

RESEARCH ARTICLE

Landscape Online | Volume 97 | 2022 | Article 1097

Submitted: 2 September 2021 | Accepted in revised version: 8 March 2022 | Published: 31 March 2022

A dynamic evaluation of landscape transformations based on land cover data

Abstract

The present era is characterized by unprecedented levels of human activity, which adapt the world to our needs and induce transformations in landscape morphology and physiognomy. The Anthropocene is a remarkable epoch, where changes in space are not only visible, but also confirmed by an extensive body of research. Human activities lead to the creation of numerous tools for measuring the scale of anthropogenic pressure. Satellite and photogrammetric data that broaden our field of vision and change the scale of reference from local to global or even beyond global. These data support observations of the present condition of the surrounding space as well as the rate of changes in space. In the present study, land cover data were used to monitor changes in the surrounding landscape. A system for classifying evolutionary changes in space was proposed to monitor land-use transformations and describe landscape stability. The applicability of CORINE Land Cover (CLC) data for such analyses was evaluated. The research hypotheses and the proposed procedure were tested in the Mazovian (Polish: Mazowieckie) Voivodeship and the city of Warsaw, the Polish capital and the central point of the analyzed voivodeship which generates continuous changes in space. The results of the study confirmed the research hypotheses and demonstrated that CLC data are suitable for monitoring spatial changes.

Iwona Cieślak¹, Andrzej Biłozor^{1*}

1) University of Warmia and Mazury in Olsztyn, Faculty of Geoengineering, Institute of Spatial Management and Geography, Department of Socio-Economic Geography, Olsztyn, Poland

*Corresponding author: University of Warmia and Mazury in Olsztyn, Faculty of Geoengineering, Institute of Spatial Management and Geography, Department of Socio-Economic Geography, ul. Pawocheńskiego 15, 10-720 Olsztyn, Poland, Email: abilozor@uwm.edu.pl

ORCID

Iwona Cieślak

 <https://orcid.org/0000-0003-4219-5718>

Andrzej Biłozor

 <https://orcid.org/0000-0002-4716-1069>

Keywords:

landscape, land cover and land use, CORINE Land Cover (CLC), spatial planning

<https://doi.org/10.3097/LO.2022.1097>

© 2022 The Authors. Published in Landscape Online – www.Landscape-Online.org

Open Access Article distributed under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

1 Introduction

We live in an era that is characterized by unprecedented levels of human pressure on the environment (Crutzen & Schwägerl 2011; Zalasiewicz et al. 2014). Landscape transformations lead not only to visual changes, but also to changes in the quality of the environment and the natural value of the surrounding space (Brown et al. 2013; Morris 2019). Visual evidence provides tangible proof that such processes are taking place (Antrop 2005). These phenomena, including changes in the physical environment, are also reflected in land cover, and they testify to the evolution of landscape (Cieślak et al. 2020). Anthropogenic landscapes presently cover large swathes of the Earth (Ellis et al. 2006; Hooke et al. 2012; Huang et al. 2010). The rapid advancement of intensive agriculture, industrialization and urbanization has transformed natural landscapes by altering topographic features, plant cover and geomorphological properties of the surrounding environment (Tarolli et al. 2014). Recent research (Chen & Liu 2014; Werner & McNamara 2007) has underlined the significance of dynamic human-environment interactions, where changes in landscape function affect human systems (Barthel et al., 2019). Analyses of human-environment interactions in anthropogenic landscapes pose a considerable challenge and are essential for understanding the evolution of our living space (Demir 2019; Hossain et al. 2020).

Diverse forms of landscape play a particularly important role in evaluations of land use, and they can be assessed based on the extent to which they are represented in land cover (Yoshioka et al. 2017). Diverse and naturally valuable land cover types are indicative of high-quality landscapes (Richling 2018). However, most changes in the landscape have anthropogenic origin (Bogaert et al. 2014; Muñoz-Pedreros 2017). Civilizational processes such as urbanization are easily discernible in the landscape, and most of them lead to the degradation of the surrounding environment (Hunziker et al. 2007). Therefore, the extent to which landscapes have been transformed by human activity can provide valuable input data for research into landscape changes (Drusa et al. 2016; Biłozor et al. 2019; 2020). Based on these assumptions, the

present study set out to evaluate landscape quality by identifying different types of land cover and the degree of their transformation. These goals were achieved with the use of the multiple criteria decision-making analysis and the entropy-based pattern analysis for evaluating landscape uniformity (Shannon 1948; Shannon & Weaver 1964).

The research hypothesis postulating that landscape diversification occurs in a sinusoidal manner was investigated. The extent of changes in land cover is low in untransformed landscapes, very high in landscapes undergoing transformation, and low in highly transformed landscapes.

In view of the above hypothesis, the main goal of the study was to determine the applicability of land cover data for classifying the stages of landscape evolution based on the observed changes in land use and the degree of anthropogenic pressure.

2 Material and methods

2.1 Research procedure

A hierarchical procedure composed of several stages was developed to determine whether land cover data can be used to identify changes in landscape (Figure 1). In the first stage, land cover data pertaining to a selected area were compiled into a database. The study focused on land cover data for dynamically developing areas under strong urbanization pressure. In the second stage, the degree of anthropogenic pressure on selected types of land cover was determined. An indicator for assessing landscape cohesion was selected in the third stage. Landscape continuity is defined as the same pattern of land use (Marzęcki, 2002), and it can denote identical land cover. This concept is closely associated with landscape diversity. In principle, landscape continuity and landscape diversity describe the same phenomenon, but in opposite directions. The greater the continuity of a landscape, the smaller its diversity (Cieślak et al. 2020).

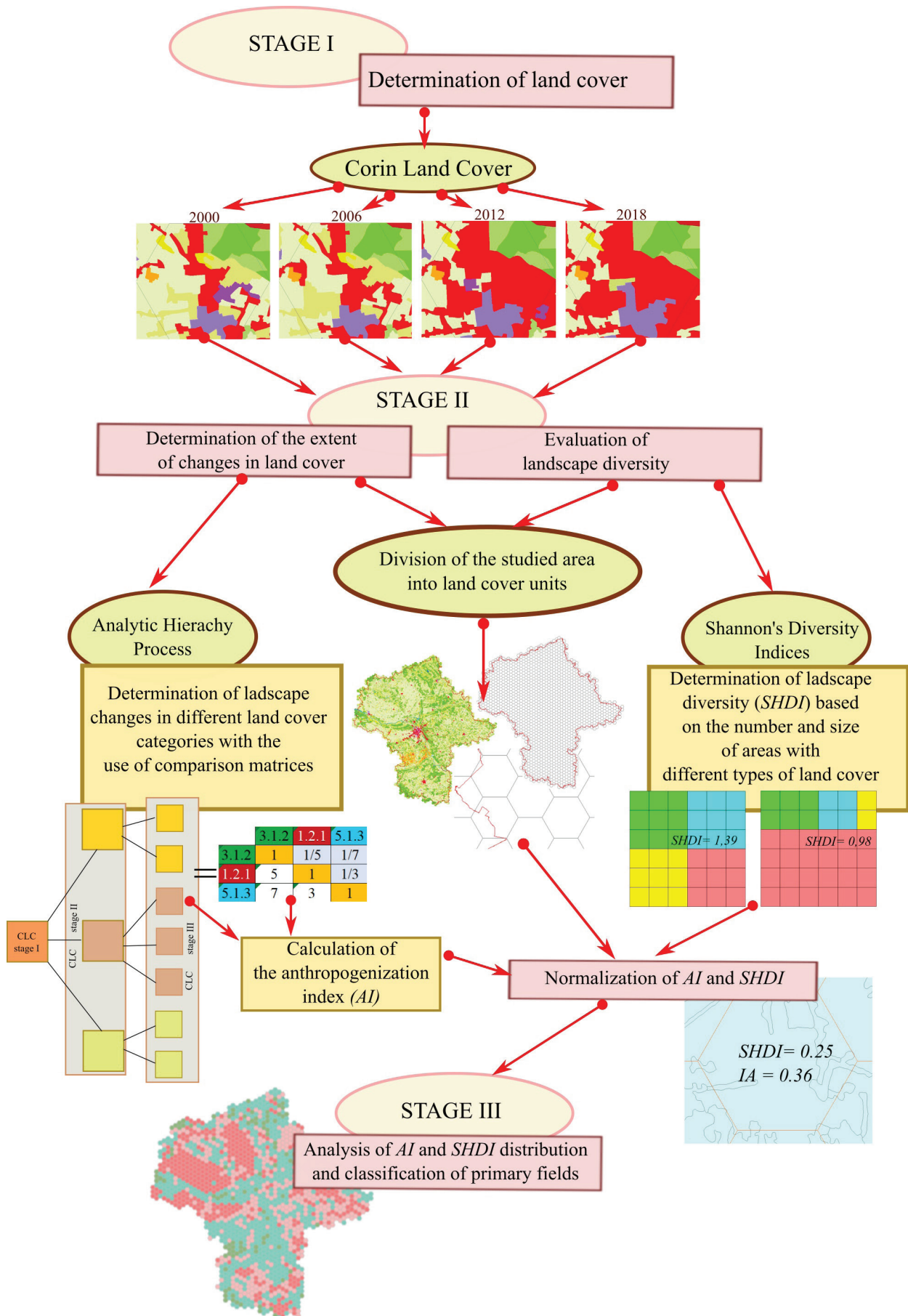


Figure 1. Diagram of the research procedure

2.2 The application of the Analytic Hierarchy Process method for determining the anthropogenic transformation of landscapes

The degree to which various land cover types are transformed under anthropogenic pressure was determined with the use of the Analytic Hierarchy Process (AHP) method developed by Saaty (Saaty 2002; 1994). One of the advantages of this method is that it enables the combined use of various numerically and verbally described criteria within the decision-making process (Forman & Gass 2001). The AHP can be used to automate the evaluation process; it supports repeated analyses and the inclusion of a large number of observers, which increases the reliability and objectivity of the results (Lipiec-Zajchowska M. 2003; Trzaskalik 2014; Moutinho et al. 2014). The evaluation process is automated by comparing pairs of criteria, which is a much simpler and a more objective procedure than a single assessment of the entire set of criteria (Saaty & Vargas 2012; Ramanathan 2001).

