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Monitoring Drought Using Spectral Drought Indices: A Case Study Canaan Forest Area, Diyala, Iraq

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Abstract

Drought determination is essential for many environmental and agricultural applications. To further understand drought, this study presented the spatio-temporal variations of drought based on the Landsat 8 index as a vegetation condition index (VCI)., vegetation health index (VHI), Thermal condition index (TCI), Water Supply Vegetation Index (WSVI) and normalized vegetation indices (NDVI) in the Canaan forest (mana-made forest) area within the administrative boundaries of the Canaan district of Diyala Governorate for the years 2016, 2019 and 2023.The results showed a clear difference between the years of study in terms of the spatial distribution of drought degrees (very severe, severe, moderate, light and non-dry). The NDVI maps also showed that there is a clear decrease in the density and areas of vegetation cover in the study area due to drought, which requires taking the necessary precautions to reduce the negative effects of drought with the help of remote sensing techniques because they shorten time and cost. According to NDVI, the vegetation cover occupied an area of 7.438 km^2 for the year 2016, while the area of 5.735 km^2 was for 2023. The Extreme Drought class occupied an area of 44.180 km^2 in 2016, while it was 44.250 km^2 in 2023 according to the VCI. In general, the year 2023 was drier than the rest of the study years.

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Introduction

Drought is a dangerous phenomenon and ranks first among all natural hazards affecting humans worldwide. The risk of drought increases slowly, which often accumulates over a long period and may continue for years after its end. It has been recognized as one of the sensitive environmental disasters affecting the natural ecosystem, agriculture and hydrological systems (Baniya *et al*., 2019). Drought can damage ecosystems and economies, leading to population displacement. Moreover, persistent drought also encourages desertification and land degradation, which is particularly detrimental to vulnerable landscapes and consequently soil degradation and vegetation cover (Ayad *et al*., 2023; Tran *et al*., 2017)

Droughts occurring on agricultural land can be broadly divided into climatic, agricultural, hydrological and socio-economic droughts (Sugianto *et al*., 2023; Rosalena *et al*., 2019). Drought resulting from climatic conditions (climatic drought) is the most important and dangerous type of drought, which has a direct impact on aspects of human life (Bageshree *et al.*, 2022). Remote sensing technologies make it possible to collect large amounts of accurate information over large areas and on different spatial and temporal accuracy scales. By characterizing the natural features of the

Earth and monitoring their changes over time, remote sensing applications can ultimately support policy-making on many environmental problems, including drought, at different scales (Hammad and Falchetta, 2022; Moesinger *et al.*, 2022).

In places with a limited number of sampling devices, remote sensing data may be the only available source of information for drought monitoring because it is difficult to assess drought expansion, severity and environmental impacts over a specific period, so drought is usually identified through drought indicators (Liu *et al*., 2016), drought indices derived from satellite data such as the Normalized Difference Vegetation Index (NDVI) and the Vegetation Condition Index (VCI) have been used over a wide range to detect drought onset and measure drought severity, duration and impact globally (Jiao *et al*., 2016). Another important indicator for drought monitoring is the Water Supply Vegetation Index (WSVI), which was used by Jain *et al.* (2010) to monitor drought in three districts of Rajasthan Province in India for the period 1981-2004 based on satellite data of The National Oceanic and Atmospheric Adminis sensor (NOAA) as well as Advanced Very High- Resolution Radiometer (AVHRR), and the study found that the region was the most affected by drought in 2002. This was validated of the basis of NDVI, WSVI, and VCI and the study clearly shows that the integrated analysis of measured data on the ground and satellite data has great potential in drought monitoring.

The vegetation health index (VHI) is one of the most popular drought monitoring indicators derived from remote sensing data. VHI is based on two indices (VCI) and thermal condition index (TCI). The VHI index takes into account local biophysical and climatic conditions and can be used to monitor actual plant drought in different agricultural areas (Zeng *et al*., 2023). The VHI index has been used by many researchers to monitor and control drought, including Jiang (2021) in the Jing-Jin-Ji region of China for the period 1982-2016 and the results were considered to be of great importance for assessing vegetation growth activity, monitoring and measuring drought in the study area using satellite-based VHI. In his study on agricultural drought monitoring for Southeast Asia, Ha *et al*. (2023) indicated that the use of drought indicators provides valuable information for drought early warning management and agricultural planning for the study area of 2 million square kilometers, as it used MODIS satellite data for the period 2000-2021, through which NDVI, VCI and Land Surface Temperature (LST) were calculated.

The Canaan Forest area is characterized by the diversity of land covers, which includes vegetation cover (forest trees and orchards), unexploited agricultural land, exploited agricultural land, buildings, facilities and barren lands (Khalaf, 2019), and the areas and proportions of these covers have changed for several reasons, including drought, global warming, lack of water resources and migration from the countryside to the city. This study aimed to test the efficiency of spectral indicators derived from remote sensing data in drought monitoring in the Canaan Forest area and thus the possibility of using these indicators in drought monitoring and placing them within drought monitoring and management programs to formulate effective management to combat the catastrophic effects of drought.

Materials and Methods

Study area

The Canaan Forest area is located within the administrative boundaries of the Canaan district in the eastern part of the sedimentary plain south of Diyala Governorate, northeast of Baghdad, the capital of Iraq, the area is almost flat and interspersed with some few altitudes, and these heights were formed due to old irrigation channels, and the general slope in the region from the north and northeast towards the south and southwest (Abdul Sattar and Kazem, 2020). Its coordinates extend between latitudes 33º 32'50"-33º 40' 22" longitude 44º 49' 29"-44º 54' 50" with an area of 115.592 km2 (Figure 1).

