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Descomposición y análisis temporal del NDVI en un predio agrícola para determinar la salud y variabilidad de cultivos de maíz en Guasave, Sinaloa

Decomposition and Temporal Analysis of NDVI in an Agricultural Plot to Determine the Health and Variability of Maize Crops in Guasave, Sinaloa

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Resumen

El avance tecnológico en la agricultura ha transformado significativamente las prácticas agrícolas tradicionales, mejorando la gestión de cultivos y la toma de decisiones. Un desarrollo clave en este campo es la teledetección, particularmente el Índice de Vegetación de Diferencia Normalizada, que proporciona información valiosa sobre la salud y densidad de la vegetación. Esta investigación se centró en Guasave, Sinaloa, una región agrícola crucial en México, para analizar la serie temporal del NDVI y descubrir tendencias y patrones a lo largo de cinco años. El análisis reveló variaciones en el NDVI que indican desde deficiencias de nutrientes hasta ataques de plagas. Además, con la influencia del cambio climático en los patrones climáticos, el NDVI ha demostrado ser esencial para la adaptación agrícola en la región. Esta herramienta se ha consolidado como fundamental para la agricultura sostenible, permitiendo a los agricultores adaptarse a desafíos cambiantes y tomar decisiones informadas. La investigación subraya la importancia del NDVI y la teledetección en la modernización de la agricultura y en la gestión efectiva de los recursos agrícolas.

Palabras clave: Teledetección, NDVI, Agricultura sostenible.

Abstract

The technological advancement in agriculture has significantly transformed traditional farming practices, enhancing crop management and decision-making. A key development in this field is remote sensing, particularly the Normalized Difference Vegetation Index, which provides valuable information about vegetation health and density. This research focused on Guasave, Sinaloa, a critical agricultural region in Mexico, to analyze the NDVI time series and uncover trends and patterns over five years. The analysis revealed NDVI variations indicating issues ranging from nutrient deficiencies to pest attacks. Moreover, with the influence of climate change on weather patterns, NDVI has proven essential for agricultural adaptation in the region. This tool has established itself as fundamental for sustainable agriculture, allowing farmers to adapt to changing challenges and make informed decisions. The research underscores the importance of NDVI and remote sensing in modernizing agriculture and effectively managing agricultural resources.

Keywords: Remote Sensing, NDVI, Sustainable Agriculture.

Introduction

Agriculture, as the cornerstone of global food security and economy, has undergone significant transformations in recent decades (Craviotti, 2023). These shifts have been partly driven by technological advancements that have enabled farmers and agricultural managers to obtain real-time information on crop health and soil conditions (López, 2021). One such advancement is remote sensing, which has proven invaluable in monitoring vast expanses of agricultural lands and in early identification of issues that could impact productivity (Chavarría & Lanuza, 2021).

Within the realm of remote sensing, the Normalized Difference Vegetation Index (NDVI) has established itself as a pivotal metric (Celemín & Arias, 2021). NDVI provides a quantitative representation of a region's greenness, serving as a direct indicator of vegetation health (Garcia Cardenas, 2019). Farmers, researchers, and agricultural managers have leveraged NDVI for informed decision-making, from planting schedules to disease and pest detection, thereby optimizing yields and minimizing losses (Rodas Escurra & Amaya Pereyra, 2019).

Mexico, with its rich agricultural tradition and its vital role in Latin American agricultural production, has been a fertile ground for the adoption of these technologies (Aranda, 2021). Sinaloa, often dubbed as the "breadbasket of Mexico" (Bojorquez & Fiscal, 2016), has been at the forefront, embracing precision agriculture and remote sensing techniques to enhance productivity and sustainability (Rosales-Soto & Arechavala-Vargas, 2020). However, with the benefits come challenges. Climatic variations, emerging diseases, and market fluctuations necessitate swift adaptation by farmers, and NDVI-based tools provide the requisite agility (Correa, 2023).

