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Current status and perspective of remote sensing application in crop management

Trenutni status i perspektiva primjene daljinskih istraživanja u upravljanju poljoprivrednim usjevima

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ABSTRACT

Knowledge of the spatial distribution of agricultural crops and crop rotation is necessary for the understanding of the farming practices concerning the long-term sustainability of agricultural production. Agricultural crops are increasingly subject to drought due to the effects of global climate change, and the same is true for Croatia due to the constant rise in mean annual temperatures and uneven rainfall distribution. Remote sensing methods have proven to be superior in the detection and monitoring of drought compared to conventional methods of observation from meteorological stations. Information on the condition of crops in the early stages of development indicates potential irregularities in the development of agricultural crops. The objective of this paper is to provide a perspective for the application of remote sensing in crop management using state-of-the-art methods. Analysis of the possible implementation of these methods in Croatia was performed on a macro- and micro-level. Spatial classification, cropland suitability multicriteria analysis, drought assessment, weed detection and crop density calculation were evaluated according to the necessary equipment and data processing segments. Remote sensing application in crop management offers a potential basis for better crop management both at the macro-level for land use planning and at the micro-level for family farms.

Keywords: machine learning, land suitability, weed detection, unmanned aerial vehicle (UAV), satellite images, variable rate technology

SAŽETAK

Poznavanje prostorne raspodjele poljoprivrednih usjeva i plodoreda neophodno je za razumijevanje poljoprivredne prakse za dugoročnu održivost poljoprivredne proizvodnje. Poljoprivredni usjevi su sve više izloženi suši zbog učinaka globalnih klimatskih promjena, a isto vrijedi i za Hrvatsku zbog stalnog porasta srednjih godišnjih temperatura i neujednačenoj količini padalina. Metode daljinskog istraživanja pokazale su se superiornima u otkrivanju i praćenju suše u usporedbi s konvencionalnim metodama promatranja s meteoroloških postaja. Podaci o stanju usjeva u ranim fazama razvoja ukazuju na potencijalne nepravilnosti u razvoju poljoprivrednih usjeva. Cilj ovog rada je pružiti perspektivu primjene daljinskog istraživanja u upravljanju usjevima korištenjem najsuvremenijih metoda. Analiza moguće primjene ovih metoda u Hrvatskoj provedena je na makro i mikro razini. Prostorna klasifikacija, multikriterijska analiza pogodnosti usjeva, procjena suše, otkrivanje korova i izračun gustoće usjeva analizirani su u odnosu na potrebnu opremu i segmente obrade podataka. Primjena daljinskog istraživanja u upravljanju usjevima nudi potencijalnu osnovu za bolje upravljanje usjevima kako na makro razini za planiranje uporabe zemljišta, tako i na mikro razini za obiteljska poljoprivredna gospodarstva.

Ključne riječi: strojno učenje, pogodnost zemljišta, detekcija korova, bespilotni zrakoplov, satelitske snimke, tehnologija varijabilnih inputa

