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GEOINFORMATION MAPPING OF ANTHROPOGENICALLY TRANSFORMED LANDSCAPES OF BILA TSERKVA (UKRAINE)

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ABSTRACT

Aim of the study

The main purpose of the study is the analysis and assessment of anthropogenically transformed landscapes of Bila Tserkva (Ukraine) based on a combination of remote sensing methods and GIS mapping.

Material and methods

Usage of geoinformatics methods for mapping anthropogenically transformed landscapes of Bila Tserkva is studied. The data was downloaded and processed using the QGIS Semi-Automatic Classification Plugin for the supervised classification of remote sensing data. Satellite images were radiometrically calibrated and atmospherically corrected, followed by a controlled classification with signature creation, visualization of spectral profiles, quality assessment and post-processing.

Results and conclusion

The main methods of landscape research are analyzed. The conclusion is made about the expediency of using spectrophotometry of satellite images in order to identify different types of landscapes based on satellite data. A supervised classification of satellite images different-time images was performed, as a result of which the main Bila Tserkva landscape types were identified. Those identified types are: water bodies, vegetation (grass, forest, parks), urban areas, and bare soils. Spatio-temporal changes of landscapes are studied and these changes are described in quantitative indicators.

Keywords: geoinformatics methods, remote sensing, supervised classification, change detection, Landsat 5 TM, Sentinel 2A

INTRODUCTION

The current environmental conditions in cities requires permanent improvement of methods for control and estimation of environmental consequences of urbanization and the impact of man-made factors. In order to develop measures to reduce the consequences of man-made impact, it is necessary to create operational and current methods of monitoring and forecasting the development of the environmental conditions in cities

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(Sokolovskaya, 2014; Dupuy et al., 2020). Among the existing modern methods of obtaining information, the most efficient one is remote sensing from space (Keshava, 2004; Richards and Jia, 2006; Bofana et al., 2020). The information obtained in this way not only facilitates continuous monitoring of urban areas and controlling potentially dangerous areas, but also creating databases of space images from different times, which are the basis for statistical research, modeling, assessment, and forecasting of the condition of urban areas (Zatserkovny et al., 2019; Martins et al., 2020; Luo, Tong and Pan, 2021; Belenok, Noszczyk, Hebryn-Baidy and Kryachok, 2021).

There is a man-made burden on the landscapes of Ukraine due to environmental pollution by chemical, metallurgical and mining industries, nuclear and thermal power plants, sugar factories, vehicles, land reclamation systems, etc. Industry affects landscapes mainly through their direct destruction, especially mining (quarries, dumps, heaps), and as a result of emissions of pollutants into the atmosphere and hydrosphere, which are spread over the atmosphere over long distances, and enter almost all landscapes (Sokolovskaya, 2014; Piestova, 2015; Belenok, Noszczyk, Hebryn-Baidy and Kryachok, 2021). According to Academician Vernadsky, man is currently one of the landscape-forming factors, responsible for transforming all natural landscapes. One of the important factors determining the degree of environmental safety of the given territory is the anthropogenic transformation of its landscapes (Shikary and Rudra, 2021).

A combination of methods for processing remote sensing data and geographic information technologies provides effective tools for monitoring anthropogenically altered areas and assessing the state of the environment (Bofana et al., 2020). The prospects for the use of spatial information in combination with GIS methods entail the possibility of integrated assessments, modeling and forecasting of sustainable development of urban agglomerations, taking into account environmental factors (Zomer, Trabucco and Ustin, 2009; Soltaninejad, Jafari, Noroozi and Javadi, 2021; Shetty, Umesh and Shetty, 2021).

There are many methods for detecting changes that occur in landscapes and for classifying remote sensing materials. As reported by (Sokolovska, 2013; Sokolovskaya, 2014; Tomchenko, Sokolovskaya and Fedorovskiy, 2015), methods of system analysis, in particular the ABC method, were applied to the study of anthropogenic changes in the ecosystem according to Landsat. A systematic modeling of the impact caused by the main components of the urban landscape on the environmental conditions within the city of Kyiv has been conducted. According to Keshava (2004), a comparison of the Spectral angle mapper and Euclidean minimum distance methods was performed for their application in hyperspectral data processing. Both metrics were described, and recommendations for their application in hyperspectral data processing were formulated. The paper (Zomer, Trabucco and Ustin, 2009) describes the creation of spectral libraries based on the collected spectra of vegetation and leaves (Canopy and leaf spectra) for the subsequent classification and mapping of vegetation. The PROBE-1 airborne hyperspectral data set (5 m pixel resolution, 128 bands) was used to solve the problem. According to Martins et al. (2020), the application of the Convolutional Neural Network for ground cover mapping based on remote sensing data was considered. A new multi-scale object-based structure of Convolutional Neural Network has been proposed for large-scale land cover classification with a resolution of 1 m over a large area. The paper (Bofana et al., 2020) performed a comparison of four classifiers: Random forest, Support vector machine, Classification, and Regression tree for mapping arable land in four different agroecological zones. Random forest proved to be the most stable and accurate classifier for different agricultural systems. Another publication (Dupuy et al., 2020) describes landscape zoning performed on the basis of satellite data from different sources (Sentinel 2 and Landsat 8) in order to identify agro-urban functional areas within the city and study their relationships. The proposed method of classification is well suited for mapping agriculture and urban land cover. In their article (Belenok, Noszczyk, Hebryn-Baidy and Kryachok, 2021) analyze the changes in the areas of different types of landscapes in Kyiv on the basis of multi-temporal Landsat images for 1985-2020. To distinguish different types of landscapes, classification methods and vegetation indices were used. A number of works (Priyadarshini et al., 2018; Shakya et al., 2018; Moazami and

Zoratipour, 2016; Abbaszadeh, Mahdavi and Rezai, 2019; Olzoev et al., 2021) compare the Maximum Likelihood, Minimum Distance, Parallelepiped, and other algorithms.

In the present work, we propose a combination of some of these methods for analysis and assessment of anthropogenically transformed landscapes of Bila Tserkva city (Ukraine) using Earth remote sensing data for 1985–2020 and GIS mapping of the changes.

