SPATIAL DROUGHT OCCURRENCE AND DISTRIBUTION USING DATA FROM SENTINEL-2 SATELLITE AND VEGETATION INDICES

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ABSTRACT

In recent years, drought has become a significant challenge for Thailand. Monitoring and surveillance of drought occurrences are therefore crucial. This research aims to present the analysis results of vegetation conditions and climate change in Maha Sarakham Province using NDVI and VCI indices, along with rainfall data from 2021 to 2023. The NDVI analysis found that the peak index in each year differed, with the highest value in 2021 being 0.395 in August, 2022 being 0.384 in September, and 2023 being 0.253 in November. The lowest index values were observed in different months each year. The VCI analysis showed similar results, with the highest and lowest indices reflecting seasonal changes. Rainfall plays a crucial role in determining vegetation conditions, with the highest rainfall observed in August and subsequently declining in the following months. Furthermore, the analysis of drought severity indicated that rainfall amounts are related to changes in the VCI, with 2021 experiencing the most severe drought, while in 2023, the drought was visibly reduced. This study concludes that there is a significant correlation between rainfall and vegetation conditions, and changes in the indices can be used as indicators to effectively monitor climate change and manage natural resources in the future.

***Key-words**: Remote Sensing, Spatial Drought, NDVI, VCI, Sentinel-2*

1. INTRODUCTION

Natural disasters are environmental phenomena caused by the Earth's natural processes, varying across different regions of the world (Sangpradid et al., 2021). Common types of natural disasters include earthquakes, storms, floods, landslides, droughts, and soil erosion (Pradabmook & Laosuwan, 2021; Ounrit et al., 2022; Itsarawisut et al., 2024). Currently, it is widely accepted that natural disasters cause significant damage to both personal and public lives and property (Samdaengchai et al., 2022). Governments and individuals often incur substantial losses when these events occur, which are likely unavoidable in the near future (Kanrawee, 2021). However, improving disaster management systems can help mitigate the level of destruction (Uchiyama et al., 2020). In the past, disaster management in Thailand has focused on assisting victims and restoring affected areas (Prakongsri & Santiboon, 2020). Preventing or reducing the impact of natural disasters requires creating risk maps to indicate vulnerable areas, which can serve as early warning information for residents in high-risk zones (Hossian & Meng, 2020; Kim et al., 2020). Such maps can also help governmental agencies develop strategies for disaster mitigation and avoidance. Moreover, both public and private sectors

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can utilize these maps for decision-making in physical infrastructure planning (Amarnath et al., 2021; Nikolakopoulos et al., 2022) .

Drought is characterized by prolonged dry weather conditions due to insufficient rainfall or extended dry spells, where precipitation is less than 1 mm per day for over 15 consecutive days (Royal Irrigation Department, n.d.). This phenomenon directly affects farmers and most water resources, leading to issues such as decreased soil moisture, stunted plant growth, reduced yields, and lower-quality agricultural products. Drought has various causes beyond low rainfall, including natural factors like dry spells, poor soil moisture retention, low groundwater levels, and human-induced factors such as deforestation and excessive water use, leading to reduced reservoir water levels and greenhouse gas effects from industrial development (Samanmit & Kwanyuen, 2022; Sriku & Oonariya, 2023; Wongtui & Nilsonthi, 2024). Thus, drought is often caused by multiple contributing factors. Droughts occur annually, particularly from mid-October through the winter until the onset of the rainy season in mid-May. Another dry period often occurs in the middle of the rainy season, from late June to July, due to the dry spell (Jiteurangkoon & Norkaew, 2024).

Rainfall is a critical factor in studying the relationship with vegetation indices to determine the timeframes when rainfall affects vegetation growth. The relationship between rainfall and vegetation indices serves as an important variable for identifying drought-prone areas (Uttaruk & Laosuwan,2019; Rotjanakusol & Laosuwan, 2019a; Jiteurangkoon & Norkaew, 2024). Satellite-based data on natural resources offer an effective tool for detecting areas with abnormal dry weather conditions (Rotjanakusol & Laosuwan, 2019b; Wongrawinan et al., 2023). Satellite data provide continuous, real-time monitoring of vegetation changes, making it possible to track drought-affected areas effectively. When satellite data are processed with mathematical models, they provide more precise insights into the subject of study (Jomsrekrayom et al., 2021; Rotjanakusol & Laosuwan, 2023). For instance, the Vegetation Condition Index (VCI) helps determine changes in vegetation conditions during different weather phases (Jiao et al., 2016; Dikici, 2022). Spatial drought problems are best addressed using satellite data to monitor and assess areas at risk of drought, improving the ability to present the issue's status. This study aims to investigate the spatial occurrence and distribution of drought using data from the Sentinel-2 satellite combined with Vegetation Indices, focusing on Wapi Pathum District, Maha Sarakham Province.

