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ASSESSMENT OF THE INTERNAL CONSISTENCY OF PHYSICO-GEOGRAPHICAL UNITS USING LANDSCAPE METRICS AND STATISTICAL METHODS: CASE STUDY OF THE KHMELNYTSKYI OBLAST, UKRAINE

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Abstract. Physico-geographical regionalisation is a major task of physical geography and involves many schemes based on different initial assumptions and different ways of dividing an area into spatial units. Satellite images can be used as a source for regionalisation; they allow the analysis of large areas and support such divisions. We examined Herenchuk's (1980) scheme of Khmelnytskyi Oblast (Ukraine), which distinguished 17 landscapes. Using unsupervised classification of Landsat 8 images, five land-cover classes were mapped, and their distribution in landscapes was described by eight FRAGSTATS metrics. Variability between and within landscapes was analysed with grids of 3×3, 4.5×4.5 and 6×6 km. It was found that the variables adopted for the analysis were strongly correlated with each other, so new variables were derived for comparison between landscapes using the Principal Components Analysis method. The most differentiating factors were the shares of forests, farmlands, bare soils and waters, as well as the landscape structure indices IJI, DIVI and SHDI. Analyses showed that landscape structure was not homogeneous, with grid size influencing some results. Threshold values suggested that regions may have lost distinctiveness, though similarities allowed links to be traced to higher-level units in Herenchuk's division. The study demonstrates the usefulness of landscape metrics and statistical methods in evaluating physico-geographical regionalisations.

Key words: geography, regionalisation, remote sensing, landscape indices, Khmelnytskyi Oblast

Introduction

Physico-geographical regionalisation is considered one of the main tasks of physical geography. According to Armand (1980), "Physico-geographical regionalisation consists in combining territories or aquatories showing the relative similarity of a certain characteristic, considered important at a given level, and separating them from territories which do not exhibit a given characteristic." In English-language literature, different terms are used, but here – following Solon *et al.* (2018) – the form "physico-geographical" is applied.

Depending on application, two methods are distinguished. Typological regionalisation groups lower-order spatial units by structural and functional similarity, irrespective of geographic contiguity, whereas individual regionalisation highlights the distinctiveness of higher-level units (Kondracki 1976). Common lower-order units include geocomplexes (geosystems), landscape patches and landscape types. Typological classification gains importance at smaller scales, but loses relevance for the highest-level units, such as physico-geographical countries or zones, which require individual regionalisation (Isachenko 1991).

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The development of regionalisation concepts has followed different national traditions. German geography, with Hettner (1859–1941), emphasised interconnected systems of phenomena, while Passarge introduced the concept of landscape geography (Kondracki 1976). After World War II, Troll proposed the paradigm of landscape ecology, marking a new stage of German physical geography (Kondracki 1976). In Russia, Dokuchaev (1948) laid the foundations of landscape studies and regionalisation through works on natural zonation, soil classification and interdependence of environmental components. His school included Krasnov, Morozov, Vysotsky, Tanfiliev, Berg and others.

In Poland, physico-geographical regionalisation has a long tradition, as discussed extensively in works by Kondracki (1986, 2002), Richling (2018b) and others. Among contemporary researchers, Solon has advanced theoretical and methodological frameworks of landscape research, integrating landscape ecology with spatial planning and environmental monitoring. His works have analysed approaches to regionalisation (Solon 2008) and proposed new methods in response to anthropogenic pressures and land-use change (Chmielewski *et al.* 2015).

Physico-geographical research analyses key landscape components (geomorphological, climatic, geological, hydrological, biotic), which form the basis for regionalisation. Even when one element is dominant, its relations with others must be considered (Richling 2018c). The choice of method depends on purpose and context, which guide the selection of criteria. In the literature, two main approaches are distinguished: (1) regionalisation based on a dominant component (e.g., climate, hydrology, geology) and (2) integrative approaches using indicators such as vegetation or soils, reflecting the combined effects of natural processes.

In Russian and Ukrainian literature, many schemes of natural regionalisation exist. Rudnytskyi (1877–1937), considered the founder of Ukrainian geographical science, emphasised the uniqueness of Ukraine's natural environment and advocated comprehensive regionalisation. According to Mikheli (2014a), the origins of landscape science in Ukraine go back to Tutkovskyi's (1858–1930) article "Zonality of Landscapes and Soils in the Volyn Province" (1910), where landscape types were defined as natural territorial complexes. Since the 1950s, comprehensive studies on landscape mapping and regionalisation have been conducted, following the landscape-genetic principle (Marynych, Shyshchenko 2005).

Key centres of Ukrainian landscape research included Kyiv University (Hrodzynskyi, Marynych, Malysheva, Shyshchenko), Lviv University (Herenchuk, Miller), Odesa University (Shvebs), Simferopol University (Bokov, Yena, Pozachenyuk), Kharkiv University (Nekos), Chernivtsi University (Hutsulyak), and the Institute of Geography of the National Academy of Sciences of Ukraine (Marynych, Pashchenko) (Marynych, Shyshchenko 2005). Marynych played a central role in developing the official scheme of regionalisation, culminating in the "Physical-Geographical Regionalisation of the Ukrainian SSR" (Marynych *et al.* 1980). Another major contribution came from Herenchuk (1904–1984), who developed schemes for Ukraine, especially Western Ukraine, which served as a foundation for further research and environmental planning.

Both typological and individual regionalisation employ the concept of the landscape patch – – a relatively homogeneous area defined by land cover and spatial features. Together, patches form a mosaic model of landscape structure, a long-standing basis for analysing configuration. One method of analysing structure is the use of measures and indicators describing natural phenomena and their relationships (Roo-Zielińska *et al.* 2007). Landscape metrics quantify composition, heterogeneity, fragmentation and connectivity (Uuemaa *et al.* 2009). Their calculation, initially based on Fragstats, has increasingly shifted to modern GIS-integrated tools such as the landscapemetrics package in R or the PyLandStats library in Python (Zwierzchowska *et al.* 2010). Research has examined both their application in environmental studies and methodological issues, such as sensitivity to scale (Zhang, Li 2013), sampling field size (Saura, Martínez-Millán 2001), or number of classes, and their mutual correlations (Szabó *et al.* 2012).

Satellite images have wide availability and great analytical potential; accordingly, they have become a key source of information in environmental research and regionalisation. Ever-higher resolutions (spatial, temporal, radiometric and spectral) allow us to carry out analyses in various natural fields: geology, oceanography, forestry, agriculture and others. Satellite images make it possible to study environmental processes from a different perspective, without coming into direct contact with the studied object, which allows an area to be analysed as a complex system of natural components (Olędzki 1992, 2007; Haglauer 1996). Nevertheless, it should be noted that not all landscape components can be fully identified or interpreted from satellite imagery alone.

For the area of Ukraine, there are many different systems of physico-geographical division, but none of the available sources on this subject relate to a regionalisation that takes into account land cover, which can be analysed using satellite images. Instead, the physico-geographical divisions of Ukraine have been based on data typical for classical geographical regionalisation – – largely, component-based data encompassing various elements of the natural environment. In particular, geomorphological data, climate, hydrology, soils and vegetation cover have been used. This is one of the reasons for undertaking the topic of research addressed in the present article, which analyses the existing scheme of regionalisation of Khmelnytskyi Oblast created by Herenchuk (1980) from a different perspective, departing from traditional methods of physico-geographical regionalisation.

In this study, an attempt was made to complement the existing physico-geographical regionalisation with data derived from satellite imagery – – specifically, land cover data. By analysing the acquired data through landscape metrics, the authors aim to determine whether these data are consistent with the established division and whether similarities can be observed between the regionalisation and the patterns of land cover.

Materials and methods

Khmelnytskyi Oblast

The research presented in this paper concerns Khmelnytskyi Oblast, which is located in the western part of Ukraine (Fig. 1). The oblast was formed on September 22, 1937. It covers an area of 20,629 km^2, located between 48°26'56” and 50°35'28” north latitude and 26°08'05” and 27°54'05” east longitude. It is located in the south-western part of the East European Plain, within the boundaries of its two main substructures – – the western part of the Ukrainian Shield and its western slope – the Volyn-Podolian Plate. The average altitude of Khmelnytskyi Oblast is 275 m a.s.l., and the maximum altitude reaches above 300 m.

The surface is a plain with diverse orographic structures, which were thoroughly described by Herenchuk (1980). The highest area is the central belt, known as the Verkhobuzka Upland (also called the Avratyn Upland), where elevations reach up to 380 m a.s.l. To the north lies the Shepetivka Plain (also referred to as the Hannopil Plateau), which has elevations of 220–240 m and is characterised by sandy and loamy soils. South of this plain rises the Northern Podolia Loess Upland (Horýn-Sluch Upland), averaging around 300 m a.s.l., distinctly separated from the plain by a 20–30-m escarpment. Further south, the terrain gradually descends toward the Dniester River, forming the area known as the Dniester Foreland (Prydnistrovia or Eastern Podillia). This region is deeply dissected by the Dniester and its tributaries, forming canyon-like valleys that segment the surface into elongated ridges. Interrupting the otherwise smooth slope is the Tovtry Ridge – a chain of reef-origin hills rising 30–50 m above the surrounding landscape and reaching absolute elevations of up to 409 m.

There is a characteristic change of landscape types from north to south, with the boundaries and number of zones differing depending on the substantive approach used by a given author. Some researchers identify only two major landscape types within the oblast (Herenchuk 1980), while others argue for the presence of three (Marynych *et al.* 2003). This difference is due to the fact that some researchers include the deciduous forest zone in Ukraine’s physico-geographical regionalisation and that they define its eastern border in different ways (Kasijanik 2012).

One of the physico-geographical regionalisation schemes of Khmelnytskyi Oblast, as cited by Kasijanik (2012), is the division proposed by Herenchuk (1980). It covers the oblast within its administrative boundaries (Fig. 2) and distinguishes two natural zones (typy), subdivided into four parts (okrugi) and, in total, 17 regions (rejony).

