

# Identification of irrigated olive growing farms using remote sensing techniques

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**Abstract** In spite of water scarcity problem in Tunisia, irrigation strategy was adopted and supported by the government. In addition, the introduction of the irrigation in olive sector was also encouraged because it will be the way for maintaining the production of this strategic product. Therefore, the main objective of this work is to detect irrigated and non-irrigated olive growing farms using remote sensing techniques which can be useful to establish efficient and sustainable strategy of water resource management. This study was conducted in olive growing farms of 04 regions (Bouhajla, Nasrallah, Chebika and Oueslatia) in Kairouan prefecture. To monitor the irrigated olive growing farms, we used multi-temporal Landsat 8 imagery from June to September 2015 which were processed to obtain specific vegetation indices such as RVI (ratio vegetation index) and NDVI (Normalized Difference

Vegetation Index). Moreover, LST (Land Surface Temperature) and BT (Brightness Temperature) are produced to assess temperature. To drought monitoring, VCI (Vegetation Condition Index), TCI (Temperature Condition Index), and VHI (Vegetation Health Index) were applied as indicators. The validation approach was based on the field survey and data collection. The main results of the study are the detection of irrigated and rainfed olive growing farms using specific vegetation indexes and indicators. The findings are validated by the field observations for checking the accuracy of the results. This study can be useful for stakeholders to detect the olive growing farms which can be helpful to estimate the olive production.

**Keywords** Olive growing farms · Landsat 8 · Remote sensing · Irrigated and non-irrigated farms

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## Introduction

Agriculture sector is very important for developing countries as it has a social and economic impact. However, agriculture activities depend on several factors, which may lead to affect the production. Weather and climate extreme events such as droughts and floods can conduct to endanger seriously farmers' livelihoods and agriculture productions [3]. Moreover, the increase of temperature combined with the decrease of the rainfall average and the enhancement of occurrences of extreme events such as droughts and floods will threat strongly water resources in quantity and quality [7]. To reduce the risk of weather conditions, irrigation may contribute to reduce yield loss due to drought and water stress and consequently lead to maintain food security [15]. For this reason, water resource strategies are required. In fact, well-managed water resources have the capacity to

generate social and economic benefits. Moreover, water used for productive activities such as agriculture may lead to realize livelihood opportunities, generate income and contribute to economic productivity [23]. Indeed, irrigation may contribute to reduce yield loss due to drought and water stress and consequently conduct to stabilize production [15]. In critical situation of water, the challenge of irrigation managements is the use of water efficiently and effectively [18]. To maintain food security and to attenuate the effect of water scarcity, several adaptation measures are implemented at local, regional and global scale by governments. Due to economic and environmental purposes, countries suffering from water scarcity support strategies of sustainable water resource systems by the improvement of irrigation techniques [21]. For this reason, several innovative techniques and tools are applied in the management of irrigated agriculture and the improvement of the irrigation performance. In some studies, researchers have used the remote sensing techniques and Geographic Information Systems (GIS) for monitoring water resources [9, 18, 21]. Remote sensing tools are very useful for monitoring drought and for detection of water stress [16, 19]. Recently, the use of indicators generated from remote sensing datasets is employed for the assessment of vegetation and temperature conditions [6, 14]. In arid and semi-arid areas such as Tunisia, monitoring and controlling water resource is the main challenge for the government to reduce the effect of water scarcity and to provide water for users. To ensure food security and to preserve the yield of the main agriculture products, the government encouraged irrigated agriculture by the improvement of water access and the introduction of irrigation to lucrative products such as olive. Tunisia is the one of the main producers of olive and olive oil in the world. For this reason, irrigation is promoted to maintain olive yield. Some authors showed that a lack of water may affect vegetative olive growth [1]. Some researches applied remote sensing data such as thermal imagery to determine the canopy temperature and consequently to detect water stress in an olive orchard [19]. Thermal data are also applied to distinguish irrigated and rainfed olive orchards [20]. The authors emphasized on the impact of temperature data obtained Aster imagery to discriminate rainfed and irrigated olive orchards in same vegetation coverage condition. Moreover, vegetation health indices are also determined to supervise drought conditions and its effects on yield reduction [3]. Several studies focused on the application of remote sensing techniques to assess irrigate areas to classify land cover but few researches emphasize on the application of an approach based on a combination of several factors such as vegetation and temperature for monitoring irrigated and rainfed olive growing farms. Therefore, the objective of this work is the identification of olive irrigated and non-irrigated olive

growing farms using remote sensing techniques. This study can be useful to establish efficient and sustainable strategy of water resource management on the one hand and to predict the yield of olive production on the other. The next section (“[Materials and methods](#)”) starts with an overview of the methodological framework with the emphasis on study areas description and remote sensing data collection and processing followed by which the results are reported. The main outcomes of this research are discussed in the subsequent section. Final section deals with the conclusion of this work.