2. MATERIALS AND METHODS

2.1. Study Area

Wapi Pathum District (**Fig. 1**) is one of the 13 districts in Maha Sarakham Province, located in the southern part of the province, 40 km away from the provincial capital. The district covers an area of 605.77 km² and is characterized by highlands with an average elevation ranging from 130 to 230 meters above sea level. The seasons are divided into three seasons: winter starts from mid-October to mid-February, summer starts from mid-February to mid-May, and rainy starts from mid-May to mid-October. The annual average temperature is 27.4°C, with a minimum average temperature of 22.4°C and a maximum average temperature of 33.7°C. The district receives an average annual rainfall of between 1,000 - 1,200 mm. Wapi Pathum has 48,692.32 hectares of agricultural land, representing 87.60% of the total district area. Rice fields cover 46,608.32 hectares, followed by upland crop areas. The district has 19.332 farming households, with an average rice yield of 58.40 kg/ha.

2.2. Data Collecting

Sentinel-2 satellite data were used, developed under the Global Monitoring for Environment and Security (GMES) program, a collaboration between the European Commission and the European Space Agency. The primary aim of the program is to enhance the European Union’s capacity to provide and utilize environmental and security-related information. The Sentinel-2 satellites were launched in 2013, consisting of two satellites, S2A and S2B, which operate in the same orbit but at 180 degrees apart, at an altitude of 786 km. The imaging swath width is 290 km. The Sentinel-2 system is equipped with a Multispectral Instrument (MSI) that captures images in 13 spectral bands, categorized by spatial resolution as follows: 1) Four bands with a spatial resolution of 10 meters, including Bands 2, 3, 4, and 8; 2) Six bands with a spatial resolution of 20 meters, including Bands 5, 6, 7, 8a, 11, and 12; and 3) Three bands with a spatial resolution of 60 meters, including Bands 1, 9, and 10.

