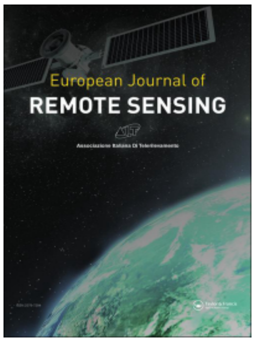

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Double cropping detection in the moderate continental climate region of Serbia using machine learning and Sentinel-2 data

Miljana Marković[a], Predrag Lugonja[a], Sanja Brdar[a], Ioannis Athanasiadis[b], Mirjana Radulović[a], Branislav Pejak[a], Minučer Mesaroš[c] and Vladimir Crnojević[a]

[a]BioSense Institute, University of Novi Sad, Novi Sad, Serbia; [b]Wageningen University and Research, Wageningen, Netherlands; [c]Faculty of Sciences, University of Novi Sad, Novi Sad, Serbia

ABSTRACT
Global food security is challenged by population growth and limited agricultural land. Intensifying existing cropland use is crucial for increasing agricultural production. Mapping cropping intensity, defined by annual crop cycles and commonly classified as single, double, or triple cropping, is vital for food production modeling. While most studies focus on regions with higher cropping intenisity, this study targets Vojvodina in northern Serbia, where double cropping is less prevalent. We investigated the impact of different vegetation indices (VIs) on detecting double cropping using machine learning (ML) and Sentinel-2 imagery with collected ground truth data over two years with contrasting weather conditions: one dry and one with above-average rainfall. Our approach improves existing methods by integrating VIs not previously examined in related studies. Alongside NDVI, indices such as CVI, VARI, and ExG significantly improved model performance. In the dry year (2022), overall accuracy reached 95.80%, with an F1-score of 91.19% for classifying double cropping, while in the wet year (2023), the accuracy was 93.56% and the F1-score 84.96%. This approach simplifies data requirements while maintaining high accuracy, making it applicable to regions with similar geographical characteristics. Additionally, this study fills a key knowledge gap on the extent and distribution of this practice in Serbia.

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Double cropping; cropping intensity; Sentinel-2; machine learning; vegetation indices

Introduction

Continually growing demand for crop production on a global scale is occurring as the world's population continues to expand (Tilman et al., 2011). Consequently, the requirements for increased food production put pressure on agricultural systems and land management. Recent research highlights a potential 1.8–2.4% reduction in global croplands by 2030 due to impending urbanization and industrialization (Bren d'Amour et al., 2017), while 60% more food will be necessary by 2050 if global population and food consumption trends continue (Food, & of the United Nations, A. O., 2024). Additionally, climate change poses a significant threat to global food security, making it crucial to enhance agricultural output to cope with these challenges (Bajželj et al., 2014; Tilman et al., 2011).

Since expanding agricultural land is limited, due to urbanization and the need to preserve natural ecosystems, the opportunity to increase global food output lies in agricultural intensification (Ruiz-Martinez et al., 2015; Shriar, 2000; Siebert et al., 2010). In addition to the yield increase, a significant factor affecting crop production and agricultural intensification is increasing cropping intensity (Biradar & Xiao, 2011; Wu et al., 2018), which is defined as the number of crop growth cycles in one year (Foley et al., 2005; Li et al., 2014). This practice represents a more efficient use of available land resources with increasing annual agricultural production. Cultivating more than one crop on a single agricultural parcel during one agricultural year is known as multi-cropping. Specifically, double cropping refers to sequentially growing two crops on the same land within a single agricultural year or a defined period, while triple cropping involves cultivating three crops sequentially during the same timeframe.

CONTACT Miljana Marković miljana.markovic@biosense.rs biosense Institute, University of Novi Sad, Dr Zorana Djindjića 1, Novi Sad 21000, Serbia

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The suitability of the climate for multi-cropping plays a key role in the successful practicing of these agricultural systems. Regions with mild and relatively uniform temperatures, extensive and evenly distributed rainfall throughout the year, and an extended growing season provide favorable conditions for the effective implementation of these practices. The absence of extreme temperature fluctuations and frost, coupled with adequate water availability either through well-distributed rainfall or reliable irrigation systems, allows farmers to cultivate multiple crops within a single calendar year (Brumatti et al., 2020; Li et al., 2014). Successful multi-cropping also depends on the compatibility of chosen crops in terms of growth cycles and resource requirements. Some regions in Asia, Africa, and South America with tropical and subtropical climates often meet these criteria and are well suited for multi-cropping (Waha et al., 2020). However, successful implementation can also be found in temperate climates with appropriate conditions and agricultural management, but its prevalence tends to be relatively low (Borchers et al., 2014). Vojvodina, located in Serbia, stands as one such region and therefore will be the area of interest in this paper. In this region, double cropping is present, although triple cropping is not practiced.

Whether we are focusing on regions suitable for double cropping or exploring areas where these practices are less common, knowing the spatial distribution of these systems can be of importance for various studies (Ellis et al., 2009). Cropping intensity maps play a significant role in gaining insights into cropland use intensity. These maps are valuable for assessing agricultural practices, understanding land use patterns, and identifying areas with high or low levels of agricultural activity (Huang et al., 2018). They contribute to the broader understanding of regional agricultural systems and help policymakers and researchers to make decisions about land and water management, as well as climate and environmental models (Mondal & Sarkar, 2021; Tashi et al., 2023). For example, optimization within the agricultural landscape is essential because new Serbian NDC targets for 2030 are almost four times higher than the initial ones −33.3% to 8.8% compared to 1990 levels (United Nations Framework Convention on Climate Change, 2022). However, adaptation and mitigation actions are only sporadically addressed in national policy documents and often lack specific objectives, such as those outlined in the National Agriculture and Rural Development Strategy (*IPARD Programme for 2014–2020*, 2023). Therefore, it is imperative to devise methods for identifying various agricultural practices to enhance our understanding of the areal extent and spatial distribution of cropping activities across extensive regions, eventually improving the estimation of current and future needs for land, water resources, and environmental sustainability (Bégué et al., 2018; Erb et al., 2013).

The method of remote sensing, coupled with the application of machine learning (ML), has proven to be a suitable and precise approach for solving various agricultural questions (Liakos et al., 2018; Shriar, 2000; Weiss et al., 2020). In recent decades, there has been a notable rise in the utilization of remote sensing methodologies to accurately map cropping practices and cropping intensity by using diverse spatial and temporal datasets. The analysis of the literature reveals the various approaches taken to achieve reliable and accurate mapping of cropping intensity. Prior to the arrival of advanced imaging platforms with higher resolution, MODIS data collections were widely used to address these challenges. Conventional methods were predominantly utilized with this dataset. These included techniques such as Fourier analysis (Mingwei et al., 2008), threshold method (Fan et al., 2014), wavelet transformation (Qiu et al., 2017), and peak counting in time series (L. Liu et al., 2020; C. Liu et al., 2020; Zhao et al., 2016). However, coarse resolution (250 m-1500 m) does not provide accurate results, especially in regions with smallholder farms.

The expansion of satellite missions such as Landsat, Sentinel-1, and Sentinel-2 has improved the monitoring of cropping practices and cropping intensity due to improved spatial and temporal resolutions, coupled with open access to data. To overcome the problem of small parcels, Jain et al. (2013), for example, combined Landsat and MODIS data, as Landsat's spatial resolution (30 m) can provide more precise representations of croplands.

Despite advances made in satellite mission capabilities, ML techniques were not largely utilized. Recent studies have started to bridge this gap. Rufin et al. (2019) used Random Forest (RF) on Landsat data to map cropping practices, Rafif et al. (2021) employed Dynamic Time Warping and different ML techniques on PlanetScope Data to map cropping intensity, while Noorazar et al. (2025) applied different ML techniques, indicating that methods applying rule-based thresholds on vegetation indices (VIs) do not work well in regions with high crop diversity when identifying cropping intensity.

In the context of optical data analysis for detecting cropping intensity, whether utilizing ML or conventional methods, studies have predominantly leaned on one or more of the following three VIs: the

Normalized Difference Vegetation Index (NDVI) (Chen et al., 2011; Estel et al., 2016; C. Liu et al., 2020; Mingwei et al., 2008), Enhanced Vegetation Index (EVI) (Hao et al., 2019; Jain et al., 2013; Noorazar et al., 2025; Qiu et al., 2014), and Land Surface Water Index (LSWI) (Biradar & Xiao, 2011; Guo et al., 2022; L. Liu et al., 2020; Pan et al., 2021; Zhang et al., 2021). Additionally, normalized difference water index (NDWI) (Rafif et al., 2021) and enhanced vegetation index 2 (EVI2) (Qiu et al., 2017) were also used as features to detect cropping intensity. A departure from this trend was observed in the work of He et al. (2021), who introduced additional indices to discern the cropping intensity specifically in rice cultivation using RF. In this context, our study seeks to contribute to this body of knowledge by identifying the other VIs crucial to improving the mapping of cropping intensity across different types of crops.

However, the majority of studies on this topic have focused on regions with high cropping intensity, where double or triple cropping is prevalent. These regions typically exhibit tropical climates and extended growing seasons, such as China and India. To our knowledge, research on areas with a moderate continental climate, where such practices are less common, remains largely unexplored. Studies conducted in Europe and on a global scale represent an exception to this trend (Estel et al., 2016; C. Liu et al., 2020; Zhang et al., 2021). However, these studies' products represent mapping on a spatial resolution of 30 m and utilize methodologies that count vegetation peaks or cropping cycles. Additionally, studies by Noorazar et al. (2025) and Hao et al. (2019) have covered certain areas with a moderate continental climate in the USA. Although these studies identified cropping intensity across various climatic conditions, they do not specifically examine how climate or weather factors affect the models' accuracy.

High crop diversity and a moderate continental climate characterize our case study area, Vojvodina. In the research presented in this paper, the aim was to utilize the RF algorithm on Sentinel-2 data to identify cropping intensity, with a particular focus on double cropping practices since it represents a high level of cropping intensity. We also sought to identify which VIs significantly enhance model performance beyond those commonly used in similar studies. Moreover, this study demonstrated the viability of this approach in regions like Vojvodina, with similar weather conditions and infrequent double cropping practices, and where there is a notable lack of statistical or empirical data on the extent of these practices (Alami Machichi et al., 2023), as well as additional classification challenges caused by weed presence in certain parcels. We achieved this by analyzing data from two years with distinct weather conditions, one dry year and one with above-average rainfall, thereby providing a comprehensive evaluation of the method's effectiveness under varying conditions. The main contributions of our work include:

(i) targeted ground truth data collection;

(ii) comprehensive review and evaluation of vegetation indices used for detecting double cropping under different weather conditions, with improved class separability in weed-affected parcels

(iii) rigorous spatial cross-validation that provided more generalized ML predictive models; and

(iv) filling the data and knowledge gaps in crop type maps and double cropping practice in Serbia. The last also aligns with efforts to collect such data across Europe (d'Andrimont et al., 2021; Schneider et al., 2023). At the local level, the results can also further serve as a baseline to monitor if double cropping practice increases along with significant investment in irrigation infrastructure (European Bank for Reconstruction and Development, 2023).

Materials

Study area

The Vojvodina region, situated in the northern part of the Republic of Serbia and covering a significant part of the Pannonian Basin, extends over approximately 21,500 km^2. It is divided into three distinct geographical regions: Bačka, Banat, and Srem (Figure 1). Vojvodina is characterized by a moderate continental climate, experiencing hot, humid summers, and cold winters, alongside a significant variance in extreme temperatures (Gavrilov et al., 2019; Hrnjak et al., 2014; Malinović-Milićević et al., 2018), a phenomenon that has become even more pronounced in recent times. This variability underscores the critical need for continuous and reliable monitoring of agricultural production within the region. The area receives an average annual precipitation of about 600 mm, although the rainfall distribution is notably irregular.

