

Spatio-Temporal Drought Monitoring in the Chi River Basin from 2001–2020 Using MODIS Time Series Data and Google Earth Engine

Suwanlee, S. R.,^{1,2} Keawsomsee, S.,^{1,2} Sangjan, W.,³ Som-ard, J.,^{1,2*} Siripattanachotikul, K.,⁴ Ninsawat, S.⁵ and Nudthawud, H.⁶

¹Department of Geography, Mahasarakham University, Mahasarakham, Thailand
E-mail: savittri.s@msu.ac.th, jaturong.s@msu.ac.th*

²Earth Observation Technologies for Land and Agricultural Development Research Unit, Faculty of Humanities and Social Sciences, Mahasarakham University, Thailand, E-mail: surasak.ke@msu.ac.th

³Department of Biological Systems Engineering, Washington State University, Pullman, WA, United States
E-mail: worasit.sangjan@wsu.edu

⁴Department of Sociology and Anthropology, Mahasarakham University, Mahasarakham, Thailand
E-mail: kritsada.c@msu.ac.th

⁵Remote Sensing and GIS Field of Study, School of Engineering and Technology, Asian Institute of Technology, Pathumthani, Thailand, E-mail: sarawutn@ait.ac.th

⁶Department of Geotechnology, Faculty of Technology, Khon Kaen University, Khon Kaen Province, 40002, Thailand, E-mail: nudth@kku.ac.th

*Corresponding Author

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Abstract

Drought is a recurring issue in South Asia (SA) caused by extreme climate events, posing ongoing challenges for food management, sustainable agricultural practices, and livelihoods, especially in frequently affected areas. Earth Observation (EO) data provides valuable information for long-term drought monitoring across broad regions. However, a need remains to map and monitor spatial drought events over large regions and extended periods, particularly in the Chi River Basin. In this region, droughts have increased frequently, leading to low water-holding capacity and adversely affecting agricultural production and productivity. In this context, this study aimed: i) to identify spatial drought from 2001 to 2020 over the Chi River Basin, Thailand, using MODIS image time series via Google Earth Engine (GEE); ii) to analyze the correlation between Temperature Vegetation Dryness Index (TVDI), Standardized Precipitation Index (SPI), and Streamflow Drought Index (SDI) and land use provided by the Land Development Department (LDD). The TVDI index was generated for dry and wet seasons to map and monitor the spatial distribution of drought events over 20 years. The spatial drought based on TVDI, SPI, and SDI was determined to identify their relationship. Historical droughts from TVDI were most frequent during the dry seasons of 2005 (82%), 2013 (80%), and 2004 (78%), and appeared in the wet seasons of 2019 (41%), 2017 (41%), and 2009 (38%). The TVDI drought map had a slightly low coefficient of determination (R^2) for SPI and SDI, under 0.22 for all study seasons. However, these findings showed similar drought trends across all study years, with drought events predominantly occurring in the central and northeast parts of the region. In comparison, the spatial drought map in the year 2020 showed severe droughts, mostly impacting cassava and rice fields during the dry season and urban areas during the wet season. Our proposed workflow is reliable and robust, providing spatial drought areas with confidence in the accuracy and validity of our results. The mapped results provide as significant tool for drought mitigation planning and management.

Keywords: Earth Observation, Hydrological Drought Assessment, Land Surface Temperature (LST) Monitoring, Land Use, Temperature Vegetation Dryness Index (TVDI)

1. Introduction

Climate change poses significant challenges to ecosystems, agriculture, and economies worldwide, with Southeast Asia being particularly vulnerable.

Thailand, ranked ninth globally for long-term climate risk from 2000 to 2019, is prone to severe impacts due to its tropical location, making it susceptible to

higher temperatures and extreme weather events such as floods and droughts. These natural disasters have adversely affected livelihoods, environmental health, and economic stability, further increasing the country's vulnerability over time [1] and [2]. The Chi River Basin, located in Northeastern Thailand and spanning approximately 49,500 km², is a vital agricultural region. Over 60% of its area is dedicated to cultivating crops such as rice, sugarcane, rubber, and cassava, making the basin crucial to Thailand's food security and economic stability [3]. However, recurrent droughts have severely impacted the region, leading to significant water shortages affecting domestic use and agricultural productivity. The basin's rainfall patterns, especially during the dry season, are a critical contributor to these droughts, often causing rivers to dry up and exacerbating the challenges faced by local communities and agricultural activities [4] and [5].

Effective natural resource management, particularly in response to climate change, is essential for mitigating the impacts of these droughts. Satellite-based remote sensing has become an invaluable tool for capturing and analyzing environmental change over time and across large areas [6] and [7]. This technology is also increasingly utilized in medium- to small-scale areas of agricultural research and practices [8] and [9]. Multi-temporal satellite imagery from platforms such as land remote-sensing satellite (LANDSAT), satellite pour l'observation de la terre (SPOT), and moderate resolution imaging spectroradiometer (MODIS) have been instrumental in monitoring land use changes, assessing vegetation health, and tracking broader climate trends [10][11][12] and [13].

Vegetation indices (VI) derived from multi-temporal satellite imagery are widely used to monitor natural resources across time. In drought assessment, VIs that utilize near-infrared (NIR) and short-wave infrared (SWIR) spectra are particularly effective due to their sensitivity to plant water content changes and stress levels [13]. Indices such as the normalized difference vegetation index (NDVI) and the temperature vegetation dryness index (TVDI), when combined with the land surface temperature (LST) and integrated with meteorological and hydrological data such as the standardized precipitation index (SPI) and the streamflow drought index (SDI), provide a potential framework for accurate drought assessment [13][14][15] and [16]. Additionally, machine learning algorithms further improve the precision of land use classification and enhance drought monitoring in complex landscape [17] and [18]. Various regions have utilized satellite-based tools to monitor drought and land use changes.