The research procedure involving the AHP method was composed of four stages (Kobryń 2014):

1. Hierarchization of the studied problem. In this stage, the problem is decomposed into main criteria-factors, and the main criteria are broken down into sub-criteria.
2. The selected criteria are evaluated by pairwise comparison. Decision makers compare pairs of criteria at every level of the hierarchy and determine their significance for the achievement of the final goal. The relations between the criteria are determined on a 9-point scale (Saaty, 2004), where 1 point denotes criteria with equal significance, and 9 points denote criteria with absolute priority. In the last step, matrix $A = [a_{ij}]$ with $n \times n$ elements is built and used to perform $n(n-1)/2$ comparisons.
3. Comparison matrices A are validated by calculating the cohesion rate (degree of agreement) for the analyzed criteria, and a random indicator, which is the mean value of the cohesion rate calculated for a large number of randomly generated comparison matrices. The procedure of evaluating the degree of agreement between matrices has been described in detail in the literature (Klutho 2013; Michnik & Lo 2009; Zahedi 1986;

Cieślak 2019).

4. The selected criteria are compared for preference, and their weights are calculated after the matrix had been built. Normalized rows of the matrix are summed up, and an eigenvector (\hat{W}) of the matrix is determined (Tułcecki & Król 2007).
5. It should be noted that the eigenvector \hat{W} represents criterion weights at only one level of the hierarchy. The product of the weights determined at each level constitutes the final weight of a hierarchical set of criteria.

However, the described method of aggregating the final weight does not always produce satisfactory results, in particular if it is applied not for decision-making purposes but to determine the importance of the observed phenomena, as in this study. In such a case, a criterion assigned a low weight at one level of the hierarchy can be completely eliminated from the analysis. This risk is particularly high in evaluations of the importance of different types of land use for various purposes. In order to achieve the main goal of this study, the AHP method used to evaluate the degree of anthropogenic pressure observed in different land cover types was modified to ensure that the weights at lower and detailed levels of the classification of land cover types do not influence the weights at higher levels.

The below formula was used to determine the final weight describing the degree of anthropogenic transformation of various land cover types:

$$w_k = \frac{w_k^n + w_k^{n-1} * w_k^{n-2}}{\max(w_k^n + w_k^{n-1} * w_k^{n-2})} \quad (1)$$

where:

w_k^n – final weight of land cover type k at hierarchy level n ;

w_k^{n-1} – weight of land cover type k at hierarchy level $n-1$;

w_k^{n-2} – weight of land cover type k calculated directly from the comparison matrix of land cover types corresponding to the hierarchy level of that land cover type - n .

The maximum theoretical value of w_k is n . The minimum value is 0.

The anthropogenization index (*AI*) was computed based on the value of the calculated weights w_k . The *AI* was expressed in spatial units referred to as primary fields (*PFs*). The *AI* was calculated with the use of the below formula as the product of weight w_k and the proportions of a given land cover type k in *PF*:

$$AI_{PF_i}^0 = \frac{\sum_{m=1}^l w_k * p_m^{ik}}{\max \sum_{m=1}^l w_k * p_m^{ik}} \quad (2)$$

where:

$AI_{PF_i}^0$ – indicator of anthropogenic transformation in the i^{th} *PF*;

p_m^{ik} – proportion of land cover type k in the i^{th} *PF*;

l – number of land cover types in the i^{th} *PF*.

The calculated *AI* was used to evaluate the extent of anthropogenic pressure in the studied area.

2.3 The application of Shannon's entropy concept for determining landscape cohesion

Shannon's Diversity Index (*SHDI*) is widely used to evaluate landscape composition by analyzing the diversity and size of landscape components based on the cohesion of land cover types (Malinowska & Szumacher 2013). This index relies on entropy, namely the degree of uncertainty in the probability distribution of random variables (Cieslak et al. 2016). The concept of entropy was originally developed to describe thermodynamic systems, but it is presently applied in numerous fields of research. Entropy was introduced to information theory by Shannon (Shannon 1997) who observed that the information carried by a random even is described by probability function p expressed by the formula $\log 1/p = -\log p$. This function is a measure of the uncertainty of an event. Therefore, if a random event is represented by x , and a series of random events is represented by x_i , $i = 1, 2, \dots, n$, where probability $p(x_i)$ meets the following condition:

$$0 \leq p(x_i) \leq 1, \sum_{i=1}^n p(x_i) = 1, \quad (3)$$

then the average (expected) outcome, i.e. entropy $H(x)$, of these probabilities is expressed by:

$$H = - \sum_{m=1}^l p(x_i) \log p(x_i) \quad (4)$$

or

$$H = - \sum_{m=1}^l p(x_i) \log_2 \frac{1}{p(x_i)} \quad (5)$$

In geography, entropy is used as a measure of spatial order or homogeneity of an empirical system. Maximum entropy is a state of the greatest spatial disorder, whereas minimum entropy denotes a completely ordered system (Czyz & Hauke 2015). The concept of entropy is widely used in contemporary geographical research, and the studies by (Batty 2010) and (Wilson 2010) have significantly contributed to its applicability in the field of geography. Entropy is also used to determine variations in land cover in analyses of landscape diversity (Shannon & Weaver 1964; Kupfer 2012; Collins et al. 2009). The *SHDI* was modified for the needs of landscape analyses by (McGarigal & Marks 1995). The probability of a random event is expressed by the proportion of a given land cover type in the evaluated landscape (P). In FRAGSTATS software (Lamine et al. 2018), *SHDI* was modified as follows:

$$SHDI = - \sum_{m=1}^l (P_i - \ln P_i) \quad (6)$$

where:

l – number of categories (patch types) (L_t),

P_i – proportion of a given category (% of the area occupied by the i^{th} category).

The modified *SHDI* can range from 0 to $\ln m_{\max}$, where m_{\max} is the maximum number of landscape types. The index equals zero when a single landscape category occupies the entire studied area (absence of diversity). The value of *SHDI* increases with a rise in the proportion of different landscape categories and a rise in the number of different patch types (to a lesser degree) (Kot & Leśniak 2006; Li et al. 2001; Espinosa et al. 2016; Barros et al. 2018). In the present study, *SHDI* was used to evaluate landscape homogeneity in *PFs* as the basic units for analyzing land cover diversity.

2.4 Classification of results

The studied area was divided into principal fields (*PFs*) for the needs of the analysis. Each *PF* was a hexagon with an area of 2500 ha. The size of *PFs* was selected to minimize the errors associated with the modifiable areal unit problem (MAUP), in particular problems related to cartographic generalization,

which prevent the identification of the studied phenomena in large-scale reference fields. The selected size also guaranteed the diversification of land cover in the analyzed area. The evaluated area was covered with a grid of 1576 (j) hexagonal PFs.

Land cover types were determined for each PF based on CORINE Land Cover (CLC) data for 2000, 2006, 2012 and 2018. The values of AI^0 and $SHDI^0$ were calculated for all fields. AI^0 was normalized relative to its maximum value. For the needs of PF classification, both indices were modified to assume values in the range of -0.5 to 0.5. This approach facilitated the distribution analysis of the values of both indices.

$$AI_{PF_i} = AI_{PF_i}^0 - 0.5 \quad (7)$$

and

$$SHDI_{PF_i} = SHDI_{PF_i}^0 - 0.5 \quad (8)$$

The mutual variations in the values of AI^0 and $SHDI^0$ (Fig. 4) and the variations in the values of both indices over time were analyzed to identify changes in landscape continuity and the degree of anthropogenic pressure that are characteristic of a given stage of landscape evolution. PFs were divided into four classes based on the calculated values of AI^0 and $SHDI^0$.

Class I includes areas with a low degree of transformation and uniform land cover, mostly ecologically valuable areas such as forests and natural river valleys ($AI \leq 0.0$ and $SHDI \leq 0.1$). Class II represents diverse landscapes with low levels of transformation, including ecologically valuable areas with various landscape categories ($AI \leq 0.0$ and $SHDI > 0.1$). Class III includes highly transformed areas with diverse landscapes, mostly urban areas with a high proportion of natural areas grouped into small-sized clusters ($AI > 0.0$ and $SHDI > 0.1$). Class IV represents the most highly transformed, large areas with low landscape diversity and the lowest landscape value ($AI > 0.0$ and $SHDI \leq 0.1$).

2.5 Data and study area

The study area was selected based on a detailed analysis of spatial processes. The optimal area had to be characterized by diverse types of anthropogenic changes. To guarantee the most reliable outcome and to achieve the goal of the study, the ana-

lyzed area had to undergo rapid urbanization and represent strongly transformed landscapes as well as relatively unmodified landscapes or even nature conservation areas. The research area had to be an administrative unit to ensure the cohesiveness of land cover data, providing the basis for the analytical process. All of the above criteria were met by the Mazovian Voivodeship, which features the Polish capital city of Warsaw.

