ASSESSMENT AND PREDICTION OF DROUGHTS IN SEMI-ARID CLIMATE USING INTEGRATED REMOTE SENSING AND METEOROLOGICAL DATA BASED INDICES

By

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(2020-NUST-MS-RS&GIS-330192)

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Remote Sensing & GIS.

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September, 2024

THESIS ACCEPTANCE CERTIFICATE

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DEDICATION

This thesis is dedicated to my family, whose unwavering support and encouragement have been instrumental in my academic journey. Their patience, love, and sacrifices have made this work possible and have also served as an endless wellspring of inspiration and strength throughout my academic journey. I also dedicate this to all those working tirelessly to understand and mitigate the impacts of drought, especially in vulnerable regions. May this research contribute, even if in a small way, to alleviating the hardships faced by communities affected by water scarcity.

ACADEMIC THESIS: DECLARATION OF AUTHORSHIP

I, **Muhammad Ali,** declare that this thesis and the work presented in it are my own and have been generated by me as the result of my original research.

"Assessment and prediction of droughts in semi-arid climate using integrated remote sensing and meteorological data based indices"

I confirm that:

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6. None of this work has been published before submission. This work is not plagiarized under the H.E.C. plagiarism policy.

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ACKNOWLEDGEMENT

In the name of Allah, the Most Gracious, the Most Merciful. “He gives wisdom to whom He wills, and whoever has been given wisdom has certainly been given much good. And none will remember except those of understanding." (Quran 2:269). All praise is due to Allah Almighty, the Lord of the worlds, for granting me the strength, knowledge, and opportunity to undertake and complete this research. May His peace and blessings be upon our beloved Prophet Muhammad (PBUH), who taught us that seeking knowledge is an obligation upon every Muslim.

I would like to express my profound gratitude to my supervisor, Dr. Ejaz Hussain, for his invaluable guidance, support, and encouragement throughout this research journey. His expertise and insights were instrumental in shaping this study. I am deeply grateful to the members of my advisory committee, Dr. Muhammad Azmat and Dr. Shakil Ahmad, for their constructive feedback and suggestions that helped refine this work. I would also like to extend my sincere thanks to my fellow researchers, Mr. Ebadat Ur Rehman and Ms. Tahira Saeed, for their assistance and collaboration during this study.

My thanks go to the Pakistan Meteorological Department for providing the meteorological data essential for this research. I also acknowledge the United States Geological Survey (USGS) and European Space Agency (ESA) for making satellite imagery freely available, without which this study would not have been possible.

I am thankful to the faculty and staff of the Institute of Geographical Information Systems at NUST for their support and for providing the resources and environment conducive to research. I would like to give special mention to Mr. Kashif Ali, whose help with paperwork and in ensuring smooth timelines was invaluable.

I am deeply indebted to my family for their unwavering support, patience, and encouragement throughout my studies. This accomplishment would not have been possible without them. I would also like to express my heartfelt gratitude to my friends who have been a constant source of support and encouragement: Ahmad Hassan Saleem, Ghazanfar Majid, Ebadat Ur Rehman, Ghazi Akbar, Ahmad Saleem, Mustabshira Rehman, Noor-Ul-Ain Afsar, Muhammad Ali Awan and Tahira Saeed. Your friendship and support have been a true blessing.

May Allah accept this work and make it beneficial for humanity. Ameen.

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LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS

ARIMA	Autoregressive Integrated Moving Average
ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
DrinC	Drought Indices Calculator
ENSO	El Niño-Southern Oscillation
ESA	European Space Agency
GEE	Google Earth Engine
IDW	Inverse Distance Weighted
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
LST	Land Surface Temperature
MAE	Mean Absolute Error
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
NIR	Near-Infrared
NOAA	National Oceanic and Atmospheric Administration
PACF	Partial Autocorrelation Function
PET	Potential Evapotranspiration
PMD	Pakistan Meteorological Department
RDI	Reconnaissance Drought Index
RMSE	Root Mean Squared Error
SPI	Standardized Precipitation Index
SPEI	Standardized Precipitation Evapotranspiration Index
TCI	Temperature Condition Index
TM	Thematic Mapper
USGS	United States Geological Survey
VCI	Vegetation Condition Index
λNIR	Reflectance in Near-Infrared band
λred	Reflectance in Red band

ABSTRACT

This research has been carried out to study the Drought conditions in semi-arid regions of Pakistan by evaluating and forecasting droughts in Bahawalpur division. We have employed an integrated approach that comprises of both Metrological and Remote Sensing based indices for drought monitoring. For temporal metrological drought assessment, we utilized SPI and RDI which were computed for 3-month and 6-month time scales. For agricultural and Thermal aspects of drought we created maps that displayed the spread of drought over the region. For these maps we used NDVI, VCI and TCI indices. We also developed a timeseries for the metrological parameters i.e. Precipitation and Potential Evapotranspiration (PET). Considerable variations in in drought patterns were discovered in the study both spatially and temporally across the study area. The southern parts of district Bahawalpur and Rahim Yar Khan were found to be having more droughts that were of high magnitude. Each index while showing a unique aspect of drought dynamics while integrated with other indices captured an overall image of water stress and vegetation health that led to an improved drought evaluation. Lack of rainfall was identified to be the primary driver of droughts in the region while temperature had a relatively less contribution. Integrated maps were generated by combining the maps from different indices in different combination for a more holistic approach using weighted overlay technique. The maps revealed 77% of the area having mild to moderate drought conditions. Time series forecast suggested the potential drought trends in the study area in future years. This research contributes to the understanding of drought dynamics in semi-arid regions by explaining the role of integrating multiple drought indices and provide implications for long-term planning by providing valuable insights of the drought conditions in the study area.

Chapter 1.

INTRODUCTION

1.1 Background of Study

Human activities are causing significant shifts in global climate systems which resulted in complex changes in the spheres of earth (Zahid et al., 2012). And these changes have posed food security threats on global scale (Khan et al., 2022). These effects are across multiple disciplines which are affecting the food resources from multiple aspects including the accessibility utilization and stability. (Farooqi et al., 2005).

Due to its unique location on globe Pakistan has been a bigger target of these changes. Considerable changes in the Precipitation patterns and temperature extremes have been observed by the studies especially over last 20 years. The country's diverse geographical landscape ranges from glaciers to arid climate zones from north to south (Rasul et al., 2005).

Monsoon rains account for 59% of Pakistan's annual precipitation, making them the principal hydro-meteorological source. Pakistan's primary economic resource is its fertile land, which contributes around 23% to the country's GDP through agriculture (Ministry of Finance, 2022). Agricultural productivity in Pakistan is heavily influenced by the Rabi and Kharif crop seasons, which depend on precise amounts of rainfall and precipitation. Deviations from optimal levels, either excessive or insufficient, can lead to reduced agricultural output due to droughts or floods. Droughts and floods imperil crop yields, food security, livestock, and land quality. They also negatively affect farm production, market access, and groundwater levels. People living in poverty, who have limited adaptive strategies, are particularly exposed to the impacts of climate change at global level, increasing their risk of famine (Hussain et al., 2022).

Droughts and floods, resulting from insufficient and excessive rainfall respectively, have been increasing in frequency over time. Reduced precipitation leads to lower stream and river flows, impacting soil moisture, irrigation timing, and plant growth. Floods occur due to either prolonged rainfall or a significant amount of rain in a short period (cloudburst) (Rasul et al., 2005). While droughts gradually spread into areas with little rainfall, floods are not influenced by precipitation patterns once initiated. Research indicates a significant likelihood of increasing drought occurrences in already susceptible regions due to global climate change (IPCC, 2007). The effects of drought are primarily non-physical and extend across a broader geographic region compared to other natural disasters.

The consequences of drought are primarily intangible and tend to affect a wider geographical area compared to other natural calamities. Effective mitigation strategies and preparedness can significantly diminish the impact of drought and similar disasters. The countries that are prone to droughts should prioritize the practices for risk management and develop policies that are tailored to address the drought conditions with their specific climate conditions so that the drought impacts can be minimized.

1.2 Understanding Drought: Definitions, Types, and Impacts

Drought is a considered as an environmental disaster which causes damage to both the human populations and other ecosystems due to the importance of water availability for these ecosystems (Amin et al., 2019). Primarily, drought can be defined as a prolonged period of abnormal aridity (Eslamian & Eslamian, 2017). Definition of droughts vary universally due because it’s a complex phenomenon that is subject to multiple aspects unlike other natural phenomena such as floods.(Changnon, 1987). Wilhite & Glantz, (1985) proposed that the droughts can be classified based on their impacts in different dimensions and unique characteristics providing a framework for understanding this complex phenomenon.

1.2.1 Meteorological Drought

This pertains to the level of dryness and the duration of time during which arid conditions persist because of different atmospheric conditions causing variations in precipitation that occur across different regions. According to (Chopra, 2006), rainfall shortage refers to a situation where precipitation in a specific area decreases by more than 25% compared to the usual amount.

1.2.2 Hydrological Drought

This concerns the impacts of inadequate rainfall on both surface and subsurface water supplies. Hydrological drought often occurs at the scale of a watershed or river basin, intensifying conflicts among various water users and stimulating actions by stakeholders negatively affected (Eslamian & Eslamian, 2017).

1.2.3 Agricultural Drought

This type primarily affects agricultural production, leading to soil water deficiencies, decreased reservoir or groundwater levels, and other related consequences.

1.2.4 Socio-Economic Drought

This pertains to the interplay between the availability and demand for a specific economic resource. “Socio-economic” drought arises when the demand for an economic commodity surpasses its availability due to water supply deficiencies caused by weather conditions.

Drought impacts both natural and human systems, influencing climatic conditions and exacerbating water scarcity issues in affected regions (Amin et al., 2020). Droughts possess distinctive physical attributes and can have wide-ranging geographic extents and specific localized effects. Contributing factors to drought include phenomena such as El Niño and La Niña, as well as the escalation of greenhouse gases (Sheikh, 2001). The impacts of drought can be categorized into environmental, economic and social dimensions.

Drought results in the loss of wildlife habitat, Species of plants and animals, biodiversity, and water and air quality. For instance, when water and crop yields decrease, livestock may struggle to find adequate food, leading to challenges in farming activities and potential famine.

It causes losses in crop yields and livestock production, increases plant diseases and insect infestations, and can severely disrupt agricultural productivity.

Drought also poses hazards to public health and safety, diminishes the overall quality of life, and often leads to population migration in search of better food and water availability.

Figure 1.1 shows an association between various forms of droughts (Chopra, 2006; NDMC, 2022).

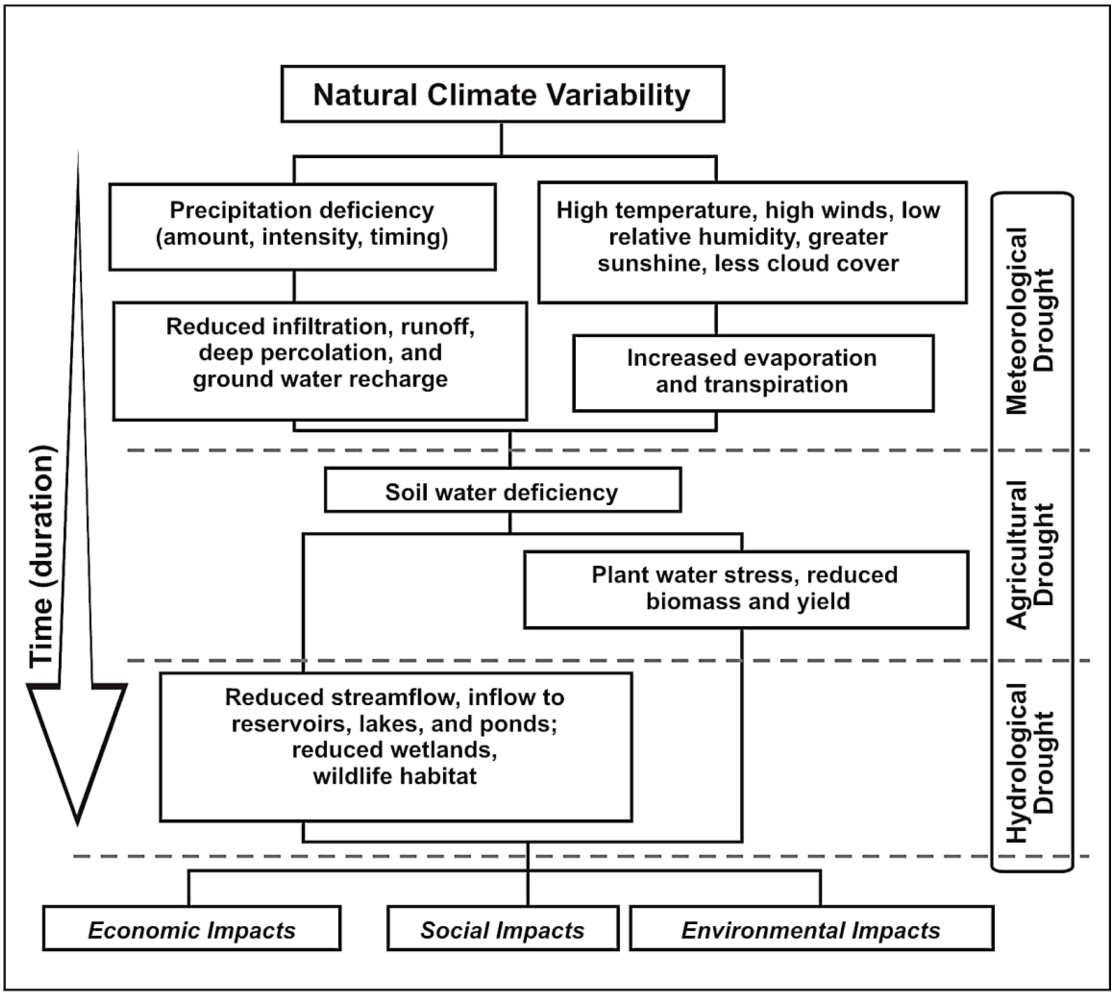


Figure 1-1: Interaction between various forms of droughts and their potential impacts.

1.3 Droughts in Pakistan

Droughts in Pakistan are primarily attributed to inadequate precipitation during the southwest monsoon season, with notable associations between El Niño and La Niña phenomena and the frequency of weak monsoons (PMD, 2013). El Niño events, characterized by abnormally high sea surface temperatures in the eastern and central tropical Pacific Ocean, disrupt atmospheric circulation patterns, reducing precipitation over regions such as Pakistan. Historical data reveals that 11 out of 21 drought years from 1871 to 1988 coincided with El Niño occurrences (PMD, 2013). On the other hand, La Niña events occurring due to unusual drop in sea surface temperatures in the Pacific Ocean's eastern and central regions, can impact on Pakistan's drought conditions. While some studies suggest that La Niña can aggravate drought conditions in some areas it may increase precipitation elsewhere(Pacheco et al., 2022). This relationship between El Niño-Southern Oscillation (ENSO) events and rainfall patterns is known to be affecting the consistency and intensity of rainfall (Ropelewski & Halpert, 1987).

From 2001 to 2003, South Asia, including Pakistan, experienced severe drought conditions, confirmed by seasonal values of various drought indices (Ali et al., 2019). In Pakistan, meteorological drought is defined as a situation where precipitation falls below 60% of the long-term average over an extended period, either monthly or seasonally (Rasul et al., 2005). Approximately 60% of Pakistan's land is classified as desert, receiving less than 200 mm of annual precipitation, with southern Punjab and northern Sindh receiving less than 125 mm annually ((SAARC, 2010) (Gadiwala, 2013)). The primary dry rangelands, including Cholistan and Tharparkar, are particularly susceptible to conditions of drought, especially when significant rainfall fails during key seasons such as the summer monsoon and winter season. Regions like southern Punjab and Sindh often experience drought during the transitional period from October to November, with minimal rainfall, heightening their drought vulnerability (Gadiwala, 2013).

The severe heat wave in Sindh in June 2015, claimed over 1,000 lives, underscores the severity of drought impacts, which exacerbate food insecurity in rural areas. Intense heatwaves devastate grasslands, disrupt agricultural activities, threaten livestock sustainability, and cause repeated water shortages (Gondal et al., 2021). While the frequency of droughts is typically 2 to 3 times lower than other disasters, the death toll is significantly higher globally (Sheikh, 2001). Research on long-term drought patterns in Punjab, Khyber Pakhtunkhwa (KPK), and Sindh showed significant occurrences at a 95% confidence interval (Hina & Saleem, 2019). Punjab experienced severe droughts in 1899, 1920, and 1935, Khyber Pakhtunkhwa in 1902 and 1951, and Sindh in 1871, 1881, 1899, 1931, 1947, and 1999 (PMD, 2013). 1998-2002 drought is considered to be the worst in the previous 50 years (Sadiq & Saboor, 2018).

Analysis of drought conditions from 1983 to 2010 revealed that Balochistan and Sindh's districts, including Kharan, Chaghi, Gwadar, Kech, Sukkur, Nawab Shah, Dadu, Khairpur, Shikarpur, Jacobabad, Nowshehro Feroz, and Larkana, were most affected (Sadiq & Saboor, 2018). The south-east portion of Pakistan, particularly the

Thal region in the semi-arid zone, is more vulnerable to droughts than the north-west region (Hina & Saleem, 2019). Drought conditions observed were severe in 2000 and 2002, but milder in 2003, 2004, 2006, and 2009 in dry regions (Amin et al., 2019). These droughts have an overwhelming impact on agriculture, socioeconomic conditions, the physical environment and livestock raising because of agriculture in this region being strongly dependent on rainfall. The wheat Rabi cropping seasons from 2000 to 2002 were marked by severe agricultural droughts, which had an extensive impact on crop production in many places in the region (Amin et al., 2020).

1.4 Problem Statement

Because of an Agriculture based country Pakistan is heavily affected by the harsh impacts of drought. Interconnected nature of droughts and complexity results in a significant damage to the economic stability of the country by effecting the agricultural production. The studies have been done on droughts in Pakistan evaluating the causes and impacts of droughts however there’s still s need to have a targeted evaluation of the impacts of droughts on focused specific locations such as Semi-Arid Regions in Southern Punjab. This gap of study in localized environments vacates the effective and focused drought mitigation strategies.

Current study aims to bridge this gap of knowledge by integrating Remote sensing-based indices with the traditional Metrological based drought indices in order to have a more reflective understanding of patterns and dynamics of droughts specific to this region. We aim to reduce the vulnerability of the region to droughts by having a better understanding of droughts in the localized environments and enabling local stakeholders and policy makers to make better use of this information for a better decision making which will result in more efficient drought management techniques ultimately contributing to the progress of Pakistan’s Agriculture Sector and economy of the country.

1.5 Study Area

The Bahawalpur Division is situated in the southeastern region of Punjab Province. It covers a total area of 45,588 square kilometres major part of which i.e. 23,467 square kilometres includes of the Cholistan Desert. It is located a at a longitude of 29.98°E and a latitude of 73.26°N. The region consists of three districts of Punjab namely Bahawalpur, Bahawalnagar, and Rahim Yar Khan. The Cholistan or Rohi desert is comprised of some areas of the Bahawalpur, Bahawalnagar, and Rahim Yar Khan districts of Punjab. The Cholistan region spans across a large area of 16,638 km2, with 10,006 km2 located in Bahawalpur, 2,528 km2 in Bahawalnagar, and 4,040 km2 in Rahim Yar Khan (Rehan, 2022). The region benefits from its fertile soil and well-developed irrigation system, which enables the growth of a various crops for example wheat, sugarcane, cotton, rice, and fruits. According to the census conducted in 2017, the population of Bahawalpur Division stands at 11,452,594 (GOP, 2022). Figure 1-2 displays the map of the study area.

The climate of Bahawalpur Division is characterized by hot, dry summers and cold winters, with an annual rainfall of 15 to 20 mm. The monsoon season, occurring between July and September, brings substantial precipitation and provides some respite from the high temperatures. The region is also affected by prevailing winds that blow from different directions depending on the season. During the summer, hot winds called "loo" can bring extremely high temperatures to the area. In contrast, winter winds may originate from the north and bring relatively cooler temperatures (PMD, 2022, 2013).

