SCIENTIFIC REPORT

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LAND USE CHANGES AND INVESTMENTS IN SELECTED REGIONS OF UKRAINE

AUTHORS
Anton Biatov
Oleh Prylutskyi
Mykhailo Amosov

EDITOR
Danya-Zee Pedra

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In lieu of a preface

How careful are the agricultural companies with the land they use? We tried to answer this question by conducting a remote assessment of the state of land in areas where businesses have invested in agriculture.

There is an assumption that when choosing crops for planting, agricultural companies in Ukraine are guided solely by forecasts of market prices for crops for the following year, and do not adhere to crop rotations either, thus violating the Resolution of the Cabinet of Ministers №164 of 11.02.2010. This study sought to investigate if this assumption is correct, given that these practices contradict the concept of sustainable land use and have severely negative impacts on the environment, in particular, soil depletion.

In order to conduct our remote assessment of the state of land use in Ukraine, we used the latest technology to analyse space images through geographic information technology. The purpose of this analysis was to check whether the companies adhere to crop rotations and whether they plough "off-limits" protected areas, including the nature reserve, coastal strips, and slope areas.

Three areas in the west and centre of Ukraine were selected for the study where, according to information provided by the Land Matrix Initiative, foreign investment companies leased land in from around 2004 to 2009.

During the study, however, it became clear that the algorithm being used, which was supposed to recognise agricultural crops automatically, lacks verified information about crops sown in previous years. For this reason, violations in compliance with crop rotations (p.23) could not be clearly recorded.

Furthermore, it was not possible to obtain more information about the crops sown in previous years, as companies treat such information as confidential. Nevertheless, the developed methodology will enable continued monitoring of land use in these areas, and gradually cover other regions of the country.

The study found that nature reserves and sloping lands in Ukraine are indeed intensively used, both of which are vulnerable to erosion, and that agricultural companies have been expanding their land banks at the expense of sloping lands since the early 2000s. As a result, water erosion develops, which simply washes away the upper fertile layer of the soil (p. 16) and contributes to a greater runoff of pesticide residues and mineral fertilisers to water bodies.

The study also recorded ploughed areas in the Halytsky National Nature Park, in the floodplain meadows of the Limnytsia River Valley, and in the middle of the forests of the National Park near the villages of Serednya and Temyrivka in the Ivano-Frankivsk Region (p. 33). According to the Public Cadastral map of Ukraine, these lands are leased by companies with foreign investment.

Overall, the results of the study show that there is a critical lack of state control over land use, which allows for ploughing of areas that should not be used for sowing.

Contents

A working methodology for crop deciphering has been developed based on machine learning principles of remote sensing data of the Earth. With its help, it was tried to identify changes in land use in three regions of Ukraine.

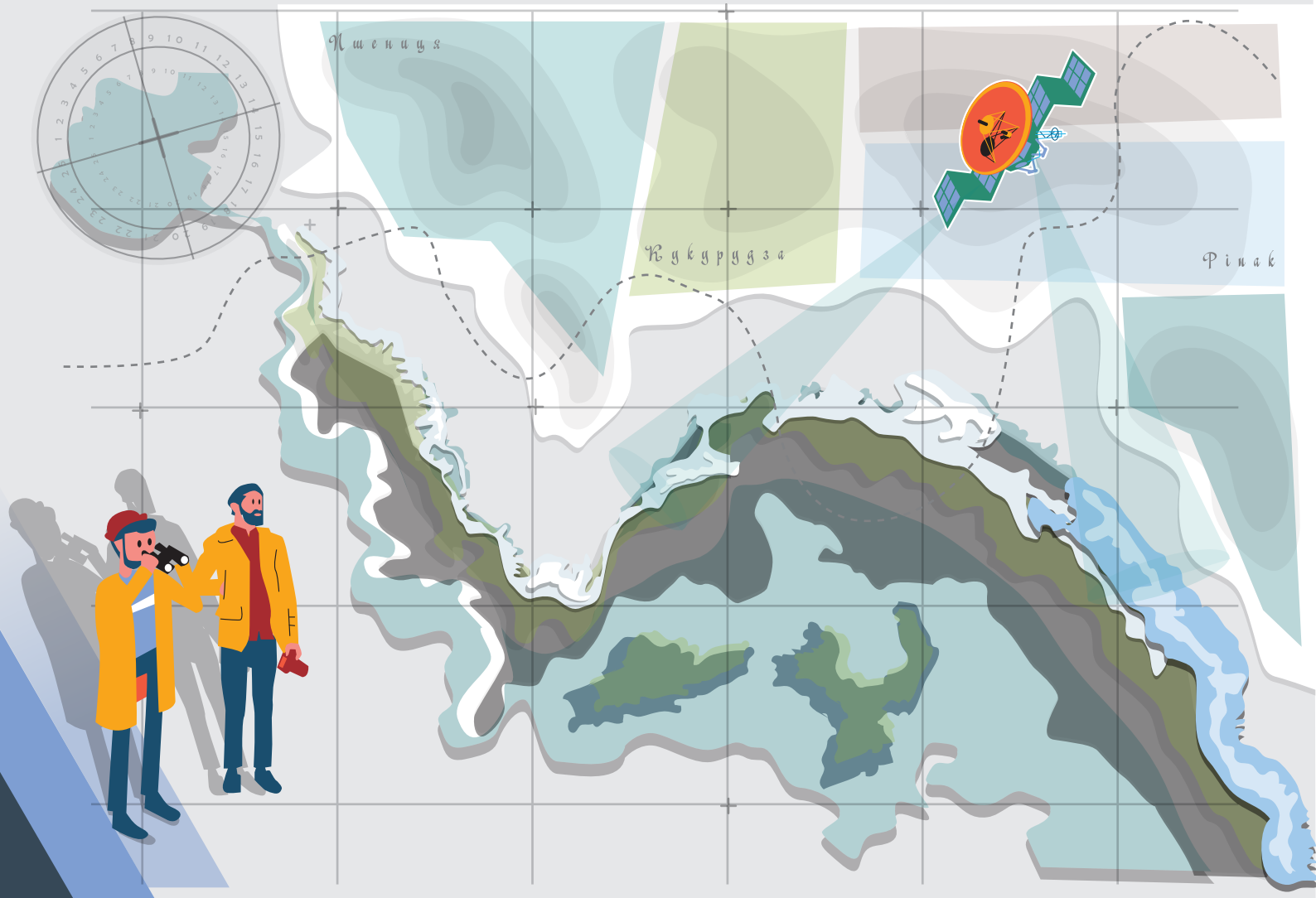
Introduction

The development of remote monitoring of land use types is becoming increasingly relevant due to the need to expand public control of business entities, identify trends in land use, and improve decision-making based on the needs of sustainable development of local communities.

There are several initiatives and mapping services that analyse and make publicly available land use data, both global (Land Matrix Global Map, 2019; Hansen et al., 2013; Earth Observing System, n.d.) and pan-European (Copernicus Land Monitoring Service, 2019; CORINE Land Cover, 2018). In Ukraine, with the support of the World Bank, an information system was also created to automatically identify types of land uses and individual classes of crops (World Bank Programme for Supporting Transparent Land Management in Ukraine, n.d.) nevertheless, a common feature of these services is the lack of ability to distinguish between different types of crops, with the vast majority of services combining all cultivated land into one class - “croplands”. At the same time, detailed information on the distribution of specific crops in space and time is required to understand the current situation in land use. In this work, we therefore attempted to develop a method of detailed identification of crops in several model territories of Central and Western Ukraine.

While there are a number of approaches to remote sensing land cover deciphering, such as k-mean clustering, object-based classification, and decision trees, as well as ensemble machine learning methods, such as the support vector machine and random forest (Belgiu and Csillik, 2018; Kamusoko, 2019; Ustuner et al., 2014), there are many factors which affect the quality of remote sensing land cover classification. These include lack of training (ground truth) data, errors in ground truth data, and incorrect satellite imagery combinations or vegetation indices calculated on its basis (Kamusoko 2019).

To minimise the errors caused by the latter factor, we chose the randomForest method, which shows low sensitivity to the variable redundancy in the source raster data. This allowed us to maximise the range of satellite bands and satellite-derived vegetation indices used in this research without risking the reduction of the model’s predictive ability (Palchowdhuri et al., 2018).



Obtaining and processing of data

Materials and methods

The study was conducted in three territories located in the Ivano-Frankivsk and Vinnytsia regions of Ukraine, under the provisional names Halych, Ladyzhyn, and Sharhorod.

Ground truth data

Remote sensing data

Obtaining and processing of data

The study was conducted in three territories located in the Ivano-Frankivsk and Vinnytsia regions of Ukraine, under the provisional names Halych, Ladyzhyn, and Sharhorod.

A
Halych

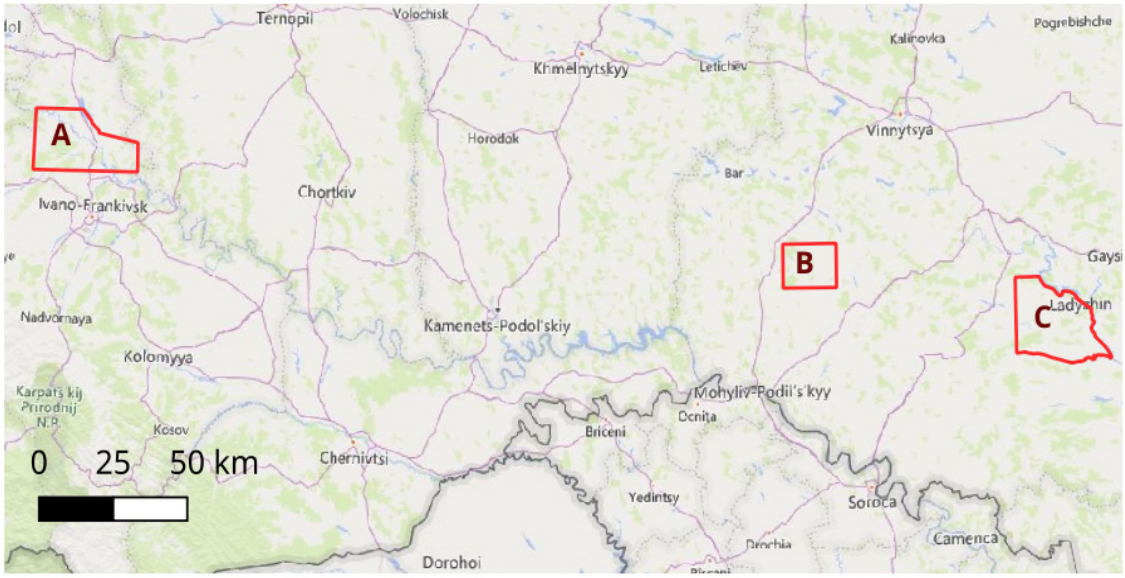
B
Sharhorod

C
Ladyzhyn

The total area of the plots is 55.17 thousand hectares (ha) in Halych, 59.27 thousand ha in Ladyzhyn, and 25.75 thousand ha in Sharhorod.

These plots were selected as the objects of study because, in these areas, the international monitoring initiative Land Matrix recorded large-scale land agreements with the participation of foreign investors. It happened in 2004 at the Halych site, in 2007–2008 at the Shargorod site, and in 2009–2010 at the Ladyzhyn site (see the official website of the Land Matrix Initiative). The study will help demonstrate land-use change before and after the acquisition of agricultural land.

Studied plots



A Halych **B** Sharhorod **C** Ladyzhyn

For each site, ground truth data (georeferenced points corresponding to specific land use classes) was collected, as well as sets of remote sensing data.

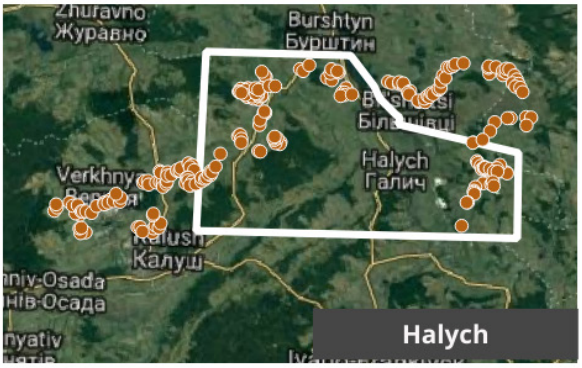
Ground truth data

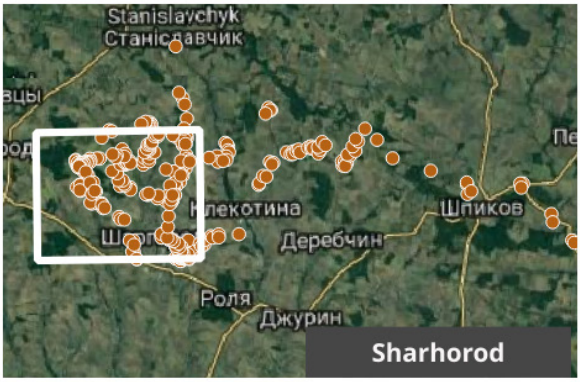
Ground truth data for model training and estimation of the accuracy of the obtained results was obtained in the period June-September 2019 by direct observation during expeditionary field trips. About 800 km of transect surveys were conducted to collect the data, during which the land use type for individual homogeneous areas was recorded (for arable land). In total, 532 points were collected for 27 classes of cover. Based on these, training sites were generated using QGIS 3.4 (Quantum GIS Development Team, 2019). In order to minimise misclassification, the following cover classes were grouped into 15 classes used in the further analysis:

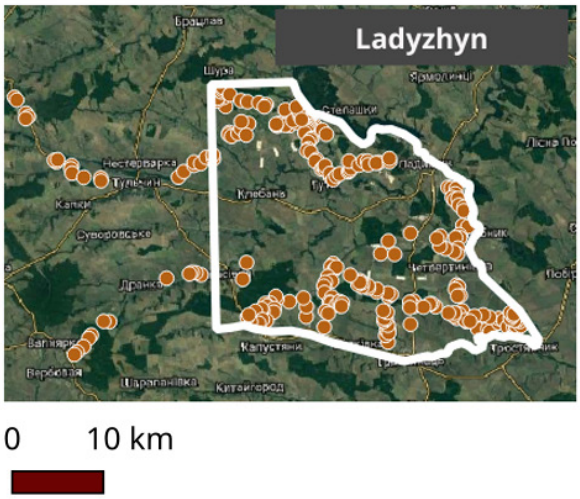
- **Cereals** mainly winter wheat
- **Rapeseed** only winter rapeseed
- **Maize**
- **Sunflower**
- **Soybean**
- **Beet**
- **Alfalfa** feeding grasses such as alfalfa or clover
- **Fallow** untilled in the current year fields
- **Gardens**
- **Deciduous forests**
- **Coniferous forests**
- **Grassland** natural vegetation such as meadows or steppes
- **Moor** bogs, marshes, reeds
- **Water** open water bodies
- **Settlement** manmade objects (ways, buildings, settlements)

GROUND TRUTH DATA

FIELD OBSERVATION FOR THE TRAINING OF MODELS AND POST-CLASSIFYING QUALITY ASSURANCE







Remote sensing data

The identification of land use types and crops was carried out by machine deciphering of remote sensing (RS) data which is provided by the Landsat Space Mission and in the public domain. With Google Earth Engine (Gorelick et al., 2017), 16-band rasters were generated for each territory annually based on 2-7 bands of Landsat satellite imageries (spatial resolutions 30 metres per pixel), as well as 10 additional pseudo-bands, created based on the calculation of a set of bands-derived vegetation indices. The bands and their short descriptions are listed in Table 1.

Table 1

(Pseudo)bands used in land use type classification

Band	Description
B1	corresponds to the 'Blue' band of Landsat 5 (B1) / Landsat 8 (B2)
B2	corresponds to the 'Green' band of Landsat 5 (B2) / Landsat 8 (B3)
B3	corresponds to the 'Red' band of Landsat 5 (B3) / Landsat 8 (B4)
B4	corresponds to the 'Near Infrared (NIR)' satellite imagery channel - Landsat 5 (B4) / Landsat 8
B5	corresponds to the 'Shortwave Infrared (SWIR 1)' band of Landsat 5 (B5) / Landsat 8 (B6)
B6	corresponds to the 'Shortwave Infrared (SWIR)' 2 band of Landsat 5 (B7) / Landsat 8 (B7)
BG	Normalized Difference Blue Green Index (Blue – Green)/(Blue+Green)
BR	Normalized Difference Blue Green Index (Blue – Red)/(Blue+Red)
BN	Normalized Difference Blue NIR Index (Blue – NIR)/(Blue+NIR)
GR	Normalized Difference Green Red Index (Green – Red)/(Green+Red)
GN	Normalized Difference Water Index (Green – NIR)/(Green+NIR)
GS1	Normalized-Difference Snow Index (Green - SWIR1)/(Green+SWIR1)
NR	Normalized difference vegetation index (NIR - Red)/(NIR+Red)
NS1	Normalized Difference Moisture Index (NIR – SWIR1)/(NIR+SWIR1)
NS2	Normalized Burn Ratio (NIR - SWIR2)/(NIR+SWIR2)
S1S2	Normalized Difference Tillage Index (SWIR1 – SWIR2)/(SWIR1+SWIR2)

01 Standartization of channel brightness values

BG, BR, BN, GR, GN, GS1, NR, NS1, NS2, S1S2 indices were added to 1 and multiplied by 1000 to bring the channel brightness values and vegetation indices to a single dimension.

02 Landsat 5 / Landsat 8 mission data

Landsat 5 / Landsat 8 mission data is not available for 2012 and is therefore not covered by the study

03 Google Earth Engine imagery correction

. Imagery correction, cloud masking, and median averaging of pixel values for images taken within a given time range were provided using Google Earth Engine workflow.

04 Cross-validation of results

Sentinel-2 data (bands 2, 3, 4, 5, 6, 7, 8, 8A, 11, 12) were additionally used for cross-validation of classification results. Using exclusively Sentinel-2 satellite data, which has a finer spatial and temporal resolutions, was not possible because this data does not cover the entire investigated period.

Land cover classification using remote sensing data

To identify crop types, we generated rasters with a median pixel value in each of the bands in a range of the 100th and 190th days of the year, which corresponds to the maximum vegetation period of both winter and spring crops in the study area.

