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Using Remote Sensing Normalised Difference Vegetation Index to Recognise Irrigated Croplands via Agroland Classifier Application

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ABSTRACT

Formulation of the problem. Recognition between irrigated and non-irrigated croplands is an important task of modern agricultural science in order to ensure efficient management of water resources in agriculture and control the usage of irrigation systems. Remote sensing data could be utilized as a means for the automation of this task through the implementation of machine classification algorithms. The normalised difference vegetation index, calculated based on aerospace images, could be of great usefulness in this regard to determine the patterns of vegetation cover in different humidification conditions and provide a key to distinguish between rainfed and irrigated crops.

The purpose of this study was to assess the accuracy of cropland meliorative status recognition using remote sensing normalised difference vegetation index through different mathematical algorithms within Agroland Classifier application and to find out whether this application could be applied for automated cropland recognition.

Methods. The study was conducted for the Southern Steppe zone of Ukraine, and included 100 randomly selected fields (50 irrigated, and 50 non-irrigated) within the boundaries of Kherson and Mykolaiv regions. The data on the values of the field normalised difference vegetation index were obtained through the calculation of the average monthly index value using free of distortion cloudless aerospace imagery with a resolution of 250 m from OneSoil remote sensing platform, and then fetched to the application Agroland Classifier to get a decision on the meliorative status of the field (irrigated or non-irrigated). Agroland Classifier utilises linear canonical discriminant function and logistic regression algorithms to distinguish between the irrigated and rainfed fields. The accuracy of the application recognition was evaluated through the calculation of general correctness rate, as well as correctness rates for each recognition algorithm separately.

Results. The study revealed that Agroland Classifier provides high general correctness rate (92% for the combined algorithms) for the recognition between the irrigated and non-irrigated croplands. Each algorithm of the application was established to have its unique advantages and disadvantages. The linear canonical discriminant function provides more stable results both for the irrigated (88% of correct assumptions) and non-irrigated lands (84% of correct assumptions). At the same time, logistic regression failed to recognize the irrigated crops (just 78% of correct assumptions), while the accuracy of the non-irrigated lands recognition was significantly higher (96% of correct assumptions).

Scientific novelty and practical significance. The article provides novel insights on the implementation of remote sensing data in the classification between irrigated and non-irrigated crops in the Southern Steppe zone of Ukraine via Agroland Classifier application. The application could be recommended for scientific and practical purposes to improve cropland mapping and monitoring of the use of water resources in agriculture.

Keywords: *crop mapping, discriminant function, irrigated agriculture, logistic regression, water resources*.

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Introduction. Irrigated agriculture is one of the greatest consumers of available freshwater resources – the uptake of water for the irrigation purposes reaches about 70% of general water consumption by all the economies. And in the context of current climate change and gradual aridization, the demand for water for irrigation is expected to increase, as sustainable crop production on most territory of Ukraine will be possible only under irrigated conditions [1, 2]. Therefore, it is so important to account for the available water resources and their efficient use. Monitoring of the irrigated areas in agricultural sector and their dynamic mapping is one of the key strategies to ensure effective water management, and remote sensing could be of great use in this regard [1].

Remote sensing applications in the field of irrigated agriculture and water resources management involves different approaches and techniques depending on the purpose. For example, satellite imagery is used to determine the areas of water bodies and the spatial distribution of water resources [3]. The remote sensing application could be applied to the accounting of water balance at different levels, starting with simple recognition and mapping of irrigated croplands and ending with spatial maps of daily evapotranspiration and water deficit [4]. Some research emphasises the importance of using remote sensing and GIS in assessing land salinisation and sodification as an additional instrument to conventional soil surveys [5].

The mapping of irrigation croplands is essential to better understand the balance of water, climate change and its impacts on crops, and the distribution and demands of irrigation water. Therefore, spatial maps of irrigated croplands are among the first0line tools used for rational agricultural planning [6].

There are different approaches to identifying irrigated crops using remote sensing data. For example, some researchers used the Moderate Resolution Imaging Spectroradiometer (MODIS) Irrigated Agriculture Dataset (MIrAD-US) to identify irrigated lands in California and the semi-arid Great Plains (USA), which were performed with general precisions of 92% and 75%, respectively [7]. Another study, conducted in the USA, reports on the successful application of the random forest classification algorithm to remote sensing data to create 30 m resolution maps of irrigated grain corn and soybeans [8]. One of the recent studies reports about the use of combined remote sensing data on Soil Moisture and Ocean Salinity (SMOS), Soil Moisture Active Passive (SMAP), and Advanced SCAT-terometer (ASCAT) through the K-means algorithm to identify and map irrigated lands with sufficient (78%) correctness rate [9]. Use of the combination of remote sensing vegetation (normalised difference vegetation index and normalised index moisture index) indices together with the land surface temperature index resulted in great accuracy of irrigated lands identification, reaching 89% [10].

