Accurate Identification of Land-Use Changes Using Open Google Earth Engine Tools

Präzise Erkennung von Landnutzungsveränderungen mithilfe von Google Earth Engine Tools

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The objective is to develop an algorithm for detecting changes in land-use classes with a focus on unambiguous identification of the type of such change, utilizing remote sensing datasets from Google Earth Engine. The algorithm involves several key steps such as data collection, processing, land-use classification, change detection, change quantification, and socio-economic impact analysis. The main task is to record the transition of one category of land to another in order to further forecast changes in socio-economic indicators. The research also included an assessment of the accuracy of the algorithm's results based on a comparison with existing land-use datasets for areas with similar characteristics. The accuracy of the change type determination corresponds to the global level of the Dynamic World dataset and follows the common classification problems for such lands as crops, built-up and grass classes. Therefore, the study aims to identify trends in land use and their socio-economic impacts, with the findings underlining the need for ongoing development of classification tools to adapt to environmental changes.

The research's practical relevance is demonstrated through an analysis of land-use changes in the Donetsk and Dnipro regions, correlating them with socio-economic indicators like the total population, emissions and gross harvest of agricultural crops by enterprises. Taking into account the long-term military conflict in this region, the proposed algorithm for detecting changes in land use in these territories was tested. The results testify to the effectiveness of the application of such a technique for fixing and assessing the economic consequences for the territories of hostilities. The research emphasizes the importance of integrating social analysis with land-use data for sustainable land management and informed policy-making.

Keywords: Monitoring, land management, land-use classification, land-use datasets, Google Earth Engine, Dynamic World, geospatial analysis, remote sensing, data processing, socio-economic indicators, sustainable development

Das Ziel der Arbeit besteht in der Entwicklung eines Algorithmus zur Erkennung von Veränderungen in Landnutzungsklassen mit dem Schwerpunkt auf einer eindeutigen Identifizierung der Art solcher Veränderungen unter Verwendung von Fernerkundungsdatensätzen aus der Google Earth Engine. Der Algorithmus umfasst mehrere zentrale Schritte wie Datenerfassung, Datenverarbeitung, Landnutzungsklassifikation, Veränderungsdetektion, Quantifizierung von Veränderungen sowie die Analyse sozioökonomischer Auswirkungen. Die Hauptaufgabe besteht darin, den Übergang einer Landnutzungskategorie in eine andere zu dokumentieren, um darauf aufbauend Veränderungen in sozioökonomischen Indikatoren zu prognostizieren. Darüber hinaus beinhaltet die Arbeit eine Bewertung der Genauigkeit der Ergebnisse des Algorithmus auf Grundlage eines Vergleichs mit bestehenden Landnutzungsdatensätzen für Gebiete mit ähnlichen Charakteristika. Die Genauigkeit der Bestimmung des Änderungstyps entspricht dem globalen Niveau

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des Dynamic-World-Datensatzes und weist die typischen Klassifikationsprobleme bei Nutzungsarten wie Ackerflächen, Bebauung und Grünland auf. Ziel dieser Untersuchung ist es daher, Trends in der Landnutzung und deren sozioökonomische Auswirkungen zu identifizieren. Die Ergebnisse unterstreichen die Notwendigkeit einer kontinuierlichen Weiterentwicklung von Klassifikationsinstrumenten zur Anpassung an Umweltveränderungen.

Die praktische Relevanz der Forschung wird durch eine Analyse der Landnutzungsänderungen in den Regionen Donezk und Dnipro verdeutlicht, bei der Korrelationen mit sozioökonomischen Indikatoren wie Gesamtbevölkerung, Emissionen und Bruttoertrag landwirtschaftlicher Kulturen in Betrieben untersucht wurden. Unter Berücksichtigung des langjährigen militärischen Konflikts in dieser Region wurde der vorgeschlagene Algorithmus zur Erkennung von Landnutzungsänderungen in diesen Gebieten getestet. Die Ergebnisse belegen die Wirksamkeit des Einsatzes einer solchen Methodik zur Erfassung und Bewertung der wirtschaftlichen Folgen für die von Kampfhandlungen betroffenen Territorien. Die Studie betont die Bedeutung der Integration sozialwissenschaftlicher Analysen mit Landnutzungsdaten für ein nachhaltiges Landmanagement und eine fundierte Politikgestaltung.

Schlüsselwörter: Monitoring, Landmanagement, Landnutzungsklassifikation, Google Earth Engine, Dynamic World, Geodatenanalyse, Fernerkundung, Datenverarbeitung, sozioökonomische Indikatoren, nachhaltige Entwicklung

1 INTRODUCTION

The classification of remote sensing data is a classic approach to creating land cover maps, and a large number of scientific publications have already been devoted to this /Stefanov et al. 2001/, /Souza et al. 2020/, /Liu et al. 2020/, /Phiri et al. 2020/. The land-use datasets created over the past decades differ in spatial, spectral and temporal resolution, primarily due to the characteristics of the input data /Ying et al. 2020/. Launch of the Sentinel-2 satellites in 2015 and the use of this data improves spatial resolution up to 10 m, but is not unambiguously the best basis for land-cover classification. The research of /Xu et al. 2022/ comparing the performance of different satellite sensors in monitoring global land cover change found that Landsat 8 OLI surpasses Sentinel-2 for global general monitoring, and PROBA-V shows the worst results /Xu et al. 2022/.

Today, a more urgent and difficult task is to define and build hypotheses based on trend research. Land-use data and/or land cover sets (LULC) accumulated over the years of observation, such as the National Aeronautics and Space Administration (NASA) MCD12Q1 500 m resolution dataset (2001 – 2018), the European Space Agency (ESA) Climate Change Initiative (CCI) 300 m dataset, version 6 (1992 – 2018), and Copernicus Global Land Service (CGLS) Land Cover 100 m dataset (4 – 8) allow using cellular automata, neural networks and artificial intelligence to analyze patterns of change and their impact on the environment. For example, the work of Mansour et al. (2020) is devoted to the spatial analysis of cities growth for assessing and forecasting changes in land cover using cellular automata. Focusing on local-scale changes, /Goebel et al. 2023/ presents an approach for the segmentation of forest vegetation layers based on geometric features extracted from 3d point clouds.