The study area is characterized by the diversity of land covers, in which wheat grains are cultivated, palms and fruit trees abound, and artificial forests were established for preventive purposes with an area of 500 hectares in 1979, but they have been degraded over time due to natural conditions such as climate changes (global warming, drought ... etc) and human conditions (wars, migration from the countryside to the city). The natural vegetation in the region is few, because the prevailing climatic conditions are characterized by a lack of rain and fluctuating quantities from year to year, and the high temperatures during the summer and their decrease during the winter made the conditions of natural plants vary in time and space in the region (Al-Jubouri and Maher, 2019) .

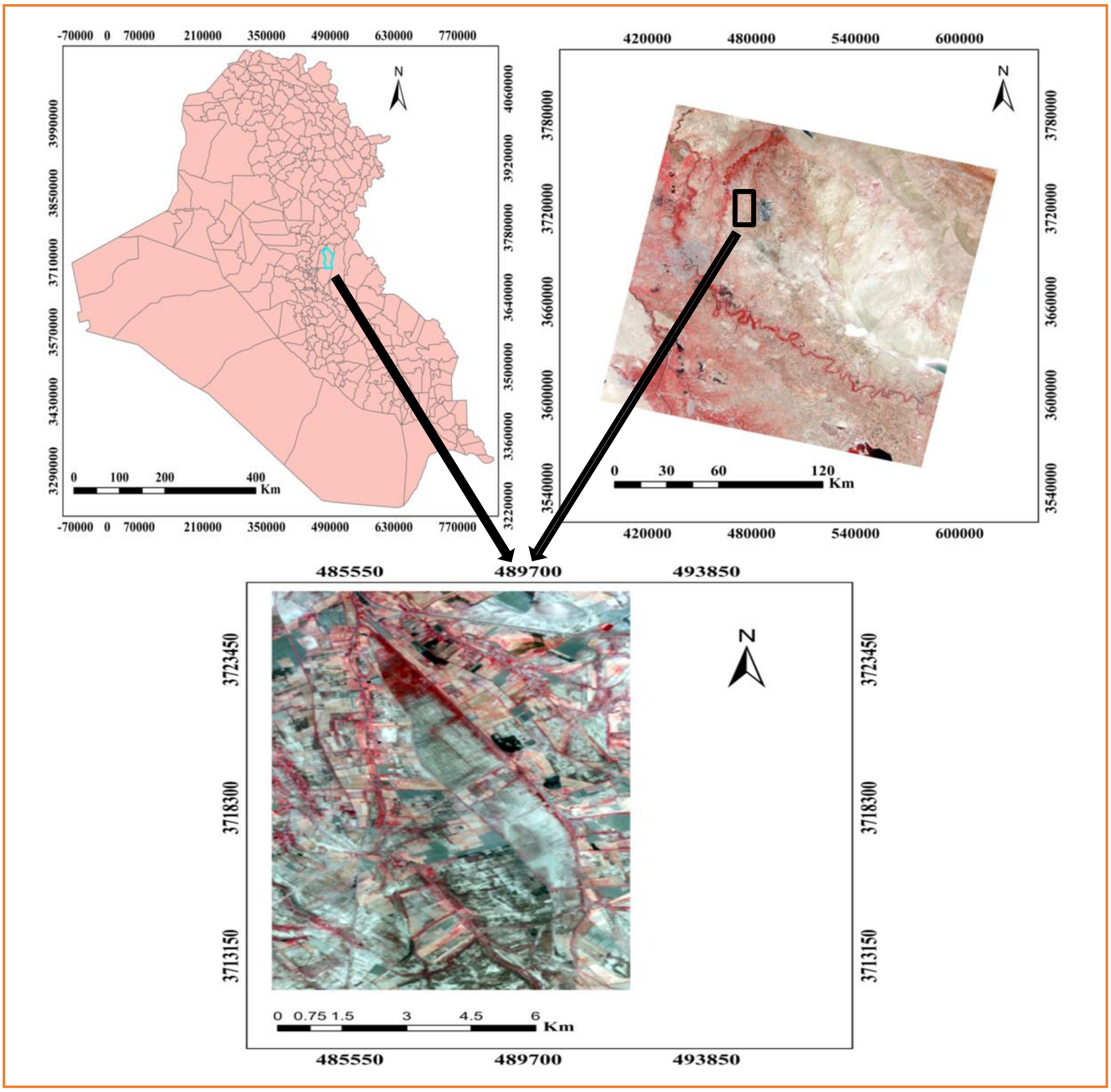

Figure 1. The study area is part of the map of Iraq and the satellite image of the satellite Landsat 8

Satellite data

In this study, 3 Landsat 8 satellite data for the years 2016, 2016 and 2023 were used, from which the spectral indices used in the study were derived after processing operations using ArcGIS Pro 2.8.6 and Erdas Imagine 2022 software. As a process, the process of merging or aggregating the bands was performed to obtain A satellite image covering the study area, from which the spectral index used was derived according to the study area, the specifications of the satellite images used in the study were listed in Table 1.

Table1. Satellite images used in the study

The satellite	Sensor	Path	Row	Acquisition Date
Landsat 8	OLI_TIRS	168	37	18/07/2016
Landsat 8	OLI_TIRS	168	73	27/07/2019
Landsat 8	OLI_TIRS	168	37	22/07/2023

The index used in drought monitoring in this study is one of the most important used globally (Duduzile, 2022) its listed in Table 2.

