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**STUDY OF CHANGES IN LAND COVER CATEGORIES IN UKRAINE
BASED ON REMOTE SENSING DATA**

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Land cover change is an important research area in global environmental change and sustainable development. Understanding land cover trends is the basis for rational planning and management of land resources, and is essential for land conservation and sustainable development. In this study, the land cover transition matrix was used because its results do not depend on the type and amount of land cover, and the data were analyzed for 2000-2015. This article proposes a method of using Google Earth to obtain public land cover datasets, and then performing mapping algebra operations on these data to construct a land cover transition matrix that can be used for a large study area to analyze land cover change in Ukraine. This method was used to construct this matrix for the period 2000-2015 in Ukraine. The matrix data show that the land cover change in Ukraine for the period 2000-2015 is moderate, with a total change of 2.244%, which is very low compared to the total area of Ukraine. The share of cropland decreased, while the share of urban and built-up land increased. The practical significance of the results is the ability to quickly and efficiently obtain data on land cover changes in the study area and to assist users in analyzing trends and patterns of land cover changes.

Keywords: *Land cover change, Google Earth Engine, Land cover transition matrix*

Problem description. As populations increase and economies grow, conflicts between people and natural resources become more apparent, and land, one of the most important natural and economic resources, becomes more vulnerable. Population growth has led to increased demand for arable land, resulting in deforestation and grassland loss, while economic development has promoted the expansion of urban areas and the conversion of arable land. Land use cover change (LCC) has been an important research topic in the field of global environmental change and sustainable development since the 1990s [1-4].

Recently, with the development of remote sensing technology and sensors, satellite remote sensing images have become an integral part of land change research. Improved long-term monitoring capabilities and high spatial resolution have made it possible to create regional and global long-term high-resolution land change datasets. For example, the Global Land Cover Characterization Database was created by USGS researchers from 1 km spatial resolution AVHRR data, the University of Nebraska-Lincoln, and the European Commission Joint Research Center [5]. The MODIS Collection 5 global land cover at 500 m spatial resolution was produced by Boston University, USA [6], and the European Commission's Joint Research Centre coordinated 30 international research groups to produce the Global Land Cover Database for the Year 2000 (GLC2000) [7]. Although these datasets have been of great value for global land use change and ecological studies, they also have problems of low resolution and official download links that not working for after the

datasets have been released.

Analysis of recent research and publications. The traditional method of land change analysis is to obtain remote sensing images of different time periods in the study area, and after classifying the land cover types by image pre-processing, image enhancement and appropriate classification algorithms, a land classification map is obtained, and then processed by using Geographic Information System (GIS) software, and finally a Land cover transition matrix is obtained to analyze the degree, location and type of land change.

The use of satellite imagery to monitor land cover changes has been studied by many scientists. Manandhar R., Odeh I. O., Pontius R. G., Mallinis G., Koutsias N., Arianoutsou M., Phalke A. R., Özdoğan M., Thenkabail P. S., Erickson T., Gorelick N., Yadav K., Congalton R. G., Tamiminia H., Salehi B., Mahdianpari M., Quackenbush L., Adeli S., Brisco B., Solomianchuk L. Y., Kohan S. S. et al. [8-12, 25, 26].

Manandhar et al. created a land cover transition matrix for an area of about 379 km² in New South Wales, Australia, to analyze land change based on classified maps obtained from ground-based satellites in 1985 and 2005. The results of the study showed that the net change in area was less than 7%, while the total change was more than 28% [8]. Mallinis et al. created three land transfer matrices for two mountainous areas within 20 km of the Greek capital to analyze changes from 1945 to 2007. The final results showed that despite the geographical proximity of the two areas, the land cover changes were different [9]. The traditional method requires a high level of remote sensing image interpretation ability for researchers to be able to identify the

differences in land cover types in the research area, and the data processing also requires certain hardware resources. Based on the current special situation, we need to find a fast processing method to achieve the assessment of land cover changes in the research area.

