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Quantifying the Effects of Drought Using the Crop Moisture Stress as an Indicator of Maize and Sunflower Yield Reduction in Serbia

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Abstract: The drought in Serbia in the summer of 2017 heavily affected agricultural production, decreasing yields of maize, sunflower, soybean, and sugar beet. Monitoring moisture levels in crops can provide timely information about potential risk within a growing season, thus helping to create an early warning system for various stakeholders. The purpose of this study was to quantify the level of moisture stress in crops during summer and the consequences that it can have on yields. For that, maize and sunflower yield data provided by an agricultural company were used at specific parcels in the Backa region of Vojvodina province (Serbia) for 2017, 2018, 2019, and 2020. The crop moisture level was estimated at each parcel by calculating the normalized difference moisture index (NDMI) from Sentinel-2 data during the summer months (June–July–August). Based on the average NDMI value in July, the new crop moisture stress (CMS) index was introduced. The results showed that the CMS values at a specific parcel could be used for within-season estimation of maize and sunflower yield and the assessment of drought effects. The CMS index was tested for the current growing season of 2022 as an early warning system for yield reduction, demonstrating the potential to be included in a platform for digital agriculture, such as AgroSens, which is operational in Serbia.

Keywords: crop yield; NDMI; agricultural drought; crop moisture stress; early warning system

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1. Introduction

Agricultural drought is a period with a soil moisture deficit resulting from the combination of a shortage of precipitation and excess evapotranspiration in a specific region. It can be considered a natural hazard if it appears during the growing season, as it has negative effects on crop production. The drought in Serbia in the summer of 2017 heavily affected agricultural production, decreasing yields of maize, sunflower, soybean, and sugar beet by up to 30–60%, while the total loss was estimated at 1.5 billion USD, which had a strong economic impact [1]. According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, there is an increase in agricultural droughts in the Mediterranean region and Western and Central Europe based on the changes observed in the total column of soil moisture. In addition, agricultural droughts are projected to be at least twice as likely at 1.5 °C of global warming, while a decreased soil moisture by up to 25% is expected in the annual mean total column soil moisture at 4 °C of global warming [2].

Experts stated that improved drought monitoring, early warning, and decision-support tools that would reduce the impact of drought on society and the environment could be beneficial for the agricultural sector, and that these tools should be considered as an integral part of drought preparedness and mitigation plans [3]. The Copernicus Emergency Management Service launched the European Drought Observatory, which provides a map of the combined drought indicator (CDI) for each ten-day period of the month with a spatial resolution of 5 km [4]. The CDI is calculated by using the standardized precipitation index for one month and three months, the soil moisture anomaly, and the anomaly of the fraction of absorbed photosynthetically active radiation [5]. The CDI has the ability to discriminate areas in which the impacts of drought are most severe, although the information is available at least 10 days later, and it is not localized for the fields.

Satellite-based remote sensing techniques can be used to measure the variations in vegetation conditions at high spatial resolutions. The potential of Sentinel-2 satellite data in assessing droughts was thoroughly reviewed, and the canopy water content was recognized as one of the key factors in estimating agricultural drought [6]. For example, the normalized difference moisture index (NDMI) is based on the effect of water content in canopy tissues on reflectance in the near-infrared (NIR) and shortwave infrared (SWIR) bands [7]. Some authors proposed the vegetation temperature condition index for the monitoring of agricultural drought, and it was calculated by using the land surface temperature (LST) and normalized difference vegetation index (NDVI) from different satellites [8,9]. Others designed the geographically independent integrated drought index (GIIDI) by using temperature, precipitation, soil moisture, and vegetation condition indices that were obtained from multi-sensor satellite data [10]. There was a study that combined satellite vegetation indices with meteorological data to calculate the Palmer drought severity index (PDSI) and vegetation health index (VHI) [11], which were used to derive two indices for the evaluation of the mitigation of agricultural drought [12].

The drought severity index (DSI) was computed based on the NDVI and evapotranspiration datasets, and the mean values of the DSI during the growing season were correlated with maize and wheat yield in China, showing that yield anomalies were related to drought [13]. One study examined the correlations of the precipitation, NDVI, and LST with maize and soybean yields at the county level in the United States. The NDVI during mid-summer was found to be positively correlated with crop yields, while daytime LST was negatively correlated at the same time. Together, they were used to build a regression tree model for within-season yield prediction, which had reasonable results, even in a drought year [14]. Optical data from Landsat, MODIS, and the Sentinel-2 satellite were used to derive indicators such as the LST, NDVI, and NDMI, along with the Sentinel-1-based backscattering intensity, in order to analyze the length of a drought and drought-impacted agricultural areas in Ukraine. Based on a comparison of parameters from different conditions, the authors used logistic regressions to classify three levels of disturbance, i.e., mild, moderate, and severe drought, in fields of maize, sunflower, and soybean [15]. Although it was shown that the monitoring of moisture levels in crops can provide timely information about potential risks within a growing season, to the best of our knowledge, none of the aforementioned indicators were used as a part of an early warning system.