Table 2. Spectral index used in the study

No.	Index	Description	Formula	Reference
1	NDVI	Normalized Difference Vegetation Index	NDVI= NIR-RED / NIR+RED	(Mancino *et al.*, 2014)
2	VCI	Vegetation Condition Index	$VCI=(NDVI-NDV_{Imin}) / (NDVI_{max}-NDVI_{min}) *100$	(Kogan *et al.*, 2004)
3	TCI	Temperature Condition Index	TCI= (LST-LSTmin) / (LSTmax-LSTmin) *100	(Kogan *et al.*, 2004)
4	VHI	Vegetation Health Index	VHI= 0.5*VCI+0.5*TCI	(Kogan *et al.*, 2004)
5	WSVI	Water Supplying Vegetation Index	WSVI = NDVI/LST	(Alsaikh, 2015)

The index used in the study relied in its derivation on the relationship with its pants, which was based on the satellite image, as in Figure 2.

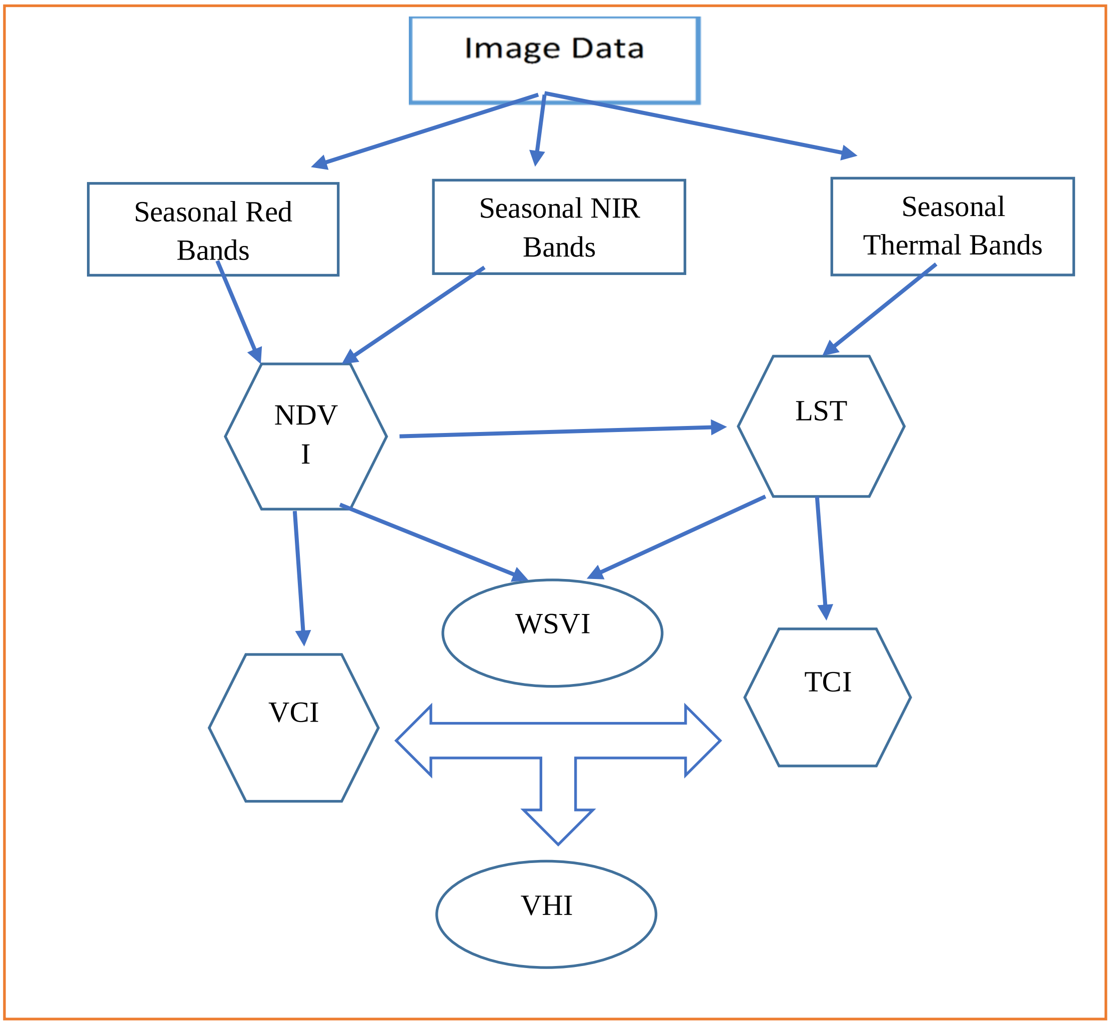

Figure 2. Flowchart for satellite image processing, analysis and evidence derivation

Results and Discussion

"Normalized Difference Vegetation Index (NDVI)"

Drought patterns in the study area were analyzed during the study years (2016-2019, and 2023) using the Vegetation Index (NDVI) approach which can be used as an indicator of the level of plant activity during the growing season. Several studies have shown that the NDVI index is associated with leaf area, green biomass, green cover percentage, and part of the active radiation absorbed by light. Furthermore, the NDVI index is a global vegetation index (Erasmi *et al*., 2021).

Spaces were extracted for the study area and for the selected years. As shown in Table 3, the values of the NDVI index were divided into 4 sections as mentioned (Al-Juraysi, 2013) and the value between barren soils and vegetation cover was 0.2 the areas were calculated for all years, so the variation was very clear due to the general weakness in the presence of vegetation cover for all years, Figure 3. The highest area of barren land in 2016 was 38%, while the area percentage was 30% is the lowest for this class in 2019, while the dry soils category occupied the largest area in 2019 with a percentage of 42%, while the lowest area of this category was recorded 36% in 2016, while the vegetation category included the third and fourth classes, and its values were very low in all years of study.