The topographical diversity of the region encompasses agricultural plains, riverine zones, and arid landscapes. Situated 889 km from Karachi, Bahawalpur borders the productive alluvial plains of Sindh to its west, benefiting from the Sutlej River's irrigation. This area is distinguished by its abundant date palm groves and high population density. The agricultural sector thrives with primary crops such as wheat, gram, cotton, sugarcane, and dates, complemented by livestock farming for wool and leather production.

Eastward lies the Pat (or Bar), an elevated desert expanse made arable through Sutlej's inundation canal system, supporting the cultivation of wheat, cotton, and sugarcane. Beyond this lies the Rohi, also known as Cholistan, a stark desert terrain home to nomadic communities and rich in historical heritage, exemplified by the ancient settlement of Uch.

Renowned for its varied crop production—wheat, cotton, millet, rice, dates, and mangoes—Bahawalpur is clearly a major agricultural hub. Many businesses, most notably cotton processing, grain milling enterprises, and traditional textile craft, support the urban economy. This mix of industry and farmland highlights Bahawalpur's economic importance for the area. Notable businesses are cotton ginning and producing cake and cottonseed oil.

Bahawalpur is seeing effects of climate change, as other parts of Pakistan. For agriculture, water resources, and the sustainability of ecosystems, rising temperatures, changed rainfall patterns, and the possibility of catastrophic weather events present major difficulties. Figure 1-2 shows the research area's map.

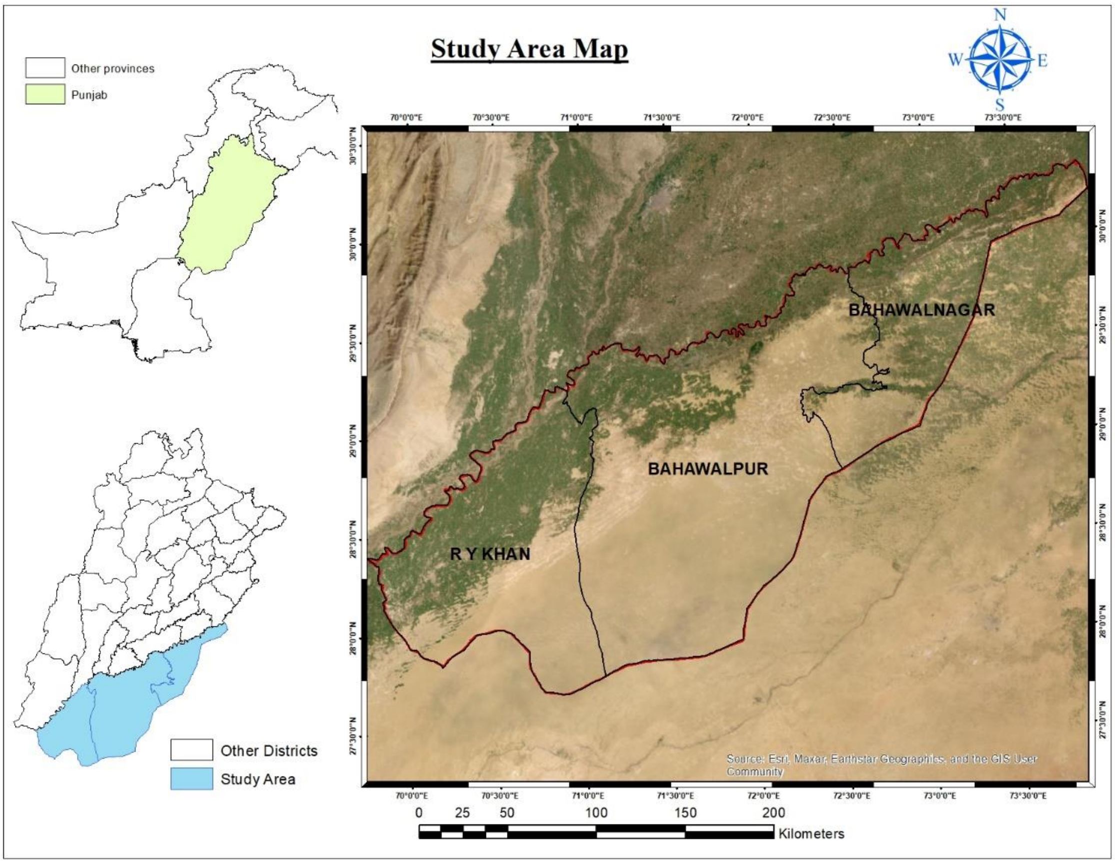


Figure 1-2: Map of the Study Area (Bahawalpur Division)

1.6 Research Objectives

The study objectives outlined below aim to overcome the existing research gap:

- To identify and map drought occurrences and patterns using remotely sensed and meteorological data-based drought indices, and assess their performance
- Develop time series forecasting models for key meteorological variables to support drought prediction capabilities in the study area.
- Investigate the impacts of drought on the study area and evaluate potential mitigation strategies to alleviate the adverse effects of drought occurrences.

1.7 Significance of Study

This study addresses the critical need to integrate current drought monitoring systems to reduce the southern region's vulnerability. By understanding the impacts and underlying causes of drought, this research aims to reduce Pakistan's sensitivity to such events. Enhancing data availability for effective mapping and monitoring of drought at various scales is crucial due to the phenomenon's spatial and temporal variability. The use of GIS for spatial analysis will enable government organizations to manage potential drought victims and those in vulnerable areas more efficiently, leading to the development of a robust decision support system.

This study aims to develop a comprehensive system for accurately monitoring, assessing the risks associated with, and mitigating the impacts of drought. This study will primarily benefit the agricultural sector and connected sectors, which will enhance the national economy. Developing drought risk maps and evaluation protocols will help in decision making and enable the implementation of specific mitigations to reduce the negative effects of drought. This might help to enhance sustainability in the semi-arid Regions. Moreover, this research will contribute to the drought monitoring and management studies and will be a basis for future investigations and enhancing the current knowledge on the topic.

The research will aid the early warning systems of drought. Many organizations such as the Pakistan Meteorological Department (PMD), National Disaster Management Authority (NDMA), Food and Agriculture Organization (FAO), Ministry of Climate Change (MoCC), Environmental Protection Agencies, and water conservation agencies may find this helpful. It will benefit the farmers for the purposes of drought-resistant measures. Determining areas susceptible to drought will allow for adjustments in agricultural techniques to mitigate the effects of water shortage on crop production. The research will improve the policy formation at all levels of government for efficient drought management.

Chapter 2.

LITERATURE REVIEW

This chapter highlights the importance of this study by addressing the previous work done on this topic through the analysis of a range of studies in scholarly publications worldwide.

2.1 Previous Studies on Drought Indices

Drought metrics are very important for accurately measuring and knowing how bad and long droughts are. They are also very important for keeping track on droughts and coming up with ways to prevent them. Early indices such as the Palmer Drought Severity Index (PDSI) concentrated on the harmony between demand and availability of water (Palmer, 1965; Alley, 1984). The PDSI's complexity and large data needs, however, hampered its general use and resulted in the creation of simpler indices such the Standardized Precipitation Index (SPI) (McKee et al., 1993). SPI has been found to be a popular choice because of its lesser data requirements for early warning systems and drought monitoring. (Zargar et al., 2011).

By offering important data on vegetation health, land surface temperature, and soil moisture, advances in satellite remote sensing technologies have transformed the drought monitoring (Thenkabail & Smakhtin, 2004). To create early warning systems and drought indicators, for example, studies have merged the SPI with satellite-derived rainfall data (Senay et al., 2014). Extensive near-surface air relative humidity data from satellite missions and sensors is a resource not being used much in efforts at drought monitoring. Remote sensing data comprehensively covers nearly all aspects of drought progression, although regular and precise observations of river flow remain a challenge. Satellite rainfall products offer global-scale precipitation data, facilitating the use of rainfall-based indicators for monitoring droughts at national and international levels (Senay et al., 2014).

Researchers in Pakistan have evaluated and explained drought trends using many drought indices. Using 12-month SPI, GPCC precipitation, and CPC soil moisture data, Amin et al. (2019) assessed Punjabi drought. Their research classified years according to precipitation anomalies, therefore distinguishing years of modest and substantial drought. With some districts like Mianwali and Jhang facing moderate to severe dry conditions, spatial analysis indicated varied drought intensities across different areas and months. Against in situ observations Ullah et al. (2021 examined the SPI and SPEI using reanalysis products including CRU TS, NCEP-2, ERA-5, and MERRA-2. Although Reanalysis products fairly depicted the historical droughts in the region, but they were found to overstress drought intensity in other regions suchas western Pakistan. During certain periods with reference to CRU TS and MERRA-2 growing trends were observed in dry regions.

The Reconnaissance Drought Index (RDI) has been used often in the studies due to its comprehensive approach that combines the Potential evapotranspiration (PET) along with precipitation for drought evaluation (Tsakiris & Vangelis, 2005). RDI is found to be more sensitive to climate change and global warming scenarios and provides a more holistic assessment of drought as compared to SPI (Zarch et al., 2015; Hina & Saleem, 2019). Studies show that RDI and SPI vary in drought evaluation where temperature plays a role in dryness of region due to global warming scenarios and also where the timescale of analysis is prolonged e.g. 6 month scale and 12 months scale (Zarch et al., 2015; Hina & Saleem, 2019). The stronger correlation is found between SPI and RDI in semi-arid climates compared to humid conditions (Zarch et al., 2011). However, the accurate calculation of PET and the need for extensive data can be challenging in the application RDI. Several studies have explored the applicability of RDI in different contexts.

The choice and combination of drought indices depend upon the data availability, and specific context. While SPI is suitable for regions with limited data, RDI and SPEI offer more comprehensive assessments when PET data are available.

The use of multiple indices and integrated approaches have often been used by research to improve the assesment of droughts. Some focus on single index for different conditions and some focus on Hybrid approach for example). Tigkas et al. (2019) found that SPI valuable in arid and semi-arid climates while Uddin et al. (2020) emphasized the value of a multi-index approach to improve drought assessment.

Alahacoon & Edirisinghe (2022) reviewed 11 indices to highlight advancements in satellite technology. They classified 44 of these as traditional and the others were RS based. Meteorological drought monitoring was done by highest number of traditional indices (22) which was approximately 20% of the total, whereas agricultural drought monitoring had the fewest (7) which were 6.3%. Remote sensing-based indices notably focused on agricultural drought monitoring (90%) but had a lesser applications in hydrological and meteorological drought monitoring (10%). Mukhawana et al. (2023) studied various drought indices, including PDSI, SWSI, VCI, SPI, SPEI, SSI, SGI, and GRACE assessing their applicability in the South African region. Due to complexity and data accessibility issues this study highlighted the PDSI and SWSI as impractical. Research suggests integrating multiple drought indices (SPI, SPEI, VCI, SSI, and SGI) using hybrid methods tailored to specific probability distributions. (Jalayer et al., 2023) examined Iranian droughts from 2000-2021 using various remote sensing and combined indices, validating them against in situ measurements. Their findings showed that composite indices correlated better with ground data than individual remote sensing indicators. Figure 2-1 shows evolution of these drought indices from metrological towards the integrated approach.

Accurate drought assessment choice and combination of drought indices requires a thorough understanding of geographical and temporal patterns data availability, and specific context. Remote sensing is found to be particularly valuable for monitoring these complex drought variables. For the geography of Pakistan, particularly southwest regions a multi-index approach which combines Remote Sensing Satellite based and ground-based indices is crucial for effective drought monitoring and mitigation.

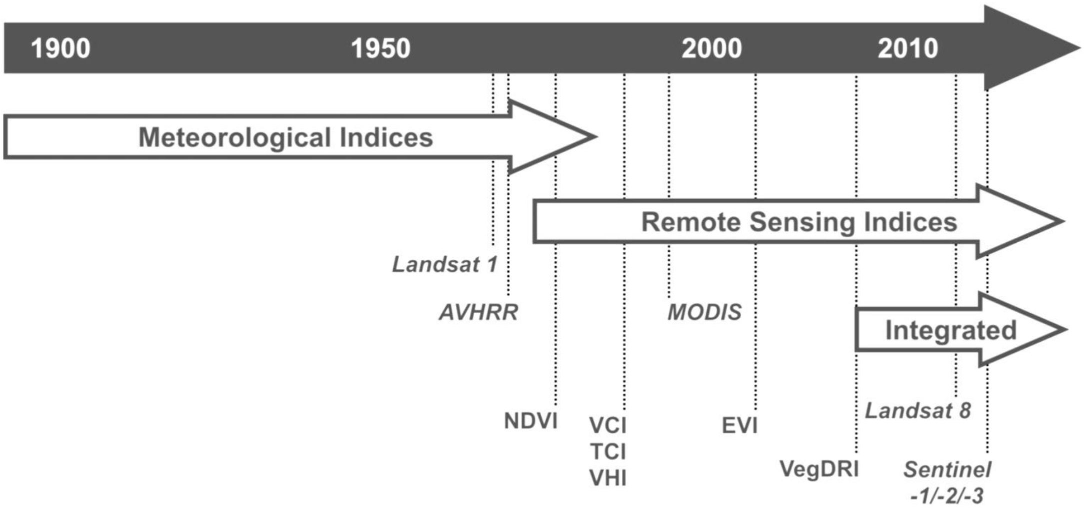


Figure 2-1: Evolution of Drought monitoring Indices over time.

2.2 Drought Indices

Various drought indices have been established to measure drought occurrences in a particular area. Due to the absence of ground-based datasets, satellites can provide valuable observations of Earth's regions. A concise overview of many vegetation indices that are resulting from remote sensing data is as follows. This section presents a discussion on some significant comprehensive and remote sensing-based drought indices.

2.2.1 Palmer Drought Severity Index (PDSI)

PDSI which was put together by (Palmer, 1965) quantifies reductions in moisture availability and represents an early attempt to characterize drought using indicators beyond precipitation alone. It assesses the balance between water supply and demand (Alley, 1984). Sensitive to abnormal weather patterns such as droughts and excessive precipitation. The PDSI provides standardized metrics for comparing moisture levels across different locations and months, and its results are accessible through the Physical Science Laboratory, NOAA. However, criticisms of the PDSI have emerged in past research (Chopra, 2006).

Unlike the PDSI, the Standardized Precipitation Index (SPI) has gained broader acceptance for both research and operational purposes due to its simplicity and reliance solely on rainfall data (Rhee et al., 2010). The SPI does not require the complete serial records of temperature and precipitation that the PDSI does, which can be limiting

(Palmer, 1965). Moreover, the PDSI's 9-month timescale may not detect droughts at shorter intervals (Alley, 1984).

2.2.2 Standardized Precipitation Index (SPI)

The SPI derived by (Mckee et al., 1993) is widely recognized and extensively developed from remote sensing data. Because of its sole reliance on precipitation data, SPI is more efficient compared to the (PDSI) (Tigkas et al., 2015; West et al., 2019). It quantifies moisture levels by comparing total rainfall received over specific time intervals with historical averages. SPI calculates drought severity by converting variation in precipitation distribution into a standardized normal distribution (Zargar et al., 2011).

A monthly precipitation data for atleast 30 years is required to Calculate SPI, It transforms cumulative precipitation probabilities into standard normal distributions (Liu et al., 2021). Each observed rainfall value is then evaluated probabilistically against the inverse normal distribution. It yields deviations in precipitation succeeding a normal distribution (Mckee et al., 1993). Consecutive negative values shows periods of low rainfall and positive values indicate high rainfall sequences as shown in (Table 2-1) (Kouchak et al., 2015). (Tigkas, 2004; Tigkas et al., 2015).

SPI offers several advantages in drought assessment due to its exclusive reliance on precipitation data, However, SPI's limitations include its inability to account for temperature effects in drought calculations, which are crucial for assessing water balance and usage. Moreover, it requires a substantial amount of Precipitation data and its reliance on a prior distribution may not be ideal for analyzing short-term drought events. Additionally, the zero rainfall events may cause accuracy errors in the gamma distribution parameters used in SPI (Copernicus European Drought Observatory, 2020).

2.2.3 Reconnaissance Drought Index (RDI)

RDI proposed by (Tsakiris & Vangelis, 2005), is utilized for drought assessment particularly in arid regions and is preferred over SPI because of its integration of PET along with precipitation unlike SPI (Thomas et al., 2016). This index can be applied across various durations and timeframes, facilitated by tools like the DrinC software, which calculates RDI, PET, and offers different values such as initial, standardized, and normalized RDI, as well as the aridity index (Table 2-2) (Ansarifard & Shamsnia, 2018).

Studies have Explored that RDI is highly responsive to changes in meteorological conditions (Jamshidi et al., 2011; Khalili et al., 2011) . PET plays a significant role in drought calculations due its part in hydrological cycle given the influence of climate change (Zarch et al., 2015).

Method used to compute PET influences the accuracy of RDI which underscores the importance of accurate meteorological data for its efficiency (Tsakiris & Vangelis, 2005). Threshold values of these indices (SPI/SPEI/RDI) for drought categorization are displayed in Table 2-1.

Table 2-1: Climatic moisture categories for SPI, SPEI & RDI

Sr. No.	SPI / SPEI / RDI	Category
1.	> 2.0	Extreme wet condition
2.	1.5 to 1.99	Very wet condition
3.	1.0 to 1.49	Moderately wet condition
4.	-0.99 to 0.99	Near normal condition
5.	-1.0 to -1.49	Moderately dry condition
6.	-1.5 to -1.99	Severely dry condition
7.	< -2.0	Extreme dry condition

Source: (Alley, 1984; Ansarifard & Shamsnia, 2018; Mckee et al., 1993; Tsakiris & Vangelis, 2005; Vicente-Serrano et al., 2010)

Table 2-2: Aridity index values and classification Source: (Colantoni et al., 2014)

Aridity Index (AI) Values	Climate Classification
AI < 0.05	Hyper-arid
0.05 < AI < 0.2	arid
0.2 < AI < 0.5	Semi-arid
0.5 < AI < 0.65	Dry sub-humid
0.65 < AI > 0.75	humid
AI > 0.75	Hyper-humid

2.2.4 Normalized Difference Vegetation Index (NDVI)

NDV was proposed by (Tucker, 1979). It represents the first application of remote sensing to monitor agricultural drought, which is a significant advancement in environmental monitoring (Kouchak et al., 2015). NDVI is given as,

$$NDVI = \frac{\lambda_{NIR} - \lambda_{red}}{\lambda_{NIR} + \lambda_{red}} \qquad 2.1$$

Where, λ_{NIR} is the reflectance in the red and λ_{red} is the reflectance in near infrared band. NDVI ranges from -1 to +1, depending on the vigour of vegetation. MODIS data is frequently utilized to calculate both NDVI and land surface temperature (LST) (Sruthi & Aslam, 2015).

NDVI proves invaluable for precise land cover assessment, vegetation classification, and continental-scale phenological studies. It also serves as a crucial tool in monitoring rainfall patterns, detecting drought conditions, and identifying ecological and economic impacts (Hielkema et al., 1986; Justice et al., 1985). Key points about NDVI include its utilization of freely available datasets, high spatial resolution, and extensive coverage. However, NDVI's conservative nature in indicating water stress means plants may remain green even under initial water stress conditions (Sandholt et al., 2002). NDVI's sensitivity to soil background influences during early crop growth stages and saturation issues post-canopy closure highlight its limitations in certain agricultural applications. Effective data processing and robust systems are essential for accurate NDVI calculations (Thenkabail & Smakhtin, 2004).

2.2.5 Vegetation Condition Index (VCI)

(Kogan, 1990) proposed the VCI as an extension of NDVI, marking a widespread adoption of remote sensing data for drought identification (Rhee et al., 2010). VCI represents a normalized version of NDVI and is given as,

$$VCI = \frac{NDVI_j - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100 \qquad 2.2$$

Where, $NDVI_{max}$ & $NDVI_{min}$ are derived from historical data for the corresponding month or week and j representing the current month’s index. The Vegetation Condition Index (VCI) quantifies the health of ground vegetation as a percentage, known for its convenience and comprehensibility among users (Kogan, 1990). It accurately reflects vegetation response to weather conditions, making it particularly valuable in monitoring agricultural drought, especially in areas with strong land management influences such as cropping (Mcvicar & Jupp, 1998).

