Theoretical background

Ecological resilience, a term introduced by Holling in 1973, is measured by the magnitude of disturbance that can be absorbed before the system changes its structure by changing the variables and processes that control behaviour.

Unlike engineering resilience (Holling, 1996), which is a measure of resistance to disturbance and the time required to return to the initial equilibrium steady-state, resilience implies that a system can move to another stability domain and that this transition can be caused by either internal or external factors. The more diverse factors and induced of them processes, the higher the resilience of a system is, and the higher of ecosystem diversity (Peterson *et al*., 1998; Brand, 2005; Folk, 2006; Virah-Sawmy *et al*., 2009; Tompson *et al*., 2009; Sendzimir, undated). This is because the non-linear system is in the phase of its dynamic far from equilibrium steady-state when system changes one near equilibrium steady-state in to another one. For example, forest-steppe, forest-tundra, semi-desert and other ecotone ecosystems exist in space and/or time in various structural states, but with the potential for moving from one state to another that is caused by internal or external factors. Such areas are characterized by having a relatively high ecosystem diversity and fragmentation. To recognize such areas, one needs to identify as detailed a set as possible of ecosystems for the research area and to assess their neighbourhood with fragmentation and diversity indices or space (landscape) metrics (Puzachenko *et al*., 2005).

In addition to living matter, ecosystems comprise elements of other systems, such as climate, relief, subsoil, bedrock and others and as ecosystems evolve they create new systems, eg. soils. Therefore, the complete identification of ecosystems has to take into account all the key features of ecosystem components.

Ecosystem parameters and organization are largely determined by the redistribution of moisture, matter and energy by relief landforms. This redistribution takes place at different scales from large to small and is determined by the landforms via elevation, slopes, different convexities, curvatures and shaded relief regards the sun angel and position. All these variables can be computed only for a selected area, so the size of this area (sliding square) must be determined. By studying relief using digital elevation models, it was observed that the greater the area is being studied, the larger is the amplitude of elevations within the area. This is typical for self-similar systems where an element of the system repeats the host system and, in turn, the element is made up of similar systems. The degree of this similarity is determined by the value of fractal dimension and is slope ratio for a graph of function relief spectral density against measurement time interval (period). When one describes relief entirely as a fractal set, identification of its hierarchical organization can be arbitrary, ie. landforms can be of any size with the same probability. However, in most cases, landforms of different size have differing frequencies of occurrence. This allows one to define the linear sizes of such landforms and to analyse DEM-derived variables of respective size.

Along with relief properties, information on ecosystem parameters can also be obtained from multi-spectral remotely sensed data (RSD).

Solar radiation reflected by the Earth surface and measured in various spectral bands (from the visible to the far-infrared) gives information on the energy state within ecosystems which is determined by the type and state of the vegetation, soil and subsoil and how they develop. Changes in energy state over time that are not attributable to seasonal cycles can relate to either self-development or external factors, including the influence of neighbouring ecosystems. Hence,

RSD, which is primarily an indicator of the energy state within an ecosystem, may also provide the basis for determining the diversity and fragmentation of an ecosystem.
Climate, in addition to being the most important environmental factor for ecosystems at global and regional levels, is also an important component of local ecosystems, where micro-climates are governed primarily by the relief and vegetation. Thus, regional climate largely determines an ecosystem's capacity to vary in space and time by restricting the magnitude of many of the ecosystem's factors and processes. Consequently, climate determines of the considerable part of potential of ecosystems space/time diversity.

Using the entire set of data available on ecosystems and their environment enables one to determine, down to the limit, typological diversity of ecosystems necessary for heterogeneity analysis. On the other hand, it enables one to also identify the factors of ecosystem variability in space and to predict their changes in the future. Such a complex approach, however, still leaves open the possibility of analyzing ecosystem diversity using available data on only their most important subsystems, such as relief and vegetation. Being one of the most important factors for many ecosystem processes and drivers, relief landforms determines the diversity of potential habitats for different hierarchical levels. Some of this potential can be expressed in the presence of plants and animals, while some can remain unrealised due to some or other reason. The energy state of ecosystems as determined through remote sensing methods, however, provides information about actual state of the ecosystems. This state may not reflect either the current climate or relief because human impact or some changes in climate may not as yet have caused the vegetation to react. Another possible reason is the self-development of ecosystems at different hierarchal levels, ie. panarchy (Gunderson & Holling, 2002).

