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Multivariate classification analysis of cultural landscapes: An example from the Czech Republic

Tomáš Chuman*, Dušan Romportl

Charles University, Faculty of Science, Department of Physical Geography and Geoecology, Albertov 6, 128 43 Prague 2, Czech Republic

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ABSTRACT

A method of landscape typology and a determination of diagnostic variables for delimiting landscape types was developed for the Czech Republic, thus fulfilling the first step of the European Landscape Convention. Eight datasets describing elevation, aspect, slope, soils, reconstructed natural vegetation, mean annual temperature, mean annual precipitation and land cover were used. The method uses a modified TWINSAPN classification, measuring cluster heterogeneity using JUICE software, and defines a statistically significant diagnostic variable for each landscape type by calculating a measure of fidelity. This hierarchical approach combines statistical methods with GIS techniques, enabling instant visualisation and a further analysis of the results obtained. It is universal when zooming in on the landscape, though higher spatial resolution datasets are needed.

1. Introduction

European landscapes are conditioned by many environmental factors including climate, geology, soils and landforms as well as by centuries of human activity leading to the formation of an outstanding diversity of man-made landscapes (Meeus, 1995). This diversity is recognised by the European Landscape Convention as a basic component of European natural and cultural heritage, contributing to human well-being and the consolidation of the European identity (Council of Europe, 2000). The specific composition, structure and scenery that are unique to every landscape are undergoing rapid change due to many forces including agricultural intensification, land abandonment, sub/urbanisation, construction of transport and logistic infrastructure and afforestation. These forces represent increasing pressure on landscapes. European landscapes are thus becoming more and more uniform and homogenous; some landscape types are disappearing completely (Wascher, 2004).

The homogenisation and unification also affect a number of landscape functions. It has been argued that ongoing landscape changes threaten biodiversity (Tropek and Konvička, 2008) because substantial proportions of European biological species are linked with traditional land uses such as grass cutting, grazing, coppicing, etc. These land uses led to the development of specific biotopes, which are occupied by a considerable diversity of species. These species are now under threat due to the decline of these biotopes caused by the abandonment of land and traditional land uses and agricultural intensification (Tropek and Konvička, 2008).

Meeus (1995) pointed out that most European landscapes are by-products of human activities; thus, what makes them vulnerable to change in management is also essential for a landscape's biodiversity conservation. The European Landscape Convention mentions this challenge and engages its signatory states to identify and describe their national landscapes and analyse their character, functions, state and quality (Council of Europe, 2000). The identification, description and assessment of landscapes constitute the preliminary phase of any landscape policy that might be created to preserve this unique European heritage.

A classification of landscapes that takes into account the underlying differences in their physical and cultural environment into either individual or typological units is one of the traditional tasks of environmental and geographical disciplines and is a great challenge of landscape research. Landscape classifications using different approaches have been presented in several studies (e.g., Bunce et al., 1975, 1996a,b; Lioubimtseva and Defourny, 1999; Meeus, 1995; Mücher et al., 2003; Van Eetvelde and Antrop, 2009; Vogiatzakis et al., 2006). These different classifications are difficult to compare because of the varying approaches and data sources that were used as well as the primary purpose for which the classifications were made. These reported classifications are, however, a good source for inspiration regarding the type of methods to use and the type of data selection to employ. All approaches reflect the relationships

* Corresponding author. Tel.: +420 22195 1371; fax: +420 22195 1367.
E-mail addresses: tomas.chuman@email.cz, chumant@natur.cuni.cz (T. Chuman), dusan@natur.cuni.cz (D. Romportl).

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among the physical (e.g., climate, relief, soils or geology) and cultural (land use and human artefacts) features that can be used to describe relatively homogenous landscape units.

In general, a classification method can be either subjective (based on intuitive expert judgment) or objective-based on quantitative statistical methods. The main limitation of subjective methods is the difficulty of classification revision by another expert or the incorporation of new data that is obtained later in the study. Objective methods are therefore the main focus of current methodological approaches. The development of remote sensing, GIS software and increased computer power have offered new ways for less subjective landscape classifications. In addition, the quality and availability of various thematic datasets have also increased.

Objective classifications include several different approaches. They are based either on a spatial overlay of selected thematic layers (Lioubimtseva and Defourny, 1999), segmentation of a “multispectral image” composed of several thematic layers (Mücher et al., 2003; Romportl and Chuman, 2007) or cluster analyses using either agglomerative or divisive clustering (Bunce et al., 1996a,b; Cherrill, 1994; Manzanares, 2007; McNab et al., 1999; Owen et al., 2006; Van Eetvelde and Antrop, 2009; Vogiatzakis et al., 2006). These objective classifications minimise the subjective aspects and are not fully dependent on expert judgement; however, one should be aware that the definitions of classification parameters and the selection of input datasets for objective classifications are subjective.

In the Czech Republic, several landscape classifications have been used (Kolejka and Lipský, 1999; Löw et al., 2005), but due to the absence of published work regarding the methodological approaches that were used, these classifications cannot be critically reviewed. None of these previous classifications are accepted widely, and none are used consistently for landscape protection and planning. The development of widely accepted landscape classification schemes is a great challenge to landscape research and is a necessary foundation for appropriate landscape protection, planning and management. Authorities who deal with landscape protection, planning and management are now facing the need to regulate new driving forces (e.g., sub/urbanisation, agricultural intensification, and changes in land uses due to subsidies) that are placing increasing pressure on the landscape. These forces are common for all European states and are particularly strong in post-communist countries like the Czech Republic that have experienced dramatic changes in society after the fall of their communist regime. This societal transformation has resulted in economic transformation, and the new economic development has been accompanied by changes in lifestyle.

With regard to the above-mentioned information, the purpose of this study is to propose a landscape classification of the Czech Republic at the national level and to take the first step toward fulfilment of the European Landscape Convention mandate. The intention of this study is to propose a method of landscape classification that is based on broadly available variables, which describe physical and cultural features. Furthermore, the classification scheme should be based on an objective method such that its use will always yield the same result on the same landscape, and should enable the classification of landscapes into typological units. In addition, the classification scheme should provide landscape protection and management authorities with necessary information regarding national landscape types including information about their extents, distributions and characteristics.

2. Materials and methods

The task consisted of three major stages: (1) selection of variables; (2) data pre-processing and preparation of the geodatabase; and (3) cluster analyses, visualisation, evaluation and characterisation of the determined landscape types.

