DROUGHT MONITORING FROM 2001-2019 IN NORTHEAST THAILAND USING MODIS NDVI IMAGE TIME SERIES AND Savitzky-Golay APPROACH

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ABSTRACT:

Drought directly threatens food security and livelihoods, thereby increasing socioeconomic risks and remains a challenge for natural resource management, particularly in frequently affected regions. Earth observation (EO) satellites provide extensive spectral and temporal data for long-term drought monitoring. This study monitored droughts in Northeast Thailand from 2001 to 2019 using the MODIS normalised difference vegetation index (NDVI) image time series. The Savitzky-Golay (S-G) method was used to remove noise and fill gaps in the image datasets. Optimal indicators as the vegetation condition index (VCI) and the standard vegetation index (SVI) were used to monitor drought distribution patterns over the previous 19 years. S-G filtering effectively reduced the impact of undetected clouds and water vapour, while VCI had the highest accuracy coefficient of determination (R^2) for rainfall data at 0.85. Long-term droughts occurred frequently in 2005, 2004, 2007, and 2001 with the northern and central regions most severely affected. Severe drought primarily impacted agricultural land, forest and miscellaneous areas. Inter-annual drought variability for one and three time steps was clearly demonstrated in May and April to June from 2001 to 2019. Overall, the VCI provided a high level of satisfaction for drought monitoring in this region and clearly displayed the spatial distribution of long-term drought regions. Our findings provide a valuable resource for drought mitigation planning and warning systems.

1. INTRODUCTION

Drought is an ubiquitous and recurring natural phenomenon worldwide, resulting in a lack of water supplies, decreased agricultural productivity, and increased socioeconomic risks (Ding et al., 2011). Drought occurrences have become more severe, prolonged, and frequent in recent decades as a result of climate change and population development, particularly in tropical and subtropical regions (AghaKouchak et al., 2015; Ullah et al., 2022). With this, drought management and monitoring offer valuable historical information.

Northeast Thailand is in the tropics, and the soil is primarily sandy with low water-holding capacity. Droughts have become more severe and frequent, wreaking havoc on agricultural and economic sectors, with farmers suffering from low crop production (Som-ard, 2020; Thavorntam et al., 2015).

Earth Observation (EO) data can be used to monitor the spatial distribution of drought occurrences and provide crucial information for response operations aimed at mitigating the most severely affected areas.

EO data has evolved into a vital tool for drought mapping, providing near-real-time global coverage as well as long-term service (Klisch & Atzberger, 2016). EO data have been collected by numerous sensors such as Landsat-5, the Thematic Mapper (L5 TM); Landsat-7, the Enhanced Thematic Mapper (L7 ETM+); Landsat-8, the Operational Land Imager (L8 OLI); and Moderate Resolution Imaging Spectroradiometer (MODIS). The EO data is increasingly being used for drought monitoring (Ghaleb et al., 2015; Klisch & Atzberger, 2016; Ullah et al., 2022). These mapping results have proven to be highly satisfactory for monitoring drought events, particularly when detailed temporal EO data is used.

The Terra and Aqua platforms' comprehensive archives of long-term MODIS satellite data provide highly efficient observation frequencies with large area coverage to capture rapidly changing land dynamics. All sensor data is open source and has been widely used in natural resource management (Justice et al., 2002; Wang et al., 2018). Numerous studies have demonstrated the high potential of MODIS dense temporal observations and large land coverage time series to track drought events under frequently cloudy conditions (Cammalleri et al., 2019; Klisch & Atzberger, 2016; Kumar et al., 2021; Thavorntam et al., 2015). MODIS time series data can be used to track drought episodes in harsh climate zones.