Agricultural production is one of the most important sectors of the economy in the Republic of Serbia, with a share of approximately 10% in the gross domestic product (GDP). Crop production makes up about 67% of the structure of value of agricultural production [16], causing Serbia to be highly ranked on the list of the top maize exporters in the world. Maize is the most cultivated grain crop, and sunflower is the most cultivated oil crop. For example, the maize-planted area in 2018 was reported to be 900,000 ha, while sunflower was planted on 250,000 ha in the same year [17].

The purpose of this study was to quantify the level of moisture stress in maize and sunflower during summer by exploiting the NDMI and to examine the consequences that stress can have on yields. Thus, the new crop moisture stress (CMS) index was introduced, and it was able to discern between different classes of yield. The CMS was tested for the current growing season of 2022 as an early warning system for agricultural drought and the following yield reduction.

2. Materials and Methods

2.1. Study Area

Vojvodina province represents the northern part of Serbia, with a total surface area of 2,150,600 ha, and it is located in the southern part of the Pannonian Plain (Figure 1). It has a moderate continental climate, with cold winters and hot and humid summers, and it has a mean annual temperature of 11.1 °C and mean annual precipitation of 606 mm [18]. Regarding its geomorphology, it is characterized by loess and sand plateaus, loess terraces, and river plains. Vojvodina is predominantly agricultural land (83%), most of which is cropland (77%), and it is, thus, characterized by intensive agriculture [19]. Backa is the largest region of Vojvodina, covering the northwestern part, where mostly maize, wheat, soybean, and sunflower are cultivated.

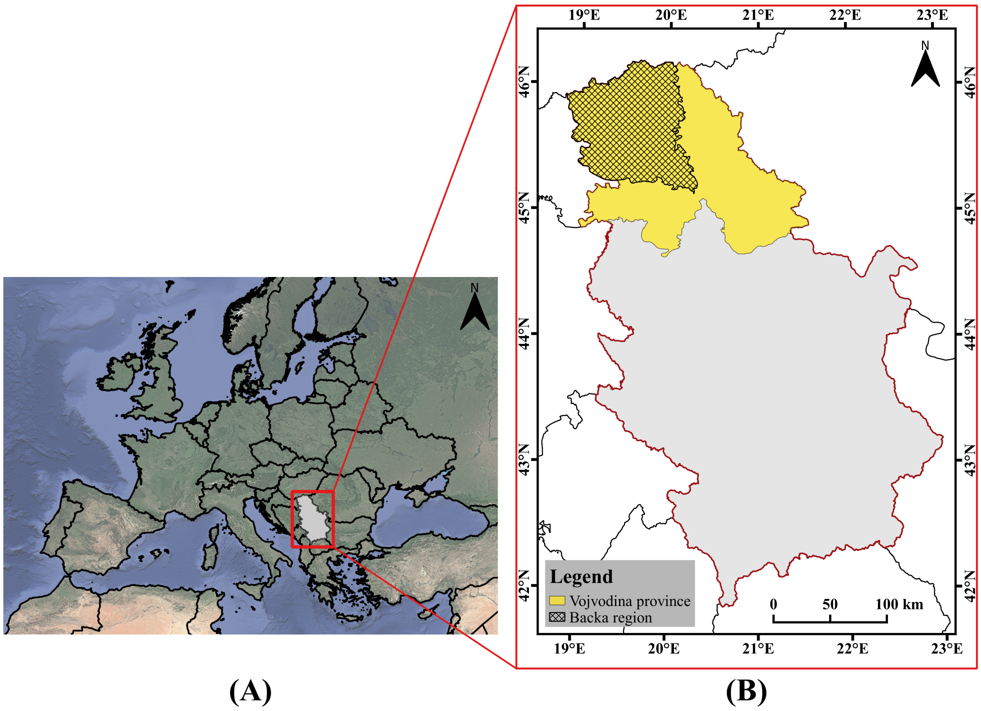

Figure 1. Location of Serbia in Southeastern Europe (**A**) and the study area (**B**).

2.2. Dataset

Maize and sunflower yield data were given in tonnes per hectare (t/ha) at the parcel level, together with the shapefiles of the parcels in Backa region. Data were provided by an agricultural company for the seasons of 2017, 2018, 2019, and 2020 (Figure 2). There were 71 samples of maize yield from 18 hybrids and 37 samples of sunflower yield from 13 hybrids in total. The yield varied from 1.4 to 16.8 t/ha for maize with a median of 10.7 t/ha and from 1.2 to 5.9 t/ha for sunflower with a median of 3.2 t/ha. For the specific year, the numbers of maize parcels were 22 (2017), 22 (2018), 16 (2019), and 11 (2020), while the numbers of sunflower parcels were 14 (2017), 11 (2018), 8 (2019), and 4 (2020). The data on the application of fertilizers and the information on which parcels were irrigated, if any, were not provided by the agricultural company.