Method

Identifying areas with high resilience requires a set of spatial analysis methods that would enable one to assess ecosystem diversity.

Identification of the hierarchical organization of the territory studied is necessary for computing relief derivatives. The linear size of structures of different hierarchical levels determines the size of moving window that is used for the analysis.

Methods of studying hierarchy based on analyzing the spectral density of images were suggested by Turcotte (1997) and described in detail by Puzachenko *et al*. (2002). Spectral density (*Sp*) is a function of frequency ($w = 1/P$ is frequency; P is period):

$$\mathrm{Log}Sp=a+b*\log(w) \text{ or } \log Sp=a+b*\log(1/P)$$

If a decline from a regression curve does not contain regular components, a set is purely fractal and hierarchical levels are absent. If there is a non-random component in the declines, periods of the highest variation of values in the image investigated may be identified. These periods reveal levels of hierarchical organization of the territory studied.

To identify ecosystems, preliminary generalization of the original data is needed to eliminate correlation between initial variables. Such generalization is conducted by the PCA method. This is based on linear algebra and is therefore the most rigorous. In applying this method, the initial variables (eg. relief variables or spectral bands) are being transformed into new variables (factors) that are independent from one another. The extent to which each new variable describes the initial variables is then computed. Due to the computing algorithm, the first of the output variables contributes the most while the last contributes the least. The number of factors cannot exceed the number of initial variables and, depending on the correlations of initial variables, can be much fewer in number.

Based on the PCA, a cluster analysis of ecosystem/habitats is then conducted. To come up with as many clusters as possible, the weighting of components compared to the initial variables is not taken into account. The clustering was calculated by Euclidean distances using the K-means method. A hierarchical procedure with a binary base was applied. This procedure divides a sample into two clusters at the first level and then each of the resulting clusters is also divided into two, and so on. If a cluster is homogeneous and not divided into two other clusters or contains only one object (e.g. pixel), it is transferred to the next hierarchical level without change. The maximum number of clusters depends on the level of clustering. There are 256 clusters for the eighth level, this being the limit for 8-bit data representation. In the majority of cases, this number is sufficient for describing all types of ecosystems at the scale required.

Heterogeneity analysis is performed on the basis of the types of ecosystems/habitats that are identified and using the spatial or landscape metrics, that reflect the diversity and complexity of the spatial organization of ecosystems within a selected area.

Landscape metrics are widely used in landscape ecology (Definition and Description of Landscape Metrics, 2002; Puzachenko *et al*., 2005). Each of the metrics reflects specific aspects of the complex spatial organization of a landscape, while some of them may be highly correlated with each other (Puzachenko *et al*., 2005). Five independent indices are considered necessary for the qualification of a territory: 1) relative richness (*R*, %), which is highly correlated with patch density (*P*), entropy (*E*) and dominance (*D*); 2) fragmentation (*Fr*); 3) fractal dimension (*FD*); 4) uniqueness (J_{av}); and 5) diversity of relations (*H*) (**Table 1**).

Table 1: Spatial metrics and their explanations (bold marked metrics were calculated)

Spatial (landscape) metrics	Formula
Diversity of relations by initial data (H)	H=Hmax-I; - Hmax=0,5Klog(2πe) – maximal diversity at Δ=1, I=-logΔ, Δ -correlation matrix determinant between RSD bands in sliding square, K - bits per pixel
Entropy (E)	E=-Σpilogpi, pi=ni/N, - ni – number of pixels i-class`s in sliding square, N -number of pixels in square.
Dominance (D)	D= Hmax- H; - Hmax=logK, - K - number of classes in sliding square
Relative richness (R%)	R%=100(n/nmax); - n - number of classes in sliding square, nmax- number of all classes for territory
Patch density (P)	P=n/N; - n - number of areas consist of only one class in sliding square, N -number of pixels in sliding square
Fragmentation (Fr)	Fr=(n-1)/(N-1); - n - number of classes differ this square from neighbors squares, N - number of pixels in sliding square
Uniqueness (Jav)	Jav=-1/N(Σlogpi); - pi=ni/K, ni – number of pixels of i-class for all territory consist of K - pixels, N - number of pixels in sliding square
Fractal dimension (FD)	FD=(7-b)/2; - logSpi=a+blog(1/P), где P-period, Spi - spectral density in sliding square, a - constant

