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Effect of Climate Indices on Monsoonal Rainfall during El Niño and La Niña Events in the India

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ABSTRACT
This study examines the association between monsoonal rainfall and climatic indicators during India's El Niño and La Niña episodes. Indian monsoon rainfall is known to be greatly influenced by large-scale climate indices like the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO).The present study was conducted utilizing meteorological data from 10 rainfall sites across India. The India Meteorological Department (IMD), located in Pune, has gathered the data, which includes mean monthly precipitation (PPT), mean monthly lowest temperature, and mean monthly maximum temperature.To examine their combined impact on Indian monsoon rainfall, ENSO and the PDO a long-term climate oscillation including changes in sea surface temperatures in the North Pacific Ocean were taken into account.The study's goals are to examine the effects of ENSO on rainfall at various Indian meteorological stations and to analyze rainfall data for these stations.The data demonstrate that during most El Niño years, a drop in precipitation was found across all stations evaluated in the study. On the other hand, majority of the stations reported higher precipitation during La Niña years. Additionally, there were differences in the correlation between PDO and monsoonal precipitation among the stations: the PDO index showed a negative correlation with the remaining five stations, while the PDO index showed a positive correlation with Cherrapunji, Delhi, Hyderabad, Kolkata, and Mumbai.
Keywords:- *Climate indices, Monsoonal Rainfall, El Niño, ENSO and PCA*

1. Introduction

Generally speaking, the Indian summer monsoon rainfall from June to September is vital to the country's agricultural and water management. he monsoon is a wind pattern that blows over India and the neighboring oceanic regions from the northeast half of the year and from the southwest the other half. Through southwesterly winds, the seasonal reversal of wind direction that takes place in May transports a large amount of moisture from the warm tropical ocean waters to the Indian continent. These extreme weather phenomena, which include heat waves, cold waves, cyclones, droughts, and heavy rainfall, pose a threat to the world's population. Aerosol emissions brought on by human activity were partly responsible for the decline in monsoon precipitation on land throughout the world in the 1950s and 1980s.
. The monsoons are crucial for the Indian economy and are often regarded as the backbone of the agricultural sector, which employs over half of India's population. The patterns of India's monsoonal rainfall have become unpredictable due to the continuous changes in climate. ENSO (El Niño-Southern Oscillation) is a shorter-term climate phenomenon, with irregular cycles that typically last 2 to 7 years. It has two primary phases: El Niño (warm) and La Niña (cool), with a neutral phase in between.
El Niño is a natural climate pattern that causes the ocean surface in the tropical Pacific to warm. It's part of the El Niño-Southern Oscillation (ENSO) cycle, which also includes La Niña, the cool phase. The ocean surface in the central and eastern tropical Pacific warms above average.(ENSO) cycle, which also includes La Niña, the cool phase. The low-level surface winds that normally blow from east to west along the equator weaken or reverse direction. The changes in wind and temperature disrupt normal weather patterns in the tropics and around the world. Events occur irregularly, every two to seven years. No two El Niño events are exactly alike. El Niño can disrupt normal weather patterns in the United States and globally. It can cause increased rainfall around the islands of Indonesia and New Guinea. It can cause the air along the coast of South America to remain relatively dry.
La Niña is a phase of the El Niño-Southern Oscillation (ENSO) cycle, where the central and eastern equatorial Pacific Ocean experiences unusually cold sea surface temperatures. La Niña is the opposite of El

Niño, which is the warm phase of ENSO. La Niña is caused by a reversal of atmospheric conditions and a large-scale cooling of the ocean surface temperatures.The easterly winds become stronger during La Niña. La Niña can impact global weather patterns. In the U.S., La Niña can cause colder than normal winters in the Northwest and warmer than normal winters in the Southeast. In the Pacific Northwest and Ohio Valley, La Niña can cause wetter than average conditions. In the southern tier of the U.S., La Niña can cause drier than average conditions. La Niña conditions typically occur every few years and can last up to three years.The last multi-year La Niña event began in September 2020 and lasted into early 2023.

There are several indices used to monitor the tropical Pacific, all of which are based on sea surface temperature (SST) anomalies averaged across a given region. Usually, the anomalies are computed relative to a base period of 30 years. The Niño 3.4 index and the Oceanic Niño Index (ONI) are the most commonly used indices to define El Niño and La Niña events. Niño 3.4 (5N-5S, 170W-120W): The Niño 3.4 anomalies may be thought of as representing the average equatorial SSTs across the Pacific from about the dateline to the South American coast.

Gadgil et al. (2005) investigated the causes of the Indian summer monsoon rainfall prediction's failure. Loo et al. (2015) have offered some information regarding the connections between monsoon rainfall and global warming. It is evident that the distribution of monsoon rainfall is significantly influenced by a number of meteorological systems. Ratna (2012) examined daily rainfall data from 329 rain gauge stations over the course of the summer monsoon season in Maharashtra, India, which lasted 11 years, from 1998 to 2008. June through September is when the state is in operation. Mesoscale analysis of the daily rainfall data is done by converting the station rainfall data into a gridded format with a 15 km resolution.

Ahmed et al. (2012) demonstrate how rainfall intensity differs for both generated and observed data using a case study of Imphal. Frequency analysis was employed to ascertain the relationships between intensity, duration, and frequency (IDF). This study attempts to ascertain the difference in rainfall intensity between calculated and observed data using rainfall data from Imphal that is available for a 15-minute time interval.