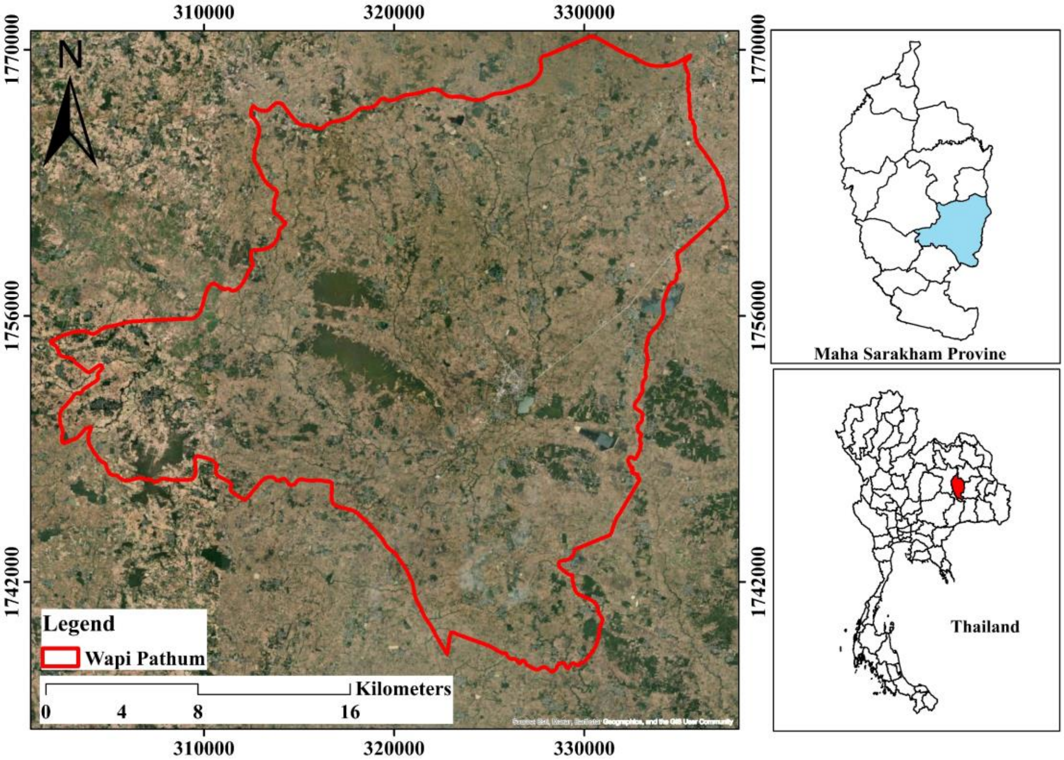

Fig. 1. Study area.

2.3. Rainfall Data

In this study, monthly rainfall data (from January to December) between 2021 - 2023 were collected from the Meteorological Department at the Maha Sarakham rainfall station [TMD, 2024].

2.4. Operation

The operation in this study will state in each step as follows:

2.4.1. NDVI Analysis

The Normalized Difference Vegetation Index (NDVI) analysis was performed by calculating the difference between the reflectance of electromagnetic waves in the red and near-infrared (NIR) bands, as shown in Equation 1 (Rouse et al., 1973). NDVI values range from -1 to +1, with negative values indicating water bodies, values near zero indicating areas with sparse vegetation, and values close to +1 indicating dense vegetation.

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

where:

NIR – light reflected in the near-infrared spectrum
RED – light reflected in the red range of the spectrum

The formula states that the vegetation density (NDVI) at a specific point in the image is calculated by taking the difference between the reflected light intensities in the red and infrared ranges and dividing it by the sum of these intensities.

2.4.2. VCI Analysis

The Vegetation Condition Index (VCI) was analyzed using Equation 2 (Kogan, 1995). This index measures the variability of NDVI during the study period (weekly or monthly) relative to the minimum NDVI values for the same period based on long-term accumulated data. A VCI value below 30% indicates severe drought, while higher VCI values suggest healthy vegetation, indicating a lower likelihood of drought occurrence.

$$VCI = \frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \times 100 \qquad (2)$$

where: NDVImax and NDVImin represent maximum and minimum NDVI of each pixel calculated for each month and i represents the index of current month

2.4.3. Drought Severity Classification

In this study, drought severity in Wapi Pathum District, Maha Sarakham Province, was classified based on VCI levels, which were divided into five categories. The classification of VCI levels is presented in **Table 1** (Uttaruk & Laosuwan, 2017).

Table 1.
Drought Severity Classification.

VCI Index	Vegetation Condition
0.00-20.00	Very Low Vegetation (Very High Drought)
21.00-40.00	Low Vegetation (High Drought)
41.00-60.00	Moderate Vegetation (Moderate Drought)
61.00-80.00	High Vegetation (Low Drought)
81.00-100.00	Very High Vegetation (Very Low Drought)

3. RESULTS AND DISCUSSION

3.1. NDVI Analysis

The Normalized Difference Vegetation Index (NDVI) is a crucial tool for monitoring and analyzing changes in vegetation and environmental conditions. Calculating NDVI from satellite imagery using the SNAP software enables us to effectively assess vegetation health. In this study, we employed remote sensing techniques to process data and generate NDVI images that depict annual vegetation changes. From **Table 2**, which presents the minimum, maximum, and average NDVI values for the year 2021, it is evident that there are variations in vegetation levels across different months.

The NDVI values range from -1 to 1, where generally, a higher average NDVI indicates healthier vegetation, while a lower average may suggest drought or vegetation scarcity. In addition, in 2021 the highest average NDVI was recorded in August, indicating peak vegetation health during that period, whereas the lowest average in May may reflect drought conditions or environmental changes affecting vegetation. Such data analysis assists researchers and stakeholders in better understanding environmental conditions and vegetation shifts, which are essential for effective natural resource planning and management.

Table 2.

NDVI Analysis in 2021.

