AGRICULTURAL DROUGHT DETECTION USING THE NORMALIZED DIFFERENCE VEGETATION INDEX AND LAND SURFACE TEMPERATURE DATA

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ABSTRACT: Global warming and climate change lead to extreme agricultural drought events which exceedingly affect agricultural production in many countries. The agricultural drought in Tien Giang Province, Viet Nam, which can be induced by inconsistent rainfall, a decrease in the freshwater resource, causes the decline in the yield of crops and affects the local economy. Hence, the detection and assessment of agricultural drought are urgent to mitigate its negative effect. Tien Giang Province, the study area, which falls in the lower section of the Mekong River Delta of Viet Nam, has a relatively gentle topography surface at low altitude and is consequently considered a drought-prone and salinity intrusion region. The objective of the study is to analyze the vegetation stress to detect agricultural drought in the province with the calculation of Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), and Land Surface Temperature (LST). This study used the Landsat 8 OLI/TIRS satellite data, CGLS-LC100 land cover map, ground-based air temperature record in 2015. To map the land cover types, the random forest supervised machine learning classifier was applied in this study. The result shows that the estimated LST was higher than the ground-based air temperature, around 4.4^0C, with the max difference at 8.4^0C. The random forest classifier categorizes the land cover into five classes (e.g., aquaculture, build-up, annual vegetation, perennial vegetation, and water) with an overall accuracy of 97.4%. The correlation between LST and NDVI, VCI can be clearly remarked as negative relationships with a correlation coefficient between LST and NDVI by - 0.439 ($p< 0.01$), LST and VCI by - 0.483 ($p< 0.01$) for the vegetation region of the study area.

1. Introduction

Global warming and climate change force the increase of drought in the agricultural region of the Mekong delta, Viet Nam. The consequence of the agriculture drought has significant effects on human life, agriculture production, food security, and the environment. Therefore, detection and assessment of drought are consequently becoming urgent these days to mitigate its effect.

Studying the drought contributing factors and vegetation signals in the affected regions can indicate the agriculture drought. Drought is highly reliable on natural factors like the weather, climate, soil moisture, and so forth, so many scientists have applied the traditional methods such as field survey and sampling questionnaires to detect this circumstance. However, these methods are still limited with the time resolution and are expensive for monitoring in a vast area.

A region's absorption and reflection of photosynthetically active radiation over a given period can be used to characterize the health of the vegetation there relative to the norm. Therefore, many remote sensing indices have been considered and applied to estimate weather impacts, crop yield loss during the drought event besides the classical methods. The advantage of sensors installed on satellite onboard provided a wide range of information about the surface reflectance, allowing humans to capture such issues at wider spatial and longer temporal. Drought can be monitored by mapping the land surface cover.

Normalized Difference Vegetation Index (NDVI) is the most straightforward, most efficient, and commonly used [5] one comparison with other vegetation indices. Tucker first proposed

NDVI in 1979 as an index of vegetation health and density. Based on NDVI value, the health of vegetation there and the norm relates to the vegetation health condition can be identified. The changes in vegetation cover present in the area and the movement in the situation of agricultural drought can be calculated by using the NDVI data of the region [6]. In addition, the comparison of the current NDVI to the range of values observed in the same period in previous years reveals the location of drought [1].

Land surface temperature (LST) is a good indicator of the energy balance at the Earth's surface, providing important information about the surface physical properties and climate. Thus, analyzing the correlation of this indicator with other indices can reveal more information about the land cover, the vegetation health condition, and so forth.

Agriculture drought attacks the coastal regions in Viet Nam, e.g. Tien Giang province, due to the freshwater shortage in the dry season. This province is highly vulnerable to lacking freshwater, which results in drought and salinity intrusion. However, the studies used remote sensing indices to reveal agriculture drought information for Tien Giang province are limited. Therefore, this study applies the up-to-date information of remote sensing indices in different spatial and temporal scales, and better displays spatial changes in surface information [4], [3], and suitable land cover data for spatial analysis on a provincial scale to retrieve the LST in the province area from Landsat 8 OLI/TIRS data and explore its relationships with NDVI, VCI of vegetation land cover for specifying drought information.