The NDMI uses the NIR and SWIR bands to detect changes in the water content of leaves. The SWIR reflectance is negatively related to the amount of water available in the internal leaf structure, while the NIR reflectance is affected by the internal leaf structure and leaf dry matter. The combination of the two bands improves the accuracy in retrieving the vegetation water content [20]. Multispectral imagery from Sentinel-2 for the T34TCR granule covering the Backa region was downloaded from the Copernicus Open Access Hub [21]. Images were collected from 1 June to 31 August for the years 2017, 2018, 2019, 2020, and 2022. The NDMI was calculated using the B8A (central wavelength at 865 nm) and B11 (central wavelength at 1610 nm) bands at a 20 m spatial resolution with the following ratio:

$$NDMI = (B8A - B11)/(B8A + B11). \quad (1)$$

All images were filtered by using the appropriate scene classification (SC) layer for cloud masking of Sentinel-2 images. Pixels contaminated by cloud cover within each parcel were discarded from the analysis. Further on, the mean value of the NDMI was calculated at the parcel level. This way, NDMI time series for summer months were created.

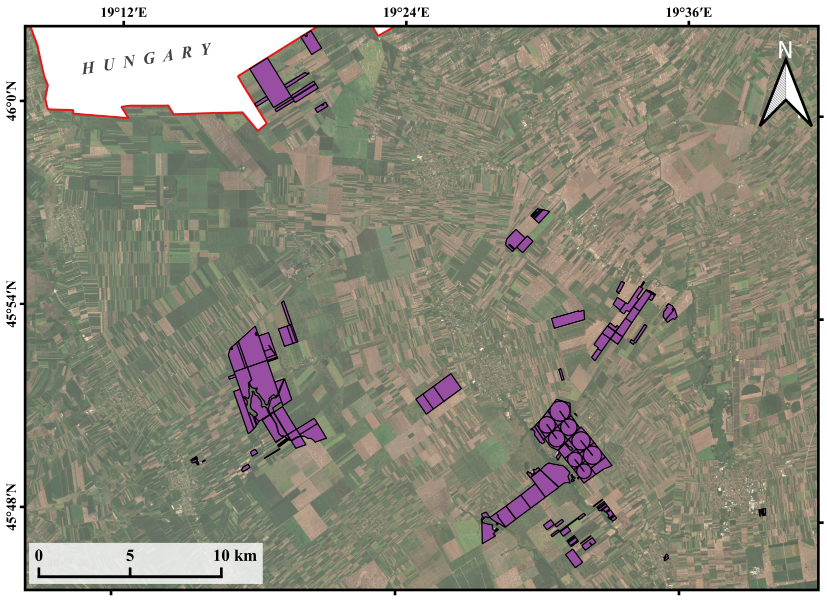

Figure 2. Location of the parcels with maize and sunflower yield provided by the agricultural company.

Data were processed and analyzed in Python, while QGIS (version 3.22.6) was used for visualization.

2.3. Crop Moisture Stress Index

Theoretically, NDMI values range within the interval from −1 to 1. Hence, their interpretation requires land-use information, since it is a significant moisture index for cases in which vegetation is dominant, while it has negative values for bare soil and water bodies [7]. The Sentinel Hub provides a moisture stress classification map based on four classes of the NDMI [22]. It can be used to detect irrigation in agricultural parcels, especially in the summer months after several weeks without rain [23]. For every image, classes are identified based on the specified threshold.

$$\text{Moisture Stress} = \begin{cases} \text{Dry}, & NDMI \leq 0 \\ \text{Low moisture}, & 0 < NDMI \leq 0.2 \\ \text{Moderate moisture}, & 0.2 < NDMI \leq 0.4 \\ \text{High moisture}, & NDMI > 0.4 \end{cases} \tag{2}$$

However, investigation of the relationship between the moisture stress and the yield of specific crops still cannot be found in the scientific literature. For that reason, the level of moisture stress was quantified in maize and sunflower fields during summer with respect to the consequences for the yield.

Both maize and sunflower are crops that are sensitive to drought, especially in their reproductive stages of development [24,25]. Drought accompanied with heat stress during silking, pollination, and grain filling can affect maize yield at the end of the season [26,27]. Sunflower is more resistant to drought, since it has better efficiency of uptake of water from the soil because the root system develops into deeper layers. However, exposure to drought at some specific stages, such as anthesis and achene filling, is the most critical factor, causing up to 50% yield reduction in sunflower [28]. According to the agricultural practice in Vojvodina province, maize and sunflower are planted approximately in April and harvested approximately in October, although that depends on the hybrids, as well as soil and weather conditions during the year. Thus, this study focused on the NDMI values in July, where the reproductive stages of both crops overlapped. Since total cloud cover can reduce the number of satellite images, the average NDMI value was calculated based on the available data in July for each parcel. The new crop moisture stress (CMS) index was defined in the following way:

$$\text{CMS} = \begin{cases} 0, & \langle NDMI \rangle_{July} \leq 0 \\ 1, & 0 < \langle NDMI \rangle_{July} \leq 0.1 \\ 2, & 0.1 < \langle NDMI \rangle_{July} \leq 0.2 \\ 3, & 0.2 < \langle NDMI \rangle_{July} \leq 0.3 \\ 4, & 0.3 < \langle NDMI \rangle_{July} \leq 0.4 \\ 5, & \langle NDMI \rangle_{July} > 0.4 \end{cases} \tag{3}$$

Further, for each crop, the mean yield and standard deviation (std) were calculated for every class of CMS. To decrease the standard deviation of the yield estimation, outliers above the 95th percentile were removed from each class. Records with very high yields could be consequences of human error, i.e., the agricultural technician entering the wrong data, or from drought-tolerant hybrids that were bred to perform well under extreme conditions [29].