For instance, MODIS-derived TVDI and weather data were applied to analyze drought trends in China from 2001 to 2010, revealing different factors influencing drought across various landscapes, such as temperature in the south, sunlight duration in the north and northeast, and humidity in plateau areas [19]. Similarly, TVDI from MODIS and meteorological data, processed through Google Earth Engine (GEE), were used to assess the relationship between land use changes and drought in central Vietnam, with the study identifying an annual increase in drought-prone areas by 0.08% to 0.1% [20]. In the Yellow River Basin, MODIS LST data from 2003 to 2019, using GEE, was used to monitor drought. The study found that the vegetation condition index (VCI) and vegetation health index (VHI) indicated drought in grasslands, while TVDI highlighted drought in agricultural areas and forests. The temperature condition index (TCI) linked high surface temperatures to drought in urban and agricultural areas [21].

A comparative analysis of SPI and SDI was conducted for drought monitoring using data from 1971 to 1972 and 2010 to 2012 in northern Morocco's Ihenoune Basin. The study found that SPI and SDI trends and correlations varied across time scales, with a high correlation observed between the January and February data of every study year [22]. Although extensive research on drought monitoring using remote sensing data, the understanding of interactions between drought indices (TVDI, SPI, and SDI) in specific localized regions, the Chi River Basin still needs to be explored. Most studies have focused on broader regional or national scales, which may overlook the fine-scale variations in drought conditions within agricultural areas.

This study aims to provide a detailed spatio-temporal analysis of drought conditions in the Chi River Basin from 2001 to 2020. Using time series MODIS and meteorological data through GEE, this research assesses agricultural drought from the TVDI and examines the relationships between TVDI, SPI, SDI, and land use changes. The findings will offer actionable insights to support policymakers in developing climate adaptation strategies and enhancing the resilience and sustainability of agriculture in the Chi River Basin.

2. Study Area and Data Used

2.1 Study Area

The Chi River Basin, located in Northeastern Thailand between 15°10' to 17°50'N and 101°00' to 105°50'E (Figure 1). The area features a mix of plains and highlands, with elevations ranging from 0 to 1,324 meters above mean sea level (MSL).

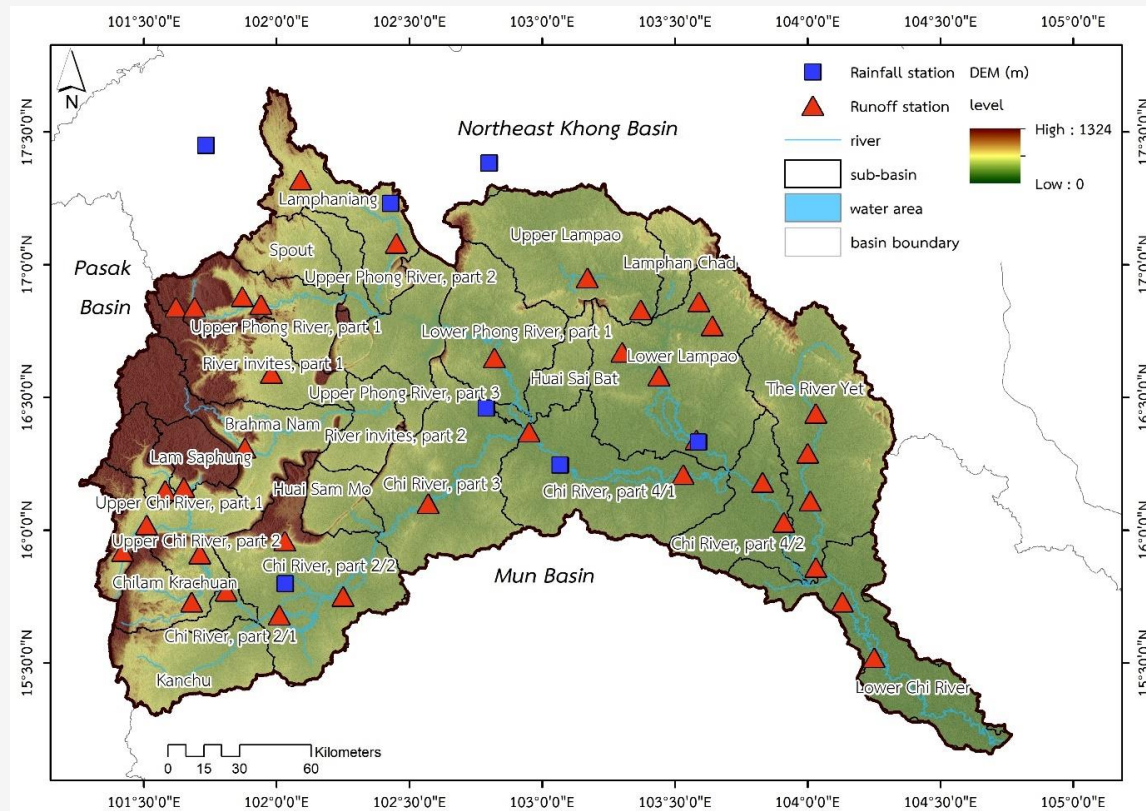


Figure 1: The Chi River Basin with rainfall and runoff stations

The basin's tributaries are vital for agriculture, supporting local production that contributes significantly to national and international markets [5]. The region is classified under the tropical semi-humid wet/dry savanna climate (Köppen climate classification: Aw), with three distinct seasons: summer (February to May), rainy (May to October), and winter (October to February). The long-term average temperature is around 27°C, with an average annual precipitation of 1,690 mm and relative humidity of 72%.