MATERIALS AND METHODS

Characteristic of the study area

Bila Tserkva is a city of regional (oblast) subordination and is the centre of the administrative district of Kyiv oblast. Bila Tserkva is the largest city in the south-western part of the Kyiv oblast of Ukraine. The current population of the city as of January 1, 2021 is 208,737 people. The share of people of working age in the population structure is higher than the national average.

The territory of Bila Tserkva is located in the forest-steppe zone, in the north-western part of the Ukrainian Crystal Shield.

Bila Tserkva has a temperate-continental climate with a south-westerly direction of wind. The average temperature in January reaches 5–9°C, and in June + 17.8°C. The average humidity reaches 71% in summer and about 90% in winter. Annual precipitation generally does not exceed 562 mm per year.

The area of the city is 3.4 thousand ha. Built-up land occupies 43.7% of the city area, forests and other forest areas – 7.4%, and 2.7% of land is under water bodies. Agricultural land is 1,555.7 ha (46.2%), including land for perennial crops – 902.24 ha, and hayfield land only 21.48 ha. The structure of built-up land of the city is as follows:

- 53.3% of land under housing construction;
- 17.2% of the land is occupied by municipal infrastructure;
- 13.1% of the land is occupied by transportation and communication systems;
- 7.9% land is used for cultural recreation and similar functions;
- 2.7% land is used for technical infrastructure;
- 5.8% land is used for commercial and mixed purposes.

Land is an investment resource of the city, indispensable for its socio-economic development (Official site of Bila Tserkva City Council, 2021).

Bila Tserkva is a competitive city and it has significant advantages over other Ukrainian cities (favorable geographical location, proximity to the capital, abundant experience and resources in terms of industry and trade), which increase the level of competitiveness of the city in the economic component of the region and the country as a whole.

It should be noted that the landscapes of the city are very diverse. In particular, the Olexandriia Landscape Park is an arboretum with a total area of over 400 ha and is the largest and oldest arboretum in Ukraine. The vegetation of the park has about 1,500 species and forms. It should be emphasized that the protection of this natural and cultural object is one of the most important goals for the preservation of the natural environment and ecological education.

The basis of the city industry is made up of enterprises in the pharmaceutical, food, rubber, light, chemical, jewelry, furniture, engineering, and agricultural industries. Trade, construction and transport industries, and public utilities sector are well developed. The city has good prerequisites for intensive development of domestic and foreign tourism.

According to the Comprehensive Environmental Protection Program in the city of Bila Tserkva for the period 2017–2021, atmospheric air pollution is a key factor that negatively affects the condition of the environment within the city. The environmental conditions of lands for various purposes can be assessed indirectly: no comprehensive system of monitoring land resources in the city has been developed or implemented to date, and data on land pollution by sources of pollution and location are fairly random and isolated. The main factor in the pollution of the city's land resources, which negatively affects the general condition of the environment, is the formation and accumulation of various types of industrial and household waste, as well as waste of biological origin.

Data

Satellite images of the Landsat 5 TM and Sentinel-2A missions were used as a data source to solve the problem of identifying different types of landscapes in Bila Tserkva in 1985 and 2020. Sentinel 2B mission provided cloud imagery as of the study date. Data were downloaded and processed with the aid of the SCP i.e. Semi-Automatic Classification Plugin (Congedo, 2016), a free open source module for QGIS, used for the supervised classification of remote sensing data. The module provides tools for downloading free satellite images (with authorization on the websites of suppliers), their pre-processing, executing supervised classification along with creation of signatures, visualization of spectral profiles, quality assessment, post-processing, and more. Landsat 5 TM and Sentinel-2A data were downloaded from the United States Geological Survey Earth Explorer and Copernicus Open Access Hub sites, respectively, with Collection 2 Level-2 Science Products processing levels for Landsat 5 TM and Level-1C for Sentinel-2A in surface reflectance values. Thus, the radiometric calibration and atmospheric correction of the data used in this work was performed by the data providers (Copernicus Open Access Hub).

Sentinel-2A with multispectral thermal imager (MSI) passes over the same point on Earth every ten days, and records data with a bandwidth of 290 km. In turn, Landsat 5 with multispectral scanner (MSS) and the thematic mapper (TM) sensors has a 16-day recycle with one sensor and a bandwidth of 185 km. Sentinel-2 MSI has 13 spectral bands that resemble Landsat spectral bands. However, new spectral regions, such as red edge bands, have been added to the MSI Sentinel-2 range. The bands have different spatial resolutions of 10, 20 or 60 m. Three visible bands: blue, green, red and a wide NIR band have a spatial resolution of 10 m (bands 2, 3, 4 and 8). The red edge bands, the narrow NIR band, and the SWIR bands have a spatial resolution of 20 m (bands 5, 6, 7, 8a, 11, and 12). Landsat 5 has 7 spectral bands. The bands have different spatial resolutions: the blue, green, red, NIR, and SWIR 1-2 have a spatial resolution of 30 m (bands 1,2,3,4,5 and 7), whereas Thermal (band 6) has a spatial resolution of 120 m.

The detailed parameters of the satellite images are listed in Table 1.

Scene LT51810251985157KIS08 of Landsat 5 TM from 06.06.1985 was used for processing. Data were downloaded from the US Geological Survey website USGS. The location of the study area is shown in Fig. 1. Fig. 1 is original study using geoinformation technologies as described in Kruse et al. (1993); Zatserkovny et al. (2019); and Liashenko et al. (2020).

After downloading the data, they were pre-processed in SCP including cropping the raster to the shape of a vector layer, corresponding to the territory of Bila Tserkva, and creating a composite image (see: Fig. 2).

When determining the pixel value on a composite multispectral image, we obtain the value of spectral radiance affected by the atmosphere.

Figure 2 shows the synthesized image in “natural colors”, which means that the channels R (Red), G (Green), and B (Blue) of the monitor correspond to the channels R (λ = 0.63–0.69 μm), G (λ = 0.52–0.60 μm), and B (λ = 0.45–0.52 μm) of the image. Because this combination uses channels in the visible range of the spectrum, objects on the Earth’s surface look similar to how they are perceived by the human eye.

