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Analysis and investigation on spatio-temporal dynamic pattern of drought in Thailand

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ABSTRACT

The spatio-temporal analysis to evaluate drought conditions in Thailand from 2000 to 2020 using indices, are SPI, NDVI, and VCI derived from MODIS based on GEE platform. This study found that NDVI could be used to assess and monitor the drought conditions in these regions. The correlation analysis between the SPI and VCI indicates the potential of VCI in measuring the direct impact of rainfall on vegetation dynamics. Analysis showed that VCI was found to be stronger in providing a detailed description of the vegetation dynamics with the corresponding level of precipitation received. The average NDVI was 0.59, the highest in 2017 at 0.74, and the lowest value at 0.39 in 2001. The average VCI was 54%, the highest in 2017 at 86%, and the lowest value at 21% in 2001. SPI is obtained from the rainfall data. The SPI value of -2.11 was the lowest with the drought severity level in 2004 and in 2000 was the highest SPI of 1.12 where were moderate to extreme wet with no drought severity level.

1. INTRODUCTION

The dynamic nature of drought causes difficulties in planning, monitoring, predicting, and providing support to the drought-stricken areas (Thiruvengadachari and Gopalkrishna 1993). The drought affects people and agriculture at the local scale as well as impacts on the economy, society, and environment. The impact of drought on precipitation, soil, agricultural fields, and water reservoirs is analyzed by hydrologic, agricultural, meteorological, and socio-economic terms (Hayes et al. 2012). Drought's problem in Thailand is not a new issue but a crucial repetitious problem. The country has been experiencing drought for decades, this is a natural disaster that appears in many areas and a vital damaging problem that obstructed national development. The areas experiencing drought greatly tend to have a shortage of water for consumption and agriculture where Thai farms primarily rely on natural rainwater. The declining crop yield causes a shortage of agricultural products and processed products for both domestic consumption and export. In other words, the drought not only directly impact to the economy but also indirectly impact to the society and culture (Meteorological Department 2011). Remote sensing provides invaluable geo-information for drought conditions with the capability of obtaining satellite images from the past to recent date, it is a relatively cost-effective method. Also, it is a source of timely continuous geo-referenced information to monitor the condition of large-scale areas especially for such remote areas (Jiao et al. 2016) with limited data to possibly create periodic and accurate drought condition maps of related areas. While MODIS data from Terra satellite is widely used for drought monitoring applications and to explore spatiotemporal drought patterns with satellite derived indices that offer effective opportunities of collecting huge volume of data and fulfill lacking area data to cover Thailand completely.

Hence, the spatiotemporal analysis of drought for this study is applied by MODIS derived indices from Google Earth Engine (GEE) to provide the Normalized Difference Vegetation Index (NDVI) (Gu et al. 2007). Vegetation Condition Index (VCI) can be obtained from NDVI and establishment of the relationship between the rainfall derived data. The amount of rainfalls, known as Standardized Precipitation Index (SPI), is conducted to obtain the sensitive indices responding to the drought condition and to assess spatiotemporal of drought. This is to correlate between MODIS satellite data derivatives and meteorological index. This study applies the GEE

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platform to automatically retrieve and analyze drought which requires long term data and good coverage of the region exposed to drought conditions. GEE is a cloud-based platform for planetary-scale geospatial analysis to store and proceed geographic data sets. It is accessible to create multi-temporal maps or conduct time series analysis by using the available satellite images in the platform by its processing capability and coding approach (Gorelick et al. 2017). Thus, GEE platform provides feasible tools and extensive geospatial data which are proficiently fit drought monitoring purposes. The GEE application automatically retrieves data that is useful to access the data scripts. This will be utilized for developing the methods and kind of data used in the countries with inadequate observation data.

Therefore, the main aim of this study to evaluate drought conditions in Thailand for a twenty-one-year period from 2000 to 2020 using main indices, which are widely used for droughts to analyze the spatio-temporal drought with the indices from satellite data in order to represent the drought rapidly is NDVI and VCI which derived indices from MODIS satellite data derived indices based on GEE platform and SPI from meteorological index which is obtained from the rainfall data, are also selected for this study as well. The representative vegetation indices are selected for the study including NDVI, VCI, and SPI. Based on the selected indices, spatiotemporal drought over Thailand is characterized using online-based remotely sensed datasets ranging from 2000 to 2020 period. Indicators such as the SPI and NDVI can be generated the best correlation-anticipation relationship for early signs of drought impacts and drought monitoring purposes (Measho et al. 2019).

