New comprehensive ensemble-based approaches for characterizing and monitoring the spatial inter-seasonal characteristics of meteorological drought

By

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In the Name of Allah, The Most Merciful and The Most Beneficent

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A THESIS SUBMITTED IN THE PARTIAL FULFILLMENT OF THE REQUIREMENTS THE DEGREE OF MASTER OF PHILOSOPHY IN STATISTICS

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Department of Statistics
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Quaid-i-Azam University, Islamabad
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CERTIFICATE

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STATISTICS

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Declaration

I "Hamza Amin" hereby solemnly declare that this thesis is titled, "New Comprehensive Ensemble-Based Approaches for Characterizing and Monitoring the Spatial Inter-Seasonal Characteristics of Meteorological Drought".

- I declare that this MPhil thesis has not previously been submitted, in part or in full, forany other academic degree at any other institution. I affirm the accuracy of the data and information given in this MPhil thesis, conforming to ethical I declare that this MPhil thesis has not been published previously.

- I worked on my MPhil thesis under the guidance of Prof. Dr. Ijaz Hussain and Co-supervisor Dr. Rizwan Niaz which I am quite proud of. All sources used are properly acknowledged.

- In my MPhil thesis, I guarantee that the accuracy of all data and material presented, following ethical norms and academic requirements throughout the data gathering and analysis procedures.

- Using a collaborative method, the thesis integrates the combined efforts of my co-supervisor, supervisor, and myself, while clearly defining each individual's function and advising input.

Dated:__________________ Signature:__________________

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Dedication

I am feeling Wonderful and pleasure to dedicate this research work to My Believed Parents,Brothers, and Sisters Whose endless affection, prayers, and wishes have been a great sourceof comfort for me during my whole education period and my life. Your unwavering support has been the cornerstone of my accomplishments, and this thesis is a humble tribute to the love and strength that you have bestowed upon me.

Abstract

The current study aimed to examine the inter-seasonal characteristics of meteorological drought. For this purpose, a new comprehensive framework is proposed. The framework consists of two major stages. In the first stage of the framework, the K-Means method is utilized to identify homogeneous clusters. Besides, the Monte Carlo Feature Selection (MCFS) is applied to select more important stations from the varying clusters. In the second stage, the Standardized Precipitation Index at a three-time scale (SPI-3), the Conditional Fixed Effect Binary Logistic Regression Model (CFEBLRM), and the Random Effect Binary Logistic Regression Model (REBLRM) are utilized. The significance of CFEBLRM and REBLRM is measured by Log-likelihood values, Log-likelihood Ratio Chi-Square Test (LRCST), Wald Chi-square Test (WCT), and p-values. The Hausman Test (HT) is applied to identify endogeneity and suggests the appropriate model in CFEBLRM and REBLRM. The results from the proposed framework indicate that the drought persists in the Summer to Autumn and Autumn to Winter seasons between 90 to 99 percent. The odd ratio of CFEBLRM for the Summer-Autumn season indicates that the increment in temperature will decrease the drought persistence in the Autumn season. The result of the current study facilitates the decision-makers to understand the effects of meteorological drought occurrences better and improve strategies for mitigating drought effects and managing seasonal crops in the Province of Punjab in Pakistan.

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Chapter 1

Introduction

1.1. Introduction

Drought is a complicated weather phenomenon with many aspects and has become important due to its far-reaching effects on nature, economies, and societies (Zhu et al. 2016; Niaz et al. 2022a). Drought is a lengthy period of below-average rainfall and limited water resources, resulting in a shortage that exceeds the affected areas to manage the water deficit (Shorachi et al. 2022; Soylu et al. 2023). Other authors characterized drought as a dynamic phenomenon that varies both in its duration and its impact depending on the location and period. (Patterson et al. 2013; Alamgir et al. 2015) and Leng et al. (2015) described drought as a natural event primarily caused by persistent insufficient rainfall. Drought occurs when a region experiences a shortage in its water resources, as noted by Afrin et al. (2018). Generally, this happens when a region consistently receives less rain than usual. Its consequences extend to various sectors, affecting agriculture, water availability, public health, energy production, and biodiversity. The importance of studying and comprehending drought has become increasingly significant because of the ongoing influence of climate change and human actions on water patterns, making droughts more frequent and severe. Droughts are primarily caused by a lack of rainfall, however, it's worth mentioning that increased temperatures are also being recognized as a factor that is playing a contributing role in making droughts last longer or become more severe, as reported in various regions around the world (Zscheischler et al. 2018; Sarhadi et al. 2018). The combination of these extreme conditions is expected to be more damaging than individual extreme events (Hao et al. 2018; Zachariah et al. 2023). For example, increased temperatures in a region during droughts can make heatwaves more severe (Sharma and Mujumdar 2017; Chiang et al. 2018). Furthermore, These conditions can also have adverse effects on crop development by causing higher evapotranspiration rates and decreasing soil moisture levels, (Kumar et al. 2017; Mishra et al. 2019), which can have significant consequences for India's agricultural economy. (Mishra et al. 2020; Zachariah et al. 2023). During droughts, water resources are also severely stressed. Reduced rainfall means less water flowing into rivers, lakes, and reservoirs. This can lead to decreased water levels and even the drying up of water bodies. Communities that rely on these sources for drinking water, sanitation, and industrial purposes face significant challenges in meeting their basic needs. In 2015, our neighbor country India encountered widespread drought conditions characterized by a shortage of rainfall and abnormally elevated temperatures across numerous regions of the nation (Ghatak et al., 2017; Pattanaik et al. 2017). The effects considerable increments in agricultural production losses and Occurrences of farmers taking their own lives, both of which have been linked to less rainfall and elevated heat caused by climate change. (Parida et al., 2018; Khairnar et al. 2015). Climate change worsens the effects of drought. changing weather patterns and rising temperatures can cause changes in rainfall and increased rates of evaporation, making droughts more common and severe. As a result, the need to understand and address drought has become increasingly critical as the world is facing tougher challenges due to climate change. Drought monitoring involves a variety of meteorological and hydrological factors for analysis, i.e. Precipitation, evapotranspiration, temperature, and Soil moisture. These indicators provide insight into when droughts begin, how long they stay, and how severe they are, allowing early warning systems and proactive attempts to mitigate their consequences. Drought monitoring has been altered by Advanced technologies, like remote sensing and Geographic Information Systems (GIS), which have improved data precision and spatial reach, making timely decision-making and resource allocation more accessible. In recent decades, the worsening of drought incidents has been associated with climate change, with increasing temperatures and changing precipitation trends increasing both the frequency and intensity of drought occurrences. Addressing and mitigating the impact of drought required a combination of strategies. Water conservation measures, such as effective irrigation systems and minimizing water waste, are critical for maximizing available water supply. Drought early warning systems and monitoring assist communities in preparing for and dealing with drought events, allowing them to implement emergency plans and resource allocation strategies. In recent times, there has been a need for an increasing awareness of the importance of managing droughts in advance. Governments, organizations, and communities are working together to develop comprehensive drought management plans. These plans involve not just immediate steps to handle drought disasters, but also long-term strategies to improve resilience and adapt to changing climatic conditions.

Drought has many types but is generally categorized into four major types: Meteorological drought, Hydrological drought, Agricultural drought, and socio-economic drought. Each type necessitates the analysis of specific factors or indicators. Meteorological drought involves assessing variables such as Precipitation, evaporation, and transpiration. soil moisture deficit, and evaporation stress for agricultural drought. Hydrological drought involves examining streamflow shortages or the depletion of groundwater sources. Socio-economic drought assessment includes information on the reliability of water supply to demand and the resilience of Storing water (Ahmadalipour et al. 2017; Danandeh et al. 2023).

I. **Meteorological drought:** Meteorological drought occurs when there is a prolonged period of below-average rainfall, resulting in a precipitation shortage (Yihdego et al. 2019; Jimenez -Donaire et al. 2020; Ellahi et al. 2023). This lack of rain can result in dry soil, lower water levels in rivers and lakes, and an overall shortage of accessible water. It's like nature's regular rainfall patterns take a pause, generating a variety of challenges. The continual absence of rain creates a link between meteorological drought and agricultural drought (Zuo et al 2022; Dukat et al. 2022). since both crops and plants rely heavily on water for their growth. Furthermore, the availability of drinking water may be compromised, and regions experiencing meteorological droughts might face a higher risk of wildfires, especially in dry conditions. To predict and get ready for meteorological droughts, it's crucial to closely monitor weather conditions and rainfall patterns. This enables communities and authorities to make well-informed decisions to minimize the effects of prolonged periods of inadequate rainfall.

II. **Hydrological drought:** Hydrological drought occurs When a river flows fall below normal levels or when the water level in an underground reservoir decreases (Van Loon 2015; Liu et al 2016). While hydrological droughts are consistently associated with meteorological droughts, there can be significant variations in their strength and length. Hydrological drought happens when there is an insufficient amount of water in lakes, rivers, and underground water storage for an extended period. It's nature's way of telling us that our water resources are insufficient to satisfy the demand (Hasan et al. 2019; Peña-Angulo et al. 2022). This scarcity of water has consequences not only for the natural environment but also for our daily lives. Water levels in rivers and lakes decrease, and wells may become exhausted. This can pose challenges for communities that rely on these water sources for drinking, agriculture, and industrial purposes. The consequences of hydrological drought are more extensive, affecting ecosystems and the diversity of species living within them. It is not just a problem of reduced human water availability; it also disturbs the entire water ecosystem. To tackle hydrological drought, we must properly manage water resources, practice water conservation, and plan for periods of water shortage.

III. **Agricultural drought:** Agricultural drought is interlinked with meteorological drought, during a period of insufficient precipitation, meteorological drought can extend into agricultural drought, causing a deficiency of moisture in formed soil. (Lee et al. 2022; Mullapudi et al. 2023). Droughts in agriculture occur when there isn't enough soil moisture to fulfill the water requirements of crops throughout their growth period. Insufficient soil moisture levels slow down crop development, leading to diminishing yields and possibly resulting in the complete loss of crops (Watson et al. 2022; Shangguan et al. 2022). Farmers require water to ensure that their plants develop properly. Plants suffer difficulties when they do not receive enough water, and this has an impact on the food we eat. It has an impact on more than just farms; it also affects the food available on the market and its pricing Addressing agricultural drought requires identifying sensible water-saving measures, selecting crops that can grow with limited water supplies, and developing strategies to support farmers when their crops are at risk.

IV. **Socio-economic drought:** Socio-economic drought occurs when a water deficit impacts not just the environment but also the well-being of individuals and economies. Socioeconomic droughts are distinct from the other three forms of drought. Their occurrence is associated with the discrepancy b/w the availability and demand for economic products connected to shortages in weather-related water supply (Wang et al. 2022; Wang et al. 2023). This creates a chain reaction – the reduced water supply affects jobs, businesses, and even the prices of things we purchase. When there is insufficient water availability for agriculture, it might result in job losses in forming and higher food prices. Industries that depend on water, such as manufacturing and energy generation, may also face disruptions, resulting in economic losses. Furthermore, socioeconomic drought can cause migration as individuals seek better opportunities where water is more available. This type of drought is complicated by the fact that it combines water scarcity with social and economic problems. To address it, communities must be prepared for emergencies, discover ways to preserve water, and develop plans to assist individuals during challenging periods.

1.2. Drought Indices

Droughts are typically classified into meteorological, agricultural, hydrological, and socio-economic categories (Zhang et al., 2021). We use things like lack of rainfall, low river flow, and groundwater shortages to measure and describe these droughts (Beguería et al. 2014;

Mullapudi et al. 2023). These measurements help us see how droughts change and spread across different places and times around the world (Huang et al., 2019). In the past decades, experts have come up with various ways to measure droughts using climate data. Early on, they used monthly rainfall to define droughts (Blumenstock Jr. 1942; Mcguire and Palmer, 1957). Later, they created different drought indices, like the Palmer Drought Severity Index (PDSI) (Palmer, 1965). PDSI is slow to show the start and end of a drought because it looks at a long period. Then, the Standardized Precipitation Index (SPI) was implemented by McKee et al. (1993) to measure meteorological drought. SPI only uses rainfall data and can be calculated for different periods (Sobral et al. 2019; Lou et al. 2019). It's a good tool to find droughts early. But SPI only looks at rainfall, not temperature. Vicente-Serrano et al. (2010) developed the Standardized Precipitation Evapotranspiration Index (SPEI) to investigate the effect of temperature in drought. It calculates drought severity by comparing rainfall and evapotranspiration, which is how water gets into the air from the ground. The way evapotranspiration is calculated can be a bit tricky. Thornthwaite's method (Thornthwaite, 1948) sometimes underestimates it in dry areas and overestimates it in humid places. In those cases, the researchers recommend using the Penman-Monteith method, which looks at temperature, wind-peed, and humidity (Richard, 1998). Chen and Sun (2015) found that the SPEI in conjunction with the Penman-Monteith technique, works better for drought monitoring than Thornthwaite's method. SPEI is calculated similarly to SPI but uses a Climatic water equilibrium, which represents the variance between precipitation and potential evapotranspiration (PET). (Vicente-Serrano et al. 2010). Once rainfall is turned into probabilities, these are changed into standard normal distribution values. SPI and SPEI values can then be interpreted statistically, showing how different they are from the typical rainfall or water equilibrium for a particular location and season. Hobbins et al. (2016) improved SPEI by providing a more precise account of potential evapotranspiration and atmospheric evaporative demand. They called this the Evaporative Demand Drought Index (EDDI), and it's a good way to measure drought over large areas, as shown by McEvoy et al. (2016) in the US. Drought also affects plants, and we use different indices to see how. Kogan (1995) used the Normalized Difference Vegetation Index (NDVI) to create a Vegetation Condition Index (VCI). NDVI looks at visible and infrared light to measure vegetation health. Other indices, like the Normalized Difference Water Index (NDWI) by Gao (1996), use different parts of the light spectrum and are less influenced by things like clouds. They can show drought effects more clearly.

Different drought indices consider various features of drought, so Kao and Govindaraju (2010) introduced the Joint Deficit Index (JDI), which uses both SPI for rainfall and streamflow. Hao and AghaKouchak (2013) created the Multivariate Standardized Drought Index (MSDI), combining SPI and a Soil Moisture Index (SSI). This helps find the start and end of droughts. A different approach is the US Drought Monitor (USDM), a drought prediction model by Hao et al. (2017), which is good for early warnings. Azmi et al. (2016) made a data fusion-based drought index, combining various indices using clustering. They also made the Standardized Precipitation Temperature Index (SPTI), which looks at temperature's effects on drought (Ali et al. 2017). The framework proposed by Khan et al. in 2022 introduces a novel indicator for monitoring drought referred to as the Multi-Scalar Seasonally Amalgamated Regional Standardized Precipitation Evapotranspiration Index (MSARSPEI). This research concludes that selecting MSARSPEI is a logically sound and more suitable choice for evaluating regional drought within the framework of global climate change compared to using SPEI. Drought occurrence and severity are influenced significantly by lower-than-average precipitation and higher-than-average air temperatures. Given the backdrop of ongoing global climate change, it becomes essential to account for rising air temperatures, a crucial climatic factor, when calculating drought indices. A recent study by Bonacci et al. in 2023 introduces a new drought index (NDI), which is calculated by deducting the standardized temperature value from the standardized precipitation value.

