Evaluation of drought on agricultural land-use change: A case study of coastal districts, Ben Tre province

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ABSTRACT

Ben Tre is a coastal province in the Mekong Delta heavily affected by negative impacts of climate change and sea level rise, such as freshwater shortage and increased salinity intrusion during the dry season. This research aimed to develop a remote sensing approach, using time series data to assess drought development for the coastal districts (Ba Tri, Binh Dai, and Thanh Phu) in Ben Tre province. The Temperature Vegetation Dryness Index (TVDI) was analyzed based on the time-series Landsat 8 OLI data, which were obtained continuously from 2009 - 2019 to evaluate drought changes over time. The drought maps of 2009 and 2019 were established and the results showed that there were four levels of drought, including non-drought, slight drought, moderate drought and severe drought. Areas with non-drought and slight drought were reported at 5.65% and 35.34% (about 6,098 ha and 38,146 ha), respectively; while about 53.14% and 5.87% of the study areas were classified as moderate and severe drought (about 57,354 ha and 6,332 ha), respectively. The assessment of fluctuations in the period 2009-2019 showed that the areas of non-drought and slight drought tended to decrease while the areas of moderate and severe drought increased. The drought was positively related to agricultural land-use change as shown by the following formula $\log_e(P_i/(1 - P_i)) = 7.985 * TVDI - 6.746$. Drought tended to decrease in the areas where the bare land was changed to lands for perennial crops, rice crops and aquaculture, while drought tended to increase in land-use types of rice and annual crops.

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1. Introduction

Drought is defined as a prolonged period of lack of rainfall, resulting in severe aridity during the dry season (Wilhite & Glantz, 1985). According to the World Meteorological Organization (WMO), droughts are classified into four types: meteorological drought, agricultural drought, hydrological drought and socio-economic drought. The study only focused on agricultural drought. Agricultural drought links various characteristics of meteorological (or hydrological) drought to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, reduced groundwater or reservoir levels, and so forth. According to the report of the Institute of Risk Analysis Mapleocroft (England, 10/2010), Vietnam ranks 13 out of 16 countries strongly affected by drought. Drought can have a significant impact on the ecology and agriculture of the affected area, promoting land-use conversion and changing land cover (Raja et al., 2013).

There are many methods to assess drought, but two common methods are used including: (1) The method of calculating drought index from hydrometeorological station data based on two main meteorological indicators such as the amount of water evaporation and rainfall; (2) Remote sensing method based on the drought index according to the temperature - vegetation relationship. The use of remote sensing for drought monitoring has the advantage of being able to receive regular and continuous information on land surface characteristics in space and time (Belal et al., 2014).

The indicators developed from remote sensing data such as Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST) are used to monitor crop growth in agriculture (Han et al., 2010). Wang et al. (2003) developed the Temperature – Vegetation Dryness Index (TVDI) based on information from the LST scatter plot compared to the number of NDVI in a triangle space is created by "wet edge" and "dry edge". The Standardized Precipitation Index (SPI) is the most widely used indicator of drought using meteorological data. SPI can be computed at different time scales and thus can quantify water deficit at different time intervals. SPI is designed to demonstrate that it is possible to experience wet conditions simultaneously over one or more dry sand conditions on a different time scale (Jain et al., 2010). Standardized Water Supply Index (SWSI) is a hydrological drought index developed to replace the Palmer Drought Severity Index (PDSI) in areas where local precipitation is not the only (or primary) source of runoff. SWSI is calculated based on monthly non-exceeded probabilities determined using historical data information available on reservoir storage, runoff flow, precipitation, and ice (Hayes et al., 2012).

In Vietnam, there are many studies on the application of GIS and remote sensing in drought risk assessment including the study of Bui et al. (2019) in Tuong Duong district, Nghe An province, using the SAVI and TVDI indexes to assess drought based on multi-spectrum satellite images. Comparing with local survey and statistics, the results calculated according to TVDI index reflect the term more accurately, in detail and more closely than the SAVI index. Therefore, TVDI is more suitable and effective in assessing drought in Tuong Duong (Bui et al., 2019). The study of the authors Trinh & Dao (2015) used the TVDI index to assess the risk of drought for Bac Binh district, Binh Thuan province. Research results show that most of Bac Binh district is forecasted to have moderate to severe and extreme drought, in which areas at risk of severe and extreme drought increase very rapidly in the years 2010, 2014 compared to previous years. Trinh (2014) studied soil moisture and the degree of dryness of the land cover based on the Temperature Vegetation Dryness Index (TVDI) using thermal image data LANDSAT TM, ETM +, LANDSAT 8 OLI.