INTRODUCTION

The implementation of remote sensing in agriculture has been initiated by the usage of sensors for an organic matter readout at the beginning of the 1990s, followed by the rapid development of remote sensing technology. Nowadays, remote observation sensors are used on satellites, aircrafts, tractors and in the form of manual sensors (Mulla, 2013). The free multispectral Sentinel-2 satellite images, owned by the European Space Agency (ESA), as well as the National Aeronautics and Space Administration (NASA)-owned Landsat 8, have a wide imaging coverage and a spatial resolution up to 10 m for Sentinel-2 (ESA, 2015) and 30 m for Landsat 8 (USGS, 2018). This enables their global application to perform the analyses on the macro- or micro-level (Hill, 2013). Remote sensing with the spectral bands in the near-infrared and shortwave infrared part of an electromagnetic wave spectrum renders the aforementioned satellite missions suitable for the determination and monitoring of phenological characteristics of agricultural crops and other vegetation (Sibanda et al., 2015). However, a limited temporal imaging resolution of five days for Sentinel-2 (ESA, 2015) and 16 days for Landsat 8 (USGS, 2018), as well as frequent cloud obscurity of an observed area (Zhu et al., 2015), confine the satellite imagery capacities for recurrent and arbitrary monitoring of agricultural crops. The unmanned aerial vehicles (UAVs) are utilized to collect the data with an arbitrary surface and temporal resolution (Gevaert et al., 2015), as well as with incorporation of sensors depending on the imaging needs, e.g., of the RGB or multispectral camera (Turner et al., 2014). Imaging by a UAV is independent of the presence of cloud cover, but the limitations concerning meteorological conditions, such as precipitation or wind strength, are existent. During imaging, the weather conditions in the field should be as harmonized as possible, so the imaging is recommended approximately at noon, when the object shadows on terrain are minimal throughout a day (Salvo et al., 2014). The satellite missions and the UAVs are mutually complementary and jointly provide for a saving possibility and a more economical production on the macro- and micro-level (Matese, 2015).

The information on the condition of crops in the early developmental phases indicates potential irregularities in the development of agricultural crops and serve as a basis for the performance of agrotechnical operations. Based on these observations, the agricultural crop monitoring systems founded on remote sensing have been developed in all parts of the world (Wu et al., 2014). The agricultural crop monitoring in such systems is successfully performed on a national and regional level while using multispectral satellite imagery (Doraiswamy et al., 2003). On a local level, the same is accomplished by using the RGB and multispectral cameras mounted on the UAVs (Jannoura et al., 2015). The multispectral cameras on satellites and UAVs equipped by a red and a near-infrared sensor facilitate computation of the Normalized Difference Vegetation Index (NDVI) (Tucker et al., 2005) and Soil-adjusted Vegetation Index (SAVI) (Huete, 1988), which are highly correlated to the crops' phenological characteristics (Prince, 1991; Baret and Guyot, 1991). Some of these are leaf area index, biomass, chlorophyll and nutrient contents in plants (Mulla, 2013). Optimal monitoring of agricultural crops is performed by remote sensing concerning their most significant phenological periods (Vina et al., 2004). Accordingly, a temporal component, as a result of multitemporal imaging via satellites and UAVs (Wardlow et al., 2007), is of the utmost importance for agricultural crops. Multitemporal imaging with a high surface resolution is a foundation for the detection of drought in agricultural crops, based on the observation of value alterations in vegetation indices, which imply water stress in plants, in combination with meteorological data (Atzberger et al., 2013). The data of an agricultural crop monitoring during multiple sowing seasons, together with the data on yield from the observed parcels, are simultaneously used as a basis for a prediction of yields in the future (Quarmby et al., 1993).

The aim of this paper was to provide a review of current state-of-the-art remote sensing methods for the application in crop management at the macro- and micro-level. Based on the necessary equipment and data processing demands, a perspective for the implementation of these methods in Croatia for more efficient crop management for both land-use planning and family farms was provided.

STATE-OF-THE-ART METHODS OF REMOTE SENSING IN CROP MANAGEMENT

Current state-of-the-art remote sensing methods for crop management were evaluated at two scales: macro and micro (Figure 1). Primary differences of these levels are the study area and the purpose of the methods, since land-use planners benefit from the data at the macro-level, while micro-level data aims at the tangible application in the agricultural fields by family farms.