The Polissia-type Podolia landscapes (Poliskyi typ) are characterised by flat relief, minimal dissection, and the absence of gullies and ravines. Poor natural drainage leads to excessive moisture in depressions. The forest-steppe type (Podilski lisostep), covering over four fifths of the oblast, is based on loess-like loams forming fertile chernozem soils. Here, strong dissection produces gullies, ravines and landslides, shaping hydrothermal conditions and causing rapid runoff

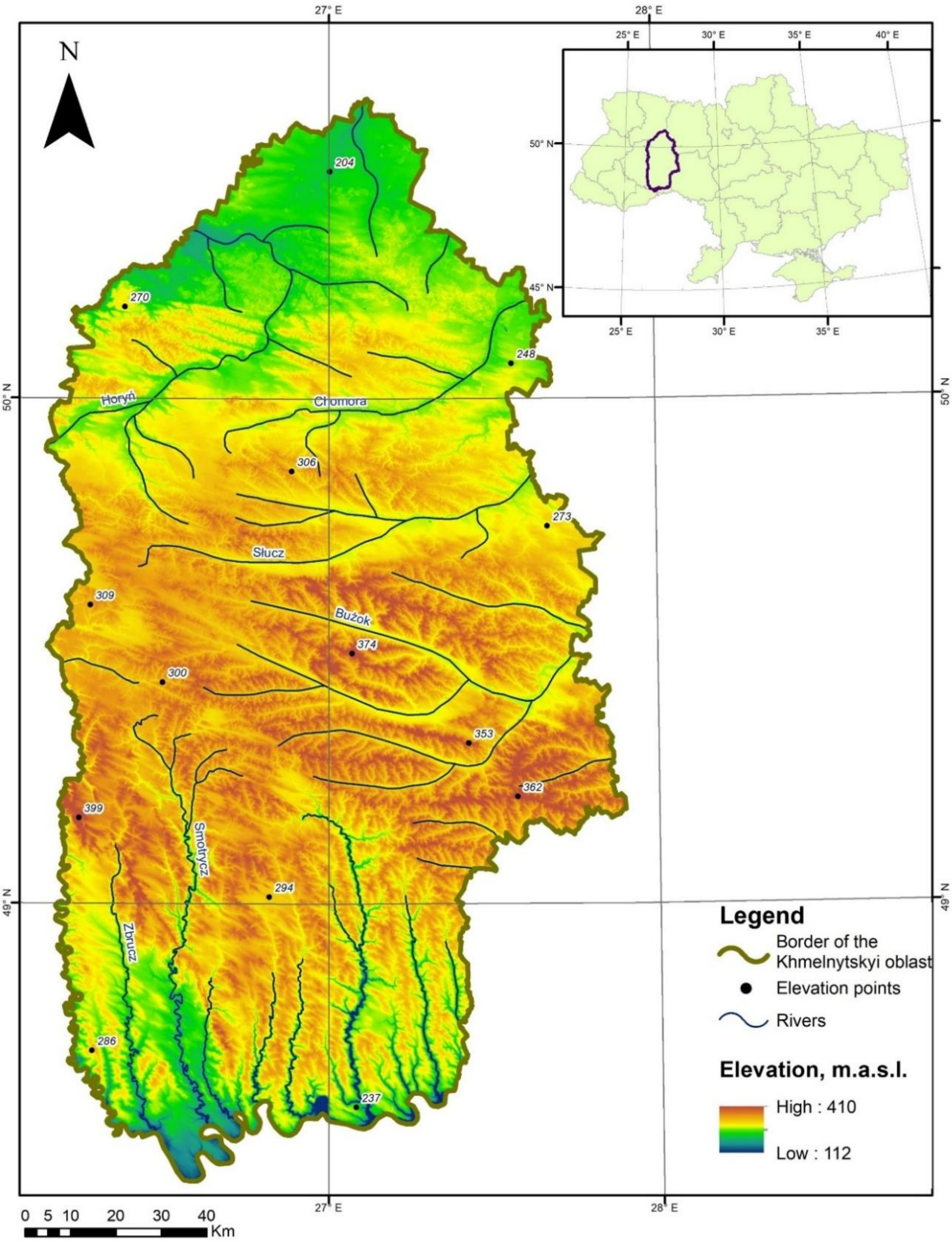

Fig. 1. Digital Elevation Model of the Khmelnytskyi oblast (based on USGS SRTM3 data)

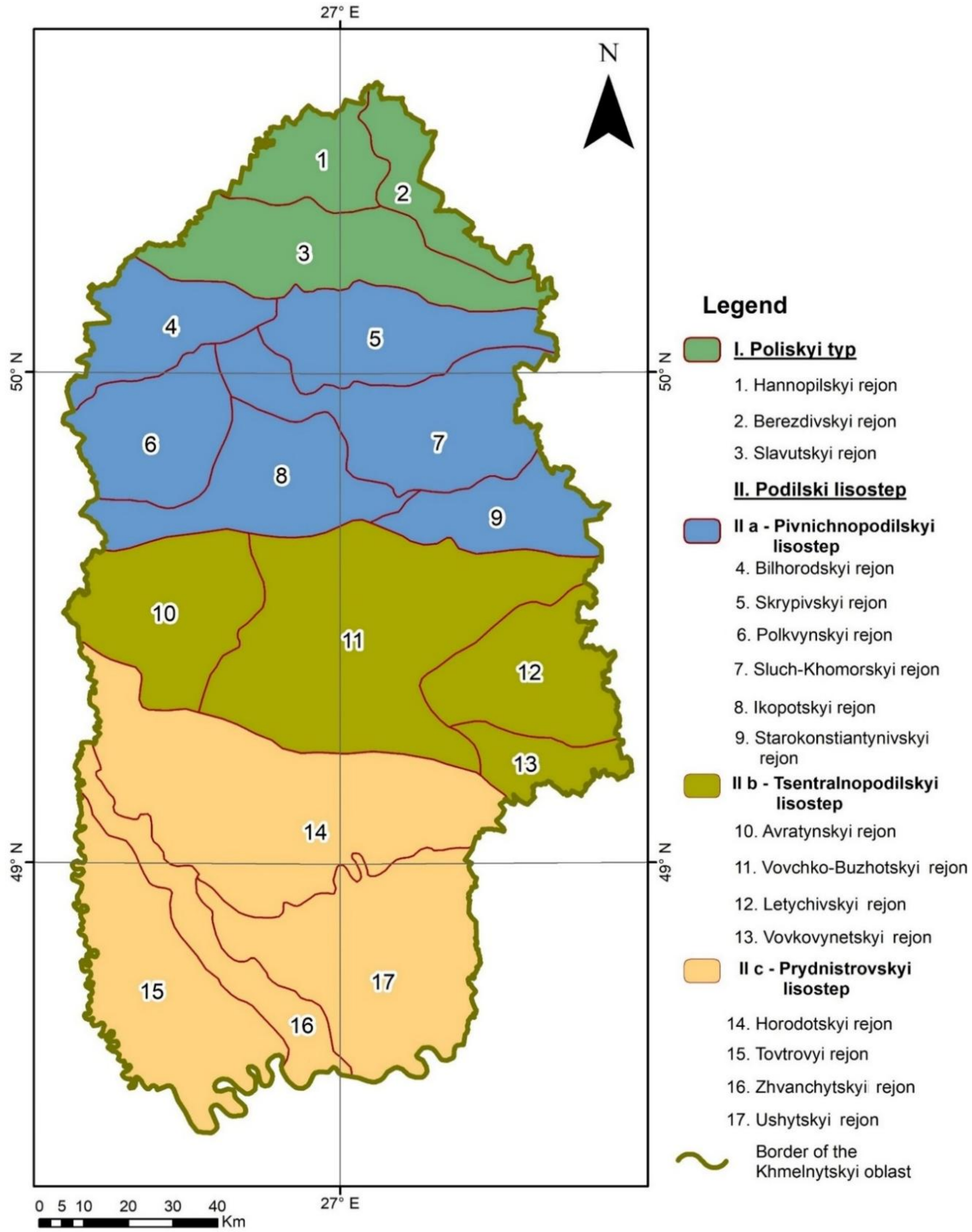

Fig. 2. Physico-geographical division made by Herenchuk (1980)

with frequent flooding. These landscapes are subdivided into three subtypes: northern (Pivnichnopodilskyi lisostep), central (Tsentralny lisostep), and Dniester-associated (Prydnistrovskyi lisostep).

As indicated in "Pryroda Khmelnytskoi oblasti" (Herenchuk 1980), the regionalisation is based on morphostructural units with specific terrain relief. Most regions (except two) have over 50% of their area within the oblast. Differences between groups are determined not by climate – which varies little – but by geological structure and relief, which shape the key natural features (Herenchuk 1980) (Tab. 1).

Table 1

Brief characteristics of the physico-geographical regions of Khmelnytskyi Oblast (Herenchuk 1980)

No	Region (Ukr. rejon)	Characteristics
		1. Shepetivske Polissya (Ukr. Shepetivske polissia)
1	Hannopilskyi	The average altitude is 220–240 m. There are no gorges or ravines; there are forested dunes. The Horyn River and its tributaries have wide, shallow valleys. There are large areas of arable land and forest areas.
2	Berezdivskyi	Varied terrain, with altitude of 230–240 m a.s.l. The bedrock west of the Korchyk River consists of Cretaceous sedimentary rocks superimposed by loess sandy loams and loams; east of the river, the bedrock rests on Precambrian crystalline rocks, overlaid with sands and sometimes loess clays.
3	Slavutskyi	Aeolian forms are common. The northern border is well defined by the range of pine forests growing on the sands, more or less along the line defined by the villages of Ostroh – Netechyn – Minkivtsi – Korchyk – Huta – Yablunivka.
		2. Forest-Steppe of North Podolia (Ukr. Pivnichnopodilskyi lisostep)
4	Bilhorodskyi	A hilly area occupying a significant part of the interfluve of the rivers Horyn and Neris, up to the line defined by the villages of Kuniv – Dertka – Pluzhne – Mokrets – Mykhlya. The average altitude reaches 280–300 m a.s.l. The surface is strongly cut by ravine erosive forms. The region is covered with easily eroded loess loams, but there are also sands that stretch in a strip of up to 10 km wide.
5	Skrypivskyi	Hilly upland with an erosive gorge cut. The southern and northern boundaries of the area are clear and distinct (Khomora in the south and the Polissia plain in the north) and the western border is rather conventional. It was marked along the line of the villages of Klubivka – Shurovechky – Sakhnivka, which separates this area from the Polkva plain. The eastern border runs along the administrative border with Zhytomyr Oblast. The average maximum altitudes in this area (290–300 m a.s.l.) gradually decrease towards the east, which causes a significant levelling of the entire area of Khmelnytskyi Oblast.
6	Polkvynskyi	The region is as flat as Avratynsky, but has lower altitudes (280–300 m). Its surface slopes northwards, towards the Horyn River, with occasional noticeable hills and depressions of 20–30 m high/deep. The borders of the region are quite clear and run along the administrative border with the Ternopil region, and then more or less through the village of Manuilske, the villages of Teofipol – Kolky – Senriukyi – Ledyanka – Kryvorudka – Khrystivka – Shurivtsi – – Klubivka, further along the Horyn River.
7	Sluch-Khomorskyi	It occupies the space between the two rivers and is characterised by an increase in altitude from north to south from 270–280 m near the Khomora River, to 320–330 m near the Sluch River. The area is intensively cut by a network of rivers and gorges, deeply indented valleys that often reach the crystalline bedrock, especially east of the Hrycov–Starokostiantynov line. The terrain's surface of the area between the rivers Derevychka and Sluch is significantly fragmented.
8	Ikopotskyi	It mainly covers the upper reaches of the Zherd and Polkva rivers and the hilly confluence of the Slucha and Ikopot rivers, and it lies at an absolute altitude of 320–330 m a.s.l. The predominant landforms are gorges and interstitial gorges, which mostly feature steep slopes subject to fairly intense surface erosion and sometimes ravine erosion.
9	Starokostiantynivskyi	The region is characterised by a flat terrain with an absolute height of 270–280 m. The northern border is clear (along the Sluch River), while the southern border runs rather conventionally at the foot of the Ikvo-Buzhok Highlands, through the villages of Kuzmyn – Movchany – – Vesnianka – Bahlayi-Adampil.
		3. Central-Podilskyi Forest (Ukr. Tsentralnopodilskyi lisostep)
10	Avratynskyi	It is the flattest area in the Verkhnobug Highlands: height fluctuations do not exceed 20 m, with a frequency of no more than 2 per 1 km. Only on the outskirts of the region, at the transition to the neighbouring highlands – the Pridnester Highlands – the depth of the indentation reaches 30–50 m, and the frequency of fragmentation increases to 3–4 m per 1 km.
11	Vovchko-Buzhotskyi	It covers the space between the Ikva and Vovchok rivers to the villages of Derazhnya – – Medzhybizh – Stara Synyava. Within these boundaries, the surface of the Verkhnobuzhan Upland has the highest absolute heights in the region (over 350 m, maximum – 384 m) and is characterised by deep erosive fragmentation, which reaches 40–70 m.
12	Letychivskyi	Only the western part of the region is located in Khmelnytskyi Oblast, while its eastern part is located in neighbouring Vinnytsia Oblast. The western border of the region is the valley of the southern Bug River from the village of Holoskiv, further to Medzhybizh and Letychiv to Novokonstantyniv, from where it turns east along the Khvosa River (Zgar basin). The southern border is marked by settlement points and runs from the village of Holoskiv to Kopachivka – Shpychyntsi – Snytivki – Hrushkivtsi. The surface of the region is flat and rises to 280–300 m a.s.l.
13	Vovkovynetskyi	The height of the land reaches 350–360 m a.s.l. This is hilly area, with a dense system of ravines, small valleys and landslide circles. Landslides are common due to the peculiarities of its geological structure.