2. Materials and methodology

2.1 Study area

Tien Giang province locates at 100 35' N - 100 12' N, 1050 50' E - 1060 45' E, one of the coastal provinces in the Mekong River Delta, Viet Nam, and lies along with the north of Tien River (Figure 1). Tien Giang has eight districts (Cai Be, Cai Lay, Chau Thanh, Cho Gao, Go Cong Dong, Go Cong Tay, Tan Phu Dong, and Tan Phuoc), two district-level towns (Cay Lay and Go Cong) and one provincial city (My Tho), with a total area of 2,484.2 km^2. Tien Giang has a tropical monsoon climate.

There are two distinct seasons: a dry season from December of the previous year to April of the following year; rainy season from May to November. According to a relevant survey, the annual temperature of Tien Giang in 2015 was 27.6 ^{0}C, the average max temperature in the dry season was 31.5 ^{0}C, and the yearly precipitation was 1,370.7 mm. This province was one of the Mekong Delta provinces most affected by the drought and salinity intrusion in the dry season.

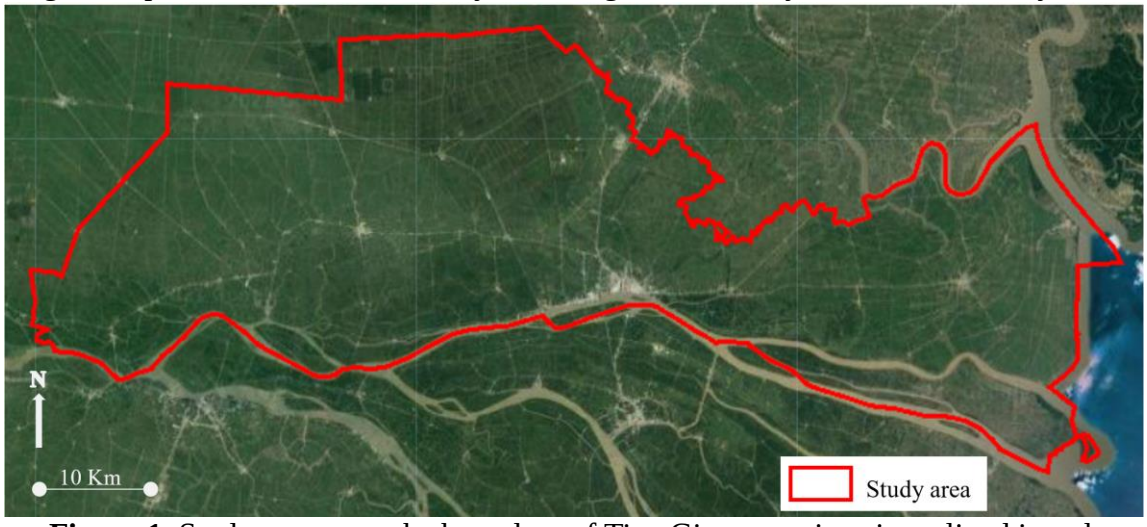

Figure 1. Study area map, the boundary of Tien Giang province is outlined in red. Base imagery source: map data @2021 provided by Google on Google Earth Engine.

2.2. Data source

The Landsat 8 Surface Reflectance Tier 2 image collection from 2015 to 2020 (LS8SR), provided by the United States Geological Survey (USGS), was used in this study. This dataset is the atmospherically corrected surface reflectance from the Landsat 8 OLI/TIRS sensors. The provided images at 30 m spatial resolution, contain five visible and near-infrared bands, two short-wave infrared bands, two thermal infrared bands. The band 3 - green (533 - 590 nm), band 4 - red (636-673 nm), band 5 - near-infrared (851- 879 nm), and band 10-brightness temperature (10.60-11.19 nm) were used to compute NDVI, VCI, LST.

The study also used the Dynamic Land Cover map at 100 m resolution (CGLS-LC100) provided by COPERNICUS to generate the individual locations of land cover types for delivering information into image classification.

The study used the ground-based daily air temperature measurement data in 2015 of My Tho station (Lat:10.35, Long:106.4) provided by the Southern Regional Hydro-meteorological Center to assess the accuracy of estimated LST.