Depending on the size of moving window, the values of indices may vary. To take this effect into account, an estimation of indices for different-sized moving windows (depending on relief hierarchy) could be used.

To identify areas with highest (lowest) heterogeneity, every index is normalised and then summed up. The next step is to allocate the percentiles and ranking. Areas with both maximum and minimum values of all indices can be identified, ie. areas of high resilience (heterogeneous) and high stability (homogeneous).

Technical procedure

Original data and their preparation for the analysis

To identify areas with high heterogeneity, two sets of data were used: 1) relief (DEM) and its variables for hierarchical levels; and 2) relief (DEM) and its variables for hierarchical levels plus multispectral remotely-sensed data and climate data. The first set of data was used to assess the habitat resilience determined by relief characteristics at different scales, while the second was used to assess the ecosystem resilience determined jointly by topography, vegetation and other ecosystem properties as well as by climate. Only data within the boundaries of the RACER terrestrial study units were used and then converted to the Longitude-Latitude projection WGS84.

Relief hierarchical organization was analysed using the GTOPO30 DEM, with an original spatial resolution of 1 km pixels (**Figure 1**).

Figure 1: Digital elevation model (lower areas are shaded dark, higher areas are shaded light)

Nine periods of high spectral density can be identified (**Figure 2**). Considering the scale of the RACER project and some technical limitations, only four levels of average linear size of 7, 11, 18 and 30 km pixels were taken to compute the relief variables. The 18 and 48 km levels were taken to compute the diversity indices.

