Estimation of Land Surface Temperature and Vegetation Dryness Index (TVDI) In Bac Binh – Binh Thuan Using Remote Sensing Images

Nguyen Thi Thuy Linh[1*] and Phung Thi Linh[1]

[1] Ha Noi University of Natural Resources and Environment, Ha Noi, Vietnam

E-mail: nttlinh.tnn@hunre.edu.vn

corresponding author

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Abstract

Nowadays, drought is considered as one of the most destructive natural disasters that negatively affects societies around the globe. Especially, in Binh Thuan Province - Vietnam, the drought tends to increase in both extent and intensity but is more difficult to predict. In recent years, with the development of remote sensing technology, its products have been effectively used in studying, monitoring, and responding to drought. Thus, in this study, we aim to determine the progress of drought through the years in Bac Binh District - Binh Thuan Province by using remote sensing images. In detail, we use images from Landsat 7 ETM+ (2002, 2005, 2010) and Landsat 8 OLI (2014 and 2017) to estimate dryness indices: temperature vegetation dryness index (TVDI) and improved temperature vegetation dryness index. These two dryness indices are based on normalized difference vegetation index (NDVI) and land surface temperature (LST) for TVDI and temperature gradient (Ts-Ta) for iTVDI. The results show that Bac Binh's area is estimated to have medium and high drought risk, and the severe drought areas increased rapidly in 2014 and 2017. Areas with high drought risk are mostly found in agricultural or non-vegetated areas in the center of Bac Binh.

Keywords: drought, surface temperature, TVDI, NDVI

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1. Introduction

Drought is regarded as a natural phenomenon that has a serious impact on the economies and societies of most countries worldwide. Also, drought stands as the third in the list of the most destructive natural disasters, after floods and storms. Droughts have tended to increase in both scale and intensity in recent years and it is more difficult to predict due to the impact of climate change. In Vietnam, most of the areas are suffering from drought to varying degrees and at different times. Nevertheless, the situation is worse in the central areas of Vietnam and Tay Nguyen regions, where severe droughts occur more frequently and cause damage to the local economy, society and agricultural production.

Assessing drought probability for agricultural areas in Africa with coarse resolution remote sensing imagery study used the per-pixel Vegetation Health Index (VHI) from the Advanced Very High Resolution Radiometer (AVHRR) averaged over the crop season as main drought indicator, after which the per-pixel average VHI is aggregated for agricultural areas at sub-national level to obtain a drought intensity indicator (Rojas, 2011). Nevertheless, the main data in this study (NOAA AVHRR) have a resolution of 16 km (for VHI data) and 8 km (for the Normalized Difference Vegetation Index), so the estimation of results will be affected if a study area is small.

The monitoring meteorological drought in semiarid regions using multi-sensor microwave remote sensing data used the Microwave Integrated Drought Index (MIDI) by integrating three variables: Tropical Rainfall Measuring Mission (TRMM) derived precipitation, Advanced Microwave Scanning Radiometer for EOS (AMSR-E) derived soil moisture, and AMSR-E derived land surface temperature. The results showed that MIDI with appropriate weights of three components outperformed individual remote sensing drought indices and other combined microwave drought indices in monitoring drought (Zhang, 2013; Ying Liu, 2021). In this study, Land Surface Temperature (LST) and soil moisture are not entirely independent according to the LPRM algorithm (Liu, 2010; Owe, 2008); further studies using independent datasets of MIDI components derived from different algorithms or sensors are needed and will be included in subsequent studies.

Droughts often occur over large areas. Therefore, observing and studying by using in situ stations is not an effective method as the installation of the stations can be very costly. Meanwhile, remote sensing technology provides information about the Earth's surface in different bands and has a fair spatial and temporal resolution, which is useful for studying drought. In the past recent years, there have been many studies about the application of remote sensing using a thermal infrared band that estimates land surface temperature and soil moisture to evaluate droughts. In Vietnam, some researchers working in this field used thermal images from MODIS, NOAA/AVHRR. However, due to the coarse spatial resolution of MODIS and NOAA/AVHRR, it is not suitable for some of those study areas.

In this study, we used the thermal infrared LANDSAT images to evaluate drought risk in Bac Binh - Binh Thuan which has a resolution of 30m. These data will provide more detailed information about changes of the land surface compared to MODIS and NOAA/AVHRR images.

2. Study Area and Datasets

2.1 Study area

Bac Binh is one of two districts in Binh Thuan Province with the highest land degradation and desertification risk in Vietnam. Due to its natural climate and topography, Bac Binh district suffers from severe droughts every year.

According to statistical data collected at the Bau Trang station from 1960 to 2010, the annual average rainfall in Bac Binh is between 700 and 1000 mm, and only occurs in the rainy season (from May to October), while in the dry season (from November to April), the amount of rainfall is low. With Tuy Phong district in Binh Thuan, Bac Binh was also predicted as the highest drought risk area in Binh Thuan (grade 4 – Meteorology index). In recent years, climate change and the effects of negative activities from people have made the situation of drought in the Southcentral coast as well as Binh Thuan Province become much more serious. Drought usually occurs, not only in the dry season but also in the rainy season. That problem has affected production activities as well as the lives of people. Therefore, applying remote sensing data to monitor and cope with a drought becomes significant.

2.2. Datasets

The remote sensing data used in this study include Landsat 7 ETM+ (5th January 2002, 13th January, 12th February 2010) and Landsat 8 OLI (15th February 2014, 23rd February 2017). The study was carried out in Bac Binh District, Vietnam. Images were taken in the dry season when the central area and highlands of Vietnam were experiencing severe drought.