Table 1. Satellite data used in the study

Dataset	The acquisition date	Path/row or Tile Identifier	Processing level	Cloud cover percentage	Spatial resolution	Source
Landsat 5 TM	1985/06/06	181/025	Collection 2 Level-2 Science Products	0.00	30 m × 30 m 120 m × 120 m	USGS
Sentinel-2A	2020/06/26	35UQR	Level-2A	0.055421	10 m ×10 m, 20 m × 20 m, 60 m × 60 m	Copernicus Open Access Hub

Source: data from USGS and Copernicus Open Access Hub

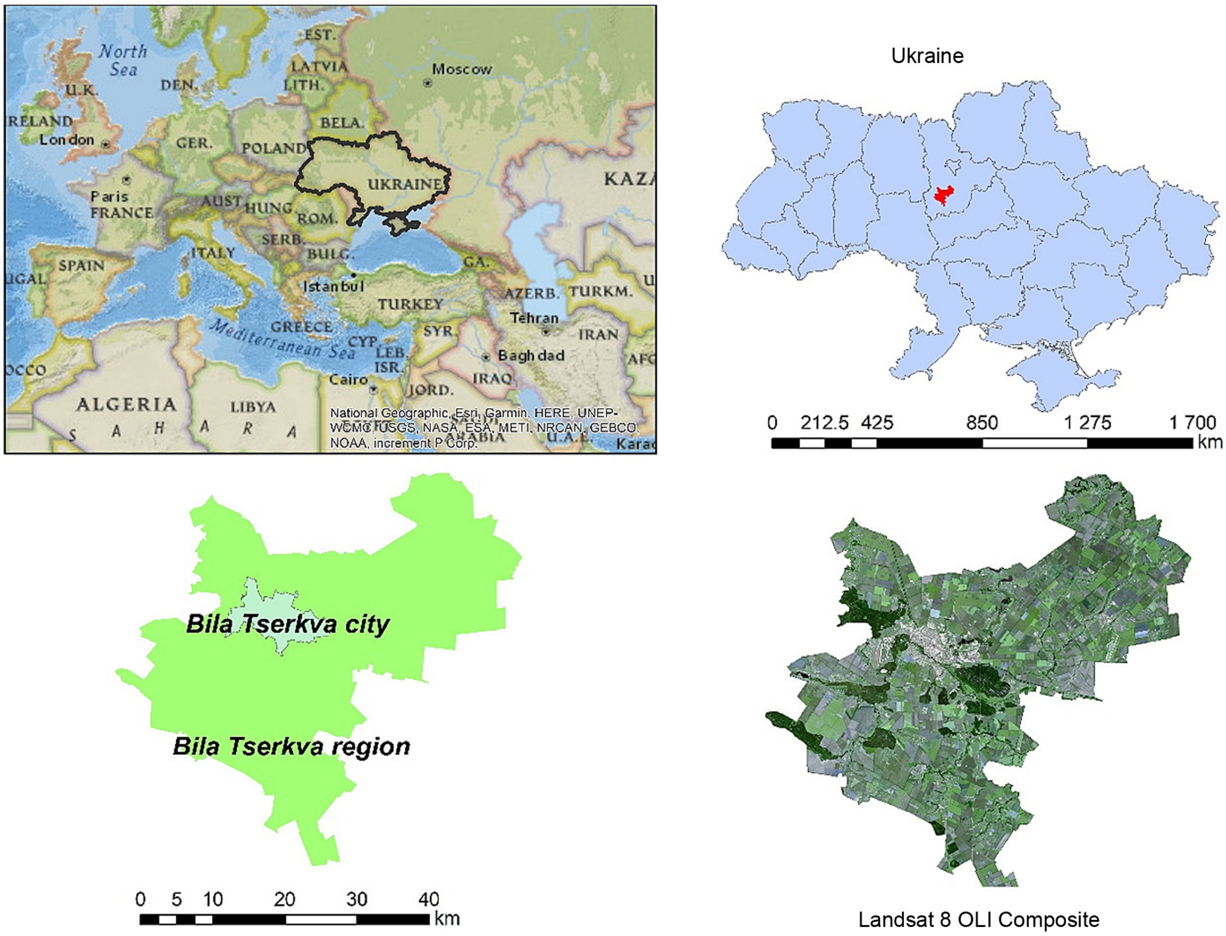


Fig. 1. Geographic location of the study area

Fig. 2. Multispectral image of Landsat TM for 1985 in “natural colors” with the border of Bila Tserkva

Atmospheric correction is a necessary step in the spectral interpretation of remote sensing data. It was noted in (Chavez, 1988) that multispectral data, such as Landsat, need to be corrected for haze values depending on the spectral range.

SCP facilitates introducing atmospheric correction by using the DOS (Dark Object Subtraction) method. The essence of this method is described, for example, in (Chavez, 1996). The resulting land surface reflectance is given by (Brief Introduction to Remote Sensing, 2021):

$$\rho = \frac{\pi d^2 \left(L_\lambda - L_p\right)}{ESUN_\lambda \cdot \cos\theta_S},$$

where:

d – the Earth-Sun distance in astronomical units,
L_λ – pectral radiance at the sensor's aperture (at-satellite radiance),
L_p – the path radiance,
$ESUN_\lambda$ – the mean solar exo-atmospheric irradiance,
$\cos\theta_S$ – the solar zenith angle.

Formulas for calculating components of Eq. can be found, for example, in (Brief Introduction to Remote Sensing, 2021).

The atmospherically corrected image obtained in this way was further used to separate different types of anthropogenically-transformed landscapes of Bila Tserkva. To this end, we applied the method of supervised classification. The initial stage of the classification is the creation of training samples (signatures) as ROI (Region Of Interest) in SCP. We classified the images into the following macroclasses: Water (microclasses Rivers and Lakes, Fig. 3), Urban (microclasses Buildings and Roads, Fig. 4), Vegetation (microclasses Forest and Grass, Fig. 5), and Bare soil (microclasses Sand and Soil, Fig. 6).