4. Dnieper Forest (Ukr. Prydnistrovskyi lisostep)		
14	Horodotskyi	It covers the northern part of Transdnistria, in the upper reaches of the Zbruch, Smotrych, Ternava, Studenica, Ushytsia and Kalyus Rivers, i.e. where the valleys do not yet have steep rocky, precipitous slopes. The region is dominated by gorge slopes with undulating slopes, where flat and linear erosion is common.
15	Tovtrovyi	The area between the villages of Satanov and Husiatyn is a strip about 20 km wide and stretches through the villages of Ivankivtsi – Kutkivtsi – Vyshnivchyk – Antonivka – Karachkivtsi – – Chechevo – Nihyn – Verbka – Pryvorotnia – Kulchyivtsi – Kitaygorod to the Dniester. These villages mark the course of the Main Tovtr Ridge, which has the highest elevations and is almost continuous. It is characterised by a flat-convex ridge of 100–300 m wide with quite steep rocky slopes.
16	Zhvanchytskyi	It is located west of the Tovtra ridge and therefore has characteristics typical of the Ternopil region. Gypsum deposits are widespread in small areas that have formed fairly large caves and karst sinkholes. The territory is almost 35% occupied by an ancient valley that stretched parallel to the Tovtra ridge from the village of Shydlivtsi on the Zbruch River through the village of Chemerivtsi, the villages of Letava – Stepanivka – Zherdia – Dumaniv – Vrublivtsi on the Dniester River.
17	Ushytskyi	It is located east of the Tovtra ridge. The valleys of the tributaries of the Dniester are deep here: the vertical walls reach 70–90 m in height. The eastern border is defined by the administrative border of Khmelnytskyi Oblast.

Remote sensing data and their processing

Three Landsat 8 satellite scenes were used in the study, two of which were recorded on 2019.08.21 and one on 2019.08.28 (scenes 183025, 183026 and 184025, respectively).

The initial stage of satellite data processing is radiometric correction (Jakomulska, Sobczak 2001; Osińska-Skotak 2007). First, the dimensionless DN values were converted to spectral radiance, according to formula (1):

$$L_{sat} = c_0 + c_1 DN \tag{1}$$

The values of the unique calibration constants c_0 and c_1 (offset and gain) were read in the metadata files of the respective satellite scenes (Landsat 2024). As a next step, the influence of the Sun's position at the time of image capture was corrected. Due to the fact that the study area is quite elongated from north to south (over 200 km), this step was considered necessary before further analysis could be performed. The calculation of the corrected radiance value was made according to formula (2):

$$L_{sun} = L_{sat} \cdot \mathrm{sinSunElevation} \tag{2}$$

Where: the SunElevation value was taken from the metadata of each satellite scene.

The study area is located in three satellite scenes, so it was necessary to create a mosaic of images before starting further stages of research. On the basis of the mosaic created, a classification was carried out (Fig. 3). All attempts to perform supervised classification using interpretative training areas yielded unsatisfactory results – – within different parts of the study area (southern, central and northern), distinct land cover classes were frequently misclassified and merged into a single category. Due to the large size of the study area (over 200 km from north to south) and its diversity, as well as the lack of data allowing for supervised classification, IsoCluster unsupervised classification (ArcMap Desktop 2024) was chosen, which resulted in the division of the scene into five classes.

In order to identify the nature of the land cover, data taken from Open Street Map (and, more specifically, from the Landuse layer) were analysed. Data from OpenStreetMap may be incomplete and, in this case, the Landuse layer covered approximately 45% of the area of Khmelnytskyi Oblast. In this layer, there were features assigned to 20 different types of land use. Analysing the land use layer in terms of land cover, which was the target aspect of the classification, it was found that the types of land cover can be divided into five classes: (1) bare soil, (2) forests, (3) shrubs, (4) arable land, (5) water. Notably, the "bare soil" class reflects surfaces lacking vegetation during the satellite overpass; as the imagery was collected in late August, this category largely represents recently harvested agricultural land. Due to the negligible share of area, the distinction of a separate building class was abandoned.

Multiple attempts were made to achieve the final classification. Various initial settings were tested, particularly the target number of classes to be identified by the algorithm. After comparing the results against OSM data (in those areas of the study region where such data were available), the classification with the highest accuracy was selected.

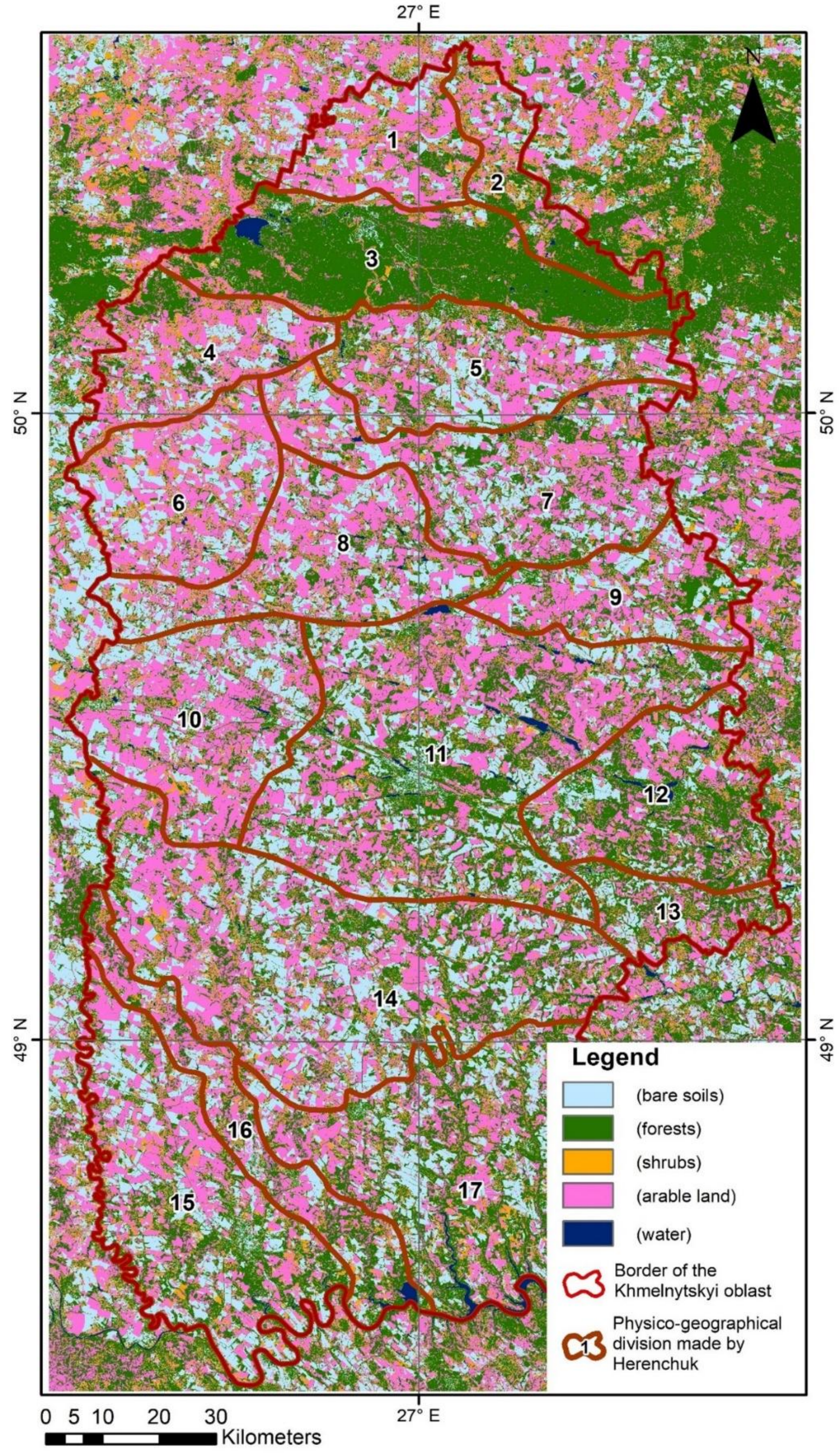

Fig. 3. The result of unsupervised classification of images of Khmelnytskyi oblast

The accuracy assessment of the unsupervised classification yielded an overall accuracy of 68.75%. The relatively low accuracy was primarily due to misclassifications between bare soil and arable land. These two classes were distinguished in the classification based on pixel values, whereas in the OSM dataset – used as the reference land use layer – only the arable land class was present. As noted above, the spectral values reflect the late-August acquisition period, when many fields appeared as bare soil after harvest.

Another common source of misclassification involved confusion between forest, shrubland and arable land classes.

The water class achieved the highest classification accuracy (94.23 %) due to additional post-classification refinement: all water objects were manually verified in ArcGIS Pro following the final unsupervised classification. This manual check was necessary because a high proportion of dark pixels representing water bodies had initially been misclassified as forest.

Landscape metrics

In physico-geographical regionalisation, apart from identifying land cover types and their surface share, it is crucial to analyse their spatial organisation, as this influences landscape functioning and underpins the delimitation of spatial units. For this study, four commonly applied landscape metrics were selected (McGarigal, Marks 1995; Urbański 2008; Fragstats 2025): PLAND – Percentage of Landscape, IJI – Interspersion and Juxtaposition Index, DIVISION – Landscape Division Index, and SHDI – Shannon's Diversity Index. Metrics were calculated in FRAGSTATS using raster data for both Herenchuk's regions and grid-based divisions.

The percentage share of individual classes in the landscape (PLAND) is often used in research to analyse the composition of a landscape. In their research on the degree of anthropogenic transformation of the environment, Roo-Zielińska *et al.* (2007) used the percentage share of individual classes (among other landscape metrics). In the present research, this indicator was also taken into account because, together with the other metrics describing the landscape configuration used, they make the studied area unique. The PLAND metric expresses the share of the five previously mentioned land cover classes in our research, which were determined using remote sensing.

The Interspersion and Juxtaposition Index (IJI), which is also a measure of aggregation, is based on the adherence of the patches to each class. It takes the value 0 when a given class is adjacent to only one other class and increases to 100 when the class is surrounded by all existing classes in the study area. In the study already mentioned, Solon (2002) also used the border differentiation index. In studies on the assessment of spatial heterogeneity in 15 floodplains (Iskin, Wohl 2023), the boundary variation index was one of the five calculated metrics.

The DIVISION – Landscape Division Index is a measure of aggregation and describes the probability of an event in which any two base cells (pixels of a raster image) are not within the same patch (McGarigal, Marks 1995). This metric has also been widely described by Jaeger (2000). The metric reaches the minimum value of 0 when the surveyed area is covered by only one patch. The maximum value of 1 is achieved when each cell of the raster image is a single patch. The landscape of the studied area is highly transformed by human activity, so it was justified to analyse the degree of fragmentation of individual regions designated by Herenchuk (1980). According to Urbański (2011), this measure may be used locally to create continuous fragmentation index maps.

