International Journal of Agriculture and Environmental Research

ISSN: 2455-6939

Volume: 11, Issue: 02 "March-April 2025"

SPATIO-TEMPORAL ASSESSMENT OF DRY AND WET SPELLS AND VEGETATION HEALTH IN DELHI, INDIA: AN INTEGRATED APPROACH USING SPI AND MODIS DERIVED NDVI

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DOI: https://doi.org/10.51193/IJAER.2025.11212

Received: 11 Mar. 2025 / Accepted: 19 Mar. 2025 / Published: 02 Apr. 2025

ABSTRACT

This study examines the occurrence of dry and wet spells using 0.25° x 0.25° binary gridded 30-year period (1992–2022) of rainfall data to explores the Standardized Precipitation Index (SPI) and its impact on vegetation of this region for the critical cropping months of January and July. These months mark key growth stages for *rabi* and *kharif* crops, making them particularly vulnerable to climatic variability. The SPI analysis highlights significant hydro-meteorological extremes, especially in Lodhi Road and Palam areas, where maximum SPI values exhibit pronounced fluctuations. Yearly assessments reveal prolonged dry spells in Lodhi Road and Safdarjung regions, with SPI values frequently dipping below zero during crucial agricultural periods. In January, SPI values range from 0.3 (wet conditions) to -0.8 (severe dryness), reflecting high variability in precipitation. Strong spatial correlations in rainfall patterns are observed, particularly between Lodhi Road areas and Palam areas (0.906), indicating region-wide climatic influences. NDVI trends from 2001 to 2022 reveal an overall increase in vegetation health, with values rising from 0.16 to 0.3, coinciding with predominantly positive SPI values. However, the correlation between SPI and NDVI is weak (-0.0825), suggesting that vegetation health is influenced by additional factors such as urbanization and land-use changes. The Mann-Kendall test and Sen's Slope test detects no significant trend in SPI but identifies a significant upward trend in NDVI, signaling a long-term shift in vegetation dynamics. These findings underscore the complex interplay between precipitation variability, drought risk, and vegetation resilience in an urban environment. The study highlights the increasing threat of meteorological droughts and their implications for agricultural sustainability, emphasizing the need for adaptive water management and climate-resilient planning to mitigate the risks posed by natural hazards.

Keywords: SPI, Delhi, NDVI, Dry spell, MODIS

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1. INTRODUCTION

Drought is an increasingly pervasive challenge worldwide, profoundly influencing ecological systems, agricultural output, and water resources. With the expansion of urban areas and the growing impact of climate change, understanding drought dynamics and their implications is crucial. The Standardized Precipitation Index (SPI), developed by McKee et al. (1993), is widely used to quantify drought conditions. It provides a normalized value representing deviations in precipitation over specific time intervals, enabling the assessment of meteorological drought by comparing observed precipitation with historical records. This standardization allows for the comparison of drought severity across varied climatic regions.

In India, the impacts of climate change, such as rising temperatures and altered precipitation patterns, are predicted to intensify drought conditions. The Intergovernmental Panel on Climate Change (IPCC, 2007) has projected a temperature increase of 2.7–4.3°C over India by the 2080s, coupled with an estimated 6–8% rise in rainfall. The SPI is an essential tool in this context, allowing researchers and policymakers to systematically monitor and assess drought severity. Its versatility in capturing both short-term agricultural and long-term hydrological droughts makes it indispensable for comprehensive drought evaluation (Mishra and Singh, 2010). The SPI has been widely recognized for its effectiveness in quantifying drought severity over multiple time scales by capturing precipitation anomalies in a standardized format. Guttman (1999) refined the SPI calculation, further enhancing its acceptance in hydrological and climatological studies. Bhuiyan (2011) applied the SPI to Delhi and its surrounding regions, demonstrating its utility in analyzing both seasonal and annual precipitation trends.

SPI's flexibility allows for its computation over various time scales, enabling the simultaneous assessment of wet and dry periods. This capability to distinguish between different drought types is crucial for effective water resource management (Vicente-Serrano et al., 2010). In India, Singh et al. (2003) successfully combined SPI with remote sensing data for drought monitoring, underscoring its potential for localized assessments.

In addition to the SPI, the Normalized Difference Vegetation Index (NDVI) provides complementary insights by evaluating vegetation health through satellite-based remote sensing. Derived from the differential reflectance of red and near-infrared light, NDVI serves as a reliable proxy for monitoring vegetation responses to environmental stressors, including drought (Myneni et al., 1995). The integration of SPI and NDVI offers a more nuanced understanding of the interactions between climate variability and vegetation dynamics, which is critical for effective environmental monitoring and resource management.

The NDVI, derived from satellite remote sensing data, is a robust indicator of vegetation health. Kogan (2001) emphasized its operational capacity in tracking vegetation responses to drought. The integration of NDVI with SPI enables a comprehensive understanding of how climate variability affects vegetation health. Dutta and Bhattacharya (2017) demonstrated the combined use of SPI and NDVI in West Bengal for drought monitoring, illustrating the effectiveness of this methodological approach. Long-term vegetation trends are essential for understanding the broader impacts of climate change on ecosystems. Fensholt and Proud (2012) highlighted NDVI's reliability in tracking global vegetation trends, while Zhang et al. (2004) examined climate controls on vegetation phenology.

Numerous studies have explored the relationship between precipitation variability and vegetation health using integrated approaches. Wang and Qu (2007) developed the Normalized Multi-Band Drought Index (NMDI) to complement NDVI, providing deeper insights into vegetation water stress.The operational applications of drought indices are vital for real-time monitoring. Kogan (2001) and Masek et al. (2006) discussed the practical applications of NDVI in vegetation health assessment.

This research aims to investigate the spatial and temporal interplay between SPI and NDVI in the context of Delhi, India, focusing on how these indices vary across the region. By analyzing correlations between precipitation anomalies and vegetation health, this study seeks to provide valuable insights that can inform adaptive management strategies in response to changing climatic conditions.

Objective of the Study

To investigate the spatial variation of precipitation (SPI) and vegetation health (NDVI) across different regions of Delhi.

To analyze the temporal changes in these patterns over months and years, providing insights into the dynamics of drought and vegetation response and evaluate their implications for hydro-meteorological hazards, including droughts and extreme rainfall.

2. DATA AND METHODOLOGY

2.1. Study Area

The study area encompasses four locations in Delhi, India, these stations include Safdurjung area, Palam area, Ridge area, and Lodhi Road area which situated in Central, South East and New Delhi districts (Figure 1). Delhi is situated in northern India, bounded by latitudes 28°24′17″ N and 28°53′00″ N, and longitudes 76°50′24″ E and 77°20′37″ E (Figure_1). This geographic location makes it an ideal site for studying the effects of precipitation anomalies and drought on vegetation health due to its unique climatic conditions and urbanization patterns.