Day-Month-Year	Min	Max	Average
19-01-21	-0.002	0.444	0.221
08-02-21	-0.002	0.41	0.204
09-03-21	0	0.389	0.194
28-04-21	-0.002	0.466	0.232
08-05-21	-0.001	0.396	0.197
27-06-21	0	0.676	0.338
27-07-21	-0.001	0.596	0.297
26-08-21	-0.001	0.791	0.395
25-09-21	-0.001	0.727	0.363
25-10-21	0	0.767	0.384
14-11-21	-0.001	0.765	0.382
24-12-21	-0.003	0.623	0.31

The analysis of NDVI results in 2022 is presented in **Table 3**. From **Table 3**, we can clearly analyze vegetation conditions and drought levels over different periods. The lowest recorded value is -0.002, occurring in February and August, indicating periods of low vegetation growth or extreme drought during those times of the year. Conversely, the highest recorded value is 0.769 in September, signifying the best vegetation growth during that period. The average values for each month differ significantly, with the highest average in September at 0.384, reflecting favourable conditions for vegetation growth at the end of the rainy season. In contrast, the lowest average in April at 0.188 indicates the early summer period with high drought conditions, resulting in reduced vegetation growth.

Table 3.

NDVI Analysis in 2022.

Day-Month-Year	Min	Max	Average
23-01-22	-0.001	0.471	0.235
22-02-22	-0.002	0.436	0.217
24-03-22	-0.001	0.452	0.225
13-04-22	-0.001	0.377	0.188
23-05-22	-0.001	0.539	0.269
22-06-22	-0.001	0.476	0.237
02-07-22	-0.001	0.498	0.248
01-08-22	-0.002	0.614	0.306
30-09-22	-0.001	0.769	0.384
30-10-22	-0.001	0.764	0.382
29-11-22	-0.001	0.57	0.285
19-12-22	0	0.461	0.231

The analysis of NDVI in 2023 demonstrates the variability in vegetation conditions across different months. The average values obtained clearly indicate the moisture or aridity of the area. During November, the highest average value suggests a more fertile environment, whereas January, with the lowest average, indicates arid conditions.

As shown in **Table 4**, it can be concluded that the monthly variations in NDVI values effectively aid in assessing the growth conditions of vegetation and the environment.

Table 4.

NDVI Analysis in 2023.

Day-Month-Year	Min	Max	Average
28-01-23	-0.001	0.281	0.14
27-02-23	-0.001	0.298	0.149
09-03-23	-0.002	0.288	0.143
28-04-23	0	0.362	0.181
18-05-23	-0.001	0.311	0.155
27-06-23	-0.001	0.417	0.208
07/07/23	-0.019	0.436	0.208
06-08-23	-0.001	0.348	0.174
10-09-23	-0.022	0.385	0.181
05-10-23	0	0.488	0.244
04-11-23	-0.001	0.508	0.253
14-12-23	-0.001	0.377	0.188

3.2. VCI Analysis

The VCI values, ranging from 0 to 100 (**Fig. 2**), reflect the varying conditions of vegetation. In 2021, the highest VCI was 70.47 in November, with the lowest VCI of 32.19 in February. In 2022, the highest VCI was 70.418 in October, with the lowest VCI of 47.317 in February.

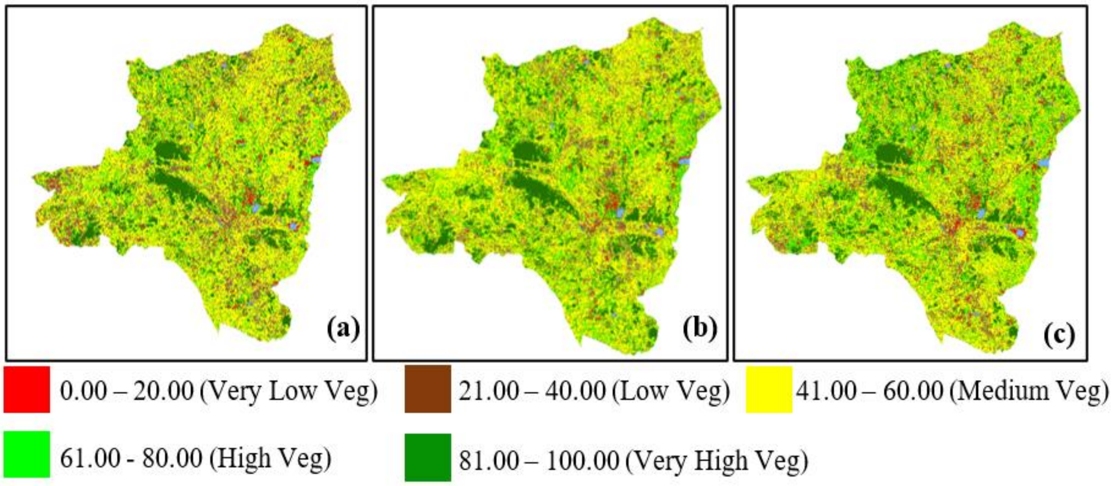

Fig. 2. VCI Analysis (a) 2021, (b) 2022, and (c) 2023.