Mazovia is one of the largest and most diverse Polish regions. It is the most highly populated Polish voivodeship with 5,425,000 people inhabiting 85 cities, 42 counties, 314 municipalities and more than 9000 villages. The population of Mazovia accounts for 14.2% of the Polish population. At the end of 2020, Mazovian cities had a combined population of 3,495,200, which accounted for 64.4% of the region's total population. The urban population decreased by 0.01%, whereas the rural population increased by 0.1% relative to 2019. The city of Warsaw had a population of 1,794,200, which accounted for 33.1% of the region's total population and 51.3% of its urban population. In addition to Warsaw, the largest cities in the Mazovian voivodeship are Radom (227,000), Płock (127,000), Siedlce (77,000), Ostrołęka (54,000) and Ciechanów (46,000). Average population density in Mazovia is 145.9 persons per km², and it is higher than the national average of 122 persons per km². According to Statistics Poland (Central Statistical Office), Mazovia had an area of 3,555,847 ha in 2021. Agricultural land occupied 2,407,529 ha (67.7% of the voivodeship's total area), forests, woody and bushy land – 847,117 ha (23.8%), water bodies – 42 641 ha (1.2%), built-up and urbanized areas – 217,338 ha (6.1%), ecological areas – 1842 ha (0.1%), wasteland – 33,918 ha (1.0%), and miscellaneous land – 5462 ha (0.2%). Protected areas of high natural value occupied 1,058,139 ha, including national parks (38,476 ha, 1.1% of the voivodeship's total area), nature reserves (19,539 ha, 0.5%), landscape parks (168,674, 4.7%), protected landscape areas (823,407 ha, 23.2%), regionally important geological sites (521 ha), natural landscape complexes (5642 ha) and ecological areas (1880 ha) (Figure 2) (Statistics Poland). The Kampinos National Park on the north-western outskirts of Warsaw is one of the most valuable natural areas in Mazovia. The park encompasses the Kampinos Primeval Forest in the gla-

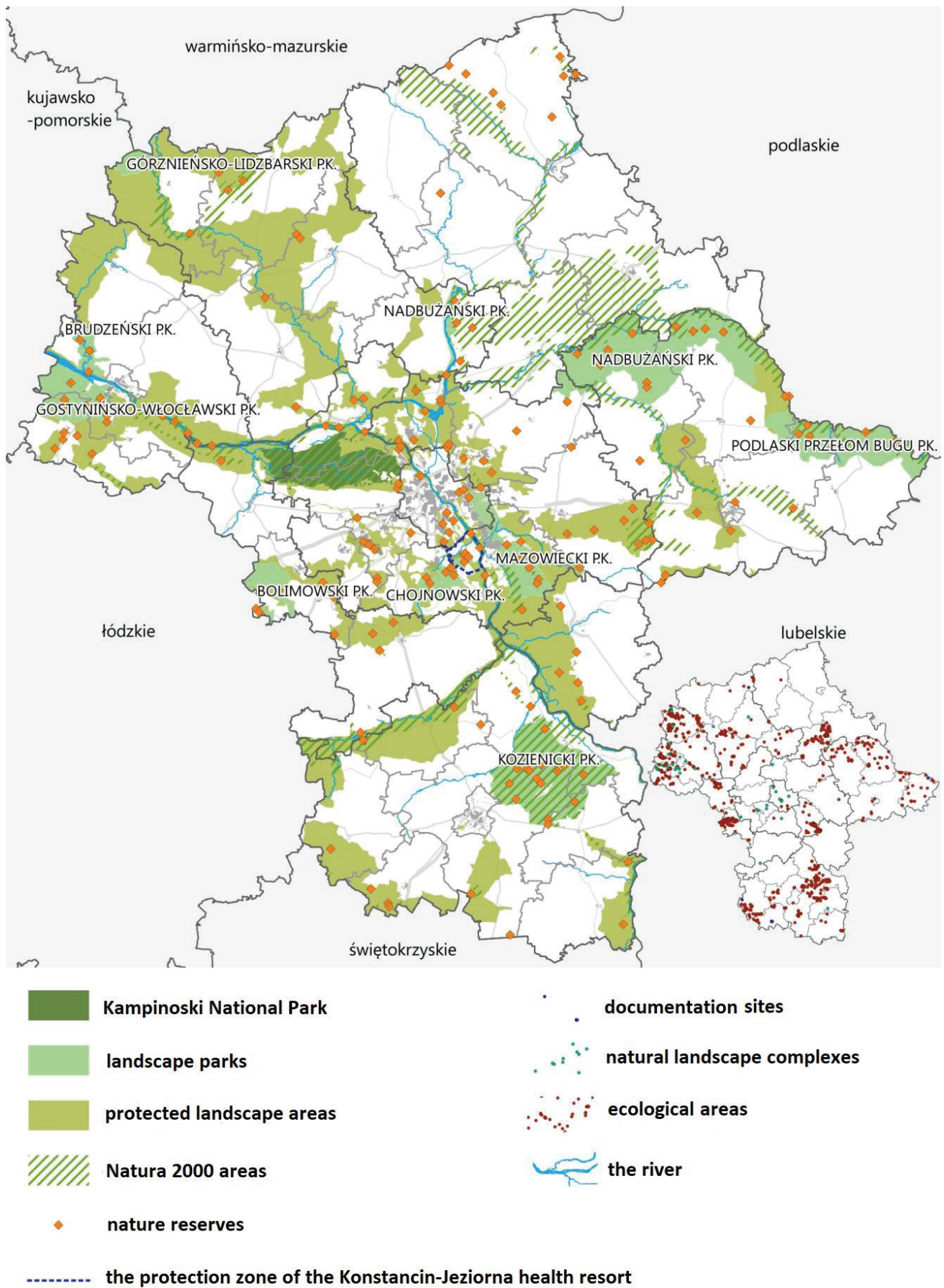


Figure 2. Natural environment resources (Spatial development plan 10 for the mazowieckie voivodeship 2018)

cial valley of the Vistula River. The forest is situated at the junction of three ecological corridors (Vistula, Bug and Narew River valleys) and has a unique ecosystem of European significance. On the territory of Mazovia, Kampinos occupies an area of 38,476 ha, including 28,190 ha of forests. Twenty-two strict nature reserves and protected wilderness sites cover 4636 ha (approx. 12% of the park's area). Four landscape conservation zones with a combined area of 3200 ha (8.3% of the park's area) have been created to protect Mazovia's traditional agrarian landscape. In 2000, the Kampinos National Park and its buffer zone were included in the UNESCO World Network of Biosphere Reserves as an area of high natural and social value. The park is a popular leisure and recreation destination for Warsaw residents. It features 350 km of hiking trails, 200 km of cycling routes, horseback riding trails and 12 picnic sites on the outskirts.

The Mazovian Voivodeship is characterized by significant differences in social and economic development that influence the voivodeship's overall growth dynamic. Warsaw is an extremely transformed area, and it is surrounded by rapidly developing municipalities that supply resources and services for the Polish capital. However, the municipalities situated further away from Warsaw are typical rural areas with the lowest rates of economic development in the entire country. In these municipalities, urbanization proceeds at a much slower rate.

Land cover data were acquired for the study area. The CLC database contain sufficiently detailed data for the presented analysis. The CLC repository is updated in regular intervals, which supports analyses of the rate at which the studied phenomena evolve over time (Cieślak et al. 2020). Land cover data were obtained from the website of the Chief Inspectorate

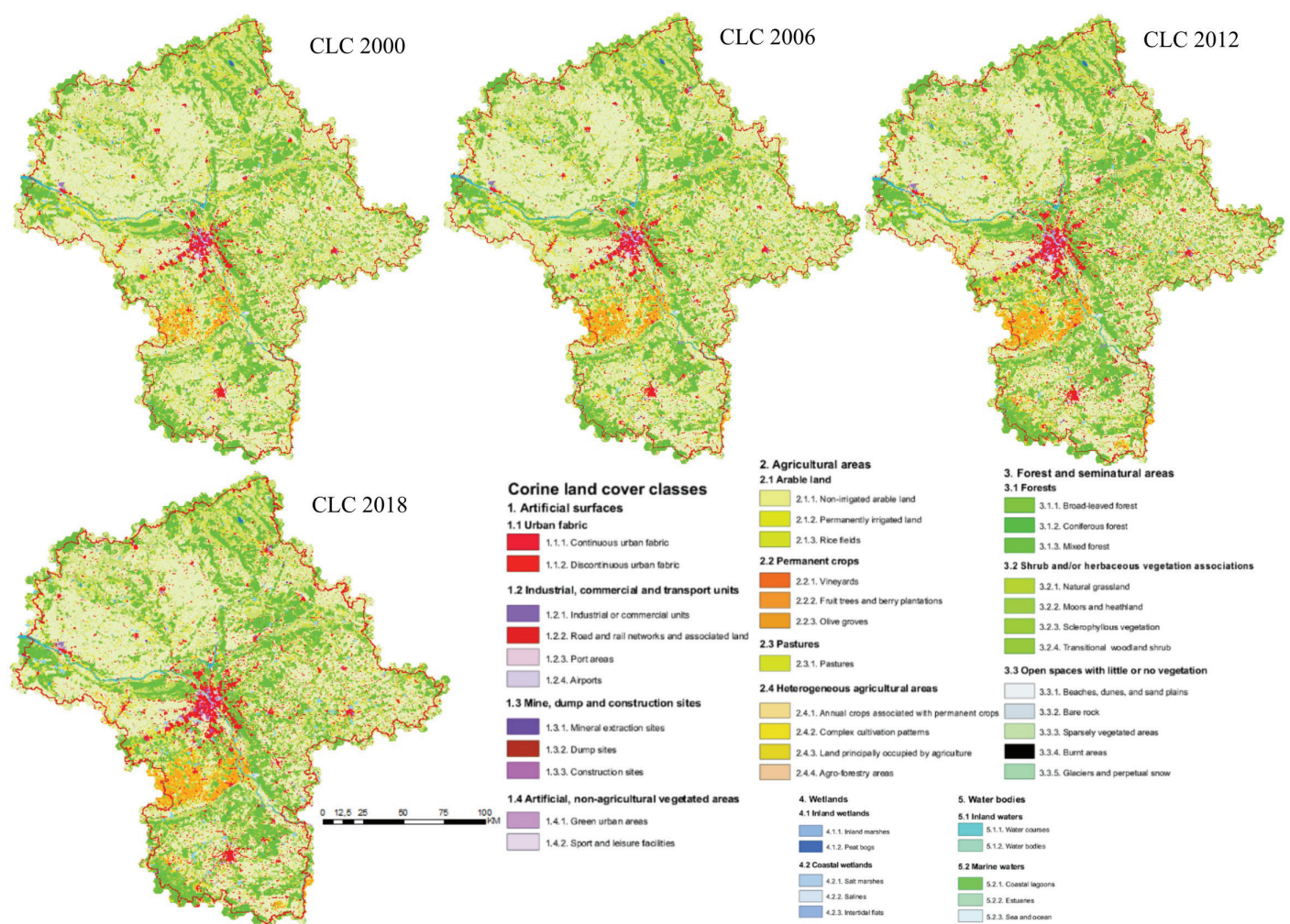


Figure 3. Land cover maps of the Mazovian Voivodeship based on CORINE Land Cover data for 2000, 2006, 2012 and 2018.

for Environmental Protection. The CLC project was implemented in Poland¹ by the Institute of Geodesy and Cartography with the support of the EU funds (CORINE Land Cover 2019). Land cover data were acquired for successive CLC updates in 2000, 2006, 2012 and 2018, which support data comparisons (Feranec et al. 2007). The obtained data were processed in ArcGIS 10.7. The resulting maps are presented in Figure 3.