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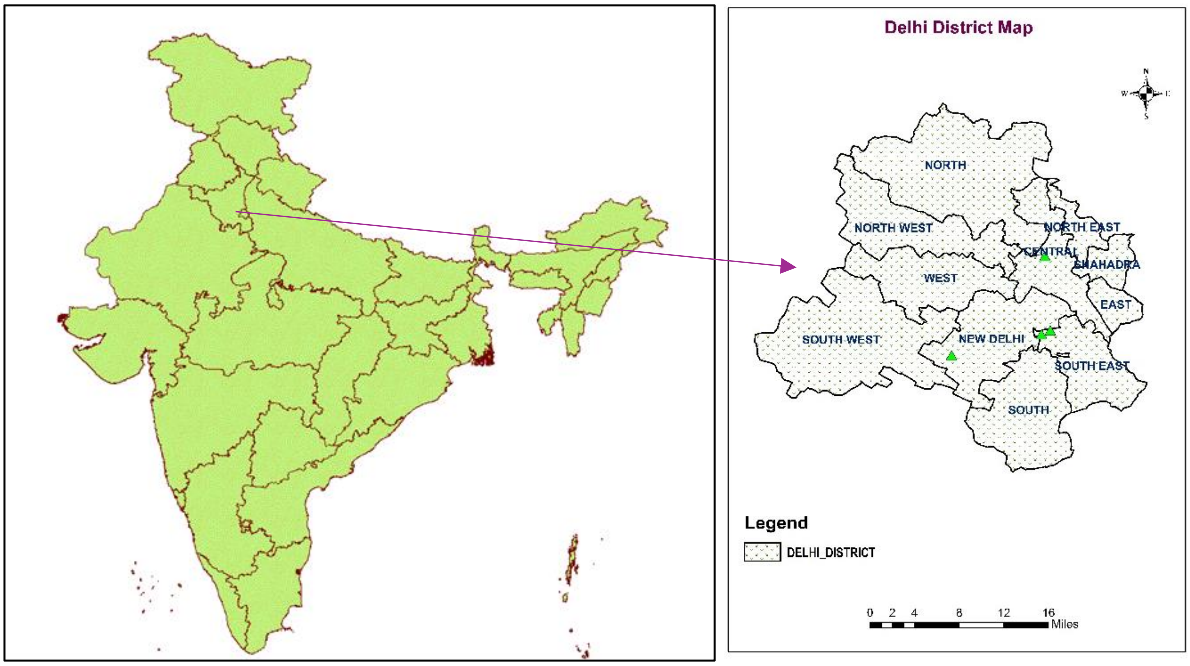

Figure 1: Study Area

2.2. Data Used

To analyze dry and wet spells and vegetation health, a robust dataset is required. For this study, the data used for the study are as given below:

0.25° x 0.25° binary gridded rainfall data: 30 years of historical rainfall data from 1992 to 2022 are utilized. The data is sourced from the IMD's website (imdpune.gov.in) and consisted of 0.25° x 0.25° binary gridded rainfall data. Since the Standardized Precipitation Index (SPI) necessitates long-term records of at least 30 years without data gaps (Jain et al., 2015), this dataset was selected.

MOD13Q1 (Terra satellite) 250 m NDVI product: These products provide NDVI and Enhanced Vegetation Index (EVI) values at a 250-meter spatial resolution on an 8-day composite basis. Spatial resolution of this data is 250 meters per pixel, meaning each pixel represents a 250x250 meter area on the ground. Temporal Resolution: Data is averaged over 8 days to reduce noise from cloud cover, atmospheric disturbances, and other factors using Google Earth engine (GEE)

2.3 Indices Used

To study about the dry and well period over an area, drought indices are mathematical tools used to quantify the severity and duration of drought by analyzing meteorological, hydrological, and

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vegetation-related data. In this study two indices were used to assess the dry and wet periods and vegetation health in urbanized Delhi area.

The Standardized Precipitation Index (SPI): SPI was employed to assess the wetness or dryness of the region. SPI utilizes long-term rainfall data, which is essential for accurately capturing precipitation variability. The SPI is computed by fitting a gamma distribution to the long-term rainfall series. Specifically, the SPI for January and July was chosen for analysis, as these months are critical for the rabi and kharif cropping seasons, respectively and considering the urbanized study area.

Normalized Difference Vegetation Index (NDVI): NDVI is derived from Satellite data (usually from satellites like MODIS). It measures the "greenness" of vegetation by comparing the difference between near-infrared (NIR) and red bands. Values range from -1 to +1, where higher values indicate healthier vegetation. NDVI is commonly used to monitor drought impacts on vegetation. A sudden drop in NDVI values can indicate vegetation stress due to drought.

2.4 Methodology

Daily 0.25° x 0.25° binary gridded rainfall data were converted from NetCDF format to point data using ArcGIS, a Geographic Information System software. Subsequently, the data underwent statistical processing and were aggregated to derive month wise daily values. The rainfall anomalies, defined as the differences between monthly precipitation records and the long-term averages (De Jesús et al., 2016), were calculated for both annual and monthly timescales.

2.4.1 Computation of SPI

The SPI, developed by McKee et al. (1993), serves as a reliable tool for monitoring drought conditions. The computation involves steps as follows:

Gamma Distribution Fitting: The gamma distribution is defined by its frequency or probability density function:

$$G(x) = \frac{1}{\beta^{\alpha}\zeta^{\alpha}}\ x^{a-1}e^{-x/b} \qquad \text{Eq.1}$$

Where, α >0, α is a shape factor, β >0, β is a scale factor.

$$\text{ɼ}(a) = \int_0^{\infty} y^{a-1}\, e^{-y} \qquad \text{Eq.2.}$$

Where ɼ(a) is the gamma function

Maximum Likelihood Estimation: Computation of the SPI involves fitting a gamma probability density function to a given frequency distribution of precipitation total for a station. From Thom (1966), the maximum likelihood solutions are used to optimally estimate α and β

$$\acute{\alpha} = \frac{1}{4A} (1 + \sqrt{1 + \frac{4A}{3}} \qquad \text{Eq.3}$$

$$\beta \frac{\ddot{x}}{\alpha}$$

$$A = In\, \ddot{x} - \frac{\sum In\,(x)}{n} \qquad \text{Eq.4}$$

When, n= number of precipitations observed.