1.3. Impacts of Drought

Drought, a natural phenomenon characterized by protracted periods of water scarcity, has far-reaching consequences for society, ecosystems, and economies. In recent years, drought has emerged as one of the most significant and dangerous natural disasters. impacting worldwide economic and environmental sectors (Williams et al.2011; Wang et al. 2015). Drought has far-reaching impacts that go beyond its immediate environmental implications, frequently resonating across multiple dimensions. Drought has a negative impact on people's life, whether through direct or indirect means (Shahpari et al., 2022; Savari et al., 2022). Drought has an impact on agriculture, the environment, and economic success (Meza et al. 2020; Elhoussaoui et al. 2021). Livestock suffer from shortages of water and forage, which affects both farmers and consumers alike. The decline of crucial water bodies essential for ecosystems disrupts aquatic habitats and biodiversity. This scarcity has far-reaching economic consequences, as it reduces farmers' incomes, leads to job losses, and increases poverty levels. Furthermore, there's a decrease in water supplies for households and industries, causing inconveniences and potentially hindering production. The challenges faced by energy generation, which relies on water, result in power shortages. Limited access to water also leads to deteriorating health conditions, impacting sanitation and hygiene. Drought-induced wildfires pose threats to forests, homes, and lives. A surge in migration occurs as people search for water and opportunities, straining urban resources. The quality of education suffers as children are called upon to assist with water collection. Undoubtedly, the effects of drought ripple across agriculture, economies, the environment, health, and societies, emphasizing the urgent need for proactive measures to mitigate its consequences. It is an evolving issue that affects a larger population than many other natural hazards (Okpara et al., 2022; Ruwanza et al., 2022). In the past times, many regions have experienced recurring droughts, presenting significant challenges in terms of the environment, socio-economics, and agriculture, particularly in developing countries like Pakistan (Godfray et al., 2010; Arnell et al., 2014). The frequent and severe droughts have raised concerns about food and freshwater security for approximately 1.4 billion individuals in India (Mishra 2020; Mishra et al. 2019). Tanner et al. (2018) discovered that Approximately 2.7 million hectares of territory in Bangladesh are susceptible to yearly droughts. These drought-induced water shortages also have repercussions for livestock, impacting livelihoods and food security. From an economic perspective, droughts negatively affect Pakistan's GDP by reducing agricultural output and increasing the cost of living. Additionally, they can lead to decreased industrial production due to energy shortages. The impact of drought in Asia is far-reaching and complex due to the region's diverse geography and heavy reliance on agriculture. Economies that depend on agriculture face the threat of reduced crop yields and livestock losses, which put food availability at risk. When there's not enough water, it can make daily life challenging, impacting things like hygiene, health, and access to clean drinking water. Industries that need a lot of water for their work can also slowdown, which directly hurts the economy. The environment takes a hit too, with less water available, which affects nature and the variety of life in it. Water sources shrink, and that means less room for fish and other water animals to live. Drought is a worldwide problem, and its impacts are felt more in developing countries around the globe, especially in South Asia. Around 2 billion people have been affected by drought, and we've spent seven to eight billion dollars trying to reduce its impact since 1990 (Rahman et al. 2023). Additionally, the drought in 1988 led to economic damages amounting to 40.8$ billion, (National Ocean and Atmospheric Administration, 2016; Apurv et al. 2019), while the more recent drought in 2012 led to $30 billion in financial disasters (Rippey, 2015; Apurv et al. 2019). It's expected that the socioeconomic consequences of droughts will continue to rise in the future due to the combination of rising temperatures and growing humans requiring water, as the recent drought made clear (He et al., 2017). Over the past few decades, severe weather events have been responsible for extensive economic and social damage on a global scale. Between 1980 and 2019, these extreme weather events tragically led to the loss of 1.15 million lives. Among these events, droughts were the deadliest, accounting for about 50% of fatalities caused by extreme weather. Storms and floods followed closely behind (Cesarini et al. 2021; Monteleone et al. 2023). The connection between weather and climate has always had a significant impact on agricultural productivity. Climate variations contribute to nearly one-third of global yield fluctuations. In many of the world's major food-producing regions, climate fluctuations explain more than 60% of variations in crop yields (Ray et al. 2015).

1.4. A Historical Overview of drought in Pakistan

Drought has become increasingly common in Pakistan, primarily due to rising pollution levels and shifts in climate patterns. According to a report from the Economic Survey of Pakistan, drought is a significant factor contributing to the country's poor economic growth. The drought that occurred from 1998 to 2002 is regarded as the worst in 50 years for Pakistan. It began in 1997 with the development of El Niño but intensified in 1998, reaching its peak from 2000 to 2001 before gradually weakening in 2002. This severe drought affected tens of thousands of people in both Balochistan and Sindh provinces. In Balochistan, around 1.2 million people were impacted and there were almost two million animals that died as a result of it. 127 people lost their lives in the province of Sindh, with the Tharparkar area, which is close to the Indian border, suffering the worst from severe water scarcity and dehydration. In Sindh, about 60 percent of the population moved to locations with better irrigation. Another drought occurred in the mid-2009 to 2010 period, affecting the upper regions of Pakistan, including Punjab and Khyber Pakhtunkhwa. This drought resulted in a 30% reduction in normal monsoon rains in these areas and had a significant impact on crop production, particularly affecting the livelihoods of farmers. The probability of a severe to extreme drought in Punjab and Khyber Pakhtunkhwa was further increment by the absence of winter precipitation.

Punjab is crucial to Pakistan's efforts to address and mitigate the effects of drought. As the country's most fertile and agriculturally productive province, Punjab plays a vital role in ensuring food security and economic stability. Implementing effective measures to manage drought, conserve water, and promote sustainable farming practices is essential to safeguarding Pakistan's critical agricultural assets and minimizing the adverse consequences of drought. Additionally, given Punjab's dense population and economic activity, it underscores the need for robust water supply systems, advanced alert systems, and community engagement projects to reduce the negative impacts of drought and water shortage in both urban and rural areas of the province.

Drought means not enough water for a long time, has had a big impact on Punjab, Pakistan. It affected the farming, economy, and people's lives there. Over the years, Punjab has faced different droughts, some worse than others. In the 1970s, Punjab had one of its first big droughts. Because the province relies a lot on farming, it was hit hard when there wasn't enough water. Less rain and not enough water made crops die, and farmers had a tough time. This made food prices go up, which affected people in cities and villages. While it might not be easy to find records of people directly dying from drought, it caused a lot of problems for everyone. In the 1980s, Punjab had another drought. Since farming is so important, less water hurts crop production. Unequal water sharing caused issues between different communities, making existing inequalities worse. Again, while we might not have the exact numbers of people who died because of the drought, it created lots of difficulties for people's lives and the economy. The 1990s brought more drought challenges to Punjab. Crops failed, and there wasn't enough water for farming. Reports mentioned that livestock suffered because they didn't have enough water and food, which made life harder for rural areas. Even though we might not have clear records of people directly dying from drought, it had a big impact on people's lives and how they made a living. In the early 2000s, more droughts were happening about every five years. These events showed that Punjab needed better ways to manage water and adapt to these changes. Crops suffered, and farmers had a hard time making money. While it's tough to count how many people died because of drought, it affected how people lived and their finances. In the 2010s, Punjab had to deal with changing weather patterns and not enough water. Farming was at risk because of unpredictable rainfall, and people had to change how they planted and watered their crops. Many people had to leave their homes and move because of drought and not being able to grow enough food. Punjab's history with drought has had moments of struggle and strength. When droughts were at their worst, there were problems with money, not enough food, and people's lives being disrupted. But in between these tough times, Punjab showed it could adapt, save water, and use smart strategies to deal with drought. This history reminds us how important it is to manage water carefully, be ready for drought, and use sustainable methods to handle the challenges of drought in Punjab, Pakistan.

1.5. Objective of the Study

To determine the frequency of drought categories based on SPI values.

To find out the inter-seasonal meteorological drought frequency using SPI.

To find the homogeneous spatio-temporal effect of drought using K-Means clustering of C-Index.

To explore the comprehensive temporal effect of meteorological drought by employing Monte Carlo Feature Selection.

To check the impact of meteorological factors using a binary panel model.

To address the spatio-temporal effect of inter-seasonal drought persistence of meteorological stations.

Chapter 2

Literature Review

Droughts are considered a natural hazard. Awchi et al. (2017) conducted a detailed examination of meteorological drought in northern Iraq utilizing the Standardized Precipitation Index (SPI) and GIS. The study's main goals were to learn more about the origins and progression of drought in the region, to estimate its frequency and spatial distribution, and to identify drought-affected areas. To achieve this, the researchers used monthly rainfall data from nine meteorological sites from 1937 through 2010. To assess the severity of drought occurrences, SPI values were determined at three distinct time frames (3, 6, 12, and 24 months). The study revealed that northern Iraq has been facing frequent and severe drought occurrences, particularly in the breadbasket region. Apurv and Ximing (2019) conducted a comprehensive investigation into meteorological drought non-stationarity over multiple decades in various Contiguous United States regions from 1901 to 2017. To compare drought risk, they develop metrics under stationary and nonstationary assumptions, finding significant interdecadal changes in drought severity probability distribution functions in certain areas, regions including the Northwest, upper Midwest, Northeast, eastern areas of the Great Plains, as well as sections of Arizona, New Mexico, Utah, and Nevada in the Southwestern United States. Notably, the assumption of stationarity resulted in the underestimation of drought risk in these places. While multidecadal drought risk shows low variability in certain regions, the study revealed an alarming rise in meteorological drought risk in recent decades due to the influence of global warming, particularly in regions like California and the Southeast, where the chance of a meteorological drought has risen over the past few decades. In additionally Vélez et al. (2022) investigate the irregularity of Precipitation and drought patterns in the Barbate River Basin of Andalusia, Spain, from 1910 to 2017. The researchers developed a 108-year monthly precipitation history and used the Standardized Precipitation Index (SPI) to analyze droughts. They also investigate future drought and rainfall trends for the region and compare their findings to past research. Surprisingly, despite climate change estimates for this region, there is no discernible decrease in precipitation. The study's findings have important implications for improving water management and planning in the region, playing a crucial role in allocating water resources and supporting economic and agricultural development in the basin. The study proposed by (Vergni et al. 2021) demonstrates the effectiveness of other meteorological indices and the newly Standardized Deficit Distance Index in estimating the Impact of the agricultural drought in Central Italy. Tmax, Tmin, and daily precipitation data for 24 provinces in central Italy were collected from 1980 to 2019. Both indices were effective in assessing agricultural drought conditions, but SDDI was particularly good in analyzing the fluctuating patterns of water deficit over a multi-month period. The study highlights the importance of using Standardized indices to make educated decisions regarding irrigation management, crop selection, and other agricultural practices.

Drought prediction is crucial, especially in regions with unpredictable rainfall like Mediterranean countries. Jiménez et al. 2020 have come up with a new combined drought indicator (CDI) that combines rainfall, vegetation, and soil moisture data. They used satellite-based technology to monitor how plants respond to drought. There are four severity categories for the CDI: watch, warning, alert type I, and alert type II. They tested it in five grain-growing areas in SW Spain from 2003 to 2013 and found it accurately predicted major crop droughts in 2004-2005 and 2011-2012, matching real crop damage. This new tool could help safeguard crops and tackle drought impacts effectively. After one year (Niaz et al., 2022), present a novel method called RCAMD for characterizing meteorological drought. The RCAMD combines three standardized indices - SPI, SPEI, and SPTI utilizing steady-state probabilities and Monte Carlo feature selection. The validation of RCAMD was conducted at six selected regions in the northern areas of Pakistan, from January 1971 to December 2017. The study not only investigates the impacts of drought but also provides valuable insights into better comprehension and management of this phenomenon. Moreover, the research addresses a gap in previous studies by gathering more comprehensive information and provides practical implications for drought management in diverse regions. In a recent article, Ellahi et al. 2023 propose a novel method for measuring and monitoring the intensity of Meteorological drought. This method is divided into three stages: using Markov chain and Bayesian estimation, dissimilarity matrix-based clustering using C-index and Monte Carlo Feature-based Selection (MCFS), and Gaussian Mixture Distribution (GMD) in the computation. The validation of the framework was carried out on 52 meteorological locations in Pakistan over 49 years. For station selection, Relative Importance (RI) values are used, while Deviance Information Criteria (DIC) and Root Mean Square Error (RMSE) are applied to assess the performance of the model and its appropriateness. The result indicates the comprehensive and precise effectiveness of the method in quantifying and monitoring meteorological drought. In their recent study, Niazi et al.2023 present A novel approach for evaluating the severity of meteorological drought. They argue that existing drought assessment approaches are limited in capturing the intricate connections between various environmental factors. To provide a more comprehensive understanding of drought severity, their framework incorporates multiple meteorological variables such as temperature, precipitation, and wind speed. The authors highlight the practical applicability of this methodology in agriculture and water resource management. However, they acknowledge certain limitations, including the need for high-quality data and the potential for modeling errors. Overall, this research presents a valuable approach to drought analysis, emphasizing the importance of more sophisticated methods to comprehend the environmental impact of droughts.

To make the result more precise (Muhajir & Sari .2018) used a technique for clustering for the Classification of Earthquakes in Indonesia. In this article, the author studied that Indonesia, located at the intersection of three tectonic plates, is extremely prone to natural disasters, particularly earthquakes, due to its location within the Pacific Ring of Fire. The country stands out globally for its elevated seismic activity, recording a staggering 59,089 earthquakes in 2017. Consequently, effective mitigation strategies are imperative to minimize the devastating impacts of these earthquakes. This study employs clustering techniques, K-Affinity Propagation, and K-Means, respectively, to categorize earthquake-prone regions, thus aiding in targeted mitigation efforts. Validation is carried out using the C-Index, Davies Bouldin Index, and Connectivity Index. For K-Means, three and five clusters are tested, while K-AP is assessed with two and four clusters. Results highlight that the most optimal solution stems from a four-cluster arrangement, offering the highest variance ratio. The ensuing clusters include a two-member cluster centered on the Celebes Sea, a twelve-member Halmahera cluster, a single-member Minahassa Peninsula cluster, and a thirty-four-member Sumba Region cluster. Further in recent study (Ali et al. 2022) focuses on introducing a novel approach for determining the optimal number of clusters in huge datasets. The new technique uses a data-driven approach to automatically figure out how many clusters are suitable from the data itself, using the symmetry that's naturally present in clusters. The k-means method is run several times with various cluster densities (k values), and the final k value is chosen by assessing how symmetric the cluster centroid values are. The performance of this fresh algorithm is tested on both computer-generated datasets and real-world datasets from the UCI machine learning repository. The outcomes reveal that the suggested algorithm performs exceptionally well in terms of accuracy and also results in a significantly reduced root mean square error compared to existing methods. Many researchers use the Monte Carlo technique for different purposes Roy& McCallum (2001) focus on their article to revolve around an active learning technique that prioritizes the optimization of anticipated future errors. These popular techniques gain prominence because, for various learning models, computing the expected future error directly is complex. Our method becomes viable by adopting a Monte Carlo strategy to gauge the projected error reduction resulting from annotating a specific query. Experimental outcomes, based on three actual datasets, demonstrate that our approach attains remarkable precision using only a quarter of the labeled instances required by competing methods. Additionally, Dramiński et al. (2008) in their study delve into a technique designed to choose valuable features before supervised classification. The authors introduce a computationally intensive strategy wherein multiple tree classifiers are created for various randomly selected training sets. The aim is to pinpoint features that significantly contribute to accurate classification. The authors validate their method using diverse data sets, spanning biological and commercial domains. They assert that their approach differs from prior methods as it can effectively assess feature informativeness along with other features. The paper provides a thorough breakdown of the procedure and demonstrates its application on two distinct data sets: leukemia and lymphoma data.

