study focuses on analysing trends across five distinct physiographic regions within Gujarat, each characterized by diverse geographic and climatic conditions. The study aims to thoroughly understand long-term variations in rainfall and temperature, including variations in both minimum and maximum temperatures, and the extremes they exhibit. This analysis will employ a combination of conventional (MK, SSE) and contemporary (Sen's ITA) trend analysis approaches to ensure reliable outcomes, showing robust and effective insights. Additionally, the study investigates the influence of global climate phenomena such as the El Niño Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) on regional climate dynamics. These phenomena not only affect seasonal weather patterns but also have the potential to exacerbate or mitigate the impacts of local climate variability. By examining the concurrent occurrences and interactions of ENSO and IOD events, the study aims to unravel the complex relation of global and regional climate factors that affect Gujarat's resilience to climate change.

In addition, the study progresses to forecast variables across different spatio-temporal scales, showing insights into future scenarios and their impacts on associated sectors. In the realm of forecasting, a multitude of methods exist, each carrying its own set of advantages and limitations. In this study, the ARIMA model is prioritized due to its numerous advantages over other methods. By employing a process that transforms non-stationary time series into stationary ones through differencing, the ARIMA model effectively extrapolates future values based on historical data (Al Balasmeh et al., 2019). This specific subtype of univariate modeling intricately utilizes past values, incorporating the autoregressive (AR) component alongside current and lag-timed values of a ‘white noise’ error term known as the moving average (MA) component (Essefiani et al., 2024). The utilization of the ARIMA model in this study not only enhances the accuracy of forecasts but also provides a robust framework for analyzing and predicting future trends effectively. Furthermore, the extension to the SARIMA model incorporates seasonality (Kabbilawsh et al., 2022), allowing for more precise forecasting of periodic patterns and trends in the data, making it particularly suited for climate and environmental datasets with inherent seasonal variations (Adineh et al., 2021; Zhao et al., 2023). This study also aims to contribute to understanding climate variability in Gujarat and its implications for sustainable development. It seeks to empower policymakers and stakeholders with actionable insights by elucidating the complex relationship between global climate phenomena and regional dynamics and by employing advanced analytical tools such as ARIMA modeling for forecasting. These insights are crucial for implementing adaptive strategies that strengthen Gujarat's resilience to climate change impacts, contributing to the development of a more sustainable and climate-resilient future for the region.

Additionally, the study projects potential water surpluses and deficits based on forecasted data. A decadal assessment will be conducted to thoroughly evaluate the reliability of the forecasts over time. This long-term analysis will help identify emerging trends in water availability, assess the impacts of climate change on regional water resources, and inform the development of effective water management and adaptation strategies.

1.8 Thesis Organization

The study has been organized into seven chapters, each highlighting relevant literature.

The first chapter, **“Introduction,”** provides an overview of the study, including the background, objectives, data sources, methodology, and significance. It explores global temperature and rainfall patterns, the climate of India and Gujarat, and modulating factors like the Indian Ocean Dipole and El Niño-Southern Oscillation and their impacts on local climate.

The second chapter, **“Profile of the Study Area,”** provides an in-depth exploration of the geographical background of the study area, focusing on Gujarat. It covers the location and extent, physiography, climate, vegetation, geomorphology, rivers, and demography, along with the historical evolution and socio-economic profile of the region.

The third chapter, **“Literature Review,”** identifies research gaps and areas requiring further investigation to understand the intricate relationship between climate variables. This review explores the approaches and models used for studying temperature and rainfall variations at different spatio-temporal scales, highlighting their strengths and weaknesses. It will pinpoint gaps in current knowledge and areas that require additional research to better understand these complex relationships. By integrating findings from a vast array of scholarly sources, it attempts to identify key trends, drivers, and impacts associated with these changes. In accordance, the literature review has been structured to explore the issues faced by changing climate on global temperature and rainfall in five subsections: "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," and "Time Series Forecasting Models.”

The fourth chapter, **“Temperature, Rainfall, and PCI Trends of Gujarat: A Spatio-Temporal Analysis**,**”** thoroughly examines the spatial and temporal distribution of climate variables across distinct physiographic regions of Gujarat. This analysis employs the basic statistical methods to assess deviations in rainfall, T_{max}, and T_{min} from their normal levels and PCI to comprehend the distribution of rainfall across regions. It also integrates advanced visualization techniques to highlight significant trends and anomalies. The chapter aims to understand the variations in these variables during periods influenced by the different phases of the ENSO and IOD, including their concurrent occurrences. This focused approach comprehensively assesses how these climate phenomena impact rainfall patterns and temperature variations in the state's distinct physiographic regions over time. Additionally, the chapter assesses rainy days on an annual and decadal scale and classifies rainfall intensities, heatwaves, and cold waves based on IMD criteria, providing a detailed examination of EWE. This analysis allows for a detailed understanding of the frequency, intensity, and duration of extreme weather phenomena in Gujarat.

The fifth chapter, **"Assessing Spatio-Temporal Trends of Rainfall and Temperature in Gujarat's Physiographic Regions,"** conducts a thorough assessment of climate variable trends across distinct physiographic regions of Gujarat. It employs both conventional methods (MK Test and SSE) and contemporary approaches (Sen's ITA) to achieve effective outcomes, providing insights into annual, seasonal, and monthly trends at varying confidence intervals (CI) across regions. By integrating traditional and contemporary methods, the chapter provides a comprehensive analysis that supports informed decision-making and strategic planning for climate adaptation and mitigation in Gujarat. Additionally, the chapter also carefully analyzes patterns in T_{min}, T_{max}, and rainfall extremes. This enhances the understanding of how these variables change over time across Gujarat's diverse regions, thereby providing a detailed perspective on regional climate dynamics.

The sixth chapter, **"Forecasting Variables using ARIMA: Comparative Analysis of Inter-Regional Changes in Gujarat**," focuses on forecasting climate variables using the seasonal ARIMA model. The chapter begins with data preprocessing, where the historical data on rainfall and temperature is prepared for analysis. Integral to this process is the Augmented Dickey-Fuller (ADF) test, a widely recognized method for assessing the stationarity of time series. This preliminary step is crucial for ARIMA modeling as it ensures the data meets the prerequisite for accurate forecasting. The chapter then delves into model identification using ACF and PACF plots to determine the appropriate order of the model parameters. Once the parameters are identified, the chapter describes the model estimation process to fit the SARIMA model to the data. This involves selecting the best model based on AIC and Log-likelihood measures. Following model estimation, the model's performance is evaluated using the MAE and RMSE. These metrics indicate a good model fit, suggesting that the model effectively captures the underlying patterns in the data and can generate accurate forecasts. The chapter then proceeds to the forecasting phase, which provides insights into how variables are expected to evolve over the next three decades in distinct regions of Gujarat. Additionally, the chapter identifies regions within Gujarat that are projected to experience water deficits and surpluses. This information is crucial for policymakers and stakeholders involved in water resource management and climate adaptation strategies, aiming to enhance the region's resilience to future climate impacts.

The seventh chapter, **"Conclusion,"** summarizes the key findings of the preceding chapters and draws overall conclusions based on the research outcomes. It provides suggestions for future research and potential actions arising from the study. This chapter aims to consolidate the research findings and offer insights for future directions, emphasizing the study's contributions to understanding climate variability in Gujarat.