The third variety, which is light vegetation cover, recorded the highest area of 26.016 km2 by 23% and was in 2023, and in 2016 the lowest area was recorded at 22.943 km^2 and amounted to 20%, while the fourth variety, which is dense vegetation, had the lowest area in 2023 amounted to 5.735 km^2 and by 5%. From the above, it is clear that sovereignty is for the first section, with its two categories, barren lands and dry soils, and this indicates that the study area is very poor vegetarian and caused by the lack of rain as well as high temperatures, and human activity may be helpful in this (Furusawa *et al*., 2023).

Table 3. The NDVI index areas and ratios in the study area

NDVI Classes		2016		2019		2023	
		Area .km^2	**%**	**Area .km^2**	**%**	**Area .km^2**	**%**
Barren Lands	<0.1	43.797	38	35.016	30	37.236	32
	0.1-0.2	41.415	36	48.503	42	46.606	40
Vegetation Cover	0.2-0.3	22.943	20	25.404	22	26.016	23
	4<	7.438	6	6.669	6	5.735	5
		115.592	100.00	115.592	100	115.592	100.00

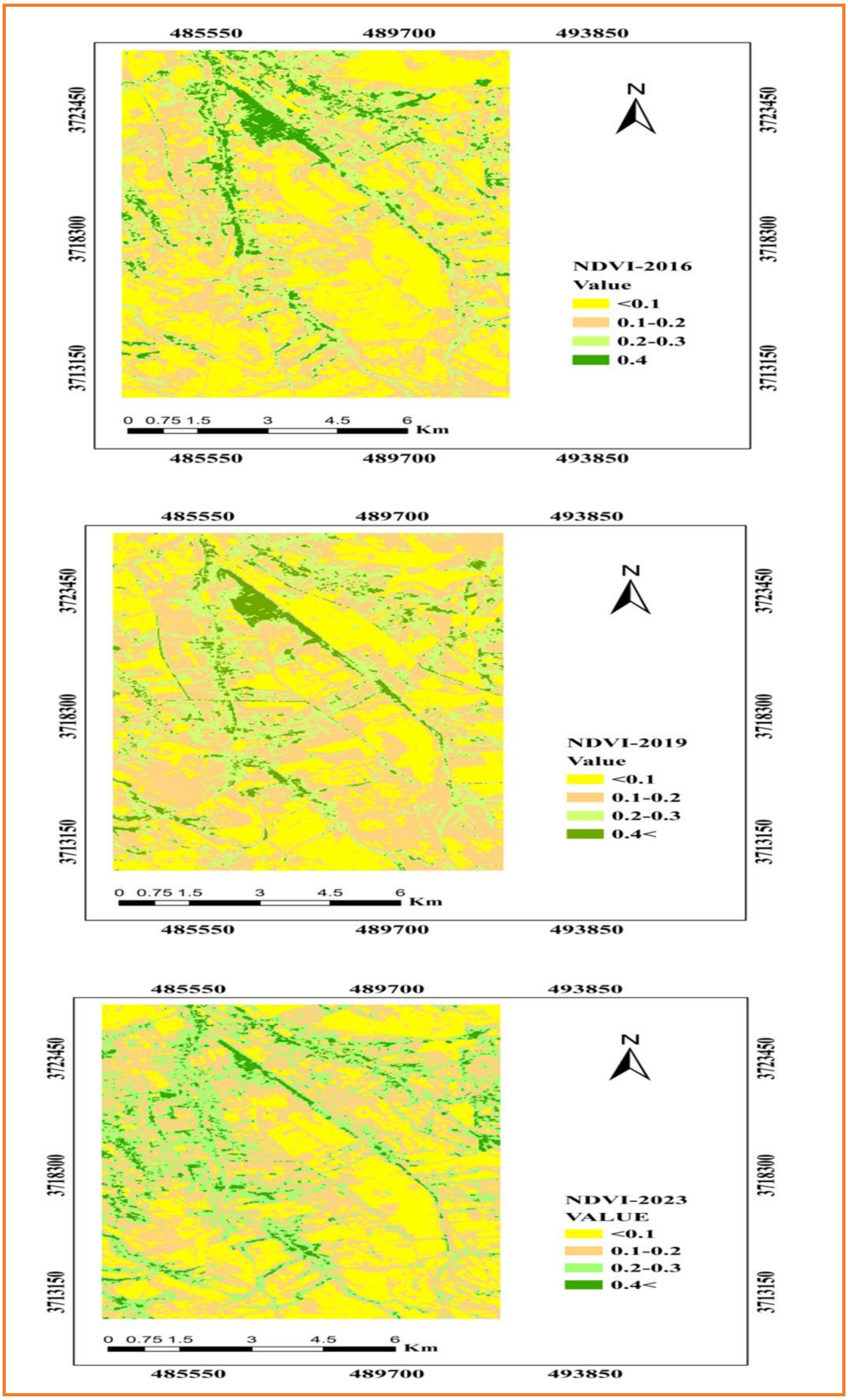

Figure 3. Maps of the study area according to the NDVI index for years of study

"**Vegetation Condition Index (VCI)**"

The use of VCI is a convenient tool to assess and analyze drought conditions using satellite images, the value of VCI is expressed as a percentage ranging from 1 to 100. A value between 50% and 100% indicates that vegetation is in good condition, while a value between 50% and 35% indicates that vegetation is in a state of drought, and a value of less than 35% indicates that vegetation is in a state of severe drought (Srinivas *et al.*, 2022). The low value of this indicator gives an indication of water stress and poor vegetation cover of the studied area. In our study, the values of this indicator were divided into five sections, as illustrated by Al-Zwbaidi (2015), Extreme drought, severe drought, moderate drought, Light Drought and No Drought (Table 4).

