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Machine learning-based detection of irrigation in Vojvodina (Serbia) using Sentinel-2 data

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ABSTRACT
With rapid population growth and the high influence of climate change on agricultural productivity, providing enough food is the main challenge in the 21st century. Irrigation, as a hydrological artificial process, has an indispensable role in achieving that goal. However, high pressure and demand on water resources could lead to serious problems in water consumption. Knowing information about the spatial distribution of irrigation parcels is essential to many aspects of Earth system science and global change research. To extract this knowledge for the main agricultural region in Serbia located in the moderate continental area, we utilized optical satellite Sentinel-2 data and collected ground truth data needed to train the machine learning model. Both satellite imagery and ground truth data were collected for the three most irrigated crops, maize, soybean, and sugar beet during 3 years (2020–2022) characterized by different weather conditions. This data was then used for training the Random Forest-based models, separately for each crop type, differentiating irrigated and rainfed crops on the parcel level. Finally, the models were run for the whole territory of Vojvodina generating 10 m resolution maps of irrigated three crops of interest. With overall accuracy for crops per year (2020: 0.76; 2021: 0.78; 2022: 0.84) results showed that this method could be successfully used for detecting the irrigation of three crops of interest. This was confirmed by validation with the national dataset from Public Water Management Company "Vode Vojvodine" which revealed that classification maps had an accuracy of 76%. These maps further allow us to understand the spatial dynamics of the most important irrigated crops and can serve for the improvement of sustainable agricultural water management.

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1. Introduction

The lack of water resources and growing demand for agricultural production at the global level cause increasing attention when it comes to water resource management. Due to global warming, 80% of the world's population faces water scarcity (Bruinsma and Bruinsma 2017). In order to adequately face emerging situations, it is important to develop adaptation strategies to answer one of the major questions of the 21st century – how to meet the freshwater needs of all users, including domestic purposes, industrial, and maybe most important, agricultural purposes. The major problem is more frequent serious hazards, among which droughts have been recognized as one of the most severe threats to agricultural production. An increase in global mean temperature and uneven distribution of precipitation is expected to decrease freshwater availability and seriously affect already water-scarce regions in the world (Kummu et al. 2016; Rockström et al. 2012). With these conditions, more and more agricultural areas will suffer from freshwater scarcity during the most important period for plant growth. Considering that, more attention should be given to planning optimal irrigation water usage.

Providing better conditions for growth and higher average crop yields, irrigation plays a key role when it comes to meeting the world's food needs. As reported by FAO, 80% of food needs will be satisfied by production from irrigated agriculture until the end of the year 2025. This implies that irrigation is one of the main measures of agricultural productivity improvement (Schaldach et al. 2012).

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With a high share in Gross Domestic Product (GDP) which was 6.29% in 2021 according to World Bank, agriculture is very important in Serbia's economy. The main agriculture area is Vojvodina which is covered with 80% of arable land and irrigation is a crucial aspect of agriculture in this area (Ninkov et al. 2017). With a long channel network of the Hydro system Danube-Tisza-Danube (HS DTD), Vojvodina has great potential for irrigation, with the possibility of irrigating around 936,000 hectares, which is more than 50% of total agricultural land (Public Water Management Company 2022). However, even with the high potential, only 3% of the cultivated area is under irrigation (Bezdan et al. 2019). As it is projected that agricultural droughts will be double as likely at 1.5°C of global warming in Serbia, while soil moisture will decrease by up to 25% in the annual mean total column soil moisture at 4°C of global warming (IPCC 2022), it is expected that it could highly affect the agricultural economy. Irrigation will be the main solution to overcome these problems, boost production and increase crop yields, raising irrigation management to the higher level.

Knowing the information about the spatial distribution of irrigated parcels is the first challenge on the way to improve both agricultural and water management. Current official records of the Statistical Office of the Republic of Serbia do not include all modern irrigation systems built by both large private landowners and small private producers ("Statistical Office of the Republic of Serbia," n.d). On the regional scale, some information about irrigation distribution exists but often they are not publicly available nor georeferenced which limits their further usage.

The technology of remote sensing (RS) and machine learning (ML) can provide beneficial information related to irrigation practice that can be applied to water management planning (Ozdogan et al. 2010). In the research (El Hajj et al. 2017), soil moisture in agricultural area were estimated from synergize of Seninel-2 and Seninel-1 satellite and it could be useful information for irrigation planning. Ozdogan and Gutman 2008 proposed a methodology based on Moderate Resolution Imaging Spectroradiometer (MODIS) ancillary sources of gridded climate and agricultural data for detecting irrigated areas in the US. Results from this research can help in understanding the effect of irrigation on the worldwide water and energy cycle, climate, as well as agricultural productivity. Also, global irrigation maps generated in several research (Thenkabail et al. 2009; Zohaib, Kim, and Choi 2019) could help in understanding climate effects regarding changes in the extent of irrigated areas and thus creating a better and sustainable water management plan in countries. However, obtaining data about the spatial distribution of irrigated parcels is difficult. Different irrigation practices and techniques such as flood, drip, or spray irrigation, as well as the spatial-temporal scheduling of irrigation, make monitoring of this land type quite complicated (Bégué et al. 2018). The difficulty of distinguishing irrigated areas varies in different climatic zones. As a highly endangered climate zone, a lot of research was done for semi-arid regions (Ambika, Wardlow, and Mishra 2016). For instance (Gao et al. 2018), used time series of Sentinel-1 Synthetic Aperture Radar (SAR) data for mapping irrigated crops, irrigated trees and non-irrigated fields over agricultural site in Urgell, Catalunya (Spain). They achieved overall accuracy which is 81%, but indicate that in more humid region soil moisture contribution will be less and thus model will be less robust. In the research (Bousbih et al. 2018), Sentinel-2 and Sentinel-1 data were used to map soil water content as an additional factor for annual irrigation mapping over cereal crops, while (Jalilvand et al. 2019) used soil moisture satellite data to estimate irrigation water usage at the catchment scale. However, both mentioned research require additional datasets including in-situ measurement.

According to satellite data usage, different papers relied on using optical and thermal sensors (AVHRR, SPOT-1, MODIS, Landsat, Sentinel-2) for differentiation of irrigated and rainfed parcels on local, regional, and global scales. For instance, researches such as (Biggs et al. 2006; Shahriar Pervez, Budde, and Rowland 2014) used MODIS data to calculate the Normalized Difference Vegetation Index (NDVI) to map irrigated areas in southern India and Afghanistan. Landsat images are useful for long historical irrigation mapping such as in (Sharma et al. 2018) where the historical evolution of irrigation cropland was generated for the period of 27 years. Similarly, Deines et al. 2019 used Landsat images for three decades to calculate different vegetation indices and to map annual irrigation across US High

Plains. Some of them used radar data (ASCAT, SMOS, Sentinel-1) for estimating soil moisture as important in irrigation practice (El Hajj et al. 2017; Kumar et al. 2015; Zappa et al. 2021). However, spatial, spectral, and temporal resolution are problematic when it comes to consistent and constant irrigation monitoring. Lately, with the high spatial, spectral, and temporal resolution, Sentinel-2 is gaining increasing importance in overcoming these limitations. High-resolution Sentinel-2 optical images give an advantage in spectral transformations that can differentiate spectral response between irrigated and non-irrigated fields. Consequently, vegetation indices provide a direct benefit as input features in the classification algorithm (Ozdogan et al. 2010).

A number of recent studies used multi-temporal Sentinel-2 data for mapping irrigation crops around the world. Tang et al. 2021 used Sentinel-2 data for mapping center pivot irrigation systems in the southern Amazon. Vogels et al. 2019 used Geographic Object-Based Image Analysis (GEOBIA) and time series of Sentinel-2 imagery to map spatio-temporal patterns of irrigated agriculture in the Horn of Africa, while Pageot et al. 2020 used a synergy of Sentinel-2, Sentinel-1, and rainfall data to classify irrigated crops in the watershed in southwestern France.

Although the situation is not like in some strongly affected regions, moderate continental areas are more and more affected by severe climate changes where a warmer and drier climate, with frequent extreme events, can be expected (Mihailović et al. 2015). The climate scenarios like this increasingly warn us that we should act preventively. Monitoring of irrigated agricultural parcels is quite complicated in regions with moderate continental climate conditions where it is expected substantial overlap in spectral signatures between irrigated and rainfed parcels. For example, irrigated soybean at certain growth stages may overlap with a rapidly growing hybrid of non-irrigated maize or natural wetlands. To overcome this limitation spatial distribution of the crop type is necessary for more precise mapping. However, there is still not so many studies that have been done this way.