For more accurate recognition of the other land use classes, we generated imageries with median pixel values in each band in the range of the 80th and 270th days of the year. Calculating the minimum pixel values for bands and pseudo-bands of imageries taken during this period can help distinguish cultivated arable land from fallow fields and varieties of native grassland vegetation. However, the disadvantage of this approach is the increase of errors caused by the effects of clouds'

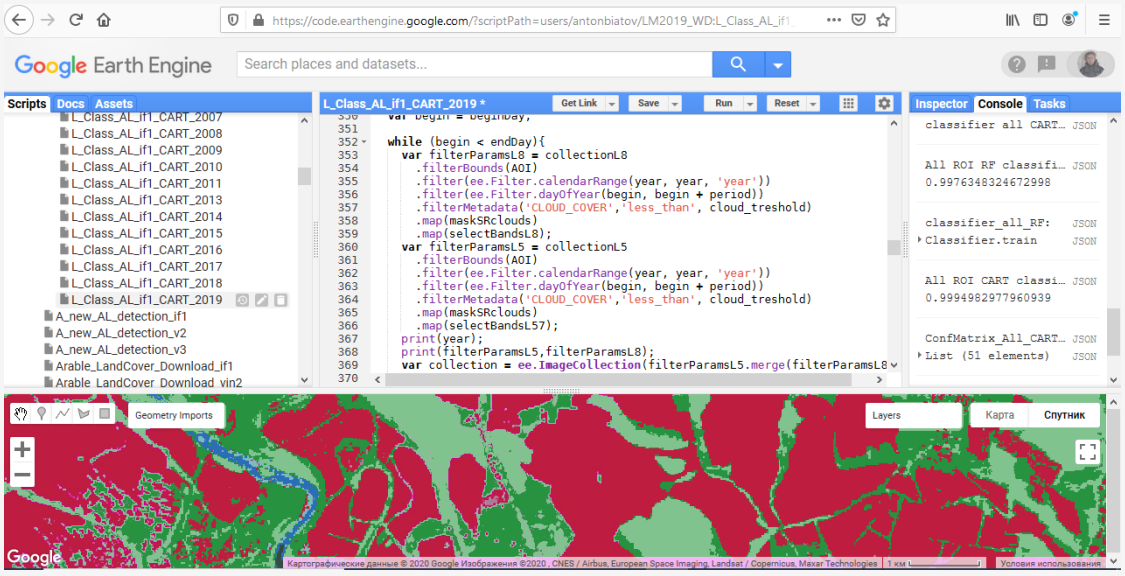
Although the untilled fields are prone to grass overgrowth and the accumulation of dry plant residues, and thus their reflectance is similar to natural grasslands, we have empirically found that by displaying the minimal composite in the combination of channels NR, GN, S1S2 and NR, GN, BN, it is possible to separate the areas where vegetation was present during the snow-free period from areas where at least for some time the vegetation was absent (recently tilled fields, buildings, roads, etc.).

TO ASSESS THE CHANGES, WE CREATED TRAINING POLYGONS FOR EACH YEAR.

The following training classes were used:

- settlements,
- water bodies,
- forests,
- moor,
- grasslands (meadows and steppes),
- arable land (fields tilled in the current year).

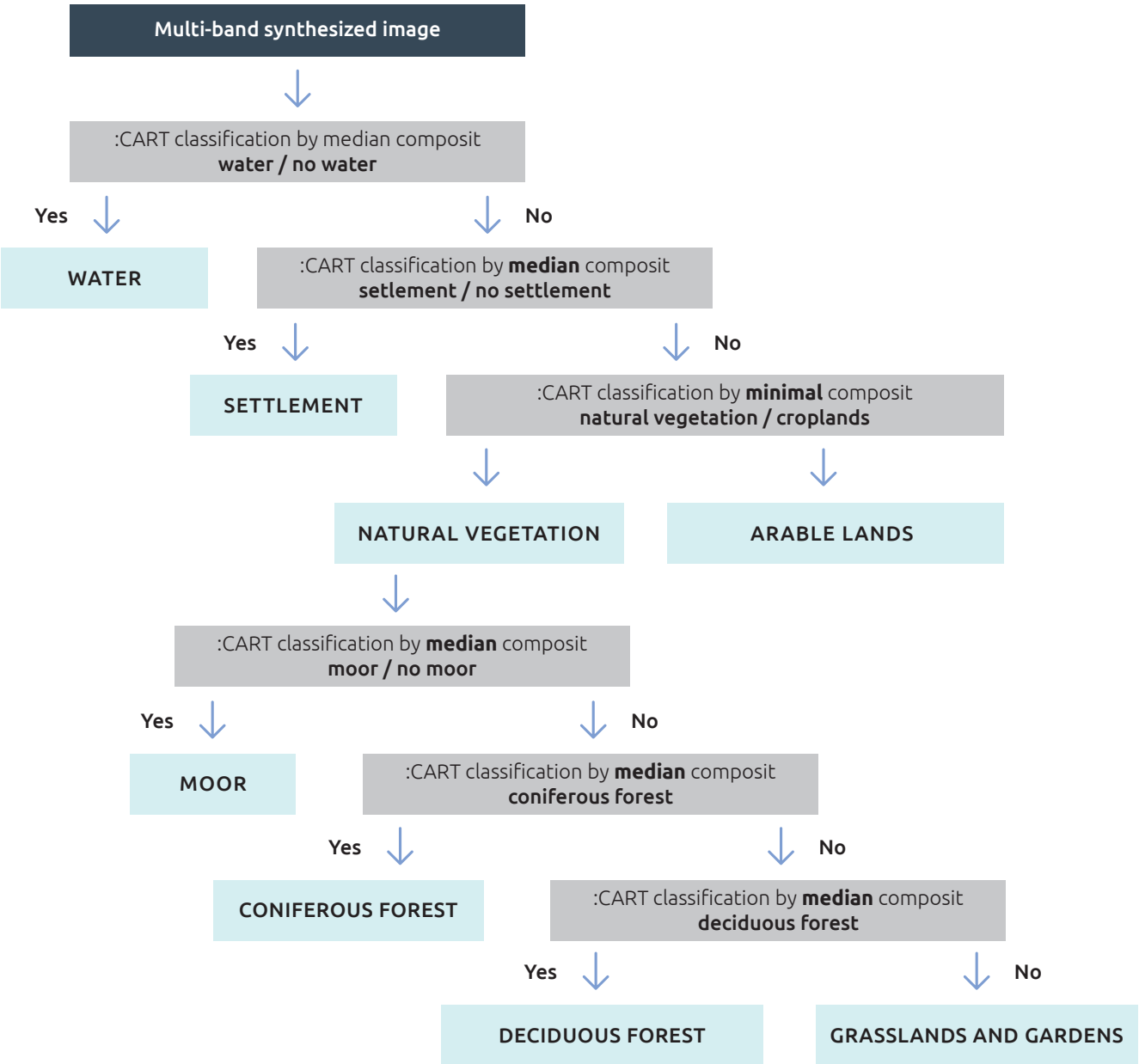
Classification model training and final classification were conducted separately for each year. Two machine learning methods were involved: randomForest and Classification And Regression Trees (CART) implemented in Google Earth Engine. Both methods were used in two variants: to distinguish all the classes of cover; and for step-by-step (hierarchical) classification. In the hierarchical classification, a step-wise separation of the land cover types was used, starting with the most spectral outlying classes. The scheme of hierarchical classification is given below.



ALL DATA PRE-PROCESSING AND CALCULATIONS WERE PERFORMED USING GOOGLE EARTH ENGINE (GORELICK ET AL., 2017) AND R 3.5.2 (R CORE TEAM, 2019), using the randomForest 4.6 library. The classification results were filtered by majority filter with a 3x3 pixel window size implemented in the focal function of raster 2.9 package for R.

Figure 1

Chart of hierarchical classification



Using training data collected during 2019, hierarchical CART classification showed the highest classification accuracy, and was therefore used as the primary method.

The calculation of surface slope angles (slope curvature) for arable land was performed in QGIS 3.4 using morphometric analysis tools based on the digital elevation model SRTM 1ArcSec (Farr et al. 2007).

Results

Results

During the visual analysis of satellite imageries, we found that in the first half of the 2000s many farmlands had not been worked or remained as fallows for several years.

Arable land dynamics

Comparison with other land use tracking systems

Arable land dynamics

During the visual analysis of satellite imageries, we found that in the first half of the 2000s many farmlands had not been worked or remained as fallows for several years.

For the Halych, Ladyzhyn, and Sharhorod plots, the area of arable land coverage for the period 2000-2019 was estimated based on the RS data (2012 - no data). The results are illustrated below.

Figure 2

Arable land dynamics for Ladyzhyn

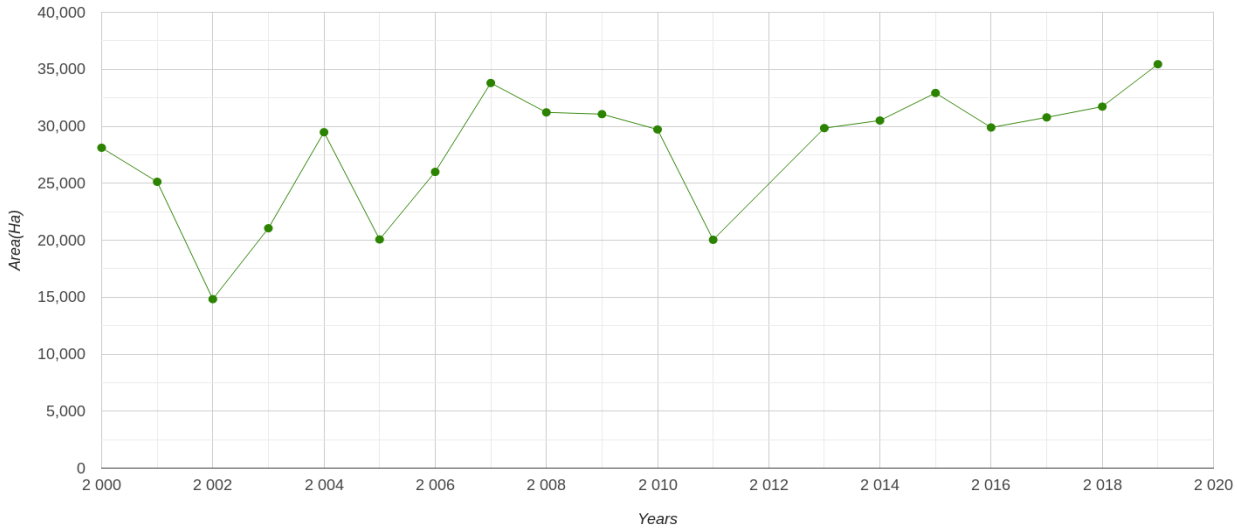


Figure 3

Arable land dynamics for Sharhorod

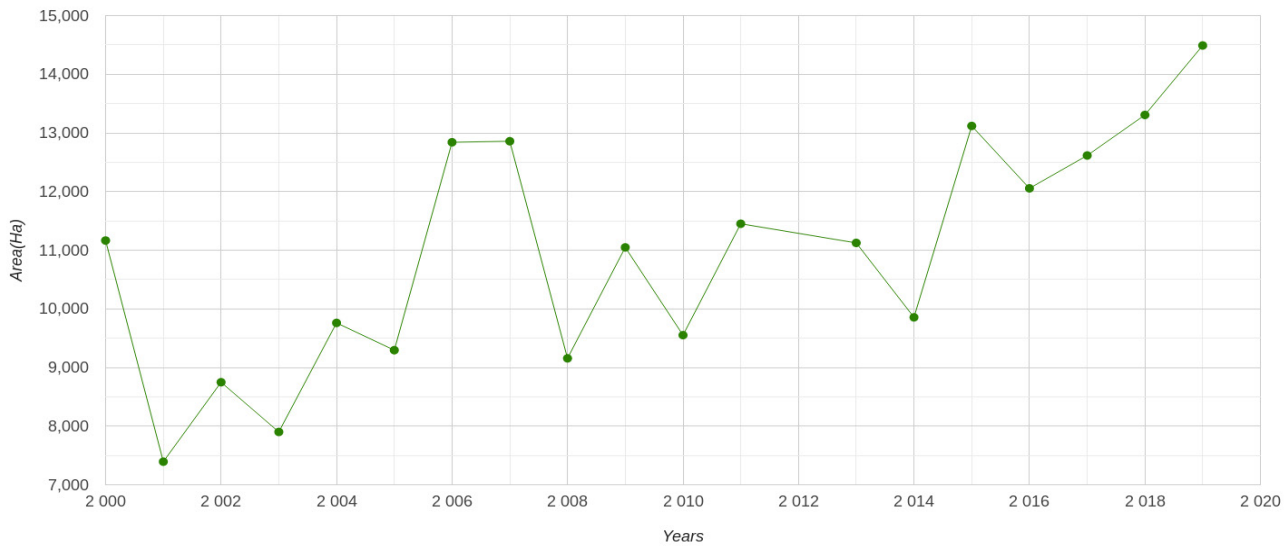
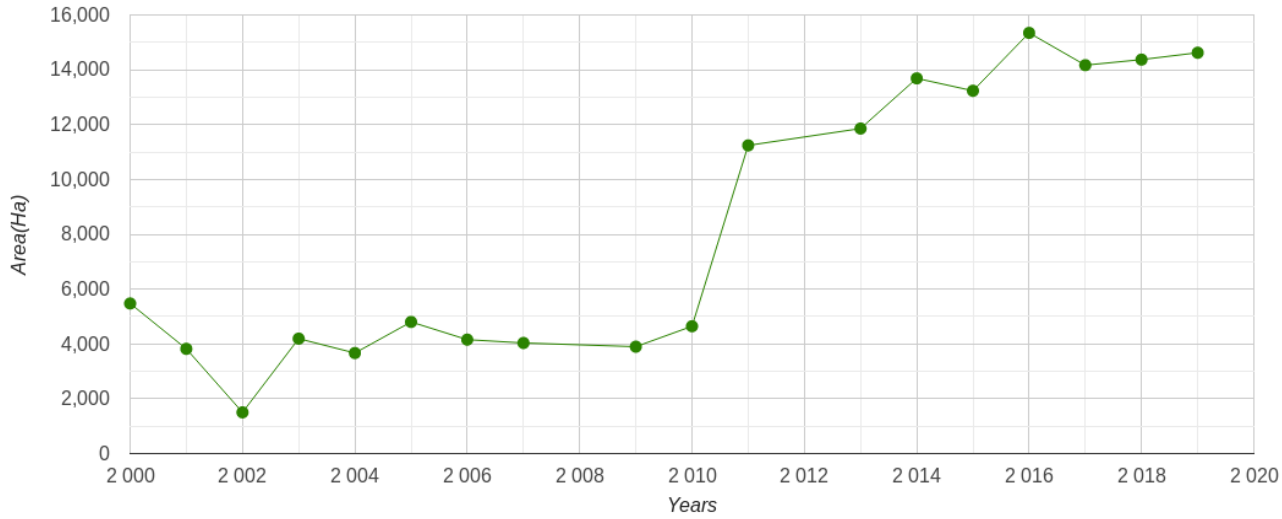


Figure 4

Arable land dynamics for Halych



Of note, we observed a dramatic increase in the arable areas of Halych since 2010, which indicates the fact that in 2010-2012 or prior to, there was an impact of some important factor. For the other two plots, fluctuations in the level of tillage are likely to be a result of complex factors.

Detailed maps of the arable lands for each year are listed in Supplementary materials 1.

Table 2

Arable land dynamics for Halych

Year	Area, thousand ha	% of the total area	Year	Area, thousand ha	% of the total area
2000	5,45	9,89	2010	4,63	8,38
2001	3,8	6,9	2011	11,22	20,33
2002	1,5	2,71	2012	no data**	
2003	4,18	7,58	2013	11,81	21,42
2004	3,64	6,6	2014	13,62	24,69
2005	4,79	8,68	2015	13,15	23,84
2006	4,15	7,52	2016	15,23	27,61
2007	4,02	7,29	2017	14,01	25,4
2008	no data*		2018	14,33	25,97
2009	3,88	7,03	2019	14,58	26,43

* Resulting data has many misclassified values, possibly due to the Dnister river flood, which caused significant increase in soil moisture that year
** No Landsat 5 or Landsat 8 data for this year

Table 3

Arable land dynamics for Ladyzhyn

Year	Area, thousand ha	% of the total area	Year	Area, thousand ha	% of the total area
2000	28,11	47,43	2010	29,72	50,14
2001	25,12	42,39	2011	20,04	33,81
2002	14,83	25,01	2012	no data	
2003	21,05	35,52	2013	29,84	50,34
2004	29,48	49,74	2014	30,5	51,47
2005	20,07	33,86	2015	32,92	55,54
2006	26	43,86	2016	29,89	50,43
2007	33,8	57,02	2017	30,78	51,93
2008	31,22	52,67	2018	31,72	53,52
2009	31,06	52,41	2019	35,44	59,8

Table 4

Arable land dynamics for Sharhorod

Year	Area, thousand ha	% of the total area	Year	Area, thousand ha	% of the total area
2000	11,16	43,35	2010	9,55	37,09
2001	7,39	28,71	2011	11,45	44,46
2002	8,75	33,97	2012	no data	
2003	7,9	30,68	2013	11,12	43,2
2004	9,76	37,9	2014	9,86	38,27
2005	9,29	36,09	2015	13,12	50,94
2006	12,84	49,86	2016	12,05	46,81
2007	12,86	49,93	2017	12,61	48,98
2008	9,16	35,55	2018	13,31	51,67
2009	11,05	42,9	2019	14,49	56,27

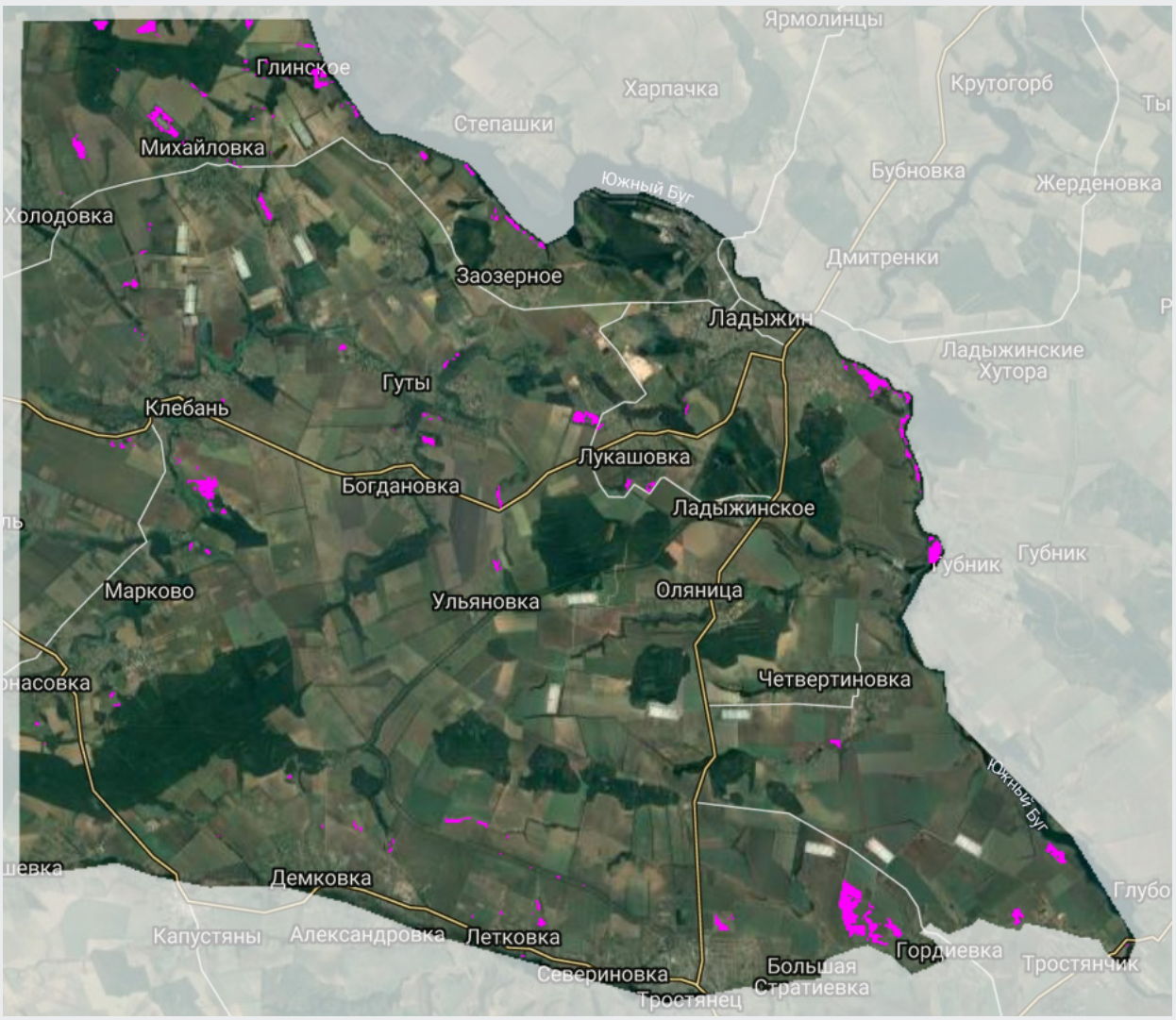
We identified several areas that were first tilled between 2008 and 2019. Between 2000 and 2008, they were occupied by herbaceous vegetation and were not used for crops.