MODIS LST images were used to compare the temperature distribution between Landsat's thermal images and MODIS images. The respective MODIS images include 5th January 2002, 13th January 2005, 12th February 2010, 15th February 2014 and 23rd February 2017 to validate the temperature images. Because of the different time periods, the two types of images have different limitations.

The resolution of the data is 30m for all the bands (the thermal infrared bands with Landsat 7 ETM+ at the 60m resolution and Landsat 8 OLI at 100m resolution). However, they were resampled to 30 meters in the delivered data product after 25th February 2010. Landsat images are provided totally free of charge for a period of 16 days, so these images are precious and important data for studying and monitoring the natural environment.

Ambient air temperature data from six meteorological stations for the years of 2002 - 2014 was used for this retrieving T_s-T_a maps. The meteorological temperature data were interpolated using the smart interpolation method (Willmott, 1995). For using this method, sixteen Radar Topography Mission (SRTM) DEM images (30 m) of the study area were obtained from Global Land Cover Facilities (GLCF). Considering the general value of the lapse rate (0.6^{0}C/100 m) is inaccurate and may differ in different places and different months, in this research, environmental lapse rates were calculated using linear regression between air temperature and elevation in each month for available meteorological stations (Rahimzadeh-Bajgiran, 2012).

3. Methodology

3.1. The Temperature Vegetation Dryness Index

Many studies around the world have shown that land surface temperature and vegetation index are important factors that can provide information about the surface moisture. Temperature can quickly increase when the surface is dry or vegetation does not have enough water. In this study, we use a temperature vegetation dryness index (TVDI) to estimate the surface drought grades, that based on the study of Sandholt on the relationship between surface temperature and vegetation cover (Sandholt, 2002). The temperature vegetation dryness index is estimated by the equation below:

$$TVDI = \frac{T_s - T_{s\min}}{T_{s\max} - T_{s\min}} \quad \text{(eq.1)}$$

Where: T_s is the surface temperature of a pixel
T_{smin}, T_{smax} are the minimum and maximum surface temperature and both of them are the linear functions of vegetation index

$$T_{s\max} = a_{\max} \times NDVI + b_{\max} \quad \text{(eq.2)}$$

$$T_{s\min} = a_{\min} \times NDVI + b_{\min}$$

Where a_{max}, b_{max} = linear regression parameters for dry edge

a_{min}, b_{min} = linear regression parameters for wet edge

Theoretically, the scatter plot formed by vegetation index and land surface temperature should be like a triangle (Figure 2). The upper edge of the triangle is defined as dry edge while the lower one is a wet edge (Ahmed Samir Abowarda, 2021). Pixels close to the dry edge are comparatively drier while those close to the wet edge are wetter. The position of the pixel in the scatter plot defines its moisture condition. Thus, the core issue of the triangle method is to calculate the ideal dry edge and wet edge. In previous research, people only calculate the dry edge while considering the wet edge as a horizontal line, However, in real situations, the wet edge may not be horizontal but a little oblique. A linear function is applied to both the upper and lower envelope of the triangle to calculate the dry edge and cold edge, respectively (Han, 2004; Mengyuan Xu, 2022). The higher the TVDI, the higher the risk of drought in the area can be. In the dry edge, the TVDI equals 1, while in the wet edge, the TVDI equals 0 (Figure 2).

To determine the surface temperature, the original values from the Landsat image are transferred to the real value of electromagnetic radiation ($Wm^{-2}\mu m^{-1}$).

For Landsat 7 ETM+ spectral radiance is calculated by using the equation as below:

$$L_\lambda = \frac{L_{\max} - L_{\min}}{DN_{\max} - DN_{\min}}\left(DN - DN_{\min}\right) + L_{\min} \quad \text{(eq.3)}$$

Where: L_λ is spectral radiance; L_{max}, L_{min} are spectral radiance correspondence with DN_{max} and DN_{min} in the thermal infrared band and are provided in metadata file of the respective Landsat images.

For Landsat 8 OLI, spectral radiance is determined by using the equation:

$$L_\lambda = M_L.Q_{cal} + A_L \quad \text{(eq.4)}$$

Where: M_L, A_L are conversion coefficients provided in the metadata file of Landsat 8; Q_{cal} is band values.

The brightness temperature is calculated from the spectral radiance as the equation:

$$T_B = \frac{K_2}{\ln\left(1 + \frac{K_1}{L_\lambda}\right)} \quad \text{(eq.5)}$$

Where K_1 and K_2 coefficients are provided in metadata file of the respective Landsat scene.

Brightness temperature is validated based on surface emissivity to determine the land surface temperature as the equation:

$$LST = \frac{T_B}{1 + \left(\frac{\lambda.T_B}{\rho}\right) * \ln\varepsilon} \quad \text{(eq.6)}$$

Where: λ is average wavelength value in the thermal infrared band; $\rho = \frac{h.c}{\sigma}$ with σ is Stefan – Boltzmann constant ($\sigma = 1.38*10^{-23}\ J/K$); h: Plank constant ($h = 6.626*10^{-34}\ J.\sec$); c: bright velocity ($c = 2{,}998*10^{8}\ m/s$); ε: surface emissivity.