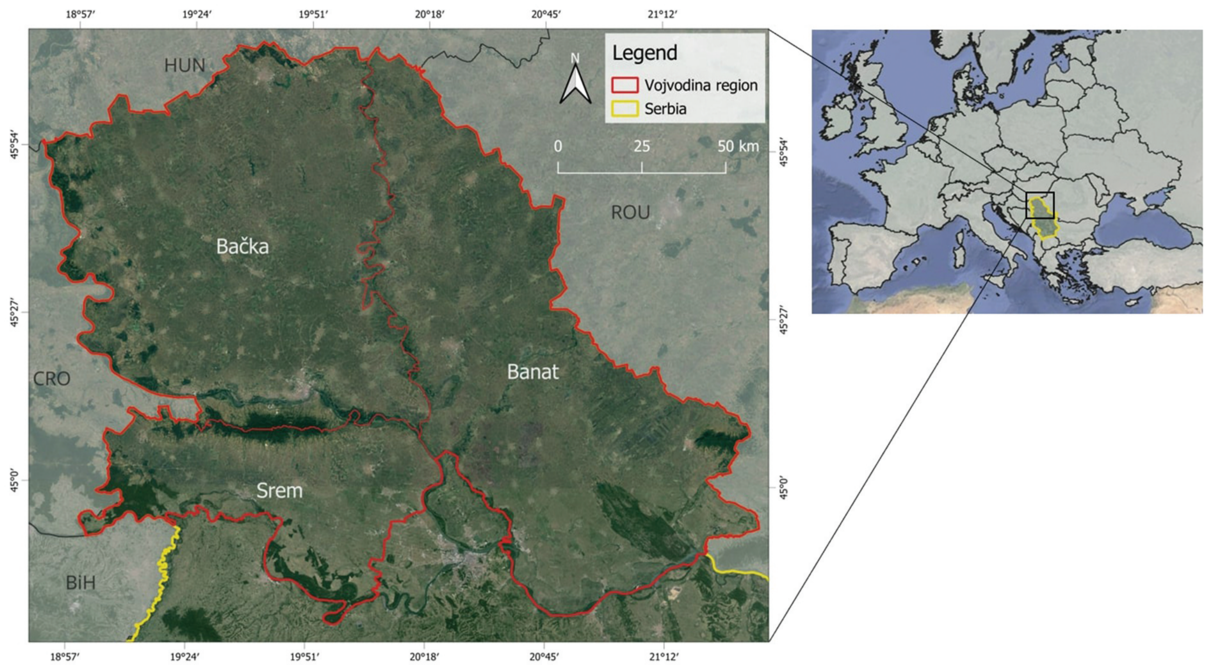

Figure 1. Study area of Vojvodina region.

Although the climate is generally moderate, the region experiences considerable variability, including frequent dry years and years with substantial rainfall (Gavrilov et al., 2015).

Vojvodina is distinguished by its flat terrain and fertile soil, with agricultural land making up 83% of the region, and 77% of that specifically used for cropland (Ćirić et al., 2017). In Serbia, smallholder farms make up over 99% of all agricultural holdings, with an average size of approximately 4.5 hectares. In contrast, commercially registered farms are typically larger, averaging about 10.6 hectares (Export.gov, 2024). Despite the prevalence of smallholder farms, the existing land division does not obstruct the application of pixel-based classification methods in agricultural monitoring, according to Crnojević et al. (2014). While statistical data on cropping intensity and the practice of double cropping are non-existent, insights from Vučić (1981) and Bošnjak (2004) suggest that achieving two harvests in a single year is feasible with the right selection of crop types and the availability of irrigation. This potential for enhanced productivity highlights the importance of strategic agricultural management and adaptation to climatic challenges to ensure the sustainability and efficiency of agricultural activities in the region. Therefore, Vojvodina's fertile land offers an ideal setting to study cropping intensity, assess current practices, and explore opportunities for improved utilization.

Sentinel-2

The classification process in this study relies on Sentinel-2 time-series data obtained from the Copernicus program of the European Space Agency. Renowned for its wide swath, multi-spectral instrument (MSI), high-resolution imagery, and open accessibility, Sentinel-2 has emerged as a major remote sensing data source across diverse applications (Cecili et al., 2023; D'Amico et al., 2021; Drusch et al., 2012; Phiri et al., 2020; Rossi et al., 2023). The MSI delivers 13 spectral bands that encompass the visible, red-edge, near-infrared, and short-wave infrared regions of the electromagnetic spectrum, achieving spatial resolutions from 10 to 60 m. Further enhancing its utility, the dual satellite constellations (S2A and S2B) provide a high temporal resolution of 5 days (European Space Agency ESA, 2024). For this investigation, Level-2A products were used, providing atmospherically corrected orthoimages organized into $110 \times 110\ km^2$ tiles in the UTM/WGS84 projection system. In our research, a total of nine clear and cloud-free images were utilized across the entire study area for the analyzed years, 2022 and 2023.

Ground truth data

The collection of ground truth data for training the machine-learning algorithm involved two annual field campaigns conducted across Vojvodina during 2022 and 2023. The initial campaign took place in May, followed by a subsequent one in September and October for both years. Data collection involved utilizing an AgroSense (BioSense Institute, 2021; Tagarakis et al., 2018) mobile application to capture georeferenced information by photographing parcels of interest and annotating their respective use.

In the initial campaign, our focus primarily was on visiting larger parcels throughout the Vojvodina region, guided by visual assessments from Google Images. This allowed us to collect both high-quality and quantity of ground truth data. Our aim during this phase of data collection was to identify the locations of both winter and summer crops, given that both types of mono-crops are prevalent during this period. This timeframe is marked by the peak phenology of winter crops and the onset of the harvest season, coinciding with the early growth phase of summer single crops' vegetation. In Serbia, winter crops typically include wheat, barley, oilseed rape, and a few types of vegetables, harvested in the observed year. Summer crops, on the other hand, commonly consist of maize, soybean, sunflower, sugar beet, and a variety of vegetables.

The second campaign was necessary to pinpoint fields practicing double cropping. After winter crops, vegetables like beans, green beans, cabbage, kale, and garden beets can be planted as a second crop (Červenski & Takač, 2012; Vasić et al., 2007), along with soybeans, maize, and sunflowers (Dragović et al., 1992). Identifying these parcels required prior knowledge of double-cropping potential locations. To achieve this, NDVI was used as a suitable indicator of vegetation dynamics throughout the year.

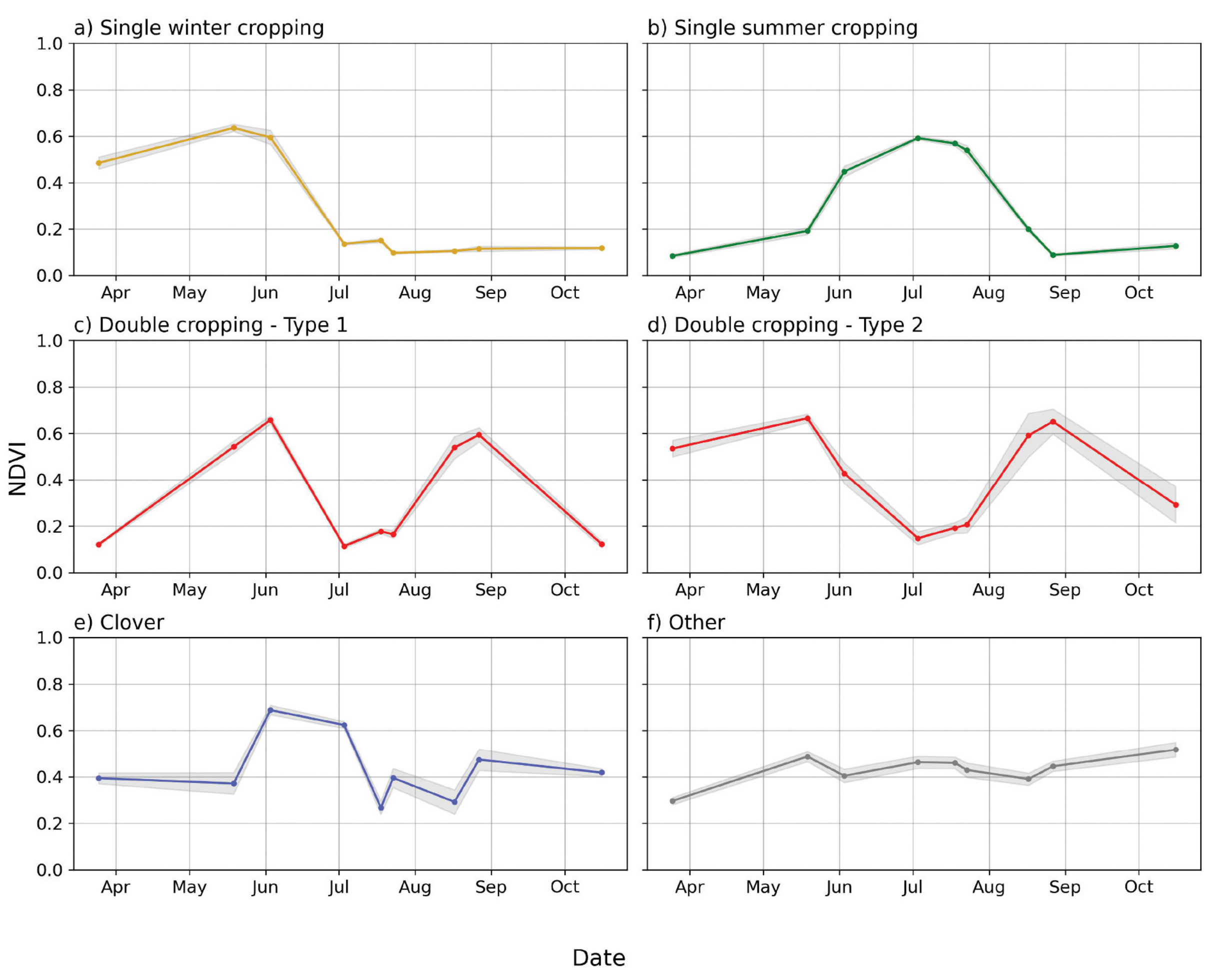

Figure 2. Examples of NDVI time-series (mean and standard deviation) for a single parcel in 2022, illustrating different cropping classes: (a) single winter cropping, (b) single summer cropping, (c) double cropping – type 1, (d) double cropping – type 2, (e) clover, and (f) other. The mean NDVI is shown as a solid line, with standard deviation represented as a shaded grey area around the line.

Table 1. Ground truth data with class labels for 2022 and 2023.

	2022		2023	
Class label	No of parcels	Area [ha]	No of parcels	Area [ha]
Single winter cropping	245	8367	278	10640
Single summer cropping	235	12727	167	9248
Double-cropping	203	4156	157	3310
Clover	71	1142	50	569
Other	143	2730	158	2893

Given the climate and agricultural practices in Vojvodina, the second crop of double cropping is typically sown directly after harvesting the winter crop or spring vegetables (therefore two types of NDVI time series on Figure 2(c,d)), usually at the end of June or early in July (Červenski & Takač, 2012; Vasić et al., 2007). This period is characterized by either bare soil or soil covered with crop residues. Accordingly, the general phenology of double cropping exhibits two NDVI peak values, one in May/June and the second in August/September (Figure 2(c,d)), with a low value in July. Utilizing this information, the NDVI threshold value was adjusted to extract potential locations of double cropping fields. NDVI values lower than 0.25, indicative of bare soil, were considered during July. In contrast, values exceeding 0.4 in May or June, marking the first peak, and in August or September, marking the second peak, indicated the presence of the second crop. Subsequently, a map of potential double cropping locations was generated, guiding field visits during the second campaign in September and October for data collection (Appendix A, Figures A1 and A2). Without this preprocessing and generation of the map of potential double cropping locations, the field visits during the second campaign would not have been possible.