Overlay analysis of arable land and the digital elevation model showed that the slope tillage was increasing in both areas over time. Although publicly available digital elevation model SRTM has an insufficient spatial resolution to detect tillage of small landforms, such as slopes of small gullies, statistical data on slopes of arable land over different periods shows that the mean slopes of arable land increased over time.

Thus, at the Ladyzhyn site, the average slope of the tilled areas after 2008 is 3.11 degrees. At the same time, the average slope of all fields is 2.32 degrees.

Figure 5

Areas tilled for the first time in 2008-2019. Ladyzhyn



In the Sharhorod plot, the average slope of the areas tilled for the first time after 2008 is 3.96 degrees. At the same time, the average slope of all fields is 2.96 degrees.

Figure 6

Areas tilled for the first time in 2008-2019. Sharhorod

Detailed information about areas which were tilled for the first time since 2008 in the Ladyzhyn and Sharhorod plots is listed in Supplementary materials 4.

The study revealed a gradual increase in the area occupied by winter crops. This is likely to be due to global warming and a decrease in soil moisture in the summer months, which is an incentive for farmers to sow more winter crops than spring crops. The dynamics of winter crops can be seen in the figures below.

Figure 7

Winter crops area dynamics, Ladyzhyn

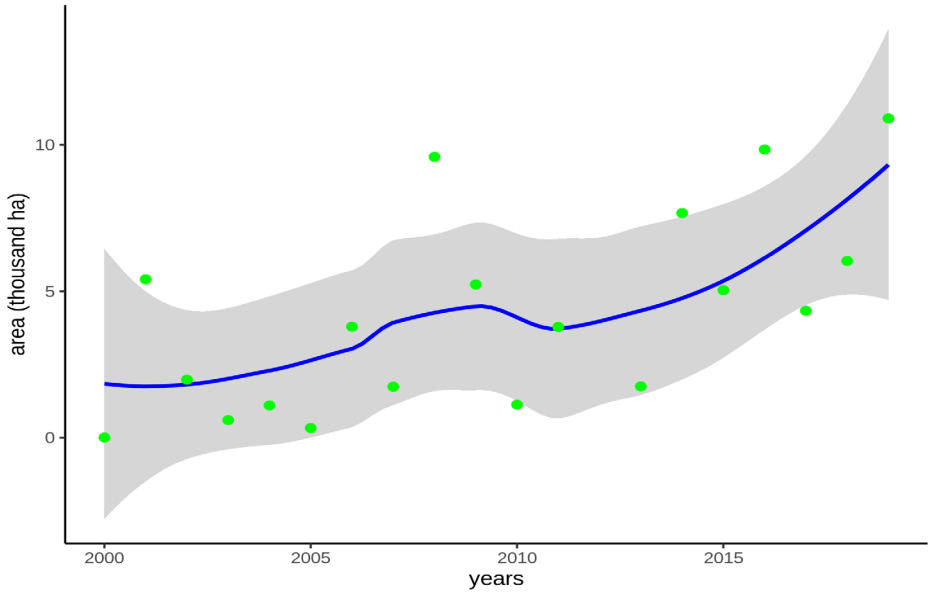
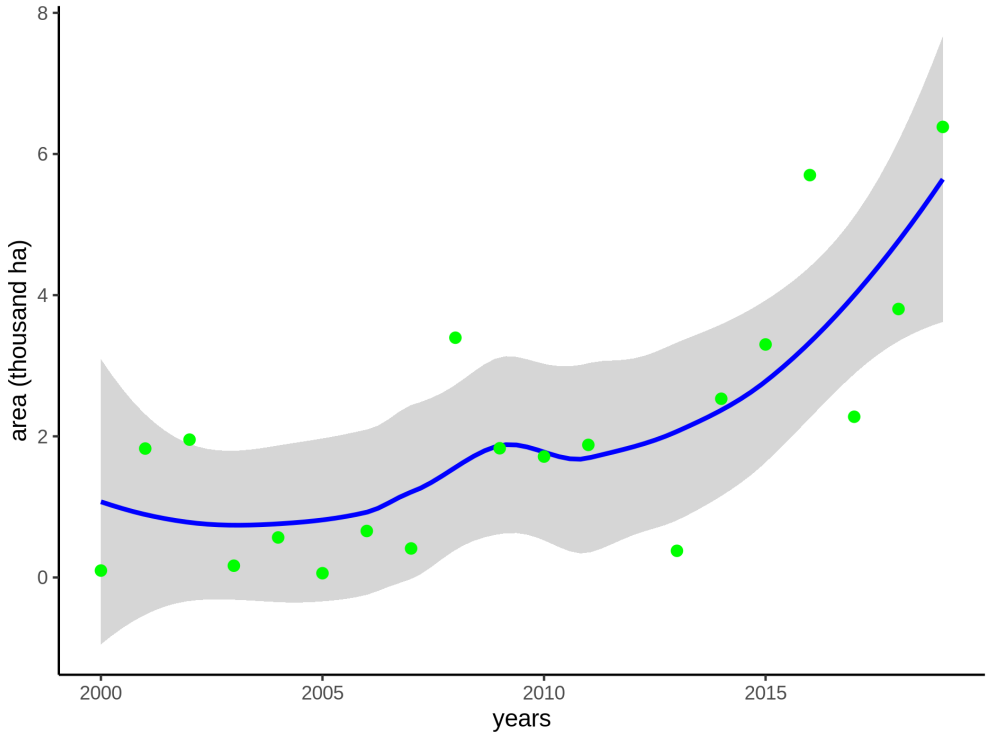


Figure 8

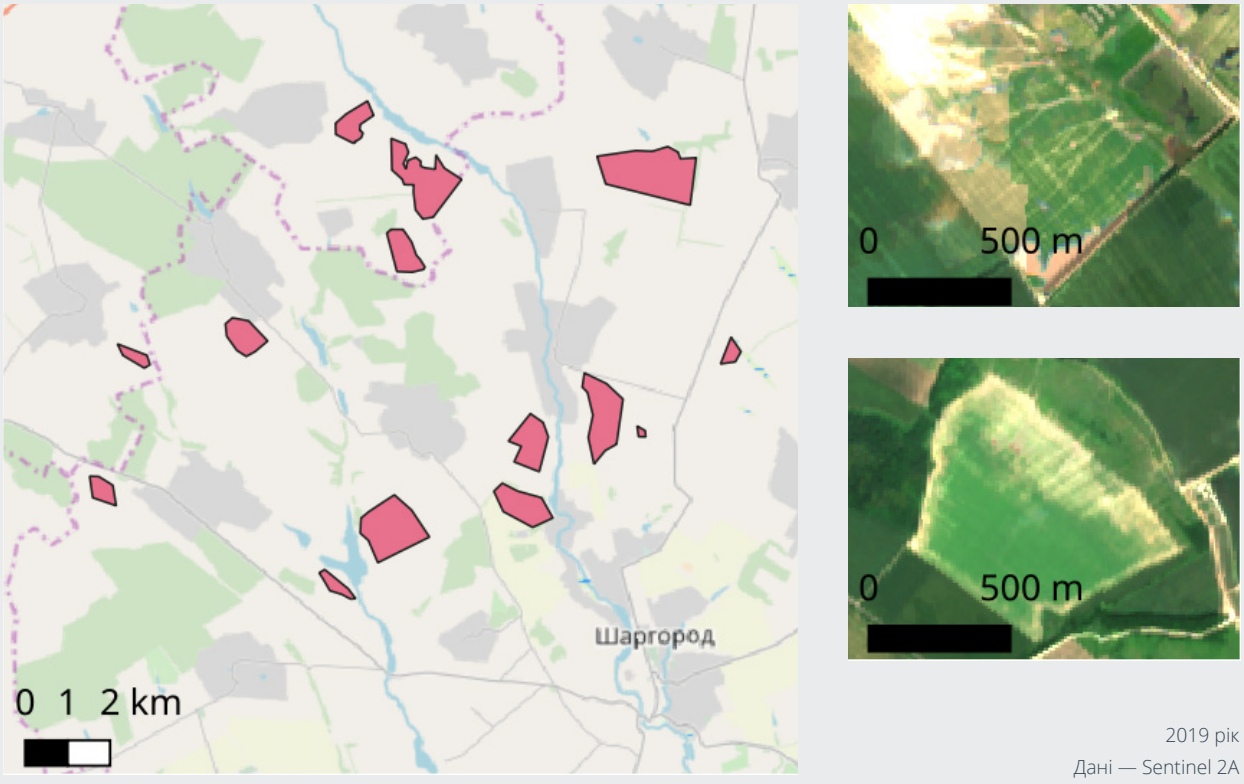
Winter crops area dynamics, Sharhorod



Visual analysis of the Sentinel-2 satellite imageries in natural colours revealed areas where progressive soil erosion is caused by the tillage of the slopes.

Figure 9

Eroded soils. Sharhorod



2019 рік
Дані — Sentinel 2A

To be expected, erosion is more developed in the Sharhorod plot, which has a generally more pronounced terrain and a greater average slope of arable land according to the analysis of the digital elevation model.

Crop type deciphering

During the study, the main types of crops were classified according to Landsat 8 (30m / pixel resolution) and Sentinel-2 (10m / pixel resolution) for 2019. The classification results are shown below.

Figure 10

Crop types deciphering according to Landsat 8 satellite imagery, Ладыжин, 2019

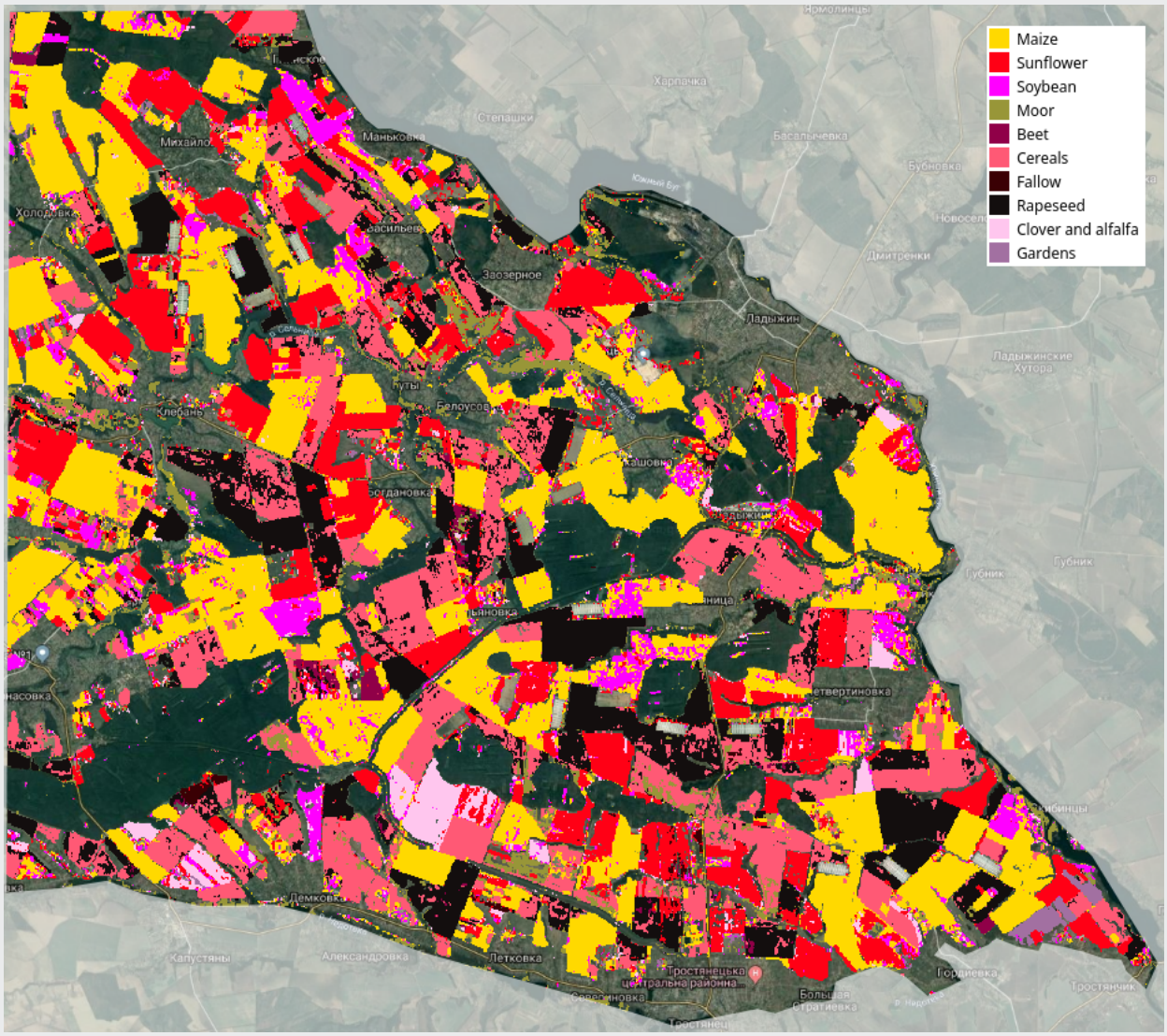


Figure 11

Crop types deciphering according to Sentinel-2 satellite imagery, Ladyzhyn, 2019

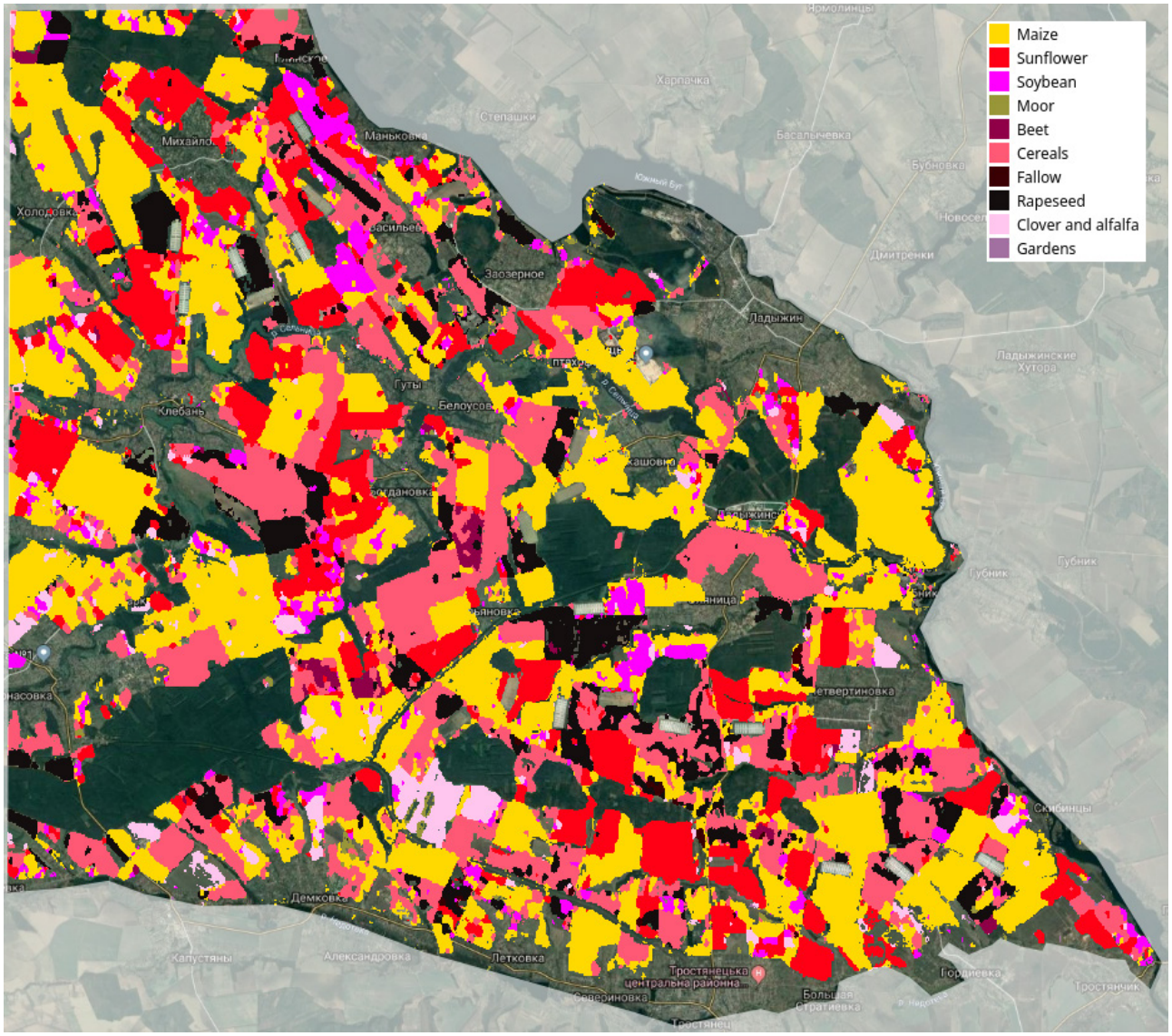


Figure 12

Crop types deciphering according to Landsat 8 satellite imagery, Sharhorod, 2019

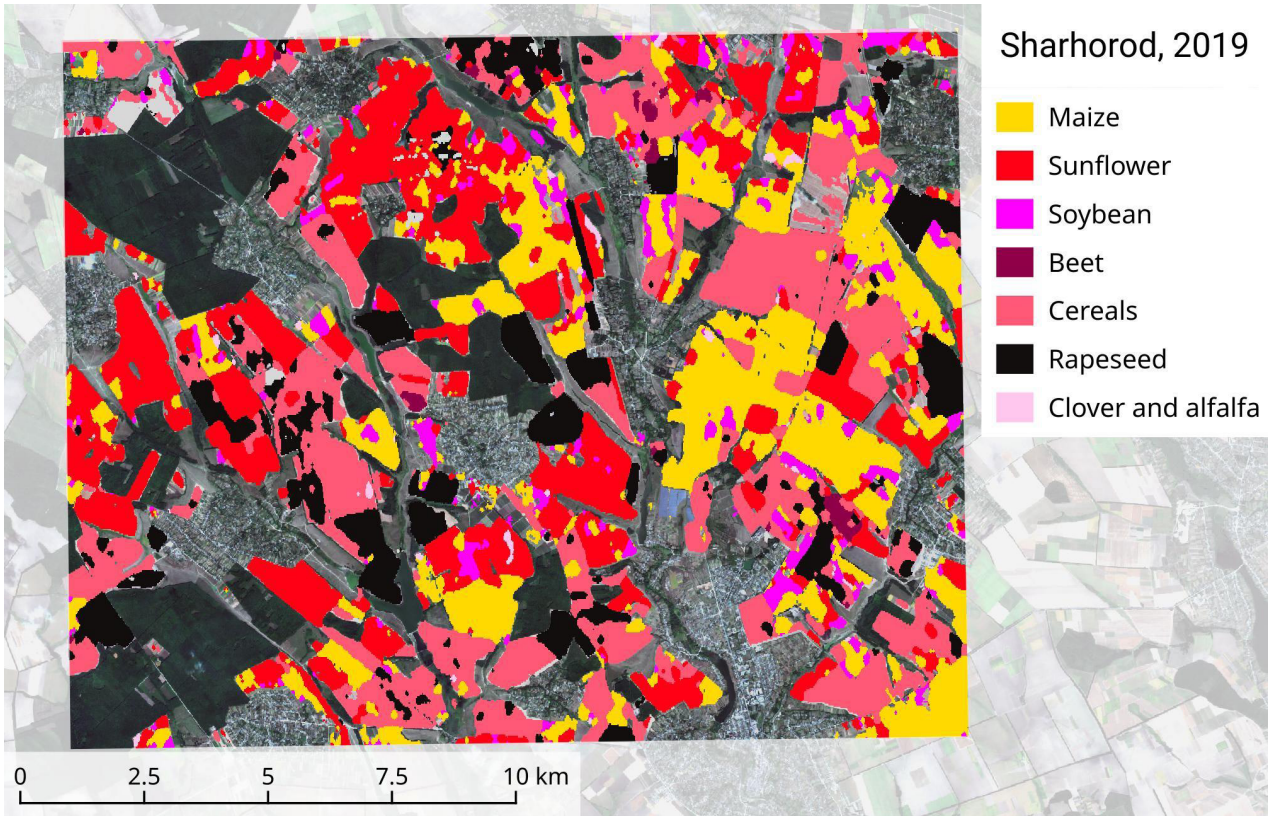


Figure 13

Crop types deciphering according to Sentinel-2 satellite imagery, Sharhorod, 2019