Utilizing earth observation data, ground truth data, and a machine learning model, this research proposed a methodology for classifying irrigated and rainfed crops at parcel level in moderate continental climate. Many studies have been published classifying irrigated agriculture as one layer of land use cover (Biggs et al. 2006; Deines et al. 2019; Gumma et al. 2011; Magidi et al. 2021; Thenkabail et al. 2009). The novelty of this research comes from classifying irrigated and rainfed parcels within the same crop types, using the already known spatial distribution of the crops helping to overcome the problem of overlapping different irrigated crops but also land use classes (Zhang, Dong, and Ge 2022). Thus, the three most irrigated summer crops in Vojvodina: maize, soybean, and sugar beet were chosen, and ground truth data were collected. To distinguish irrigated from rainfed parcels, multispectral bands from Sentinel-2 were used to calculate relevant vegetation indices and observe phenological changes in vegetation. Both ground truth data and satellite imagery covered 3 years (2020, 2021, and 2022) characterized by different weather conditions. Further, this data was used for training the Random Forest models, separately for each crop type, and then the models were run for the whole territory of Vojvodina. The final products are 10 m resolution maps of irrigated crops of interest in Vojvodina.

2. Research area and data

2.1. Research area

The study area is the main agricultural region in the Republic of Serbia – Vojvodina (Figure 1). It is located in the northern part of the country (44°37″–46°11″ N, 18°51″–21°33″ E) encompassing the confluence area of the Danube, Sava, and Tisza rivers covering 21,506 km^2. Due to the geographical position in the southern part of the Pannonian Basin, the impact of western air currents, and the greater impact of Eurasian continental climate conditions, this area has characteristics of a moderately continental climate. Winters are cold and summers are hot and humid (the warmest month is July with $T = 21–23$°C) with irregular distribution of rainfall and a huge range of extreme temperatures which caused different values of aridity types (Gavrilov et al. 2019; Hrnjak et al. 2014; Malinovic-Milicevic et al. 2018). The average annual precipitation is approximately 600 mm (Gavrilov et al. 2015, 2016).

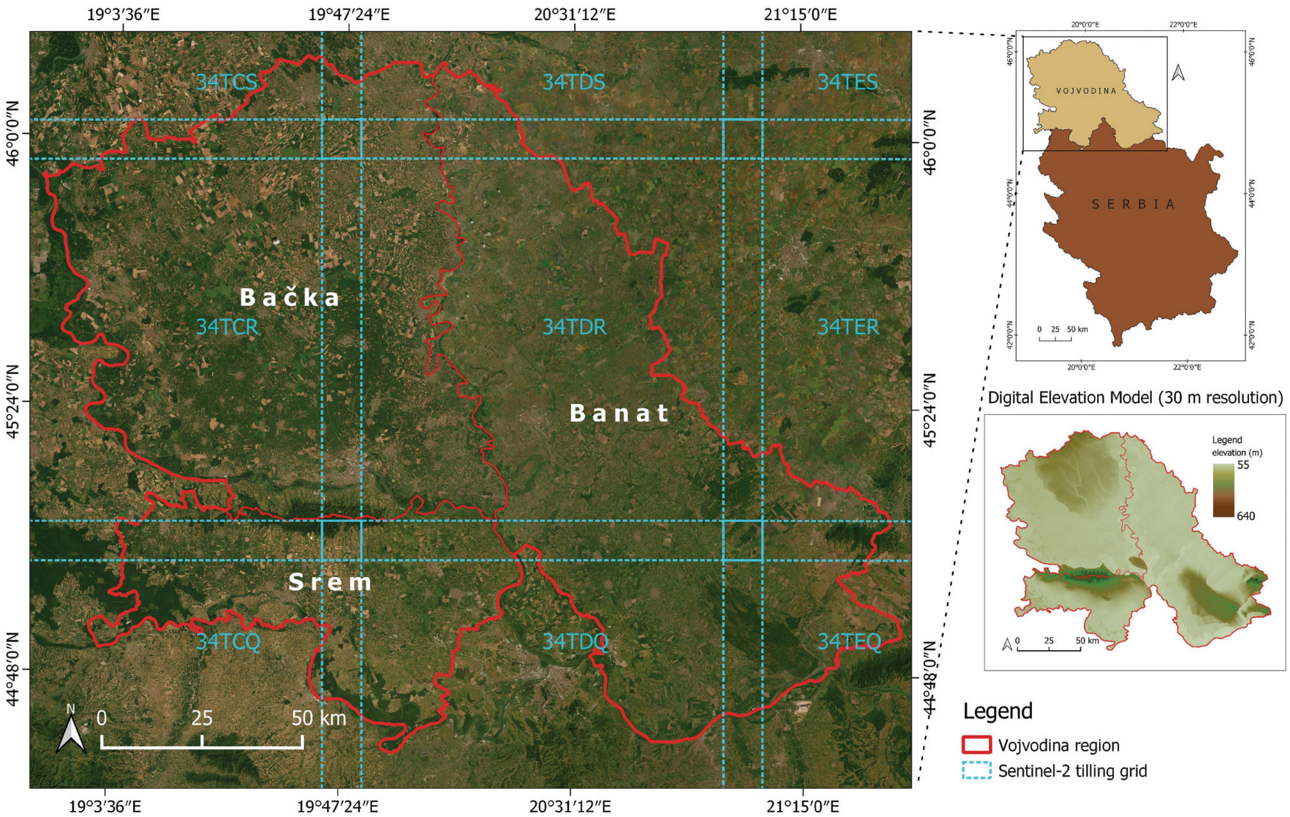

Figure 1. Study area of Vojvodina region with Sentinel-2 footprint and digital elevation model at 30 m pixel resolution.

According to the Statistical Office of the Republic of Serbia, Vojvodina is covered with 1.69 million ha of arable land (Ninkov et al. 2017). As the relief is predominantly flat with low altitude, covered with the most suitable lands for irrigation – Chernozem and Eutric Cambisol, agricultural productivity is possible on 80% of the Vojvodina territory (Gavrilov et al. 2018; Pavlović et al. 2021). The main cultivated crops in the area are maize with 35% of the production of total arable land and wheat with 20% after which goes soybean and sugar beet with a total production of over 90% (Pavlović et al. 2021). Considering that, the research is focused on the most important irrigated crops in Vojvodina: maize, soybean, and sugar beet (Table 1), while other crops were not taken into account because data are missing, or it does not require the additional artificial application of water in this region. The primary sources of irrigation water in Vojvodina are surface water from the Danube and Tisza rivers and groundwater. Maize requires irrigation in phases of germination and emergence, the vegetative stage, tasseling and silking, and grain fill. When it comes to water requirements for soybean, the critical stages are when the first flowers open, during the formation of pods and grains and during the pouring of grains. For sugar beet, a critical phase occurs during intense root growth, after which the water requirements decrease sharply. However, the exact date when the irrigation needs to be applied highly depends on the sowing date, growing progress, and climate and soil conditions (Stričević 2007).

Table 1. Growing calendar for crops of interest: the green squares illustrate the theoretical period when the crop is sown, and the brown squares illustrate the period when the crop is harvested.

	Growing calendar											
	Jan.	Feb.	Mar.	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
Maize												
Soybean												
Sugar beet												

2.2. Data

2.2.1. Ground truth data

The reference data for training ML models for three crops of interest – maize, soybean, and sugar beet were collected for three seasons – 2020 when the above-average precipitation amount during the irrigation season was recorded, and 2021 and 2022 with dry and extremely dry conditions ("WWW n.d.). Collecting ground truth data had several steps. Firstly, in order to save time and collect data as efficiently as possible on a large territory such as Vojvodina, visual detection on Google satellite was done. This was the way to observe where large parcels are located with the assumption that irrigation exists. It also was good in a way that we could plan to collect data evenly in all parts of the region. The second part was the collection of data where during the field campaigns in May and June, the team of researchers collected georeferenced information across the Vojvodina region. For that purpose, a mobile application that works on the principle of georeferenced picture capturing was used. The picture was captured on the field where we also noted information about crop type and whether that parcel is irrigated or not. If the irrigation equipment was installed or working during the visit parcels were labeled as irrigated. Also, non-irrigated parcels were labeled to allow the building of a machine-learning model. And finally, the third part implied the import of georeferenced pictures into QGIS software and drawing all parcels containing already mentioned information. After that, datasets were established for each year and each crop type separately containing 258 parcels in 2020, 439 in 2021, and 579 in 2022 (Table 2). These datasets will be used for extracting information from satellite data and building a machine-learning model.