Table 4. VCI index varieties and area in the study area

VCI Classes	2016		2019		2023	
	Area.km^2	%	Area.km^2	%	Area.km^2	%
Extreme Drought	44.180	38	28.741	25	44.250	38
Severe Drought	20.066	17	10.966	9	17.510	15
Moderate Drought	18.160	16	11.239	10	17.399	15
Light Drought	14.111	12	10.747	9	14.400	12
No Drought	19.076	17	53.899	47	22.033	19
	115.592	100	115.592	100	115.592	100

From Table 4, we find that the highest area of the Extreme Drought variety was (44.250 km^2) for the year 2023 and by 38%, which indicates the impact of climate change more than the rest of the study years, while the highest area (53.899 km^2) was for the No Drought variety for the year 2019 and by 47%, due to rainfall and the abundance and activity or growth of vegetation cover to a better degree than the rest of the study years.

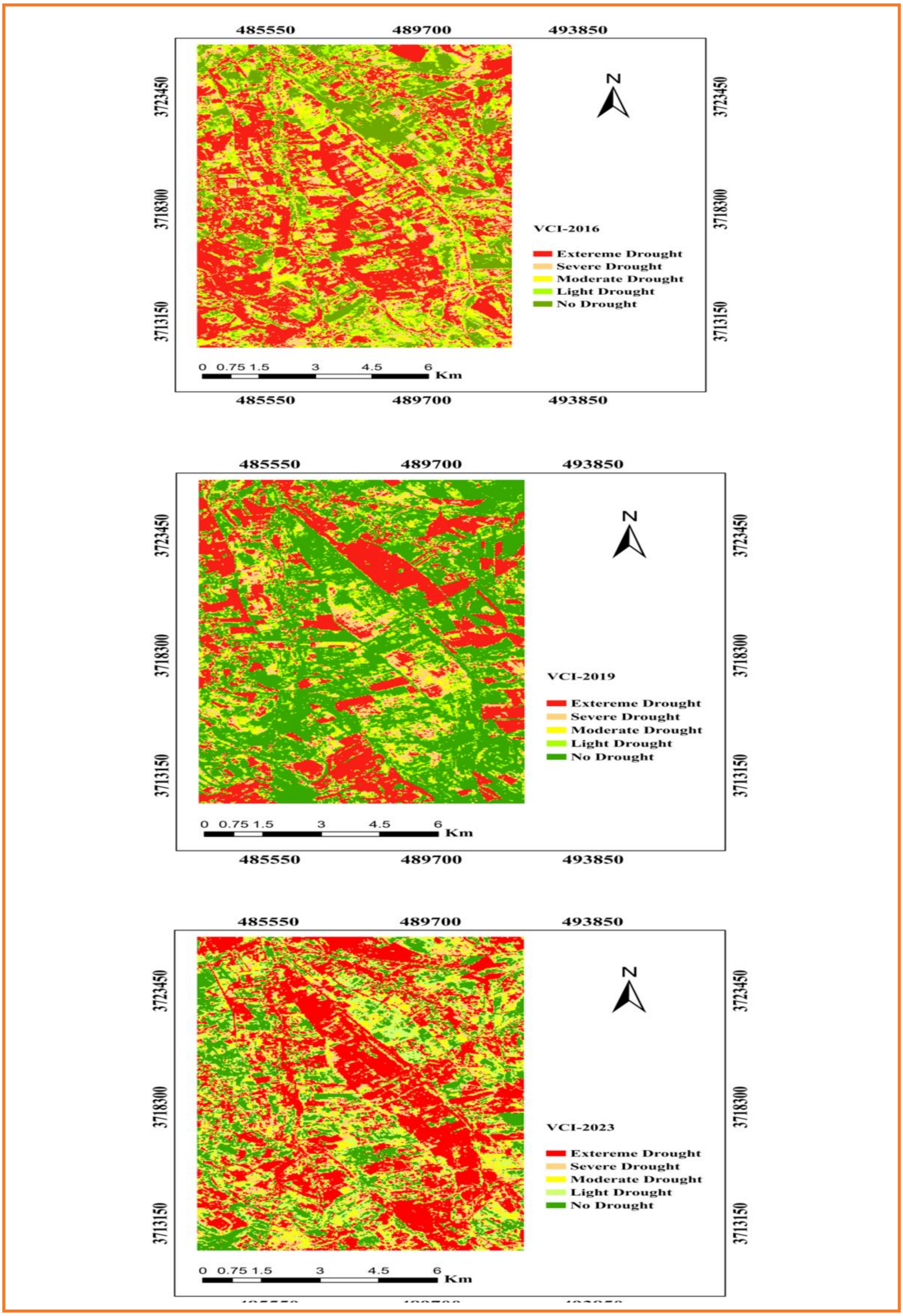

Figure 4. VCI index maps for the study area

"Temperature Condition Index (TCI)"

This indicator represents the state of heat stress affected by the study area for the selected years. The TCI index was classified into five categories: Extreme Drought, severe drought, Moderate Drought, Light Drought and No Drought, Table 5.

