



AGRICULTURAL DROUGHT MONITORING BASED ON LANDSAT 8 DERIVED VEGETATION HEALTH INDICES: CASE STUDY OF MEZŐHEGYES, SOUTH-EASTERN HUNGARY

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Abstract: Agricultural drought causes many economic and social problems in various communities. Advanced Geographic Information Systems (GIS) and remote sensing techniques play a significant role in the mapping and monitoring of agricultural drought. The main objective of this paper is to monitor agricultural drought using a remote sensing-based vegetation health index (VHI) derived from Landsat 8 during 2020 and 2021. VHI was calculated based on temperature condition (VCI) and thermal condition of vegetation (TCI). Both indices were generated from Normalized Difference Vegetation Index and land surface temperature (LST) data respectively. The result indicates that there is no extreme drought occurred in the research area. The VHI classes demonstrate that large area of study site faced drought from moderate to mild from 2020 to 2021. Mild drought, covering an area, 50.2 percent in 2020 while 64.5 percent in 2021 was registered all across Mezohegyes. This is due to the rising of NDVI from 0.46 in 2020 to 0.55 in 2021 whereas LST decreased slightly from 62°C to 51°C respectively.

Keywords: remote sensing, drought, agriculture, Landsat, VCI, LST.

Introduction.

Drought can have a devastating effect on water supply, and crops resulting in famine, malnutrition, epidemics, and large-scale migration. Its impact on agriculture is enormous. Almost a drought occurs frequently in Hungary, which causes serious damage to agriculture every year (Gulácsi and Kovács, 2018). Early detection and assessment of drought-prone areas will help reduce the likelihood of drought. This, in turn, will help prevent risks, increase food security and ensure efficient delivery (Rojas et al., 2011). Since the 1970s, much research has been done by satellite, which in turn has served to determine the appearance of the earth, the effects of drought, and many scientific approaches (Gu et al., 2007). Drought can be monitored effectively over large areas using remote sensing technology. Remote sensing data helps to monitor and easily obtain drought conditions. With this, we can see the effectiveness of real-time monitoring and assessment of plant health in drought conditions (Masroor et al., 2022). Several remotely perceived drought indices have been developed and applied, including duration, intensity, severity, and spatial level of drought (Mishra et al., 2015). Among those indices, to monitor and analyse drought continuously, Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) are used (Brema et al., 2019). The Normalized Difference Vegetation Index (NDVI) as a probe for vegetation health has been one of the most commonly used approaches to drought events monitoring. Satellite land surface temperature (LST) is used individually or in combination with NDVI to detect and monitor drought

(Hu et al., 2019). One of the most widely used satellite indices for drought monitoring is the Vegetation Health Index (VHI). This can be determined using two indices, the Vegetation Condition Index (VCI) and the Thermal Condition Index (TCI) (Zeng et al., 2022). Therefore, VHI consequently evaluates vegetation drought stressed by temperature. Both parameters can be derived from Normalized Difference Vegetation Index (NDVI) and land surface temperature (LST) data. Due to the availability of sufficient data in this study, VHI was obtained in 2020 and 2021 using the Landsat satellite. Landsat is considered in this paper due to its open-access policy while having a relatively fine temporal and spatial resolution for drought monitoring. The purpose of this article is to determine the level of drought in the agricultural lands of the Mezőhegyes and to compare the droughts of 2020 and 2021.

2. Study area

The experimental farm of Mezőhegyes is located in Mezőhegyes town, Békés and Csongrád-Csanád counties, Hungary, next to the Romanian border (latitude 46° 19' N, longitude 20° 49' E) (Figure 1). The total administrative area of the town is 15 544 hectares, and its population is 4950 people. Chernozem is a very common type of soil that supports both plant growth and high yields (Amankulova et al., 2021). The meadow and lowland chernozem, with their high lime content, provides an excellent basis for field plant cultivation. Chernozem is a very fertile soil that produces high agricultural yields and offers excellent agronomic conditions to produce crops, especially cereals and oilseeds. Mezőhegyesi Ménesbirtok Zrt. (the experimental farm of Mezőhegyes) plays an important role in the lives of both Mezőhegyes and the neighbouring settlements. According to the operational water scarcity assessment and forecasting system in Hungary and the experimental farm of Mezőhegyes, between May 21 and June 28, 2020, a very high rainfall for this agricultural area was recorded at 190.6 mm. Climate records at Mezőhegyes station (next to the selected fields) show that annual rainfall there was 575 mm (458 mm in-crop) for the 2020 season. The result indicates that there is no any extreme drought occurred in the research area. The VHI classes demonstrates that large area of study site faced drought from moderate to mild from 2020 to 2021. Mild drought, covering an area, 50.2 percent in 2020 while 64.5 percent in 2021 was registered all across Mezohegyes. This is due to the rising of NDVI from 0.46 in 2020 to 0.55 in 2021 whereas LST decreased slightly from 62°C to 51°C respectively.