The advantages of using MODIS time series data together with several vegetation indices such as the normalized difference vegetation index (NDVI), vegetation condition index (VCI), temperature condition index (TCI), temperature-vegetation drought index (TVDI), vegetation health index (VHI), standardized vegetation index (SVI) for drought mapping have been shown in several studies. For example, Zhao et al. (2021) detected drought areas in the Yellow River Basin in China from 2003 to 2019 using MODIS data, while Kumar et al. (2021) developed a tool to monitor agricultural drought in the Tamil Nadu State of India. Klisch and Atzberger (2016) evaluated the optimal monitoring systems for drought events in Kenya using MODIS NDVI time series, while Rotjanakusol and Laosuwan (2019) tracked drought using Terra-MODIS from 2014 to 2016 in the lower northeast of Thailand. Their results showed highly

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temporal and spatio-temporal drought patterns from various vegetation indices. Long-term drought monitoring across wide regions has been neglected in developing countries including Thailand. Monthly drought monitoring in Thailand remains a challenge due to highly cloudy conditions and inclement weather regions.

Therefore, the main objectives of this study were to:

- analyze the optimal vegetation index in Northeast Thailand from 2001 to 2019 using MODIS NDVI time series.
- identify the most severe drought distribution patterns between 2001 and 2019 in Northeast Thailand.

2. MATERIAL AND METHODS

The implemented methods included filtering image time series, analyzing the optimal drought index and mapping drought distribution patterns (Figure 1).

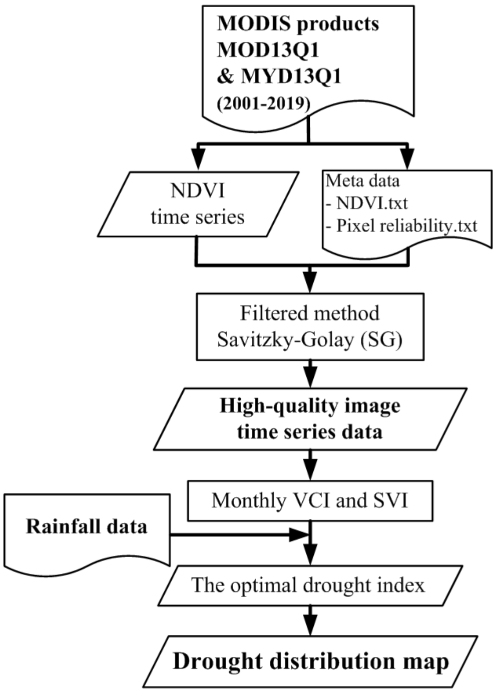

Figure 1. Illustration of the implemented workflow diagram for drought monitoring from 2001 to 2019 in Northeast Thailand.

2.1 Study Area

Northeast Thailand was selected as the study covers 14°00´ to 18°27´ and 101°00´ to 105°35´ with an area of 168,854 km^2 (Figure 2). The 30-year average temperature is 26.9 °C and the average annual rainfall is 1,446 mm. This region is categorized as having a tropical semi-humid dry-savannah climate (Köppen climate, classification: Aw) with three seasons of summer, rainy season and winter.

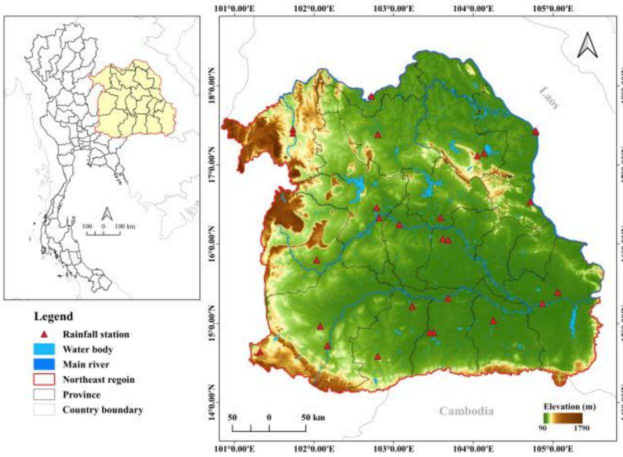

Figure 2. Study region (Northeast Thailand): background shows elevation with a height of 90-1,790 mm. The red triangle points are the rainfall stations of the Thai Meteorological Department.