In Andhra Pradesh, India, Dourte et al. (2013) investigated the relationships between rainfall frequency, duration, and intensity. Two sets of rainfall data were obtained from Hyderabad, the state capital of Andhra Pradesh: hourly data for the 19 years from 1993 to 2011 and daily data for the 30 years from 1982 to 2011. In 2009, Sharif and Burn looked into the relationships between climate indices and severe flow measurements for a number of Canadian stations. To find potential connections with multiple large-scale climate indices, 62 hydrometric stations in Canada are examined for a variety of extreme flow and timing measurements, such as high flow and low flow measures. The study employed a composite analysis approach to ascertain the relationships between climatic indices and extreme flow and timing variables. The findings enable the identification of any correlation between the stations displaying a trend that is statistically significant and those where there is a correlation between the climatic indices and the extreme measures.

The impact of the Interdecadal Pacific Oscillation on global temperature and precipitation is discussed by Dong and Dai (2015). The 40–60 year Interdecadal Pacific Oscillation (IPO) is a quasi-oscillation that is primarily observed in the Pacific basin, but it has also been observed to affect surface temperature (T) and precipitation (P) over Australia, the South West of the United States, and other places. Amudha et al. (2016) examined the spatial variation of cloud cover and rainfall over the southeast Indian peninsula and the adjacent Bay of Bengal in relation to active and dry spells of the northeast monsoon, 559–570.

Cl´ementGuilloteau et. al (2021) argues that in contrast to classical PCA, spectral PCA (sPCA) has the benefit of recognising and extracting ordered spatio-temporal sample within specified frequency bands. However, the inescapable trade-off between frequency resolution and PC robustness results in significant noise sensitivity and over fitting, limiting the interpretation of sPCA results. The approach accurately captures the El Nino-Southern Oscillation (ENSO) at low frequency when applied to historical SST data series over the Pacific Ocean (2 to 7 years periodicity). The discovery of higher frequency space-time climate modes has the potential to improve seasonal to subseasonal forecasting and climate model diagnostics.

Ocean-atmosphere interconnections in the Pacific, Atlantic, and Indian Oceans can both cause and have an impact on variation in climate, according to Chunzai Wang (2019). Oceanic Indonesian throughflow (ITF) and atmospheric bridges allow ENSO, which is mostly located in the Pacific, to affect other oceans. Singh et al. (2017) investiagted how the ENSO, resulting from temperature variations in the tropical Pacific Ocean, can exert a substantial influence on global climatic conditions. A pivotal factor in understanding the local

impacts on maximum precipitation and stream flow patterns is the presence of large-scale climate signals and their interactions with land surface hydrology. Importantly, ENSO has demonstrated increased variability in recent years, raising the possibility that climate change could intensify its effects.
A research by Deng et al. (2007) investigated the potential for ENSO to significantly affect Chinese rice production. Gershunov et al. (1998) looked into how ENSO affected the cold-season maximum temperatures and high rainfall frequencies.According to Cobb et al. (2013), there is still uncertainty regarding ENSO's susceptibility to human greenhouse effects.
A new multivariable prediction technique has been created by Chen et al. (2023) to improve El Nino-Southern Oscillation (ENSO) forecasts. To automatically find the best predictors, this system combines observational data with deep learning (DL) methods, particularly the residual neural network. Fang et al. (2022) focused attention on the enormous impact of natural disasters such as floods and droughts, which have substantial human, economic, and safety costs. They highlight ENSO as a crucial interannual climate indicator that influences global air circulation and precipitation patterns. Accurate ENSO predictions are vital for mitigating the impacts of climate change and associated catastrophic events. Roy et al. (2003) collected monthly rainfall data for 18 grid cells across India and generate ENSO, PDO, and local SST statistical indices for the years 1925–1998. Roy and Collins (2017) demonstrated that during the past few decades, the spatial form of ENSO over Australia has rotated. Loo et al. (2015) observed that the dispersion of rainfall during the rainy season is significantly influenced by meteorological systems. Sharif and Burn (2009) analyzed the relationships between a number of Canadian stations' maximum flow measurements and climate season indicators.
Wang et al. (2023) describe the importance of analyzing and forecasting the periodic El Nino-Southern Oscillation (ENSO) in the tropical Pacific Ocean. The authors note that traditional analytical models face challenges due to data limitations and the spring predictability barrier (SPB). Consequently, researchers have turned to deep learning (DL) techniques to overcome these challenges. The study provides insights into the characteristics of ENSO, introduces the framework of DL technologies, and explores various angles from which DL can be applied to ENSO prediction.

2. Study Area and Data Collection

The weather data from ten stations throughout the Indai was used to conduct the current study. Multiple meteorological stations provided data for the mean monthly minimum temperature, mean monthly maximum temperature, and mean monthly precipitation (PPT), which were produced by the India Meteorological Department (IMD), located in Pune, India. A total of ten rainfall stations were considered in this study. The locations of the several rainfall monitoring stations used in this investigation are shown in Figure 1. All stations, except for Agra, have precipitation data available from 1950 to 2015..