The method was validated using leave-one-year-out cross-validation, which is an application of the leave-one-out approach [30] and is a more rigorous technique in the case of yield estimation compared to a cross-validation that would mix samples from all available years. Since the total number of yield samples in the four seasons was not large, yield data from three seasons were used for training, while data from one season were left over for validation, and all of the possible combinations were examined. Standard statistical metrics were used for validation, such as the mean bias error (MBE), which provides the general trend towards over- or underestimation, mean absolute error (MAE), and root-mean-square error (RMSE), with both quantifying the amount of error and with RMSE being more sensitive to outliers [31–34]. The results were given as the average of all different combinations.

During the campaign of scouting fields in the Backa region in June 2022, the locations of 340 maize fields and 89 sunflower fields were recorded. The polygons of the exact parcels were created in QGIS using Sentinel-2 images with the RGB channel. Thus, it was possible to calculate the CMS at the specific fields and give yield estimations for the current growing season.

3. Results

Time series of the NDMI values in four different summer seasons (1 June–31 August) for maize and sunflower parcels are shown in Figures 3 and 4, respectively. Different shades of the background correspond to the classes of moisture stress. The dots represent the exact NDMI values on the given date of observation, while the lines are simple linear interpolations that are used for the purpose of visualization. The discontinuity of the lines is explained by the fact that on certain dates, some parcels were totally covered by clouds and, thus, were not used for the NDMI calculation.

In 2018, the images for the Backa region had total cloud cover during June and the first half of July; therefore, they were not eligible for calculation. The prime example of a complete time series during the summer season is the year 2020.