Figure 14

Crop types deciphering according to Landsat 8 satellite imagery, Halych, 2019

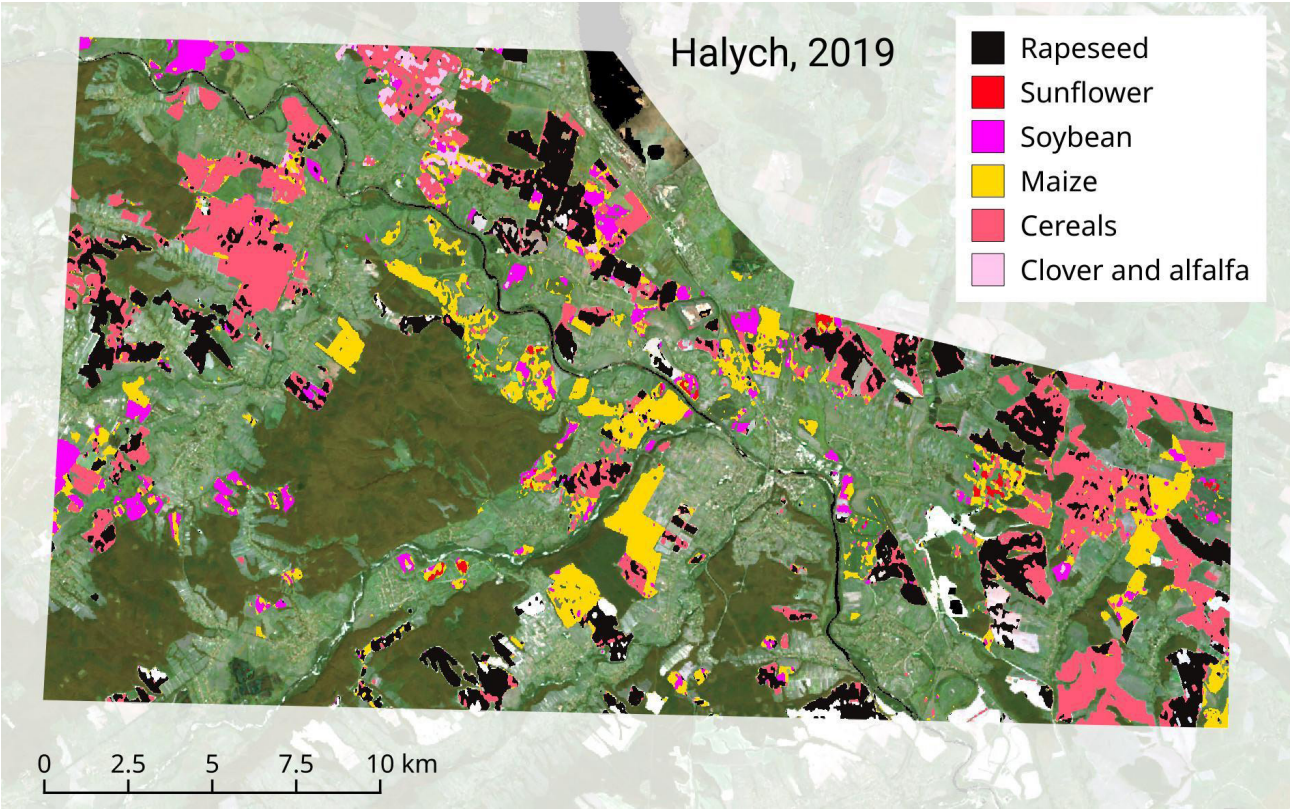


Table 5

Cropland areas, Halych, 2019

	Crop type	Area, thousand ha	% of the total area
1	Rapeseed	3,92	26,89
2	Sunflower	0,1	0,69
3	Soybean	1,04	7,13
4	Maize	2,87	19,68
5	Cereals	4,64	31,82
6	Alfalfa	0,25	1,71
7	Unclassified	1,76	12,08

Table 6

Cropland areas, Ladyzhyn, 2019

	Crop type	Area, thousand ha	% of the total area
1	Rapeseed	3,19	9,0
2	Sunflower	6,09	17,18
3	Soybean	1,73	4,88
4	Maize	13,97	39,42
5	Cereals	7,67	21,64
6	Alfalfa	1,14	3,22
7	Unclassified	1,65	4,66

Table 7

Cropland areas, Sharhorod, 2019

	Crop type	Area, thousand ha	% of the total area
1	Rapeseed	1,8	12,42
2	Sunflower	3,94	27,19
3	Soybean	0,72	4,97
4	Maize	3,31	22,84
5	Cereals	3,84	26,51
6	Alfalfa	0,07	0,48
7	Unclassified	0,81	5,59

Retrospective analysis of crops showed that the quality of classification decreases in proportion to the time distance from the moment of collection of training data, for example, the recognition of the 2019 satellite data will be the most reliable, while 2000 satellite data will be the least reliable. In addition, the quality of crop recognition according to Landsat 5 and Landsat 8 sharply decreases in some years due to a large amount of noise. We assume that this is due to the climatic characteristics of a particular year, which are significantly different from 2019, the year of training data collection. Maps of crop recognition results are given in Supplementary materials 2.

If necessary, the accuracy of crop recognition for previous years can be improved through the Normalised Difference Vegetation Index (NDVI) seasonal variation signatures for each year. Since Sentinel-2 imageries are the only open satellite data with the relevant temporal resolution, the crop rotation history can be more or less reliably traced back to 2016. The situation is complicated by the fact that in different natural and climatic zones, the same crops undergo different phenological stages of development at different times and have a different rate of vegetation. An example of the NDVI seasonal variation signatures for some crops is given in Supplementary materials 3.

Comparison with other land use tracking systems

Visually comparing the 2019 data from the Land Transparency geo-portal supported by the World Bank's Transparent Land Management in Ukraine programme (https://map.geoportalua.com/worldbank/) with the results obtained through the classification of remote sensing data of Landsat 8 and Sentinel-2, we found that the method we developed allows us to identify a much wider range of land use classes, both in terms of crop diversity and the natural types of land cover, which makes it a far more useful land-use remote monitoring tool

Figure 15

Data of Land Transparency geoportal. Ladyzhyn, *2019*

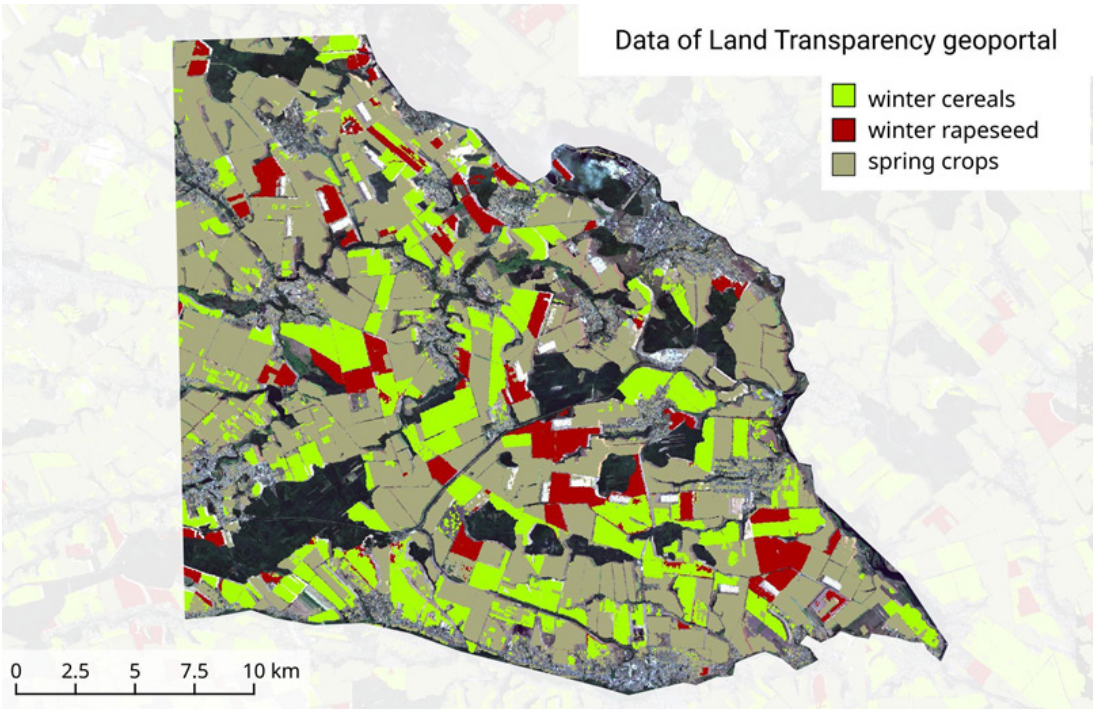


Figure 16

Satellite data: Landsat-8. Ladyzhyn, *2019*

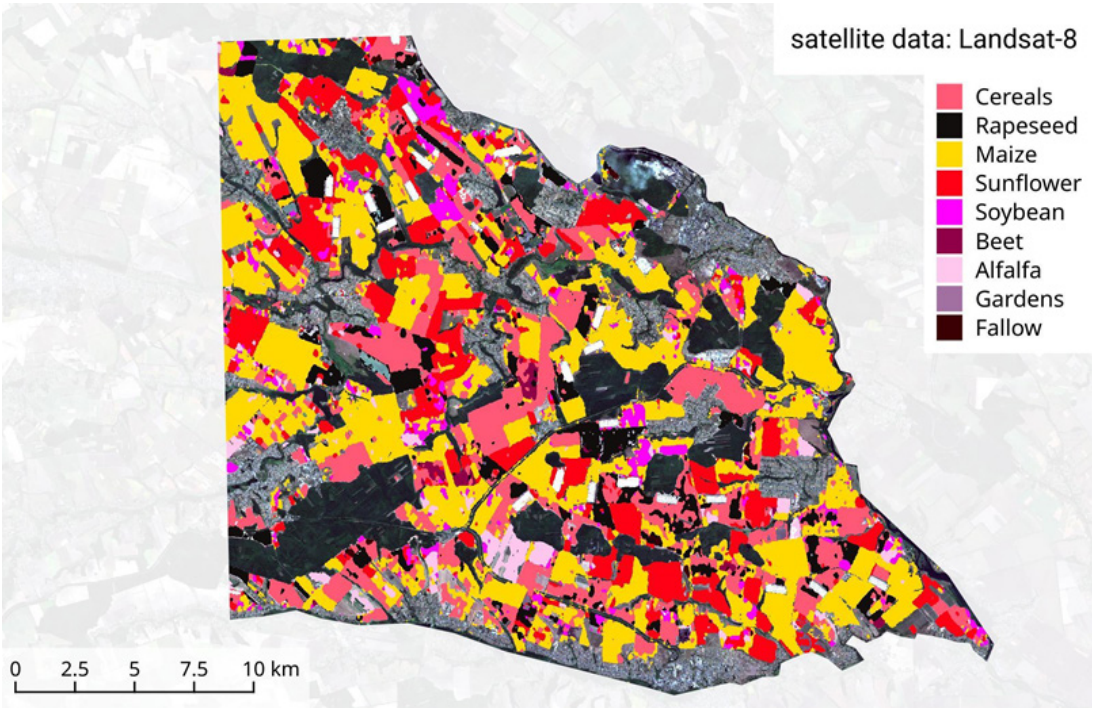


Figure 17

Satellite data: Sentinel-2. Ladyzhyn, *2019*

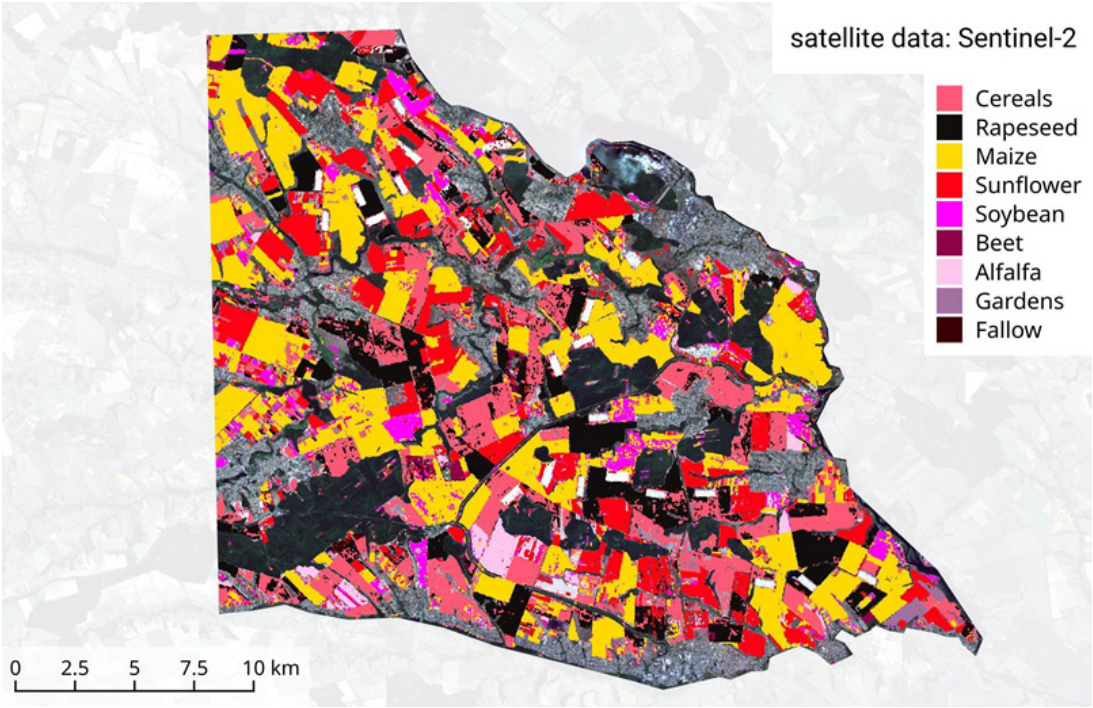


Figure 18

Data of Land Transparency geoportal. Sharhorod, *2019*

Figure 19

Satellite data: Landsat-8. Sharhorod, *2019*

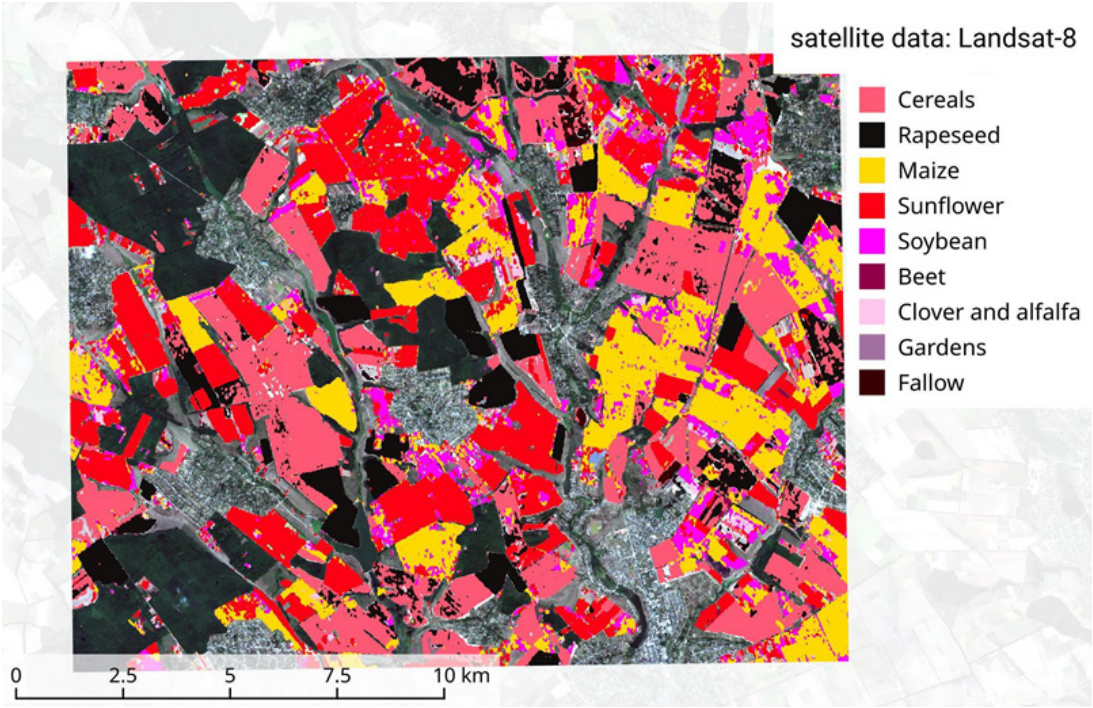
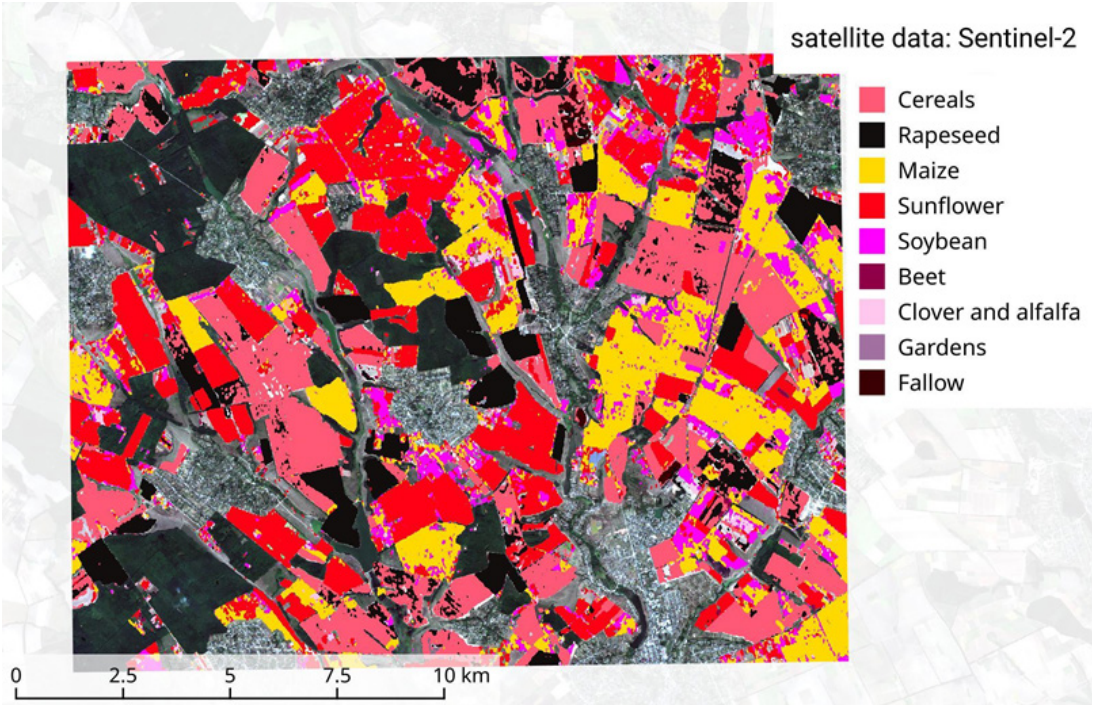