2.2 MODIS Data Sets

2.2.1 Data Acquisition: MOD13Q1 and MYD13Q1 NDVI with five MODIS Terra and Aqua satellite products, were obtained through the University of Natural Resources and Life Sciences (BOKU) online platforms. These products were mosaicked, multi-tiled, and re-projected to geographic coordinates (datum WGS84) by the BOKU Geomatics server (http://ivfl-info.boku.ac.at/) (Vuolo et al., 2012). NDVI products were selected from both sensor data acquired every 8 days (temporal resolution) at 250 m spatial resolution. A total of 874 images were collected, taken between 2001 and 2019 across the study region.

2.2.2 Filtered Image Time Series: MODIS NDVI time series data are affected by environmental conditions such as clouds, water vapor and smoke, resulting in poor image data quality. This study adapted the Savitzky-Golay (S-G) filtering approach to eliminate noise and fill gaps for the time series data. S-G filtering can be employed to smooth, reconstruct and fit spectral values using the least square algorithm (Savitzky & Golay, 1964). The S-G filtering was conducted in TIMESAT software with two setting parameters: the half-width of the smoothing window (*m*) and the number of degrees of the smoothing polynomial (*n*). The S-G filtering was utilized to derive the smoothed image time series data using equation 1. This analysis fitted the optimal filter parameters of 8 (*m*) and 3 (*n*), and used 10 iterations to determine the best fitting effect for processing. High-quality time series datasets were then applied to the study region as the image output.

$$Y_j^* = \sum_{i=-m}^{i=m} \frac{C_i Y_{j+1}}{n} , \tag{1}$$

where Y^*_j is the filtered image time series data, Y_j is the input data, C_i is the coefficient of filter fitting, i.e., the weight of input data, n is the filtered processing data and the smoothing window size ($2m+1$), and m is the half-size of the smoothing window.

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2.3 Calculated Drought Indices

2.3.1 The VCI is ideal for assessing the impact of weather on vegetation by enhancing inter-annual vegetation index variations based on EO satellite data (Kogan et al., 2003). The maximum VCI value is 100% with minimum of zero. For this study the VCI was used to map drought anomalies following equation 2, by utilizing the *raster* package in R software (version 3.6.2) (Hijmans et al., 2015) for this study.

$$VCI_i = 100 \text{ x } (NDVI_i - NDVI_{min,i})/(NDVImax,i - NDVImin,i), \qquad (2)$$

where VCI_i is the updated vegetation condition index (VCI) at time step i, $NDVI_i$ is the filtered NDVI image at time i and $NDVImin,i$ or $NDVImax,i$ are the lowest/highest values of filtered NDVI pixels from 2001 to 2019 during eight days.

The VCI categorized the thresholds for drought anomalies compared to rainfall data, with drought ranks shown in Table 1.

VCI (%)	Drought category
≤ 15	Extreme drought
16 to 35	Severe drought
36 to 50	Moderate drought
51 to 65	Normal/ No drought
> 65	Wet

Table 1. Thresholds used to update the vegetation condition index (VCI) and related drought categories based on rainfall data.

2.3.2 The SVI measures: the probability of vegetation condition deviation from normal preferred to NDVI value in a year. The performed SVI was summarized by Peters et al. (2002). SVI values between 0 and 1 were applied for assessing drought, as calculated in equation 3.

$$SVI_i = (Z_{ijk} - Z_{ijMIN})/(Z_{ijMAX} - Z_{ijMIN}), \qquad (3)$$

where SVI_i is the updated standardized vegetation index (SVI) at time step j, Z_{ijk} is z-value of the filtered NDVI pixel i at time j for year k and Z_{ijMIN} or Z_{ijMAX} are the lowest/highest filtered NDVI pixels i from 2001 to 2019 at time j during eight days.

The SVI was defined as the threshold of drought anomalies in comparison to rainfall data. The vegetation anomalies were classified and shown in Table 2.

SVI	Drought category
≤ 0.05	Extreme drought
0.06 to 0.25	Severe drought
0.26 to 0.75	Moderate drought
0.76 to 0.95	Normal/ No drought
≥ 0.96	Wet

Table 2. Thresholds related to vegetation anomalies using the standardized vegetation index (SVI) based on rainfall data.