Apart from the data set used, the classification accuracy rates depend greatly on the mathematical algorithm applied. Usually, the best results are reported when machine learning approaches are used. However, it is not always the case, as sometimes less complicated and demanding for the calculation power mathematical algorithms can provide the results which are not greatly inferior to those of machine learning [11, 12].

Notwithstanding the fact that NDVI itself was not designed as an indicator for the recognition between irrigated and non-irrigated croplands, it fairly well characterizes general health of agricultural plants and crop status, which in its turn, is strongly dependent on irrigation water supply in the arid and semi-arid climates, where moisture availability is the main limitation factor of the plant's growth and development. Besides, some previously conducted studies support the idea of using the NDVI as a reliable and ready-to-use indirect marker of drought stress effects on agricultural plants on the land plots of different scale [13, 14]. The main purpose of this study was to determine the accuracy rates of the classification of irrigated and non-irrigated land by the means of the Agroland Classifier application (which uses linear canonical discriminant function and logistic regression algorithms) using time series of the normalised difference vegetation index (NDVI) from the fields of the South of Ukraine.

Materials and methods. The study was carried out for the Southern Steppe zone of Ukraine, which is sufficiently represented with both irrigated and non-irrigated croplands. The studied fields were located in Kherson and Mykolaiv regions, which are characterized with semi-arid climatic conditions with a strong tendency to further drought events aggravation and great demand for irrigation for sustainable crop production [15]. The investigation included 50 non-irrigated and 50 irrigated fields.

The spatial imagery of the fields with 250 m resolution during the active growing season (the period May – October) was retrieved from OneSoil (https://onesoil.ai/en/about) online platform. The service is widely used by Ukrainian farmers for remote croplands monitoring. It fetches users pre-processed combined imagery both from Sentinel-2 and Landsat-8 satellites. Image processing on the service is claimed to be performed with strict accordance to internationally validated methodology of the normalised difference vegetation index calculation [16]. The values of the NDVI are provided as a historical trend line for each plot, field, or polygon with some level of time inconsistency. In the intercourse of the study, the NDVI values were recalculated to the monthly average values in common arithmetical procedure. Only cloud-free (the percents of clouds < 10%) and free from gaps and distortion images were involved in the study to minimize misleading results. The index values were summarised monthly to correspond to the data requirements of the Agroland Classifier application. General workflow of the study conduction was close to the conditions of real practical implementation of OneSoil and Agroland Classifier products by stakeholders and farmers (Figure 1).

Agroland Classifier is an HTML-based application, developed to automate the recognition between different cultivated crops, irrigated and non-irrigated lands using the algorithms of linear canonical discri-