In this article Orimoloye and Israel. 2022 investigated how droughts impact food security in South Africa's Free State Province, focusing on important crops like maize and sorghum. Researchers analyzed data from satellites and crop records spanning from 2011 to 2020. They found that extreme drought events in 2015 and 2018 had a devastating effect on the agricultural sector. During drought years, especially in 2014, 2015, 2016, and 2019, maize and sorghum production hit their lowest levels. These findings underscore the need to address the effects of drought on food production and can help policymakers develop better strategies to enhance food security in vulnerable regions. In this study, Kafy et al. 2023 examine the impact of droughts in the Barind Tract, a place in Bangladesh prone to droughts. They used satellite images to understand and predict how severe droughts have become over time. To evaluate and forecast drought vulnerability, several indices are used, including the Normalised Difference Vegetation Index (NDVI), Modified Normalised Difference Water Index (MNDWI), Soil Moisture Content (SMC), Temperature Condition Index (TCI), Vegetation Condition Index (VCI), and Vegetation Health Index (VHI). The results showed that droughts are getting worse, with less healthy plants and water bodies, and higher temperatures. They also predict that extreme droughts may increase in the future. This information can help decision-makers take action to better prepare communities and deal with droughts. A recent study by Rahman et al. 2023 examined the effects of drought on wheat and rice crops in Punjab from 2000 to 2020. Severe drought events were noted during 2000–2003, 2006–2008, 2013, 2017, and 2018. Using the Standardized Precipitation Evapotranspiration Index (SPEI), researchers found that southern Punjab faced more intense droughts due to higher temperatures. Districts like Layyah, D.G. Khan, Bahawalpur, and others were identified as mostly harmed. Wheat losses were particularly high in Attock, Bahawalpur, Chakwal, Pakpattan, and Sargodha, with monetary losses linked to SPEI coefficients. Drought significantly impacted crop yields, especially in D. G Khan. The findings emphasize the need for effective drought management strategies in the region.

The recent study conducted by Raza et al. (2023), in the northeastern part of Pakistan, investigated the spatial patterns of inter-seasonal drought persistence using Bayesian logistic regression. The analysis focused on meteorological drought using the Standardized Precipitation Index (SPI) in at three-month timeframe. Bayesian logistic regression was utilized to calculate the likelihood and odds ratios of drought happening in the present season, using SPI values from the preceding season as a basis. The results indicated a higher susceptibility to winter-to-spring drought persistence and lower vulnerability to summer-to-autumn drought persistence across the study region. Notably, the Bayesian logistic regression model provided more accurate and precise seasonal drought forecasts for the region. Additionally, In recent study, Niaz et al. 2023 Concentrates on the spatiotemporal and inter-seasonal attributes of meteorological drought, employing both the Random Effect Logistic Regression Model (RELRM) and the Conditional Fixed Effect Logistic Regression Model (CFELRM) at specific stations. The research results were gathered from 42 meteorological stations located throughout Pakistan between January 1971 and December 2017. The log-likelihood Ratio Chi-Square test (LRCST) and Wald Chi-square tests (WCTs) were employed to assess the significance of RELRM and CFELRM. Through the application of the Hausman test (HT), CFELRM emerged as the appropriate model for modeling Spring to Summer spatiotemporal drought. Similarly, in Summer to Autumn modeling using RELRM.

Chapter 3

A new comprehensive framework for identifying and monitoring the seasonal characteristics of meteorological drought

3.1. Introduction

A drought is defined as an extended period of precipitation shortage that exceeds the normal range, resulting in sustained insufficiencies in the availability of atmospheric, surface, or groundwater resources (Awchi et al. 2017; Ellahi et al. 2023). Drought occurs when an extended period of extremely dry circumstances results in a major shortage in water availability, either due to a severe lack of rainfall or an unexpectedly lower precipitation amount than projected (Amin et al. 2019). Global warming is becoming more severe on a worldwide scale. Several locations around the world have experienced rising temperatures and less precipitation in recent decades (Jiménez et al. 2020; Shah et al. 2021; Rahman et al. 2023), leading to an increase in severe drought occurrences. This warming trend is anticipated to worsen in the future, resulting in even more adverse conditions. The impact of global warming extends to weather phenomena, changes in climate patterns, and the availability of water resources (Niaz et al.2022a). Climate change directly affects agriculture and water resources (Wang et al. 2011; Nasrollahi et al. 2015), which means that droughts have a big effect on food availability and financial stability. For instance, drought in South Asia has impacted over 2 billion people, and since 1990, about 7 to 8 billion dollars have been spent to decrease the effects of droughts (Zipper et al. 2016; Rahman et al. 2023). Future forecasts predict a growth in the negative consequences of droughts on society and the economy. This is due to rising temperatures and increased human demand for water (Tushar and Ximing 2018). The ability to forecast and detect early indications of drought is vital for efficient management and Strategic preparation for agricultural resource management ahead of the onset of drought (Zhang et al. 2019). General drought is categorized into four primary types: Meteorological drought, i.e insufficient precipitation, Hydrological drought, i.e. groundwater & water flow reduction Agricultural drought, i.e. insufficient soil moisture and socio-economic drought i.e. the gap between water demand and supply (Jiménez et al. 2020; Shah et al. 2021; Lee et al. 2022;

Danandeh et al.2023). Among the several types of droughts, Meteorological drought is the most important because the severity of meteorological drought directly affects the presence of surface water and moisture in the soil (Rahman et al. 2023).

Meteorological drought can arise from a deficiency in Precipitation defined as a divergence from ordinary meteorological circumstances that causes the Earth's surface to dry out (Zhao et al. 2023; Danandeh et al.2023). Over the last 30 years, scientific studies have observed a gradual rise in the average global temperature of the Earth (Karl 2009; Liu et al. 2012). Multiple studies have indicated that Various climate change scenarios have been linked to an observed increase in temperature and greater fluctuations in Precipitation (Funk et al. 2014; Mao et al. 2015). Drought poses a significant threat to the environment and natural systems, with profound implications for the sustainable development of a society. It represents one of the primary natural hazards, with long-lasting effects on ecosystems, given that water serves as a fundamental lifeline for countries and regions (Amin et al. 2019; Ellahi et al. 2021). Meteorological drought and agricultural drought are interconnected through various aspects, such as the scarcity of rainfall, deviation from normal meteorological factors like evapotranspiration, insufficiency of soil moisture, and a decline in groundwater levels (Rodziewicz and Dice 2020; Iese et al. 2021; Niaz et al. 2022b). When a meteorological drought persists for an extended period, it can cause an agricultural drought because the lack of precipitation leads to a lack of soil moisture, resulting in lower crop production (Awchi et al. 2017). In addition to impacting crops, droughts also have adverse effects on orchards, forests, and the overall environment. Hence, droughts are recognized as significant obstacles to achieving optimal agricultural growth and ensuring food security (Alamgir et al. 2015). The extended duration of insufficient soil moisture is remarkably associated with hydrological drought, which affects the lack of water for a long period (Shah et al. 2021). All the types of droughts are interrelated with one another. Hence monitoring and evaluating meteorological drought is the first step towards improving the performance of operational drought monitoring systems (Niaz et al. 2023a). Meteorological drought can cause socioeconomic shifts that might lead to hunger, driving migration and causing large refugee crises (Wilhite 2000; Awchi et al. 2017). The severity of the consequences of meteorological droughts could potentially increase in the future, as the climate changes due to increased greenhouse gas concentrations in the atmosphere (Liu et al. 2021). Drought is a complicated natural phenomenon that cannot be eliminated. However, the impact of drought can be managed or reduced by using decision support systems to measure the physical attributes of droughts (such as duration, intensity, and severity) (Orimoloye 2022). To achieve this objective, researchers and climatologists worldwide have used drought indicators or indices to investigate meteorological droughts. They utilize this information to monitor the drought situation, inform the drought community, develop drought policies, and facilitate decision-making processes (Kafy et al. 2023).

Several indices have been derived to evaluate meteorological drought in different publications (Awchi et al. 2017; Liu et al.2021; Vélez-Nicolás et al. 2022;) are used for forecasting events. The Standardized Precipitation Index (SPI) is the most recommended and utilized measure to assess meteorological drought due to its ease of computation and capacity to evaluate drought over various periods. (Begueria et al. 2010; Rahman et al. 2023). Drought indices are extremely useful instruments in drought assessment because they play an important role in monitoring droughts and providing a comprehensive overview of drought conditions (Alahacoon and Amarnath 2022; Ellahi et al. 2021). The selection of an appropriate drought index is very important for effective drought monitoring in any region (Amin et al. 2019). Various research studies employ the SPI for standardizing observed precipitation data to calculate SPI values (Farahmand and AghaKouchak 2015; Jordaan et al. 2019). The SPI value can be converted in the third scale SPI-3 by the moving average method. Sein et al. (2021) utilized a three-month Standardized Precipitation Index (SPI) to assess agricultural drought, examining the spatio-temporal drought pattern and its impact on crop yields in Myanmar. Several research published using binary outcomes to identify the impact of drought (Bachmair et al. 2017; Niaz et al. 2021a; Niaz et al. 2022a). The problem is that the condition of drought persistence is not the same for all Seasons in Pakistan it changes from Season to Season. The inter-seasonal drought characteristics lessen the drought's potential drawbacks. Thus, it is crucial to identify the inter-seasonal aspects of meteorological drought for prediction (Niaz et al. 2022b; Raza et al. 2023). The Logistic regression model is appropriate for the binary dependent variable. Recently (Niaz et al. 2023b) used a logistic regression model for binary dependent variables to predict the meteorological drought persistence but it used all the locations in a study which is very complex to handle, and it used only one independent variable to analyze the drought persistence which does not give the comprehensive result of the spatio-temporal effect of inter-seasonal meteorological data. Thus, this issue of concern forms the basis for the creation of the novel approach. Therefore, in current research, we develop a new comprehensive ensemble-based approach for characterizing and monitoring the spatial attributes of inter-seasonal meteorological drought. we utilized the SPI-3 of the binary dependent variable with four independent variables at three three-month time scales (Temperature, Precipitation, Wind_Speed, and Profile_soil_moisture) and examined the inter-seasonal drought persistence for the representative locations only which have high RI values for each cluster. The C-Index uses the K-means method which makes eight appropriate clusters for the current analysis of homogeneous characteristics for precipitation of different locations. Ali et al. (2022) and Oliveira et al. (2023) introduced the K-Means method for clustering in their research. Monte Carlo Feature Selection is used to select the Relative Important (RI) locations from each cluster for analysis which choose eight locations for analysis and represent all the locations in Punjab. The Monty Carlo method has already been used in (Dramiński et al. 2008; Niaz et al. 2022a; Ellahi et al. 2023) research for different purposes. The logistic regression model is used for the binary dependent variable (i.e. one indicates drought persistence) and four independent variables. CFEBLRM and REBLRM are used to utilize the inter-seasonal drought persistence for eight representative locations that have high RI values in clusters. Further, the Wald Chi-square Test and Log-likelihood Ratio Chi-Square Test are utilized for the significance of CFEBLRM and REBLRM and the Hausman test is used to choose a more appropriate model in both for inter-seasonal drought persistence. This study aims to propose a new method to improve the result of the Binary Logistic Regression model to evaluate inter-seasonal drought persistence. This highlights the important information about meteorological drought to understand drought risk, develop drought monitoring, and mitigate measures for managing water resources to reduce the negative impacts of drought in the Punjab region of Pakistan.

3.2. Application

3.2.1. Description of the study area

The study focuses on stations of the Punjab Province of Pakistan located in the central-eastern region of the country with an area of about 205,344 square kilometers (79,284 square miles). Punjab consists of mostly landscape, and it is amongst the most heavily irrigated on the earth, there are several mountain regions including the Suleiman mountains in the southwest part of the province and the Margelle hills in the north of near Islamabad. The major rivers Indus and its tributaries Ravi, Jhelum, Chenab, and Sutlej flow through it. Punjab is the second-largest province of Pakistan. It is more fertilizer and most industrialized provinces and 24% of GDP are contributed by their industrial sectors. Due to these several properties Punjab region is vital for other regions, and it has the lowest rate of poverty among all the regions of Pakistan. Moreover, data from 24 stations are chosen as a representative sample of the climate in the study area. Punjab is facing severe water scarcity due to an increasing demand for water resources by the population's livelihood, agricultural, energy, and industry sectors therefore

Punjab province has become a drought-prone region. Climate change caused significant disturbances across the entire globe. A result of differences in climate change scenarios such as an increase in temperature and variability in precipitation cause the unsustainability of Punjab and it affects negatively the economic and agricultural sectors (Syed et al. 2021; Niaz et al. 2022b). Therefore, it is important to monitor drought characteristics by getting information about annual drought frequency for a selected station.

3.2.2. Data

We retrieved the time series 40 years of metrological monthly data ranging from Jan 1981 to Dec 2021 for 24 stations in the Province of Pakistan. These stations have been chosen because of their significant climatological attributes, which play a crucial role in accurately defining and observing the risks associated with droughts. We have included the variables Precipitation(mm/day), Temperature(2m), Wind, Profile Soil Moisture, and Dew which are suitable for the analysis of metrological drought. The data are taken from the NASA Power Data Access online website with a resolution of 0.5*0.625 degrees. This is a web mapping application that is used to show a quick look at metrological data products. On the web the data are available for the whole country we separate it for the Province of Punjab which we need and prepare it for every variable which is helpful for our analysis. The climate changes from season to season in Pakistan. Hence, these fluctuations in climatic characteristics in inter-seasonal are important to be recognized (Nawaz et al. 2019). Therefore, we arrange the data in four seasons due to their homogeneous characteristics Winter (Dec to Feb), Spring (March to May), Summer (Jun to Aug), and Autumn (Sep to Nov) for inter-seasonal drought characteristics. For the current analysis, the SPI is utilized for a three-month scale SPI-3. The dependent variable is binary in which 1 shows the persistence of the drought in the current season. The entire globe is significantly affected by climatological change which damages the balance of nature. With a single drought, the country loses millions of dollars which damages the whole economy of the country and is intact for several years. A metrological drought can affect agriculture, food production, and human health, limit worker productivity and increase mortality even a single drought brings a lot of risk. The prediction and early signs of drought are particularly important for the management and planning of agricultural resources before the onset of drought, so we must pay attention to the people and drought management to improve their stratifies. Therefore, it is important to monitor meteorological drought characteristics to see the seasonal drought persistence in selected stations.

3.3. Methodology

3.3.1. K-Means Clustering

Clustering is an unsupervised machine-learning technique that allows one to find patterns and identify groups of similar observations in multivariate data to extract relevant information. Thus, clustering can be very helpful for forming groups according to the object (Oliveira et al.2023). Clustering aims to partition data into homogeneous groups to reduce heterogeneity such that the data in the same cluster are more similar to each other than the data in other clusters. (Wang et al. 2017). Different datasets require different clustering methods chosen from different categories of clustering (e.g., Partitioning Methods, Density-based Clustering, K-Means clustering, and Hierarchical Clustering) (Xu and Tian. 2015; Oliveira et al.2023). Within these categories, k-means is one of the most widely used clustering algorithms due to its ease of implementation, simplicity, efficiency, and empirical success (Steinle and Douglas. 2006; Wang et al. 2017). Here the K-Means is the suitable method for clustering by using Precipitation data. K-Means is a distance-based clustering method that looks for the division of the data into K clusters on similar characteristics that minimize the within-cluster sum of squares and maximize the sum of squares between the clusters (Syakur et al.2018; Muhajir et al. 2018). K-Means algorithm starts with a random selection of k, where k is the number of clusters to be formed (Muhajir et al. 2018). It randomly initializes the cluster centroids and assigns data points to the nearest (closest) cluster centroid based on the Euclidian distance between data points x_i} and centroids {$\bar{X}$k } (Ali et al. 2022). The distance calculated between any two points is defined as:

$$\text{Euclidean distance} = \mathrm{d}(x_i, \bar{x}_k) = \sqrt{\sum_{i=1}^{n}(x_i - \bar{x}_k)^2} \quad (1)$$

The objective is to minimize the sum of squared error among data points and their respective clusters are defined as

$$S = \sum_{k=1}^{k} \sum_{c(i)=k} \mathrm{d}(x_i, \bar{x}_k) \quad (2)$$

x_i is ith data point and $\bar{x}_k$ is the cluster centroid. In the current study, eight clusters are formed for twenty-four locations and the locations are assigned to these clusters by the same means.