2. METHOD

2.1. Study area

The study area focuses on Thailand country, located in the center of mainland of Southeast Asia (Fig. 1). This located wholly within the tropics. Thailand encompasses with diverse ecosystems including the hilly forested areas of the northern frontier, the fertile rice fields in the central plains, the broad plateau of the northeastern part and the rugged coasts along the narrow southern peninsula. There are 77 provinces and over 69 million people. Thailand has a land area of 513,115 sq.km, bounded within 5°37′N - 20°27′N Latitudes and 97°22′E - 105°37′E Longitudes. Thailand bordered by Myanmar and the Andaman Sea to the west, Laos to the northeast, Cambodia to the southeast, the Gulf of Thailand and Malaysia to the South.

2.2. Data Acquisition

Datasets analyzed the Spatial-temporal distribution of drought conditions in Thailand is shown in Table 1. The integration of remotely sensed data with meteorological datasets, MODIS-derived NDVI in the GEE platform and SPI derived from rainfall data for the period of 30-years from 1990 to 2020 for 126 rain-gauge stations to generate the correlation to determine the spatiotemporal drought patterns in Thailand for 21-years period from 2000 to 2020.

Table 1. Dataset characteristics and source used

Dataset	Variables	Spatial resolution	Temporal resolution	Source
Precipitation (rain gauge stations)	SPI	95 stations	Monthly	TMD
Terra-MODIS (MOD13Q1)	NDVI/ VCI	250-m	16-Day	GEE

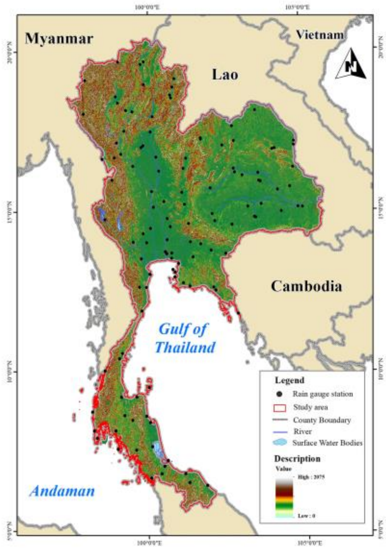

Figure 1. This is topography map of Thailand.

2.3. Data Pre-processing

2.3.1. Computation of NDVI

From 16-day MOD13Q1 V6 images, monthly NDVI were calculated using surface reflectance (ρ) from MODIS red and near infrared by dividing the difference between them and their sum.

$$NDVI = \frac{\rho \text{NIR} - \rho \text{RED}}{\rho \text{NIR} + \rho \text{RED}}$$

where ρRED and ρNIR are spectral reflectance measurements that were acquired in the red and near-infrared regions, respectively. NDVI ranges from −1 to +1, with +1 indicating healthy vegetation cover, lower values representing stressed vegetation, negative values representing open water or high moisture content, and 0.1 value, indicating bare soil. The valid data was used in the analysis is thus from 0.1 to 1.0

2.3.2. Computation of VCI

The VCI derived from NDVI (Reddy et al. 2020) was widely used for detecting the onset of drought, its intensity, duration, and impact (Kogan 1995) In the study, atmospherically corrected NDVI products derived from MODIS 250 m. time series data of growing season were used to generate monthly VCI and subsequently mean VCI for the growing season during the period from 2000 to 2020. VCI provides the information on the current status of vegetation compared with the historical maximum and minimum, the following equation was used to derive VCI

$$VCI = \frac{NDVIi - NDVImin}{NDVImax - NDVImin} \times 100$$

where NDVIi represents the mean Vegetation Index values in a certain year, NDVImin and NDVImax are the multiple-year minimum and maximum NDVI values calculated for each pixel from 2000 to 2020. VCI provides the deviation of each pixel from the historical NDVI values. VCI value is being measured in percentage ranging from 1 to 100. VCI value below 35% indicates severe drought condition, 35 to 50%shows the drought condition, and 50 to 100% indicates above normal condition of vegetation (Kogan 1995).

2.3.3. Computation of SPI

The calculation of this index is based on long-term precipitation data. The SPI can be calculated in the monthly, 3-month, 6-month, 9-month and 12-month interval. For this study, monthly rainfall data for the period of 31 years from 1990 to 2020, for 126 rain-gauge stations were used to compute 3-month SPI using the software developed by the National Drought Mitigation Center (UNL. 2018). The 3-month SPI was computed by using the following mathematical equation to assess the wet and dry conditions based on precipitation variables.

$$SPI = \frac{Xij - Ximean}{\sigma}$$

where, Xi is the precipitation for the ith station and jth observation, Ximean is long-term average rainfall of ith station, and σ is standard deviation.