/Balvanera et al. 2022/ present another fundamental work in the field of monitoring changes where the goal is to define changes in those indicators of ecosystem functioning that have a direct impact on the quality of life and sustainable development of mankind. These indicators include, in particular: wild food from marine fisheries, a provisioning service or material contribution, crop pollination by wild insects, a regulating service/contribution, and physical and psychological experiences from wildlife viewing, a cultural service or non-material contribution. The source of data for calculating indicators is also remote sensing data with different spatial and temporal resolutions. However, the definition of factors and their indicators does not solve the problem of global monitoring. According to the authors, the development of algorithms and tools for calculating heterogeneous indicators are future steps for successful monitoring and forecasting. /Brochhagen et al. 2024/ address the challenge of variable satellite image quality by adapting the state-of-the-art super-resolution convolutional neural network Real-ESRGAN via transfer learning to Sentinel-2 and PlanetScope data. This approach yields realistic, detail-rich super-resolved imagery that narrows the low/high-resolution gap and provides an accessible, cost-effective route to analyses approaching premium satellite standards.

In our opinion, the most interesting is the analysis of the form and intensity of changes in land-use classes, as well as the search for regularities regarding the impact of such changes on socio-economic factors. The focus of attention of European programs today is shifted to climate-neutral continent and benefits of the green transition in people's daily lives and living spaces, according to the New European Bauhaus. At the same time, environmental sustainability remains the core around which future strategies are built with the introduction of such important factors as inclusion, aesthetics, competitiveness /Rosado-García et al. 2021/.

Today, the pace of land-cover change has become incredibly fast, and the processing of the results of satellite observations and data updates takes place "on the fly". Quantitative and qualitative analysis of land-use changes in the context of social and economic processes in a certain territory is possible provided that there is an algorithm for detecting such changes in real time. A reliable and accurate interactive tool for finding significant changes in land use will make it possible to predict the pace of sustainable development of society in accordance with the norms approved by the EU.

Given the extensive damage to infrastructure, agriculture, and urban fabric caused by the ongoing war in Ukraine, it is crucial to conduct land-use change analysis in regions that have undergone substantial transformations. War-affected territories, particularly in Eastern Ukraine, exhibit rapid and often undocumented alterations in settlement structure, vegetation cover, and land function. Systematic, quantitative monitoring of these changes is essential not only for assessing the environmental and socio-economic impacts of the conflict, but also for planning recovery and reconstruction strategies. By identifying measurable indicators of land-use changes, this research contributes to evidence-based policy-making, prioritization of interventions, and long-term spatial planning in post-conflict settings. Furthermore, it demonstrates the relevance of open-access geospatial data and automated analytical tools for resilient governance and crisis response.

1.1 Objectives

The goal of the study is to develop an algorithm for detecting changes in land-use classes based on the analysis of remote sensing data for mapping and analysis of land cover transitions. It should be noted that our research considers the global level of change analysis, based on the use of global data sets. The algorithm should be universal for any territory, independent of tools or special programming skills of the end user. One of the fundamental tasks of the algorithm is the unambiguous identification of change – that is, the exact determination of the transition of one category of land use to another.

The results of this algorithm will allow us to identify trends in the functional use of land and analyze their impact on socio-economic indicators of society. It is the direction and form of such changes that will determine the further development of society in this territory. However, all metric indicators of changes such as area, shape or direction of change in land use-class are the subject of future research and remain outside the developed algorithm.

The algorithm was tested and verified with remote sensing data captured over the Donetsk and Dnipro regions, both located in Eastern Ukraine.

1.2 Methodology

The methodology for research land-use changes involves several key steps that utilize geospatial analysis and data processing techniques. This scientific approach allows researchers and analysts to better understand changes in land-use patterns, their implications, and the impact on socio-economic indicators (*Fig. 1*).

1. *Data Collection* is the first step to gathering relevant data for the study area. This data can include satellite images, aerial images, remote sensing data, land survey records, and socio-economic indicators, e. g., population data, economic data, agricultural statistics. High-resolution satellite images are obtained from sources like Landsat, Sentinel, or MODIS, which can be accessed via USGS Earth Explorer or Copernicus Open Access Hub. Current or historical aerial images can be accessed, if available, from local authorities or historical archives. Relevant data can be collected from government databases, statistical agencies, or research institutions. The data should cover multiple time periods to analyze changes over time effectively. It must be ensured that the satellite and aerial images are geometrically and radiometrically corrected and geo-referenced. Socio-economic data from reliable sources should be validated to ensure accuracy.
2. Data processing or pre-processing of the collected data represents the second step of the workflow. This stage involves cleaning the datasets, performing georeferencing, and converting between raster and vector formats as needed. The accuracy of georeferencing and projection must be validated to ensure spatial consistency. Following this, land-use classification is carried out by categorizing the landscape into predefined classes such as urban, agricultural, or forested areas. This can be done manually or by employing machine learning algorithms. Commonly used techniques include Random Forest, Support Vector Machines (SVM), or k-means clustering, which can be implemented using platforms such as Google Earth Engine (GEE) or GIS software. The classification outcomes must be validated through ground-truth data to assess their accuracy and reliability.
3. *Land-Use Classification* involves categorizing the land into different classes based on its usage, e. g., urban, agricultural, forest, water bodies. This can be done manually or using machine learning algorithms applied to the processed data. The output will be a raster with each pixel representing a land-use class or a vector layer with land plots assigned to specific land-use classes. Employ supervised or unsupervised classification algorithms, such as Random Forest, SVM, or k-means clustering, using software like GEE, scikit-learn, or ENVI. Some regions have pre-existing land cover databases, such as the Corine Land Cover dataset for Europe. Ground-truth data is essential to validate the accuracy of the land-use classification. Field surveys or ground-based data collection can be used to validate the results. It is quite simple to identify the areas of greatest land-use change using the algebraic difference between different time data. But it is much more difficult to identify this change precisely, i. e., which class has moved to which other land-use class. The encoding we have proposed is called "exponential encoding" or "powers-of-two encoding". In this encoding scheme, each digit is associated with a power of 2, and the value of the digit is calculated as 2 raised to the power of the digit itself, e. g., $0 = 2^0 = 1$; $1 = 2^1 = 2$; $2 = 2^2 = 4$; $3 = 2^3 = 8$; $4 = 2^4 = 16$; $5 = 2^5 = 32$; $6 = 2^6 = 64$; $7 = 2^7 = 128$; $8 = 2^8 = 256$; $9 = 2^9 = 512$; $10 = 2^{10} = 1024$. This encoding can be used to represent numbers in a concise way, particularly in computer systems, where powers of 2 are commonly used due to their relationship with binary representation and memory address calculations. This approach to coding land use-classes will be called Class Change Coding (CCC) in the following. If you reclassify an image using this approach, the set of possible values for the differences between classes will look like shown in *Tab. 1*. In this case, these are unique values that allow for identifying the type of change and calculate its analytics.