Table 5. Types of the TCI index and their area in the study area

TCI Classes	2016		2019		2023	
	Area.km^2	%	Area.km^2	%	Area.km^2	%
Extreme Drought	6.524	5.6	1.880	1.6	115.340	99.8
Severe Drought	15.872	13.7	5.239	4.5	0.109	0.1
Moderate Drought	20.670	17.9	8.486	7.3	0.075	0.1
Light Drought	25.175	21.8	13.053	11.3	0.043	0.0
No Drought	47.352	41.0	86.935	75.2	0.025	0.0
	115.592	100	115.592	100	115.592	100

The results shown in Table 5 the highest area of 115.340 km^2 of the Extreme Drought variety was for the year 2023 and the lowest area was 1.880 km^2 for the year 2019, while the fifth variety showed the highest percentage and area of 75.2% and 86.935 km^2 respectively. These results indicate the direct effect of temperature on vegetation cover and thus its exposure to heat stress and drought in proportions that vary from year to year, which showed in our study its peak effect in 2023 within the first class, and this is consistent with the findings of Liu *et al.* (2016). To represent the spatial distribution of the TCI index, the maps shown in Figure 5 are derived.

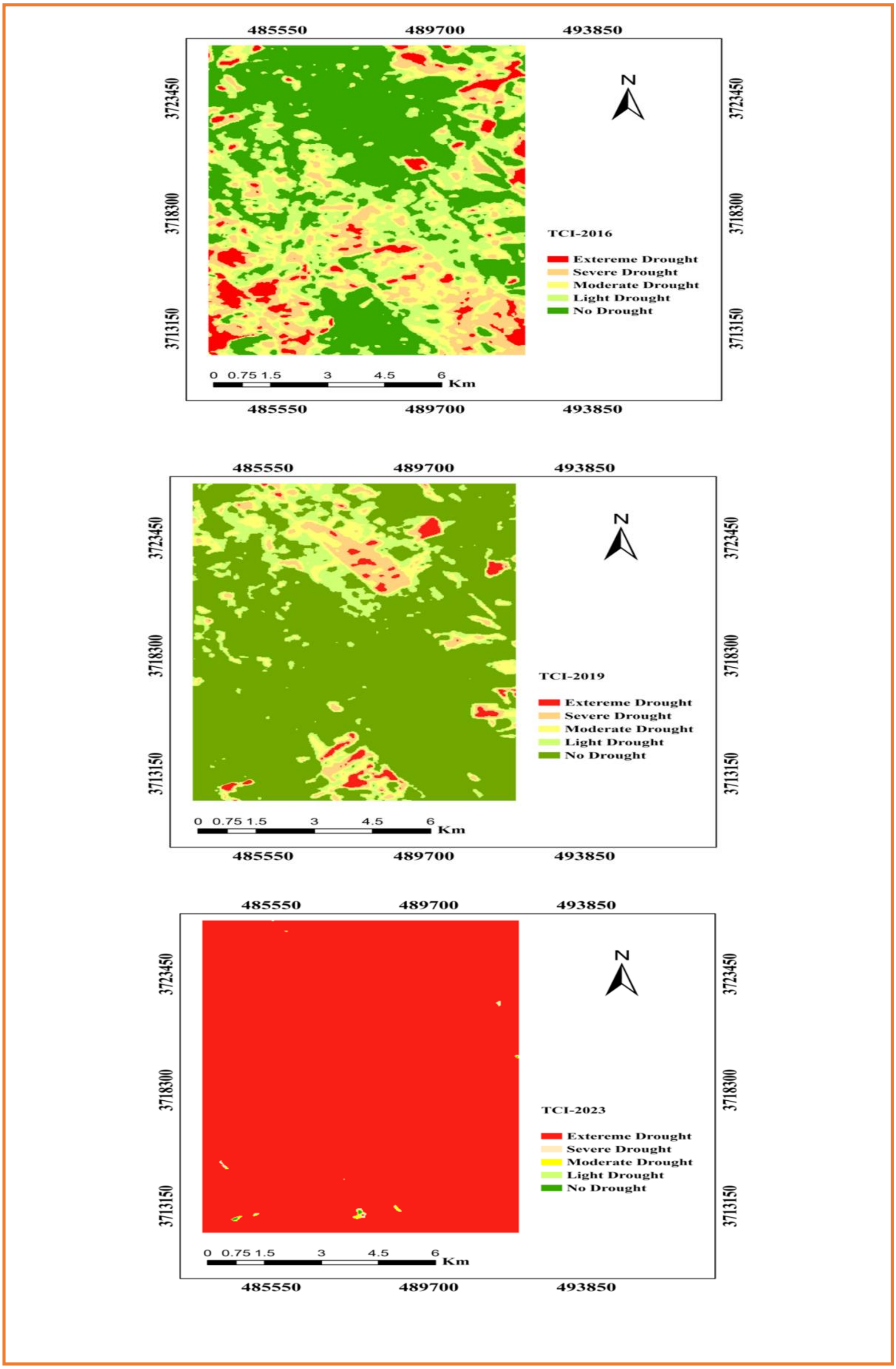

Figure 5. TCI index maps for the study area.

"Health Vegetation Index (VHI)"

The VHI index, derived from satellite data, can be used to monitor humidity, temperature and vegetation health conditions, in addition to drought, the VHI index refers to the combination of VCI and TCI for overall phytosanitary assessment (Kogan *et al.*, 2013) .Table 6 shows the variability of drought-affected areas according to this indicator, which indicates phytosanitary in the study area.

