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SPATIAL-TEMPORAL GEODYNAMICS MONITORING OF LAND USE AND LAND COVER CHANGES IN STEBNYK, UKRAINE BASED ON EARTH REMOTE SENSING DATA

The article presents the analysis and monitoring of land-use/land cover (LULC) changes considering the case study of Stebnyk, Lviv region, Ukraine, as an area of increased anthropogenic hazard impact (characterized by the karst sinkholes creation which is the result of extracting the potassium salt from underground mines and the violation of their conservation). The extraction was carried out without backfilling the underground excavations, resulting in the void formation of about 33 million m^3 lying under the residential sector and road infrastructure, and could potentially be the site of future landslides/sinkholes that threaten the inhabitants and landscape ecosystem of the region as a whole. The research is based on Landsat 7 and 8 satellite images (made in February 2002 and December 2019, respectively), and ETM+ (Enhanced Thematic Mapper) data. Supervised classification conducted by maximum likelihood method was used to identify and analyze the spatial and temporal LULC changes on the territory divided into four classes. Vegetation indices NDVI have been calculated, analyzed and featured for further supervised classification. The accuracy of the obtained data had been improved by raster image filtering. A post-classification comparison approach was used to analyze LULC changes over the research period. It was established that for the period 2002–2019 the built-up area has increased by 5.61 %, and the areas of forests and fields have decreased by 2.77 % and 2.36%, respectively. The area of water bodies has undergone the least changes (+0.37%). The accuracy estimation of carried out classifications showed that the classification based on RGB images is more accurate than the classification based on the NDVI; the filtered classification showed more accurate results for most classes, than the unfiltered one. LULC monitoring for balanced regional, local and national development, as well as territorial planning, is a new area of the application of the Earth remote sensing (ERS) data in Ukraine. It allows assessing the state of the geocomponents system and predicting their further changes. The study of anthropogenic activity makes it possible to predict dangerous technogenic processes and thus avoid or reduce their consequences. The results of the research can be used as a basis for further monitoring of the Stebnyk region. They will also be useful to territorial communities for harmonious, sustainable development and land management of the studied area.

Key words: Earth remote sensing data; monitoring, anthropogenic activity, supervised image classification, NDVI.

Introduction

Modern landscapes and ecologically destabilized environments are characterized by abnormally rapid changes in the geocomponents structural organization, landscape complexes, and their interconnections. Geographical envelope anthropization and, especially, surface anthropization, have escalated over the past 150–170 years [Tarolli et al., 2016] and transformed the natural environment to such an extent that this new era has been called the Anthropocene [Gaffney et al., 2017].

The new types of anthropogenic activities have caused changes in the dynamics of the atmosphere, hydrosphere, biosphere, and geosphere, particularly due to the shifts in the interactions of terrestrial systems and land use change [Steffen et al., 2015]. Today, human activity continues to alter landscapes through urbanization, further industrial development, and agricultural expansion [Waters et al., 2014; Li-An et al., 2018].

Szabó, et al. (2010) suggest that contemporary landscape research provides a scientific foundation for landscape planning and regional development. Researchers [Chiesura et al., 2003; Pelenc et al., 2015] emphasize that a complete replacement of natural landscapes with anthropogenic ones cannot maintain balanced regional or national development and would significantly accelerate their destruction. With the monitoring of the LULC changes, it is possible to effectively observe the increase or decrease in anthropogenic impact on a particular area and take these data into account for balanced terrestrial planning.

Since the 1970s, ERS data have been actively used to monitor and identify geomorphological changes [Cracknell, 2018]. ERS data depict the objective situation of processes and phenomena on the Earth's surface at a particular time, and regular repetition of images allows tracing their dynamics.

The technical development of space imaging systems and sensors placed on spacecraft and artificial satellites made it possible to obtain ultrahigh and high-resolution data and significantly improved its final quality [Cracknell, 2018]. Modern ERS data may sometimes compete in accuracy with data obtained from direct field surveys.

Considering the pace of landscape transformations, data taken within a wide time range were used to monitor them. ETM+ Landsat data falls under this category [Gong, 2013].

It should be noted that ultrahigh and high-precision ERS data are in most cases commercial and costly which makes regional and local monitoring based on them inefficient.

However, some space agencies provide free access to medium and low-resolution data, including data from Landsat satellite missions. These data allow conducting global monitoring, developing and evaluating the methods and algorithms of processing, analyzing, and using ERS data for both scientific and applied purposes [Burshtinska, Stankevich, 2010; Huan et al., 2019].

The publication [Newton et al., 2009] presents a critical assessment of using the remote sensing data for solving landscape ecology problems based on the analysis of 438 scientific papers (2004–2008). As a result, it was determined that 36 % of the studies directly mentioned remote sensing, and almost half of them used the Landsat data. The vast majority of research using remote sensing data are cartographic investigations. Remote sensing has become an important tool for studying the spatial structure of ecosystems at the global level [Gergel, Turner, 2017]. It is noted [Newton et al., 2009], that the possibilities of remote sensing are still not fully used by researchers of landscape changes and,herefore, this opens further prospects for the development of cooperation between remote sensing researchers, experts in geoinformation technologies, and landscape scientists.