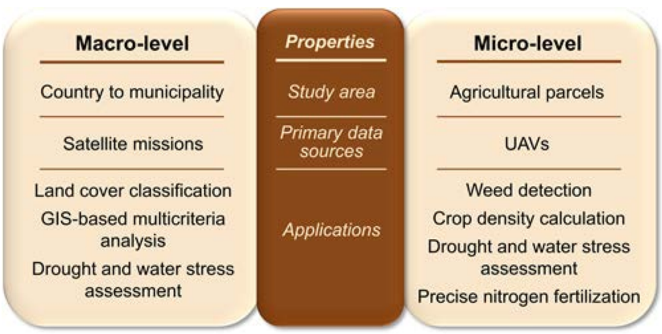

Figure 1. Macro and micro scales of the research and their properties

Supervised classification using machine learning algorithms

A classification of land cover types is one of the most frequent applications of remote sensing methods (Rogan and Chen, 2004). The data on the spatial distribution of agricultural crops and crop rotation are used for a better comprehension of a farming practice with regard to the modifications in the environment, such as climate changes, subterranean water abstraction and soil erosion, which potentially endanger a long-term agricultural production sustainability (Galford et al., 2008). An obstacle to the classification of agricultural crops by species is construed by variability in a phenological growth stage for an individual agricultural crop species in an area, thereby also implying a variability in their spectral values, which thus may be difficult to completely differentiate them from the rest of the vegetation (Price, 1992). A solution is represented by the usage of multitemporal images because a change in spectral values of agricultural crops proceeds in time significantly more rapidly with regard to the pastures or permanent crops (Gómez et al., 2016). By such a method, it is possible to reliably separate the agricultural crops that have an approximately equal vegetative period. A mutual differentiation of such agricultural crops subsequently proceeds while emphasizing their spectral differences, which may be observed in the red-edge or near-infrared spectral bands of the multispectral satellite missions (Rao, 2008). An object-oriented classification approach, based on a pixel aggregation of the proximate spectral values in objects through a satellite imagery segmentation process, provides for a possibility to obtain the more high-quality classification results when compared to the pixel-based methods (Blaschke, 2010). The results obtained in that manner comprise the zoned entities, as a substratum adjusted to the implementation of precise agrotechnical measures in the field (Seelan et al., 2003), differentiated by the conventional pixel-based classification methods, in which noise is frequently manifested in the classification results (Jiang et al., 2014). By the automation of an algorithm of an agricultural crop classification, the application of the algorithm itself is being accelerated, while a possibility of a classification error is being reduced due to the elimination of a human factor during classification (Dannenberg et al., 2016). Recently, the algorithms for the classification of agricultural crop species are based on machine learning methods, which have demonstrated more superior results concerning the conventional classification methods (Belgiu and Drăguţ, 2016). Random Forest, Artificial Neural Networks and Support Vector Machines are some of the most commonly applied machine learning classification algorithms for remotely sensed data (Yuan et al., 2017). Deep machine learning algorithms in remote sensing are a subject of intensive research and are expected to outperform conventional machine learning algorithms in the near future.

GIS-based multicriteria analysis for suitability evaluation

Suitable areas for cultivation of a certain agricultural crop are conditioned by climate, soil, relief, infrastructure and related local constraints (Šiljeg et al., 2020). Due to a fact that each agricultural crop has special conditions related to the adduced criteria, a determination of the optimal areas for the cultivation of a crop results in better utilization of natural and human resources, with a potentially larger yield (Kazemi and Akinci, 2018). Remotely sensed data is often used for spatial modeling of topographic criteria, as well as for the accuracy assessment of calculated suitability using multitemporal vegetation indices (Radočaj et al., 2020a). Inappropriate usage of agricultural land also exerts a negative influence on the quality of an environment due to an excessive application of pesticides, fertilizers, and water on the areas that are objectively optimal for the cultivation of other crops (Mendas and Delali, 2012). Regarding a spatial character of the criteria important for agricultural production, GIS is imposed as a favorable environment for the implementation of multicriteria spatial data analysis (Malczewski, 2006). Various forms of a multicriteria analysis are successfully applied to the agricultural crops, resulting in the recommendations for better agricultural land management (Radočaj et al., 2020b). An analytical hierarchical process (AHP) is one of the multicriteria analysis methods with a broad application in numerous activities worldwide (Cobuloglu and Büyüktahtakın, 2015; Jurišić et al., 2020). Its main feature is a mutual comparison of the relative influence of criteria pairs on an end result, which enables a more objective user's influence on an advantage calculation (Saaty, 1977).