Table 1. The calculated values of weights w and w_k

Level 1	w_{k0}	Level 2	w_{k0}	Level 3	w_{k0}	w_k		
1- Artificial surfaces	0.49	1.1 – Urban fabric	0.13	111 Continuous urban fabric	0.88	0.92		
				112 Discontinuous urban fabric	0.13	0.55		
		1.2 - Industrial, commercial and transport units	0.27	121 Industrial or commercial units	0.21	0.68		
				122 Road and rail networks and associated land	0.48	0.83		
				123 Port areas	0.21	0.68		
				124 Airports	0.10	0.61		
		1.3 - Mine, dump and construction sites	0.56	131 Mineral extraction sites	0.45	1.00		
				132 Dump sites	0.45	1.00		
				133 Construction sites	0.09	0.75		
		1.4 - Artificial, non-agricultural vegetated areas	0.04	141 Green urban areas	0.25	0.57		
				142 Sport and leisure facilities	0.75	0.80		
		2 – Agricultural areas	0.31	2.1 - Arable land	0.54	211 Non-irrigated arable land	0.67	0.71
						212 Permanently irrigated land	0.24	0.53
213 Rice fields	0.09					0.46		
221 Vineyards	0.43					0.44		
2.2 - Permanent crops	0.12			222 Orchards and plantations	0.43	0.40		
				223 Olive groves	0.14	0.32		
				231 Meadows and pastures	1.00	0.60		
2.3 – Meadows and pastures	0.09			241 Annual crops associated with permanent crops	0.39	0.48		
				242 Complex cultivation patterns	0.39	0.48		
2.4 - Heterogeneous agricultural areas	0.26			243 Land principally occupied by agriculture, with significant areas of natural vegetation	0.16	0.41		
				244 Agro-forestry areas	0.05	0.36		
				3.1 - Forests	0.07	311 Broad-leaved forest	0.20	0.13
		312 Coniferous forest	0.60			0.17		
313 Mixed forest	0.20	0.13						
3.2 - Scrub and/or herbaceous vegetation associations	0.28	321 Natural grasslands	0.51	0.19				
		322 Moors and heathland	0.07	0.13				
		323 Sclerophyllous vegetation	0.23	0.15				
		324 Transitional woodland-shrub	0.19	0.15				
3.3 - Open spaces with little or no vegetation	0.64	331 Beaches, dunes, sands	0.24	0.20				
		332 Bare rocks	0.11	0.18				
		333 Sparsely vegetated areas	0.14	0.18				
		334 Burnt areas	0.46	0.23				
		335 Glaciers and perpetual snow	0.05	0.17				
4 - Wetlands	0.05	4.1 - Inland wetlands	0.50	411 Inland marshes	0.25	0.08		
				412 Peat bogs	0.75	0.11		
		4.2 - Maritime wetlands	0.50	421 Salt marshes	0.11	0.07		
				422 Salines	0.41	0.09		
				423 Intertidal flats	0.48	0.10		
				5.1 - Inland waters	0.75	0.25	0.09	
5 – Water bodies	0.04	5.1 - Inland waters	0.75	511 Water courses	0.25	0.09		
				512 Water bodies	0.75	0.12		
		5.2 - Marine waters	0.25	521 Coastal lagoons	0.63	0.08		
				522 Estuaries	0.26	0.06		
				523 Sea and ocean	0.11	0.06		

3 Result

The degree of anthropogenic transformation w_k of the land cover types identified in CLC was calculated with the use of formula (1). The significance of the evaluated land cover types and the normalized value of AI^0 are shown in Table 1. The cohesiveness of all comparison matrices was validated by iteration, and the cohesion ratio (CR) was below 0.1. Weights w and the landscape transformation weights w_k were calculated for each land cover type with the use of comparison matrices and formula (1). The results are presented in Table 1.

The calculated values of w_k were used to compute AI_{PF}^0 and AI_{PF_i} for each PF based on CLC data for 2000, 2006, 2012 and 2018. The above data were also used to calculate $SHDI_{PF_i}^0$ and $SHDI_{PF_i}$ in PFs . The calculated values were assigned to the corresponding year and ordered based on increasing values of AI_{PF_i} . The results are presented in Figure 4.

The changes in the values of both indices were also analyzed in a dynamic approach. The examined PFs represented different stages of development; therefore, the corresponding increase in the values of AI was calculated, and changes in $SHDI$ were analyzed in PFs with positive values of $SHDI$ in 2000-2006, 2006-2012, 2012-2018, i.e. in PFs where anthropogenic pressure continued to increase in the studied period. Forty-six such PFs were identified.

The results of the analysis validated the research hypothesis; therefore, both indices were used to classify the study area. The classification was based on land cover data for 2000, 2006, 2012 and 2018. The spatial distribution of classes is presented in Figure 5.

The spatial distribution of land cover classes in the studied area points to the stability of highly urbanized areas as well as agricultural areas. These areas have been transformed, but they are characterized by homogeneous land cover. River valleys represent valuable, uniform and untransformed landscapes.

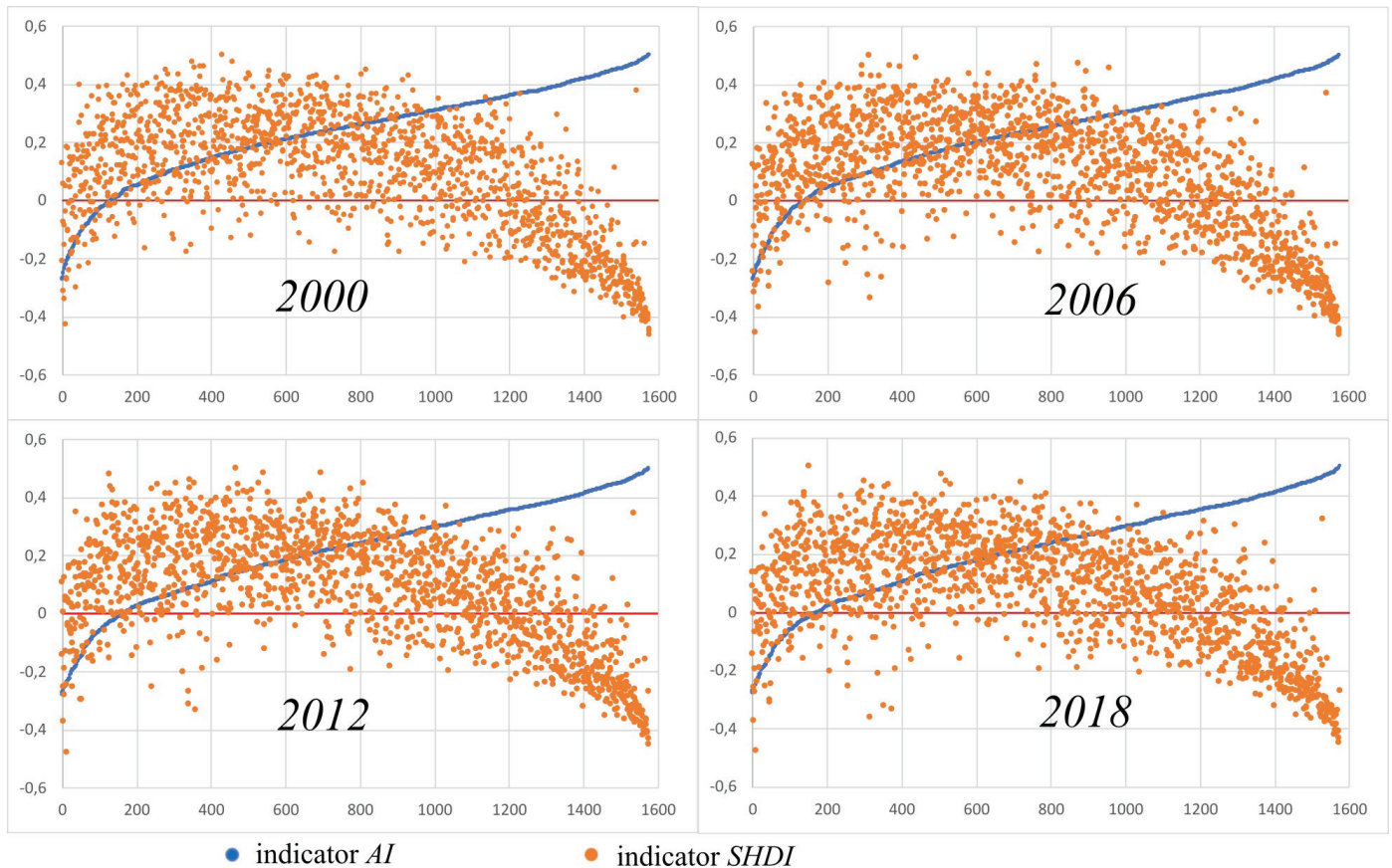


Figure 4. Distribution of AI and $SHDI$ values in PFs for 2000, 2006, 2012 and 2018 data.