The spread of ERS data application coincided with the rapid development of geoinformation technologies, which today have become an integral part of the research on the collection, processing, analysis, systematization and preservation of various data types.

Modern geoinformation systems (GIS) provide effective tools for studying, modeling and visualizing the spatial structure and dynamics of landscapes, especially the complex relationships between physical, biological and anthropogenic processes.

In the [Huan et al., 2019], authors analyzed articles published in the period 1990 – to 2019 on the Web of Science platform. The total number of publications in the field of GIS and landscape geomorphology for the specified period is 365. Compared to 1990, in 2016 the number of articles in these fields increased fivefold, which indicates a high interest, importance, and relevance of these investigations.

The study [Ayele et al., 2018] presents an assessment of the LULC changes dynamics in Northern Ethiopia between 1995 and 2014 based on Landsat images. The authors applied an object-based classification algorithm for the satellite image analysis. The vegetation index NDVI was also used to pre-detect land-use changes. Bayesian method in the maximum likelihood classification was tested for a detailed dynamics analysis of the spatiotemporal changes. The article demonstrates that using Landsat data to monitor surface changes of a large area (18,772.78 km^2) is possible and effective. But the issue of local LULC monitoring based on Landsat data remains open, as well as the accuracy of these classifications.

One of the branches of environmental monitoring is the study of geomorphological processes [Li et al., 2016]. Such studies include the monitoring of man-made objects as areas extremely hazardous for the environment, in the case when the regulations of their operation or conservation are violated.

The research [Thilagavathi et al., 2015] was conducted to monitor LULC changes in the Salem region, South India, which is the extraction site with a significant number of mines. The authors used three data sources: Landsat, IRS P6 LISS IV MX Image, and topographic maps (for 2002–2012). The research methodology is based on the method of supervised image classification to obtain and record spatiotemporal changes. The article does not contain information about the classification and accuracy of final results.

The publication [Kolios et al., 2013] is aimed at the LULC changes research of the coastal zone of Preveza, Northwestern Greece. Monitoring based on Landsat data was carried out in the period 2000–2009. The authors used vegetation indices (NDVI, EVI, RVI, SAVI, BI, CI) and band combinations, as well as image classification methods (parallelepiped method, minimum distance, maximum likelihood, the Mahalanobis distance, support vector machines, and neural networks). In conclusion, the possibility of improving the results by increasing the input data resolution and monitoring on a seasonal basis is indicated.

The reviewed articles confirm the monitoring relevance of LULC changes for further analysis of the anthropogenic impact on the territory. The considered articles demonstrate the possibility of using ETM+ Landsat data to determine and record land-use changes and their spatiotemporal geodynamic.

The remote sensing methods are the predominant components in modern geomorphological research, and the analysis of the literary sources confirms this. The high demand makes it possible and relevant to expand the latest technological schemes and hardware for further development in this direction.

Purpose

The research was carried out to monitor LULC changes in the Stebnyk region, being based on ERS data, namely satellite images Landsat 7 and Landsat 8. In addition, there is an appeal to adjust the technological scheme, answering the question whether the quantitative and qualitative information is sufficient when using the data from these satellites.

Methodology

The research is based on publicly available ERS data: ETM+, Landsat 7, and Landsat 8 scenes for 2002 and 2019, respectively.

To achieve the research purpose, satellite image classification is used as one of the common methods for analyzing ERS data [Dhingra et. Al., 2019]. The purpose of image classification is to arrange separate pixels forming the image into groups according to the land cover type which they represent.

The image classification process is based on categorizing each of the pixels into the appropriate class within the captured scene. Each pixel of a multispectral image corresponds to a set of values of spectral characteristics or a vector in the spectral space, whose dimension is equal to the total number of zonal images in the multispectral image.

Therefore, the classification process may be summarized as the pixel distribution into classes according to a certain algorithm in obedience to the surface/objects which they display in the image, reflectivity characteristics (spectral brightness value) in one or more zones of the electromagnetic spectrum. [Riese et al., 2019].

The research used the supervised classification according to the method of maximum likelihood with the optimal selection of training samples (signatures) to achieve the purpose. The supervised classification process was divided into the following main stages: classification planning; selection of reference sites (formation clusters); classification process; assessment of the classification quality, registration of the results; evaluation of the classification accuracy.

Within classification methods, there is a direct relation between the accuracy of the obtained results and the spatial resolution of the input data, because the classes are formed on the basis of pixel data (the higher the pixel resolution, the more objects on the ground can be identified with better accuracy).

To ensure classification accuracy, it is important to analyze the region of study, its geomorphological features, and types of land cover to form the appropriate classes and samples.

One of the methods for improving the quality of acquired classifications is to filter raster images. In accordance with the results, the optimal filter is selected and the filtering effect on the classification quality is analyzed (for example, by taking into account the change in areas of selected land cover types after the effect of filtering).