2.2.6 Temperature Condition Index (TCI)

The Temperature Condition Index (TCI), proposed by (Kogan, 1995), utilizes the thermal band of AVHRR to derive brightness temperature. It is employed to evaluate vegetation stress resulting from temperature and excessive wetness, as noted by (Singh et al., 2003). It is given as

$$TCI = \frac{BT_{max} - BT_j}{BT_{max} - BT_{min}} \times 100 \qquad 2.3$$

Here, *BT* represents the brightness temperature. The upper and lower limits of *BT* are determined by analysing the extensive collection of remote-sensing photos during a given time, either on a monthly or weekly basis (Thenkabail & Smakhtin, 2004). TCI relies only on averaged weekly temperatures, and it doesn't consider specific days or time of your that could impact it's accuracy (Kouchak et al., 2015).).

Chapter 3.

MATERIALS & METHODS

This chapter discusses the datasets, tools and methodologies employed to assess the drought indices mentioned earlier to gather the results discussed in later chapters and the conclusions derived from those results.

3.1 Data Acquisition

Both metrological data and Satellite data was utilized to assess drought conditions in the study area.

3.1.1 Meteorological Data

Metrological data were acquired from Pakistan Metrological department (PMD) including Monthly averaged precipitation (mm), maximum and minimum temperature (°C) and mean temperature for the period from 1992 to 2021 for all three stations of the study area. These data were utilized for calculating meteorological drought indices. Locations and Elevation of these stations are shown in Table 3-1(RMC Lahore, 2023).

Table 3-1: The geographical location and Elevation of meteorological Stations

Station	Code	Latitude	Longitude	Elevation (m)
Bahawalnagar	41678	29.98	73.25	161
Bahawalpur	41700	29.40	71.28	110
RY Khan	41716	28.39	70.28	83

3.1.2 Satellite Data

Satellite imagery was downloaded for satellites Landsat 5 Thematic Mapper, Landsat 8 Original Land Imager/Thematic Infrared Sensor and Sentinel-2 Multi Spectral Instrument from the United States Geological Survey Earth Explorer platform, from 1995 to 2023 (Drusch et al., 2012; Zomer et al., 2009). Table 3-2 demonstrates the datasets used in the study and their features.

Table 3-2: Remote Sensing based Datasets

Satellite Mission	Sensor	Spatial Resolution	Temporal Resolution	Bands Used	Source	Time Period
Landsat 5	TM	30 meters	16 days	Red, NIR, Thermal	USGS	1995-2013
Landsat 8	OLI/TIRS	30 meters	16 days	Red, NIR, Thermal	USGS	2013-2023
Sentinel-2	MSI	10 meters	5 days	Red, NIR, Thermal	ESA Copernicus Open Access Hub	2024

3.1.3 Software & Tools Used

3.1.3.1 <u>Drought Indices Calculator (DrinC)</u>

DrinC which was developed by the National Drought Mitigation Center (NDMC) was used to process the meteorological data i.e. precipitation and temperature. (Svoboda et al., 2012). Drinc is a user-friendly tool and offers a variety of options for calculation of drought indices including the selection of different time scales (3month to 24month) and probability distributions (Mckee et al., 1993).

3.1.3.2 <u>Google Earth Engine and ArcMap</u>

Google earth Engine has been popular among researchers lately because of its readily available of Satellite data repository and cloud based powerful computational capability (Gorelick et al., 2017). We used the JavaScript API to develop custom scripts for calculation of drought indices.

3.1.3.3 <u>ESRI ArcMap</u>

ArcMap was developed by ESRI. It is a desktop GIS software. we used it for visualizing and analysing the spatial distribution of drought indices. Geoprocessing tools such as buffer, clip, interpolate were employed to create drought risk maps while overlaying different data layers. (ESRI, 2011).

3.1.3.4 Microsoft Excel:

Microsoft Excel was used for statistical analysis such as corelation and regression. It was also utilized to generate graphs and charts for better visualization.

3.2 Methodology

As presented in Figure 3-1This section shows a detailed schematic flow diagram of the framework employed in this study for a comprehensive drought risk analysis. It consists of Data acquisition, preprocessing, processing and results.

Figure 3-1 Research Methodology Flowchart

3.2.1 Pre-Processing of Data

The meteorological data was pre-processed for data errors. Missing values in the precipitation and temperature datasets were filled using linear interpolation, a method that estimates missing values based on the linear relationship between adjacent data points (McKee et al., 1993).

The satellite imagery was pre-processed for atmospheric correction and cloud masking such as the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Main-Knorn et al., 2017; Masek et al., 2006)) to retrieve surface reflectance values and remove cloud contamination effects. (Zhu & Woodcock, 2014).

3.2.2 Meteorological Drought Estimation

SPI and RDI were used for the identification of drought trends for a 30-year span across the study area.

3.2.2.1 SPI and Meteorological Drought

SPI is widely used in drought studies as it evaluates the dryness due to precipitation deficits for specific locations and timescales. It normalizes the precipitation probability to a standard distribution over the given (Mckee et al., 1993). Negative SPI values indicate drought conditions. The lower the SPI values the severer is the drought.

SPI is calculated using a "Probability distribution function (PDF)" function that is applied over the historical precipitation data. Gamma distribution was for its suitability to model the rainfall patterns. Maximum likelihood was adopted to estimate the distribution's shape (α) and scale (β) parameters for each station and all timeframes.

The gamma distribution's probability density function is:

$$g(x) = \left(\frac{1}{\beta^{\alpha} * \Gamma(\alpha)}\right) * x^{\alpha-1} * e^{-\frac{x}{\beta}} \, for \, x > 0 \qquad 3.1$$

Where:

- α is the shape parameter (> 0)
- β is the scale parameter (> 0)
- x is the amount of precipitation
- Γ(α) is the gamma function

The parameters α and β are estimated using the following equations:

$$\alpha = (1 / 4A) * (1 + \sqrt{}(1 + (4A/3))) \qquad 3.1$$

Where:

$$A = ln(\bar{x}) - (\sum ln(x) / n)$$

And n is the number of observations.

$$\beta = \bar{x} / \alpha$$

Where $\bar{x}$ is the mean precipitation.

After the PDF, we computed "Cumulative Precipitation Probabilities (H(x))" for various timescales using:

$$H(x) = q + (1 - q) * G(x) \qquad 3.3$$

Where:

- q = zero precipitation probability
- G(x) = incomplete gamma function's cumulative probability

The probabilities were converted to standard normal deviates (z), which were then converted to SPI values. These values were then categorized into drought classes based on threshold established by literature review (Mckee et al., 1993).

3.2.2.2 RDI and Meteorological Drought

RDI was also calculated using the DrinC software. The RDI is derived by comparing the cumulative precipitation versus cumulative PET over the specified time intervals (Tsakiris et al., 2005). **Error! Reference source not found.** shows the flow diagram for calculation of RDI using DrinC.

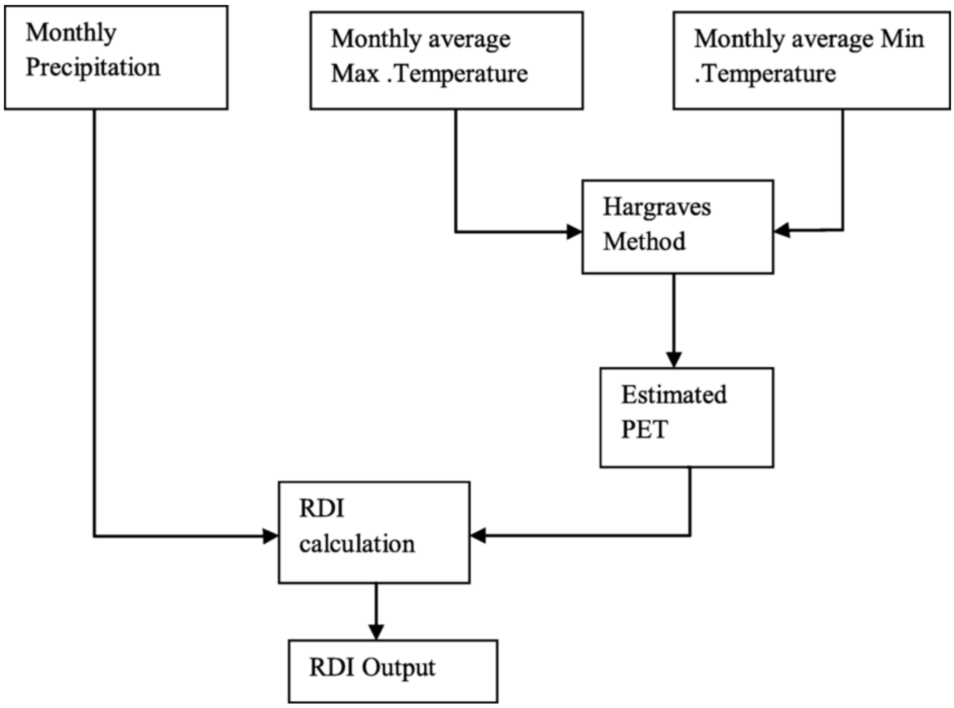


Figure 3-2 The flowchart of DrinC software for RDI.

RDI is calculated by standardizing the ratio between precipitation and PET for different timescales across different climatic regions. Due to the inclusion of PET, RDI may offer better insights of drought trends than calculating it with precipitation data especially the effect of temperature on drought trends of the region.

3.2.2.3 Meteorological Drought Calculation

For metrological Drought calculation we utilized SPI and RDI outputs of 3 month and 6 month timescales.

These values were then categorized into drought classes based on threshold established by literature review (Mckee et al., 1993; Vicente-Serrano et al., 2011) as displayed in Table 3-3.

Table 3-3: Drought severity thresholds for SPI, and RDI

SPI/RDI Value	Drought Category
> 2.0	Extremely wet
1.5 to 1.99	Severely wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
< -2.0	Extremely dry

3.2.3 Remote Sensing Based Drought Estimation

We utilized the NDVI, VCI, and TCI for agricultural drought calculation due to their connection with deficiency of soil moisture that affects crop growth and its yield.

3.2.3.1 Normalized Difference Vegetation Index (NDVI) and Agricultural Drought

The NDVI was calculated using the following equation:

$$NDVI = (NIR - Red) / (NIR + Red) \tag{3.4}$$

Where NIR and Red represent the reflectance values in the near-infrared and red bands, respectively. NDVI ranges from -1 to +1, depending on the vigour of vegetation. MODIS data is frequently utilized to calculate both NDVI and land surface temperature (LST) (Sruthi & Aslam, 2015). Lower NDVI values shows reduced vegetation health and vigour that can be qualified for water stress or drought conditions (Rhee et al., 2010).

NDVI was calculated and averaged for each month from Landsat images using GEE for study area. These averages were then used to assess the spatial patterns of vegetation health which helped in identification of areas experiencing agricultural drought.

3.2.3.2 Vegetation Condition Index (VCI)

VCI involves the comparison of current NDVI values with its historical extremes and is more sensitive to changes in vegetation health caused by drought (Kogan, 1995). It is calculated as:

$$VCI = ((NDVI - NDVImin) / (NDVImax - NDVImin)) * 100 \quad 3.5$$

Where:

- NDVI is the current NDVI value
- $NDVI_{min}$ is the minimum NDVI value for the given time period
- $NDVI_{max}$ is the maximum NDVI value for the given time period

Higher values of VCI indicate healthier vegetation. The VCI typically ranges from 0 to 100 and described as percentage. VCI takes into account the factors other than current drought conditions such as seasonality and land cover type to assess vegetation growth changes.

3.2.3.3 Temperature Condition Index (TCI)

TCI is calculated as:

$$TCI = ((LSTmax - LST) / (LSTmax - LSTmin)) * 100 \quad 3.6$$

where:

- LST is the current land surface temperature value.
- LST_{max} is the maximum LST value for the given time period.
- LST_{min} is the minimum LST value for the given time period.

The value TCI ranges between 0 and 100 Like VCI. By normalizing the LST values TCI takes into account other factors than current drought conditions that cause variability in temperatures.

3.3 Statistical Analysis

3.3.1 Correlation Analysis

Statistical analysis of metrological data was carried out by using Microsoft excel where we created corelation matrices between SPI and RDI indices for both the 3-month and 6-month time scales for all three stations of the study area in order to assess their relationships. The Pearson correlation coefficient (r) was calculated to quantify the corelation between indices.

The corelation analysis was carried including correlation of indices between different stations and correlation indices within stations between SPI and RDI for both 3-month and 6-month timescales.

This comprehensive analysis allows us to assess both the consistency of drought indices spatially and their relationship at specific locations.

These matrices provided a detailed overview of the pairwise correlations providing valuable insights into the relationships between the two drought indices and their potential for integrated drought assessment.

3.4 Integration of Maps for Final Output

We created drought composites by employing different combinations of drought indices each highlighting a different aspect of drought in the study area using ArcMap software.

Interpolated point data from SPI and RDI was integrated to generate Meteorological drought composite map. For agricultural drought composite the NDVI, VCI and SPI. The NDVI and VCI layers were resampled to a common resolution and integrated using weighted overlay with the following weights:

- NDVI: 0.4
- VCI: 0.4
- SPI: 0.2

The higher weights for NDVI and VCI reflect their direct relationship with vegetation health, while SPI provides context for meteorological conditions.

Temperature-based drought Composite map combined the Temperature Condition Index (TCI) and RDI. The TCI raster layer was integrated with the interpolated RDI surface using a weighted overlay analysis:

- TCI: 0.7
- RDI: 0.3

The higher weight for TCI emphasizes the temperature-based aspect of drought in this composite.

Remote sensing based integrated drought map integrated NDVI, VCI, and TCI using a fuzzy overlay technique. Each index was first standardized to a common scale (0-1) using fuzzy membership functions. The fuzzy overlay was then performed using the gamma operation with a parameter of 0.7, which provides a balance between the "fuzzy AND" and "fuzzy OR" operations.

The final drought risk map integrated all available indices: NDVI, VCI, TCI, SPI, and RDI. Given the limitations in meteorological data coverage, higher weights were assigned to the remote sensing-based indices. The weighted overlay analysis used the following weights:

- NDVI: 0.3
- VCI: 0.25
- TCI: 0.25
- SPI: 0.1
- RDI: 0.1

For each composite map, the resulting raster was reclassified into drought severity categories (e.g., No Drought, Mild Drought, Moderate Drought, Severe Drought) based on natural breaks in the data distribution.

The choice of integration method and weights for each composite map was based on a combination of literature review, expert consultation, and the specific objectives of each drought assessment. The weighted overlay method was primarily used due to its flexibility in assigning relative importance to different factors and its interpretability. The final maps were symbolized using a colour ramp that visually emphasizes the gradient of drought severity.

Chapter 4.

RESULTS & DISCUSSION

This chapter is a detailed overview of the results generated from the analysis detailing the results from metrological, remote sensing based and integrated indices maps and forecasting analysis and their interpretations.

4.1 Analysis of Potential Evapotranspiration & Precipitation Trends

The Box and Whisker plots for precipitation and PET shown in Figure 4-1and Figure 4-2 provide a detailed view of distribution of these parameters across all three stations. It reveals significant climatic patterns and variations, spanning from 1992 to 2021.

In Bahawalnagar, variability between precipitation events can be seen ranging broadly from 0 mm to 263.1 mm suggesting substantial fluctuations which could have significant implications for local water resources and environmental conditions. Similarly, Bahawalpur ranged from 0 mm to 161.6 mm and Rahim Yar Khan recorded lower precipitation values from 0 mm to 177.4 mm. This comparatively narrower range of these stations might reflect specific local factors affecting rainfall.

The presence of outliers in the precipitation data highlights the unpredictability in the extremes of rainfall that could impact the region's water resources and agricultural activities. These spatio-temporal dynamics of rainfall are helpful in effective water management strategies.

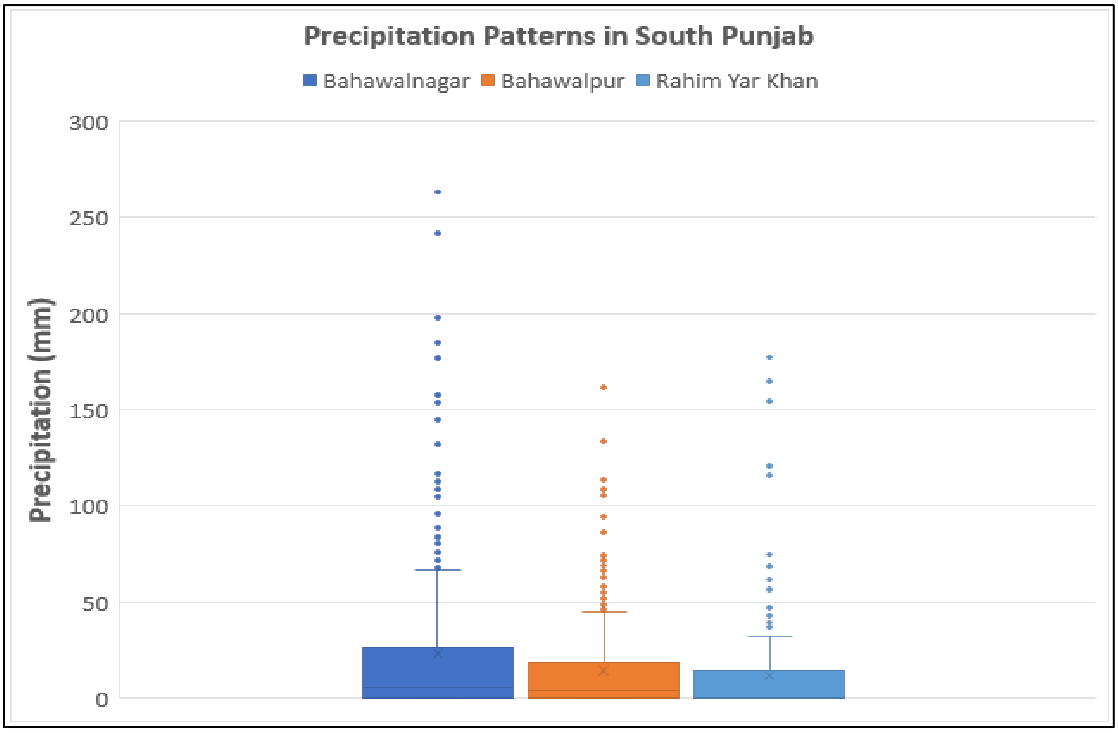


Figure 4-1: Box and Whisker plot showing precipitation pattern over the study area

As displayed in Figure 4-1, the minimum PET values ranged from 51.66 mm/month in Bahawalnagar to 70.49 mm/month in Rahim Yar Khan while the maximum PET values were notably higher highlighting differences in atmospheric conditions across the stations.