Table 6. Varieties of the VHI index and their area in the study area

VHI Classes	2016		2019		2023	
	Area.km^2	%	Area.km2	%	Area.km^2	%
Extreme Drought	43.989	38	28.584	25	44.212	38
Severe Drought	19.706	17	11.150	10	17.638	15
Moderate Drought	18.107	16	11.459	10	17.214	15
Light Drought	13.911	12	10.795	9	14.376	12
No Drought	19.880	17	53.604	46	22.153	19
	115.592	100	115.592	100	115.592	100

It is noted from Table 6 that the largest area of the first variety (Extreme Drought) was 44.212 km2 for the year 2013, which indicates the seriousness of climate change, especially drought and its impact on the health of vegetation cover, which requires taking appropriate measures to reduce the impact of drought to a minimum. For the year 2016, the second and third classes occupied the largest areas, which were 19.706 km^2 and 18.107 km^2 respectively. The largest area of the fourth class was for 2023, as it amounted to 14.376 km2, while the fifth class (No Drought) occupied in 2019 the largest area of 53.604 km2 by 46%. From the above, we find the fluctuation of areas and proportions of drought varieties for the years of study, and this is related to climatic conditions (humidity and temperature in the first place) and the availability of other water resources (wells for example), which negatively or positively affects plant health, and this is consistent with the findings of Bageshree *et al.* (2022). Figure 5 represents the VHI maps of the study area, which corresponds to Table 4 in terms of the spatial distribution of the five classes.

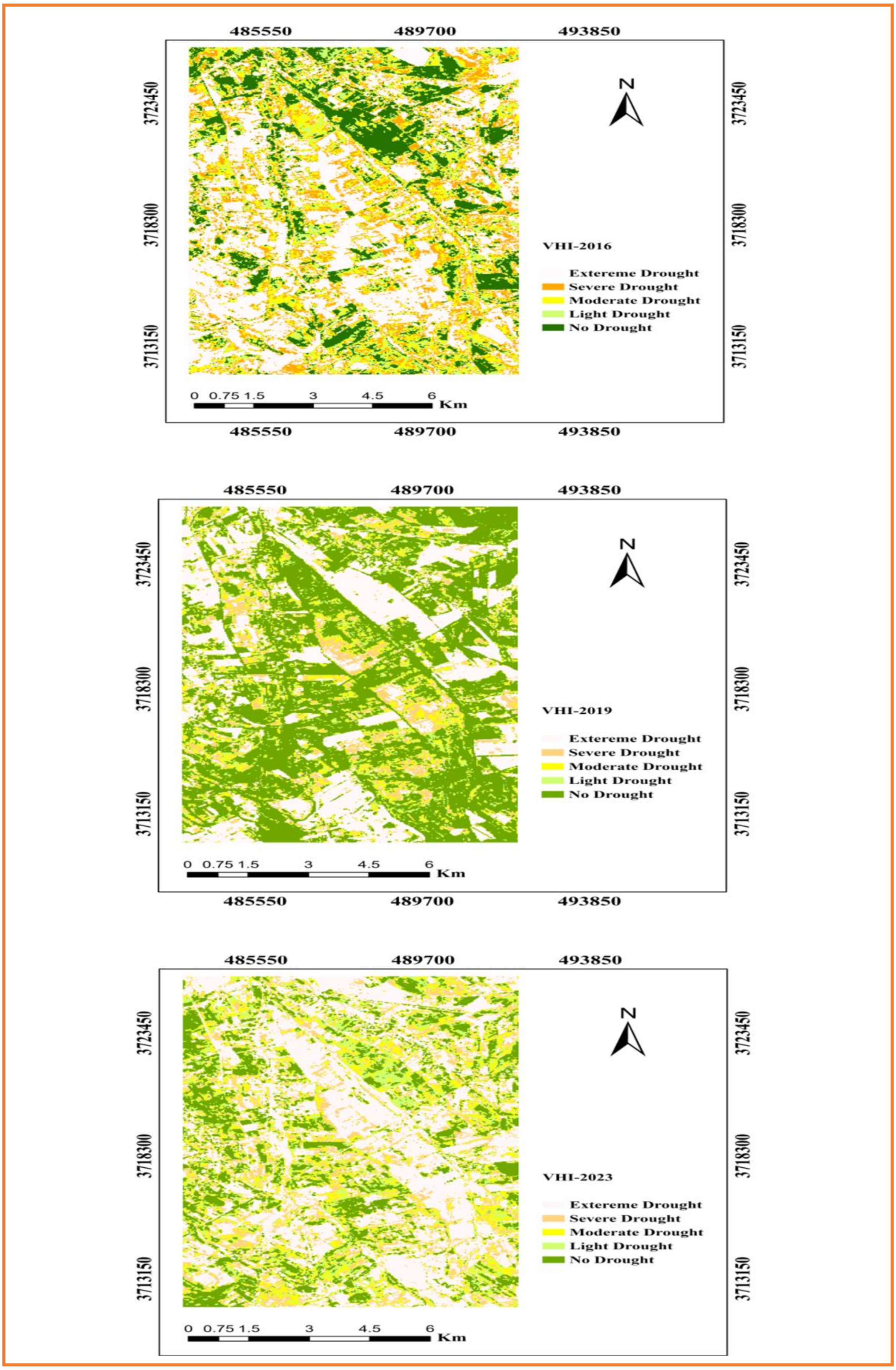

Figure 6. VHI maps of the study area

"Water Supplying Vegetation Index (WSVI)"

The WSVI was developed to collect NDVI and LST data to detect the humidity condition (Alsaikh, 2015). The study area was classified based on the WSVI index into four categories: areas with severe drought, areas with moderate drought, areas with mild (slight) drought and areas with no drought as shown in Table 7.