Considering the analyzed sources [Kolios et al., 2013; Ayele et al., 2018], it is advisable to use vegetation indices for an extended analysis of LULC changes on the territory (the vegetation index should be selected with taking into account the properties and characteristics of the studied region surface). As a result, a comparative analysis of the quality of determining the areas of the classes based on different data is possible.

Geomorphological analysis of the study region

Stebnyk is a city in the Drohobych-Boryslav district, Lviv region, a separate unit of the Carpathian agglomeration, Ukraine. The study region extends to the mixed-forest piedmont hill and meadow pebble mountain and foothill areas surrounded by coniferous-deciduous lowlands. The research region is known for one of the largest potassium salt deposits in Ukraine. The potassium salt deposit in Stebnyk is located on the territory of the nappe of the Boryslav-Pokutsky geological region.

The deposit was discovered in 1834. Its chemical composition contains mainly the salts of sulfate type characterized by complex and unique salt minerals and an extremely high clay material content. Among the potassium-magnesium salts, kainite and langbeinite are the most common, while sylvite and carnallite are of subordinate importance. Much less common are polyhalite, shungite, leonite, epsomite, kieserite, anhydrite, astrakhanite, and occasionally vantgophyte, leveite, syngenite, etc. In addition, halite is an integral part of all potassium salt rocks [Dyakiv et al., 2019; Snitynskyi et al., 2021].

The mining allotment territory is a field with small river valleys and a ravine (clough) network [Gotinyan et al., 2009].

The potassium salt deposits in Stebnyk were mined by two underground mines with a total production capacity of 4 million tons per year. The development system is room-and-pillar mining; the chambers are 60–120 m high, 15–42 m wide, and by 100 m long. The produced space was maintained by leaving inter-chamber and inter-floor pillars 12–24 m wide [Rudko et al., 2001].

Potassium salts mining, according to the initial projects, was carried out without the backfilling of spent underground excavations, resulting in the formation of the voids of about 33 million m^3, which led to the Earth's surface subsidence and dips formation [Rudko et al., 2001; Chepurna, Samborska, 2017].

The total volume of underground karst cavities is 440 thousand m^3, posing a significant danger and creating prospects for an anthropogenic disaster. The increase of aggressive water inflow into the mines has intensified the karst emptiness formation, represented by leaching pores, cracks, flushes, caverns, sinkholes, and chambers. Karst phenomena violated the integrity of functioning structures, buildings, and utilities. The deposit development caused surface deflection [Savchyn et al., 2019; Zaiats et al., 2017], underground and surface karst formation. Its number and intensity, despite the mining cessation due to complicated hydrogeological conditions, increases over time [Chepurna, Samborska, 2017].

In September 2017, on the territory of the Stebnyk deposit, a karst failure occurred, whose funnel reached 220–230 m in diameter, and 45–47 m in depth (see Fig. 1). Power transmission line 220 failed, as its pillars fell into a funnel. Also, the failure damaged the Drohobych water supply system [Dyakiv et al., 2019; Zaiats et al., 2017].

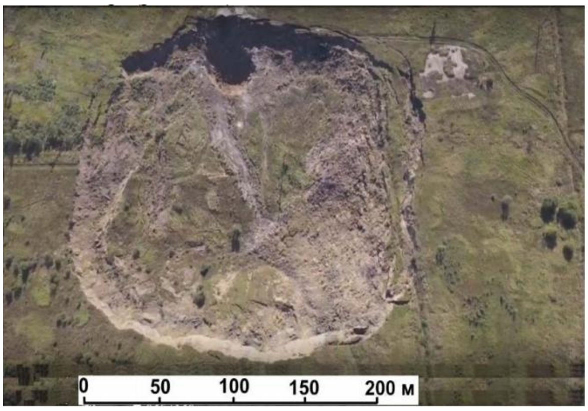


Fig. 1. Form and size of the landslide, having occurred on September 30, 2017, at the mine No. 2 [Dyakiv et al., 2019].

The landslide is located nearby the highway Pisochne – Skhidnytsia – the main highway to the resort of national importance, Truskavets. The distance from the highway to the karst sinkhole is about 300 m, while the salt bed and mining chambers lie under the road [Kuzmenko et al., 2019]. The place of the landslide continues to deform; further development of the failure with the formation of a karst lake is shown in Fig. 2.

Fig. 2. Fragment of the failures obtained from the unmanned aerial vehicle (UAV) Arrow in April 2020.

In the Stebnyk research region (Fig. 3), human activity has caused such landscape and geomorphological changes which are hazards for the inhabitants right now. The landslides that occurred on the territory testify that the regulations for the potash salts extraction were not executed and the environmental foundations of mine conservation after their closure were neglected. This can lead to landslides in other parts of mines, where residential buildings, highways, hydro and power supply facilities are located [Savchyn et al., 2019; Zaiats et al., 2017]. This indicates dangerous technogenic activity in the region that impend the population and infrastructure.