The 3-month SPI raster was used to reflect the impacts of drought on different water-related sector makers (WMO, 2012) mean 3-month SPI raster for the period, and the same was used for further analysis with the vegetation indices derived from time-series MODIS datasets. Meteorological and soil moisture conditions (agriculture) respond to precipitation anomalies on relatively short timescales. Classification of SPI proposed by McKee et al. (1993), i.e., extremely wet (≥ 2.00), very wet (1.50 to −1.99), moderately wet (1.00 to −1.49), near normal (−0.99 to 0.99), moderately dry (−1.00 to −1.49), severely dry (−1.50 to −1.99), and extremely dry (≤− 2.00) was adopted to define the wet and dryness intensities of the study area.

2.4. Data analysis for spatio-temporal drought

In order to specifically understand the drought conditions and vegetation development, more emphasis was given to the main season (Measho et al. 2019), which was mapped in detail view and in comparison, to the average drought conditions of the last 20 years based on MODIS NDVI datasets. Moreover, time-series VCI maps of all the years were generated and interpreted to identify areas of drought vulnerability at a pixel level of analysis. SPI is used to determine meteorological drought, but it can be helpful for finding parallel drought patterns with VCI. It is one of the most commonly used indices for characterizing drought dynamics applied similar drought categories with an aggregated dataset of SPI is a recommended index for drought purposes for identifying spatio-temporal drought patterns in Thailand from 2000 to 2020.

3. RESULTS

3.1. Meteorological datasets

Precipitation data collected rainfall data from TMD. Selected 95 stations that have the amount of rainfall data for the full 30 years from 126 rainfall gauge stations. The average monthly rainfall was 20-250 mm and the highest monthly average rainfall between May to September (180-250 mm). The average of 21-year annual precipitation is more than 1,600 mm/year. and the average precipitation is in the range of 1,300-1,900 mm per year, with the highest average in 2019 at 1,995 mm. and the lowest mean value in 2017 at 1,329 mm. below the average over the last 21-years (Fig. 2). SPI from 95 rainfall data each station that has the amount of rainfall data for the full 30 years from 126 rainfall gauge stations, the average SPI 3-month. The average monthly SPI 3-month value was between -2.211 to 1.263. The average SPI-3 value with the drought severity level where was the lowest in December 2004 was -2.211 follow by April 2016 was -1.565 and December 2002 was -1.194 and the highest SPI in June 2000 was 1.126 follow by June 2017 was 1.127 and April 2000 was 1.057 where were moderate to extreme wet with the no drought severity level. (Fig. 3).

3.2. Remotely sensed datasets

The average NDVI in 2000–2020 was 0.59 from the range of 0.30 – 0.75, the highest average in October 2017 at 0.74 and the lowest average value in June 2001 at 0.39 (Fig. 4). The average VCI in 2000–2020 was 54.31% from the range of 81-86%, the highest average in October 2017 at 86.26% and the lowest average value in June 2001 at 21.75% (Fig. 5).

3.3. Correlation of meteorological datasets and Remotely sensed datasets

The correlation analysis between mean 3-month SPI and mean NDVI during 2000-2020 shows a positive correlation with a correlation coefficient (r) of 0.37 (Fig. 6). It indicates that a low rainfall pattern clearly affects the vegetation conditions. The correlation analysis between mean 3-month SPI and mean VCI during 2000-2020 showed a positive correlation with a correlation coefficient (r) of 0.31 (Fig. 7). It is evident from the analysis that SPI trends are in agreement with the VCI patterns.

4. CONCLUSION

This study intended to evaluate drought conditions in Thailand for a twenty-one-year period from 2000 to 2020 using main droughts indices to analyze the spatio-temporal drought with the indices found that the analysis showed that NDVI could be used as an indicator to assess and monitor the drought conditions in semi-arid and arid regions. The correlation analysis between the mean 3-month SPI and VCI indicates the potential of VCI in measuring the direct impact of rainfall on vegetation dynamics. Analysis showed that VCI was found to be stronger in providing a detailed description of the vegetation dynamics with the corresponding level of precipitation received.