2.3. Techniques for processing and analyzing data

It is essential to analyze vegetation indices (NDVI, VCI) changes and their correlation to LST. The software used for this investigation were Google Earth Engine Cloud Computing. NDVI is the most widely used vegetation index. NDVI can be averaged to establish the normal growing condition for the vegetation in a given region for a given time of year. From the data collection, Band 4 and Band 5 of each image belong to the collection were used to calculate the NDVI. NDVI data values range from -1 to 1. Time-series NDVI from 2015 to 2020 in the Tien Giang province was derived using the computed NDVI in the dry season (from February to April). The computed NDVI was applied to generate the maximum, minimum, average NDVI value and the anomalous NDVI during the time-bound.

Land Surface Temperature (LST) of the study area in the dry season of each year in the 2015-2020 period was calculated from the thermal infrared (Band 10) of the Landsat 8 OLI/TIRS. In this data, temperatures are extracted in Kelvin. The digital numbers of Band 10 data are converted to degrees Celsius for analysis. To indicate the water stress region, NDVI anomalies were generated by the Eq. (1):

$$\text{Index anomaly}_i = \frac{X_i - \overline{X}}{\delta} \quad (1)$$

The Vegetation Condition Index (VCI) is proposed by Kogan in 1996, based on the relative NDVI change concerning minimum historical NDVI value. The VCI, therefore, compares the current NDVI to the values observed in the same period in previous years within a specific pixel [6]. The following formula computes VCI:

$$VCI_{ijk} = \frac{NDVI_{ijk} - NDVI_{i,min}}{NDVI_{i,max} - NDVI_{i,min}} \times 100 \quad (2)$$

where: VCI_{ijk} is the VCI value for the pixel *i* during 16-day *j* for year *k*, $NDVI_{ijk}$ is the 16-day NDVI value for pixel *i* in 16- day *j* for year *k*, $NDVI_{i,\ min}$ and $NDVI_{i,\ max}$ are the multiyear minimum and maximum NDVI, respectively, for pixel *i*. $NDVI_{min}$ is defined as the minimum value of NDVI in years (2015-2015). First, the min value of NDVI for each year is computed, after that $NDVI_{min}$ from 2015 to 2020 can be computed. $NDVI_{max}$ is performed in a similar procedure with the max value of NDVI. The resulting percentage of the observed value is situated between the extreme values (minimum and maximum) in the previous years. Lower and higher values indicate bad and good vegetation state conditions correspond to drought, respectively.

2.4. Classification

Random forest classifier, a pixel-based supervised machine learning method image classification, was implemented. To train and test the classifier, we derived a total of 544 sample points based on the CGLS-LC100 image in 2019 for image classifier training and testing purpose. Of the 544 samples, 124 represented water bodies including lakes, rivers, and sea; 100 aquacultures/wetlands where the lands with a permanent mixture of water and herbaceous or woody vegetation; 100 build-up/urban; 100 annual vegetation where the lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple rice cropping field); 120 perennial vegetation represented for the fruit garden areas or cultivated forest areas including the shrubs, herbaceous vegetation, closed evergreen broadleaf forest, open evergreen broadleaf forest within the study area. The corresponding input image values for the 544 point samples were extracted at the Landsat image resolution level by a function for extracting a stratified random sample of points from an image in Google Earth Engine.

3. Results and discussion

3.1. NDVI and LST

Table 1 shows the statistical value of NDVI and LST of the vegetation area in the study area from 2015 to 2020. The maximum, minimum, mean, and standard deviation values of NDVI are ranged from 0.88 to 0.92, -0.31 to - 0.24, 0.5 to 0.58, and 0.24 to 0.26, respectively. The NDVI values of each year were classified and depicted in Figure 2. As similar to NDVI values, LST values of each year in the study period were presented with Maximum LST ranged from 40.76 to 45.90 ^{0}C, minimum 11.22 to 21.59 ^{0}C, mean from 26.11 to 33.32^{0}C, and Std. from 3.44 to 6.69^{0}C.