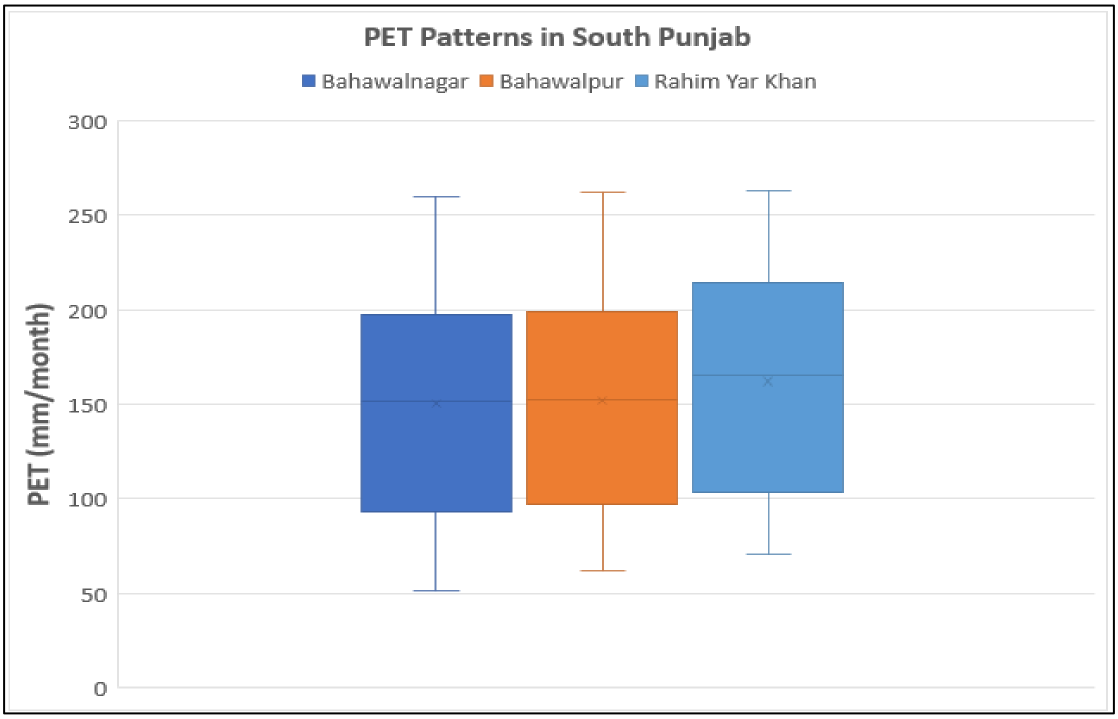


Figure 4-2: Box and Whisker plot showing PET pattern over the study area

The observed patterns in precipitation and PET have significant implications for the region's water balance and agricultural practices. The Bahawalpur region was observed with high PET values and variability in precipitation which suggests that the region might be prone periodic water stress which may be escalated during years with low rainfall, potentially leading to drought conditions (Figure 4-2).

The spatial differences have been observed in both parameters across the three stations which highlight the importance for localized water management strategies.

Ullah et al., (2021) reported similar variability in precipitation patterns across Pakistan. And the observed PET trends were consistent with the findings of (Mahmood et al., 2019) as they observed increasing evapotranspiration rates in the Punjab region due to rising temperatures which emphasizes the need for robust drought monitoring systems

4.2 Time Series Forecasting of Meteorological Parameters over Bahawalpur Division

We utilized ARIMA model for the time series forecasting of meteorological parameters for the Bahawalpur Division for precipitation and PET using monthly data.

The forecasting was done for the period 2022 to 2026. We started with creating time series plots followed by decomposition into trend, seasonality, and remainder. Seasonal analyses were used to identify patterns and trends in both precipitation and PET.

Bahawalnagar with a strength of 0.1 showed a weak positive trend in precipitation, indicating a gradual increase over time. The seasonal strength 0.3 suggested weak seasonal patterns. On the other hand, PET trends 0.3 exhibited a moderate strength while it showed a strong seasonal value of 1 in result reflecting pronounced repeating patterns.

Bahawalpur had a precipitation trend strength of 0.2 highlighting a relatively weak positive trend. The seasonal strength 0.2 indicated moderately weak seasonal patterns. For PET, the trend strength 0.4 suggested a noticeable moderate trend again with a strong seasonal strength of 1.

Similarly, Rahim Yar Khan's precipitation data showed a strength of 0.1, a weak positive trend and a moderate positive trend (0.3) for PET. Seasonal data for Rahim Yar Khan showed a moderate positive trend (0.2) for precipitation and a strong trend of 1 for PET.

4.2.1 Model Development:

The dataset was split into two parts. 80% of the total was used for training and remaining 20% for testing. KPSS (Kwiatkowski–Phillips–Schmidt–Shin) and ADF (Augmented Dickey-Fuller) tests were used to assess Stationarity. The KPSS test was used to check if the test statistic was below critical values at various significance levels. If the null hypothesis is not rejected stationarity was confirmed. The ADF test assumes the null hypothesis of non-stationarity. It was evaluated by comparing p-values to a threshold of 0.05. Test statistics and p-values confirmed that all data sets for both precipitation and PET were stationary.

ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots were used to determine the appropriate ARIMA model, with the Akaike Information Criterion (AIC) values guiding the selection process (Figure 4-3 & Figure 4-4). Selected models showing better performance are listed in Table 4-1 and Table 4-2.

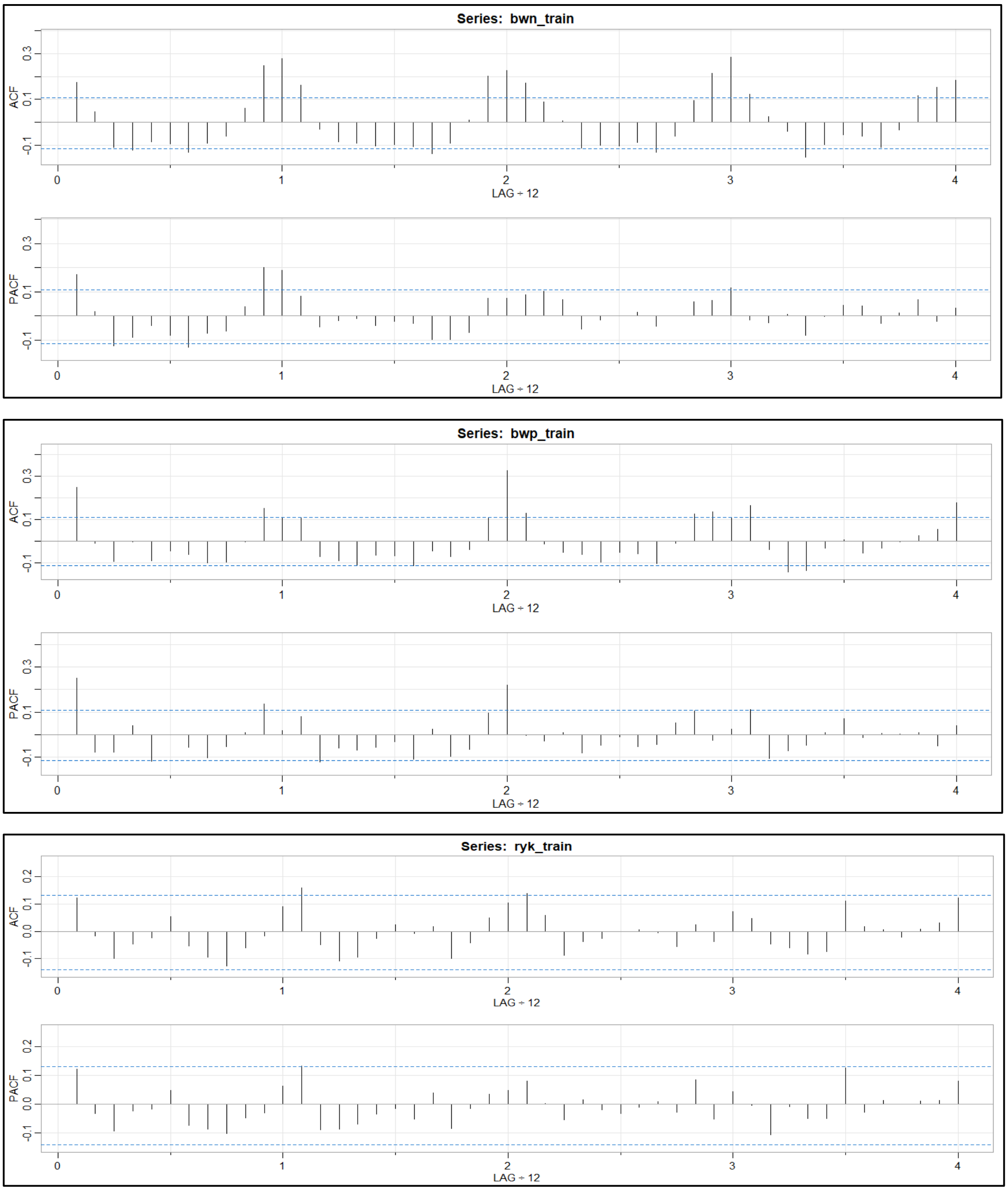


Figure 4-3: ACF PACF plots of precipitation data of 3 stations

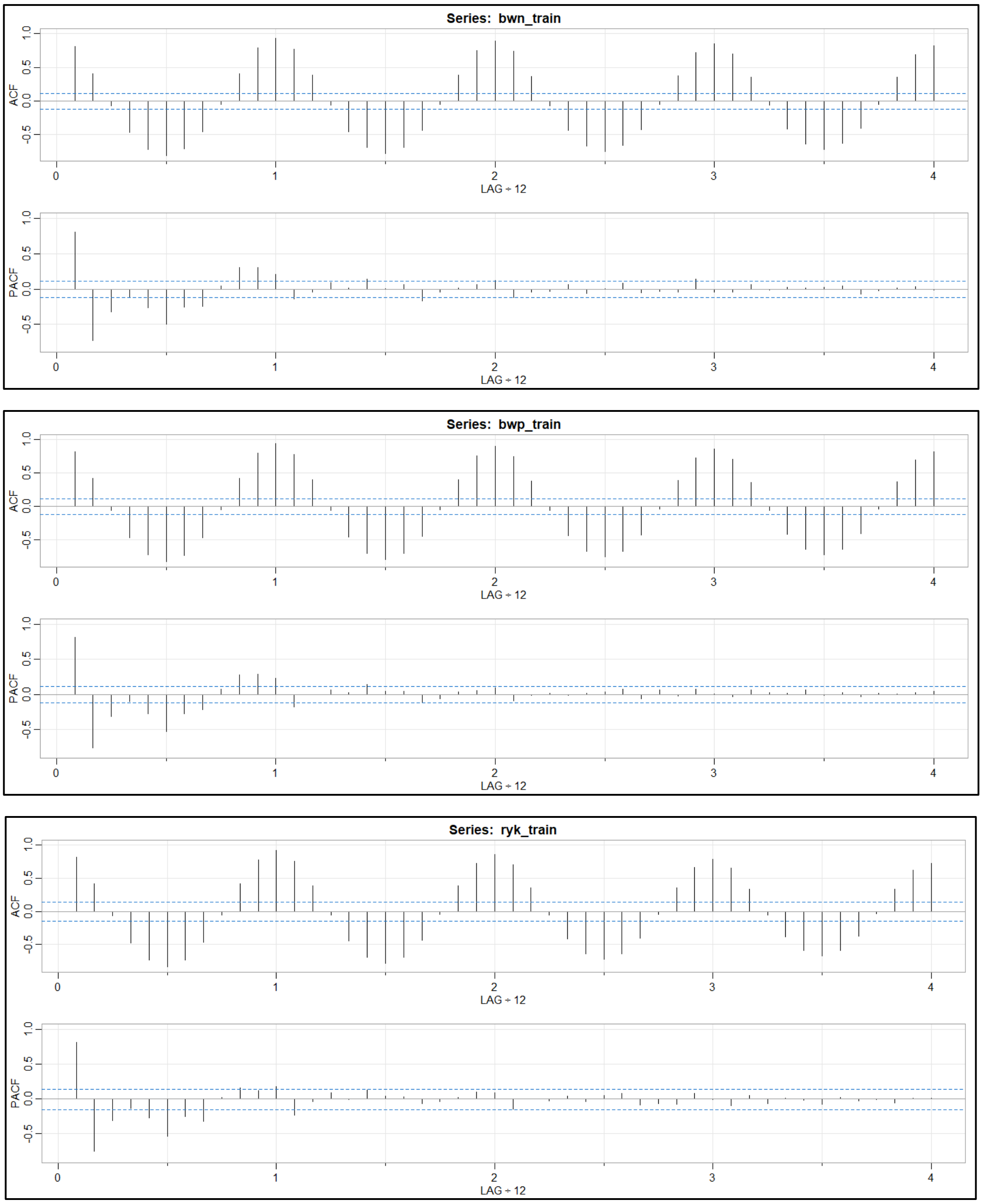


Figure 4-4: ACF PACF plots of PET data of 3 stations

Table 4-1: Selected models and AIC values for precipitation data forecasting

Sr. no.	Station	ARIMA Order (p, d, q), Seasonal order (P, D, Q)	AIC Value
1.	Bahawalnagar	order = c(1,1,2), seasonal = c(1,1,2)	3169.279
2.	Bahawalpur	order = c(1,2,2), seasonal = c(1,2,2)	2895.863
3.	Rahim Yar Khan	order = c(0,1,1), seasonal = c(0,1,1)	1922.968

Table 4-2: Selected models and AIC values for PET data forecasting

Sr. no.	Station	ARIMA Order (p, d, q), Seasonal order (P, D, Q)	AIC Value
1.	Bahawalnagar	order = c(1,1,2), seasonal = c(1,1,2)	2148.844
2.	Bahawalpur	order = c(4,0,0), seasonal = c(0,1,1)	2070.566
3.	Rahim Yar Khan	order = c(0,1,1), seasonal = c(0,1,1)	1922.968

4.2.2 Model Evaluation:

The Ljung-Box test was applied to evaluate autocorrelation in residuals for the forecasting models. For precipitation, the ARIMA(1,1,2)(1,1,2)[12] model for Bahawalnagar and the ARIMA(0,1,1)(0,1,1)[12] model for Rahim Yar Khan showed satisfactory results with high p-values indicating no significant autocorrelation. The ARIMA(1,2,2)(1,2,2)[12] model for Bahawalpur showed residual autocorrelation, suggesting the need for model refinement. For PET, the ARIMA(1,1,2)(1,1,2)[12] model for Bahawalnagar and the ARIMA(1,1,2)(1,1,2)[12] model for Rahim Yar Khan exhibited effective autocorrelation management, while the ARIMA(4,0,0)(0,1,1)[12] model for Bahawalpur showed some autocorrelation.

Performance metrics including “Root Mean Squared Error (RMSE)”, “Mean Absolute Error (MAE)”, and “Autocorrelation Function (ACF1)”, were used to assess the models. The models generally exhibited good accuracy, as shown in Table 4-3 and Table 4-4.

Table 4-3: Model accuracy metrics for precipitation forecasting

Stations	Dataset	RMSE	MAE	ACF1
Bahawalnagar	Train Set	36.42	21.53	0.0113
	Test Set	28.45	21.14	-0.122
Bahawalpur	Train Set	25.39	16.06	0.0125
	Test Set	32.61	23.77	0.0491
Rahim Yar Khan	Train Set	23.68	13.72	0.0483
	Test Set	17.57	12.29	0.0407

Table 4-4: Model accuracy metrics for PET forecasting

Stations	Dataset	RMSE	MAE	ACF1
Bahawalnagar	Train Set	9.109	7.042	-0.00395
	Test Set	11.353	8.683	0.512
Bahawalpur	Train Set	8.232	6.193	-0.00375
	Test Set	8.385	6.39	0.293
Rahim Yar Khan	Train Set	7.848	6.027	-0.00056
	Test Set	15.476	13.556	0.071

Forecasts were extended over a 5-year period (60 months) for both parameters. Figures 4.5 to 4.7 the precipitation forecasts for all three stations for projected values from 2022 to 2026. Similarly, figures 4.9 to 4.10 provide graphs of the PET forecasts for stations in study area.

The forecasts suggested recurring trends aiding in long-term planning and decision-making. Mahmood et al. (2019) used the similar ARIMA models to forecast precipitation in arid regions of Pakistan, finding comparable accuracy and utility for water resource planning. This suggests that our study findings were consistent with previous studies.