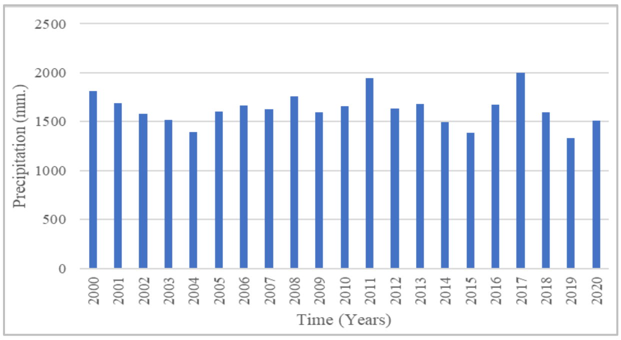

Figure 2. Annual precipitation data

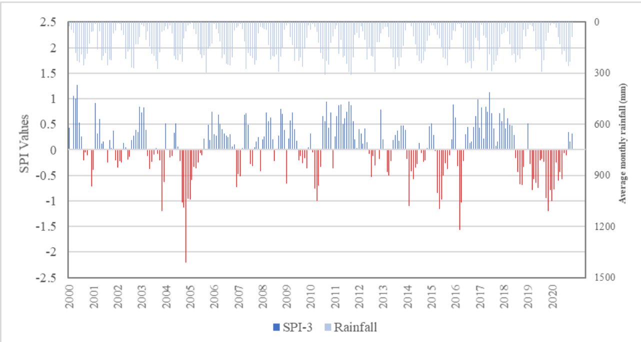

Figure 3. Average 3-month SPI

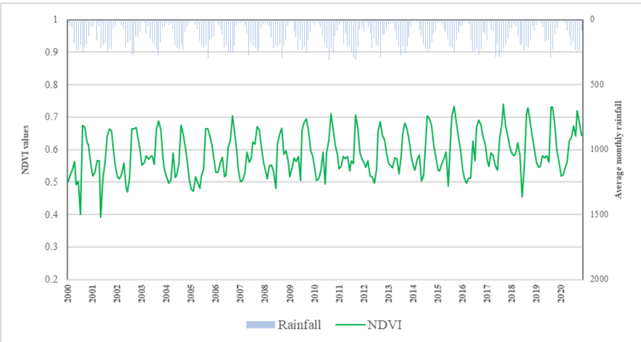

Figure 4. Average NDVI (2000 - 2020)

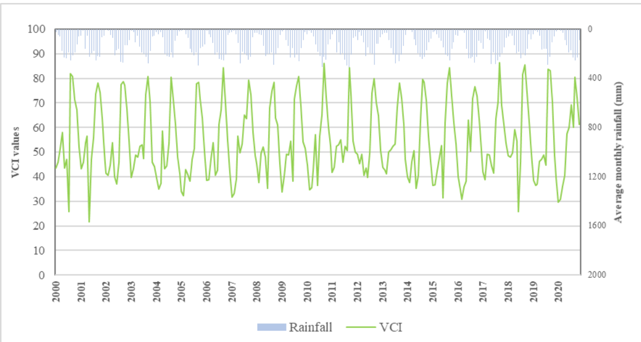

Figure 5. Average VCI (2000 - 2020)

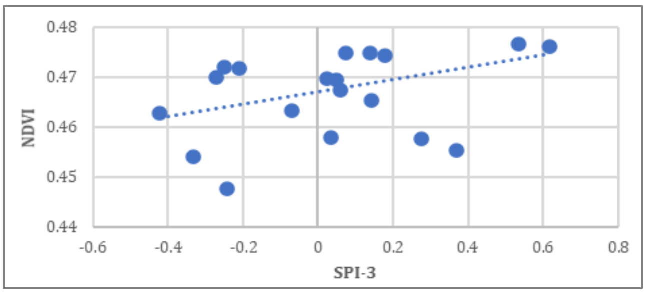

Figure 6. The correlation analysis between mean SPI-3 and mean NDVI in 2000-2020

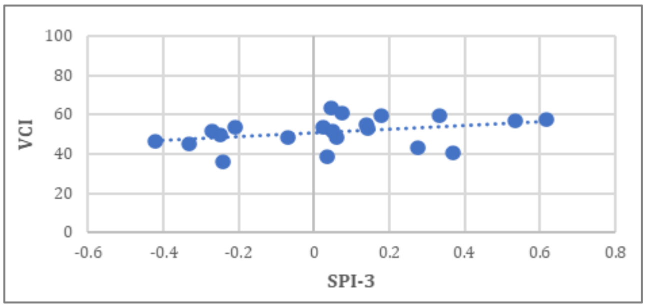

Figure 7. The correlation analysis between mean SPI-3 and mean VCI in 2000-2020

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