Surface emissivity can be determined from remote sensing data based on the type of vegetation cover or the normalized difference vegetation index (NDVI). However, the method based on the NDVI index has advantages because it can be computed for each pixel. To estimate the surface emissivity, this study uses a method of Valor, and Caselles that applies NDVI apply to heterogeneous areas with various

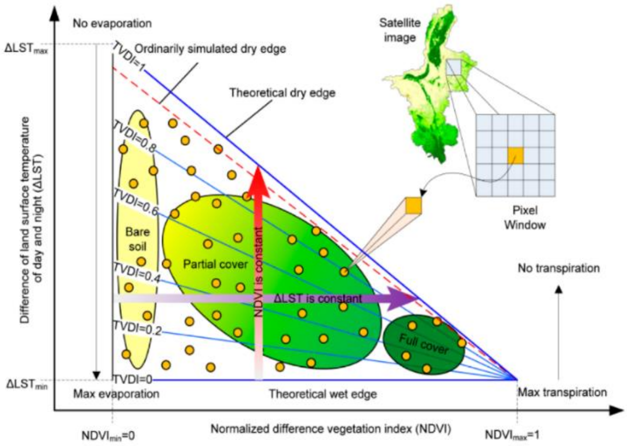

Fig 2. The triangle temperature T_s/NDVI (or Ts-Ta/NDVI) (Petropoulos *et al.*, 2015)

types of vegetation (Zunjian Bian, 2023). In this method, a surface emissivity of each pixel is calculated by the sum of its component emissivities.

$$\varepsilon = \varepsilon_v P_v + \varepsilon_s (1 - P_v) \quad \text{(eq.7)}$$

Where $\varepsilon_v, \varepsilon_s$ are emissivity that represents the hot and cold pixels. A hot pixel is regarded as the location of a dry and non-vegetated (or sparsely vegetated) area, while a cold pixel is a well-watered, healthy and fully vegetated area. P_v is a value that equals 0 for the vacant land area and equals 1 for full vegetation area. P_v is determined by the equation:

$$P_v = \left[\frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \right]^2 \quad \text{(eq.8)}$$

Where NDVI is the observed normalized difference vegetation index, and it can be defined as:

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad \text{(eq.9)}$$

where ρ_{nir} is the near-infrared band reflectance and ρ_{red} is the red band reflectance. In this study, NDVI was calculated using LANDSAT-7 ETM+ Band 3 (the red band) reflectance and Band 4 (the near-infrared band) reflectance and LANDSAT-8 OLI Band 4 (the red band) reflectance and Band 5 (the near-infrared band) reflectance.

3.2. The improved Temperature Vegetation Dryness Index

A modified approach to the Temperature Vegetation Dryness Index (TVDI) concept, incorporating air temperature and a Digital Elevation Model (DEM) to develop the improved TVDI (iTVDI) is also estimated and the results are compared with the original TVDI.

As the main source of variation in the TVDI is assumed to be soil moisture, air temperature is not included in the model which may increase the uncertainty of the TVDI for larger areas and higher NDVI values (Sandholt, 2002). An inherent assumption in the application of the TVDI is that Ta is constant for the subset or window over which the index is estimated. A typical error in studies based on the TVDI is that this assumption is violated in selecting too large an area. On the other hand, when using the TVDI to estimate soil moisture status, heterogeneity of the earth's surfaces increases the uncertainty of the TVDI to estimate soil moisture. Therefore, the TVDI should ideally only be applied in regions with small topography changing. To correct for the effect of topography, Ran, (2005) used an approach to correct Ts with a DEM before constructing the AVHRR Ts/NDVI space. Hassan (2007) proposed a correction method to use a DEM to infer local pressure from altitude and then transform surface temperature to potential temperature.

Air temperature decreases with increasing altitude, a phenomenon known as the environmental lapse rate. Therefore, a Digital Elevation Model (DEM) of the study area has also been used to calculate the lapse rate to improve the index performance in estimating evapotranspiration at different altitudes in each specific month. The new index hereafter called the improved TVDI (iTVDI) is calculated using the below equation and is schematically presented in Figure 2.

$$iTVDI = \frac{\Delta T_{obs} - \Delta T_{\min}}{\Delta T_{\max} - \Delta T_{\min}} \quad \text{(eq.10)}$$

Where ΔT_{obs} is observed Ts-Ta and Ta are observed air temperature calibrated using DEM. $\Delta T_{\min}$ and $\Delta T_{\max}$ are the minimum and maximum ΔT, respectively, for the same vegetation index value (here the NDVI). AB and BC are the distances represented on Figure 3, between the dry edge and wet edge in the ΔT vs. NDVI scatter plot as described by Sandholt (2002). The iTVDI is lower for wet and higher for dry conditions, and similar to the TVDI varies between 0 and 1.

4. Results and Discussions

4.1. Determining the corresponding parameters

4.1.1. The Normalized Difference Vegetation Index (NDVI)

To estimate the emissivity based on NDVI, we need to know the emissivity of the hot and cold pixels. Many researchers in the past took these emissivities by getting the result of experimental measurement in representative samples. However, in this study, the condition does not allow us to conduct the measurements. Instead, we get the values from another report that has been done with the measurements in the same area**.** The values of NDVI for a hot and cold pixel are 0.127 and 0.515. Using Van De Griend method, the emissivity for a hot and cold pixel can be estimated by the following equation:

$$\varepsilon = 1.0094 + 0.047\ln(NDVI) \qquad \text{(eq.11)}$$

4.1.2. The Land Surface Temperature (LST)

The results of land surface temperature in the area of Bac Binh district (Binh Thuan) are presented in Figure 4. Through these results, it is clear to be seen that there are some areas with high temperature which are found mainly in the non-vegetated regions. The differences of temperature between vegetable area and non-vegetable area are significant, with 297.6; 301.93; 301.71; 298.71; 291.15 Kenvin on the year of 2002; 2005; 2010; 2014; 2017 respectively.