Based on agricultural practices in our study region and after collecting ground truth data, four primary classes were assigned to define cropping intensity: single winter cropping, single summer cropping, double cropping, and clover. Due to its unique spectral characteristics resulting from frequent mowing practices throughout the year and its continuous presence on the parcel, clover has been designated as a distinct class (Figure 2(e)). Additionally, a fifth class, denoted as "other", included all uncategorized vegetation such as orchards, vineyards, pastures, and similar land cover types. This classification system aligns with the main agricultural practices in the region, relying on their distinct spectral signature.

Field visits, based on maps generated through a threshold method applied to NDVI data, revealed that some parcels initially identified as double cropping were actually weedy after the first crop, indicating they were in fact single cropping. By analyzing NDVI time series data, we assigned these fields to either the "winter crop" or "summer crop" class. In 2022, a year characterized by dry conditions (Store, 2024) and therefore minimal weed growth, about 10% of the fields visited in September and October turned out not to be double crops. In contrast, due to increased rainfall, especially during summer when is the beginning of the growing season for the second crop, this percentage increased to 39% in 2023.

Based on satellite images and annotated ground truth data, we generated a labeled dataset for supervised classification by creating polygons for each parcel. The collected ground truth dataset comprised 897 parcels for 2022 and 810 for 2023, evenly distributed across the region of Vojvodina (Table 1, Figure 3).

Methods

Feature selection

We aimed to optimize the forward feature selection process for models. Forward feature selection was chosen because it evaluates VIs across their entire temporal profiles, automatically identifying the smallest effective subset of indices without extensive experimentation. This aligns well with our objective of providing a straightforward workflow for cropping intensity detection, interpretable for agronomists and operational monitoring, although selecting indices based on feature importance or recursive feature selection also remains a viable alternative.

The primary focus was on exploring a diverse range of VIs beyond the commonly used NDVI for cropping intensity detection. Initial experimentation involved training an RF using only NDVI features, considering its established utility in the literature and its proven effectiveness in distinguishing between

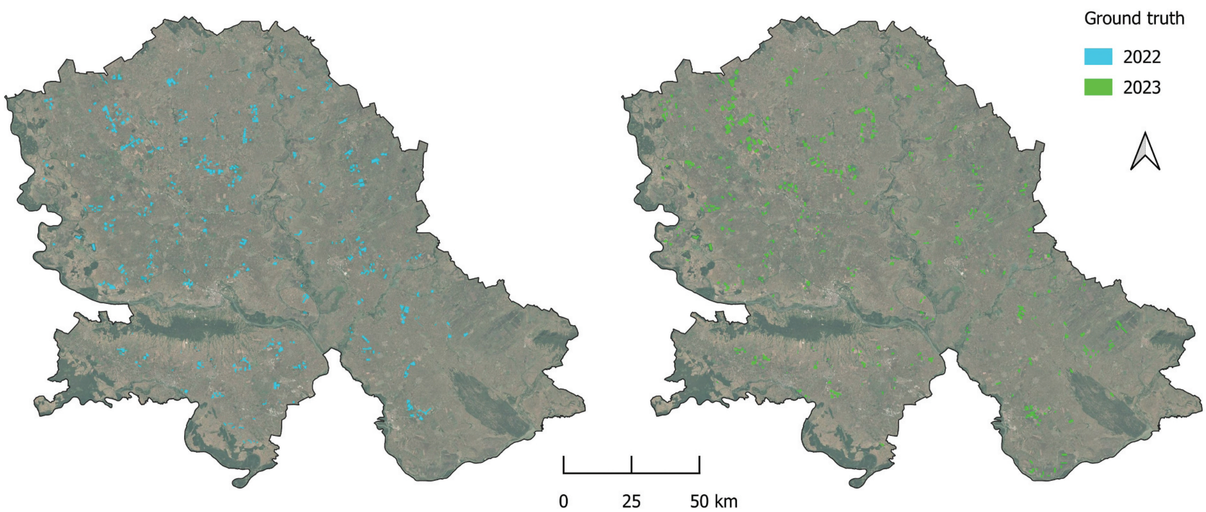

Figure 3. Spatial distribution of collected ground truth data.

Table 2. Vis and their equations.

Vegetation Index	Description	Equation
NDVI	Normalized Difference Vegetation Index	$\frac{Band8-Band4}{Band8+Band4}$
EVI	Enhanced Vegetation Index	$2.5 \cdot \frac{Band8-Band4}{(Band8+6 \cdot Band4-7.5 \cdot Band2)+1}$
EVI2	Enhanced Vegetation Index 2	$2.4 \cdot \frac{Band8-Band4}{Band8+Band4+1}$
LSWI	Land Surface Water Index	$\frac{Band8-Band11}{Band8+Band11}$
NDWI	Normalized Difference Water Index	$\frac{Band3-Band8}{Band3+Band8}$
NDRE	Normalized Difference Red Edge Index	$\frac{Band8-Band5}{Band8+Band5}$
SAVI	Soil-Adjusted Vegetation Index	$\frac{(Band8-Band4)}{(Band8+Band4+L)} \cdot (1+L)$
GLI	Green Leaf Index	$\frac{2 \cdot Band3-Band4-Band2}{2 \cdot Band3+Band4+Band2}$
VARI	Visible Atmospherically Resistant Index	$\frac{Band3-Band4}{Band3+Band4-Band2}$
CVI	Chlorophyll Vegetation Index	$\frac{Band8}{(Band4)^2}$
CIVE	Color Index of Vegetation	$0.441 \cdot Band4 - 0.811 \cdot Band3 + 0.385 \cdot Band2 + 18.78745$
ExG	Excess Green	$2 \cdot Band3 - Band4 - Band2$

vegetative states and crop classifications in general (Bouskour et al., 2023; Radočaj et al., 2023; Sishodia et al., 2020; Sun et al., 2019; Wang et al., 2022; Chen et al., 2011; Estel et al., 2016; C. Liu et al., 2020; Mingwei et al., 2008).

Subsequently, a forward selection approach was utilized to systematically include additional indices into the model. This entailed the systematic inspection of various indices (Table 2). Based on a review of the literature on cropping intensity mapping, indices such as EVI (Hao et al., 2019; Jain et al., 2013; Noorazar et al., 2025; Qiu et al., 2014), EVI2 (Qiu et al., 2017), LSWI (Biradar & Xiao, 2011; Guo et al., 2022; L. Liu et al., 2020; Pan et al., 2021; Zhang et al., 2021), and NDWI (Rafif et al., 2021) were chosen due to their prevalent use in this domain. NDRE (Kang et al., 2021; Ustuner et al., 2014), SAVI (Niazmardi et al., 2018; Sonobe et al., 2018), GLI (Eng et al., 2019; Louhaichi et al., 2001), VARI (Eng et al., 2019; Gitelson et al., 2002), and CVI (Vincini et al., 2008) were included based on their effectiveness in monitoring crop phenology, vegetation health or various crop-related classifications. Additionally, ExG Beniaich et al. (2019); Woebbecke et al. (1995); Zheng et al. (2017) and CIVE (Kataoka et al., 2003; Suh et al., 2020) were identified as very effective indices for weed identification. These were included to address the challenge identified through a targeted ground truth collection that revealed how single cropping fields with weeds after the crop could be misclassified as double cropping. While they have predominantly been used in image segmentation methods, we aimed to evaluate their performance with our methodology to determine if they could successfully help in distinguishing between single cropping fields affected by residual weed presence and double cropping fields.

Each model iteration involved including a new index, followed by an evaluation to identify the most effective one, based on the overall accuracy (OA) of the model obtained through the spatial cross-validation procedure (see Section Spatial cross-validation) to provide a good generalization of the model. When the highest-performing vegetation index was identified, it was retained, and the iteration process continued with the remaining five best-performing indices. This iterative process was repeated to refine the final set of indices that collectively demonstrated optimal performance characteristics. The iterative nature of our approach allowed us to discern the incremental impact of each vegetation index on model performance. This process was carried out independently for both years. The final outcome of this methodology was the identification of the most influential VIs for each year, forming the foundation for our optimized RF models.

Classification

A pixel-based RF classification was performed using ground truth data and a selected subset of vegetation indices identified via forward selection. Each of the selected vegetation indices is computed for all available satellite imagery dates over a growing season. This method has demonstrated exceptional capabilities in various studies related to crop classification (Belgiu & Drăguţ, 2016; Pelletier et al., 2016; Rodriguez-Galiano et al., 2012; Ghassemi, Immitzer, et al., 2022; Ghassemi, Dujakovic, et al., 2022; Watzig et al., 2023). The ability of RF to handle large and complex datasets while minimizing overfitting has made it a valuable tool in agricultural research and management. Consequently, it has become a popular choice for crop monitoring and mapping, offering precise and reliable results that can aid in making informed decisions for agricultural planning and resource management (Breiman, 2001; Dadi, 2019; Rußwurm & Körner, 2020).

Spatial cross-valdiation

The performance evaluation was conducted using the spatial 8-fold cross-validation technique to mitigate data autocorrelation and ensure the spatial stability of the model. The division of folds was predicated on the spatial distribution of districts within Vojvodina Province, with one fold being split in half to account for its extensive area while also ensuring a balanced distribution of parcels across all folds. Furthermore, the labeled data were equilibrated around district borders to maintain a similar number of pixels in each subset (Figure 4). To maintain data integrity, we ensured that the connection between each pixel and its respective field was retained throughout the data extraction process. This precautionary step was taken to prevent instances where pixels from the same field might inadvertently appear in both the training and test sets.

Hyperparameter optimization

Starting with an initial model, using only NDVI values across the growing season as features, hyperparameter tuning was conducted for both years. We prioritized flexibility in the optimization

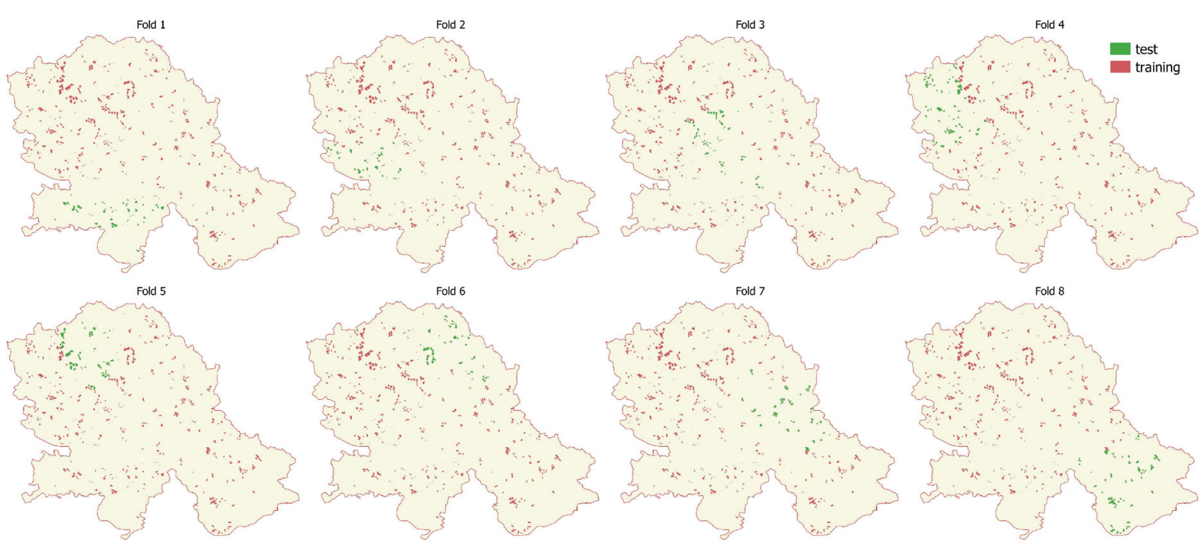

Figure 4. Splitting of data on training and test set for spatial cross-validation.

