

Geospatial Analysis of Leased Lands in Ukraine

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Abstract – With the opening of the land market, the analysis of leased land in Ukraine becomes more and more important. On the base of remote sensing data we can use additional capabilities and tools to analyze and predict the state of the land. Thanks to the public cadastral map, we can check our results on the base of up-to date official information.

In this article we have analyzed the large leased fields in the Kyiv region. In particular, operations had performed on geospatial objects with georeference, as on sets of pixels. The main purpose of this work is to use a crop classification map and geographic information systems in order to find large areas, and check the information about the tenant using the service of state geocadastre.

Keywords—remote sensing, land lease, cadaster

I. INTRODUCTION

Land is the best unit for describing the location, boundaries and ownership of land. Land survey is the most popular way to identify land in the history of land management. However, land surveys have high financial costs for agricultural management. The development of a remote sensing data usage has introduced a new way of collecting, storing and analyzing information on agricultural land [1].

Land is the main natural resource for agriculture, and the material condition of human life and activity. Lease of agricultural land in Ukraine is the most common tool for land use, as the main form of realization of legal and economic rights of peasants on agricultural land. Therefore, an important and topical issue of land management at the present stage is to determine the optimal ratio between landowners and land users, which create certain conditions for efficient agriculture and reproduction of land resource potential. [2][3]. Analysis of land status using geographic information systems is quite slow because it is due to insufficient research in this area. As a result, there is uncontrollability, opacity, inefficiency of land use. Therefore, there is a need to develop additional automated methods that can be used for effective leased land assessment and its areas on the base of classification map [4].

Using satellite data, we can easily analyze geospatial data. Calculate crop areas, identify crop rotations, make yield forecasts and others. Remote sensing of the Earth is primarily a work with large amounts of data. Therefore, the analysis of leased land is quite a difficult task because this task requires large computing resources. Therefore, it is advisable to solve this problem on cloud platforms such as AWS.

With crop classification maps, you can analyze land plots because each plot has its own boundaries certain rights of use and information about the tenant. [5]. Another important point is that thanks to the classification maps, the area of crops is estimated [6][7].

An objective study of this article is a large agricultural field leased in Ukraine. The main work is the use of methods of geospatial analysis, namely the performance of operations on geospatial objects, as on many pixels, using the methods described in section 3. Almost all geospatial analysis has been done using Quantum GIS software, but classification map was developed on the base of original realization provided by Space Research Institute NASU-SSAU.

II. FORMULATION OF THE PROBLEM

The main purpose of this study is on the base of crop classification map obtained by neural network methods from satellite data and vector layers of roads taken from the OpenStreetMap service, and the methods described in Part III, to separate large fields into small ones and get additional information on separate tenants, which are presented in StateGeoCadastre service.

To achieve the main goal, the raster map of crop classification should be vectorized and calculated areas for each object and in result get a vector mask of leased fields for the entire Kyiv region. In some cases, the paths between the fields are less than 10 meters and quite a lot of fields are glued into fairly large objects. To get around it on the base of roads vector layer from the OSM service.

And, finally, as the next step is to count the number of fields that are part of the field sown with a certain crop type. In our case, we are interested in large sown fields. Information about leased parcels can be received from StateGeoCadastre service.

III. METHODS

It is very important to select right methods for the geospatial data analysis. First of all, in order to choose a method for data analysis, you need to understand what data we will work with (vector or raster), because the same methods are not applicable in each case.

With remote sensing data, each point of the Earth is covered by satellite images with a certain frequency. On the basis of time series of satellite data Sentinel-1 and Sentinel-2 and with the use of machine learning methods, the staff of the Space Research Institute NAS Ukraine and SSA Ukraine built maps of land cover and crop classification map [8]. Most optical images are clouded and a large amount of data is lost, the map is based on a combination of Sentinel-1 SAR and Sentinel-2 satellite data. The time series of these satellite data consist of approximately 16-20 days during the growing season for each point of the Earth's cover. Sentinel-1 radar satellite data has VH and VV polarization bands, which allow you to see the earth at any time of day or night, regardless of the clouds. Optical satellite data is also used Sentinel-2A/B. The Copernicus Sentinel-2 mission comprises a constellation

of two polar-orbiting satellites placed in the same sun-synchronous orbit, phased at 180° to each other and allow to get data every 5 days [9]. The Sentinel-2 satellite has 13 multispectral bands. Bands were used to construct the classification map RED, GREEN, BLUE, NIR which have a high resolution images, such as 10 m per pixel. An important point is the choice of method for classification because each method has its advantages and disadvantages. The most popular methods are Random Forest (RF) [10], Support Vector Machine (SVM) [11] and Artificial Neural Network (NN) [12] – [14]. In this research classification maps were created using our own developed method, based on multilayer perceptron [8]. 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. Also, the accuracy of the crop classification map depends not only on the correctly selected parameters of the machine learning method, but also on the training data, because the result of the crop classification map is most affected by the quality of the prepared data for the classifier training.

