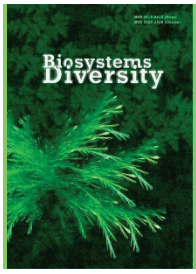

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Using normalised difference vegetation index in classification and agroecological zoning of spring row crops

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Remote sensing is an important branch of modern science and technology with various applications in different branches of life sciences. Its application in agriculture is focused mainly on crop monitoring and yield prediction. However, the value of remote sensing in the systems of automated crop mapping and agroecological zoning of plant species is increasing. The main purpose of this study is to establish the possibility of using normalised difference vegetation index in the main spring row crops, namely maize, soybeans, sunflower, to precisely classify the fields with each crop, and to evaluate the best agroecological zones for their cultivation in rainfed conditions in Ukraine. The study was carried out using the data on the normalised difference vegetation index for the period May – November 2018 from 750 fields and experimental plots, randomly scattered over the territory of Ukraine with equal representation by every administrative district of the country. The index values were calculated using combined Landsat-8 and Sentinel-2 images, with further generalisation for every crop and region. Multiclass linear discriminant analysis and canonical discriminant analysis were applied to determine whether it is possible to distinguish between the studied crops using the values of the normalised difference vegetation index as the only input. As a result, it was established that the best zone for crop cultivation is the west of the country: NDVI values for the growing season averaged to 0.34 for sunflower, 0.36 for soybeans, and 0.36 for maize, respectively. The worst growing conditions, based on the lowest NDVI values, were observed in the east for sunflower (0.26) and maize (0.25), but the minimum NDVI for soybeans (0.27) was observed in the south. Regarding the classification problem, it was found that the highest importance for the classification of crops is attributed to the values of the normalised difference vegetation index, recorded in August. The supervised learning using canonical discriminant function resulted in mediocre predictive performance of the multiple linear function with general classification accuracy of 56.5%. The best accuracy of classification was achieved for sunflower (70.4%), while it is difficult to distinguish between maize and soybeans because these crops have quite similar intra-seasonal dynamics of the vegetation index (classification accuracy was 46.8% and 52.4%, respectively; the total number of incorrectly predicted samples in the "maize-soybeans" group was 134 or 26.8%). The main limitation of this study is its single year basis, notwithstanding the fact that the year of the study was characterized as a typical one for most territory of Ukraine in terms of meteorological conditions. Therefore, more studies are required to clarify the possibility of a classification between maize and soybeans based on remote sensing data.

Keywords: agrometeorology; crop mapping; maize; soybeans; sunflower; remote sensing.

Introduction

Remote sensing has a wide range of applications in agriculture and crop science, including horticulture, irrigation water management, precision agriculture, and plant health monitoring. Usha & Singh (2013) and Sishodia et al. (2020) both highlight the potential of remote sensing in these areas, while the first authors focus mainly on the use of sensors to collect information on crop management, and others discuss the potential of applying high resolution satellite imagery to crop monitoring, irrigation management, and yield prediction. Bastiaanssen et al. (2000) emphasizes great prospects for the implementation of remote sensing in irrigation water management. Weiss et al. (2020) provides a comprehensive overview of the current remote sensing techniques and their applications in agriculture, including such branches as crop breeding, land use monitoring, and crop yield forecasting. In addition, remote sensing data is applied to crop monitoring in terms of identifying growth and development patterns. For most agricultural purposes, the normalised difference vegetation index (hereafter referred to as NDVI) is mainly used. The NDVI was introduced by Rouse et al. (1974) as a method for assessing and monitoring plant health and vegetation cover. In recent decades, it has been widely implemented in various studies on vegetation cover. Today, NDVI is the most widely used tool in agricultural purposes despite the fact that its use can be limited by some factors, including atmospheric effects, saturation, and sensor factors, making its evaluation and accessibility sometimes questionable due to significant distortion (Huang et al., 2021). Studies on annual NDVI dynamics in different crops are crucial for understanding the impact of various biotic and abiotic factors on their development and yield formation. The annual dynamics of NDVI in crops are influenced by a range of factors, including cropping systems (Hangbin et al., 2011), meteorological conditions, soil moisture (Zhang et al., 2018), as well as climate features in general (Paruelo & Lauenroth, 1998). Tamás et al. (2023) found that NDVI dynamics can be used to evaluate the effects of nitrogen dose, soil tillage, and irrigation on maize hybrids, with a strong correlation between NDVI and grain yield. Lin & Perng (2011) further emphasised the importance of terrain factors, such as aspect and slope, in influencing NDVI dynamics in maize. Jiang et al. (2003) highlighted the potential of NDVI in monitoring crop growth and estimating yield, particularly in winter wheat.

In addition, NDVI has been widely implemented in crop mapping due to its ability to reflect vegetation cover status and quantify its attributes (Huang et al., 2020). High-resolution satellite data provide a valuable tool for vegetation mapping and monitoring at regional and global scales (Justice et al., 1985). A range of studies have explored the use of the index for crop mapping. Multispectral remote sensing images are often used to map crops in extensive agricultural systems on a global and regional scale (Ouzemou et al., 2018). Lykhovyd (2021) found that each crop has a unique pattern of NDVI dynamics, with peak values occurring at different stages of growth. Bellone et al. (2009) used a historical NDVI time series to identify long-term trends in vegetation dynamics, which could be related to land degradation or improvement. Bukhovets et al. (2020) developed a dynamic model for NDVI winter wheat, which can estimate the optimal harvesting time for the crop. Chen et al. (2018) developed a new approach in the use of the MODIS time-series data to map croplands, cropping patterns, and crop types with high accuracy. Previously, Hao et al. (2016) used NDVI time series profiles to identify crop types, even in the years without data, describing the soil surface features. Li et al. (2019) proposed a method for monitoring the growth of winter wheat in real time using NDVI percentiles. All these studies demonstrate the potential of NDVI in crop mapping, especially when combined with other data sources and innovative approaches.

