The Wetland Map Validation for Ukraine

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Abstract—**This paper considers the topical issue of using data from a drone with a very high spatial resolution to solve the problems of validation of individual classes on land cover maps obtained at the national level with a 10-meter spatial resolution. In particular, this study validated the land cover map for the territory of Ukraine for 2020 and conducted a comparative analysis of orthophoto data with open Sentinel-2 satellite data, as well as validated some wetland locations from the classification map for Ukraine. Comparative analysis showed that orthophotoplane data have a correlation from 0.3 to 0.7 depending on the drone survey parameters with the Sentinel-2 satellite, and large wetlands on data with 10-meter spatial resolution are identified with an overall accuracy of 90%, but for more accurate details of wetlands contours correct will be the use of orthophotos data.**

Keywords—orthophotoplan; drone data; classification; validation.

I. Introduction

With the launch of the Copernicus Sentinel-1 and Sentinel-2 satellites, the scientific community has received an extremely large number of scientific and applied problems that can be solved using satellite information. A significant number of countries (EU, US, Australia and Ukraine) have started to create global and national products on a regular basis using satellite data that is freely available. These are annual land cover and crop types maps [1], maps of deforestation [2], [3], maps of fires and floods [4], [5], the crop state maps [6] and land degradation maps [7]. Environmental unions have joined in obtaining products for monitoring water bodies, soil erosion, the level of landscaping and urban growth [8], monitoring peatlands and wetlands, as well as analysis of types of land cover in time, falling on the territory of peatlands and wetlands, monitoring of mining areas etc. For many of these tasks, as they are mostly considered at the country or regional level, a 10-meter spatial resolution is sufficient [9]. However, there are some types of tasks that require a more detailed display of the object in the image. Such problems arise when reducing the study area (the level of the city or village, the level of the agricultural field, the level of a particular peat bog or swamp, the level of a particular part of the forest to monitor deforestation, for exploration tasks, etc.). In such cases, they use either paid satellite data with a higher resolution than Sentinel (such data are Planet or Spot), or use their own devices for orthophoto planning of the required area. The disadvantage of satellite data has been and remains their sensitivity to clouds, and the disadvantage of using drones is the restriction of areas where departures are allowed. The Space Research Institute NASU and SSAU in cooperation with the National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute” since 2016 create land cover and crops type maps for the whole territory of Ukraine using own technology for classifying time series of satellite data based on neural networks and deep learning. These products are a powerful basis for analytical tasks, estimation of crop areas, monitoring of crop rotations, deforestation, urban growth, etc. [10], [11]. As products increase over the years, new, more global challenges arise, such as identifying changes in major crops due to climate change, tracking and analyzing land degradation and productivity, and plowing meadows, peatlands, or wetland.

In 2020, National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute” won a grant[1] from the National Research Fund of Ukraine with the project, which provides for the use of drone data to monitor agricultural fields and deforestation detection.

In this work, the validation of the map of wetlands and their comparison with the data from the drone. As the survey took place in early spring (April 2021), work on agricultural fields and deforestation will be carried out during the growing season.

II. Data

A. Pilot Region

The first test site, which was used to survey the land cover using a drone in the class of grassland, is located in the city of Kyiv near Pirogovo (Point 1). The other two flights captured the territory of the land covered with wetland - in Zaporizhia region (Point 2) and in Kherson region (Point 3). The territorial location of these areas is shown in Fig. 1. The surface area removed from the drone

[1] The National Research Foundation of Ukraine project 2020.01/0273 "Intelligent models and methods for determining land degradation indicators based on satellite data"

is 2.5 ha for Point 1, 0.7 ha for Point 2 and 0.4 ha for Point 3.