Table 3. Hyperparameters used in classification models.

Parameters	2022	2023
number of trees	200	100
max. depth	15	15
min. samples at leaf	20	50

process to adapt to each year's unique data characteristics, ensuring that the number of trees selected balance model stability with computational efficiency. The hyperparameters considered included: the number of trees with values of 100, 200, and 500; maximum depth options of None, 10, 15, and 20; and minimum samples at leaf settings of 1, 20, and 50. All other parameters were maintained at their default settings, with the exception of the class weight, which was adjusted to "balanced". The model optimization was conducted using Scikit-learn's GridSearchCV with 8-fold spatial cross-validation, and the optimal model was then utilized in a forward feature selection process (Table 3).

Wilcoxon signed-rank test

To evaluate the effectiveness of adding new indices and to determine whether there was a significant difference between the initial and next iteration model outputs, we applied the Wilcoxon Signed-Rank Test. This test is non-parametric and is valued for its ability to handle data that may not follow a normal distribution (Woolson, 2005). Specifically, the test compared the F1 metrics for predicting the double cropping class per fold from cross-validation of the initial model and the model chosen after the first iteration. Subsequently, the metrics from this model were compared to those from the final model after the second iteration. The differences in these metrics were then calculated and ranked. The Wilcoxon test uses these ranks to determine whether the median difference between the model metrics is statistically significant, thus indicating whether the new indices meaningfully improve the model's accuracy with a one-sided alternative hypothesis. Test statistics are calculated as:

$$W = \sum_{i=1}^{n} \mathrm{sign}(d_i) \times \mathrm{rank}(|d_i|) \tag{1}$$

where d_i is the difference between the paired ranks, $sign(d_i)$ is the sign of the difference for each pair, and $rank(|d_i|)$ is the rank of the absolute values of the differences.

Maps generation

After finalizing the models, classification was performed on the agricultural land layer of Vojvodina, extracted from the Corine Landcover Classification 2018. To ensure accuracy, the focus was on correcting mistakes and removing outlying pixels for raster data filtering using the polygonal geometries of parcels based on cadastral information stored in a vector file. Our method corrects errors where isolated pixels within a plot might be misclassified. Statistical techniques were used within the boundaries of these parcel shapes to identify the most common pixel values. For parcels smaller than 5 hectares, all pixels were adjusted based on the most common value. For larger areas, techniques such as bounding rectangles were used to optimize perimeter delineation and a kernel filter of size $8 \times 8$to remove incorrectly classified pixels within a parcel.

Error-adjusted area estimation

It is acknowledged that the area, when calculated directly from the classified map, may not accurately reflect the true area due to potential classification errors (Foody, 2002; Olofsson et al., 2013, 2014; Stehman, 2014). To address potential inaccuracies in area estimation caused by classification errors, the error-adjusted area estimation approach was applied using stratified estimation to account for classification errors in the area calculations (Olofsson et al., 2013). The initial pixel-based area estimates are adjusted by incorporating the probabilities of misclassification derived from the confusion matrix. By treating each map class as a stratum, stratified random sampling principles were utilized to compute the adjusted area estimates and their associated uncertainties. The variance and standard error of the adjusted area estimates were also calculated. This involves the computation of the variance of the adjusted proportions based on the conditional probabilities and the number of reference samples in each map class. Confidence intervals were also calculated, providing a range within which the true area is likely to fall.

Results

Performance evaluation

As mentioned, pixel-level classification was performed using models with different feature sets for 2022 and 2023. Since parcel-level metrics are more relevant for decision-making in agricultural management, they are also calculated in this study. However, due to the variability in parcel sizes, the results will primarily be analyzed at the pixel level. Table 4 and Figures 5 and 6 provide the OA of each experiment as well as metrics for predicting the double cropping class: precision, recall, and F1-score. For further analysis of results, alongside OA, the F1-score will be used since it provides a single metric that balances both false positives and false negatives, offering a more comprehensive evaluation of a model's performance, particularly in cases of imbalanced class distributions, as is the case in our study.

Initially, the performance of the initial models, which use only NDVI features, indicates a distinct difference between the two years. In 2022, the initial model achieved an OA of 95.01%, and in 2023 the OA was 90.71%. The F1-score for the double cropping class was 89.71% in 2022 and 76.85% in 2023 (Table 4). Through the next iterations, i.e. forward feature selection, additional indices that improve performance were selected.

Results for the year 2022 indicate that the addition of new indices did not notably enhance OA or metrics specifically for the double cropping class (Figure 5). As mentioned, additional indices from each iteration were adopted based on the highest OA. The VARI index contributed to OA of 95.66% (Figure 5) while in the second iteration, the CVI was selected, finalizing the OA at 95.80% and improving the F1-score for the double cropping class to 91.19% (Figure 6). The Wilcoxon signed-rank test revealed a significant difference in the F1-scores between the initial model and the model from the first iteration across eight cross-validation folds, with a p-value of 0.039. However, the same test showed no significant performance difference between the models from the first and second iterations. This finding suggests that satisfactory results can be achieved using only NDVI and VARI.

Regarding the 2023 model's performances, the first iteration resulted in an increase from 90.71% to 92.97%, with the CVI identified as the most significant feature (Figure 5). In the second iteration, the ExG index proved to be the most effective, elevating the OA to 93.56% and boosting the F1-score of the double cropping class to a final score of 84.96% (Figure 6). The Wilcoxon test revealed significant differences between the initial model's metrics and those following each subsequent iteration with $p < 0.05$.

Despite additional iterations, there was no further increase in OA or the F1-score for the double cropping class beyond the second iteration. Consequently, our models were finalized using three indices. Although the model for 2022 could be simplified using just two VIs, the third index, CVI, was still included. This decision was based on its ability to improve performance metrics and its proven effectiveness in 2023 as well. The confusion matrices of finalized models for both years at pixel and parcel levels are illustrated in Figure 7.

To validate this approach, we trained an RF model using all 12 vegetation indices, which achieved an OA of 95.64% in 2022 and 93.45% in 2023, compared to 95.80% and 93.56% obtained with our model using only

Table 4. Metrics of the initial model using NDVI across years where recall, precision, and F1-score refer to double cropping class.

Experiment	Year	OA	Recall	Precision	F1-score
NDVI	2022	95.01	91.92	87.60	89.71
	2023	90.71	81.73	72.52	78.65

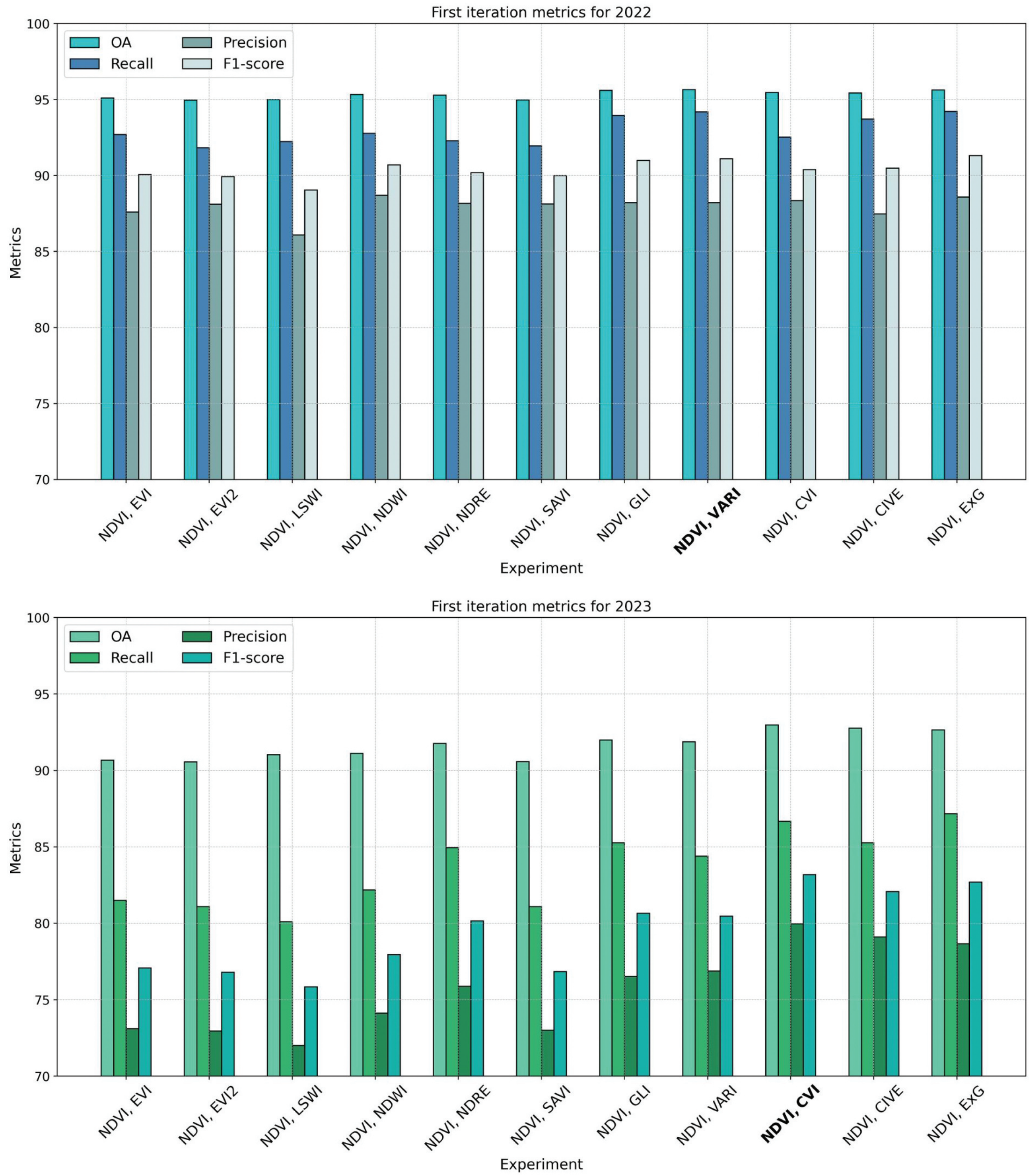

Figure 5. First iteration metrics: the plots illustrate the OA and precision, recall, and F1-score for double cropping class for different experiments in the years 2022(top) and 2023 (bottom). The bolded experiment represents the one with the highest OA.

three indices. These results demonstrate that the three-index model is not only simpler but also slightly more accurate, supporting the effectiveness of our iterative selection approach.

Additionally, we conducted an experiment by limiting the sample size to 50 pixels per polygon to compare these results with those from the entire dataset and assess how smaller samples impact the accuracy of our analysis. This approach resulted in OA of 94.00% for 2022 and 88.46% for 2023, which are 1.8% and 6% lower, respectively, than the accuracies obtained using the full dataset. These findings suggest that limiting pixels per polygon may reduce model performance, likely due to a smaller representation of spatial variability within each class.