Drought and crop water stress assessment

The agricultural crops are increasingly subject to drought due to the impact of global climatological changes (Leng and Hall, 2019), and the same is valid for Croatia because of a constant increase in the median annual temperatures and irregular rainfall distribution. The researches in the world have evidenced significant economic consequences in the drought-affected areas, primarily in the form of a lack of the produced food and a reduced agricultural production yields, as a direct result of the abovementioned factors (Christian-Smith et al., 2015). Accordingly, a necessity has emerged to inventory and monitor the drought of the agricultural crops for the sake of insurance and possible damage assessment (Hazell and Hess, 2010). The remote sensing methods have been proven more superior when detecting and monitoring the drought if compared to the conventional observation methods related to the meteorological stations (Skakun et al., 2016). A high-quality drought assessment by the remote sensing methods is achieved via a combination of vegetation and spectral indices that refer to the share of water in plants (Bajgain et al., 2015). Based on the same fact, several spectral indices for drought detection have been developed, out of which the Normalized Difference Drought Index (NDDI) is among the most important ones, being successfully applied while using the Landsat 8 satellite imagery (Gu et al., 2007). The results obtained in that way are used to devise the drought maps, which represent a foundation for precise irrigation in agriculture (Cammalleri et al., 2014).

Weed detection

The presence of weeds on agricultural parcels may reduce a potential agricultural crop yield up to 35% (Pérez-Ortiz et al., 2016). A most frequent practice in weed treatment is the application of a fixed amount of herbicide on an entire agricultural parcel, resulting in an inappropriate and excessive herbicide application. This causes unnecessary pollution and a negative environmental impact (López-Granados et al., 2011). A detection of weeds in an early stage of agricultural crops' growth is founded on a geometrical determination of crop rows and on a separation of vegetation located outside the crop rows (Peña et al., 2015). Using a binary classification and the Hough transformation on a digital orthophoto, a reliable determination of rows in agricultural crops is accomplished (Jones et al., 2009). The parts of agricultural parcels outside the crop rows are subsequently classified pursuant to the spectral values, with an objective to distinguish vegetation from a soil (Zwiggelaar, 1998). For detected vegetation, a thematic weed map is devised as a basis for the implementation of the adequate agrotechnical weed removal measures (Slaughter et al., 2008), of either the weeds or to the crops outside the rows. When detecting the weeds in a late stage, the emphasis lies on the differentiation of spectral values of agricultural crops, which are then dry and assume the nuances of a brown color and of a green-colored weed (López-Granados, 2011). Due to a principle of plant competitiveness, in a late developmental stage of agricultural crops, only the weeds of an approximate or of a larger height with regard to the agricultural crops will survive, whereby it is possible to detect them while imaging them by a UAV. A thematic weed map in a late crop growth stage is used for validation of the implemented weed suppression measures in an early stage and as a basis for weed treatment in the next sowing season, for the spatial distribution of weeds on agricultural parcels to be stable annually (Koger et al., 2003).

Crop density calculation

A density value of an agricultural crop canopy is highly correlated to a green matter quantity, accumulated dry matter, and crop yield (Whaley et al., 2000). The most frequently used method for density quantification of an agricultural crop canopy, or a number of plants per unit area, is based on a visual plant counting from the ground. Such a procedure is uneconomical, subject to human errors, and causes physical crop damage due to a movement of people (Jin et al., 2017). To eliminate the aforementioned influences, a canopy density determination is increasingly performed while deploying the UAVs. For the detection of certain plants, segmentation from the UAVs imagery is frequently used, whereby the objects containing all the pixels representing an identical plant are being created (Kang et al., 2017). On a segmented area, a binary plant classification with regard to soil, based upon the spectral values, is subsequently being performed (Gnädinger and Schmidhalter, 2017). A similar principle was applied by Chen et al. (2017) while using a plant counting method pursuant to a principle determining an individual plant's geometrical center. For reliable detection of individual stems, while imaging them by the UAVs, a high surface resolution during imaging is necessary, not lesser than five centimeters (Rokhmana, 2015). A digital surface model, as one of the additional results of imaging by a UAV, was successfully used as a supplement to the existent methods when determining a canopy density (Bareth et al., 2016).