Figure 1. Location of the study.

3. Methodology

Landsat 8 OLI/TIRS Level-2 datasets were downloaded from The USGS Earth Explorer website (<https://earthexplorer.usgs.gov/>). Atmospherically corrected images from 2020 to 2021 were used for drought monitoring. Landsat 8 satellite carries two Operational Land Imager and Thermal Infrared sensors (launched on 11 February 2013) and acquires earth surface with 11 multispectral and thermal bands. Landsat images are a collection of high-resolution satellite imagery, with a spatial resolution of 30 m, provided in a standardized, orthorectified format. Multispectral and thermal bands from Landsat 8 were used to calculate Normalized Difference Vegetation Index (NDVI) and land surface temperature (LST) indices. Time-series of NDVI and LST can be useful to demonstrate the dry season and the effect of the weather anomaly on vegetation (Wang et al., 2014).

3.1 NDVI.

Landsat Normalized Difference Vegetation Index (NDVI) is used to quantify vegetation greenness and is useful in understanding vegetation density and assessing changes in plant health. NDVI was calculated as follows:

In Landsat 8-9, $NDVI = (Band\ 5 - Band\ 4) / (Band\ 5 + Band\ 4)$.

where NDVI values range between -1 and 1.

3.2 LST

The Land Surface Temperature (LST) was calculated from an atmospherically corrected thermal band of Landsat 8 based on at-sensor brightness temperature was derived using the equation developed by Chander et al. (2009).

3.3 VCI, TCI, VHI.

The vegetation condition index (VCI) was obtained from Normalized Difference Vegetation Index (NDVI) to monitor vegetation conditions (Kogan, 1995). The temperature condition (TCI) was developed to capture different responses of vegetation to in-situ temperature as additional information. This can be achieved by employing thermal channels for drought monitoring. Finally, the vegetation health index (VHI) was calculated to assess both vegetation stress and temperature to evaluate drought severity (Kogan et al., 2004).

$$\begin{aligned}
 &= 100 * \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right) / \left(\frac{T_c - T_{min}}{T_{max} - T_{min}} \right) \\
 &= 100 * \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right) / \left(\frac{T_c - T_{min}}{T_{max} - T_{min}} \right) \\
 &= 0.5 * \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right) + 0.5 * \left(\frac{T_c - T_{min}}{T_{max} - T_{min}} \right)
 \end{aligned}$$

where:

NDVI, $NDVI_{min}$, and $NDVI_{max}$ are the seasonal average of the smoothed weekly NDVI, its multiyear absolute minimum and it is maximum, respectively;

T_c , T_{min} , and T_{max} are similar values for land surface temperature in Celsius.

The following table is provided for drought monitoring in this study (Table 1).

No	Drought category	Value
1	Extreme	<10
2	Severe	<20
3	Moderate	<30
4	Mild	<40
5	No	≥40

4. Result and Discussion

This study used Landsat data to determine the agricultural drought of the Mezöhegyes in 2020 and 2021. NDVI could be used as a variable response to identify and quantify drought disturbance in semi-arid and arid lands, with low values corresponding to stressed vegetation. NDVI is an effective indicator of vegetation response to drought, based on the relationships between NDVI and a meteorologically based drought index. According to the time series of NDVI. Low rainfall, high temperatures and low soil moisture

can lead to severe droughts in agriculture (Sruthi and Aslam, 2015).