2.2.2. Sentinel-2 data

Optical images for the study area were downloaded from Copernicus Open Access Hub. The constellations of two polar-orbiting Sentinel-2 satellites, S2A and S2B were used. As the atmospherically corrected (Bottom of Atmosphere) images were required, we used Level-2A (Atmospherically corrected Surface Reflectance) Sentinel-2 product composed of 110 km × 110 km tiles in the UTM/WGS84 projection. For some dates, only Level-1C (Top-of-atmosphere reflectances – TOA) products were available. To produce Sentinel-2 Level-2A, atmospheric, terrain, and cirrus correction of TOA data was performed using Sen2Cor software (released by European Space Agency-ESA). As Vojvodina region is embedded in eight Sentinel-2 tiles (TCS, TCR, TCQ, TDS, TDR, TDQ, TER, TEQ) (Figure 1) cloud-free images were downloaded for 7 acquisition date in 2020, 10 dates in 2021, and 6 dates in 2022 during the irrigation season (April – September). The spatial resolution of the images used in this research is 10 m per pixel. Eight out of thirteen bands of Sentinel-2 images will be used for the calculation of 11 vegetation indices that will be input features for training ML models.

2.2.3. Crop classification – mask generation

As this research aimed to classify irrigated and rainfed parcels within the same crop types, it was necessary to create separable binary masks and then train separate models for each crop type. For that purpose, information about the spatial distribution of maize, soybean, and sugar beet in a certain year was needed for the creation of masks. Considering that, the crop classification maps for all 3 years were used (Figure 2).

These crop maps were created using a supervised Random Forest classification algorithm (Table 3) based on a time series of satellite data as well as ground truth data collected during field campaigns. The maps were generated for the five most important crops in Vojvodina: maize, soybean, sugar beet, sunflower, and wheat (Crnojevic et al. 2014; Lugonja et al. 2019). After that, generated maps were used to create masks for three crops of interest, while other crops were excluded from the research.

Table 2. Distribution of ground truth data by the class label for 3 years.

	Number of parcels			Total area (ha)		
Class label	2020	2021	2022	2020	2021	2022
Maize irrigated	51	129	157	2238	4653	6404
Maize rainfed	66	109	139	2715	4130	7204
Soybean irrigated	41	49	109	1354	1473	3112
Soybean rainfed	51	51	86	1824	1647	3684
Sugar beet irrigated	18	47	53	717	2005	1829
Sugar beet rainfed	31	54	35	1713	2299	2411

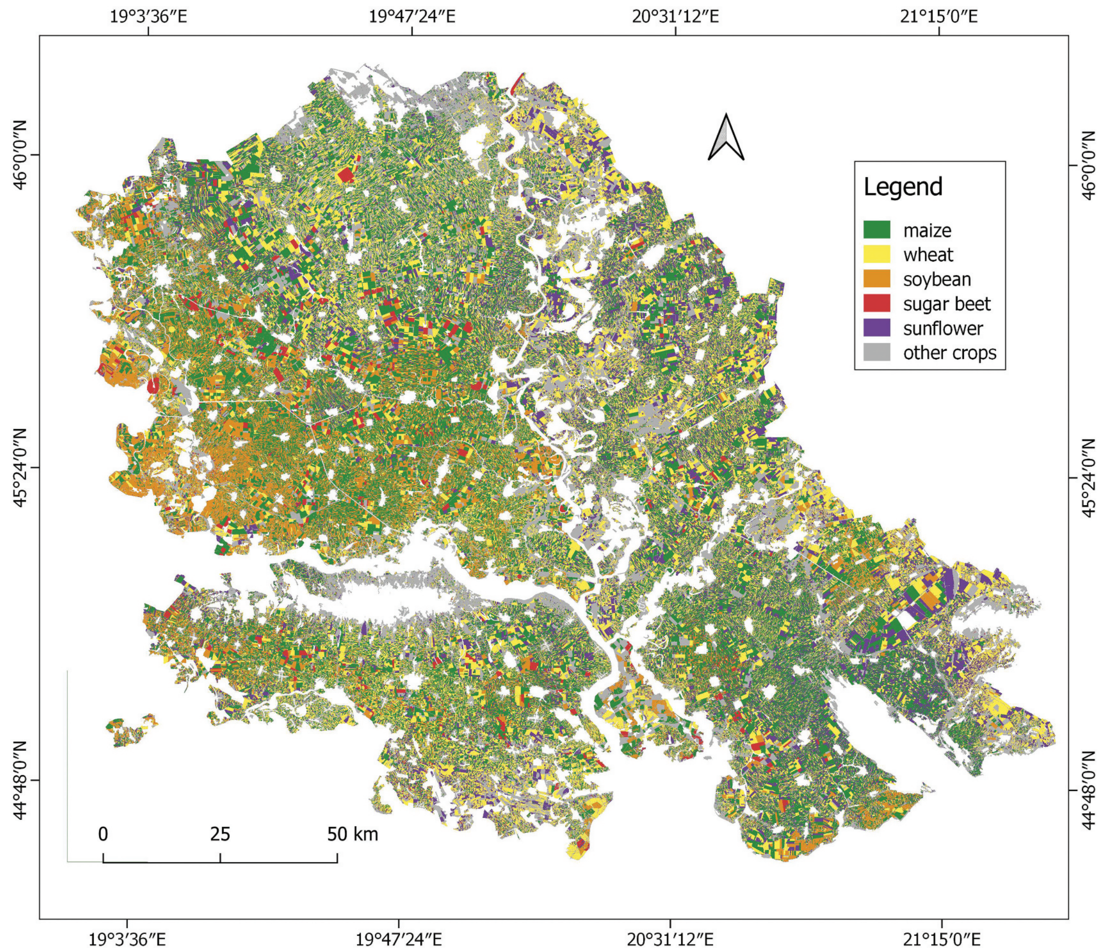

Figure 2. Crop classification maps for year 2022 – spatial distribution of five main crop types in Vojvodina: maize, wheat, soybean, sugar beet, and sunflower.

Table 3. Model performance for crop classification for maize, soybean, and sugarbeet for 3 years.

	Crop	Recall	Precision	OA	Fscore
2020	maize	0.99	0.96	0.98	0.97
	soybean	0.95	0.97	0.99	0.96
	sugar beet	0.97	0.98	1.00	0.98
2021	maize	0.97	0.96	0.98	0.96
	soybean	0.93	0.95	0.99	0.94
	sugar beet	0.99	0.99	1.00	0.99
2022	maize	0.96	0.91	0.96	0.94
	soybean	0.82	0.91	0.97	0.86
	sugar beet	0.96	0.97	0.99	0.97

3. Methods

3.1. Calculation of vegetation indices (VIs)

We selected Sentinel-2 bands at 10 m: the blue (BLUE = 490 nm), green (GREEN = 560 nm), red (RED = 665 nm), and near infra-red (NIR = 842 nm), and at 20 m: red edge (RE = 705 nm), narrow nir (NIR2 = 865 nm), the short-wave infrared (SWIR1 = 1610 nm and SWIR2 = 2190 nm) bands to calculate vegetation indices relevant for distinguishing irrigated from rainfed crops (Ozdogan and Gutman 2008; Pageot et al. 2020). To reduce all indices to the same resolution, the Nearest Neighbour resampling method was applied in python to obtain 10 m resolution images. Pre-processed images than were used for calculation.

Several indices such as NDVI (Huang et al. 2021), NDRE (Zhang et al. 2019), EVI (Huete et al. 2002), and

Table 4. Optical features description – vegetation indices.

Name	Description	Formula
NDVI	Normalized Difference Vegetation Index	$\frac{NIR-RED}{NIR+RED}$
NDRE	Normalized Difference Red Edge	$\frac{NIR-RE}{NIR+RE}$
NDMI	Normalized Difference Moisture Index	$\frac{NIR-SWIR1}{NIR+SWIR1}$
NDWI	Normalized Difference Water Index	$\frac{GREEN-NIR}{GREEN+NIR}$
MNDWI	Modified Normalized Difference Water Index	$\frac{GREEN-SWIR1}{GREEN+SWIR1}$
$AWEI_{nsh}$	Automated Water Extraction Index - no shadow	$4(GREEN - SWIR1) - 0.25NIR + 2.75SWIR2$
$AWEI_{sh}$	Automated Water Extraction Index – shadow	$BLUE + 2.5GREEN - 1.5(NIR + SWIR1) - 0.25SWIR2$
EVI	Enhanced Vegetation Index	$\frac{2.5(NIR-RED)}{NIR+6RED-7.5BLUE+1}$
SAVI	Soil Adjusted Vegetation Index	$\left(\frac{NIR-RED}{NIR+RED+L}\right)(1+L)$
MSI	Moisture index	$\frac{SWIR1}{NIR}$
NMDI	Normalized Multi-Band Drought Index	$\frac{NIR2-(SWIR1-SWIR2)}{NIR2+(SWIR1-SWIR2)}$

SAVI (Huete 1988) were used as they are sensitive to biomass and vegetation density, while NDMI (Masina et al. 2020), MSI (Hunt and Rock 1989), and NMDI (Wang and Qu 2007) are proposed for monitoring soil and vegetation moisture. NDWI (Bhandari, Kumar, and Singh 2015), MNDWI (Xu 2005), and AWEI (Feyisa et al. 2014) are water indices that have wide usage in various applications including agriculture.