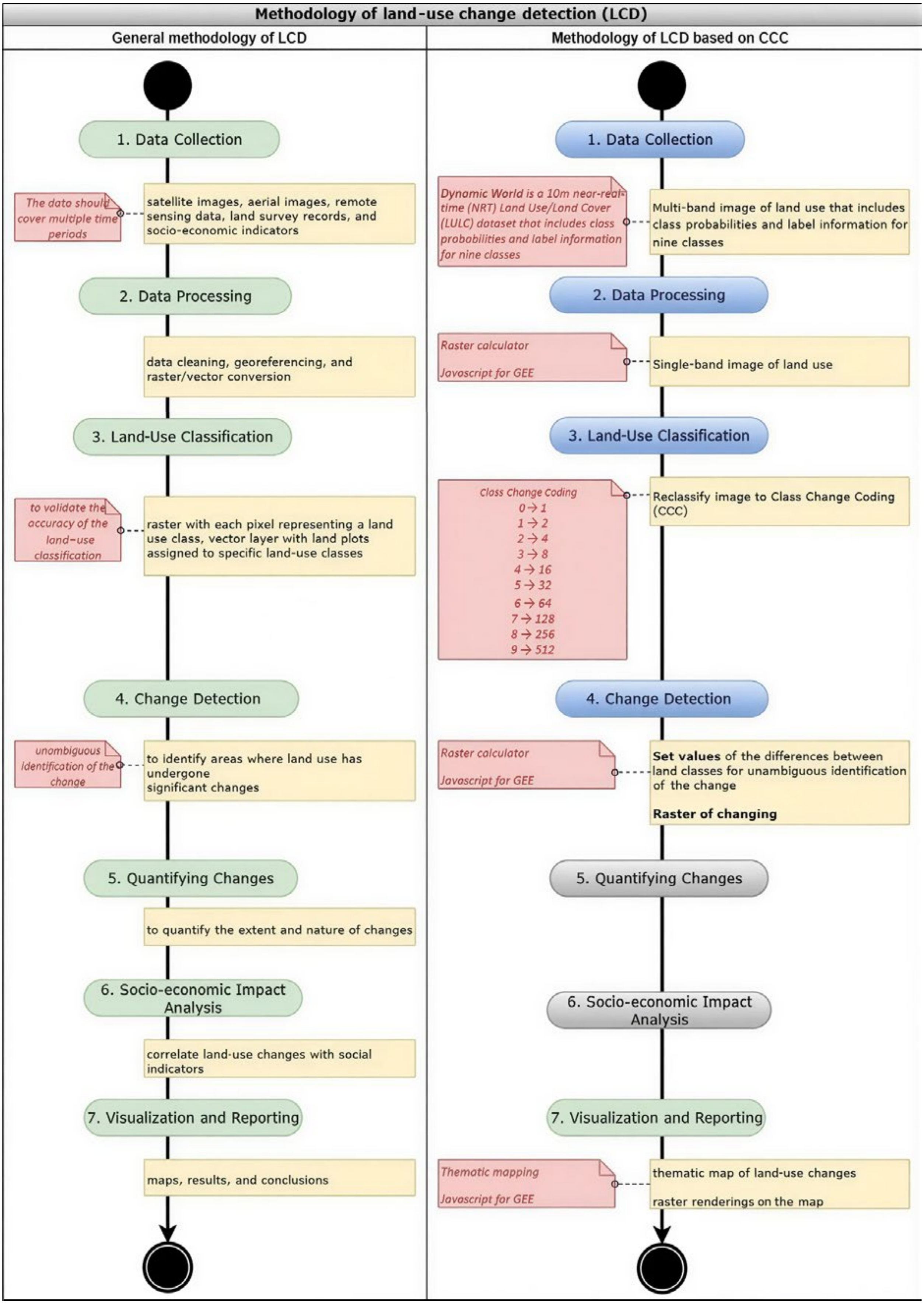

Fig. 1 | The methodology of land-use change detection

			No data	Water	Trees	Grass	Flooded vegetation	Crops	Shrub and scrub	Built	Bare	Snow and ice
			0	1	2	3	4	5	6	7	8	9
			1	2	4	8	16	32	64	128	256	512
No data	0	1	0	–1	–3	–7	–15	–31	–63	–127	–255	–511
Water	1	2	1	0	–2	–6	–14	–30	–62	–126	–254	–510
Trees	2	4	3	2	0	–4	–12	–28	–60	–124	–252	–508
Grass	3	8	7	6	4	0	–8	–24	–56	–120	–248	–504
Flooded vegetation	4	16	15	14	12	8	0	–16	–48	–112	–240	–496
Crops	5	32	31	30	28	24	16	0	–32	–96	–224	–480
Shrub and scrub	6	64	63	62	60	56	48	32	0	–64	–192	–448
Built	7	128	127	126	124	120	112	96	64	0	–128	–384
Bare	8	256	255	254	252	248	240	224	192	128	0	–256
Snow and ice	9	512	511	510	508	504	496	480	448	384	256	0

Tab. 1 I A set of unique values representing changes from one land-use class to another

4. *Change Detection* is the key operation in the algorithm. Geospatial analysis is applied to compare land-use data from different time periods. Change detection algorithms are employed to identify areas where land use has undergone significant changes. These algorithms analyze pixel values or vector attributes to detect changes in land-use classes over time. It should be noted that potential errors in change detection due to seasonal variations, cloud cover, or sensor differences between datasets may occur. According to this approach, the algebraic difference between two land-use images will have the form of a single-channel image, each pixel of which contains unambiguous information about the change in land-use class. Further geostatistical analysis is a classic GIS task, therefore the choice of tools depends on the specific issue and user preferences.
5. *Change quantification* is the step to quantify the extent and nature of land-use changes. This involves measuring the area of land that has transitioned from one land use class to another and identifying the specific classes involved in each change. Statistical techniques can be used to analyze the magnitude and significance of the changes. Consistent and accurate land-use classifications for accurate calculations must be ensured.
6. *Socio-economic Impact Analysis* aims to understand the implications of land-use changes, analyzing socio-economic indicators such as population growth, economic development, agricultural productivity, and environmental factors. By correlating land-use changes with these indicators, researchers can identify the impact of land-use transitions on various aspects of society and the environment.
7. *Visualization and Reporting* is the final step presenting results through maps, charts, and graphs. GIS tools are commonly used to create visual representations of the analyzed data.

The goal of this research is to create an automated tool for recording changes in land-use types based on remote sensing data. However, based on previous fundamental research and publicly available data, it was decided to focus on the development and testing of a change detection algorithm, and to use existing datasets on land-use classes as input. It is also worth noting that there are several possibilities for implementing the proposed algorithm both in the environment of GIS tools and directly in the environment of global online services, such as GEE. At the stage of algorithm research, both approaches were implemented, so in the further teaching of the material, both applied GIS tools and functions of the Java programming language will be indicated. For automation of the process, the GEE environment is chosen, which offers easy and affordable means of implementing interfaces and publishing similar algorithms, and therefore provides easy access to the development results of a wide range of stakeholders.