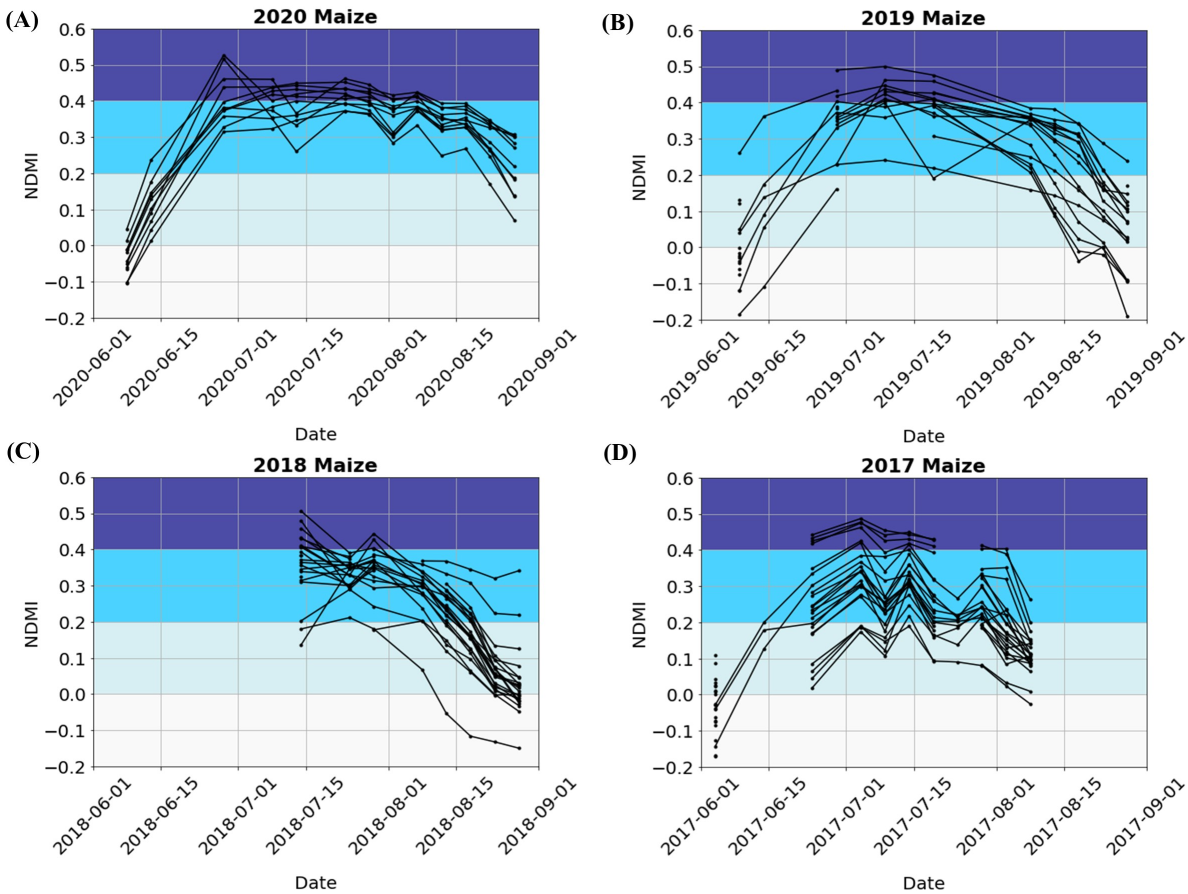

Figure 3. Time series of NDMI values at maize parcels in four growing seasons: 2020 (**A**), 2019 (**B**), 2018 (**C**), and 2017 (**D**).

The NDMI reached its maximum values during July when the canopy cover was fully developed, which is also the period with a critical moisture requirement, since it overlapped with the reproductive stages of maize (Figure 3). The NDMI started to decline in the beginning of August, but the decline was steeper during dry summer seasons with a rainfall deficit, such as in 2017 [35]. For the same season, it was notable that the time series among the parcels varied the most, assuming that some parcels were irrigated. The parcels that had NDMI values of less than 0.2 during July corresponded to lower yields that were recorded in the ground-truth data. Therefore, a moisture deficit can lead to a significant yield reduction. For all other seasons, the time series showed moderate moisture content in the canopy as a result of average (2019, 2020) and above-average (2018) rainfall in June and July [36–38]. Although sunflower is more resilient to dry conditions than maize, the NDMI also showed lower values during July 2017 when compared to the values in other seasons, while it generally started to decline in the second half of July (Figure 4).

The average NDMI value in July was calculated at each parcel, and adequate moisture stress classes were assigned. Thus, it was possible to compare the mean yield for each class of moisture stress and CMS. The mean yields for maize and sunflower are presented in Tables 1 and 2, respectively. By definition, a high level of moisture in the moisture stress corresponded to class 5 of the CMS, while dry conditions corresponded to class 0 of the CMS. In the 2017–2020 seasons, classes 1 and 0 of the CMS were not observed for maize and sunflower. The difference between moisture stress and CMS could be seen in the cases of moderate moisture, since CMS gave a more detailed estimation of yield. The mean yield of maize increased with each class of CMS. A similar trend could be seen in the case of sunflower, except for the mean yield for class 5 of the CMS, which was less than the one for class 4 with a difference of 0.606 t/ha. Class 5 of the CMS included only three parcels with average NDMI values in July that were slightly above the predefined threshold (0.428, 0.411, and 0.412); hence, the mean yield for class 5 of the CMS was calculated using only three available records, and it was not reliable for the yield estimation in 2022.