2.2 Data Used

2.2.1 MODIS dataset and pre-processing

MODIS Terra satellite imagery with less than 40% cloud cover was used for the study. Data from two tiles (h27v07 and h28v07) were collected. Product MOD11A1 (version 6), which provides LST in the LST_DAY_1 km band, was used and multiplied by a scaling factor of 0.02 to obtain the actual LST [23]. In addition, product MOD09Q1 (version 6) was also used, which provides surface reflectance in bands 1 (RED) and 2 (NIR) to calculate NDVI [24]. Imagery from 2001 to 2020 was composited into six months using the mean compositing method, dividing the data into two periods: the wet season (May to October) and the dry season (November to April)

according to the Thai Meteorological Department [25]. The compositing method calculated the average pixel value over six-month periods. This method is suitable for continuous data but can be affected by cloud and environmental conditions, as mentioned in [26] and [27]. These composite images were then combined or mosaicked to create a complete image of the study area. The final mosaicked images were trimmed to the Chi River basin's boundaries and then downloaded for further analysis. All processing was conducted using the GEE platform.

2.2.2 Meteorological and hydrological datasets

Monthly rainfall data was obtained from the Thai Meteorological Department, and monthly streamflow data was gathered from the Royal Irrigation Department for 2001–2020 at the Chi River Basin. Seven rainfall stations and 37 streamflow stations were considered, with five rainfall stations (Chaiyaphum, Khon Kaen, Mahasarakham, Kalasin, and Roi Et provinces) and three streamflow stations in Khon Kaen, Roi Et01, and Roi Et02 provinces having continuous data for 20 years (Figure 1). The monthly rainfall and streamflow data were used to calculate the SPI to indicate droughts caused by rainfall deficiencies. SDI was also generated to indicate hydrological droughts resulting from

reduced streamflow. Both indices were computed for six-month and 12-month time scales. The SPI-6 and SDI-6 periods were divided into the wet season (characterized by high moisture) and the dry season (characterized by low moisture). SPI-12 and SDI-12 were used to analyze the occurrence of meteorological and hydrological droughts [28]. Thus, in this study, SPI and SDI indices were used to compare with indicators from satellite data. These can determine the severity of drought from ground observation, which is essential information for

validating and monitoring drought events together with satellite data over time and space.

3. Methodology

This study monitored the spatio-temporal drought events in the Chi River Basin from 2001 to 2020, using three steps: i) data collection and pre-processing; ii) spatial analysis of drought events; and iii) comparison of drought indicators with SPI, SDI, and land use (Figure 2).