The global GEE database offers spatio-temporal remote sensing data, leading to improved land-use datasets like Dynamic World V1. This provides geo-referenced raster images with probabilities of functional land use by different classes /Brown et al. 2022/.

2 TESTING

The global GEE database provides access to spatio-temporal remote sensing data of various resolutions, which leads to the emergence of new, more accurate and detailed land-use datasets. One of these is Dynamic World – near-real-time global 10 m land-use/land-cover mapping /Brown et al. 2022/. As a result, we have georeferenced raster images of the land with 9 channels – each containing information on the probability of functional use of the territory by a certain class.

The proposed algorithm was tested in the Mariupol district of Donetsk region, Ukraine, an area significantly affected by the Russian Federation's military invasion. Remote sensing data provides a comprehensive way to assess the impact of such events on land-use changes, including economic and social losses. Converting multi-channel probability images to a single-channel land-use rasters can be achieved through geoinformation tools like *Raster calculator* or using GEE's *reduce()* function, which identifies the dominant channel for each pixel. Reclassification of the land-use raster to the CCC system has been done using tool *Reclassify*, or function *reclassify(image)* in GEE:

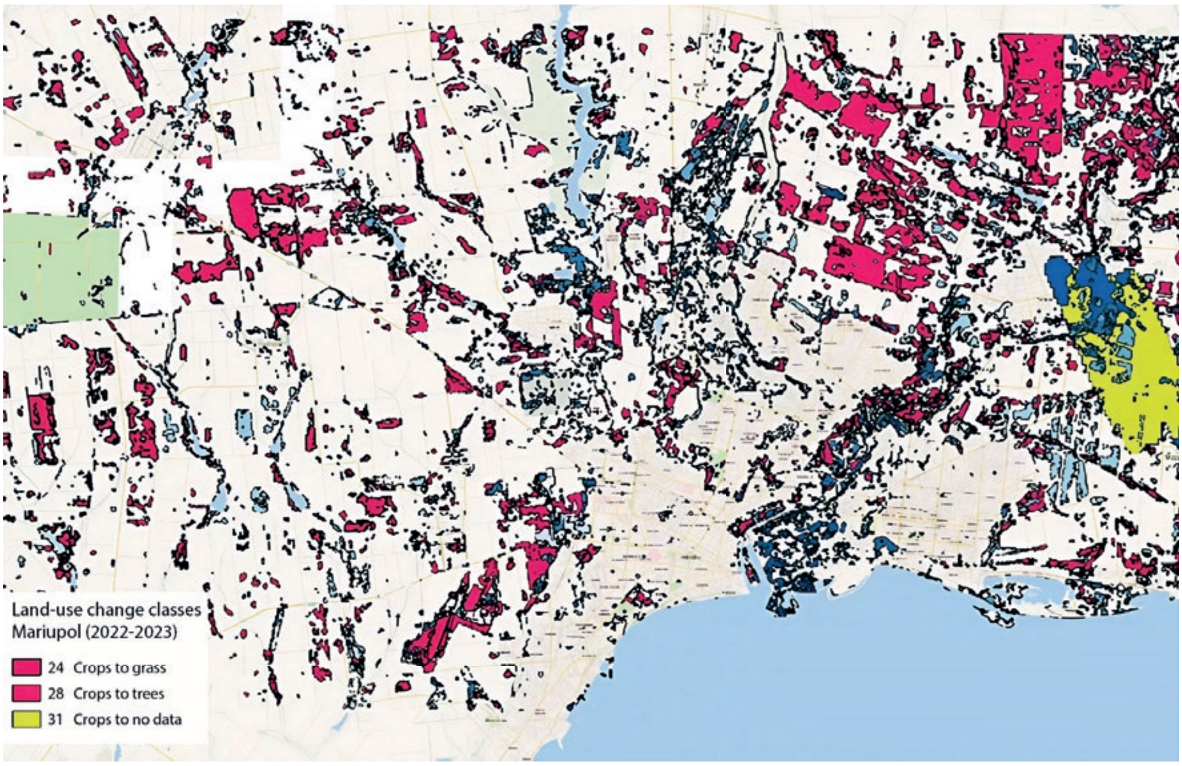

Fig. 2 | Example of calculating the change in land-use classes visualizing three types of them 24 (crops to grass), 28 (crops to trees) and 31(crops to no data), part of Mariupol, Ukraine

```
function reclassify(image)
var reclassifiedImage = image.remap([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], [1, 2, 4, 8, 16, 32, 64, 128, 256, 512], 0).rename('reclassified_values');
return reclassifiedImage;
```

where the reclassify function takes an input raster image. The remap function maps the original values [0, 1, ..., 9] to new values [1, 2, 4, ..., 512]. The third parameter, 0, serves as the default value if an input pixel value does not match the original set. In summary, this script takes an image with values from 0 to 9, remaps these values to a new set of values (likely corresponding to binary representations of the original values), and returns the resulting image with the reclassified values. According to this approach, the algebraic difference between two land-use images will have the form of a single-channel image, each pixel of which contains unambiguous information about the change in land-use class (*Fig. 2*). Further geostatistical analysis is a classic GIS task, and therefore the choice of application tools depends on the specific issue and user preferences.

2.1 Accuracy

The methodology for detecting changes in land-use classes requires thorough accuracy assessment. The dataset's spatial resolution matches the original Sentinel-2 data, varying from 10 m to 60 m based on location. Research on ESA Sentinel-2 land-cover/land-use monitoring /Phiri et al. 2020/ indicates classification accuracy exceeding 80%, with the need for separate assessment procedures due to factors like satellite image frequency and territorial heterogeneity. To evaluate dataset accuracy, a task involves comparing it to other available land-use data and interpolating values to the research's date and location. Open vector data sets from trustworthy sources are used for comparison: Urban zoning of Mykolaivka urban community (OTG Mykolaivka), Donetsk region; Urban Atlas 2018 data; Land coverage dataset in Valencia scale at 1 : 5000. Mariupol, Constanta, and Valencia, coastal cities with similar metrics, allow reliable quality assessment results interpolation.

The comparison algorithm begins with reclassifying the data using the CCC classification for clear class identification and then comparing it with GEE data. Next, a conversion to a uniform format involves both raster-to-vector and vector-to-raster transformations. Two distinct approaches for data comparison are implemented: the first involves comparing raster data using overlay functions after converting it to vector format, and the second entails converting reference vector data to raster format and determining differences through mathematical operations. The final step involves a statistical analysis of differences between land-use classes in different datasets for enhanced accuracy assessment (*Fig. 3*). Temporal inconsistencies between the datasets were successfully avoided, as satellite images corresponding to the respective publication years of each dataset – Atlas Urban (2018), Ukrainian Zoning (2022), and COVSCV Valencia (2023) – were available within the global Dynamic World dataset. This ensured a consistent temporal basis for comparison across all three cases.