Ben Tre is one of the provinces heavily affected by drought and saltwater intrusion, especially in the coastal districts of Ba Tri, Binh Dai and Thanh Phu, where the outlet of the main rivers has very different types of land use sensitive to drought and saltwater intrusion such as rice land and aquacultural land (Figure 1). This paper introduces the application of remote sensing in drought zoning and evaluates the effects of drought on agricultural land use change in coastal districts of Ben Tre province.

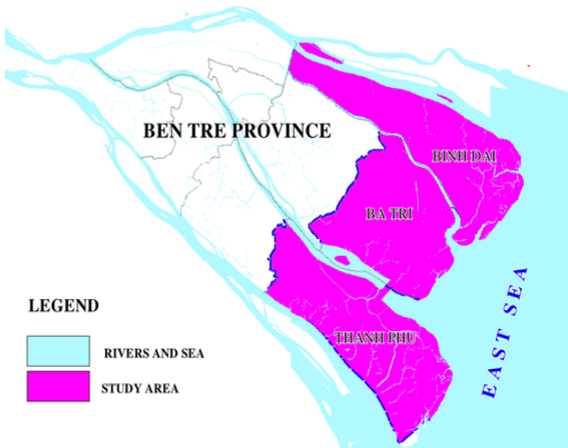

Figure 1. Location of the study area.

2. Materials and Methods

2.1. Materials

Satellite images (Landsat 7 and Landsat 8) are used for land use mapping, surface temperature maps, and vegetation growth index maps. Thematic maps are used to assist in sampling and classifying images for land use types mapping. Socio-economic and land statistics in 2019 data are used in the assessment of socioeconomic and land use status. Field survey data used to assess drought.

2.2. Research methods

2.2.1. Images classification method

With the input data source is Landsat 7,8 satellite image, the study uses the Maximum Likelihood Classification method (MLC). MLC is a supervised image classification method based on Bayes theorem that is considered to have high accuracy and is widely used. The MLC algorithm will consider each class in each spectral channel to have a normal distribution. The pixels will be assigned to the category that has the highest probability. The calculation is not only based on the value of the spectral distance, but also on the trend of brightness variation in each type.

2.2.2. The method of calculating the drought index from remote sensing images

The remote sensing method for drought zonning based on the drought index according to the vegetation and temperature relationship (Temperature Vegetation Dryness Index – TVDI). The TVDI is calculated using the following equation:

$$TVDI = ((T_s - T_{smin})/((T_{smax} - T_{smin})))$$
$$= ((T_s - T_{smin})/((a + b * NDVI - T_{smin})))$$

where T_{smin} is the minimum surface temperature in the triangle to determine the wet edge; Ts is the observed temperature at the image pixel to be calculated; Tsmax is the maximum observed surface temperature for each range of NDVI values. The parameters a and b of the "dry edge" line for a Landsat image are determined by the least squares regression function of the maximum values Ts for the NDVI ranges. The parameters a, b are coefficients of the following equation:

$$T_{smax} = a + b * NDVI$$

Where: NDVI = (NIR - RED)/(NIR_RED)

To determine the coefficients a and b in the above linear function, it is necessary to select the sample points that are the points with the center value of the divided values of the independent variable NDVI and the temperature value corresponding to the dependent variable temperature surface LST. TVDI index received the value from 0 to 1. Classification of surface drought level for TVDI is presented in Table 1.

Table 1. TVDI drought index classification[1]

No	TVDI ranges	Drought levels
1	0.0 - 0.4	No drought
2	0.4 - 0.6	Slight drought
3	0.6 - 0.8	Moderate drought
4	0.8 - 1.0	Severe drought

[1]TVDI: Temperature Vegetation Dryness Index

2.2.3. Statistical method

Includes descriptive statistics and binary logistic regression to determine the correlation between LST and NDVI, degree of drought to land use change. Regression analysis is to find the dependence of one variable, called the dependent variable on one or more other variables, called the independent variable, to estimate or predict the expected value of the dependent variable when knowing the value of the independent variable. In this study, the dependent variable is determined as land use change (with the value 0 being unchanged and 1 being changed) and the independent variable is the degree of aridity calculated by the TVDI index value (with value from 0 to 1).

2.2.4. Research process

To assess the impact of drought on agricultural land use change, the study used Landsat images, thematic maps combined with field surveys (Figure 2).