Shannon's Diversity Index (SHDI) is one of the indicators that determines landscape diversity. It takes into account two factors: the number of land cover classes in a given landscape and their mutual proportions. The SHDI has values close to 0 when the landscape consists of one patch and raises with the increase in the number of patches and/or when the proportions of the area occupied by different patches are equal. This indicator is quite often used in works related to the assessment of landscape structure. Solon (2002) used it among other selected metrics to assess the spatial configuration of landscapes. In studies on the assessment of the degree of anthropogenic transformation of the landscape (Pukowiec-Kudra, Sobala 2016), this indicator was used to find a new way of quantifying the phenomenon. This indicator was also used in the above-mentioned study by Roo-Zielińska *et al.* (2007).

It is worth noting that all the calculated metrics were used for the analysis of the studied spatial units as a set of indicators describing landscapes in the analysed areas – both the regions distinguished by Herenchuk and the landscape sections represented by grid cells of selected sizes. It was justified to use metrics describing both the composition and configuration of the landscape, also taking into account the diversity and degree of fragmentation of the area of interest.

Analysis of the diversity of landscape structure

The structure of the landscape was described by eight indicators (variables, V_i) determining the share of spatial units of these land cover classes in the area, which were distinguished on the basis of remote sensing data, i.e. (V_1) bare soils, (V_2) forests, (V_3) shrub, (V_4) arable land, (V_5) water. These data were obtained after calculating the PLAND landscape metric on a class level and the previously described three landscape metrics characterising the spatial distribution of these classes, i.e. (V_6) IJI, (V_7) DIVISION and (V_8) SHDI calculated on a landscape level. In our work, these indicators are land cover structure indicators. They jointly represent the current spatial presence of natural areas, land development and use, and the landscape physiognomy visible in the remote sensing image (Richling 2018b).

The above-mentioned indicators were calculated for seventeen regions distinguished by Herenchuk (1980). In the following part we call them "landscapes". Similar calculations were made for smaller space units, such as squares of 3×3 km, 4.5×4.5 km and 6×6 km. The size of the squares is a multiple of the pixel dimensions of the Landsat 8 image, i.e. 30×30 m. The adoption of three variants of square sizes results from the intention to check how the obtained results are affected by the size of the chosen basic area of analysis.

Analysis of the variation of land cover structure between landscapes

The indices (variables) were analysed to check whether and to what extent they are differentiated in the 17 landscapes distinguished by Herenchuk. In other words, do they reflect the diversity of land cover, and can the units distinguished by Herenchuk be characterised not only by their origin and landform development, but also by distinctive land cover patterns? In all analyses at the landscape level, standardised variables were used, which were calculated according to the formula (3):

$$V'_{ij} = \frac{(V_{ij} - V_{\min j})}{(V_{\max j} - V_{\min j})} \quad (3)$$

where:
V_{ij} – the value of landscape structure variable j for landscape i (j = 1, 2,... N, i = 1, 2,... L),
$V_{\min j}$, $V_{\max j}$ – the minimum and maximum value of variable j for landscape i,
N, L – the number of variables and number of landscapes respectively (N = 8, L = 17).

As a result of the transformation, each of the eight variables took a value from 0 to 1. For the sake of simplicity, the standardised variables V_{ij}' were further marked as V_j.

In this type of research, it is important that the variables not be related to each other. The collinearity of variables is an unfavourable feature (Ratajczak 2003), because it indicates that subsequent variables do not bring significantly new information to the model. In order to check the degree of association of the original variables, the value of the linear correlation coefficient was calculated (Tab. 2, 3). The original variables were then analysed using Principal Component Analysis, PCA (Singh, Harrison 1985). The purpose of this analysis was to transform the variables V_1, V_2, …V_8, into a new set of variables C_1, C_2, …C_8, which are not correlated with each other and whose order results from the degree to which they explain (in descending order, Tab. 4, 5) the variance of the analysed dataset (Parysek, Ratajczak 2002). A subsequent comparison of the original variables with the new variables, using the linear correlation index (Tab. 6, 7), allows for an assessment of which of the original data express the diversity of Herenchuk's landscapes – and to what extent.

The analysis described above was carried out in two variants. In the first one, the values of the V_j variables were used, describing, in each of the 17 landscapes, the surface share of landforms (j = 1, 2, ... 5) and another three variables calculated using the FRAGSTATS program, i.e. describing the spatial structure of the landscape (j = 6, 7, 8). In the second variant, the values of these eight variables were obtained by averaging, at the level of each landscape, the results obtained in the corresponding 3×3-km squares (no squares of other sizes were tested). The purpose of distinguishing these two variants was to check whether the analysis of landscape in squares yields similar results for individual landscapes as does the analysis carried out without division into these schematic spatial units.

Analysis of the variation of land cover structure inside landscapes

To analyse the uniformity of the structure of each landscape as a separate spatial unit, the value of the Z-Score statistic was used. This statistic is used as a measure of the similarity of lower-order spatial units to the total community of similar units located in higher-order units. It is used in object-based image classification procedures to extract spatial structures in the landscape, as well as to detect changes occurring in a given area (Büscher *et al.* 2008; Tarantino *et al.* 2016ab; Wang *et al.* 2020). In our research, the lower-order units are squares (3×3, 4.5×4.5 or 6×6 km), while the higher-order units are landscapes. A given landscape included those squares whose centroids were located within its boundaries determined by Herenchuk. Separately, for each of the 17 landscapes, according to the Cross-Correlation algorithm (Tarantino *et al.* 2016ab), the mean value (4) and standard deviation (5) were calculated for each of the eight variables describing the landscape; then, the value of the Z-score statistic (6) for each square was calculated:

$$u_j = \frac{1}{n}\sum_{i=1}^{n} V_{ij} \tag{4}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{n}\left(V_{ij} - \mu_j\right)^2}{n}} \tag{5}$$

$$z_i = \sqrt{\sum_{j=1}^{N}\left(\frac{V_{ij} - \mu_j}{\sigma_j}\right)^2} \tag{6}$$

where:
V_{ij} – the value of variable j in a square i,
μ_j – the mean value of variable j (j = 1, 2,... N),
i – the index of square (i = 1, 2,… n) within given landscape,
n – the number of squares within given landscape,
σ_j – the standard deviation of variable j,
N – the number of variables.

Note that i has now (eq. 4–5) another meaning than in equation (3). Squares are 3×3, 4.5×4.5 or 6×6 km, according to grid used.

The Z-score statistic can be interpreted geometrically as the standardised distance of the point representing a given square from the point determined by the mean values of variables in a given landscape, in an eight-dimensional feature space. Its equivalent is the Minkowski metric (Runge 2006).

The Z-score statistic takes the highest values for those squares that differ from the rest of the community of squares in a given landscape. We decided to select the most different squares in individual landscapes (we call them "outliers"). This allowed to determine areas that deviate from the dominant structure of the cover and spatial arrangement in a given landscape. Thus, for each landscape, the threshold values of the Z-score statistics were calculated. For the calculation of these threshold values, the mean values of μ_{Zscore} and the corresponding standard deviations σ_{Zscore} were first taken in each landscape:

$$\mu_{Zscore} = \frac{1}{n}\sum_{i=1}^{n} z_i \tag{7}$$

$$\sigma_{Zscore} = \sqrt{\frac{\sum_{i=1}^{n}(z_i - \mu_{Zscore})^2}{n}} \tag{8}$$

Symbols used are the same as for equations 4–6.

For the purposes of further analysis, the three limit values were calculated on the basis of formulas (9–11):

$$TH_1 = \mu_{Zscore} + 1\sigma_{Zscore} \tag{9}$$

$$TH_2 = \mu_{Zscore} + 2\sigma_{Zscore} \tag{10}$$

$$TH_3 = \mu_{Zscore} + 3\sigma_{Zscore} \tag{11}$$

where:
μ_{Zscore} – the average value of the Z-score statistic calculated according to the formula (7),
σ_{Zscore} – the standard deviation of Z-score statistic for a given landscape (8).

For each region, the squares whose Z-score values are above the calculated limit values have been indicated. Next, a static analysis of the results was carried out in order to check the heterogeneity of the landscapes separated by Herenchuk. When analysing landscape heterogeneity, all squares whose Z-score values were above TH_1 were included. Squares whose Z-score values were above TH_2 and TH_3 generally designated areas in which one or two of the classes had a significant percentage advantage, or the patches within them were not as heavily divided as in other squares. They obtained their high values based on the nature of landscape metrics calculations, which capture such dissimilarities, so they could not be the only basis for the analysis presented.

All calculations were carried out on the basis of three variants of grids: 3×3 km, 4.5×4.5 km and 6×6 km. The results of this comparison are also intended to allow conclusions to be drawn about whether the landscape features of the analysed Khmelnytskyi Oblast are sensitive to the size of the basic field.

Results

Results of the analysis of the variation in land cover structure among landscapes

The variables V_j used in the analysis (j = 1, 2, 3, 4, 5) describe the share of individual forms of land cover, so they complement each other to unity and, in this sense, are related to each other. As can be seen from Tables 2 and 3, there is a strong correlation between them – the strongest being between the variables V_2 (area share of forests) and V_4 (area share of agricultural crops). This means that, in landscapes with a high proportion of forests, the proportion of arable land is usually low, and vice versa, which reflects a basic ecological and land-use trade-off.

The same is true for the variables V_j (j = 6, 7, 8) describing the spatial structure of the landscape: the strongest relationship is between the variables V_7 (DIVISION) and V_8 (SHDI). The calculations confirm that both indices capture landscape heterogeneity, which explains why they increase or decrease together. In other words, landscapes that are more fragmented tend also to be more diverse.

In both variants of calculations (Tables 2 and 3), i.e. using variables describing the entire landscapes of Herenchuk and variables calculated for these landscapes as mean values from squares of 3×3 km, similar results were obtained, which confirms the consistency of the observed relationships.

Table 2

Linear correlation coefficient describing the strength of relationships between variables calculated with FRAGSTATS for entire Herenchuk landscapes

Variable	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8
V_1 (Bare soils)	1	-0.8948	0.1915	0.7583	-0.3118	0.8428	0.8349	0.7392
V_2 (Forests)		1	-0.4424	-0.9581	0.4683	-0.8424	-0.8731	-0.7094
V_3 (Shrubs)			1	0.3957	-0.4807	0.4553	0.4801	0.4188
V_4 (Arable land)				1	-0.5220	0.7150	0.7692	0.5621
V_5 (Water)					1	-0.2733	-0.3217	-0.0974
V_6 (IJI)						1	0.7698	0.6573
V_7 (DIVI)							1	0.9436
V_8 (SHDI)								1

Table 3

Linear correlation coefficient expressing strength of relationships between variables calculated with FRAGSTATS by averaging, at the level of each landscape, the results obtained in the corresponding squares of 3×3 km

Variable	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8
V_1 (Bare soils)	1	-0.8813	0.1688	0.7250	-0.298	0.7865	0.8146	0.8229
V_2 (Forests)		1	-0.4358	-0.9525	0.5219	-0.8947	-0.7844	-0.7845
V_3 (Shrubs)			1	0.3892	-0.5376	0.6231	0.3244	0.3451
V_4 (Arable land)				1	-0.5886	0.7977	0.6533	0.6415
V_5 (Water)					1	-0.4835	-0.2443	-0.2293
V_6 (IJI)						1	0.7797	0.7861
V_7 (DIVI)							1	0.9971
V_8 (SHDI)								1

The results of Principal Component Analysis (Tables 4, 5) indicate that the first components account for a significant part of the variability occurring within the analysed set of 17 landscapes. In both variants of calculations, the first three components of C_j (j = 1, 2, 3) together represent 91.42% (Tab. 4) and 93.03% (Tab. 5) of the variation. This means that, despite the relatively large number of original variables (eight), most of the landscape variation can be summarised in only three synthetic dimensions, which greatly simplifies interpretation. The C_8 component was given a value of zero because its share is too low at the assumed level of accuracy.