3.3.2. Monte Carlo Feature Selection (MCFS)

Monte Carlo is the algorithm for feature selection by ranking each attribute or feature in terms of Relative importance in high-dimensional data problems (Draminski et al. 2008; Ellahi et al.2023). Recently (Niaz et al. 2022a) used MCFS to select important stations in the northern region for their analysis. we estimate the relative importance of features by constructing thousands of trees for randomly selected subsets of features. More precisely, from a set of d features, s subsets of m features are chosen (with m being fixed and smaller than d). For each feature subset, t trees are created. In the inner loop, each of these t trees is trained on a random 66% of samples and tested on the remaining 34%. Overall, st trees are constructed and evaluated. Both s and t should be sufficiently large to ensure that each feature has opportunities to appear in various feature subsets.

To determine relative importance, let us first introduce weighted accuracy which is denoted as

$$wAcc = \frac{1}{p} \sum_{i=1}^{p} \frac{n_{ii}}{n_{i1} + n_{i2} + \cdots + n_{np}} \tag{3}$$

$wAcc$ is weighted accuracy, p is a true positive rate, n_{ij} denote the number of samples from class i classified as those from class j. i, j = 1, 2, ..., c and $\sum_{i,j} n_{ij} = n$

Where the Relative Importance can be defined as

$$RI_{hk} = \sum_{\tau=1}^{st} (wAcc)^{u} \sum_{n_{hk}(\tau)} \left(GR\left(n_{hk}(\tau)\right)\right) \left(\frac{no.\ in\ n_{hk}(\tau)}{no.in\ \tau}\right)^{v} \tag{4}$$

$GR\left(n_{hk}(\tau)\right)$ denotes the gain ratio for tree nodes, no. $n_{hk}(\tau)$ is the number of samples in the node $n_{hk}(\tau)$, no. in τ is the number of samples in the root of τ^{th} tree. The values of three parameters, m, s, and t were prespecified by a practitioner and set $u = v = 1$. In the current study, the Punjab regions of Pakistan are divided into eight clusters by a method of K-Means clusters. The selected stations in clusters provide a homogeneous pattern of meteorological drought. Here we use MCFS to Select the important stations in different clusters for analysis, based on this method we select one station from each cluster which have a large relative importance value as compared to other stations. For instance, Pakpattan is selected as the important station for cluster1and in cluster2 Gujranwala is selected as an informative station. In this way, the MCFS selects the informative stations for our analysis.

3.3.3. Standardized precipitation index at scale-3 (SPI-3)

The Standardized Precipitation Index (SPI) method created by McKee et al. (1993) is used in the current study to evaluate and track the drought condition. SPI has demonstrated its effectiveness in comparing drought conditions between different regions, offering a valuable tool for understanding and comparing drought patterns across various geographical areas (Guttman 1998; Alamgir et al. 2015). The SPI was developed to measure the extent of precipitation deficiency across various time frames, such as one, three, six, nine, and twelve months. These time scales help in determining the impact of drought on the availability of different water resources. Each time scale represents a distinct aspect of drought, where shorter periods assess shorter-term drought events, and longer periods provide insights into longer-term drought patterns (Hayes et al. 2007). The SPI allows for a comparison of precipitation amounts over a specified time and historical precipitation totals for that same period across all available years. For example, a six-month SPI produced at the end of October compares total precipitation from May to October of a particular year to total precipitation from May to October of preceding years in the historical record (Alamgir et al. 2015). To identify an appropriate time scale for the SPI, we examine the monthly correlation between streamflow anomalies and the SPI across a range of time scales ranging from 1 to 24 months (Haslinger et al. 2014) if the highest correlations occur during the low-flow season, specifically from August to October at a time scale of 3 months, we can assume that a 3-month time aggregation is most suitable for conducting further investigations. To compute SPI, a long-term precipitation record of at least 30 years is required (Wu et al. 2001) The SPI has several distinguishing features, including simplicity, spatial consistency, a probabilistic nature, and a capacity to represent droughts across both spatial and temporal dimensions. While the SPI is relatively easy to calculate in comparison to other indices, the SPI helps provide early warnings for drought events and helps in drought damage reduction (Liu et al. 2012; Awchi et al. 2017). The process of SPI analysis involves transforming the rainfall data into a normal distribution using the Gamma probability distribution (Awchi et al. 2017). The SPI can also be calculated by using the marginal probability of precipitation formula instead of the gamma distribution function (Farahmand et al. 2015).

$$p(\mathrm{x_i}) = \frac{\mathrm{i}-0.44}{n+0.12} \tag{5}$$

i denotes the rank of non-zero precipitation data and n denotes the sample size.

The output of this equation is transformed into a Standardized Index (SI) as

$$SPI = \Phi^{-1}(P) \tag{6}$$

Where Φ is the standard normal distribution function, and p is the empirical probabilities.

$$SPI = \begin{cases} -\left(t-\frac{l_0+l_1t+l_2t^2}{1+z_1t+z_2t^2+z_3t^3}\right) & \text{if } 0 < \mathrm{p} \leq 0.5 \\ +\left(t-\frac{l+l_1t+l_2t^2}{1+z_1t+z_2t^2+z_3t^3}\right) & \text{if } 0.5 < \mathrm{p} \leq 1 \end{cases} \tag{7}$$

where

$$t = \begin{cases} \sqrt{ln\frac{1}{p^2}} \\ \sqrt{ln\frac{1}{(1-p)^2}} \end{cases}$$

Where $l_0 = 2.515517$; $l_1 = 0.802583$; $l_2 = 0.010328$; $z_1 = 1.432788$; $z_2 = 0.010328$ $z_3 = 0.001308$

Positive values of the SPI indicate above-average precipitation or wet periods, whereas negative values indicate below-average precipitation or dry periods (Al-Qinna et al. 2011; Awchi et al. 2017). The SPI provides a clear classification of different levels of drought severity. When the SPI number falls below -1.5, the drought is deemed severe, and when it falls below -2, it is considered extreme. As a probability-based index, the intensity of a precipitation event in the SPI is determined relative to the typical rainfall patterns of a specific area. Calculating the SPI requires a long-term record of precipitation data (Liu et al. 2012). This research paper utilizes the SPI-3, which corresponds to a three-month time scale typically used for evaluating medium-term drought conditions (Jiménez et al. 2020). SPI-3 helps smooth out short-term fluctuations and provides a better understanding of medium-term trends. The SPI-3 is calculated using precipitation data collected over the previous three months and converted the SPI to SPI-3 by the Moving average Method. In SPI-3 each month of precipitation is equal to the average of the last three months for each month. for example, if we want to calculate the three-month precipitation moving average for November, we calculate the average of September and October of the given year. The formula for the moving average is defined as:

$$\bar{y}_t = \frac{y_t + y_{t-1} + \cdots + y_{t-n}}{n} \tag{8}$$

3.3.4. Panel Binary Logistic Regression Model

In panel data observations are collected over time for multiple individuals or groups. Logistic or Logit regression models are very common in the fields of healthcare, business, banking, and sociology. We commonly used a logistic model for fixed versus random effects. We can categorize the responses as binary, ordinal, or nominal, here we focus on binary logistic regression models, in which we have two outcomes for the dependent variable.

The binary panel model as

$$z_{it}^{*} = \alpha_i + \beta X_{it} + \varepsilon_{it} \quad \mathrm{i} = 1,2,\ldots,\mathrm{n}, \ \mathrm{t} = 1,2,\ldots,\mathrm{T} \tag{9}$$

$$\mathrm{z_{it}} = 1 \ if \ z_{it}^{*} > 0, \text{and zero otherwise}$$

Z_{it} be the binary dependent variable for individual i at time t, X_{it} be a vector of independent variables for individual i at time t, β be a vector of coefficients associated with each independent variable, $\alpha_i$be the individual-specific intercept which captured the unobserved heterogeneity and represents the baseline log odds of the dependent variable (drought=1) for each group, and the coefficients represent how the log odds change for the independent variables. and ε_{it} is called idiosyncratic errors because these vary across i as well as across t. Ideally, we are interested in the correlation of ε_{it} and ε_{is} within the group but uncorrelated across the groups. The logistic model assumes a linear relationship between the log odds of the probability of Z being 1 (success) and the independent variables. $Z_{it}$is the linear combination of the independent variables and their corresponding coefficients, also known as the log odd. In the context of panel considers, both fixed and random logit models are extensions of the standard logit model that consider the presence of individual-specific or group-specific effects. These models are commonly used when analyzing panel data, where observations are grouped into different entities (e.g., locations) and are observed over multiple periods. The key difference between fixed and random logit models lies in how they treat these individual-specific or group-specific effects. The fixed effect is used when the $\alpha_i$and $X_{it}$is correlated it means that the conditional distribution of $f\left({\alpha_i}/{X_{it}}\right)$ is not correlated with $X_{it}$and the Random effect model is used when the $\alpha_i$and $X_{it}$is not correlated.

3.3.4.1. Conditional Fixed Effect Binary Logistic Regression Model: (CFEBLRM)

The CFEBLRM individual-specific effects are treated as fixed parameters. It assumes that these effects are constant and do not vary across individuals or groups in the population. Essentially, the fixed logit model estimates separate intercepts for each individual or group, but these intercepts are not allowed to vary based on any underlying distribution. This model is also known as the "within-subjects" or "entity-specific" model. The conditional fixed effect binary logistic regression model gives a more consistent estimate than the unconditional fixed effect binary logistic regression model. The most common nonlinear function is the logistic function.

The probability of binary response for a nonlinear model is.

$$p_r(z_{it} = 1/X_{it}\,, \alpha_i \,) = \frac{\exp(\beta X_{it} + \varepsilon_{it})}{(1+\exp(\beta X_{it} + \varepsilon_{it}))} \tag{10}$$

And

$$p_r(\, z_{it} = 0/X_{it}\, , \alpha_i\,) = \frac{1}{(1+\exp(\beta X_{it} + \varepsilon_{it}))} \quad (11)$$

$p_r(\, z_{it} = 1/X_{it}\, , \alpha_i\,)$is the probability of z_{it}being 1 (persistence drought) and 0 (not persistence drought) given the values of the independent variables X.

z_{it} is the linear combination of the independent variables and their corresponding coefficients, also known as the log odd.

$f(X_{it}\beta + \varepsilon_{it})$ is a cumulative distribution function for the logistic variable with a range of zero to one.

The conditional probability for the response variable is given as:

$$p_r\left({}^{Y_i}\!\Big/_{X_i, \sum_{t=1}^{T} z_{it}} \right) = \frac{\exp \sum_{t=1}^{T} Y_{it}\beta X_{it}}{\sum_{d_i \in A_i} \exp \sum_{t=1}^{T} d_{it}\, \beta X_{it}} \quad (12)$$

Where

$$Ai = di1\, , di2\, , \ldots\ldots, \qquad dit\ /\ dit\ \ for\ response = 0\, , 1$$

And

$$\sum_{d_i} A_i = \sum_{t} z_{it}$$

The Conditional probabilities for t=2

$$p_r(z_{i1} = 0, z_{i2} = 1/X_{i1}, X_{i2}\, , z_{i1} + z_{i2} = 1\,) = \frac{\exp(X_{i2} - X_{i1})\beta}{1+\exp(X_{i2} - X_{i1})\beta} \quad if\ z_{i1}, z_{i2} = (0{,}1) \quad (13)$$

$$\Pr(z_{i1} = 1, z_{i2} = 0/X_{i1}, X_{i2}\, , z_{i1} + z_{i2} = 1\,) = \frac{1}{1+\exp(X_{i2} - X_{i1})\beta} \quad if\ z_{i1}, z_{i2} = (1{,}0) \quad (14)$$

There is involve the unobserved α_i in the model which makes it complex to estimate the parameters for the logistic model. The conditioning minimum sufficient statistic for α_i is used for estimating the equation to eliminate the α_i. Then the parameters for the model are estimated by conditional log-likelihood.

The conditional Log-likelihood function is:

$$lnL = \sum_{i=1}^{N} \left\{ d_{01} ln\left(\frac{\exp(X_{i2} - X_{i1})\beta}{1+\exp(X_{i2} - X_{i1})\beta} \right) + d_{10} \ln\left(\frac{1}{1+\exp(X_{i2} - X_{i1})\beta} \right) \right\} \quad (15)$$

The low p-value of the Hausman test indicates the endogeneity in the model and such cases, it recommends the CFEBLRM because it is less susceptible to endogeneity concern and can help to mitigate the impact of endogeneity and omitted variable bias.

3.3.4.2. Random Effect Binary Logistic Regression Model: (REBLRM)

Also called the component of the variance model. The REBLRM is used when there is no endogeneity in the model it means the independent variable and error term are not correlated. It also controls the unobserved heterogeneity between the groups in the model.

The REBLRM is defined as

$$z_{it} = \alpha_i + \beta X_{it} + u_i \qquad i = 1,2,\ldots,n, \; t = 1,2,\ldots,T \tag{16}$$

Here the u_i is random error effect. In random effect the α_i is a random individual-specific effect and it is specified as distributed by Gaussian.

$$f(z_{it}/X_{it}\;,\alpha_i) = \exp\{\textstyle\sum_{i=1}[z_{it}\,(\alpha_i + \beta X_{it}) - \ln(1 + \exp(\alpha_i + \beta X_{it}))]\} \tag{17}$$

M is the binomial denominator of binomial logistic model. The probability function in exponential family form as:

$$f(z_{it}/X_{it}\,M_{it}\,,\alpha_i) = \exp\left\{\textstyle\sum_{i=1}\left[z_{it}\,(\alpha_i + \beta X_{it}) - M_{ij}\ln(1 + \exp(\alpha_i + \beta X_{it})) + ln\binom{M_{it}}{z_{it}}\right]\right\} \tag{18}$$

For estimating the parameter of the Random Effect Binary Logistic Model, the Log-likelihood function for the Bernoulli model is given as:

$$L(z_{it}/X_{it}\;,\alpha_i) = \textstyle\sum_{i=1}[z_{it}\,(\alpha_i + \beta X_{it}) - \ln(1 + \exp(\alpha_i + \beta X_{it}))] \tag{19}$$

3.4. Results

The Persistence of drought has a negative impact on agriculture, economic structure, and living organisms. In the current study, we investigate the characteristics and persistence of meteorological drought in several meteorological stations of Punjab. The 24 stations are selected from the Province of Punjab Pakistan for analysis. The selection of the province Punjab is a significant attraction and relative importance for the country due to Various industrial goods and services. Several researchers used this region for drought analysis (Waseem et al. 2022; Niaz et al. 2022b; Rahman et al. 2023). Further, the stations are divided into Eight appropriate clusters based on the C-Index K-Means method and MCFS is chosen as one relative importance station for each cluster. The selected locations play a significant role in the agricultural sector of the country. Moreover, the SPI-3 seasonal data of precipitation with four independent variables of a three-month time scale are utilized for drought analysis of the final selected stations. Multiple scholars have conducted research on inter-seasonal drought persistence (Meng et al. 2017; Niaz, et al. 2021b; Niaz et al. 2022b; Niaz et al. 2023b). The dependent variable is binary with one indicating drought persistence and zero indicating No drought persistence. The analysis involves evaluating drought persistence within four different periods for selected stations, such as the winter and spring season data utilized to calculate the Winter-to-Spring drought persistence for selected stations. Hence for Winter-to-Spring drought persistence the Precipitation, Temperature, Wind_Speed, and Profile_soil_moisture of a three-month time scale are used as independent variables. Further, the odd ratio defines the relationship between the binary dependent variable and independent variables. In the current analysis, the binary variable identified the significance of the preceding season to the current season by including the CFEBLM and REBLM. The significance of CFEBLM and REBLM is evaluated by LRCST and WCT and the Hausman test is used to check the endogeneity in independent and error terms and then select the appropriate model to find the inter-seasonal meteorological drought persistence for selected stations in the Province of Punjab Pakistan.