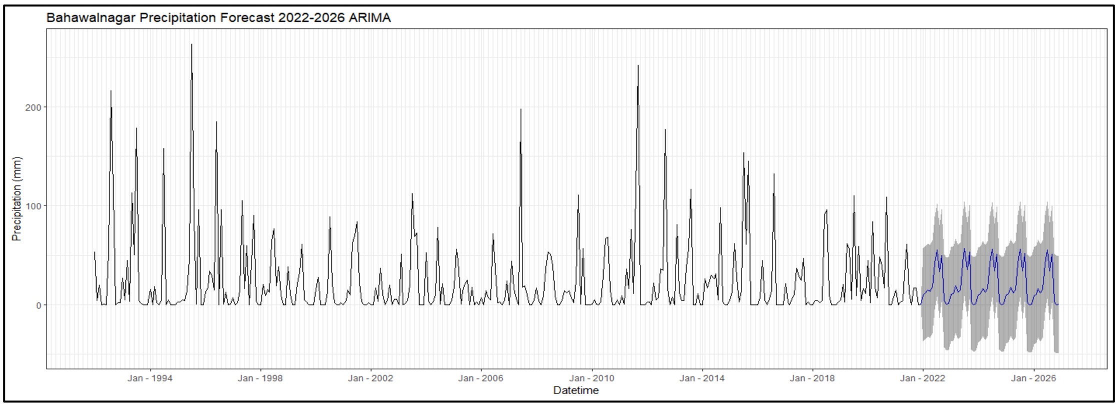


Figure 4-5: Forecast of monthly precipitation in Bahawalnagar using ARIMA model

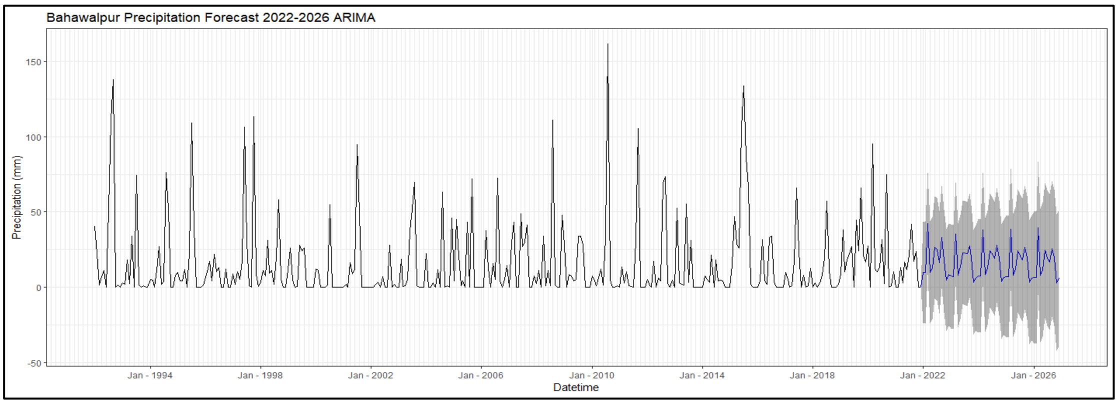


Figure 4-6: Forecast of monthly precipitation in Bahawalpur using ARIMA model

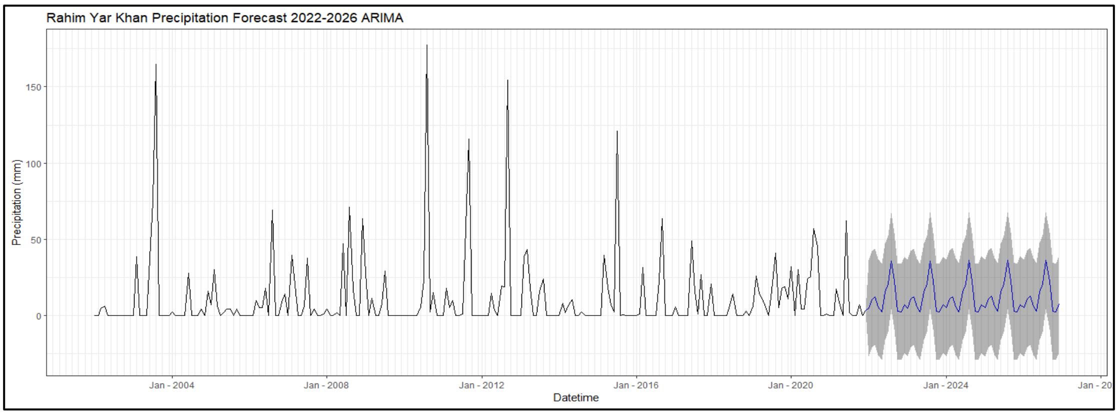


Figure 4-7: Forecast of monthly precipitation in Rahim Yar Khan using ARIMA

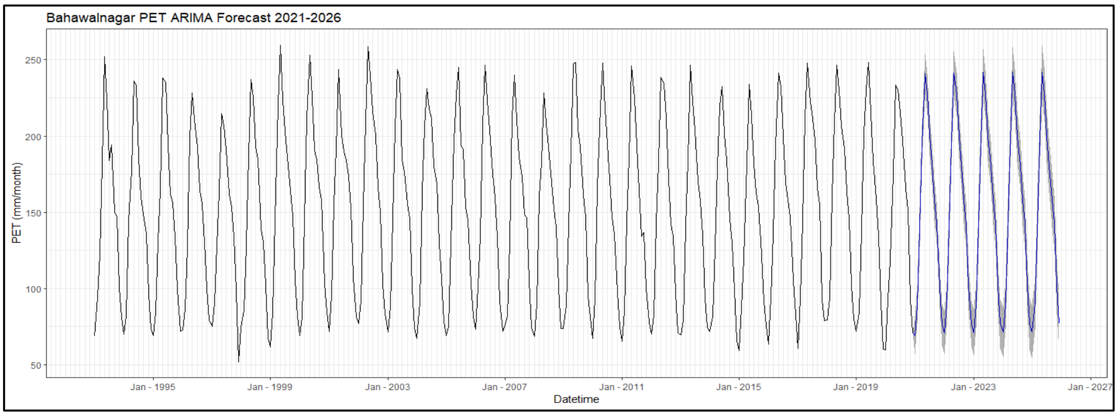


Figure 4-8: Forecast of monthly PET in Bahawalnagar using ARIMA model

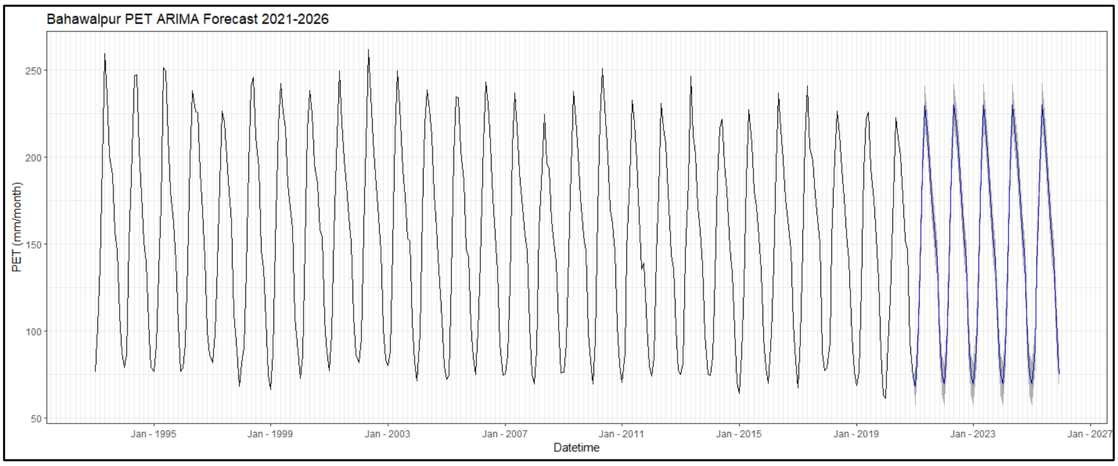


Figure 4-9: Monthly PET forecast of Bahawalpur using ARIMA model

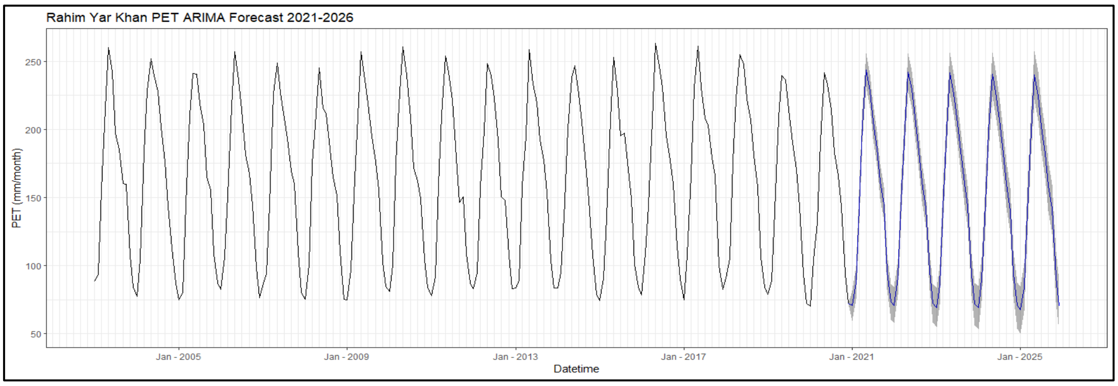


Figure 4-10: Monthly PET forecast of Rahim Yar Khan using ARIMA model

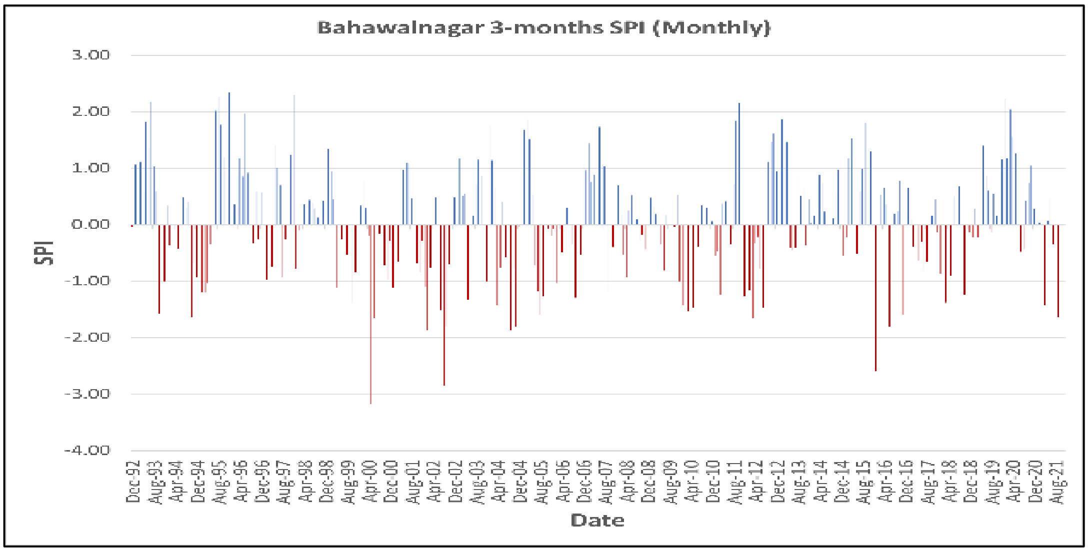
4.3 Meteorological Drought Indices

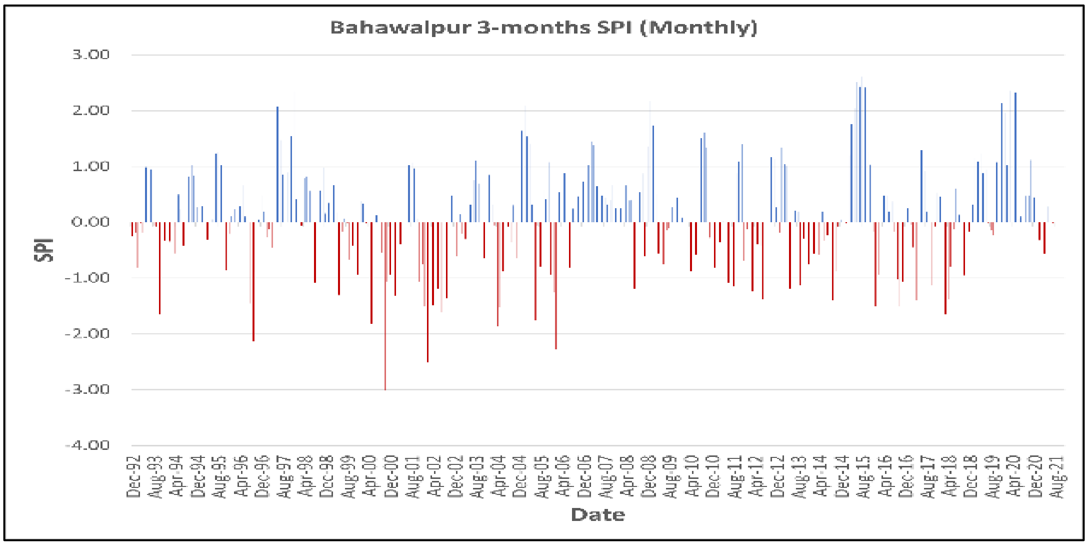
To identify drought trends across the study area we utilized SPI and RDI that were computed using the DrinC software. Bahawalnagar and Bahawalpur were evaluated with datasets from 1992 to 2021 and Rahim Yar Khan from 2002 to 2021.

4.3.1 Assessment of Drought Trends using SPI and RDI

3-month timescale SPI drought trends in Study area are depicted in Figure 4-11. Severe drought conditions were observed in 2000. Both Bahawalnagar and Bahawalpur showed SPI values below -3. This extreme drought is likely associated with the El Niño phenomenon that began in 1997 as detailed by Slingo & Annamalai, (1999).

SPI values for Rahim Yar Khan were less extreme compared to Bahawalnagar and Bahawalpur but it also experienced severe dry periods, with the most severe being -2.84 in June 2016.





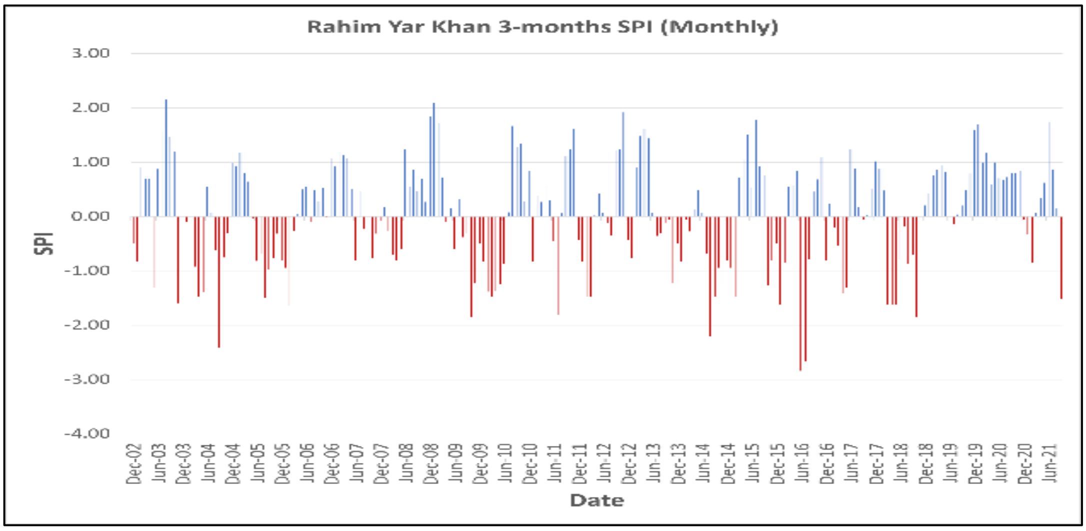
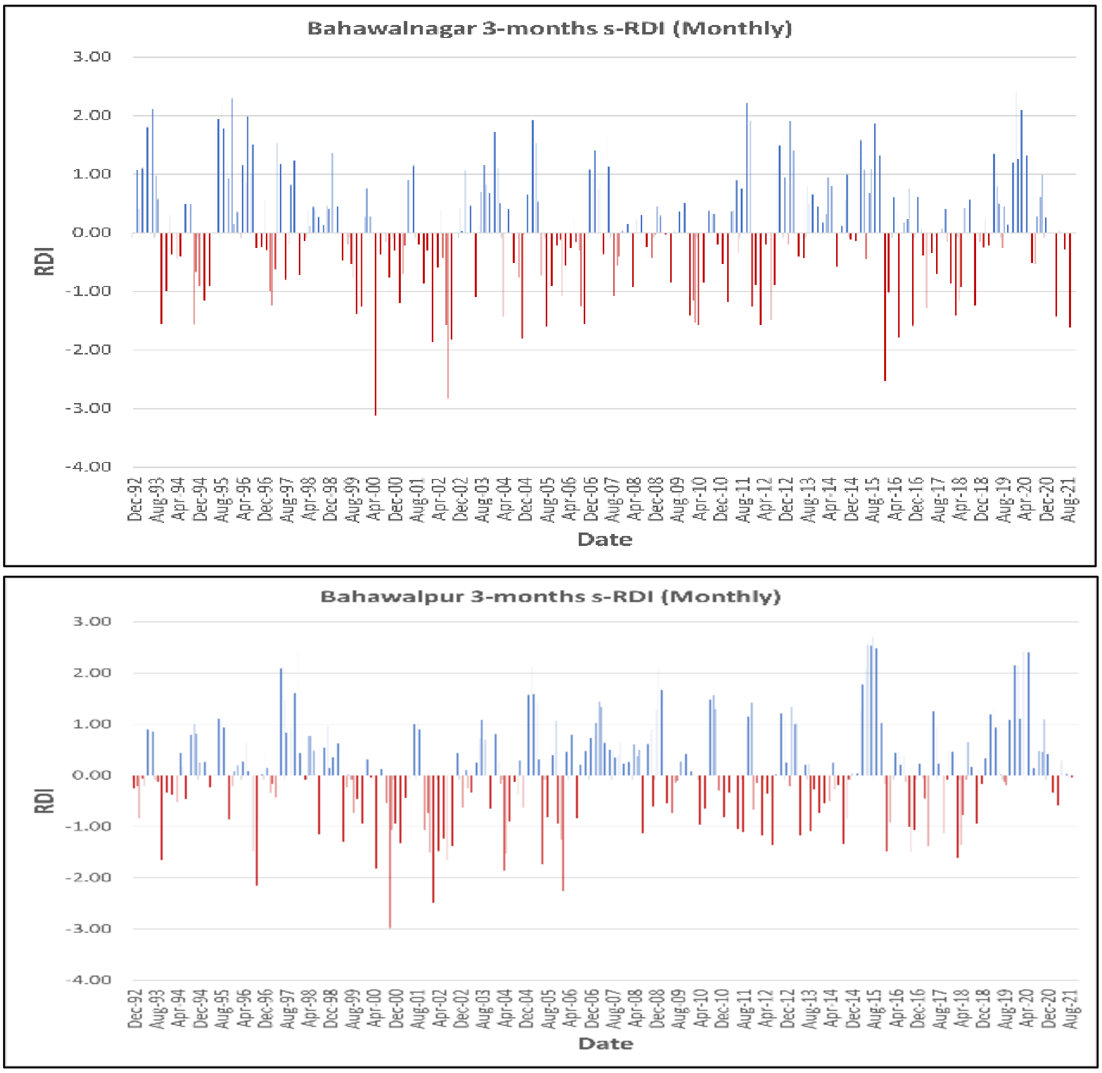


Figure 4-11: 3-month SPI values with monthly time step

3-month time series RDI exhibited similar trends to those of the SPI as evident in Figure 4-12. In 2000 Bahawalnagar and Bahawalpur experienced severe drought conditions. RDI values reflected this event to a little lesser extent compared to SPI values. Bahawalnagar had an RDI of -3.13 in May 2000 and Bahawalpur -2.98 in October 2000. (Buttafuoco et al., 2016; Hina & Saleem, 2019; Shah et al., 2013) found that the standardized RDI has an identical pattern to the SPI in their study for similar regions.

Both indices indicated the highest frequency of wet periods During the period of 2019-2020 in all three study stations. However, a few instances of dry periods concentrated primarily in July and August were observed. An extended wet period in 1996 in Bahawalnagar further explains the variability in precipitation and drought conditions.



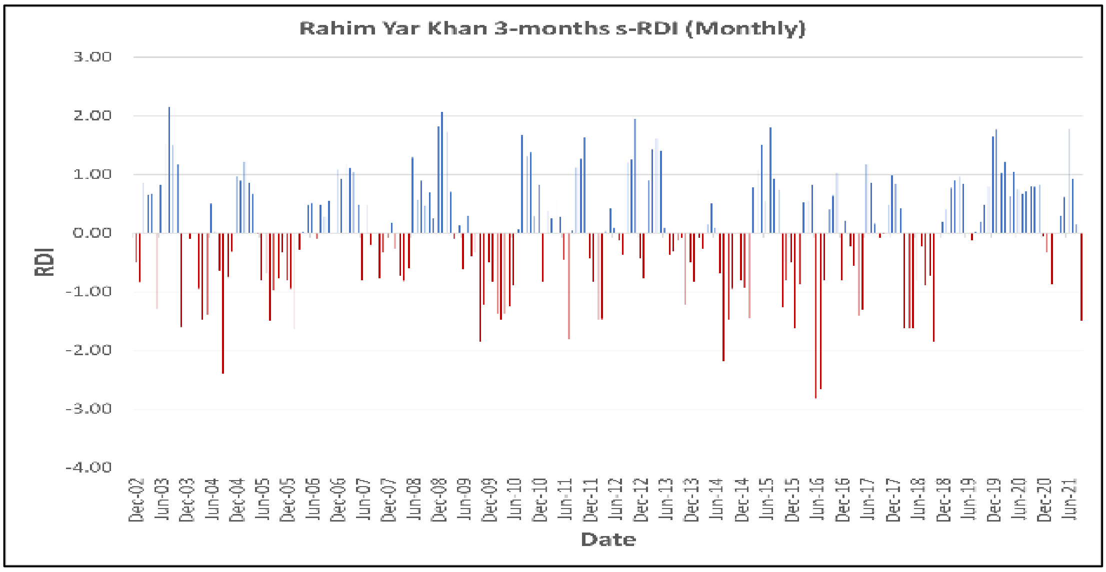
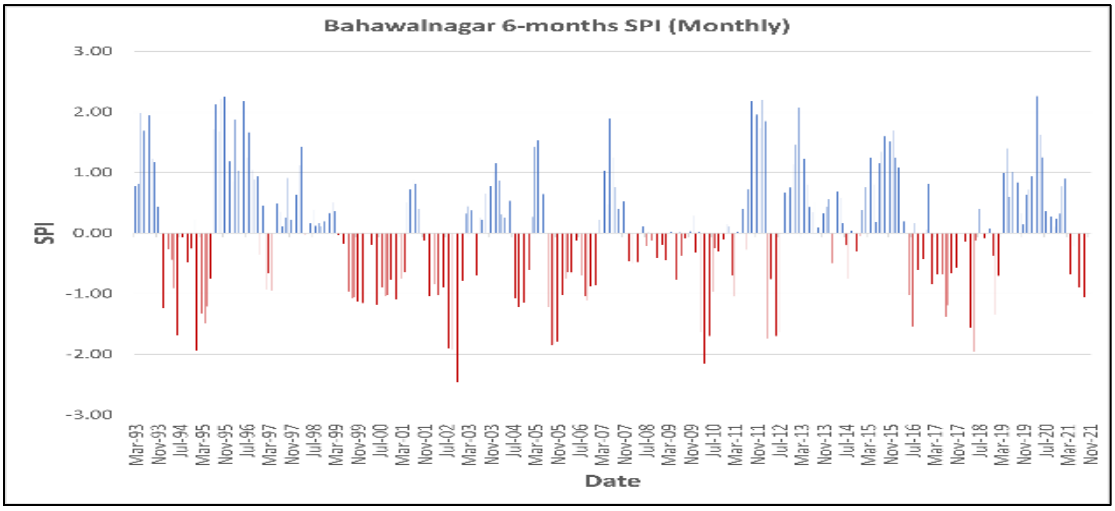


Figure 4-12: 3-month RDI values with monthly time step

Figure 4-13 illustrates the 6-month Standardized Precipitation Index (SPI) drought trends across Bahawalpur. It is evident that all stations experienced notable drought periods, with specific values such as -2.46 in November 2002 at Bahawalnagar, -3.35 in January 2001 at Bahawalpur, and -2.49 in January 2001 at Rahim Yar Khan. Among these, Bahawalpur faced the most severe drought conditions.

The 6-month RDI trends also reflected similar patterns. Values like -2.45 in November 2002 at Bahawalnagar, -3.32 in January 2001 at Bahawalpur, and -2.47 in January 2001 at Rahim Yar Khan can be observed as severe drought events. The onset of the La Niña phenomenon which led to a series of rainfall events across the country at the end of 2002 and the beginning of 2003 helped in taking away this prolonged spell of dryness (Rahman, 2020).