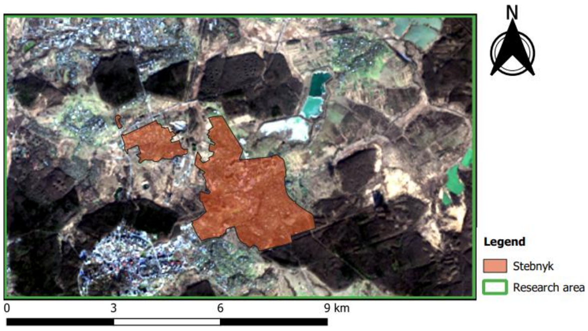


Fig. 3. Research region with Stebnyk city border on RGB Landsat 8 image (December 2019).

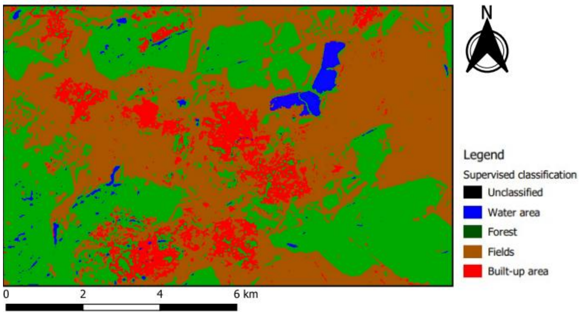
Results

The classification was done in the QGIS software environment by using the SACP plugin based on multispectral satellite images Landsat 7 (February 2002) and Landsat 8 (December 2019). To be able to use images as the basis for classification, n-bit digital numbers were converted to Top of Atmosphere (ToA) Reflectance, and a procedure for radiometric correction of sensory and atmospheric effects was performed. To improve the quality of the further classifications, a pansharpening procedure was performed, and the pixel resolution was increased to 15 m.

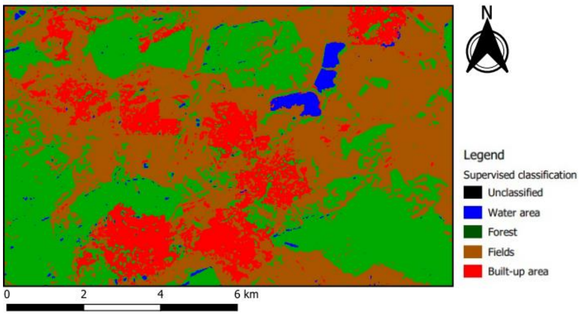
After deciphering and analyzing the research area, an initial decision was made to classify the territory and subdivide it into 4 classes (built-up area; forests; water objects; fields).

The classification process was based on collected regions of interest (training samples or clusters) that characterize typical sites for each class. The results of the supervised classification of RGB images are shown in Fig. 4.

With a small number of clusters, different land cover types were grouped into classes with the most similar pixel characteristics during the classification process. For example, the class of built-up area also includes road and rail networks, open-pit mining sites; fields include deforestation areas, urban green areas, grass-covered areas, arable land, and pastures.



a



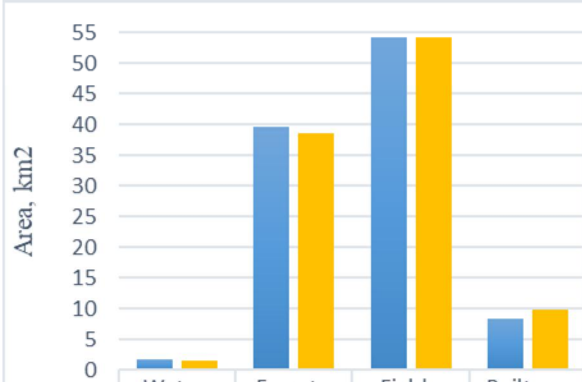
b

Fig. 4. The supervised classification of Stebnyk research region (green color – forests; blue – water; red – build-up and brown – fields areas); a) on the basis of the Landsat 7, 2002, b) on the basis of the Landsat 8, 2019.

A visual analysis of the classifications revealed correctly identified forest areas, but the classification of water objects and built-up areas is somewhat ambiguous. Due to the width of the rivers and streams flowing in the research area (on average 2 m), it is impossible to identify individual pixels of the river network, the classification algorithm had not detected rivers. The results reflect some water objects in areas that are not covered with water according to geomorphological analysis, but it cannot be stated unequivocally that this is incorrect, since increased soil moisture (marshland) in this area is possible, which is difficult to identify when deciphering images. The research region is characterized by a suburban type of buildings (houses are loosely located, surrounded by yards, gardens, and orchards; a low percentage of multi-story buildings), which means that built-up occupies a small percentage of the pixel and is less than the area of other classes (mainly fields).

According to the visual analysis of the images classification when comparing the 2002 and 2019 results, there is a noticeable increase in the built-up area and an increase in the heterogeneity of the forest area and fields. Landsat 8 image classification was made with higher quality than Landsat 7 classification. Thus there are fewer small groups of pixels, which do not reflect the real characteristics of the territory due to the improved shooting system characteristics.

A classified raster can be assessed not only visually but also mathematically based on the automatic calculation of the number of pixels that fall into each of the classes. In this way, the area of classes was determined and the dynamics analysis of the LULC changes in the areas was carried out. The obtained data are presented in the form of a diagram in Fig. 5.



