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Evaluating the Effectiveness of Phase Difference in Early Drought Detection

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This research investigates how different phase relationships can enhance our understanding of drought effects on moisture deficiency in desert ecosystems—a significant and damaging environmental issue impacting natural ecosystems, economies, health, agriculture, and society. The primary objective is to examine the variance in lag times between fixed and dynamic lag windows correlated with the NDVI (Normalized Difference Vegetation Index), aiming to develop an optimal methodology for drought analysis in the Thar Desert. Utilizing remote sensing data, the study explores the complex drought dynamics of the Thar Desert by analyzing 22 years of CHIRPS rainfall time series data and MODIS NDVI product. The research involves cross-correlating rainfall with NDVI, comparing lag time differences between fixed lag windows (16, 32, 48, 64 days) and dynamic lag windows (ranging from 4 to 64 days with incremental steps) against 22 years of MODIS NDVI data. Preliminary results indicate that dynamic lag windows of 4, 8, 12, 16, and 64 days exhibit the highest correlation with NDVI, with a lag time of 40 days showing the maximum correlation. These findings suggest that dynamic lag windows more effectively capture the temporal variability of drought impacts on vegetation compared to fixed lag windows in the Thar Desert. Further analysis with a sub-dynamic lag window, incorporating the highly correlated lag episodes of both dynamic and fixed windows (i.e., 40 days and 48 days), revealed that a lag phase of 42 days provides the highest correlation with vegetation. Additionally, the study identifies a significant drought event in 2002, highlighting the sensitivity of the dynamic lag approach in detecting extreme drought occurrences. This research not only advances drought analysis methodologies for arid regions but also underscores the need for future studies to explore the applicability of dynamic lag windows in diverse regions and assess their predictive capacity for forecasting drought-induced vegetation changes.

Keywords: Lag Time, NDVI, Rainfall, Drought, Thar Dessert.

Introduction:

Climate change, a global phenomenon with far-reaching effects, poses significant challenges, particularly in developing countries. The Intergovernmental Panel on Climate Change (IPCC) has reported a notable increase in global surface temperatures since 1861 (IPCC 2019) [1]. Among various environmental phenomena, drought stands out due to its substantial risks to human health, agriculture, natural ecosystems, economics, and societal structures. Given its extensive consequences, understanding drought dynamics, especially in arid regions, is crucial. The Thar Desert in Southern Asia exemplifies a dry habitat where drought exerts considerable stress on biological and socioeconomic processes.

Drought is challenging to measure and quantify due to its operation across multiple spatial and temporal scales. A defining characteristic of drought is moisture deficiency resulting from abnormal weather patterns [2]. To develop effective mitigation and adaptation strategies, it is essential to understand drought dynamics and their impact on moisture availability in desert ecosystems. Precipitation, a key parameter for monitoring natural disasters like drought [3], influences most parts of the Earth. Historically, site-based precipitation measurements were vital for meteorological drought monitoring. However, the advent of remote sensing precipitation products has improved the efficiency and spatial-temporal coverage of rainfall mapping and drought monitoring [4]. Satellite remote sensing provides a valuable tool for studying droughts and their impacts on ecosystems. The global scale of available observations has advanced our understanding of drought biophysics and led to the development of new drought indicators for research and practical applications [5].

Precipitation is critical for defining drought indices, but the sparse and uneven distribution of rain gauges limits long-term and reliable in situ observations. Remote sensing techniques enhance precipitation data at various temporal and spatial resolutions [4], [6]. Unlike many other natural hazards, drought develops gradually as an accumulated result of prolonged water scarcity [7]. The massive volume of remote sensing and meteorological data presents new challenges to existing empirical and theoretical methods, necessitating adjustments for specific regions [7]. The correlation between annual maximum NDVI (Normalized Difference Vegetation Index) and annual effective precipitation is similar to that between maximum yearly NDVI and growing season precipitation. Precipitation significantly impacts vegetation in certain areas, particularly meadows and meadow-grasslands, but is less effective in forested and desert regions [8]. Remote sensing observations have been employed to monitor drought-related variables from a climatological perspective and to assess and quantify drought impacts from an ecosystem perspective [5]. Identifying variations in rainfall lag-time relationships among land cover types using a remote sensing-based integrated drought index enables more accurate drought prediction and aids in developing targeted drought adaptation strategies [9]. A novel approach using the phase spectrum of cross-spectral density measures the time lag in vegetation response to precipitation, offering valuable insights for early drought detection [10]. By analyzing predicted lag time relationships, remote sensing datasets can provide advance warnings of droughts across landscapes [9]. These lag time relationships enhance remote sensing-based integrated drought monitoring and predictions tailored to land cover types. Understanding how vegetation activity responds to varying precipitation levels, including corresponding time lags, provides crucial information for drought-prone areas [10]. A similar study using fixed lag windows to assess the relationship between rainfall and vegetation moisture conditions found that a 64-day lag time exhibited the strongest correlation coefficient [2].