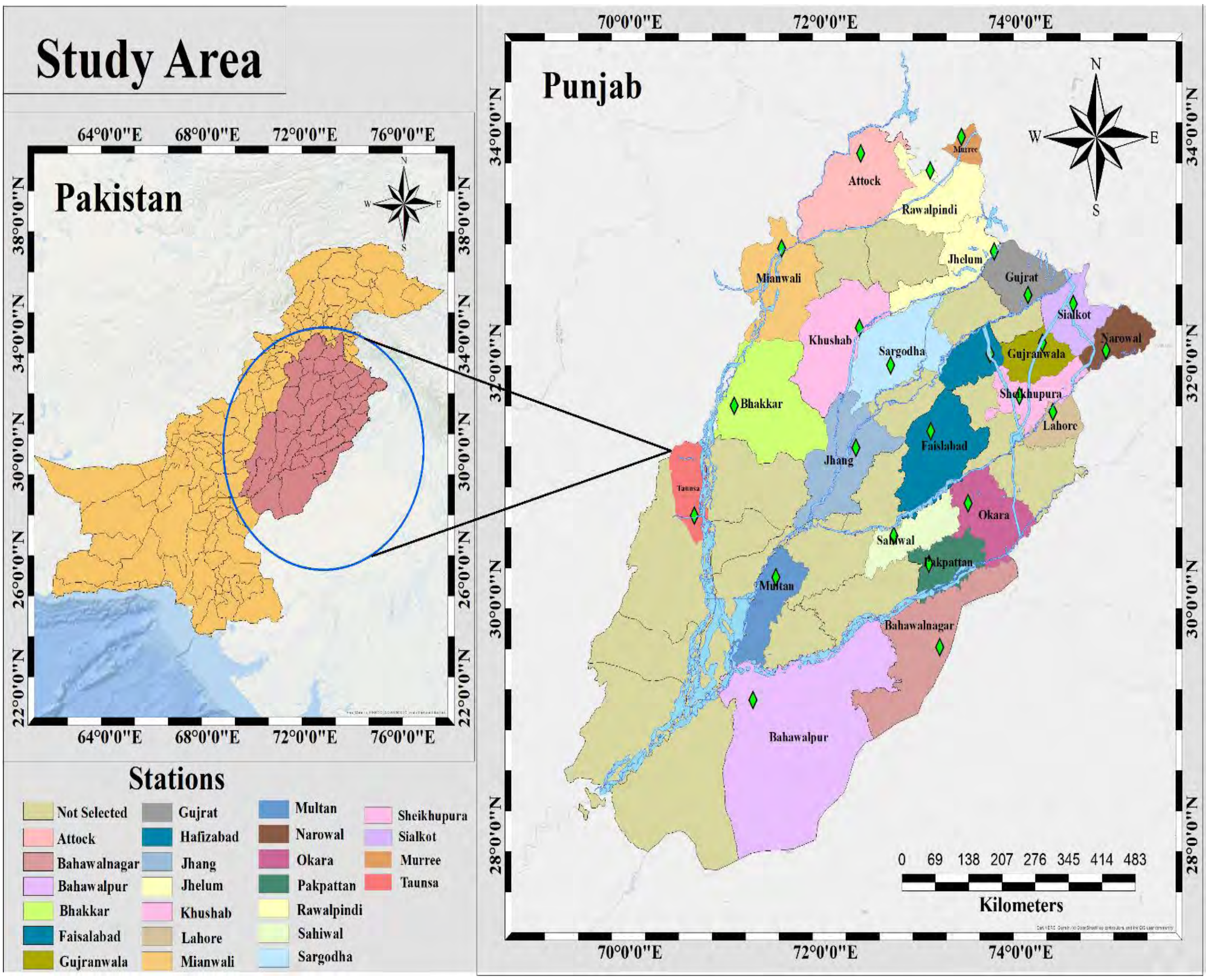

Figure 1. The Study Area of geographical locations for selected locations.

Figure 1 presents all the selected locations of meteorological data of the Punjab region for analysis. The eight representative locations are selected from these locations by using K-means and MCFS to find the comprehensive temporal effect of meteorological drought.

Table 1. Metrological Characteristics of the precipitation are given for the various stations.

Variable	Stations	Latitude	Longitude	Elevation(m)	Mean	1st Quartile	Median	3rd Quartile	Kurtosis	St.Dev
Precipitation	Bahawalpur	29.14	71.26	103.43	10.10	0.00	0.00	15.77	26.14	18.69
	Taunsa	30.71	70.66	380.65	15.73	0.00	5.27	21.09	107.09	30.10
	Faisalabad	31.42	73.08	182.92	28.88	5.27	13.19	36.91	9.69	40.99
	Jhang	31.28	72.31	166.19	26.69	0.00	10.55	31.64	9.99	38.69
	Gujrat	32.57	74.08	259.97	62.71	10.55	31.64	79.10	4.53	81.24
	Hafizabad	32.07	73.69	205.86	45.12	5.27	21.09	56.69	5.74	60.65
	Gujranwala	32.17	74.22	222.55	53.52	5.27	26.37	68.55	5.65	74.04
	Narowal	32.10	74.87	246.55	60.20	5.27	26.37	73.83	5.14	84.17
	Sialkot	32.50	74.54	259.97	62.71	10.55	31.64	79.10	4.53	81.24
	Lahore	31.58	74.33	209.49	43.51	5.27	21.09	56.69	6.76	62.19
	Sheikhupura	31.72	73.99	196.55	35.42	5.27	15.82	42.19	7.46	50.08
	Bhakkar	31.63	71.07	165.67	21.40	0.00	10.55	31.64	18.82	32.69
	Mianwali	32.97	71.55	483.96	35.39	5.27	21.09	52.73	7.87	41.63
	Multan	30.18	71.49	118.02	13.63	0.00	5.27	15.82	82.05	27.77
	Attock	33.77	72.36	451.02	56.32	10.55	31.64	73.83	15.94	71.23
	Rawalpindi	33.63	73.07	543.83	74.54	15.82	36.91	100.20	18.69	98.00
	Jhelum	32.94	73.73	384.47	65.65	10.55	36.91	85.44	3.77	80.66
	Sahiwal	30.54	72.70	149.30	17.57	0.00	5.27	21.09	40.57	31.69
	Pakpattan	30.30	73.06	162.38	19.50	0.00	7.75	26.37	47.79	34.09
	Okara	30.81	73.46	184.88	28.53	0.00	10.55	36.78	8.98	40.98
	Khushab	32.29	72.35	407.13	37.45	5.27	21.09	47.46	10.65	51.55
	Sargodha	31.98	72.67	178.57	30.88	3.95	15.82	36.91	7.43	43.95
	Murree	33.91	73.39	2291.00	75.71	15.82	44.83	105.47	7.27	85.81
	Bahawalnagar	29.59	73.17	163	17.41	0	5.27	21.09	71.63	32.75

The features of precipitations are given for selected meteorological stations. These features indicate the climate pattern of various stations.

The above table shows the characteristics of precipitation for various meteorological data. Each row corresponds to a specific station and includes information such as its geographical coordinates (latitude and longitude), and elevation above sea level. The statistical metrics encompass the mean precipitation, quartile values (1st, 2nd, and 3rd), kurtosis, and standard deviation. The mean precipitation values provide an understanding of the average amount of rainfall encountered at each station. For example, the high mean of precipitation recorded in this table for Rawalpindi and Jhelum is 74.54 and 65.65. at the same time, quartiles provide an understanding of the distribution of rainfall data. Stations with higher quartile values indicate regions with heavier rainfall occurrences. The kurtosis values characterize the shape of the distribution, with positive values suggesting more extreme events. All the row value of standard deviation shows different variation for different stations. The standard deviation indicates the variability of precipitation around the mean. For example, the high variation record for Rawalpindi is 98.00 from the high mean. This comprehensive dataset provides a basis for analyzing and comprehending the diverse precipitation patterns that exist across the different stations.

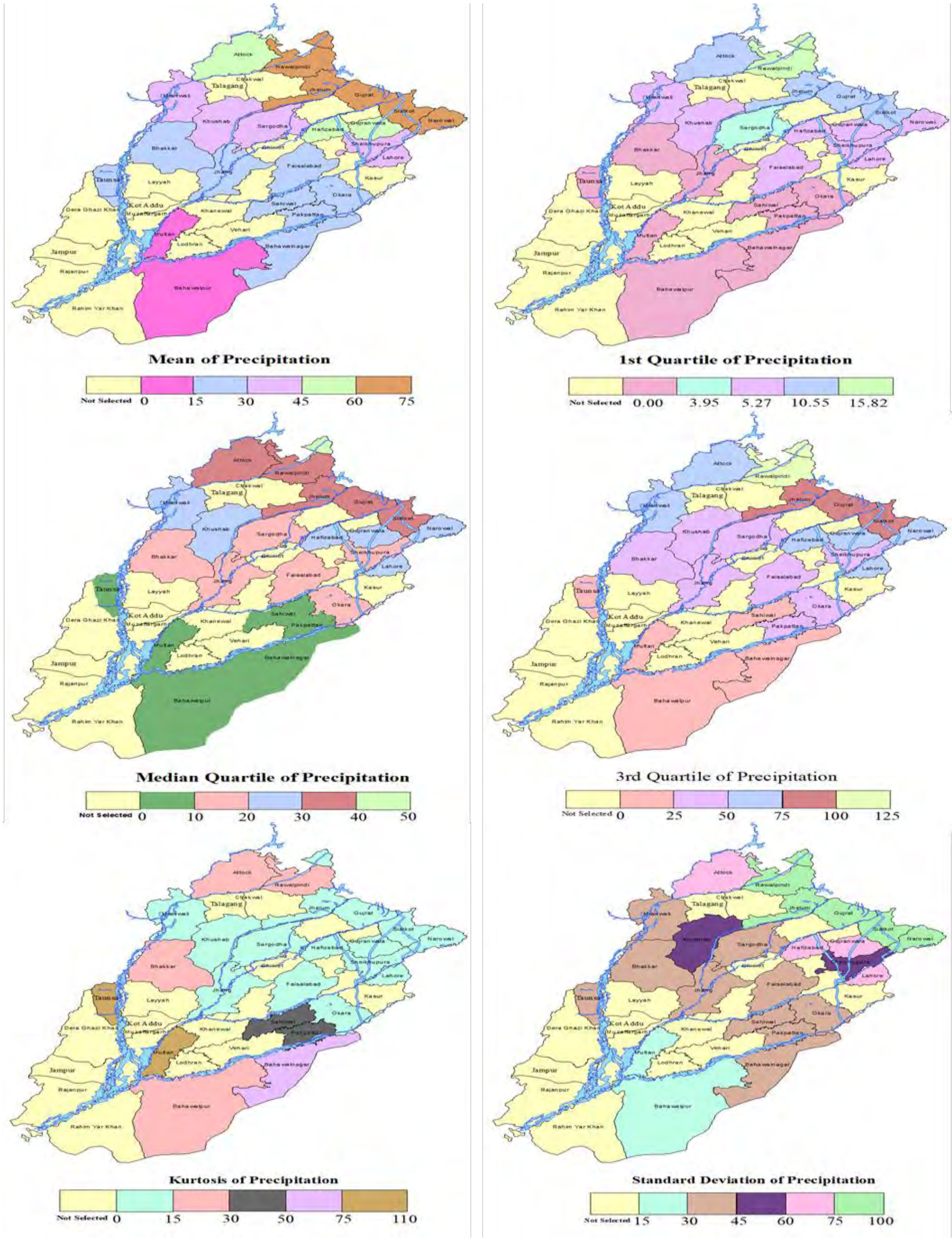

Figure 2. The characteristics of the precipitation for Selected Geographical Stations.

The above figure shows the characteristics of precipitation visually for the selected stations of meteorological data. Which is already interpreted in Table 1. Here the first map shows the precipitation of all selected stations, and its values are defined by legend. The second, third, and fourth maps indicate the first, second, and third quartiles of precipitation. Similarly, the fifth map indicates the shape of precipitation and the last map shows the variation of each station from its mean values. The figure defined the behavior of precipitation for selected stations of range 1981 to 2021 then we easily worked on this data to use for our analysis.

Table 2. The best-fitted probability distributions of SPI-3 and their BIC values.

Stations	Distribution	BIC	Stations	Distribution	BIC
Faisalabad	Log-normal	-1032.76	Gujranwala	Generalized Extreme Value	-1577.67
Rawalpindi	Generalized normal	-1226.28	Gujrat	Johnson SU	-941.68
Sargodha	Johnson SU	-1201.68	Hafizabad	Johnson SU	-1555.51
Sialkot	Johnson SU	-941.68	Jhang	Generalized Extreme Value	-1023.96
Murree	3P Weibull	-1636.71	Khushab	Johnson SU	-962.62
Bahawalpur	3P Weibull	-657.84	Narowal	Johnson SU	-989.77
Mianwali	Gamma	-1372.44	Okara	Johnson SU	-919.24
Lahore	Johnson SU	-1357.45	Pakpattan	Generalized normal	-1123.60
Jhelum	Log-normal	-1255.70	Sahiwal	Generalized normal	-946.97
Multan	Gamma	-1085.42	Sheikhupura	Johnson SU	-1099.03
Attock	3P Weibull	-1698.43	Taunsa	Gamma	-1402.96
Bhakkar	Generalized normal	-951.88	Bahawalnagar	Generalized normal	-1195.27

The appropriate Probability distributions and their BIC values for the Standardized Precipitations Index of selected stations at a three-month time scale.

The above table provides a summary of different statistical distributions fitted to data from various stations of Province Punjab in Pakistan. Each station is associated with a specific distribution, and the goodness of fit for each distribution is indicated by the corresponding Bayesian Information Criterion (BIC) value. The distributions used include Log-normal, Generalized Extreme Value, Johnson SU, 3P Weibull, Generalized normal, Gamma, and others. These distributions are used to model the characteristics of certain variables in each station data. The negative BIC values suggest the relative quality of the distribution fits, with lower values indicating better fits. For instance, the Johnson SU distribution fits the data from Gujranwala and Hafizabad stations well, as indicated by their comparatively lower BIC values, while in stations like Murree and Attock, the 3P Weibull distribution provides better fits. The table presents a summarized comparison of distribution fits and their quality across different stations.