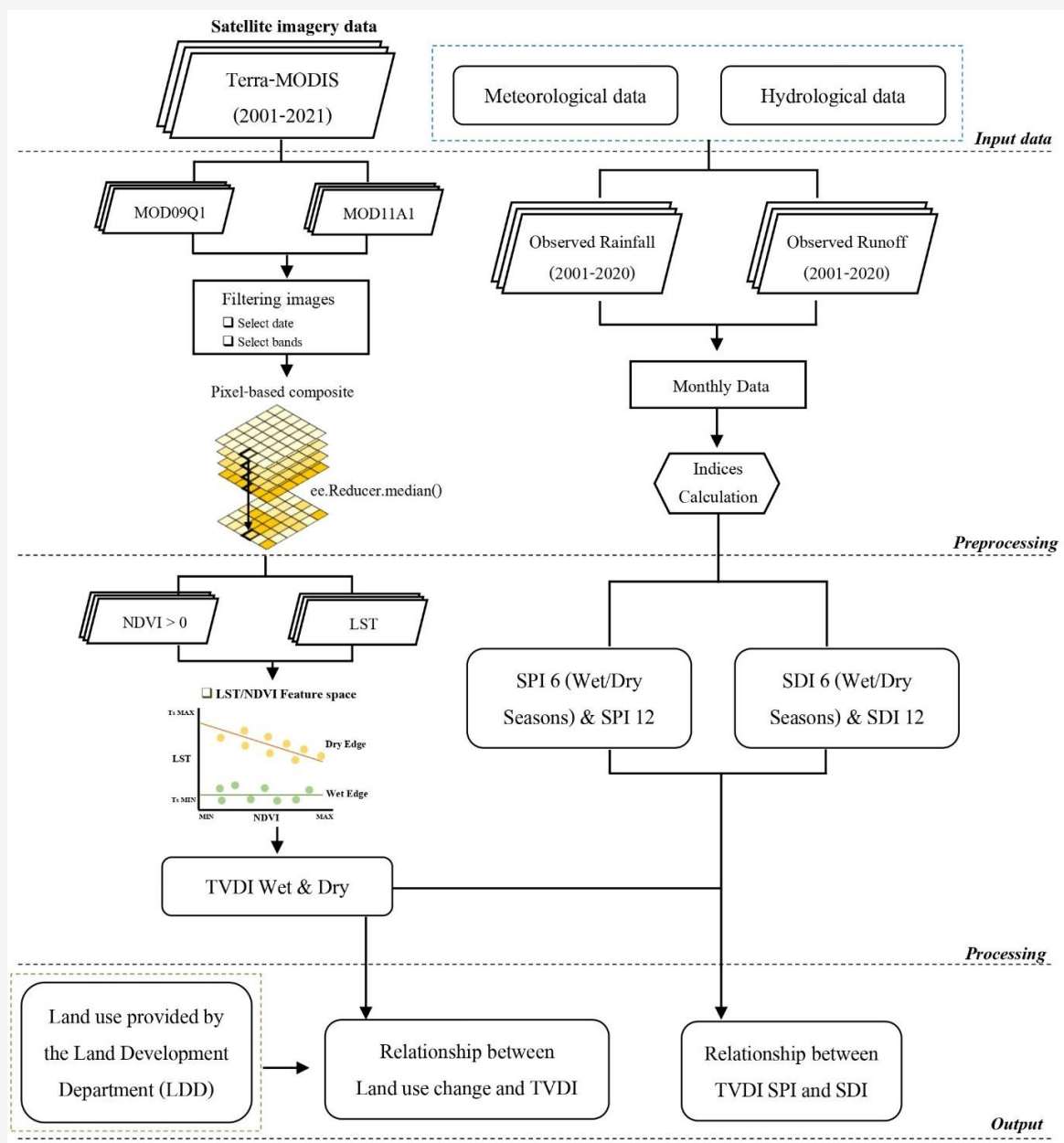


Figure 2: The implemented workflow of spatio-temporal drought monitoring in the Chi River Basin from 2001 to 2020 using MODIS time series data and Google Earth Engine

3.1 Mapping Spatio-Temporal Distribution of Drought Events

In this study, TVDI was calculated to assess drought conditions over the agricultural land in the study region. The TVDI was conducted for two periods: six months (May to October for the wet season and November to April for the dry season) and 12 months to study agricultural drought trends. The severity of drought based on TVDI values was classified into five levels: very wet (0.00 – 0.20), wet (0.21 – 0.40), normal (0.41 – 0.60), dry (0.61 – 0.80), very dry (0.81 – 1.00) [29]. The TVDI ranges from 0 to 1, and this indicator is calculated using Equations 1-3 [29].

$$TDVI = \frac{LST - LST_{\min}}{(a + b \cdot NDVI)LST_{\max} - LST_{\min}}$$

Equation 1

Where:

TDVI is the Temperature Vegetation Dryness Index from 2001 to 2020

LST is land surface temperature

LST_{min} is minimum of land surface temperature corresponding to a certain NDVI

LST_{max} is maximum of land surface temperature corresponding to a certain NDVI

$$LST_{\min} = a_1 + b_1NDVI$$

Equation 2

$$LST_{\max} = a_2 + b_2NDVI$$

Equation 3

Where:

a₁, *b₁* are the coefficients of the linear fitting equation for the wet edge

a₂, *b₂* are the coefficients of the linear fitting equation for the dry edge

In the analysis, NDVI values greater than zero was selected, and corresponding LST value were used to calculate TVDI for each pixel. NDVI values lower than zero, typically represent water bodies, were excluded to avoid introducing anomalous TVDI values [30]. This study used *caret* package version in R studio [31].

3.2 Relation between Indicators

Simple linear regression was used to analyze the correlations between TVDI, SPI, and SDI over six-month and 12-month periods. The coefficient of determination (*R*²) was calculated to assess the strength of the relationships between the indices and evaluate the effectiveness of the regression model to fit the data.

3.3 Comparison of Drought Indicator and Land Use

The relationship between drought severity and land use was analyzed by comparing TVDI results (five severity levels) with land use data from the land development department (LDD) for the years 2002, 2005, 2010, 2015, and 2020. The study examined how drought impacted major crops rice, sugarcane, cassava, and rubber trees. A chord diagram was created to visualize the transformation of the drought indicators across these crop types over the selected time periods.

4. Results

4.1 Monitoring Spatio-Temporal Drought Events

The TVDI graphs for the Chi River Basin from 2001 to 2020 were divided into dry season from November to April (Figure 3(a)) and wet season from May to October (Figure 3(b)). Most of the basin experienced moderate to severe drought during the dry season. The years with the most severe drought were 2005, 2013, 2011, and 2014, accounting for 82.04%, 80.14%, 77.47%, and 76.59% of the total area, respectively. In contrast, 2010, 2002, and 2001 exhibited the most minor drought, covering 21.81%, 35.83%, and 36.44% of the area, respectively. Most of the basin remained at normal moisture levels during the wet season. However, in 2019, 2017, 2009, and 2011, severe droughts were observed in the central and southwestern parts of the basin, affecting 40.96%, 40.74%, 38.60%, and 33.88% of the total area, respectively. The minor drought during the wet season occurred in 2004, 2018, and 2011, covering 2.73%, 9.03%, and 11.89% of the area, respectively. The map in Figure 4 shows that the most severe droughts occurred in 2005, 2013, 2011, and 2014. The central and southwestern parts of the Chi River Basin were the hardest hit during the dry season, with TVDI values ranging from 0.49 to 0.71. During the wet season, most areas of the basin remained at normal levels. However, severe droughts were observed in 2019, 2017, 2009, and 2011, primarily affecting the central and southwestern parts of the basin.

4.2 Relationships between TVDI, SPI, and SDI Indicators

A weak correlation was observed when the five rainfall stations' TVDI and SPI indices in the Chi River Basin were compared in 2005, 2013, and 2019. Both six-month (wet and dry season) and 12-month SPI values showed decreasing *R*² values, indicating drought conditions. TVDI values predominantly ranged from 0.0001 to 0.1209, signaling severe drought, as shown in Table 1.