## Materials and methods

### Study areas

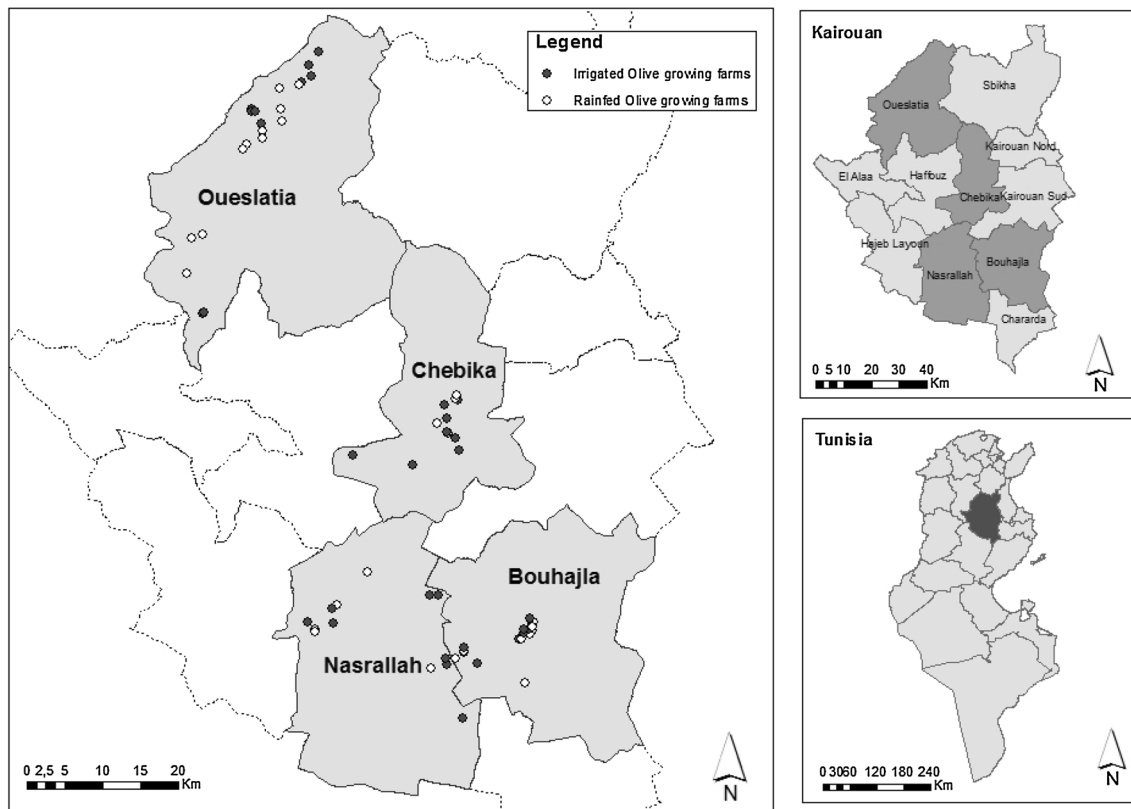
This study was conducted in olive growing farms of Kairouan prefecture, which is located in the central area of Tunisia. The climate is characterized by variability of precipitation and the average of rainfall is about 300 mm/year concentrated from October to January. Kairouan is one of the hottest prefectures in Tunisia. The highest temperature is recorded in July and August. This area is also marked by the increase of the frequency of drought.

During the period 2014/2015, total olive production is estimated to about 153 000 tons. Rainfed and irrigated olive trees represent about, respectively, 84 and 16 % of the whole olive trees [5]. The main cultivars in Kairouan are Chemlali and Oueslatia. Through our discussion with local stakeholders and following several factors such as cultivars, production and water access, 4 regions are selected as study areas: Bouhajla and Nasrallah as main producers; Chebika for irrigated areas managed by water user association; Oueslatia because it is distinguished by Oueslati Cultivar. About 65 rainfed and irrigated farms were visited randomly. Figure 1 shows the studies areas.

### Data collection and processing

#### *Data acquisition*

Multi-temporal medium resolution LANDSAT 8 imagery was used to archive temporal changes of NDVI (Normalized Difference Vegetation Index) and RVI (Ratio Vegetation Index) as well as LST (Land Surface Temperature) and BT (Brightness Temperature) for 2015. In fact, several scenes selected from June, July, August and September 2015 were included in this research. Data were chosen following three parameters: (1) period of our investigation field; (2) high intensity of drought due to summer season; (3) olive trees irrigation period to enhance fruit size and yield.



**Fig. 1** Study areas location

The used imagery was acquired by two different satellite sensors of LANDSAT 8 including LANDSAT OLI (Operational Land Imager) and LANDSAT 8 TIRS (Thermal Infrared Sensor) as shown in Table 1.

LANDSAT 8 OLI and LANDSAT 8 TIRS images were acquired from the USGS, NASA from Glovis (<http://glovis.usgs.gov/>).

*Field survey data*

The field data were collected during several field trips carried out throughout the year 2014/2015. The objective

of these investigations was the collection of information on olive farms (irrigated and rainfed farms). Four regions (Oueslatia/Chebika/Nasrallah/Bouhajla) of Kairouan prefecture were visited and we recorded ground truth points (GTPs) using GPS (Global Positioning Systems) to identify locations of different olive farm types. In fact, 65 GTPs were collected during the field survey in which 34 points were recorded as the location of irrigated growing olive farms and the rest (31) were identified as the location of rainfed olive farms. Figs. 2 and 3 represent, respectively, irrigated and rainfed olive trees.