Figure 20

Satellite data: Sentinel-2. Sharhorod, *2019*



Impact of farming

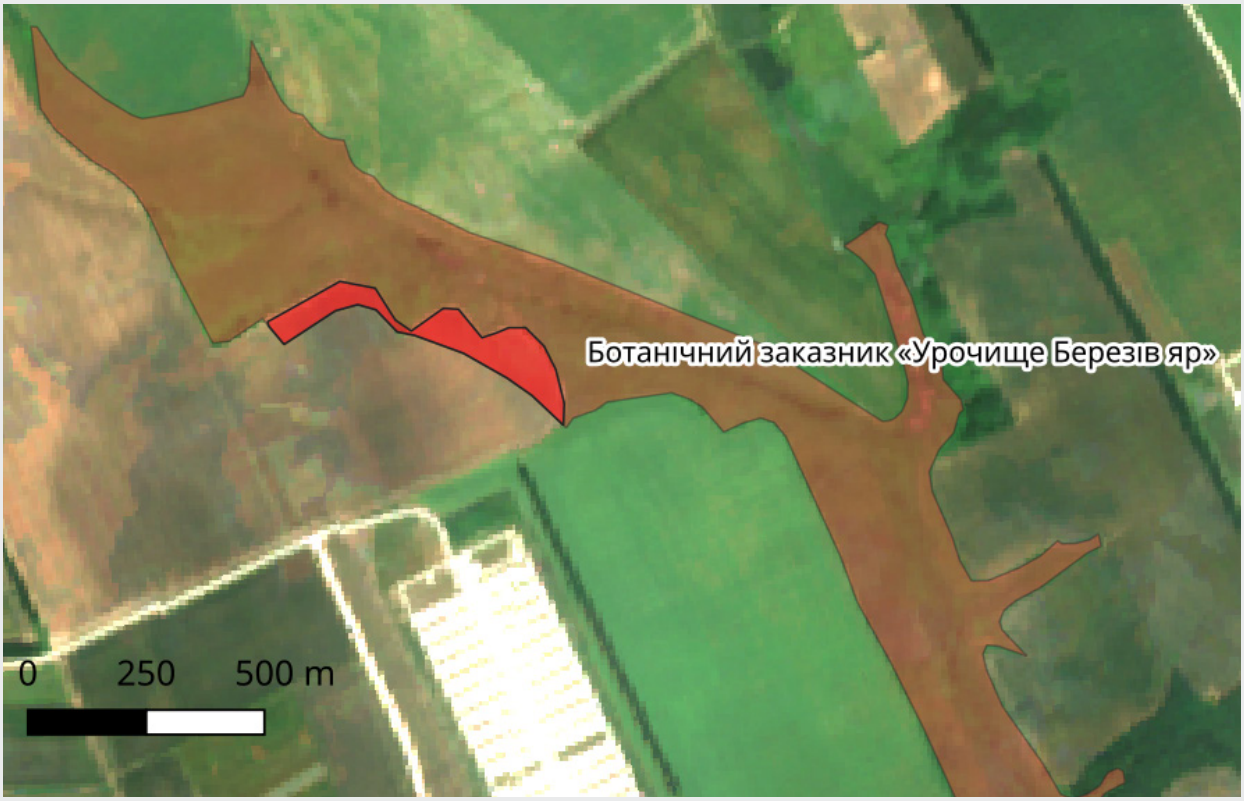
on the natural environment, protected areas and Emerald network sites

Agriculture is a leader in the transformation of natural ecosystems among all human activities. We analysed the overlapping of areas occupied by agriculture with the protected areas (PA) of Ukraine (https://scgis.org.ua/en/projects/cadastre/) and the Emerald Network sites (http://emerald.net.ua/).

On the Ladyzhyn plot, we detected five PA, of which three are forest or wetlands, where agricultural activity is impossible for natural reasons (Ladyzhinskaya Dibrova, Ladyzhynsky Yaseny, and Urochysche Dzerivka), and two are examples of steppe gullies that border the arable land (the Urochysche Fedkovske landscape reserve and Urochysche Bereziv Yar botanical reserve). For the latter, the penetration of tillage into the territory of the reserve was detected (coordinates in WGS84 systems: 48.705309, 29.043040).

Figure 21

Tilled part of the "Bereziv Yar" local protected area, Ladyzhyn



Emerald Network site Ladyzhyn Reservoir, which constitutes a water body of the eponymous reservoir and adjacent forests in the water protection zone, is adjacent to the plot. The north-west side of the arable land is close to the water body, but the width of the water buffer zone is maintained according to the established 50m.

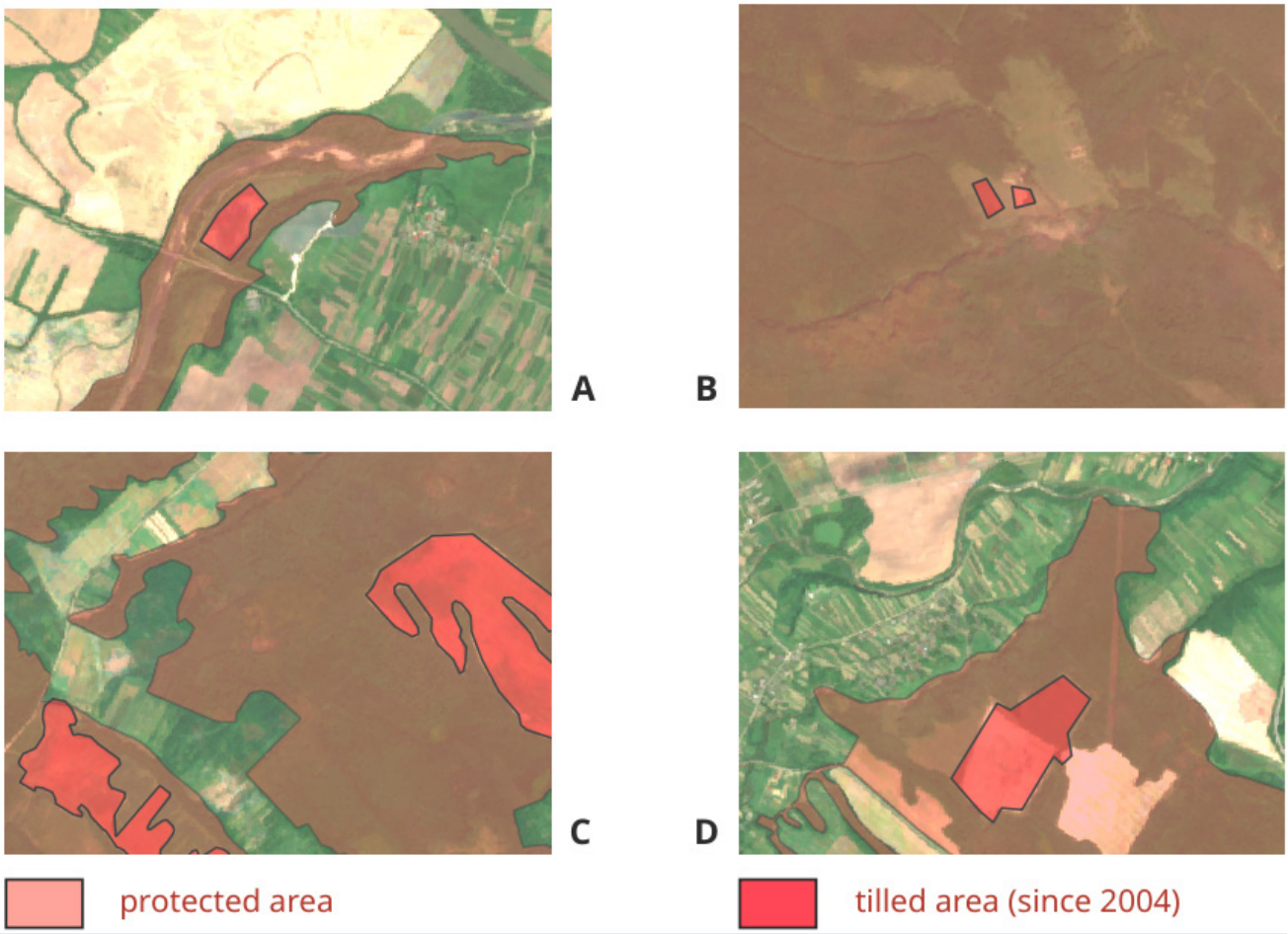
No overlaps or neighbourhoods with protected areas were identified for the Sharhorod site.

The only PA on the Halych plot is the Halytskyi national nature park. Established in 2004, the park has received quite complex outlines that avoid overlapping with agricultural lands. However, remote sensing methods have identified several areas that were tilled after the park was created or just before its creation that intersect with the territory of the protected site.

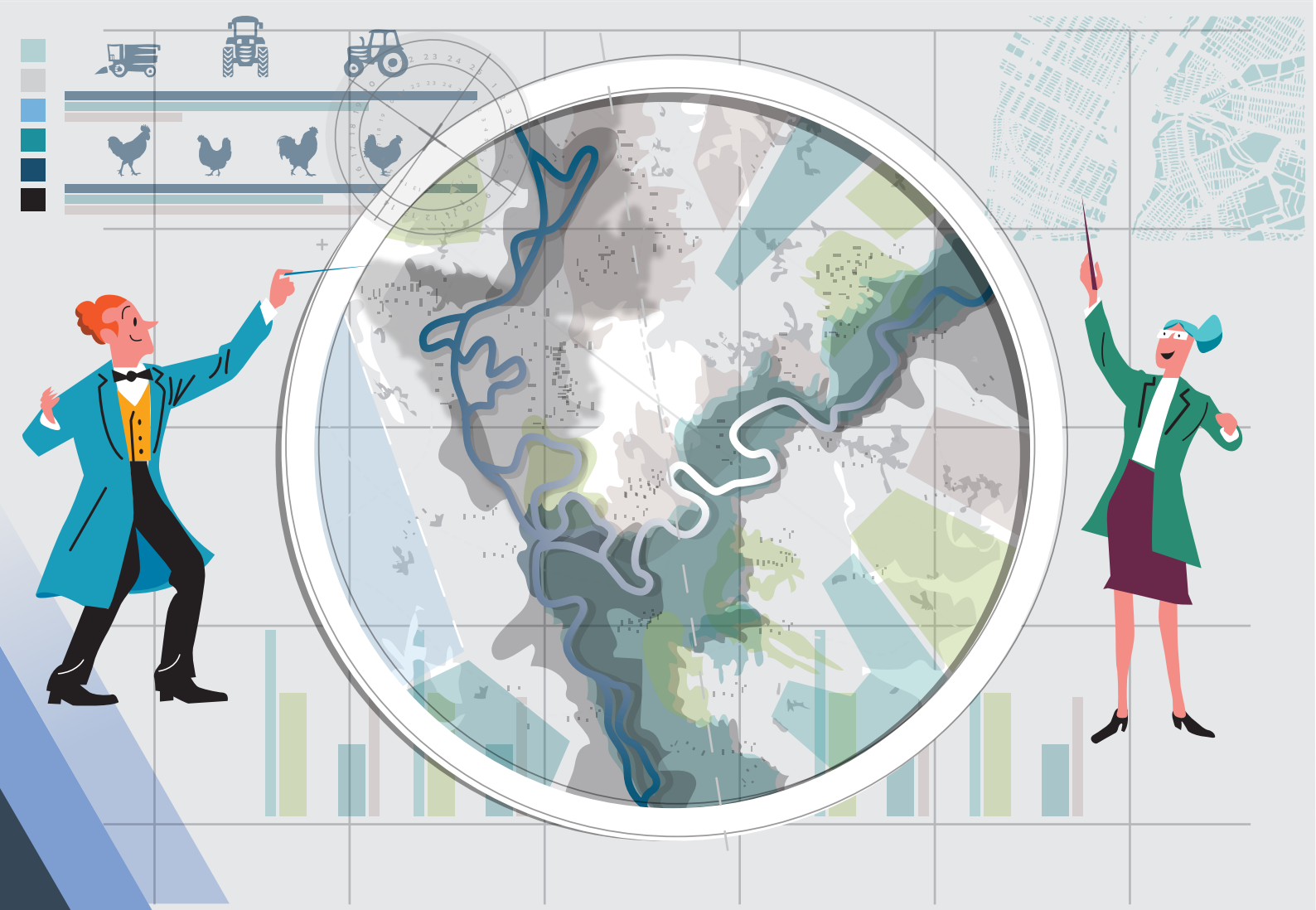
IT SHOULD BE NOTED THAT INCREASED LAND USE A YEAR OR TWO BEFORE THE FORMAL COMPLETION OF THE PROCEDURE FOR THE CREATION OF A PROTECTED OBJECT IS A COMMON ISSUE IN UKRAINE.

Figure 22

Tilled parts of the National Park "Halytskyi", Halych



A) tillage in the meadow in Limnytsia river valley (tilled for the first time in 2015; 49.13272086, 24.67838462);
B) small arable lands among forest meadows (49.12555,24.57330);
C) tilled for the first time in 2013 (49.06468,24.56479) and 2003 (49.07533,24.59390);
D) tilled for the first time in 2004 (49.06668,24.67653).



Based on the results of this investigation, a working methodology for crop deciphering was developed based on the machine learning classification of remote sensing data.

Discussion

For areas with sufficiently large and high-quality ground truth data (which presents at least 1000 pixels of each cover class, no significant imbalances in favour of certain classes, and minimal identification errors in the field), the methodology showed high recognition results.

However, we faced some significant obstacles, including that the models appeared to be intolerable over long distances. For reliable recognition, training data should be collected within the study area, although the latest satellite imagery alignment technologies hope for substantial progress in this area soon. The depth of retrospect, in which recognition accuracy is satisfactory, also needs further investigation, but has suffered from a lack of remote sensing data over the past decades.

Further, because there were no reliable wetland boundaries in previous years, some fallows have been misclassified as wetlands in some years. Part of the forests was classified as marshes or meadows in some years as well, which is likely due to fluctuations in humidity and forest management in the respective periods.

The class of human infrastructure objects (settlements, industrial sites) remains difficult to machine deciphering. High heterogeneity, the combination of small artificial (buildings, roads), and semi-natural objects (backyard, lawns, wastelands) makes machine recognition significantly complicated.