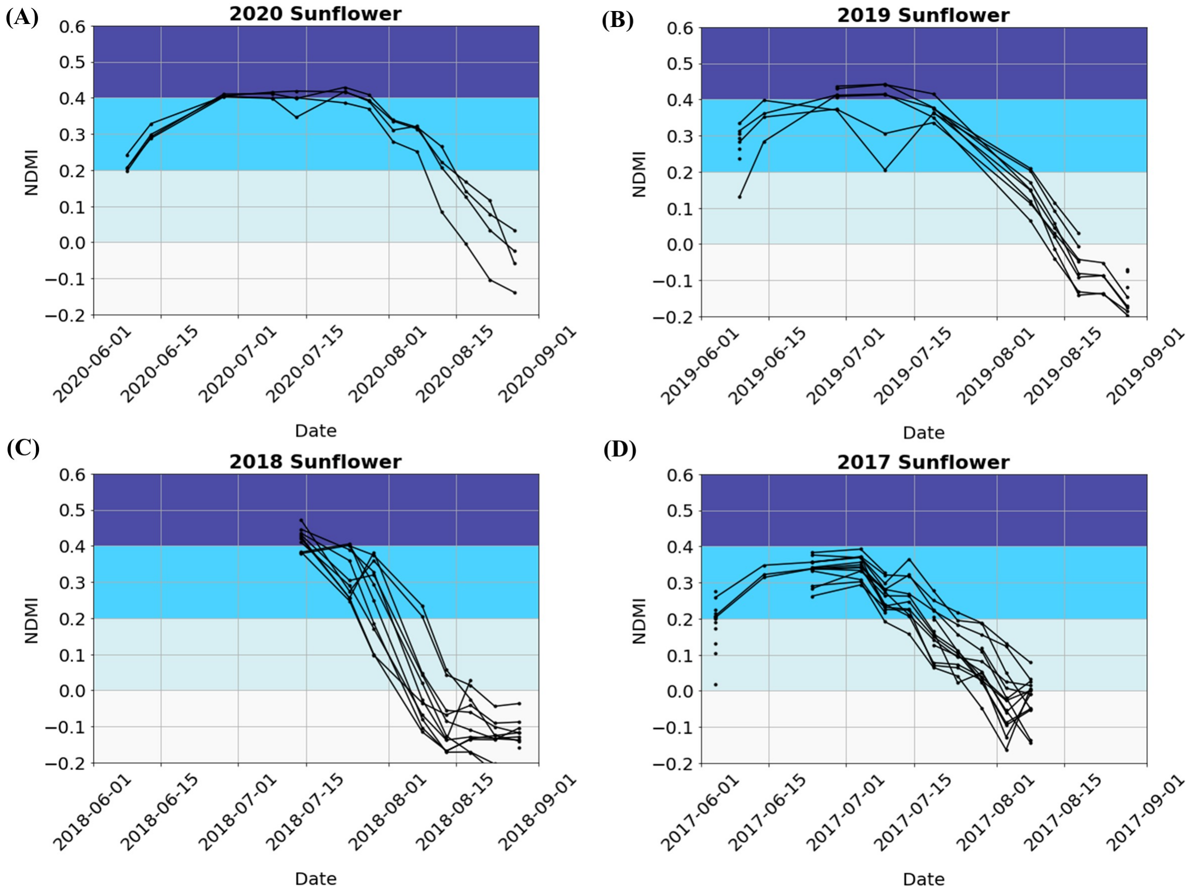

Figure 4. Time series of NDMI values at sunflower parcels in four growing seasons: 2020 (**A**), 2019 (**B**), 2018 (**C**), and 2017 (**D**).

Table 1. Comparison between moisture stress in July and CMS for maize yields.

Moisture Stress	Yield (t/ha)	Std (t/ha)	CMS	Yield (t/ha)	Std (t/ha)
Dry	-	-	0	-	-
Low	4.168	4.604	1	-	-
Moderate	9.491	3.019	2	4.168	4.604
High	11.310	1.738	3	7.415	2.902
			4	10.594	2.479
			5	11.310	1.738

Table 2. Comparison between moisture stress in July and CMS for sunflower yields.

Moisture Stress	Yield (t/ha)	Std (t/ha)	CMS	Yield (t/ha)	Std (t/ha)
Dry	-	-	0	-	-
Low	2.510	0.501	1	-	-
Moderate	3.440	0.841	2	2.510	0.501
High	3.015	0.244	3	3.167	0.802
			4	3.621	0.842
			5	3.015	0.244

After excluding yield outliers for each CMS class, the validation was performed. The results of leave-one-year-out cross-validation are presented in Table 3 with standard statistical metrics. MBE indicated that for maize, the estimations were slightly overfitted for the observed yields, while for sunflower, the estimations were slightly underfitted for the observations. The MAE was less than 1 t/ha for both crops, with a value for sunflower that was a bit lower, which was expected due to the higher average yields of maize. The same pattern could be seen for RMSE.

Table 3. Validation scores given with standard statistical metrics.

Crop	MBE (t/ha)	MAE (t/ha)	RMSE (t/ha)
Maize	0.0497	0.8498	1.0867
Sunflower	−0.1894	0.6051	0.8288

Further on, the yield was estimated for the 2022 season and given with the standard deviation. Since there were no parcels detected in class 5 for either maize or sunflower, yield estimation was not applicable (N/A). In accordance with the extremely dry conditions observed during July 2022 in Vojvodina province [4], most of the maize fields were in classes 1, 2, and 3, with an expected yields of 7.154 t/ha for class 3 and 1.873 t/ha for class 2 (Table 4). Since classes 1 and 0 were not observed in the 2017–2020 seasons, it can only be assumed that the yield would be less than 1.873 t/ha or even that there would be no yield at those parcels due to dry conditions in the critical reproductive period of maize. There were 39 parcels in class 4, and presumably, those were the irrigated fields. In the case of sunflower, the expected yield for all CMS classes did not vary as much as in maize (Table 5). The majority of the parcels belonged to classes 2 and 1, with expected yields of 2.421 t/ha and lower or no yield at all. At the parcels classified as classes 4 and 3 of the CMS, the expected yields were 3.456 and 3.070 t/ha, respectively, with a standard deviation of less than 1 t/h.

Table 4. Yield estimation for maize in the 2022 growing season.

CMS Class	Field Count	Yield (t/ha)	Std (t/ha)
0	7	-	-
1	94	-	-
2	100	1.873	0.440
3	100	7.154	2.784
4	39	10.254	2.140
5	0	N/A	N/A

Table 5. Yield estimation for sunflower in the 2022 growing season.

CMS Class	Field Count	Yield (t/ha)	Std (t/ha)
0	2	-	-
1	32	-	-
2	22	2.421	0.469
3	18	3.070	0.786
4	15	3.456	0.572
5	0	N/A	N/A

Figures 5 and 6 represent maps of parcels with the CMS classes in the 2022 growing season. Only the northern part of the Backa region is shown, since the majority of the scouted maize and sunflower fields were located there. Notwithstanding that the parcels were scouted randomly, it can be seen that most of them were in classes 2 and 1 of the CMS for both maize and sunflower, indicating serious agricultural drought and a yield reduction in the current growing season. With CMS, this information is potentially available in the middle of August, and yield estimation is given early within the growing season.