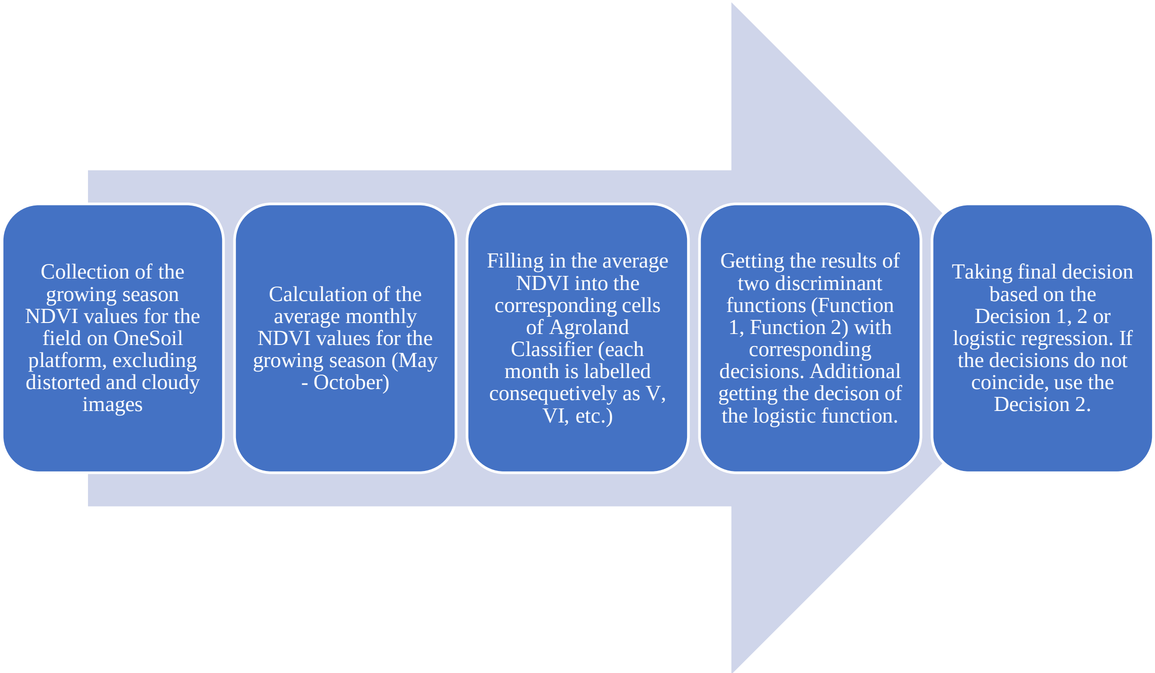

Fig. 1. Methodological workflow of the study

minant analysis and logistic regression. The application was developed at the Institute of Climate-Smart Agriculture of NAAS in the intercourse of the scientific work within the framework of the Program of Scientific Work No. 7 “Agrospace” of the National Academy of Agrarian Sciences of Ukraine. The methodology and algorithms, laid in the basis of the application, passed robust scientific validation [17]. Agroland Classifier is passing practical external testing at the moment, and it is available free of charge on the reasonable request to the Institute of Climate-Smart Agriculture of NAAS. The application has a user-friendly interface with classification and explanatory sections (Figure 2). The classification of croplands into irrigated and non-irrigated is carried out in the "Irrigated lands classifier" section of the application. Classification can be performed both by the algorithm of linear canonical discriminant analysis, and by the algorithm of logistic regression. The pre-calculated average monthly values of the normalised difference vegetation index for the growing season (the period from May to October) are entered into the corresponding cells of the application. When performing recognition using the discriminant analysis algorithm, decisions can be made based on two canonical functions. In most times, their answers will match. In the case when the answers do not match, the user must decide according to function 2 (Decision 2). The logistic regression algorithm can also be used as a test or as an independent method.