Time series of vegetation indices were used as input features for machine learning models training. The list of vegetation indices is shown in Table 4.

3.2. Model training

The next step was to access the machine learning process to distinguish between irrigated and rainfed parcels. Random Forest (RF) is a well-known ensemble learning method that has a long history in achieving efficient classification results in different Earth system experiments, including agriculture (Belgiu and Drăguț 2016; Cutler et al. 2007; Lebourgeois et al. 2017). In combination with remote sensing data, this algorithm has been long used for identifying, classifying, and mapping various land cover classes (Crnojevic et al. 2014; Ibrahim et al. 2021; Kulkarni and Lowe 2016; Lugonja et al. 2019; Tariq et al. 2022). As the simplest to parametrize, with high speed and good performances (Belgiu and Drăguț 2016; Breiman 2001; Pal 2005; Pelletier et al. 2016; Shi and Horvath 2006) this method was used for the pixel-based classification process As input features, already calculated time series of VIs were used. The number of trees was set to 100 and max-features to $\sqrt{\text{number features}}$.

Due to spectral similarity between the three crops of interest, separate datasets for each crop type were created and classification models for maize, soybean, and sugar beet for each year were trained independently. For splitting data into training and test sets, 10-fold cross-validation was used. The data set samples represent individual pixels and when dividing data into training and test sets, the belonging of the pixels to certain parcels was considered. All pixels of one parcel had to belong to either a training or test set to avoid an optimistic estimation of the model performance.

3.3. Performance of mapping irrigated areas

As an important part of any classification, the performance of each classifier was evaluated by deriving confusion matrices and calculating the Overall Accuracy (OA) and F-score. Overall Accuracy presents the ratio of the total number of correctly classified pixels and the number of reference pixels and it was calculated using the formula from (Story and Congalton 1986).

$$OA = \frac{\text{correctly classified pixels}}{\text{reference pixels}} \quad (1)$$

To evaluate the performance of each class an F-score (Balfe and Smyth 2005) was used. The higher the F-score, the more accurate a model is.

$$Fscore = 2 \times \frac{precision \times recall}{precision + recall} \quad (2)$$

where *precision* is a measure of the correctness of a positive prediction and *recall* is the measure of how many true positives get predicted out of all the positives in the dataset.

Performance measures were calculated at the pixel level, but also further aggregated by majority voting on parcel level that allows filtering some pixel level errors.

3.4. Probability maps generation

After training, RF models were applied to the entire territory of the Vojvodina using already prepared masks for the three crops of interest. Thus, 10 m probability maps of irrigated maize, soybean, and sugar beet in Vojvodina were created. These maps contain information about the probability of irrigation for each pixel based on decisions from all decision trees in the forest.

3.5. Validation

In order to validate the precision of our classification, the final classified map of irrigated plots in the Vojvodina region will be compared with the National Statistics data (further validation polygons). These data were obtained by the Public Water Management Company "Vode Vojvodine" (PWMC "Vode Vojvodine") responsible for managing irrigation systems in Vojvodina. Unfortunately, precise yearly monitoring of the irrigation systems installation, the number of hectares under irrigation, and the type of crop which was irrigated in the given year are missing. According to the last available data from PWMC "Vode Vojvodine," the total area under installed irrigation systems in Vojvodina was 72,128 ha in 2022. However, some of the irrigation systems were not used during the irrigation season and thus, PWMC recorded that only 59,447 ha were irrigated in year 2022. In order to do validation, only systems that were active in 2022 were used. This includes the irrigation systems managed by the PWMC that utilize both surface water and groundwater sources. The validation dataset is organized as large polygons consisting of several irrigation systems (which usually present one agriculture company that owns more irrigation systems). These polygons (further validation polygons) will be used for comparison between the spatial distribution of classified and real irrigation parcels, taking into account the uncertainties in the validation dataset. The validation methodology will contain three steps.

Firstly, calculation of percentage of the crop coverage of interest will be done. Having in mind that within these validation polygons could occur other irrigated crops which are none of the interest in this research, firstly, crop classification for year 2022 was used for calculating the percentage of the crop coverage of interest – maize, soybean, and sugar beet, while other classified crops were excluded (Figure 3).

Secondly, the calculation of irrigation percentages for crops of interest will be done using information from Figure 3. Generated irrigation maps for 2022 will be overlapped with these polygons, and irrigation percentages for crops of interest will be calculated within each of them. And finally, the third step will be additional validation for low irrigation percentage detection within each polygon which has a high percentage of crop coverage.

4. Results

4.1. Precision of irrigated crop detection

In this research, models were trained and validated on collected ground truth data over the Vojvodina region in 3 years: 2020, 2021, and 2022. Even if classifications were done on the pixel level, for decision-makers it is necessary to know how many parcels are irrigated in the Vojvodina region. Considering that, confusion matrices (Figure 4) are shown for both pixel and parcel levels, but further results will be analyzed on the parcel level.

According to the confusion matrices (Figure 4), model performances are the best for the 2022 year. The highest overall accuracies are achieved for soybean and sugar beet (OA = 0.86 for both) with the highest detection score (F-score) for irrigated class (F-score = 0.89 and F-score = 0.87 respectively) (Table 5). Slightly lower performances of the model are observed for 2021. where the best OA is for soybean (OA = 0.82, F-score = 0.82). Results showed that for 2020 year model accuracy was the lowest. The best OA is for sugar beet (OA = 0.84, F-score = 0.78), while the lowest accuracy (OA = 0.69, F-score = 0.62) was achieved for maize. Observed by class, F-scores are higher for irrigated class in 2021 and 2022, while the reverse case is noticed for 2020.

Looking according to crop type over the research period, the conclusion is that classification worked better for soybean (OA 0.75–0.86) and sugar beet (OA 0.74–0.86), while slightly lower performances were gained for maize (OA 0.69–0.79).

Such results analysis per year indicates that models work better during dry years than during years with

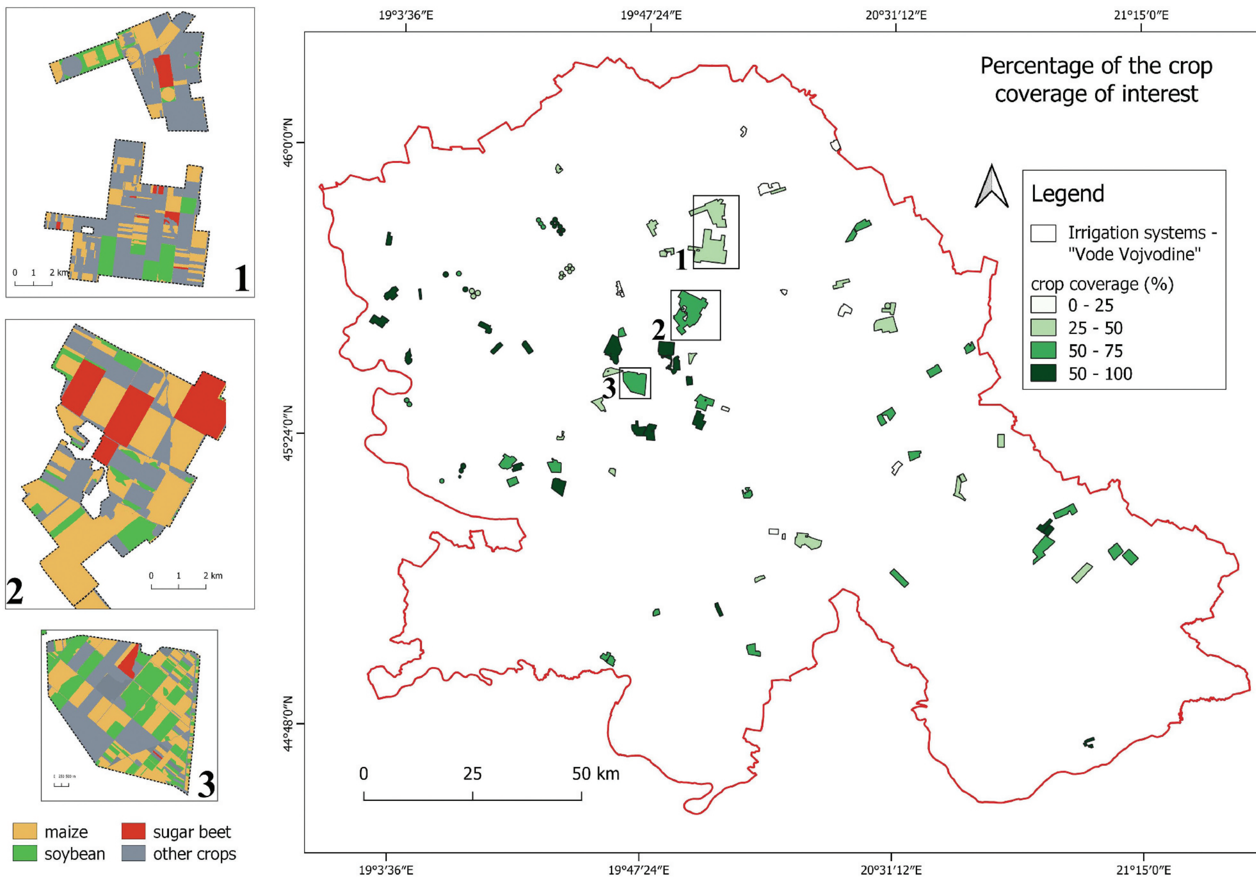

Figure 3. Distribution of the maize, soybean, and sugar beet within validation polygons from PWMC "Vode Vojvodine" for the year 2022 presented as % of the crop coverage of interest. Examples 1, 2, and 3 are given for a more detailed insight into how the spatial distribution of three crops of interest and other crops that are non of interest looks.