	Water, km2	Forests, km2	Fields, km2	Built-up, km2
2002	1.76	39.74	54.32	8.48
2019	1.45	38.63	54.36	9.86

Fig. 5. Bar chart of LULC changes in the Stebnyk region for the period 2002–2019.

The bar chart in Fig. 5. shows that over 17 years the built-up area has increased largely due to a decrease in the forest area. The area of water objects did not change significantly. The area of the fields remained practically unchanged.

To improve the quality of the classification, filtering was applied by using the majority filter. We set the search for pixels that do not border on the same class pixels (cluster). There is a following condition: at least a pixel of one cluster border denser on 4 pixels of the same cluster; if it borders on 3 or less pixels, it is filtered out, and the raster cell is filled with the cluster of pixels, which border on it the most. Single pixels that are considered to be random were filtered out. The filtration results are shown in Fig. 6, 7.

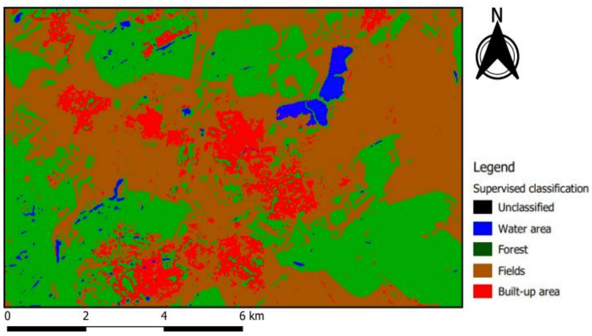


Fig. 6. Classification based on Landsat 7 RGB image (2002) after the application of the majority filter.

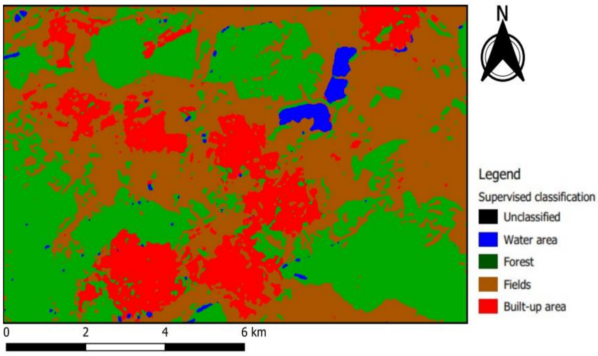


Fig. 7. Classification based on Landsat 8 RGB image (2019) after the application of the majority filter.

The number of random points that incorrectly characterized the surface has decreased significantly. The classification of the built-up area has become denser, fields and forests have become homogeneous. To analyze the effect of filtration on the area of various classes, reports on filtered classifications were generated, and the report data were processed. A bar chart is used (Fig. 8.) to visualize the comparison results of the class areas on unfiltered and filtered classifications.

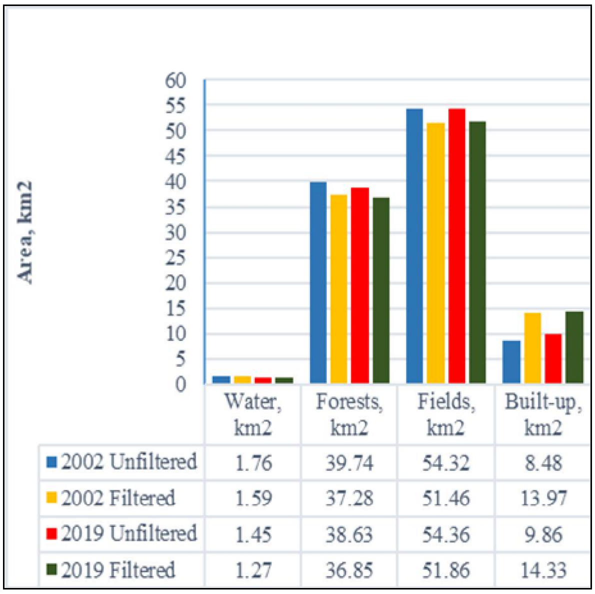


Fig. 8. Comparison between areas calculated by unfiltered and filtered classifications based on RGB images.

The research surface is characterized by a significant area covered with forests and fields. Taking these characteristics into account, a normalized difference vegetation index (NDVI) was used as a foundation for supervised classification, further analysis and comparison of the spatiotemporal LULC changes.

The index is the difference between the bands of multispectral images calculated to create a new raster layer to highlight certain attributes [Coops, Tooke, 2017]. NDVI is a common index in remote sensing and is a combination of surface reflectance at two or more wavelengths that are used to highlight a particular feature of the vegetation [Hatfield, Moran, 2014]. This index uses the difference between the near-infrared spectral region of the electromagnetic spectrum (where vegetation shows high reflectivity) and the red one (where vegetation has very low reflectivity). It is calculated according to the formula [Tucker, 1979]:

$$NDVI = \frac{NIR - RED}{NIR + RED}. \quad (1)$$

where *NIR* is the reflection in the near-infrared spectral region; *RED* is the reflection in the spectral region of the electromagnetic spectrum.