Table 4

Share in overall landscape variability of C_j variables, derived by PCA analysis transforming V_j variables calculated by FRAGSTATS for whole landscapes (not divided into squares)

Variable	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
% Var.	67.29	14.60	9.53	4.60	3.16	0.70	0.12	0

Table 5

Contribution in overall landscape variability of C_j variables derived by PCA analysis transforming V_j variables calculated for landscapes by averaging the corresponding quantities obtained in the corresponding squares of size 3×3 km

Variable	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
% Var.	68.72	16.03	8.28	3.85	2.20	0.90	0.02	0

A comparison of the original variables and the variables transformed by the PCA method (Tab. 6, 7) allows us to determine which of the original variables V_j are best explained by the variables C_j. The most important is, of course, the reference to the variable C_1, which, according to the rules of the PCA procedure, has the largest share in the overall variance. The original variable V_2 (area share of forests) is the variable most strongly correlated with the C_1 variable. This shows that the presence of forests is the single most important factor differentiating the landscapes, and it is closely linked with both bare soils (V_1) and agricultural crops (V_4). The clustering of V_6, V_7 and V_8 within the same component shows that forest cover is not only related to the share of other land uses but also strongly influences the spatial pattern of the landscape, i.e., its fragmentation and diversity.

Further components cannot be neglected in the PCA analysis (Kotkowski, Ratajczak 2003). The C_2 variable derived by the PCA procedure is most strongly related to the V_5 variable (surface share of waters), highlighting that the presence of lakes and rivers forms a distinct dimension of variability, independently of forest–agriculture gradients. The next one (C_3) is most strongly related to the original V_3 variable (share of shrubs), suggesting that shrubland areas provide another differentiating factor, even though their total share is smaller. The C_4 variable, describing only 3.85–4.60% of the variability, is most strongly associated with the variable V_6 (IJI) in Table 6 or V_5 (surface fraction of water) in Table 7. This indicates that the role of landscape configuration and local water patches, although minor compared to forest cover, may still explain some fine-scale differences among landscapes.

Similar results were obtained in both variants of the calculations, i.e. the variables C_j ($j = 1, 2, 3$) show strong relationships with the same variables V_j. Differences are visible only with the variable C_4 and further, but these variables are much less important, because, as can be seen from Tables 4 and 5, together they explain, at most, 6.70–8.58% of the variance.

Table 6

Linear correlation coefficient expressing the strength of relationships between original variables describing landscape diversity (calculated for each landscape) and variables derived by PCA
The highest absolute value in each column is highlighted in bold

Variable	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
V_1	0.8957	-0.2737	-0.2420	0.0109	0.1999	**-0.1548**	-0.0098	0
V_2	**-0.9719**	-0.0004	0.1762	-0.0571	0.1371	0.0590	-0.0039	0
V_3	0.5420	0.5642	**0.5948**	0.1595	-0.0489	-0.0794	-0.0062	0
V_4	0.8865	0.1203	-0.2880	0.0303	**-0.3382**	0.0333	0.0157	0
V_5	-0.4746	**-0.7779**	0.2812	0.2188	-0.2012	-0.0413	-0.0111	0
V_6	0.8779	-0.1235	0.0047	**0.4062**	0.1876	0.1168	0.0110	0
V_7	0.9442	-0.1619	0.1647	-0.2102	-0.0122	0.0731	**-0.0738**	0
V_8	0.8191	-0.3365	0.3598	-0.2843	0.0383	0.0222	0.0603	0

Table 7

Linear correlation coefficient expressing the strength of relationships between original variables describing landscape diversity (calculated by averaging, at the level of each landscape, the results obtained in the corresponding squares of size 3×3 km) and variables derived by PCA
The highest absolute value in each column is highlighted in bold

Variable	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
V1	0.8736	-0.3404	-0.1701	-0.0192	**-0.2846**	-0.1031	0.0023	0
V2	**-0.9676**	0.0054	0.1847	0.1569	-0.0249	0.0667	-0.0007	0
V3	0.5296	0.6516	**0.5221**	-0.1060	-0.0140	-0.1044	0.0019	0
V4	0.8835	0.1203	-0.3351	-0.1904	0.2374	-0.0098	-0.0011	0
V5	-0.5431	**-0.6941**	0.3133	**-0.3484**	0.0554	-0.0253	0.0010	0
V6	0.9409	0.0882	0.1333	-0.1610	-0.1256	**0.2112**	-0.0011	0
V7	0.8818	-0.3447	0.2076	0.2166	0.1122	0.0174	0.0257	0
V8	0.8828	-0.3452	0.2362	0.1956	0.0809	-0.0105	**-0.0269**	0

Results of the analysis of the variation in land cover structure within landscapes

Based on the calculated landscape metrics, we can add such characteristics to each of the regions distinguished by Herenchuk (Tab. 8).

After analysing the results of the calculations performed to examine the diversity of landscapes, it was found that, in some cases, they are consistent for the grid sizes used, whereas in others they are not. In the case of the 3×3 km grid, the most homogeneous landscape was landscape No. 16, whereas in the case of the 4.5×4.5 and 6×6 km grids, it was landscape No. 4 (Fig. 4).

The landscapes with the most outlying squares are: for the 3×3 km grid – landscape No. 8, for the 4.5×4.5 km grid – landscape No. 9 and, for the 6×6 km grid – landscape No. 15 (Fig. 4).

Taking into account all 17 landscapes, in the case of each of the grids in the northern part of the perimeter, there are landscapes in which the outlier squares are mostly concentrated at their borders. With a grid of 6×6 km, these are landscapes No. 2, 3, 4, 6, 7, 8; with a grid of 4.5×4.5 km, these are landscapes No. 2, 3, 4, 5, 6; with a grid of 3×3 km, these are landscapes No. 2, 3, 4, 6 (Fig. 4). In the central and southern parts of the region, outlier squares are located both at the borders and in the middle of the landscapes (Fig. 4).

The above analysis revealed that the results of calculations differ among the basic fields of different dimensions. Therefore, it is necessary to analyse whether the results obtained on the basis of equal grids of squares have similarities, which of these grids are closest to each other, and which of the grids taken into account allows the area of interest to be best examined.

With each grid size applied, the analysis resulted in squares that overlap, either in whole or in part, the outlying squares identified in the analyses that applied a different grid size, and, conversely, there are those that define the terrain that do not overlap the outlying squares of other grids. The reasons for this are both the composition of the landscape section contained in the grids of individual dimensions (PLAND) and the difference in the values obtained when calculating the landscape metrics (SHDI, IJI, DIVISION).

Taking into account the interrelation of the outlier squares of the differently sized grids, the pair of grids 3×3 km and 4.5×4.5 km correlate with each other the most: 62% of the outliers for the grid with the smaller side of the square intersect with the outliers at the grid with the larger base area. When comparing pairs of 4.5×4.5 km and 6×6 km grids, this value is 61%; and for pairs of 3×3 km and 6×6 km, only 39% of the squares of the outliers of both grids coincide in whole or partially. Exact data for individual landscapes are presented in Table 9.

Table 8

Land cover characteristics of Herenchuk regions based on calculated landscape metrics

No.	Region (Ukr. rejon)	Characteristics
		1. Shepetivske Polissya (Ukr. Shepetivske polissia)
1	Hannopilskyi	The dominant land cover type in the region is arable land, which occupies 46.3% of the area. Forests and bare soils are equally represented, each covering 20.6%, followed by shrub vegetation at 12%. Water bodies are nearly absent, accounting for only 0.1% of the total surface.
2	Berezdivskyi	The dominant land cover type in the region is forest, which occupies nearly half of the total area (47.4%). Arable land covers approximately one quarter of the region, while both bare soils and shrub vegetation each account for 13%. Water bodies are scarcely present, representing only 0.4% of the total surface.
3	Slavutskyi	The region is characterised by a large, forested area, which covers 75.7% of its total surface. This is followed by arable land (12.9%), shrub vegetation (5.2%) and bare soils (4.3%). In the north-west of the region lies the Khmelnytskyi Nuclear Power Plant reservoir, which contributes to the high homogeneity of this area compared to others, as the water body occupies a relatively large continuous patch, accounting for 1.7% of the region's surface. Due to the extensive forest area, this region recorded the lowest values of both the division index and the Shannon diversity index compared to other regions.
		2. Forest-Steppe of North Podolia (Ukr. Pivnichnopodilskyi lisostep)
4	Bilhorodskyi	The dominant land cover type in the region is arable land, which occupies 43.3% of the total area. Forests follow with 24.1%, while bare soils account for 19.6% and shrub vegetation for 12%. Water bodies are minimally represented, covering only 0.3% of the region's surface.
5	Skrypivskyi	The dominant land cover type in the region is arable land, occupying 36.7% of the area. It is followed by forests (27.99%), open soils (23.3%), and shrub vegetation (11.01%). Water bodies cover only 0.8% of the region. The relatively balanced proportions of several land cover types, which are not clearly dominated by any single category, may indicate a higher degree of landscape heterogeneity.
6	Polkvynskyi	This is a highly agriculturally transformed region – arable land accounts for 46.1% of the area, while open soils cover 29.6%, which is the highest value among all the regions analysed. Forests (12.8%) and shrub vegetation (10.9%) occur in nearly equal proportions. Water bodies were identified on only 0.4% of the region's surface.
7	Sluch-Khomorskyi	Arable land occupies the largest share of the region's area at 39.5%. Forests (26.7%) and open soils (25.5%) are present in nearly equal proportions. Shrub vegetation covers 7.5% of the area, while water bodies were identified on only 0.7% of the surface.
8	Ikopotskyi	This is an agriculturally transformed area. Arable land occupies 41.5% of the total surface, followed by bare soils, which account for 27.6%. Forests cover 20.6%, while shrub vegetation represents 9.08%. Water bodies were detected across 0.8% of the region's surface.
9	Starokostiantynivskyi	Arable land covers 41.5% of the area, forests account for 28.6%, and bare soils make up 23.6%. Shrub vegetation was detected on 7.8% of the surface, while water bodies were identified across 0.4% of the region's area.
		3. Central-Podilskyi Forest (Ukr. Tsentralnopodilskyi lisostep)
10	Avratynskyi	Nearly half of the region's surface is occupied by arable land (45.7%), while bare soils cover approximately one quarter of the area (25.7%). This is an agriculturally transformed region, with forests covering 19% of the surface and shrub vegetation accounting for 8.2%. Water bodies were detected across 0.9% of the region's area.
11	Vovchko-Buzhotskyi	This area is characterised by relatively balanced proportions of land cover types: arable land and forests each occupy 33.3% of the surface, while bare soils cover 23.95%. Shrub vegetation was identified on 7.7% of the area and water bodies on 1.5% of the region's surface.
12	Letychivskyi	In this region, the dominant land cover is forest, which occupies 43.9% of the total area. This is followed by arable land at 30.4% and bare soils at 16.3%. Shrub vegetation was identified on 7.3% of the surface, while water bodies account for 1.9% of the region's area.
13	Vovkovynetskyi	The land cover classes in this region are distributed very similarly to the previous one. Forests are the dominant class, covering 43.1% of the area, followed by arable land at 29.2% and bare soils at 19.43%. Shrub vegetation was identified on 7.4% of the surface. However, compared to the previous region, water bodies cover a smaller share, accounting for just 0.6% of the area.