Signatures were created by using twofold methods: (1) manual digitization of pixels with homogeneous

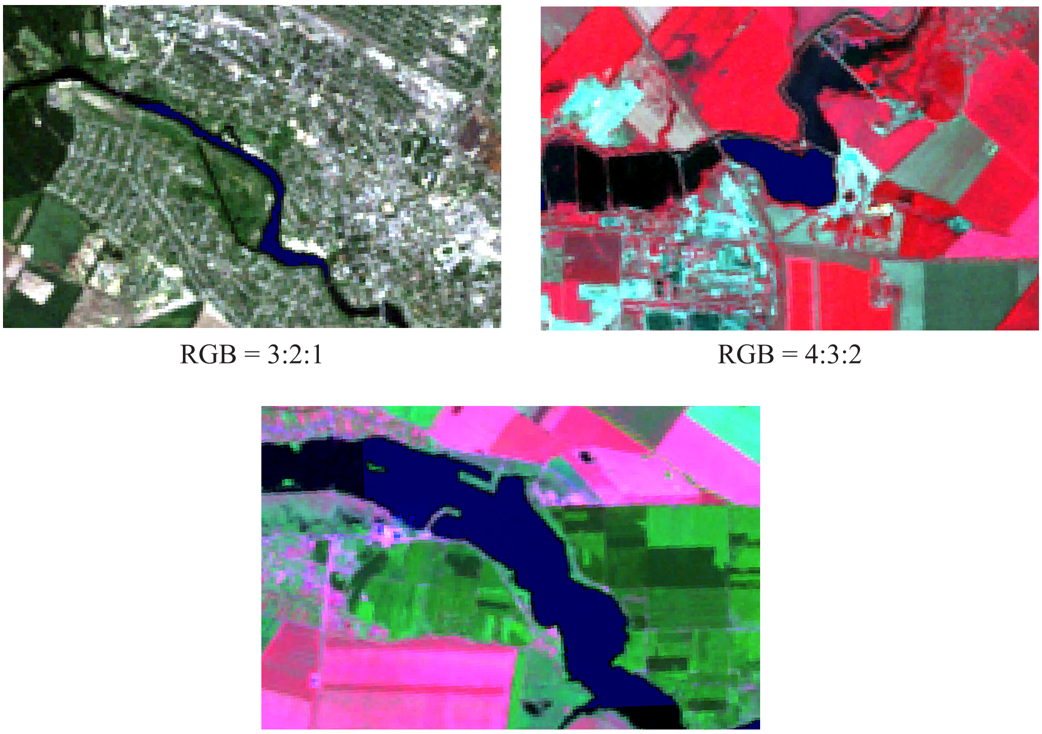
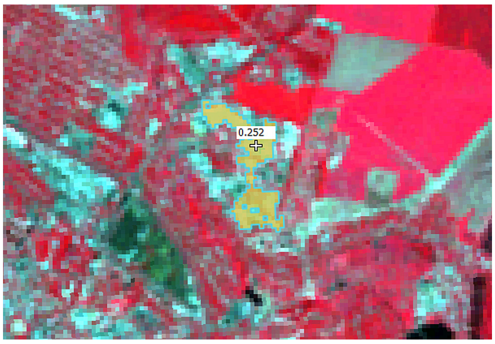


Fig. 3. ROI Water: River

RGB = 3:2:1


RGB = 4:3:2


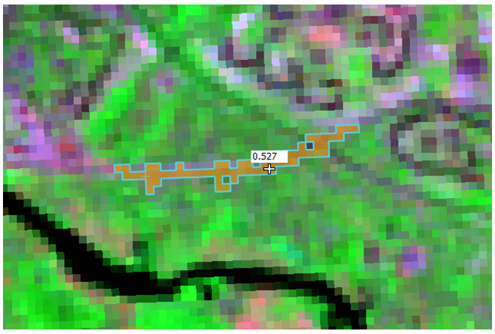
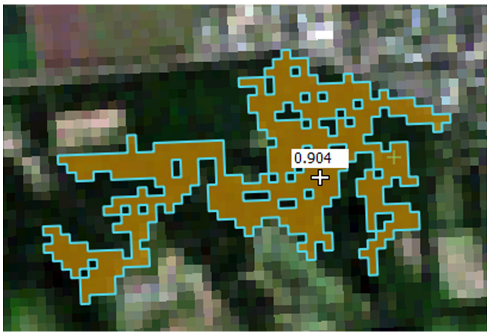
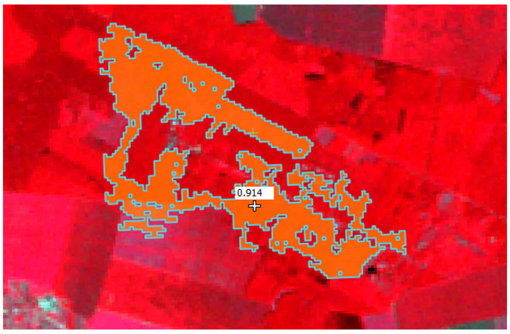
RGB = 7:4:2