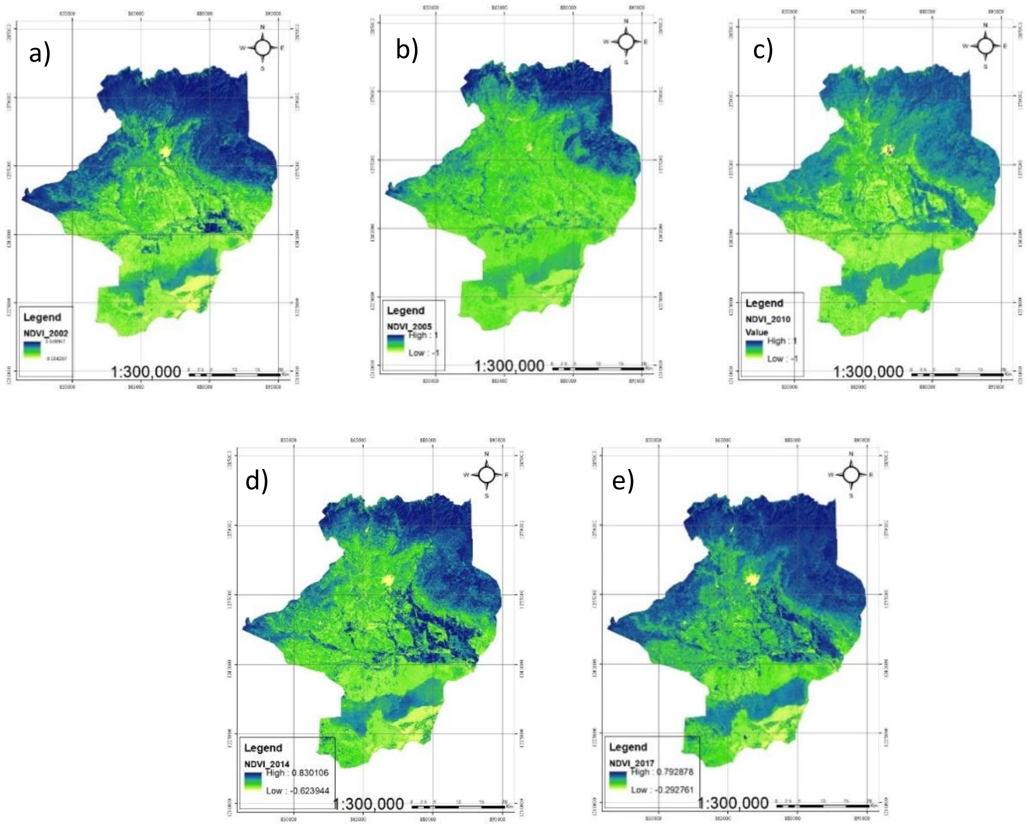

Fig 3. NDVI maps for Bac Binh district (Binh Thuan) in 2002(a); 2005(b); 2010(c); 2014(d) and 2017(e)

4.1.3. Comparison of Land Surface Temperature between Landsat image and MODIS image

The land surface temperature (LST) calculated from the Landsat image is compared to the product of MODIS. The pixels value are scattered in a two-dimensional space. Due to the different resolution of the two images (Landsat and MODIS), the Landsat's LST is downscaled. Figure 5 shows the relationship between the values of the two temperature images from 2002 to 2014. The correlation coefficients (R^2) are relatively low (< 0.15) due to downscaling and the difference in acquisition time between Landsat and MODIS. Remarkably, the temperature calculated from the Landsat image is 5°C lower value compared to the MODIS image.