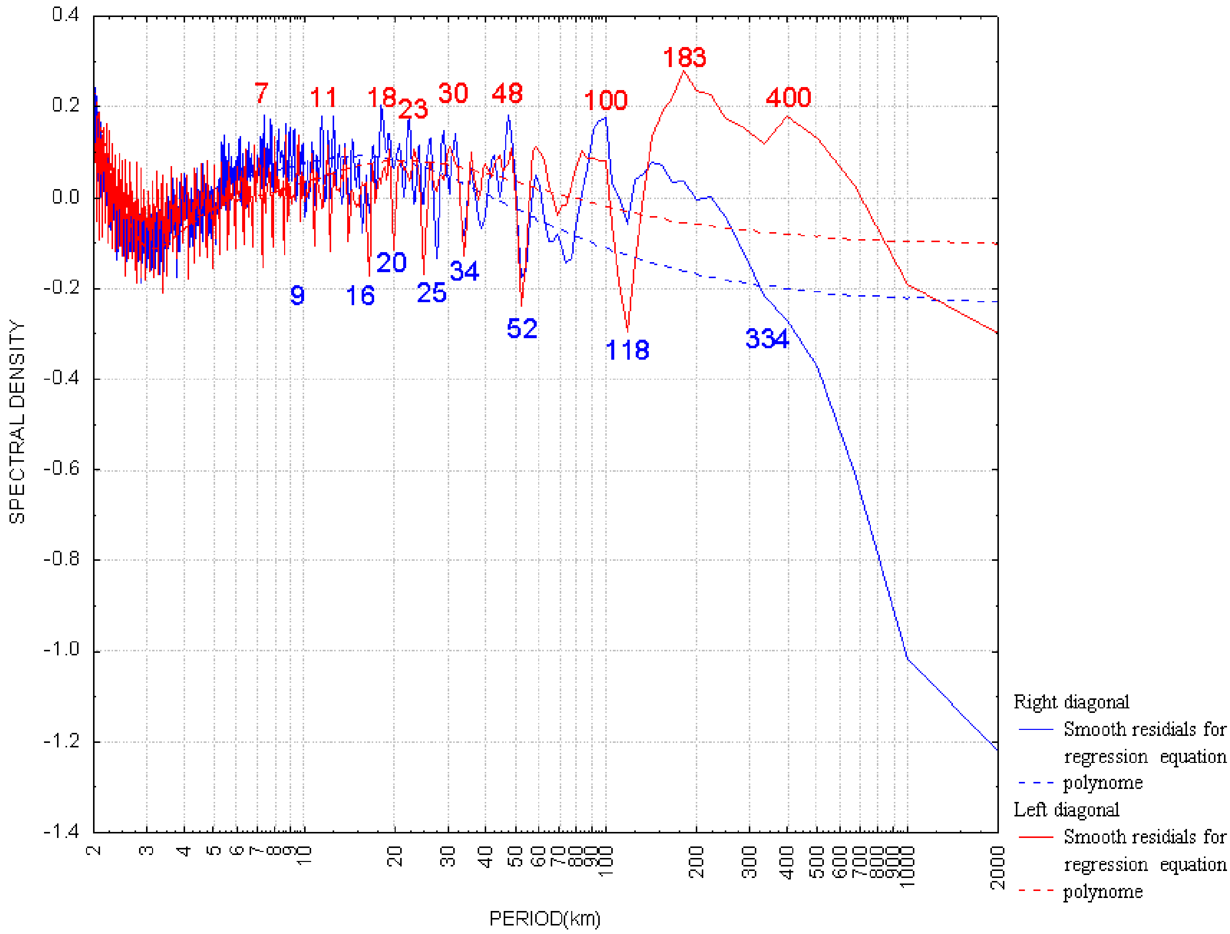

Figure 2: Smoothed residuals of relief spectral density from regression equation

DEM-based variables were computed using the ENVI program which allows one to use any size of moving window. The set of variables includes the following: slope; shaded relief at 45^0 sun elevation in a 90^0 and 180^0 direction; profile convexity; plan convexity; longitudinal convexity; cross-sectional convexity; minimum curvature; and maximum curvature. This allows the entire diversity of the relief forms to be described. Thus, elevations together with other relief variables calculated for four different hierarchical levels serve as input data for habitat diversity analysis.

To analyse landscape heterogeneity, multispectral remotely-sensed data and climatic variables were used in addition to the topographic variables.

A composite product MCD43B4 at 1 km pixel resolution, comprising minimal cloud MODIS Terra and Aqua images taken within the 16 days covering the period before and after the 225^{th} day of 2007, was obtained. This data contains corrected information for seven spectral bands of visible and near- and medium-infrared light. The time that the images were taken (13 August) corresponds to the period of least snow cover in the Northern hemisphere. The least cloud cover for this time between 2004 and 2009 (when the mosaic product is available) was observed in 2007. Based on the data for all the spectral bands, 19 different indices (similar to NDVI) were calculated in order to use as much of the available information as possible (**Table 2**).

Table 2: Indexes calculated by spectral bands of RSD (B1-blue, B2-green, B3-red, B4-near infrared, B5-near middle infrared, B7- far middle infrared).

Name of indexes	**Формула**	**Интерпретация**
Red-green ratio	B3/B2	разделяет различные типы