Bands 4,5 of Landsat images are used to generate NDVI maps, band 10 is used to generate land surface temperature (LST) maps. The drought map is created from the correlation relationship between LST and NDVI. Bands 4,5,7 are used to interpret images and create land use maps in 2009 and 2019. From land use maps and drought maps to assess the effects of drought on agricultural land use changes.

3. Results and Discussion

3.1. Characteristics of natural conditions

Ben Tre province has a natural area of 2,360 km^2. There are coordinates from 9°48' – 10°20' North latitude to 105°57' – 106°48' East longitude. Ben Tre's topography is flat, with mangroves along the coast and rivers. Ben Tre is located in the sub-equatorial monsoon tropical

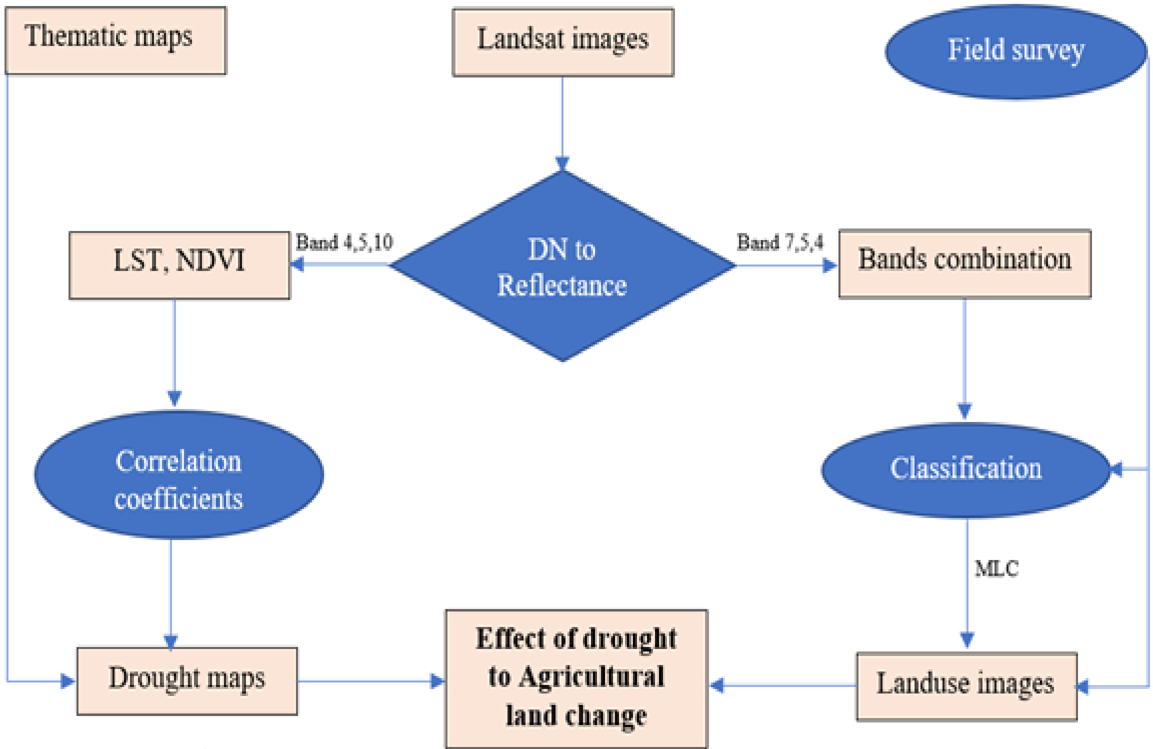

Figure 2. Research process.

climate with annual average rainfall from 2,000 to 2,300 mm, average annual temperature from 26°C to 27°C. According to Ben Tre province's land degradation synthesis report in 2019, there were 5 main soil groups in Ben Tre province, including Artificial (man-made) soil 94,359 ha, saline soil 58,173 ha, alluvial soil 25,225 ha, and alkaline soil 9,915 ha and sandy soil 15,233 ha, of which mainly man-made and saline soils. The current state of land use in 2019 showed that the agricultural land group had an area of 181,821 ha, of which was mainly aquaculture land, followed by land for perennial crops, land for annual crops (mainly rice land). Non-agricultural land group 57,180 ha includes main types of land such as water bodies, specialized land, residential land and other types of non-agricultural land. Unused land group 433 ha is unused flat land. Due to the characteristics of natural conditions, the flow from the headwaters of the Mekong River to the delta is rapidly decreasing and is at a very low level compared to the average document for many years from 1980 to now, the prolonged lack of rain combined with the use and exploitation of water resources in the basin (increasing water use on tributaries and storing water in dams) will make droughts, water shortages, and saltwater intrusion more prolonged and severe in the coastal districts of Ben Tre province.