**Table 1** Acquired satellite remote sensing data

Satellite sensor	Date of acquisition	Pixel size (m)	Path/row	Spectral resolution	Band used
Landsat 8 OLI	15 June	30	191/35	Multi-spectral (8 bands)	4, 5
	1 July				
	17 July				
	18 Aug				
	3 Sep				
Landsat 8 TIRS	15 June	100	191/35	Thermal (2 bands)	10, 11
	1 July				
	17 July				
	18 Aug				
	3 Sep				



**Fig. 2** Irrigated olive tree in Bouhajla



**Fig. 3** Rainfed olive tree in Bouhajla

### Data processing

Relevant indicators are generated from Landsat satellite images. In fact, remote sensing tools can provide large amount of data to avoid information gap [15]. These indicators will lead us to monitor vegetation condition as RVI and NDVI. However, BT (Brightness Temperature) and LST (Land Surface Temperature) are appropriate for the assessment of land temperature. In addition, VCI (Vegetation Condition Index), TCI (Temperature Condition Index) and VHI (Vegetation Health Index) are applied for monitoring drought conditions.

#### Vegetation indicators: RVI and NDVI

The DN (Digital Number) value of each band of selected scenes was converted into surface reflectance value (range from 0.0 to 1.0) at top of atmosphere for each OLI bands using the calibrating tool in ENVI 5.2, and then, the NDVI value and RVI were obtained by the following formulas (Eqs. 1, 2) [24]

$$\text{NDVI} = \frac{\rho_4 - \rho_3}{\rho_4 + \rho_3} \quad (1)$$

and

$$\text{RVI} = \frac{\rho_4}{\rho_3} \quad (2)$$

where  $\rho_4$  and  $\rho_3$  are the TOA reflectance for the near infrared band (band 5) and red band (band 4) of Landsat 8 OLI, respectively. The NDVI values are between  $-1$  and  $1$ .

#### Thermal assessment: BT and LST

To analyze temporal changes of temperature in the olive farms, thermal bands (bands 10 and band 11) of Landsat 8 TIRS were used for calculating BT (Brightness Temperature) and LST (Land Surface Temperature) for four periods from June to September during the year 2015. There are several steps involved in the conversion of the DN (Digital Number) to BT and LST

First, DN was converted from spectral radiance to BT using the formula (Eq. 3) [24]

$$\text{BT} = K2 / \ln(K1/L_\lambda + 1) \quad (3)$$

where BT is the top of atmosphere brightness temperature in Kelvin;  $L_\lambda$  the spectral radiance ( $\text{Watts}/(\text{m}^2 \cdot \text{sr} \cdot \mu\text{m})$ );  $K1$  the thermal conversion constant for the band ( $K1 = 774.89$  and  $480.89$  for band 10 and band 11, respectively from the metadata in the header file);  $K2$  the thermal conversion constant for the band ( $K2 = 1321.08$  and  $12,001.14$  for band 10 and band 11, respectively, from metadata in the header file).

Second, LST in Kelvin retrieval from Landsat 8 TIRS was calculated using the formula (Eq. 4)

$$\text{LST}_K = \text{BT} / [1 + (\lambda * \text{BT} / \rho) \ln \varepsilon] \quad (4)$$

where  $\text{LST}_K$  is the land surface temperature in Kelvin;  $\lambda$  the wavelength of emitted radiance ( $\lambda = 10.8$  and  $12$  for band 10 and band 11, respectively);  $\rho = h * c / \sigma$  ( $1.438 \times 10^{-2} \text{m K}$ ) =  $14380$ ;  $\varepsilon$  the emissivity which is given by  $\varepsilon = 1.009 + 0.047 \ln(\text{NDVI})$

Finally, LST in Kelvin is converted to Celsius using the formula (Eq. 5)

$$\text{LST} = \text{LST}_K - 273.15 \quad (5)$$

#### Drought indicators: VCI, TCI and VHI

Three important indexes for drought classification such as the Vegetation Condition Index (VCI), the Temperature Condition Index (TCI), and the Vegetation Health Index (VHI) were calculated using the following equations (Eqs. 6–8) [11, 22]



$$VCI = 100 * (NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min}) \quad (6)$$

$$TCI = 100 * (LST_{max} - LST) / (LST_{max} - LST_{min}) \quad (7)$$

$$VHI = 0.5 * VCI + 0.5 * TCI \quad (8)$$

Finally, the VCI, TCI, and VHI of the study sites have been classified in Table 2 [6]. Both indexes were reclassified between 0 and 100 using ArcGIS10.3 (Table 2).

The VCI represented vegetation dynamics and depicted the moisture condition changes. This index at high values indicates healthy and unstressed vegetation [12]. Nevertheless, the TCI at low values corresponds to the vegetation stress because of high temperature [2]. These indexes play an important role as indicators in identifying the location of olive farms and distinguish irrigated areas.

To eliminate cloud, water, snow or ice, urban areas and bare soil, we applied a threshold of NDVI as follows: if NDVI value  $<0.1 \rightarrow$  Value = NODATA

If NDVI value  $>0.1 \rightarrow$  same value applies

where 0.1 is the threshold value for vegetated area including olive farms. By checking the Google Earth and pixels extracted from GTP (Ground Truth Points) collected from field survey, we determined this threshold value. This threshold is similar to the threshold provided by the NOAA which indicated that the NDVI at very low values of NDVI (0.1 and below) correspond to barren areas of rock, sand, or snow. Moderate values represent shrub and grassland (0.2–0.3), while high values indicate temperate and tropical rainforests (0.6–0.8) (<http://www.ospo.noaa.gov/Products/land/gvi/NDVI.html>).