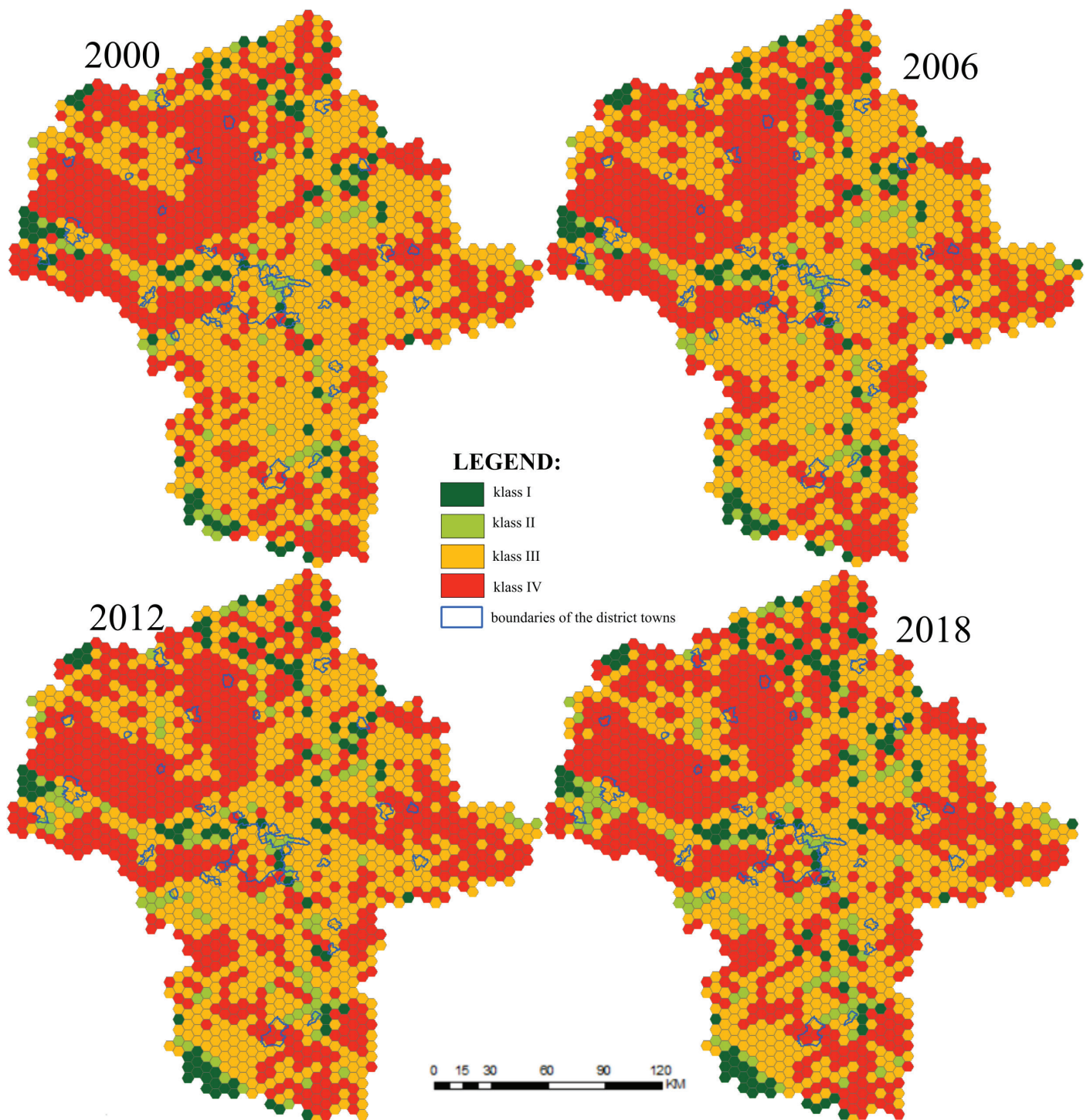


Figure 5. Spatial distribution of land transformation classes in 2000, 2006, 2016 and 2018.

The analysis revealed areas that changed dynamically as well as areas with stable land-use patterns. The studied area was also characterized by an increase in forest cover, which resulted from the afforestation of low-quality farmland. Changes in land cover based on CLC data and the proposed classification are presented in Figure 6.

Anthropogenic pressure increased steadily from 2000. The largest classes (III and IV) accounted for around 90% of all *PFs*, which testifies to high levels of landscape transformation. The number and area of land cover classes in 2000, 2006, 2012 and 2018 are presented in Table 2.

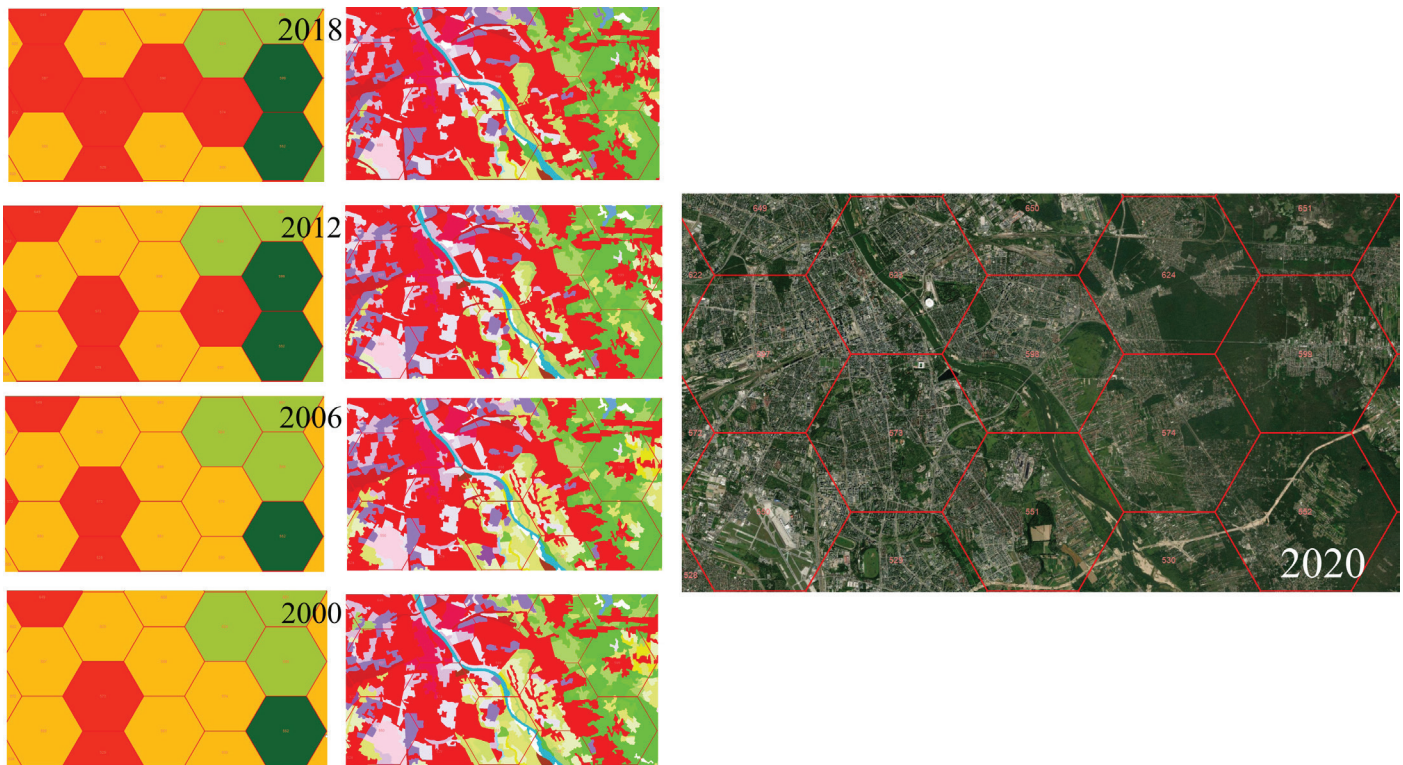


Figure 6. Changes in land cover based on CLC data and the proposed classification relative to the satellite images acquired in 2020.

Table 2. Number and area of land cover classes in 2000, 2006, 2012 and 2018.

	2000		2006		2012		2018	
	Number	Area (ha)	Number	Area (ha)	Number	Area (ha)	Number	Area (ha)
1	76	190000	79	197500	86	215000	96	240000
2	57	142500	65	162500	84	210000	88	220000
3	782	1955000	771	1927500	709	1772500	672	1680000
4	661	1652500	661	1652500	697	1742500	720	1800000

The greatest increase of 59 *PFs* (+4%) was noted in class IV. The number of *PFs* increased by 31 (+1%) in class II and by 20 (+1%) in class I. In class III, the number of *PFs* decreased by 110 (-7%) between 2000 and 2018. Therefore, the studied area witnessed the highest increase in the number of highly transformed, least diverse and least valuable landscapes between 2000 and 2018. Interestingly, an increase was also observed in the number of diverse and ecologically valuable landscapes with low levels of anthropogenic transformation. These findings could suggest that landscapes undergoing strong anthropogenization (class III) can be restored to environmentally valuable land cover types. However, the highest number of *PFs* transitioned to class IV in the analyzed period.

The greatest changes in the number of land cover types occurred after 2006. In Poland, this period was marked by rapid economic growth and a high demand for new land for development projects. Anthropogenic pressure was particularly strong in the municipalities surrounding Warsaw (Fig. 7). The classified *PFs* were also highly dispersed. Land cover classes formed clusters, but they were far more scattered (in particular class IV). This process can exert a negative effect on areas that had been initially assigned to classes I and II. It can be assumed that class IV areas will compromise environmentally valuable, untransformed areas in the future. Anthropogenic changes were observed in the entire studied area, which implies that these processes are not a consequence of individual development projects, but are a part of a continuous trend.