The differences in the definition of land-use classes between the Dynamic World and Urban Atlas datasets are about 25 % for raster and vector data, but within one single class the difference does not

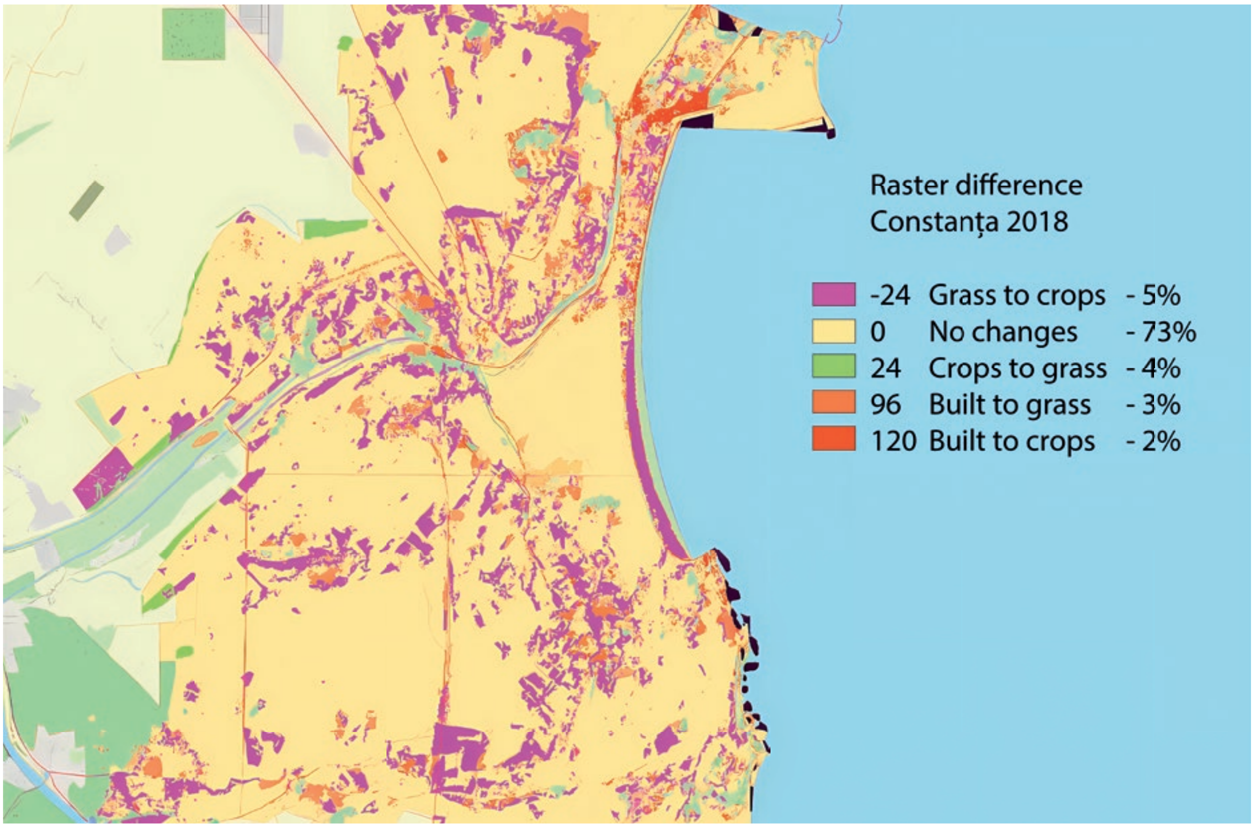

Fig. 3 | Result of comparing Urban Atlas and DW land use by raster data, Constanta, Romania

CCC code	Description	Atlas Urban		Ukrainian zoning		COVSCV Valencia	
		By raster	By vector	By raster	By vector	By raster	By vector
0	No different	83.78 %	83.79 %	73.20 %	73.20 %	70.59 %	70.59 %
24	Crops to grass	5.81 %	5.81 %	0.64 %	2.96 %	1.7 %	1.7 %
-24	Grass to crops	1.01 %	1.02 %	2.98 %	0.64 %	1.07 %	0.0 %
120	Built to grass	2.78 %	2.79 %	0.00 %	0.00 %	2.10 %	2.10 %
-4	Trees to grass	1.14 %	1.14 %	4.07 %	4.08 %	0.00 %	0.00 %
56	Grass to shrub	0.00 %	0.00 %	3.46 %	3.47 %	0.00 %	0.00 %
96	Built to crops	0.52 %	0.51 %	1.5 %	1.32 %	5.06 %	5.06 %
-96	Crops to built	1.07 %	1.07 %	1.33 %	1.49 %	0.91 %	0.00 %
128	Built to bare	0.00 %	0.00 %	0.00 %	0.00 %	4.58 %	4.59 %
-128	Bare to built	0.00 %	0.00 %	0.00 %	0.00 %	2.35 %	2.35 %
124	Built to trees	0.00 %	0.00 %	0.00 %	2.25 %	2.54 %	2.56 %

Tab. 2 | Statistics on differences between different sets and GEE land-use data

exceed 6 % (*Tab. 2*). The comparison result of land-use data for the Valencian Community also shows the high accuracy of the results of classification of remote sensing data in the Dynamic World dataset, and the differences in classes are most likely due to reclassification errors during the transition to the unified CCC classification. The greatest differences are maintained by the crops, built and grass classes, due to the complexity of classifying these land-use categories.

Therefore, the differences in determining the land-use classes of the Dynamic World dataset with the reference data do not exceed 6 %, and consequently, it can be argued that the accuracy of class determination for a coastal city of up to 350 000 inhabitants at a latitude of 40 degrees meets the declared accuracy and validation values of more than 75 % for class determination while maintaining a maximum spatial resolution of 10 m, which is the best indicator among all existing ready-made datasets.