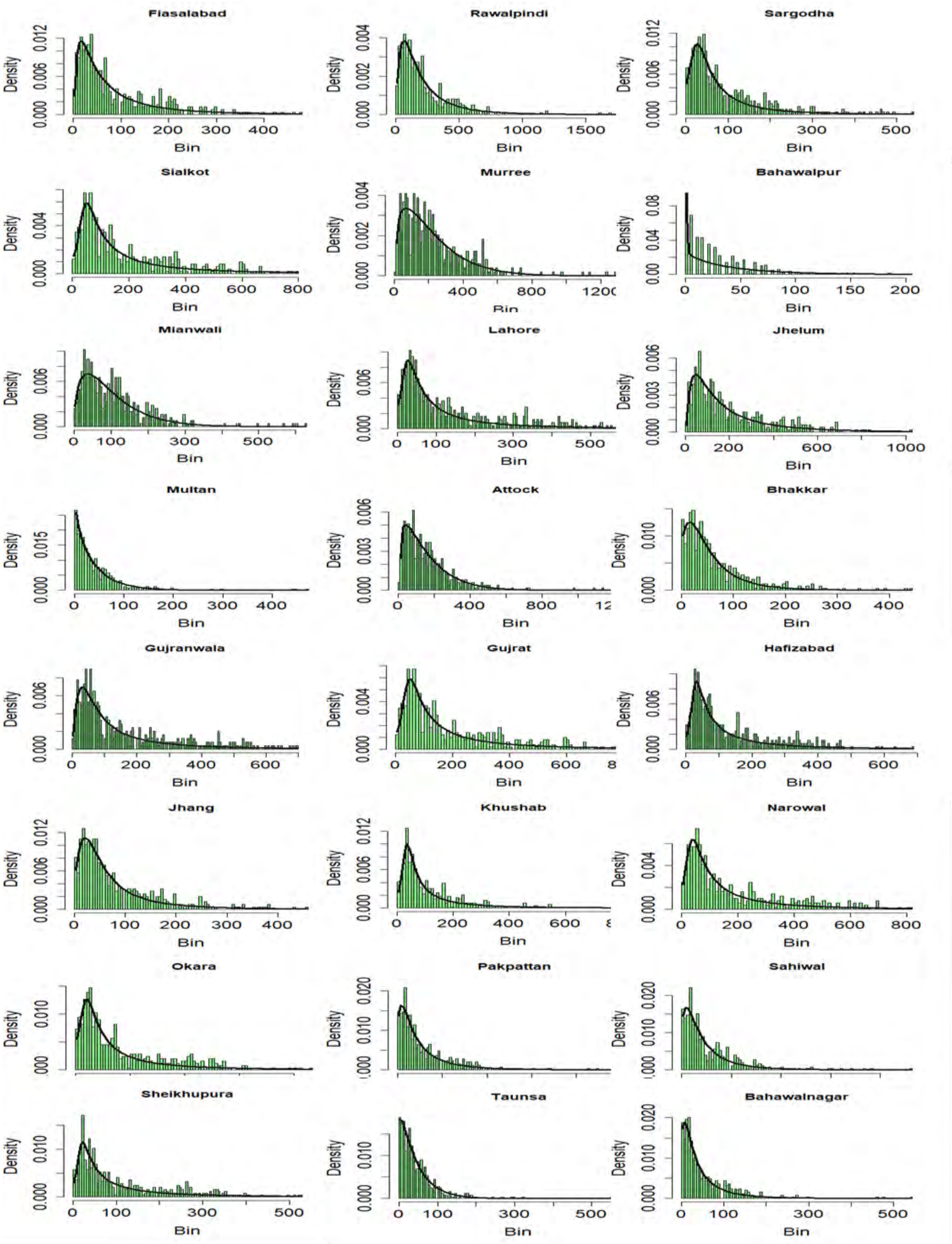

Figure 3. Histograms of appropriate probability distributions for SPI-3 at selected meteorological stations.

The figure shows a summary of various statistical distributions that were used to fit data from different stations. Each station presents best fitted distribution with have small Bayesian Information Criterion (BIC) value. We already described these distributions of various stations of Punjab in the previous Table 2, but here the distribution is defined graphically which is easy to understand and looks beautiful. but here, we're showing them visually, which makes it easy to understand and visually attractive.

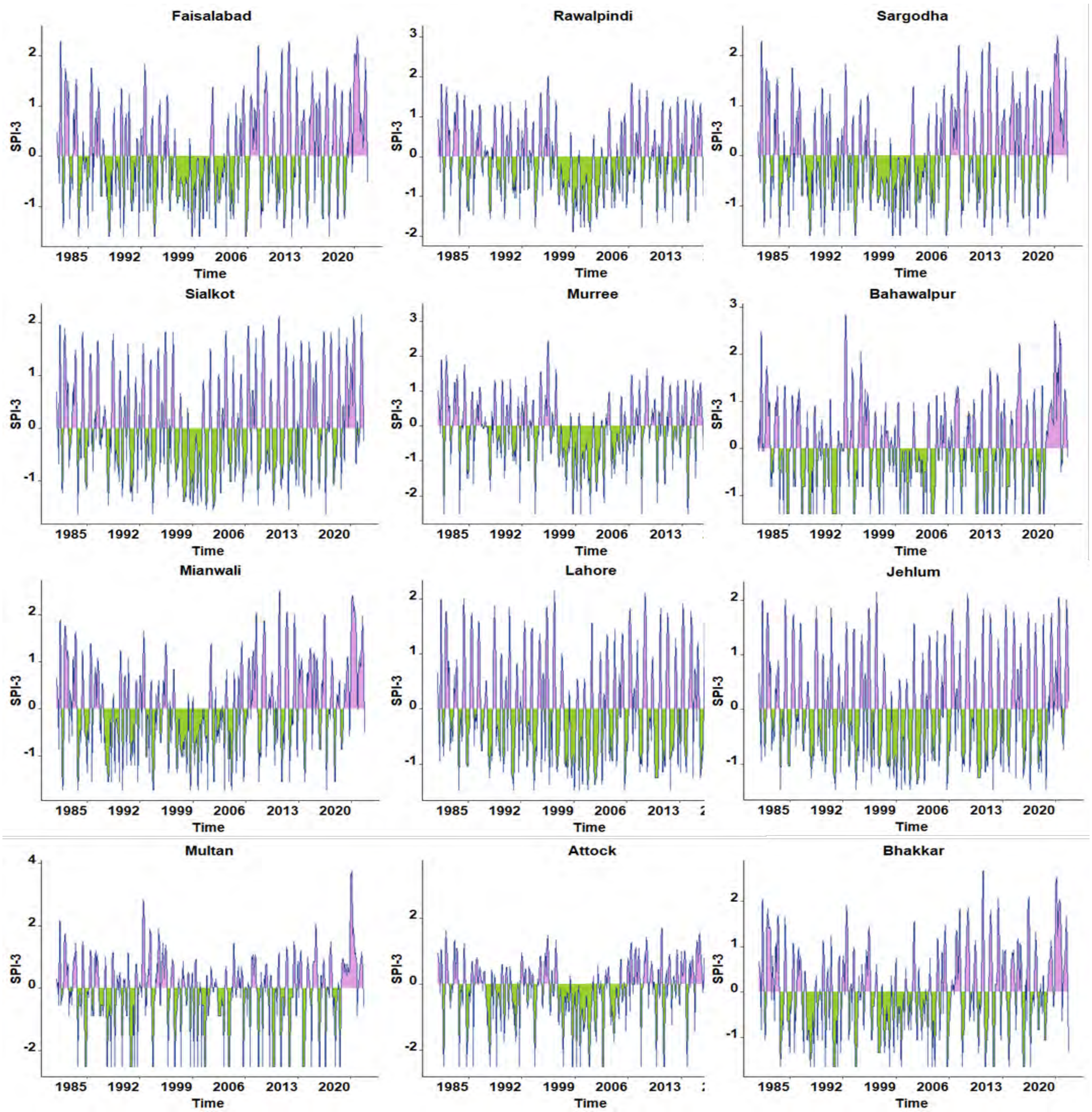

Figure 4. The temporal plots for SPI-3 for several stations are given.

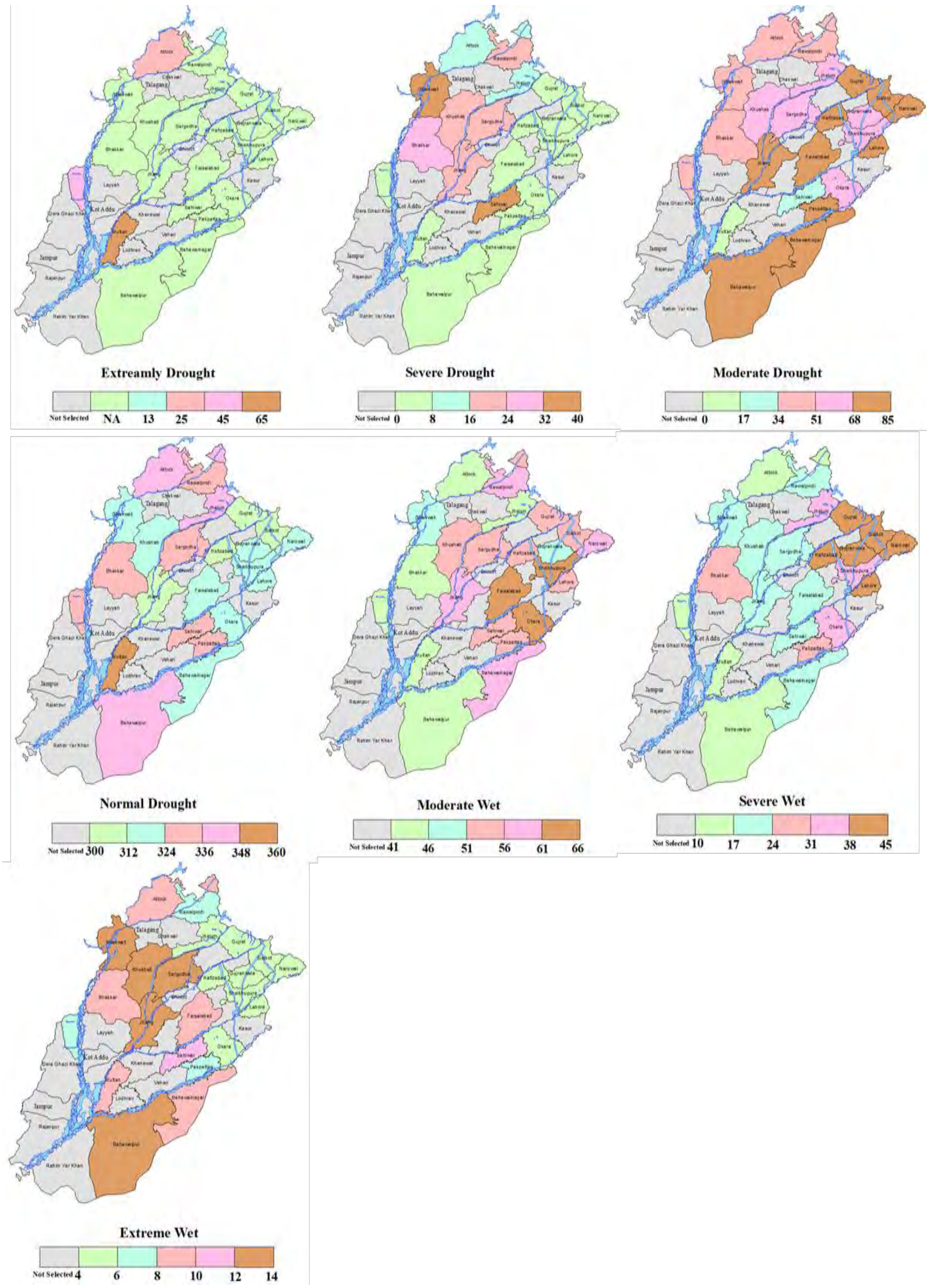

Figure 5. Varying drought categories are observed in selected stations for SPI-3.

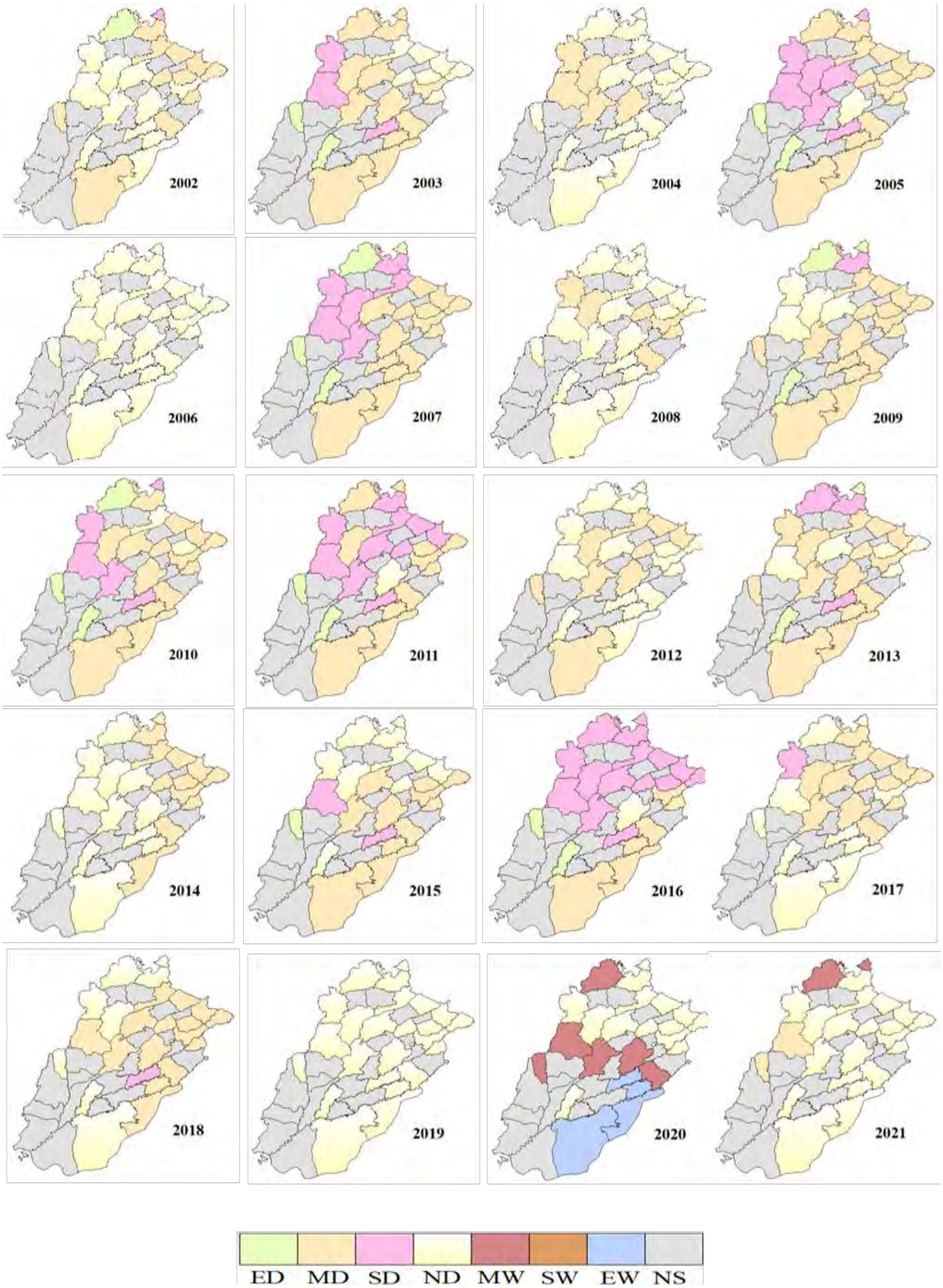

Figure 6. Monthly drought conditions of October of SPI-3 in various years of meteorological stations and the conditions of drought of other months can be observed accordingly.