Finally, NDVI could be applied for agroecological zoning of plants and crops. Seasonal variation in NDVI can be used to distinguish between different land cover transitions in the study region of Mexico (Neeti et al., 2012). The use of NDVI for the agroecological zoning of some crops has been explored in several studies. Damian et al. (2020) found that NDVI can effectively replace or complement productivity data in delimiting management zones for annual cropping systems. Verhulst et al. (2008) used NDVI to assess the influence of agronomic management on within-plot spatial variability and factors limiting production, highlighting the importance of soil moisture. These studies justify the assumption that NDVI could be a prospective tool in agroecological zoning, particularly in assessing crop performance and identifying limiting environmental factors.

Currently, remote sensing has limited applications in Ukrainian agriculture. One of the main reasons for this is the low number of scientific studies and scientifically sound recommendations on practical application of remote sensing data. For example, there are a few studies devoted to the investigation of seasonal NDVI dynamics and phenology monitoring in crops, as well as agroecological zoning of plants using remote sensing data (Lykhovyd, 2021; Lykhovyd et al., 2022; Pichura et al., 2023). But they are limited to specific crops and areas, and there are almost no studies that cover the entire territory of Ukraine with its unique agroecological subdivision.

The main purposes of this study were: i) to investigate the intra-seasonal growth dynamics of the main spring row crops, namely maize, soybeans, and sunflower, to find out whether their NDVI patterns could be used in crop mapping and automated crop identification systems in Ukraine; ii) to establish the best zones of Ukraine for the cultivation of crops in non-irrigated conditions based on the average annual NDVI values for their growing season.

Materials and methods

The study was conducted using the data on historical NDVI, retrieved from the pre-processed images of the service Agromonitoring (https://agromonitoring.com). The NDVI was calculated based on the combined cloudless images of the satellites Landsat-8 and Sentinel-2 using the services of the platform. The NDVI images, used in the study, had spatial resolution of 250 m and were free from atmospheric distortion. The average monthly values of the index were calculated for each month of the growing season, that is, for the period May – November. The study was conducted for the year 2018 in randomly selected polygons that represent one of the studied crops: maize, soybeans, or sunflower. We choose ten random non-irrigated polygons for every region of Ukraine to represent each crop. In total, there were ten random polygons per crop in each administrative region of the country, therefore, thirty polygons of the studied crops were analysed in every region, and 250 polygons were analysed for each crop. The full dataset accounted for 750 polygons, the data were characterised with normal distribution of the inputs. Annual intra-seasonal dynamics of the NDVI values were used to establish the patterns of the index change in the course of the crop growth and development and determine its suitability for the implementation in the automated systems of crop mapping. The latter was evaluated using the procedure of multiclass linear discriminant analysis (MLDA) and canonical discriminant analysis (CDA), the algorithm of which was described by Li et al. (2006) and Cruz-Castillo et al. (1994). To ease the computations, BioStat v.7 package was applied for statistical data processing and evaluation. Canonical coefficients and constants were used to build canonical discriminant functions for every crop. The functions were further analysed for their accuracy in identification of the studied crops. All statistical calculations were performed at $P < 0.05$.

The average values of the NDVI per growing season, generalised for every geographical region, were used to establish the best zones of Ukraine for the cultivation of crops in non-irrigated conditions. It should be noted that the general geographical zoning of Ukraine was assumed to be a basis for the agroecological zoning. In this case, five major zones are distinguished as follows: the south (Kherson, Mykolaiv, Odesa, Zaporizhzhia, Dnipropetrovsk regions and the Crimea); the centre (Kirovohrad, Poltava, Cherkasy, Vinnytsia regions); the east (Luhansk, Donetsk, Kharkiv regions); the north (Sumy, Chernihiv, Kyiv, Zhytomyr regions); the west (Zakarpattia, Lviv, Volyn, Rivne, Ternopil, Ivano-Frankivsk, Khmelnytskyi, Chernivtsi regions). It should be stressed that the meteorological conditions of Crimea were evaluated only for the steppe zone of the region, while the mountainous and coastal climatic zones were excluded from the evaluation as they are not representative of croplands. Meteorological data, including air temperature, precipitation amount, and potential evapotranspiration (assessed by the method of Holdridge), for each region were collected from regional hydrometeorological centres to establish the climatological typicalness of the year (Holdridge, 1959). Meteorological data were evaluated for the entire growing season (May – November 2018). The web-sites https://meteopost.com and www.meteoblue.com were used as additional sources of meteorological data to avoid mistakes and data gaps. The long-term meteorological norms were calculated based on the data of Galik & Basiuk (2014). The typicalness of the year was assessed by the discrepancy with the long-term means in percents. The discrepancy of less than 15% is usually taken as low and very low (very typical year); between 15% and 30% – moderately reasonable (typical or slightly different from typical); exceeding 39% – high (not typical); exceeding 50% – extremely high (absolutely not typical).

Results

First of all, it is necessary to characterize meteorological conditions for the growing season of the year 2018 and compare them with the average long-term norms. Analysis of generalised meteorological data, combining every geographical zone in Ukraine, shows that the study year differed slightly from long-term norms in terms of natural moisture supply (the discrepancy in precipitation amounts fluctuated between the minimum 2.1% for the centre and the maximum of 21.6% for the north of the country). The discrepancy in air temperature and potential evapotranspiration had less fluctuation by regions (the least of 12.7% in the south and the highest of 20.1% in the east). The south of Ukraine is traditionally the driest zone of the country, while the west is characterised by the best natural moisture supply. Generally, there were no discepancies exceeding 30%, therefore, meteorological conditions of the year 2018 are characterized as mildly-to-moderately different from the long-term norms, and the year could be assumed as typical enough (Everitt & Skrondal, 2010) (Table 1).

The dynamics of NDVI within the growing season of the crops studied are presented in Figures 1–3. Analyzing 250 input samples for each studied crop allowed us to establish that the peak values of the NDVI are reached in August for sunflower crops independently of the region of cultivation (average NDVI is 0.60); in August for maize crops (average NDVI for Ukraine on the whole is 0.56), but with some dependence on the region of cultivation (in the west and north the peak is reached in September); in September for soybean crops (average NDVI for Ukraine on the whole is 0.53), but with significant fluctuation by the regions of the country (the peak values are reached in July in the east, in August in the south and centre, and in September in the west and north). The greatest equality of the NDVI distribution within the growing season by country is observed in sunflower crops, while soybeans are characterised with the greatest difference depending on the cultivation region.