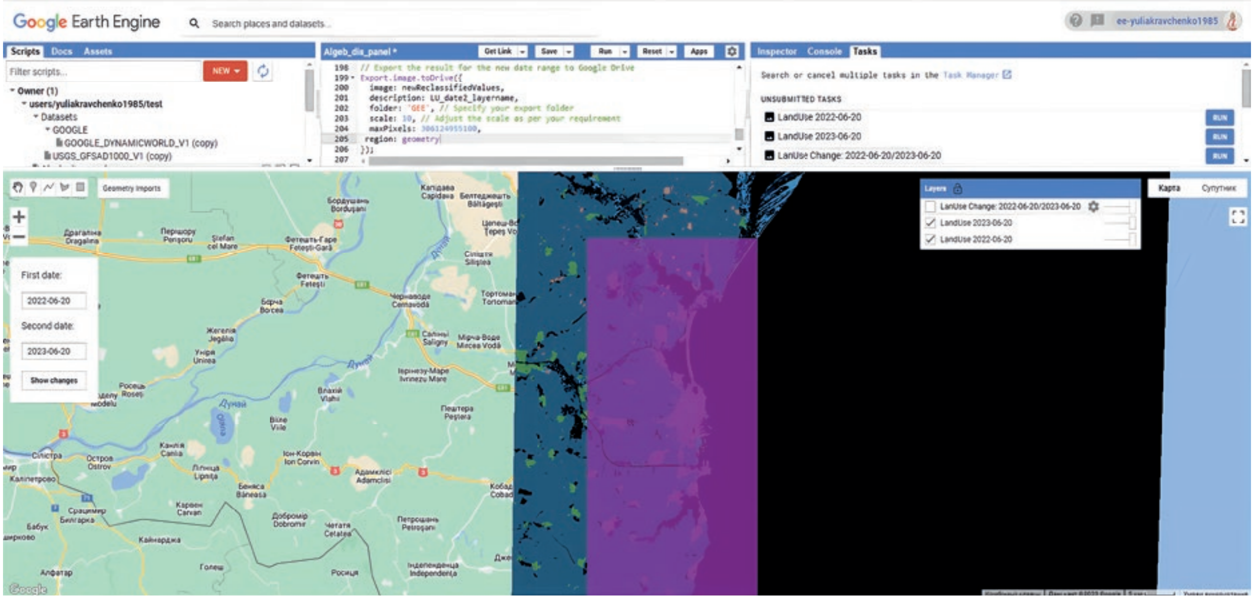

Fig. 4 | Interface for implementing the algorithm for searching of changes based on remote sensing and CCC data of land-use classification (available under /Horkovchuk 2024/)

Statistical analysis of the difference in land-use categories indicates a high degree of identity between the datasets, which in the end confirms the high accuracy of the input set of Dynamic World land cover classes. The high accuracy of Dynamic World dataset in classifying remote sensing data demonstrates its reliability for monitoring and analyzing land-use changes. The small discrepancies between Dynamic World and other datasets are likely due to reclassification errors during the process of transitioning to the unified CCC classification system. Such errors are not unexpected when dealing with large-scale and complex datasets.

2.2 Results

An automated algorithm for detecting land-use changes was developed and published as part of this study, enabling reproducible identification and visualization of land-use transformation. Since the proposed algorithm is based on the processing of remote sensing data using open-access data sets of land-use classes, it is obvious to form an application based on the programming language Java. Today, the GEE environment also provides developers with advanced capabilities to implement user-friendly interfaces for accessing and operating satellite images and global datasets /Google n.d./.

Thus, the developed algorithm for searching for land-use changes based on the CCC classification is implemented in the GEE environment and published under /Horkovchuk 2024/. The interface is available in any browser and has a dialog box for setting time periods and visualizing changes, which are calculated using the approach above. Taking into account the frequency of satellite images, the algorithm searches for satellite images in the appropriate area within the next two weeks from the specified date and calculates land-use classes and their changes based on them. The results can be downloaded to Google Drive via the GEE Code Editor taskbar (*Fig. 4*).

To ensure proper functionality of the developed plugin within the GEE environment, a standard three-step procedure must be followed to configure access and permissions:

- Step 1: Project Creation and Registration. A new project must be created or an existing one selected in the Google Cloud Console. The project should then be registered for *non-commercial use* within the Earth Engine platform to obtain appropriate access rights.
- Step 2: Enabling the GEE API. Once the project is created, the user should open it in the Cloud Console and navigate to API & Services → Library. By searching for "Google Earth Engine API", the corresponding service can be selected and activated by clicking Enable API. After a short activation period, the API will be ready for use.
- Step 3: Platform Access. Following successful activation, users can proceed to the GEE platform. The registered project will now be fully integrated and ready to operate with the necessary permissions for executing scripts, accessing datasets, and running applications within the GEE environment.

3 PRACTICAL RELEVANCE

The analysis of changes in land use in the context of socio-economic indicators was conducted in the administrative districts of the Donetsk region for the period from 2017 to 2020. The following socio-economic indicators were considered:

- change in the total population;
- change in emissions;
- gross harvest of agricultural crops by enterprises (cereals and legumes).

The choice was based on the availability of data and the desire for diversity to maintain high representativeness of the results.

The percentage of the area of change to the area of the district was calculated using QGIS and Excel tools. Among the calculated indicators of land-use category change, the largest are: –28 trees to crops (11 %), 28 crops to trees (4 %), 60 trees to shrub (4 %), –24 grass to crops (4 %) (*Fig. 5*).

It is worth noting a fairly high rate (more than 75 % of the total land area) of no change in the districts, which indicates no significant changes in land use. This is correlated with the absence of significant changes in the economic and social situation in the region. Changes in statistical indicators from 2017 to 2020 do not exceed 7 % for the population, 8 % for the emission volumes indicator and 11 % for the gross harvest of crops indicator. It is important to note the difficulty of comparing statistical data after the administrative reform in Ukraine in 2020, which changed administrative units, resulting in certain inaccuracies in the data. Administrative districts that were not changed have been selected for comparison, but it is worth keeping this in mind.

The analysis of land-use changes and their impact on socio-economic indicators at the district level confirms the general trends. A reduction in agricultural land leads to a reduction in gross output, and a reduction in green space and a change to the category of agricultural land is accompanied by a sharp increase in emissions