Table 1. Data of minimum, maximum, average and standard deviation values of NDVI, LST

Year	NDVI				LST (^{0}C)			
	Mean	Min	Max	Std.	Mean	Min	Max	Std.
2015	0.55	-0.30	0.89	0.26	31.80	17.43	45.37	4.40
2016	0.56	-0.24	0.92	0.25	33.32	21.59	45.90	3.44
2017	0.58	-0.31	0.92	0.25	30.86	15.68	44.15	4.15
2018	0.55	-0.26	0.88	0.24	30.57	10.93	44.45	4.99
2019	0.57	-0.30	0.91	0.24	32.41	11.47	44.58	4.28
2020	0.50	-0.28	0.88	0.25	26.11	11.22	40.76	6.96

Table 2 shows the area of 10 levels of LTS in the study area. The areas with the temperate range from 29 to 37^{0}C account for the most extensive area of the years. The years (2016, 2019, 2020) were recognized as the drought years so that regions with higher temperatures (36^0 C to 37 ^{0}C) increased.

Table 2. Area of LST values in the study area

Year	Temperature (^{0}C)									
	< 29	29-31	31-33	33-35	35-36	36-37	37-38	38-39	39-40	> 40
2015	72.1	689.9	623.3	446.4	139.6	86.8	51.6	33.4	18.4	18.9
2016	4.3	162.5	493.3	618.7	278.6	225.9	157.1	102.1	60.2	71.6
2017	973.7	167.3	437.5	318.6	103.4	73.4	49.0	27.0	14.7	16.0
2018	19.6	307.7	598.5	648.1	237.1	164.3	97.5	51.6	25.6	27.5
2019	1.4	81.6	442.4	708.8	290.3	231.9	171.2	112.1	64.7	76.4
2020	52.0	144.5	503.7	687.4	264.2	201.5	143.1	91.2	49.5	43.8