The above figure 4 defines the temporal plot for various stations of meteorological data, it is also known as a time series plot. The temporal plots in the above figure for different stations present the graphical representations that show how the SPI-3 (Standardized Precipitation Index at a 3-month timescale) values vary over time from 1981 to 2021 at various monitoring stations. These plots help visualize the trends and fluctuations in SPI-3 values for different locations, allowing for insights into the patterns of precipitation and drought conditions over time. Figure 5 virtual representation of the different drought categories for selected stations of standardized precipitation at a three-time scale. The first map indicates the extreme drought count values and his legend shows the extreme drought value by different colors in the map. Similarly, the second and third maps indicate the severe and moderate drought count values. The fourth map presents the normal drought count in selected stations. The large count of values of normal drought occurs in intervals of 348 to 360 in different stations. which indicates that normal drought occurs in different stations mostly at various times. Similarly, we can see that the other map indicates different categories of drought with different time intervals. Figure 6 shows the drought categories in October month for various years. It's worth noting that October is chosen because it often experiences fluctuations in drought levels. Different colors indicate the severity of the drought each year. In the above figure, we can see that the normal drought mostly occurred in 2019 and similarly moderate categories of drought occurred in different years especially in 2013 in October month. The other levels are shown accordingly in the figure. This data holds significant importance for both water resource managers and policymakers, as it underscores the predictable seasonal nature of drought occurrences in the region. It implies the necessity of taking proactive steps, including the initiation of water conservation campaigns and adjustments in resource allocation, ahead of the dry season. Gaining insight into these monthly variations in drought conditions aids us in shaping our resource management strategies, ultimately facilitating the sustainable utilization of water resources throughout the entire year.

Table 3. Monte Carlo feature section with relative importance values.

Cluster 1	**RI**	**Cluster 2**	**RI**
Pakpattan	**0.103**	**Gujranwala**	**0.163**
Sahiwal	0.094	Narowal	0.146
		Sialkot	0.113
		Gujrat	0.110
		Jhelum	0.105
Cluster 3	**RI**	**Cluster 4**	**RI**
Lahore	**0.137**	**Bhakkar**	**0.095**
Hafizabad	0.128	Taunsa	0.065
Sheikhupura	0.074	Bahawalpur	0.056
Okara	0.072	Multan	0.055
Cluster 5	**RI**	**Cluster 6**	**RI**
Attock	Auto selected	**Rawalpindi**	Auto selected
Cluster 7	**RI**	**Cluster 8**	**RI**
Khushab	**0.139**	**Murree**	Auto selected
Faisalabad	0.117		
Mianwali	0.097		
Jhang	0.086		
Sargodha	0.083		

The above table shows the relative impotence values for selected locations by the Monte Carlo feature section. We will select the locations of high relative importance values of each cluster for our analysis. We can see that in cluster 1 we have two locations, we select Pakpattan which has a relative importance value is (0.103) which is higher than the other location value in that cluster. In cluster 2 we select Lahore in five locations with a relative importance value is (0.137). Similarly, we select one location for each cluster that has a high RI value. Only selected locations by Monte Carlo feature selection will be used for our analysis because these locations are representative of all locations in clusters, and it’s also reduced the dimension of the data.

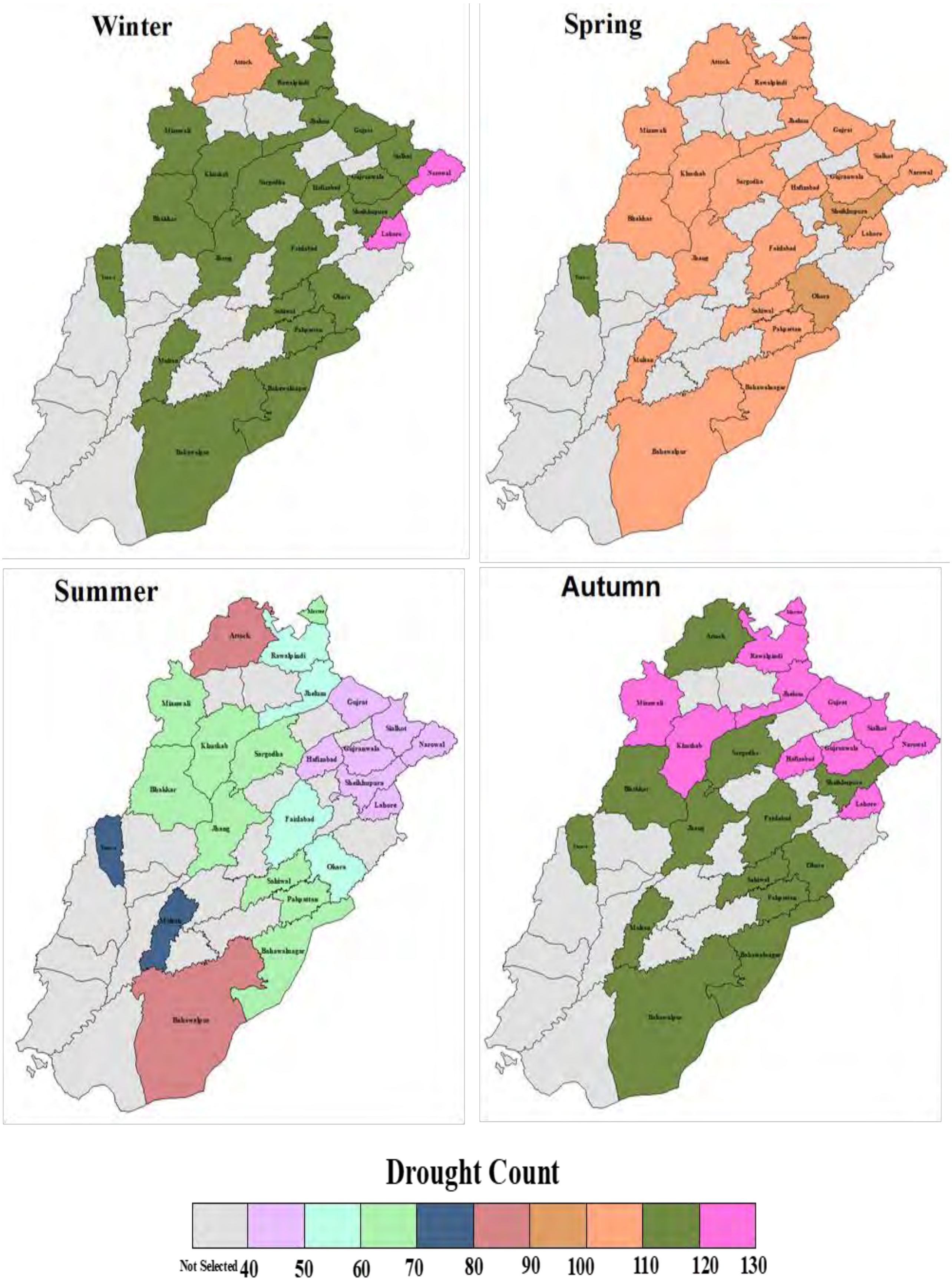

Figure 7. Total number of counts of drought (SPI-3 < 0) in all selected seasons of meteorological data.

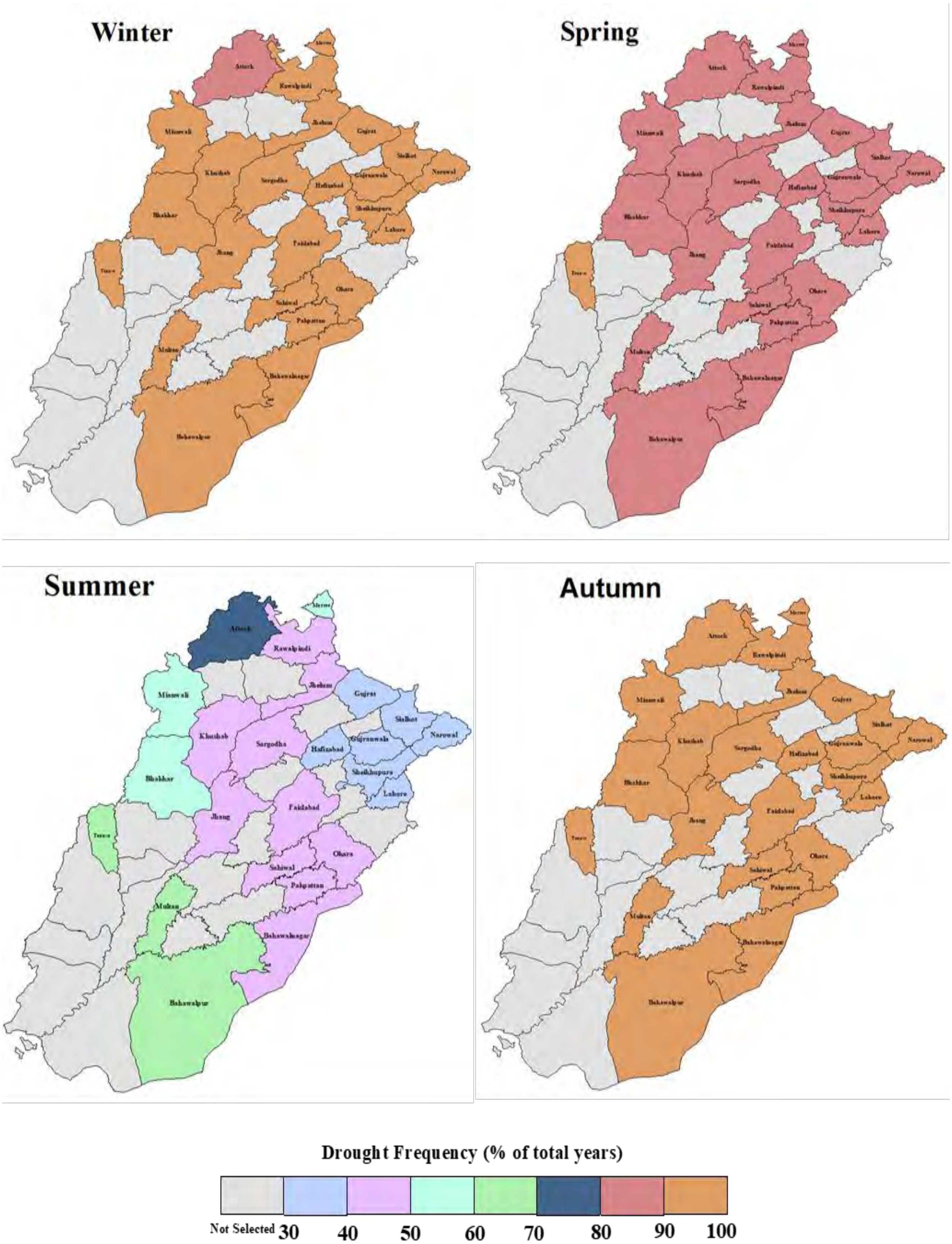

Figure 8. Total number of drought frequency percentages in meteorological seasonal data for all selected stations.

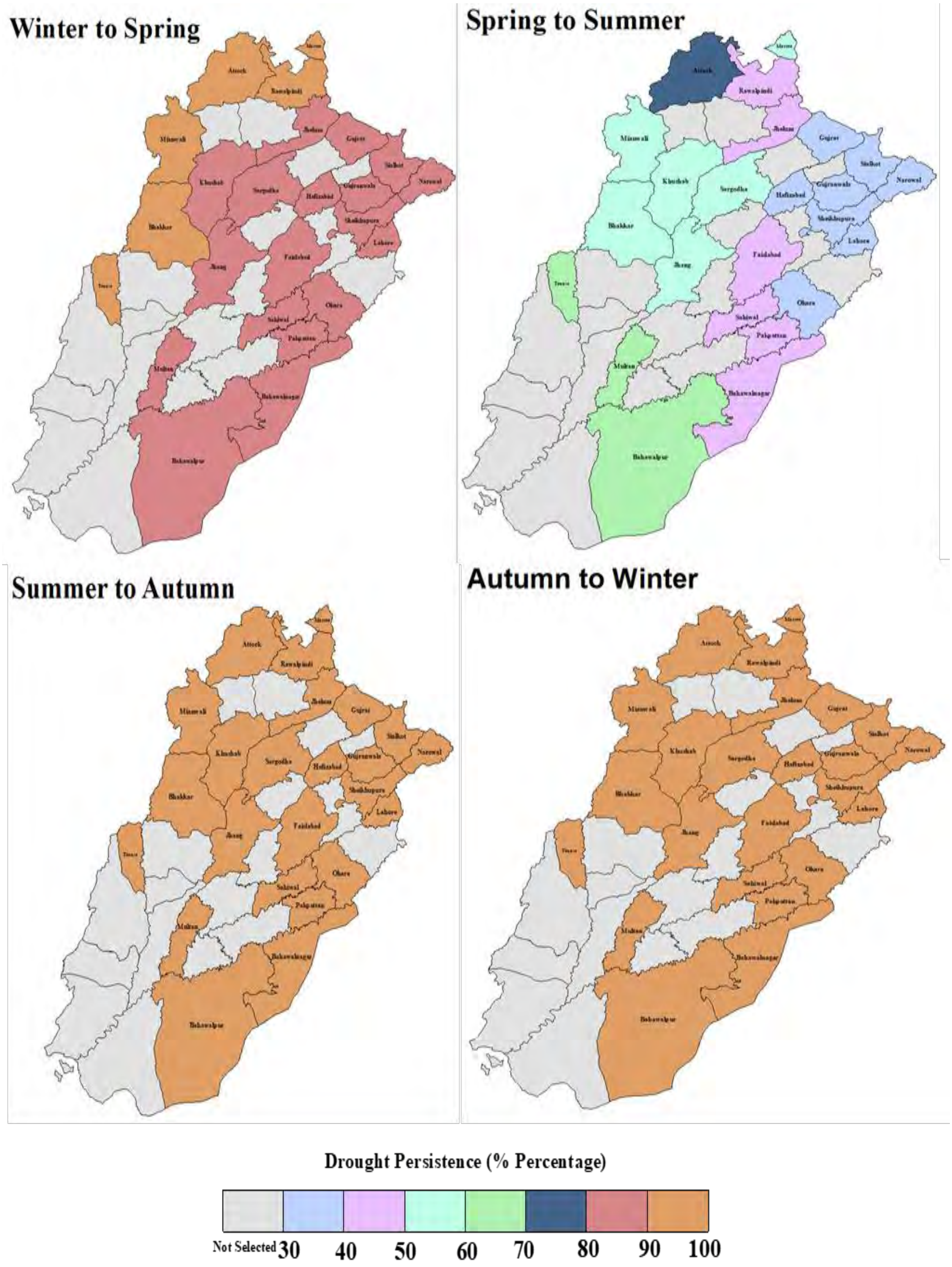

Figure 9. Inter-seasonal drought persistence percentage for selected stations.

Figure 7 indicates the drought count in representative selected stations. These locations are classified based on the Standardized Precipitation Index (SPI), where SPI values less than 0 signify drought and SPI values greater than 0 indicate the absence of drought in different locations at various times. In the above figure, we can see that the most drought occur in the autumn and winter season with most instances falling within the range of 110 to 130 drought occurrences and the figure also displays variations in drought counts for other seasons accordingly. Every season shows a different number of drought counts in locations for example the drought count in Lahore, Jhelum, and Mianwali is 121,122 and 121 in the Autumn season and the drought count in Lahore, Jhelum, and Mianwali is 121,117, and 111 in Winter season. however, the count was observed for other locations accordingly. In Figure 8 the drought frequency is evaluated as the total number of droughts that occur in total months in a specific location divided by the total number of months in that season. The drought frequency indicates the number of drought presences in total years of the specific location in a specific season. For example, in the Summer season, the drought frequency for Faisalabad, Rawalpindi, and Sialkot is 85, 89, and 86 percent similarly in Sahiwal, Taunsa, and Bahawalnagar is 62, 79, and 62, and in Winter season the drought frequency for Faisalabad, Rawalpindi and Sialkot is 97, 92 and 97 percent. In the above figure, we can see that the drought frequency is mostly recorded as very high in the Autumn and Winter seasons. which occur in the interval of 80 to 100 and similarly observed for the other seasons in the figure. The seasonal drought persistence is presented in Figure 9. Which is evaluated as the total number of droughts that persist in the current season from the previous season divided by the total number of droughts in the previous season. For example, in the Spring to Summer season, the total number of droughts that persist in Faisalabad Summer season is 46 and the total number of droughts in the previous season is 104 so the drought persistence in Spring to Summer in Faisalabad is 44 percent. We can see that the persistence of drought is very high in the Summer to Autumn season and Autumn to Winter season and low in other seasons. Drought persistence serves as a warning of potential water shortages in a region, urging us to formulate effective policies for monitoring and conserving water resources.