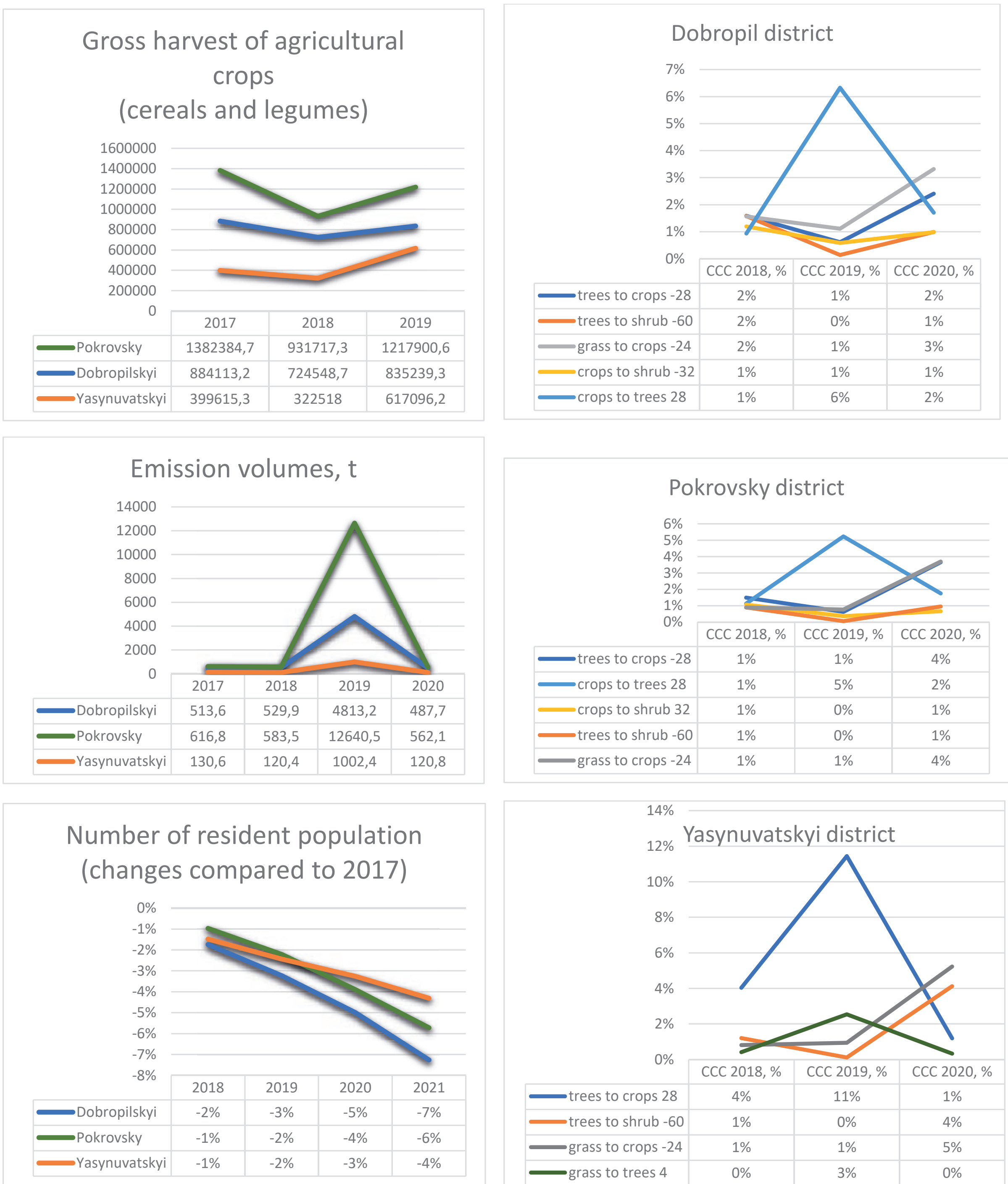

Fig. 5 | Statistical analysis of indicators changes at the level of administrative districts

(*Fig. 5*). At the same time, population decline does not depend on the category of land use or does not significantly affect its change. It is a natural process of reducing the number of rural population through internal and external migration.

Considering the macro-level of land classification in the Dynamic World dataset, which is the basis for testing the methodology for determining changes in the CCC, the calculation of percentage changes in the total area of the district is comparable to the magnitude of the classification error and therefore is considered only as a confirmation of the existence of a relationship between the indicators. At the same time, the analysis at the level of administrative region will show more relevant results.

To present more substantial results of the analysis of the impact of land-use changes on socio-economic factors, the research considered two administrative regions of Ukraine: Donetsk and Dnipro (*Fig. 6*). The relatively small values of the areas that have changed are due to the stable state of economic activity. It can be noted up to 18 % of the total area of the region and up to 7 % within one land-use class in Donetsk region and, consequently, 11 % of the total and 2 % within one class in Dnipro region. The regions are quite developed, with defined areas of activity, dominated by metallurgy, machine building, metalworking, energy, and agriculture [Main Department of Statistics in Donetsk Oblast, n.d.]. A 2 % change in agricultural land is directly correlated with a 3 % decrease in population in both regions. The increase in gross output by more than 25 % in the context of land-use change is due to a significant decrease in the shrub category (over 5 % in Donetsk oblast). As a rule, these are lands that are not used in economic activity and their involvement in economic assets is directly reflected in the indicators. At the same time, changes in emissions are not correlated with