Google Earth Engine (GEE) is a Cloud-based geospatial data processing platform that relies on Google's high performance computing resources for the computation of planetary-level geoscience data. The platform also includes a large collection of publicly available geospatial datasets, such as Landsat, MODIS, Sentinel 1, 2, 3, and climate and socio-economic datasets, totaling petabytes and currently being updated. Users can work with the datasets directly on the GEE platform without having to download the data to a local computer. Tamiminia et al. analyzed 349 scientific articles on GEE published in 146 different journals from 2010 to 2019 and found that 90% of the studies used remote sensing datasets and 10% used ready-to-use products [11]. Phalke et al. used Landsat-7 and Landsat-8 data from the GEE platform combined with random forest algorithms to map the area of agricultural land in 64 countries in Europe, the Middle East, Russia and Central Asia in 2015 [12]. All of them confirmed the reliability and potential of the GEE platform when dealing with large-scale geographic data.

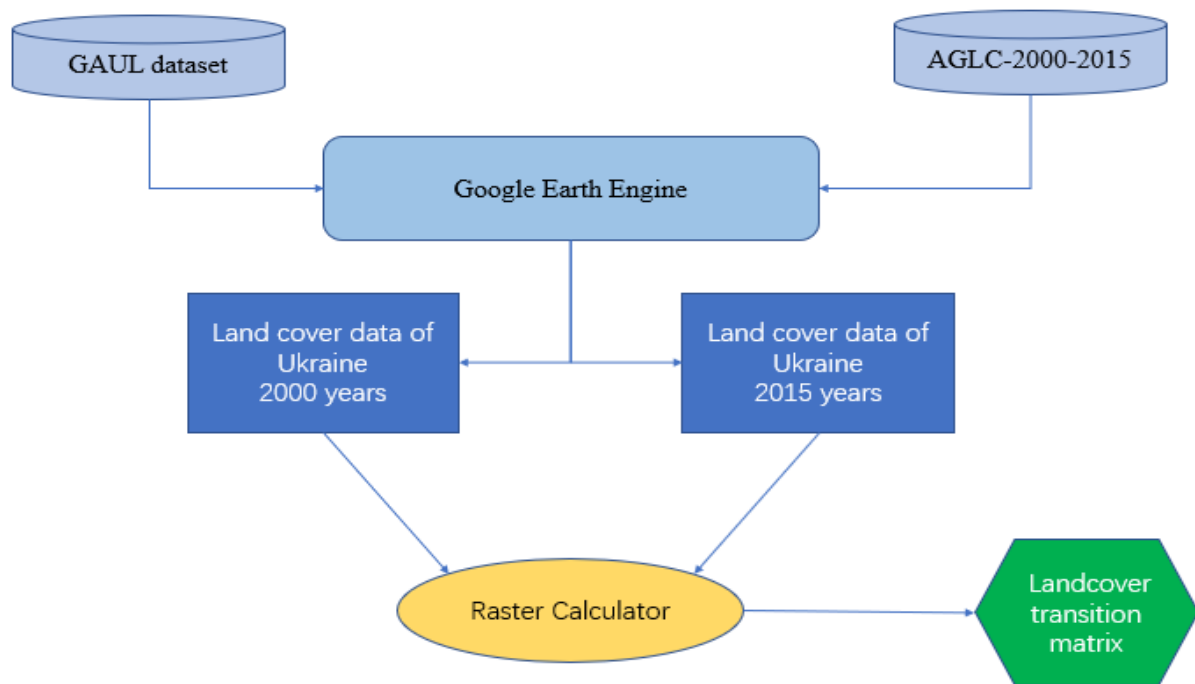


Fig. 1. Process of producing Land cover transition matrix.

The purpose of this study is to analyze land cover changes in Ukraine over 15 years by producing a land cover transition matrix after obtaining land cover classification data for Ukraine from 2000-2015 through GEE.

