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Research Article

DROUGHTS ASSESSMENT IN THE VUGIA-THUBON RIVER BASIN USING REMOTE SENSING

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ABSTRACT

This study has implemented an index-based approach for monitoring the droughts in the Vu Gia – Thu Bon river basin using remote sensing data and the Google Earth Engine cloud computing service. Landsat series remotely sensed data had been used effectively for the time-series calculation of the indices related to the drought hazard. In this study, we examined the performance of several remote sensing-based drought indices (RSDI) for monitoring droughts in the VuGia - ThuBon river basin (VGTB) from January 2010 to December 2020 using the cloud-based Google Earth Engine (GEE) computational platform. When tested again in-situ Potential Evapotranspiration (PET) and Soil temperature, a high agreement exists between our RSDI and PET. These results prove that remote sensing data can be an alternative solution for monitoring drought when remote sensing is the only available source.

Keywords: drought; Google Earth Engine; Landsat; Remote Sensing; RSDI; VGTB

1. Introduction

Drought is a complex natural phenomenon that usually starts with a precipitation deficit (lower-than-average) and spreads to hydrological drought (Van Loon, 2015). The conventional research approaches have effectively monitored drought based on the in-situ data at meteorological stations (Newman & Oliver, 2005). However, these stations lack spatial continuity coverage, which is insufficient to monitor the regional spatial pattern of drought conditions in detail, especially in areas with sparse weather stations or high spatial variability. As a developing country, drought monitoring in Vietnam is even more difficult due to the lack of well-instrumented weather observation stations. Drought monitoring based on remote sensing data can overcome the challenges mentioned earlier in collecting ground observation data and can be used to continuously monitor the processes of and changes in

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drought across both temporal and spatial (AghaKouchak et al., 2015). Moreover, drought is a common hydrometeorological hazard and second only to flooding in its influence on social-economic (Nagarajan, 2010). Therefore, monitoring drought over long periods is crucial for various applications.

There have been numerous studies that focus on measuring droughts using different approaches. Drought can be monitored effectively using drought indices such as the Palmer Drought Severity Index (PDSI) (Palmer, 1965) or the Standardized Precipitation Index (SPI) (McKee et al., 1993) calculated with *in-situ* meteorological data from weather stations. However, these conventional methods require well-equipped instruments and a considerable number of observational stations which provide precise measurements of drought-related parameters like precipitation, temperature, and evapotranspiration. Moreover, insufficient survey data may cause uncertainties in the interpolation process. Recently, remote sensing data with flexible spatial and temporal resolutions has been widely applied in many applications, including drought monitoring (Abdourahamane et al., 2022; Amoli et al., 2022). Several remote sensing-based drought indices, including Normalized Difference Vegetation Index (Rouse et al., 1973), Vegetation Condition Index (VCI), Temperature Condition Index (TCI), Vegetation Health Index (VHI) (Kogan, 1995), Temperature–Vegetation Dryness Index (TVDI) (Sandholt et al., 2002), Temperature-soil moisture Dryness Index (Le & Liou, 2022) have been offered for monitoring drought. As drought is a complicated phenomenon, assessing its severity and environmental effects requires studying over large-scale areas and long periods. However, this process limits its application due to the requirement of high computational complexity. The cloud-based Google Earth Engine (GEE), characterized by high-performance computing and provides a geospatial data repository with a petabyte scale, is a potential solution to tackle this limitation (Gorelick et al., 2017; Sazib et al., 2018).

The Vu Gia Thu Bon (VGTB) river basin is the most essential and major river basin in central Vietnam. Located in a tropical monsoon with uneven rainfall distributed region, VGTB is also among the most sensitive vulnerable basins to drought, which notably affect sustainable development (Du et al., 2018). Therefore, finer satellite imagery, such as the Landsat series, is more suitable for monitoring drought impacts. In Vietnam, Nguyen Thanh Son et al. (2012) used the TVDI index to observe drought in the lower Mekong from 2001-2010. In his study, the efficiency of the TVDI index was verified by comparing it with the CWSI water pressure index. Hung et al. (2015) assessed the drought situation in an arid and semi-arid rural district of Binh Thuan province by employing the Landsat-8 image and TVDI index. However, these studies were conducted on individual images, and there is no consistency in the study period.

Due to the complex propagation of drought and its monitoring relying on the availability of quality data, the efficiency of RSDI can vary from place to place (Jain et al., 2015). Therefore, this study attempts to identify the appropriate drought indices by examining the performance of multiple satellite-based indices for drought monitoring in the VGTB river basin. The study selected six leading indices, including NDVI, NDWI, VCI, TCI, VHI, and TVDI, which were widely used for monitoring droughts. The analysis of the Landsat series and the extraction of the RSDI has been accomplished using the Google Earth Engine cloud computing platform. This study also compared the performance of each drought index with a meteorological-based index PET and Soil temperature to expect a better understanding of the operation of these indicators.