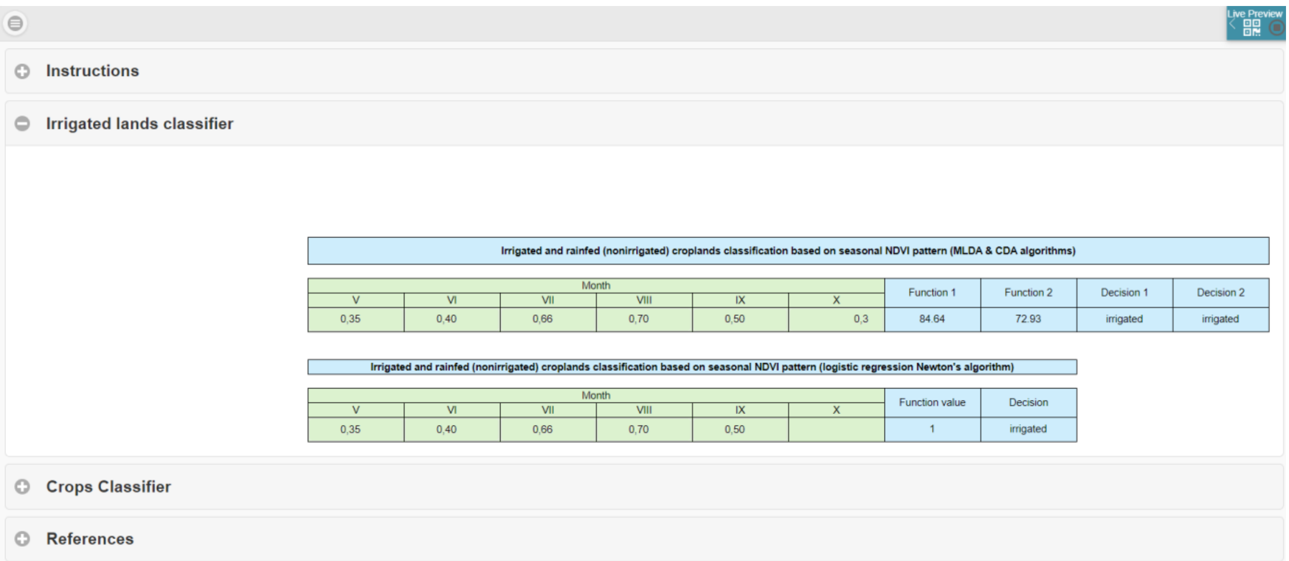

Fig. 2. User interface of the Agroland Classifier application

The correctness rates of the recognition in the Agroland Classifier application were calculated using the following equations (1–3) for each algorithm:

$$CRI = \frac{Number\ of\ correct\ irrigated\ lands\ recognition}{Total\ number\ of\ irrigated\ fields} \times 100\% \quad (1)$$

$$CRNI = \frac{Number\ of\ correct\ non-irrigated\ lands\ recognition}{Total\ number\ of\ non-irrigated\ fields} \times 100\% \quad (2)$$

$$GCR = \frac{Number\ of\ correct\ recognition}{Total\ number\ of\ fields} \times 100\% \quad (3)$$

where *CRI* – correctness rates for irrigated fields; *CRNI* – correctness rates for non-irrigated fields; *GCR* – general correctness rates.

The correctness rates of 80% and higher could be considered as reliable enough to recommend scientific and practical use of the application.

Results. Based on the remote sensing data and knowledge on the status of the studied fields, the initial data set for the Agroland Classifier application was created (Table 1). The results of the recognition through the algorithms of linear canonical discriminant function (LDA & CDA) and logistic regression analysis are also represented as correct (+) or incorrect (-).

Table 1

The data set and the results of the recognition of the irrigated and non-irrigated croplands of the Southern Steppe one of Ukraine using the values of normalised difference vegetation index (NDVI)

No.	Crop	Irrigation	Google Maps coordinates of the field	NDVI						Recognition results (LDA & CDA / Log Regression)
				May	June	July	August	September	October	
1	Alfalfa	Yes	46.738890, 33.247821	0.20	0.25	0.60	0.80	0.40	0.25	+ / +
2	Soybean	Yes	46.729566, 33.266876	0.20	0.20	0.45	0.80	0.70	0.20	+ / +
3	Sunflower	Yes	46.846354, 32.961750	0.20	0.10	0.20	0.65	0.65	0.20	+ / +
4	Grain corn	Yes	46.570638, 32.327839	0.20	0.20	0.40	0.75	0.30	0.10	+ / +
5	Grain corn	Yes	46.585495, 32.326714	0.20	0.20	0.50	0.60	0.30	0.20	+ / +
6	Rice	Yes	46.116381, 32.319588	0.20	0.30	0.60	0.65	0.60	0.40	+ / +
7	Rice	Yes	46.140251, 33.095785	0.10	0.10	0.40	0.60	0.60	0.30	+ / +
8	Soybean	Yes	46.351458, 34.261931	0.10	0.20	0.60	0.80	0.70	0.35	+ / +
9	Sunflower	Yes	46.373716, 34.248273	0.10	0.15	0.40	0.60	0.45	0.30	+ / +
10	Alfalfa	Yes	46.366703, 33.708774	0.10	0.20	0.45	0.75	0.50	0.10	+ / +
11	Soybean	No	46.723234, 32.530540	0.10	0.20	0.40	0.40	0.30	0.15	+ / +
12	Grain corn	No	46.750323, 32.479007	0.10	0.10	0.50	0.45	0.30	0.15	+ / +
13	Winter wheat	No	46.760487, 32.234667	0.40	0.60	0.20	0.10	0.10.	0.15	+ / +
14	Spring barley	No	46.793297, 32.071016	0.20	0.25	0.40	0.20	0.15	0.10	+ / +
15	Spring wheat	No	46.151307, 32.703008	0.25	0.40	0.30	0.10	0.15	0.20	+ / +
16	Grain corn	No	46.269378, 32.313710	0.10	0.25	0.60	0.60	0.20	0.15	- / -
17	Grain corn	No	46.715366, 35.284792	0.10	0.15	0.40	0.30	0.20	0.10	+ / +
18	Soybean	No	46.775067, 32.791990	0.30	0.25	0.30	0.30	0.35	0.30	+ / +