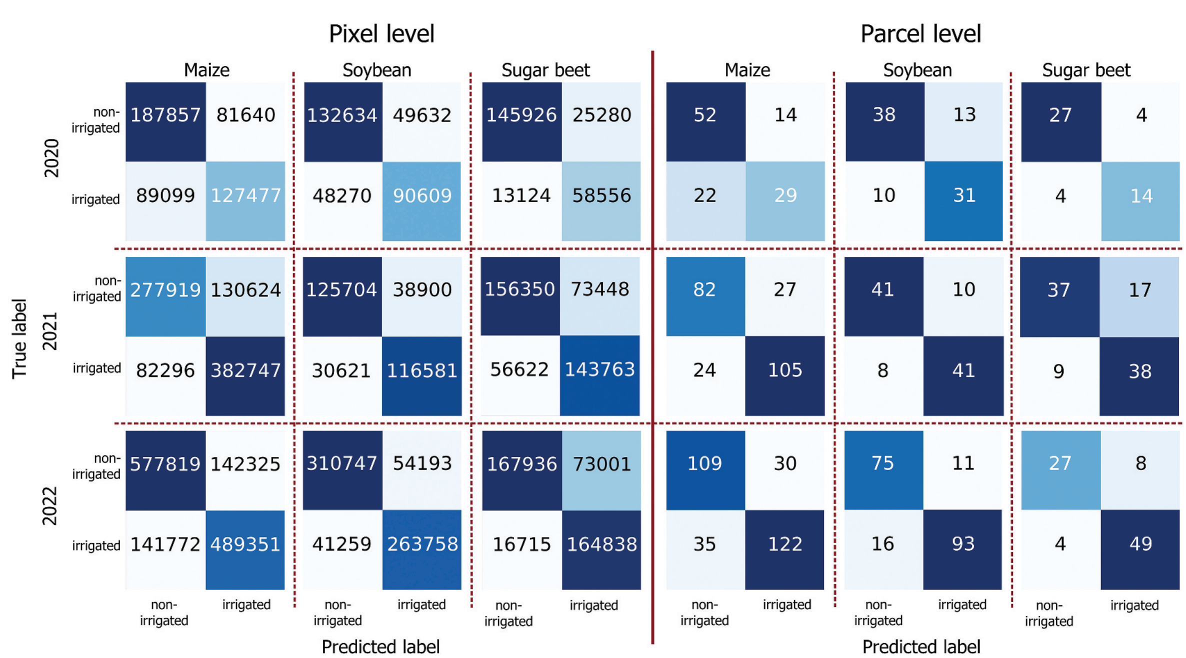

Figure 4. Confusion matrices for each crops per each year; left - pixel level, right - parcel level.

Table 5. Performance of Random Forest models at parcel level for maize, soybean, and sugar beet per each year.

		2020		2021		2022	
		Irrigated	Rainfed	Irrigated	Rainfed	Irrigated	Rainfed
maize	Precision	0.67	0.70	0.80	0.77	0.80	0.76
	Recall	0.57	0.79	0.81	0.75	0.78	0.78
	F-score	0.62	0.74	0.80	0.76	0.79	0.77
soybean	Precision	0.70	0.79	0.80	0.84	0.89	0.82
	Recall	0.76	0.75	0.84	0.80	0.85	0.87
	F-score	0.73	0.77	0.82	0.82	0.87	0.85
sugar beet	Precision	0.78	0.87	0.69	0.80	0.86	0.87
	Recall	0.78	0.87	0.81	0.69	0.92	0.77
	F-score	0.78	0.87	0.75	0.74	0.89	0.82

optimal climate conditions. Also, the classification of irrigated fields during dry years is possible by combining all three crops and training one model instead of three. During the year when more rainfall days are recorded, it is harder to distinguish irrigated and rainfed fields without knowledge about crop type. Due to that, this research proposed a unique methodology that does not depend on climatic conditions and accordingly, results of separate models were analyzed.

4.2. Spatial distribution of irrigated croplands

This study generated annual 10-m resolution maps of irrigated maize, soybean, and sugar beet in Vojvodina for 3 years: 2020 with above-average precipitation amount during the irrigation season, and 2021 and 2022 when drought was recorded. Observing in relation to the total agriculture area in Vojvodina, irrigated area continuously increased from 1.30% (20,666 ha) in 2020, 1.98% (31,517 ha) in 2021, to 3.35% (53,148 ha) in 2022. Analyzing only within the area of three crops of interest, it is noticeable that maize was the most irrigated crop among crops of interest in all 3 years (1.46% in 2020–4.09% in 2022), while sugar beet is least under irrigation (0.27% in 2020–0.93% in 2022). Looking proportionally to the area under the same crop type (Table 6), we can conclude that sugar beet has increasingly the highest percentage of irrigation in all 3 years (5.44%, 12.82%, and 23.27%, respectively), but it should be noticed that the least area is under this crop type and has a trend of decreasing (Novković et al. 2023).

According to the map (Figure 5) which present merged probability maps of maize, soybean, and sugar beet, it is evident that major irrigated areas are in Bačka region, while Srem has the smallest number of detected parcels. The reason for that could be found in the dense channel network within HS DTD, but also in artificial water objects intended for irrigation located in this region. This good irrigation infrastructure enables easier water supply to the parcels from large water sources such as Tisza and Danube rivers.

On the other side, Banat region has the densest channel network where it is possible to irrigate more than 400,000 ha of arable land, but the potential for irrigation is not used as much as it could be. The same situation is with Srem where the potential of 184,000 ha suitable for irrigation is not used (Public Water Management Company 2022).

4.3. Comparison with national statistics

According to the calculated percentage of the crop coverage of interest (Figure 3), 61% of validation polygons are covered by more than 50% of crops of interest, while 12% have less than one-quarter of crop coverage of interest. For these polygons, it is expected to have a low percentage of detected irrigation parcels.

Further, to validate our results, generated irrigation maps for 2022 were overlapped with layer crop

Table 6. Percentage of the irrigated area within the total area of examined crops.

	2020			2021			2022		
	Crop area (ha)	Irrigated (ha)	Irrigated (%)	Crop area (ha)	Irrigated (ha)	Irrigated (%)	Crop area (ha)	Irrigated (ha)	Irrigated (%)
maize	580,972	11,846	2.04	568,990	21,288	3.74	50,8127	29,136	5.73
soybean	192,248	6,617	3.44	198,789	5,869	2.95	17,6898	17,382	9.83
sugar beet	40,521	2,204	5.44	34,002	4,360	12.82	27,950	6,631	23.72