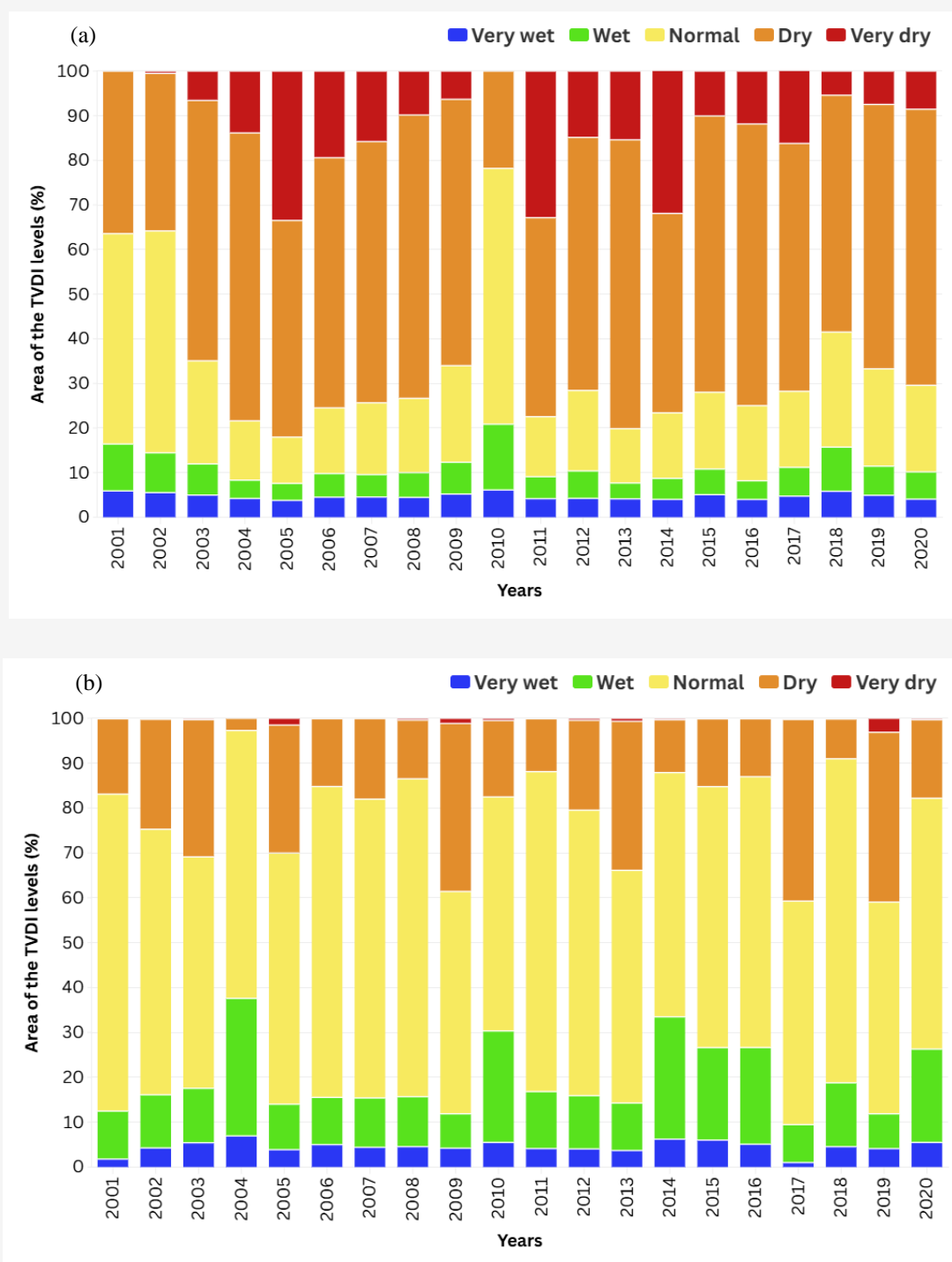


Figure 3: Drought areas from 2001 to 2020 during dry and wet seasons in the Chi River Basin, Thailand, created by the Temperature Vegetation Drought Index (TVDI):
 (a) dry season (b) wet seasons from a time series of MODIS datasets