2. Methodology

2.1. Study Area

The study area is located in the VG-TB river basin formed by the Thu Bon River and the Vu Gia River, major river systems in Central Vietnam (Figure 1). Located in the tropical monsoon climate region, this area is characterized by the highest rainfall in the country. The rainy season spans from September to December. The average annual rainfall varies between 2100 mm in the coastal area to about 4100 mm in the southern mountains (Ho & Umitsu, 2011). Approximately 70% of the annual rainfall is received in the rainy season, while the drought happens in the driest months from Feb to May (Figure 2). The western part of the basin is mountainous and sparsely populated, while the flat delta area in the east is used for agriculture and urban development. Da Nang (about 1 million inhabitants) and Hoi An (about 150,000 inhabitants) are the main cities, while the entire basin houses about 2.5 million people (*Statistical Handbook of Vietnam 2016*). The river basin covers most of Quang Nam and Da Nang provinces and is approximately 10,350 square kilometers (Buurman et al., 2015).

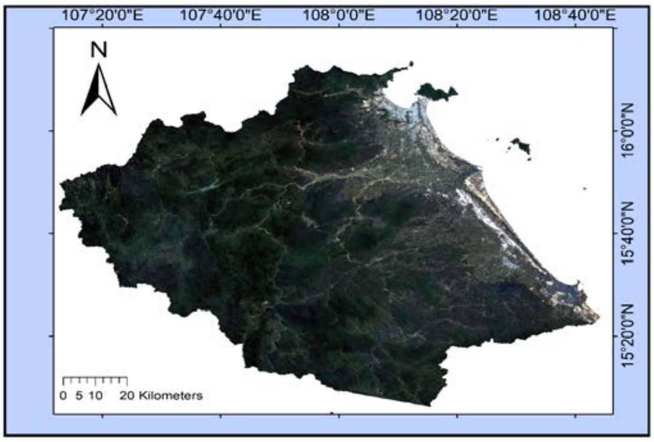

Figure 1. *Vu Gia – Thu Bon river basin*

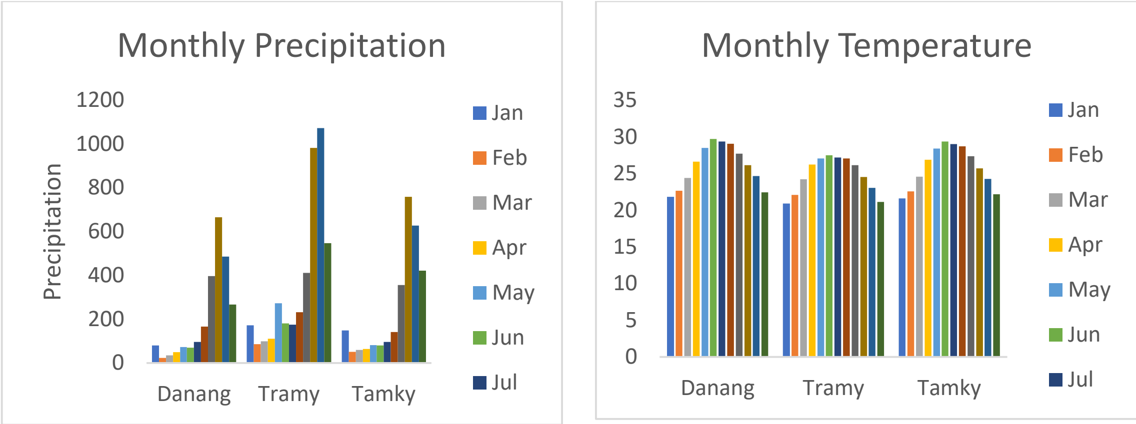

Figure 2. *Monthly precipitation and temperature of three ground meteorological stations, including Danang, Tamky, and Tramy, from 1990-2020*

2.2. Data Used

2.2.1. Landsat Data

Landsat series of satellites are provided by the United States Geological Survey (USGS) and are available in the GEE platform for Landsats 4–9. In this study, we use Landsat collection 2 which contains surface reflectance and surface temperature scene-based products for derived drought indices. The Surface Reflectance data are generated using the Land Surface Reflectance Code (LaSRC) and auxiliary climate data from MODIS to correct the varying scattering and absorbing effects of the atmosphere (Masek et al., 2006). While surface temperature products are generated using the Landsat surface temperature algorithm, developed in cooperation with the Rochester Institute of Technology and NASA Jet Propulsion Laboratory. Both surface reflectance and surface temperature have been resampled to 30 m spatial resolution using cubic convolution. The data are organized into tiers based on their quality, with the highest available data quality placed into Tier 1 while the remainder is assigned to Tier 2. In our study, the Tier 1 collection was employed. Then, we limited our collection by selecting images with a cloud cover of less than 30 percent. The QA band also is utilized to mask cloud and low-quality pixels. Finally, a total of 140 scenes of the Landsat series from 2010 to 2020 are retrieved to derive drought indices.