2.1. Selection of variables

Landscape types are complex systems, which integrate geology, soil, vegetation, fauna, climate, relief and records of human activities. These data are interrelated and linked in a functional hierarchy that influences landscape character. A hierarchy showing the relative dependence of the major landscape components has been summarised by Klijn and de Haes (1994) and by Mücher et al. (2003). Regarding the functional hierarchy influencing landscape character and landscape classifications that have been used in other countries, the landscape variability in this study was described by the following datasets summarised in Table 1:

- Climate was characterised by mean annual precipitation and mean annual temperature derived from the Climate Atlas of Czechia (Tolasz et al., 2007) at a scale of 1:1,000,000.
- Soil types were taken from a Soil map of the Czech Republic at a scale of 1:500,000 published in the Landscape Atlas of the Czech Republic (Hrnčiarová et al., 2009).
- Topography was described by elevation, slope and aspect, all derived from a digital elevation model of the Czech Republic with 200-m resolution (Arc CR 500).
- A Map of reconstructed natural vegetation of the Czech Republic (Mikyška et al., 1968–1972) at a scale of 1:200,000, showing the state of the vegetation before its deterioration or destruction by man, was used to include the phytogeographical aspects of the landscapes. This map takes into account all of the aforementioned variables, thus can refine the information about the environmental conditions as the scale of the climate or soil type dataset is rather coarse. There were 20 categories of reconstructed vegetation, as shown in Table 1. These categories were derived from classification units of actually existing natural and semi-natural plant communities, outlined during extensive field mapping in the period from 1955 to 1960, even in altered places, thus the term reconstructed is used and the result is corresponding to a map of climaxes (Mikyška et al., 1968).
- The cultural features of the landscape were expressed using the CORINE Land Cover database. The most up-to-date vector layer was used at a scale of 1:100,000 with a minimum mapping unit of 25 ha reflecting the state of land cover in the year 2006 (CENIA). Out of the 44 classes of the CORINE Land Cover nomenclature, in the third level, there were present only 29 classes in the Czech Republic, as shown in Table 1.

A number of datasets could express landscape features in more detail; however, only a few datasets exist that have consistent geographical resolution that covers the whole country. In this study, we intended to use commonly available national data, to enable repeatability of this method in other countries.

2.2. Data pre-processing and preparation of the geodatabase prior to cluster analysis

The Czech Republic was divided into 2 km × 2 km grid cells, each associated with the environmental variables mentioned above (Fig. 1). All variables, including those originally recorded as continuous variables such as aspect, elevation and slope, were expressed as the proportion of the area covered by a particular class in each square (as percentages). More specifically, this means that continuous variables were converted into nominal variables by reclassifying them into several classes (Table 1). This step was necessary for the analysis, as all of the data needed to be in the same format. Such conversion of continuous variables into nominal vari-

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Table 1
Variables used for landscape classifications.

	Acronym
Mean annual precipitation (mm)	
Less than 450	Prec1
450–500	Prec2
500–550	Prec3
550–600	Prec4
600–650	Prec5
650–700	Prec6
700–800	Prec7
800–1000	Prec8
1000–1200	Prec9
More than 1200	Prec10
Mean annual temperature (°C)	
Less than 2	Temp1
2–3	Temp2
3–4	Temp3
4–5	Temp4
5–6	Temp5
6–7	Temp6
7–8	Temp7
8–9	Temp8
9–10	Temp9
More than 10	Temp10
Altitude (m a.s.l.)	
<250	DEM_1
250–500	DEM_2
500–750	DEM_3
750–1000	DEM_4
1000–1250	DEM_5
Above 1250	DEM_6
Slope (°)	
0–2	SLP1
2–5	SLP2
5–10	SLP3
10–15	SLP4
>15	SLP5
Aspect (°)	
−1	Flat
315–0; 0–45	North
45–135	South
135–225	East
225–315	West
Soil type	
Anthrosols	SOIL1
Phaeozems	SOIL2
Chernozems	SOIL3
Fluvisols	SOIL4
Gleysols	SOIL5
Haplic Luvisols	SOIL6
Cambisols	SOIL7
Entic Podzols	SOIL8
Albeluvisols	SOIL9
Histosols	SOIL10
Pellosols	SOIL11
Stagnosols	SOIL12
Calcic Leptosols	SOIL13
Haplic Podzols	SOIL14
Rendzic Leptosols	SOIL15
Greyic Phaeozems	SOIL16
Pellic Vertisols	SOIL17
Land use/cover	
Continuous urban fabric	CLC_111
Discontinuous urban fabric	CLC_112
Industrial or commercial units	CLC_121
Road and rail networks and associated land	CLC_122
Port areas	CLC_123
Airports	CLC_124
Mineral extraction sites	CLC_131
Dump sites	CLC_132
Construction sites	CLC_133
Green urban areas	CLC_141
Sport and leisure facilities	CLC_142
Non-irrigated arable land	CLC_211
Vineyards	CLC_221
Fruit trees and berry plantations	CLC_222
Pastures	CLC_231
Complex cultivation patterns	CLC_242
Land principally occupied by agriculture, with significant areas of natural vegetation	CLC_243
Broad-leaved forest	CLC_311
Coniferous forest	CLC_312
Mixed forest	CLC_313
Natural grassland	CLC_321
Moors and heathland	CLC_322
Transitional woodland-scrub	CLC_324
Bare rocks	CLC_332
Sparsely vegetated areas	CLC_333
Inland marshes	CLC_411
Peat bogs	CLC_412
Water courses	CLC_511
Water bodies	CLC_512
Reconstructed natural vegetation	
Acidophilous pine forest	VEG_1
Acidophilous oak forest	VEG_2
Mountain acidophilous beech forest	VEG_3
Birch-oak forest with Molinia arundinacea	VEG_4
Acidophilous beech and silver fir forest	VEG_5
Pine-oak forest	VEG_6
Oak-hornbeam forest	VEG_7
Climax mountain spruce forest	VEG_8
Herb-rich beech forest	VEG_9
Alluvial forest	VEG_10
Waterlogged pedunculate oak-beech forest	VEG_11
Waterlogged spruce forest	VEG_12
Fens	VEG_13
Subalpine and alpine vegetation	VEG_14
Sub-xerophilous oak forest	VEG_15
Ravine forest	VEG_16
Perialpidic basiphilous termophilous oak forest and rocky-outcrop forest steppe	VEG_17
Calcicolous beech forest	VEG_18
Wetland vegetation	VEG_19
Raised bogs	VEG_20

ables does not significantly influence the results (Jones and Bunce, 1985). All spatial analysis and construction of the geodatabase were performed using ArcGIS (ESRI, 2008).

2.3. Cluster analyses, visualisation, evaluation and characterisation of the determined landscape types

To identify contemporary landscape types at the national level, we decided to execute hierarchical divisive cluster analyses using a modified TWINSPAN (two way indicator species analysis) algorithm (Roleček et al., 2009) incorporated in the JUICE 7.0 software package (Tichý, 2002). This method uses the standard TWINSPAN algorithm proposed by Hill (1979) but calculates the heterogeneity of each cluster prior to each division. The classification starts by dividing the dataset into two clusters based on correspondence analysis ordination. The samples are divided into the left (negative) side and the right (positive) side of the dichotomy according to their score on the first CA axis (Lepš and Šmilauer, 1999). Then the division is stopped, and a preselected measure of heterogeneity is calculated for both clusters. In the next step, only the more heterogeneous cluster is divided by TWINSPAN algorithm into two smaller clusters. Then the preselected measure of heterogeneity is calculated again and only the most heterogeneous cluster is divided by TWINSPAN. The whole procedure is rather complex (see Hill and Šmilauer, 2005; Roleček et al., 2009), but the explanation is beyond of the scope of this study. These steps are repeated until the final number of clusters, hierarchical levels or the low satisfying level of heterogeneity is reached.