		растительности, водные объекты, заболоченные земли
First middle infrared-green ratio	B5/B2	разделяет различные типы растительности, водные объекты, заболоченные земли
Vegetation Index (VI)	(B7-B5)/(B7+B5)	выделяет различия биомассы и разделяет типы растительности
Normalized difference Vegetation Index (NDVI)	(B4-B3)/(B4+B3)	выделяет различия чистой продукции и транспирации
Relative Vegetation Index (RVI)	(B4/B3)	разделяет типы растительности с различной биомассой
Transformed Relative Vegetation Index	(B4/B3)**0.5	разделяет типы растительности с различной биомассой
Difference Vegetation Index (DVI)	B4-B3	разделяет типы растительности с различной биомассой
Transformed Normalized difference Vegetation Index (TNDVI)	(((B4-B3)/(B4+B3))+0.5)**0.5	выделяет различия в интенсивности фотосинтеза, чистой продукции, транспирации, типов растительности
Green Normalized Difference Vegetation Index (GNDVI)	(B4-B2)/(B4+B2)	разделяет растительность по активности хлорофилла
Normalized Difference near infrared, green and red bands	(B4-B2)/(B4+B3)	выделяет различия в интенсивности фотосинтеза, чистой продукции, транспирации, типов растительности, разделяет растительность по активности хлорофилла
Soil adjusted Normalized difference Vegetation Index (SAVI)	((B4-B3)/(B4+B3)+0.5)*1.5	выделяет различия чистой продукции и транспирации
Blue-green ratio	B1/B2	выделяет почвы и горные породы с высоким содержанием железа
Ferrum Oxide Index	B3/B1	выделяет почвы и горные породы с высоким содержанием оксида железа
Red-second middle infrared ratio	B3/B7	выделяет дороги, селитебные земли, поля и другие антропогенные объекты
Clay Mineral Index	B5/B7	выделяет глинистые отложения и горные породы, богатые глиной
Ferrum Mineral Index	B5/B4	выделяет почвы и горные породы с высоким содержанием железистых минералов и высокое содержание влаги в зеленой биомассе
Normalized Difference Snow Index (NDSI)	(B1-B4)/(B1+B4)	выделяет снег, лед, воду, различия во влажности почв
Normalized Difference Wetness Index (NDWI)	(B5-B4)/(B5+B4)	различает содержание воды в зеленой биомассе и влажности почвы
Normalized Difference green and red bans	(B2-B3)/(B2+B3)	разделяет различные типы растительности, водные объекты, заболоченные земли

Climate data were taken from the www.worldclim.org spatial database. Variables included were total monthly precipitation and monthly mean, minimum and maximum temperatures, as well as 19 derived bioclimatic variables. The 1 km pixel resolution grids were generated by interpolation with DEM usage of average monthly climate data obtained from weather stations.

Data analysis

To carry out the analysis, the initial 1 km pixel resolution had to be aggregated to 3 km. This was due to limitations in computing capacity.

Generalization of DEM and DEM-based variables by PCA showed that, according to the Scree criteria (**Figure 3**), the four first factors (**Table 3**) are adequate in describing the whole range of DEM-based variables (ie. they describe 80% of the initial variability).