Precise nitrogen fertilization

Conventional farming is based on the application of the uniform quantity of agricultural inputs (seed, pesticides, fertilizer) over an entire agricultural parcel. This agricultural parcel is considered as a homogenous area, whose current state of soil and crop properties is determined as an average value of multiple discrete point observations within the parcel. This approach results in an optimal average application of agricultural inputs but its distribution does not consider existing variabilities within the field. Previous deficiencies of soil and crop properties still remain at some parts of the parcel, resulting in an inadequate crop cultivation condition. At the same time, a surplus of these nutrients is being created at other parts, where the excess application of pesticides and fertilizer cause unnecessary contamination of the environment and excess cost. Precision farming overcomes these limitations by implementing the variable rate technology (VRT), where an agricultural parcel is considered as a heterogeneous area (Bora et al., 2012). Agricultural inputs are customized to meet the demands of specific parts of the study area, resulting in an optimal state of soil and crop properties. Besides the optimal distribution of agricultural input, the precision agriculture approach usually results in their lower quantity, allowing farmers to save money.

Precise fertilization is one of the most important aspects of precision agriculture, allowing 5–45% in fertilizer savings with no drops in crop yield, compared to the conventional approach (Colaço and Bramley, 2018). This particularly refers to the precise nitrogen fertilization, which was a dominant subject of research in precise fertilization recently. The two general approaches to precise fertilization can be divided into a map-based and sensor-based approach. Both of these approaches should result in prescription zones for VRT application in ESRI Shapefile format, which is supported by the majority of controllers in agricultural machinery. The map-based approach is intended for pre-sowing fertilization, based on soil sampling and laboratory analysis for soil nutrients. This results in highly accurate maps but the entire process is time-inefficient compared to the sensor-based approach. The sensor-based approach incorporates remote sensing technology via UAVs or crop sensors for the determination of crop nitrogen content through vegetation indices, primarily NDVI and Normalized Difference Red-Edge Index (NDRE). These vegetation indices are mutually complementary and produce high correlation with crop nitrogen content (Amaral et al., 2015). Multispectral sensors should preferably be used for UAVs, but low-cost RGB cameras could also produce solid results after the analysis in GIS environment (Gašparović et al., 2020). This process results in the real-time calculation of nitrogen prescription rates with the use of crop sensors or the creation of more accurate prescription zones using UAVs in supplementary precise fertilization.

PERSPECTIVE OF REMOTE SENSING APPLICATIONS IN CROP MANAGEMENT IN CROATIA

Implementation on a macro-level

Preparatory activities for the application of remote sensing for crop management generally consist of the workspace establishment and collection of remotely sensed and other necessary data. The average equipment for on a macro- and micro-level includes a UAV, a Global Navigation Satellite System (GNSS) Real-time-Kinematic (RTK) individual receiver or integrated on a UAV, a workstation and a spectrometer. The meteorological data on precipitation and air and soil temperatures are available from the meteorological stations of the Croatian Meteorological and Hydrological Service (DHMZ). The collected satellite images should be preprocessed, which includes a conversion to the bottom of the atmosphere (BOA) reflectance data, georeferencing to a single coordinate reference system (preferably HTRS96/TM in Croatia) and raster clipping to a study area. The ground-truth data for the agricultural parcels for which the agricultural incentives were granted during the research period are available from the Paying Agency for Agriculture, Fisheries, and Rural Development (APPRRR). All discrete point data (soil samples, meteorological station data) should be interpolated by an optimal interpolation method, depending on the existence of a normal distribution, stationarity, or a data value trend (Radočaj et al., 2020b).