As for the highest average seasonal value of the NDVI for each crop, it was 0.33–0.34 for sunflower, cultivated in the north and west; 0.35–0.36 for maize and soybeans, which also were cultivated in the north and west of Ukraine. The lowest NDVI values were observed in the east for sunflower (0.26) and maize (0.25), but the minimum NDVI for soybeans (0.27) was observed in the south. This is mainly due to the highest inequality between natural moisture supply and potential evapotranspiration in these regions. Therefore, it is unreasonable to cultivate the studied crops in the south and east of Ukraine in the rainfed conditions, while western and northern regions are the most favourable for the crops' cultivation. The methodological workflow for conducting agroecological zoning of plants species or vegetation type is proposed in Figure 4.

Table 1
Comparison of meteorological conditions during the growing season in the year of the study with the long-term norms by the agroecological zones of Ukraine

Zone	Air temperature, °C				Precipitation amounts, mm				Potential evapotranspiration, mm			
	2018	norm	Δ	Δ, %	2018	norm	Δ	Δ, %	2018	norm	Δ	Δ, %
South	17.7	15.7	2.0	12.7	239.6	297.3	57.7	19.4	1044	926	118	12.7
West	15.2	13.0	2.2	16.6	387.2	474.4	87.2	18.4	894	767	127	16.6
East	17.3	14.4	2.9	20.1	282.0	325.7	43.6	13.4	1019	849	171	20.1
North	15.2	12.9	2.3	17.4	324.2	413.3	89.1	21.6	893	760	133	17.4
Centre	15.6	13.6	2.0	14.7	360.6	368.3	7.7	2.1	919	801	118	14.7

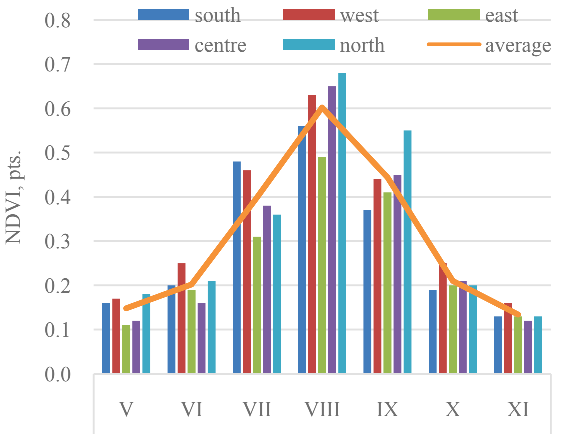

Fig. 1. The characteristics of the NDVI dynamics within the growing season of sunflower depending on the cultivation zone

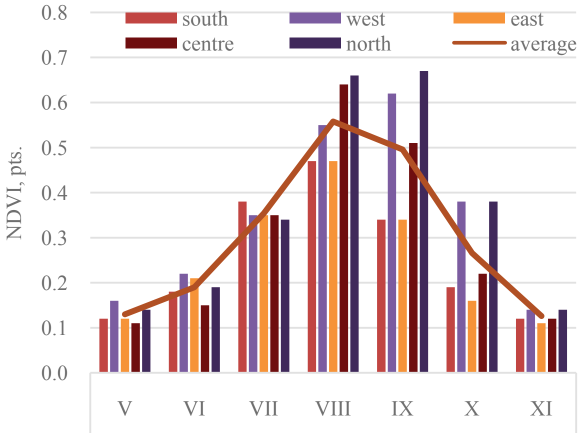

Fig. 2. The characteristics of the NDVI dynamics within the growing season of maize depending on the cultivation zone

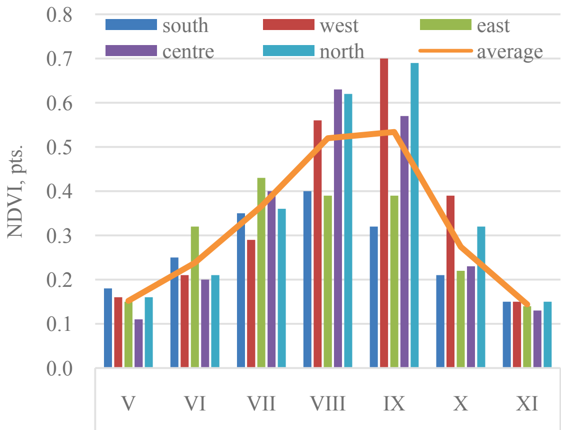

Fig. 3. The characteristics of the NDVI dynamics within the growing season of soybeans depending on the cultivation zone

Discriminant analysis of the generalised sample of 750 plots (Table 2) revealed major regularities in the NDVI dynamics within the growing season of the studied crops and the possibility of using NDVI in the systems of automated crop identification and mapping.

The calculation of Wilk's lambda (λ) with statistical approximation by Bartlett and Rao allowed to us decline the null hypothesis about the connection between the NDVI intra-seasonal pattern and crop characteristics (Tables 3, 4).

Analysis of the canonical coefficients (Table 5) allows us to conclude that the main role in the crops' identification is played by the NDVI values in August (canonical function 1) and September (canonical function 2). Thus, the latest stages of the crops' growth in the pre-harvesting period (mainly the stages, which embrace the period from the initiation of ripeness until complete ripeness) are of great importance for successful distinguishing of the species. Analysis of the canonical variables, depicted in the Figure 5, testifies that the canonical function 1 is much more decisive than the canonical function 2. Thus, August values of the NDVI are the main predictor for automated distinguishing between sunflower, maize and soybeans, cultivated in the non- irrigated conditions of Ukraine.