3.2. Land use/land cover change evaluation in the period of 2009 - 2019

3.2.1. Images classification

The maximum likelihood classification (MLC) method was applied with 115 sample points and 25,460 training pixels selected. Five land use types were classified including rice land, perennial land, aquaculture land, residential land and water bodies. The image classification results show that rice land is concentrated in Ba Tri district where there is Kenh Lap freshwater lake with an area of 151 ha; perennial land is concentrated in the northeast of the districts where it is adjacent to coconut and fruit trees of Ben Tre province; aquaculture land distributed along the coast and main rivers; residential land is distributed in urban centers of districts and along traffic roads; water bodies are the main rivers. The area of the land use/land cover types is shown in Table 2 and the distribution of land use/land cover types is shown in Figure 3.

Classification accuracy was assessed by random

Table 2. Land use/Land cover area of 2009, 2019

Land use/Land cover	2009 (ha)	2019 (ha)	Change (ha)
Rice land	12,725	3,747	-8,979
Perennial land	33,754	37,737	3,984
Aquaculture land	45,305	48,379	3,075
Residential land	7,923	9,843	1,921
Water bodies	8,222	8,222	0
Total	107,929	107,929	0

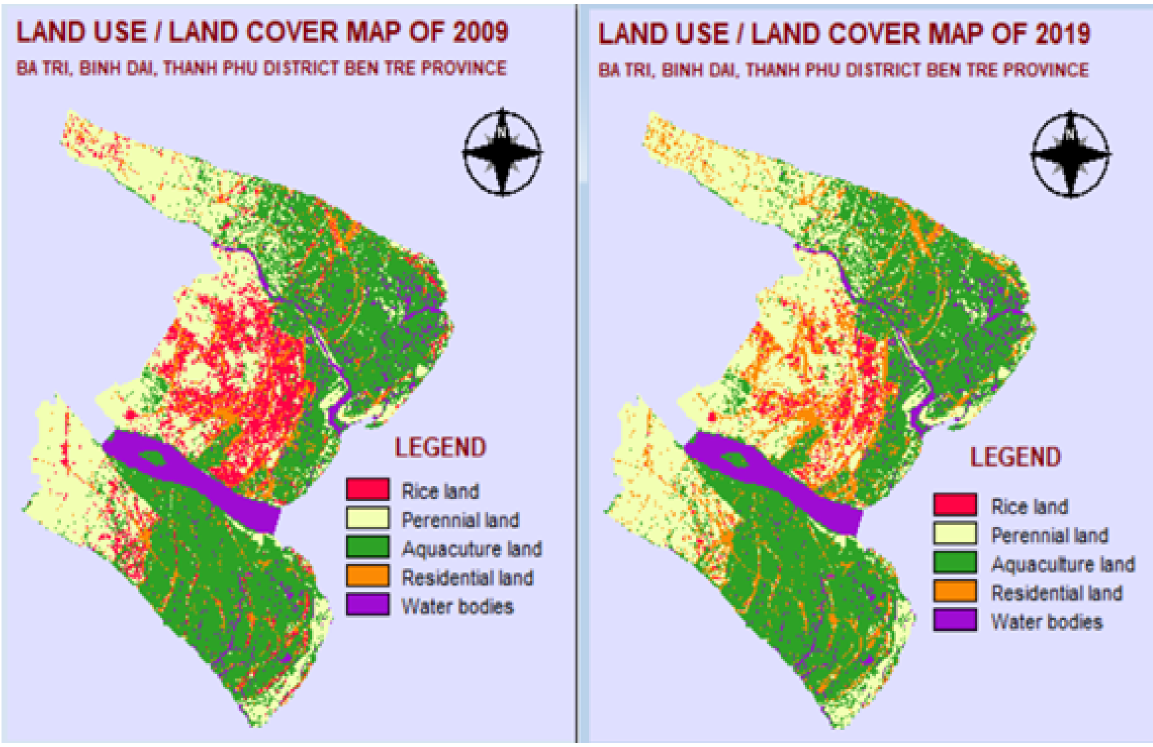

Figure 3. Image classification of 2009 and 2019.

sampling. Pixels belonging to the sample regions (ROIs) of each class are called sample pixels or trained pixels. High-resolution Google earth images combined with land use maps of the study area are used both as a basis for sample zoning and to check classification results. Kappa index and overall accuracy of 2009 images are 0.79 and 83%, respectively; corresponding to the 2019 image is 0.91 and 93%.