According to the formula (1), the density of vegetation (NDVI) at a certain moment of the image is equal to the difference between the intensity of the reflected light in the infrared and red spectral regions, divided by the sum of their intensity.

To display the NDVI values ranging from -1.0 to +1.0, a discrete scale is used. According to this scale, natural objects not associated with vegetation have a constant NDVI value (which can be used to determine this parameter) [Hatfield, Moran, 2014]. Table 1 presents the NDVI scale, where each value corresponds to a certain type of object on the surface.

Table 1

NDVI values characteristics

NDVI values	Land cover type
-0.50	Artificial materials (concrete, asphalt)
-0.25	Water
-0.05	Snow, ice
0.00	Clouds
0.03	Arable land
0.50	Sparse vegetation
0.70	Dense vegetation

Fig. 9. and Fig. 10 show the results of calculating the NDVI for the research area.

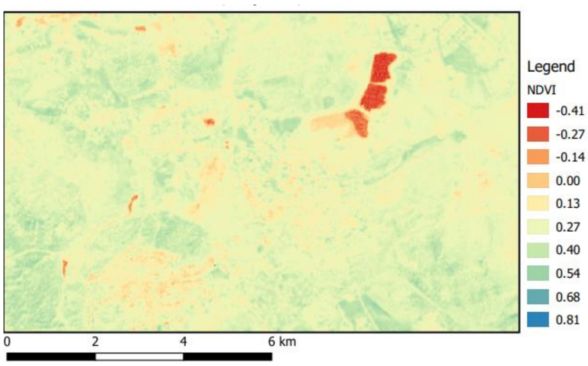


Fig. 9. NDVI based on the image of Landsat 7 (2002).

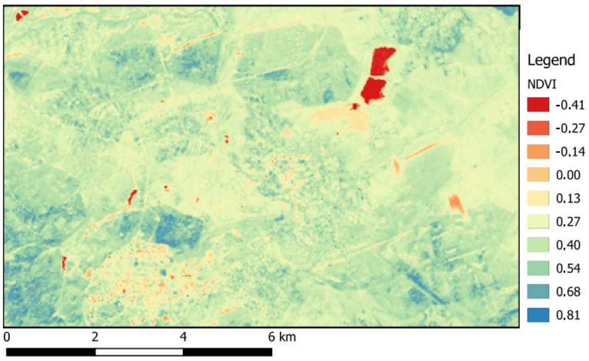


Fig. 10. NDVI based on the image of Landsat 8 (2019).

Close attention should be drawn to displaying the tailing dump, which is interpreted in the RGB image as a water object. However, according to NDVI, even without a preliminary retrospective study of the research region, an unnatural chemical composition that is not inherent to water bodies is obvious. Due to the dating of the multispectral data used (non-vegetation period), as well as the species composition of the region forests (not coniferous plantations), dense vegetation is not interpreted.

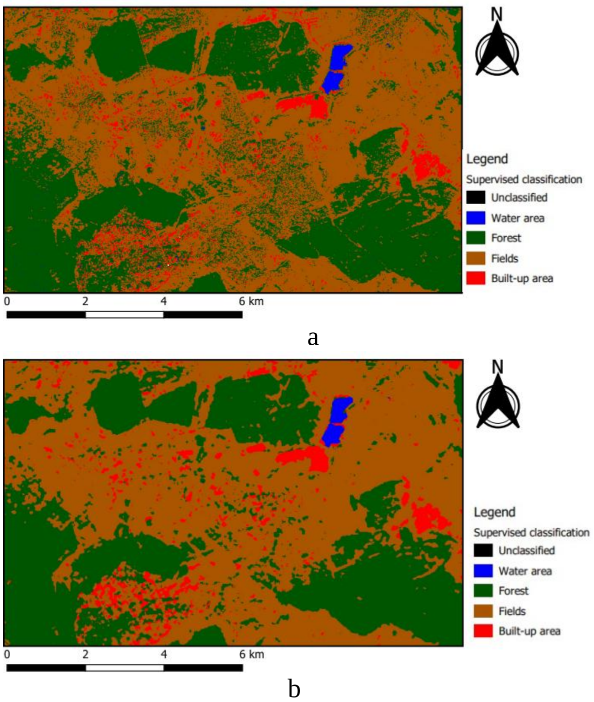


Fig. 11. Classification based on NDVI rasters (2002); a) unfiltered classification, b) filtered classification.

Being based on vegetation indices, a controlled classification was carried out. Similar to the above image filtering example, the majority filter is applied. The results of unfiltered and filtered classification based on the calculated NDVI are shown in Fig. 11 and Fig. 12, respectively.