Crop classification map obtained on the base of ground data collected by the staff of the Space Research Institute NASU-SSAU according to the international standards of the international network of agricultural test sites JECAM (Joint Experiment of Crop Assessment and Monitoring) [15]. The accuracy of the classification map for 2019 is 94.8% [14], and 98.3% for 2021 (Fig.1).

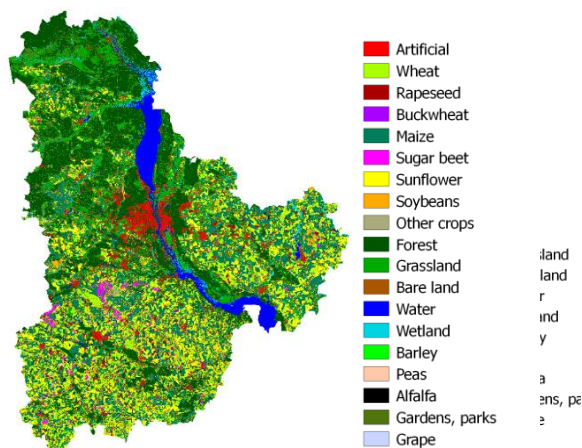


Fig. 1 Classification map of Kyiv area

In this research a raster map of crop classification for the Kiev region for 2021 is used. This map contains 19 different classes (Table 1). This map was used as the basis for further research. Using this map, we can separate agricultural fields because we have a list of unique classes that correspond to agricultural fields.

This map has a raster format. It is a matrix of $n \times n$ pixels, where each pixel corresponds to a certain class, and each pixel has a size and corresponds to a certain coordinate system. In our case, the pixel size is 10×10 meters, and has an EPSG coordinate system: 32636 — WGS 84 / UTM zone 36N.

TABLE I. CLASSES OF CROP CLASSIFICATION MAP 2021

№	Name of class
1	Artificial
2	Wheat
3	Rapeseed
4	Buckwheat
5	Maize
6	Sugar beet
7	Sunflower
8	Soybeans
9	Other crops
10	Forest
11	Grassland
12	Bare land
13	Water
14	Wetland
15	Barley
16	Peas
17	Alfalfa
18	Garden, parks
19	Grape

Because the spatial resolution of the crop classification map is 10 meters, and paths or roads between fields can be less than 10 meters, sometimes the fields can be merged into one solid object. Therefore, it is advisable to use the roads from the open service OpenStreetMap [16]. This service is the most popular and free source of vector data. This service is aimed to collecting, storing and disseminating geospatial data. The OpenStreetMap service provides free access to the borders of forests, water bodies, cities and roads.

Roads from the OpenStreetMap service are divided into classes, which are shown in Table 2.

TABLE II. CLASSIFICATION OF ROADS OF OPENSTREETMAP SERVICE

Class	Description
motorway	highway
trunk	Interregional route roads
primary	Roads connecting areas
secondary	Roads connecting district centers
tertiary	Roads connecting villages
service	Business travel (e.g. gas station)
track	Field roads
path	Stitches

For validate data we use the State Geocadastre service for analyzed results. This data is in vector format, using the tools of analysis of this geospatial data, we count the number of fields that are part of a large sown field. The Public Cadastral Map is an information portal on which information from the State Land Cadaster is published [17]. The data is stored in the form of parcels, where each parcel contains information about the land plot, namely the cadastral number of the field, information about the owner of the field, and in some cases information about the tenant. Parcels of cadastral fields on (Fig. 2).

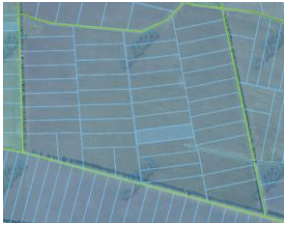


Fig. 2 Example of parcels from the public cadastral map service

In this research, we will work with vector data. With vectors data we can group our objects, where each object will have a certain attribute, and accordingly the attribute will correspond to the class. In order to vectorize the data, we need to have a raster map. In our case, this is a crop classification map for 2021. After vectorization, we save our georeference, ie the top of the vectorized object will correspond to each pixel (Fig. 3). Thus, the relevance of our data is maintained.