2.4 Drought Indicator Assessment

The VCI and SVI were compared to rainfall data using the coefficient of determination (R^2) to determine the best drought index for this research region. R^2 was calculated by collecting VCI and SVI pixel values at a Sisaket rainfall station and utilizing monthly rainfall data from 2007 to 2017. The optimal indicator was then used to monitor the spatial distribution of drought patterns from 2001 to 2019.

2.5 Mapping Drought Distribution Patterns

To monitor drought affected regions, the monthly indicator was temporally and spatially aggregated to map drought occurrences. One month demonstrated short-term drought from 2001 to 2019, with three months of VCI (VCI3M) aggregated to map drought distribution patterns. Annual maps showed long-term trends for the most severe drought years between 2001 and 2019.

3. RESULTS

3.1 MODIS NDVI Image Time Series Dataset

The NDVI profile of a randomly selected pixel in the center of an arid region (row 1228, column 946) is shown in Figure 3. The filtered result was consolidated (smoothed) as the brown line compared to the original observation data.

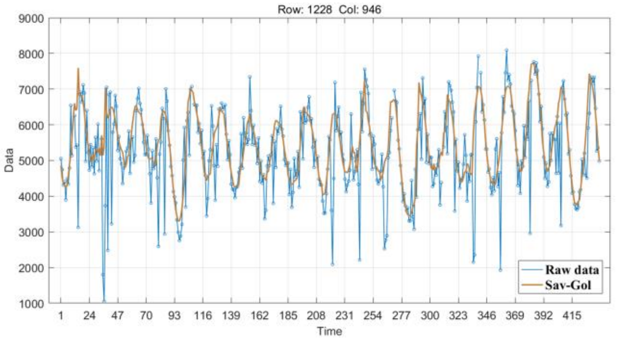

Figure 3. MODIS NDVI pixels of raw data (blue line) and filtered information (brown line) of filtered NDVI image time series data from 2001 to 2019 using the Savitzky-Golay (S-G) method.

A comparison between the original and filtered MODIS NDVI image time series data (exemplary output in August 2019) is demonstrated in Figure 4. Filtered map values were smoothed, with noise pixel time series values masked to improve the image datasets. The map results presented a high-quality dataset by fitting the best parameters of the S-G method.

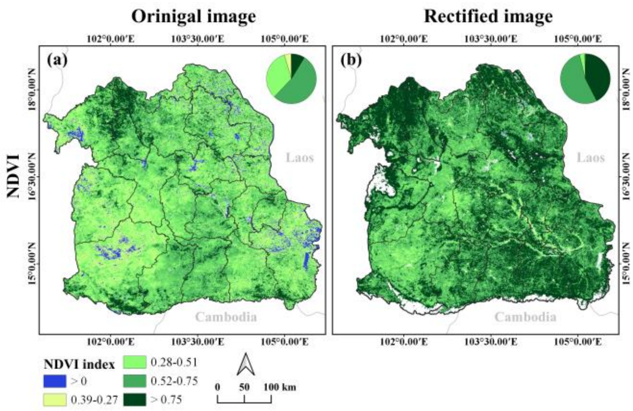

Figure 4. Comparison of MODIS NDVI image time series data with exemplary of the observed images in August 2019: (a) original and (b) filtered image dataset.

3.3 Drought Indicator

Figure 5 illustrates the R^2 values of the VCI and SVI monthly vegetation indices, as well as rainfall data, from 2007 to 2017. In 2017, the R^2 values were 0.85 (VCI) and 0.74 SVI. The VCI value was slightly greater than the SVI. The VCI indicator demonstrated remarkable sensitivity for extremely variable monthly rainfall levels, such as those found in Thailand.

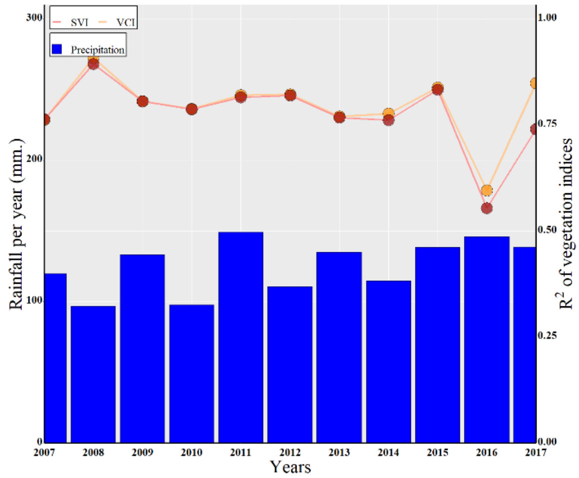

Figure 5. R^2 values of SVI and VCI monthly vegetation indices and rainfall data from 2007 to 2017 in Northeast Thailand.