19	Sunflower	Yes	46.807847, 32.402425	0.10	0.15	0.40	0.60	0.30	0.10	- / -
20	Sunflower	No	46.836204, 32.379765	0.10	0.25	0.50	0.30	0.20	0.10	+ / +
21	Soybean	No	46.763956, 32.332405	0.30	0.50	0.20	0.10	0.10	0.15	+ / +
22	Winter barley	No	46.788003, 32.316890	0.40	0.35	0.15	0.10	0.10	0.15	+ / +
23	Winter rapeseed	Yes	46.714991, 32.222985	0.70	0.75	0.30	0.20	0.20	0.20	+ / +
24	Winter wheat	Yes	46.711492, 32.227272	0.50	0.70	0.30	0.10	0.10	0.10	+ / +
25	Winter rapeseed	No	46.699733, 32.252994	0.50	0.50	0.15	0.10	0.10	0.20	+ / +
26	Winter wheat	Yes	46.669063, 32.241358	0.70	0.70	0.20	0.10	0.10	0.10	+ / +
27	Alfalfa	Yes	46.754586, 32.253402	0.20	0.20	0.70	0.40	0.20	0.20	+ / -
28	Spring barley	No	46.751090, 32.183178	0.10	0.25	0.40	0.10	0.10	0.10	+ / +
29	Winter wheat	No	46.775422, 32.240745	0.40	0.60	0.15	0.10	0.10	0.10	+ / +
30	Grain corn	No	46.762838, 32.268100	0.10	0.20	0.50	0.35	0.20	0.20	+ / +
31	Grain corn	Yes	46.787863, 32.429780	0.10	0.20	0.50	0.75	0.40	0.15	+ / +
32	Grain corn	No	46.789541, 32.439783	0.10	0.20	0.50	0.40	0.30	0.10	+ / +
33	Grain corn	Yes	46.801839, 32.426718	0.10	0.10	0.50	0.70	0.60	0.20	+ / +
34	Winter wheat	No	46.764376, 32.433454	0.30	0.50	0.20	0.10	0.10	0.10	+ / +
35	Soybean	Yes	46.742382, 32.704859	0.20	0.10	0.35	0.65	0.60	0.20	+ / +
36	Soybean	Yes	46.743969, 32.703190	0.20	0.25	0.30	0.75	0.50	0.15	+ / +
37	Potato	Yes	46.776567, 32.754896	0.10	0.10	0.10	0.25	0.60	0.70	- / -
38	Rice	Yes	46.134200, 33.099698	0.10	0.15	0.40	0.65	0.60	0.30	+ / +
39	Soybean	Yes	46.403136, 33.130148	0.10	0.10	0.40	0.70	0.65	0.25	+ / +
40	Soybean	Yes	46.392744, 33.080406	0.20	0.20	0.35	0.75	0.60	0.15	+ / +
41	Grain corn	Yes	46.385591, 33.053185	0.40	0.20	0.40	0.70	0.60	0.35	+ / +
42	Grain corn	Yes	46.831453, 32.407744	0.10	0.15	0.40	0.60	0.50	0.15	+ / +
43	Grain corn	No	46.746490, 32.706392	0.10	0.10	0.30	0.50	0.40	0.20	+ / +
44	Grain corn	No	46.756269, 32.722264	0.10	0.15	0.25	0.35	0.30	0.20	+ / +
45	Spring barley	No	46.760306, 32.728157	0.10	0.45	0.50	0.10	0.10	0.15	+ / +
46	Spring wheat	No	46.775657, 32.744575	0.10	0.30	0.45	0.10	0.10	0.10	+ / +
47	Soybean	No	46.786573, 32.732687	0.10	0.30	0.45	0.15	0.20	0.10	+ / +
48	Winter barley	No	46.773115, 32.708299	0.40	0.60	0.15	0.10	0.10	0.10	+ / +