2.2.2. Meteorological data

The in-situ soil temperature was collected at two Hydrometeorological stations available in the VG-TB basin from January 2010 to 2020 (Tramy and Danang). These data were provided by the Vietnam Meteorological and Hydrological Administration (http://vnmha.gov.vn) and were used to calculate the Potential Evapotranspiration (PET).

Potential evapotranspiration (PET) indicates the amount of water that has been lost through the plant's transpiration and evaporation of water from the earth's surface. PET is computed using Thornthwaite's method (1948), which relies upon temperature and latitude values as input.

$$PET = 1.6 * \left(\frac{L}{12}\right)\left(\frac{N}{30}\right)\left(\frac{10T_a}{I}\right)\alpha \quad (1)$$

Where: T_a is the mean daily air temperature in degrees Celsius;

N is the number of days in the month being calculated;

L is the mean day length, in hours, of the month being calculated.

In our study, the monthly PET and Soil temperature were calculated from meteorological data to validate and compare with satellite-based drought indices.

2.3. Remote sensing-based drought indices

The six indices most widely used (i.e., NDVI, NDWI, VCI, TCI, VHI, and TVDI) were tested with PET and Soil temperature to examine the performance of multiple satellite-based indices for drought monitoring in the VG-TB basin.

Normalized difference vegetation index

NDVI is one of the most widely used vegetation indices in remote sensing and is defined as follows (Tucker, 1979)

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \quad (2)$$

Where ρ_{NIR} is the reflectance in the near-infrared band and ρ_{Red} is the reflectance in the red band. NDVI allows discrimination between healthy and stressed vegetation, thus determining the growth status of vegetation(AghaKouchak et al., 2015). Furthermore, NDVI also effectively indicate the vegetation moisture condition (Ji & Peters, 2003).

Normalized Difference Water Index (NDWI)

NDWI was proposed to estimate the moisture condition of vegetation from the Near-Infrared (NIR) and Short Wave Infrared (SWIR) channels (Gao, 1996). The SWIR reflects changes in both water content and mesophyll in vegetation canopies, while NIR is influenced by internal leaf structure and leaf dry matter content. Combining the NIR with the SWIR removes variations generated by internal leaf structure and leaf dry matter content, improving the accuracy in retrieving the vegetation moisture condition. Moreover, NDWI consider had a quicker response to drought conditions than NDVI (Gu et al., 2008).

$$NDWI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}} \quad (3)$$

Where ρ_{SWIR} is the reflectance in the short wave near-infrared band

Drought indices VCI, TCI, and VHI

Since the change of NDVI is related to weather conditions, thus detecting drought impacts from NDVI data is challenging (Du et al., 2013). The VCI index was developed by Kogan (1995) to distinguish the meteorological component from the vegetation component in NDVI values. VCI is scaled from 0 to 100, corresponding to changes from extreme stress vegetation conditions to optimal conditions.

$$VCI = 100 * \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (4)$$

Where $NDVI_{max}$ and $NDVI_{min}$ are the corresponding multiyear absolute maximum and minimum NDVI of the study period (January 2010 until December 2020).

For the region where vegetation stress is due to dryness or excessive wetness, the VCI is insufficient to interpret vegetation health conditions. Therefore, Kogan (1995) developed the Temperature Condition Index (TCI) to monitor the vegetation stress from the change in land surface temperature and quantified it according to the following formula:

$$TCI = 100 * \frac{LST_{max} - LST_i}{LST_{max} - LST_{min}} \quad (5)$$

Where LST_{max} and LST_{min} are the multiyear absolute maximum and minimum LST of the study period (January 2010 until December 2020). The TCI is also scaled from 0 to 100, corresponding to changes from extreme stress (high temperature) to optimal (low temperature) vegetation conditions.