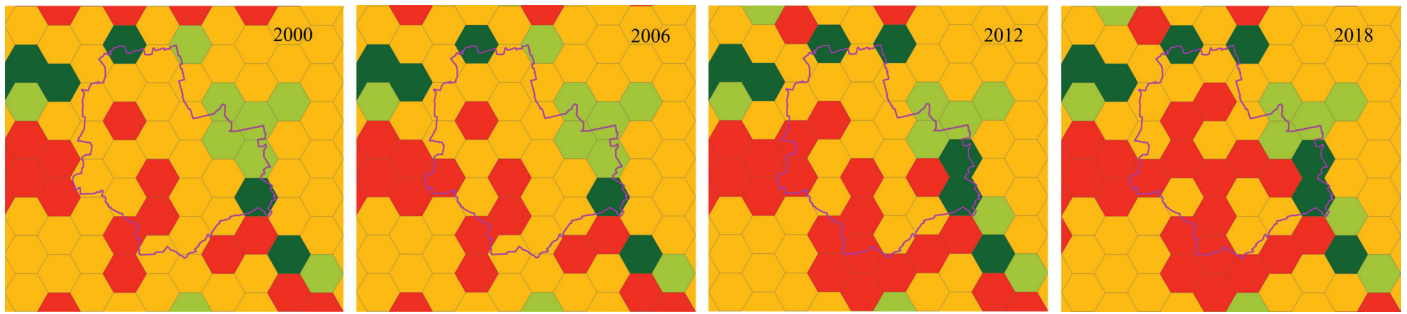


Figure 7. Changes in the classification of primary fields in Warsaw and the surrounding municipalities.

4 Discussion

In this study, landscapes were classified in view of the evolution of various land cover types on the assumption that landscape transformation occurs in a sinusoidal fashion (Raszeja 2013). Landscape diversity is generally low in natural and untransformed areas, very high in areas undergoing transformation, and low in highly transformed areas. The AHP method was applied to evaluate the degree of anthropogenic changes in the landscape. This method has certain limitations. In analyses involving a large number of criteria with a complex hierarchy, the final weights assigned to different land cover types may be insufficient to denote statistical significance. This is an important limitation, and several modifications were introduced to eliminate the associated defects. The final values of the weights assigned to different land cover types were modified in the AHP method to minimize the effect of individual weights at a given level of the hierarchy on the final criterion weights. The applicability of other methods for assigning weights to land cover types should be compared and analyzed in the future.

Dynamic assessments of landscape transformations require valid land cover data. Land cover databases and advanced data processing and modeling techniques are extensive sources of knowledge, and they can be used to develop new tools for identifying and monitoring landscape changes (Pelorosso et al 2009, Cieślak et al. 2016, Ustaoglu et al. 2019, Cieślak et al. 2019). These resources speed up analyses of landscape transformation even in large areas (Cieślak et al. 2017). In the present study, landscape changes were evaluated based on CLC data, which are characterized by spatial continuity

and support unambiguous identification of various land-use types. The analyzed data were generated by remote sensing. CLC data were processed by integrating remote sensing data in a mixed approach combining automatic methods and interpretation tools for digital image analysis. The processed data were Landsat TM multispectral satellite images and aerial images (Stathopoulou et al. 2017). Most importantly, CLC databases are developed regularly, which facilitates analyses and predictions of the rate of landscape change. In this study, landscape transformations were evaluated based on CLC data for 2000, 2006, 2012 and 2018. In research of the type, the quality of spatial data is an important consideration. The thematic accuracy of the CLC dataset is limited (Aune-Lundberg, Strand 2021). The standard map sheets in the CLC project have a working scale of 1:100,000; the minimum mapping unit (MMU) is 25 ha, and the minimum width of linear features for mapping the boundaries of different land cover types is 100 m (Ben-Asher et al., 2013). As a result, minor changes that can give rise to landscape transformation processes may not be revealed. In areas characterized by considerable land fragmentation, there is a risk that only the dominant land-use types will be identified and that important information will be lost. Nonetheless, the CLC database is useful for identifying units of territorial administration (municipalities, metropolitan areas) and primary geometric fields. The CLC inventory is a particularly reliable source of information in analyses of rapidly evolving urban areas (Cieślak et al. 2020, Myga-Piątek et al. 2021, Jucha et al. 2014). The CLC database relies on satellite imagery, and the methods of collecting and interpreting satellite data have also evolved over the years. Despite the above, CLC reliably accounts for temporal and spatial changes in land cover. The CLC

project was launched in 2000, and the inventory is updated every 6 years. Therefore, the CLC database is useful for comparing the rate of changes in land cover across the European Union.

The selection of methods and indicators for describing landscape diversity and changes in land cover also plays an important role. Various methods for assessing landscape transformations have been proposed in the literature, including the straight line method that relies on the geometric properties of diverse land-use types (Janecki 1983), the flora anthropogenization index (Kostrowicki et al. 1988), the 12-point scale for assessing anthropogenic changes in landscape and sustainable land use (Chmielewski, 2012), as well as geobotanical and soil indicators (Roo-Zielińska et al. 2007). Some of these approaches, including the Landscape Transformation Index (LTI) (Lowicki, 2008) and the Shishchenko coefficient (Shishchenko 1988), rely on natural data (plant, soil) which are more difficult to measure in large areas. Other methods analyze specific ecosystem functions and compare them with the existing land-use patterns (Patil et al. 2001). Various indicators for analyzing the spatial structure of landscapes based on land cover data have also been proposed (Pukowiec-Kurda, Sobala 2016. Huang et al. 2006; McAlpine, Eyre 2002; Solon 2002). One of the best-known tools for quantifying landscape structures is the FRAGSTATS program developed by McGarigal and Marks (1995). These and other approaches significantly contribute to progress in landscape research. However, landscapes continually evolve, and new tools are needed to accurately capture the dynamic changes in land cover.

Effective land management requires robust planning and development strategies (Jaszczak 2019). Land management always leads to landscape transformation. Sustainable land management strategies are needed to preserve diverse and naturally valuable landscapes. Landscape transformations should be continuously monitored to identify the causes of the observed changes, predict their course and outcome. Landscapes are altered for a variety of reasons. In the proximity of large cities such as Warsaw, suburbanization is one of the key drivers of landscape change. Suburbanization typically leads to an increase in built-up areas and a decrease in the

area of arable land (Pukowiec-Kurda, Vavrouchová 2020). Similar observations have been made by numerous researchers, including Pan et al. (2004), Antrop (2005) and Tikka et al. (2001). The expansion of transport networks linked with urban hubs also contributes to anthropogenic pressure. The extent to which road construction projects exert pressure on the natural environment was discussed by Mothorpe et al. (2013), Jedlička et al. (2019) and Hadi et al. (2021). An analysis of maps 4 and 8 indicates that the development of transport networks induced clear changes in land cover in the studied voivodeship.

The stages of landscape evolution should also be identified in research studies. The beginning and end of transformation processes and the rate and magnitude of landscape changes should be diagnosed to facilitate the implementation of effective land management strategies and protective measures. The described methodology offers novel insights in this respect. The proposed approach is an innovative method of measuring changes in land cover. The AI relies on simple data and is easier to calculate than similar metrics. The AI is based only on land cover data and weights describing the degree of transformation of different land cover types. The proposed indicator can be used to identify changes in landscape continuity that are characteristic of a given stage of landscape evolution. The developed method can be applied in the process of managing valuable landscapes and identifying areas that can be lost unless protective measures are implemented. The study also demonstrated that fragmentation of natural habitats affects their stability. These findings can assist experts and urban planning authorities in the process of developing land management plans and landscape conservation strategies.

The study demonstrated that mineral extraction sites, dump sites, continuous urban fabric, transport networks and construction sites induce the most extensive changes in land cover and that these areas should regularly be monitored. The extent to which these sites transform the local landscape is clearly visible in the Warsaw area, which is characterized by rapid suburbanization. Over time, suburbanization processes were shifted further away from the city limits, and urbanization processes were intensified

in the urban core. The study also revealed that the distance between highly transformed areas (class IV) and ecologically valuable areas (class I) continues to decrease at an alarming rate. The above is particularly visible in the proximity of the Vistula River valley (Fig. 7). These findings indicate that effective conservation measures should be initiated to protect valuable natural habitats against the adverse consequences of anthropogenic pressure. The analysis (Fig. 7) revealed that transformed areas in the south-eastern part of the Mazovian voivodeship, characterized by a high degree of anthropogenic pressure and diverse landscapes, had undergone even greater changes and were converted to identical land-use types in the evaluated period. An analysis of maps 5 and 7 indicates that urban expansion did not drive the observed changes in the south-eastern part of the studied voivodeship. The towns in south-eastern Mazovia are characterized by low levels of economic growth, and changes in the local landscape result mainly from scattered development. The rapid transformation of arable land to non-agricultural uses gives serious cause for concern because it thwarts any attempts to restore Mazovia's traditional rural landscape. The transition of class III areas to class IV areas points to a high rate of landscape transformation. This process began to stabilize in 2012-2018, but mostly to the benefit of highly urbanized areas. Effective planning measures are needed to restrict landscape transformations, protect landscape diversity or even restore ecologically valuable areas (class II).

5. Conclusions

A landscape is composed of numerous elements with different change dynamics. Landscapes are transformed mainly due to changes in land use, most of which result from anthropogenic pressure. Human-induced changes in landscape are inevitable, and the attributes and parameters of transformed landscapes have to be continuously monitored. Land cover data provide a wealth of information and constitute a reference point for developing new tools for analyzing landscape transformations. The above applies particularly to areas experiencing strong urban-

ization pressure where the most dynamic landscape changes are observed. The degree and rate of landscape transformation are most effectively diagnosed by monitoring changes in land cover. Widely available land cover data and GIS tools that support fast processing of geospatial data significantly facilitate analyses of landscape transformation.