Moreover, NDVI has not only reshaped how crops are monitored but also how agricultural challenges are understood and addressed (Sebastián Cantalejo, 2020). NDVI fluctuations can signify a myriad of issues or shifts, ranging from nutrient deficiencies to pest infestations, and even changes in soil conditions (ALEXIS, 2020). This capability to detect and diagnose issues in real-time is especially pivotal in regions like Guasave, where the margins for error are slim and decisions need swift enactment to avert substantial losses. Additionally, with climate change and its unpredictable effects on weather patterns, tools like NDVI become even more indispensable, offering a lens into current crop conditions and enabling farmers to adapt to shifting scenarios (Lizcano, 2018). Research in this domain, hence, is not only pertinent but vital for the future of sustainable agriculture in the region and beyond.

Materials and methods

In this study, satellite NDVI data from Sentinel Hub were used to analyze the health and variability of corn crops in an agricultural plot in Guasave, Sinaloa. The following details the methods and tools employed in the acquisition, processing, and analysis of this data.

Data Acquisition:

The Normalized Difference Vegetation Index (NDVI) data were acquired from the Sentinel Hub platform. These data correspond to an agricultural plot located in the ejido El Tajito, Guasave, Sinaloa. The plot spans an area of 8.01 hectares, and its geographical coordinates are 25°39'18" North latitude of the Tropic of Cancer and 108°38'14" West longitude from the Greenwich meridian, as shown in Figure 1.

Figure 1. Satellite View of the Agricultural Plot in Ejido El Tajito, Guasave, Sinaloa.

The data acquisition period spans from October 6, 2018, to October 16, 2023, covering a total of 5 years. During this time, corn was cultivated on the plot.

Description of the NDVI:

The NDVI is an index that measures the health and vigor of vegetation using the difference between near-infrared reflectance and visible reflectance (Strashok, Ziemiańska, & Strashok, 2022). It is calculated using Equation 1:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \qquad \text{Equation 1}$$

Where:

NIR represents the near-infrared reflectance.

RED represents the reflectance in the visible (red) spectrum.

Details about Sentinel Hub:

Sentinel Hub is a cloud-based platform developed by Sinergise, which allows access to and analysis of large satellite data sets (Ortega & Pérez, 2020). For this study, data from the Sentinel-2 satellite was used, which is especially relevant for agricultural remote sensing due to its resolution and revisit frequency.

Data Preparation and Processing:

Once acquired, the NDVI data were loaded into a computational environment using Python. The data were presented in JSON format, which was processed and structured for further analysis. Dates were converted to a standard date and time format, and data were sorted chronologically. To ensure the accuracy of the NDVI values, atmospheric corrections were made to adjust for potential distortions caused by the atmosphere. This correction was carried out using Equation 2:

$$\rho_{\mathrm{surface}} = \frac{\rho_{\mathrm{measured}} - \rho_{\mathrm{atmosphere}}}{T} \qquad \text{Equation 2}$$

Where:

$\rho_{surface}$ is the reflectance at the Earth's surface.

$\rho_{measured}$ is the reflectance measured by the satellite.

$\rho_{atmosphere}$ is the atmospheric reflectance.

T is the atmospheric transmittance.

Time Series Decomposition:

To identify and understand the underlying variations in the NDVI over time, a time series decomposition was carried out. This decomposition separated the series into three main components: trend, seasonality, and residue. The additive model was used for the decomposition, which is governed by Equation 3:

$$Yt = Tt + St + Rt \qquad \text{Equation 3}$$

Where Yt is the observed value at time t.

Anomaly Detection:

A standard deviation-based method was employed to detect NDVI values that deviated significantly from the expected trend and seasonality. Specifically, values that satisfy the following condition were considered anomalies:

$$\text{Anomaly if: } |x - \mu| > k \times \sigma$$

Where:

x is the NDVI value at a specific point

μ is the average NDVI.

σ is the standard deviation of the NDVI.

k is the threshold value, which determines how strict the anomaly detection is. Common values for *k* are 2 or 3, depending on the application and desired confidence level.

Tools and Software:

For data analysis and visualization, Python was used with specific libraries such as pandas, statsmodels, and matplotlib. Additionally, remote sensing tools and specialized platforms were employed for spatial visualization and analysis of the NDVI data.