The Vegetation Health Index (VHI) retrieves information on vegetation conditions by combining VCI and TCI indexes. The reliability of VHI is based on the assumption that NDVI and LST at a given pixel will vary inversely over time (Karnieli et al., 2010).

$$VHI = \alpha * VCI + (1 - \alpha) * TCI \quad (6)$$

Where α determine the weight of VCI and TCI in the VHI, the value of "α" depends on different temperature and precipitation conditions. In unknown environmental conditions, the share of both indices was assumed to be equal ($\alpha = 0.5$) (Gidey et al., 2018). The value range of the VHI is also from 0 (unfavorable conditions) to 100 (optimal vegetation conditions)

Temperature Vegetation Dryness Index

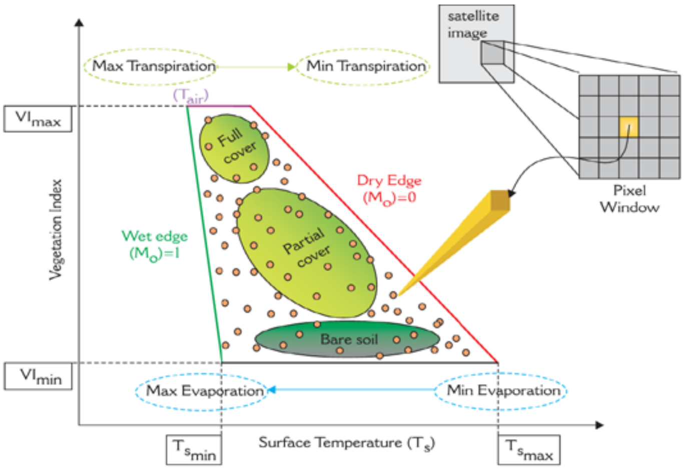

Figure 3. *Definition of the TVDI (Petropoulos et al., 2009)*

Sandholt et al. (2002) proposed a technique for estimating surface soil moisture content by linking the relationship between LST and NDVI with an index named TemperatureVegetation-Dryness-Index (TVDI). The principle of this technique is based on the assumption that NDVI can monitor vegetation status and relate to water stress. At the same time, the land surface temperature (LST) will increase rapidly with water stress

(Goward et al., 2002). Hence, the potential for obtaining soil moisture through the LST/ NDVI plot. The TVDI is defined by the following formula:

$$TVDI = \frac{LST - LST_{min}}{LST_{max} - LST_{min}} \quad (7)$$

Where LSTmin represents the wet edge of the triangle, and LSTmax represents the dry edge (Figure 3).

$LSTmin=a_1+b_1*NDVI$

$LSTmax=a_2+b_2*NDVI$

Among them, a_1, b_1, and a_2, b_2 are the coefficients of the dry and wet edge equations determined by the least squares fit of actual data. The TVDI value ranges from 0 to 1, with a value closer to 1 meaning more drought. Due to its simplicity and clarity, TVDI is widely used for monitoring drought (He et al., 2020). The classified drought indices is shown in Table 1.

Table 1. *Classification of the drought indices compared in this study*

	TCI	VCI	VHI	TVDI
Extreme drought	0-0.1	0-0.1	0-0.1	0.86-1
Severe drought	0.1-0.2	0.1-0.2	0.1-0.2	0.76-0.86
Moderate drought	0.2-0.3	0.2-0.3	0.2-0.3	0.57-0.76
Mild drought	0.3-0.4	0.3-0.4	0.3-0.4	0.46-0.57
No drought	0.5-1	0.5-1	0.5-1	0-0.46

2.4. Data Processing

The study aims to derive monthly drought intensity from 2010 to 2020 in the VGTB basin by employing several RSDI (i.e., NDVI, NDWI, VCI, TCI, VHI, and TVDI) with the support of a cloud-based GEE computing platform. The workflow of this study is illustrated in Figure 4

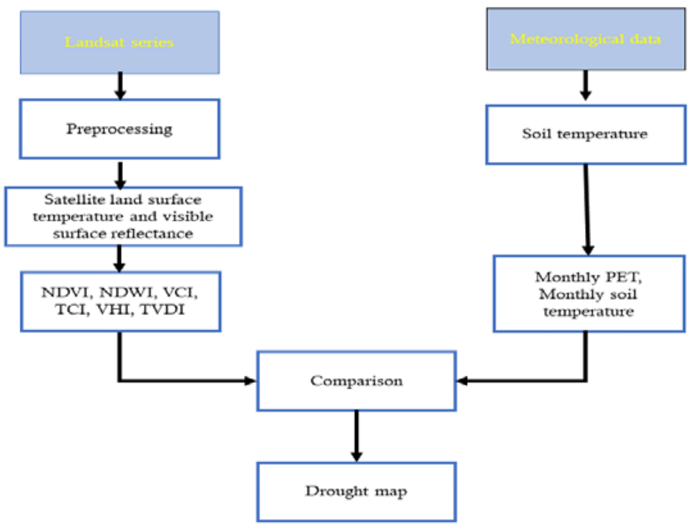

Figure 4. *The processing chain for drought monitoring in the VGTB basin*

(1)Collecting data: Landsat satellite images (5,7,8) in the VG-TB basin from 2010 to 2020 were collected for drought monitoring. Meantime, the daily meteorological data was also used to obtain monthly precipitation and soil temperature average, which was utilized to validate and compare the performance of satellite-based drought indices.