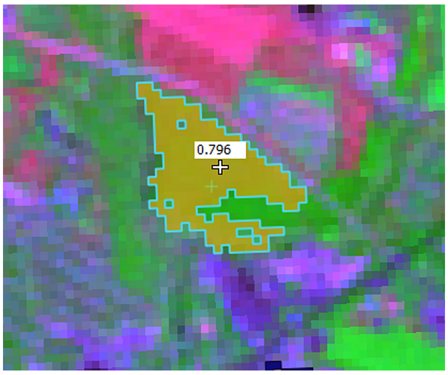
Fig. 4. ROI Urban: buildings and roads



RGB = 3:2:1



RGB = 4:3:2



RGB = 7:4:2

Fig. 5. ROI Vegetation: forest, grass

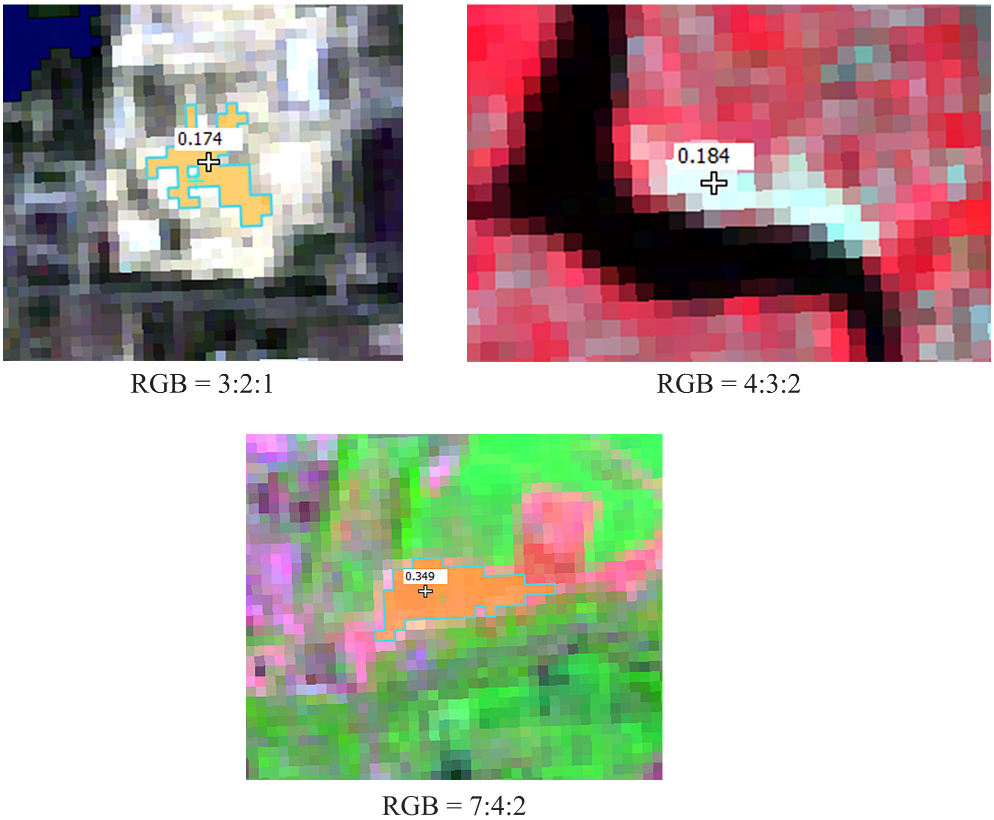


Fig. 6. ROI Bare soil: sand, soil

radiance, and (2) region growing where one reference pixel is set manually, and then a sample is built around it using comparison with neighboring pixels in sliding windows of a given size (3 × 3, 5 × 5, etc.). Neighboring pixels are added to the sample either on the basis of Euclidean distance, or on the basis of statistical indicators (the mean and standard deviation of the radiance for each zone).

To verify the correctness of the assignment of pixels to a particular class we used: the value of the vegetation index NDVI (its numerical value is shown in the figures), the profiles of spectral signatures, and spectral distances.

Spectral signature profiles were built for each class. For example, Fig. 7 shows a profile for the Vegetation class, which reveals the vegetation-specific global maximum in the near infrared zone ($\lambda \approx 0.76$–0.90 µm in Fig. 7) and the local minimum for the red zone of the spectrum ($\lambda \approx 0.63$–0.69 µm in Fig. 7). A description of the spectral profiles of different types of objects on the Earth's surface can be found, for example, in (Keshava, 2004). Note that the vertical dotted lines in Figure 7 show the channels of Landsat 5 TM.

It is useful to compare the radiance of pixels assigned to different classes. SCP allows us to compare different spectral signatures in the space of spectral features, in order to estimate the probability of error in further classification based on similar classes. To do this, we used the following algorithms: Jeffries-Matusita Distance, Spectral Angle, Euclidean Distance, and Bray-Curtis Similarity. Let us compare, for example, classes Urban and Vegetation (see: Fig. 8).

Jeffries-Matusita Distance calculates the separability of a pair of probability distributions. This can be particularly meaningful for evaluating the results of Maximum Likelihood classifications. The Jeffries-Matusita Distance J_{xy} is calculated as (Richards and Jia, 2006):

$$J_{xy} = 2(1 - e^{-B})$$

where:

$$B = \frac{1}{8}(x-y)^t \left(\frac{\Sigma_x + \Sigma_y}{2}\right)^{-1}(x-y) + \frac{1}{2}\ln\left(\frac{\left|\frac{\Sigma_x + \Sigma_y}{2}\right|}{|\Sigma_x|^{\frac{1}{2}}|\Sigma_y|^{\frac{1}{2}}}\right)$$

x – first spectral signature vector,
y – second spectral signature vector,
Σ_x – covariance matrix of sample x,
Σ_y – covariance matrix of sample y.

The Jeffries-Matusita Distance is asymptotic to 2 when signatures are completely different, and tends to 0 when signatures are identical. As it is apparent from Figure 8, the classes of Urban and Vegetation, by Jeffries-Matusita Distance, can be considered completely separated in the space of spectral features, because the minimum value of the criterion for these two classes is $J_{xy} \approx 1.9998$.

An explanation of the other criteria can be found, for example, in (Kruse et al., 1993); whereas at this point we note only that the Spectral Angle criterion

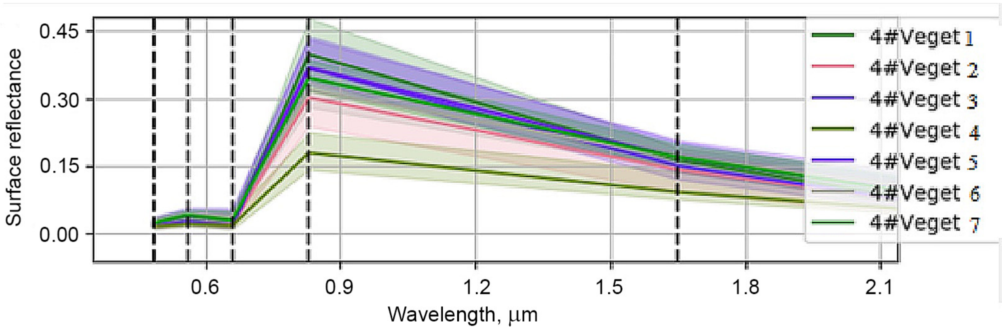


Fig. 7. Spectral signature profile for the Vegetation class

	MC_ID = 2 MC_info = Urban C_ID = 3 C_info = buildings
	MC_ID = 4 MC_info = Vegetation C_ID = 2 C_info = forest
Jeffries-Matusita distance	1.99998153502
Spectral angle	33.6344358928
Euclidean distance	0.208915919424
Bray-Curtis similarity [%]	65.5440305054