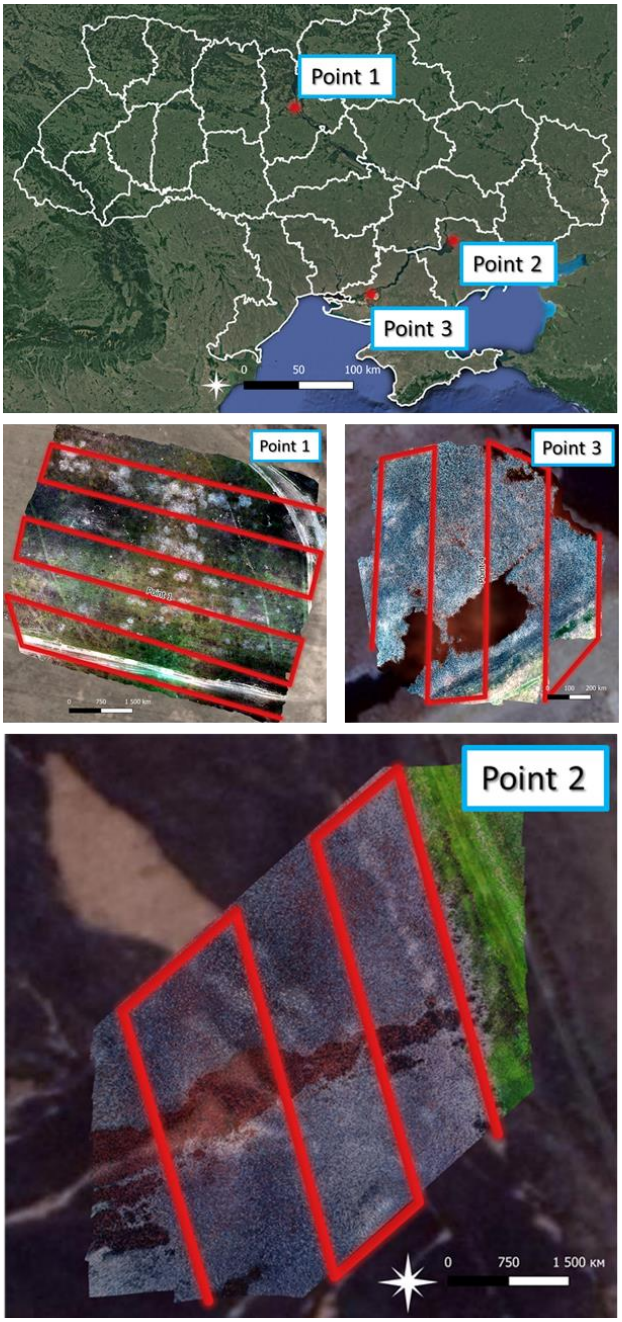

Figure 1. Grassland and wetland samples obtained from the drone

B. Satellite and Drone Data

The DJI Phantom 4 Multispectral drone was used for the flights, which was purchased as part of the project with the grant support of NRDU. Its main characteristics can be found on the official website of Drone UA [12]. The images obtained from the drone contain 5 multispectral channels (Red Edge, Near-Infrared, Green, Red, Blue) and have the following characteristics, which are listed in Table 1. Also here are the dates of the images with which the orthophotos were compared.

TABLE I. THE DRONE DATA CHARACTERISTICS

Flight characteristic	Point 1	Point 2	Point 3
Date	14/04/21	27/04/21	28/04/21
The height (m)	70	50	50
Resolution (sm/px)	3.7	2.6	2.6
Sentinel-2 data	10/04/21	26/04/21	01/05/21

Copernicus Sentinel-2 optical satellite data with a spatial resolution of 10 m and similar multispectral channels were used to validate the obtained data from the drone.

C. Wetland Classification for Ukraine

The map of wetland was obtained as a mask from the map of the land cover for the territory of Ukraine for 2020. To obtain a map of the land cover, we used own deep learning algorithms, which were developed at the Space Research Institute NASU and SSAU for the time series of satellite data for 2020. The total set of classes on the 2020 classification map consists of agricultural fields, artifitial objects, forests, grassland, bareland, water bodies and wetlands (Fig. 2). The cropland mask for 2020 was obtained within the EU-funded project "Support to Agriculture and Food Policy Implementation (SAFPI)" [13], using own developed method based on multilayer perceptron. In order to enhance efficiency of classification, it is reasonable to use not an individual perceptron, but an ensemble of them. At the same time, data merging at the decision-making level takes place during classification.

Another important output of the model after classification is the probability channel, which indicates the probability of recognition by the neural network of each pixel separately.