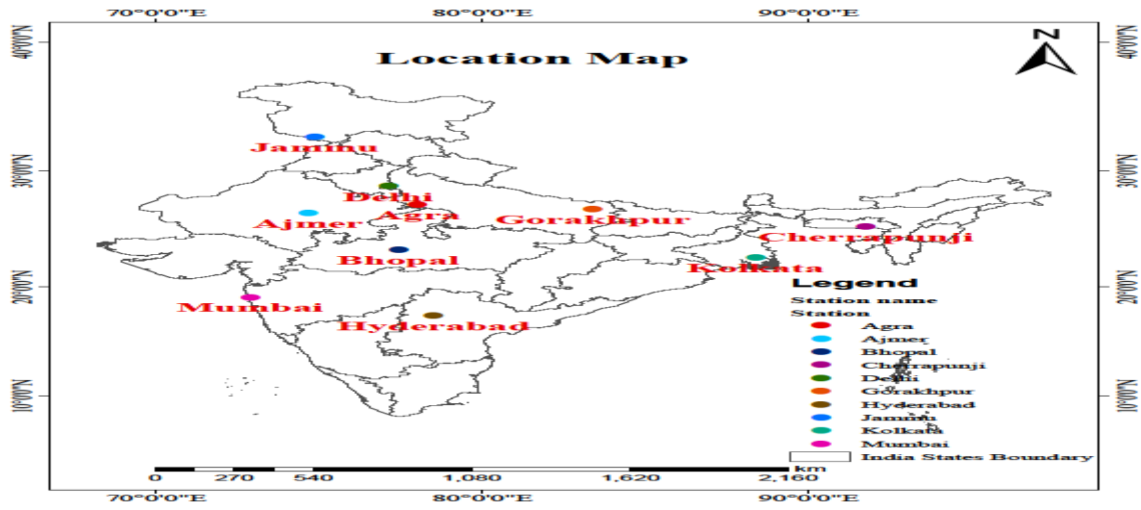

Figure 1 Geographical locations of Rainfall Stations

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3. METHODOLOGY

The study's methodology comprised analyzing the relationships between ENSO and precipitation data at several regional meteorological stations, accounting for both warm and cold phases. The India Meteorological Department (IMD) in Pune provided the mean monthly rainfall data for these stations. The monthly rainfall measurements at several stations from June to September were added up to determine the monsoonal rainfall. The National Center for Atmospheric Research (NCAR) in the United States of America's Climate Analysis Section provided the data for the NINO 3.4 index, which shows the sea surface temperature anomaly in the Nino3.4 region (1200 W–1700 W, 50 S–50 N) (http://www.cgd.ucar.edu/).

The initial step in the employed methodology involved identifying years marked by either El-Nino or La-Nina events

To classify El-Nino years, we calculated sea surface temperature anomalies for the June to September period using data obtained from NCAR. A year is designated as an El-Nino year if its anomaly for that specific year exceeds the threshold value of 0.4 °C. Alternatively, a year with an anomaly exceeding 0.4 °C is classified as a La-Nina year. **Error! Reference source not found.** shows the grouping of years into three distinct categories – El-Nino, La-Nina, and normal years – based on the 0.4 °C threshold temperature anomaly, as shown in the figure. **Error! Reference source not found.** provides a breakdown of these categories. Notably, out of a total of 61 years, there were 17 El-Nino years, suggesting a periodicity of approximately 4 years. The number of La-Nina years was 18 out of 61. Additionally, 35 out of 61 years were associated with either the El-Nino or La-Nina phases of the southern oscillation, while the remaining years were categorized as normal years.

Table 1 Classification of normal, El-Nino and La-Nina years

Normal years		El-Nino years	La-Nina years
1952, 1958, 1960, 1961, 1962, 1966, 1967, 1968, 1976, 1977, 1979, 1980, 1981, 1983, 1984, 1986, 1989, 1990, 1992, 1995, 1996, 2001, 2003, 2005, 2007, 2008		1951, 1953, 1957, 1963, 1965, 1969, 1972, 1982, 1987, 1991, 1993, 1994, 1997, 2002, 2004, 2006, 2009	1950, 1954, 1955, 1956, 1959, 1964, 1970, 1971, 1973, 1974, 1975, 1978, 1985, 1988, 1998, 1999, 2000, 2010
Total	26	17	18

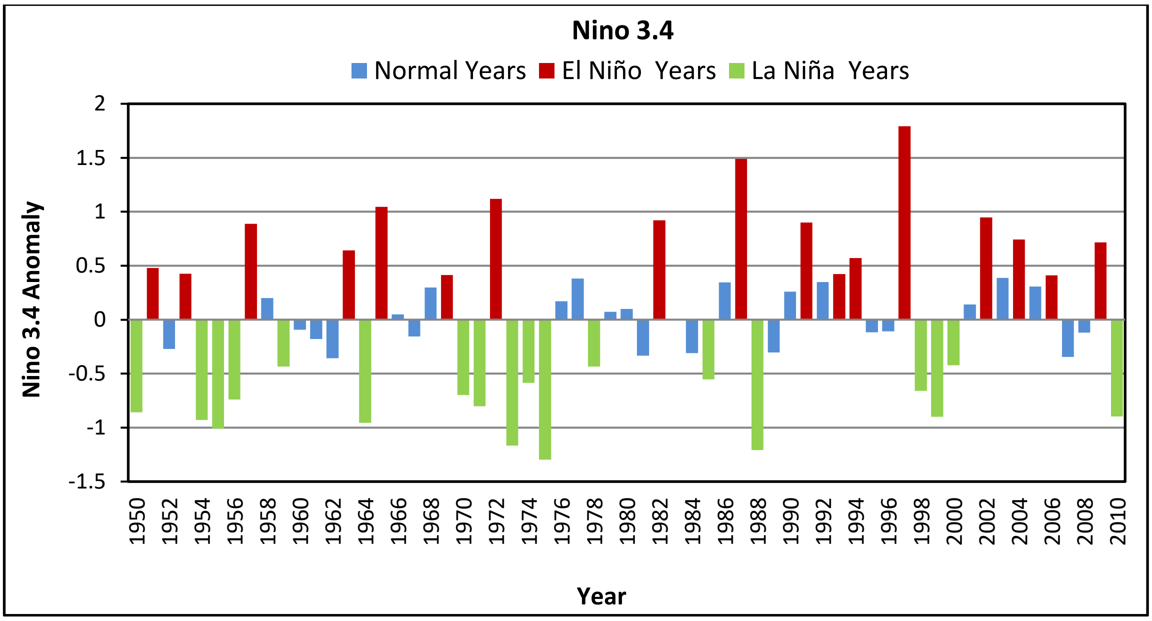

Figure 2 Classification of El-Nino, La-Nina and normal years. The time series bar plot using data from NOAA and relative to a base period climatology from 1950 to 2010. Values exceeding thresholds of ±0.4°C for Niño 3.4 are stippled to indicate ENSO events.