Results and Discussion

Following the rigorous process of acquiring and analyzing the NDVI data from Sentinel Hub, a series of pertinent findings and observations have been derived. These results, shedding light on the vegetative dynamics of the analyzed agricultural plot, are detailed and discussed in the subsequent sections:

1 - Time Series Decomposition

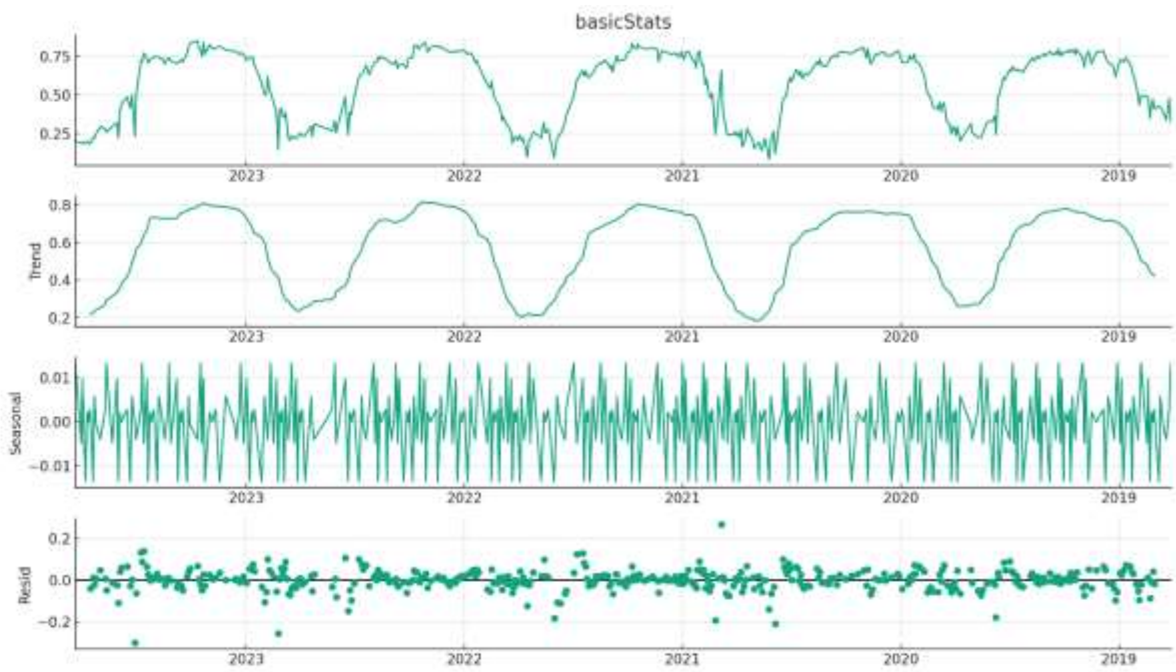

Figure 1. Time Series Decomposition of the NDVI for the Agricultural Plot.

Figure 1 displays the time series decomposition of the NDVI, for the agricultural plot over a five-year period (2018-2023). The original NDVI time series (top graph) represents the evolution of the index over time. The trend (second graph) reveals the NDVI's long-term patterns, indicating changes in vegetation health over time. The seasonality (third graph) highlights annual cyclical patterns, likely associated with the corn planting and harvesting seasons in the region. Lastly, the residuals (fourth graph) show the NDVI variations that cannot be explained by trend or seasonality and can be useful in identifying anomalies or unexpected events.

Findings:

Underlying Trend:

The trend component revealed how the NDVI evolved on the agricultural plot over the years, independent of the annual cyclical patterns. This trend can reflect long-term changes in vegetation health, whether due to agricultural practices, soil quality, or broader climatic factors.

Seasonal Patterns:

The seasonal component displayed clear cyclical patterns that repeat annually. These seasonal patterns are likely related to the growth, maturity, and harvest phases of the corn, as well as the climatic conditions of the region.

Residuals or Anomalies:

The residuals represent the NDVI variability that is not explained by either the trend or seasonality. A more detailed analysis of the residuals could. identify anomalies or unexpected events like pest damage, diseases, or extreme weather impacts.

Utility of Decomposition

Agricultural Planning:

Understanding the trend and seasonality of the NDVI can assist farmers in better planning their activities, from choosing the right time to plant to optimizing irrigation and fertilization practices.