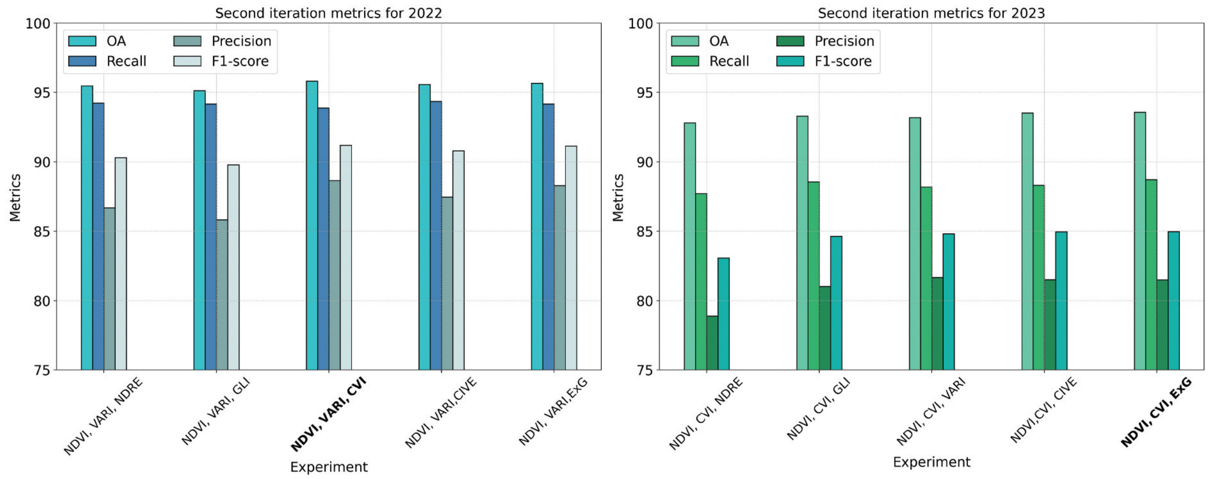

Figure 6. Second iteration metrics: the plots illustrate the OA and precision, recall, and F1-score for the double cropping class for different experiments in the years 2022 (left) and 2023 (right). The bolded experiment represents the one with the highest OA and constitutes the final set of features for the corresponding year.

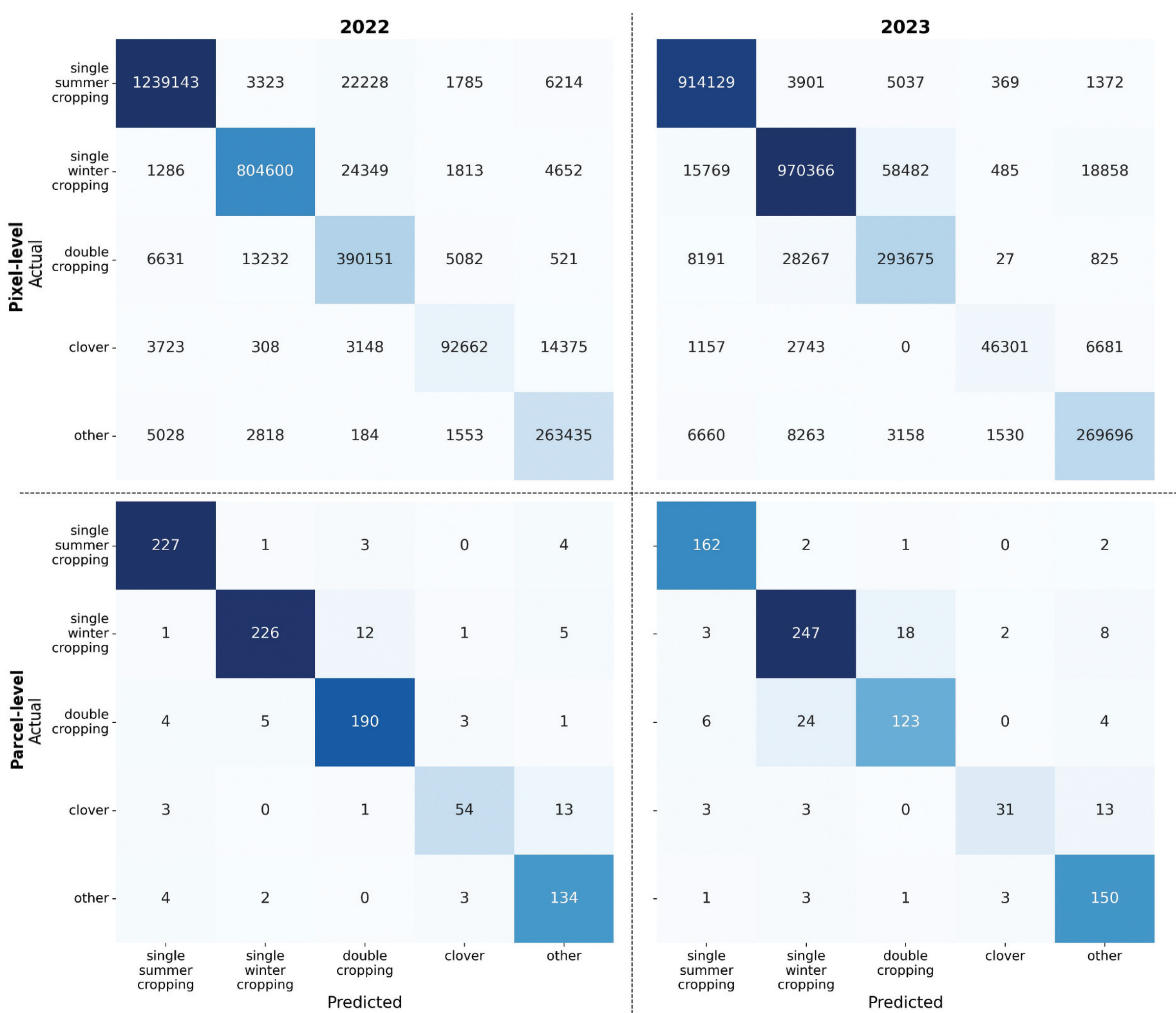

Figure 7. Confusion matrices on pixel (top) and parcel (bottom) level for 2022 (left) and 2023 (right).

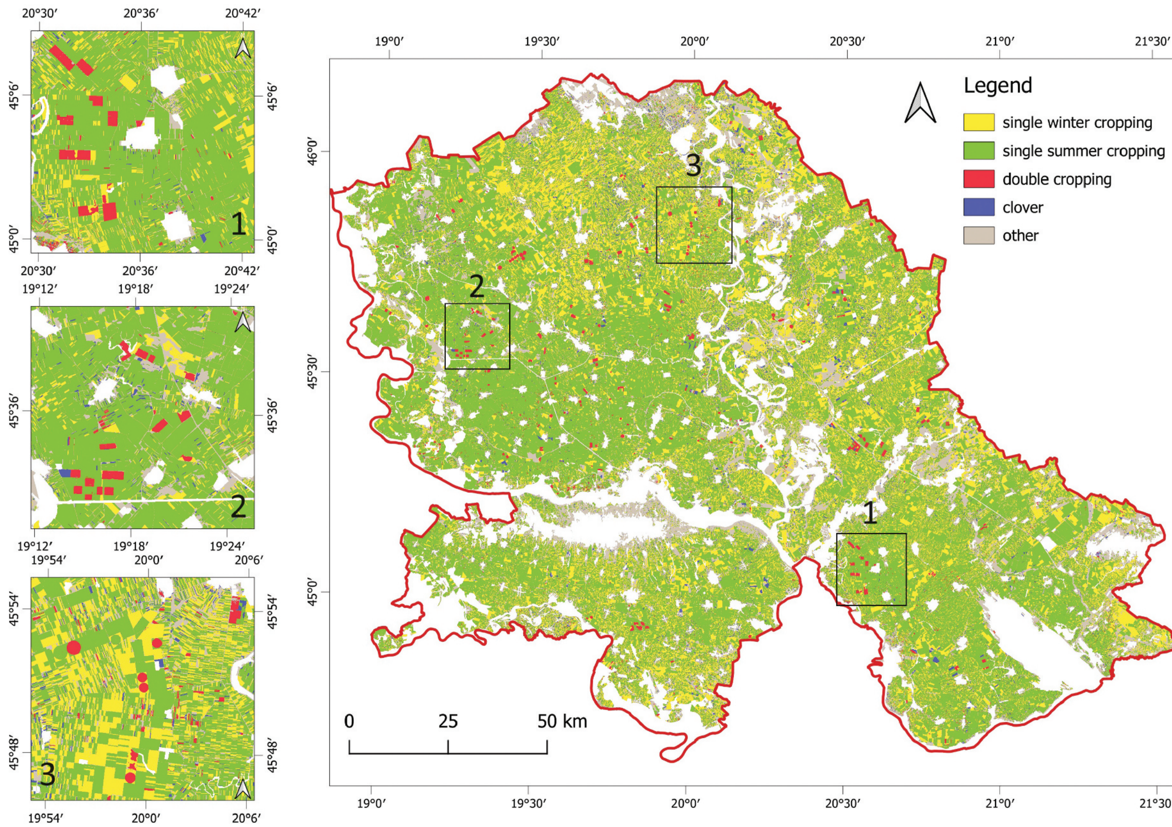

Figure 8. Cropping intensity classification map for 2022. Examples 1, 2, and 3 provide an enlarged view of the classification results.

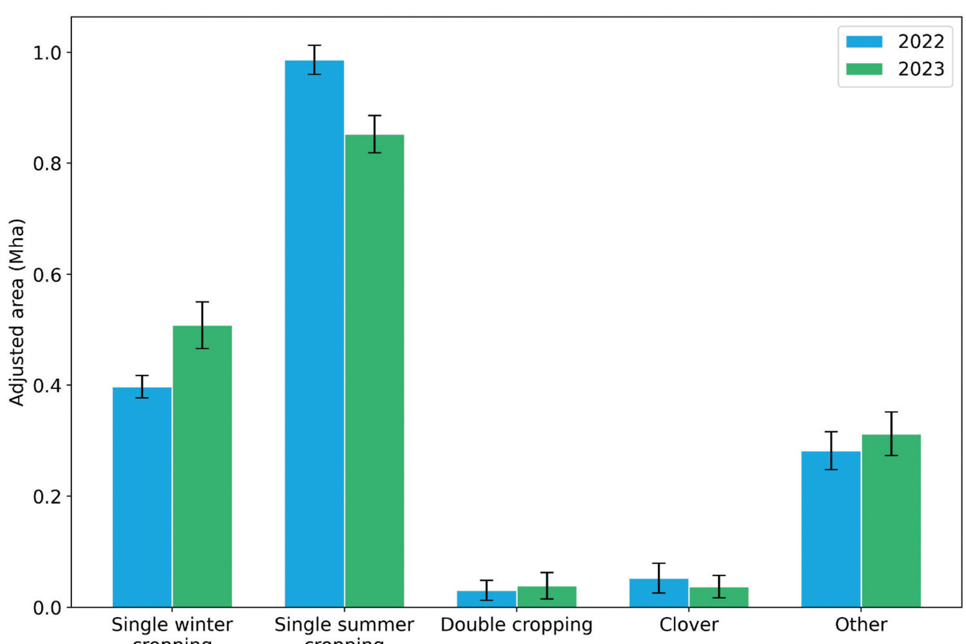

Figure 9. Adjusted area estimates with 95% confidence intervals.

Table 5. Unadjusted and adjusted area proportions for 2022 and 2023.