4. Dnieper Forest (Ukr. Prydnistrovskyi lisostep)		
14	Horodotskyi	In this region, arable land covers 35.5% of the area. Bare soils and forests are represented in relatively equal proportions, accounting for 27.7% and 27.5%, respectively. Shrub vegetation was detected on 8.7% of the region, while water bodies occupy 0.4% of the surface.
15	Tovtrovyi	In this region, arable land and forests occur in comparable proportions, covering 34.8% and 30.2% of the area, respectively. Bare soils were identified on 26.3% of the surface, while shrub vegetation and water bodies account for 9.8% and 1.7%, respectively.
16	Zhvanchytskyi	Arable land and forests occur in comparable proportions, covering 34.8% and 34.09% of the area, respectively. Bare soils were detected on 19.5%, and shrub vegetation on 8.7% of the surface. Water bodies, mostly represented by the Dniester River and its tributaries, were identified on 2.7% of the region's area.
17	Ushytskyi	In this region, forests prevail, covering 38.1% of the area. Arable land and bare soils occupy 26.8% and 22.9%, respectively, while shrub vegetation accounts for 9.42%. Water bodies were detected on 2.5% of the region's surface and are mainly represented by the Dniester River and its watercourses.

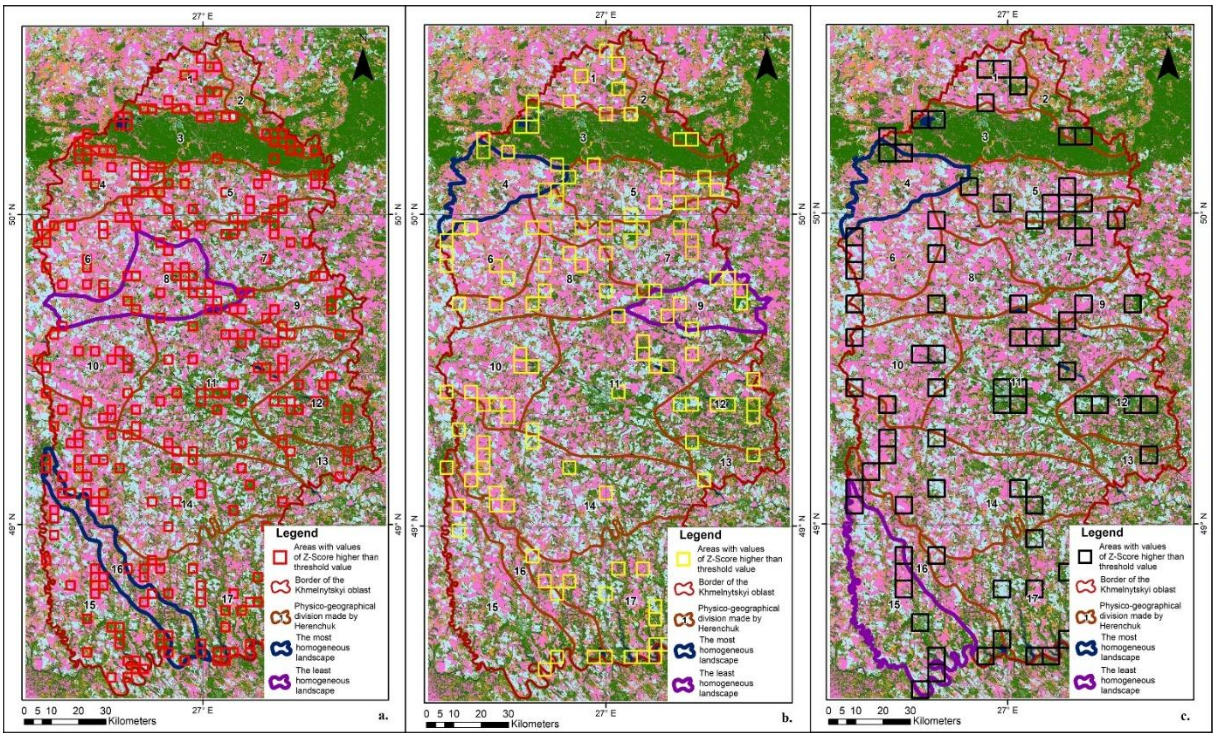

Fig. 4. Areas with values of the Z-score higher than threshold value.
Calculations were based on three different grids (from left to right):
a – 3×3 km
b – 4,5×4,5 km
c – 6×6 km

The landscape in which the outlier squares have the highest percentage of mutual coverage is landscape No. 2. On the other hand, the landscape in which these squares overlap the least is landscape No. 8 (Fig. 5).

In terms of the distribution of protruding landscape segments, the 3×3- and 4.5×4.5-km grid pair and the 4.5×4.5- and 6×6-km grid pair obtained the highest comparable degree of overlapping squares. Similar results of the analysis of landscape homogeneity can be observed for these two pairs of grids (Tab. 9). In the case of the 4.5×4.5- and 6×6-km grids, similarities can be seen: the same regions have similar degrees of homogeneity. Landscapes with a high degree of heterogeneity are comparable. As in the case of the 4.5×4.5-km grid, the regions with the highest percentage of outlier squares are landscapes 1, 5, 6, 15. With a grid of 4.5×4.5 km, landscape 9 has the highest percentage of outlier squares, but the 6×6 km grid did not give a similar result. The landscape with the lowest degree of heterogeneity in these two grids turned out to be the same landscape No. 4. Comparing the 3×3- and 4.5×4.5-km grids, four landscapes also obtained comparable results: 3, 6, 8, 15.

Table 9

Analysis of the spatial distribution of squares with value of Z-score higher than threshold value for three grids: 3×3 km, 4.5×4.5 km, 6×6 km

Landscape number	Number of squares in each landscape (based on 3×3 km grid)	Number of squares 3×3km, with value of Z-Score higher than threshold value (outliers)	Number of outliers, wchich are intersected by outliers from the grid 4.5×4.5km	Number of outliers, wchich are intersected by outliers from the grid 6×6km	Percentage of intersect crossing of outliers from pair of grids: 4.5×4.5 km and 3×3km	Percentage of intersect crossing of outliers from pair of grids: 6×6 km and 3×3km	Number of squares in each landscape (based on 4.5×4.5 km grid)	Number of squares 4.5×4.5 km, with value of Z-Score higher than threshold value (outliers)	Number of outliers, wchich are intersected by outliers from the grid 6×6km	Percentage of intersect crossing of outliers from pair of grids: 6×6 km and 4.5×4.5km
Landscape1	67	9	7	4	78%	44%	27	5	2	40%
Landscape2	**57**	**9**	**6**	**5**	**67%**	**56%**	**23**	**3**	**3**	**100%**
Landscape3	147	20	16	10	80%	50%	64	9	5	56%
Landscape4	83	12	6	4	50%	33%	37	2	1	50%
Landscape5	111	16	10	8	63%	50%	52	9	6	67%
Landscape6	102	16	12	4	75%	25%	46	8	5	63%
Landscape7	157	20	16	3	80%	15%	67	11	7	64%
Landscape8	**125**	**20**	**8**	**3**	**40%**	**15%**	**56**	**9**	**3**	**33%**
Landscape9	80	11	9	4	82%	36%	35	8	4	50%
Landscape10	134	14	8	6	57%	43%	59	8	5	63%
Landscape11	309	37	17	18	46%	49%	139	20	13	65%
Landscape12	115	12	9	7	75%	58%	49	7	6	86%
Landscape13	43	5	3	2	60%	40%	22	3	1	33%
Landscape14	289	31	16	9	52%	29%	134	12	10	83%
Landscape15	179	26	18	13	69%	50%	77	14	8	57%
Landscape16	77	8	5	1	63%	13%	36	4	2	50%
Landscape17	217	27	16	12	59%	44%	94	14	8	57%

Table 10

Analysis of landscape homogeneity

3×3 km grid					**4,5×4,5 km grid**					**6×6 km grid**				
Landscape number	Number of squares in each landscape	Number of outlier squares	Percentage of outlier squares	Homogeneity index	Landscape number	Number of squares in each landscape	Number of outlier squares	Percentage of outlier squares	Homogeneity index	Landscape number	Number of squares in each landscape	Number of outlier squares	Percentage of outlier squares	Homogeneity index
Landscape1	67	9	13%	0,87	Landscape1	27	5	19%	0,81	Landscape1	17	3	18%	0,82
Landscape2	57	9	16%	0,84	Landscape2	23	3	13%	0,87	Landscape2	14	2	14%	0,86
Landscape3	147	20	14%	0,86	Landscape3	64	9	14%	0,86	Landscape3	39	5	13%	0,87
Landscape4	83	12	14%	0,86	Landscape4	37	2	5%	0,95	Landscape4	19	1	5%	0,95
Landscape5	111	16	14%	0,86	Landscape5	52	9	17%	0,83	Landscape5	26	5	19%	0,81
Landscape6	102	16	16%	0,84	Landscape6	46	8	17%	0,83	Landscape6	27	5	19%	0,81
Landscape7	157	20	13%	0,87	Landscape7	67	11	16%	0,84	Landscape7	38	4	11%	0,89
Landscape8	125	20	16%	0,84	Landscape8	56	9	16%	0,84	Landscape8	31	3	10%	0,90
Landscape9	80	11	14%	0,86	Landscape9	35	8	23%	0,77	Landscape9	20	3	15%	0,85
Landscape10	134	14	10%	0,90	Landscape10	59	8	14%	0,86	Landscape10	34	5	15%	0,85
Landscape11	309	37	12%	0,88	Landscape11	139	20	14%	0,86	Landscape11	76	8	11%	0,89
Landscape12	115	12	10%	0,90	Landscape12	49	7	14%	0,86	Landscape12	26	4	15%	0,85
Landscape13	43	5	12%	0,88	Landscape13	22	3	14%	0,86	Landscape13	11	1	9%	0,91
Landscape14	289	31	11%	0,89	Landscape14	134	12	9%	0,91	Landscape14	76	9	12%	0,88
Landscape15	179	26	15%	0,85	Landscape15	77	14	18%	0,82	Landscape15	45	9	20%	0,80
Landscape16	77	8	10%	0,90	Landscape16	36	4	11%	0,89	Landscape16	17	2	12%	0,88
Landscape17	217	27	12%	0,88	Landscape17	94	14	15%	0,85	Landscape17	56	9	16%	0,84

From the above, it follows that the results are more comparable for the sizes of fundamental fields that are close to each other in terms of surface area. The obtained values describing the homogeneity of the landscape differ significantly with the basic field twice as large as the first one.