This study utilizes remote sensing technologies to investigate the complex dynamics of drought in the Thar Desert. By integrating datasets from CHIRPS rainfall time series and MODIS NDVI products, the research employs Google Earth Engine for a comprehensive 20-year analysis. The primary goal is to enhance understanding of drought-induced moisture deprivation and its effects on vegetation in the Thar Desert, focusing on fixed and dynamic lag windows. Additionally, the study evaluates the potential effects of a sub-dynamic lag window derived from the highest correlation of fixed and dynamic lag windows. Examining the lag time between rainfall episodes and subsequent vegetation response is crucial for determining drought impact. The research compares temporal dynamics of drought-induced vegetation changes captured by dynamic lag windows (ranging from 4 to 64 days) with fixed lag windows (16 to 64 days). This study explores both fixed and dynamic lag windows and investigates a sub-dynamic lag window between the 40 and 48-day lag phases to identify the strongest correlation with vegetation dynamics. By examining the relationship between rainfall and NDVI across different time intervals, the study aims to determine optimal techniques for drought analysis tailored to the Thar Desert's unique features.

Objective:

This research thoroughly investigates the effects of varying rainfall patterns on plant health, focusing on the consequences of drought in desert ecosystems, particularly the Thar Desert. The study aims to evaluate the resilience of dry region ecosystems by examining the relationship between rainfall and changes in vegetation. This involves analyzing fixed and dynamic lag windows, representing the time between rainfall episodes and subsequent changes in plant cover.

Materials and Methods:

Study Area:

The research area encompasses the Thar Desert, which spans approximately 200,000 square kilometers across the Indian states of Rajasthan, Gujarat, Punjab, and Haryana, and the southern parts of Pakistan, including Sindh province. Located between latitudes 24° to 28° North and longitudes 66° to 77° East, the Thar Desert features a varied topography of large dunes, rocky outcrops, and patches of vegetation. The region experiences extreme temperatures, with summers exceeding 50°C and winters dropping to around 5–10°C, accompanied by minimal precipitation averaging between 100 and 500 millimeters annually. Rainfall is highly variable, with about 90% occurring during the southwest monsoon season from July to September [11].

May and June are the hottest months, with temperatures reaching up to 122°F (50°C), while January is the coldest month, with mean minimum temperatures ranging from 41 to 50°F (5 to 10°C) and frequent frost. Dust storms and high-velocity winds, reaching 87 to 93 miles (140 to 150 km) per hour, are common in May and June. The Thar Desert's history of recurrent drought events exacerbates environmental degradation and water scarcity, highlighting the need for sustainable development and adaptation strategies [11].

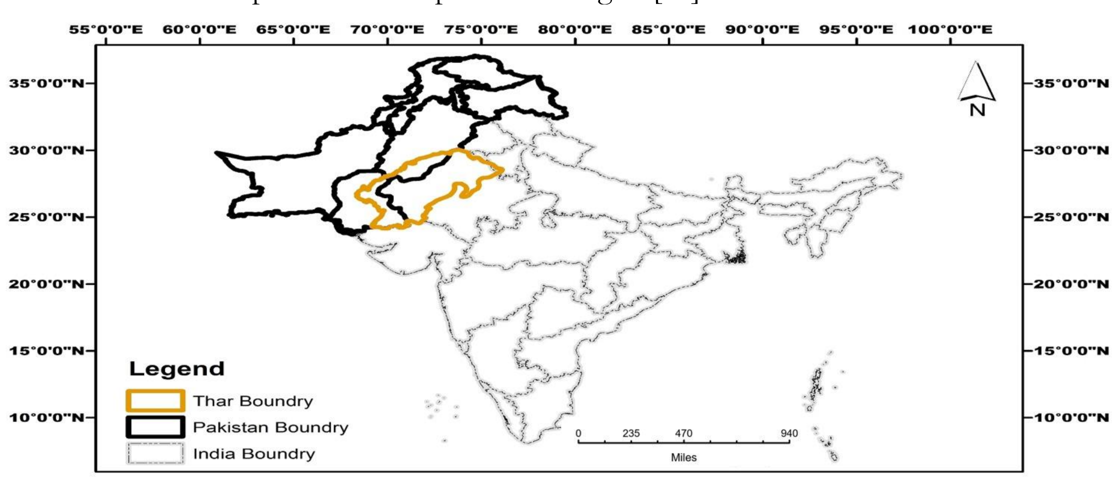

Figure 1: Study area map of Thar desert of the Southern Asia

Data sets:

MODIS Data:

This study utilized biweekly (16-day) composite NDVI data at a 250m resolution from MODIS (MOD13Q1) on the Terra platform for the period 2000-2022 [12]. The data was processed using Google Earth Engine (GEE), a cloud-based platform offering extensive geospatial data, analytical tools, and computational resources for analyzing and visualizing satellite imagery and other geospatial information. GEE supports various programming languages, including Python and JavaScript, and provides a comprehensive suite of tools for data processing, including machine learning algorithms for image classification and time-series analysis [13]. The current study used JavaScript API in Earth Engine Code Editor.

$$\mathrm{NDVI} = \frac{\mathrm{NIR-Red}}{\mathrm{NIR+Red}} \qquad \textbf{Equation 1}$$

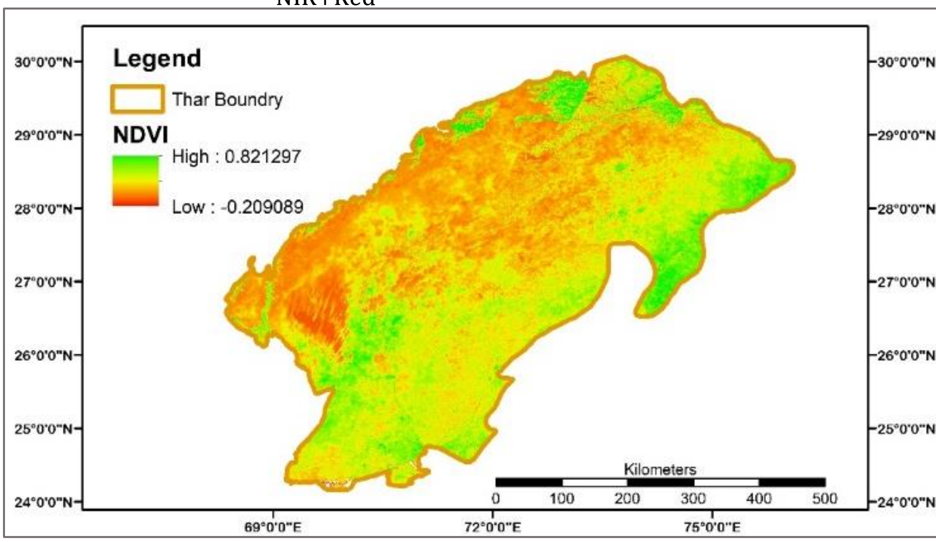

Figure 2: MODIS 1q31 NDVI Raster Image of the Thar desert.

Climate Data:

The CHIRPS Daily (Climate Hazards Group InfraRed Precipitation with Station data) dataset was utilized to generate precipitation time series from 2002 to 2022 through Google Earth Engine (GEE). This dataset advances traditional interpolation techniques by incorporating high-resolution precipitation estimates derived from infrared Cold Cloud Duration (CCD) observations. Specifically, it employs a 0.05° climatology that integrates satellite data to enhance precipitation estimates in areas with sparse ground-based measurements. The dataset encompasses daily, pentad, and monthly CCD-based precipitation estimates dating back to 1981. It combines station data to produce preliminary precipitation products with a latency of approximately 2 days and final products with an average latency of around 3 weeks. Additionally, CHIRPS uses a novel blending procedure that incorporates the spatial correlation structure of CCD estimates to determine interpolation weights. Initially available at a spatial resolution of 0.05° (approximately 5 kilometers), the daily CHIRPS data was aggregated to a biweekly (16-day) interval and resampled to 250 meters to align with the resolution of the NDVI time series used in this study.