	2022		2023	
Cropping type	Unadjusted (%)	Adjusted (%)	Unadjusted (%)	Adjusted (%)
Single winter cropping	22.85	22.71	28.01	29.03
Single summer cropping	56.63	56.37	50.23	48.71
Double cropping	1.07	1.75	1.18	2.23
Clover	2.19	3.02	1.67	2.15
Other	17.38	16.15	19.03	17.88

Maps

This study produced annual 10-meter resolution maps of cropping intensity in Vojvodina over a two-year period (Figure 8 and B3). Adjusted area estimates with 95% confidence intervals are presented in Figure 9. The adjusted area estimates differed from the unadjusted estimates by up to 1.52% for single summer cropping in 2023, highlighting the impact of accounting for classification errors. The area of the double cropping class increased from 1.07% to 1.75% in 2022 and from 1.18% to 2.23% in 2023, reflecting the correction for misclassified pixels (Table 5).

The adjustments made to the area estimates significantly improve the reliability of our cropping intensity classifications by mitigating the effects of misclassification errors. Therefore, we utilized these adjusted areas and proportions. Between 2022 and 2023, there were several differences in the distribution of cropping types across agricultural areas. Single summer cropping saw a decrease from 56.37% to 48.71% (Table 5), suggesting a reduction in these practices over the years. Conversely, single winter cropping increased by 6.32%, rising from 22.71% to 29.03%. Double cropping covered 1.75% and 2.23% of the agricultural area in 2022 and 2023, respectively, pointing to a consistently low presence of this practice in the Vojvodina region. The area planted with clover decreased from 3.02% to 2.15%.

Discussion

Weather impact on model performance

In this study, we classified cropping intensity in a moderate continental climate region by comparing two years characterized by different weather conditions. As mentioned, despite the generally moderate climate, the region exhibits significant variability, characterized by frequent periods of drought as well as years with higher rainfall. Final models for both years provided good performance, however, the lower performance of the model for 2023 can be indirectly influenced by that year's weather conditions. As mentioned, that year experienced higher rainfall levels, especially during summer, which caused more weed growth on some parcels after a single crop. This type of vegetation often shows a spectral signature similar to double cropping, thereby complicating the classification process. However, during a dry year, the vegetation peak of weeds was significantly smaller. Figure 10 presents a continuous time series of NDVI and normalized ExG for single cropping followed by a period of weed growth across both analyzed years. Vegetation index ExG demonstrated strong performance in our modeling approach for 2023 and, as mentioned in Section Feature selection, is widely recognized in the literature as a key index for identifying weeds. In summary, the drought in 2022 limited the growth of weeds to a lesser extent than observed in 2023, as noticed in Section Ground turth data. Therefore, detecting double cropping was less challenging in 2022. Consequently, the confusion matrix from 2023 shows an increase in both false negatives and false positives for the classification of single winter and double cropping classes due to that problem, while in 2022, there was only a slight increase in false positives for the single winter cropping class.

As noted in the result section, in addition to NDVI, the key indices for the final model in 2022 were VARI and CVI, while in 2023, CVI and ExG were the most effective. Results suggest that under dry weather conditions, NDVI alone can provide substantial model performance. However, the Wilcoxon test confirmed that the inclusion of VARI significantly enhances the model's predictive accuracy, as discussed in Section Performance evaluation, where the rationale for including CVI was

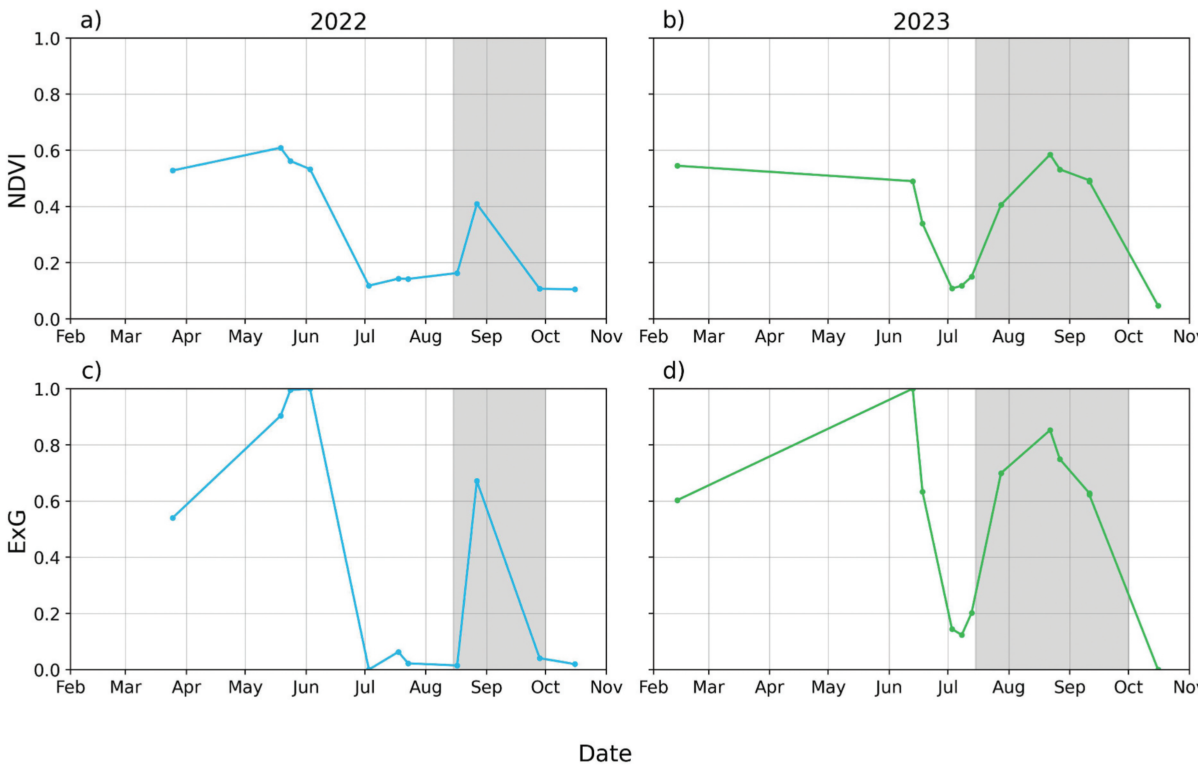

Figure 10. Example of NDVI (a and b) and ExG time series (c and d) for single cropping and weeds (shaded in grey) in 2022 (left) and 2023 (right).

also explained. In contrast, during a year with higher rainfall, additional VIs had a greater impact on the model performance, with OA increasing by 2.85% and the F1-score for the double cropping class rising markedly by 8.11%. These findings underline the importance of tailoring feature selection to address weather variability.

Significant VIs and their influence

Data from Figure 6 highlight that, besides the indices CVI, VARI, and ExG, which most significantly improved our models, NDRE, GLI, and CIVE also substantially influenced performance for both years. Notably, for both models, CVI was among the most effective indices. A typical characteristic of all these indices is their exclusive use of the red, blue, green, NIR, and red edge channels. In the first iteration, those indices showed absolute improvement in predicting double cropping class from 0.48% to 1.61% for 2022 and from 3.32% to 6.34% for 2023, regarding F1-score. Originally derived mostly from studies that use UAV images, ExG, GLI, and CIVE have proven their effectiveness with Sentinel-2 images in this study. To our knowledge, these VIs have not been previously considered in research related to crop intensity detection.

The remaining analysis indices, which are commonly used in studies related to cropping intensity – EVI, EVI2, LSWI, NDWI – and SAVI, often used for crop classification, showed notably less improvement in our model or did not enhance the model at all. The F1-score for the double cropping class for 2022 changed from decreasing by an absolute difference of 0.65% to increasing by 0.99%, and for 2023, it decreased from an absolute difference of −1% to increasing by 1.10%.

It is notable that LSWI, despite being a commonly utilized index for mapping cropping intensity together with NDVI, did not impact OA in 2022 and slightly decreased in 2023. Additionally, using this feature resulted in a decrease in the F1-score for double cropping in both years. LSWI is sensitive to vegetation moisture and water content, so it would be expected to improve the identification of double cropping fields, which are mostly irrigated in our study area (Vučić, 1981). However, its signal may miss key irrigation events if satellite image timing is off. In addition, variations in irrigation practices and atmospheric conditions, even in predominantly irrigated double cropping fields, can introduce noise, reducing LSWI's reliability and explaining its limited impact on OA (Chandrasekar et al., 2010; Xiao et al., 2005). Similarly, the EVI, often used in related studies, either negatively affected some metrics or only made slight improvements. EVI is more suitable for dense vegetation where NDVI tends to saturate (Son et al., 2014; Wardlow et al., 2007). However, in our study, NDVI did not reach that saturation point, making the additional complexity of EVI redundant and potentially introducing variability that slightly impaired some metrics.

In numerous studies related to mapping-cropping intensity where these indices were used, methodologies mainly relied on threshold techniques or peak detection to detect these practices. However, these studies mostly neglect the emergence of weeds following a single cropping cycle, which can be mistaken for double cropping. C. Liu et al. (2020) have attempted to resolve this issue through smoothing techniques, assuming its NDVI profile is low. Pan et al. (2021) adjusted the NDVI threshold to 0.6 and L. Liu et al. (2020) also relied on lower values of NDVI when it comes to the problem of weeds. Nevertheless, in our case study, the occurrence of weed values after single cropping appeared to closely resemble those of double cropping during periods of excessive rainfall, such as in 2023, which would not be solved by setting a threshold on NDVI, as confirmed in Section Ground truth data. This makes differentiation between the two more challenging. Studies on weed recognition have demonstrated the use and high effectiveness of the ExG and CIVE indices (Suh et al., 2020; Woebbecke et al., 1995). Therefore, we incorporated them in our study and confirmed their utility, especially for ExG in 2023, when this issue was pronounced. ExG intensifies the green component in the imagery, which is critical because weeds generally have strong green reflectance due to their high chlorophyll content (Saberioon et al., 2014). This allows ExG to differentiate the weeds from the double cropping, whose spectral signature may be less intense in the green band. By integrating these indices, we were able to significantly mitigate this problem and improve classification accuracy. Starting from using only NDVI, where true positive parcels of the double cropping were 108, until the final model, this number increased to 123 parcels of 157 (Figure 7 and B1).

Machine learning approaches have been underutilized in this domain. However, He et al. (2021) used an RF algorithm with a diverse set of features to detect rice cropping intensity. We evaluated the VIs used in their study. Figure B2 presents the OA and metrics for the double cropping class using VIs not included in our initial experiments (Table 2). We evaluated these VIs in combination with our initial NDVI-based model and also tested all the VIs from their study together. These indices are predominantly based on the red edge and SWIR bands, which have demonstrated strong performance in other crop-related studies as well (Immitzer et al., 2016). However, in all cases, we found that these experiments did not outperform the performance of our model, especially for 2023.

Irrigation and potential of increasing double cropping

The role of irrigation in analyzing cropping intensity is crucial, particularly in the Vojvodina region, where it is predominantly necessary for practicing double cropping (Immitzer et al., 2016). To understand the extent of irrigation usage for double cropping, we referred to the annual irrigation maps produced by Radulović et al. (2023) over a three-year period. These maps, initially created separately for maize, soybean, and sugar beet each year, were merged to represent parcels where irrigation systems are presumably available. It's important to note that there may be irrigated parcels where, over the three years analyzed, none of the crops being studied (maize, soybean, or sugar beet) were present. This indicates that these crops were not included in the crop rotations for these parcels, although such cases are expected to be rare. The integrated data reveal that only 6.26% (86 657 ha) of Vojvodina's agricultural areas are equipped with irrigation systems. Despite this infrastructure, the study shows limited utilization regarding double cropping practice: only 4.17% of all irrigated areas were used for double cropping in 2022, and 5.6% in 2023. This indicates that the potential for practicing double cropping in Vojvodina is underutilized since approximately 95% of the area equipped with irrigation systems is not used.