3.2.2. Land use/land cover change detection in the period of 2009 - 2019

From the 2009 and 2019 land use / land cover maps, a change assessment was carried out to calculate the changing area and the probability of conversion between types of land use / land cover. The change of area in the period 2009 - 2019 is shown in Figure 4.

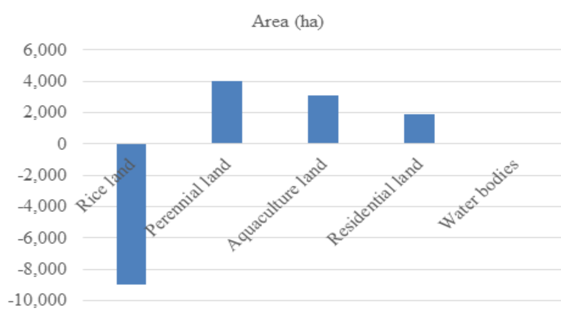

Figure 4. Change area in the period 2009 – 2019.

The results of the assessment of changes in the period 2009 - 2019 showed that the area of rice land decreased by 8,979 ha, of which the area changed to perennial land 3,984 ha, changed to aquaculture land 3,075 ha, converted to residential land 1,921 ha. The transition probabilities between land use / land cover types are shown in the following map (Figure 5):

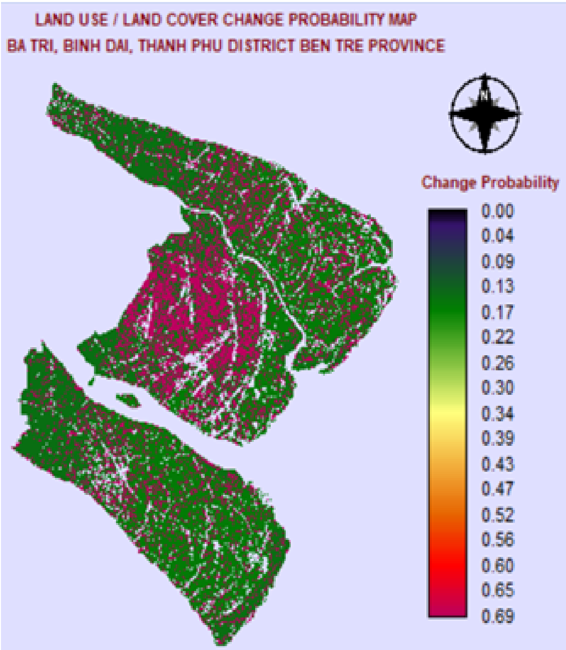

Figure 5. Land use/Land cover change probability.

From the change analysis results, it shows that the changeability of rice land is the highest (69%), aquaculture land and perennial land has little change (from 10 - 20%) while residential land and water bodies hardly change (0%).

3.3. Establishing drought maps of 2009 and 2019

To create a drought map, it is necessary to use band 10 (thermal band) to calculate LST, band 4,5 of Landsat 8 images to calculate the NDVI index. Sample points are selected to calculate the correlation coefficient between LST and NDVI. The coefficients in the correlation equation will be used to create the TVDI index map. From the TVDI index map, a map of drought zoning will be created. The steps to create a drought zoning map are shown in Figure 6.

$$TVDI = ((T_s - T_{smin})/((T_{smax} - T_{smin}))) = ((T_s - T_{smin})/((a + b * NDVI - T_{smin})))$$

Where: $T_{smax} = a + b * NDVI$

To determine the coefficients a and b in the above linear function, it is necessary to select the sample points that are the points with the center value of the divided values of the independent variable NDVI and the temperature value corresponding to the dependent variable temperature surface LST.

From the above linear equation determine the coefficients a and b, respectively a = -11.975 and b = 27.291 (Figrue 7). T_{smin} and T_{smax} are the highest and lowest temperatures of the surface temperature (LST) map made above, respectively Tsmin = 21°C and Tsmax = 39°C. Substituting the above coefficients into the equation we have:

$$TVDI = (T_s - 21)/(27.291 * NDVI - 32.975)$$

From the above equation, it can be seen that the TVDI drought index is calculated according to the relationship between LST and NDVI index. Using the Band Math function in Envi 5.2 software with two images, LST in 2009, 2019 and NDVI in 2009, 2019 to create a TVDI index map in 2009, 2019. Based on the table of TVDI value classification (Table 3), to establish drought zoning maps for the study area.