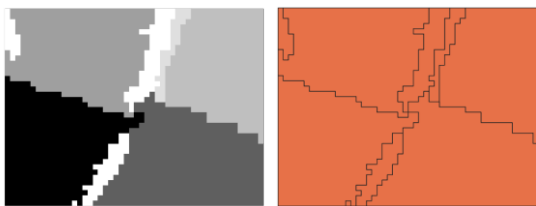


Fig. 3 Example of raster format on the left, vector format on the right

Each object is separated by black lines of MultiPolygon. That is, it is a set of nodes (coordinates) that are interconnected and thus we get a geometric object with certain attributes.

$$A = \{x_1, x_2, \dots, x_n\},$$

where A – is MultiPolygon, x – coordinates of vertices.

As long as we only need work with large fields in the process of research, it is advisable to calculate the area of each object. After calculating the areas, you need to divide the vector fields into large and small by area. The calculation of the area is performed according to the following formula:

$$S = \frac{a * px}{10000},$$

where S – area of the object in hectares, a – the number of pixels in the object, px – size of pixels.

During our research we encountered one problem that spatial resolution of a classification map is 10 meters, and paths or roads between fields can be less than 10 meters, sometimes the fields can be joined into one object. (Fig. 4).



Fig. 4 Open the classification of maps in raster format, pay attention to the classification of maps with a road layer

After vectorization, large fields will look like this (Fig. 5).



Fig. 5 On the left is a vectorized classification map with large fields, on the right is a vectorized classification map with large fields and a layer

It follows that several large fields can merge into one, and using sets operations we can subtract vector and split fields:

$$C = A \setminus B,$$

where A is a vector layer with large fields, B — vector layer with roads.

By performing this operation, we obtain more precise boundaries of vector fields.

In our research we pay attention mainly to large fields, because they are the basis of agricultural production. After all, there is an assumption that large fields are leased and therefore may contain many of the parcel fields of the State Geocadastre. Therefore, to calculate the number of parcels that are part of a large sown field, we will use a set of sets. In this way we will use a large vectorized field as a basis, and count the number of objects that are part of our large sown field.

$$A \subset B,$$

where A – vector fields from the State Geocadastre, B – vector layer with large fields, on the classification map.

This method can be used for counting the number of fields that include several parcels from the state geocadastre. After all, we have the assumption that a large field sown by one crop contains several parcels from the state geocadastre.

IV. RESULTS

Using the methods described above, we obtained statistics on the number of parcels that are part of a large sown field. Also, the online resource of the State Geocadastre allows to check this information on whether the field is leased as on the example (Fig. 6).

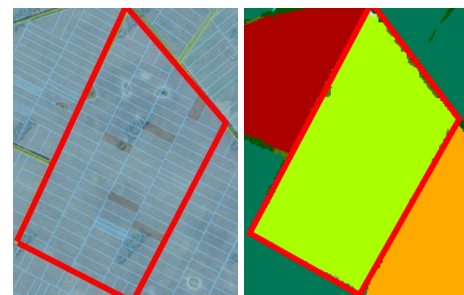


Fig. 6 On the left is a parcel from the State Geocadastre, on the right is a classification map in raster format.

This field on the classification map is marked in green and belongs to class 2 (wheat). After vectorization, we get a solid object within which we can count how many parcels are in it. As a result, this field includes 90 parcels (Fig. 7).

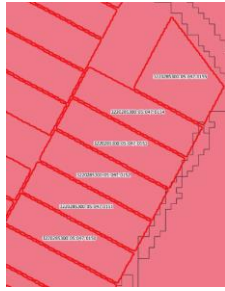


Fig. 7 Parsels on the vectorization

Using the service of the State Geocadastre, according to the cadastral number of the field, we can check the information about the owner of the field and the tenant. All 90 parcels of these sown field are rented.

Interesting fact is that there are unregistered plots of land in the entire sown field. That is, it indicates that some land plots have been sown illegally or their owners have not yet entered information into the State Geocadastre.

V. CONCLUSIONS

During this research operation with raster classification map and vector data were performed together. Such an approach provides the possibilities of monitoring the official cadastral parcels as parts of large agricultural fields.

Using the proposed methods, we can calculate the vector layer with registered fields for the Kyiv region. The map with leased fields for the Kyiv region is presented in (Fig. 8).

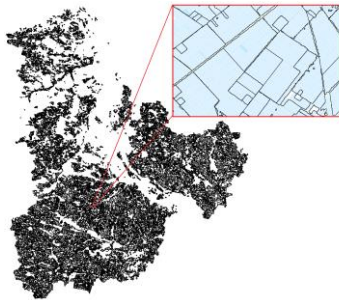


Fig. 8 Map of registered fields for Kyiv region for satellite data

Using the methods described in part III, we were able to calculate the vector layer with registered fields for the Kyiv region. According to the obtained results 61.8% of fields are leased for the territory of Kyiv region (Fig. 9).



Fig. 9 Information on leased and non-leased fields for the territory of Kyiv region according to satellite data.

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