	MC_ID = 2 MC_info = Urban C_ID = 3 C_info = buildings
	MC_ID = 4 MC_info = Vegetation C_ID = 3 C_info = forest
Jeffries-Matusita distance	1.99999999486
Spectral angle	36.876554627
Euclidean distance	0.247074508403
Bray-Curtis similarity [%]	63.2618970341

	MC_ID = 2 MC_info = Urban C_ID = 3 C_info = buildings
	MC_ID = 4 MC_info = Vegetation C_ID = 4 C_info = forest
Jeffries-Matusita distance	1.99981688825
Spectral angle	29.6641812488
Euclidean distance	0.217612847182
Bray-Curtis similarity [%]	61.0096131363

Fig. 8. Spectral distances calculated for classes Urban and Vegetation

varies from 0, when the signatures are identical, to 90, when they do not intersect in the space of spectral features. For the samples compared within the classes of the Urban-Vegetation, for instance, the Spectral Angle varies in the range 29.7–36.9, which is a high result. After the formation of training samples and their verification, the supervised classification was performed using the Maximum Likelihood algorithm, which is described, for example, in (Richards and Jia, 2006). Then we performed the conversion of the obtained raster into vector format (Raster to Shape), merging polygonal objects corresponding to one landscape into a single spatial polygonal object, followed by the determination of the areas of particular landscapes.

To select the landscapes as of 2020, the satellite image Sentinel-2A L1C_T35UQR_A026173_20200626T085651 for 26.06.2020 was downloaded and processed. The processing was similar to the processing of Landsat 5 TM and was performed in SCP.

RESULTS AND DISCUSSION

As a result of thematic processing of Landsat 5 TM and Sentinel-2a satellite images, the main types of landscapes in Bila Tserkva were identified: urbanized areas (buildings and roads), vegetation, hydrographic objects, and open soils. To improve the accuracy of spectral interpretation and identification of objects, spectral libraries and existing cartographic materials for the territory of Bila Tserkva were used. A pixel-by-pixel calculation of the area of all types of landscapes was performed for the classified images using geoinformation technologies. A significant increase in the area of anthropogenically transformed landscapes (approximately twofold) over the period 1985–2020 was revealed, which is due to the expansion of the total area of the city, and the transformation of existing natural landscapes into anthropogenically transformed ones as a result of the development of urban infrastructure. An adverse effect is a gradual decrease in the area of water landscapes, which can be explained by the

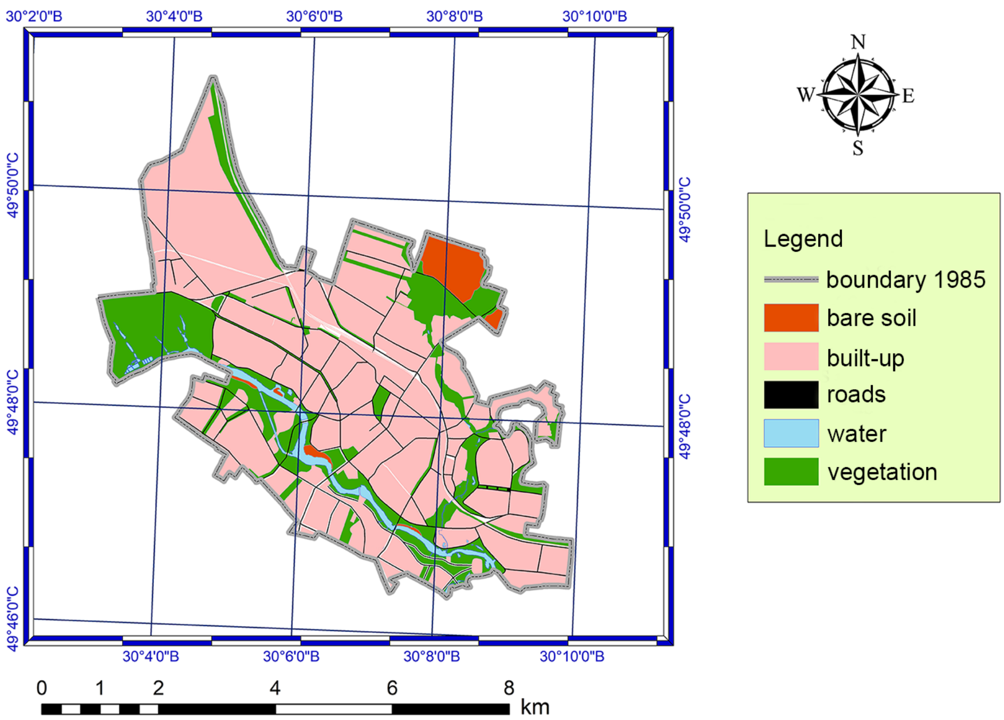


Fig. 9. Anthropogenically transformed landscapes of Bila Tserkva in 1985

Belenok, V., Hebryn-Baidy, L., Bielousova, N., Zavarika, H., Sakal, O., Kovalenko, A. (2022). Geoinformation mapping of anthropogenically transformed landscapes... Acta Sci. Pol., Formatio Circumiectus, 21 (1), 69–84. DOI: http://dx.doi.org/10.15576/ASP.FC/2022.21.1.69

impact of climate change, by human activities leading to a decrease in water resources due to pollution of freshwater ecosystems, as well as by the consequences of urbanization and changes in land use. Based on the results of the classification, a thematic map of anthropogenically transformed landscapes of Bila Tserkva for 1985 was built (see: Fig. 9).