The advantage of TWINSPAN classification is that each division is accompanied by a set of indicators (in this case environmental variables), which discriminate between the two sub-groups arising from the dichotomy. The indicators are variables preferring

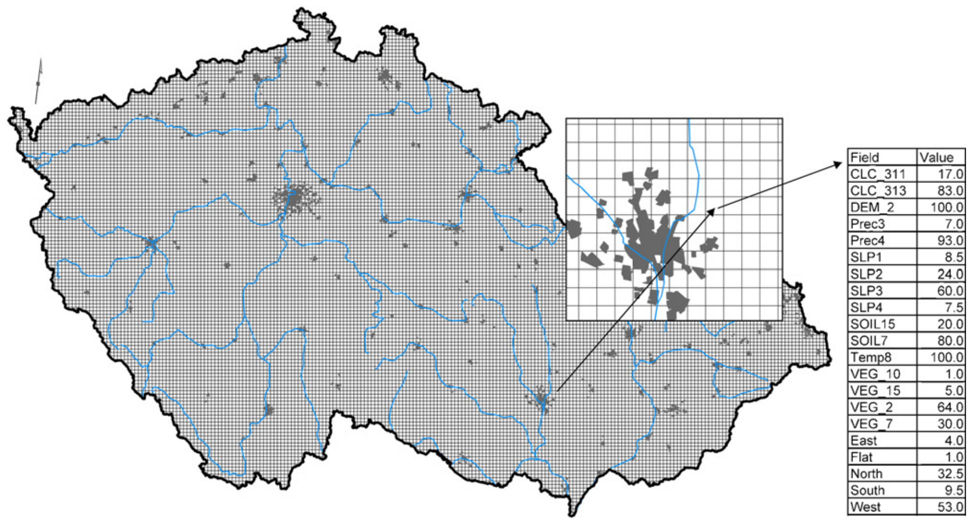

Fig. 1. An example of an input grid square with associated environmental variables. Values next to the variables express the proportion of the area each variable covers in a particular grid square as a percentage.

one or the other side of the dichotomy. The basis of the indicators in TWINSPAN is basically qualitative (Lepš and Šmilauer, 1999). Consequently, TWINSPAN only works with qualitative data. Therefore, in order not to lose information on the quantity of the variables, which entered the analysis, Hill (1979) introduced pseudo-variables and pseudo-variable cut levels. This means that each variable can be present as several pseudo-variables, according to its quantity in the object. The pseudo-variables are present if their quantities exceed their corresponding cut levels for a particular object. In this way, quantitative data are translated by the TWINSPAN into qualitative (presence/absence) data (Lepš and Šmilauer, 1999).

All nominal variables entering the analysis were expressed as proportions of the area covered by a particular class in each square (as percentages). Cut levels were set at 0, 5, 26, 51 and 76. Given the information defined above, this setting can be expressed in terms of pseudo-variables by saying that grid squares with 16 and 30% forest cover, as examples, contain the following pseudo-variables: both contain pseudo-variables *Forest1* (forest cover is exceeding cut level 0) and *Forest2* (forest cover is exceeding cut level 5) but the square with 30% forest cover contains an additional pseudo-variable *Forest3* (forest cover is exceeding also cut level 26).The grid squares are registered as having two pseudo-variables in common, and one different. The minimum number of objects per division was set to five. The total inertia (the sum of the eigenvalues of the correspondence analysis) was used as a measure of heterogeneity that determined which cluster would be divided into two smaller clusters in the next hierarchical level. The further division was stopped when the total inertia of a cluster was lower than 0.15.

The result was then projected to the input square grid, as each object of the TWINSPAN classifications was accompanied by a code identifying to which cluster it belonged. The obvious advantage of TWINSPAN is the potential to combine the result with GIS software and visualise it. It is also possible to execute further spatial analysis in defined clusters. All spatial calculations were carried out using ArcGIS 9.2 software (ESRI, 2008).

An important part of each landscape classification should be the determination of diagnostic variables for each landscape type. In vegetation science, the determination of diagnostic species of plant communities is based on fidelity (Chytrý et al., 2002). The fidelity measures species concentration in a particular unit (cluster) relative to other units (Tichý and Chytrý, 2006). The distribution of these occurrences within the dataset is compared to what would theoretically be expected if such occurrences were independent of the cluster. Species occurring mostly in a particular cluster that are rare or absent in others have high positive fidelity values. Species occurring mostly outside a particular cluster have a negative fidelity value. The higher the value for a species, the more likely the species only exists in the specific cluster. This concept could be applied also to environmental variables that characterise the landscape types. Given this fact, we used the fidelity measure to recognise the diagnostic variables. Analogously environmental variables occurring mostly in a particular cluster that are rare or absent in others have high positive fidelity values. Variables occurring mostly outside a particular cluster have a negative fidelity value. Measures of fidelity are available from the JUICE software package (Tichý, 2002). We used the phi coefficient of the variable presence/absence, which is independent of the total number of objects in the defined cluster (Chytrý et al., 2002). The value of the phi coefficients ranges from −1 to 1. According to Chytrý et al. (2002), the highest phi value of

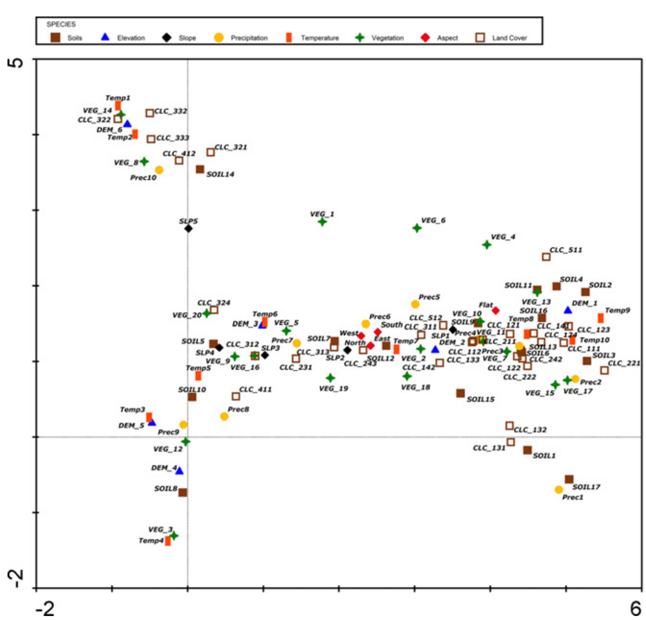

Fig. 2. DCA ordination diagram showing correlations of input variables. For meanings of acronyms see the input datasets descriptions (Table 1).