In the period of 2019-20 an increase in wet periods across all three stations was observed similar with the 3-month trends that we saw in the study area. While a few dry periods mainly in July and August were also seen.


Bahawalnagar 6-months SPI (Monthly)
SPI
3.00
2.00
1.00
0.00
-1.00
-2.00
-3.00
Mar-93
Nov-93
Jul-94
Mar-95
Nov-95
Jul-96
Mar-97
Nov-97
Jul-98
Mar-99
Nov-99
Jul-00
Mar-01
Nov-01
Jul-02
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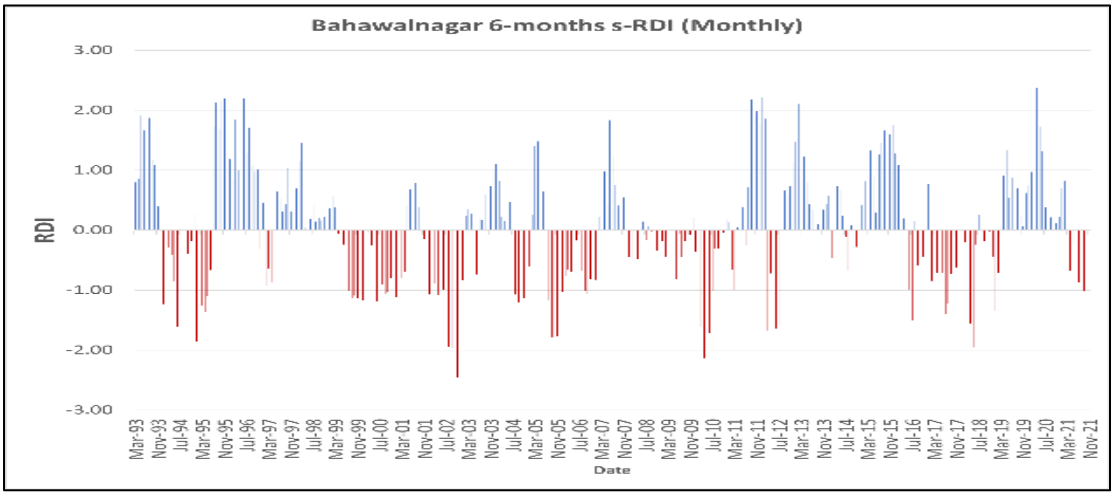
Mar-21
Nov-21
Date


Bahawalnagar 6-months s-RDI (Monthly)
RDI
3.00
2.00
1.00
0.00
-1.00
-2.00
-3.00
Mar-93
Nov-93
Jul-94
Mar-95
Nov-95
Jul-96
Mar-97
Nov-97
Jul-98
Mar-99
Nov-99
Jul-00
Mar-01
Nov-01
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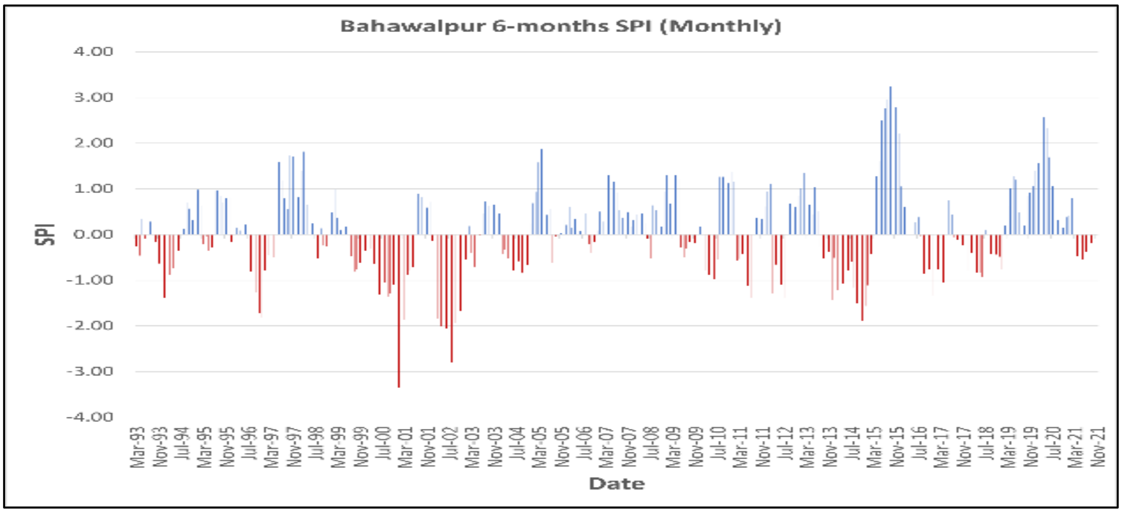
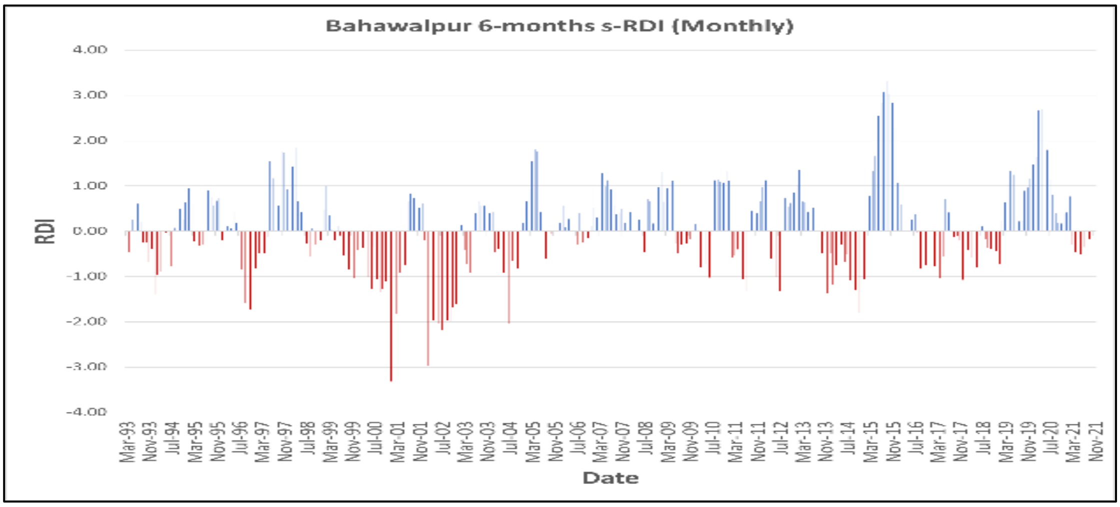
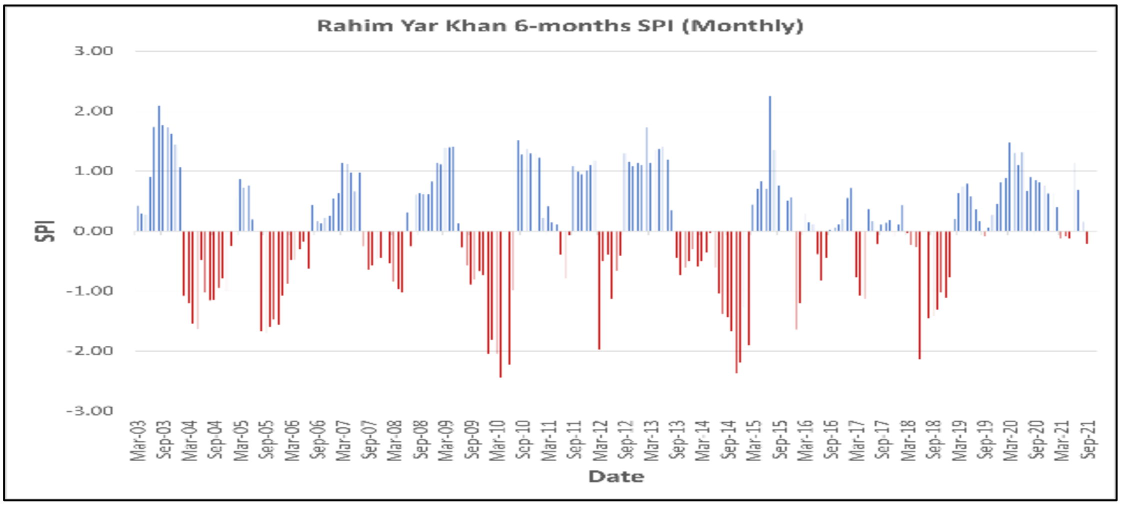


Bahawalpur 6-months SPI (Monthly)
SPI
Date



Bahawalpur 6-months s-RDI (Monthly)
RDI
Date



Rahim Yar Khan 6-months SPI (Monthly)
SPI
Date

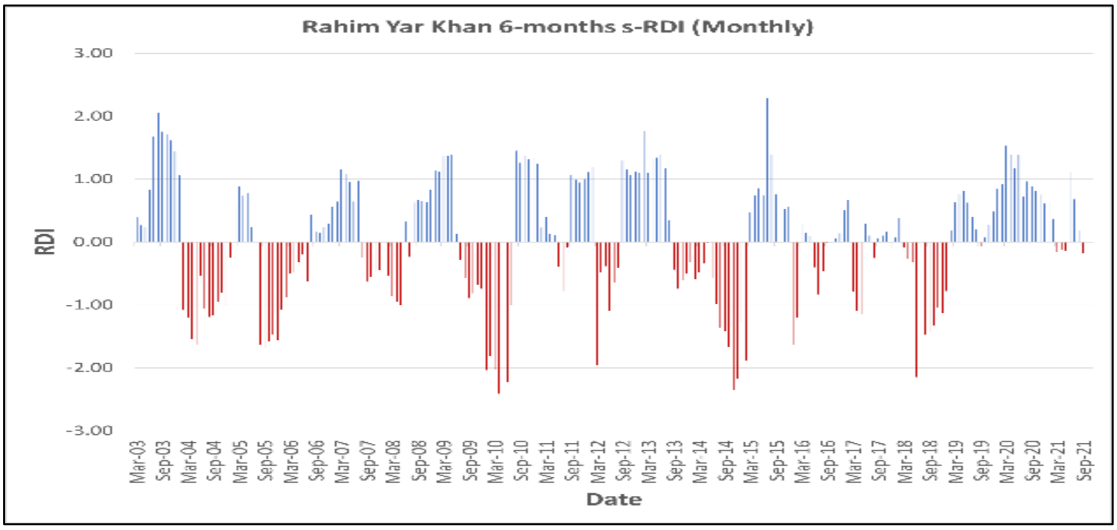


Figure 4-13: 6-month SPI & RDI values with monthly time step

4.3.2 Correlation Analysis of Meteorological Drought Indices

To examine the relationship between Metrological indices the correlation matrices for both the 3-month SPI and RDI were created and analysed t across different meteorological stations, as depicted in Table 4-5. The diagonal values of correlation of each index with itself in the correlation analysis were closer to 1.00 as expected. The off-diagonal values displayed correlation coefficients ranging from 0.57 to 1.00. These values reflected the strength of the correlation between corresponding pairs of SPI and RDI for each station.

SPI and RDI data showed perfect positive linear relationship within same meteorological stations highlighting their ability to capture precipitation and drought conditions in a corresponding manner.

According to a study by Zarch et al. (2015), in arid climates, the relationship between the RDI and SPI was more strongly correlated as suggested in the current study underscoring the effectiveness of these indices in reflecting precipitation and drought patterns at the local level.

the weaker positive correlation between SPI and RDI across different station, ranging from 0.57 to 0.63, compared to the within-station correlations suggests the spatial variability of climate patterns at regional level.

SPI and |RDI were found to be reliable and consistent in capturing and characterizing drought conditions with higher correlation between indices at similar stations suggesting the local coherence of these indices, while the weaker but positive correlation across different stations indicating regional alignments.

Table 4-5: Correlation matrix of 3-month SPI & RDI

	Bahawalnagar *3month_SPI*	**Bahawalnagar** *3month_RDI*	**Bahawalpur** *3month_SPI*	**Bahawalpur** *3month_RDI*	**Rahim Yar Khan** *3month_SPI*	**Rahim Yar Khan** *3month_RDI*
Bahawalnagar 3 month_SPI	**1.00**					
Bahawalnagar 3 month_RDI	**0.99**	**1.00**				
Bahawalpur 3 month_SPI	**0.57**	**0.58**	**1.00**			
Bahawalpur 3 month_RDI	**0.58**	**0.59**	**0.99**	**1.00**		
Rahim Yar Khan 3 month_SPI	**0.58**	**0.58**	**0.62**	**0.63**	**1.00**	
Rahim Yar Khan 3 month_RDI	**0.58**	**0.58**	**0.63**	**0.63**	**0.99**	**1.00**

4.3.3 Comparative Evaluation of Drought Patterns

The comparative evaluation of drought patterns was done by counting drought instances where SPI and RDI values fell below -1 while the values less than -2 were counted as extreme droughts. This analysis focused on identifying drought periods (Table 4-6).

It was observed that RDI followed the SPI data in most cases, aligning with the findings of Tsakiris & Vangelis (2005) highlighting the effectiveness of both the indices in capturing meteorological drought conditions in the semi-arid climates.

Among all three stations, the highest frequency of drought periods was observed at Bahawalnagar stations, while Rahim Yar Khan had the fewest. This spatial variability in drought occurrence highlights the regional nature of drought events and further implicate the need for localized drought management strategies. Bahawalpur exhibited the greater number of extreme drought months highlighting the district's susceptibility to prolonged drought conditions.

Significance water stress in Bahawalnagar is suggested due to the highest maximum drought magnitudes suggesting significant water stress in this region. This indicates that Bahawalnagar is prone to intense drought events although it may not experience the most frequent ones.

Drought characteristics vary greatly across the different stations that are classified as same climate aridity index. This highlights contribution of local factors such as topography and land use. (Vicente-Serrano et al., 2011).

Since The stations with higher mean PET values like Rahim Yar Khan, did not necessarily experience more frequent or severe droughts as compared to others. This suggests that other factors that may include precipitation patterns and local water availability have crucial roles in determining drought dynamics in the study area.

This comparative analysis highlights utility of both indices i.e. SPI and RDI as it shows up the distinct drought patterns captured by both the indices. However, to study the spatial variability in drought dynamics across there's need for regional drought monitoring strategies.

Table 4-6: Evaluation in drought patterns captured by drought indices

Station	**BWN (1992-2021)**		**BWP (1992-2021)**		**RYK (2002-2021)**	
Climatic Zone	Semi-Arid		Semi-Arid		Semi-Arid	
	SPI	**RDI**	**SPI**	**RDI**	**SPI**	**RDI**
Mean PET (mm/mon.)	150.34		152.11		162.21	
Mean PPT (mm)	23.33		14.87		11.79	
No. of Droughts	61	57	52	51	32	32
Maximum of Drought Magnitude	-3.19	-3.13	-3.01	-2.98	-2.82	-2.82
No. of Extremely Drought Months	5	5	7	7	4	4

4.4 Remote Sensing-Based Drought Indices

4.4.1 NDVI-Based Drought Assessment

NDVI-based drought map for 1995 to 2023 (Figure 4-14) shows nearly 56% of the region categorized as "severely to mildly dry," highlighting a concerning spatial extent of drought across the study area. Map indicates a substantial stress on vegetation and that may cause negative effects on agriculture, ecosystems, and water resources of the region. The map distinctly displays the spatial variability of drought, with large areas experiencing moderate to severe dryness.

The drought conditions in the study area are classified on map based on the NDVI ranges suggested in the Table 4-7. The implications of this widespread drought are extensive. Rahim Yar Khan is experiencing a range of conditions from no drought to severe drought, indicating significant vegetation stress that could severely impact agriculture and ecosystems. In Bahawalpur, moderate to severe drought conditions prevail, further stressing vegetation and potentially affecting agricultural productivity and environmental health. Meanwhile, Bahawalnagar shows conditions ranging from no drought to mild drought, suggesting relatively less vegetation stress but still highlighting a need for attention to maintain stability (Figure 4-14).

Table 4-7: NDVI classes for drought characterization

NDVI Ranges	Drought
<-0.2	Extremely Dry
-0.2 - -0.05	Severe Dry
-0.05 - -0.01	Moderate Dry
-0.01 - 0.1	Mild Dry
≥0.1	Wet

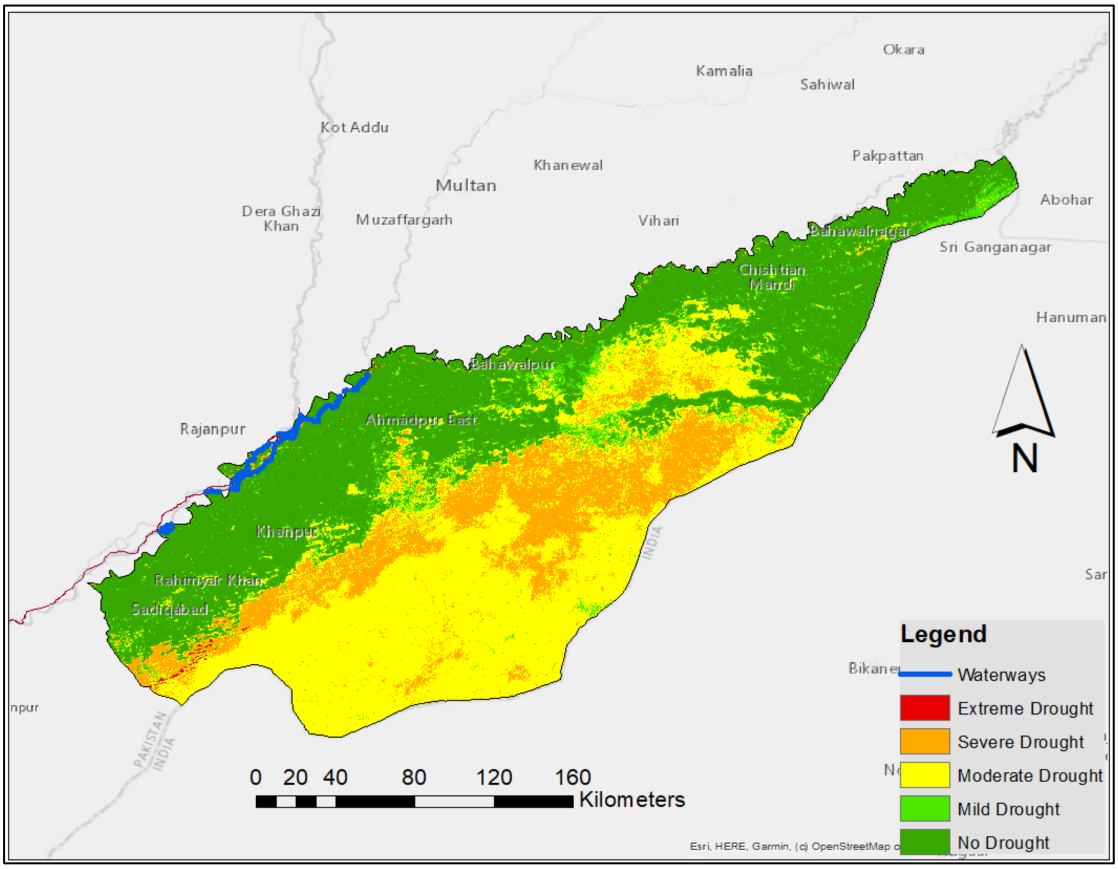


Figure 4-14: Normalized Vegetation Difference Index Based Drought Map 1995-2023

4.4.2 VCI-Based Drought Analysis

The VCI-based drought map for the period 1995-2023 provides a more optimistic outlook compared to the NDVI-based map, as shown in Figure 4-15. It revealed about 56% of the total area has experienced severe to mild drought conditions, suggesting that a larger portion of the region has enjoyed relatively favourable vegetation health over these years.

The drought conditions are classified based on the VCI ranges provided in Table 4-8. Key observations from the VCI map include a significantly reduced extent of drought compared to the NDVI map, particularly in the central and eastern regions of the study area. This reduction indicates that these areas have generally maintained better vegetation health. However, pockets of moderate and severe drought persist, particularly in the part of the study area around Bahawalpur, where significant vegetation stress is evident. On the other hand, most of the study area falls into the mild drought or no drought categories, reflecting relatively healthy vegetation conditions throughout most of the region.