3.4 Spatial Drought Distribution Pattern

Figure 6 shows a boxplot of annual VCI (%) from 2001 to 2019. The presence of mean VCI (%) values below 50% (red line) indicated a drought anomaly. Drought events were detected in the seven years ranked in regard to their severity as 2005, 2004, 2007, 2001, 2010, 2002, and 2006.

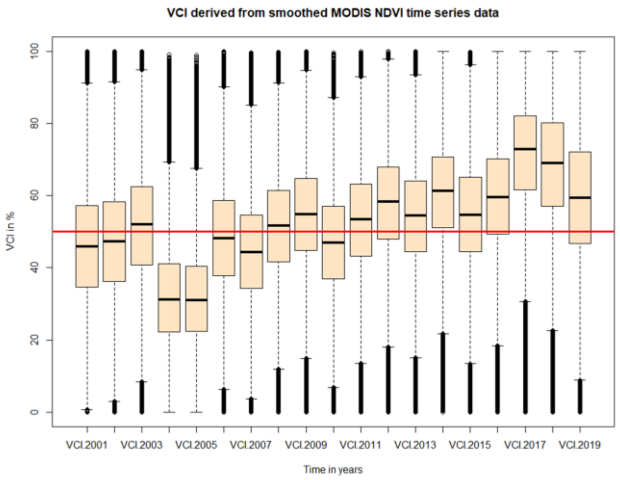

Figure 6. Boxplot of mean annual vegetation condition index (VCI) (%) from 2001 to 2019 in Northeast Thailand. Years under the red line indicate drought anomalies.

Long-term drought monitoring from 2001 to 2019 is shown in Figure 7. Drought distribution patterns are based on VCI (%), with the worst drought areas located in north and central areas.

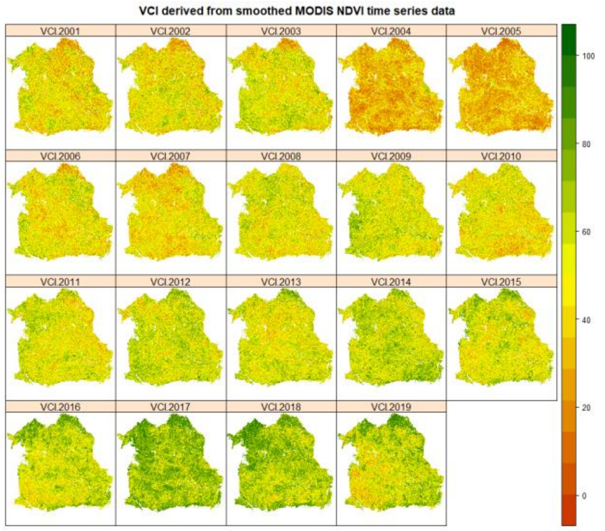

Figure 7. Long-term drought monitoring in Northeast Thailand from 2001 to 2019 derived from the mean annual vegetation condition index (VCI) (%).

Temporal and spatial VCI (%) for the three months April to June were aggregated to show spatial distribution patterns of the worst drought years (Figure 8), with mean VCI3M (%) values of 27.24 (2005), 45.30 (2004), 45.50 (2007), and 46.16 (2001). The VCI3M of 2005 shows the greatest drought anomaly over the four years. Droughts were most severe in the north, center, and south, where they predominantly affected agricultural areas.