Advantages and limitations

In contrast to previous studies that typically categorized cropping intensity into two or three classes denoting single, double, and triple cropping occurrences, our approach involves a more detailed classification. We delineated cropping intensity into distinct categories, specifically distinguishing between single summer and winter cropping, with the inclusion of clover as an additional indicator of cropping intensity. This offers a more comprehensive understanding of the spatial distribution of cropping intensity, which is crucial for policymakers and land management. Additionally, this study provides the first statistical and spatial insights into cropping intensity and the occurrence of double cropping in the Vojvodina region. However, due to the lack of directly comparable datasets for this region, we were unable to perform dataset comparisons. Existing global datasets, such as those of X. Liu et al. (2021) and Zhang et al. (2021), cover earlier years than our study period and are therefore unsuitable for direct comparison, given that cropping patterns vary from year to year (Živaljević et al., 2024).

Although some studies have used the same or similar methodologies to distinguish double cropping, they often relied only on visual inspections of satellite imagery, without on-site verification, to collect ground truth data or validate results (Pan et al., 2021; Remelgado et al., 2020; Zhao et al., 2021). Based on our field visits, it has been demonstrated that visual inspection of satellite imagery alone cannot definitively distinguish between crops and weeds, underscoring the importance of collecting ground truth data on-site to properly train the model with high-quality data.

Previous studies have often combined various optical or radar data. Widely used satellite data sources, such as MODIS and Landsat, do not offer the high spatial resolution that is critical in regions like Vojvodina, where small parcels are prevalent. In contrast, our research demonstrates that effective results can be achieved using only optical Sentinel-2 data, generating 10-m resolution maps. By using ML with a suitable combination of VIs, our approach simplifies data requirements while achieving high accuracy for two weather-distinct years. Additionally, the good accuracy with the use of spatial cross-validation in our study demonstrates the robust performance of our approach across various test scenarios. The results suggest a strong potential for applying our methodology in regions characterized by a temperate climate and diverse crop types, similar to those found in our test area.

Although the Sentinel-2 satellites offer a 5-day revisit time, the prevalence of clouds can often limit the availability of clear images. This limitation can affect the usability of the data and potentially decrease the accuracy of analyses. Furthermore, while this study introduces initial statistical and spatial data on cropping intensity in Vojvodina, there are no estimates from other studies or governmental data for additional comparison of the results. Also, even though the weather occurrences of the analyzed years are becoming more often in this region, for the comprehensiveness and robustness of our approach, it would be of great importance to have ground truth data for a regular year, with average rainfall.

Conclusion

In this study, we utilized ML and Sentinel-2 data to analyze cropping intensity across two weather-distinct years in a moderate continental region, with a particular emphasis on the double crop class as an indicator of the highest cropland intensity. Our research shows that reliable results can be achieved using only optical Sentinel-2 data and ML with the appropriate combination of VIs. Therefore, our approach simplifies data needs while maintaining high accuracy.

By analyzing two weather-distinct years, one dry and one with above-average rainfall, we demonstrated that only three indices are necessary to address issues like this. Commonly used VIs in related studies did not significantly enhance model accuracy. However, the analysis of other VIs in our study revealed that CVI, VARI, and ExG contributed to improved predictions, particularly in years with higher rainfall, where problem with increased weed presence was observed on parcels. Vegetation indices that use only RGB bands have proven to be highly effective. Even though the model performs well in dry conditions using only NDVI, incorporating additional indices that demonstrated the best performance further improved the metrics for the double cropping class, especially when issues with weeds occur. The presence of weeds in the fields underscores the importance of on-site ground truth data collection, rather than solely relying on visual inspection of satellite imagery. Spatial cross-validation demonstrated our method's robustness across various scenarios, confirming this approach is well-suited for temperate regions with diverse crops, similar to our study area.

No statistical data or studies have been conducted on the spatial representations of double cropping in Serbia. Although it is recognized that this practice is uncommon in the region due to unfavorable climatic conditions and the need for irrigation, there is a significant gap in scientific knowledge regarding its extent and distribution. Our study addresses this gap and provides the first insights of their kind, offering an innovative contribution to the field and revealing that around 2% of agriculture area corresponds to double cropping practice. In addition, our analysis indicates that with the existing irrigation infrastructure in the region, although scarce, the potential for double cropping remains underutilized.

Given the constraints on optical data due to cloud cover, future work might include incorporating radar data from Sentinel-1 to improve temporal resolution when optical images are lacking. Additionally, since our data are restricted to two years, further collecting data in subsequent years would enhance the robustness of our findings and allow for a more comprehensive analysis of trends and variability in double cropping practices and cropping intensity in general. Including data from additional years could provide better generalization and create a unique model that would incorporate distinct seasons. However, the generated maps still offer valuable insights and serve as effective inputs for decision-makers and will be used as input for further cropland-use intensity analysis.

CRediT authorship contribution statement

Miljana Marković: Conceptualization, Methodology, Software, Validation, Resources, Investigation, Writing – original draft, Writing – review & editing. **Predrag Lugonja**: Conceptualization, Methodology, Software, Writing – review & editing. **Sanja Brdar**: Supervision, Writing – review & editing. **Ioannis Athanasiadis** Conceptualization, Supervision, Writing – review & editing. **Mirjana Radulović**: Writing – review & editing. **Branislav Pejak**: Software, Writing – review & editing. **Minučer Mesaroš**: Writing – review & editing. **Vladimir Crnojević**: Funding acquisition.

Data availability statement

The data that support the findings of this study are openly available in "Zenodo" at https://doi.org/10.5281/zenodo.12748991, reference number 10.5281/zenodo.12748991.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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ORCID

Miljana Marković http://orcid.org/0000-0001-6702-5702
Predrag Lugonja http://orcid.org/0000-0001-7399-8789
Sanja Brdar http://orcid.org/0000-0002-2259-4693
Ioannis Athanasiadis http://orcid.org/0000-0003-2764-0078

Mirjana Radulović http://orcid.org/0000-0001-6429-1845
Branislav Pejak http://orcid.org/0000-0003-1094-8770
Minučer Mesaroš http://orcid.org/0000-0003-2505-5633
Vladimir Crnojević http://orcid.org/0000-0001-7144-378X

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Appendix

Appendix A. Materials

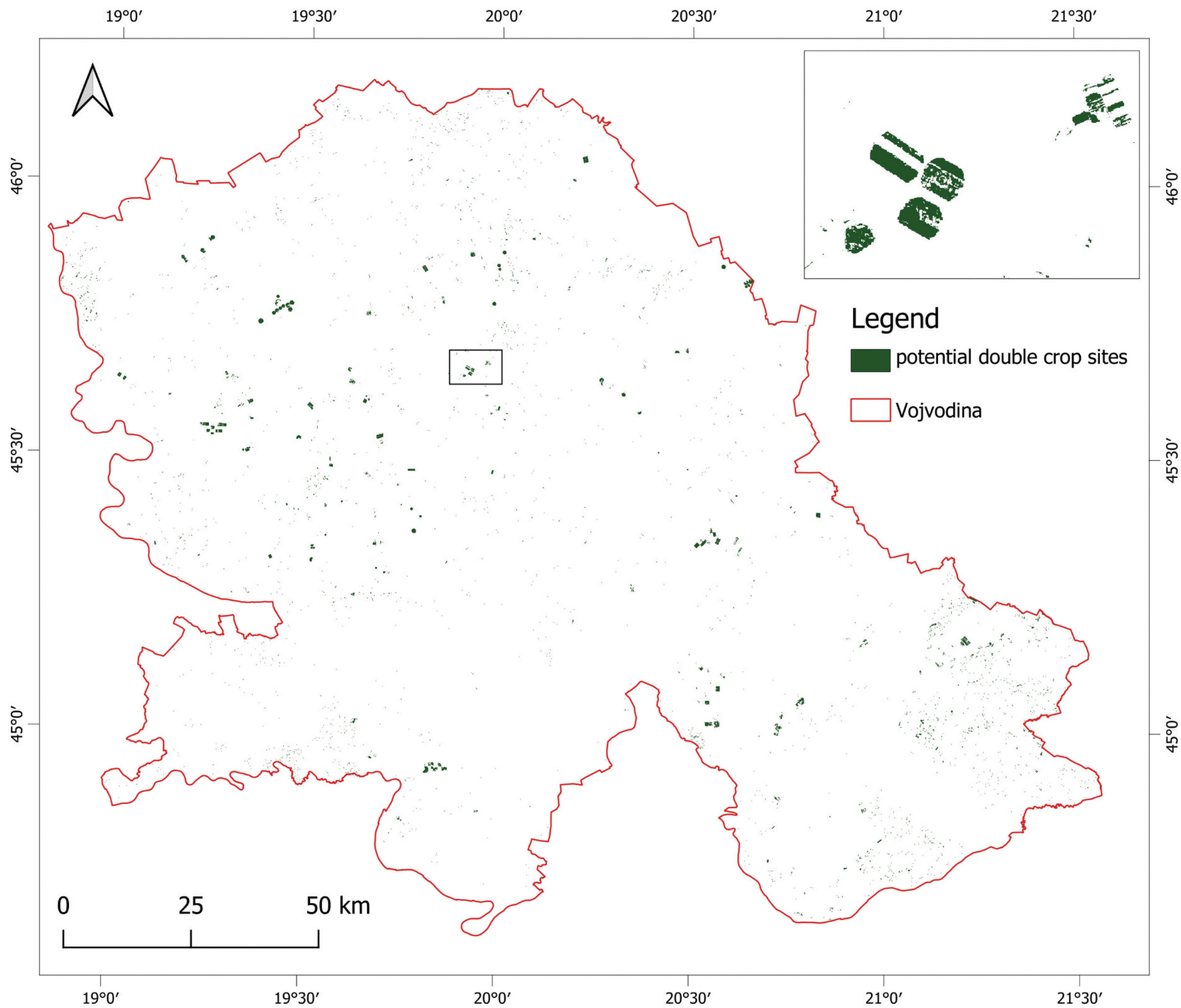

Figure A1. Map of potential double cropping sites identified using the threshold method for 2022.