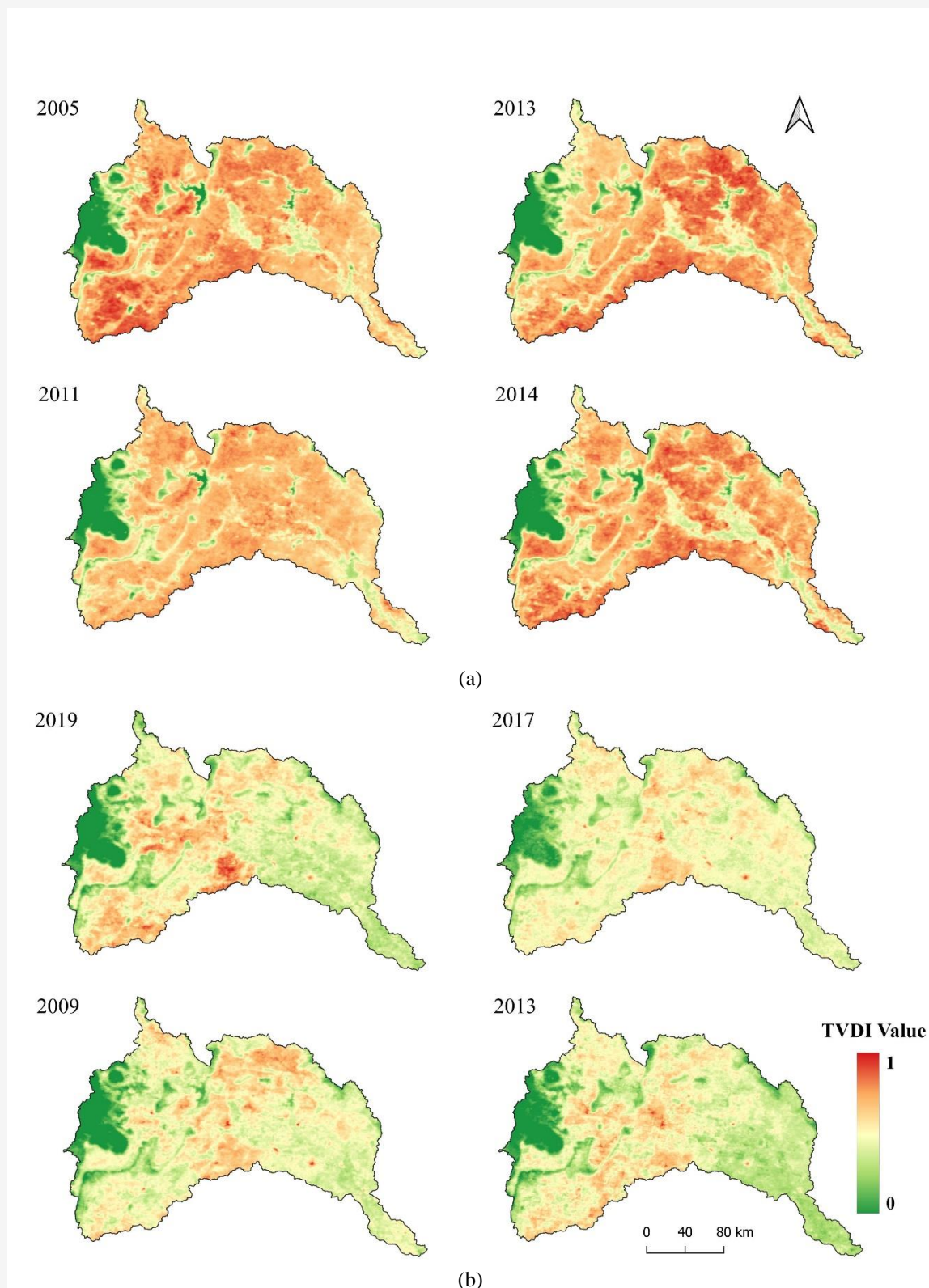


Figure 4: Variations of TVDI in the Chi River Basin:
 (a) dry season (b) wet season

Table 1: Coefficient of determination (R^2) between TVDI and SPI indicators from five rainfall stations

Stations	TVDI ¹ in Dry Season			TVDI in Wet Season		
	SPI ² -12 ³	SPI-6 Dry ⁴	SPI-6 Wet ⁵	SPI-12	SPI-6 Dry	SPI-6 Wet
Khon Kaen	0.0096	0.0315	0.0016	0.0398	0.0111	0.0994
Chaiyaphum	0.0009	0.0013	0.0001	0.1173	0.0200	0.0851
Maharakham	0.0556	0.0334	0.0048	0.1209	0.0524	0.0696
Kalasin	0.0804	0.0846	0.0802	0.0292	0.0032	0.0687
Roi Et	0.0161	0.0228	0.0488	0.0001	0.0010	0.0026

¹TVDI: Temperature Vegetation Drought Index; ²SPI: Standardized Precipitation Index; ³SPI-12: SPI in 12-months; ⁴SPI-6 Dry: SPI in dry season (6 months; November to April); ⁵SPI-6 Wet: SPI in wet season (6 months; May to October)

Table 2: Coefficient of determination (R^2) between TVDI and SDI indicators from three streamflow stations

Stations	TVDI ¹ in Dry Season			TVDI in Wet Season		
	SDI ² -12 ³	SDI-6 Dry ⁴	SDI-6 Wet ⁵	SDI-12	SDI-6 Dry	SDI-6 Wet
Khon Kaen	0.1010	0.0666	0.0667	0.0433	0.0027	0.0272
Roi Et01	0.0311	0.1315	0.0647	0.0069	0.0042	0.0072
Roi Et02	0.0006	0.0091	0.0492	0.2209	0.1400	0.2183

¹TVDI: Temperature Vegetation Drought Index; ²SDI: Streamflow Drought Index; ³SDI-12: SDI in 12-months; ⁴SDI-6 Dry: SDI in dry season (6 months; November to April); ⁵SDI-6 Wet: SPI in wet season (6 months; May to October)

By comparing pixel-based TVDI and SPI values from five meteorological stations in the Chi River basin over the period 2001–2020, this study examined the relationship between these two drought indices. The correlation was evident, but statistical significance was not found. In the results, the R^2 at 0.11 and 0.12 for TVDI (wet season) and SPI-12 were presented in Table 1, suggesting a weak relationship between the two indices. Comparing TVDI and SDI data collected from three streamflow stations across two provinces in the Chi River basin, we found a correlation in drought levels among these stations during the 20 years. The decreasing R^2 values in both 6-month (SDI-6) and 12-month (SDI-12) values indicated drought conditions. Moreover, the majority of TVDI values fell within the range of 0.0006 to 0.2183, which is indicative of severe drought. By comparing pixel-based TVDI and SDI values from three stations in the Chi River basin over the period 2001–2020, the R^2 value ranged from 0.1 to 0.2 as indicating a weak relationship, as presented in Table 2, was a weak relationship between the two indices, especially when comparing TVDI (wet season) with SDI-6 (wet season), SDI-6 (dry season), and SDI-12, and TVDI (dry season) with these same SDI indices. The results between TVDI and SDI showed slightly higher relationships (R^2) than TVDI and SPI indicators. This result showed the potential of TVDI indicator for mapping the spatial distribution of drought conditions regarding soil moisture, vegetation, streamflow, and groundwater.