The flowchart to identify irrigated olive growing farm using remote sensing approach is shown in Fig. 4.

### Statistical analysis

Correlation and regression analyses were used in this research to examine the relationship between different indexes and olive farms in the study sites. Moreover, parameters that contribute efficiently to the detection of irrigated and non-irrigated were identified. In this case, a correlation matrix was used to evaluate the interrelations among indexes. Moreover, multiple linear regression based

**Table 2** Drought classification of VCI, TCI and VHI values

Drought class	Values
Extreme drought	$<10$
Severe drought	$<20$
Moderate drought	$<30$
Mild drought	$<40$
No drought	$\geq 40$

on dependent variables and several explanatory variables is established using Eq. 9:

$$y_i = \alpha + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_m x_{mi} \varepsilon_i \quad (9)$$

where  $i$  is the observation from 1 to 65;  $m$  number of explanatory variable;  $y$  dependent variable;  $x$  explanatory variable;  $\alpha$  intercept term;  $\beta$  an unknown parameter to be estimated;  $\varepsilon$  error term.

In this study, the method of Ordinary Least Squares (OLS) is used to estimate the unknown parameters. SPSS18 is applied to perform the statistical analysis.

## Results

### Trends between rainfed and irrigated index

#### NDVI, RVI calculation

The average NDVI and RVI are used to compare the difference between irrigated and rainfed olive farms. In fact, NDVI for irrigated olive growing farms during the year 2015 is greater than NDVI for rainfed areas. In fact, high values of vegetation indices can be an indicator of healthy vegetation [4]. In addition, the increase of NDVI value proved a well-watered situation and there is no moisture stressed vegetation [3]. Our findings corroborated also with the work of Sepulcre-Canto et al. [20]. They mentioned that the NDVI for the irrigated orchards had higher values than rainfed fields. Figure 5 shows maps of the average NDVI and RVI of olive farms in the study sites and Fig. 6 depicts the significant differences of NDVI and RVI values between two kinds of olive growing farms.

#### BT and LST

Our finding indicates that irrigated olive farm areas are cooler than rainfed farms (Fig. 7). In fact, thermal infrared canopy temperature points out that stressed trees have higher crown temperature than well-irrigated olive trees [19]. Another research proposed by Sepulcre-Canto et al. [20] confirmed our findings. The authors show that rainfed orchards had higher temperature values than irrigated orchards.

In addition, maps of BT and LST for irrigated and rainfed olive farms were produced. The results are shown in Fig. 8.

In the study site, July seems to be the hottest month and the BT and LST appear the highest ranging from 28.4 to 46.2 °C (Fig. 8).

#### VCI, TCI, and VHI

VCI, TCI and VHI maps are presented in Fig. 9. Maps represent different levels of drought in four regions of our

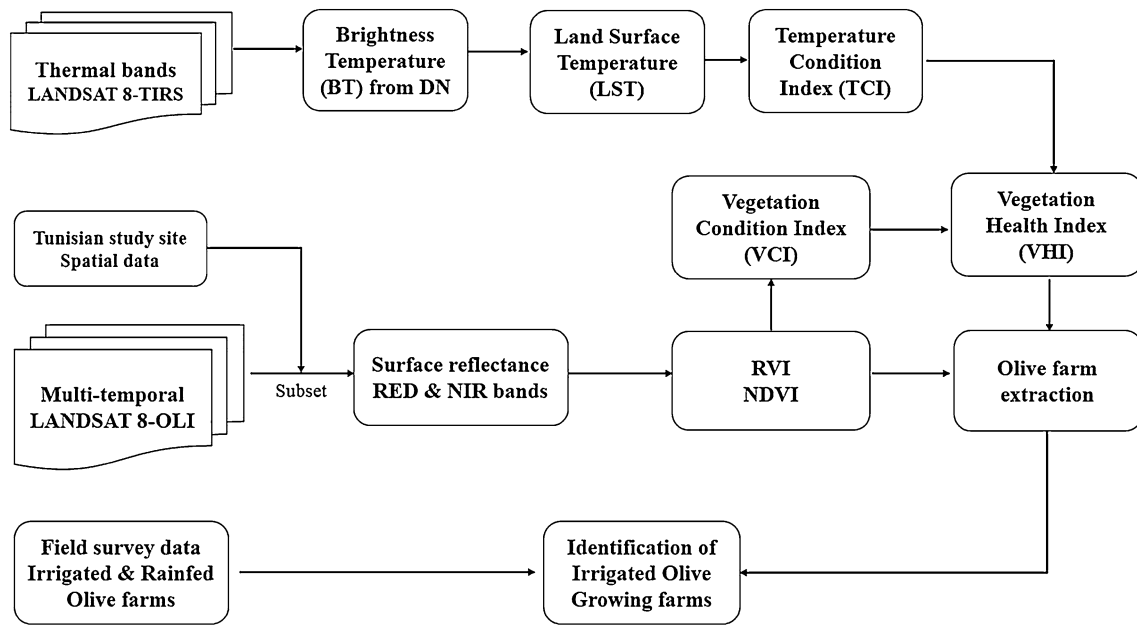


Fig. 4 Flowchart used to identify irrigated growing olive farms using remote sensing data