Flow of Study:

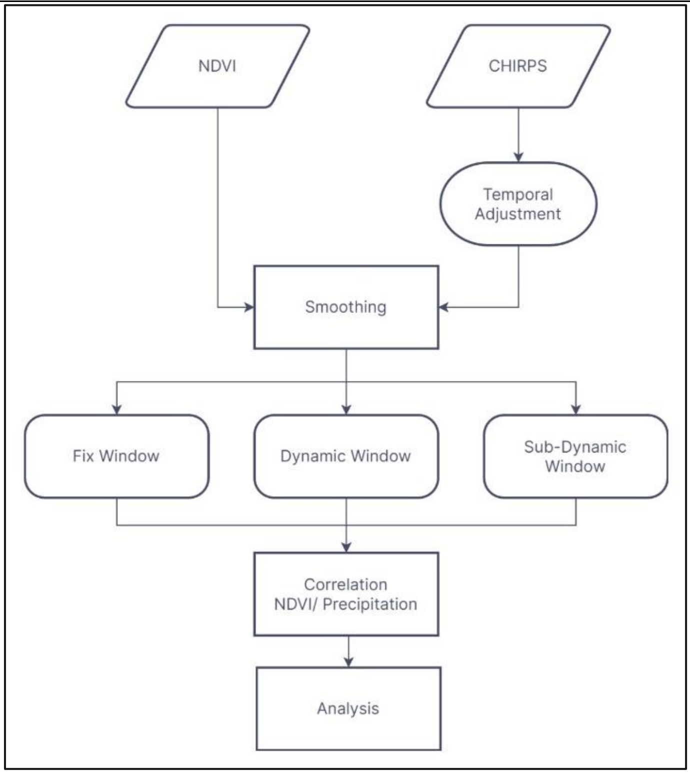

Figure 3: Flow of the Study Diagram

Methodology:

The study was conducted in the drought-prone Thar Desert of Southern Asia to analyze phase relationships between historical rainfall and observed drought conditions over a 22-year period from 2001 to 2022, including a particularly severe drought in 2002. This region experiences significant impacts from fall droughts, which occur at the start of the growing season and depend on rainfall from the previous November to February. Drought observations were based on MODIS NDVI (Normalized Difference Vegetation Index) standard products, which provide 16-day interval data at a 250-meter resolution. The NDVI data, reflecting vegetation changes, follows an annual cycle of growth and decline. To address issues such as cloud cover and poor atmospheric conditions that can cause sudden, unrepresentative drops in NDVI, Savitzky-Golay filtering was employed to remove these anomalies, which are considered noise. Rainfall estimates were obtained from the CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) dataset, which offers a more comprehensive view compared to spatially limited climate station data. The CHIRPS daily rainfall data was aggregated into 16-day intervals and resampled from its original resolution of 0.5° to 250 meters. Subsequently, lagged precipitation was computed for fixed, dynamic, and sub-dynamic windows of 16, 32, ..., 64, 4, 8, 12, ..., 64, and 36, 37, 38, ..., 44 days using Google Earth Engine (GEE).

Correlation Between NDVI and Precipitation Series:

To assess the relationship between rainfall and vegetation, the response between Precipitation and NDVI time series was analyzed using the Pearson Cross-Correlation (PCC) analysis. The Pearson correlation coefficient (often denoted as r) is a measure of the linear relationship between two variables. It ranges from -1 to 1, where 1 indicates a perfect positive linear relationship, -1 indicates a perfect negative linear relationship, and 0 indicates no linear relationship. The formula for the Pearson correlation coefficient between two variables X and Y is given:

$$\mathbf{r} = \frac{\sum(\mathbf{xi}-\bar{\mathbf{x}})(\mathbf{yi}-\bar{\mathbf{y}})}{\sqrt{\Sigma(\mathbf{xi}-\bar{\mathbf{x}})^2\Sigma(\mathbf{yi}-\bar{\mathbf{y}})^2}} \qquad \textbf{Equation 2}$$

Here's a breakdown of the terms in the formula:

- **xi** and **yi**: Individual sample points for the variables X and Y.
- $\bar{x}$: The mean of the variable X.
- $\bar{y}$: The mean of the variable Y.
- **Σ**: The summation symbol indicates that the calculation is performed for all corresponding pairs of xi and yi.

It standardizes the measure, ensuring that the coefficient is dimensionless and lies between -1 and 1. This analysis is for different lag times with different windows such as a 16-day fix window (16,32,48,64) as temporal resolution of the series, then a dynamic window (4,8,12 … 64), and a sub-dynamic window (36,37,38 … 44) with 16-day NDVI series over a study period of 2001-2021.