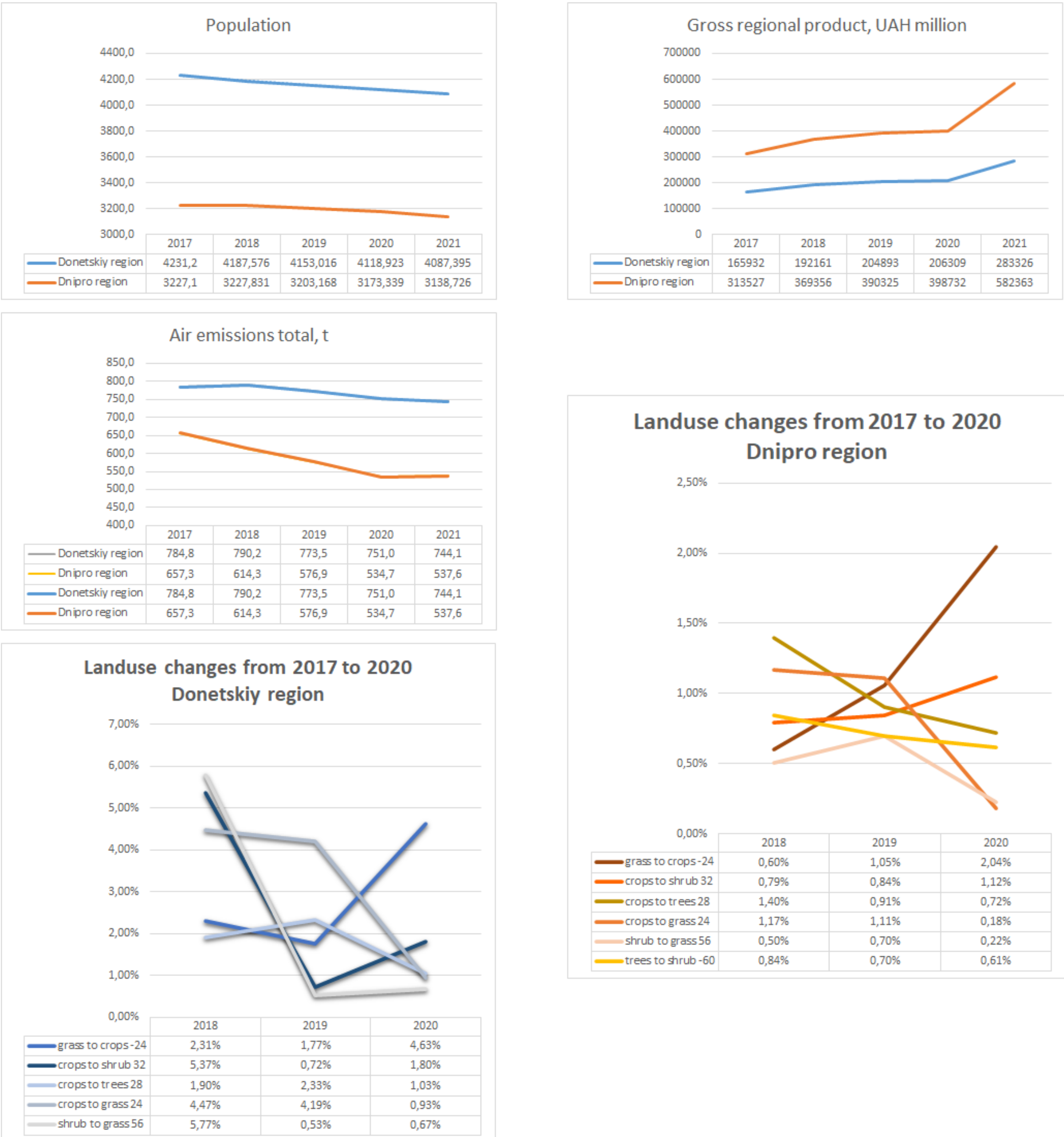

Fig. 6 | Statistical analysis of CCC changes at the level of regions

CCC	Dnipro Region CCC	Dnipro Region CCC	Donetsk Region CCC	Donetsk Region CCC
0 no change	2 355 116 ha	74 %	1 727 145 ha	65 %
24 crops to grass	414 845 ha	13 %	395 826 ha	15 %
28 crops to trees	53 956 ha	2 %	316 395 ha	12 %
–32 shrub to crops	31 150 ha	1 %	59 398 ha	2 %

Tab. 3 | Land-use changes from 2020 to 2023

changes in land use. The significant reduction of emissions by more than 19 % in Dnipropetrovska Oblast is not accompanied by drastic changes in significant areas of the land category. Accordingly, it can be concluded that this indicator is more influenced by factors such as the type of production in the region, the level of infrastructure renewal, or the installation of modern equipment at wastewater treatment plants.

To demonstrate global land-use changes, it is advisable to analyze the period from 2020 to 2023 when such fundamental events as the full-scale invasion of Ukraine by the Russian Federation took place. Unfortunately, statistical information is currently not available in the regions that are the location of military operations, so it is impossible to conduct a correlation analysis with the impact on socio-economic indicators. However, the total number of changes in land use indicates the huge impact of the conflict on the economic situation in the region. It can be noted more than 26 % of the total area in Dnipro region and 65 % in Donetsk region (*Tab. 3*). Another striking indicator is the significant change within the same class has been reclassified as grass and trees, which will certainly have a direct impact on the region's economic development and Gross Domestic Product (GDP). In can be noted more than 15 % of agricultural land in Dnipro region and more than 27 % in Donetsk region. This analysis allows us to quantify the economic losses from military operations in the region. Further development of the algorithm could be aimed at fixing the exact changes in land use and calculating direct losses from such changes during military conflicts. However, it should be mentioned that along with advantages such as the availability of raw data, such algorithms will always have questions about the accuracy and relevance of the final results, especially at larger scales such as local communities or administrative districts.

4 CONCLUSION

The statistical analysis conducted in this study reveals a significant correlation between the datasets, affirming the high accuracy of the Dynamic World land cover classes. This outcome not only demonstrates Dynamic World's efficiency in tracking land-use changes but also establishes its reliability as a pivotal tool in environmental monitoring.

The innovative algorithm proposed in this research marks a significant advancement in identifying land-use class changes. While it brings a transformative approach to change detection and analysis, it also acknowledges the inherent complexities in classifying certain land-use categories such as crops, grass, and built structures. These categories pose a challenge due to their intricate nature and spectral similarities.

An essential component of this research is the integration of social analysis following the detection of land-use changes. This step is crucial as it connects environmental shifts to societal impacts, including demographic changes, emission variations, and alterations in agricultural yields. By analyzing these correlations and visualizing patterns, the study not only quantifies the effects but also models potential scenarios, thereby offering specific policy recommendations.

The practical implications of this research are significant, particularly in the realms of policy formulation and strategic planning for sustainable land management. The detailed and accurate data provided by this study enhances the quality of decision-making processes, ensuring they are informed and effective.

The findings of this research underscore the importance of ongoing development and refinement of land-use classification tools. These tools must evolve to keep pace with changing environmental and socio-economic landscapes. Future research should focus on improving the algorithm's ability to navigate the complexities of diverse land-use categories and overcome the challenges posed by spectral similarity.

The benefits of an algorithm for monitoring land-use changes during military actions are multifaceted. Such an algorithm can provide critical insights into the environmental and infrastructural impacts of conflict. By analyzing land-use changes, stakeholders can better understand the extent of damage, prioritize areas for reconstruction, and plan sustainable development initiatives. This tool is particularly valuable in post-conflict scenarios for guiding recovery efforts, ensuring efficient allocation of resources, and aiding in the restoration of affected communities and ecosystems.

By providing a framework for monitoring and quantifying land-use changes, the proposed algorithm supports data-driven decision-making essential for sustainable urban development, environmental protection, and post-conflict recovery that correlates with several United Nations Sustainable Development Goals (SDG), particularly SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 15 (Life on Land). Furthermore, the integration of socio-economic and environmental analyses aligns with the UN 2030 Agenda's emphasis on building resilient infrastructure, fostering inclusive and ensuring responsible management of terrestrial ecosystems /United Nations 2015/.

Furthermore, the algorithm aligns with broader European Union (EU) priorities in land use and sustainability. The EU emphasizes responsible land management, environmental protection, and sustainable urban development. By integrating these priorities into future steps, the algorithm can be developed further to not only assess the impact of military actions but also to contribute to ongoing EU efforts in sustainable land-use planning. This includes the development of strategies for resilient urban and rural landscapes, adherence to environmental regulations, and contribution to EU-wide initiatives such as the European Green Deal, which aims to make the EU's economy sustainable.

Future steps could involve:

- enhancing algorithm accuracy: continuously improving the algorithm's precision and reliability through advanced data analytics and machine learning techniques;
- expanding the scope of analysis: extending the algorithm's functionality to monitor other aspects of land use relevant to EU priorities, such as agricultural productivity, urban expansion, and conservation areas.

By aligning with EU priorities and enhancing its capabilities, the algorithm can become an extremely useful tool not just for post-conflict reconstruction but also for broader land-use management and sustainability efforts within the European context.

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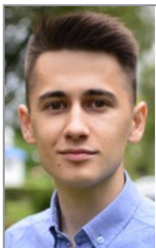

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