Monitoring and Alerting:

Identifying anomalies in the NDVI through residuals can serve as an early warning system for potential crop issues, allowing for timely interventions.

Research and Enhancement:

For researchers and agronomists, understanding the dynamics of the NDVI can aid in devising new strategies, or agricultural practices that enhance crop health and yield.

Climatic Contextualization:

The time series and its components can be correlated with climatic data to better understand how events such as droughts, heavy rains, or temperature changes affect vegetation health.

2 - Anomaly Detection.

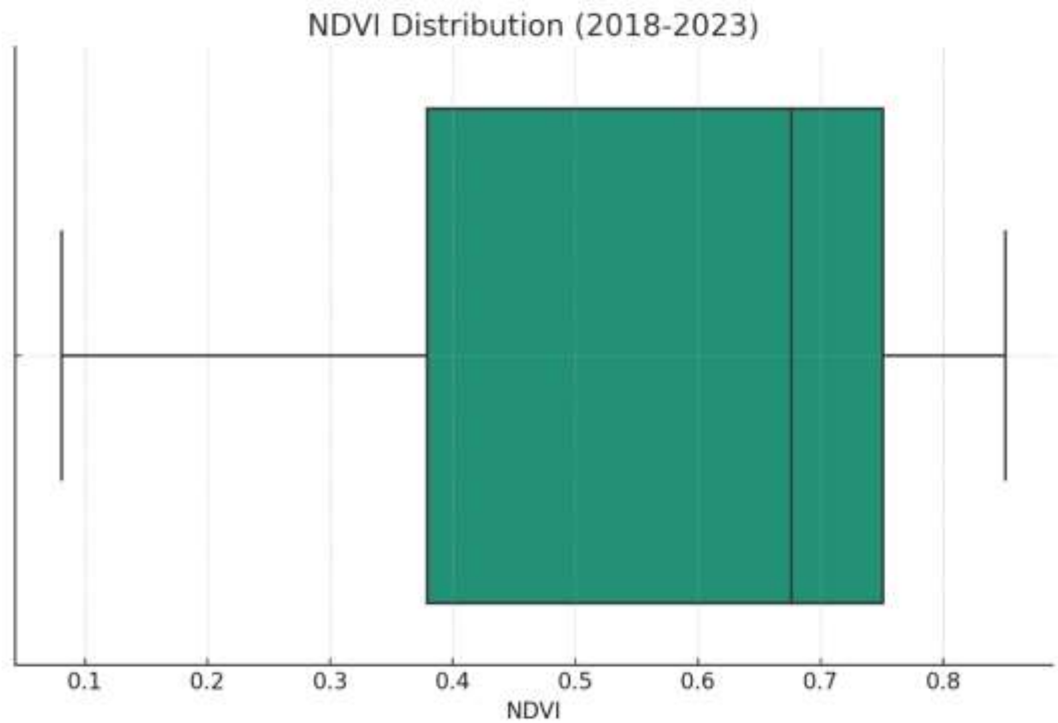

Figure 2: Distribution of the Normalized Difference Vegetation Index (NDVI) in the Agricultural Plot (2018-2023)

Figure 2 displays the distribution of the Normalized Difference Vegetation Index (NDVI) for the agricultural plot over a five-year period, from 2018 to 2023.

Median: The central line in the box represents the median of the NDVI, which is the value that splits the time series in half, with half of the observations falling below and half above this value. A higher median NDVI generally indicates denser and healthier vegetation coverage.

Interquartile Range (IQR): The height of the box represents the interquartile range, which is the difference between the third and first quartiles. This range provides insight into the dispersion of the central half of the data. A wider IQR might indicate greater variability in vegetation health during the studied period.

Outliers: The points outside the whiskers represent outliers. These are NDVI values that significantly deviate from the general trend. They might indicate specific events, such as diseases, pests, droughts, or floods that affected the vegetation.