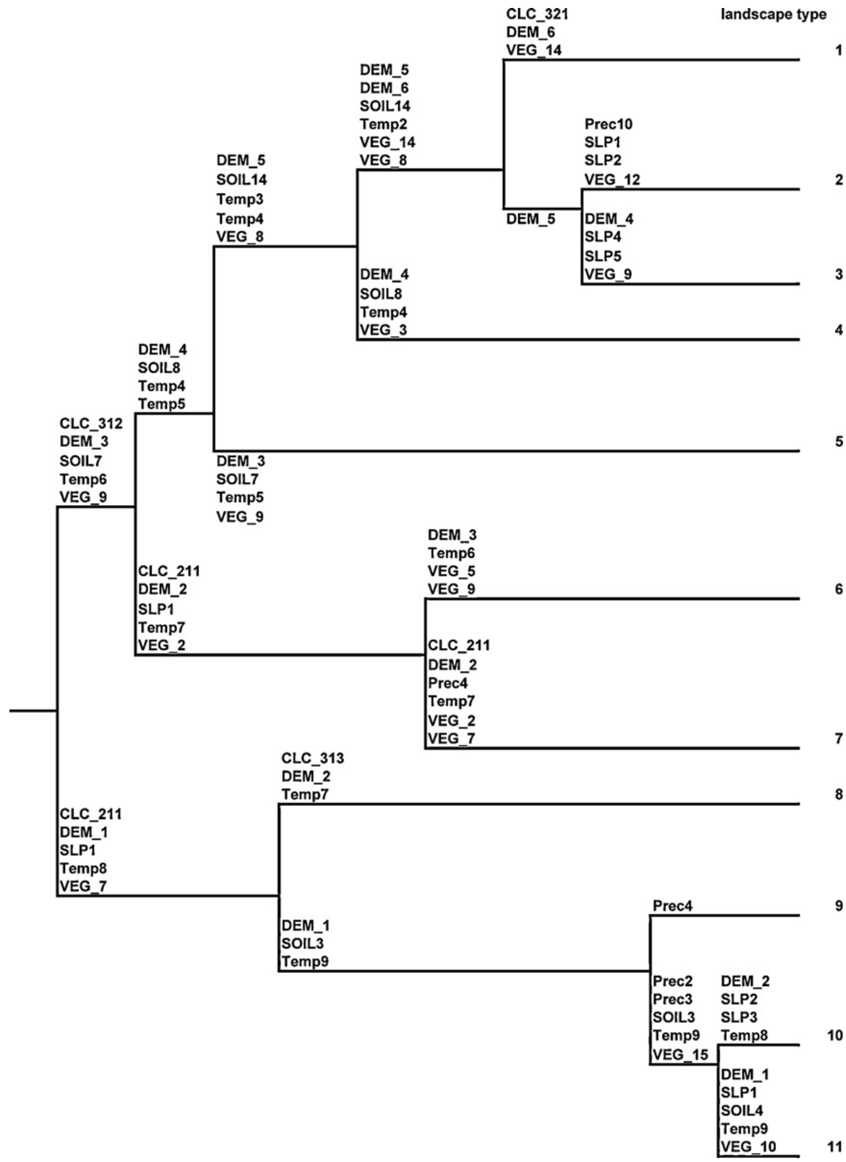

Fig. 3. Dendrogram showing hierarchical levels of the modified TWINSPAN classification with indicative variables at each level.

one is achieved if the variable occurs in all objects of the particular cluster and is absent in all other clusters. A value of zero is obtained when the relative frequency of the variable in the cluster equals the relative frequency in other clusters. The relationships among the variables were further investigated by detrended correspondence analysis (DCA), which is perhaps the most common technique of indirect ordination. The DCA was performed and the ordination diagram visualised using CANOCO 4.5 (ter Braak and Šmilauer, 2002).

3. Results

A total of 102 attributes (response variables) in 20,339 squares were processed via TWINSPAN cluster analysis. Some variables show a high correlation, as is illustrated by the indirect gradient analysis (DCA) (Fig. 2). The highest elevations strongly correlate with steep slopes, high precipitation, low temperature and natural vegetation consisting of climax mountain spruce forest and subalpine and alpine vegetation. The lowest altitudes strongly correlate with high temperature, low precipitation and natural vegetation consisting of sub-xerophilous oak forest or xerothermic oak forest and rocky-outcrop forest steppe vegetation, which was often converted to vineyards (Fig. 2).

The hierarchical classification was stopped at the 10th level. The TWINSPAN classification of the Czech landscape yielded 11 divisions (national landscape types) at 10 levels, shown as a dendrogram with indicators used for division at each level (Fig. 3). The division of the 20,339 squares into 11 landscape types produced 17 objects in the smallest group and 6071 objects in the largest group. The smallest landscape type covered 41 km^2 within the Czech Republic and the largest covered 23,911 km^2. The average landscape type consisted of 1848 objects and covered 7891 km^2.

The resulting 11 national landscape types showed well-defined patterns of distribution that related to recognisable combinations of landscape features. The smallest type occurred in the highest parts of the Czech mountains, the coldest and wettest areas, which are covered by alpine and subalpine vegetation. The most extensive landscape type covered the intermediate altitudes that had high levels of agricultural land use.

At the first hierarchical level, the territory of the Czech Republic was divided primarily into two landscape types: (i) warm flat to gently sloping, dry lowlands and downs dominated by agriculture,

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Table 2
Counts of indicators used for divisions at each hierarchical level summarised per each thematic layer entering the cluster analysis.

Indicator used qty.	Hierarchical level										
	1	2	3	4	5	6	7	8	9	10	sum
Elevation	2	2	2	2	3	2	2	1		2	18
Mean annual temperature	2	3	3	2	2	2			1	2	17
Reconstructed natural vegetation	2	1	2		3	4	1	2	1	1	17
Slope	1	1						4		3	9
Soil	1	1	2	1	2				1	1	9
Land cover	2	1		1		1	1				6
Mean annual precipitation						1		1	3		5

which extend over 31,957 km^2 and (ii) colder to cold, humid hilly lands, highlands and mountains dominated by forests and pastures, which also include subalpine and alpine vegetation and extend over 46,956 km^2. This larger cluster showed higher heterogeneity and thus was divided more often than the smaller one at the next hierarchical levels, producing 7 out of the 11 final clusters.

From the indicators, it is clear that the primary landscape structures of *elevation* and the strongly correlated *mean annual temperature* play a dominant role in the landscape classification. The *mean annual precipitation* was the least common indicator used only 5 times. *Aspect* was not, however, used a single time. The *elevation* was the most common indicator, used 18 times, followed by *mean annual temperature* and *reconstructed natural vegetation* that were used 17 times, as shown in Table 2. *Slope* and *soil* variables were used 9 times. The *land cover* was not a frequently used indicator, being utilised only 6 times.

The statistical evaluation of the diagnostic variables for each landscape type was performed using the phi coefficient as a measure of fidelity (Chytrý et al., 2002) and calculated using JUICE software (Tichý, 2002). Fisher's exact test was calculated simultaneously to exclude variables with non-significant fidelity (at the 99% significance level) as proposed by Tichý (2002). The analysis yielded 101 variables with positive fidelity, which characterised the 11 landscape types, as summarised in Table 3. There was only one variable, VEG_18 (Calcicolous beech forest), without significant positive fidelity in any landscape type. Most of the variables showed positive fidelity to more than one landscape type; however, every landscape type could be characterised with a specific and meaningful combination of variables, as shown in Table 3.

The distinctiveness of the delimited landscape types could be assessed with the average positive fidelity value. Higher average fidelity showed more distinctive landscape types. From this point of view, the landscape type no. 1 showed the highest average fidelity value, which indicates its distinctive character that can be contrasted to the low average fidelity of landscape type no. 8.

The landscape types delimited in Fig. 4 can be described as follows:

Type 1: Extremely cold to very cold mountains or alpine mountains close to or above the tree line that receive more than 1200 mm of precipitation per year on average. Haplic podzol is the most characteristic soil type. Natural vegetation consists mainly of subalpine and alpine vegetation. Natural grasslands, moors and heath land are the predominant land covers. This landscape type only occurs in the highest parts of the Giant Mountains and is the rarest type in the Czech Republic.

Type 2: Very cold to cold, flat mountaintops that receive more than 1200 mm of precipitation per year on average. Gleysols and histosols are the dominant soil types. Natural vegetation consists of waterlogged spruce forest and climax mountain spruce forest. Transitional woodland-scrub and peat bogs are the dominant land covers. This second rarest landscape type was found mainly in the highest flat parts of the Bohemian Forest.