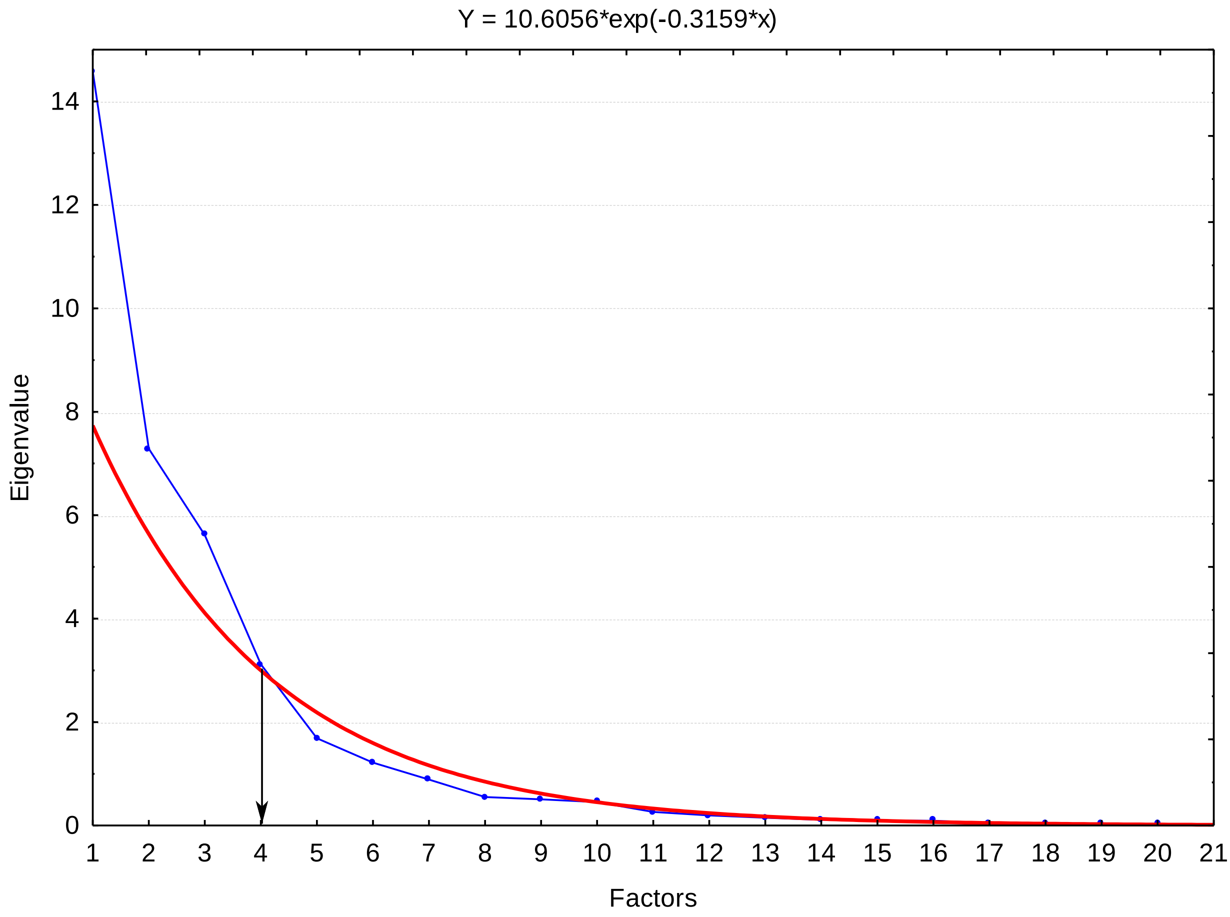

Figure 3: Scree plot of factors and their approximation by exponential function

Table 3: Factor Eigenvalues

Factor	Eigenvalue	% Total variance	Cumulative Eigenvalue	Cumulative %
1	**14.578**	**39.401**	**14.578**	**39.401**
2	**7.284**	**19.687**	**21.863**	**59.088**
3	**5.617**	**15.181**	**27.479**	**74.269**
4	**3.118**	**8.427**	**30.597**	**82.695**
5	*1.688*	*4.561*	*32.285*	*87.256*

6	*1.216*	*3.287*	*33.501*	*90.544*
7	*0.889*	*2.403*	*34.390*	*92.947*
8	*0.551*	*1.488*	*34.941*	*94.435*
9	*0.507*	*1.371*	*35.448*	*95.806*
10	*0.451*	*1.220*	*35.900*	*97.026*
11	*0.262*	*0.708*	*36.162*	*97.734*
12	*0.193*	*0.523*	*36.355*	*98.257*
13	*0.150*	*0.406*	*36.505*	*98.662*
14	*0.110*	*0.298*	*36.615*	*98.960*
15	*0.095*	*0.257*	*36.710*	*99.217*
16	*0.091*	*0.247*	*36.802*	*99.464*
17	*0.048*	*0.130*	*36.850*	*99.594*
18	*0.038*	*0.102*	*36.888*	*99.697*
19	*0.032*	*0.087*	*36.920*	*99.783*
20	*0.028*	*0.075*	*36.947*	*99.858*

The first factor (**Figure 4a**) was shown to be negatively correlated (**Table 4**) with elevation, plan convexity and maximum curvature and to be positively correlated with cross-sectional convexity and minimum curvature. The second factor (**Figure 4b**) is positively correlated with profile convexity and longitudinal convexity. The third factor (**Figure 4c**) is positively correlated with slopes and negatively correlated with shaded relief from the east. The fourth (**Figure 4d**) factor is determined by shaded relief from the south.