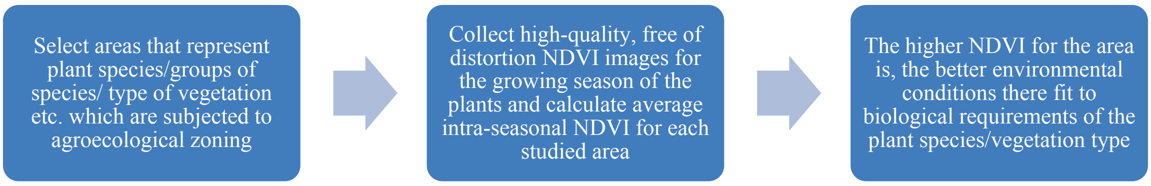

Fig. 4. The methodological workflow for agroecological zoning of plants and vegetation types using remote sensing NDVI

The coefficients and constants for the discriminant classification functions and the functions at the group centroids are presented in Tables 6 and 7, while Table 8 presents the classification matrix, based on the results of MLDA and CDA. This matrix allows one to evaluate the accuracy of the prediction in classification analysis, using the stipulated inputs as a rule for distinguishing classes. The best classification precision is recorded for sunflower (70.4%), while the accuracy for soybeans (52.4%) and maize (46.8%) is poor. The general prediction accuracy for all the row crops studied was 56.5%. Maize has the lowest detection accuracy compared to soybeans and sunflowers (Fig. 6). It was established that maize is most often misrecognised as soybeans (in 26.4–27.2% of cases), while sunflower has the most unique NDVI pattern, which is strongly different from soybeans (misrecognition just in 12.4% of cases) and maize (somewhat higher level of misrecognition – 17.2%). It was established that soybeans and maize, cultivated in the non-irrigated lands of Ukraine, have quite similar intra-seasonal dynamics in biomass accumulation and, consequently, NDVI values. This fact makes identification of these two crops a difficult task, which requires additional deep investigation or the inclusion of additional inputs along with the values of the vegetation index.

Table 2
The probability of *a priori* classification for each group of the studied spring row crops depending on their individual NDVI patterns during the growing season

Group	N	P
Sunflower	250	0.33
Maize	250	0.33
Soybeans	250	0.33
Total	750	1.00

Table 3
Wilk's lambda (approximation by Bartlett) for the discriminant analysis of the groups of the studied spring row crops depending on their individual NDVI patterns during the growing season

Canonical function	Wilk's λ	χ^2	df	P
Canonical function 1–2	0.7138	250.860	14	0
Canonical function 2	0.9285	55.212	6	4.2011×10^{-10}

Table 4
Wilk's lambda (approximation by Rao) for the discriminant analysis of the groups of the studied spring row crops depending on their individual NDVI patterns during the growing season

Statistical parameter	Value
Wilk's λ	0.7138
F (Fisher's criterion)	19.4390
P-value	0
F critical	1.6984
Null hypothesis	Declined

Table 5
Canonical coefficients and completed canonical structure of the groups of the studied spring row crops depending on their individual NDVI patterns during the growing season

Variables	Canonical coefficients		Standardised canonical coefficients		Full canonical structure	
	canonical function 1	canonical function 2	canonical function 1	canonical function 2	canonical function 1	canonical function 2
May	-4.2620	4.5721	-0.2239	0.2402	-0.0436	0.5798
June	1.1546	4.9345	0.0934	0.3991	0.0250	0.6755
July	-1.0560	1.8225	-0.1197	0.2067	-0.5038	0.2071
August	-6.5555	-1.9442	-0.9070	-0.2690	-0.4935	-0.1969
September	4.0306	4.6711	0.7266	0.8421	0.5080	0.1872
October	2.7626	-6.1681	0.3289	-0.7343	0.5321	0.0110
November	-7.9549	12.4817	-0.3823	0.5999	-0.1092	0.6068

Table 6
Functions at the studied spring row crops groups centroids

Variable	Canonical function 1	Canonical function 2
Maize	0.2671	–0.3677
Soybeans	0.4956	0.3009
Sunflower	–0.7627	0.0668

Table 7
Canonical discriminant functions for the studied spring row crops depending on their individual NDVI patterns during the growing season

Group	May	June	July	August	September	October	November	Constant
Maize	30.20	19.49	30.94	29.09	10.71	2.86	39.51	–23.06
Soybeans	32.28	23.05	31.92	26.29	14.75	–0.64	46.04	–24.97
Sunflower	36.58	20.44	32.82	34.99	8.59	–2.67	53.12	–27.77

Based on the study outcomes, it is proposed to apply the developed canonical function 1 (as this function is decisive in the crop identification model with a share of 79.6% in the final result) for the automated identification of the non-irrigated sunflower crops using the following workflow (Fig. 7).

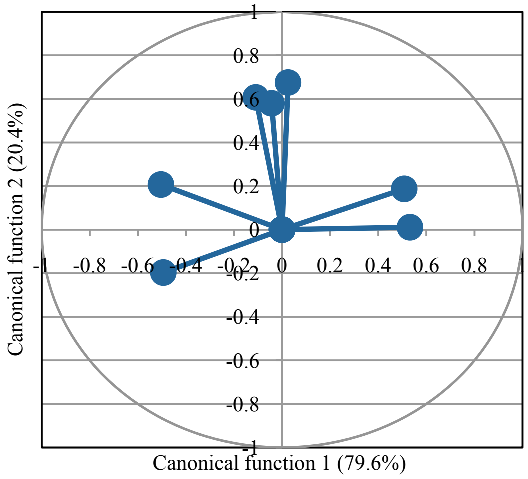

Fig. 5. The plot of the canonical independent variables, used for the identification of the studied spring row crops depending on their individual NDVI patterns during the growing season

Table 8
Classification matrix and the accuracy of the supervised prediction for the identification of the studied spring row crops

Group/ prediction	Maize	Soybeans	Sunflower	Total	Share of correct identification, %
Maize	117	68	65	250	46.8
Soybeans	66	131	53	250	52.4
Sunflower	43	31	176	250	70.4
Total	226	230	294	750	56.5