Materials and methods of research. The main research methods are analysis and synthesis. Also, the theory of map algebra and mathematical models were used for statistical analysis of changes in the areas of land cover types. It should be noted that GEE was used to obtain land cover data for Ukraine for 2000 and 2015 from the publicly available global land cover dataset AGLC-2000-2015. The data were represented as raster images, where the value of each pixel represents the class code of the land cover classification. Next, the raster data were processed using map algebra and GIS techniques to determine the number of areas where changes occurred, after which the data were exported to CSV format and statistical calculations were performed to create a land cover transition matrix. Finally, the data obtained from the

land cover transition matrix were analyzed to determine trends in land cover change over 15 years in Ukraine.

Research results and discussion. This paper provides an example for other researchers by quickly constructing a land cover transition matrix for the study area through the GEE platform using a publicly available land cover dataset. Other researchers can refer to this paper to quickly construct the land cover transition matrix for the study area and start the analysis.

The Land cover transition matrix provides valuable information for analyzing the changes, losses, gains, and exchanges of land cover categories, but the matrix cannot show the changes of land in continuous time and thus cannot show the land change process comprehensively. Also, if the study area is too large, such as at the national level, dramatic local regional changes may be missed.

The study area is the whole territory of Ukraine, and the national administrative boundaries use the Global Administrative Unit Layer (GAUL) dataset included in the GEE platform. This dataset was implemented by FAO in the CountrySTAT and Agricultural Market Information System (AMIS) projects. This version of the GAUL dataset is simplified with a resolution of 500 meters [13].

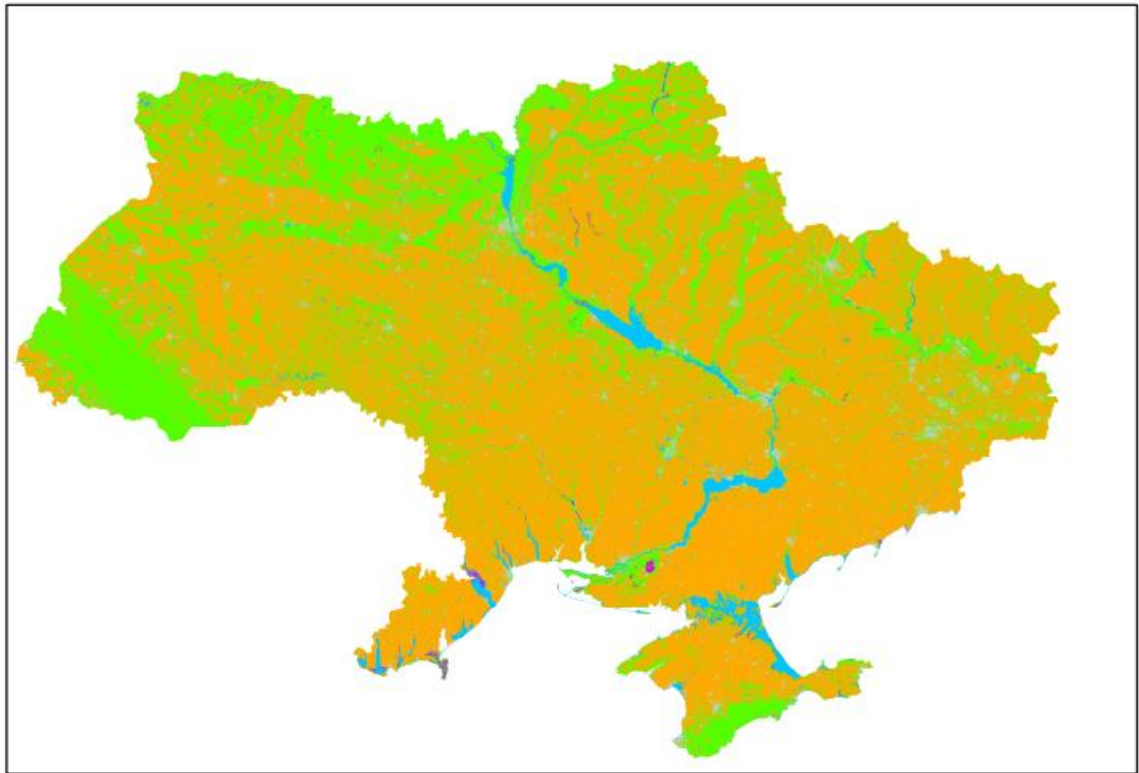
The land cover dataset uses the Annual Global Land Cover 2000-2015 dataset (AGLC-2000-2015) produced by Xu et al. in 2021[14]. The dataset was generated using multiple global land cover products, imagery data generated by the Landsat satellite series and large number of manually interpreted samples combined with various machine learning algorithms, and through the Google Earth Engine platform. The mean overall accuracy based on random forest classification models is more than