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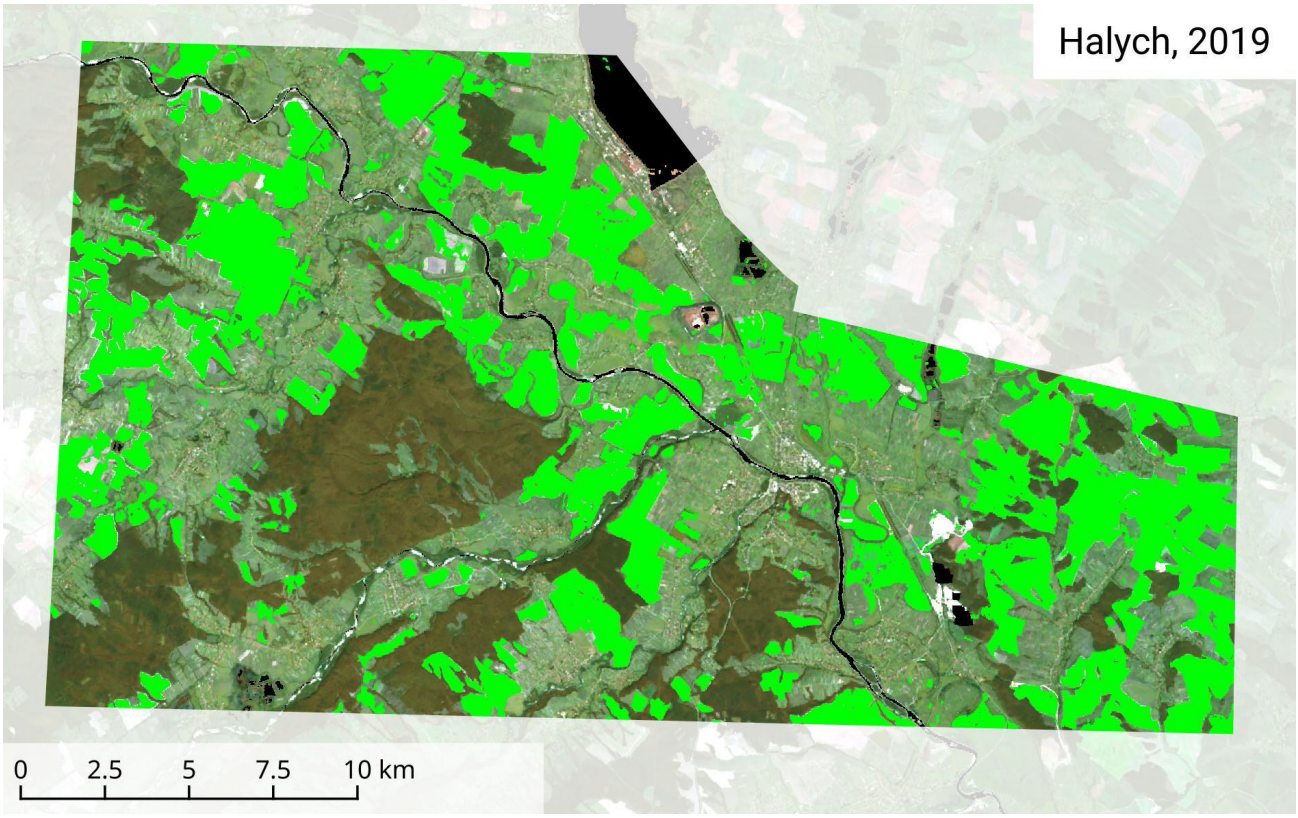
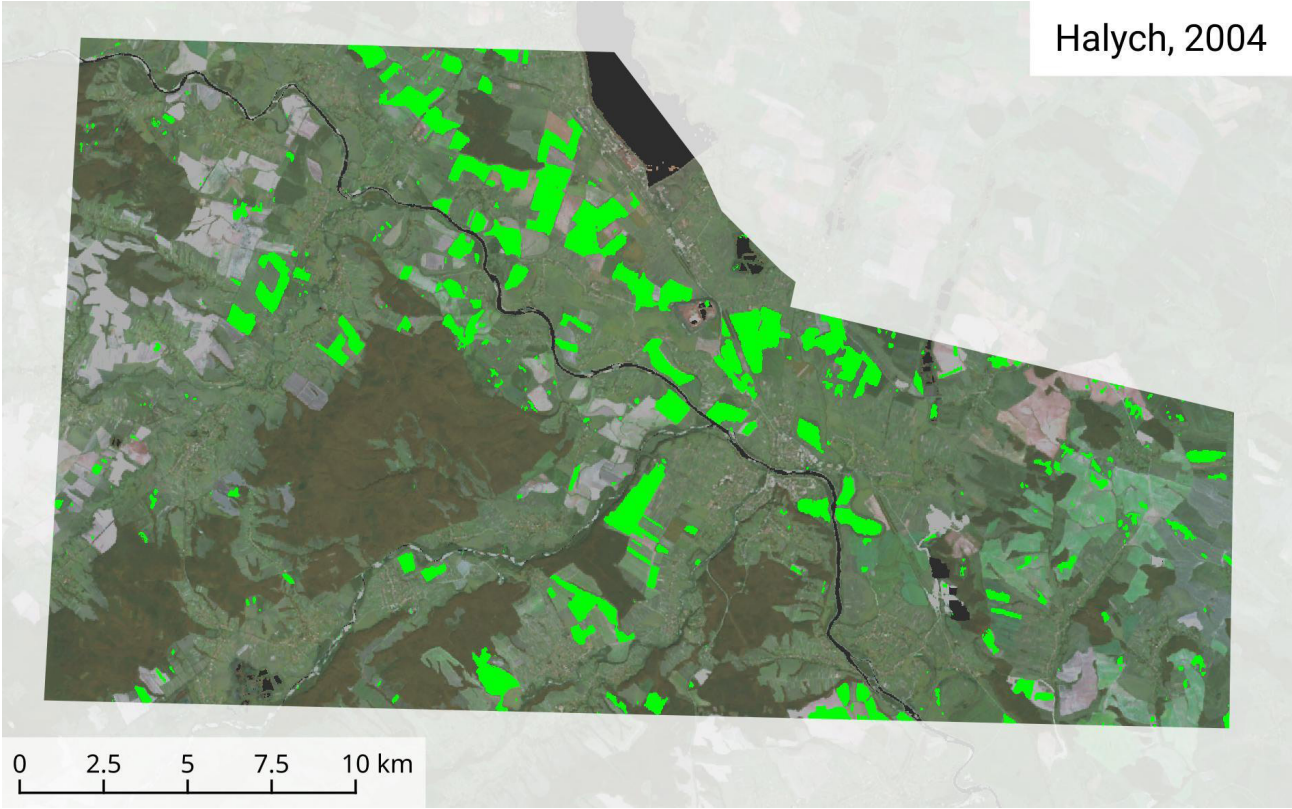
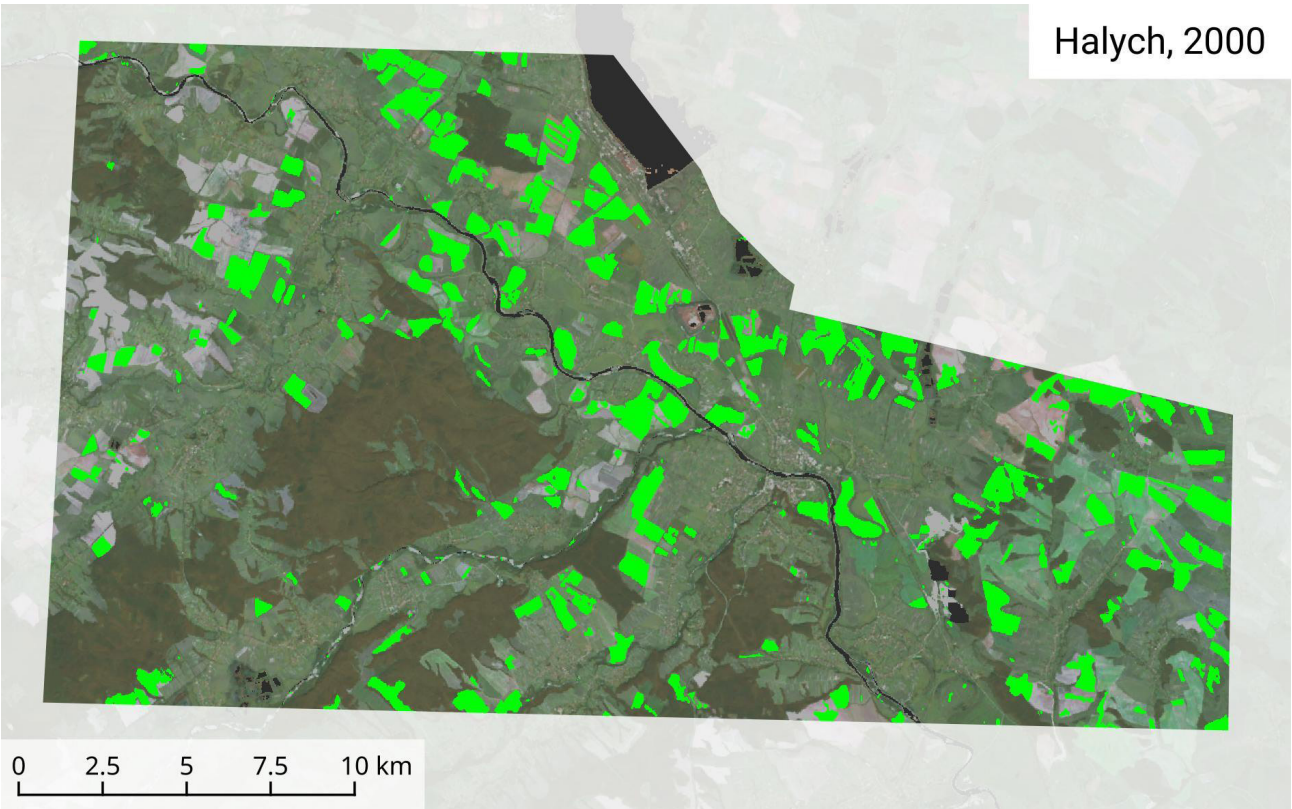
Supplementary materials

Supplementary materials 1

MAPS OF ARABLE LAND




Halych, 2004
0
2.5
5
7.5
10 km


Halych, 2000
0
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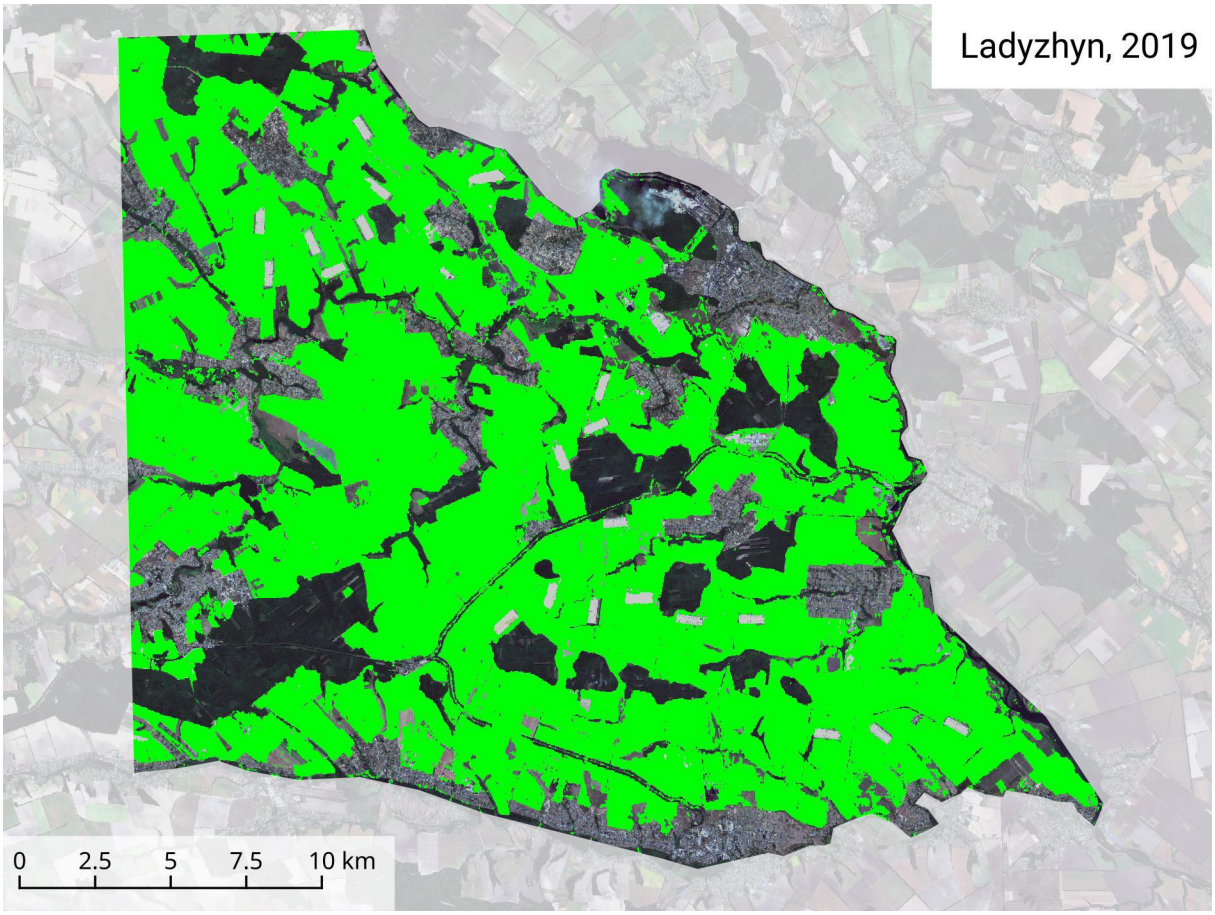
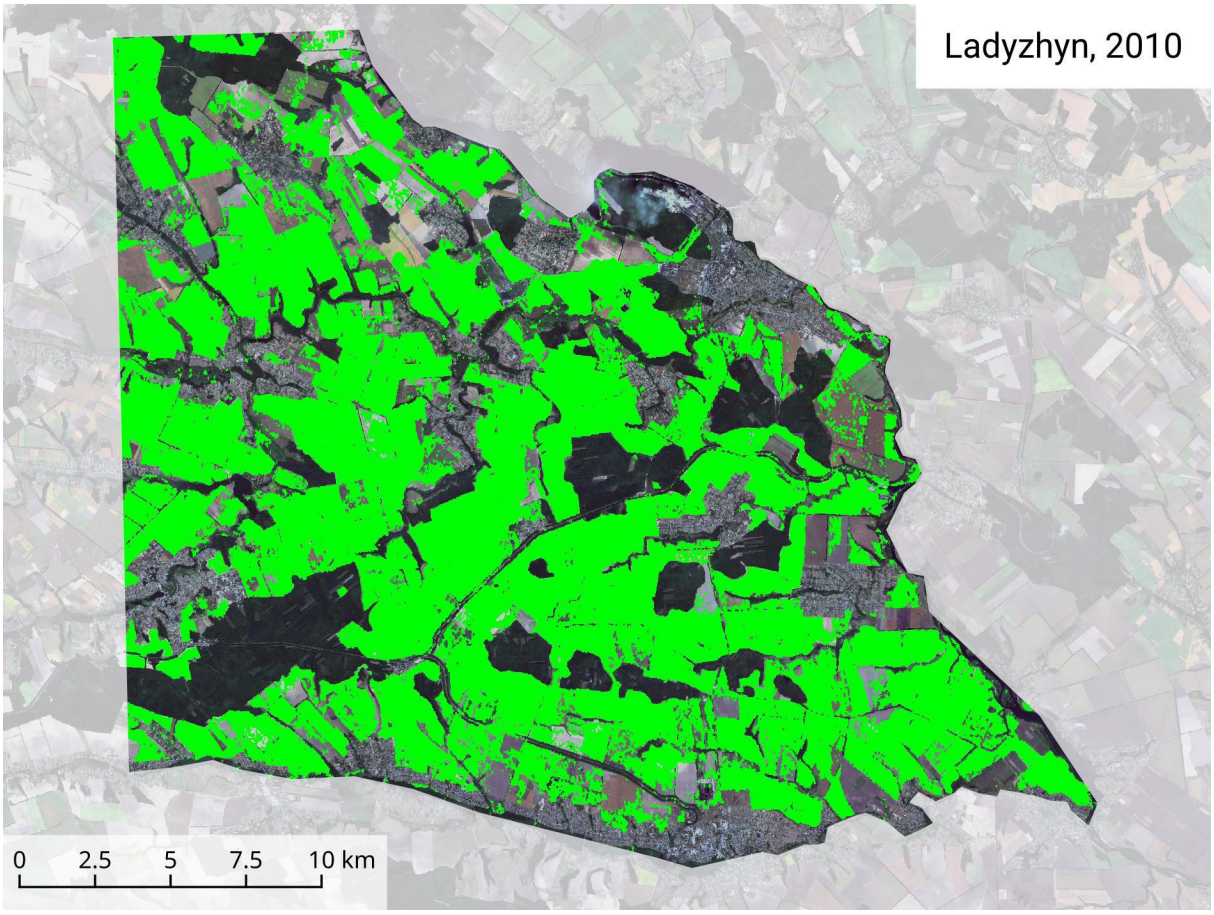
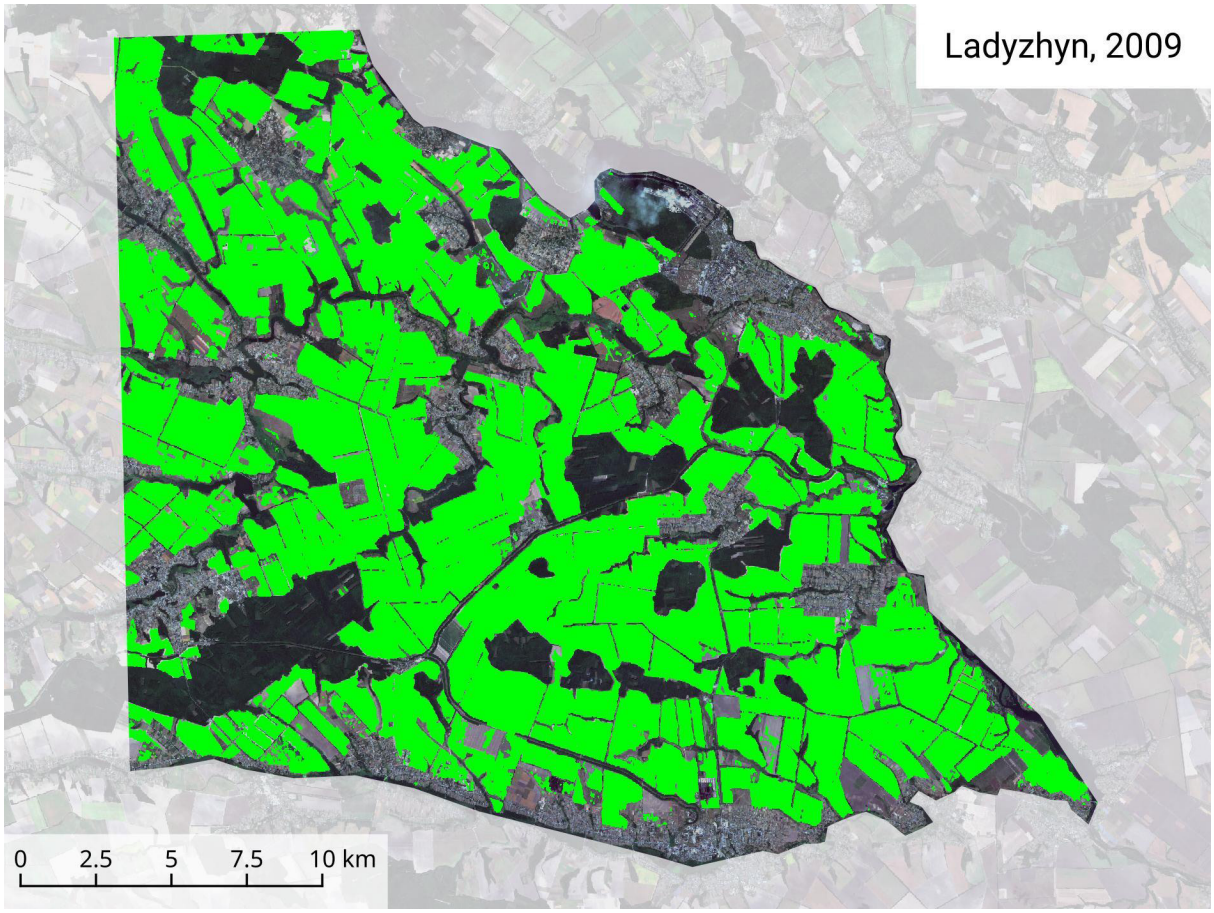
5
7.5
10 km