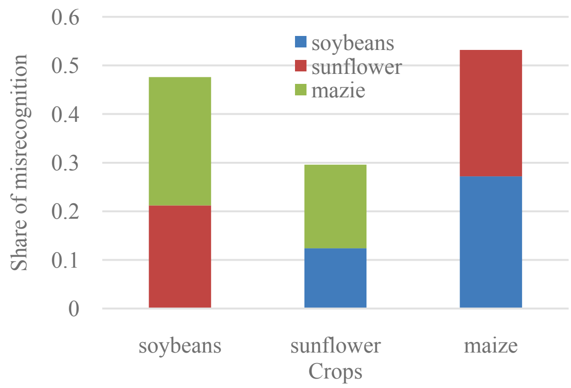

Fig. 6. Percentage of misrecognition of the studied spring row crops using their NDVI patterns in the growing season

It should be noted that the function presented in the study is relevant for the conditions in Ukraine. The coefficients and constant of the function will be different for other environmental conditions. However, the general methodological workflow for crop identification will be the same for any region of the world, but previous regional calibration is required.

Discussion

The results of our study revealed several important things about the application of NDVI in agriculture, namely the possibility of the implementation of the index in crop identification and its utilisation in the field of determination of the best zones for the cultivation of spring row crops in the rainfed conditions of Ukraine.

First of all, it is necessary to mention the results of the most prominent studies related to spatial crop monitoring in terms of the purposes of our study. Research, previously conducted on annual NDVI patterns in maize, has revealed several key findings. Venancio et al. (2020) and Wang et al. (2016) both found that NDVI can be used to track the phenological stages of maize; additionally, Venancio et al. (2020) also claimed its potential to detect biotic and abiotic stresses in the crop. Henik (2012) and Yin et al. (2010) both found that NDVI can be used to identify spatial variability in plant growth. Regarding the annual patterns of NDVI in sunflowers, it has been found that NDVI values increase during the growing season of the crop, reaching a peak at flowering and then decreasing during physiological maturity until complete cessation of the plant (Herbei & Florin, 2015). These changes in NDVI are closely related to the variations in photosynthetic activity and leaf area index of sunflower plants (Pinar & Erpul, 2019). Successful crop mapping for maize and soybeans using NDVI values was performed by Shao et al. (2010) with the accuracy of 87% and 82%, respectively. Remote sensing indices were also efficiently implemented for soybeans and maize differential mapping (with the errors of 6% and 11%, respectively) by de Souza et al. (2015). Both studies were carried out in Brazil, but it is obvious that their results correspond well to the results of our study with the only difference in the accuracy percentage. Similar work with results that agree with ours and are mentioned above was carried out by Zhong et al. (2016). Another claim in support of our results is provided by the study of Wardlow & Egbert (2008), who conducted robust large-scale research on crop identification and mapping using MODIS NDVI images in the Central Great Plains, USA. The average accuracy of crop mapping and classification reached 80%, which is much higher than in our study.

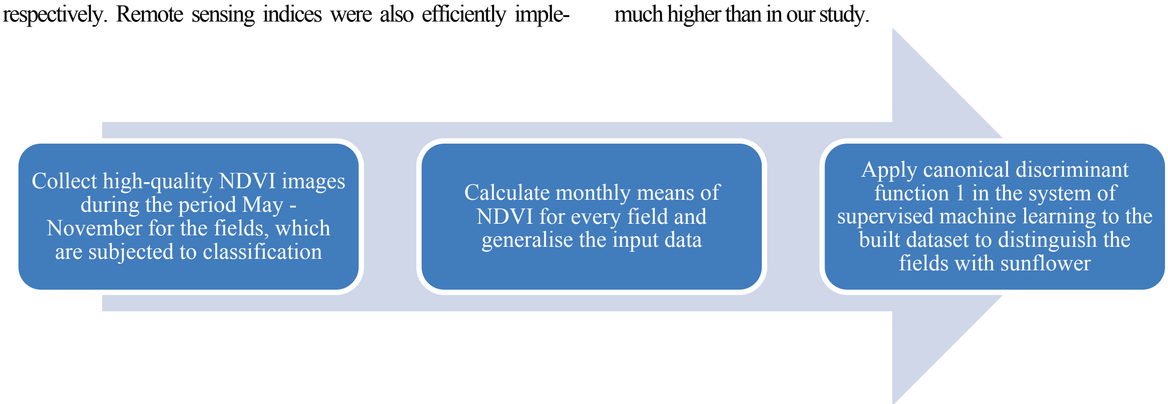

Fig. 7. Methodological workflow for the application of canonical discriminant function 1 to identify sunflower crops in Ukraine

At the same time, it should be emphasised that the current study provides novel insights into the methodological approach of applying multiple linear discriminant and canonical analysis for crop identification using remote sensing NDVI as the only input. One of the first studies to apply discriminant analysis was the study on agricultural land use prediction using different input variables by Fotheringham & Reeds (1979). Further, this approach was implemented in various agricultural studies, but mainly for economic (Satish & Sahu, 2017) and ecological analysis (Matthew et al., 1994). Another branch of application for this mathematical method is genetics and plant breeding (Chen et al., 2010). However, there are only a few scientific studies related to the subject of discriminant analysis application in NDVI-based crop identification. One of the first successful works on this subject was conducted by Silleos et al. (1992), who applied discriminant analysis to classify between sugar beets, alfalfa and cotton crops based on different vegetation indices, including the NDVI. Another work, conducted on this subject, utilised the capacities of artificial neural networks (multilayer perceptron and radial basis function) and stepwise discriminant analysis, to classify between some irrigated crops and bare soil (López-Granados et al., 2010). The best accuracy was achieved for the multilayer perceptron (89.8–96.4% of correct predictions depending on the crop), but the main drawback of the referred study is that it does not provide an applicable function for use in classification models, because neural networks are closed mathematical systems, and it is difficult to guess the way of achieving the results. In our case, full canonical structure, function coefficients and constants are clear, so that the canonical discriminant function could be applied in any independent system of machine learning for automated crop identification. Special attention should be paid to the study by Varmaghani & Eichinger (2016), who used Bayesian discriminant analysis to distinguish between maize and soybeans in Iowa state, USA. The study claims high precision of crop type prediction (88% for maize and 83% for soybeans, respectively), while our results showed the opposite. Zhang et al (2012) successfully applied discriminant analysis to distinguish cotton plants from maize, sorghum, and soybeans using remote sensing reflectance data.