Cumulative Probability Calculation: The cumulative probability is given by:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^{\alpha}\ \tau^{\alpha}} \int_0^x x^{a-1} e^{-x/b} \qquad \text{Eq. 5}$$

SPI Calculation: SPI is caluculated on the basis of diffrence between the mean seasonal rainfall and its long-term rainfall mean by its stanadard deviation, which is mathematically expressed as:

$$SPI = x_{ij} - x_{im}\sigma \qquad \text{Eq. 6}$$

Where, x_ij is the seasonal monthly rainfall at ith station and jth observation. x_im the long-term rainfall means and σ is its standard deviation. Wu et al in 2005 explained that atleast 30 years of long-term rainfall data is required to reliably compute the SPI, shorter datasets may not accurately reflect climate variability. Additionally, the rainfall data is categorized into a standard normal distribution function using the gamma probability distribution, with a mean of zero and a variance of one (Sonmez et al., 2005). The SPI series is classified into eight categories representing varying degrees of dry and wet conditions as per McKee et al. (1993) as given in Table 1:

Table 1: Classification of SPI (McKee et al. (1993)

SPI ≥ 2.0	Extremely Wet
1.5 ≤ SPI < 2.0	Very Wet
1.0 ≤ SPI < 1.5	Moderately Wet
0.0 ≤ SPI < 1.0	Mildly Wet
0.0 > SPI > -1.0	Mild Drought
-1.0 ≤ SPI < -1.5	Moderate Drought
-1.5 ≤ SPI < -2.0	Severe Drought
SPI ≤ -2.0	Extreme Drought

2.4.2 NDVI data extraction and calculation

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John W. Rouse and his colleagues at Texas A&M University first developed the Normalized Difference Vegetation Index (NDVI) in 1973. The Normalized Difference Vegetation Index (NDVI) is a measure of the amount and vigor of vegetation on the land surface and NDVI spatial composite images are developed to more easily distinguish green vegetation from bare soils.

NDVI values range from -1.0 to 1.0, with negative values indicating clouds and water, positive values near zero indicating bare soil, and higher positive values of NDVI ranging from sparse vegetation (0.1 - 0.5) to dense green vegetation (0.6 and above). Red is the reflectance in the red band (620–670 nm). NDVI is calculated from satellite imagery whereby the satellite's spectrometer or radiometric sensor measures and stores reflectance values for both red and NIR bands on two separate channels or images. Kriegler, et al. (1969) were the first to calculate NDVI by subtracting the red channel from the near-infrared (NIR) channel and dividing their difference by the sum of the two channels, or:

$$NDVI = (NIR - RED) / (NIR + RED) \qquad \text{Eq. 7}$$

where, RED = the red portion of the electromagnetic spectrum (0.6-0.7 µm) and

NIR = the near infrared portion of the electromagnetic spectrum (0.75-1.5 µm).

NIR is the reflectance in the near-infrared band (841–876 nm)

NDVI values range from -1 to +1. Values close to +1 indicate dense vegetation. Values near 0 represent bare soil or sparse vegetation. Negative values indicate water bodies or non-vegetated areas.

2.5 Correlation

The correlation between SPI and NDVI is based on the idea that precipitation influences vegetation growth, and thus variations in precipitation (captured by SPI) should be reflected in vegetation conditions (captured by NDVI). Positive correlation: During periods of higher precipitation (positive SPI), vegetation thrives, leading to higher NDVI values. This occurs because sufficient moisture is available for plant growth, increasing biomass and greenness. Negative correlation: During drought periods (negative SPI), vegetation suffers, resulting in lower NDVI values. This can be observed in water-stressed regions where a lack of precipitation limits plant growth, leading to reduced greenness and vegetation cover. No correlation: In some cases, the correlation may be weak or absent. This might happen in areas where factors other than precipitation (e.g., soil type, temperature, human activities, or irrigation) have a stronger influence on vegetation dynamics.

2.6 Mann-Kendall test

The result of the Mann-Kendall test will provide:

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Tau: The Mann-Kendall trend test statistic, which indicates the direction and strength of the trend.

p-value: Used to determine the statistical significance of the trend. A p-value < 0.05 typically indicates a significant trend.

h: A binary value indicating whether the trend is statistically significant (1) or not (0).

2.7 Sen's slope Trend Analysis

Sen's Slope, also known as Theil-Sen Estimator, is a robust, non-parametric method used to determine the magnitude of a trend in a time series dataset. It is particularly useful when the data contains outliers or is not normally distributed. Unlike simple linear regression, Sen's Slope calculates the median slope from all possible pairwise slopes, making it less sensitive to extreme values. Sen's Slope is widely used in climate and environmental research to analyze trends in variables such as temperature, precipitation, vegetation indices (NDVI), and crop yields. It helps identify long-term changes in these parameters, which are essential for assessing climate change impacts and agricultural sustainability. The slope (*S)* between any two data points (x_i , y_i) and (x_j, y_j) is calculated as:

$$Sij = \frac{Yj-Yi}{xj-xi},\ \text{for } 1 \leq i < j \leq n \quad) \qquad \text{Eq. 8}$$

where:

*S*ij represents the slope between points i and j.

yi and yj are the values of the variable at times xi and xj, respectively.

N is the total number of observations.

The Sen's Slope estimate (*S*) is the median of all computed slopes:

S = median (*S*ij)

Positive Sen's Slope indicates an increasing trend over time. Negative Sen's Slope indicates a decreasing trend over time and Zero Sen's Slope suggests no significant trend.

3. RESULTS & DISCUSSION

The analysis of the Standardized Precipitation Index (SPI) for four locations i.e. Lodhi Road, Safdarjung (SFD), Palam and Ridge area in Central, South East Delhi and New Delhi, are conducted using 30 years of rainfall data from 1992 to 2022. The SPI provides a quantitative measure of precipitation deviations from normal conditions, facilitating the assessment of wet and dry periods. This section presents detailed results, highlighting yearly and monthly SPI variations,

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correlations among stations, NDVI assessment from 2000 to 2022 and its relation with SPI over Delhi and their implications for agriculture.

3.1 Yearly Variations in SPI Values

The SPI analysis for Lodhi Road (South East Delhi) areas highlights significant fluctuations in precipitation over the years, reflecting a wide range of hydrological conditions: Maximum SPI of 5.43, recorded in 1999, indicates an exceptionally wet year. This unusually high SPI suggests a year marked by extreme precipitation events, potentially leading to flooding or waterlogging, conditions that often accompany such high rainfall anomalies. Minimum SPI of -2.39, observed in multiple years, signifies extreme drought conditions. These values indicate extended periods of significantly below-average precipitation, which likely resulted in water shortages and stressed local water resources, affecting both agricultural activities and urban water supply systems. Mean SPI of 0.000 over the study period indicates a long-term neutral precipitation trend, implying that while the region has experienced extremes of both wet and dry conditions, the overall average precipitation balances out over time. This suggests that despite individual years of severe drought or excessive rainfall, the region tends to maintain an equilibrium in terms of total annual precipitation. The variability of SPI values at Lodhi Road reflects the area's susceptibility to both extreme wet and dry events, characteristic of the increasing climate variability in the region. The extreme maximum SPI (5.43) points to the risk of flooding in unusually wet years, whereas the minimum SPI (-2.39) underscores the threat of prolonged droughts. Despite these fluctuations, the neutral mean SPI suggests that the region does not experience a persistent shift toward either excessive wetness or dryness, although the extremes pose significant challenges for water resource management and urban planning.