Figure 4a

Figure 4b

Figure 4c

Figure 4d

Figure 4: First four common factors for DEM and DEM-based variables (dark tone – low values, light tone – high values)

Table 4: Factor loading

Variable	Factor 1	Factor 2	Factor 3	Factor 4
REL	**-0.93**	-0.26	0.12	-0.02
SL7	0.07	0.30	**0.79**	-0.16
SH7	-0.02	-0.25	**-0.79**	0.16
PRC7	-0.30	**0.86**	-0.25	0.01
PLC7	**-0.80**	-0.09	-0.15	0.07
LC7	-0.30	**0.87**	-0.23	0.00
CSC7	**0.93**	-0.09	-0.06	0.02
MINC7	**0.93**	0.26	-0.12	0.02
MAXC7	**-0.93**	-0.26	0.12	-0.02
SH_1_7	-0.01	-0.12	-0.37	**-0.79**
SL11	0.04	0.33	**0.83**	-0.17
SH11	-0.00	-0.27	**-0.81**	0.16
PRC11	-0.32	**0.88**	-0.24	0.00
PLC11	**-0.80**	-0.09	-0.15	0.07
LC11	-0.32	**0.88**	-0.22	0.00
CSC11	**0.94**	-0.10	-0.05	0.02
MINC11	**0.93**	0.26	-0.11	0.02
MAXC11	**-0.93**	-0.26	0.12	-0.02
SH_1_11	-0.01	-0.12	-0.36	**-0.88**
SL_18	0.02	0.33	**0.81**	-0.17
SH_18	0.01	-0.24	**-0.75**	0.16
PRC_18	-0.31	**0.88**	-0.23	-0.00
PLC_18	**-0.79**	-0.08	-0.15	0.07
LC_18	-0.31	**0.88**	-0.22	-0.00
CSC_18	**0.94**	-0.10	-0.05	0.02
MINC_18	**0.93**	0.26	-0.11	0.02
MAXC_18	**-0.93**	-0.26	0.11	-0.02
SH_1_18	-0.01	-0.10	-0.30	**-0.90**
SL30	-0.02	0.30	**0.70**	-0.18
SH30	0.01	-0.16	**-0.54**	0.15
PRC30	-0.29	**0.83**	-0.23	-0.01
PLC30	**-0.79**	-0.08	-0.14	0.06
LC30	-0.29	**0.83**	-0.22	-0.01
CSC30	**0.93**	-0.10	-0.04	0.02
MINC30	**0.93**	0.26	-0.11	0.02
MAXC30	**-0.93**	-0.26	0.11	-0.02
SH_1_30	-0.01	-0.08	-0.19	**-0.81**
Expl.Var	14.58	7.28	5.62	3.12
Prp.Totl	0.39	0.20	0.15	0.08

Through clustering using four relief factors, 256 clusters were identified at the 8th classification level (**Figure 5**). This number of clusters is the maximum for the 8th level of dichotomised clustering, demonstrating the high diversity of relief for the whole RACER area, including Greenland

Figure 5: Clustering according to the most important relief variables (Idrisi colour chart, grey colors = flat plains)

Based on this classification, landscape metrics were computed for two sizes of moving window. Metric values are normalised to 8-bit format and summed up (**Figure 6**).

Figure 6: Sum of normalised values for all landscape metrics (NDVI color chart)

Maximum and minimum values (each of them represented by 10% of all the values) are separated and scores are allocated according to the proportion of their values in the whole set of data (**Figure 7**).

Figure 7: Scores allocated to the sums of normalised landscape metrics (**1** [white] - water bodies; **2** and **3** together [dark blue] - 2 % most homogenous and greatly homogenous; **4** [blue] – 3% homogenous; **5** [light blue] – 5% weakly homogenous; **6** [grey] – 80% average conditions; **7** [very dark red] – 5% weakly heterogeneous; **8** [dark red] – 3% heterogeneous; **9** [red] – 1.5% greatly heterogeneous; **10** [light red] – 0.5% most heterogeneous).

During the landscape (ecosystem) part of the analysis, individual factors for relief, remotely-sensed data and climate data are generalised within the PCA method, too. The most important common factors identified using this method would adequately describe most of the variability of the individual factors and, respectively, initial parameters for relief, vegetation and climate. Clustering of territory based on common ecosystem factors identify various categories that reflect different combinations of ecosystem characteristics.

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