4.3 Comparison Between Drought Events and Agricultural Land

Figure 5 shows TVDI trends during the dry season. It shows worsening drought conditions in cassava and sugarcane plantations, which expanded by 242.31 km² and 73.35 km² from 2001 to 2020, respectively. In contrast, drought-affected rice fields decreased by 104.3 km². During the wet season, the drought-affected rice, cassava, and sugarcane areas decreased by 176.74 km², 52.91 km², and 18.28 km², respectively. Interestingly, rubber plantations slightly increased in drought-affected areas, expanding by 3.66 km². In the spatial distribution of TVDI and its relationship with land use in 2020, Figure 6 revealed that cassava, rice, and sugarcane plantations were the most severely affected by drought during the dry season, covering 50.15%, 25.76%, and 17.77% of the total area, respectively. Although the severity decreased in the wet season, cassava (10.72%) and rice (7.96%) remained the most vulnerable crops. These findings suggest that agricultural areas, particularly those growing cassava, rice, and sugarcane, experienced more severe drought conditions during the dry season compared to the wet season. Normal levels showed similar patterns in both seasons, predominantly impacting rice and cassava. Interestingly, rubber plantations were generally classified as non-drought areas throughout the year.

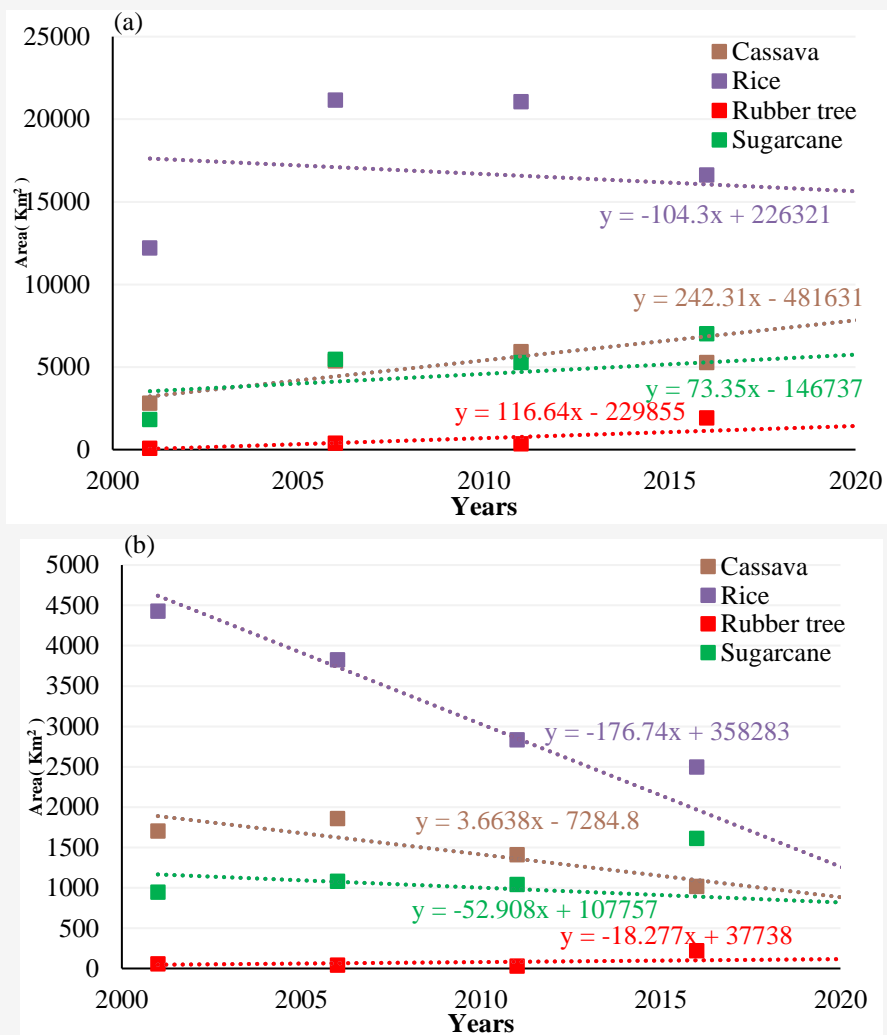


Figure 5: The line graph of the drought trends from 2001-2020 between TVDI: (a) dry season (b) wet season and main agricultural land patterns. The dot line is linear regression for each model of each crop type