(2)Preprocessing: We filtered the Landsat series collection by selecting images with cloud cover <30%. Furthermore, cloud and cloud shadows were masked using the Quality Assessment Band, which was generated by the CFMask algorithm. Finally, to avoid excessive wetness, which often represents open water or high moisture content, we remove water bodies from all images.

(3)Remote sensing-based drought indices: Firstly, we compare satellite land surface temperature with the ground temperature at meteorological stations to evaluate the quality of our Landsat collection. Then, the NDVI, NDWI, VCI, TCI, VHI, and TVDI were employed to monitor drought. The monthly time series of those variables were calculated at the corresponding locations of hydrometeorological stations available in the study site. Then, the results were compared with the ground-based index to examine the efficiency of each index.

(4)The ground-based index calculation: the monthly PET and Soil temperature index were estimated from monthly weather data.

(5)Examine the performance of satellite-based indices: The Pearson correlation between PET with corresponding RSDI for all weather stations has been analyzed. The correlation coefficients were used to assess the accuracy of each RSDI.

(6)Generate the drought map: To monitor the drought over study period, drought maps were produced for yearly intervals.

3. Results and discussion

3.1. Examine RSDI

The monthly drought map of all RSDI was first generated. Then the remote sensing-based index values were directly extracted at point locations of the reference stations. In order to use the same number of samples for in-situ and remote sensing data pairs, data were excluded if any reference data or remote sensing drought index value for the station and year was missing. Before comparison, all RSDI values need to be normalized between 0 and 1 (Rhee et al., 2010). The

The scatter plot of monthly RSDI values and monthly average soil temperature in the Tramy station is illustrated in Figure 5. In each plot, a total of 73 points represent the available monthly value of RDSI.