Results:

The results of this research revealed significant insights: while both fixed and dynamic lag windows demonstrated relationships with vegetation health, the highest correlations were observed with the dynamic lag windows. These dynamic windows adapt to changing climatic conditions, thereby providing a more nuanced understanding of vegetation responses. The correlation analysis between spatially averaged NDVI and precipitation indicated that vegetation moisture conditions vary considerably with lag time. Fixed lag windows, such as those of 16, 32, and 64 days (as shown in Figure 4), exhibited a relatively weaker association with vegetation health. In contrast, the strongest relationship was identified at a lag duration of approximately 48 days.

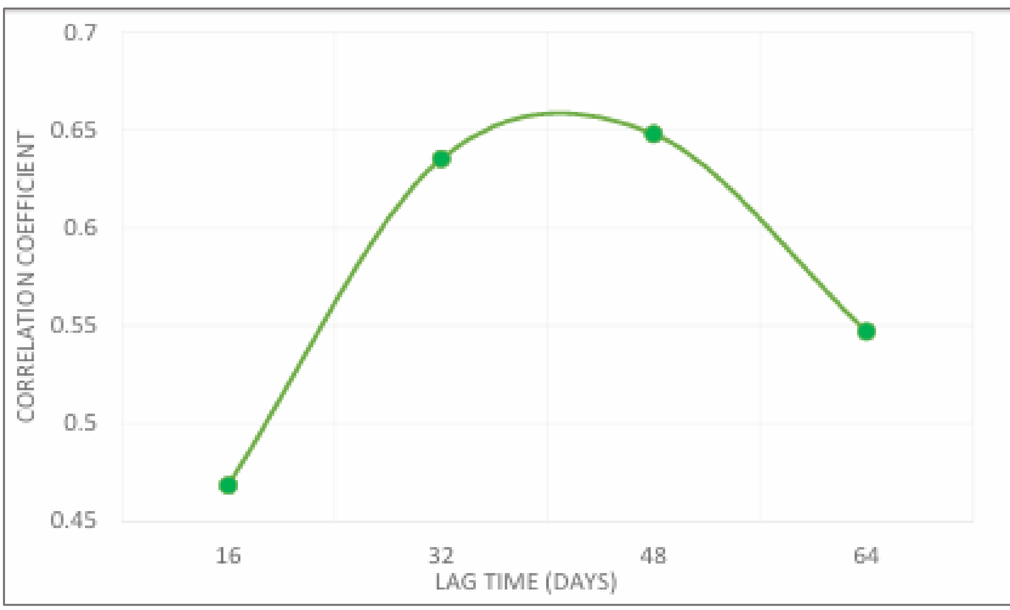

Figure 4: Fix lag window correlation between NDVI and Precipitation

Also, the dynamic lag windows shown in Figure 5, between 4 and 64 days showed the most association with vegetation health, with the strongest relationship seen at a lag duration of about 40 days.

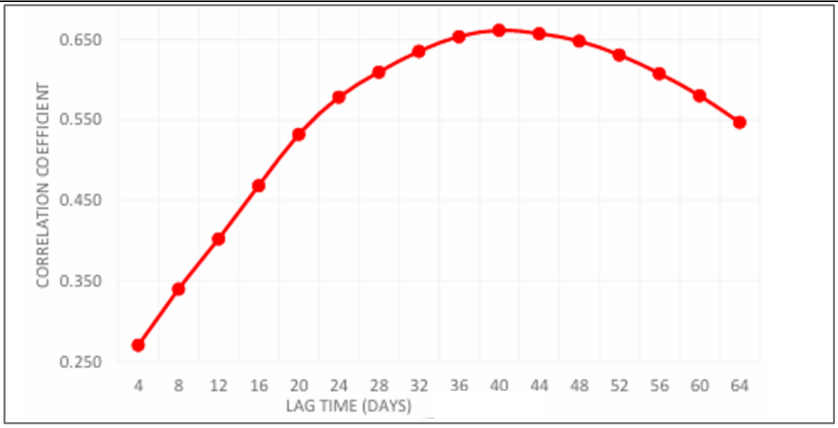

Figure 5: Fix lag window correlation between NDVI and Precipitation

The investigation continued with a deeper analysis to uncover the subtleties of the relationship between rainfall and vegetation dynamics. Specifically, the study explored a sub-lag window within the range of strongly associated lag phases observed in both fixed and dynamic windows (between 40 and 48 days). Remarkably, the analysis identified a 42-day lag period as the most crucial in terms of its correlation with vegetation dynamics. This finding underscores the intricate temporal variability in how drought impacts vegetation and highlights the importance of pinpointing specific time intervals for a more accurate understanding of ecosystem responses to external stresses. Figure 6 illustrates the correlation values of fixed, dynamic, and sub-dynamic lag windows across different lag days, providing a comprehensive view of their respective relationships with vegetation dynamics. By systematically varying the lag window duration from 4 to 64 days, the study assessed how different temporal scales affect the correlation between rainfall and NDVI.