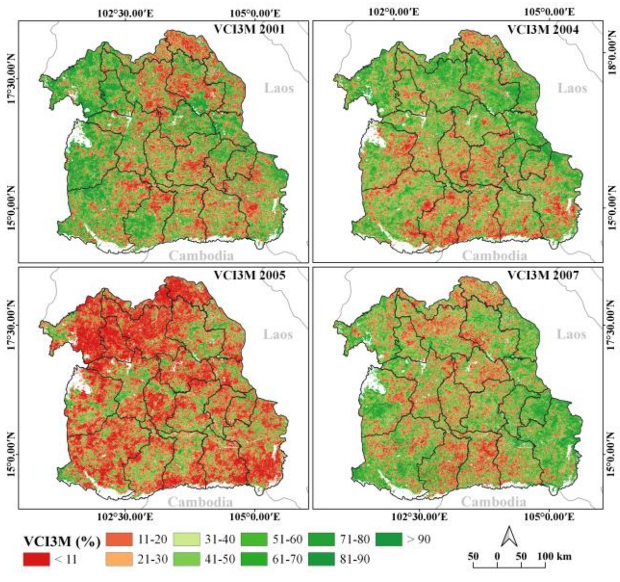

Figure 8. Inter-annual variability of three time steps (April to June) for drought in Northeast Thailand in 2001, 2004, 2005, and 2007 based on the vegetation condition index (VCI) (%).

The inter-annual variability for a single time-step in May for the years of the most severe drought occurrences (2001, 2004, 2005, and 2007) is illustrated in Figure 9. This month is generally the beginning of the rainy season in Thailand and is highly effective in presenting different vegetation growth due to rainfall. The map result showed the high frequency and extreme intensity of drought event patterns, which mostly appeared in the central, south, and southeast. The drought mostly impacted agricultural land and miscellaneous areas. Results suggested repeated drought events across Northeast Thailand.

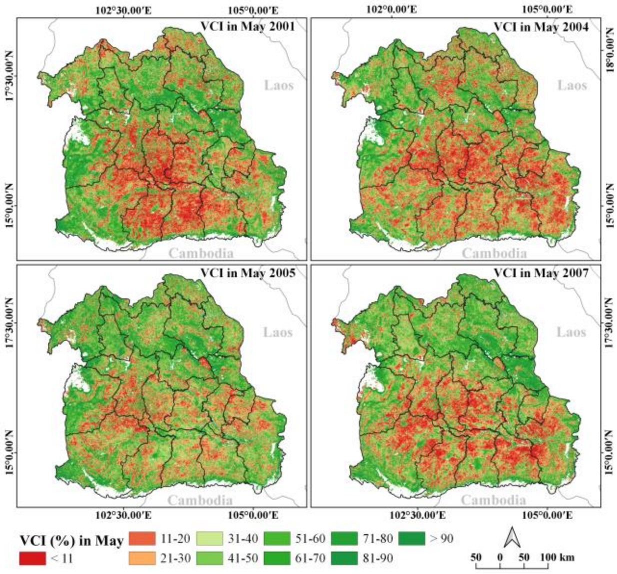

Figure 9. Inter-annual variability for single-time step (May) with drought in Northeast Thailand in 2001, 2004, 2005 and 2007 based on the vegetation condition index (VCI) (%).

4. DISCUSSION

The S-G method showed high potential to remove noise and fill gaps in the MODIS NDVI image time series data. Our findings agreed with those of Cai et al., (2017), emphasizing the ability to predict average phenology across the entire region. This study also achieved highly smoothed NDVI image time series data for estimating drought events in high cloud coverage areas like Northeastern Thailand, highlighting the performance for predicting average phenology over the entire region. This study also achieved highly smoothed NDVI image time series data for estimating drought events in high cloud coverage areas like Northeastern Thailand.

The VCI was the optimal indicator for monitoring drought events in this region. The VCI value is highly related to the R^2 value when compared to monthly rainfall data, concurring with Klisch and Atzberger (2016). Their findings demonstrated that it is more efficient to monitor drought dynamics. AghaKouchak et al. (2015), Thavorntam et al. (2015), Kumar et al. (2021) and Zhao et al. (2021) demonstrated VCI as a powerful tool for monitoring long-term vegetation conditions and drought events. The SVI showed promising results, but accuracy decreased with high differences in monthly rainfall (Luetkemeier et al., 2017). Our findings confirmed that VCI derived from the smoothed NDVI image time series datasets provided high efficiency for monitoring drought events in this region from 2001 to 2019.