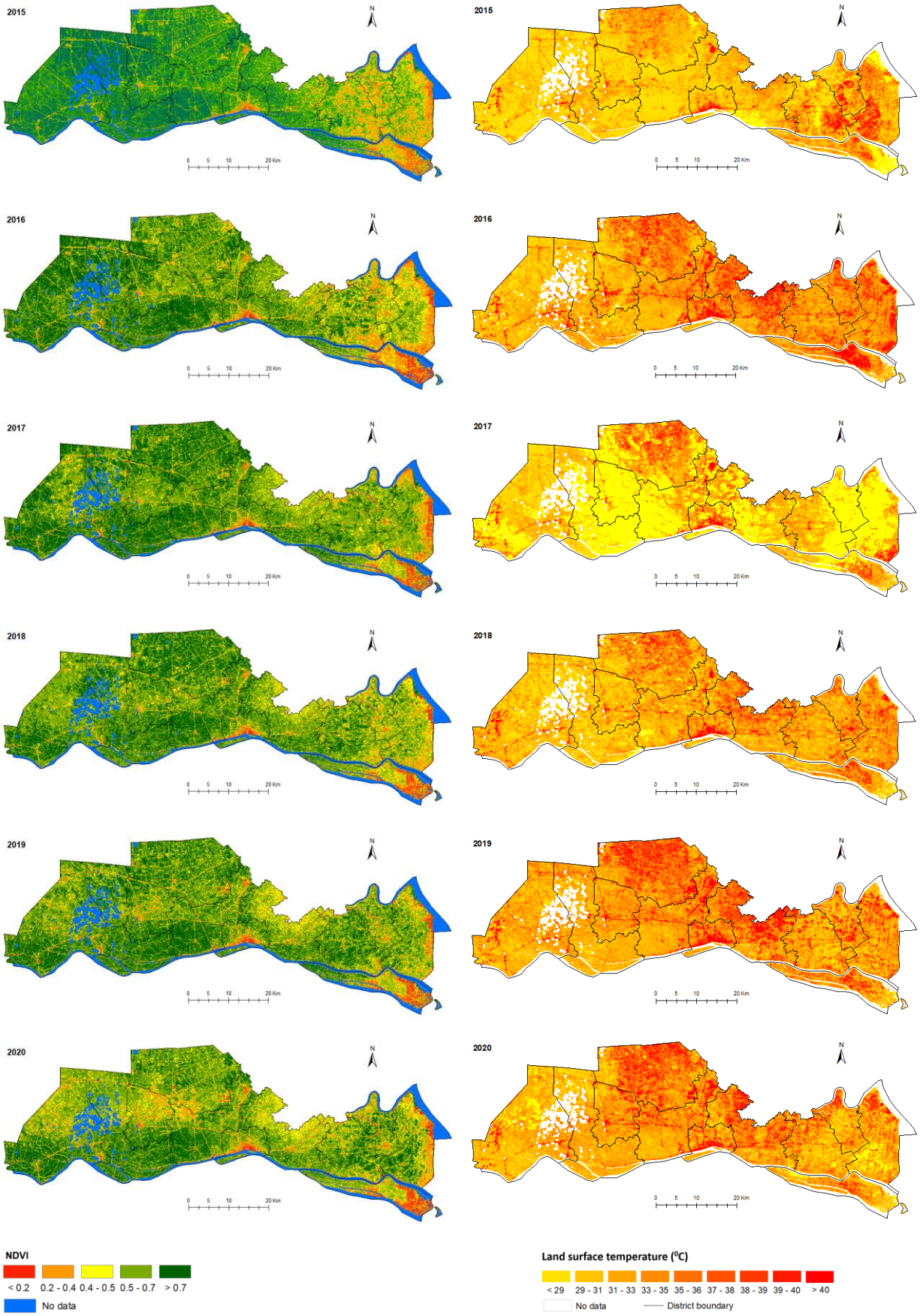

Figure 2: NDVI (on the left side) and LST (on the right side)

Figure 2 depicts the NDVI (on the left side) and LST (on the right size) over the study period from 2015 to 2020. In general, the NDVI value less than 0.4 (color from dark yellow to red-orange) concentrated on the east of the study area. The LST maps also have the similar trend with the dark yellow to red settled in the eastern regions where belong to Go Cong Dong, Go Cong, Tan Phu Dong districts in 2015. From 2016 to 2020 the high-temperature area (value more significant than 33 ^{0}C) expanded to other neighborhoods like Go Cong Tay, Cho Gao, My Tho, Chau Thanh, Tan Phuoc. The highest temperature areas may be closely related to the shortage of fresh water in the dry season of the years.

3.2. Computed Vegetation Condition Index

Figure 3 shows the map of VCI in the study area in the 2015- 2020 period. The yellow to red color indicates the drought status. The drought areas are mostly concentrated on the coastal districts such as Go Cong Dong and Tan Phu Dong District. The VCI lower than 40% scatters in other regions such as Cho Gao, Tan Phuoc, Chau Thanh districts, Cai Lay ward, and My Tho city. The reason may go together with the urbanization in these regions.

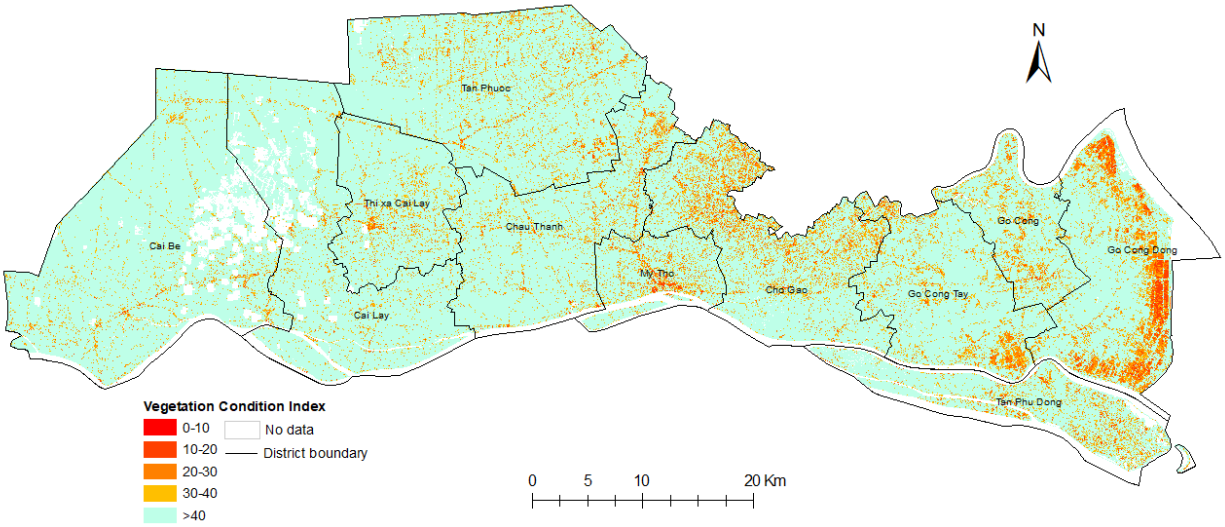

Figure 3. The map of six successive years (2015 - 2020) of VCI value integrated with Tien Giang province's rough district boundary map to show the drought augmented the vegetation water-stressed area in Go Cong Dong district and the neighboring districts.