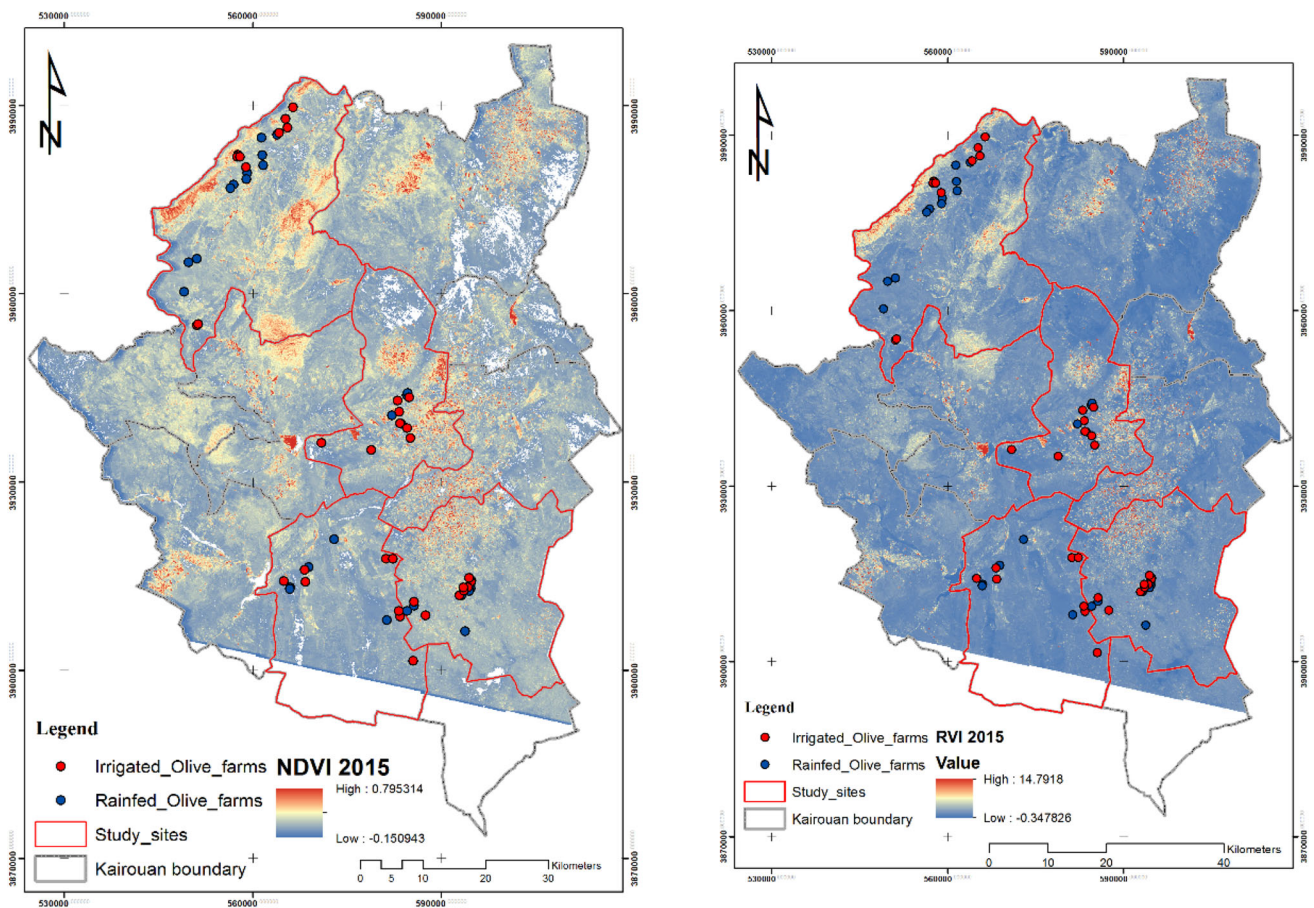
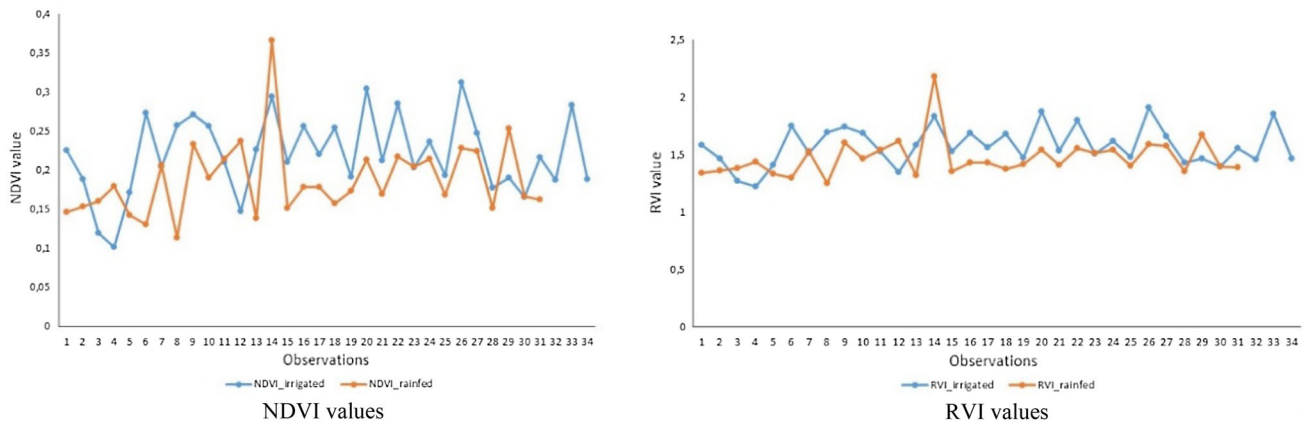
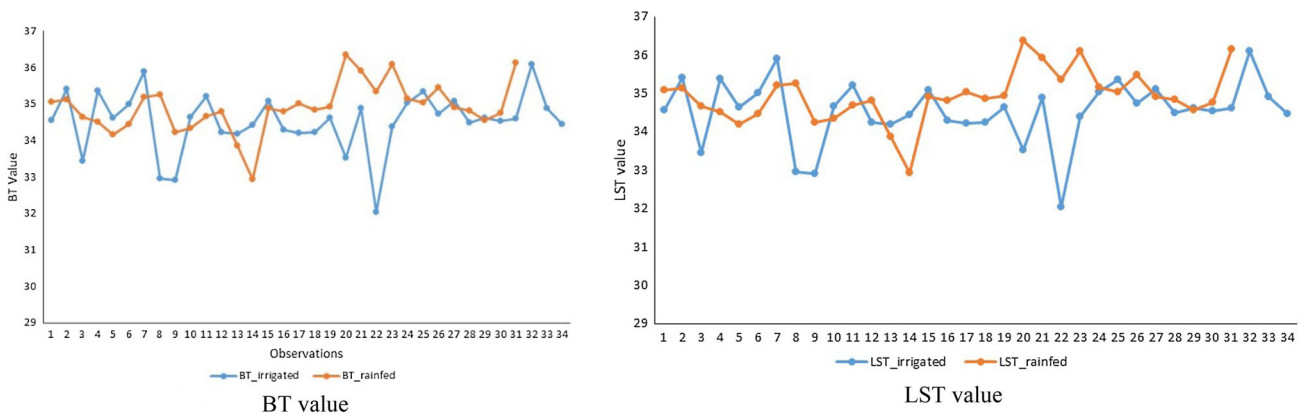