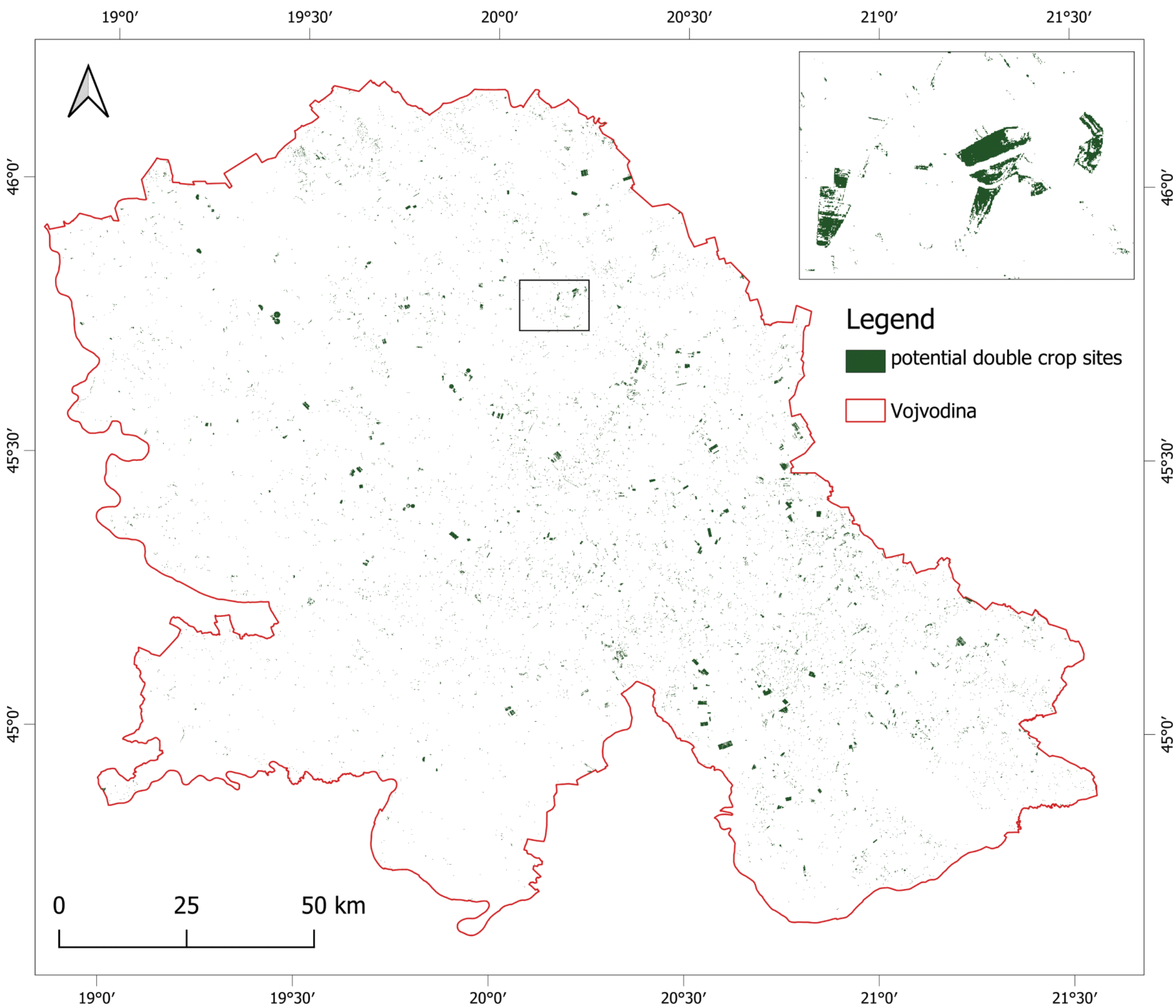

Figure A2. Map of potential double cropping sites identified using the threshold method for 2023.

Appendix B

Results

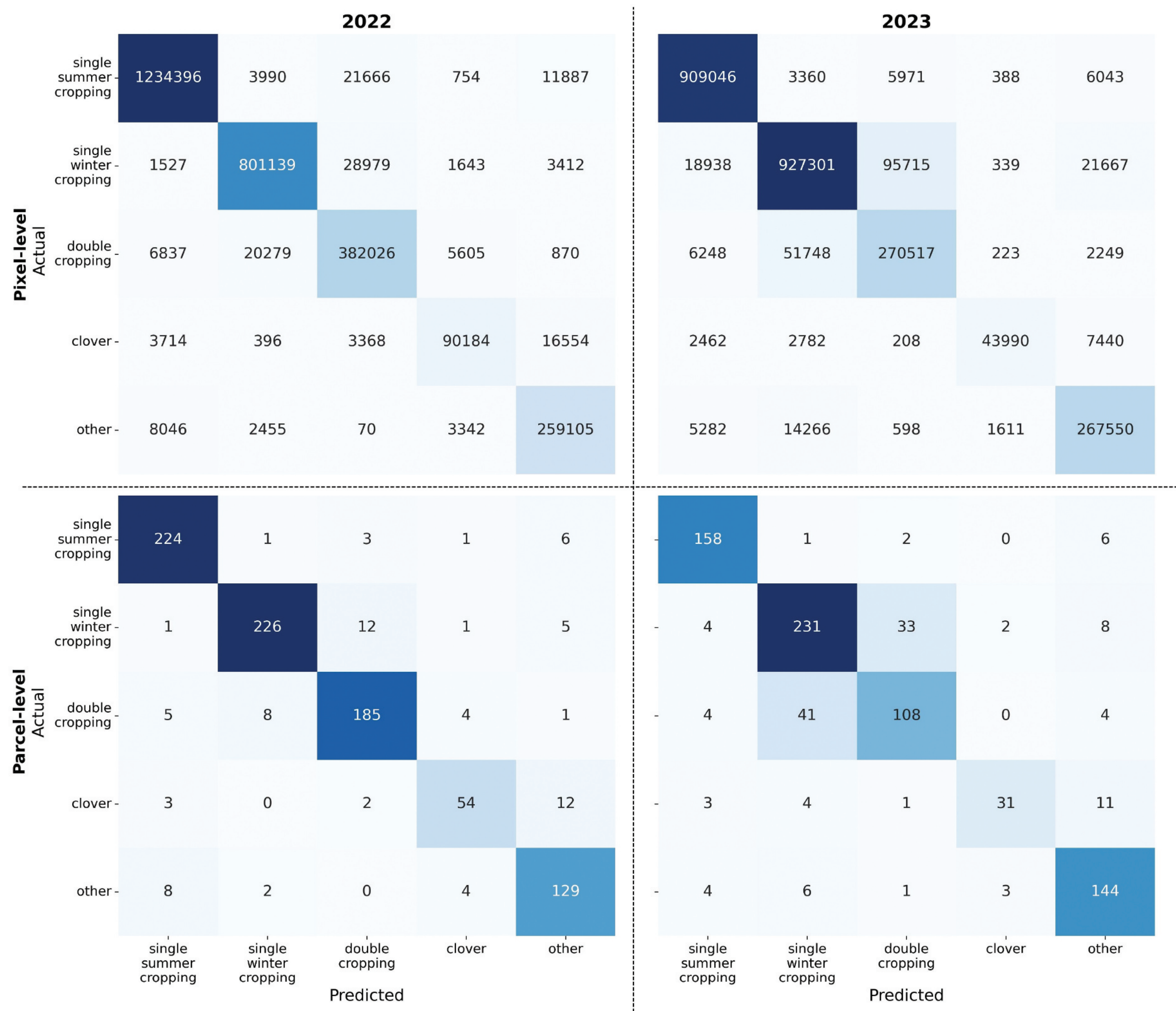

Figure B1. Confusion matrices on pixel (top) and parcel (bottom) level of the initial model using NDVI for 2022 (left) and 2023 (right).

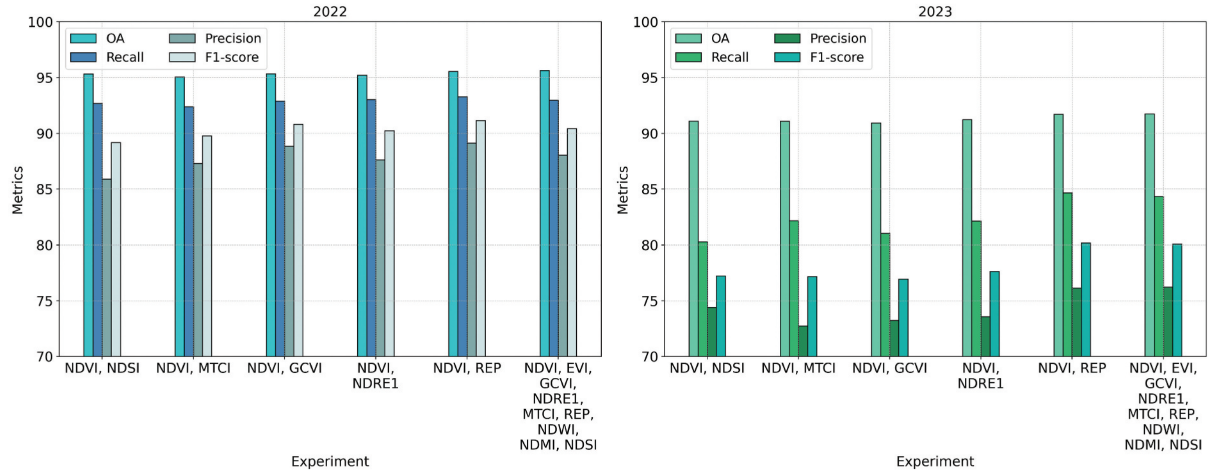

Figure B2. OA and metrics for double cropping class for indices used by He et al. (2021), and combined with the initial model in 2022 and 2023.

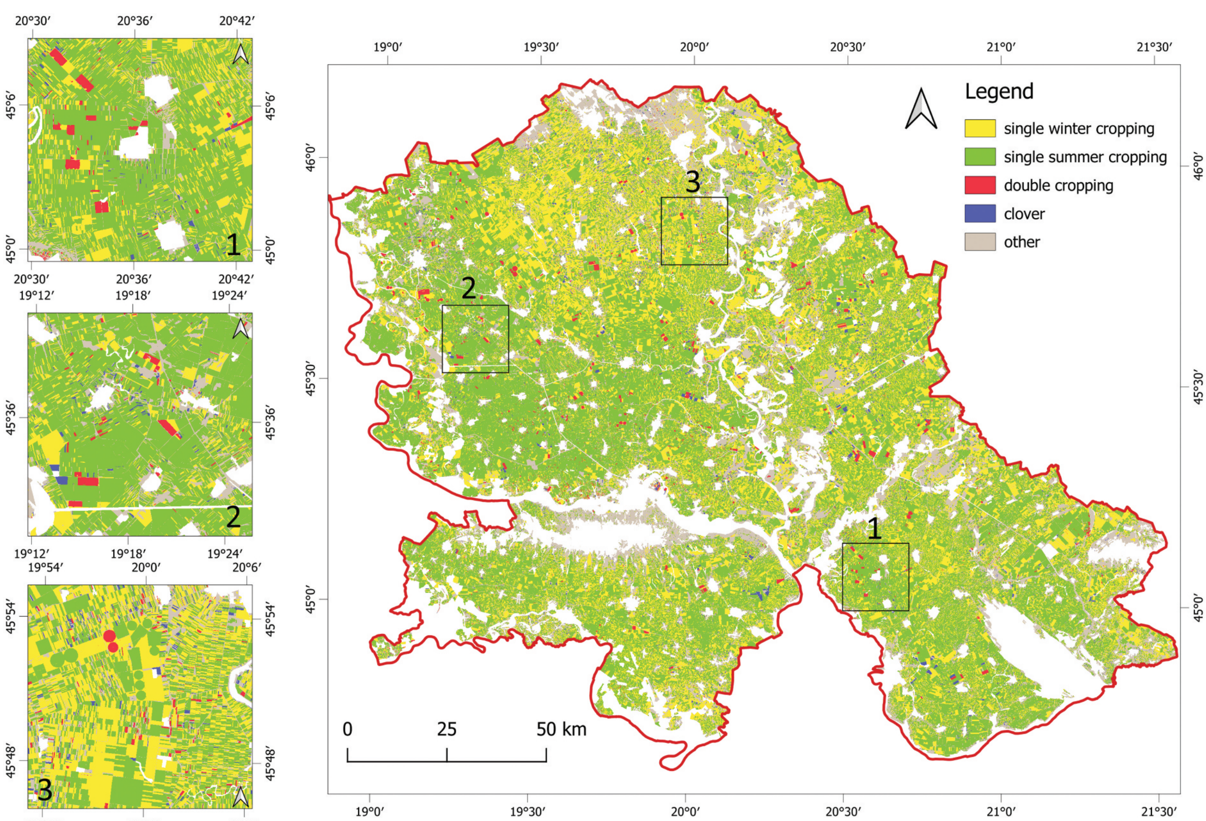

Figure B3. Cropping intensity classification map for 2023. Examples 1, 2, and 3 provide an enlarged view of the classification results.