Type 3: Very cold to cold steeply sloping mountains that receive between 1000 and 1200 mm of precipitation per year on average. Haplic podzol is the most characteristic soil type. Natural vegetation consists mainly of climax mountain spruce forest, subalpine and alpine vegetation and mountain acidophilous beech forest. Transitional woodland-scrub, moors and heathland are the dominant land covers. Such conditions were identified in the Giant Mountains, the Jeseníky Mountains and in few sites of the Bohemian Forest. The total area of 122 km^2 makes this landscape type the last of the rare ones, as all following types cover more than 1000 km^2.

Type 4: Cold to moderate cold uplands to mountains that receive more than 800 mm of precipitation per year on average. Entic podzol or haplic podzol are the most characteristic soil type. Natural vegetation consists mainly of mountain acidophilous beech forest or waterlogged spruce forest. Transitional woodland-scrub and coniferous forest are the dominant land covers. This landscape type was found in most of the Czech mountains higher than 1000 m a.s.l., with a high occurrence in the Bohemian Forest, the Jeseníky Mountains and the Jizerské hory Mountains. This type represents the typical mountain landscape that covers more than 1100 km^2.

Type 5: Moderate cold to moderate warm uplands and hills that receive up to 1000 mm of precipitation per year on average. Entic podzol is the most characteristic soil type. Natural vegetation consists mainly of herb-rich beech forest. Coniferous forest and pastures are the predominant land covers. Landscape type no. 5 covers the majority of foothills of the mountain ranges mentioned above and the upper parts of the highlands. This type represents the typical Czech upland landscape that covers almost 6300 km^2.

Type 6: Moderate warm hilly lands up to 750 m a.s.l. that receive up to 800 mm of precipitation per year on average. Cambisols are the most characteristic soil types. Natural vegetation consists mainly of acidophilous beech and silver fir forest or herb-rich beech forest. The land is occupied principally by agriculture, with significant areas of natural vegetation. These conditions were classified in extensive parts of the Czech-Moravian Highland as well as in the Lower Jeseník Highland. Similar landscape features were recorded in the foothills of other uplands within all of the Czech Republic. The total area of nearly 15,300 km^2 makes this landscape type the third most common in the country.

Type 7: Moderate warm downs and hilly lands extending between 250 and 750 m a.s.l. that receive up to 800 mm of precipitation per year on average. Cambisols and stagnosols are the most characteristic soil types. Natural vegetation consists mainly of acidophilous oak forest or acidophilous beech and silver fir forest. Land cover is dominated by arable land or a mosaic of agriculture plots with significant areas of natural vegetation. This type covers almost one third of the country's area and is the most common type recorded in the majority of downs and hilly lands of the Czech Republic. This type represents the typical Czech landscape.

Type 8: Moderate warm to warm downs predominantly up to 500 m a.s.l. that receive up to 650 mm of precipitation per year

Table 3
An overview of variables based on fidelity measures. Highlighted values are those with the highest phi coefficient for each variable. Dashes in the table indicate negative fidelity.

Landscape type	1	2	3	4	5	6	7	8	9	10	11
Extent km^2	41.3	50.7	122.1	1151.1	6286.3	15,394.1	23,911.2	18,479.3	6330.2	4679.1	2469.2
No. of variables with positive fidelity	16	16	23	25	24	18	28	32	32	36	25
Average fidelity value	41.7	38.3	31.5	23.9	21.3	22.2	17.8	15.2	18.6	21.3	25.3
Variable	Phi coefficient × 100										
CLC_111	–	–	–	–	–	–	–	–	–	**5.4**	–
CLC_112	–	–	–	–	–	–	–	22	**29.3**	21.9	15.3
CLC_121	–	–	–	–	–	–	–	4.5	**16.3**	13.9	12.4
CLC_122	–	–	–	–	–	–	–	–	7.5	**13.4**	–
CLC_123	–	–	–	–	–	–	–	–	–	–	**5.4**
CLC_124	–	–	–	–	–	–	–	–	**8.8**	5.4	–
CLC_131	–	–	–	–	–	–	–	–	–	**11.8**	–
CLC_132	–	–	–	–	–	–	–	–	6.3	**8.8**	4.5
CLC_133	–	–	–	–	–	–	–	–	**8.4**	–	–
CLC_141	–	–	–	–	–	–	–	–	5	**12.9**	–
CLC_142	–	–	–	–	–	–	–	4	–	**5.1**	–
CLC_211	–	–	–	–	–	–	23.1	29.9	**30.4**	28.5	27.5
CLC_221	–	–	–	–	–	–	–	–	–	**24.5**	24
CLC_222	–	–	–	–	–	–	–	3.1	–	**23.2**	12.4
CLC_231	–	–	–	–	21.2	**33.9**	24	–	–	–	–
CLC_242	–	–	–	–	–	–	–	3.6	4.5	**26.5**	18.8
CLC_243	–	–	–	–	–	**22.9**	22.7	–	–	–	–
CLC_311	–	–	–	–	–	–	–	6.6	10.8	9.6	**21.1**
CLC_312	–	–	**24.8**	24	21.6	20.1	17.4	–	–	–	–
CLC_313	–	–	–	–	**18.3**	–	14.8	16.8	–	–	–
CLC_321	**69**	–	24.1	–	–	–	–	–	–	–	–
CLC_322	**66.4**	–	26.5	–	–	–	–	–	–	–	–
CLC_324	21.5	33.1	**36.5**	24.9	–	–	–	–	–	–	–
CLC_332	**28.5**	–	–	–	–	–	–	–	–	–	–
CLC_333	**28.7**	–	–	–	–	–	–	–	–	–	–
CLC_411	–	–	–	**12.2**	0.5	–	–	–	–	–	1.7
CLC_412	–	**20.4**	–	9.9	–	–	–	–	–	–	–
CLC_511	–	–	–	–	–	–	–	–	2.2	6.9	**20.2**
CLC_512	–	–	–	–	–	–	4.6	4.9	8.2	–	**9.6**
DEM_1	–	–	–	–	–	–	–	–	48.7	40.2	**50.9**
DEM_2	–	–	–	–	–	–	42.2	**44.4**	–	30.4	–
DEM_3	–	–	–	–	45.1	**56.5**	23.7	–	–	–	–
DEM_4	–	–	33.3	**45.7**	44.2	–	–	–	–	–	–
DEM_5	25.2	**45**	**45**	33.2	–	–	–	–	–	–	–
DEM_6	**54.1**	35	52	–	–	–	–	–	–	–	–
East	–	–	–	–	–	**4.9**	3.4	3.1	–	–	–
Flat	–	–	–	–	–	–	–	10.6	21.7	11.4	**23.2**
North	–	–	–	–	–	–	**6.4**	–	–	–	–
South	–	–	–	–	–	3.1	**3.7**	–	–	–	–
West	–	–	–	–	–	**4.7**	4.8	–	–	–	–
Prec1	–	–	–	–	–	–	–	–	–	**24.2**	–
Prec2	–	–	–	–	–	–	–	–	–	36.4	**47.4**
Prec3	–	–	–	–	–	–	–	7.8	–	**42.1**	35.4
Prec4	–	–	–	–	–	–	13.5	20.3	**47.7**	–	–
Prec5	–	–	–	–	–	16.6	**20.3**	**20.3**	16.9	–	–
Prec6	–	–	–	–	–	**28.9**	17	–	–	–	–
Prec7	–	–	–	–	19.2	**30.4**	15.6	–	–	–	–
Prec8	–	–	–	14.8	**44.8**	7.2	–	–	–	–	–
Prec9	–	–	**39.4**	35.8	9.6	–	–	–	–	–	–
Prec10	41.7	**54.6**	10.8	12.3	–	–	–	–	–	–	–
SLP1	–	–	–	–	–	8.7	8.9	9.6	**9.8**	**9.8**	**9.8**
SLP2	–	–	–	12.4	**12.6**	11.2	8.7	–	–	–	–
SLP3	–	**21.7**	**21.7**	18.5	18.8	6.2	4.7	–	–	–	–
SLP4	23.4	17.9	**32.8**	19.5	18.2	–	–	–	–	–	–
SLP5	25.6	–	**49.7**	15.2	7.4	–	–	–	–	–	–
SOIL1	–	–	–	–	–	–	–	–	–	**19.2**	–
SOIL2	–	–	–	–	–	–	–	–	17.8	5.1	**28.4**
SOIL3	–	–	–	–	–	–	–	–	19.2	**51.8**	47.1
SOIL4	–	–	–	–	–	–	–	0.2	30.3	2	**40.1**
SOIL5	–	**52**	–	1.7	0.9	–	–	–	–	–	–
SOIL6	–	–	–	–	–	–	–	**34**	22.6	13.4	–
SOIL7	–	–	–	–	–	**36.2**	33.8	–	–	–	–
SOIL8	–	–	21.9	**46.6**	34.7	–	–	–	–	–	–
SOIL9	–	–	–	–	–	–	–	**38**	14.5	–	–
SOIL10	–	**43.2**	–	28.9	0.9	–	–	–	–	–	–
SOIL11	–	–	–	–	–	–	–	7.4	**28.8**	–	–
SOIL12	–	–	–	–	–	19	**22.8**	18.1	–	–	–
SOIL13	–	–	–	–	–	–	–	5.5	11.8	**20.9**	–
SOIL14	**40.6**	**40.6**	**40.6**	30.9	–	–	–	–	–	–	–
SOIL15	–	–	–	–	–	–	–	**8.3**	–	–	–