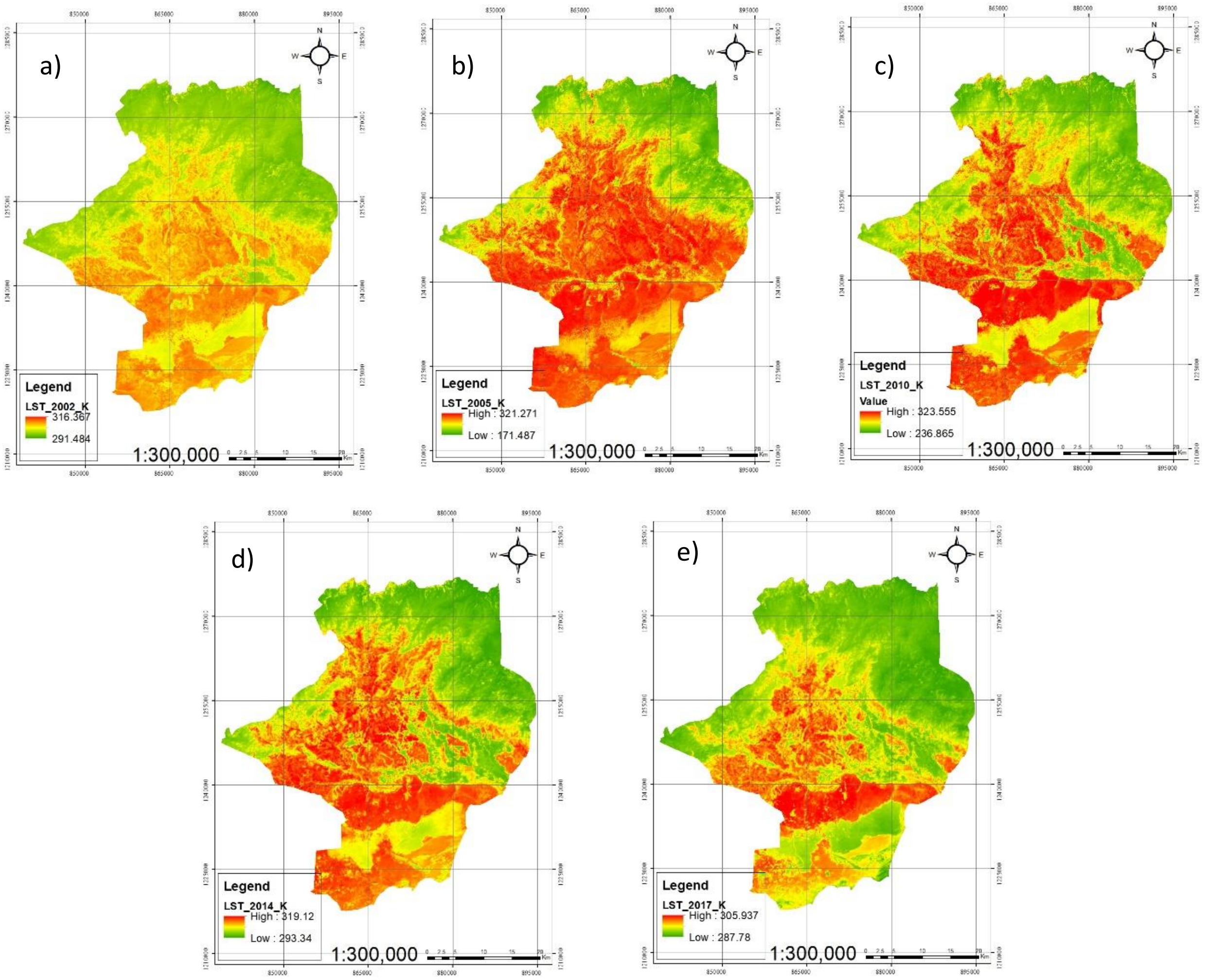

Fig 4. The land surface temperature of Bac Binh district (Binh Thuan) in 2002(a); 2005(b); 2010(c); 2014(d) and 2017(e)

4.1.4. The observed Ts-Ta temperature

This study uses the DEM image with 30m resolution to calibrate the observed air temperature Ta, after that the land surface temperature is used to calculate the Ts-Ta. To correct for the effect of topography, we used Ts-Ta to consider local pressure from altitude and the transform surface temperature to potential temperature.

To determine the dry edge of the relationship between LST and NDVI as well as Ts-Ta (ΔT) and NDVI, in this study, we divided the NDVI into 15 segments and determine the maximum temperature at these segments. Figure 5 shows the results of the scatter diagrams between the land surface temperature and the NDVI over the years from 2002 to 2017 to determine the equations of dry edge and wet edge. The details of these equations in Table 1. Similarly, with the LST/NDVI, the triangular shapes of ΔT/NDVI relationship showed in figure 7 and the equations of ΔT_{max} and ΔT_{min} and presented in Table 2. These results show that surface temperature decreases with increasing of vegetation cover when the trapezoid shape can change to the triangular shape according to lots of remote data. For a heterogeneous surface, the temperature is an indicator of surface energy fluxes partitioning rather than an indicator of soil moisture. Thus the warm edge is more likely to represent limiting values for surface evaporation rather than a purely dry soil surface. Within each type of land surface, the warm edge of the triangle is the lower bound of evapotranspiration and the upper bound of vegetation foliage temperature. The cold edge of the triangle is the upper bound evapotranspiration when actual evapotranspiration is equal to potential evapotranspiration near the cold edge.

4.2. Estimating the TVDI and iTVDI

The TVDI or iTVDI values range from 0 to 1. We classified the levels for temperature vegetation dryness index which is shown in Table 3.

Table 1. The dry edge and wet edge (LST/NDVI) for the years of 2002, 2005, 2010, 2014 and 2017

Year	LST_{max} (K°)	LST_{min} (K°)
2002	-27.8631 NDVI + 321.8861	-8.9040 NDVI + 298.6472
2005	-24.1558 NDVI + 322.3543	-8.9730 NDVI +299.0820
2010	-9.9723 NDVI +322.9200	-8.9609 NDVI +305.8564
2014	-14.8577 NDVI +320.1936	-12.7504 NDVI +303.0350
2017	-16.5339 NDVI +309.2286	-1.4143 NDVI +289.9726

Table 2. The dry edge and wet edge (Ts-Ta/NDVI) for the years of 2002, 2005, 2010, and 2014

Year	ΔT_{max} (K°)	ΔT_{min} (K°)
2002	-24.4810 NDVI + 24.3367	-6.8970 NDVI + 2.9584
2005	-21.9738 NDVI + 26.4341	-5.8838 NDVI +3.3268
2010	-4.4785 NDVI + 23.0267	-7.4154 NDVI + 6.5539
2014	-12.6023 NDVI + 22.9592	-6.9774 NDVI + 5.8902