80% at the continental scale.

The GEE also includes other land cover datasets, such as ESA World Cover 10m v100 is produced by the European Space Agency (ESA) based on Sentinel-1 and Sentinel-2 data, it contains global land cover data for the year 2020 [15]. CGLS-LC100 Collection 3, a component of the Copernicus Global Land Service (CGLS), this dataset provides global land cover maps at 100m spatial resolution for the years 2015-2019 [16]. MCD12Q1 is produced by the U.S. Geological Survey (USGS) and provides global land cover maps at 500 m spatial resolution for the years 2001-2021 [17].

Compared to these datasets, AGLC-2000-2015 has a more appropriate temporal and spatial resolution and can effectively reflect the distribution and annual changes of land cover in Ukraine at 30m resolution since 2000.

In AGLC-2000-2015, land cover is classified into 10 categories: Cropland, Forest, Grassland, Shrublands, Wetland, Water bodies, Tundra, Urban and Built-up Lands, Barren, Permanent snow and ice. According to the actual situation, we reclassify the land cover data into 5 categories: Cropland, Forest and Grassland (F&G), Urban and Built-up Land (UABL), Water, Other (Fig. 2-4). Other includes Barren, Shrublands, Wetland, Permanent snow and ice.



Year 2000

Land Cover Categories

- Cropland
- Forest and Grassland
- Water
- Urban and Built-up Land
- Other

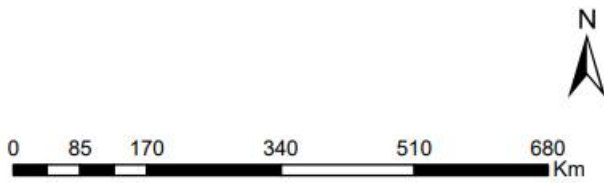
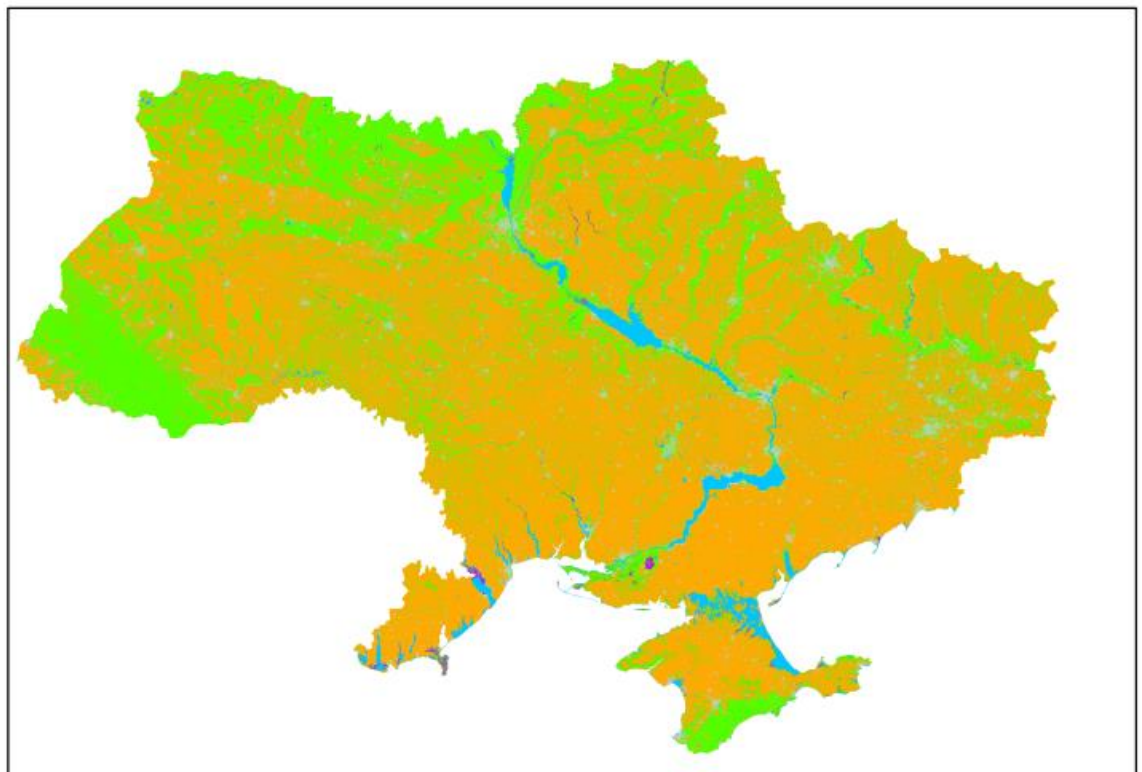