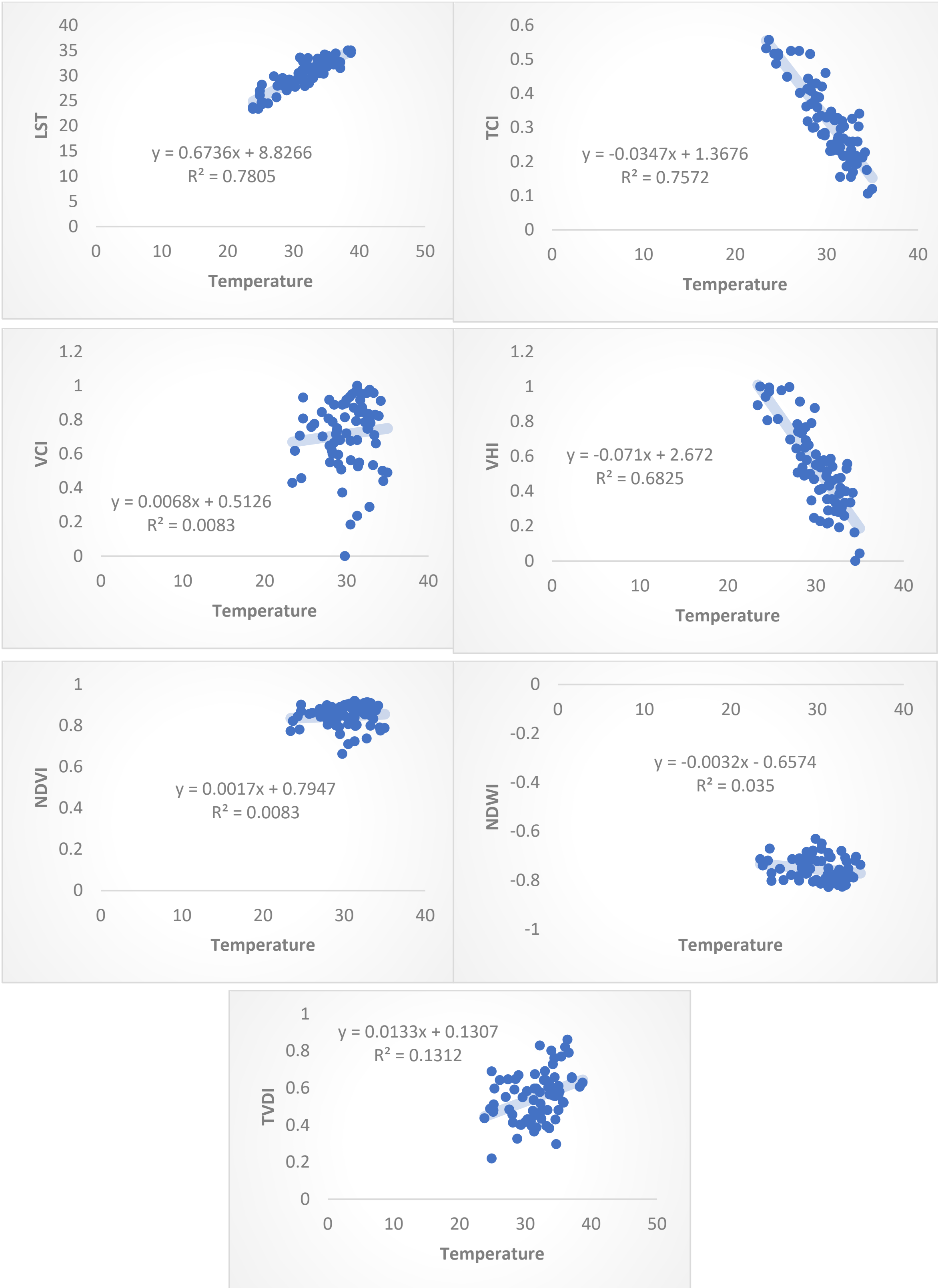

Figure 5. *Scatter plot of month RDSI and monthly Soil temperature in Tramy station*

Table 2 represents the correlation of determination between RDSI and meteorological temperature (Table 1). According to Table 1, VHI indicated the highest agreement when compared with Soil temperature (0.82), PET (0.75) in Tramy station and Soil temperature (0.8), PET (0.8) in Danang station, respectively. However, TCI could outperform the other RSDI compared to monthly soil temperature. On the other hand, the VCI and NDWI showed the weakest performances, respectively.

Table 2. *Validation results of RSDI*

	RDSI	LST	TCI	VCI	VHI	NDVI	NDWI	TVDI
Tramy	Soil temperature	0.88	0.87	0.09	**0.82**	0.09	0.19	0.36
	PET	0.79	0.79	0.096	**0.75**	0.096	0.16	0.27
Danang	Soil temperature	0.82	0.82	0.39	**0.8**	0.39	0.3	0.52
	PET	0.78	0.78	0.49	**0.8**	0.49	0.42	0.57

The temporal drought variation in VGTB using the RSDI during 2010-2020 was also calculated and shown in Figure 6. These charts help in understanding the overall drought trend in the study period. Based on the drought trendlines, we realize that drought happens regularly in the VG-TB basin.