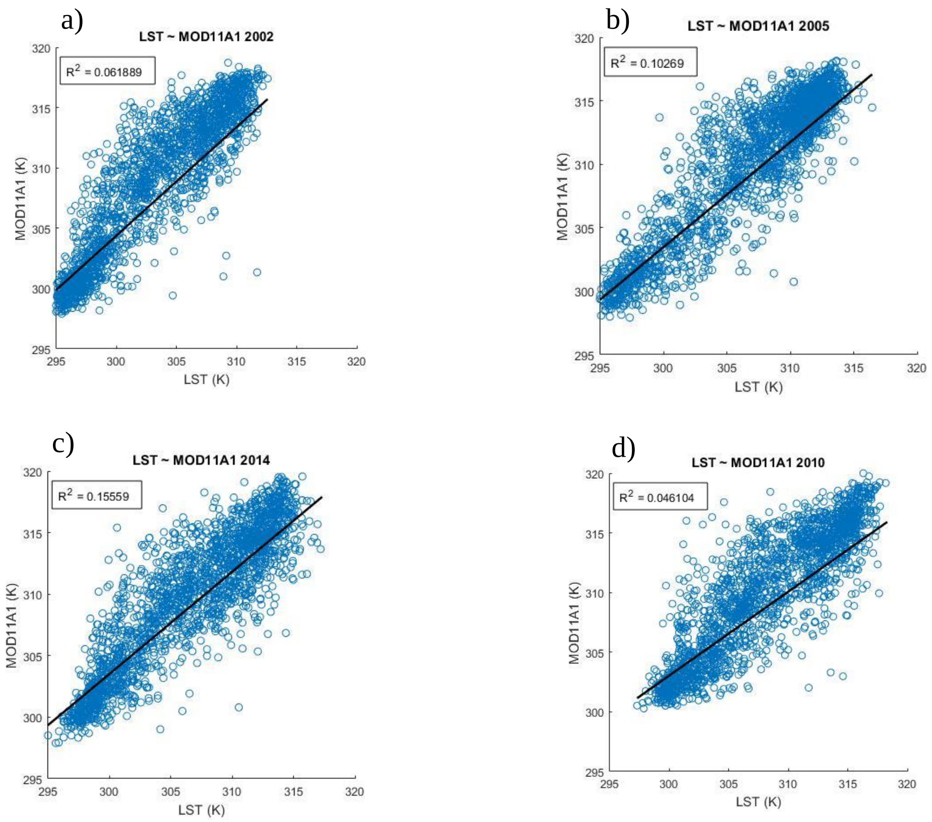

Fig 5. Comparison of LST between Landsat image and MODIS image in 2002(a); 2005(b); 2010(c) and 2014(d)

In particular, the TVDI or iTVDI values which are smaller than 0.2 represents the no drought risk area (well-watered, healthy and fully vegetated, agriculture land). If the value lies between 0.2 and 0.4, the area will have a low risk of drought (forest area). For the next 2 segments (0.4 - 0.6 and 0.6 - 0.8), the areas are regarded as medium drought risk and drought risk areas. If the TVDI larger than 0.8, this area will have severe drought risk.

4.2.1. The Temperature Vegetation Dryness Index (TVDI)

The classified TVDI maps for Bac Binh district (Binh Thuan) basing on LST and TVDI are shown in Figure 9. Looking at these results, it is clear to be seen that a large area of Bac Binh district is regarded as medium and higher drought risk and concentrated in the centre part of the area. Areas with low drought risk located mainly at the north of Bac Binh. In fact, this is a hilly area covered with forest.

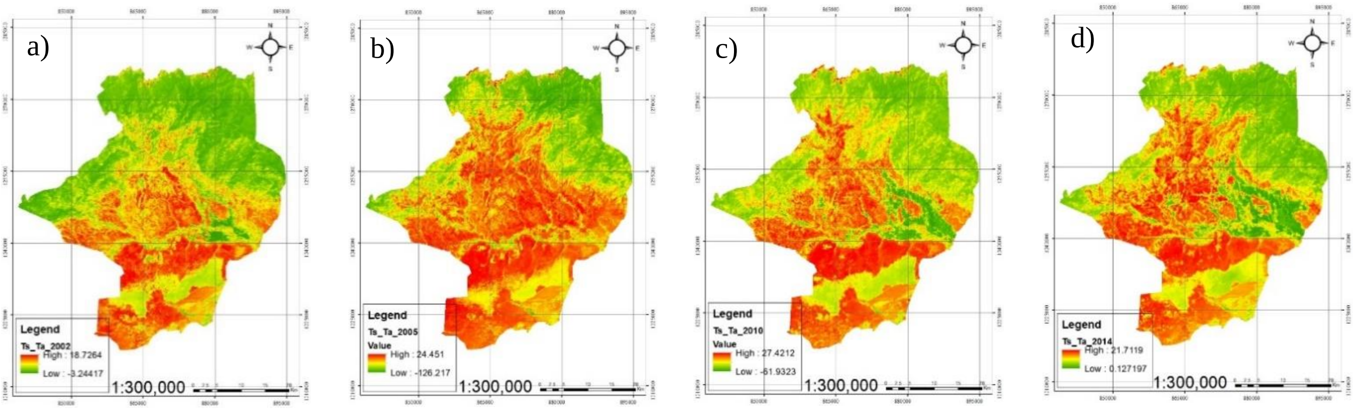

Fig 6. The Ta of Bac Binh district (Binh Thuan) in 2002(a); 2005(b); 2010(c) and 2014(d)