Table 3. Area of vegetation condition index in the study area

Unit: km^2

	Level	Year					
		2015	2016	2017	2018	2019	2020
vegetation condition index	> 40	1680.05	1658.74	1867.86	1830.30	1740.56	1539.35
	0-10	15.03	35.27	20.89	13.10	19.83	35.93
	10-20	152.22	122.39	60.13	57.34	102.33	179.32
	20-30	152.89	159.87	95.29	110.23	142.07	196.65
	30-40	196.47	214.05	152.50	182.31	191.87	245.42

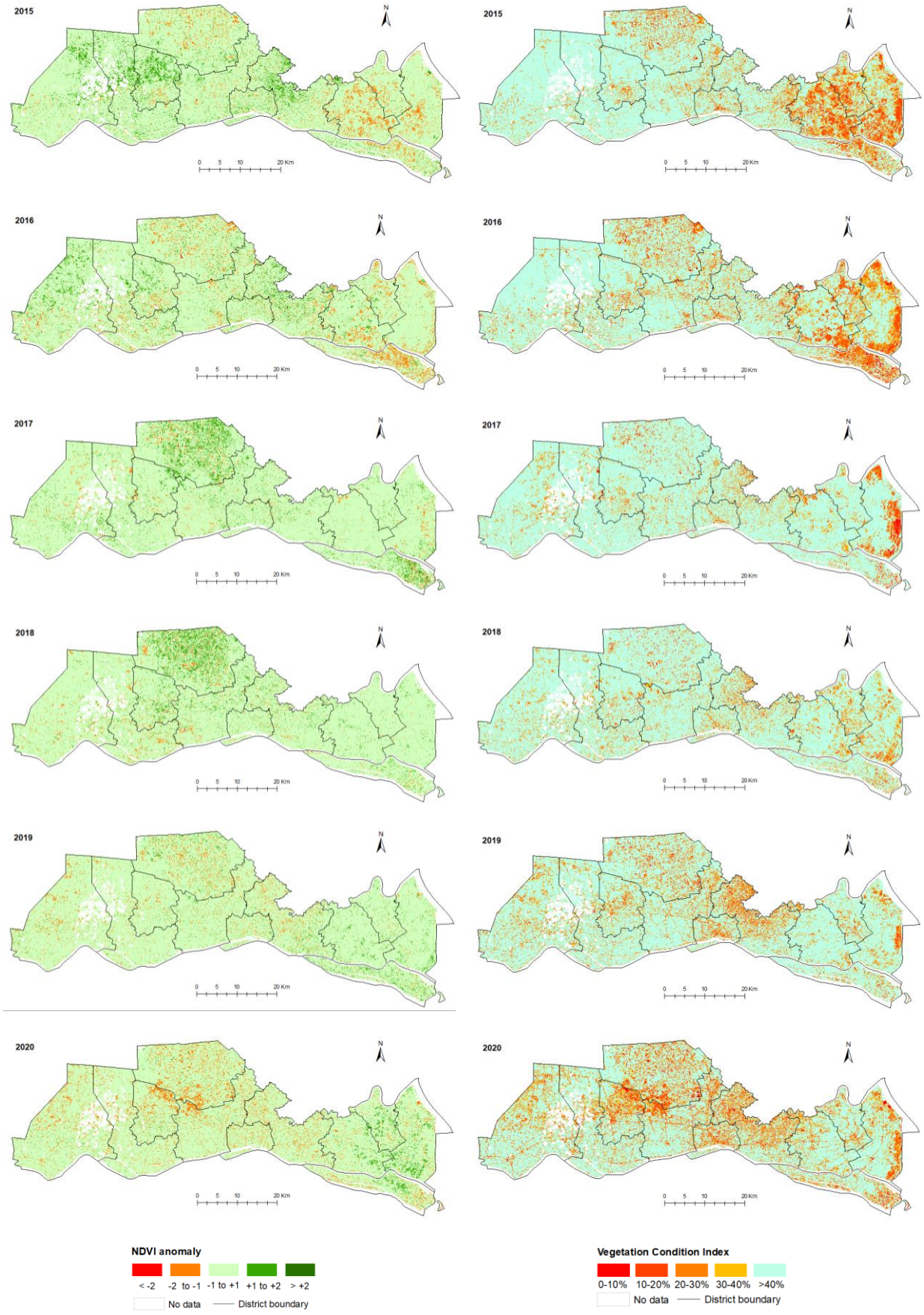

Figure 4. NDVI anomaly (on the left side) and VCI (on the right side)

3.3. Computed NDVI anomaly

NDVI anomaly is the difference between current NDVI and average NDVI over a long period. NDVI anomaly was calculated, extracted the area (in km^2) for each year in the study period are shown in Table 4 and depicted in Figure 4 (on the left side).

Table 4. Area of NDVI anomaly in the study area

Unit: km^2

Describe	Value	Year					
		2015	2016	2017	2018	2019	2020
Lower than normal	< -2	0.13	1.53	1.53	1.23	0.10	0.06
Light lower than normal	-2 to -1	132.8	161.4	62.8	75.0	108.9	209.4
Normal	-1 to +1	1909.1	1904.1	1980.8	1978.2	2009.4	1925.3
Light higher than normal	+1 to +2	152.8	121.4	148.8	135.6	78.01	61.6
Higher than normal	> +2	1.78	1.78	2.71	3.22	0.22	0.28

3.4. Compute the relationship between NDVI, VCI and LST

Correlation between LST as a predictor parameter and NDVI, VCI as a response parameter was built to determine whether there was a relationship between these parameters. Statistical results showed the Pearson's correlation coefficient between LST and NDVI by - 0.439 ($p< 0.01$), LST and VCI by - 0.483 ($p < 0.01$). These showed that there was negative relationship between LST and NDVI, VCI. In other words, the NDVI, VCI of vegetation regions in the study area were influenced by LST with estimated values of 44% and 48%, and the remaining 56% and 53% were influenced by other factors. The obtained regression equations were NDVI= - 0.0279.LST (^{0}C) + 1.5245, and VCI (%) = - 0.03261.LST (^{0}C) + 1.746208. Based on the regression equations, an increase in LST of 1^0C in the study area can decrease the NDVI by 0.0279 and VCI by 0.03261%.