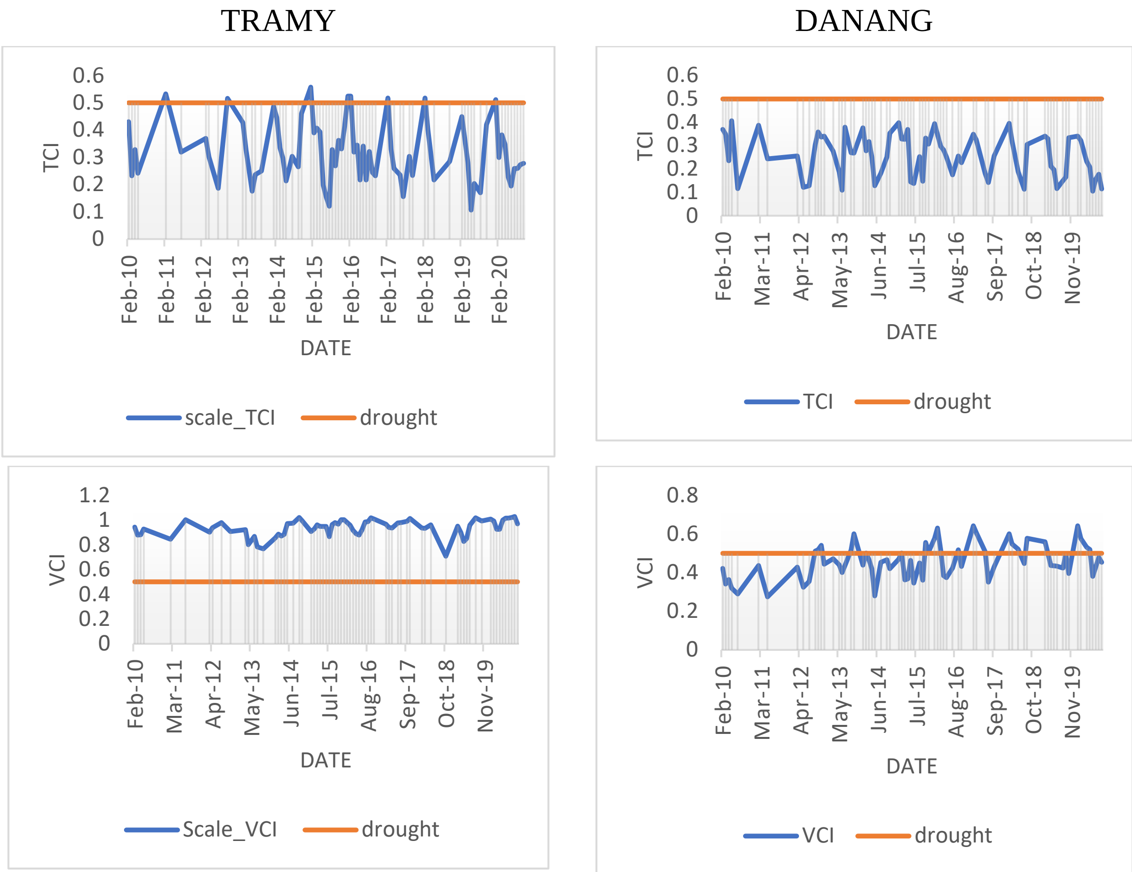

Figure 6. *The drought variation of VGTB in 2010-2020*

When combining VCI, TCI, VHI, and TVDI in Figure 7, we analyzed the long-term drought characteristics of VGTB. As Figure 7 shows, the VHI, TCI, and VCI have good temporal consistency in the overall change trend over time, while TVDI has an inverse tendency with the others.

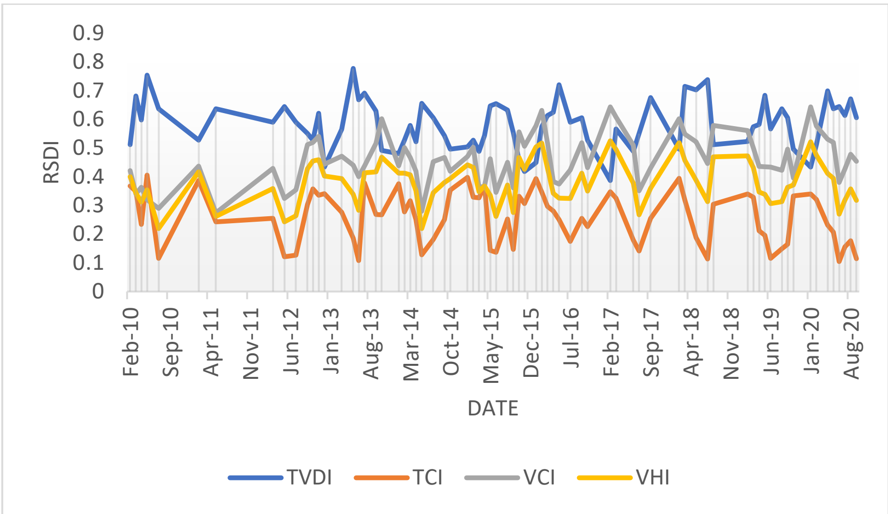

Figure 7. *Time series of various drought indices in the VGTB basin*

3.2. Drought map

As analyzed above, the VHI has shown the outperformance of all other indices. Thus, VHI was chosen to monitor the drought in the VG-TB basin.

The spatial drought risk maps of the VGTB corresponding to the years 2010, 2015, and 2020 are respectively demonstrated in Figure 8. The classification ranges of VHI are used in Figure. 8 and is also provided in Table 1.