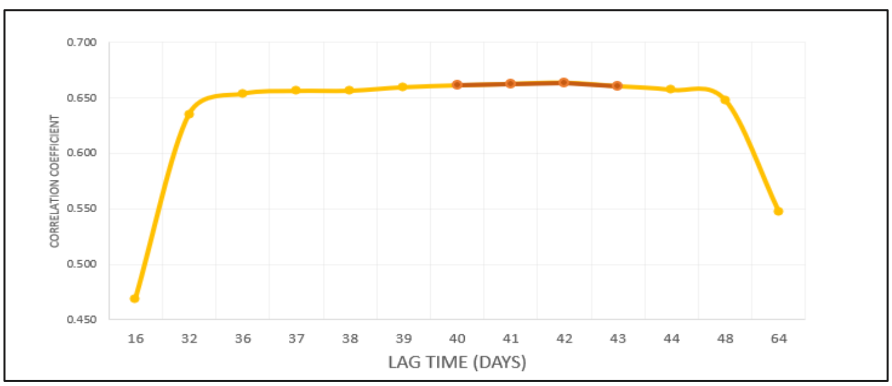

Figure 6: Combined lag windows correlation between NDVI and Precipitation

The time series comparison highlights the intricate relationship between the highly correlated 42-day precipitation lag series and the NDVI, which serves as a proxy for vegetation health. The research identified variations in vegetation dynamics in response to specific rainfall events across the 22-year study period. By analyzing these datasets, the study provides valuable insights into how drought affects desert ecosystems. Notably, a significant drought period with below-average annual precipitation rates was observed in 2002 and 2003. Additionally, the study can identify anomalies or deviations from typical patterns, which helps in recognizing severe drought events or rapid recovery periods.

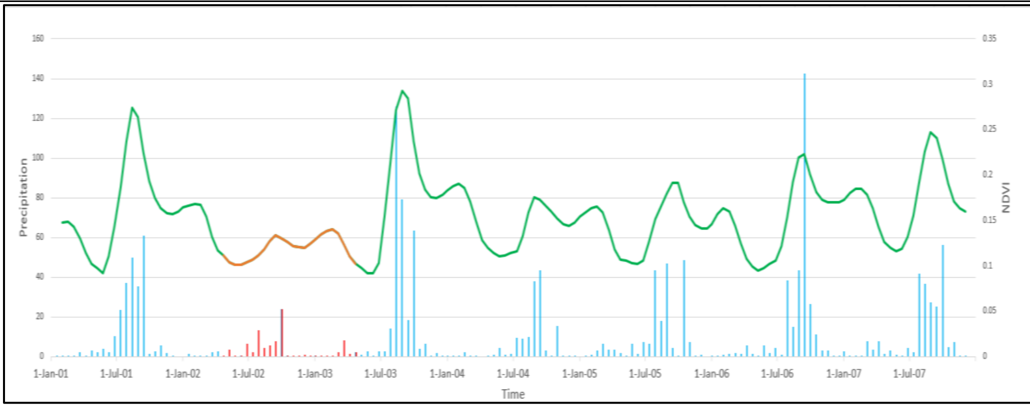

Figure 7: Time series comparison of 42 days lag and 16 days NDVI

The correlation table (Table 1) offers a detailed breakdown of lag days and their corresponding correlation values, covering the full range from 4 to 64 days. This in-depth analysis facilitates the examination of correlation trends across different temporal scales, revealing a pattern of increasing correlation from shorter to intermediate lag periods, followed by a decline in correlation beyond 42 days.