49	Winter barley	No	46.741684, 32.706609	0.55	0.45	0.20	0.10	0.10	0.10	+ / +
50	Grain corn	No	46.708450, 32.687959	0.20	0.25	0.50	0.40	0.30	0.30	- / +
51	Grain corn	No	46.474467, 32.500164	0.20	0.20	0.45	0.25	0.30	0.25	+ / +
52	Soybean	No	46.509685, 32.527629	0.20	0.25	0.30	0.45	0.40	0.40	- / +
53	Soybean	No	46.517718, 32.537672	0.20	0.25	0.35	0.55	0.50	0.40	- / -
54	Winter rapeseed	No	46.396412, 32.639977	0.60	0.50	0.15	0.15	0.15	0.10	+ / +
55	Winter wheat	No	46.358309, 32.557194	0.40	0.40	0.20	0.10	0.10	0.15	+ / +
56	Winter wheat	No	46.354224, 32.139980	0.40	0.65	0.10	0.10	0.20	0.20	+ / +
57	Soybean	No	46.362539, 32.190505	0.20	0.20	0.40	0.50	0.30	0.20	- / +
58	Winter wheat	No	46.691493, 32.721901	0.45	0.60	0.20	0.10	0.10	0.10	+ / +
59	Winter wheat	No	46.722678, 32.706908	0.35	0.55	0.20	0.10	0.10	0.10	+ / +
60	Grain corn	No	46.732185, 32.675548	0.10	0.10	0.20	0.55	0.30	0.15	+ / +
61	Rice	Yes	46.520612, 32.496301	0.20	0.60	0.70	0.70	0.65	0.50	+ / +
62	Spring rapeseed	Yes	46.501532, 32.508232	0.20	0.20	0.50	0.70	0.20	0.20	+ / +
63	Winter barley	Yes	46.486642, 32.507803	0.80	0.80	0.25	0.10	0.15	0.15	+ / +
64	Winter wheat	Yes	46.479846, 32.502653	0.60	0.55	0.15	0.10	0.10	0.10	- / -
65	Winter wheat	Yes	46.357201, 32.231212	0.60	0.60	0.10	0.10	0.10	0.10	- / -
66	Spring wheat	Yes	46.357372, 32.137650	0.15	0.20	0.20	0.40	0.75	0.70	+ / +
67	Grain corn	Yes	46.121883, 32.316052	0.20	0.25	0.40	0.65	0.70	0.40	+ / +
68	Soybean	Yes	46.767254, 33.565501	0.20	0.20	0.60	0.75	0.50	0.10	+ / +
69	Grain corn	Yes	46.773594, 33.577702	0.20	0.20	0.50	0.60	0.50	0.10	+ / +
70	Winter wheat	Yes	46.755438, 33.581068	0.45	0.70	0.25	0.10	0.10	0.10	+ / -
71	Grain corn	Yes	47.049545, 32.459099	0.10	0.20	0.40	0.70	0.40	0.15	+ / +
72	Grain corn	Yes	47.051695, 32.473665	0.10	0.20	0.40	0.70	0.35	0.10	+ / +
73	Grain corn	Yes	47.051695, 32.490173	0.10	0.10	0.35	0.75	0.40	0.15	+ / +
74	Potato	Yes	47.004368, 32.361507	0.10	0.10	0.15	0.45	0.70	0.40	- / -
75	Potato	Yes	46.990460, 32.350340	0.10	0.10	0.20	0.70	0.60	0.30	+ / +
76	Sunflower	Yes	46.999070, 32.336017	0.10	0.10	0.20	0.75	0.70	0.35	+ / +
77	Vegetables	Yes	46.994434, 32.325335	0.10	0.10	0.20	0.70	0.65	0.20	+ / +
78	Beans	Yes	47.018604, 32.599661	0.10	0.30	0.75	0.70	0.70	0.20	+ / +