4. RESULTS AND DISCUSSION

The seasonal variation of monsoonal precipitations at 10 various rainfall stations considered in current research is shown in figure 3 to figure 12.The analysis of monsoonal rainfall data reveals that Agra experienced its highest annual precipitation of 1138.5 mm in 1952. In 1975, the Delhi station recorded its maximum annual precipitation at 1164.30 mm, while the lowest normal annual precipitation was 363.30 mm in Delhi in 1992. The highest annual precipitation f 18655.4 mm occurred on record in Cheerapunji in 1974.

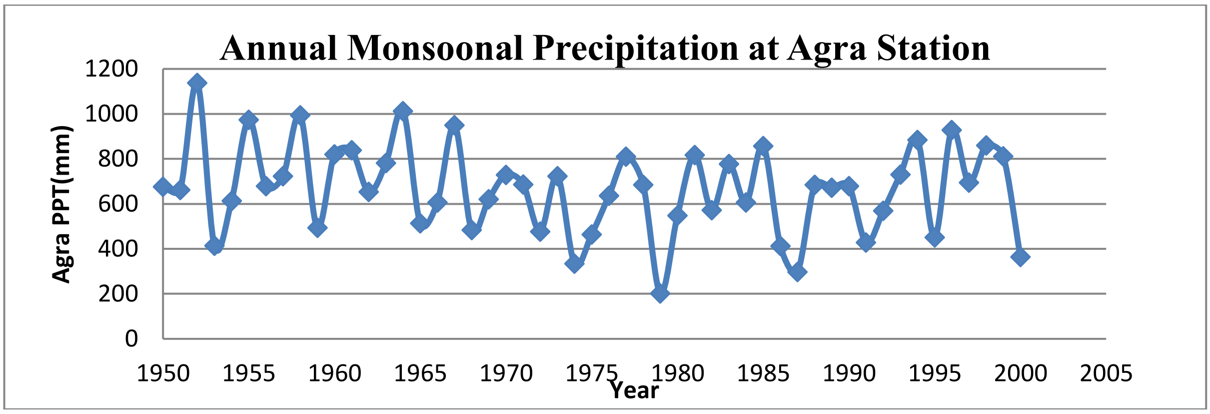

Figure 3 Annual Monsoonal Precipitation at Agra Station

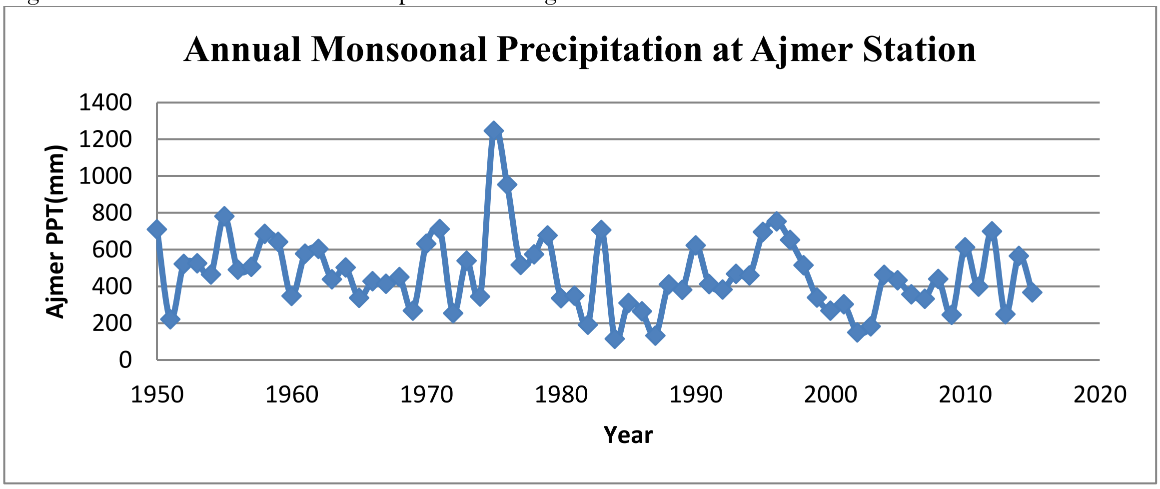

Figure 4 Annual Monsoonal Precipitation at Ajmer Station

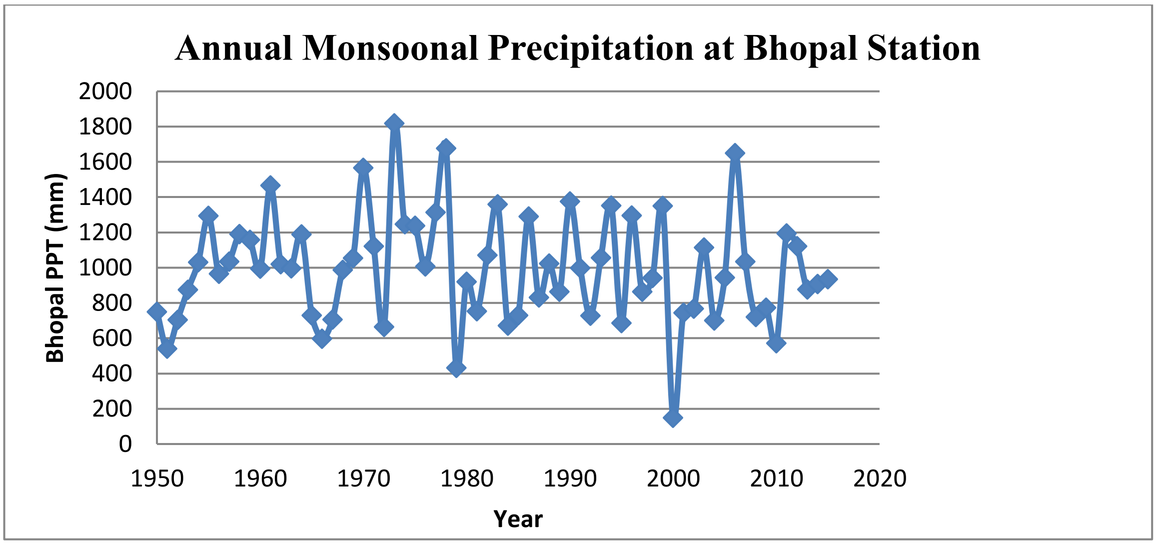

Figure 5 Annual Monsoonal Precipitation at Bhopal Station

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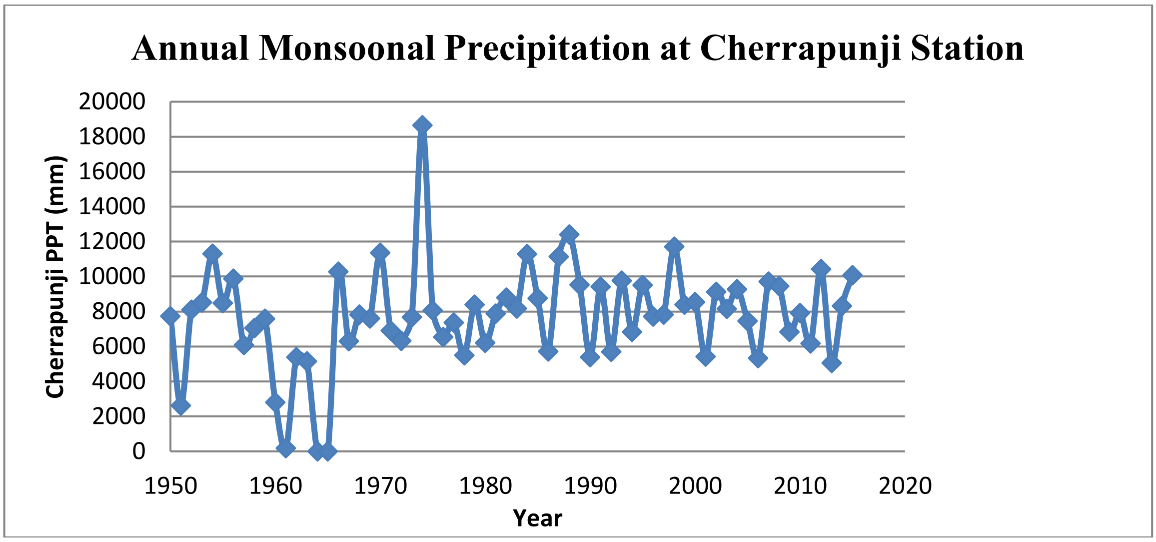