Table7. WSVI index varieties and area in the study area

WSVI Classes	2016		2019		2023	
	Area.km^2	%	Area.km^2	%	Area.km^2	%
Severe Drought	50.544	43.7	39.099	33.8	40.749	35.3
Moderate Drought	38.917	33.7	47.927	41.5	45.801	39.6
Light Drought	20.825	18.0	22.981	19.9	23.900	20.7
No Drought	5.306	4.6	5.586	4.8	5.143	4.4
	115.592	100	115.592	100	115.592	100

The results obtained from the analysis of satellite visualizations for the years of study, as shown in Table 7, indicated the heterogeneity of the drought situation between these varieties. As the variety Severe Drought recorded the highest area 50.544 km^2 and the highest percentage 43.7% for the year 2016, while the Moderate Drought variety recorded the highest value for the area and percentages for 2019, and the Light Drought variety recorded the highest area 23.900 km^2 for the year 2023, while the No Drought variety recorded the lowest area 5.143 km^2 for the year 2023, which indicates the occurrence of a state of hydrological drought for the study area, which is increased by the lack of rain. Figure 7 shows the WSVI maps.

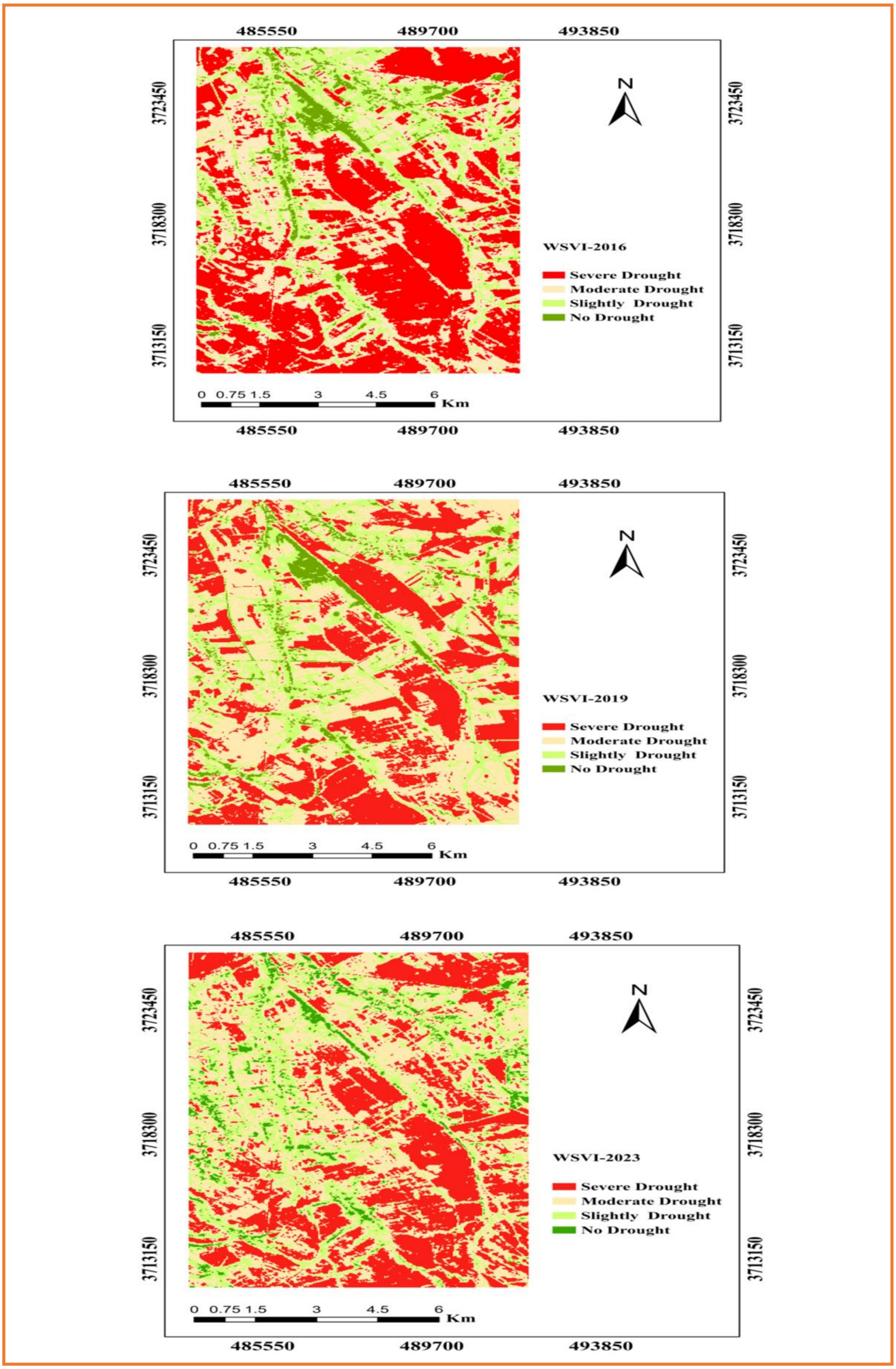

Figure 7. WSVI index maps for the threshing area

From the above, we find that the natural and human conditions that helped drought, if they continue in this way or pattern, will have a negative impact on the environment in general and vegetation in particular, which requires taking the necessary measures to preserve the environment in a sustainable manner.

Conclusions

The results indicate the importance of using remote sensing techniques in monitoring drought because it reduces time, effort, and cost. Analysis of the current challenges in monitoring agricultural drought revealed future research horizons for monitoring agricultural drought, such as studying the direct effects of agricultural drought, identifying factors affecting agricultural drought, developing multiple temporal and spatial measurement models for monitoring agricultural drought, and qualitative and standard coupling to agricultural drought. As well as preparing quantitative assessment models for agricultural drought, and improving the levels of application of remote sensing data in monitoring agricultural drought. It should provide sufficient information to monitor drought and mitigate its effects, especially in areas where agriculture is widespread in semi-arid climates. To improve drought monitoring and forecasting, broad studies can be conducted using remote sensing data from different sources and a variety of drought indicators in the study areas.

Conflicts of Interest

The authors declare there are no conflicts of interest among all authors.

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