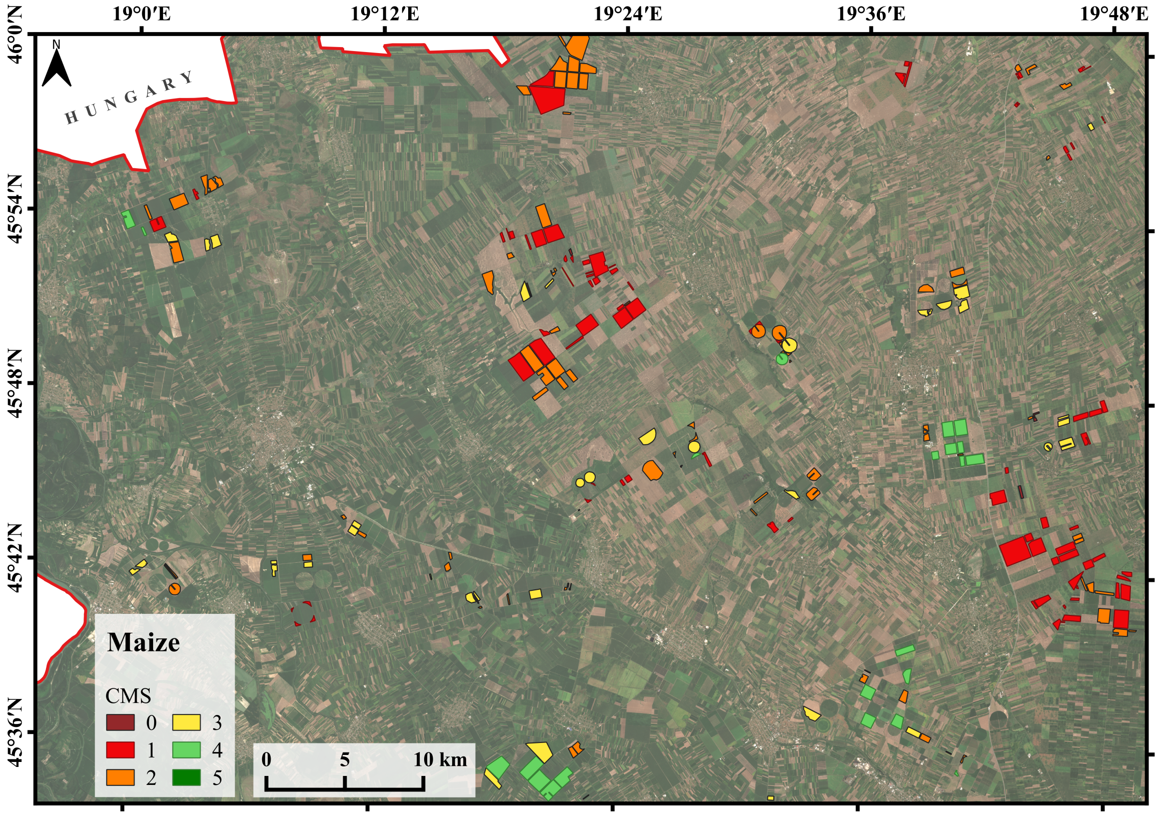

Figure 5. Map of maize fields with CMS classes for 2022.