Table 1: Comparison of Correlation between NDVI and different lag precipitation series

Lag Time (Days)	4	8	12	16	20	24	28	32	36	37	38
Correlation Coefficient	0.270	0.340	0.402	0.468	0.532	0.578	0.609	0.635	0.654	0.656	0.656
Lag Time (Days)	39	40	41	42	43	44	48	52	56	60	64
Correlation Coefficient	0.660	0.661	0.663	0.664	0.661	0.657	0.648	0.631	0.608	0.580	0.547

The following inset chart offers a comparative analysis of correlation values against lag days for fixed, dynamic, and sub-dynamic lag windows. By plotting these correlation trends side by side, we can assess the relative performance of each lag window type in capturing drought-induced vegetation changes. This comparative analysis facilitates the identification of optimal methodologies for drought analysis, considering both the temporal variability of vegetation responses and the adaptability

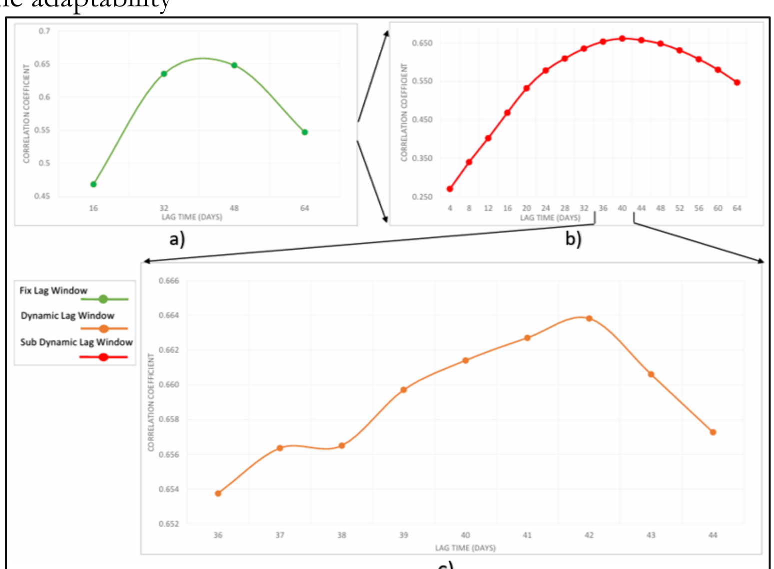

Figure 8: Comparison of Correlation Coefficients for Different Lag Windows: Fix Lag 8a, dynamic 8b, and sub dynamic lag windows 8c of precipitation and NDVI

Figure 8 presents the correlation values for three distinct lag window types: fixed, dynamic, and sub-dynamic. In Subplot 8a, the fixed lag window is illustrated, with correlation coefficients varying across lag periods from 16 to 64 days. The data reveals a peak at approximately 48 days, indicating the strongest temporal correlation at this interval. Subplot 8b depicts the sub-dynamic lag window, covering lag times from 4 to 64 days. Here, the correlation coefficients rise up to around 40 days before gradually declining, suggesting that the sub-dynamic window performs better at shorter lag periods. Subplot 8c focuses on the dynamic lag window, with lag periods ranging from 36 to 44 days. The correlation coefficients within this range also peak at 42 days, highlighting its effectiveness for this specific duration.

Additionally, Figure 9 provides a combined drought distribution image, offering a spatially detailed representation of drought occurrences across the Thar Desert over the 22-year study period. By classifying NDVI values into drought severity categories (no drought, mild drought, moderate drought, severe drought), this analysis maps the spatial and temporal variability of drought impacts on vegetation health. The distribution map facilitates the identification of significant drought events, including the severe drought of 2002, and emphasizes the role of extreme climatic events in influencing desert ecosystems. This spatial context enriches the interpretation of temporal dynamics observed in the time series data and correlation analyses.

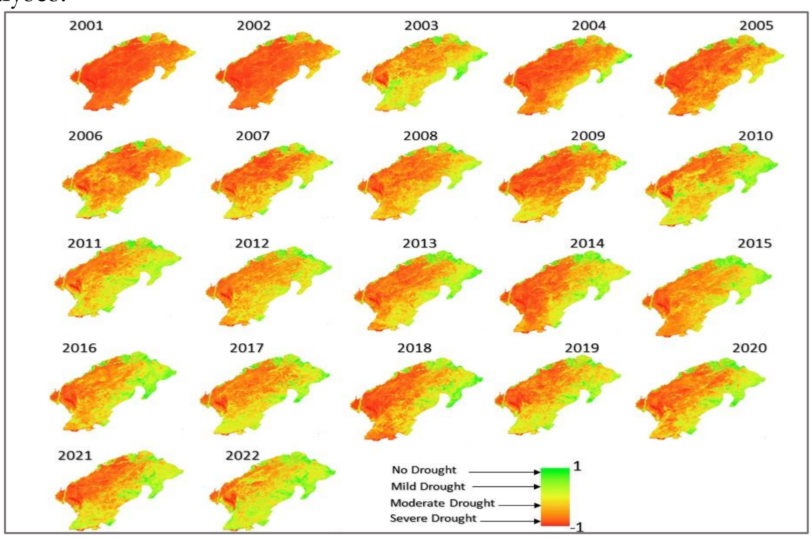

Figure 9: A spatially explicit representation of drought occurrences throughout the Thar Desert over a period of 22 years