Fig. 2. Land Cover Categories Map - Ukraine 2000.



Year 2015

Land Cover Categories

-  Cropland
-  Forest and Grassland
-  Water
-  Urban and Built-up Land
-  Other

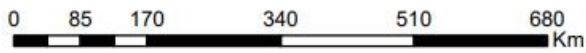


Fig. 3. Land Cover Categories Map - Ukraine 2015.

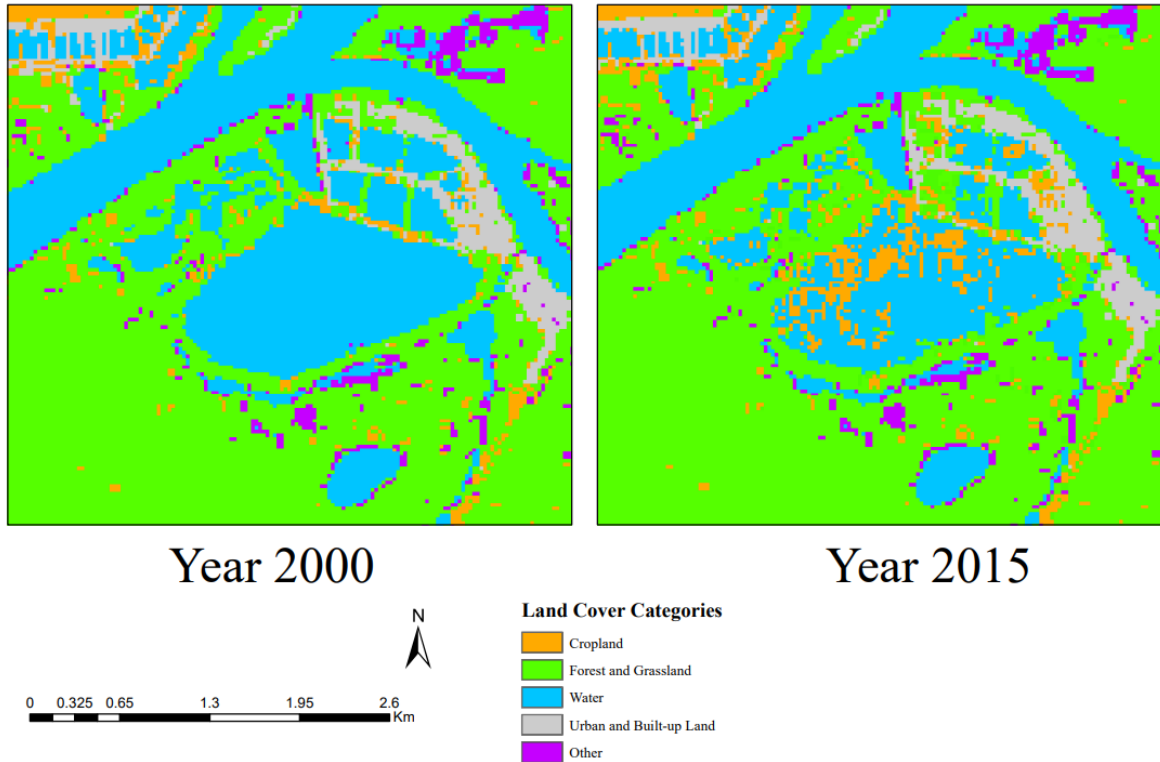


Fig. 4. Land Cover Categories Map -parts of an area.

The Land cover transition matrix describes the change of land use status over time, and its principle is to list the type transfer probability of land use change in the form of a matrix , which can visually reflect the change of land use area in a certain region, The value of its area is determined by the method described in [24], and also reflect the inter-transformation relationship and source probability between each category in detail, and then understand the structural characteristics of land cover types before and after the transfer,. Although this method has some limitations, it is one of the most commonly used methods to study the process of land use change [18-22]. The mathematical expressions are as follows:

$$P = (P_{ij}) = \begin{pmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \dots & \dots & \dots & \dots \\ P_{n1} & P_{n2} & \dots & P_{nn} \end{pmatrix}$$

n is the number of land use types. P_{ij} is the transfer probability of type i changing to type j , and the following conditions are:

$$0 \leq P_{ij} \leq 1 (i, j = 1, 2, 3, \dots, n)$$

$$\sum_{i=1}^n P_{ij} = 1$$

In this study, raster images of land cover for different years were processed directly using map algebra. After that, the product of the area of land cover category change (the number of pixels changed multiplied by the area of that pixel) was found, and finally, the percentage was calculated to create the land cover transition matrix. Detailed statistical information is provided in Table 1.

In Figure 5, the squares represent pixels, the numbers in the squares represent land cover classification numbers, and the green color indicates pixels that have not changed. Yellow indicates pixels that have changed.