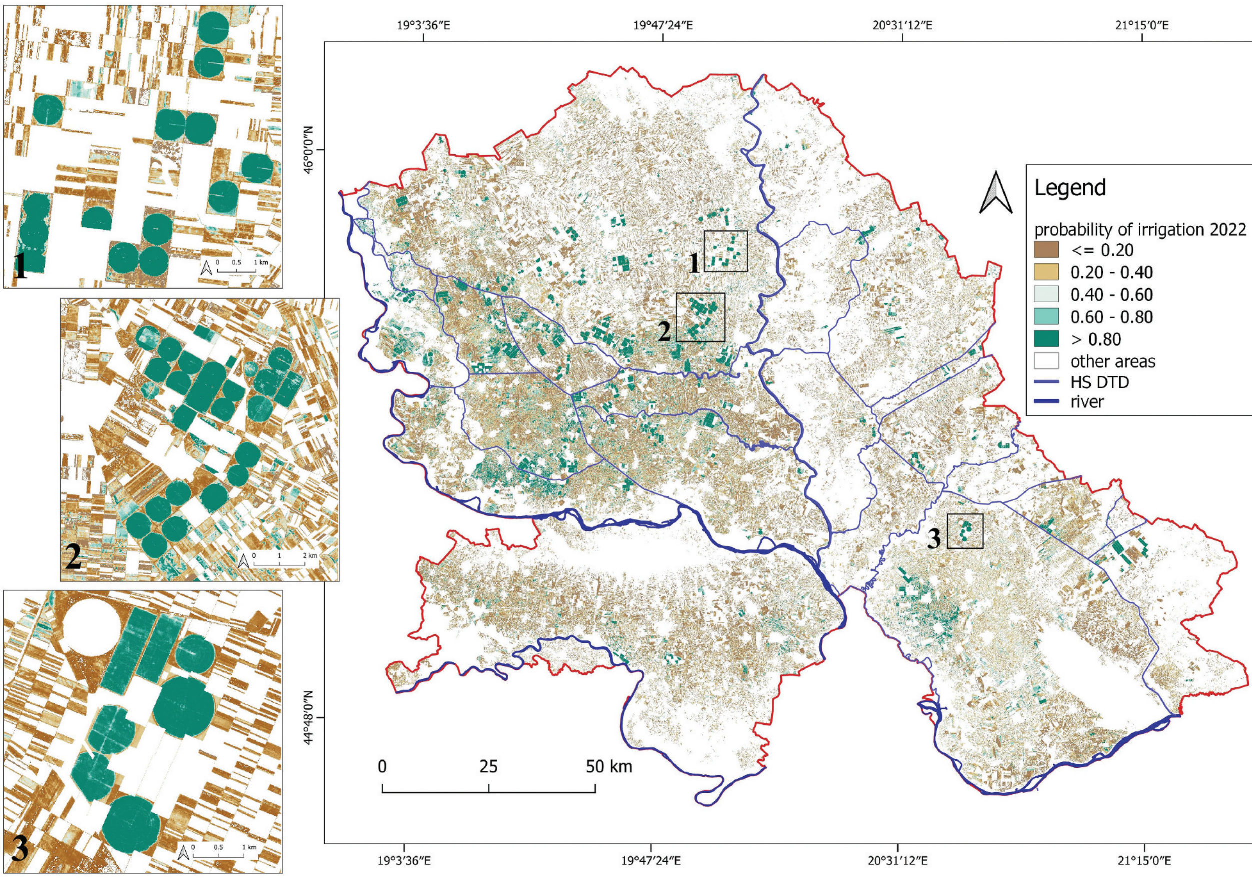

Figure 5. Probability map of irrigated three crops of interest in Vojvodina region in 2022. Examples 1, 2, and 3 are given as an enlarged view of classification results.

coverage of interest and irrigation percentages were calculated within each of the polygon (Figure 6). The calculation showed that among the total of 77 polygons, 29% (22 polygons) have more than 50% of irrigated crops detected, 21% (16 polygons) have between 25–50% of irrigation, 18% (14 polygons) have between 10–25%, and 32% (25 polygons) were detected with less than 10% of irrigation.

(1) Analysing Figure 6, it is noticed that a low percentage of irrigation is detected in 25 polygons among which some of them (17 polygons) have a high percentage of crop coverage. In order to see what is the reason for such a mistake in classification, additional validation was done. For those polygons, it was hypothesized that there was irrigation in 2020 and 2021, but some other crops not included in our study were irrigated in the year 2022,
(2) irrigation systems moved to another nearest area,
(3) there was irrigation according to PWMC, but it was not detected in the classification.

Figure 7 shows some examples of irrigation occurrence during all research periods but only within validation polygons where at least 25% of crop coverage of interest occurred and less than 10% of irrigation was detected in 2022. It follows that example e confirms hypothesis (1) where irrigation was applied in recent years, but for 2022, some other crops which are not of interest were irrigated. This was the case for four polygons and for them, it could be said that classification worked well. Examples c, f, and h showed that movement or permanent shutdown of the irrigation system is possible, which corresponds to hypothesis (2). Such polygons (3 of them) were not used in the final validation accuracy assessment. Finally, examples a, b, d, and g confirm hypothesis (3) where according to PWMC there is irrigation equipment, but according to classification the crops of interest were not detected as irrigated. These polygons (10 of them) are considered as wrongly classified.

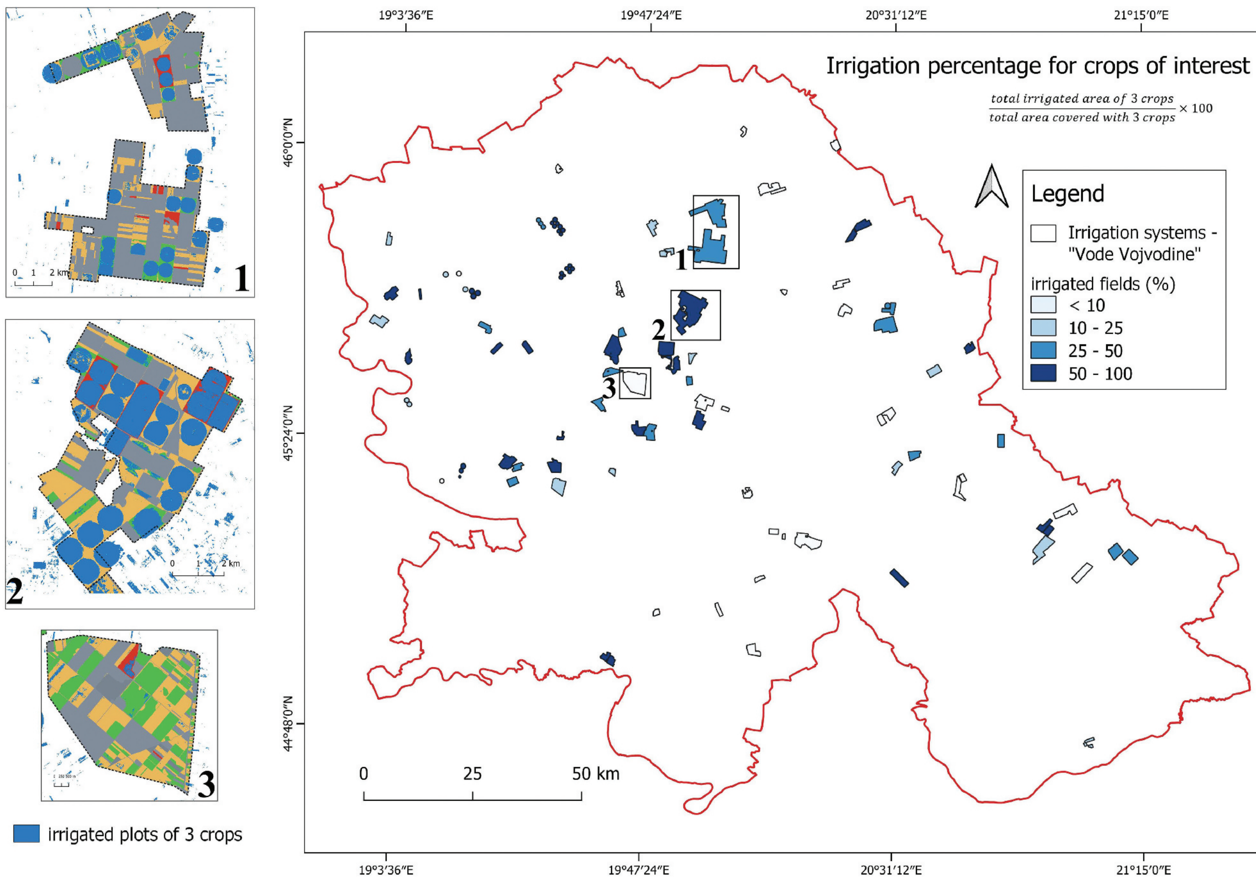

Figure 6. Irrigation percentage of maize, soybean, and sugar beet within validation polygons from PWMC "Vode Vojvodine" for the year 2022 categorized into four classes. Examples 1, 2, and 3 are given for a more detailed insight into how much of the area of interest is under irrigation.

Considering the results from hypothesis (2), the number of validation polygons was reduced from 77 to 74 where the total number of wrongly classified polygons is 18. Eventually, results showed that the classification for 2022 has an accuracy of 76%. With that, it is confirmed that the method proposed in this study could be successfully used for detecting irrigated parcels of three crops of interest.

5. Discussion

5.1. Classification accuracy in different climatic conditions

This study investigates the capability of Sentinel-2 images in combination with a machine learning method for detecting irrigated parcels in the moderate continental climate area. Thus, 3 years characterized by contrasted meteorological conditions were used.