Figure 6 Annual Monsoonal Precipitation at Cherrapunji Station

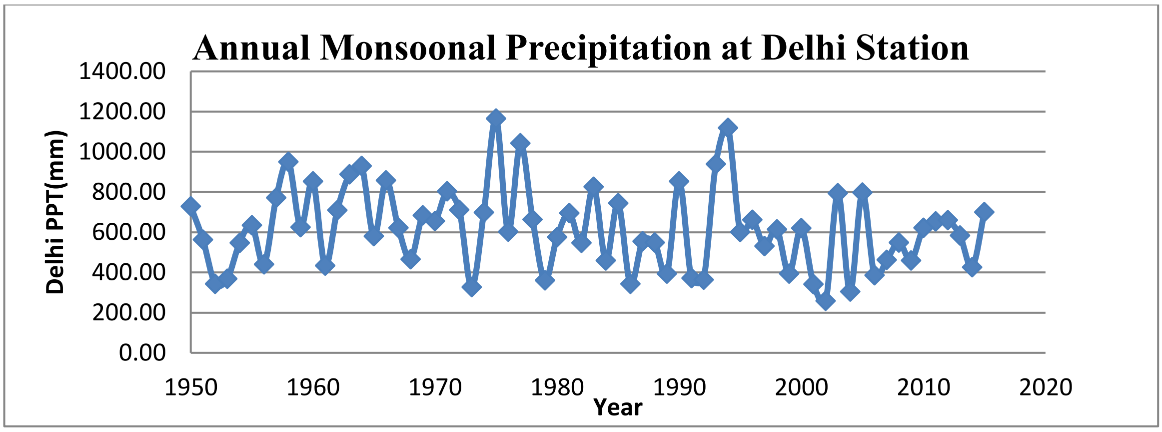

Figure 7 Annual Monsoonal Precipitation at Delhi Station

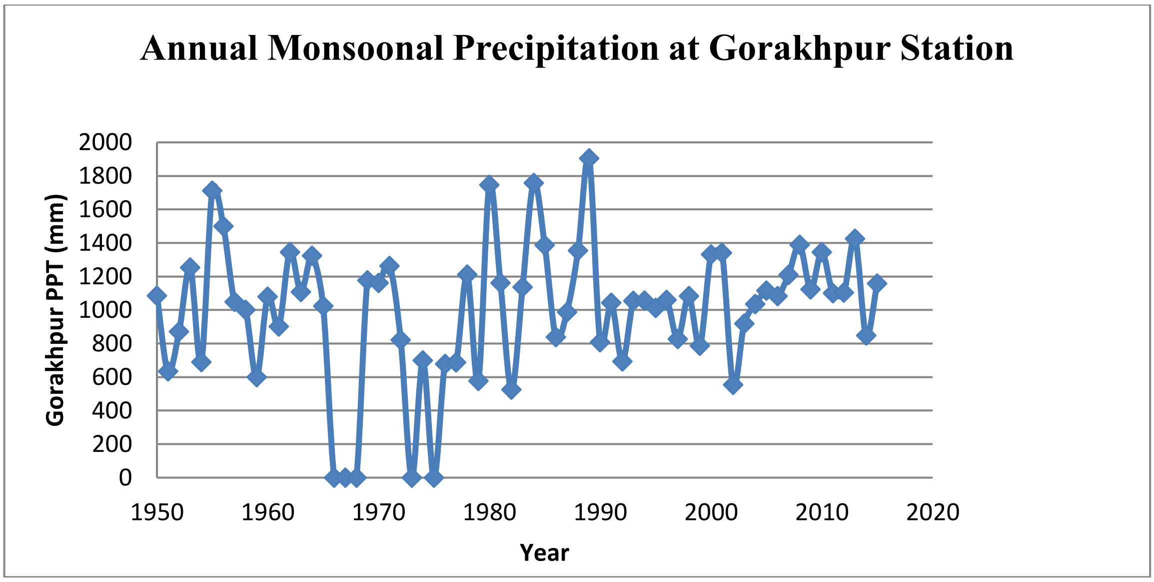

Figure 8 Annual Monsoonal Precipitation at Gorakhpur Station

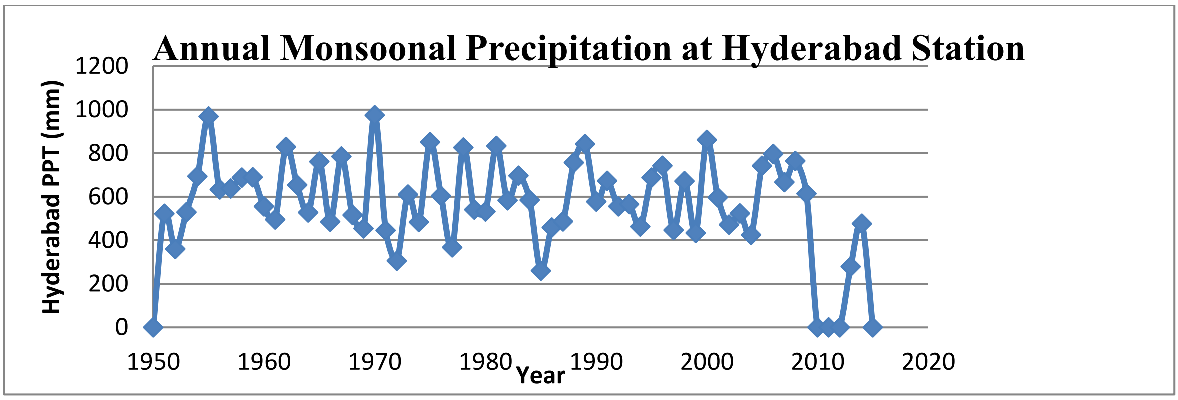

Figure 9 Annual Monsoonal Precipitation at Hyderabad Station

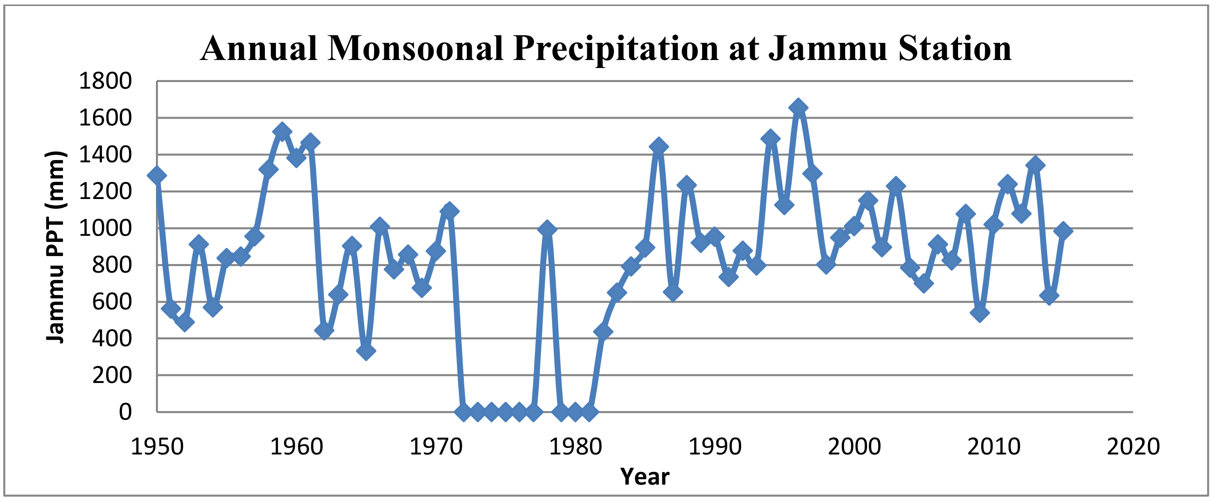

Figure 10 Annual Monsoonal Precipitation at Jammu Station

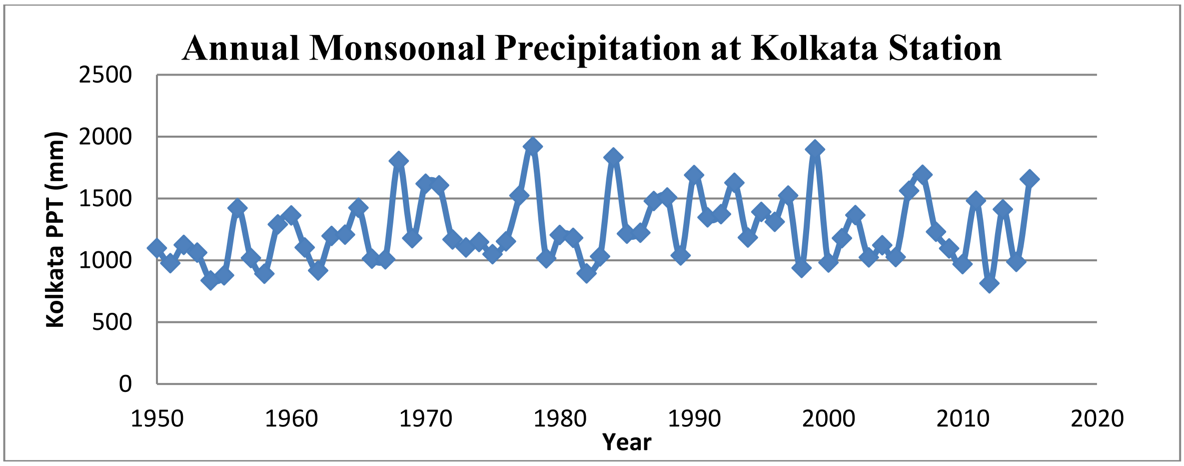

Figure 11 Annual Monsoonal Precipitation at Kolkata Station