Fig. 5 Maps of NDVI and RVI values in the study site



**Fig. 6** Comparison of NDVI and RVI values between two kinds of olive farms



**Fig. 7** Comparison of BT and LST between two kinds of olive farms

study areas. The classes are ranging from no drought to extreme drought. Classes of severe and moderate drought are the most important. 91.43 % of Bouhajla, 73.8 % of Nasrallah, 79.93 % of Chebika and 74.82 % of Oueslatia are affected by these two classes. Moreover, about 43 % of the area are classified as severe drought. About 47.07 % of Bouhajla and 47.76 % of Chebika are located in severe drought class. The comparison of NDVI and VHI map shows that NDVI value is varying following the severity of drought conditions. Interestingly, olive growing farms are presented in moderate to severe drought condition, which is quite obvious since olive trees are able to tolerate drought climate conditions. However, the irrigation of olive can be a good way to maintain the production. Therefore, the correlation between several indicators could be a valuable approach to distinguish irrigated and rainfed olive areas.

We also calculated the total area in hectare and percentage of drought in four regions. The results are shown in Table 3.

### Correlation between indexes

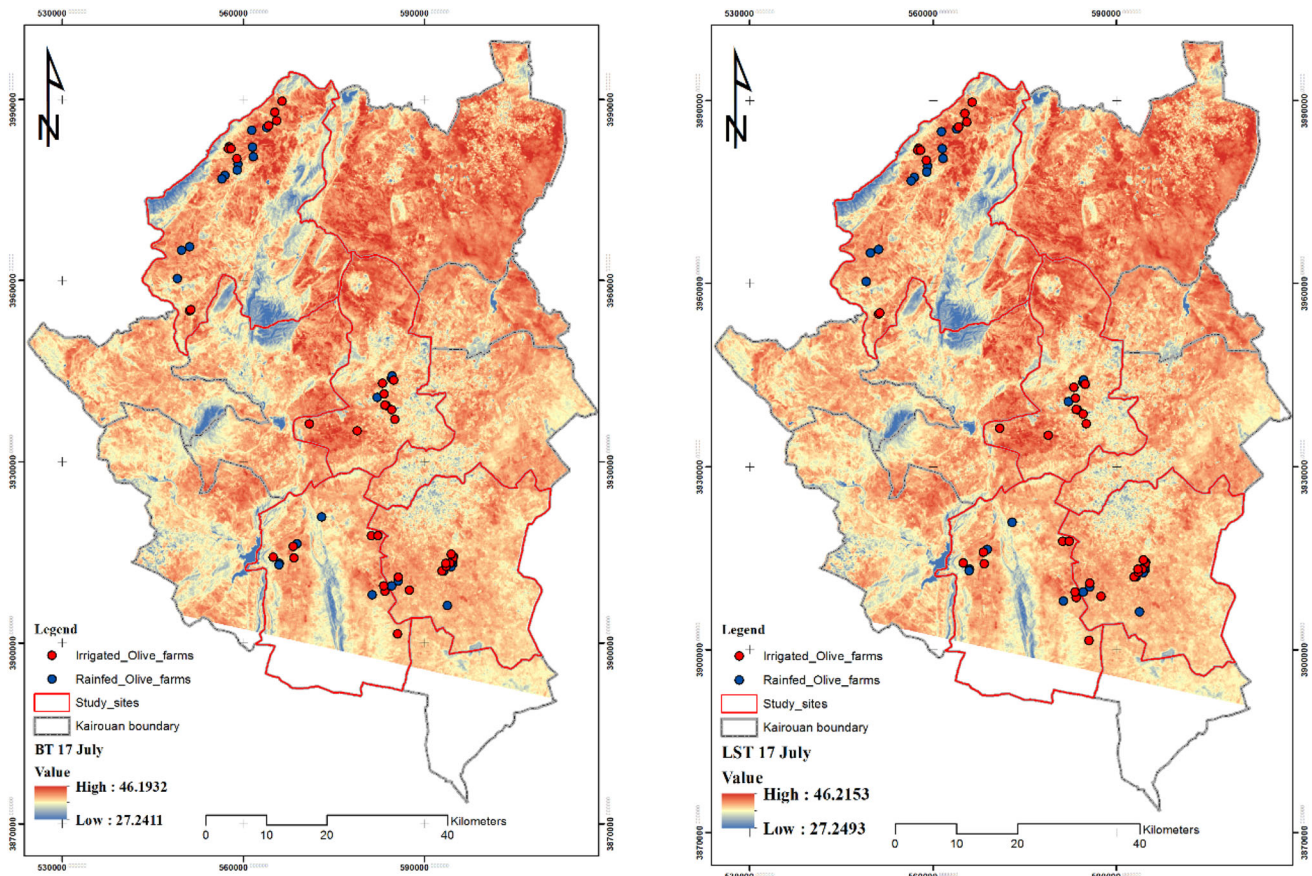
Table 4 shows the correlation matrix between indexes based on Pearson correlation.

The results show that a positive high correlation was observed between NDVI, RVI, VCI and VHI. It is quite clear because VCI and VHI are generated from NDVI. However, NDVI and RVI have a negative correlation with BT and LST. Moreover, we also noted a negative high correlation between VHI, TCI, LST and VCI. Due to this correlation, a multiple linear regression analysis was applied to estimate NDVI using VHI and LST. This model based on data derived from Landsat images is a relevant approach to predict the spatial distribution of irrigated and non-irrigated olive growing farms.

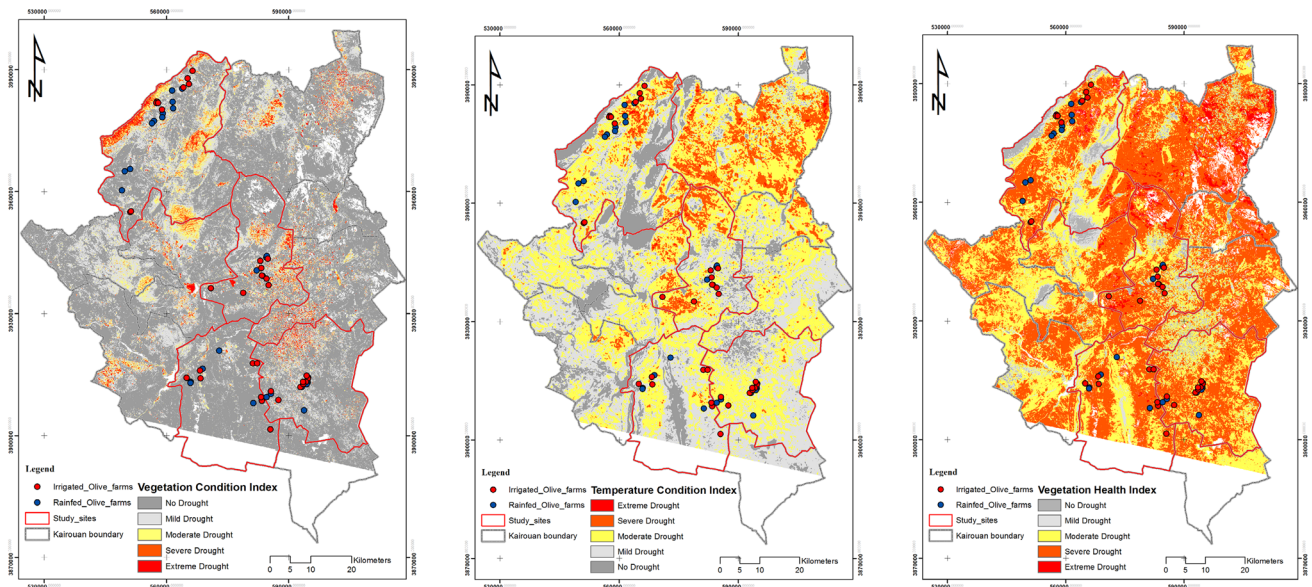
### Regression analysis

The main result of the regression analysis is presented in Table 5.