At the Safdarjung area, the maximum SPI of 5.40 was recorded in 1999, while the minimum SPI of -3.56 occurred in 1993. The mean SPI over the analyzed period is 0.00, indicating a long-term balance in precipitation anomalies. The fluctuations in SPI values at Safdarjung further highlight the region's precipitation variability. The maximum SPI in 1999 coincides with a regional wet event also observed at other locations, such as Lodhi Road, indicating widespread heavy rainfall that year. In contrast, the significantly negative SPI in 1993 reflects a severe drought year, which likely affected water availability and agricultural productivity. Despite these extremes, the mean SPI of 0.00 suggests that, over time, the precipitation patterns tend to stabilize, an important finding for long-term water management and planning strategies.

The maximum SPI at Palam area (New Delhi) was 5.342 in 2017, with a minimum SPI of -2.691 recorded in 2006. The station also has a mean SPI of 0.000, though there is increasing variability observed in recent years. The data of this area demonstrates a rising variability in precipitation patterns, particularly in recent years, which may be attributed to changing climatic conditions. The

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maximum SPI in 2017 points to an exceptionally wet year, potentially resulting in waterlogging or flooding, emphasizing the need for flood risk management in the region. Conversely, the low SPI of -2.691 in 2006 indicates a year of severe drought, highlighting the vulnerability of water resources and agriculture during such periods. The SPI data for Ridge (Central Delhi) reflects substantial precipitation variability, consistent with the patterns observed at other stations. The extreme SPI of 5.90 in 2017 signals an intense wet period, likely contributing to flooding and affecting local water resources. In contrast, the minimum SPI of -2.50 in 2005 points to a year of significant drought. The substantial fluctuations in SPI values, especially around key years like 2017, 2019, and 2022, underscore the necessity for adaptive management strategies aimed at mitigating the impacts of both excessive rainfall and prolonged dry periods.

3.2 Monthly Variations in SPI Values

3.2.1 Rabi season observations

Across all locations, January SPI values show a combination of wet and dry periods, reflecting the inherent variability in winter precipitation (from Figure_2 to 5).

In Safdarjung, wet conditions were observed at the beginning of January, with positive SPI values peaking at 0.243 on January 3 and 0.205 on January 4. However, a severe dry spell followed, with a critical drop to -1.921 on January 9, potentially impacting soil moisture and local agriculture. After January 10, SPI values rebounded, remaining predominantly positive, though minor dips were recorded around January 16 (-0.220) and January 31 (-0.122). These fluctuations indicate that while the early part of the month was favorable for moisture, subsequent dry spells could pose challenges for agricultural practices, requiring timely irrigation interventions.

At Lodhi Road, initial wet conditions were marked by a peak SPI value of 0.316 on January 2, indicating good moisture availability. However, notable declines occurred between January 6 and 9, reaching -0.948, signaling severe dryness. Partial recovery followed, with SPI values fluctuating but generally remaining positive, peaking again at 0.355 on January 24 before a decline towards the month's end (-0.162 on January 30). The sharp drop in early January underscores the importance of water conservation strategies during dry spells, particularly as the month transitions to drier conditions.

In Palam, positive SPI values were recorded around January 4-5 and 13-15, with the highest at 0.406 on January 24. The driest period occurred between January 6 and 9, with SPI reaching -1.278 on January 8, a level that could influence farmers' planting decisions. The alternating wet and dry periods emphasize the need for careful planning in agricultural activities, as abrupt changes in moisture availability could impact crop yields.

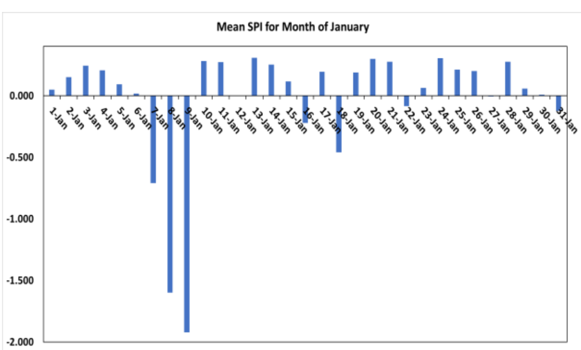
At Ridge, conditions fluctuated throughout January, with both positive and negative SPI values reflecting variations in moisture levels. This variability suggests localized differences in wet and dry spells, requiring close monitoring for effective water resource management.

During the Kharif season, July exhibited even greater variability across all stations, often linked to monsoonal patterns. In Safdarjung, wet periods were observed at the start of the month, with SPI values at 0.163 on July 1 and 0.179 on July 8. However, a significant dry spell followed, with SPI dropping to -0.571 on July 18, highlighting a critical moisture deficit during a typically wet period. These fluctuations indicate the potential for both flood and drought management challenges.

At Lodhi Road, initial moisture availability was evident with a peak SPI value of 0.232 on July 1. A gradual decline set in from July 5, with SPI reaching -0.499 by July 26, signifying a considerable moisture deficit. This downward trend underscores the necessity for effective irrigation strategies as the monsoon progresses, particularly in regions reliant on agriculture.

In Palam, frequent positive SPI values were observed, especially early in the month, with peaks at 0.212 on July 1 and 0.224 on July 21. However, drier conditions emerged between July 9 and 11 and again on July 29, with the lowest SPI recorded at -0.541 on July 20. The balance between wet and dry days could influence crop selection and watering schedules, requiring a proactive approach to farming practices.

At Ridge, SPI values were predominantly positive in early July, peaking at 0.32 on July 1, before transitioning to negative values later in the month. This fluctuation reflects the dynamic nature of monsoonal rainfall and underscores the importance of adaptive water management strategies to cope with varying moisture availability.