In 2023, the highest VCI was 62.925 in November, with the lowest VCI of 49 in March. Additionally, when the VCI results were plotted on a graph (**Fig. 3**) to show seasonal variations, it was observed that VCI trends increased and decreased similarly each year. VCI values were higher during the rainy season through early winter and declined in late winter, reaching their lowest values during the summer months.

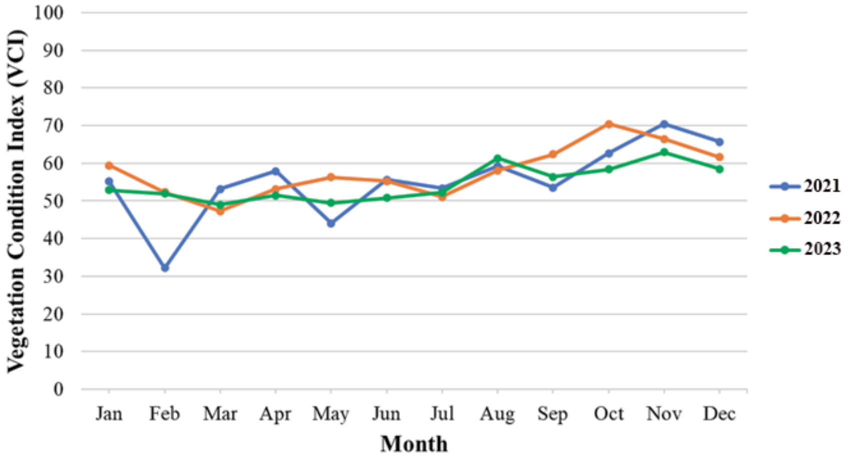

Fig. 3. VCI trends increased and decreased similarly each year.

3.3 Rainfall Analysis

The monthly rainfall data collected from the Meteorological Department at the Maha Sarakham rainfall station between 2021 - 2023 are presented in **Fig. 4**.

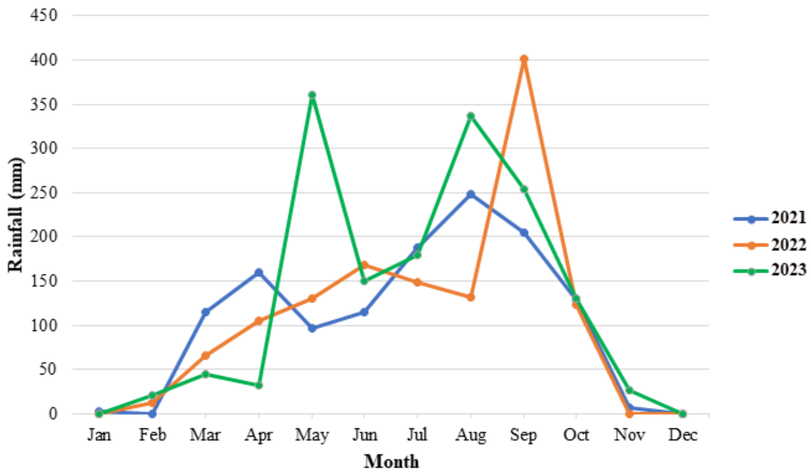

Fig. 4. Monthly rainfall between 2021 – 2023.