Ladyzhyn, 2019
0
2.5
5
7.5
10 km


Ladyzhyn, 2010
0
2.5
5
7.5
10 km


Ladyzhyn, 2009
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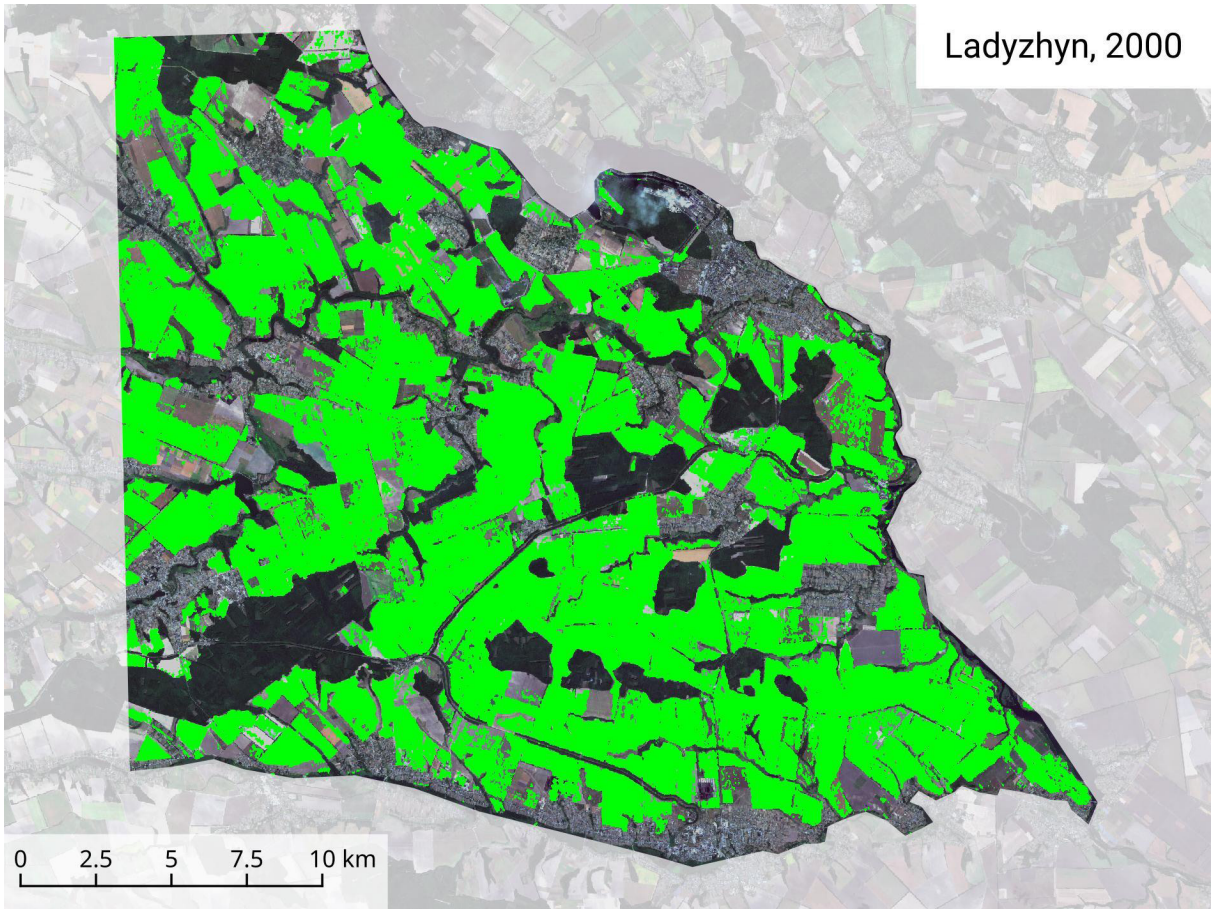
2.5
5
7.5
10 km


Ladyzhyn, 2000
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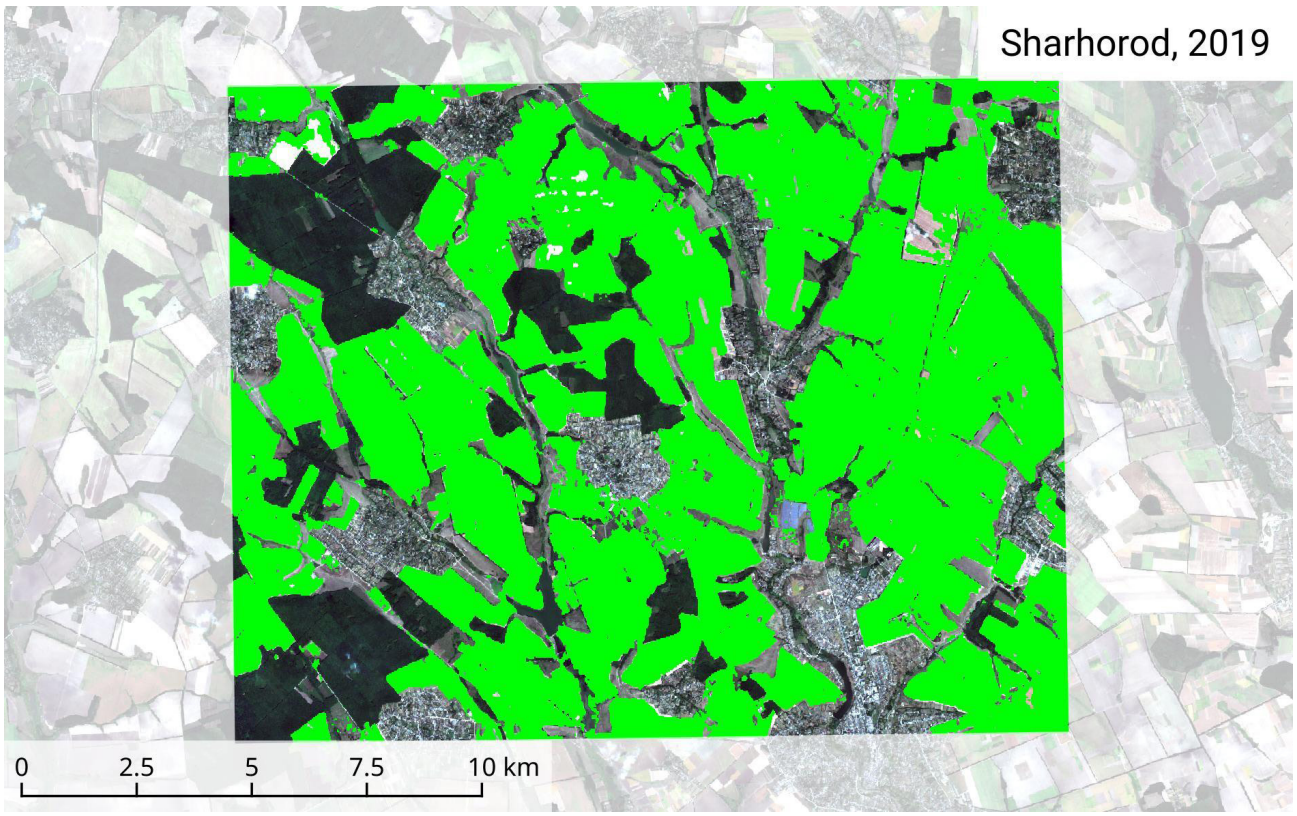
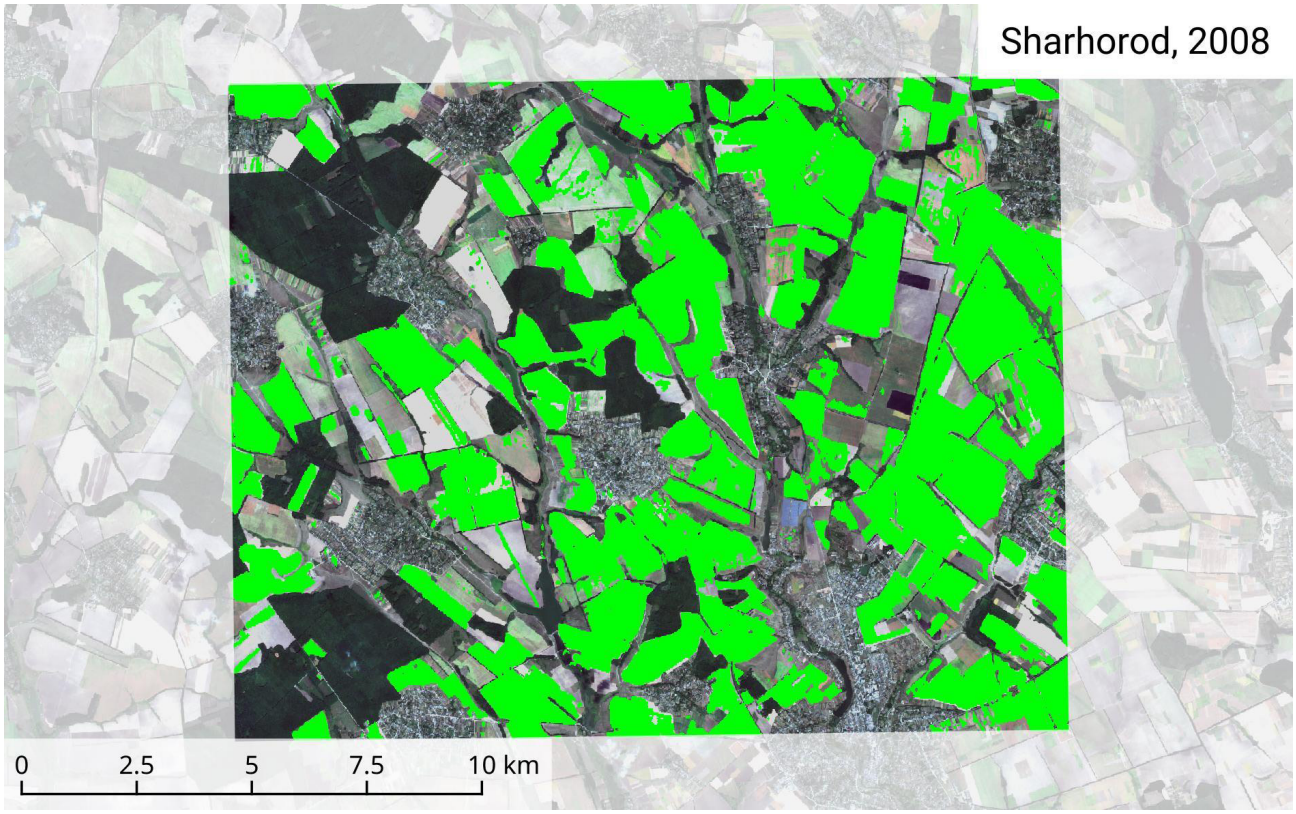
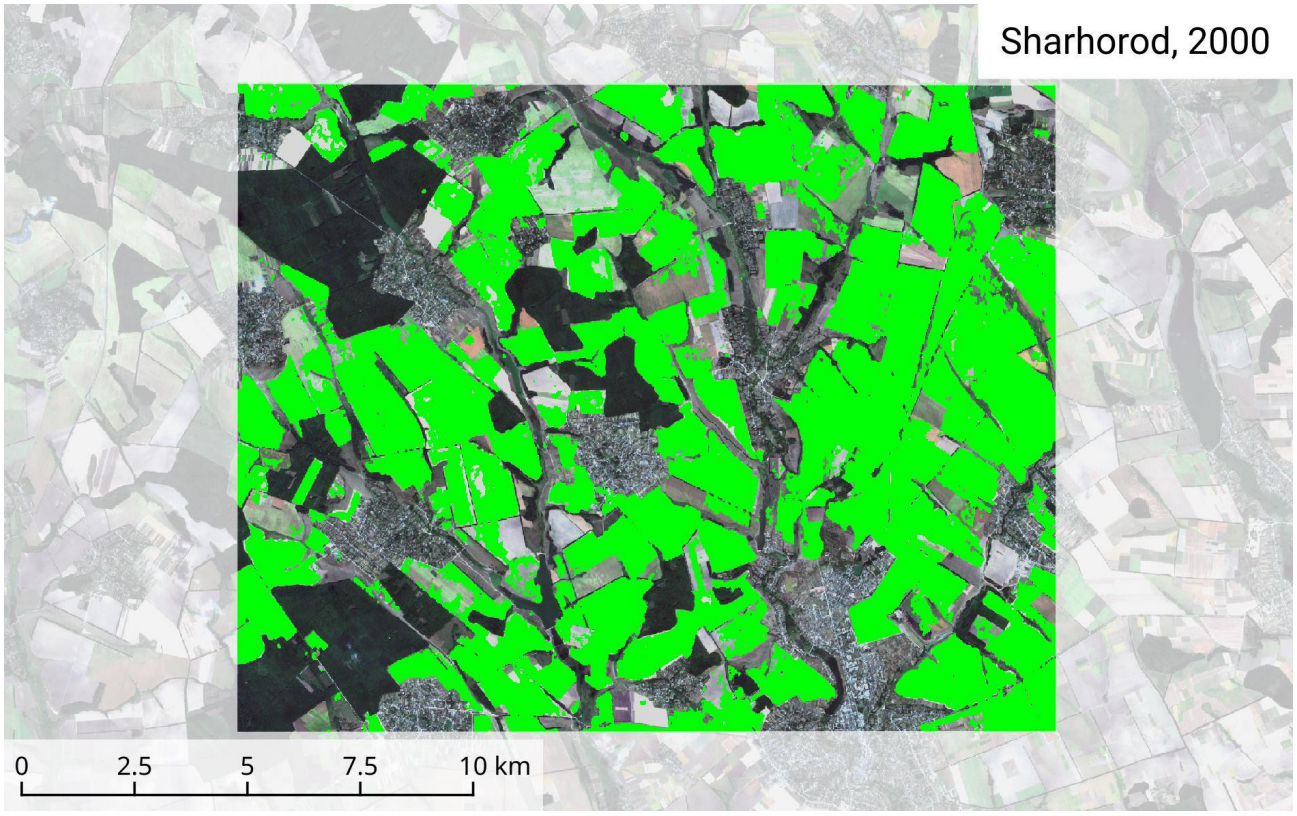
5
7.5
10 km