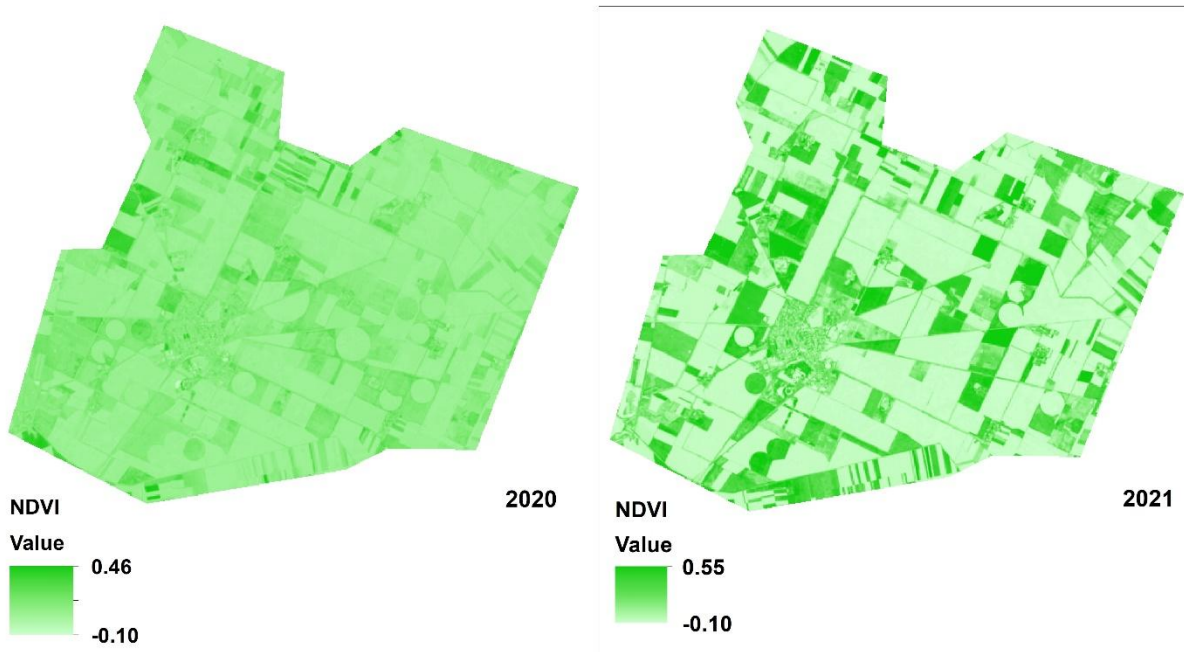


Figure 2. Spatial variation of NDVI.

Fig. 2 represents that the NDVI value increased slightly during the observation period. Drought monitoring using NDVI alone as the important parameter was not enough to investigate drought in small scale. Thus, it is important to combine another parameter to improve the accuracy. In this research, we used LST as a second parameter from 2020 and 2021 are presented in Figure 3.

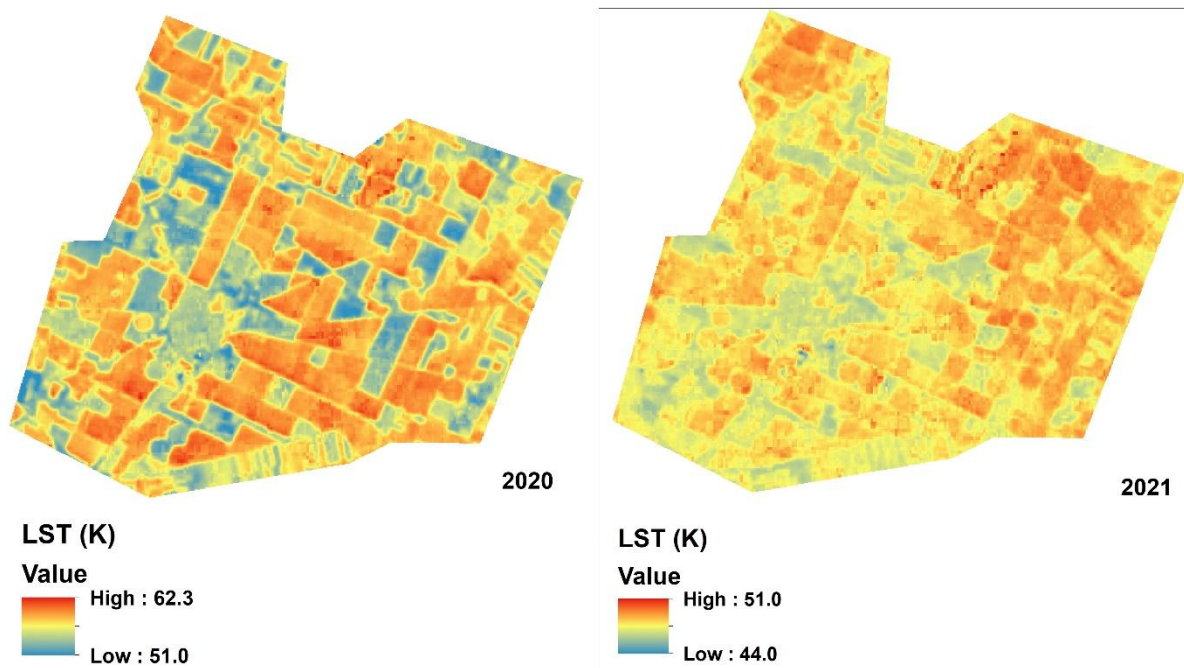


Figure 3.