The results indicate that rainfall was low between January and February each year, increased in March, and peaked in August before declining steadily from September to December. Overall, 2023 recorded the highest rainfall, followed by 2022, with 2021 having the lowest rainfall. When rainfall data were compared with VCI values (**Fig. 5**), it was found that the changes in VCI lagged behind rainfall changes due to the delayed response of vegetation growth to adequate water supply. This study presents an analysis of the relationship between NDVI, VCI, and rainfall in Wapi Pathum District, Maha Sarakham Province, during the years 2021 to 2023. The results indicate a significant correlation between rainfall and vegetation moisture, which can be assessed through the NDVI and VCI indices used for drought monitoring and evaluation. The NDVI analysis revealed changes in vegetation coverage throughout the year, with notable differences between the highest and lowest values each year. These variations reflect the impact of climatic conditions and environmental factors on vegetation growth. Pettorelli et al. (2005) identified NDVI as an effective tool for monitoring regional vegetation changes. Similarly, the VCI analysis highlighted seasonal fluctuations in vegetation conditions, with VCI values tending to increase during the rainy season and decrease during the winter and summer months. Kogan (1995) supported that VCI is an efficient index for drought assessment, as it clearly reflects vegetation status. The rainfall analysis demonstrated a relationship between rainfall and VCI, consistent with the findings of Wang et al. (2001), which showed that rainfall plays a crucial role in vegetation changes and can serve as an indicator for predicting future droughts. The spatial classification of drought severity based on overlying data provides an overview of the drought conditions for each year, showing that 2021 experienced the most severe drought. This aligns with the study by Brown et al. (2008), which indicated that climate change significantly influences drought occurrences. Therefore, this research confirms the importance of using NDVI and VCI indices to assess vegetation and drought conditions, essential for natural resource management and future agricultural planning. Further research by Tucker et al. (1985) also supports the use of satellite imagery and index analysis as a strategic decision-making tool for land and agricultural management.

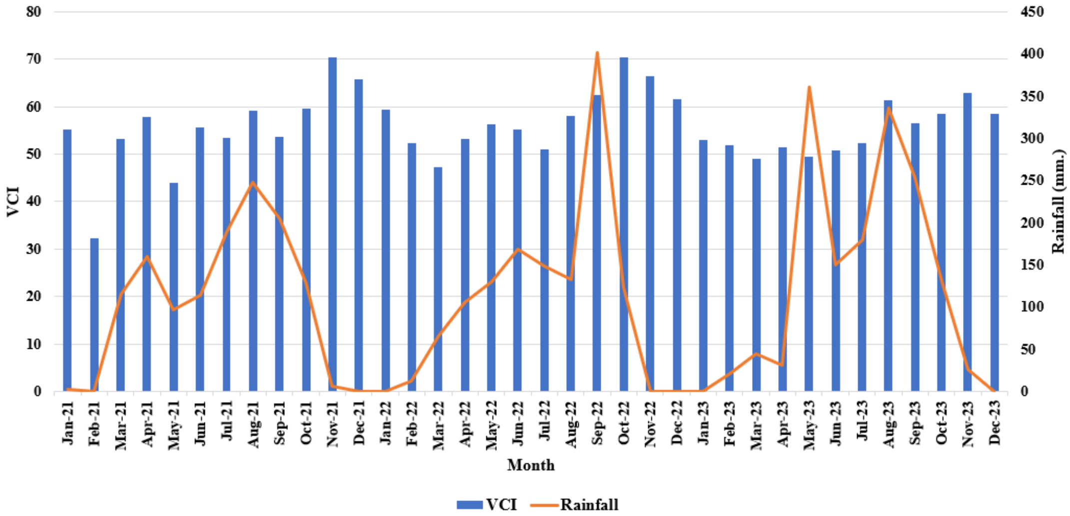

Fig. 5. Rainfall data compared with VCI.

5. CONCLUSION

The NDVI analysis revealed distinct seasonal changes, with the highest NDVI value in August and the lowest in May of 2021, indicating seasonal fluctuations in vegetation health, which were similarly observed in 2022 and 2023. The VCI analysis showed that VCI values in all three years correlated with monthly rainfall, with higher VCI values during the rainy season and lower values during the winter and summer months. These changes highlight the relationship between rainfall and vegetation health. The rainfall analysis showed that 2023 recorded the highest rainfall, consistent with the higher VCI values observed that year. The results also showed that VCI values lagged behind rainfall changes, as vegetation requires time to adapt and grow following adequate water availability. The drought severity classification indicated that 2021 experienced the most severe drought, especially during the summer, corresponding to very low VCI values, while 2023 had the least drought. This underscores the importance of spatial data analysis for effective water resource monitoring and management. In conclusion, this research reaffirms the significance of using NDVI and VCI indices, alongside rainfall data, to evaluate vegetation and drought conditions, which is valuable for future agricultural planning and natural resource management.

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