In the moderate continental area, the effectiveness of classifying irrigated and rainfed parcels is challenging due to the high similarity between the spectral signature of these two classes (Shahriar Pervez, Budde, and Rowland 2014). When the climate condition during the season is not characterized as dry, the plant progress on irrigated and rainfed parcels could be similar due to more frequent rain and less irrigation application. This was the case for season 2020 when the above-average precipitation amount during the irrigation season was recorded (Climate Data Store, n.d.) and plants had enough water in the critical month for growth. In such cases, irrigation is rarely applied, and there is no significant difference in plant growth between irrigated and rainfed parcels. That could cause confusion during model training and due to that slightly lower performances of the classifier were gained for this year. The model achieved the best performance for 2022 where the driest climate

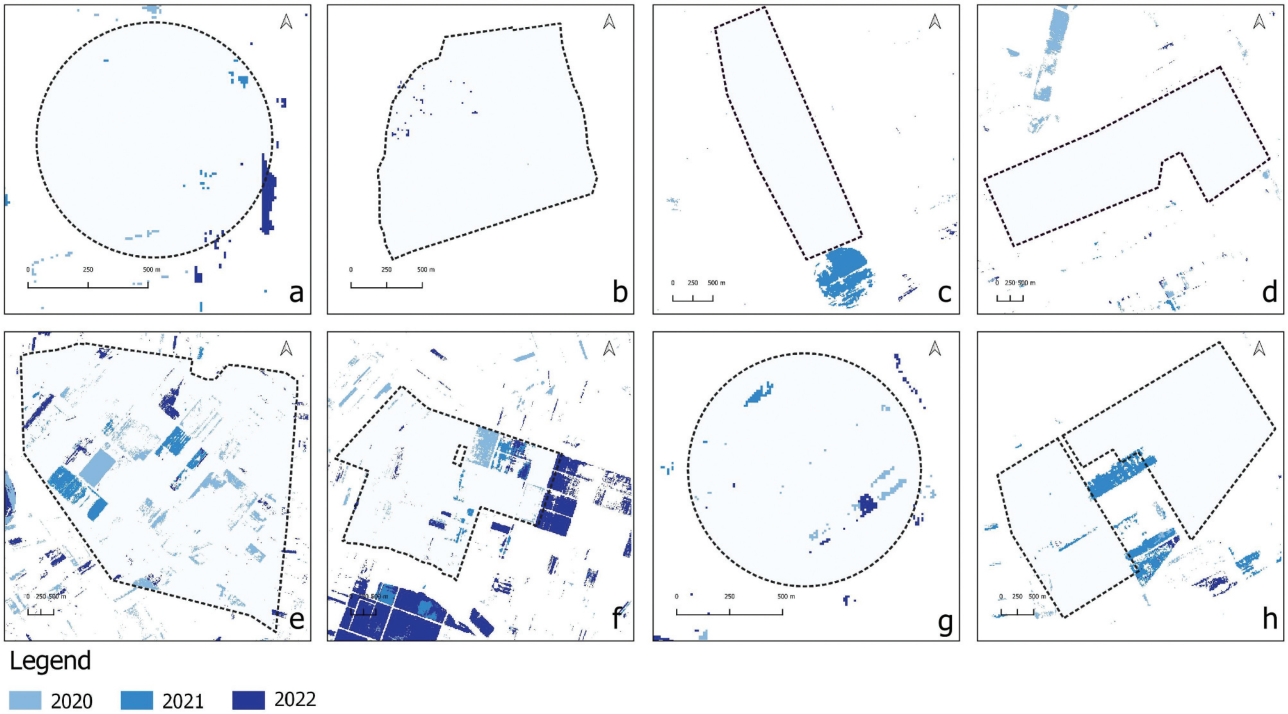

Figure 7. Examples of the absence of irrigation during three years in polygons with high coverage of crops of interest.

conditions were recorded, and differentiation of irrigated and rainfed parcels was easier.

When it comes to the percentage of area under irrigation systems, the least number of irrigated parcels were detected in 2020 (1.3%). Besides the uncertainty of the classifier, the reason for the low percentage of area detection could be that people did not irrigate as much as in 2022, when extremely dry conditions were recorded and 3.35% of irrigated crops were detected. Considering that but also previous validation, the conclusion is that if irrigation was detected at least 1 year of the research period, irrigation equipment exists but it was used according to climate conditions and the need for the sowed crop in a certain year.

5.2. Challenge in differentiating irrigated from rainfed parcels

Even if the Vojvodina province is part of the Pannonian Basin which is predominantly plain, the diversity of the geomorphological units, distribution of the river network as well as soil types could affect classification accuracy. Detecting irrigation on higher relief units with porous soil could be challenging because water is not retained long enough in the root zone and plant growth would not be faster as it is expected compared with rainfed crops (Gumma and Pavelic 2013; Radulović et al. 2022; Rajaveni, Brindha, and Elango 2017).

Uncertainty of the classifier could also occur in the area near a river where water exchanges between rivers and alluvial aquifers are significant (Sophocleous et al. 1988). Other phenomena occur in areas with micro depressions, where groundwater table near the topography surface is a common case, affecting the increase of soil moisture and further crop growth. In the Vojvodina region, shallow groundwater is continuously widespread, and it can induce faster crop growth, feeding plants through the root zone (Polomcic et al. 2012). In such conditions, some crops could have similar growth progress than irrigated crops and it can cause the classifier to detect more parcels as irrigated than it is supposed to be. It is important to emphasize that this phenomenon could occur also during the dry year when even though a meteorological drought appeared, there is a time gap until the hydrological drought and the plants still have enough water supply (Huang et al. 2017).

According to generated maps and previous knowledge, the assumption is that wrongly classified parcels near the Danube riverbed in western Vojvodina are consequences of the combination of these phenomena (Figure 8).

Observing each parcel as a set of pixels, highly heterogeneous in the spectral signature could occur. That happens because of different elevations and micro soil characteristics within large parcels, because of which the irrigation effect is unequal. Plants on such parcels could have uneven growth and part of the parcel with less progress could be classified as non-irrigated even if it is actually irrigated. Figure 9

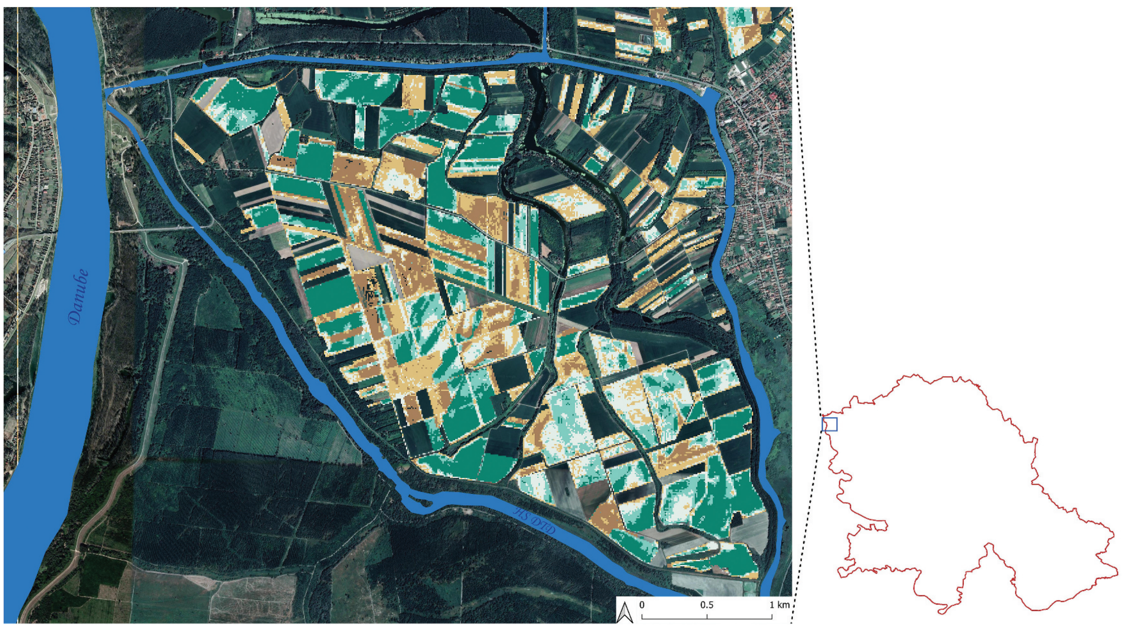

Figure 8. Overclassified irrigated parcels near the Danube riverbed (base map source: Google satellite).