When examining specific meteorological stations, Rahim Yar Khan and Bahawalnagar are largely free from drought or only experience mild drought conditions in case of Rahim Yar Khan, indicating favourable moisture levels for vegetation growth. In contrast, Bahawalpur is situated within a zone experiencing severe drought, highlighting the significant challenges related to vegetation health and water scarcity in this area (Figure 4-15).

Table 4-8: VCI Classes for drought characterization

VCI Ranges	**Drought**
≤10	Extremely Dry
10-20	Severe Dry
20-30	Moderate Dry
30-40	Mild Dry
≥ 40	Wet

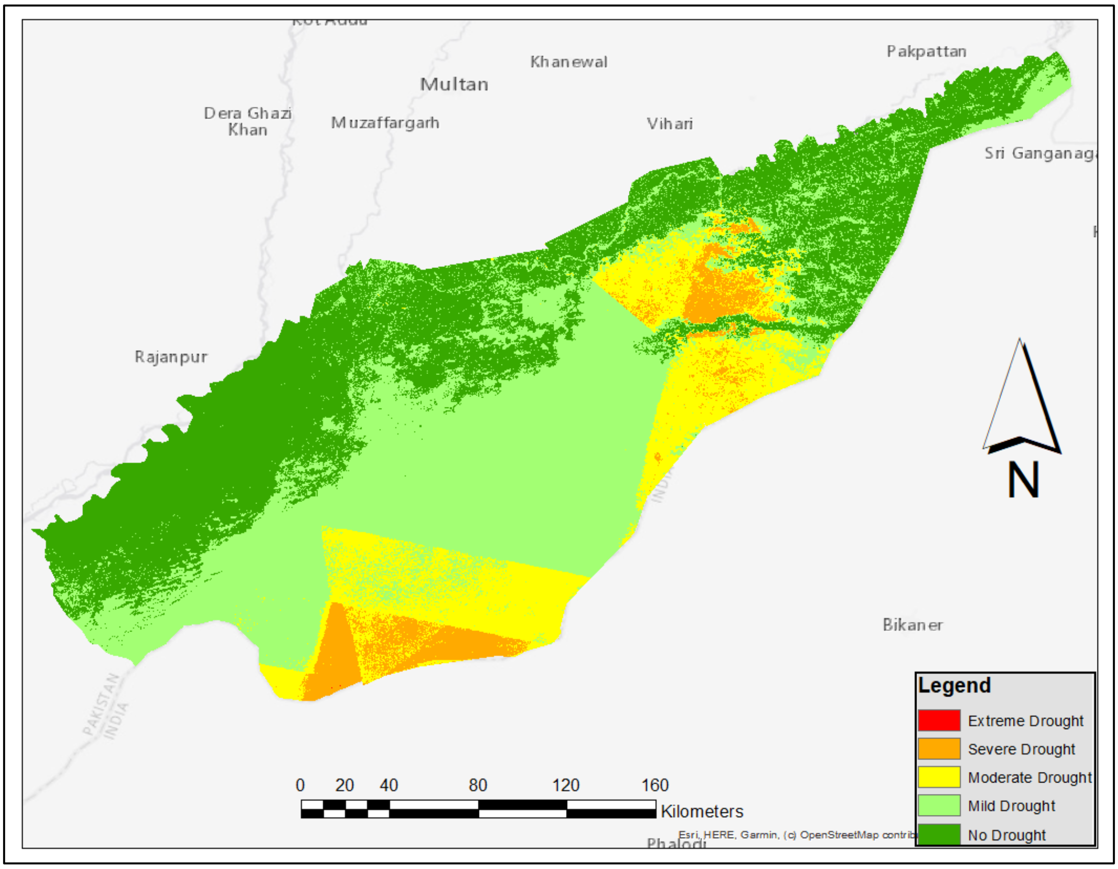


Figure 4-15: Vegetation Condition Index Based Drought Map 1995-2023

4.4.3 TCI-Based Drought Evaluation

The TCI-based drought map for the period 1995-2023 revealed a troubling picture of widespread drought conditions across the study area, as given in Figure 4-16. A substantial portion, nearly 77% of the total region, falls into the "severely to mild dry" categories. This indicates that a large segment of the region has faced considerable heat stress and potential water scarcity throughout these years.

The drought conditions are classified based on the TCI ranges provided in Table 4-9. Key observations from the TCI map highlighted the extensive reach of drought, with significant areas, particularly in the western and southern parts of the region, experiencing moderate to severe dryness. The map also identified pockets of extreme drought scattered throughout the region, suggesting localized zones of intense heat and aridity. Despite the overall widespread drought conditions, there are spatial variations in severity. Some regions, especially in the northeast, showed no drought or only mild dryness, providing a contrast to the more severely affected areas.

When assessing specific meteorological stations, Bahawalpur and Rahim Yar Khan appears to be in an area experiencing moderate to mild drought, highlighting the significant challenges related to high temperatures and water availability in this area. In contrast, majority of Bahawalnagar is situated in a region with no drought or potentially mild drought, reflecting relatively favourable conditions (Figure 4-16).

Table 4-9: TCI Classes for drought characterization

TCI Ranges	**Drought**
≤10	Extremely Dry
10-20	Severe Dry
20-30	Moderate Dry
30-40	Mild Dry
≥ 40	Wet

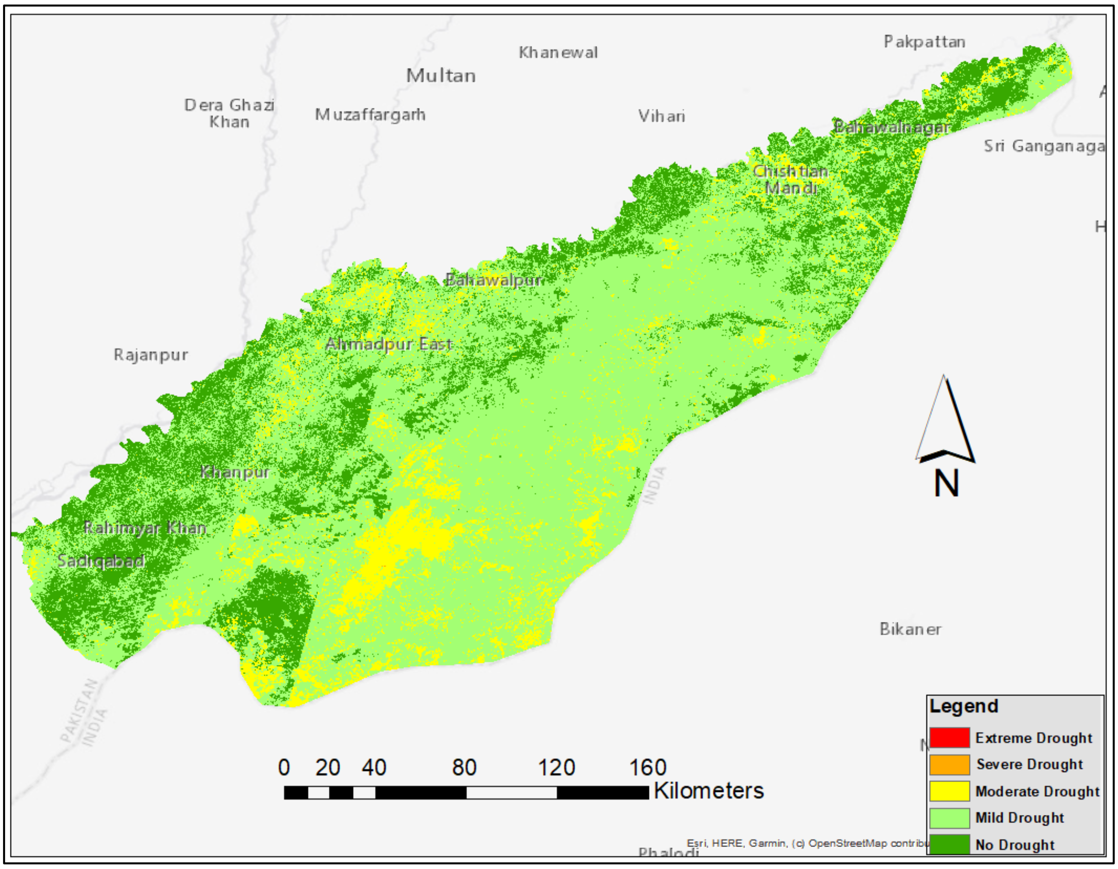


Figure 4-16: Temperature Condition Index Based Drought Map 1995-2023

4.4.4 Integrated Drought Map Using Remote Sensing-Based Indices

We employed fuzzy overlay technique to create the Integrated Drought Map for the period 1995-2023 using Remote Sensing-Based Indices, NDVI, TCI, and VCI. Map revealed distinct drought conditions in the region (Figure 4-17). This approach of integrated drought indices often provides a more comprehensive assessment of drought conditions as suggested by recent studies in drought mitigation (Hao et al., 2015; Zhang et al., 2017).

As suggested by the individual indices the integrated map itself showed Bahawalnagar as experiencing "No Drought to Mild Drought," zone (Figure 4-17). While "Severe to Moderate Drought," conditions reflecting significant drought stress and challenges were observed in southern regions of Bahawalpur and Rahim Yar Khan.

This pattern found in the integrated analysis also compliments the NDVI and TCI analyses as both indicated more severe drought conditions in similar parts of study area. As the same area has been highlighted in multiple indices, it suggests a higher confidence in the severity of drought conditions in that particular region.

As noted by Ashraf & Routray (2015) in their study of semi-arid climates northern boundaries of Bahawalpur and Rahim Yar Khan were displaying a gradation range of moderate to relatively stable moisture levels due to spatial variability of drought conditions in semi-arid regions.

By combining these indices, the integrated map credits for various aspects of drought as each of these indices captures a different aspect of drought. Analysis highlight better assessment of drought conditions is done by the integration of multiple remote sensing-based indices as compared to any single drought index. (Hao et al., 2015).

The spatial patterns discovered in this integrated drought map are crucial for water resource management and agricultural planning in the Bahawalpur Division.

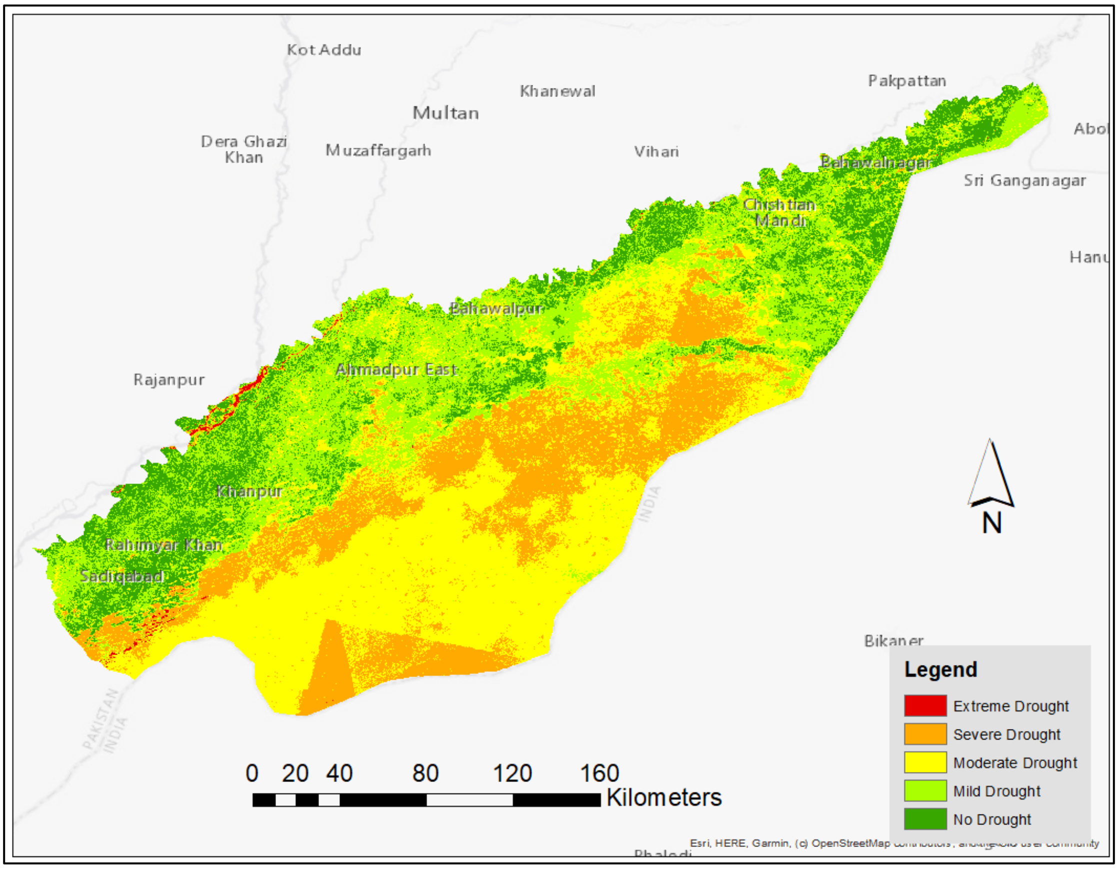


Figure 4-17: Integrated Drought Map Using Remote Sensing-Based Indices 1995-2023

4.4.5 Comparative Analysis of Remote Sensing-Based Drought Maps

We utilized three most used remote sensing-based drought indices i.e. NDVI, VCI, and TCI to get valuable insights in the context of spatial distribution of drought patterns in the study area. Each of these indices highlighted a unique aspect of drought, highlighting their distinct strengths in representation of drought conditions.

The NDVI map indicated approximately 56% of the area experiencing severe to mild dryness. VCI map depicted a less severe impact, with about 62% of the area falling into moderately to severe dry categories. While the TCI-based map showed 77% of the area classified in this category standing as the most widespread drought. This differences in results underscored sensitivity of each index to different drought drivers. TCI was particularly responsive to heat stress capturing the thermal aspects of drought effectively. VCI, as it is derived from NDVI provided insights into vegetation health and water availability. While the NDVI, which measures vegetation greenness primarily indicated plant health.

All three indices revealed spatial variability in drought conditions, but the severity and distribution of drought differed among them. For instance, the TCI map illustrated a more extensive drought impact in the western and southern regions, whereas the VCI map suggested relatively favourable conditions in the central and eastern parts of the study area. This spatial heterogeneity highlighted how each index responded to different environmental factors.

By integrating the results from TCI, VCI, and NDVI, the combined map offered a comprehensive view of drought conditions. This map synthesized the different aspects captured by each index, providing an integrated picture of drought impacts across the region. It shows not only where temperature stress is prevalent but also where vegetation health is compromised and how vegetation presence varies, offering a nuanced understanding of drought across the study area.

The analysis highlighted the value of employing multiple drought indices to obtain a comprehensive understanding of drought conditions. Each index offered a unique perspective, and their combined analysis provided a more detailed view of drought severity and its causes. This approach underscored the need for targeted drought management strategies based on the specific drivers affecting different regions.

4.5 Integrated Drought Analysis: Drought Composites

Three drought composites i.e. meteorological, agricultural, and temperature-based were created by overlaying the relevant indices using a comprehensive approach. Each composite highlighted a unique picture of drought patterns in the region.

4.5.1 Meteorological Drought Composite

The meteorological drought composite depicted the spatial distribution of drought intensity across Bahawalpur division using a colour gradient to illustrate varying levels of drought conditions (Figure 4-18). The map revealed that the southwestern and northeastern areas, particularly around Rahim Yar Khan and Bahawalnagar, experienced the moderate to severe drought, as indicated by deep orange and red hues. This suggested a significant deficit in precipitation and potentially elevated temperatures, leading to arid conditions. In the central part of the region, including Bahawalpur, the colours transitioned to orange and yellow, indicating moderate drought conditions. These areas, though less severely affected than the southwest, still faced water scarcity and its associated impacts.

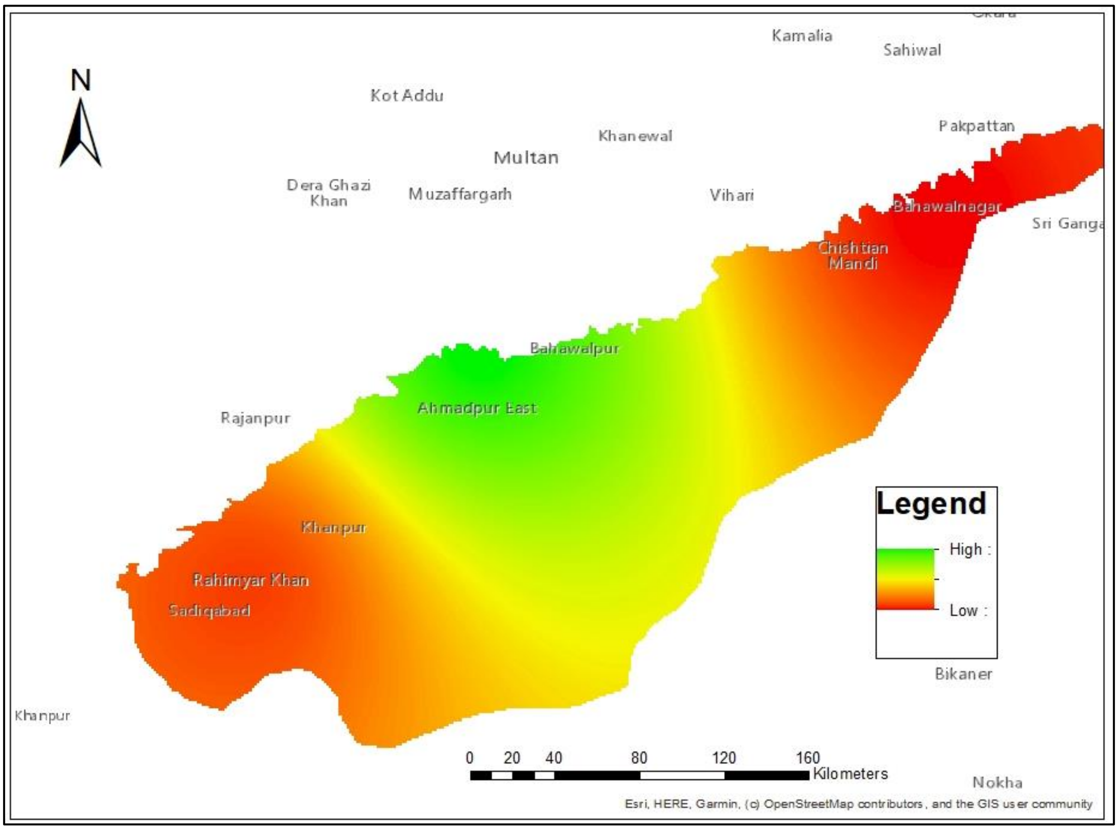


Figure 4-18: Meteorological Drought Map

4.5.2 Agricultural Drought Composite

The agricultural drought composite provided a detailed visualization of drought severity across study area from 1995 to 2023, as given in Figure 4-19. This map was developed using a weighted overlay approach that integrates data from the NDVI, VCI & SPI. Given the limitations in meteorological data, more emphasis was placed on NDVI and VCI, which are directly tied to the health of vegetation.

The map displayed in Figure 4-19 revealed that approximately 63% of the area has experienced some level of drought, ranging from severe to mild, indicating significant agricultural stress across much of the region. Severe drought conditions are predominantly concentrated in the parts of study area, particularly around Rahim Yar Khan and Bahawalnagar. In contrast, moderate drought is more widespread in central areas, including parts of Bahawalpur. Meanwhile, the northern regions of study area primarily displayed mild drought or no drought conditions.

A notable aspect of the map is its apparent bias towards areas with healthier vegetation, resulting in larger "no drought" zones. This bias is likely due to the greater weight given to NDVI and VCI, which focus more on vegetation health than on precipitation patterns.