In this study, an attempt was made to assess landscape transformations based on land cover data. The proposed methodology can be applied to evaluate the extent of changes in land cover and landscape cohesion. The study was conducted on the assumption that landscape diversification is a process that occurs in a sinusoidal manner. It is low in areas with natural land cover, very high in areas undergoing strong anthropogenization, and low in highly transformed areas. Land use types were adopted as the main criterion for assessing the degree of landscape transformation. Land cover data were obtained from the CLC repository which supports analyses of changes in landscape continuity and the classification of land in different stages of evolutionary change. The presented methodology can be used to evaluate the extent of changes in various land cover types based on a comparison matrix and the degree of landscape cohesion. Land cover types were grouped into classes, and classes characterized by similar landscape continuity and anthropogenic pressure were indicative of a given stage of landscape evolution. An analysis of the results revealed that mineral extraction sites, dump sites, continuous urban fabric, road and rail networks, and construction sites were the most highly transformed types of land cover. The least transformed landscapes were inland and marine waters, wetlands and forests at the third level of the CLC hierarchy.

The described procedure is a reliable method for determining the extent of changes in land cover and landscape cohesion. The accuracy of the results is influenced mainly by the size of PFs, and the repeatability of results is determined by the analyzed land use types. The proposed methodology is largely universal, and it can be applied in analyses of other land use types. In the present study, land cover databases were used to assess changes in land cover. The stages of landscape evolution were divided into classes to monitor changes in land cover and evaluate land-

scape stability. The applicability of CLC data for landscape transformation analyses was evaluated. The results of the study indicate that CLC data are highly useful for examining the rate of changes in land cover and landscape transformations. Analyses based on CLC data support the formulation of far-reaching conclusions regarding the extent and dynamics of changes in space.

Acknowledgements

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sector.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- Antrop, M. 2005. Why landscapes of the past are important for the future. *Landscape and Urban Planning*, 70(1–2). <https://doi.org/10.1016/j.landurbplan.2003.10.002>
- Barros, J. L., Tavares, A. O., Monteiro, M., Santos, P. P. 2018. Peri-urbanization and rurbanization in Leiria city: The importance of a planning framework. *Sustainability (Switzerland)*, 10(7). <https://doi.org/10.3390/su10072501>
- Barthel, S., Isendahl, C., Vis, B. N., Drescher, A., Evans, D. L., van Timmeren, A. 2019. Global urbanization and food production in direct competition for land: Leverage places to mitigate impacts on SDG2 and on the Earth System. *Anthropocene Review*, 6(1–2). <https://doi.org/10.1177/2053019619856672>
- Batty, M. 2010. Space, scale, and scaling in entropy maximizing. *Geographical Analysis*, 42(4). <https://doi.org/10.1111/j.1538-4632.2010.00800.x>
- Biłozor, A., Czyża, S., Bajerowski, T. 2019. Identification and Location of a Transitional Zone between an Urban and a Rural Area Using Fuzzy Set Theory, CLC, and HRL Data. *Sustainability*, 11(24), 7014. <https://doi.org/10.3390/su11247014>
- Bogaert, J., Vranken, I., André, M. 2014. Anthropogenic Effects in Landscapes: Historical Context and Spatial Pattern. In *Biocultural Landscapes*. https://doi.org/10.1007/978-94-017-8941-7_8
- Brown, A. G., Tooth, S., Chiverrell, R. C., Rose, J., Thomas, D. S. G., Wainwright, J., Bullard, J. E., Thorndycraft, V. R., Aalto, R., Downs, P. 2013. The Anthropocene: Is there a geomorphological case? In *Earth Surface Processes and Landforms* (Vol. 38, Issue 4). <https://doi.org/10.1002/esp.3368>
- Chen, J., Liu, Y. 2014. Coupled natural and human systems: a landscape ecology perspective. In *Landscape Ecology* (Vol. 29, Issue 10). <https://doi.org/10.1007/s10980-014-0125-9>
- Cieślak, I. 2019. Identification of areas exposed to land use conflict with the use of multiple-criteria decision-making methods. *Land Use Policy*, 89. <https://doi.org/10.1016/j.landusepol.2019.104225>
- Cieślak, I., Szuniewicz, K., Czyża, S. 2016. Analysis of the Variation of the Areas under Urbanization Pressure Using Entropy Index. *Procedia Engineering*, 161. <https://doi.org/10.1016/j.proeng.2016.08.793>
- Cieślak, I., Szuniewicz, K., Pawlewicz, K., Czyża, S. 2017. Land Use Changes Monitoring with CORINE Land Cover Data. In *IOP Conference Series: Materials Science and Engineering*; IOP Publishing: Bristol, UK, Volume 245, p. 052049. <https://doi.org/10.1088/1757-899X/245/5/052049>
- Cieślak, I., Biłozor, A., Szuniewicz, K. 2020. The use of the CORINE Land Cover (CLC) database for analyzing urban sprawl. *Remote Sensing*, 12(2). <https://doi.org/10.3390/rs12020282>
- Collins, C. D., Holt, R. D., Foster, B. L. 2009. Patch size effects on plant species decline in an experimentally fragmented landscape. *Ecology*, 90(9). <https://doi.org/10.1890/08-1405.1>
- CORINE Land Cover. (n.d.). 2018. Retrieved June 20, 2019, from clc.gios.gov.pl
- Crutzen, P., Schwägerl, C. 2011. Living in the Anthropocene: Toward a new global ethos. *Yale Environment*.
- Czyż, T., Hauke, J. 2015. Entropy in Regional Analysis. *Quaestiones Geographicae*, 34(4). <https://doi.org/10.1515/quageo-2015-0037>
- Demir, S. 2019. Landscape dynamics changes of the protected Mary valley, Turkey. *Applied Ecology and Environmental Research*, 17(2). https://doi.org/10.15666/aeer/1702_35913613
- Drusa, M., Yilmaz, I., Marschalko, M., Coisson, E., Segalini, A. 2016. Analysis of the variation of the areas under urbanization pressure using entropy index. In *World multidisciplinary civil engineering-architecture-urban planning symposium- WMCAUS 2016*
- Ellis, E. C., Wang, H., Xiao, H. S., Peng, K., Liu, X. P., Li, S. C., Ouyang, H., Cheng, X., Yang, L. Z. 2006. Measuring long-term ecological changes in densely populated landscapes using current and historical high resolution imagery. *Remote Sensing of Environment*, 100(4). <https://doi.org/10.1016/j.rse.2005.11.002>
- Espinosa, M. O., Polop, F., Rotela, C. H., Abril, M., Scavuzzo, C. M. 2016. Spatial pattern evolution of *Aedes aegypti* breeding sites in an Argentinean city without a dengue vector control programme. *Geospatial Health*. <https://doi.org/10.4081/gh.2016.471>