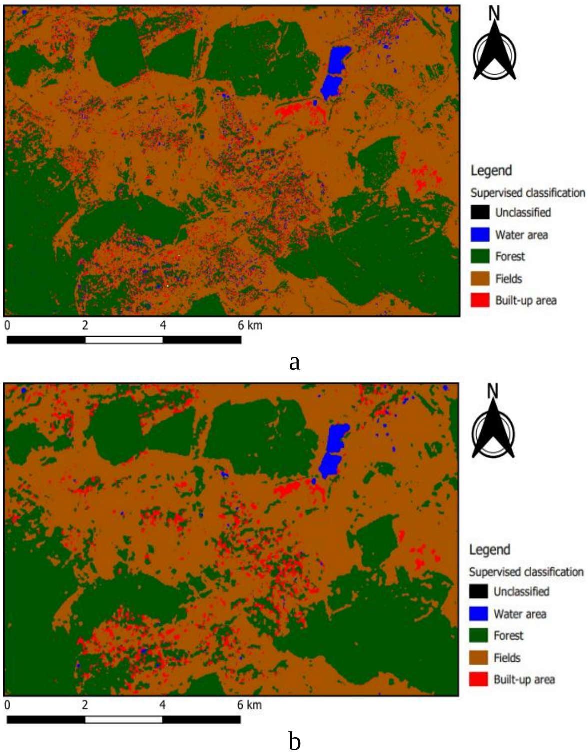
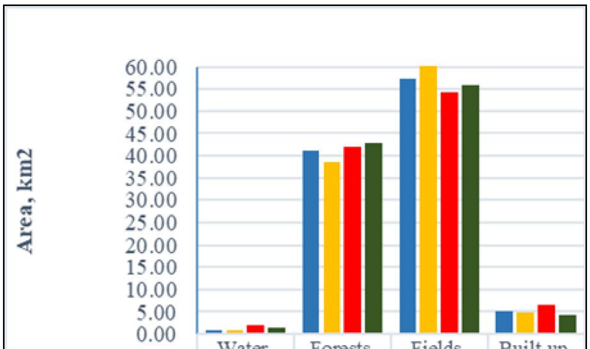


Fig. 12. Classification based on NDVI rasters (2019); a) unfiltered classification, b) filtered classification.

The areas of each of the classes were calculated to analyze the LULC geodynamic changes in the region, according to the classification data carried out on the basis of the NDVI. The results are shown in Fig. 13.



	Water, km2	Forests, km2	Fields, km2	Built-up, km2
2002 Unfiltered	0.88	41.05	57.39	4.98
2002 Filtered	0.87	38.46	60.29	4.68
2019 Unfiltered	1.86	41.93	54.06	6.45
2019 Filtered	1.27	42.93	55.81	4.29

Fig. 13. Comparison between areas calculated via unfiltered and filtered classifications based on NDVI rasters.

The next step after the classification process is to assess its accuracy, which allows identifying and measuring errors. As a rule, classification accuracy is assessed by calculating the error matrix. The error matrix is a comparison table of classification data with reference data for a given number of samples.

The reliability of the conducted classifications based on RGB images and NDVI data was estimated by formula (2) [Shalan et al., 2004]:

$$P_{overall} = \frac{\sum_{i=1}^{n} n_{ii}}{N} \times 100\%, \qquad (2)$$

where $P_{overall}$ is overall, or complete, classification accuracy,%;
n is the number of classes;
n_{ii} is the number of correctly classified pixels in a class;
N is the total number of pixels.

The results of calculations are shown in Table 2.

The Kappa coefficient is also calculated to improve the computation of classification accuracy (3) [Shalan et al., 2004].

$$k = \frac{\sum_{i=1}^{n} x_{ij} - \sum_{i=1}^{n} (x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{n} (x_{i+} \times x_{+i})}, \qquad (3)$$

where n is the number of rows, columns in an error matrix;
N is the total number of pixels in the error matrix;
x_{ij} is a major diagonal element for the i-th class;
x_{i+} is the total number of pixels in the i-th row;
x_{+i} is the total number of pixels in the i-th column.

Table 2

Estimation of carried-out classifications accuracy

Land cover types	The RGB image is a foundation							
	2002				2019			
	Unfiltered classification		Filtered classification		Unfiltered classification		Filtered classification	
	Overall accuracy, %	Kappa coefficient	Overall accuracy, %	Kappa coefficient	Overall accuracy, %	Kappa coefficient	Overall accuracy, %	Kappa coefficient
Water	63.57	0.56	66.74	0.59	77.60	0.71	88.45	0.85
Forests	89.40	0.87	84.37	0.81	85.06	0.82	89.89	0.87
Fields	87.30	0.84	87.29	0.84	81.71	0.79	83.69	0.80
Built-up	68.71	0.60	60.33	0.53	61.01	0.54	78.68	0.72
Land cover types	NDVI is a foundation							
	2002				2019			
	Unfiltered classification		Filtered classification		Unfiltered classification		Filtered classification	
	Overall accuracy, %	Kappa coefficient	Overall accuracy, %	Kappa coefficient	Overall accuracy, %	Kappa coefficient	Overall accuracy, %	Kappa coefficient
Water	68.41	0.60	67.43	0.59	51.03	0.45	78.47	0.71
Forests	86.08	0.83	87.37	0.84	76.08	0.69	73.38	0.67
Fields	81.50	0.78	76.02	0.69	72.30	0.66	68.82	0.61
Built-up	46.21	0.41	43.46	0.38	39.92	0.35	26.57	0.23

Conclusions

Anthropogenic activity has significantly accelerated the rate of geomorphological changes in landscapes which affect all processes in the geosphere and carry a potential danger at the regional, local and global levels. Consequently, the monitoring of spatiotemporal LULC geodynamic changes makes it possible to identify and predict the development of such processes as erosion, displacement, subsidence, karst formation, etc.