Fig. 5. Theory of raster calculation.

Table 1 shows the land cover transition matrix of Ukraine in 2000-2015, where the values represent the percentage of each land category. Decimals are kept to the last 3 digits. The transformation matrix is actually a two-dimensional table. The row totals show the proportion of land cover categories at the starting time, the column

totals show the proportion of land cover categories at the ending date, and the diagonal values indicate the probability of no change.

Table 1. Land cover transition matrix 2000–2015 (%)

Year 2000	Year 2005					Total 2015(P_{i+})	Loss
	Cropland	F&G	UABL	Water	Other		
Cropland	64.477	0.209	0.571	0.001	0.002	65.261	0.784
F&G	0.144	28.233	0.022	0.025	0.005	28.429	0.196
UABL	0.028	0.007	3.370	0.001	0.001	3.407	0.037
Water	0.037	0.042	0.003	2.547	0.004	2.633	0.087
Other	0.002	0.013	0.001	0.002	0.252	0.270	0.018
Total 2015(P_{+j})	64.688	28.505	3.966	2.576	0.264		
Gain	0.212	0.272	0.597	0.030	0.012		

The net change (D_j) represents the difference in the overall quantity. The net change for a land cover category is the difference between the proportion in the starting period and the proportion at the end, that is, the difference between the row totals and column totals for a particular land cover category in the matrix, with the result taken as an absolute value. It is calculated using the following formula:

$$D_j = |P_{+j} - P_{j+}| \quad (1)$$

P_{+j} , Proportion of land cover category J at the beginning of the research

P_{j+} , Proportion of land cover category J at the end of the research

However, the net change only reflects the proportional change of a certain category of land cover, and cannot reflect the change of spatial location of that category of land cover. For example, if agricultural land is acquired for construction and the same area of agricultural land is compensated at another location, the net change in agricultural land is zero, but the actual spatial location has changed. This

type of change is called a swap change.