**Fig. 8** Maps of the BT and LST in the study site on July 17, 2015



**Fig. 9** VCI, TCI and VHI maps in Kairouan prefecture on July 2015

Regarding the result, NDVI can be predicted through Eq. 10.

$$NDVI = -1.032 + 0.028LST + 0.012VHI \quad (10)$$

The estimated coefficients of LST and VHI have significant impact on the prediction of NDVI. Both parameters are statistically significant at 1 % level. The combination



**Table 3** Drought areas in hectares and percentage in 4 regions

Regions Classification	BOUHAJLA		NASRALLAH		CHEBIKA		OUESLATIA	
	ha	%	ha	%	ha	%	ha	%
Extreme drought	39.42	0.06	60.12	0.09	2152.71	4.17	1993.05	2.20
Severe drought	30424.14	47.07	27312.48	38.88	24627.42	47.76	36412.29	40.11
Moderate drought	28668.96	44.36	24531.39	34.92	16591.95	32.17	31508.19	34.71
Mild drought	2475.81	3.83	2121.66	3.02	3691.17	7.16	12161.16	13.40
No drought	1408.95	2.18	210.96	0.30	2048.13	3.97	7668.90	8.45
Non-vegetated areas/NODATA	1612.63	2.50	16015.18	22.80	2458.66	4.77	1029.22	1.13
Total	64629.91	100	70251.79	100	51570.04	100	90772.81	100

**Table 4** Correlation matrix between indexes

	NDVI	RVI	BT	LST	VCI	TCI	VHI
NDVI	<b>1</b>						
RVI	0.993	<b>1</b>					
BT	-0.355	-0.381	<b>1</b>				
LST	-0.355	-0.381	1	<b>1</b>			
VCI	0.948	0.943	-0.382	-0.382	<b>1</b>		
TCI	0.268	0.303	-0.854	-0.854	0.332	<b>1</b>	
VHI	0.811	0.825	-0.703	-0.703	0.880	0.741	<b>1</b>

**Table 5** Regression analysis

Variables	Value	Standard error
Intercept	-1.032*** (-4.649)	0.222
LST	0.028*** (4.731)	0.006
VHI	0.012*** (12.369)	0.001
No. of observations	65	
$R^2$	0.748	
F test	92	

\*, \*\*, \*\*\* Indicate significance at the 10, 5, 1 % level, respectively. Student's  $t$  are in parentheses

of LST and VHI may conduct efficiently to identify NDVI in irrigated and non-irrigated olive growing farms. The correlation ( $R^2$ ) is high with a value of about 0.748.

## Discussion

Olive trees are characterized by a high capacity of adaption in a severe water stress [13]. However, the introduction of irrigation to non-irrigated farms may lead to increased production levels [10]. For this reason, the identification of irrigated olive growing farms by remote sensing can be a good solution to sustainable water management strategies and for the monitoring of irrigated farms. The results of NDVI showed that the values of irrigated olive growing farms are greater than values of rainfed farms (Fig. 6) in summer season in

particular. It can be an indicator of relative abundance and activity of green vegetation [8]. Moreover, NDVI pattern without irrigation is varying, greening of vegetation in the fall and winter and browning in summer. However, irrigation can maintain NDVI value constant [9]. The assessment of BT and LST indexes was conducted to assess the temperature of olive growing farm, which is very high in summer season (July). Indeed, olive tree is an arid species, which can resist hard climatic conditions [1]. Moreover, the results showed that irrigated farms are cooler than rainfed (Fig. 7). This finding is corroborated with some studies [17, 25]. Kairouan is one of the hottest prefectures in Tunisia. For this reason, the assessment of indexes for agricultural drought is essential for our analysis. The findings show that 43 % of the area was classified as severe drought. We noted that VCI and VHI in irrigated farms are greater than rainfed farms. Indeed, vegetation is sensitive to both moisture and thermal conditions. The severity of moisture stress and thermal stress induces the overall vegetation health as well as the drought impact on vegetation [2]. VCI is an indicator of the vigor of the vegetation cover which is a good indicator of water stress conditions. Moreover, the variation of spatial distribution of NDVI value is affected by the intensity of drought. For this reason, the establishment of correlation between NDVI and index of drought and thermal condition can conduct to identify the irrigated olive growing farms easily. The model obtained can be a relevant tool to predict the location of olive growing farmers. It will be useful for decision makers to monitor olive growing farms production and to assess the performance of irrigation in drought period. In this study, Landsat satellite images were applied but higher resolution data can be very useful to get more accurate spatial distribution of olive growing farms.

## Conclusion

Olive production is very important in Tunisia because it has economic and social impacts. For this reason, monitoring the production is useful for decision makers to

establish strategies and to stabilize the yield. The use of remote sensing techniques and indicators is a relevant approach to detect irrigated and non-irrigated olive trees areas. Furthermore, the application of predictive model based on NDVI and thermal and health vegetation indicators will be helpful for managers and policy makers to assess olive yield production. Moreover, in situations of agricultural drought and water stress as in Tunisia, the identification of irrigated olive growing farms using remote sensing techniques may conduct to sustainable strategies of water resources and to improve the olive production. It can be also useful for stakeholders to detect the olive growing farms and to estimate the olive production. Finally, this research indicates the potential for use of multi-temporal LANDSAT 8 data together with a GIS approach for mapping olive farm in the semi-arid regions.

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#### Compliance with ethical standards

**Conflict of interest** On behalf of all authors, the corresponding author states that there is no conflict of interest.

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