The 2019 drought zoning map shows that there are four levels of drought, which are mainly non-drought and slight drought areas in rice and aquaculture areas, distributed in all three districts, in which most of them are concentrated in Thanh Phu district. The moderate drought area is actively irrigated, so the drought level of the soil does not affect the crops because the soil is increased moisture by irrigation. The area of severe drought is scatteredly distributed in the districts with an insignificant area (Figure 8).

Statistical results of fluctuations in the period 2009 - 2019 show that the non drought and slight drought areas tend to decrease while the moderate and severe drought areas increase. The following are some drought images from the field survey results used to verify and correct the drought map (Figure 9 và 10).

3.4. Assessing the impact of drought on agricultural land use change

Conduct a drought value survey at 1,000 sample points to determine correlation with land use change. The value of land use change is recorded in two states of change (value is 1) and unchanged (value is 0). Applying the binary logistics regres-

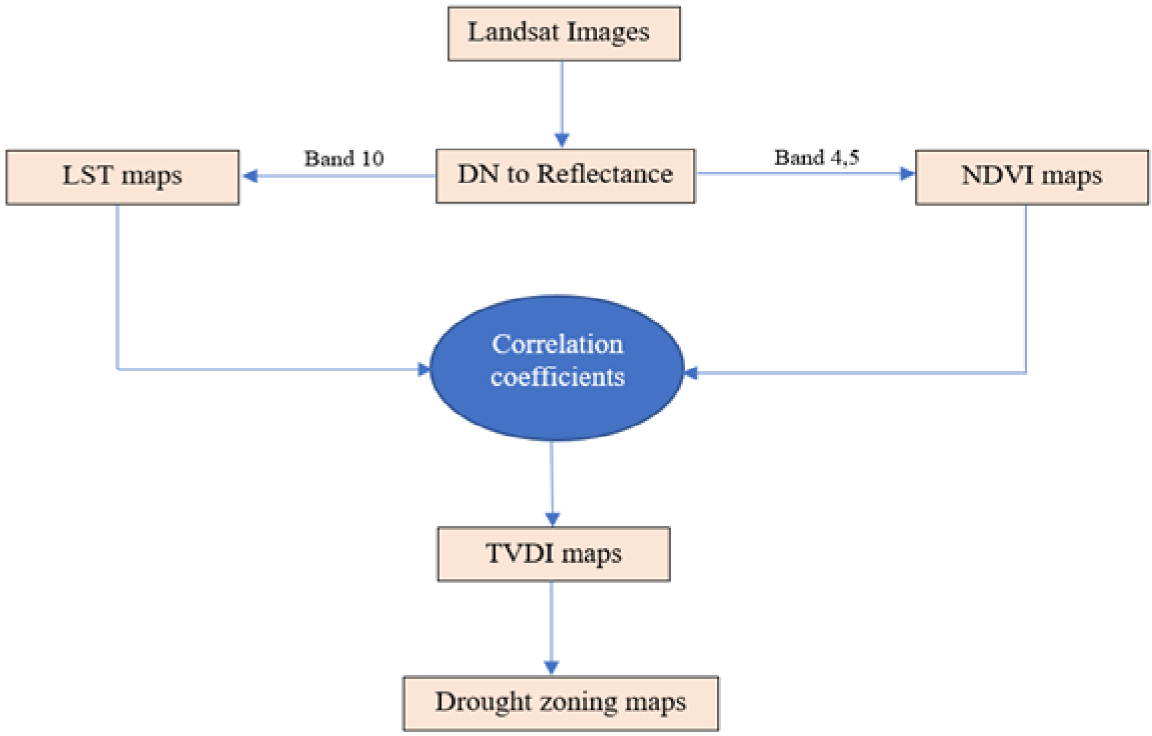

Figure 6. The process of creating drought zoning maps.