The swap change (S_j) refers to the gains and losses for a Land category at different locations and is calculated as twice the minimum value of gains and losses [23], it is calculated using the following formula:

$$S_j = 2 * \text{MIN}(P_{+j} - P_{jj}, P_{+j} - P_{jj}) \quad (2)$$

The total change in land cover category, which is the sum of net change and swap change, is calculated using the following formula:

$$C_j = D_j + S_j \quad (3)$$

According to the data in Table 1, all land use types in Ukraine have changed, but the magnitude of the changes is not obvious. The largest land cover category is cropland, followed by forest and grassland, and then Urban and Built-up Lands.

The diagonal line in Table 1 shows the percentage of different land cover categories that remained unchanged between 2000 and 2015. About 64.477% of Cropland in 2000 remained unchanged in 2015, but the largest losses of Cropland over the 15-year period were Urban and Built-up Lands and Forest and Grassland. Urban and Built-up Lands had the largest percentage increase.

Table 2, Summary of landscape changes (%)

	Total 2000	Total 2015	Gain	Loss	Total change	Swap	Absolute value of net change
Cropland	65.261	64.688	0.212	0.784	0.996	0.423	0.573
F&G	28.429	28.505	0.272	0.196	0.468	0.392	0.076
UABL	3.407	3.966	0.597	0.037	0.634	0.074	0.559
Water	2.633	2.576	0.030	0.087	0.116	0.059	0.057
Other	0.270	0.264	0.012	0.018	0.030	0.025	0.006
Total	100	100	1.122	1.122	2.244	0.973	1.271

Based on the data in Table I and equations (1), (2) and (3), the data in Table 2 are calculated. According to the data in Table 2, Urban and Built-up Lands received the largest proportion of transfers from other land categories. Cropland lost the most percentage of cover, mainly in terms of amount change. The changes in Forest and Grassland are mainly reflected in the spatial location changes.

Conclusion. This paper proposes a method that involves the minimum number of steps required to construct a land cover transition matrix and perform statistical analysis based on the matrix data. As one of the most important natural resources closely related to human activities, land resources are often influenced by various complex factors such as socio-cultural environment, economic interests, and politics and regulations. In order to determine its change pattern, further research is needed by synthesizing various data, which will be explored in a future work.

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Л.Жень

ДОСЛІДЖЕННЯ ЗМІН ТИПІВ ЗЕМЕЛЬНОГО ПОКРИВУ В УКРАЇНІ НА

ОСНОВІ ДАНИХ ДИСТАНЦІЙНОГО ЗОНДУВАННЯ ЗЕМЛІ

Зміна ґрунтового покриву є актуальним напрямком досліджень глобальних екологічних змін та сталого розвитку. Розуміння тенденцій змін земного покриву є основою для раціонального планування та управління земельними ресурсами і має важливе значення для забезпечення охорони земель та сталого розвитку. У цьому дослідженні було використано матрицю змін земельного покриву (land-cover transition matrix), оскільки її результати не залежать від типів та кількості земного покриву, а дані були проаналізовані за 2000-2015 роки. У цій статті запропоновано метод використання сервісу Google Earth для отримання публічних наборів даних про земний покрив, а потім виконання операцій картографічної алгебри над цими даними для побудови матриці змін земельного покриву, яка може бути використана для великої досліджуваної території з метою аналізу змін земного покриву в Україні. Використано цей метод для побудови цієї матриці за період 2000-2015 рр. на території України. Дані матриці показують, що зміна земельного покриву в Україні за період 2000-2015 рр. є помірною, із загальною зміною 2,244%, що є дуже низьким відносно усієї площі України. Частка орних земель зменшилася, а частка міських та забудованих земель збільшилася. Практичною значущістю результатів є можливість оперативно та ефективно отримувати дані про зміни земного покриву на досліджуваній території та надавати допомогу користувачам в аналізі тенденцій та закономірностей змін земного покриву.

Ключові слова: *зміна земного покриву, Google Earth Engine, матриця змін земельного покриву*