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Table 3 (*Continued*)

Landscape type	1	2	3	4	5	6	7	8	9	10	11
Extent km^2	41.3	50.7	122.1	1151.1	6286.3	15,394.1	23,911.2	18,479.3	6330.2	4679.1	2469.2
No. of variables with positive fidelity	16	16	23	25	24	18	28	32	32	36	25
Average fidelity value	41.7	38.3	31.5	23.9	21.3	22.2	17.8	15.2	18.6	21.3	25.3
Variable	Phi coefficient × 100										
SOIL16	–	–	–	–	–	–	–	6.9	12.7	–	–
SOIL17	–	–	–	–	–	–	–	–	–	18.4	–
Temp1	67.5	–	14.5	–	–	–	–	–	–	–	–
Temp2	50.7	39.6	46.6	–	–	–	–	–	–	–	–
Temp3	21.2	42.6	46	27.9	–	–	–	–	–	–	–
Temp4	–	–	22.5	60	14.1	–	–	–	–	–	–
Temp5	–	–	–	10.5	76	1.7	–	–	–	–	–
Temp6	–	–	–	–	27.4	73.3	–	–	–	–	–
Temp7	–	–	–	–	–	–	66.8	34.7	–	–	–
Temp8	–	–	–	–	–	–	–	30.6	50.9	45.1	–
Temp9	–	–	–	–	–	–	–	–	–	21.3	79.1
Temp10	–	–	–	–	–	–	–	–	–	5	–
VEG_1	–	–	–	–	–	–	8.1	–	–	–	–
VEG_2	–	–	–	–	–	–	37.6	30.8	–	–	–
VEG_3	–	21.3	28.8	42.9	10.1	–	–	–	–	–	–
VEG_4	–	–	–	–	–	–	–	6.5	6.6	–	–
VEG_5	–	–	–	–	–	51.5	20.9	–	–	–	–
VEG_6	–	–	–	–	–	–	7.6	–	19	–	–
VEG_7	–	–	–	–	–	–	–	29.7	29.4	40.8	28.8
VEG_8	25.3	50	50	13.1	–	–	–	–	–	–	–
VEG_9	–	–	23	16	37.7	24.2	8	–	–	–	–
VEG_10	–	–	–	–	–	–	14	17.1	27.5	17.7	25.5
VEG_11	–	–	–	–	–	–	–	5.8	19.2	–	–
VEG_12	–	51.3	–	28	7.3	–	–	–	–	–	–
VEG_13	–	–	–	–	–	–	–	–	3.8	–	–
VEG_14	77.1	–	33.3	–	–	–	–	–	–	–	–
VEG_15	–	–	–	–	–	–	–	2	–	54.7	37.8
VEG_16	–	–	–	–	10.6	4	–	–	–	–	–
VEG_17	–	–	–	–	–	–	–	–	–	37.7	6.8
VEG_19	–	–	–	–	9	–	–	–	–	–	–
VEG_20	–	45.1	1.6	12.7	–	–	–	–	–	–	–

on average. Albeluvisols, haplic luvisols and stagnosols are the most characteristic soil types. Natural vegetation consists mainly of acidophilous oak forest or oak-hornbeam forest. Arable land and discontinuous urban fabric are characteristic land covers for this landscape type. This landscape type is widespread in downs and basins in the whole Czech Republic. Its total area of almost 18,500 km^2 makes this type the second largest one in the country.

Type 9: Warm lowlands that receive up to 650 mm of precipitation per year on average. Fluvisols, haplic luvisols and pellosols are the most characteristic soil types. Natural vegetation consists mainly of oak-hornbeam forest, alluvial forest or waterlogged pedunculate oak-beech forest. A high proportion of this land has been converted to urban fabric. Arable land, discontinuous urban fabric and industrial or commercial units are characteristic land covers

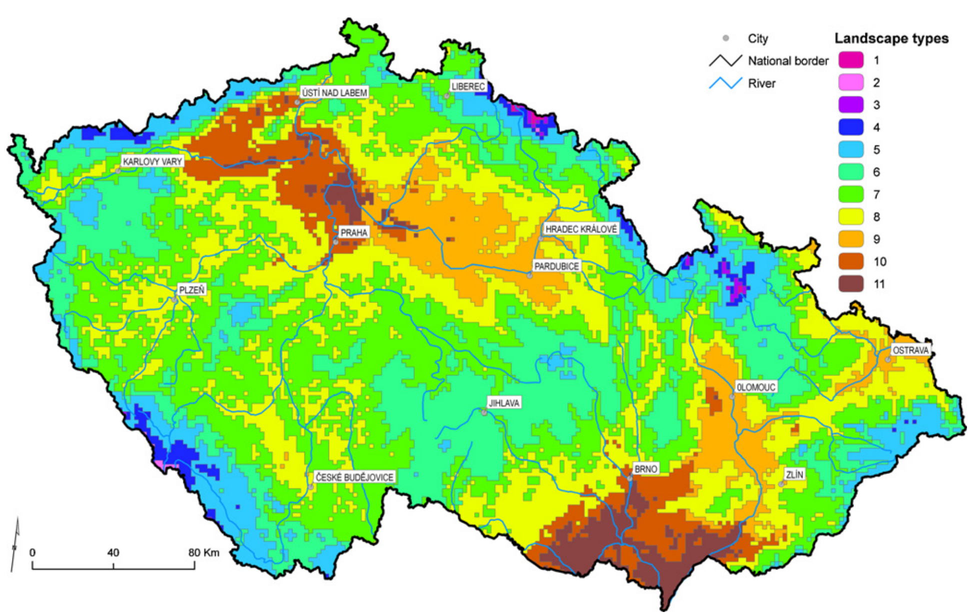

Fig. 4. The 11 delimited landscape types of the Czech Republic.