Table 3. Statistics of drought areas in 2009, 2019

Drought levels	Area 2009 (ha)	Ratio (%)	Area 2019 (ha)	Ratio (%)	Change 2009 - 2019 (ha)
Non-drought	5,317.83	4.93	6,097.59	5.65	779.76
Slight drought	50,753.43	47.02	38,145.87	35.34	-12,607.56
Moderate drought	47,539.26	44.05	57,354.48	53.14	9,815.22
Severe drought	4,319.37	4.00	6,331.95	5.87	2,012.58
Total	107,929.89	100.00	107,929.89	100.00	0.00

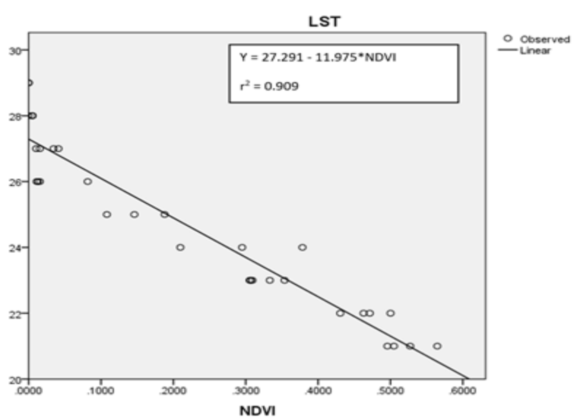

Figure 7. Correlation between LST and NDVI.

sion technique with the following results (Table 4):

Table 4. Omnibus tests of model coefficients

		Chi-square	df	Sig.
Step 1	Step	102.055	1	.000
	Block	102.055	1	.000
	Model	102.055	1	.000

The Omnibus Tests of Model Coefficients table shows that the sig of all 3 Step Block Model indexes is equal to 0.000 < 0.05 (95% confidence level), so the regression model is statistically significant.

Statistical results showed that: In 639 cases where land use did not changed, it is predicted that 537 cases do not change. The correct predic-

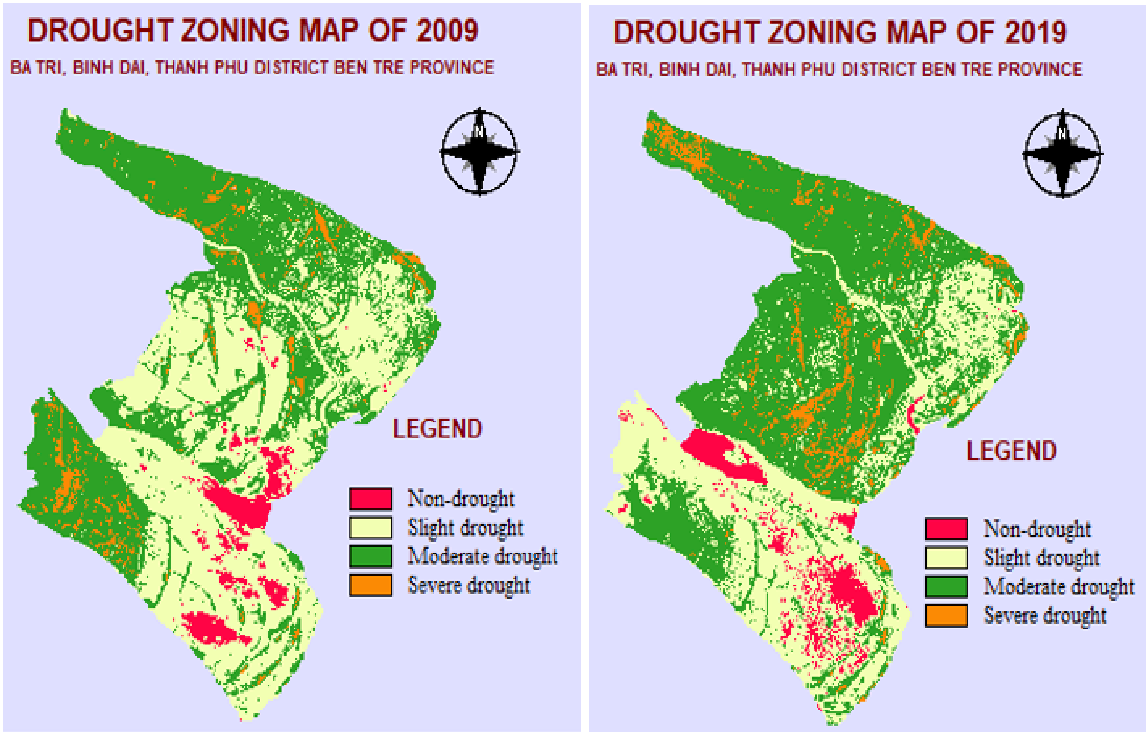

Figure 8. Drought zoning maps of 2009, 2019.