Automatic classification of agricultural parcels per cultivated crop type commences with the collection of spectral signatures of the existing crops in their vegetative period, as well as other present land cover types. The spectral signatures are a foundation for a spectral analysis when discerning crop from other land covers present. The first step in classification is a computation of vegetation indices on the macro-level from the two-satellite image sets: prior to the sowing of all spring crops, when the soil is situated at their location, and at the moment at which the spring crops possess the largest biomass, prior to the harvest. Out of a difference of the select vegetation index at these observation moments, a spring crop mask can be produced out of a binary classification using the value difference of a vegetation index. A threshold value of binary classification should be set based upon the data obtained by the APPRRR, whereby the crops will have high values caused by a high vegetation index value at maximum biomass and a low value until the sowing of spring crops be performed, due to the soil dominance. The grasslands, permanent crops, and artificial objects will have a difference close to zero because their spectral values are not significantly altered during a spring crops' vegetative period, while the straw cereals harvested at the time of the spring crops' growth will have the negative values concerning the vegetation index differences. The classification of the extracted mixed crops can be performed with some of the previously mentioned machine learning classification algorithms. An accuracy assessment concerning different result variants will be performed on the basis of the APPRRR data, divided in a ratio amounting to 70% for training of the classification algorithm and to 30% for the classification accuracy assessment. An interactive web-GIS map of the obtained results can be freely made in the QGIS software, based upon the QGIS2Web plugin.

The land suitability evaluation for crop cultivation is founded on a multicriteria analysis procedure while using the AHP method, and the first step in its implementation is a definition of all spatial criteria that may be modeled in a GIS environment and that influence the crop growth. The basic criteria categories are the evaluation criteria: the geomorphological (terrain, terrain inclination, precipitation retention, insolation), climatological (precipitations, air and soil temperature), and pedological ones, with possible addition of the criteria related to the infrastructure and finances, and of the limitation criteria, such as an inadequate manner of use regarding land for agricultural production (waters, residential areas, forests). The criteria should be arranged in a table, in which the classes of the criteria inputs can be defined for the standardization of all values in a unique numeral interval. The individual criteria weights should be determined by the experts in crop production on the basis of a comparison of the criteria pairs within the AHP method. A weighted linear combination is commonly used for the suitability calculation based on standardized values and criteria weights. The calculated suitability values and ground-truth yield data offer a basis for the detection of good and bad practice and possible recommendations for more high-quality exploitation of natural resources.

Implementation on a micro-level

Multitemporal UAV imaging should be initiated by the zeroth imaging prior to the crop sowing to obtain a digital terrain model without any vegetation cover, as a basis for a successive vegetation height model calculation. For the needs of multitemporal imaging, the phenological stages of a particular crop type are divided into regular time periods between each UAV flight. In the initial crop development stage, the UAV imaging and measurement collection in the field should be performed for the purpose of training and validating the remote sensing data retrieval (spectrometer readouts, counted crop stems within a 1 x 1 m square, identification and documentation of the weed data). UAV data processing should start with the creation of digital orthophotos and digital surface models in the photogrammetric software using Structure-from-Motion algorithms. For all developmental phases, the vegetation indices can be calculated, which presents a base for statistical analysis in the form of a correlation coefficient calculation of the vegetation indices and spectrometer readouts for an individual crop development stage. The vegetation height models per developmental phases are calculated while subtracting the altitudes from the digital surface models with a digital terrain model concerning the zeroth imaging. Agricultural crops are isolated from other objects in the process using a binary classification of a selected vegetation index. The produced vegetation height models contain the vegetation height attributes, vegetation volume, and an estimated chlorophyll quantity based upon the vegetation indices. Impact analysis of a potential drought or natural disasters can be quantified on the basis of a conducted spatial-temporal analysis of vegetation indices per developmental phase. The damaged areas will be classified per damage categories, while the area and an estimated pecuniary loss can be calculated for each class concerning the respective sowing season, by means of an average buyout price and percentage of a current yield related to a maximal one.