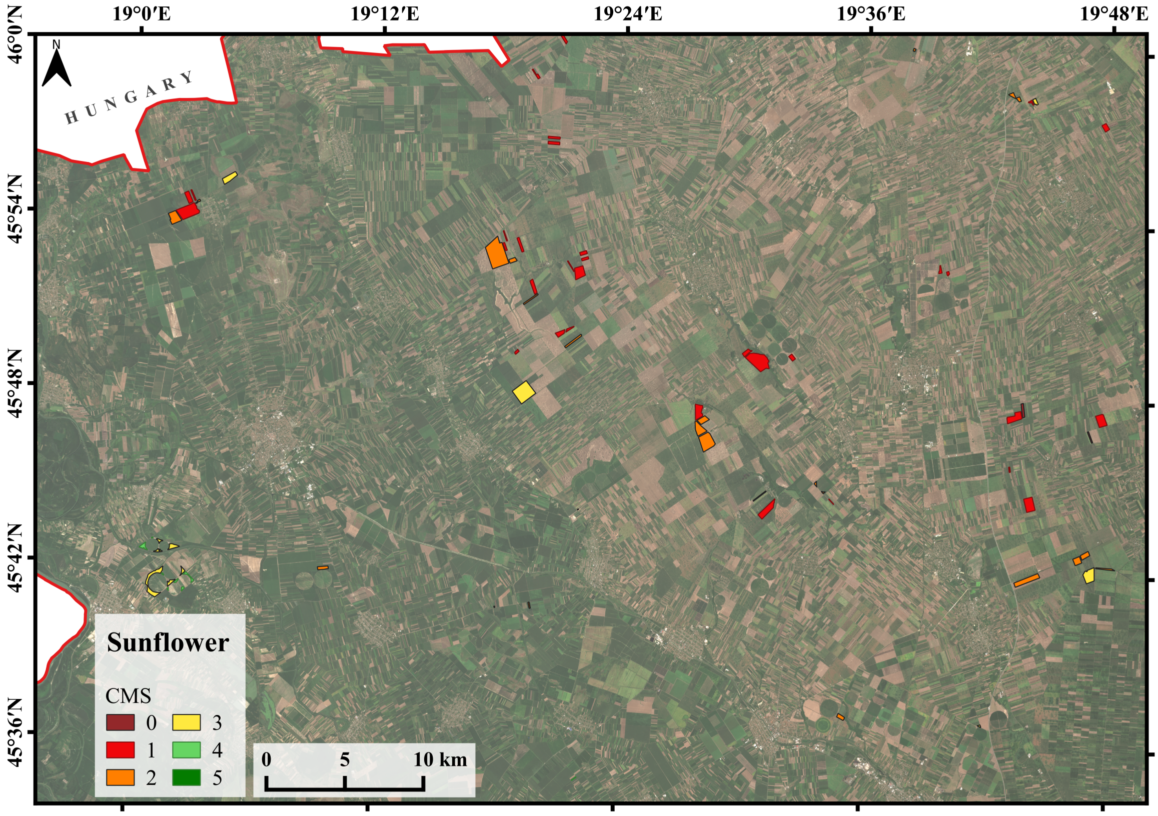

Figure 6. Map of sunflower fields with CMS classes for 2022.

4. Discussion

The results of this research align with the findings of [15], who showed that maize was the most sensitive to a drought of one month occurring in July, which corresponded to its early reproductive stages. For the same period, researchers managed to demonstrate how remotely sensed indices are sensitive to drought by showing their positive relationship with low soil moisture values [39]. Moreover, a period between mid-July and mid-August is considered the most suitable for maize yield prediction within a growing season [40]. In a recent paper [41], the authors used data of 10 multi-spectral bands from Sentinel-2 during the growing season to feed a random forest model for the prediction of sunflower yield at the pixel level within a field. Yield data with a high spatial resolution were obtained from a combine harvester. The lowest root-mean-square error (RMSE) of yield prediction was achieved using images from the end of June and middle of July, in which the most sensitive periods of development overlap. However, they did not discuss the effects of drought on sunflower yield. These effects are harmful to sunflower leaf area, leading to a decrease in the photosynthetic substances needed for adequate seed formation. Finally, this kind of plant stress results in yield reduction [42].

The CMS demonstrated potential as an early warning system for agricultural drought and yield reduction. Thus, it can be integrated into AgroSens [43], a platform for digital agriculture that is freely available for farmers in Serbia. To use the platform, the only thing required is registration. Then, farmers draw a parcel at the exact location in which they grow specific crops during a season. From Sentinel-2 satellite images, NDMI values are calculated for each pixel within a parcel. Based on the data available on the platform, additional information about the CMS and the expected yield can be given to the farmers. In the first decade of August 2022, 47% of the territory of the European Union was under warning conditions due to soil moisture deficit, while there was an alert for most of Vojvodina province, which indicated vegetation stress [4]. Hence, agricultural drought is expected, leading to a decreased yield and possible shortages in food production. Farmers can even ask the question of if it makes sense to carry out a harvest at all or to save the costs of diesel if maize has not been able to be properly pollinated in some fields. As an agricultural drought indicator for yield reduction, the CMS can help in making this kind of decision on time.

Crop classification maps for the current growing season could be obtained through crop monitoring in the Vojvodina region by using artificial intelligence algorithms and satellite images [44]. Based on that, CMS maps could be created, and they can provide timely information to governmental institutions about the expected amount of crop yield, which is important for planning storage space and exports.

There are several directions for future research:

(1) The CMS index is data-hungry, and an enriched dataset of maize and sunflower yield covering many seasons and a wider area of Vojvodina province would lead to more precise yield estimations within growing seasons;
(2) The CMS index can be tested for maize and sunflower in other regions/countries based on local yield records and depending on the hybrids used in those areas;
(3) The CMS could potentially be improved by combining the NDMI with some other vegetation index, e.g., the normalized multi-band drought index (NMDI), which is also based on the NIR and SWIR bands sensitive to the leaf water content [45].

Author Contributions: Conceptualization and methodology, G.M.; codes, D.B.; formal analysis, investigation and visualization B.Ž.; data curation, B.P.; writing—original draft preparation, G.M.; writing—review and editing, B.Ž., D.B. and B.P.; supervision, project administration and funding acquisition, S.B. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Sentinel-2 satellite images are freely available at the Copernicus Open Access Hub. Maize and sunflower yield records are the property of the agricultural company Krivaja d.o.o and cannot be shared with third parties.

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