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for this landscape type. Such conditions were classified in the eastern part of the Elbe valley downs, in Upper Moravian Basin and along the Odra river in the northeastern part of the Czech Republic. Isolated occurrences were recorded in other warm lowlands in the western and southern parts of the country.

Type 10: Warm to very warm gently sloping lowlands and downs up to 500 m a.s.l. that receive up to 550 mm of precipitation per year on average. Chernozems are the most characteristic soil types in this landscape. Natural vegetation consists mainly of sub-xerophilous oak forest, oak-hornbeam forest and perialpidic basiphilous termophilous oak forest and rocky-outcrop forest steppe. The land cover is highly variable. Arable land, urban areas, complex cultivation patterns, fruit trees, berry plantations and vineyards are characteristic land covers. This landscape type was found in the warm and dry gently sloping lowlands in the western and southeastern part of the Czech Republic.

Type 11: Very warm flat lowlands up to 250 m a.s.l., receiving 450–550 mm of precipitation per year on average. Chernozems, fluvisols and phaeozems are the most characteristic soil types. Natural vegetation consists mainly of sub-xerophilous oak forest and oak-hornbeam forest.

The land cover is highly variable. Arable land, broad-leaved forest and water courses are characteristic land covers. This landscape type was recorded in the driest and warmest regions of the Czech Republic. Specifically, this landscape type was found in the lowlands along the river Dyje in southeastern Moravia and the lowlands along the confluence of the rivers Vltava and Labe in the central part of Bohemia.

4. Discussion

The 11 national landscape types obtained by TWINSPAN divisive cluster analysis show a well-defined pattern of distribution that relates to recognisable combinations of landscape features. TWINSPAN is one of the most popular software packages for hierarchical divisive classification techniques. Though the technique was designed originally for vegetation classification, it has been shown to yield valid results when used for environmental stratification or landscape classification (Bunce et al., 1996a,b; Cherrill, 1994; Manzanares et al., 2007; McNab et al., 1999). The application of modified TWINSPAN algorithm (Roleček et al., 2009) demonstrated here increased the flexibility of the classification, enabling one to provide any number of clusters and avoiding the division of homogenous clusters. The number of clusters does not increase twice at every hierarchical level as was the case when using the original TWINSPAN algorithm.

The distinct advantage of this method is the hierarchical system that is able to describe the national and regional levels, and a set of indicators that reveals what defines the levels (unlike other clustering techniques). As the TWINSPAN classification was originally designed to identify associated species, the indicators are often highly correlated input variables (Bunce et al., 1996a,b).

The only constraint of the TWINSPAN classification is the limitation of its being only able to handle a maximum of 25,000 objects, which did not allow us to use a cell size of smaller than 2 km × 2 km (regarding the extent of the Czech Republic). Larger cells cause the landscape units to look coarse. This could be overcome by performing the analysis on a stratified selection of squares, as has been performed for environmental stratification in England (Bunce et al., 1996a,b). This stratification can be followed by classifying the remaining subset of squares into landscape types based on the indicative variables. Bunce et al. (1996a,b) mentioned that it is important to have a reasonably high number of objects on which to base the subset classification in order to minimise the influence of unusual objects. Due to high variability of the environmental conditions in the Czech Republic, we decided to analyse the whole dataset and not to bias the classification by the rare combination of variables. We are aware of the coarse resolution of our results. Additionally, when we considered the spatial scale of the input datasets and the classification levels involving the entire Czech Republic, the final outputs represented reasonable and precise landscape types.

It can be argued that using a grid cell and cluster analysis results in isolated cells that belong to one landscape type surrounded by another type. This was the case in our classification mainly when isolated hills or patches of different soil types, reconstructed natural vegetation categories or land cover classes occurred. Local differences in physical features such as trophic parameters or moisture regimes might lead to the development of different vegetation assemblages forming a unique landscape type within a broader surrounding. Isolated units of 4 km^2 sizes could represent characteristic landscape types, and, therefore, no generalisations were applied.

Another controversial step of the presented method is our definition of cut levels. The use of different threshold values could have yielded different results. We assume that for landscape classification the cut levels used (presence – up to 5%, less then quarter, less then half, less then three quarters and above three quarters for each variable) are sufficient. However, the definition of threshold values, the number of clusters and the dissimilarity measures are the main limitations of every method used for classification (Bunce et al., 1996a,b).

The use of fidelity as computed by JUICE (Tichý, 2002) to find statistically significant diagnostic species for the final clusters was found to be highly rewarding. The phi coefficient was used as a measure of fidelity simultaneously with Fisher's exact test to exclude variables with non-significant fidelity, as it does not depend on cluster size (Tichý and Chytrý, 2006).

Most of the variables (e.g., land cover, mean annual temperature and elevation) showed positive fidelity in more than one landscape type; however, every landscape type could be characterised with specific combination of variables. The results show a foundational role of the primary landscape structure in landscape classification. This supports Meeus's (1995) Pan-European landscape classification showing that variables such as climate, parent geological substrate and altitude are key factors in human exploitation of the environment and consequently determine cultural landscape conditions.

The main limitation of every method used for landscape classification, even those that are objective, is input data selection (Bunce et al., 1996a,b) and data availability. Therefore, approaches to landscape classification are often highly contentious because landscape types depend on a whole range of factors, many of which are difficult to specify objectively. In this study, broadly available national datasets that are used commonly in landscape classifications (Bunce et al., 1996a,b; Lioubimtseva and Defourny, 1999; Manzanares et al., 2007) were used.

Climatic variables and soil types were of lower spatial resolution than those derived from the digital elevation model (elevation, aspect and slope), but there are no such data covering whole country in high detail. The reconstructed natural vegetation at a scale of 1:200,000, however, refines the information about the environmental conditions by showing the state of vegetation before its deterioration or destruction by man. The corresponding map of climaxes (Mikyška et al., 1968) is thus a function of climate, geology and relief. The cultural landscape conditions were represented only by CORINE Land Cover, which is the only dataset expressing the impact of society.

More variables might have been included such as landscape structure (Van Eetvelde and Antrop, 2009), visual criteria (Meeus, 1995) or cultural, historical, archaeological or aesthetic features.

Information about such landscape characteristics are rarely available in the form of a spatial database and are based, to a large extent, on subjective judgement. The use of this data is more appropriate at local levels that are beyond of the scope of this study.

The most problematic aspect of any landscape classification involves testing the validity of the result because there is no agreed set of standards against which the results can be compared (Haines-Young, 1992). The DCA ordination and fidelity measures show that every landscape type can be characterised with specific and meaningful combinations of variables. According to Bunce et al. (1996a,b) or Jongman et al. (2006), cluster analysis results in a meaningful classification of landscape types. The originality of this method arises from the hierarchical system that takes into account cluster heterogeneity and produces indicators for each division as well as fidelity measures, which show characteristic sets of variables for each landscape type.