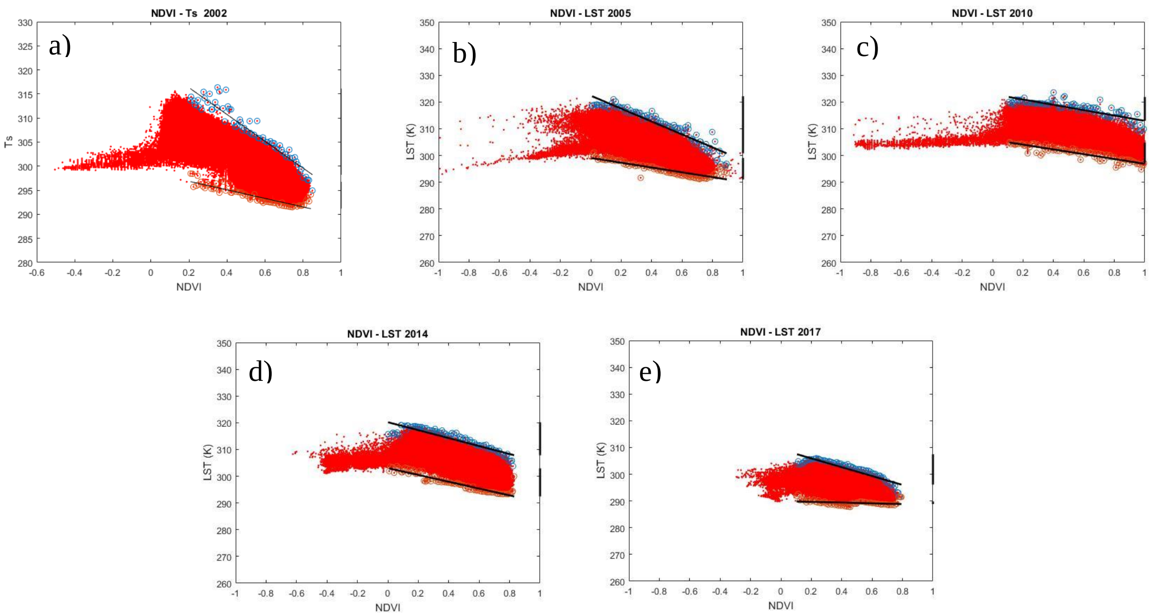

Fig 7. The triangle temperature Ts/NDVI in 2002(a); 2005(b); 2010(c); 2014(d) and 2017(e)

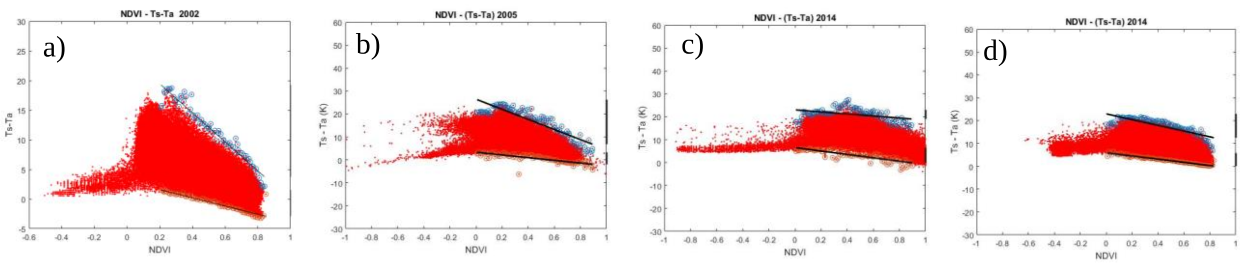

Fig 8. The triangle temperature Ts-Ta/NDVI in 2002(a); 2005(b); 2010(c) and 2014(d)

Table 4 shows proportions of each classified drought risk area by TVDI and iTVDI. It can be seen that the areas affected by drought and severe drought account for about 40% to 50%. Although this proportion tended to remain constantly (from 46.22% in 2002 to roughly 47% in 2017), but the change is significant, moving from drought to severe drought. In other words, the intensity of drought in Bac Binh rose through time. This can be clearly seen in the results of TDVI in 2014 and 2017 when the proportions of severe drought risk areas soared up to 17.18 % in 2014 and 14.77% in 2017 compared to less than 0.3% in the former years.

Table 3. Classification of the drought risk for the TVDI map (Trinh Le Hung, 2015)

No.	TVDI/iTVDI values	Drought grade
1	0 – 0.2	Not drought
2	0.2 – 0.4	Light drought
3	0.4 – 0.6	Medium drought
4	0.6 – 0.8	Drought
5	0.8 – 1	Severe drought