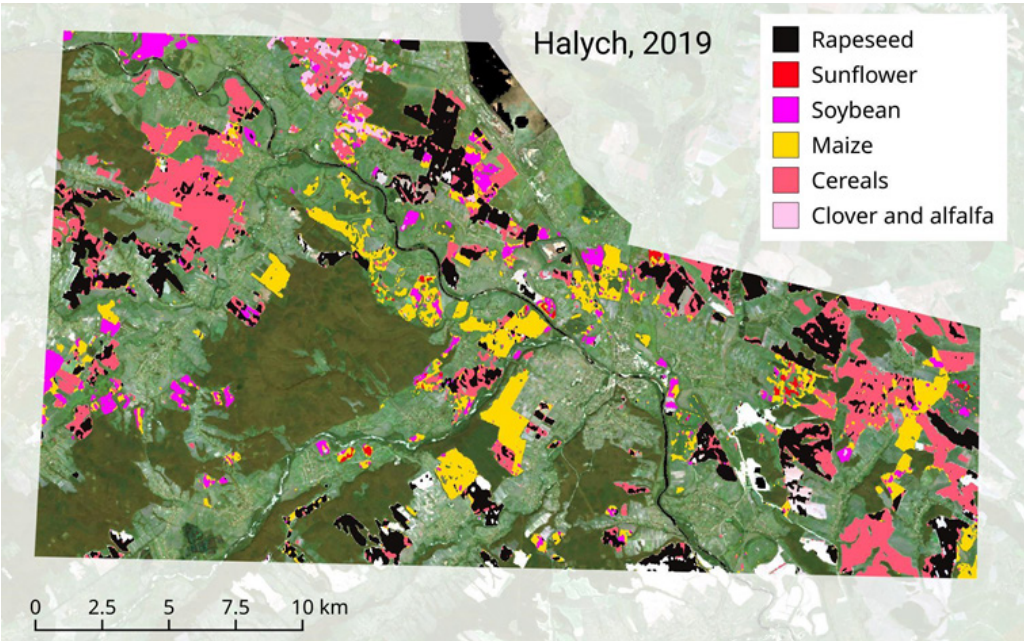

Sharhorod, 2019
0
2.5
5
7.5
10 km

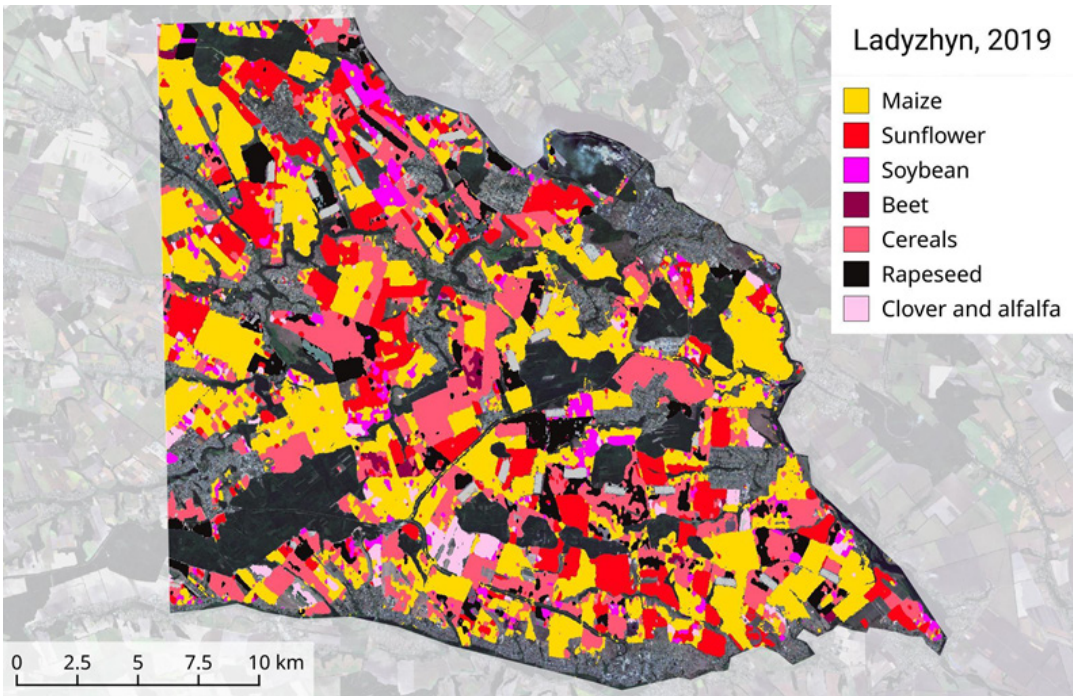

Sharhorod, 2008
0
2.5
5
7.5
10 km

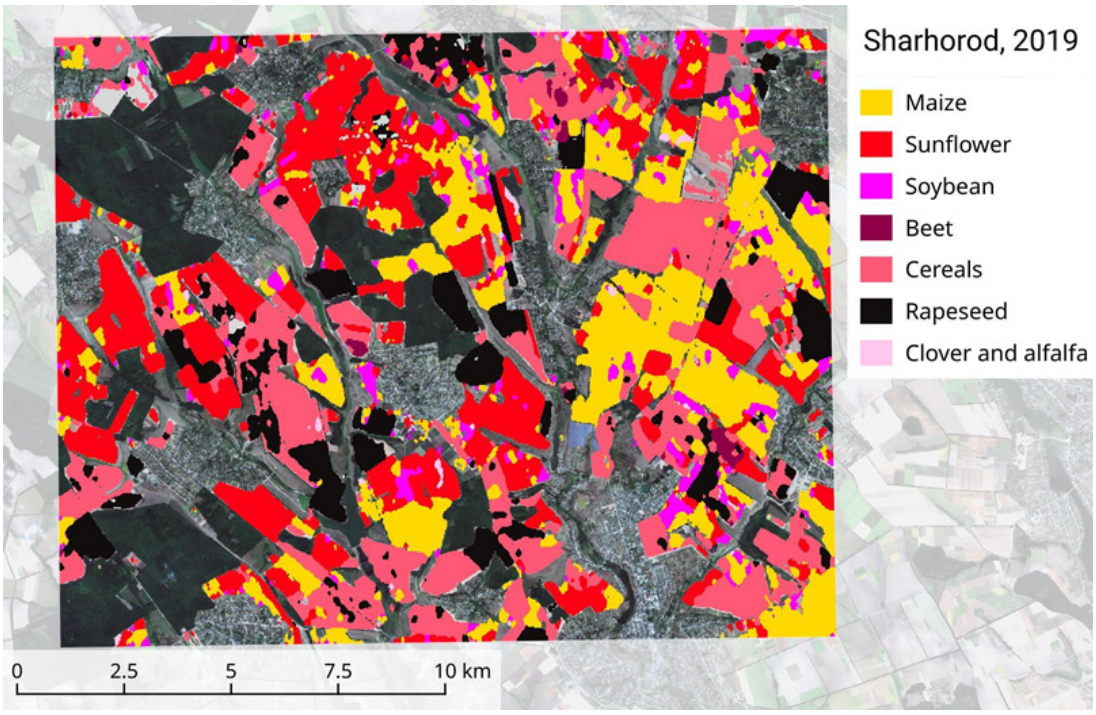

Sharhorod, 2000
0
2.5
5
7.5
10 km

Supplementary materials 2

MAPS OF CROP RECOGNITION



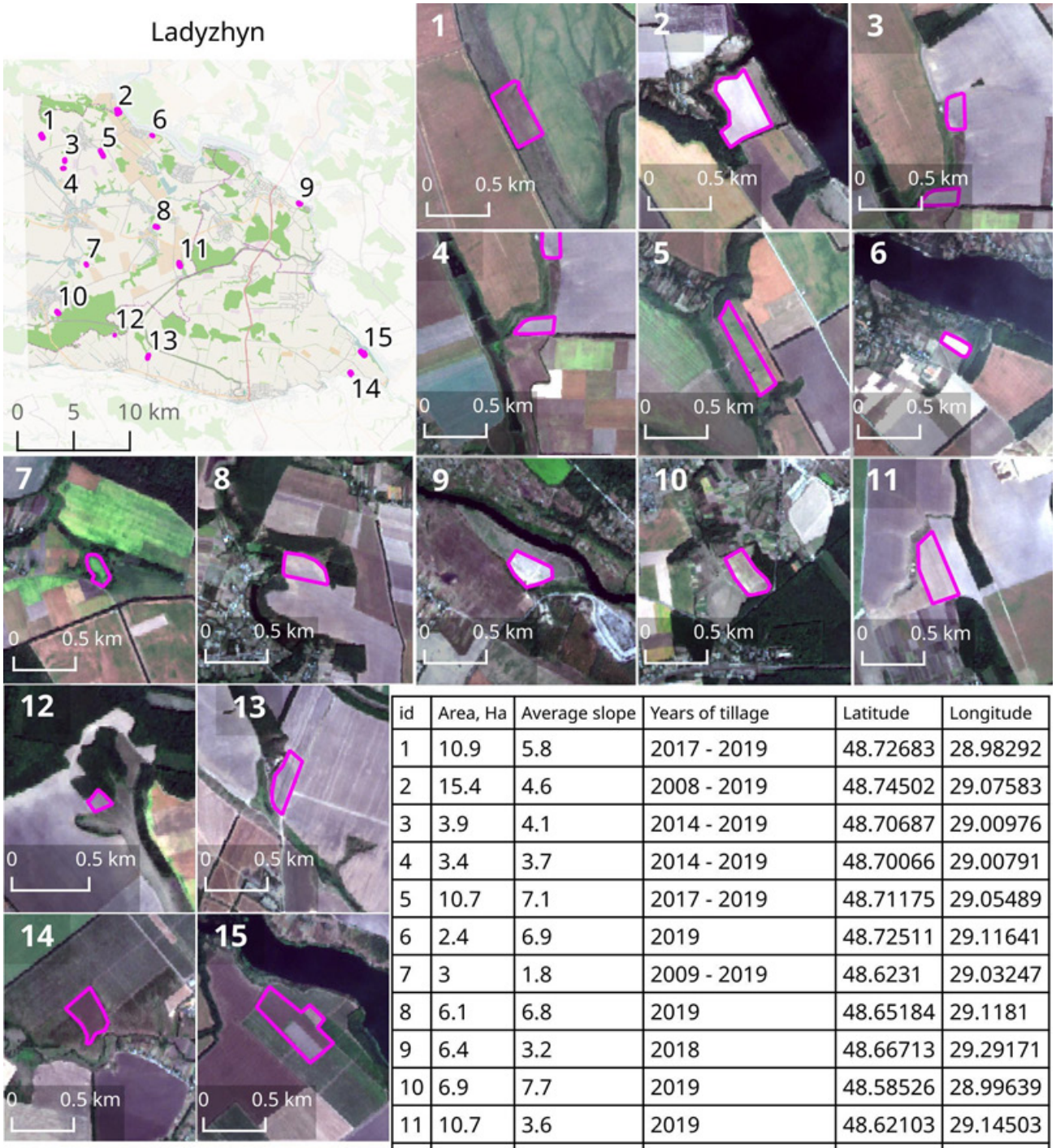




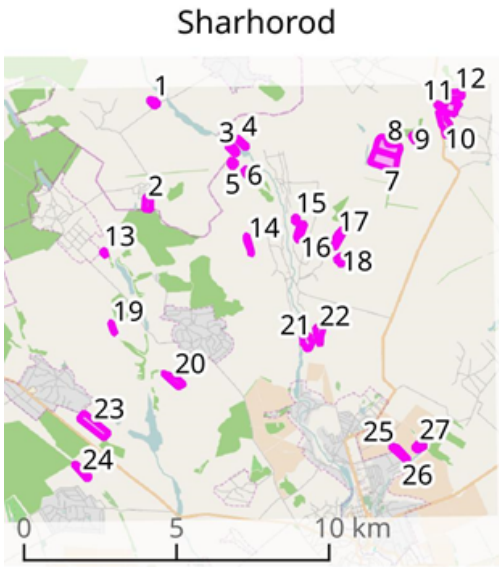
Detailed maps of plots can be found here:
http://bit.ly/agromap4ea

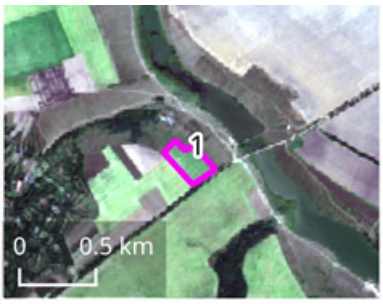
Supplementary materials 3

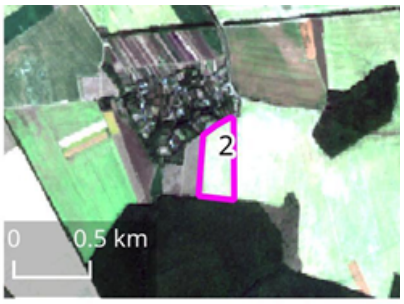
MAPS OF LAND AREAS PLOWED AFTER 2008, LADYZHYN AND SHARGOROD PLOTS

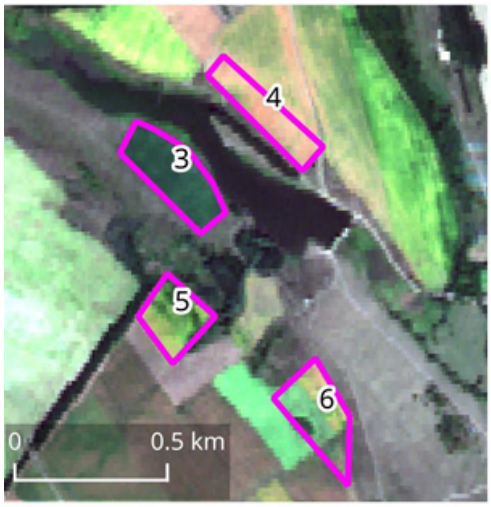


id	Area, Ha	Average slope	Years of tillage	Latitude	Longitude
1	10.9	5.8	2017 - 2019	48.72683	28.98292
2	15.4	4.6	2008 - 2019	48.74502	29.07583
3	3.9	4.1	2014 - 2019	48.70687	29.00976
4	3.4	3.7	2014 - 2019	48.70066	29.00791
5	10.7	7.1	2017 - 2019	48.71175	29.05489
6	2.4	6.9	2019	48.72511	29.11641
7	3	1.8	2009 - 2019	48.6231	29.03247
8	6.1	6.8	2019	48.65184	29.1181
9	6.4	3.2	2018	48.66713	29.29171
10	6.9	7.7	2019	48.58526	28.99639
11	10.7	3.6	2019	48.62103	29.14503
12	1.2	6.5	2014 - 2019	48.5659	29.06447
13	6.4	5	2008 - 2019	48.54794	29.10386
14	7.4	3.9	2013, 2015 - 2019	48.52996	29.34727
15	16.5	3	2017 - 2019	48.5456	29.36273

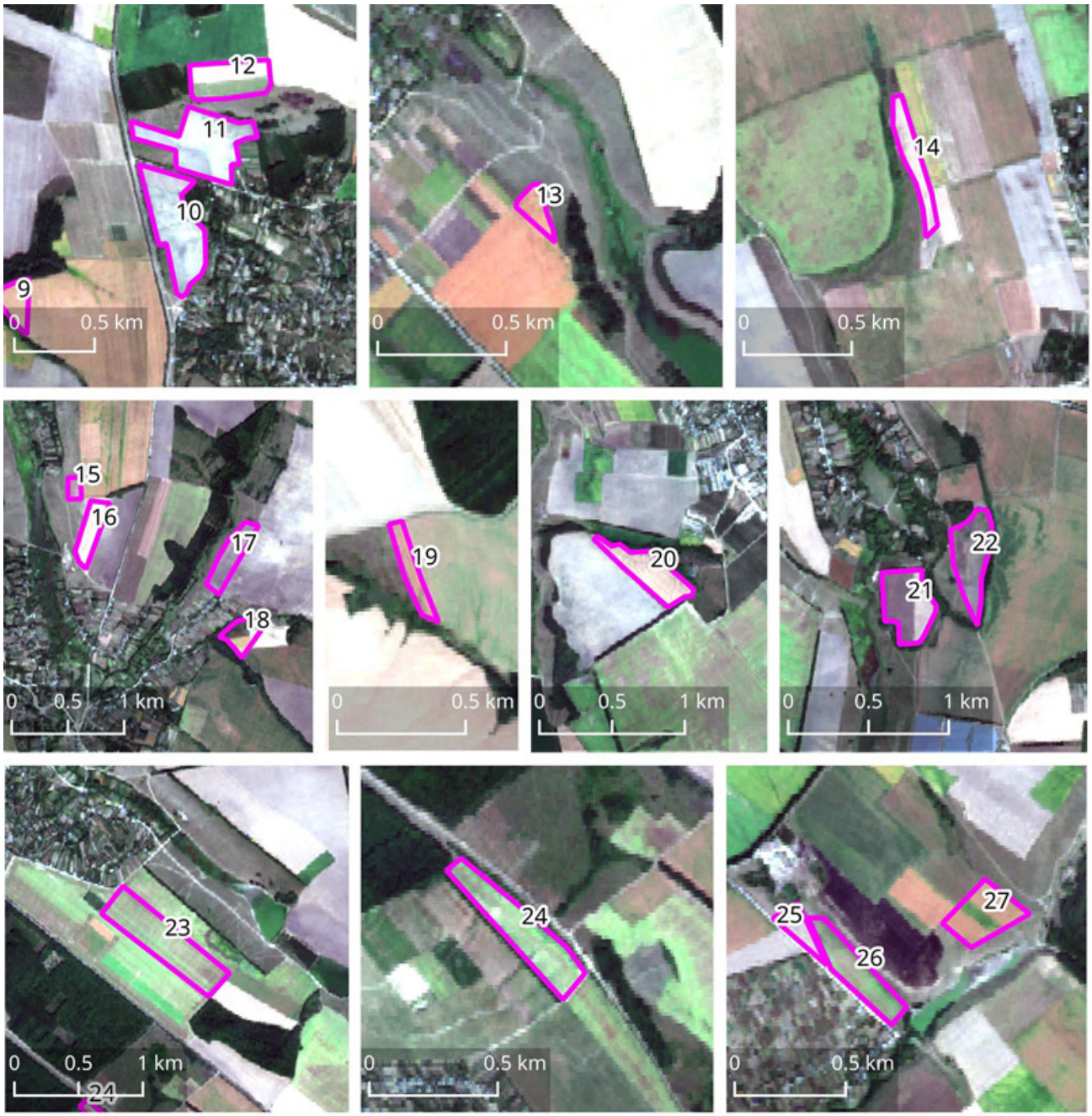






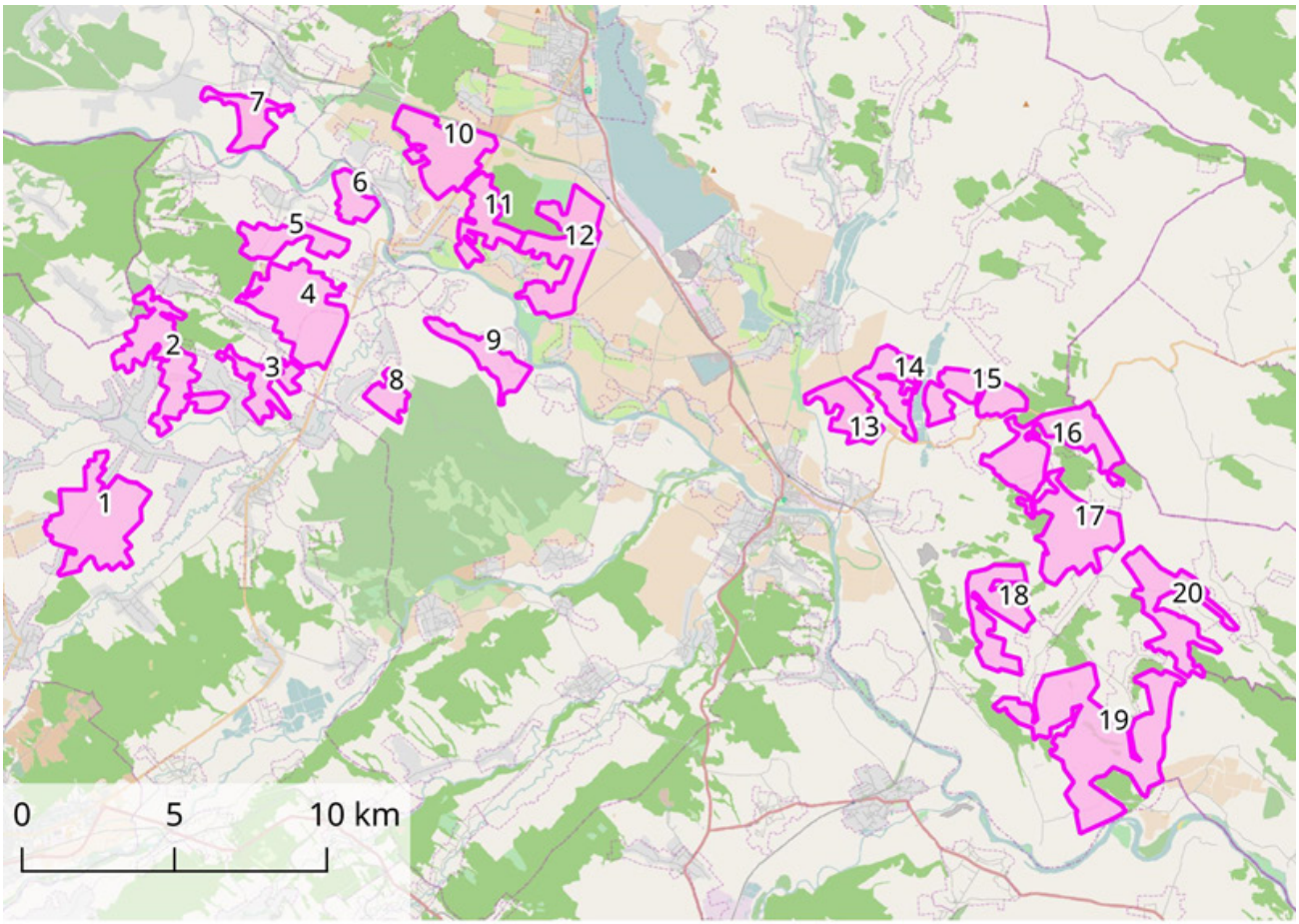


id	Area, Ha	Average slope	Years of tillage	Latitude	Longitude
1	4.7	5.9	2019	48.86424	27.98955
2	10.4	3	2008 - 2019	48.83464	27.98643
3	5.7	4.8	2017 - 2019	48.85016	28.02455
4	4.2	7.2	2010 - 2019	48.85194	28.02869
5	3.8	4.4	2009 - 2019	48.84595	28.02449
6	4.9	5.8	2019	48.84301	28.03089
7	37.8	4.8	2008 - 2019	48.84624	28.09232
8	29.1	4	2010 - 2019	48.85007	28.09373
9	4.2	3.6	2009 - 2019	48.8529	28.10587
10	17.5	3.5	2018, 2019	48.85708	28.11945
11	17.8	3.3	2018, 2019	48.86169	28.1218
12	10.6	2.2	2016 - 2019	48.86524	28.12422
13	1.5	5.9	2018, 2019	48.81997	27.96659
14	4.2	6.1	2018, 2019	48.82192	28.03116
15	2.2	6	2018, 2019	48.82906	28.05232
16	8.7	4.8	2018, 2019	48.82562	28.05423
17	10.6	4.9	2018, 2019	48.82341	28.07113
18	7.4	5	2018, 2019	48.81722	28.07255
19	2.2	4.1	2008 - 2019	48.79779	27.96995
20	11.2	4.2	2015 - 2019	48.78205	27.99732
21	11.2	2.6	2015 - 2019	48.79294	28.05662
22	10.8	6.1	2019	48.79557	28.06215
23	27.7	3.6	2013 - 2019	48.76902	27.96091
24	7.9	5.4	2019	48.7554	27.95559
25	2	5.6	2018 - 2019	48.76108	28.09469
26	6.4	6.7	2019	48.75929	28.09817
27	6	6.1	2017 - 2019	48.76154	28.10602


12
11
10
9
0 0.5 km
13
0 0.5 km
14
0 0.5 km
15
16
17
18
0 0.5 1 km
19
0 0.5 km
20
0 0.5 1 km
22
21
0 0.5 1 km
23
0 0.5 1 km
24
0 0.5 km
25
26
27
0 0.5 km

Supplementary materials 4

MAP OF THE BIGGEST FIELDS UNDER ONE CROP IN 2019, HALYCH PLOT.



id	Area_Ha	Latitude	Longitude
1	715.3	49.11752	24.42265
2	580.5	49.16201	24.45437
3	251.1	49.15943	24.4958
4	704.4	49.18144	24.51075
5	267.2	49.20248	24.5004
6	151.6	49.21495	24.53249
7	223	49.2377	24.48502
8	130.5	49.15684	24.5518
9	257.6	49.16956	24.59493
10	514.3	49.23013	24.57256

id	Area_Ha	Latitude	Longitude
11	293.1	49.20965	24.59194
12	576.2	49.20119	24.62838
13	267	49.15686	24.75878
14	301.2	49.16517	24.77857
15	357.4	49.16248	24.81366
16	612.5	49.1466	24.8438
17	569.6	49.12277	24.86167
18	460.1	49.09863	24.82859
19	1396.4	49.06255	24.87512
20	510	49.09831	24.9056

УДК 528:633

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LAND MATRIX

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екодія
ecoaction.org.ua

Kyiv, Ukraine
Saksahanskoho str., 52a

+38 (044) 353-78-41

info@ecoaction.org.ua

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