Outlier squares can have distinctive values due to the size of the landscape patches of each class and the percentage of each class. When a section of the landscape is very divided and all five, or even four, classes are present in it (water has a very small share comparable to other classes, and in some squares it does not occur at all), the values of the calculated metrics have results comparable to other, also very divided sections of the landscape. On the other hand, when there are three or fewer classes in a section of the landscape and one of them has a high share or one of the patches covers most of the square, the Z-Score value is already higher. These more homogeneous squares appear as outliers. This may mean that, on average, the landscape structure of the studied area is equally divided, which would be consistent in the translation into the actual use of the area, which has resulted in the landscape of the perimeter being largely transformed by man. On the other hand, squares with slightly larger, less divided patches are already distinctive. This statement is

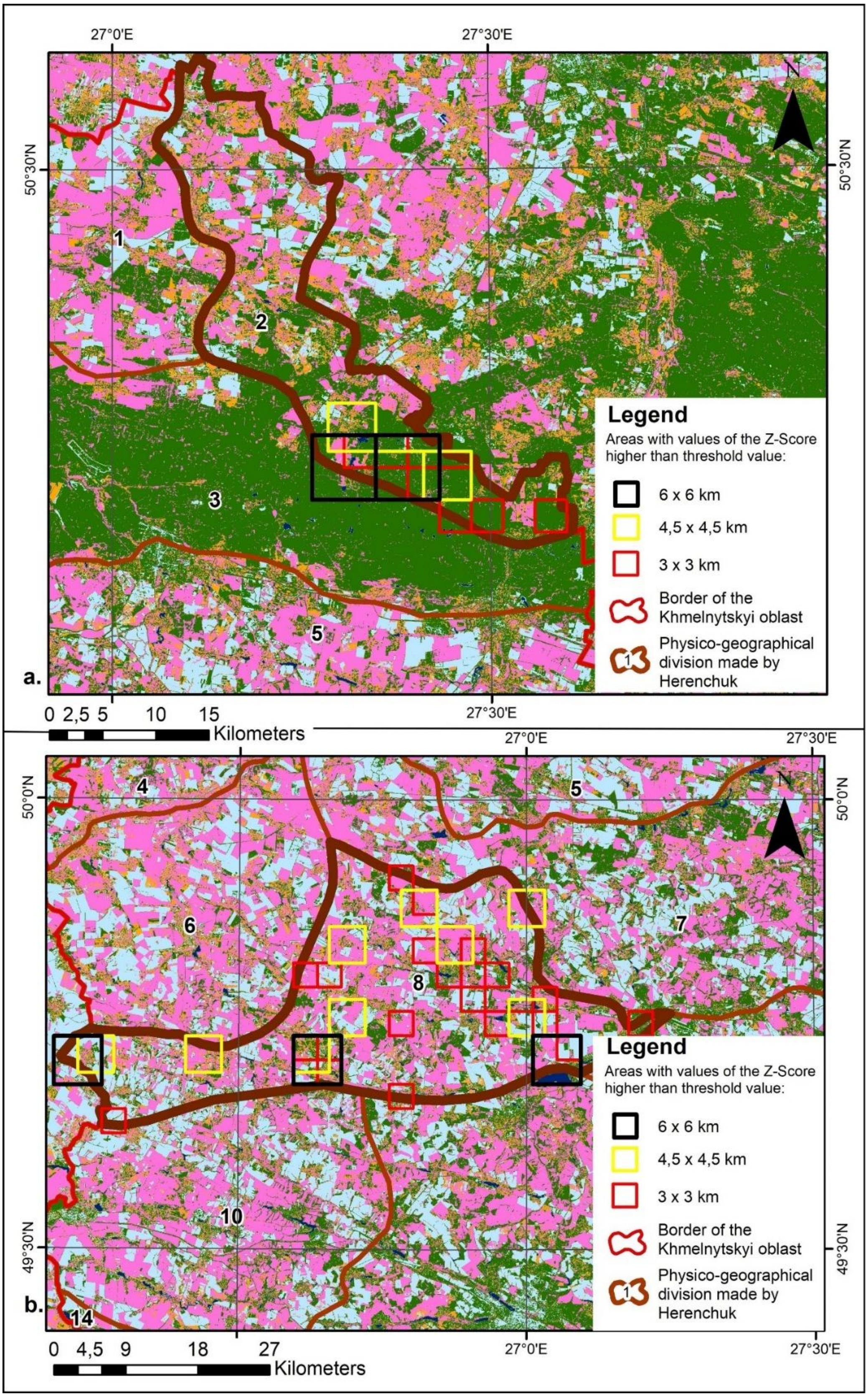

Fig. 5. Analysis of the spatial distribution of squares:
a – landscape with the highest percentage of spatial crossing of squares which value of Z-score higher than threshold value which were calculated for the different grids
b – landscape with the lowest percentage of spatial crossing of squares which value of Z-score higher than threshold value which were calculated for different grids

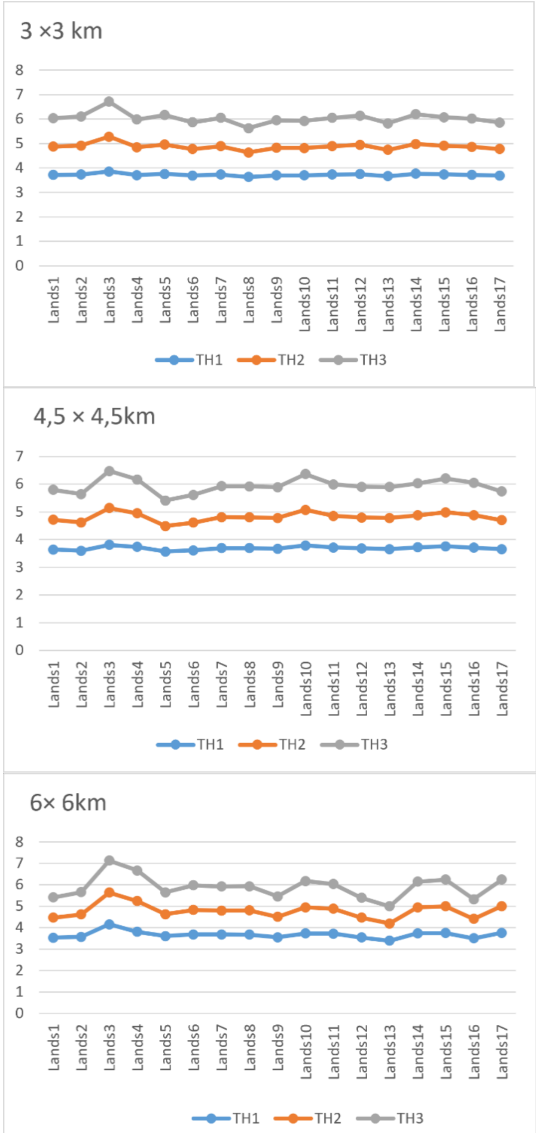

Fig. 6. Values of thresholds for the Z-score for three grids (3×3, 4.5×4.5, 6×6 km)

also confirmed by the fact that the limit values calculated for all landscapes are very similar to each other (Fig. 6). Only one landscape (no. 3), the majority of which is occupied by a forest belt, is less divided compared to the others, and its limit values are higher than the other 16 landscapes. This landscape is also the only one to be highly homogeneous, as expressed by outlier squares being distributed only at its borders on all the analysed grids (Fig. 4).

Limit values behave differently depending on the size of the analysed field. For the 3×3-km grid, all values differ by no more than 0.5 units. On the other hand, when the analysed area is increased, the limit values for individual landscapes differ more. Such behaviour of limit values once again confirms that, in landscape analysis, when dividing the studied area into smaller elements, it is important to analyse which size will help to best reproduce the studied phenomenon.

Analysing the similarity of the obtained values of homogeneity among landscapes, looking at them from the point of view of the analysed physico-geographical division, it turned out that all landscapes that Herenchuk combined into one of the four higher-order units (Tsentralnopodilskyi Lisostep) have similar values of landscape homogeneity.

In the case of the grid with 4.5-km squares, landscapes included in this unit (10, 11, 12, 13) obtained exactly the same percentage of outlier squares, because 14% of squares have Z-score values higher than the limit values (Tab. 10). In the case of basic squares with sides of 3 km and 6 km, these values are in the range of 10 to 15% of the outlier squares. On the basis of these results, it is possible to trace the similarity of the homogeneity of landscapes 10, 11, 12, 13, which may justify combining them into one unit of higher rank. Landscapes 11, 12 and 13 also exhibit strong similarities in their land cover characteristics. It can also be noted that, for another higher-order unit – – the Poliskiy type, the results of landscape homogeneity calculations have a common spatial distribution of outlier squares for all the applied meshes. In areas 1, 2 and 3, most of them are located at the borders of units. This may to some extent justify the boundaries of these regions set by Herenchuk.

Conclusions

The variables we selected describe the synergy effect of the current features of the natural environment, land development and use, and land physiognomy that are expressed in landscapes and thus on satellite images. This is in line with contemporary concepts of describing the natural and cultural landscapes together (Richling 2018a). In this context, our analysis can complement Herenchuk's physico-geographical regionalisation (1980) by adding a general view of land cover patterns, even though it does not aim to provide a more detailed description than geomorphological features.

Although the analysis of the diversity of land cover structure within landscapes for all three grids had similarities in the presented results, there were also many inconsistencies. According to Saura and Martínez-Millán (2001), an important problem when comparing land-cover patterns is the scale of the analysed spatial data, because this has been shown to greatly influence values of pattern metrics. It is therefore worth understanding that the size of the basic field is of great importance when performing an analysis using landscape metrics.

The Interspersion and Juxtaposition Index (IJI) is the most sensitive to the size of the basic field among the calculated variables. The minimum value of this variable for the 6×6-km grid is up to twice as high as the minimum value for the 3×3-km grid. Looking at the spatial arrangement of squares reaching the minimum and maximum values of the IJI variable, it does not converge in any of the three grids. That is, a square that has obtained the minimum value of the IJI variable on the grid of 3×3 km does not intersect with any square that has obtained the minimum value of the same variable on the grid of either 4.5×4.5 km or 6×6 km.

On the basis of the calculations performed, it can be concluded that the results obtained for the grids that are close in basic field size have a higher percentage of similarity compared to those whose basic fields were twice as large. Comparing the results obtained for different grids, it can be seen that the results obtained for the 4.5×4.5-km grid seem to be mostly related to the source division done by Herenchuk. It can therefore be concluded that, in the case of the analysed physico-geographical division, the most appropriate basic field of the three tested is 4.5×4.5-km squares.

The thresholds obtained for individual regions may help identify the processes of landscape change driven by human economic activity. According to Chmielewski (2023), the natural variability of landscapes is further diversified by human activity, introducing numerous anthropogenic forms of land cover and use. In his characteristics of individual regions, Herenchuk referred to the physiognomic structure of separate units, which is difficult to trace on the basis of analysed satellite scenes. The reason for this may be human activity, which has transformed the landscape and made it very divided, as a result of which individual regions could lose the uniqueness that would otherwise result from the characteristics of the natural landscape. This phenomenon may explain the inability to trace the reflection of the calculations made for all the landscapes distinguished by Herenchuk.

The primary determinants of the diversity of the landscape of Khmelnytskyi Oblast are the shares of individual land cover forms: mainly forests, fields without vegetation cover and fields with agricultural crops, then waters and shrubs. These variables describe the composition of the landscape and, in combination with landscape structure indices, make the area unique. The strongest correlation relationship was found between the variables V_2 (area share of forests) and V_4 (area share of agricultural crops). The surface share of forests in the studied landscape defines an element of the natural landscape, which is also transformed over time by human economic activity, thus increasing the area share of agricultural crops. According to one conceptual view of anthropogenic landscape change, described by Mikheli (2014b), landscape changes are mostly reversible if they affect vegetation or biogenic components of nature that have the ability to be restored. This may mean that the studied landscape may change in the future as if it were even more transformed, but also that the changes may be reversed if it ceases to be so strongly influenced by human use.

The relationship between the (V_7) DIVISION and (V_8) SHDI variables shows that these variables were strongly related. They were selected to analyse the diversity and fragmentation of individual landscapes on the basis of analysed sources on a given topic. Looking at the results of the analysis, it is clearly more reasonable to select more landscape metrics, to perform calculations for all of them and, only then, after conducting the analysis of the main components, to select the metrics that contribute the largest percentage of new information to the analysis.