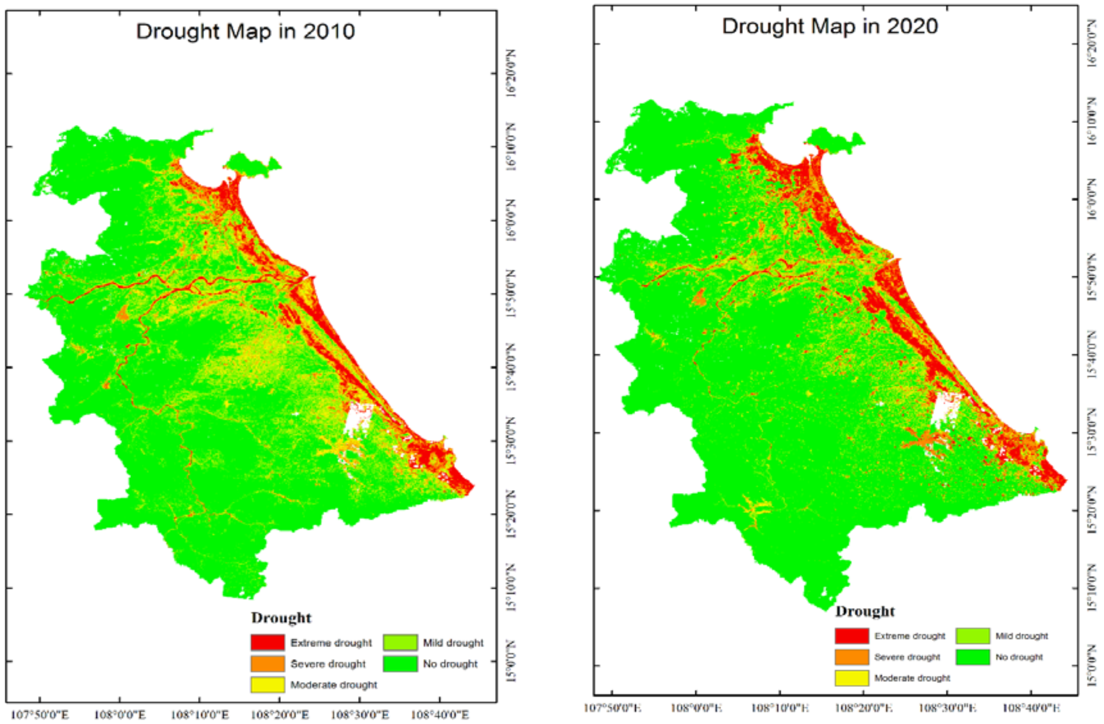

Figure 8. *The spatial drought risk map across the VG-TB basin in 2010 and 2020*

As a result, the drought maps for the VGTB river basin represent the high-risk regions correlating to the coastal lowland in the eastern of the study area. These areas are characterized by the low alluvial topography of the VGTB river system and sparse density of vegetation. These territories are also the home of residents and agricultural activities that are suffering the negative impacts from drought hazards. The western part of the study area, mainly mountainous and forest landscapes with high precipitation volume, is categorized as having no drought in the drought hazard map. Results from this study are an essential source for proposing sustainable economic activities in response to the drought hazard in the VGTB river basin.

4. Conclusions

This study has experienced a remote sensing-based approach for assessing drought hazards in the VGTB basin, one of the largest river basins in Central Vietnam. Utilizing cloud computing GEE integrated with various RSDI indices, including TCI, VCI, VHI, NDVI, NDWI, and TVDI, could help effectively identify the optimal remote sensing-based indices for drought monitoring in the VGTB river basin. This empirical research shows that VHI is the most suitable index for monitoring the drought hazard in the VGTB river basin, with the best performance on the correlation to in-situ data. Results from this study could be valuable for assessing the drought risk using remote sensing and GEE from the data-scarce regions.

❖ ***Conflict of Interest:*** *Authors have no conflict of interest to declare.*

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ĐÁNH GIÁ HẠN HÁN TRÊN LƯU VỰC SÔNG VU GIA – THU BỒN BẰNG PHƯƠNG PHÁP VIỄN THÁM

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TÓM TẮT

Nghiên cứu này được thực hiện nhằm áp dụng các chỉ số viễn thám để theo dõi tình trạng hạn hán ở lưu vực sông Vu Gia – Thu Bồn (VG-TB) bằng cách sử dụng dữ liệu vệ tinh và nền tảng điện toán Google Earth Engine. Dữ liệu viễn thám từ chuỗi vệ tinh Landsat đã chứng tỏ hiệu quả trong việc tính toán các chỉ số hạn hán theo chuỗi thời gian. Cũng trong nghiên cứu này, chúng tôi đã kiểm tra sự hiệu quả của một số chỉ số trong theo dõi hạn hán ở lưu vực sông VG-TB từ 01/2010 đến 12/2020. Kết quả đã cho thấy, khi kiểm tra đối chiếu giữa các chỉ số hạn tại trạm như chỉ số thoát hơi nước tiềm năng, nhiệt độ của bề mặt đất tại trạm khí tượng và các chỉ số hạn hán tính từ dữ liệu vệ tinh có sự tương quan thống nhất tương đối cao. Kết quả này một lần nữa chứng minh dữ liệu viễn thám có thể là một giải pháp thay thế hiệu quả để theo dõi hạn hán khi viễn thám là nguồn dữ liệu khả dụng duy nhất.

Từ khóa: hạn hán; Google Earth Engine; Landsat; viễn thám; RSDI; VGTB