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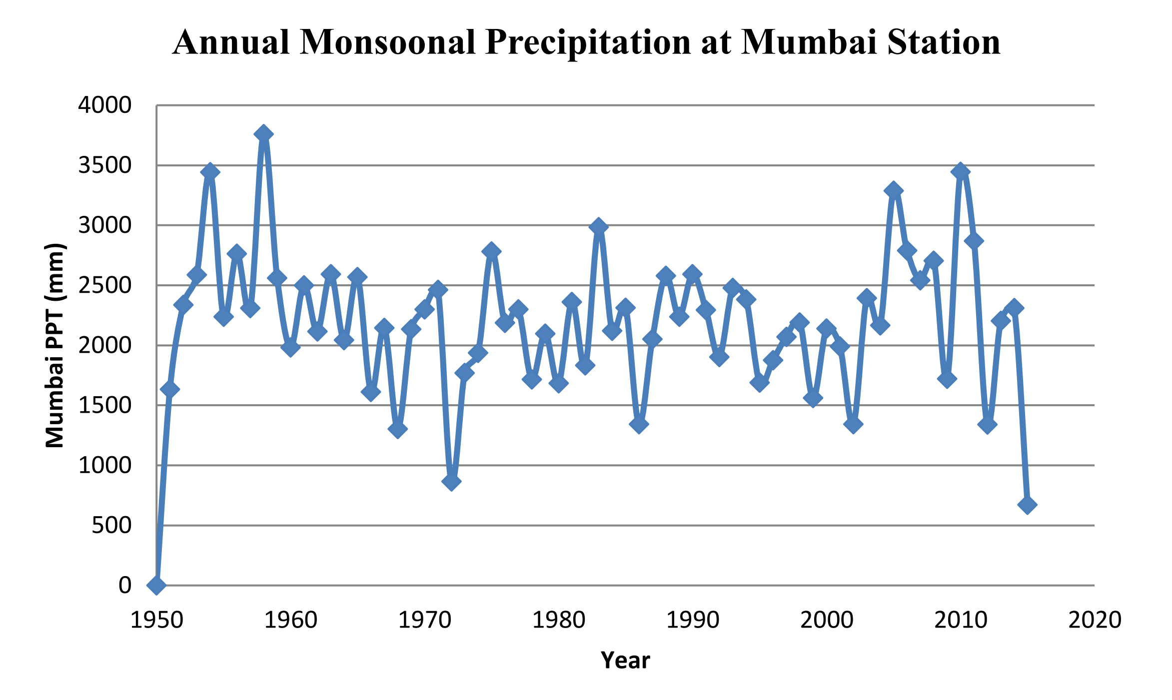

Figure 12 Annual Monsoonal Precipitation at Mumbai Station

Principal Components Analysis

The primary objective of PCA is to simplify intricate high-dimensional data while retaining crucial information. This is accomplished by converting the initial variables into a fresh set of variables, termed principal components, constructed through linear combinations of the original features. These principal components are orthogonal to each other and are expected to capture the highest amount of variance within the data. In the present research PCA has been performed Python.