In reference to the stated research objective, which was to complement Herenchuk's regionalisation with land cover data using landscape metrics and statistical methods based on satellite data, it can be noted that the calculated landscape metrics made it possible to trace the similarity of the homogeneity of certain regions. Regions 10, 11, 12, and 13 were combined into a higher-order unit – Central-Podilskyi Forest (Ukr. Tsentralnopodilskyi lisostep), while regions 1, 2 and 3 merged into another higher-level unit – Shepetivske Polissya. The other two regions are characterised by a different degree of homogeneity of regions and the location of outlier squares in them. The other two regions are characterised by a different degree of homogeneity of regions and the location of outlier squares in them.

We believe that landscape metrics can be used both to analyse existing physico-geographical regionalisations and to assess the coherence of landscape units, using information extracted from the applied satellite or aerial imagery. It should be remembered that no single metric analyses the diversity of the landscape (Saura, Martínez-Millán 2001); hence, studies often use such metrics in sets selected such that each one describes the landscape differently and brings significantly new information. Despite landscape metrics having been used in scientific research for a long time, there is still no certainty as to how individual metrics are affected by the scale of the analysed spatial data, so, when conducting a similar type of analysis, it is worth testing its various variants.

The findings presented here have not only theoretical but also practical implications. In the context of Ukraine, the applied approach based on landscape metrics and satellite data can become an important tool for environmental monitoring, allowing for the systematic detection of anthropogenic transformations and the assessment of their reversibility. At the same time, it may provide a methodological basis for spatial planning, by helping to identify areas of high landscape coherence and those subject to fragmentation. Such information may prove useful for the sustainable management of land resources, the designation of zones requiring protection, and the development of planning strategies that integrate both natural and cultural values of the landscape. In this way, the present research may serve as a reference point for strengthening the evidence base supporting decision-making in environmental governance and regional development.

References

ArcMap. Executing the Iso Cluster Unsupervised Classification tool. Online: https://desktop.arcgis.com/en/arcmap/latest/extensions/spatial-analyst/image-classification/executing-the-iso-cluster-unsupervised-classification-tool.htm (last access: 15.05.2024).

Armand D.L. 1980. Nauka o krajobrazie. PWN, Warszawa.

Büscher O., Buck O., Lohmann P., Hofmann P., Müller S., Schenkel R., Wiese C. 2008. Einsatz von Change Detection Methoden zur Fortführung von DeCOVER Objektarten. *Photogrammetrie – Fernerkundung – Geoinformation* 5: 395-407.

Chmielewski T. 2023. Przestrzeń i granice w krajobrazie. *Studia i Materiały Lubelskie* 21. DOI: 10.61464/siml.95.

Chmielewski T.J., Myga-Piątek U., Solon J. 2015. Typologia aktualnych krajobrazów Polski. *Przegląd Geograficzny* 87(3): 377-408.

Dokuchaev V. 1948. Uchienie o zonach prirody. Geografgiz, Moskva.

Fichera C.R., Modica G., Pollino M. 2012. Land Cover classification and change-detection analysis using multi-temporal remote sensed imagery and landscape metrics. *European Journal of Remote Sensing* 45(1): 1-18. DOI: 10.5721/EuJRS20124501.

Fragstats. A Spatial Pattern Analysis Program for Categorical Maps. Online: https://fragstats.org/index.php (last access 15.09.2024).

Haglauer D. 1996. Zdjęcia lotnicze jako podstawa regionalizacji geograficznej. *Fotointerpretacja w Geografii* 3: 45-53.

Herenchuk K.I. (ed.). 1980. Pryroda Khmelnytskoi oblasti. Vischa shkola, Lvov.

Isachenko A. 1991. Landshaftovedeniye i fizikogeograficheskoye rayonirovaniye. Vysshaya shkola, Moskva.

Iskin E.P., Wohl E. 2023. Beyond the case study: Characterizing natural floodplain heterogeneity in the United States. *Water Resources Research* 59: e2023WR035162. DOI: 10.1029/2023WR035162.

Jaeger J.A.G. 2000. Landscape division, splitting index, and effective mesh size: new measures of landscape fragmentation. *Landscape Ecology* 15: 115-130.

Jakomulska A., Sobczak M. 2001. Korekcja radiometryczna obrazów satelitarnych – metodyka i przykłady. *Teledetekcja Środowiska* 32: 152-171.

Kasijanik I. 2012. Pidchodi do fiziko-geographichnogo raionuvania teritorii Khmelnytskyi oblasti. *Geografia. Naukovi Notatki* 1: 42-48.

Kondracki J. 1976. Podstawy regionalizacji fizycznogeograficznej. PWN, Warszawa.

Kondracki J. 2002. Geografia regionalna Polski. PWN, Warszawa.

Kotkowski B., Ratajczak W. 2003. Składowe główne o najmniejszej wariancji a regresja ortogonalna. In: H. Rogacki (ed.) *Problemy interpretacji wyników metod badawczych stosowanych w geografii społeczno-ekonomicznej i gospodarce przestrzennej*. Bogucki Wyd. Naukowe, Poznań: 71-81.

Landsat Science. NASA. Online: https://landsat.gsfc.nas.gov/landsat-8/landsat-8-overwiew (last access: 06.08.2024).

Marynych O., Shyshchenko P. 2005. Fizychna heohrafiia Ukrainy: pidruch. – Kyiv, Znannia.

Marynych O., Shyshchenko P., Ivanina L. 1980. Fizyko-heohrafichne raionuvannia URSR. Kyiv, Vyshcha shkola.

Marynych O., Parkhomenko H., Petrenko O., Shyshchenko P. 2003. Udoskonalena skhema fizyko-heohrafichnoho rayonuvannya Ukrainy. *Ukr. heohraf. zhurnal* 1: 16-21.

McGarigal K., Marks B. J. 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. USDA Forest Service. *Technical Reports* PNW-351, Portland.

Mikheli S. 2014a. Ukrainske landshaftoznavstvo: vytoky, stanovlennia, suchasnyi stan: Monohrafiia. NPU imeni D. P. Drahomanova,

Mikheli S. 2014b. Antropogenizaciya ukrainskogo landshaftovedeneiya. *Aktualnyje problemy gumanitarnych i estestvennych nauk* 2: 2-6.

Olędzki J.R. 1992. Geograficzne uwarunkowania zróżnicowania obrazu satelitarnego Polski i jego podziału na jednostki fotomorficzne. Wyd. Uniwersytetu Warszawskiego, Warszawa.

Olędzki J.R. 2007. Regiony geograficzne Polski. *Teledetekcja Środowiska* 38: 1-337.

Osińska-Skotak K. 2007. Znaczenie korekcji radiometrycznej w procesie przetwarzania zdjęć satelitarnych. *Archiwum Fotogrametrii, Kartografii i Teledetekcji* 17B: 577-590.

Parysek J., Ratajczak W. 2002. Analiza składowych głównych, jej korzyści i ograniczenia z punktu widzenia badań geograficznych. In: H. Rogacki (ed.) *Możliwości i ograniczenia zastosowań metod badawczych w geografii społeczno-ekonomicznej i gospodarce przestrzennej*. Bogucki Wyd. Naukowe, Poznań: 61-73.

Pukowiec-Kurda K., Sobala M. 2016. Nowa metoda oceny stopnia antropogenicznego przekształcenia krajobrazu na podstawie metryk krajobrazowych. *Prace Komisji Krajobrazu Kulturowego* 31: 73-86.

Ratajczak W. 2003. Analiza regresji a składowe główne. In: H. Rogacki (ed.) *Problemy interpretacji wyników metod badawczych stosowanych w geografii społeczno-ekonomicznej i gospodarce przestrzennej*. Bogucki Wyd. Naukowe, Poznań: 61-70.

Richling A. 2018a. Typologia krajobrazu Polski – – rozwój i terminologia. *Problemy Ekologii Krajobrazu* 46: 5-21.

Richling A. 2018b. Rozwój XIX i XX-wiecznych poglądów na temat regionalizacji fizycznogeograficznej Polski In: M. Kistowski, U. Myga-Piątek, J. Solon (eds.) *Studia nad regionalizacją fizycznogeograficzną Polski*: 13-32.

Richling A. 2018c. Regionalizacja – wybrane zagadnienia. *Prace i Studia Geograficzne* 63(1): 9-18.

Richling A., Solon J. 2011. Ekologia krajobrazu. PWN, Warszawa.

Roo-Zielińska E., Solon J., Degórski M. 2007. Ocena stanu i przekształceń środowiska przyrodniczego na podstawie wskaźników geobotanicznych, krajobrazowych i glebowych (podstawy teoretyczne i przykłady zastosowań). Polska Akademia Nauk, Instytut Geografii i Przestrzennego Zagospodarowania im. Stanisława Leszczyckiego, Warszawa.

Runge J. 2006. Metody badań w geografii społeczono-ekonomicznej – elementy metodologii, wybrane narzędzia badawcze. Wyd. Uniwersytetu Śląskiego, Katowice.

Saura S., Martínez-Millán J. 2001. Sensitivity of Landscape Pattern Metrics to Map Spatial Extent. *Photogrammetric Engineering and Remote Sensing* 67(9): 1027-1036.

Singh A., Harrison A. 1985. Standardized principal components. *International Journal of Remote Sensing* 6(6): 883-896.

Solon J. 2002. Ocena różnorodności krajobrazu na podstawie analizy struktury przestrzennej roślinności. *Prace Geograficzne* 185.

Solon J. 2008. Przegląd wybranych podejść do typologii krajobrazu. *Problemy Ekologii Krajobrazu* 20.

Solon J., Borzyszkowski J., Bidłasik M., Richling A., Badora K., Balon J., Brzezińska-Wójcik T., Chab L., Dobrowolski R., Grzegorczyk I., Jodłowski M., Kistowski M., Kot R., Krąż P., Lechnio J., Macias A., Majchrowska A., Malinowska E., Migoń P., Ziaja W. 2018. Physico-geographical mesoregions of Poland: Verification and adjustment of boundaries on the basis of contemporary spatial data. *Geographia Polonica* 91(2): 143-170. https://doi.org/10.7163/GPol.0115

Szabó S., Csorba P., Szilassi P. 2012. Tools for landscape ecological planning – scale, and aggregation sensitivity of the contagion type landscape metric indices. *Carpathian Journal of Earth Environmental Sciences* 7: 127-136.

Tarantino C., Adamo M., Lucas R., Blonda P. 2016a. Detection of changes in semi-natural grasslands by cross correlation analysis with WorldView-2 images and new Landsat 8 data. *Remote Sensing of Environment* 175: 65-72. DOI: 10.1016/j.rse.2015.12.031.

Tarantino C., Lovergine F., Niphadkar M., Lucas R., Nativi S., Blonda P. 2016b. Towards Operational Detection of Forest Ecosystem Changes in Protected Areas. *Remote Sensing* 8: 850. DOI: 10.3390/rs8100850.

Urbański J. 2008. GIS w badaniach przyrodniczych. Wyd. Uniwersytetu Gdańskiego, Gdańsk.

Uuemaa E., Antrop M., Roosaare J., Marja R., Mander Ü. 2009 . Landscape metrics and indices: an overview of their use in landscape research. *Living reviews in landscape research* 3(1): 1-28.

Wang W., Hall-Beyer M., Wu C., Fang W., Nsengiyumva W. 2020. Uncertainty Problems in Image Change Detection. *Sustainability* 12: 274. DOI:10.3390/su12010274.

Zhang N., Li H. 2013. Sensitivity and effectiveness of landscape metric scalograms in determining the characteristic scale of a hierarchically structured landscape. *Landscape Ecology* 28: 343-363.
DOI: 10.1007/s10980-012-9837-x.

Zwierzchowska I., Stępniewska M., Łowicki D. 2010. Możliwości wykorzystania programu Fragstats w badaniach środowiska przyrodniczego. *Przegląd Geograficzny* 82(1): 85-102.