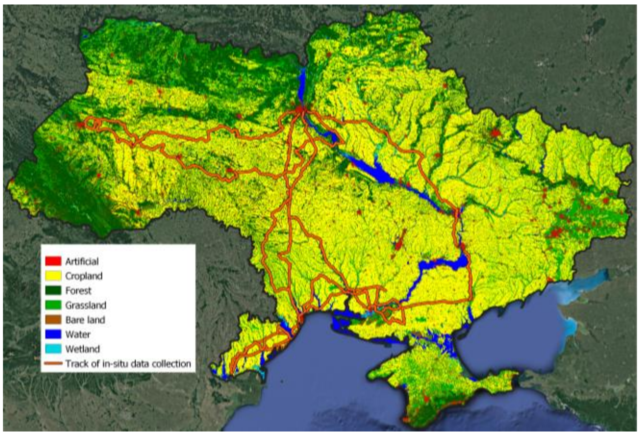

Figure 2. Classification map for Ukraine in 2020 with in-situ data tracks

The collected in-situ data along roads and on photointerpretation, which were used to obtain a classification map in 2020, are presented in Table 2.

TABLE II. THE DISTRIBUTION OF LAND COVER CLASSES IN THE IN-SITU DATA SET FOR CLASSIFICATION IN 2020

Class	In-situ	Photointerpretation	Total
Cropland	10686	-	10686
Grassland	472	1542	2014
Water	90	616	706
Forest	153	451	604
Grape	102	433	535
Artificial	41	442	483
Garden	85	343	428
Wetland	57	209	266
Bareland	3	257	260
Total	11689	4293	15982

III. METHODOLOGY

In this study the classification map for Ukraine validated. The wetland class was validated in more detail. To assess the accuracy of land cover classification maps, as a rule, a confusion matrix is used, obtained from an independent test sample, as well as the following metrics: Overall Accuracy (OA), Kappa index, Producer Accuracy (PA), and User Accuracy (UA) by formulas

$$PA_j = \frac{n_{jj}}{\sum_{i=1}^{q} n_{ij}}\ ; UA_i = \frac{n_{ii}}{\sum_{j=1}^{q} n_{ij}}\ ;$$

$$OA = \frac{\sum_{i=1}^{q} n_{ii}}{\sum_{i=1}^{q}\sum_{j=1}^{q} n_{ij}},$$

where q is the number of classes on the land cover map and test data. Confusion matrix is presented as a rectangular table, where n_{ij} – is the number of pixels which actually belong to the *i* class and were placed in the j class on the classification map [14]. To obtain a confusion matrix, a land cover map and an independent test sample (which is located within the land cover map and contains information on the land cover type) are submitted as input data.

Based on the probability channel of the classifier, the frequency of the corresponding probabilities in the intervals of 10% for each pixel of the swamp class is calculated.

Such metrics as RMSE, correlation, and R^2 are used in mathematics to compare two data sets. Since the data in this study are satellite images, each channel of which is mathematically a two-dimensional array, and each pixel is a separate cell of this matrix, the corresponding values were calculated for matrices at the pixel level for each spectral channel separately. Because the spatial distinction between drone and Sentinel-2 data differs significantly, validation was performed by averaging drone data over 10-meter cells and comparing the obtained values with satellite data. Pearson's correlation coefficient was calculated to verify the relationship between Sentinel-2 and drone multispectral bands. Pearson's correlation coefficient describes the magnitude of the linear relationship between the data. Pearson correlation coefficient formula [15] is

$$R = \frac{\sum_{i=1}^{n}(o_i-\bar{o})(p_i-\bar{p})}{\sqrt{\sum_{i=1}^{n}(o_i-\bar{o})^2}\sqrt{\sum_{i=1}^{n}(p_i-\bar{p})^2}},$$

where o_i denotes the mean value within the i-th pixel for one band of Sentinel-2 data and p_i represents the mean value within the i-th pixel for one band of drone, respectively. o and p are arithmetic means of Sentinel-2 and drone data values, while n denotes the number of pairs.

IV. RESULTS

The overall accuracy of the classification map on the test independent in-situ data set is 95%, and UA, PA, and F1-score are in the Table 3.

TABLE III. UA, PA AND F1-SCORE ACCURACIES FOR DIFFERENT CLASSES

	UA	PA	F1-score
Cropland	99.1	99.4	99.3
Artificial	71.9	88.6	79.3
Forest	85.7	99.9	92.2
Grassland	81.4	97.3	88.7
Bareland	84.6	60.9	70.8
Water	99	99	99
Wetland	90.8	89.3	90

The probability distribution by wetland class pixels for regions of Ukraine with wetland areas over 500 ha (Chernihiv - 878 ha, Poltava - 825 ha, Odessa - 663 ha, Sumy - 619 ha, Kherson - 514 ha) is shown in the diagram (Fig. 3).