3 – Statistical Analysis

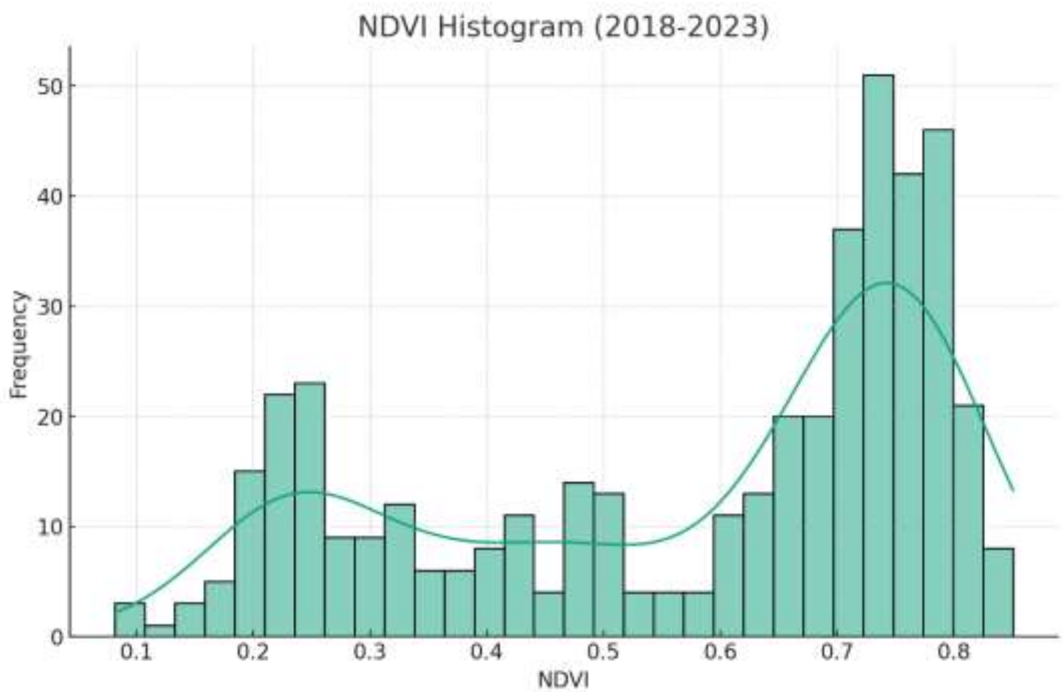

Figure 3: NDVI Histogram

In Figure 3, a histogram is displayed which is a graphical representation of the distribution of a dataset. In this case, it shows the frequency of different ranges of NDVI values.

X-Axis (NDVI): Represents different ranges of NDVI values.

Y-Axis (Frequency): Indicates how often NDVI values appear within a specific range.

The smooth line (kernel density estimation or KDE) provides a continuous and smoothed visualization of the distribution, helping to identify the general shape of the NDVI distribution.

At first glance, it is observed that most NDVI values are concentrated in certain ranges, indicating that for most of the study period, the vegetation in the agricultural plot maintained consistent health and density.