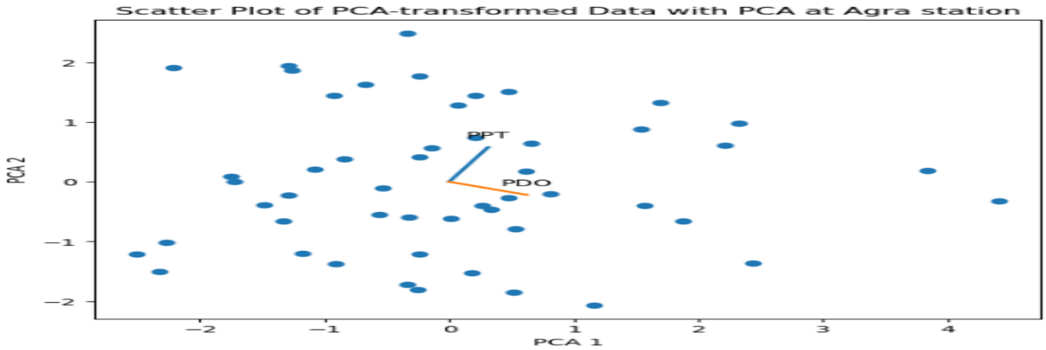

Figure 13 PCA biplot at Agra Station

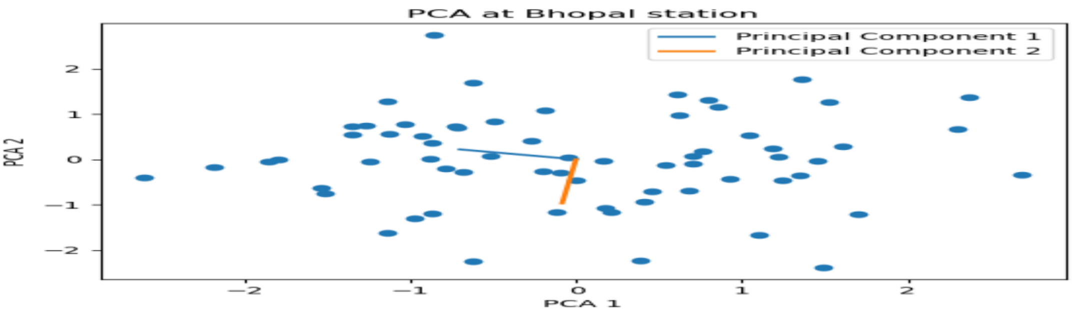

Figure 14 PCA biplot at Bhopal Station

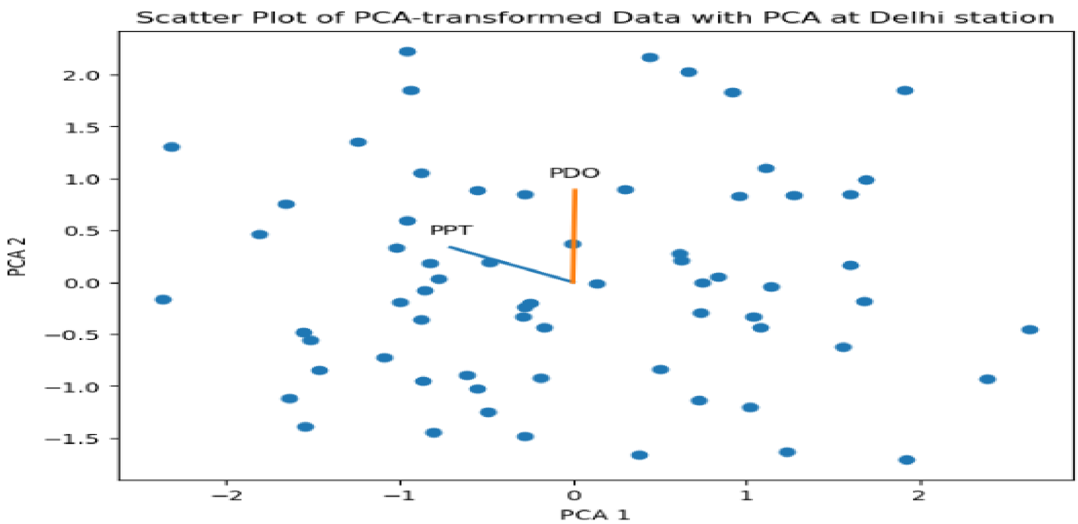

Figure 15 PCA biplot at Bhopal Station

Table 2Coefficient of Correlation with related P-values at 10 Rainfall stations

Rainfall Station	Correlation Coefficients	P value
Agra	-0.396	0.062
Ajmer	-0.350	0.003
Bhopal	-0.21	0.090
Cherrapunji	0.164	0.182
Delhi	0.104	0.412
Gorakhpur	-0.121	0.34
Hyderabad	0.144	0.255
Jammu	-0.032	0.803
Kolkata	0.028	0.816
Mumbai	0.290	0.018

5. CONCLUSIONS

When two vectors' cosine angles are either 0° or 180°, it indicates a strong link between the variables. There is a positive connection and a correlation coefficient value of 1 when the angle is 0°. When the angle is 180 degrees, the correlation is negative and the correlation coefficient value is -1. Monsoonal rainfall data study shows that 1952 saw the highest annual precipitation in Agra, with 1138.5 mm. While the lowest typical annual precipitation in Delhi was 363.30 mm in 1992, the highest recorded annual precipitation at the Delhi station was 1164.30 mm in 1975. Cheerapunji saw its greatest yearly precipitation of 18655.4 mm in 1974. The only stations where monsoonal precipitation and PDO temperature index have a positive link are Cherrapunji, Delhi, Hyderabad, Kolkata, and Mumbai. Monsoonal precipitation and PDO are negatively correlated at the five rainfall sites that remain. For ten rainfall stations in northern India, correlations between El Nino and monsoonal precipitation have been found. At every location taken into consideration in this study, precipitation decreased during the majority of El Nino years.At the majority of the sites taken into consideration in this study, higher precipitation is seen during La Nina years.

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