Over the period of 19 years, long-term spatial drought monitoring revealed anomalous distribution patterns. Our data revealed drought anomalies in seven years, with the greatest variation occurring in 2005, 2004, 2007, 2001, 2010, 2002, and 2006. These drought occurrences were caused by variability in rainfall data, which resulted in insufficient chlorophyll for vegetation phenology (Thavorntam et al., 2015). According to Limsakul and Singhruck (2016), the mean VCI3M (April to June) map in 2005 exhibited Thailand's greatest drought due to the El Niño event (2016). The monthly drought maps produced excellent outcomes for this region's drought distribution patterns, with drought occurrences primarily occurring in agricultural and forest areas. Over a 9-year period, Thavorntam et al. (2015) observed widespread and intense drought occurrences, mainly in the north, central, and southern areas.

Droughts are common in the Northeast Thailand, and their effects on agriculture are significant, as plant growth is heavily reliant on rainwater, irrigation, and groundwater during seasons of low rainfall. However, the region has continued to experience drought occurrences, which cause rice harvests to perish, cows to go without grazing, and natural water levels to plummet. The main cause of drought is a lack of rainfall, as well as the absence of seasonal rain, which usually happens from late June to the end of July. An extended period of no rainfall is frequently encountered in the region's middle and lower reaches. Because these two areas are not impacted by the Southeast Asian Monsoon, there is less water in natural sources and groundwater bodies. As a result, moisture in the soil is drained, impacting plant growth (Sumpong et al., 2021), particularly in the paddy fields of Thung Kula Rong Hai district, which is a key area for jasmine rice cultivation and received first prize in the 2020 World's Best Rice Award (Jirapornvaree et al., 2021; Chouichom, 2021).

As a result, the government has assessed which regions are ideal for rice farming and which should be used instead for the growth of other crops that require minimal water during the dry season. Because water is limited, certain places may be converted into something, such as rice fields to crop farms cultivating sugarcane, cassava, maize, or rubber-all of which have now become the country's principal economic crops, as well as important exported items. Finally, drought is clearly a crucial problem that causes economic, social, and environmental damage, particularly in agricultural sectors; hence, solid planning as well as rapid effective technologies, including quick accurate forecast, are essential to prevent and mitigate the effects of drought. We utilized high temporal MODIS time series datasets to track the spatial spread of drought from 2001 to 2019. Drought maps with one and three time increments can also be used to properly evaluate and monitor the spatiotemporal changes of agricultural drought occurrences. The results demonstrated great efficiency as a tool for providing critical information to relevant stakeholders for well-organized drought management and planning.

Our study highlighted anomalies in drought distribution patterns from 2001 to 2019 across Northeast Thailand. Future studies should apply climatic and dynamic factors for large-scale drought monitoring, following the recent study of Ullah et al. (2022), to further improve the accuracy of drought monitoring.

5. CONCLUSIONS AND OUTLOOK

High temporal data from the MODIS time series datasets can be used to monitor drought. This study tracked long-term drought events over cloudy and rainy days in Thailand. Results showed high efficiency as an essential tool for drought management.

Key findings and further recommendations are presented below:

- Map results showed drought distribution patterns from 2001 to 2019 that can be used as essential land management and planting tools.

- To provide high-quality NDVI time series datasets for inclement weather regions, the Savitzky-Golay (S-G) method effectively reduced pixel error in time series by smoothing and removing. Future studies can use our proposed method.

- The VCI had high efficiency. However, other drought indices (i.e., temperature condition index (TCI), temperature-vegetation drought index (TVDI), and vegetation health index (VHI)) together with other climatic data and powerful machine learning methods such as random forest (RF), support vector machines (SVM), and artificial neural networks (ANN) should also be used to improve drought monitoring in this highly adverse region.

- Our results are useful for drought mitigation planning and warning systems. Long-term Earth Observation (EO) and dense temporal data provide highly accurate drought mapping in areas where drought events repeatedly occur to improve land management and agricultural cultivation.

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