Based on the results of the managed classification, a thematic map of anthropogenically transformed landscapes of Bila Tserkva for 2020 was developed (see: Fig. 10).

Comparing the thematic maps and the calculated areas, we note a significant increase in the development of Bila Tserkva over the past 35 years.

A common method for accuracy assessment is through the use of an error matrix. Also, different accuracy assessment parameters, such as overall classification accuracy (OCA), producer's accuracy (PA), user's accuracy (UA), and overall Kappa coefficient (OKC) can be calculated from the error matrix (Congalton and Green, 2008). The overall accuracy of the classification maps for 1985 and 2020 according to Landsat 5 TM and Sentinel-2A was 80.96% and 83.99% with Kappa HAT values of 73.39 and 81.14, respectively. The detailed parameters of the overall accuracy of the classification are listed in Tables 2–4.

The overall accuracy of the classification maps for 1985 and 2020 according to Landsat 5 TM and Sentinel-2A was 80.96% and 83.99% with Kappa HAT values of 73.39 and 81.14, respectively. The detailed parameters of the overall accuracy of the classification are presented in Table 4.

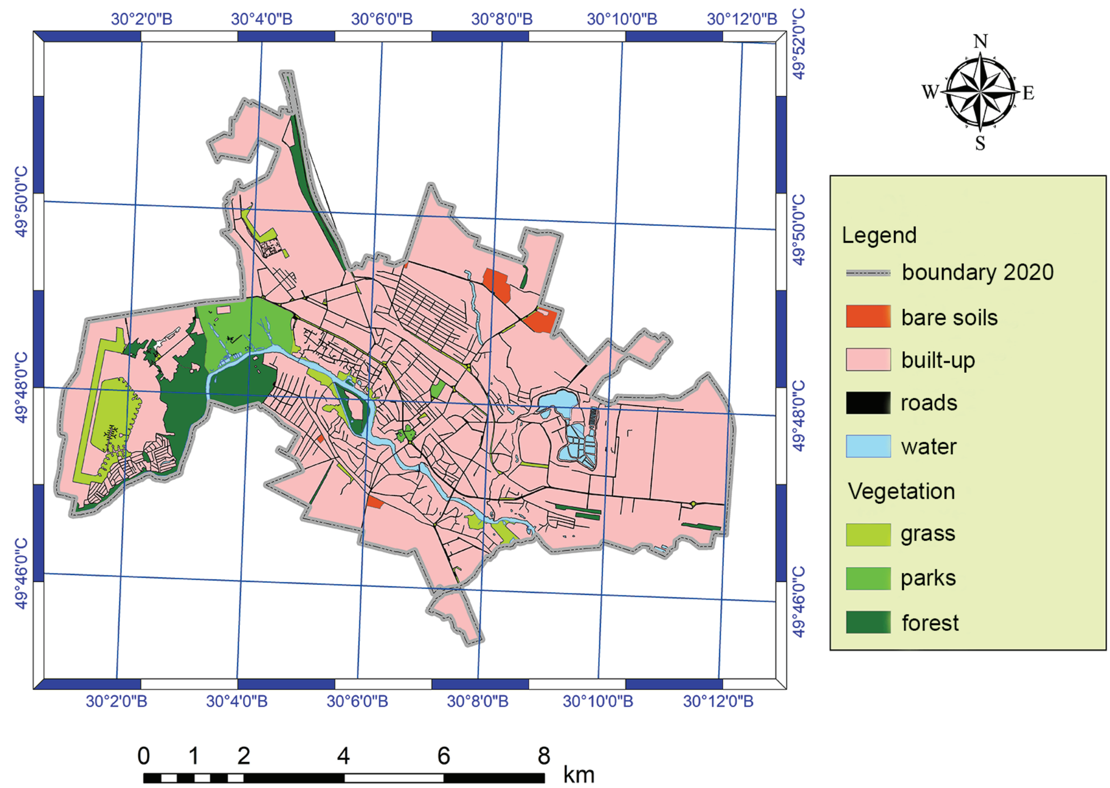


Fig. 10. Anthropogenically transformed landscapes of Bila Tserkva in 2020

Table 2. Confusion matrix for the classification of Bila Tserkva's anthropogenically transformed landscapes according to Landsat 5 TM for 1985, %

		Reference						
		Bare soils	Water	Roads	Built-up	Vegetation	Total	UA (%)
Class	Bare soils	205	15	10	5	15	250	71.93
	Water	55	1565	330	65	25	2040	90.99
	Roads	5	105	520	50	20	700	55.61
	Built-up	10	25	70	1130	10	1245	88.28
	Vegetation	10	10	5	30	280	335	80.00
	Total	285	1720	935	1280	350	4570	
	PA (%)	82.00	76.72	74.29	90.76	83.58		
	Overall accuracy (%)			80.96				
	Kappa HAT			73.39				

Source: original study

Table 3. Confusion matrix for the classification of Bila Tserkva's anthropogenically transformed landscapes according to Sentinel-2A for 2020, %

		Reference								
		Bare soils	Water	Roads	Built-up	Grass	Parks	Forest	Total	UA (%)
Class	Bare soils	153	9	21	9	9	0	3	204	83.61
	Water	9	231	15	12	6	9	9	291	85.56
	Roads	6	3	246	6	15	6	6	288	78.85
	Built-up	3	12	6	249	12	3	6	291	83.84
	Grass	3	9	12	12	312	15	9	372	85.25
	Parks	6	0	9	3	6	129	0	153	79.63
	Forest	3	6	3	6	6	0	270	294	89.11
	Total	183	270	312	297	366	162	303	1893	
	PA (%)	75	79.38	85.42	85.57	83.87	84.31	91.84		
	Overall accuracy (%)				83.99					
	Kappa HAT				81.14					

Source: original study

Table 4. The results of images classification, ha and %

Year	Data source	Area, ha					Accuracy	
		Bare soils	Water	Roads	Built-up	Vegetation	Overall accuracy (%)	Kappa HAT
1985	Landsat 5 TM	105.14	98.90	292.91	2184.63	789.89	80.96	73.39
2020	Sentinel-2A	82.73	232.81	354.31	4959.60	847.69	83.99	81.14