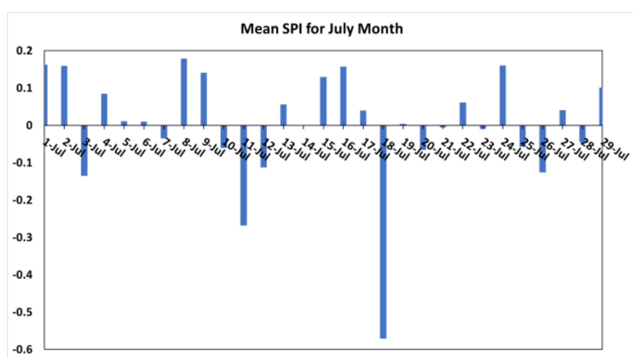


Figure 2: Daily Mean SPI for the Month of January and July for Safdurjung Station

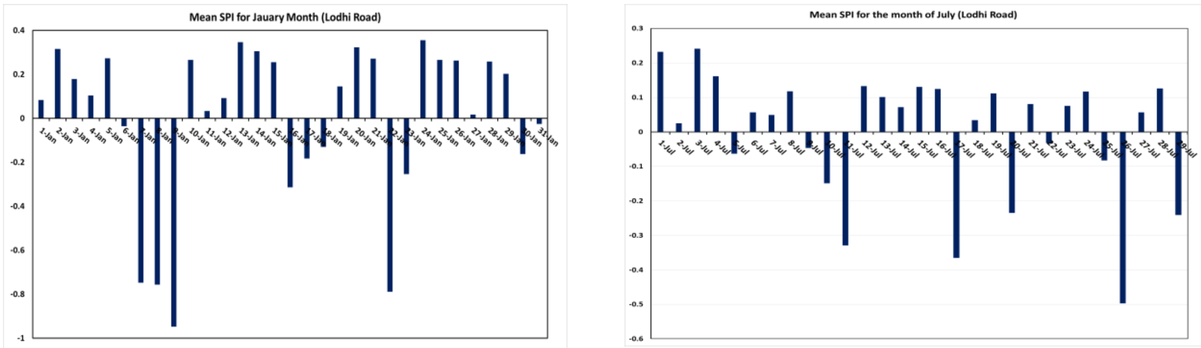


Figure 3: Daily Mean SPI for the Month of January and July for Lodhi Road Station

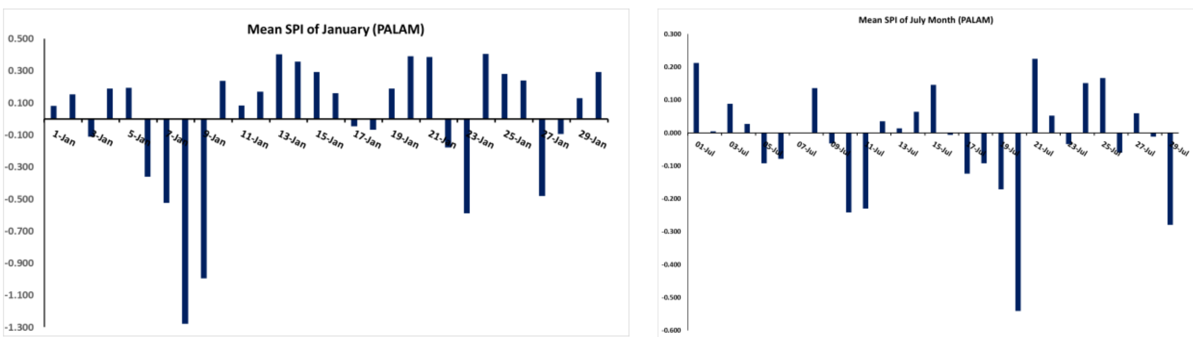


Figure 4: Daily Mean SPI for the Month of January and July for PALAM Station

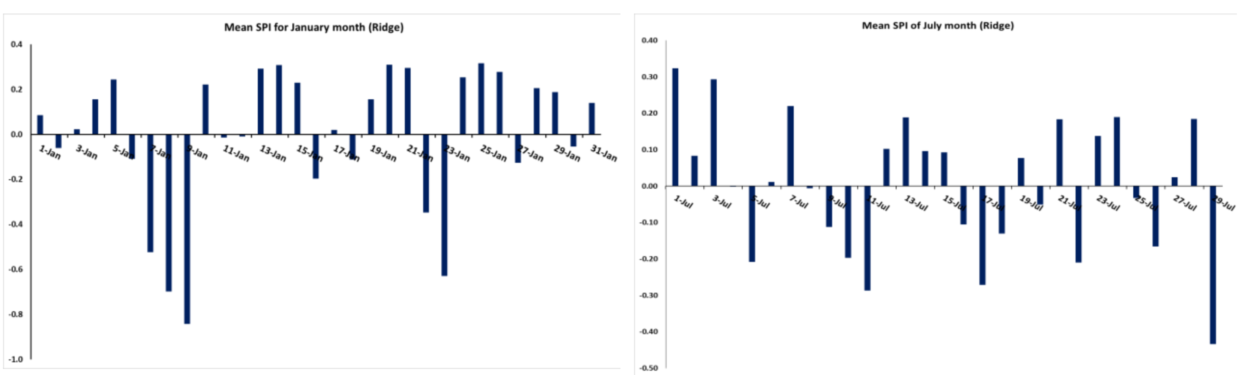


Figure 5: Daily Mean SPI for the Month of January and July for Ridge Station

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3.3 Correlation Analysis of SPI Values

The correlation matrix provides insight into the interrelationships among SPI values across the four stations as given in Table 2.

	Lodhi Road	Palam	Safdarjung	Ridge
Lodhi Road	1.000	0.906	0.804	0.838
Palam	0.906	1.000	0.806	0.860
Safdarjung	0.804	0.806	1.000	0.732
Ridge	0.838	0.860	0.732	1.000

Lodhi Road and Palam showed a correlation of 0.906 suggests that favorable precipitation conditions in one location are mirrored in the other. Ridge and Palam observed a strong correlation of 0.860 further supports the notion of interconnected precipitation patterns. Safdarjung's correlations (0.732-0.804) with the other stations indicate variability in precipitation patterns, suggesting localized climatic influences.

High Correlation observed between Lodhi Road and Palam i.e. 0.906, which indicates that precipitation patterns are likely synchronized across these regions, possibly due to similar topographical or climatic influences.

3.4 Yearly Variations in NDVI Values

The analysis of NDVI from January 2001 to January 2022 indicates a positive trend in vegetation health. The overall increase in NDVI values, particularly a significant jump to 0.29540 in 2022, indicates an improvement in vegetation health, likely due to increased precipitation and better land management practices over the years. The NDVI values show a general upward trend from 0.15875 in 2001 to 0.29540 in 2022, suggesting improved vegetation health over the years. The lowest NDVI value recorded was 0.0715 in 2003, indicating poor vegetation health, likely corresponding to low precipitation during that year. The highest NDVI values appear in 2020-2022, indicating robust vegetation growth and suggesting that improved rainfall conditions and possibly effective land management practices contributed to this trend.