The article presents the monitoring of LULC changes in the technogenically hazardous Stebnyk region, Ukraine, in the period from 2002 to 2019. The possibility of using open-source ETM+ data to detect local surface changes in a 104.31 km^2 area was considered. The territory was divided into 4 classes (water, forest, fields, and built-up areas) for the supervised classification based on the maximum likelihood method. Changes were also analyzed on the basis of the NDVI data.

The study presents information about the areas changes of classes due to the classifications accuracy assessment, data comparisons from the 2002 and 2019 classifications according to the accuracy. The built-up territory underwent the greatest changes. Its area increased by 5.61 %, due to a rather uniform decrease in the areas of forests (2.77 %) and fields (2.36 %). The area of water objects increased by 0.37 %.

It should be noted that the classifications accuracy of water objects and built-up areas is an order of magnitude lower than the accuracy of the classification of forest and field areas. This phenomenon occurs due to the peculiarities of the research region, namely, sparse buildings, and the lack of a multi-lane developed road network. As for water objects, the tailing dump is a well-classified object in the image, but there are no other large water objects on the territory, the width of the river valley in most cases does not exceed two meters, which makes it impossible to detect them in the image.

The obtained results provide an important basis for further monitoring of landscape changes in the investigated region, confirm the relevance of the anthropogenic processes in the region and represent the spatiotemporal dynamics of LULC changes.

The accuracy assessment and monitoring analysis demonstrate the possibility of using ETM+ Landsat data to test the methodology for identifying LULC changes at the local level. However, the insufficient resolution does not allow studying geomorphological processes and identifying dangerous anthropogenic areas (karst formation, subsidence territory in Stebnyk region. Therefore, for further research, it is planned to use UAV materials as the UAV survey is an optimal method for obtaining information for studying LULC and geomorphological changes in the region of research.

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МОНІТОРИНГ ПРОСТОРОВО-ЧАСОВИХ ГЕОДИНАМІЧНИХ ЗМІН СКЛАДУ КАТЕГОРІЙ ЗЕМЕЛЬ НА ПРИКЛАДІ РЕГІОНУ МІСТА СТЕБНИК ЗА ДАНИМИ ДИСТАНЦІЙНОГО ЗОНДУВАННЯ ЗЕМЛІ

Подано результати аналізу та моніторинг змін складу категорій земель регіону міста Стебник (Львівська область, Україна), як об’єкта підвищеної техногенної небезпеки (на території спостерігаються карстові провали, що є наслідком порушення умов консервації підземних шахт видобутку калійної солі). Видобуток здійснювався без закладання відпрацьованих порожнин, унаслідок чого утворилися пустоти близько 33 млн м^3, які пролягають під житловим сектором та дорожньою інфраструктурою, і потенційно можуть бути місцем наступного провалу, що загрожує населенню та ландшафтній екосистемі регіону загалом. Дослідження ґрунтувалось на супутникових знімках Landsat 7 та 8 станом на лютий 2002 р. та грудень 2019 р. відповідно, та даних ETM+. Для виявлення та аналізу просторово-часової динаміки змін типів земельного покриву використано методику контрольованої класифікації за методом максимальної вірогідності із поділом на чотири класи. Також апробовано застосування вегетаційного індексу NDVI та проведення на його основі класифікації. Для підвищення точності даних використана растрова фільтрація зображень. Для аналізу зміни складу категорій земель за досліджуваний період застосовано підхід порівняння після класифікації. Виявлено, що за 2002–2019 рр. забудована територія зросла на 5,61 %, площі лісів та полів зменшились на 2,77 % та 2,36 % відповідно. Площа водних об’єктів зазнала найменших змін (+0,37 %). Оцінка якості класифікацій продемонструвала, що класифікація, виконана на основі RGB знімків, точна порівняно з класифікацією на основі вегетаційного індексу NDVI, за більшістю класів фільтрована класифікація дала точніші результати. Моніторинг змін земної поверхні задля збалансованого локального, регіонального та національного розвитку і планування територій є новим напрямом застосування даних дистанційного зондування Землі (ДЗЗ) в Україні, що дає змогу оцінити наявний стан геокомпонентів системи та спрогнозувати їх подальші зміни. Вивчення антропогенної активності дає можливість передбачити небезпечні техногенні процеси і завдяки цьому уникнути чи зменшити їх наслідки. Результати дослідження можуть використовуватись як основа для подальшого моніторингу регіону, а також бути корисними для територіальних громад з метою гармонійного, сталого розвитку та управління земельними ресурсами досліджуваної ділянки.

Ключові слова: дані дистанційного зондування Землі; моніторинг; антропогенна активність; контрольована класифікація; NDVI.

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