Source: original study

Rapid population growth, increasing population needs, vehicles and migration from rural areas to cities have accelerated the pace of urbanization. Today, this issue can be best solved based on the analysis of data from aerial / space surveys of different times. These methods are used, for example, to study deforestation, urbanization, or reduction of water bodies (Lu, Mausel, Brondízio and Moran, 2004; Lu, Li and Moran, 2014). There is a constant search for new means and methods of detecting modifications, as well as ways to improve then existing tools, which would allow to obtain the result as accurately and quickly as possible (Hussain et al., 2013). To study this process, the spatio-temporal changes of the territory of the main landscapes of Bila Tserkva for the period 1985–2020 were determined on the basis of Landsat and Sentinel images. When processing satellite images, a classification method was used, which is one of the main methods applicable for urban landscapes changes identification. The classification method in relation to the study of Land Use / Land Cover (LULC) changes is used in following studies (Shetty, Umesh and Shetty, 2021; Shikary and Rudra, 2021; Shah, Ali and Nizami, 2021). Most often, supervised classification and combinational identification methods, called hybrid ones, are used to study LULC changes (Hussain et al., 2013; Luo, Tong and Pan, 2021).

According to Priyadarshini et al. (2018) it was found that Maximum Likelihood, Parallelepiped, Support Vector Machine classification results rendered the best results, and LULC features were well identified. The authors (Abbaszadeh, Mahdavi and Rezai, 2019) compared the algorithms of Maximum Likelihood, Minimum Distance, and Parallelepiped. It is indicated that the accuracy of the Maximum Likelihood algorithm is usually high for large-scale studies. According to Moazami and Zoratipour (2016), the authors applied classification methods to study flood propagation. Using a Maximum Likelihood algorithm, they tracked the sedimentation process on the flood propagation system for 13 years. The overall accuracy was 85%. The authors (Shakya et al., 2018) concluded that the Maximum Likelihood classification method produces the best result in terms of visualization of classification categories (classes), and generally provides better classification results than other classification methods. The authors compared the classification results of seven methods. The Maximum Likelihood method rendered the best values of Kappa coefficient and overall accuracy. The authors (Olzoev et al., 2021) concluded that the method of Maximum Likelihood classification is the most suitable for the study of vegetation from the satellite images. The comparison of the Kappa coefficient values for the results of classification obtained by different methods was also performed. The Maximum Likelihood method produced the best Kappa coefficient values.

According to Jat, Garg and Khare (2008), the use of supervised classification and calculation of landscape metrics shows that that urban growth has been taking place continuously at a faster rate. It is found that the change in built-up area over the period of nearly 29 years is 200%. The study (Dhali, Chakraborty and Shahana, 2019) presented a methodology for the analysis of spatial dispersion and consistency of urbanization using Shannon's Entropy Model and Principle Component Analysis, and demonstrated that spatio-temporal expansion of urban cities is predicted.

The remote sensing and GIS techniques are very useful to assessing and monitoring urban patterns and growth. Presented research allows one to identify landscape different types and may be fond quite useful for effective land management and administration.

CONCLUSION

The main general conclusion from the present study is the proven feasibility of using spectrophotometry of satellite images to identify different types of landscapes based on satellite data. According to the results of aerospace monitoring using the results of the classification, the anthropogenically-transformed landscapes of Bila Tserkva are mapped, and the change of their areas is estimated for period 1985 and 2020. Those identified types are: water bodies, vegetation (grass, forest, parks), urban areas, and bare soils. According to the results, it is shown that the area of bare soils decreased by 22.40 ha, which indicates a trend of anthropogenical development of the area here discussed. The fact that the size of built-up areas increased by 2774.97 hectares proves the high level of urbanization of the territory in question. This also applies to the area under roads, which increased by 61.4 hectares. The aforementioned trend leads to the destruction of green areas, the size of which has decreased by 60 hectares. In the future, this may lead to a deterioration of the environmental conditions within the city.

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MAPOWANIE GEOINFORMACYJNE ANTROPOGENICZNIE PRZEKSZTAŁCONYCH KRAJOBRAZÓW BIAŁEJ CERKWI (UKRAINA)

ABSTRAKT

Cel pracy

Głównym celem pracy jest analiza i ocena antropogenicznie przekształconych krajobrazów Białej Cerkwi (Ukraina) za pomocą połączonych metod teledetekcyjnych i mapowania GIS.

Materiał i metody

Zbadano wykorzystanie metod geoinformatycznych do mapowania antropogenicznie przekształconych krajobrazów Białej Cerkwi. Dane zostały pobrane i przetworzone za pomocą wtyczki QGIS Semi-Automatic Classification Plugin, służącej do nadzorowanej klasyfikacji danych teledetekcyjnych. Obrazy satelitarne zostały skalibrowane radiometrycznie i skorygowane pod kątem atmosfery. Następnie przeprowadzono kontrolowaną klasyfikację, wraz z tworzeniem sygnatur, wizualizacją profili spektralnych, oceną jakości i przetwarzaniem końcowym.

Wyniki i wnioski

Przeanalizowano główne metody badań krajobrazowych. Wyciągnięto wnioski na temat celowości wykorzystania spektrofotometrii obrazów satelitarnych do identyfikacji różnych typów krajobrazów na podstawie danych satelitarnych. Przeprowadzono nadzorowaną klasyfikację zdjęć satelitarnych w różnym czasie, w wyniku której zidentyfikowano główne typy krajobrazu występujące na terenie Białej Cerkwii. Wskazano następujące typy: zbiorniki wodne, roślinność (łąki, lasy, parki), tereny miejskie i tereny jałowe (goła gleba). Zbadano przestrzenno-czasowe zmiany krajobrazów. Zmiany te opisano za pomocą wskaźników ilościowych.

Słowa kluczowe: metody geoinformatyczne, teledetekcja, klasyfikacja nadzorowana, wykrywanie zmian, Landsat 5 TM, Sentinel 2A