Dry soil can be observed where where LST is higher. The result shows that LST increased moderately by 10°C from 2020 to 2021. If we describe LST in general, in the dry condition LST is high and NDVI is low.

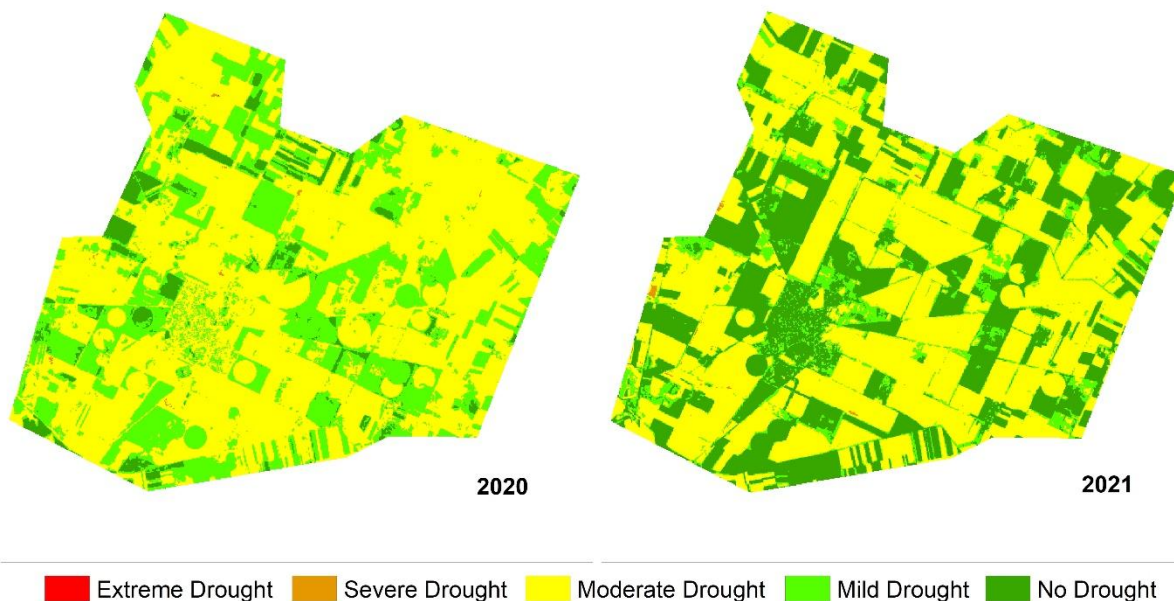


Figure 4. Vegetation Health Index (VHI) classes in Lebanon, 2014

To determine the vegetation health index (VHI), we combined two indicators, VCI and TCI, and obtained the following result. The VHI index was generated for the two years 2020 and 2021. Almost no extreme and severe drought was detected in the vegetated area of Mezohegyes. VHI value was 39.5 in 2020 describes moderate drought, however it was 49.9 in 2021. Mild drought, covering an area, 50.2 percent in 2020 while 64.5 percent in 2021 was registered all across Mezohegyes. This is due to the rising of NDVI from 0.46 in 2020 to 0.55 in 2021 whereas LST decreased slightly from 62°C to 51°C respectively. However, the this study site, constituted the largest moderate and mild drought areas. The two years (VHI) for the Mezöhegyes region was derived from a combination of NDVI and LST. According to the result, the drought conditions were moderate, mild or no drought condition. In most parts of the Mezöhegyes, no extreme drought was observed at 30 m high resolution. This means that the agricultural lands of the Mezohegyes region were almost stable in both years.

Conclusion

This study was carried out to detect agricultural drought extent over the Mezöhegyes using satellite remote sensing based index, vegetation health index (VHI) derived from Landsat 8 satellite. We found that this index could be used successfully to determine the spatio-temporal level of drought in agricultural areas. Moreover, drought can be identified in the study area through composite analysis of vegetation health by vegetation condition and temperature condition of vegetation. Our mapping method is rapid, straightforward and principally fed by remote sensing data.

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