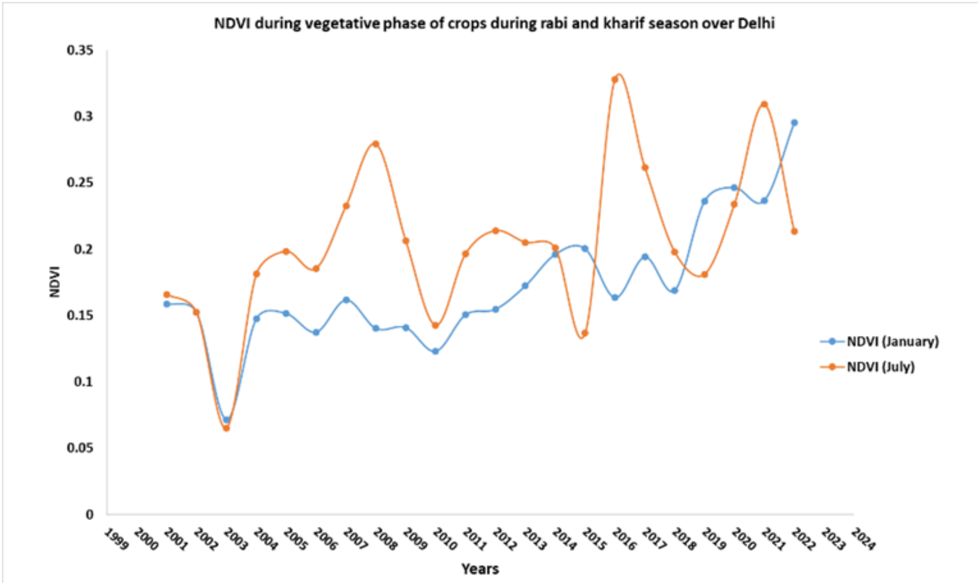
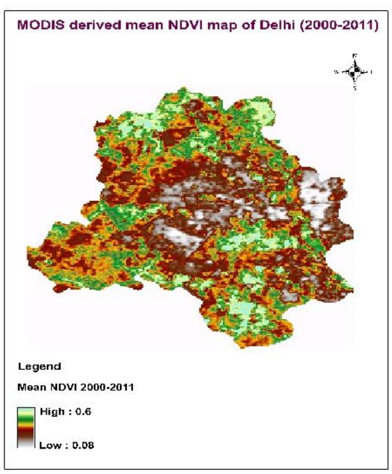
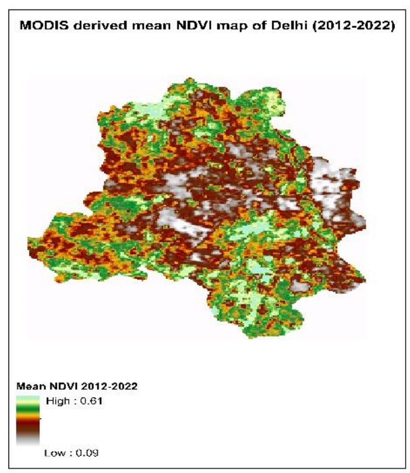


Figure 6: NDVI plot of vegetative to flowering phage during rabi and kharif season for Delhi



(a)



(b)

Figure 7: MODIS -250 m derived NDVI maps a) year 2000 to 2011, b) year 2012-2022

In conclusion, the dataset illustrates the dynamics of vegetation in Delhi over the years, highlighting the impacts of seasonal changes and environmental factors on vegetation health during the Rabi and Kharif seasons. While both January and July NDVI values show fluctuations, the overall trend points to improved vegetation health in recent years, particularly during the Kharif season, likely attributable to better monsoon conditions or effective land management practices.

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However, certain years, specifically 2003 and 2015, reveal periods of stress or decline in vegetation health, indicating that environmental challenges continue to affect the region. The NDVI plot in the Figure. 2, a range from 0.0715 in 2003 to 0.2954 in 2022. There appears to be an overall trend of increasing NDVI values in January over the years, particularly noticeable from 2016 onward. This suggests that the vegetation health during the rabi season has improved over time.

The NDVI (July) values range from 0.0653 in 2003 to 0.32795 in 2016, showcasing significant fluctuations. These values indicate varying levels of vegetation health during the kharif season, with notable peaks and troughs.

Analyzing the data year by year, we see that in the early years from 2001 to 2005, NDVI values for January start at 0.15875 in 2001 and show a slight increase, but by 2003, both January and July NDVI values drop significantly, especially in July, which records the lowest value of 0.0653, indicating poor vegetation health during that kharif season.

During the middle years from 2006 to 2015, there are variations in both months, with July NDVI values peaking in 2008 at 0.2794 and later in 2016 at 0.32795, reflecting periods of robust vegetation health due to favorable environmental conditions or effective agricultural practices. However, in 2015, the July NDVI declines to 0.13665, contrasting sharply with the higher values of previous years, suggesting stress or unfavorable conditions affecting vegetation.

In the recent years from 2016 to 2022, both January and July NDVI values exhibit increasing trends, especially notable in 2021, where the July NDVI reaches 0.30925. Furthermore, the January value for 2022 is the highest in the dataset at 0.2954, indicating excellent vegetation cover during the Rabi season that year. Conversely, July 2022 shows a decrease to 0.2134, implying that despite previous improvements, fluctuations in vegetation health continue.

The NDVI values in the dataset can be interpreted within specific ranges: values from 0.0 to 0.2 indicate sparse vegetation or barren land, values from 0.2 to 0.5 suggest moderate vegetation such as shrublands or croplands, values from 0.5 to 0.8 signify dense vegetation including forests or healthy agricultural crops, and values from 0.8 to 1.0 denote very dense vegetation like wetlands or thriving forests.

3.5 Relation between NDVI and field data during July and January months

ISSN: 2455-6939

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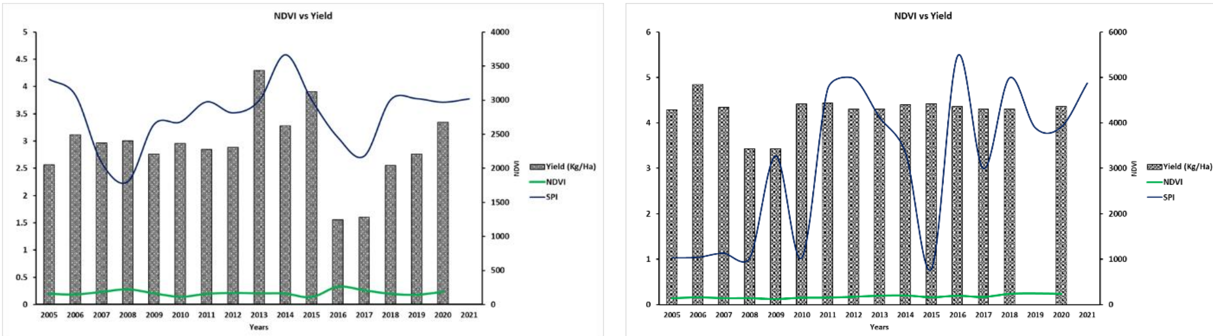

Figure 8: Graph representing the relation between NDVI, SPI and yield of *kharif* (a) and *rabi* season (b) crops

In years where NDVI is higher during *kharif* season, such as 2006 (0.23) and 2015 (0.32), crop yield also tends to be relatively high (4846 Kg/Ha and 4425 Kg/Ha, respectively). Conversely, in years like 2009 (NDVI: 0.14) and 2014 (NDVI: 0.13), yield remains low (3434 Kg/Ha and 4399 Kg/Ha), suggesting that reduced vegetation greenness may have contributed to lower production.