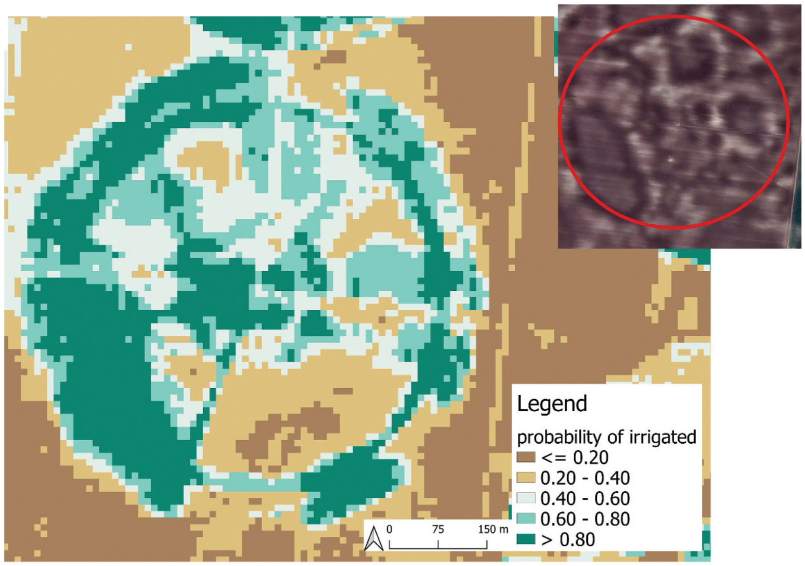

Figure 9. Example of unstable classification for irrigation parcel.

shows an example where the classifier was uncertain about the probability of irrigation due to less plant progress. These are borderline cases where the classifier decision depends on the occurrence of the already-mentioned conditions on the parcels.

5.3. Trends in irrigation in Vojvodina

The hydrographic network which can be used for irrigation in Vojvodina consists of large rivers such as the Danube, Tisza, and Sava, smaller watercourses, HS DTD with 930 km of channel network, more than 20,000 km of the detailed channel network, and numerous accumulations built for the purpose of irrigation. With this wealth of surface water and infrastructure, as well as abounded groundwater reservoirs, Vojvodina has the potential to irrigate 936,000 ha of agricultural land (Savić et al. 2013). Results from this research indicated that the irrigated area in Vojvodina continuously increased from 20,666 ha in 2020 to 53,148 ha in 2022. Compared to the statistics for Serbia, it is worth notable that the increase in water abstraction is also evident, from 69,113 thous. m^3 in 2020 to 99,355 thous. m^3 in 2022 what is one more proof that irrigation is more applicable, both on the national and regional level.

Although it is known that better production and higher yield can be achieved by irrigation (Kang, Khan, and Ma 2009; Payero et al. 2008; Popova and Kercheva 2005), the area under irrigation systems in Vojvodina has never achieved the planned capacity and that is hereby confirmed in this research. Besides good infrastructure for irrigation, it is necessary to encourage the investment of irrigation equipment installation through co-financed and subsidies as help to farmers, companies, and other interested parties. Some already installed systems are usually in poor condition or outdated and abandoned which is the consequence of a lack of money for renovation and new investments. This trend leads to a decrease in total irrigated agriculture in Vojvodina, instead of increasing and maximal capacity usage (Savić et al. 2013).

It is worth noting that irrigated agriculture in this region may oscillate from year to year depending on factors such as weather patterns, water availability, as well as agricultural practices. As more irrigated parcels were detected during drought conditions in 2021 and 2022, than in 2020, one positive note could be that farmers follow the principle that irrigation as a measure does not have to be used always and at any cost, but only when it is really needed according to the weather conditions and crop water requirement. From that, it is also evident that farmers in the Vojvodina region still use irrigation as a supplementary measure during extreme drought conditions. Our research, for the first time, estimated the current situation of irrigation in this region providing useful information that together with water potential resources can be utilized for policymakers aiming to balance between the necessity to increase irrigation capacity and the availability of water resources.

5.4. Strength, limitations, and future directions

Using only satellite data, this research provides the first product about the annual spatial distribution of the main irrigated crops in Vojvodina giving a possibility for further monitoring of irrigation. Sentinel-2 data with a 5-day revisit time allows enough precise temporal and spectral resolution for monitoring irrigation over some regions. Compared with other similar research such as (Pageot et al. 2020) where they classified irrigated and rainfed crops at the plot scale in southwest France, our approach with separate model training for each crop type improved classification precision. They examined five different scenarios with a synergy of Senitnel-1, Sentinel-2, and rainfall data, the OA range from 0.63 to 0.78 for the dry year and 0.54–0.73 for the wet year. Compared with the results in our research, OA is better in dry years (2021: 0.78 and 2022: 0.84), while for the wet year (2020: 0.76) both researches have similar results. Pageot et al., (2020) also proved that using low-resolution (8 km) rainfall data may increase confusion on the distinction between irrigated and rainfall.

It should be noted that even if it is possible to train one model for all three crops together (Pageot et al. 2020; Zhang, Dong, and Ge 2022), this research proposed a unique methodology that does not depend on climatic conditions and could successfully distinguish irrigated and rainfed parcels. It is also important to emphasize that research that does not have a crop classification map, still can perform irrigation classification, but the effectiveness of irrigation mapping will be better with knowing crop type and that is also emphasized by (Xie and Lark, 2021; Zhang, Dong, and Ge 2022).

The simplicity of the data used, calculating only vegetation indices, is important in a way that methodology could be applied not only in this particular region but also in some others. Spatial transferability between Vojvodina regions (Bačka, Banat, and Srem) (Figure 1) characterized by different physical-geographical conditions showed that OA in validation may drop for 0.08 for maize, 0.18 for soybean, and 0.31 for sugar beet compared with the performance of the models for Vojvodina (Figure 4). These lower performances are the consequences of the unbalanced datasets as well as geographical characteristics that differ between regions. Also, according to the Census of Agriculture Census of Agriculture 2013, the spatial distribution of these three crops is not equal in each region. For example, maize is spread in all three regions and we can see that transferability has the highest potential. However, soybean is much more characteristic for Bačka, not much for Banat and Srem. The same situation is for sugar beet. On the other side, applying spatial transferability within the same geographical region (a case study of Bačka) resulted in a negligible drop in OA for maize and soybean (0.03 and 0.05 respectively) while for the sugar beet, OA was higher (for 0.12). Due to that, spatial transferability is certainly possible in the same geographical regions; however, additional data sets from the targeted region are desirable in order to fine-tune a predefined machine learning model (Antonijević et al. 2023; Mirzaeitalarposhti et al. 2022; Nowakowski et al. 2021). Herewith, for the first time, this research emphasized the importance of the main physical-geographical characteristics of the region for achieving and explaining better results using the ML approach. There are some limitations in the proposed methodology that could be possibly overcome in future research. This research suffered from the absence of data such as depth of groundwater, as well as high-resolution soil data which have not been researched enough for this problem. With these datasets, additional features could be used for training the model and all the above-mentioned phenomena will be addressed, resulting in better accuracies of model training and generating more precise irrigation maps. However, it should be kept in mind that if we strive for high-resolution maps, we should have high-resolution data; otherwise, the low-resolution data will not contribute to the improvement of the model results (Pageot et al. 2020). The other limitation of this method is that this could be used for detecting the spatial distribution of parcels at the end of the growing season, but to provide information about when the parcel is exactly irrigated and how many times additional ground truth data and analysis would be necessary.

Further research can consider using radar data from Sentinel-1, improving temporal resolution when cloud coverage does not allow the usage of a high frequency of optical data (Bazzi et al. 2019; Gao et al. 2018). This also could be useful for adapting the model for other regions which have more cloudy days and where data acquisition will be problematic. Therefore, transfer learning would be easier and more effective for applying and enabling geographical analysis of classification work in physical-geographical different regions. The developed methodology in this research will enable the possibility for further research about irrigation as well as planning and development of irrigation management in this region.

6. Conclusion

Advanced new technologies by combining remote sensing and machine learning significantly contributed to estimating the spatial distribution of irrigated areas. In this study, we utilized Sentinel-2 data, ground truth data, and a machine learning approach to classify irrigated and rainfed parcels in the moderate continental area. The novelty of this research came from classifying at the parcel level within three crops of interest: maize, soybean, and sugar beet. Ground truth data were collected for 3 years (2020–2022) with both optimal and dry climate conditions. Final datasets consisting of a time series of 11 vegetation indices calculated from Sentinel-2 images were created for Random Forest classification. Model training was conducted for each crop type separately. The best accuracy was gained for soybean and sugar beet, while maize gained the lower accuracy. Observed by years, the performances showed that classification worked the best in 2022 (OA = 0.84) and 2021 (OA = 0.78) when extremely dry conditions were recorded, while lower performances were gained for the 2020 (OA = 0.76) year characterized by contrasted meteorological conditions. Validations through the dataset from PWMC "Vode Vojvodine" indicated that maps generated in this study had high accuracy. With that, it is confirmed that the classification of irrigated and rainfed parcels could be done using Sentinel-2 images, but improvement with additional data should be considered in the future. Generated maps are valuable enough for creating a general overview of the situation of irrigation in the region allowing making the next step in research. The results are expected to serve as a good input for decision-makers when it comes to the development of sustainable agriculture and water management in the region.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data that support the findings of this study are available from the corresponding author M.R. upon reasonable request.

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