The automation of a crop stem counting algorithm (a determination of the crop canopy density) can be performed via segmentation procedures, binary classification of crops in soil, and via isolated polygon counting. The segmentation parameters and binary classifications should be developed and tested with regard to the counting data from the field, on the 1 x 1 m square areas. An optimal period for imaging using UAV concerning the crop canopy density determination, the most beneficial spectral bands for imaging, and an optimal flight altitude should preferably be investigated during the research. Weed detection in an early crop development stage is based on a geometrical weed detection, comprised of a crop row determination and of detection of all vegetation outside the rows, whether they are the weeds or the crops outside the rows. For a determination of crop rows, the existent methods are based upon the Hough transformation. In the detected rows, the buffer zones should be created, according to the largest diameter of a crop plant measured in the field during the fieldwork. An area outside a buffer zone should be classified concerning vegetation and soil, enabling weed detection on a micro-level. Weed detection in the advanced crop growth stage is preferably based upon a spectral weed detection, imaging at the moment at which a yellow and dry crops may be discerned from the green weeds (Gašparović et al., 2020). Based upon the training and validation data collected in the field, segmentation and a supporting object-oriented classification can be performed while applying the machine learning classification algorithm. For each class of the weed presence levels, a covered surface is established. Using the weed treatment data in a study area, a correlation analysis of a spatial weed distribution in an early and in an advanced crop development stage can be conducted in the identical sowing season, whereby a herbicide treatment efficacy should be established.

The implementation of precise nitrogen fertilization using a remote sensing sensor-based approach requires GNSS receivers and ISOBUS compatibility of agricultural tractors. As nitrogen prescription rates using both UAV and crop sensors are based on the vegetation indices, calibration of these data is necessary for the effective implementation of precise fertilization (Ji et al., 2020). Handheld devices like Trimble Greenseeker deserve attention in cases of approximate determination of prescription rates but are inefficient in case of high soil nutrient variability. Chlorophyll meters provide reliable field data for nitrogen fertilization that should be collected in multiple discrete point locations within the agricultural parcel. These observations must be georeferenced using GNSS and ideally randomly split to training and test data for the calibration of UAV and crop sensor readings. Prescription zones should be formed by grouping the image pixels of UAV or crop sensor readings with similar values to enable their application by agricultural mechanization. Reliable methods of prescription zones creation in the GIS environment are either image segmentation or unsupervised classification algorithms, as manual classification could be susceptible to the operator's subjective errors (Radočaj et al., 2020a). After the calibration, an agronomy expert should designate fertilization rates to each created prescription zone based on crop type and its properties. These zones should be exported to ESRI Shapefile format in the GIS environment, which is widely available in open-source GIS software.

CONCLUSION

The importance of perspective for remote sensing applications in crop management is in the initiation of research and increasing people awareness of their advantages for the application in agriculture in Croatia. Existing methodologies for crop management using remote sensing are evaluated according to the unique geographical and natural characteristics of Croatia. Another contribution of the research is related to the automation of algorithms for the application of remote sensing in agriculture. Such an approach allows a considerably faster processing and analysis of data than conventional methods. Determination of the optimum scale for remote sensing of certain crop characteristics of should be conducted based on this perspective, expressed through the smallest area of agricultural parcels for possible monitoring via satellite or UAV. The control of the agricultural subsidies' allocation, based on the processing of multispectral satellite images, would allow control of a significantly higher number of agricultural parcels, compared to the current 5% of subsided parcels. The information obtained by crop monitoring and drought detection can serve to categorize agricultural parcels according to the drought exposure. Using the results of weed detection and determination of the crop canopy density, farmers will be able to apply herbicides more economically and conduct agrotechnical operations more efficiently. Regular crop monitoring will give farmers the possibility of early detection of pests or lack of nutrients in the soil, which will enable them to protect their crops on time.

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