5. Conclusions

The method of landscape typology presented here using divisive cluster analysis performed by a modified TWINSPAN classification in combination with GIS and JUICE software yielded satisfactory results. The method fits the most commonly used methods in other European countries. The main advantages of this method lie in the hierarchy of landscape types, the determination of statistically significant variables that are characteristic to each landscape type and the interconnection between the TWINSPAN classification and the GIS software that helps to visualise and further analyse results. The visualisation of landscape types is a necessary tool for landscape planning and management, as well as being important for assessments of landscape changes. This method could also be applied by other countries as it is very flexible in the number and spatial resolution of input datasets, the number of hierarchical levels and the number of final landscape types.

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References

Bunce, R.G.H., Morrell, S.K., Stel, H.E., 1975. The application of multivariate analysis to regional survey. J. Environ. Manage. 3, 151–165.

Bunce, R.G.H., Barr, C.J., Gillespie, M.K., Howard, D.C., 1996a. The ITE land classification: providing an environmental stratification of Great Britain. Environ. Monit. Assess. 39, 39–46.

Bunce, R.G.H., Barr, C.J., Clarke, R.T., Howard, D.C., Lane, A.M.J., 1996b. ITE Merlewood land classification of Great Britain. J. Biogeogr. 23, 625–634.

Cherrill, A., 1994. A comparison of three landscape classifications and investigation of the potential for using remotely sensed land cover data for landscape classification. J. Rural Stud. 10, 275–289.

Chytrý, M., Tichý, L., Jason, H., Botta-Dukát, Z., 2002. Determination of diagnostic species with statistical fidelity measures. J. Veg. Sci. 13, 79–90.

Council of Europe, 2000. European Landscape Convention. Council of Europe Publishing Division, Strasbourg.

Haines-Young, R.H., 1992. The use of remotely-sensed satellite imagery for landscape classification in Wales (U.K.). Landsc. Ecol. 4, 253–274.

Hill, M.O., 1979. TWINSPAN. A Fortran Program for Arranging Multivariate Data in an Ordered Two-way Table by Classification of the Individuals and Attributes. Cornell University, Ithaca, NY, US.

Hill, M.O., Šmilauer, P., 2005. TWINSPAN for Windows Version 2.3. Centre for Ecology and Hydrology/University of South Bohemia, Huntingdon/České Budějovice.

Hrnčiarová, T., Mackovčin, P., Zvara, I., et al., 2009. Atlas krajiny České republiky (Landscape Atlas of the Czech Republic). Ministry of Environment of the Czech Republic, The Silva Tarouca Research Institute for Landscape and Ornamental Gardening, Prague – Průhonice.

Jones, H.E., Bunce, R.G.H., 1985. A preliminary classification of the climate of Europe from temperature and precipitation records. J. Environ. Manage. 20, 17–29.

Jongman, R.H.G., Bunce, R.G.H., Metzger, M.J., Mücher, C.A., Howard, D.C., Mateus, V.L., 2006. Objectives and applications of a statistical environmental stratification of Europe. Landsc. Ecol. 21, 409–419.

Klijn, F., de Haes, H.A.U., 1994. A hierarchical approach to ecosystems and its implications for ecological land classification. Landsc. Ecol. 9, 89–104.

Kolejka, J., Lipský, Z., 1999. Mapy současné krajiny (Maps of current landscape). Geografie 104, 161–175.

Lepš, J., Šmilauer, P., 1999. Multivariate Analysis of Ecological Data. Faculty of Biological Sciences, University of South Bohemia, České Budějovice.

Lioubimtseva, E., Defourny, P., 1999. GIS-based landscape classification and mapping of European Russia. Landsc. Urban Plan 44, 63–75.

Löw, J., et al., 2005. Typologie České Krajiny (Typology of Czech Landscape). Final Report of the Project VaV 640/01/03, Programme Biosphere, Dep. Ministry of Environmnet of the Czech Republic.

Manzanares, J.A., et al., 2007. Classification of the Landscape of Huelva (Andalusia, Spain) using multivariate methods. In: Bunce, R.G.H., Jongman, R.H.G., Hojas, L., Weel, S. (Eds.), 25 Years of Landscape Ecology: Scientific Principles in Practice. Proceedings of the 7th IALE World Congress 8–12 July. Wageningen, The Netherlands. IALE Publication Series 4, Wageningen, pp. 175–177.

McNab, W.H., Browning, S.A., Simon, S.A., Foutsa, P.E., 1999. An unconventional approach to ecosystem unit classification in western North Carolina, USA. For. Ecol. Manage. 114, 405–420.

Meeus, J.H.A., 1995. Pan-European landscapes. Landsc. Urban Plan 31, 57–79.

Mikyška, R. et al., 1968–1972. Geobotanická Mapa ČSSR (Geobotanical Map of the CSSR) 1. České země. Vegetace ČSSR. Soubor map 1:200,000. Academia, Prague.

Mücher, C.A., Bunce, R.G.H., Jongman, R.H.G., Klijn, J.A., Koomen, A., Metzger, M.J., et al., 2003. Identification and Characterisation of Environments and Landscapes in Europe. Alterra Rapport 832. Alterra, Wageningen.

Owen, S.M., MacKenzie, A.R., Bunce, R.G.H., Stewart, H.E., Donovan, R.G., Stark, G., et al., 2006. Urban land classification and its uncertainties using principal component and cluster analysis: a case study for the UK West Midlands. Landsc. Urban Plan 78, 311–321.

Roleček, J., Tichý, L., Zelený, D., Chytrý, M., 2009. Modified TWINSPAN classification in which the hierarchy respects cluster heterogeneity. J. Veg. Sci. 20, 596–602.

Romportl, D., Chuman, T., 2007. Proposal method of landscape typology in the Czech Republic. J. Landsc. Ecol. 0, 119–124.

ter Braak, C.J.F., Šmilauer, P., 2002. CANOCO Reference Manual and CanoDraw for Windows User's Guide: Software for Canonical Community Ordination (version 4.5). Microcomputer Power, Ithaca, NY, US.

Tichý, L., 2002. JUICE, software for vegetation classification. J. Veg. Sci. 13, 451–453.

Tichý, L., Chytrý, M., 2006. Statistical determination of diagnostic species for site groups of unequal size. J. Veg. Sci. 17, 809–818.

Tolasz, R., Míková, T., Valeriánová, A., Voženílek, V. (Eds.), 2007. Climate Atlas of Czechia. Czech Hydrometeorological Institute, Prague.

Tropek, R., Konvička, M., 2008. Can quarries supplement rare xeric habitats in a piedmont region? Spiders of the Blansky Les MTS. Czech Republic. Land Degrad. Dev. 17, 101–114.

Van Eetvelde, V., Antrop, M., 2009. A stepwise multi-scaled landscape typology and characterisation for trans-regional integration, applied on the federal state of Belgium. Landsc. Urban Plan 91, 160–170.

Vogiatzakis, I.N., Griffiths, G.H., Melis, M.T., Marini, A., Careddu, M.B., 2006. Landscape typology in the Mediterranean context: a tool for habitat restoration. J. Mediterr. Ecol. 7, 23–30.

Wascher, D., 2004. Landscape-indicator development: steps towards a European approach. In: Jongman, R.H. (Ed.), The New Dimensions of the European Landscape. Springer, Wageningen, pp. 237–252.

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