- Feranec, J., Hazeu, G., Christensen, S., Jaffrain, G. 2007. Corine land cover change detection in Europe (case studies of the Netherlands and Slovakia). *Land Use Policy*. <https://doi.org/10.1016/j.landusepol.2006.02.002>
- Forman, E. H., Gass, S. I. 2001. The analytic hierarchy process - An exposition. *Operations Research*. <https://doi.org/10.1287/opre.49.4.469.11231>
- Hadi, P. L., Wasanta, T., Santosa, W. 2021. Land use change due to road construction. In *IOP Conference Series: Earth and Environmental Science*, Vol. 920, No. 1, p. 012003. IOP Publishing. <https://doi.org/10.1088/1755-1315/920/1/012003>
- Hooke, R. L. B., Martín-Duque, J. F., Pedraza, J. 2012. Land transformation by humans: A review. *GSA Today*, 22(12). <https://doi.org/10.1130/GSAT151A.1>
- Hossain, M. S., Ramirez, J. A., Haisch, T., Speranza, C. I., Martius, O., Mayer, H., Keiler, M. 2020. A coupled human and landscape conceptual model of risk and resilience in Swiss Alpine communities. *Science of the Total Environment*, 730. <https://doi.org/10.1016/j.scitotenv.2020.138322>
- Huang C., Geiger E., Kupfer J.A., 2006. Sensitivity of landscape metrics to classification scheme, *International Journal of Remote Sensing*, 27:2927-2948 <https://doi.org/10.1080/01431160600554330>
- Huang, S. L., Yeh, C. T., Chang, L. F. 2010. The transition to an urbanizing world and the demand for natural resources. In *Current Opinion in Environmental Sustainability* (Vol. 2, Issue 3). <https://doi.org/10.1016/j.cosust.2010.06.004>
- Hunziker, M., Buchecker, M., Hartig, T. 2007. Space and Place – Two Aspects of the Human-landscape Relationship. https://doi.org/10.1007/978-1-4020-4436-6_5
- Janecki J. 1983. Człowiek a roślinność synantropijna miasta na przykładzie Warszawy. Wyd. SGGW – AR.
- Jucha, W., Krocak, R. 2014. Comparison of land use data from the CORINE Land Cover program with data obtained from orthophotomaps. In *Socio-Economic and Spatial Transformation of Regional Structures*; Kaczmarska, E., Raźniak, P., Eds.; Oficyna Wydawnicza AFM: Kraków, Poland, 2014; pp. 123–136. (In Polish)
- Klutho, S. 2013. Mathematical Decision Making - An overview of the analytic hierarchy process and its applications. *European Journal of Operational Research*, 48(1).
- Kobryń, A. 2014. Wielokryterialne wspomaganie decyzji w gospodarowaniu przestrzenią. Difin S.A.
- Kostrowicki A.S., Plit J., Solon J. 1988. Przekształcenie środowiska geograficznego. *Prace Geograficzne IGiPZ PAN* 147: 108-115.
- Kot, R., Leśniak, K. 2006. Geodiversity valuation with the aid of landscape indices - Basic methodological obstructions. *Przegląd Geograficzny*, 78(1).
- Kupfer, J. A. 2012. Landscape ecology and biogeography: Rethinking landscape metrics in a post-FRAGSTATS landscape. *Progress in Physical Geography*, 36(3). <https://doi.org/10.1177/0309133312439594>
- Lamine, S., Petropoulos, G. P., Singh, S. K., Szabó, S., Bachari, N. E. I., Srivastava, P. K., Suman, S. 2018. Quantifying land use/land cover spatio-temporal landscape pattern dynamics from Hyperion using SVMs classifier and FRAGSTATS®. *Geocarto International*, 33(8). <https://doi.org/10.1080/10106049.2017.1307460>
- Li, X., Lu, L., Cheng, G., Xiao, H. 2001. Quantifying landscape structure of the Heihe River Basin, north-west China using FRAGSTATS. *Journal of Arid Environments*, 48(4). <https://doi.org/10.1006/jare.2000.0715>
- Lipiec-Zajchowska M. B. W. C. 2003. Wspomaganie procesów decyzyjnych: Badania operacyjne (B. W. C. Lipiec-Zajchowska M. (Ed.)). CH Beck.
- Lowicki, D. 2008. Land use changes in Poland during transformation Case study of Wielkopolska region. *Landsc. Urban Plan*, 87, issue 4, pp. 279-288. <https://doi.org/10.1016/j.landurbplan.2008.06.010>
- Malinowska, E., Szumacher, I. 2013. Application of landscape metrics in the evaluation of geodiversity. *Miscellanea Geographica*, 17(4). <https://doi.org/10.2478/v10288-012-0045-y>
- Marzęcki, W. 2002. Ciągłość kulturowa w kształtowaniu przestrzeni miejskiej. Charakterystyka i metoda oceny jakości i zmienności tej przestrzeni, Wydawnictwo Uczelniane Politechniki Szczecińskiej, Szczecin.
- McGarigal, K., Marks, B. J. 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. General Technical Report - US Department of Agriculture, Forest Service, PNW-GTR-351. <https://doi.org/10.2737/PNW-GTR-351>
- Michnik, J., Lo, M. C. 2009. The assessment of the information quality with the aid of multiple criteria analysis. *European Journal of Operational Research*. <https://doi.org/10.1016/j.ejor.2007.11.017>
- Morris, D. W. 2019. A human tragedy? The pace of negative global change exceeds human progress. *Anthropocene Review*, 6(1–2). <https://doi.org/10.1177/2053019619848216>
- Mothorpe C., Hanson A., Schnier K. 2013. The impact of interstate highways on land use conversion *The Annals of Regional Science* 5 33-70. <https://doi.org/10.1007/s00168-013-0564-2>
- Moutinho, L., Hutcheson, G., Beynon, M. J. 2014. Analytic Hierarchy Process. In *The SAGE Dictionary of Quantitative Management Research*. <https://doi.org/10.4135/9781446251119.n3>
- Muñoz-Pedreras, A. 2017. The visual landscape: An important and poorly conserved resource. *Ambiente e Sociedade*, 20(1). <https://doi.org/10.1590/1809-4422ASOC20150088R1V2012017>
- Myga-Piątek, U., Żemła-Siesicka, A., Pukowiec-Kurda, K., Sobala, M., Nita, J. 2021. Is There Urban Landscape in Metropolitan Areas? An Unobvious Answer Based on Corine Land Cover Analyses. *Land*, 10, 51. <https://doi.org/10.3390/land10010051>

- Pan, W. K., Walsh, S. J., Bilsborrow, R. E., Frizzelle, B. G., Erlien, C. M., Baquero, F. 2004. Farm-level models of spatial patterns of land use and land cover dynamics in the Ecuadorian Amazon. *Agriculture, Ecosystems & Environment*, 101(2-3), 117-134. <https://doi.org/10.1016/j.agee.2003.09.022>
- Patil G. P., Brooks R. P., Myer W. L., Rapport D. J., Taillie C. 2001. Ecosystem Health and Its Measurement at Landscape Scale: Towards the Next Generation of Quantitative Assessment, *Ecosystem Health* 7.4: 307-316.
- Pelorusso, R., Leone, A., Boccia, L. 2009. Land cover and land use change in the Italian central Apennines: A comparison of assessment methods. *Appl. Geogr.* 29, 35–48. <https://doi.org/10.1016/j.apgeog.2008.07.003>
- Pukowiec-Kurda K., Sobala M. 2016. Nowa metoda oceny stopnia antropogenicznego przekształcenia krajobrazu na podstawie metryk krajobrazowych. The new method of evaluating the degree of anthropogenic landscape transformation based on landscape metrics. *Prace Komisji Krajobrazu Kulturowego*, vol. 31, pp. 71–84.
- Pukowiec-Kurda, K., Vavrouchová, H. 2020. Land cover change and landscape transformations (2000–2018) in the rural municipalities of the upper Silesia-Zagłębie metropolis. *Sustainability*, 12(23), 9911. <https://doi.org/10.3390/su12239911>
- Ramanathan, R. 2001. A note on the use of the analytic hierarchy process for environmental impact assessment. *Journal of Environmental Management*. <https://doi.org/10.1006/jema.2001.0455>
- Raszeja, E. 2013. Ochrona krajobrazu w procesie przekształceń obszarów wiejskich. Wyd. Uniwersytetu przyrodniczego w Poznaniu. Poznań.
- Richling, A. 2018. The map of landscape use of Central Europe. *Miscellanea Geographica*, 7(1). <https://doi.org/10.2478/mgrsd-1996-070102>
- 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). PAN IGiPZ im. S. Leszczyckiego. Monografie, 9, Warszawa, ss. 317
- Saaty, T. L. 2002. Decision making with the Analytic Hierarchy Process. *Scientia Iranica*. <https://doi.org/10.1504/ijssci.2008.017590>
- Saaty, T., Vargas, L. 2012. Models, methods, concepts & applications of the analytic hierarchy process. In ... -Driven Demand and Operations Management Models. <https://doi.org/10.1007/978-1-4614-3597-6>
- Saaty, T. L. 1994. How to Make a Decision: The Analytic Hierarchy Process. *Interfaces*. <https://doi.org/10.1287/inte.24.6.19>
- Saaty, T. L. 2004. Decision making — the Analytic Hierarchy and Network Processes (AHP/ANP). *Journal of Systems Science and Systems Engineering*. <https://doi.org/10.1007/s11518-006-0151-5>
- Shannon, C. E. 1948. A Mathematical Theory of Communication. *Bell System Technical Journal*, 27(3). <https://doi.org/10.1002/j.1538-7305.1948.tb01338.x>
- Shannon, C. E. 1997. The Mathematical Theory of Communication. *M.D. Computing*, 14(4). <https://doi.org/10.2307/410457>
- Shannon, Claude E., Weaver, W. 1964. La teoria matematica de la comunicacion. In *International Business*.
- Shishchenko P. G. 1988. Applied physical geography. Kyiv. Higher school. (In Russian).
- Solon J. 2002. Ocena różnorodności krajobrazu na podstawie analizy struktury przestrzennej roślinności, *Prace Geograficzne, IGiPZ PAN*, 185.
- Spatial development plan for the mazowieckie voivodeship, 2018. <https://www.mbpr.pl/zmianaplanu2018.html> (access on 15.01.2022)
- Stathopoulou, M., Cartalis, C., Petrakis, M. 2017. Integrating Corine Land Cover data and Landsat TM for surface emissivity definition: Application to the urban area of Athens, Greece. *Int. J. Remote Sens.* 2017, 28, 3291–3304. <https://doi.org/10.1080/01431160600993421>
- Statistics Poland - <https://stat.gov.pl/> (access on 20.01.2022)
- Tarolli, P., Vanacker, V., Middelkoop, H., Brown, A. G. 2014. Landscapes in the Anthropocene: State of the art and future directions. In *Anthropocene* (Vol. 6). <https://doi.org/10.1016/j.ancene.2014.11.003>
- Tikka, P. M., Högmänder, H., Koski, P. S. 2001. Road and railway verges serve as dispersal corridors for grassland plants. *Landscape ecology*, 16(7), 659-666. <https://doi.org/10.1023/A:1013120529382>
- Trzaskalik, T. 2014. Wielokryterialne wspomaganie decyzji. *Przegląd metod i zastosowań. Zeszyty Naukowe. Organizacja i Zarządzanie / Politechnika Śląska*.
- Tulecki, A., Król, S. 2007. Modele decyzyjne z wykorzystaniem metody analytic hierarchy process (AHP) w obszarze transportu. *Problemy Eksploatacji*, 171–179.
- Ustaoglu, E., Aydinoglu, A.C. 2019. Regional Variations of Land-Use Development and Land-Use/Cover Change Dynamics: A Case Study of Turkey. *Remote Sens.* 11, 885. <https://doi.org/10.3390/rs11070885>
- Werner, B. T., McNamara, D. E. 2007. Dynamics of coupled human-landscape systems. *Geomorphology*, 91(3–4). <https://doi.org/10.1016/j.geomorph.2007.04.020>
- Wilson, A. 2010. Entropy in urban and regional modelling: Retrospect and prospect. *Geographical Analysis*, 42(4). <https://doi.org/10.1111/j.1538-4632.2010.00799.x>
- Yoshioka, A., Fukasawa, K., Mishima, Y., Sasaki, K., Kadoya, T. 2017. Ecological dissimilarity among land-use/land-cover types improves a heterogeneity index for predicting biodiversity in agricultural landscapes. *Ambio*, 46(8). <https://doi.org/10.1007/s13280-017-0925-7>
- Zahedi, F. 1986. The Analytic Hierarchy Process—A Survey of the Method and its Applications. *Interfaces*. <https://doi.org/10.1287/inte.16.4.96>
- Zalasiewicz, J., Waters, C. N., Williams, M. 2014. Human bioturbation, and the subterranean landscape of the Anthropocene. *Anthropocene*, 6. <https://doi.org/10.1016/j.ancene.2014.07.002>