Figure 9. Drought image at Ba Tri.

tion rate was 84.0%. Out of 361 cases of observed land use change, 118 cases of land use change are predicted. The correct prediction rate was 32.7%. Thus, the average rate of correct prediction was $(84.0 + 32.7)/2 = 65.5\%$.

From the results (Table 5), the regression equation has the following form:

$$\log_e(P_i/(1 - P_i))=7.985 * TVDI - 6.746$$

The results of the regression analysis show that drought is positively related to agricultural land

Figure 10. Drought image at Binh Dai.

Table 5. Variables in the equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Drought	7.985	.866	84.997	1	.000	2.817
	Constant	-6.746	.681	98.035	1	.000	.001

a. Variable(s) entered on step 1: Drought.

use change. That is, the more drought areas are, the higher the probability of agricultural land use change and vice versa.

The map of drought change in the period 2009 - 2019 was established with three states: The decreased degree of drought (pixels with TVDI index in 2019 was smaller than TVDI index in 2009); Unchange drought (pixels have TVDI values unchanged between 2009 and 2019) and drought tends to increase (pixels have TVDI values in 2019 was greater than TVDI values in 2009) (Figure 11).

The results of zoning drought fluctuations in Ba Tri, Binh Dai and Thanh Phu districts of Ben Tre province show that the drought area reduced by 5,399 ha, concentrated in Thanh Phu district where formerly bare land and annual crops were transferred to perennial land and rice land. The area does not change 43,982 ha, concentrated in Thanh Phu and Binh Dai districts where the water surface for aquaculture is located. The drought area increased by 58,548 ha distributed in all three districts but mainly concentrated in

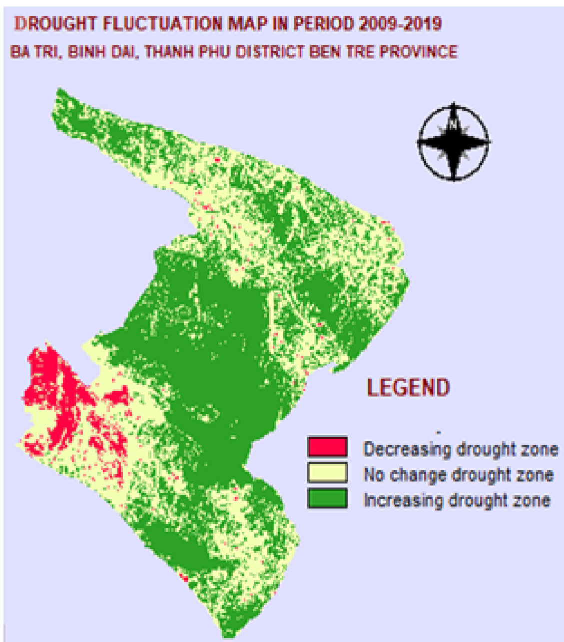

Figure 11. Drought fluctuation in the period 2009 - 2019.

Ba Tri district. Evaluation of the effect of drought on agricultural land use change showed that increased drought leads to changes in annual land and rice land. Drought is reduced in bare land and annual land where they tend to be converted to perennials and aquaculture land. While land use change between types of land for perennial crops and aquaculture land, drought did not change.

4. Conclusions

The coastal districts of Ben Tre province are vulnerable to drought and saltwater intrusion caused by characteristics of natural conditions. The image classification results with five land use types showed that rice land is concentrated in Ba Tri district where there is Kenh Lap freshwater lake; perennial land is concentrated in the northeast of the districts where it is adjacent to coconut and fruit trees of Ben Tre province; aquaculture land distributed along the coast and main rivers; residential land is distributed in urban centers of districts and along traffic roads; water bodies are the main rivers. The drought maps of 2009 and 2019 were established showing that there are four levels of drought, including non-drought, slight drought, moderate drought and severe drought. Areas with non-drought and slight drought were reported at 5.65% and 35.34%, respectively (about 6,098 ha and 38,146 ha); while about 53.14% and 5.87% of the study areas were under moderate and severe drought, respectively (about 57,354 ha and 6,332 ha). The assessment of fluctuations in the period 2009 - 2019 shows that the areas of non-drought and slight drought tend to decrease while the areas of moderate and severe drought increase. There was a positive correlation between drought and agricultural land use change. Drought tended to decrease in the areas where the bare land is changed to lands for perennial crops, rice crops and aquaculture, while drought tended to increase in land use types of rice and annual crops.

Conflict of interest

The authors declare no conflict of interest.

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