79	Sugar beets	Yes	47.019266, 32.604273	0.10	0.15	0.15	0.40	0.75	0.70	+ / -
80	Sunflower	Yes	46.999733, 32.569072	0.10	0.15	0.25	0.75	0.40	0.15	+ / +
81	Sunflower	Yes	46.977873, 32.544553	0.10	0.10	0.25	0.70	0.40	0.20	- / -
82	Alfalfa	Yes	46.967769, 32.536784	0.60	0.70	0.60	0.55	0.60	0.40	+ / +
83	Sunflower	Yes	46.808482, 32.424160	0.10	0.15	0.40	0.70	0.25	0.10	+ / -
84	Grain corn	Yes	46.788788, 32.428287	0.10	0.20	0.60	0.70	0.40	0.15	+ / +
85	Potato	Yes	46.816291, 32.362862	0.15	0.40	0.60	0.20	0.15	0.10	+ / -
86	Soybean	No	46.739153, 31.979514	0.15	0.20	0.45	0.40	0.20	0.15	+ / +
87	Winter wheat	No	46.798529, 32.704831	0.60	0.60	0.20	0.10	0.10	0.10	+ / +
88	Winter barley	No	46.811425, 32.705088	0.40	0.60	0.15	0.10	0.20	0.15	+ / +
89	Soybean	No	46.820710, 32.710939	0.15	0.20	0.40	0.50	0.30	0.15	- / +
90	Winter barley	No	46.822910, 32.701230	0.40	0.60	0.10	0.10	0.10	0.10	+ / +
91	Grain corn	No	46.827353, 32.715119	0.10	0.10	0.40	0.60	0.25	0.15	+ / +
92	Grain corn	No	46.835228, 32.718591	0.15	0.20	0.40	0.55	0.25	0.15	- / +
93	Grain corn	No	46.828541, 32.754535	0.15	0.15	0.40	0.45	0.25	0.15	+ / +
94	Sunflower	No	46.829289, 32.767138	0.15	0.20	0.45	0.30	0.20	0.15	+ / +
95	Winter wheat	No	46.823394, 32.770031	0.35	0.45	0.20	0.10	0.15	0.15	+ / +
96	Grain corn	No	46.825549, 32.761222	0.20	0.25	0.50	0.40	0.20	0.15	- / +
97	Sunflower	No	46.813053, 32.763601	0.15	0.15	0.30	0.50	0.30	0.20	+ / +
98	Grain corn	No	46.809357, 32.767524	0.15	0.20	0.40	0.35	0.25	0.20	+ / +
99	Winter wheat	No	46.804031, 32.766945	0.40	0.35	0.20	0.10	0.10	0.10	+ / +
100	Spring barley	No	46.806276, 32.744375	0.20	0.40	0.40	0.10	0.10	0.10	+ / +

As a result of the computation of the correctness rates, it was established that the GCR of the Agroland Classifier reached 92%. As for the separate algorithms, a great difference has been found between the canonical function and the logistic regression performance. CRI for the canonical function was 88%, while for logistic function it was just 78%. At the same time, CRNI for the canonical function was 84%, while for logistic regression – 96%. Therefore, it is concluded that linear discriminant function performs much better in the recognition of irrigated croplands, while logistic regression is especially accurate when distinguishing non-irrigated land arrays. This specific should be taken into consideration when using Agroland Classifier in science and practice, and both application algorithms should be used to obtain the greatest reliability of agricultural land classification.

Discussion. Recently, there has been a lot of focus on the issue of utilising remote sensing data to categorise croplands as either irrigated or non-irrigated. Nevertheless, there isn't currently a general fix for this problem. The majority of methodological strategies created by scientists are regionally focused, meaning that in environments other than those used in actual research, they cannot ensure the same level of categorisation accuracy. As a result, the issue of identifying irrigated croplands requires the creation of relevant algorithms as well as their unification and universalisation.

In modern science, agricultural land is classified as either irrigated or non-irrigated using vegetation indices, specifically the normalised difference vegetation index. One of the most practical spatial indices is the normalized difference vegetation index because of its extensive availability across multiple platforms, relative ease of computation, and strong relationship with crop green biomass – virtually the primary factor that allows one to distinguish between rainfed and irrigated crops.

The Ghanaian study verified that agricultural land types could be accurately classified using NDVI readings. The decision tree algorithm served as the systematic foundation for land recognition, guaranteeing 67–93% accuracy in determining irrigated land, depending on the crop [18]. One of the largest scientific investigations worldwide on the composition and geographic location of irrigated land during the years 1999–2012 employed a comparable approach. According to another study [19], the accuracy of the model was 83–92% for irrigated areas and 82–88% for non-irrigated lands, indicating a quite high indication. It should be mentioned that in our study the correctness results for irrigated and non-irrigated croplands were also different.

Studies on potatoes conducted in the UK have revealed that it is practically hard to distinguish between irrigated and non-irrigated potatoes due to the humid environment of the nation. Thus, the authors concluded that only in situations where there is a stark difference between irrigated and non-irrigated conditions, i.e., in an arid climate, can Earth remote sensing data be used as a useful measure for identifying reclaimed land [20]. Due to recent climatic changes in Ukraine, situations have arisen that distinguish irrigated and rainfed agriculture. For this reason, it seems very promising to use aeronautical surveillance to identify reclaimed land [21]. However, our research also supports the notion that it is challenging to identify the irrigated potato.