The main feature of our study is that multiple linear canonical discriminant analysis was first applied to such a large scale geographical point-of-view dataset, as most studies quoted above mainly refer to much smaller experimental areas. Furthermore, it is established that the identification functions and patterns differ significantly under different environmental conditions, and the presented study is the first to investigate this subject in Ukraine. It should be noted that in the case of Iowa no difficulty was found in distinguishing between maize and soybeans, however, our results testify that these crops are hard to identify. This is because of difference not only in environmental conditions, but also agrotechnology and genetic characteristics of hybrids and varieties, sown in Ukraine and the USA.

Considering the provided scientific evidence, it is possible to state that remote sensing is a reliable and promising tool for its implementation in the systems of automated crop identification and mapping. The major impact on the quality and accuracy of land cover mapping is attributed to the quality of spatial images and the algorithms for identification, separation and mapping of crops. The patterns, described in the results section of this paper, could be used for automated identification of the studied crops, especially, sunflower, which is a strategic oil crop for Ukraine. The accuracy of 70.4% is good enough to provide crop identification. For maize and soybeans, the results are inconclusive, as these two crops have quite close NDVI patterns, and their identification precision is just about 50%, as mentioned above. This is mainly due to the relatively similar dynamics of the NDVI in these crops, therefore, further detailed investigation is required to finally conclude whether it is possible to distinguish between maize and soybean crops using NDVI as the only guidance or not. Besides, an additional clue to resolving this problem could be provided by the implementation of the logistic regression approach in addition to discriminant analysis, because this mathematical technique is referred to as another powerful tool in classification problems, which sometimes outperforms traditional discriminant analysis (Green et al., 1998).

Studies on agroecological zoning of crops using remote sensing data are not as widely conducted as other studies on remote sensing applications in agriculture. Agroecological zoning is a complex scientific problem, and in its traditional scheme it employs the combination of thermal, water, soil regime, land slope, elevation, vegetation biomass variability, etc. to derive the classification of the territory regarding its suitability for cultivation of certain crops (Patel, 2003). As far as current applications of remote sensing in general and NDVI in particular embrace almost all the mentioned features, it is possible to provide an approximate agroecological zoning based on this vegetation index. For example, agroecological zoning of Zambia was successfully performed by Menenti et al. (1993) using NDVI time series images. Furthermore, NDVI was also integrated into some agroecological zoning systems as a predictor of vegetation biomass characteristics, as in the study by Bala et al. (2009). We went farther and used NDVI values as the parameter for determination of the best agroecological zones for concrete species of agricultural plants. Our assumption is that the highest average intra-seasonal NDVI value predicts the best biomass development, and the better the biomass accumulation, the more optimal are environmental conditions for a particular crop in this area. This hypothesis finds support in the study by Cabrera-Bosquet et al. (2011), who claimed that NDVI values are strongly correlated with such plant parameters as dry biomass, green canopy cover, and nitrogen content in the biomass. In this regard it is surprising that there are almost no scientific studies devoted to the issue of agroecological zoning for different plant species, including agricultural ones, by the values of remote sensing NDVI, as this method is accurate, time-saving, and cost-effective for the conduction of large-scale studies.

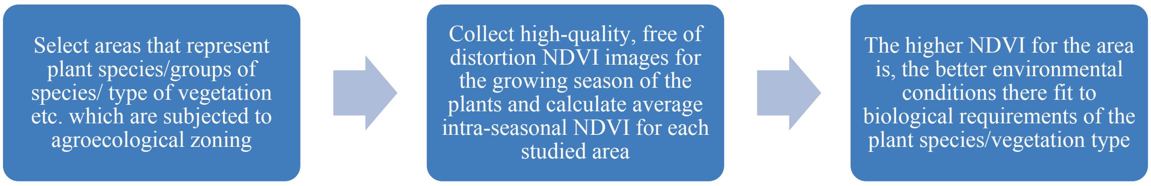

Fig. 8. The methodological workflow for agroecological zoning of plants and vegetation types using remote sensing NDVI

Considering the agroecological zoning of the studied spring row crops, it was established that the west of Ukraine is the most suitable zone for their cultivation in non-irrigated conditions. This is mainly because of better natural water supply, which has dramatically diminished in recent years on most of the territory of the country in the course of climate change (Lykhovyd, 2021). Thus, rainfed spring row crops should be relocated to less traditional zones of their cultivation. Cultivation in the south and in the east of the country appears to be reasonable under irrigated conditions only.

Conclusion

The results of the study allowed us to define that sunflower has the most unique intra-seasonal NDVI pattern, while soybeans and maize are crops with quite similar vegetation index dynamics. Therefore, sunflower crops could be easily identified using NDVI as the only basis for crop classification, while the distinguishing between maize and soybeans remains questionable.

As for agroecological zoning of the studied crops, it was established that the west of Ukraine is the most favourable zone for the crop cultivation, while the south and the east of the country provide the poorest results because of significant lack of natural water supply and high potential evapotranspiration.

Although this preliminary study has some limitations, mainly related to the number of years included into the study, it provides important insights on the possibility of remote sensing application in the agriculture of Ukraine. More research is required to support the results of this study and clarify some inconclusive points in terms of soybean and maize classification based on the NDVI images.

References

Bala, S. K., Choudhury, B. U., Sood, A., Bains, G. S., & Mukherjee, J. (2009). Characterization of agro-ecological zones of Punjab state using remote sensing and GIS tools. In: ISPRS/XXXVIII-8/W3 Workshop Proceedings: Impact of Climate Change on Agriculture. Ahmedabad. Pp. 331–335.

Bastiaanssen, W. G., Molden, D. J., & Makin, I. W. (2000). Remote sensing for irrigated agriculture: Examples from research and possible applications. Agricultural Water Management, 46(2), 137–155.