The widespread drought conditions highlighted by this map underscore the vulnerability of agriculture in the region. The impacts on crop yields, livestock productivity, and agricultural livelihoods are likely to be significant, necessitating urgent attention. Furthermore, the map emphasizes the need for effective water resource management strategies to mitigate the effects of drought on agriculture. This might include enhancing irrigation efficiency, promoting drought-resistant crops, and implementing water conservation measures. The bias towards vegetation also underscores the importance of improving meteorological monitoring networks to enhance the accuracy of future drought assessments.

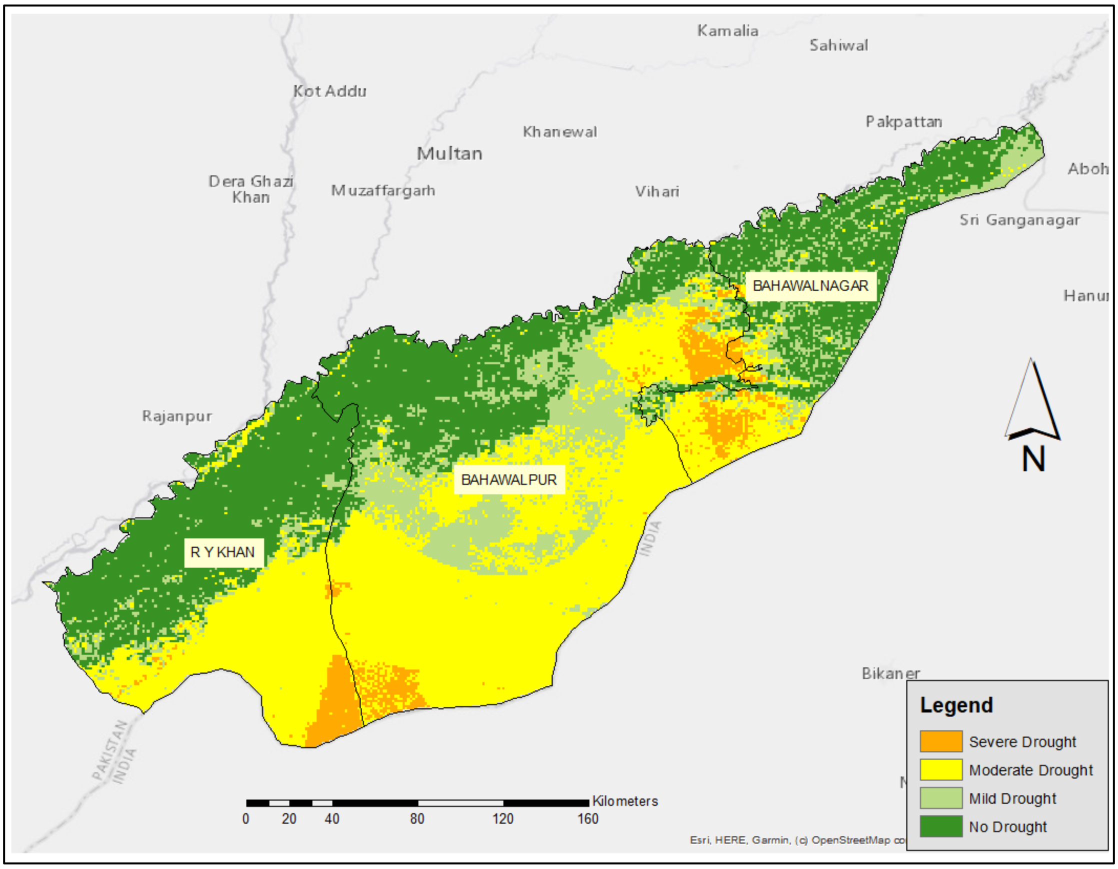


Figure 4-19: Agricultural Drought Map 1995 - 2023

4.5.3 Temperature-Based Drought Composite

The temperature-based drought map provided a visual representation of drought conditions in Bahawalpur Division, Pakistan, from 1995 to 2023, using a weighted overlay of the Temperature Condition Index (TCI) and Reconnaissance Drought Index (RDI), as shown in Figure 4-20. The map uses a colour gradient ranging from green, indicating "no drought," to orange, signifying "severe drought," to illustrate varying levels of drought severity across the region.

The map revealed that a significant portion of the study area falls within the "no drought" to "mild drought" categories, represented by dark and light green hues. This suggested that temperature, as captured by the TCI, has had a relatively low impact on drought conditions over the analysed period. However, pockets of moderate drought were observed, particularly in the southwestern part of the region around Rahim Yar Khan and Bahawalpur. These areas likely reflect the influence of RDI, which seem to play a more significant role in driving drought in these localized regions.

The overall pattern of the map suggested a bias towards the TCI, likely due to the higher weight assigned to it in the overlay analysis. This indicates that while temperature fluctuations have influenced drought conditions, they have not been the primary driver in the region. Instead, factors such as precipitation may appear to be more critical in shaping the drought landscape.

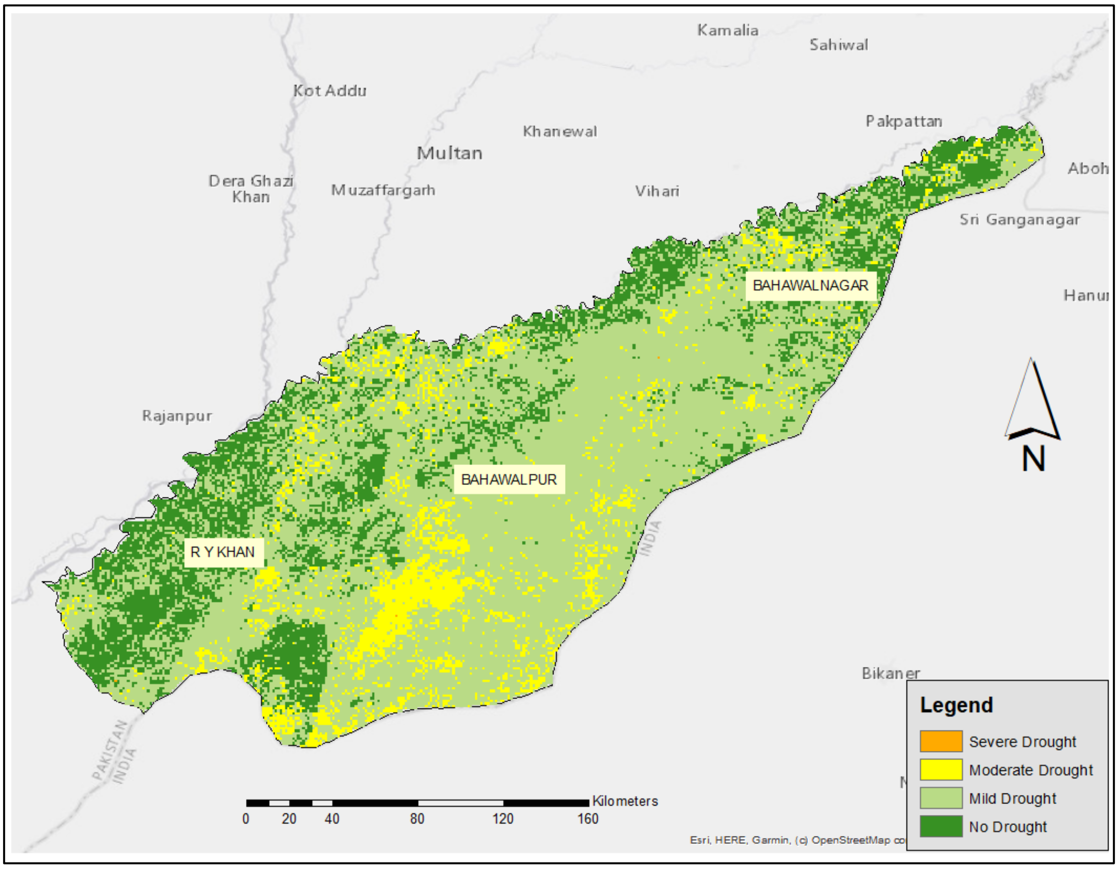


Figure 4-20: Temperature-based Drought Map 1995-2023

4.5.4 Integrated Drought Risk Map 1995-2023

The integrated drought risk map for the study area i.e., Bahawalpur divison, covering the period from 1995 to 2023, illustrated the combined severity of drought conditions by synthesizing multiple indices including NDVI, VCI, TCI, SPI, and RDI. The map is depicted in Figure 4-21. Due to limitations in meteorological data, a heavier emphasis was placed on remote sensing-based indices (NDVI, VCI, and TCI). The weights assigned to each index are discussed in Section 3.4.

Key observations revealed that despite the predominant focus on vegetation health indicators, approximately 77% of the area fell within 'mild to moderate drought' categories. This indicated significant drought stress across the region over the 28-year period. Severe drought conditions were notably concentrated in the southern regions around all three districts of Bahawalpur. Mild drought was widespread in the central regions, including parts of Bahawalpur, while the northeastern areas near Bahawalnagar generally exhibited 'no drought' or mild drought conditions. The northern part of the study area showed majority of no drought conditions.

The map also exhibited a noticeable bias towards the locations of meteorological stations, where 'no drought' zones were prominent. This bias was likely influenced by the proximity of these stations to the northern border of the study area, where data might have been more readily available or more reliable. This distribution underscored the limitations of the current dataset and the potential for skewed representations of drought severity due to the reliance on these station locations.

Overall, the integrated drought risk map provided valuable insights into the complex drought dynamics within the Bahawalpur division. Despite the limitations posed by the data and methodology, it underscored the persistent drought challenges and emphasized the need for a more nuanced and comprehensive approach to drought assessment and management, incorporating both remote sensing and ground-based observations for future studies.

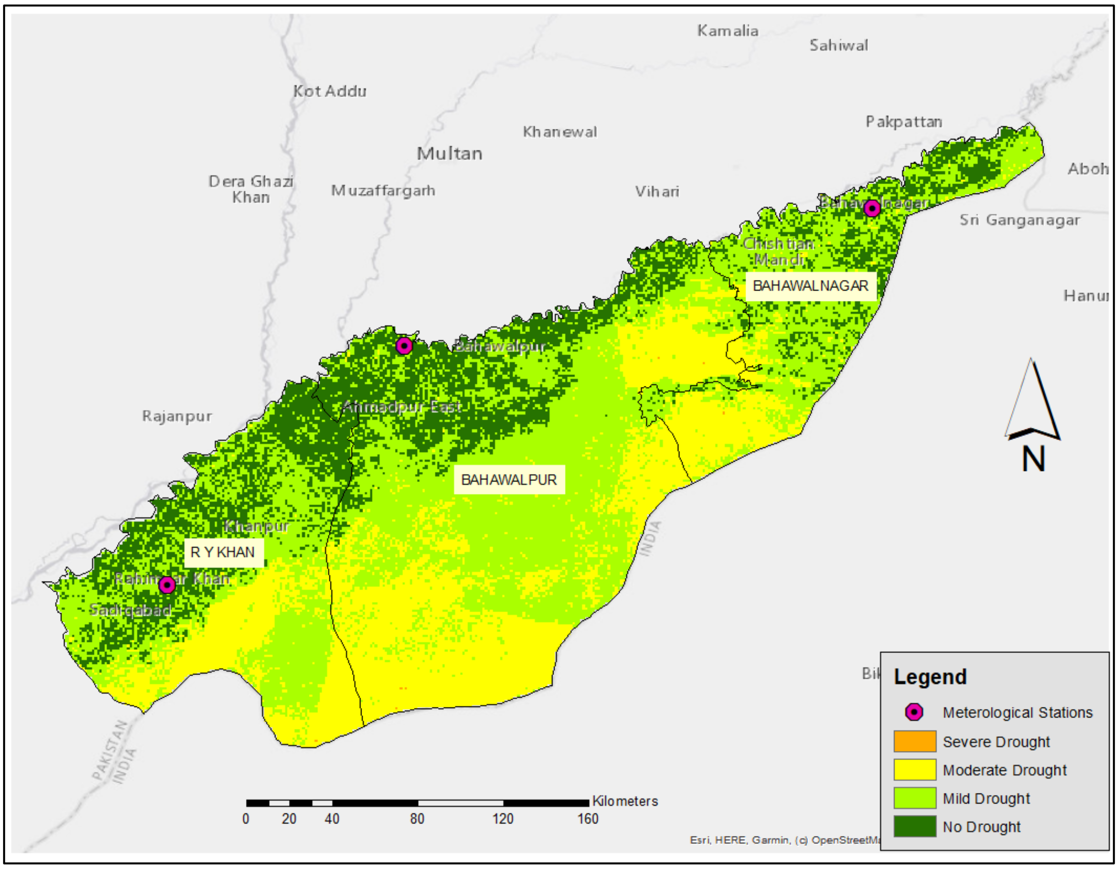


Figure 4-21: Integrated Drought Risk Map 1995-2023

4.5.5 Comparative Analysis of Drought Composites

The integration of remote sensing and meteorological indices has provided a comprehensive approach to assessing drought conditions in Southern Punjab from 1995 to 2023. This analysis utilized various drought composites to deliver a nuanced understanding of drought severity, spatial distribution, and temporal trends. Our approach involved using remote sensing data for spatial analysis to identify drought-affected areas and meteorological data for examining temporal trends and forecasting. This dual approach allowed for a comprehensive understanding of drought dynamics, capturing both spatial variations and temporal changes. Key insights from comparative analysis are as follows:

1. Remote sensing data, including the NDVI, VCI and TCI offered detailed spatial information and a more granular estimation of drought conditions. These indices highlighted areas of reduced vegetation cover and varying drought severity, revealing significant drought stress across the region. The composite maps generated from these indices demonstrated that most drought impact was

attributed to reduced vegetation and water availability, rather than temperature fluctuations.

2. Meteorological indices, such as the Standardized Precipitation Index (SPI) and Reconnaissance Drought Index (RDI), provided valuable insights into temporal drought trends and forecasting. These indices captured precipitation deficits and assessed drought conditions over time.
3. Temperature-based indices like TCI showed a minimal impact on overall drought patterns. The TCI map indicated a relatively smaller area under drought risk compared to the SPI and RDI maps. This suggested that temperature variations contribute less to drought severity in Bahawalpur District, as evidenced by lower TCI values and the limited effect of temperature changes compared to precipitation deficits.
4. The comparative analysis revealed that the primary factors influencing drought in the region are reduced water availability and decreased vegetation cover, rather than temperature changes. The high correlation between SPI and RDI underscores the significance of precipitation deficits in driving drought conditions. In contrast, temperature variations, as indicated by the lower TCI values, have a less pronounced effect on drought severity.

Overall, integrating remote sensing and meteorological data offered a robust framework for drought assessment. The findings highlighted the importance of precipitation and vegetation health in understanding drought patterns and underscore the need for continued monitoring and analysis to effectively manage and mitigate drought impacts in the region.

4.6 Potential Drought Impacts & Proposed Recommendations

Agricultural Impacts: The study identified significant reductions in crop yields in areas categorized as "Severe to Moderate Drought," particularly in the southern districts of Bahawalpur and Rahim Yar Khan. These regions, experiencing substantial drought stress, face challenges that may include diminished agricultural productivity and potential shifts in crop suitability. Areas consistently showing low NDVI values may necessitate changes in crop types to ensure better alignment with the prevailing environmental conditions.

Hydrological Impacts: The drought conditions have intensified pressure on groundwater resources, especially in regions with persistently low SPI and RDI values. This increased demand may strain existing water supplies and impact the sustainability of irrigation systems. Additionally, potential changes in the river flow patterns of the Sutlej could disrupt irrigation practices, affecting the agricultural productivity of the region.

Socio-economic Impacts: Economic stress is expected to rise among farmers in the severely affected areas, particularly in southern Bahawalpur and Rahim Yar Khan. This stress could lead to migration of agricultural workers from drought-stricken regions to urban centers or less affected areas, potentially exacerbating economic challenges in both the source and destination locations.

4.6.1 Proposed Recommendations

To enhance the accuracy and granularity of drought assessments in the Bahawalpur Division, it is crucial to increase the density of weather stations throughout the region. By expanding the network of weather stations, more precise and localized climatic data can be collected, which will improve the monitoring of drought conditions and allow for more accurate assessments. This approach will provide a clearer picture of local weather patterns and contribute to better-informed decision-making regarding drought management.

In addition to increasing weather station density, it is recommended to utilize an integrated approach that combines both meteorological and remote sensing data. This multi-faceted method offers a comprehensive view of drought conditions by incorporating diverse data sources, including satellite imagery and weather station reports. The integration of these data types enables more precise evaluations and supports effective decision-making processes by providing a fuller understanding of drought dynamics.

Water management strategies should be tailored to address the specific needs of high-risk areas identified through the integrated drought map. Implementing water conservation techniques, such as adopting efficient irrigation systems and reducing overall water usage, can help mitigate the impacts of drought. These measures will conserve valuable water resources and help manage the challenges posed by reduced rainfall and increased water scarcity.

Localized water harvesting systems should be developed in regions that consistently show low values for the Standardized Precipitation Index (SPI). These systems are designed to capture and store rainwater, providing an additional resource for irrigation during drought periods. By creating supplementary water sources, such systems can reduce dependency on groundwater and enhance water availability for agricultural and other uses.

To support agricultural resilience, it is important to promote the use of drought-resistant crop varieties in areas that consistently exhibit low NDVI and VCI values. Drought-resistant crops are better suited to withstand dry conditions and can help maintain agricultural productivity despite adverse weather. Additionally, implementing crop rotation strategies based on the spatial patterns of drought risk identified in the study can enhance soil health and reduce the likelihood of crop failure. Effective crop rotation can optimize soil nutrients and improve overall crop resilience to drought.

Capacity building and community engagement are also critical components of effective drought management. Targeted training programs should be conducted for farmers in high-risk areas, focusing on drought-adaptive agricultural practices. These programs will provide farmers with the knowledge and skills necessary to manage drought conditions and adapt their farming practices to changing environmental factors. Establishing community-based drought management committees in severely affected areas can further support local drought response efforts. These committees can use the spatial information from the study to develop and implement localized strategies for managing drought and supporting affected communities.

Investing in research and development is essential for long-term drought management. Research should focus on developing drought-tolerant crop varieties that are specifically suited to the climatic conditions of the Bahawalpur Division. Such research will enhance agricultural resilience and productivity in drought-prone areas by identifying and promoting crops that can better withstand water scarcity. Additionally, further studies on the relationship between temperature and drought are recommended. Although temperature has been found to have a relatively low contribution to drought factors, understanding its role can provide valuable insights for more comprehensive drought management strategies and inform future adaptation measures.

These recommendations aim to address the multifaceted impacts of drought identified in the study and to enhance the resilience of the Bahawalpur Division's agricultural and water management systems. By implementing these strategies, stakeholders can better mitigate the adverse effects of drought and promote sustainable agricultural practices in the region.

Chapter 5.

CONCLUSIONS & RECOMMENDATIONS

By exploring the role of meteorological and remote sensing-based drought indices, this study provides a detailed and nuanced understanding of drought conditions in the Bahawalpur Division, Pakistan, over the period from 1995 to 2023. The findings underscore that the primary driver of drought in this region is the lack of rainfall, with temperature having a relatively minor impact. This conclusion is consistent with previous research by Rahimi et al. (2013), which highlighted similar patterns in regions with comparable aridity indices.

The multi-index approach employed in this study, incorporating NDVI, VCI, and TCI, proved effective in capturing different aspects of drought. Each index offered unique insights into the drought dynamics, supporting the recommendations of Zhang et al. (2017)for using a combination of indices to achieve a comprehensive drought assessment. The study also revealed significant spatial heterogeneity in drought severity, with the southern regions of the Bahawalpur Division experiencing the highest levels of drought stress. This pattern aligns with the observations of Amin et al. (2019), who documented similar variations in drought severity over time, including extreme events such as the drought of 2000-2002.

While the inclusion of meteorological data improved the validity of the results, it was clear that sparse station coverage limited the temporal resolution of drought assessments. In contrast, remote sensing data provided valuable continuous spatial coverage, addressing some of the limitations associated with meteorological station gaps.

Overall, the study highlights the importance of integrating both remote sensing and meteorological data to achieve a comprehensive understanding of drought dynamics. The insights gained are crucial for developing targeted drought management strategies and enhancing the resilience of the Bahawalpur Division's agricultural sector in the face of ongoing climate challenges.

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