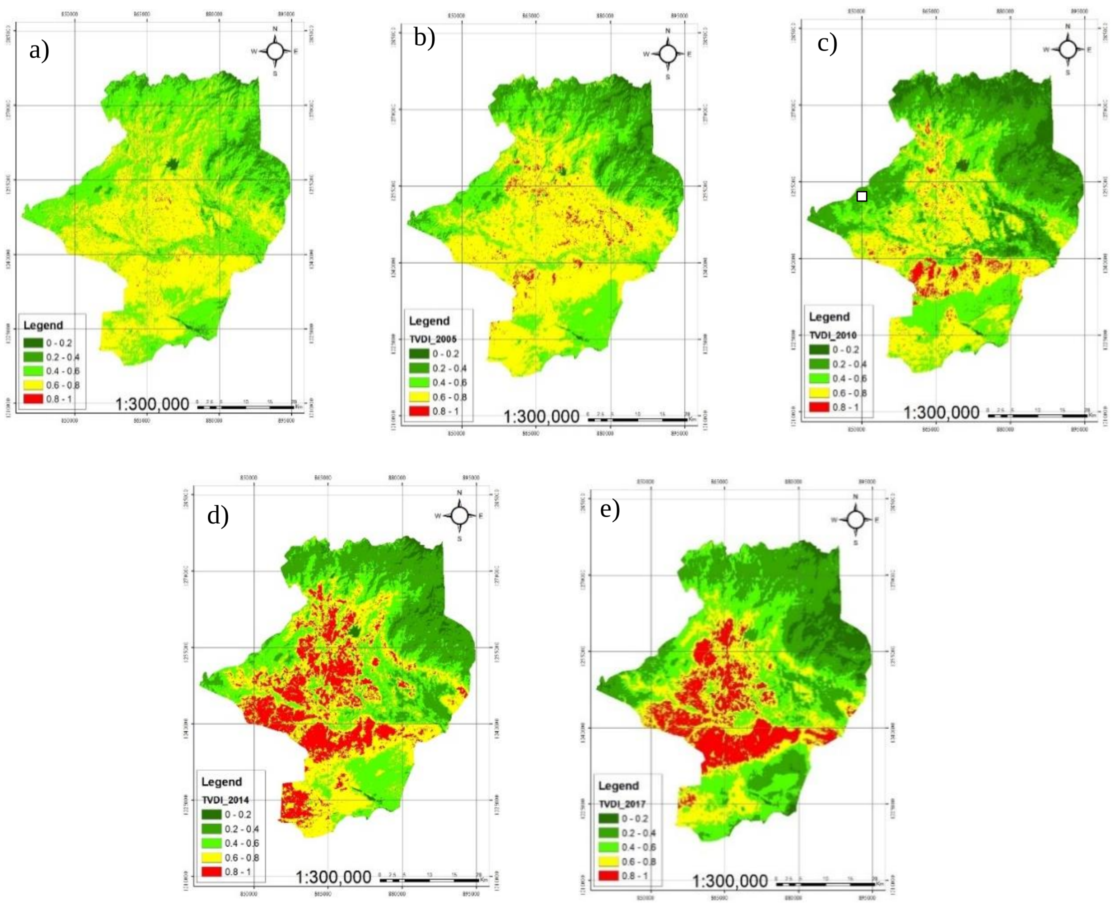

Fig 9. The drop classified TVDI maps for Bac Binh district in 2002 (a), 2005 (b), 2010 (c), 2014 (d) and 2017(e)

Table 4. Proportions of each classified drought risk area (Bac Binh)

Year	Areas (%)									
	No drought		*Low drought*		*Medium drought*		*Drought*		*Severe drought*	
	TVDI	*iTVDI*	*TVDI*	*iTVDI*	*TVDI*	*iTVDI*	*TVDI*	*iTVDI*	*TVDI*	*iTVDI*
2002	0.99	6.81	9.60	37.18	43.20	50.47	45.66	5.49	0.56	0.06
2005	2.45	6.08	16.38	26.46	28.97	46.91	49.98	20.42	2.22	0.12
2010	10.24	3.94	27.29	36.50	28.10	29.70	31.26	26.87	3.11	2.98
2014	2.28	6.82	22.66	28.38	26.99	25.78	30.89	29.23	17.18	9.80
2017	5.91		28.78		27.28		23.27		14.77	

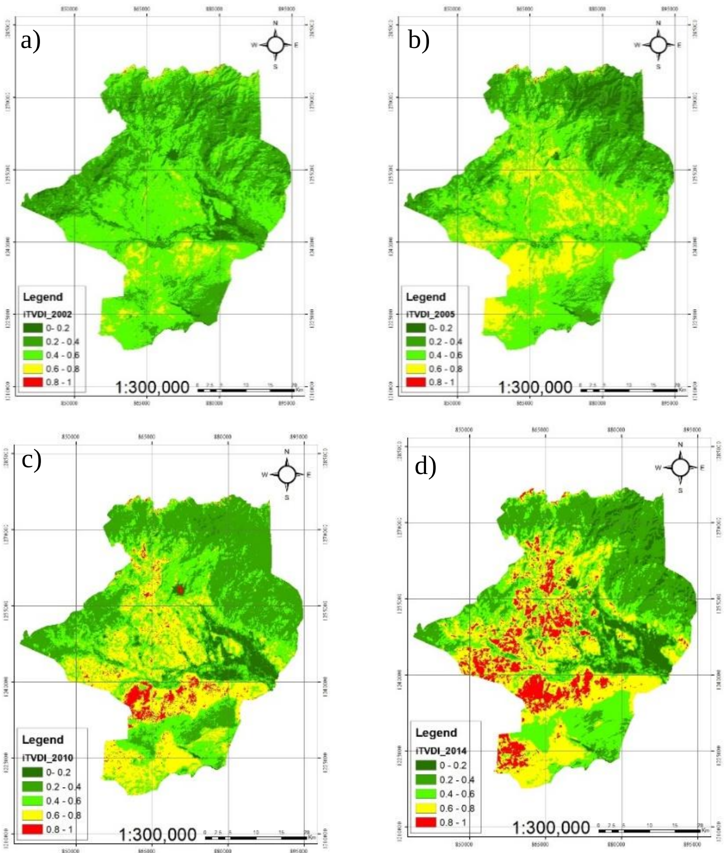

Fig 10. The drop classified iTVDI maps for Bac Binh district (Binh Thuan) in 2002 (a), 2005 (b), 2010 (c) and 2014 (d)

5. Conclusions

In conclusion, this study conducted a drought assessment in Bac Binh, Binh Thuan, Vietnam using TVDI and iTVDI. The results of surface temperature calculations are compared with the results from the MODIS image to check the accuracy of the calculation. The results of the drought assessment from 2002 to 2014 by the TVDI and iTVDI indices indicate that the area of the significant area is at high risk of severe drought and drought. The study also compared the two drought indices and found that TVDI tended to have a higher drought rating than the iTVDI. The effects of climate change and human activities in recent years have increased the risk of drought in Bac Binh district (Binh Thuan). Most of Bac Binh's area is estimated to have medium and higher drought risk, with severe drought areas increased rapidly in 2014, 2017 compared to previous years. Drought risk areas are found mostly in agricultural areas and non-vegetated areas. Landsat data with an average spatial resolution, integrated with thermal bands, which is provided freely is regarded as precious and useful data in researching and monitoring drought phenomena. The results obtained in this study may be used in the establishment of a 1:100000 drought risk map which contributes to respond and mitigate the effects of drought on the local environment, economic activities, and society.

There are some limitations to the study. The comparison of land surface temperature between Landsat and MODIS images for correlation coefficient is not high due to the downscaling of the Landsat image to the lower MODIS resolution. Another issue is that the drought index changed significantly from 2010 (Landsat 7) to 2014 (Landsat 8) in both indices. There is, therefore, a need to study whether this change is due to the difference between the two satellites' images, or indeed because the drought rate in the study area has increased.

Conflict of Interest Statement

The authors declare that there is no conflict of interest.

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