Discussions:

The study explored the potential of various time delays between rainfall and plant response for early drought detection. Understanding the patterns and relationships between vegetation productivity and climatic conditions is essential for predicting the future impacts of climate change. While most researchers have used monthly precipitation data to correlate with NDVI, they have not seriously considered the varying lag phases of precipitation. A similar study in China examined the relationship between NDVI and precipitation by calculating accumulated precipitation over antecedent durations of 10, 60, and 150 days. This study found that a longer duration of antecedent precipitation resulted in slightly higher cross-power values for the annual component, but the time lag values for the annual component became negative with durations longer than 60 days. The study discovered an interesting twist when analyzing longer stretches of rain (up to 150 days) compared to shorter periods. Although more rain over a longer period generally meant healthier plants (higher correlation between rainfall and plant health), the lag time, which is the usual delay between rain and plant response, appeared to flip after 60 days.

Instead of plants gradually responding to rain, longer stretches of rain seemed to produce unexpected effects after 2 months. This suggests a more complex relationship between rain and plant health, particularly for extended droughts or very wet periods. Another study found low correlations between drought indices and monthly precipitation data. Thus, this study applied different lag windows of meteorological data to analyze 22 years of satellite data from the Thar Desert, focusing on plant health (using MODIS NDVI) and rainfall (from CHIRPS) relationships. Additionally, a study noted that the correlation between annual maximum NDVI and growing season precipitation is similar to that between annual maximum NDVI and annual effective precipitation.

The primary finding of this study is that the timing of rainfall is more crucial than traditionally believed. "Lag time" refers to the process where plants respond gradually to precipitation. Although this lag is not fixed, the research demonstrated that understanding this precise lag time is vital for comprehending how droughts impact plant life. The study evaluated three methods for estimating lag time: fixed windows, which remain constant over the years, dynamic windows, which vary based on the climate, and sub-dynamic windows. Dynamic windows offered an even more accurate view of the association between plant health and rainfall. The optimal lag time in the Thar Desert appears to be approximately 40 days. The research found an even higher lag period of 42 days when comparing the most effective fixed and dynamic windows. This highlights the importance of precision in monitoring droughts. Similar results could improve drought coping strategies and serve as a foundation for additional studies to refine and extend these techniques to other areas. Enhancing our understanding of drought impacts on vegetation may help in making better decisions regarding adaptability and sustainable development in dry regions like the Thar Desert.

Conclusions:

This study offers an in-depth examination of drought dynamics in the Thar Desert, emphasizing the need for accurate and flexible techniques for understanding and managing drought's impact in desert areas. Utilizing data from satellite remote sensing, including MODIS NDVI products and CHIRPS rainfall time series, the research provided important insights into the temporal connection between precipitation and vegetation health. It found that dynamic lag windows respond more to changing climatic situations than fixed lag windows. Additionally, a greater association was observed when examining a sub-dynamic lag window, specifically the 42-day lag phase, which underscores the complex temporal variability of drought impacts on vegetation. The study advanced our understanding of the temporal associations between precipitation and vegetation response through the application of fixed, dynamic, and sub-dynamic lag windows. However, developing broader drought indicators to enhance prediction accuracy is essential. Extending the research to include temperature, evapotranspiration, and soil moisture could provide a more comprehensive view of drought dynamics. This thorough approach is necessary for discovering long-term and scalable drought mitigation solutions, ultimately improving resilience and sustainability in vulnerable regions globally. The study indicates that the most effective approach for analyzing droughts is to use dynamic lag windows, and it encourages further research into this method's efficacy in other areas. A 22-year regional analysis of drought patterns highlighted the importance of extreme weather conditions, such as the severe drought of 2002, in shaping arid ecosystems. Extending the study to include temperature, evapotranspiration, and soil moisture may provide a more thorough understanding of drought dynamics, which is crucial for identifying effective drought mitigation strategies and improving resilience in vulnerable areas worldwide.

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Author's Contribution:

All authors contributed to the manuscript and discussed the results. This research was supervised by SA.; conceptualization, SA, and ATM; data curation and methodology, formal analysis, writing and reviewing ATM and NH. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest: The authors declare they have no conflict of interest in publishing this manuscript in this Journal

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