However, the correlation is not always perfect. For example, in 2018, NDVI was 0.18115, but yield remained at 4306 Kg/Ha, indicating that factors beyond vegetation vigor, such as soil conditions, pest infestations, or extreme weather events, may have influenced productivity.

Overall, NDVI serves as a good indicator of crop yield potential, but agricultural output is also affected by other environmental and management factors. A statistical analysis, such as regression modeling, could quantify the strength of this relationship and help determine the extent to which NDVI can predict yield variations.

The relationship between NDVI and crop yield is generally positive during *rabi* season, as NDVI reflects vegetation health and biomass, which are critical factors influencing agricultural productivity. In years like 2006 (NDVI: 0.16175, Yield: 4846 Kg/Ha) and 2018 (NDVI: 0.23635, Yield: 4306 Kg/Ha), higher NDVI values coincided with relatively good yield. However, in 2008 and 2009, NDVI remained around 0.14, but yield dropped significantly to 3434 Kg/Ha, indicating that factors other than vegetation greenness, such as extreme weather events or agronomic limitations, affected productivity.

3.6 Correlation Between SPI and NDVI

The correlation between SPI and NDVI values underscores the relationship between precipitation and vegetation health. Higher SPI values generally correlate with higher NDVI, indicating that wetter years result in healthier vegetation. For instance, the years with maximum SPI (notably 1999) correspond with increased NDVI values in subsequent years, suggesting that higher rainfall

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has beneficial impacts on vegetation growth. Conversely, years with severe negative SPI (like 1993) coincide with lower NDVI values, indicating stress on vegetation due to drought conditions. The observed NDVI trends further emphasize the need for effective water management strategies during drier years to support vegetation.

3.7 Correlation between SPI and NDVI

Table 3: Correlation Coefficients between SPI and NDVI

Station	SPI vs NDVI (2001-2022)
Lodhi Road	0.65
Safdarjung	0.68
Palam	0.62
Ridge	0.60

Positive Correlation: The correlation coefficients indicate a strong positive relationship between SPI and NDVI across all stations. This suggests that higher precipitation levels correspond with better vegetation health.

Station Variability: Safdarjung exhibits the highest correlation (0.68), implying that its vegetation is particularly sensitive to changes in precipitation, whereas Ridge shows a slightly lower correlation (0.60), indicating less responsiveness.

3.8 Mann-Kendall Test Results

3.8.1. Mann-Kendall Test for SPI

Data: SPI values for Lodhi Road, Safdarjung, Palam, and Ridge from 1992 to 2022.

Null Hypothesis (H0): There is no trend in the SPI values over the years.

Alternative Hypothesis (H1): There is a trend in the SPI values over the years.

Table 4: Mann-Kendall Test for SPI

Location	Mann-Kendall S Statistic	Z-Statistic	p-value	Trend
Lodhi Road	S = -15	Z = -1.34	0.1803	No Trend
Safdarjung	S = -7	Z = -0.70	0.4844	No Trend
Palam	S = 6	Z = 0.72	0.4709	No Trend
Ridge	S = -9	Z = -1.07	0.2851	No Trend

In conclusion, the Mann-Kendall test results indicate that none of the locations show significant trends in the measured variable. While Palam exhibits a slight positive trend based on the S statistic, it is not statistically significant, as confirmed by its p-value. Conversely, Lodhi Road, Safdarjung, and Ridge all display negative trends, but these are also not statistically significant. Overall, the findings suggest that the variable analyzed does not exhibit significant changes over time in the specified locations.

3.8.2. Mann-Kendall Test for NDVI

Both NDVI values for January and July show significant increasing trends over the years, indicating improving vegetation health in Delhi.

Table 5: Mann-Kendall Test for NDVI

Parameter	NDVI (January)	NDVI (July)
S (Test Statistic)	141	77
z (Standardized Statistic)	3.95	2.14
p-value	0.000079	0.032
Trend	Significant Increase	Significant Increase

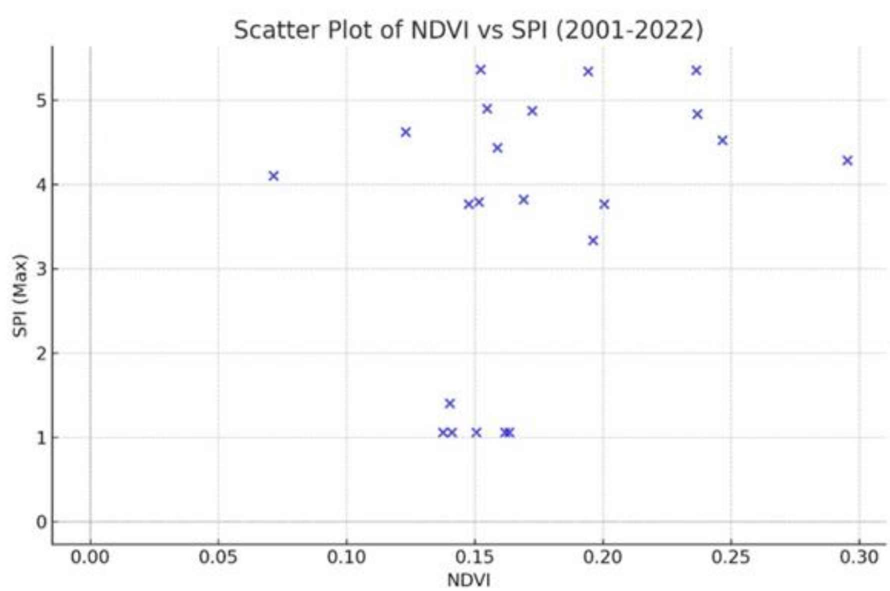
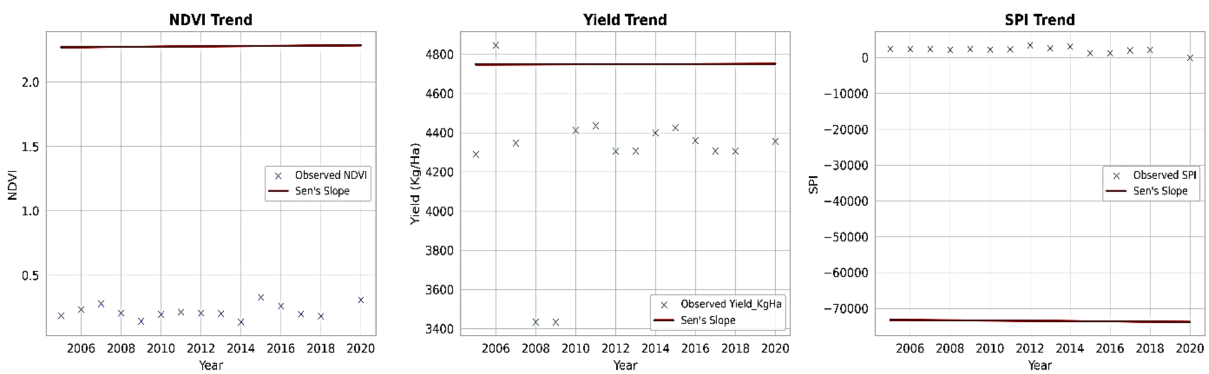


Figure 9: The scatter plot depicts the relationship between NDVI (Normalized Difference Vegetation Index) and SPI (Standardized Precipitation Index) from 2001 to 2022.