Decision tree techniques are typically used to identify meliorated croplands based on remote sensing data [22]. While more conventional techniques such as binary and multiple logistic regression, ensemble machine learning, and random forest machine learning are still widely used, they are less frequently used than artificial neural networks with various learning algorithms and architectures [23]. Even though neural networks are nearly the best machine learning technique for achieving the highest levels of sensitivity and accuracy in recognition, they are computationally demanding and have a complex and ambiguous classification algorithm, which is a drawback if we wish to investigate the relationships and influences between model inputs and create a universal open function that can be integrated into other programs [24]. The Agroland Classifier uses conventional mathematical methods with clear functions used for recognition, and this is another fact in favour of this application as its algorithms are more open and universal.

It should also be noted that the application was originally developed to facilitate the classification of reclaimed croplands under crops such as corn, soybeans, sunflowers, and winter cereals. Notwithstanding the fact, the Agroland Classifier performed well enough even for the classification of crops, which were not used to build the functions, for example, rice and beans. However, potato crops are recognised much worse than the other.

Apart from the advantages mentioned above, it should be noted that there is no alternative for the Agroland Classifier. Notwithstanding the fact that there are numerous studies devoted to the problem of irrigated lands mapping using remotely sensed NDVI, none of the research groups proposed the software instrument, therefore, Agroland Classifier is not only quite accurate, but also unique tool for the semi-automated irrigated and non-irrigated croplands recognition using remote sensing data.

Conclusions. The Agroland Classifier application provides high general correctness rates in the recognition between the irrigated and non-irrigated crops, cultivated in the South of Ukraine. However, the algorithms used in the application have great variation in their accuracy, therefore, it is essential to use both to obtain the best classification correctness. Notwithstanding the fact that the application was originally designed for the limited assortment of crops (namely, sunflower, grain corn, soybeans and cereals), it performed good even for the crops, which were not claimed by the developers, such as rice, alfalfa, beans and vegetables. The application has no analogues both in Ukraine and worldwide. Further investigation of the methodological approach to the classification of the irrigated and non-irrigated lands by the means of remote sensing vegetation indices should be conducted.

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Використання супутникового нормалізованого диференційного вегетаційного індексу для розпізнавання зрошуваних земель у додатку Agroland Classifier

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Розрізнення зрошуваних і незрошуваних земель є важливим завданням сучасної аграрної науки для забезпечення ефективного управління водними ресурсами та контролю використання зрошувальних систем. Дані дистанційного зондування (зокрема, нормалізований диференційний вегетаційний індекс) можуть бути використані як засіб виконання цього завдання в парі з алгоритмами машинної класифікації. Метою дослідження було оцінити точність розпізнавання сільськогосподарських земель за даними нормалізованого диференційного вегетаційного індексу за допомогою алгоритмів додатку Agroland Classifier. Дослідження виконували для зони Південного Степу України на 100 випадково відібраних полях (50 зрошуваних і 50 незрошуваних), розташованих у межах Херсонської та Миколаївської областей. Дані щодо величини польового нормалізованого диференційного вегетаційного індексу було отримано шляхом розрахунку усередненого значення за вільними від спотворень безхмарними супутниковими знімками з роздільною здатністю 250 м, одержаними на платформі дистанційного моніторингу OneSoil, і введено в додаток Agroland Classifier для отримання рішення щодо меліоративного статусу поля (зрошуване або незрошуване). Точність розпізнавання оцінювали шляхом розрахунку коефіцієнтів коректності. Встановлено, що Agroland Classifier забезпечує високий загальний рівень коректності (92%) для розпізнавання між зрошуваними та незрошуваними землями. Кожен алгоритм додатку має свої унікальні переваги та недоліки. Лінійна канонічна дискримінантна функція забезпечує більш стабільні результати як для зрошуваних (88% коректності), так і для незрошуваних земель (84% коректності), тоді як логістична регресія гірше розпізнає зрошувані поля (78% коректності), і набагато краще – незрошувані (96% коректності). Таким чином, Agroland Classifier може бути рекомендовано для наукових і практичних цілей для напівавтоматичного розпізнавання зрошуваних і незрошуваних угідь та моніторингу використання водних ресурсів у сільському господарстві.

Ключові слова*: картування посівів, дискримінантна функція, зрошуване землеробство, логістична регресія, водні ресурси*.

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