Table 4. Results of the Winter-Spring Seasonal drought persistence modeling are presented.

REBLRM		CFEBLRM	
Test	Values	Test	Values
Log-likelihood	-287.99306	Log-likelihood	-258.5770
Wald chi2(5)	132.84	LR chi2(5)	308.52
Prob>chi2	0.000	Prob>chi2	0.000

Table 4 provides details about the winter-spring Season drought persistence modeling. In the table, the log-likelihood values, WCT, LRCST, and P-values for the CFEBLRM & REBLRM are given. The p-values of both models are significant which indicates that both the models are important. However, the HT is used to test the endogeneity in independent variables and error terms and suggest the significant model in both CFEBLRM and REBLRM for the Winter to Spring season for the selected location of the province of Punjab Pakistan. The p-value of the HT is 0.0591 which confirms that there is no endogeneity in the model in Winter-Spring season data and indicates that REBLRM is an appropriate choice for the Winter-Spring spatiotemporal drought persistence modeling.

Table 5. The result derived from REBLRM is presented for Winter-Spring Seasonal meteorological drought persistence.

Variables	Odd-ratio	Stand. error	z	P > |z|	[95 % conf.	interval]
Precipitation	0.9809516	0.0022391	-10.81	0.000	0.9782103	0.9848485
Temperature	0.870262	0.0138564	-8.73	0.000	0.8435233	0.8978482
Wind_Speed	3.370334	1.330939	3.08	0.002	1.5543	7.308208
Profile_soil_moisture	4.493826	4.618677	1.46	0.144	0.5994678	33.68733
cons	44.21388	90.486	1.85	0.064	0.8008119	2441.107
sigma_u	0.7945432	0.2607437			0.4176192	1.511662
rho	0.1609977	0.0886562			0.0503441	0.409888

Table 5 Presents the result derived from REBLRM for the Winter to Spring Season. The P-values of most variables show a significant effect on meteorological drought persistence which shows the importance of the variables like Precipitation, Temperature, and Wind_Speed. The Profile_soil_moisture is insignificant, so it does not have a statistical impact on drought persistence. The odd ratio values in the table represent how much the odds of the persistence occurring event change by one-unit change in the independent variables. The odd ratio of precipitation (0.981) with significant P-value and 95% confidence intervals indicate that the increase in Precipitation in the Winter season will decrease the probability of the drought in Spring season. So, the odd ratio of precipitation (0.981) means that a one mm increase in precipitation increases the odds of drought persistence in the Spring Season by 0.02. Similarly, by one-unit change in Temperature decreases the drought persistence by 0.13 in the Spring Season. Additionally, the $rho = \frac{\delta_u^2}{\delta_u^2 + \delta_\varepsilon^2}$ is the proportion of total variance attributed to the random effects in panel data. δ_u^2 represent the variance associated with the random effects within the model. It captures the variability observed between different groups or units. δ_ε^2 represent the residual variance, which captures the unexplained variability within each group after accounting for the random effects. If rho is closer to 1, it means that a significant portion of the total variance in the data is explained by the random effects between the groups, and the residual variance is relatively small. And if rho is close to zero means the total variance is mostly explained by residual variance between the groups. In the current study, the rho value (0.160) represents the 16% variation of random effects between the groups.

Table 6. The outcome obtained for Spring-Summer Season drought persistence modelling.

REBLRM		CFEBLRM	
Test	Values	Test	Values
Log-likelihood	-583.49	Log-likelihood	-539.981
Wald chi2(5)	97.59	LR chi2(5)	175.2
Prob > chi2	0.000	Prob > chi2	0.000

Table 6 provides details concerning the Spring-Summer season drought persistence modeling. The table includes log-likelihood values, WCT, LRCST values, and P-values for both the

CFEBLRM and REBLRM models. The significant p-values for both models indicate their importance. Additionally, the Hausman test (HT) is employed to examine endogeneity within the independent and error term and suggest significance for both CFEBLRM and REBLRM The HT p-value of 0.0006 confirms the presence of endogeneity in the Spring-Summer season data. This underscores that CFEBLRM is the suitable choice for modeling spatiotemporal Winter-Spring drought persistence.

Table 7. The results derived from CFEBLRM for Spring-Summer spatiotemporal meteorological drought persistence modeling are given.

Variables	odd ratio	Std. error	z	P>|z|	[95% conf.	interval]
Precipitation	0.997701	0.001218	-1.89	0.05	0.995316	1.000091
Temperature	1.020439	0.00949	2.18	0.03	1.002008	1.03921
Wind_Speed	1.39937	0.203224	2.31	0.021	1.05273	1.860152
Profile_soil_moisture	0.000721	0.001048	-4.98	0.000	4.18E-05	0.012445

Table 7 The result obtained from CFEBLRM analysis for the Spring to Summer Season is given. The p-values associated with all variables demonstrate a significant impact on meteorological drought persistence, indicating the importance of Precipitation, Temperature, Wind_Speed and Profile_soil_moisture. The odd ratio of Precipitation (0.99), with a 95% confidence interval and significance value, suggests that an increment in Precipitation during the Spring season diminishes the likelihood of Summer season drought. Thus, a one mm increment in precipitation in Spring corresponds to the reduction in drought persistence during Summer by 0.01, Similarly, Profile_soil_moisture has a parallel behavior. The temperature and Wind_Speed odd ratio shows that by increment in one-unit change in temperature and Wind_Speed in the Spring season increases the drought persistence in the Summer season by 0.02 and 0.39.

Table 8. The outcome provided for modeling of spatiotemporal patterns during the Summer-Autumn season are provided as follows.

REBLRM		CFEBLRM	
Test	Values	Test	Values
Log-likelihood	-86.62508	Log-likelihood	-76.7501
Wald chi2(5)	61	LR chi2(5)	1124.76
Prob > chi2	0.000	Prob > chi2	0.000

In Table 8 Present the log-likelihood values, WCT, LRCST values. The REBLRM and CFEBLRM both have a high negative log-likelihood value which indicates both the model is significant. The log-likelihood for the REBLRM value is -86.6251 and for CFEBLRM is -76.750 which indicate that both the model is significant for Summer to Autumn season. The Hausman test with a p-value of 0.000 indicates that there is endogeneity occurring in the model and the Hausman test suggests the CFELRM is appropriate for the analysis of Summer to Autumn spatiotemporal meteorological persistence modeling.

Table 9. The results computed from CFEBLRM for Summer-Autumn spatiotemporal modeling are given below.

Variables	Odds ratio	Std. error	z	P>|z|	[95% conf.	interval]
Precipitation	0.94073	0.005592	-10.28	0.000	0.9298334	0.9517543
Temperature	0.9571586	0.0391633	-1.07	0.285	0.8833971	1.037079
Wind_Speed	1.431375	0.3830463	1.34	0.18	0.8471602	2.418472
Profile_soil_moisture	0.12157	0.3945979	-1.47	0.516	0.0002099	70.42042

Table 9 displays the outcomes of the CFEBLRM analysis applied to model spatiotemporal drought persistence trends during the transition from Summer to Autumn. The P-value in the table indicates that Precipitation significantly impacts the persistence of drought from Summer to Autumn and Wind_Speed and all other independent variables do not significantly impact the persistence of drought modeling for the selected location in Punjab province Pakistan. The odd ratio of Precipitation is 0.941 with a 95% confidence interval is (0.929 to 0.952). The odd ratio of precipitation indicates the one-unit change in precipitation in Summer spatiotemporal drought is the decline persistence of the meteorological drought of the Autumn season by 0.06 for the selected locations.

Table 10. The log-likelihood, WCTS, LRCST, and P-value results were obtained for Autumn-Winter season meteorological drought persistence.

REBLRM		CFEBLRM	
Test	Values	Test	Values
Log-likelihood	-174.72817	Log-likelihood	-143.998
Wald chi2(5)	80.19	LR chi2(5)	177.37
Prob > chi2	0.000	Prob > chi2	0.000

In table 10 gives the log-likelihood values, WCT, and LRCST values. The p-values of CFEBLRM and REBLRM indicate that both models are significant. The Hausman test with a p-value of 0.2244 indicates that there is no endogeneity in the model and therefore Hausman test suggests the REBLRM is appropriate for the analysis of Autumn to Winter meteorological persistence modeling.

Table 11. The result computed for Autumn-Winter spatiotemporal meteorological drought persistence from REBLRM.

Drought	Odds ratio	Std. error	z	P>|z|	[95% conf.	interval]
Precipitation	0.9839924	0.0037244	-4.26	0.000	0.9767198	0.991319
Temperature	1.054548	0.0146408	3.83	0.000	1.02624	1.083638
Wind_Speed	0.1657607	0.1021909	-2.92	0.004	0.049513	0.554938
Profile_soil_moisture	0.0098197	0.0207069	-2.19	0.028	0.0001575	0.612408
cons	2765030	1.28E+07	3.19	0.001	306.6434	2.49E+10
sigma_u	1.86941	0.7032194			0.8943478	3.907532
rho	0.5150949	0.1879145			0.1955774	0.822732

Table 11 present the result obtained from REBLRM are given accordingly. The p-values are significant for all variables for meteorological drought persistence in the Autumn to Winter Season. which indicates the significant effect of drought persistence in the Winter season. The coefficient of precipitation odd ratio (0.983) presents the increment in precipitation decline the drought persistence in the Winter season by 0.02 similarly, the unit change in Wind_Speed and Profile_soil_moisture will decline the drought persistence in the Winter season by 0.84 and 0.99. and the odd ratio of Temperature (1.054) indicates that the increment of one unit in temperature will increase the drought persistence in the Winter season by 0.05. Additionally, the $rho = \frac{\delta_u^2}{\delta_u^2 \ + \delta_\varepsilon^2}$ is the proportion of total variance attributed to the random effects in panel data. δ_u^2 represent the variance associated with the random effects within the model. It captures the variability observed between different groups or units. δ_ε^2 represent the residual variance, which captures the unexplained variability within each group after accounting for the random effects. If rho is closer to 1, it means that a significant portion of the total variance in the data is explained by the random effects between the groups, and the residual variance is relatively small. And if rho is close to zero means the total variance is mostly explained by residual variance between the groups. In the current study, the rho value (0.515) represents the 51% variation of random effects between the groups.

Chapter 4

Discussion and Conclusion

4.1. Discussion

Multiple researchers have published various frameworks aimed at assessing drought conditions across diverse climate conditions and geographical regions (Elbeltagi et al. 2023; Ellahi et al. 2023; Zheng et al. 2023). The drought persistence estimation describes the effect of change in Precipitation, Temperature, Wind_Speed, and Profile_soil_moisture for a three-month time scale in one season from the succeeding season. The linear regression model cannot work properly for categorical variables. The logistic regression model is used in the case of categorical variables. Several researchers use a logistic regression model for panel data (Kuwayama et al. 2019; Sun et al. 2019; Defrance et al. 2020; Niaz et al.2023b) to evaluate the drought conditions in different regions. However, since drought conditions vary from one season to another, it is crucial to identify the characteristics of inter-seasonal droughts. Many researchers studied inter-seasonal drought persistence (Stahle et al. 2009; Li et al. 2022; Raza et al. 2023). To address this objective Recently Niaz et al. (2023) employed a logistic regression model to binary panel data to evaluate inter-seasonal drought persistence in different regions of Pakistan. The issue lies in the researcher's utilization of all chosen regions for analysis, wherein a majority of these locations do not adequately represent the entire country. Furthermore, the methodology employed is very complex for high dimensional study and uses only soil_moisture variable for drought persistence which does not give the comprehensive result of inter-seasonal meteorological data. Thus, this issue of concern forms the basis for the creation of the novel approach. In the current study, we focus on the binary outcome panel data model to evaluate the inter-seasonal drought persistence by logistic model for RI locations which represents all the regions and makes the result more comprehensive and effective for spatio-temporal inter-seasonal drought persistence. The Standardized Precipitation Index (SPI) is employed at a 3-month time scale to discern drought characteristics across different seasons. The K-means method is employed to create suitable clusters for dividing the locations into homogeneous groups and the Monte Carlo method is utilized to select one Relative important (RI) location for each cluster. In MCFS location is ranked based on their relative importance for each cluster. The binary panel logistic model is used to evaluate the inter-seasonal drought persistence for final selected locations. The significance of the CFEBLRM and REBLRM is measured by LRCST and WCT tests. The Hausman test is used to choose the appropriate model in both CFEBLRM and REBLRM for analysis of inter-seasonal drought persistence. The metrological drought has a negative impact on agriculture and the socioeconomic of the country. The current study will help the researcher to evaluate the more accurate drought monitoring and early warning systems and help to inform the drought community to develop drought policies and facilitate the drought management strategies to avoid the negative impact in the region of Punjab.

4.2. Conclusion

Drought is a harmful natural hazard, not well understood to monitor, and happens in almost all different climate areas around the world. Hence, it introduces challenges to achieving precise and effective drought monitoring within various regions of Meteorological research. Therefore, in the current study, we are developing a new framework to significantly enhance the precision of drought monitoring and the assessment of its impacts. In this regard, we utilized the SPI-3 of the binary dependent variable with four independent variables of a three-month time scale and assessed 24 locations in the province of Punjab Pakistan, to affirm the validity of the framework. The K-Means clustering generates appropriate clusters in the framework and Monte Carlo performs to select the representative station for each cluster. The CFEBLRM and REBLRM are utilized for Panel Binary data to evaluate the inter-seasonal drought persistence for representative selected stations. The significance of CFEBLRM and REBLRM is measured by log-likelihood values, LRCST, WCT, and p-values. The HT is applied to identify endogeneity within independent variables and the error term and select the appropriate model in CFEBLRM and REBLRM. In the current analysis, the inter-seasonal drought persists in mostly seasonal especially from Summer to Autumn and from Autumn to Winter. The likelihood value indicates the significance of both models, but the HT (0.000) value confirms the endogeneity in Summer to Autumn and confirms the CFEBLRM for drought persistence modeling. The drought persistence for Summer to Autumn is between 90% to 99% and the odd ratio (0.93) value of Precipitation (95% confidence Interval 0.94 to 1.01) indicates the one mm change in precipitation in Summer spatiotemporal drought persistence is a decline persistence of meteorological drought of the Autumn season by 0.07 for the selected locations. The likelihood value (-461.24) shows the significance of CFEBLRM. Similarly, in the Autumn to Winter season, the Hausman test with a p-value of 0.1189 indicates that there is no endogeneity in the independent and error term and therefore Hausman test suggests the REBLRM is appropriate for the analysis of meteorological persistence modeling. The likelihood (-519.91) indicates the significance of REBLRM. The drought persistence from Autumn to Winter ranges between 90% to 98%, signifying a significant continuation of drought conditions from the Autumn season to Winter. The odd ratio (1.06) indicates that the increment of temperature in the Autumn season will increase by 6% the drought persistence in the Winter season similarly the odd ratio of precipitation 0.973 and Wind-Speed 0.213 indicate that the increase of one unit in precipitation and Wind-Speed in Autumn season decline the drought persistence in Winter season by 0.3 and 0.79 and in binary panel data modeling the rho value (0.346) represents the 34% variation of random effects between the groups. The result of the present binary panel model with four independent variables delivers accurate and precise information on drought persistence in the selected station of Punjab. The outcome of the current study facilitates the decision-makers to understand the effects of meteorological drought occurrences better and execute strategies for mitigating drought effects to reduce the losses caused by it.

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