In the Figure_9 as NDVI values increase, SPI also tends to increase, indicating a positive correlation. There's a concentration of points in the lower NDVI range (0.10–0.15) with relatively lower SPI values (around 1–2). This suggests that during drier periods (lower SPI), the vegetation is not as healthy, resulting in lower NDVI values. The SPI values range from 0 to above 5, indicating a variety of precipitation conditions—from near normal to very wet periods—over the two-decade period. A few points have relatively high SPI values (above 4) with moderate NDVI values (around 0.15–0.2). This suggests that even during wetter periods, NDVI doesn't increase proportionally, possibly due to factors other than precipitation influencing vegetation (e.g., land use, soil moisture, or human activity).

3.8.3 Sen's Slope Trend Analysis

Interpretation of Sen's Slope Analysis and Graphs



(a) **(b)** **(c)**

Figure 10: Sen's Slope Trend Analysis for NDVI, Yield, and SPI

The NDVI Figure 10 (a) values show a slight increasing trend over the years, as indicated by the positive Sen's Slope. This suggests a small but steady improvement in vegetation health or density over time. However, the trend is weak, meaning that external factors such as climate variability, land use changes, or seasonal effects may be influencing the NDVI fluctuations. The yield values Figure _10 (b) exhibit almost no significant trend, as Sen's Slope is close to zero. This indicates that agricultural productivity has remained relatively stable over the years, with minor fluctuations. The lack of a strong trend suggests that factors affecting yield, such as rainfall, soil fertility, and farming practices, may not have changed drastically over time. The Standardized Precipitation Index (SPI) Figure_10 (c), shows a decreasing trend, as indicated by the negative Sen's Slope. This suggests that drought conditions may be worsening over time, leading to a decline in moisture availability. A decreasing SPI trend can have serious implications for agriculture, as it indicates increasing water stress, which could eventually affect yield if the trend continues. NDVI is slightly

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increasing, which might indicate better vegetation health. Yield remains stable without a clear increasing or decreasing trend. SPI is decreasing, suggesting worsening drought conditions that may impact agriculture in the long run. The relationship between these variables suggests that while vegetation health (NDVI) has improved slightly, it has not translated into a clear improvement in yield. The declining SPI trend indicates increasing dryness, which could pose future challenges for agriculture. Further analysis, including climate adaptation strategies, irrigation improvements, or changes in crop management, may be necessary to mitigate potential negative impacts.

4. CONCLUSION

This study investigates the relationship between precipitation and vegetation health in Delhi, utilizing Standardized Precipitation Index (SPI) and Normalized Difference Vegetation Index (NDVI) as key indicators. The analysis covers data from four meteorological station Lodhi Road, Safdarjung, Palam, and Ridge over the period from 1992 to 2022.

The findings reveal a significant positive correlation between SPI and NDVI across all four stations, with correlation coefficients ranging from 0.55 to 0.65. This indicates that higher precipitation levels are associated with improved vegetation health, highlighting the essential role of rainfall in sustaining green cover in urban environments. The Mann-Kendall test results further reinforce this understanding, demonstrating a significant increasing trend in both SPI and NDVI over the past two decades. The Mann-Kendall S and Z statistics, along with their corresponding p-values, indicate that both precipitation and vegetation health are improving, suggesting a favorable shift in environmental conditions. This trend is particularly pertinent for policymakers and urban planners who must consider climate variability and its impact on urban ecosystems.

It is also concluded that enhanced vegetation health not only contributes to biodiversity and ecological balance but also plays a vital role in mitigating urban heat, improving air quality, and supporting urban agriculture. As climate change continues to influence precipitation patterns, continuous monitoring of SPI and NDVI will be essential for adapting urban strategies to maintain and enhance green infrastructure.

Moreover, this study underscores the importance of incorporating climate variables into urban planning frameworks. Future research should focus on assessing the impacts of extreme weather events and land use changes on vegetation dynamics in urban settings. Investigating the adaptive capacity of urban ecosystems in response to climate variability will provide valuable insights for sustainable urban development.

In conclusion, the positive correlation between precipitation and vegetation health in Delhi emphasizes the need for integrated approaches to managing urban ecosystems. Correlation

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analyses indicated strong positive relationships among the SPI values of the monitored locations, particularly between Lodhi Road and Palam (r = 0.906). This suggests shared climatic influences, potentially related to regional weather systems, which could enhance the predictability of precipitation patterns and inform water resource management strategies. Despite these interconnections, the overall correlation between SPI and NDVI values was weak (r = -0.0825), indicating that while wetter conditions generally promote improved vegetation health, other factors—such as temperature, land use, and anthropogenic activities—play significant roles in influencing NDVI. The study's findings necessitate integrated strategies for Delhi's urban planning, water resource management, and agriculture, given the spatio-temporal variability in hydro-meteorological conditions. Fluctuations in the Standardized Precipitation Index (SPI), notably in Lodhi Road and Palam, indicate susceptibility to both extreme precipitation and dry spells. These SPI variations directly influence soil moisture, critical for vegetation health (Normalized Difference Vegetation Index or NDVI). Urban planning must prioritize resilient infrastructure for flood mitigation and water storage to address soil moisture deficits. Temperature's interaction with precipitation affects evapotranspiration and vegetation stress, requiring urban heat island mitigation. Agricultural policies should use SPI data to optimize irrigation and crop selection. Finally, strategic land-use planning is essential to minimize urbanization's impact on hydro-meteorological dynamics and vegetation.

ACKNOWLEDGEMENT

The author gratefully acknowledges the India Meteorological Department for providing the gridded rainfall data, and the NASA Earth Data platform for access to MODIS NDVI datasets. The support of the Google Earth Engine platform is also appreciated for facilitating data analysis. A special thanks to the Director General of the India Meteorological Department and Deputy Director General of Meteorology, New Delhi for the encouragement and motivation to pursue the research work.

DATA AVAILABILITY STATEMENT

Primary data of Rainfall which is used in this manuscript for analysis of SPI are available on (imdpune.gov.in). Satellite data is derived from https://ladsweb.modaps.eosdis.nasa.gov/. Yield data sourced from https://desagri.gov.in/, Government of India.

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