4. Conclusion

This study used an integration method from band combination, conversion algorithms, machine learning classification, network computing technique via Google Earth Engine to retrieve NDVI, LST, and VCI from Landsat 8 data. The LST spatial distribution patterns and the vegetation stress water area in the study area were depicted by VCI value. The estimated land surface temperature was higher than the station air temperature measurement in 2015.

During the study period, the high LST area (LST > 35 ^{0}C) and low VCI (< 40%, light to extreme drought levels or drought area) have scattered patterns. While the high LST area concentrated on the center area (e.g., My Tho, Tan Phuoc) and along with the main road system, the moderate LST areas (LST > 31^0C to LST ≤ 35^0C) and drought areas distributed from the middle to the east coast district zones. The study also found a large proportion of vegetation getting water stress (VCI <40%) over drought areas in the Go Cong Dong district.

The random forest classifier afforded a high overall accuracy (97.4%) when applying to categorize the relatively complex land use of the study area. The high accuracy classified map was used to identify the correlation of indices according to the land cover type. There was a negative linear relationship between LST and NDVI, VCI with a correlation coefficient between LST and NDVI by - 0.439 ($p< 0.01$), LST and VCI by - 0.483 ($p< 0.01$) for the vegetation region of the study area in the 2015-2020 period. An increase in LST of 1^0C in the study area can decrease the NDVI by 0.0279 and VCI by 0.03261%. Above all, the NDVI, VCI, and LST indices and derived correlation between them are helpful to expose and judge the agricultural drought for the study area in the further analysis.

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