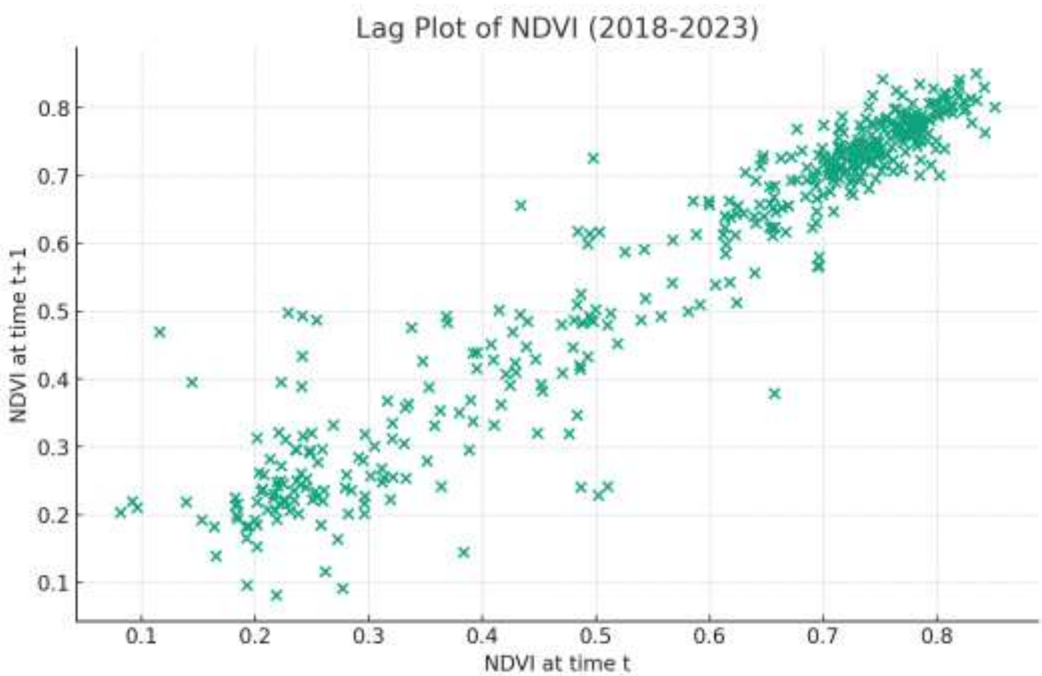

Figure 4: NDVI Lag Scatter Plot

In Figure 4, a prominent clustering of points aligning along the diagonal line is observed, which is a clear indication of a strong positive correlation between the variables under study. This correlation suggests that the NDVI (Normalized Difference Vegetation Index) tends to maintain similar values from one time point to another. This consistency in NDVI values can be interpreted as a sign that the vegetation in the agricultural plot maintains a stable health status over time. This stability may result from appropriate agricultural practices, consistent irrigation, and favorable climatic conditions. It is essential to consider these factors to better understand the behavior of the NDVI and, consequently, the health of the vegetation in the plot in question.

When contrasting our findings with previous studies, significant similarities and differences are evident, enriching our understanding of NDVI in precision agriculture. In line with works such as those by García Cárdenas (2019), our results confirm that NDVI is an effective indicator for monitoring crop health. These studies also highlighted the relevance of NDVI in the early detection of problems, such as nutrient deficiencies and pest attacks, an aspect corroborated in our study. Additionally, our analysis of the seasonal variability of NDVI finds parallels with the observations of Sebastián Cantalejo (2020), who identified similar patterns in other agricultural contexts.

However, our study contributes new insights by integrating a detailed analysis over five years, offering a longitudinal perspective that has been less explored in previous studies. While research like that of Lizcano Toledo et al. (2018) focused on specific nutritional diagnoses, our work expands this view by analyzing long-term trends and their relation to climate change, an aspect less addressed in previous studies.

Conclusions

The detailed analysis of the Normalized Difference Vegetation Index (NDVI) of the analyzed agricultural plot has revealed significant insights into the health and density of the vegetation over a five-year period. These insights, derived from satellite data and advanced time series analysis techniques, have direct implications for agricultural management and decision-making. Below are the main conclusions drawn from this study:

- Significance of NDVI in Modern Agriculture: The Normalized Difference Vegetation Index (NDVI) has proven to be an invaluable tool in assessing the health and vigor of vegetation over time. Its ability to provide real-time insights into vegetation dynamics makes it indispensable for modern agricultural practices.
- Stable Vegetation Health: The time series decomposition and lag scatter plot suggest a stable vegetation health in the studied agricultural plot over the five-year period. This stability is likely a result of consistent agricultural practices and possibly favorable environmental conditions.
- Seasonal Patterns: The evident seasonal patterns in NDVI values reflect the agricultural cycles of maize cultivation in the region, demonstrating the utility of NDVI in tracking crop growth phases.
- Anomaly Detection: The identification of anomalies using standard deviation-based methods serves as a robust early warning system. This system can alert farmers and agricultural managers to potential issues, allowing for timely interventions.
- Role of Advanced Technologies: Platforms like Sentinel Hub play a crucial role in modern agriculture by providing easy access to vast amounts of satellite data. When combined with

computational tools and methodologies, these platforms enable detailed analyses that were previously challenging to conduct.

- Future Implications: As global challenges like climate change introduce more uncertainties into agriculture, tools like NDVI will become even more vital. They will aid in monitoring changes, adapting practices, and ensuring sustainable and productive agricultural systems.

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