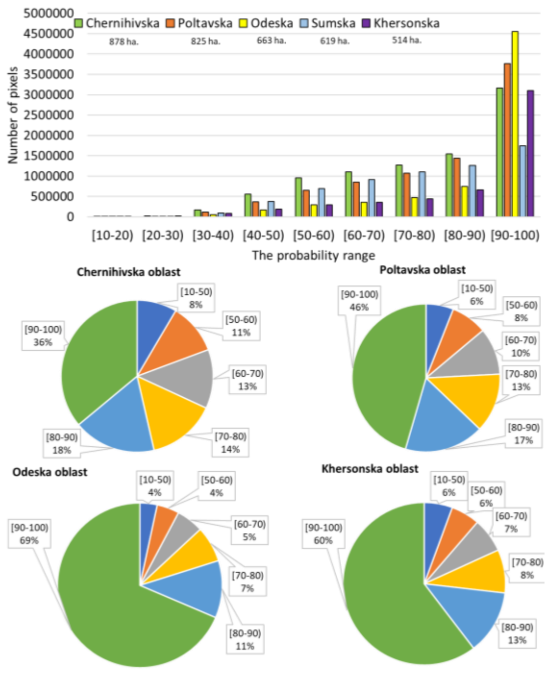

Figure 3. The distribution of probability of wetland pixels for 5 oblasts of Ukraine for 2020

To compare the obtained data from the drone and satellite data, the grid with a cell size of 10 by 10 meters was created in accordance with the spatial resolution of Sentinel-2 (Fig. 4).

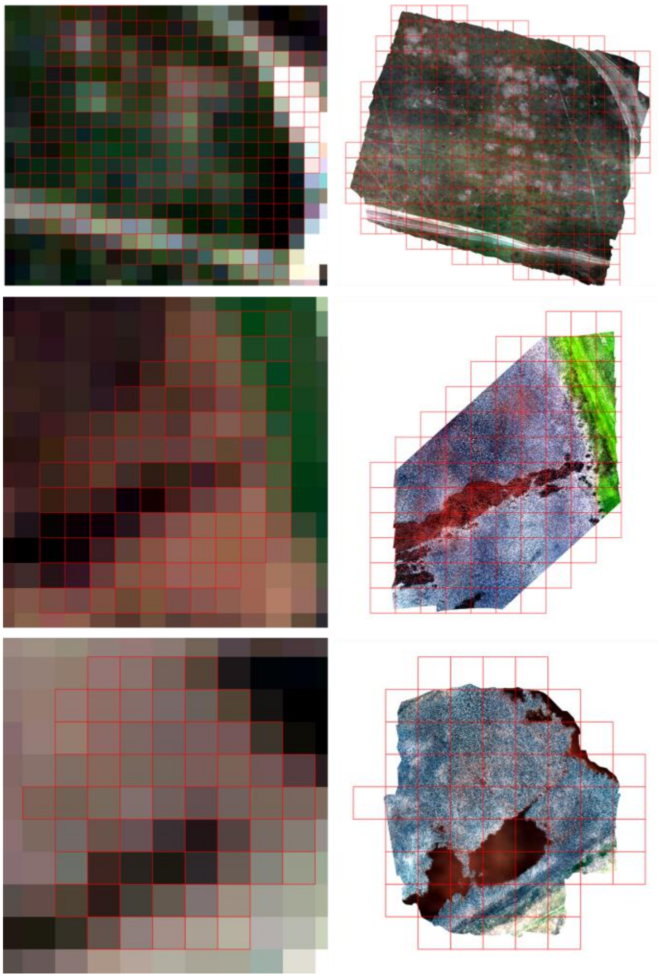

Figure 4. An example of validation cells based on Sentinel-2 satellite data (left) and drone data (right)

Table 4 shows the obtained correlations when comparing the respective channels.

TABLE IV. CORRELATION COEFFICIENTS FOR MULTISPECTRAL BANDS

	Red	**Green**	**Blue**	**Nir-infrared**
Point 1	0.3	0.28	0.35	0.45
Point 2	0.35	0.4	0.48	0.71
Point 3	0.6	0.79	0.83	0.6

V. CONCLUSIONS

After validating the land cover map and detailed validation of the wetland class for the territory of Ukraine, the following conclusions can be drawn. The spatial resolution of 10 meters is quite sufficient for tasks related to global processes in the country. In the case where a detailed study of a small area is required (in our case it is wetland as natural ecosystems), special devices are needed, such as drones, which have a very high spatial distinction and make it possible to identify the smallest changes in the land surface.

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