Bellone, T., Boccardo, P., & Perez, F. (2009). Investigation of vegetation dynamics using long-term normalized difference vegetation index time-series. American Journal of Environmental Sciences, 5(4), 461.

Bukhovets, A. G., Semin, E. A., Kucherenko, M. V., & Yablonovskaya, S. I. (2020). Dynamic model of crops' normalized difference vegetation index in Central Federal District environment. IOP Conference Series: Earth and Environmental Science, 548(4), 042019.

Cabrera-Bosquet, L., Molero, G., Stellacci, A. N. N. A., Bort, J., Nogués, S., & Araus, J. (2011). NDVI as a potential tool for predicting biomass, plant nitrogen content and growth in wheat genotypes subjected to different water and nitrogen conditions. Cereal Research Communications, 39(1), 147–159.

Chen, X., Xun, Y., Li, W., & Zhang, J. (2010). Combining discriminant analysis and neural networks for corn variety identification. Computers and Electronics in Agriculture, 71, S48–S53.

Chen, Y., Lu, D., Moran, E., Batistella, M., Dutra, L. V., Sanches, I. D. A., da Silva, R. F. B., Huang, J., Luiz, A. J. B., & de Oliveira, M. A. F. (2018). Mapping croplands, cropping patterns, and crop types using MODIS time-series data. International Journal of Applied Earth Observation and Geoinformation, 69, 133–147.

Cruz-Castillo, J. G., Ganeshanandam, S., MacKay, B. R., Lawes, G. S., Lawoko, C. R. O., & Woolley, D. J. (1994). Applications of canonical discriminant analysis in horticultural research. HortScience, 29(10), 1115–1119.

Damian, J. M., Pias, O. H. D. C., Cherubin, M. R., Fonseca, A. Z. D., Fornari, E. Z., & Santi, A. L. (2019). Applying the NDVI from satellite images in delimiting management zones for annual crops. Scientia Agricola, 77(1), e20180055.

de Souza, C. H. W., Mercante, E., Johann, J. A., Lamparelli, R. A. C., & Uribe-Opazo, M. A. (2015). Mapping and discrimination of soya bean and corn crops using spectro-temporal profiles of vegetation indices. International Journal of Remote Sensing, 36(7), 1809–1824.

Everitt, B. S., & Skrondal, A. (2010). The Cambridge dictionary of statistics. 4th edition. Cambridge University Press, Cambridge.

Fotheringham, A. S., & Reeds, L. G. (1979). An application of discriminant analysis to agricultural land use prediction. Economic Geography, 55(2), 114–122.

Galik, O. I., & Basiuk, T. O. (2014). Dovidkovi dani z klimatu Ukrajiny [The reference book on the climate of Ukraine]. Publishing House of the National University of Water Economy and Environmental Use, Rivne (in Ukrainian).

Green, G. H., Boze, B. V., Choundhury, A. H., & Power, S. (1998). Using logistic regression in classification. Marketing Research, 10(3), 5.

Hangbin, Z., Xiaoping, Y., & Jialin, L. (2011). MODIS data based NDVI seasonal dynamics in agro-ecosystems of south bank Hangzhouwan bay. African Journal of Agricultural Research, 6(17), 4025–4033.

Hao, P., Wang, L., Zhan, Y., & Niu, Z. (2016). Using moderate-resolution temporal NDVI profiles for high-resolution crop mapping in years of absent ground reference data: A case study of bole and manas counties in Xinjiang, China. ISPRS International Journal of Geo-Information, 5(5), 67.

Henik, J. J. (2012). Utilizing NDVI and remote sensing data to identify spatial variability in plant stress as influenced by management. Iowa State University, Ames.

Herbei, M. V., & Florin, S. A. L. A. (2015). Use Landsat image to evaluate vegetation stage in sunflower crops. AgroLife Scientific Journal, 4(1), 79–86.

Holdridge, L. R. (1959). Simple method for determining potential evapotranspiration from temperature data. Science, 130(3375), 572–572.

Huang, S., Tang, L., Hupy, J. P., Wang, Y., & Shao, G. (2021). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. Journal of Forestry Research, 32(1), 1–6.

Jiang, D., Wang, N. B., Yang, X. H., & Wang, J. H. (2003). Study on the interaction between NDVI profile and the growing status of crops. Chinese Geographical Science, 13, 62–65.

Justice, C. O., Townshend, J. R. G., Holben, B. N., & Tucker, E. C. (1985). Analysis of the phenology of global vegetation using meteorological satellite data. International Journal of Remote Sensing, 6(8), 1271–1318.

Li, C., Li, H., Li, J., Lei, Y., Li, C., Manevski, K., & Shen, Y. (2019). Using NDVI percentiles to monitor real-time crop growth. Computers and Electronics in Agriculture, 162, 357–363.

Li, T., Zhu, S., & Ogihara, M. (2006). Using discriminant analysis for multi-class classification: An experimental investigation. Knowledge and Information Systems, 10, 453–472.

Lin, M. L., & Perng, C. H. (2011). The impact of terrain on NDVI dynamics of corn field using generalized estimating equations and time-series MODIS images. In: 2011 IEEE International Geoscience and Remote Sensing Symposium. Vancouver. Pp. 3342–3345.

López-Granados, F., Gómez-Casero, M. T., Pena-Barragán, J. M., Jurado-Expósito, M., & Garcia-Torres, L. (2010). Classifying irrigated crops as affected by phenological stage using discriminant analysis and neural networks. Journal of the American Society for Horticultural Science, 135(5), 465–473.

Lykhovyd, P. (2021). Irrigation needs in Ukraine according to current aridity level. Journal of Ecological Engineering, 22(8), 11–18.

Lykhovyd, P. V. (2021). Seasonal dynamics of normalized difference vegetation index in some winter and spring crops in the South of Ukraine. Agrology, 4(4), 187–193.