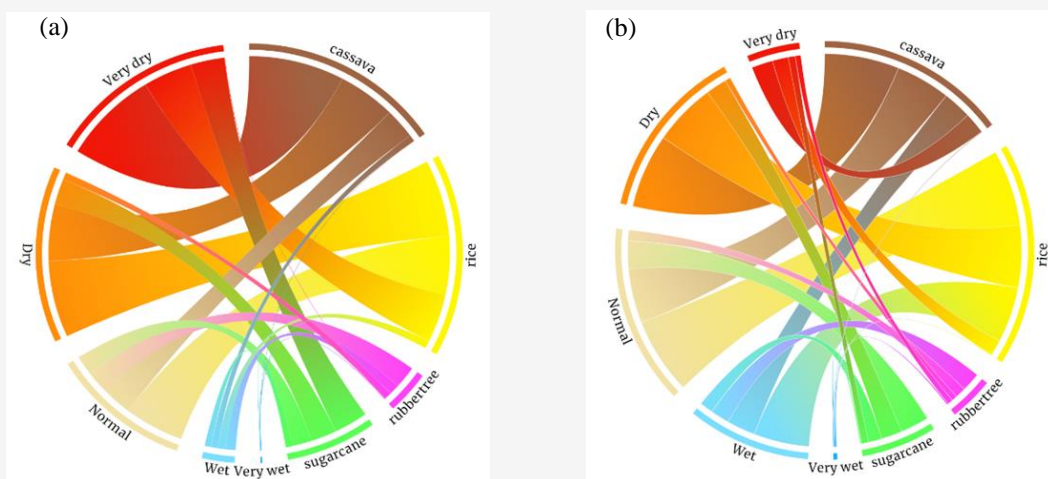


Figure 6: Comparison of the TVDI for different crops in 2020 (a) dry season (b) wet season

5. Discussion

5.1 Spatio-Temporal Drought Assessment

The results from the TVDI demonstrated its high potential in monitoring drought dynamics, particularly in agricultural areas. The spatial distribution of drought severities was captured, aligning with previous studies [11] [13] and [20], which confirmed the utility of TVDI values for identifying severe drought areas. The analysis showed fluctuating drought conditions between 2001 and 2020, with severe drought primarily occurring during the dry season in 2005 and the least severe in 2010. For the wet season, 2019 was the driest year, while 2004 experienced the least drought. Overall, moderate to severe drought conditions were prevalent throughout the study period. These findings are consistent with the results [32] and [4], which linked drought anomalies in the region to the El Niño phenomenon. This study successfully generated a spatial distribution of drought events from 2001 to 2020 using vegetation coverage and land surface temperature. These findings provide a feasible tool for understanding drought severity in relation to crop management practices such as irrigation and water allocation. Moreover, the results offer critical insights for drought mitigation planning, contributing valuable information for managing agricultural productivity and water resources over large areas.

5.2 Relationships Between TVDI, SPI, and SDI Indicators

This study examined the relationship between the TVDI, SPI, and SDI. The R^2 values between SPI and both TVDI-Dry and TVDI-Wet were under 0.12 and 0.11, respectively, indicating a slightly low correlation. Similarly, the R^2 values between SDI and both TVDI-Dry and TVDI-Wet were under 0.22 and 0.21, also showing the lowest relation with no significant correlation. The limited correlation is likely due to the highly variable rainfall in northeast Thailand, as observed [4] and [20] similarly reported a weak relationship between TVDI and meteorological data for drought mapping in Vietnam's Ba River Basin. However, [10] demonstrated a strong correlation between the standardized precipitation evapotranspiration index (SPEI) and TVDI for drought monitoring in the Yangtze River Basin, China. Our findings did not correlate highly in this basin when compared between the TVDI, SPI and SDI indicators. However, anomaly years with high severe drought aligned with the study of [5], showing drought events in 2005, 2011 and 2013, respectively. Future works may analyze the relationships between these indicators to improve spatial droughts over large regions.

In addition, future research should explore integrating TVDI with SPEI across different timescales (e.g., 1-, 3-, 6-, and 12-month intervals) to improve the accuracy of long-term drought monitoring in cloudy regions.

5.3 Comparison between Drought Events and Land Use

The results revealed the efficiency of comparisons between the drought indicator (TVDI) and agricultural land uses, including rice, sugarcane, cassava, and rubber trees, in 2020. This is consistent with [20], who recommended analyzing detailed crop classes to understand drought impacts better. This study demonstrated drought conditions across both the dry and wet seasons. During the dry season, the most severe drought conditions were observed in cassava, rice, and sugarcane plantations, with cassava showing a notable increase in drought severity. In the wet season, severe drought primarily affected cassava and rice fields, aligning with the findings of [32]. Interestingly, drought severity decreased for most crops during the wet season, except for rubber plantations, which remained relatively unaffected. These results highlight the potential of TVDI as a tool for monitoring drought over large agricultural areas, making it suitable for tracking drought conditions at regional and national scales. TVDI's ability to differentiate between crop types and their varying responses to drought further underscores its value in agricultural drought management.

6. Conclusion

The study demonstrates the potential of long-term, high-frequency data MODIS time series data for drought mapping across large regions. By utilizing MODIS imagery through GEE, we identified spatial drought patterns from 2001 to 2020 in Thailand's Chi River Basin. The analysis revealed correlations between the TVDI, SPI, and SDI in relation to major land use types, confirming that the TVDI has the potential for mapping droughts in cloudy and complex landscapes. The proposed workflow generates reliable drought maps across large or national areas, especially in regions prone to cloud cover and complex landscapes, such as Thailand. Future studies can use our proposed workflow to map droughts on a large scale. In addition, high temporal and spatial resolution from multi-sensor data (e.g., Landsat 8/9 and Sentinel-2 data) can be used for accurate drought mapping and monitoring. Our findings provide valuable insights for drought management, supporting mitigation planning, strategic interventions, and early warning systems.

Given the increasing frequency and severity of droughts due to climate change, this integrated model can be a critical tool for policymakers and resource managers. Future research should improve drought monitoring by incorporating additional factors, such as soil moisture and evapotranspiration, which are crucial for understanding and predicting drought conditions. Enhanced resolution and artificial intelligence techniques could also help refine drought assessments, providing more localized and actionable insights.

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