Lykhovyd, P., Vozhehova, R., & Lavrenko, S. (2022). Annual NDVI dynamics observed in industrial tomato grown in the south of Ukraine. Modern Phytomorphology, 16, 160–164.
Matthew, C., Lawoko, C. R. O., Korte, C. J., & Smith, D. (1994). Application of canonical discriminant analysis, principal component analysis, and canonical correlation analysis as tools for evaluating differences in pasture botanical composition. New Zealand Journal of Agricultural Research, 37(4), 509–520.
Menenti, M., Azzali, S., Verhoef, W., & Van Swol, R. (1993). Mapping agroecological zones and time lag in vegetation growth by means of Fourier analysis of time series of NDVI images. Advances in Space Research, 13(5), 233–237.
Neeti, N., Rogan, J., Christman, Z., Eastman, J. R., Millones, M., Schneider, L., Nickl, E., Schmook, B., Turner II, B. L., & Ghimire, B. (2012). Mapping seasonal trends in vegetation using AVHRR-NDVI time series in the Yucatán Peninsula, Mexico. Remote Sensing Letters, 3(5), 433–442.
Ouzemou, J. E., El Harti, A., Lhissou, R., El Moujahid, A., Bouch, N., El Ouazzani, R., Bachaoui, E. M., & El Ghmari, A. (2018). Crop type mapping from pansharpened Landsat 8 NDVI data: A case of a highly fragmented and intensive agricultural system. Remote Sensing Applications: Society and Environment, 11, 94–103.
Paruelo, J. M., & Lauenroth, W. K. (1998). Interannual variability of NDVI and its relationship to climate for North American shrublands and grasslands. Journal of Biogeography, 25(4), 721–733.
Patel, N. R. (2003). Remote sensing and GIS application in agro-ecological zoning. In: Satellite remote sensing and GIS application in agro-ecological zoning. Proceedings of the Training Workshop. Dehra Dun. Pp. 213–235.
Pichura, V., Domaratskiy, Y., Potravla, L., Biloshkurenko, O., & Dobrovol'skiy, A. (2023). Application of the research on spatio-temporal differentiation of a vegetation index in evaluating sunflower hybrid plasticity and growth-regulators in the steppe zone of Ukraine. Journal of Ecological Engineering, 24(6), 144–165.
Pinar, M. Ö., & Erpul, G. (2019). Monitoring land cover changes during different growth stages of semi-arid cropping systems of wheat and sunflower by NDVI and LAI. In: 2019 8th International Conference on Agro-Geoinformatics. Istanbul. Pp. 1–5.
Rouse Jr., J. W., Haas, R. H., Deering, D. W., Schell, J. A., & Harlan, J. C. (1974). Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation (No. E75-10354). Remote Sensing Center Texas A&M University, Texas.
Satish, G., & Sahu, P. (2017). Discriminant analysis: A tool for identifying significant socio-economic correlates in farming system-a case study. Journal of Crop and Weed, 13(1), 42–45.
Shao, Y., Lunetta, R. S., Ediriwickrema, J., & Iiames, J. (2010). Mapping cropland and major crop types across the Great Lakes Basin using MODIS-NDVI data. Photogrammetric Engineering and Remote Sensing, 76(1), 73–84.
Silleos, N., Misopolinos, N., & Perakis, K. (1992). Relationships between remote sensing spectral indices and crops discrimination. Geocarto International, 7(2), 41–51.
Sishodia, R. P., Ray, R. L., & Singh, S. K. (2020). Applications of remote sensing in precision agriculture: A review. Remote Sensing, 12(19), 3136.
Tamás, A., Kovács, E., Horváth, É., Juhász, C., Radócz, L., Rátonyi, T., & Ragán, P. (2023). Assessment of NDVI dynamics of maize (*Zea mays* L.) and its relation to grain yield in a polyfactorial experiment based on remote sensing. Agriculture, 13(3), 689.
Usha, K., & Singh, B. (2013). Potential applications of remote sensing in horticulture – A review. Scientia Horticulturae, 153, 71–83.
Varmaghani, A., & Eichinger, W. E. (2016). Early-season classification of corn and soybean using bayesian discriminant analysis on satellite images. Agronomy Journal, 108(5), 1880–1889.
Venancio, L. P., Filgueiras, R., da Cunha, F. F., dos Santos Silva, F. C., dos Santos, R. A., & Mantovani, E. C. (2020). Mapping of corn phenological stages using NDVI from OLI and MODIS sensors. Semina: Ciências Agrárias, Londrina, 41(5), 1517–1534.
Verhulst, N., Govaerts, B., Sayre, K. D., Deckers, J., François, I. M., & Dendooven, L. (2009). Using NDVI and soil quality analysis to assess influence of agronomic management on within-plot spatial variability and factors limiting production. Plant and Soil, 317, 41–59.
Wang, R., Cherkauer, K., & Bowling, L. (2016). Corn response to climate stress detected with satellite-based NDVI time series. Remote Sensing, 8(4), 269.
Weiss, M., Jacob, F., & Duveiller, G. (2020). Remote sensing for agricultural applications: A meta-review. Remote Sensing of Environment, 236, 111402.
Yin, X., McClure, A., & Tyler, D. (2010). Relationships of plant height and canopy NDVI with nitrogen nutrition and yields of corn. In: Proceedings of the 19th World Congress of Soil Science, Soil Solutions for a Changing World. Brisbane. Pp. 40–42.
Zhang, H., Chang, J., Zhang, L., Wang, Y., Li, Y., & Wang, X. (2018). NDVI dynamic changes and their relationship with meteorological factors and soil moisture. Environmental Earth Sciences, 77, 582.
Zhang, H., Lan, Y., Suh, C. P., Westbrook, J. K., Lacey, R., & Hoffmann, W. C. (2012). Differentiation of cotton from other crops at different growth stages using spectral properties and discriminant analysis. Transactions of the ASABE, 55(4), 1623–1630.
Zhong, L., Hu, L., Yu, L., Gong, P., & Biging, G. S. (2016). Automated mapping of soybean and corn using phenology. ISPRS Journal of Photogrammetry and Remote Sensing, 119, 151–164.