DISSERTATIONES GEOGRAPHICAE UNIVERSITATIS TARTUENSIS

32

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INDICATORY VALUE OF LANDSCAPE METRICS FOR RIVER WATER QUALITY AND LANDSCAPE PATTERN

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ABSTRACT

In this thesis, the scale dependence of landscape metrics and the relationship between landscape metrics (Edge Density (ED), Patch Density (PD), Mean Shape Index (SHAPE_MN), Mean Euclidean Nearest Neighbor Distance (ENN_MN), Contagion (CONTAG), Patch Richness Density (PRD), and Shannon's Diversity Index (SHDI)) and river water quality indicators (BOD_7, COD_{KMnO4} values, total-N, total-P concentrations) were analyzed in 24 catchments in Estonia. We used the Estonian Basic Map (1:10,000), Estonian Base Map (1:50,000) and CORINE Land Cover Map (1:100,000). The spatial autocorrelation (Moran's I) of raster format soil maps (1:10,000; 10m pixel size) in 35 study areas representing all landscape regions in Estonia was also studied. The carbonate concentration of soils, volumetric soil moisture (%) and the depth of the groundwater table were taken into consideration in compiling the scale of contrast of 17 soil groups. A simple characteristic based on spatial correlograms: a half-value distance lag, $h_{I=0.5}$ – a distance where Moran's I drops below 0.5 was also introduced. In scale analysis, we calculated landscape metrics on artificial and real landscapes. Scale analysis showed that the responses of landscape metrics to changing grain size vary among landscapes and metrics. In finding relationships between landscape metrics and water quality indicators, multiple regression analysis showed that for BOD_7, total-N and total-P, the most important predictor was the proportion of urban areas. However, for total-N, Edge Density and for BOD_7, Patch Density were also important predictors. Catchments with complex landscape configurations have lower nitrogen and organic matter runoff. Mean Shape Index and Contagion were the most important predictors for COD_{KMnO4}, but as the Mean Shape Index is also positively correlated with the proportion of natural areas, and Contagion is positively correlated with the proportion of agricultural land use, then the relationship between COD_{KMnO4} and landscape metrics is most likely not causal. Knowledge about the land-water relationship can be used in watershed management planning. Spatial correlation analysis showed that the spatial autocorrelation decreased very rapidly in the case of heights with very heterogeneous landscape pattern, showing low values of $h_{I=0.5}$ (<100m). In uplands and depressions the spatial autocorrelation also decreased quite rapidly ($h_{I=0.5}$ <200m). In most of the plains, coastal lowlands, sea islands and inland paludified lowlands, the values of Moran's I did decrease slowly with increasing lag, being >200m. Thus spatial correlograms of soil cover can be used for the characterization of human-influenced landscape (land-use) pattern.

1. INTRODUCTION

Urbanization, industrialization and intensive agriculture result in rapid landscape change, in losses of ecological capacities, biodiversity, and in the loss of historically valuable cultural landscapes. Scientists and environmental managers alike are concerned about broad-scale changes in land use and landscape pattern and their cumulative impact on hydrological and ecological processes. Therefore there is an increasing need for sustainable landscape planning and management. Indicators are needed to evaluate how far planning objectives have come, and to improve decision making.

Hundreds of landscape metrics have been developed for the quantifying of landscape pattern. The term "landscape metrics" is generally used for all measures that quantify the spatial pattern of landscape, from topographic measures (Vivoni et al., 2005) to proportions of land use/cover, and shape and area metrics (Li et al., 200; Palmer, 2004). Spatial pattern is represented and quantified in a number of different ways (Table 1). Most of the landscape pattern analysis is performed on categorical maps which tend to ignore the spatial variation within spatial units and trends in system properties across landscapes (Gustafson, 1998). A large number of metrics have been developed to quantify spatial heterogeneity on categorical maps. These metrics fall into two general categories: those that evaluate the composition of the map without reference to spatial attributes, and those that evaluate the spatial configuration of system properties, requiring spatial information for their calculation (McGarigal and Marks, 1995; Gustafson, 1998). Most of these are covered by the computer program FRAGSTATS (McGarigal and Marks, 1995). Since the emergence of FRAGTATS in 1993, the measures and methods incorporated in this software have been very widely used in characterizing patterns (Li et al., 2001; Corry, 2004), detecting land use changes (Egbert et al., 2002; Li et al., 2004; Southworth, 2004) and predicting ecological processes (Bender et al., 2003; Coulson et al., 2005; Fearer et al., 2007).

Table 1. Methods for representing and quantifying spatial pattern (Gustafson, 1998).

Representation/data type	Description	Quantification
Categorical maps	Qualitative data	
Non spatial	*Composition*	Number of categories, proportions, diversity (richness, evenness)
Spatial	*Configuration*	Size, shape, patch density, connectivity, fractal dimension, contagion, etc.
Dot maps, isarithmic maps	Quantitative data	Trend surface, correlogram, semivariogram, fractal dimension, autocorrelation indices, interpolation (e.g., kriging)

Despite the many advantages of landscape metrics and their extensive use, there are also inherent limitations to landscape metrics (Li and Wu, 2004): many landscape metrics are correlated to each other (O'Neill et al., 1999; Hargis et al., 1998; Botequilha and Ahern, 2002); there are difficulties in interpreting landscape metrics (Gustafson, 1998; Hargis et al., 1998; Turner et al., 2001) and they are scale-dependent (Wickham and Riitters, 1995; Griffith et al., 2000; Wu et al., 2002). Two primary scaling factors affect measures of landscape pattern: grain is the resolution of the data (pixel size) and extent refers to the size of the area mapped or studied (Gustafson, 1998). As FRAGSTATS uses a raster model, some geometric generalization takes place, and the issue of optimal grain size becomes important. It is essential to find the optimal value for grain size for every study. The first part of the current thesis focuses mainly on how changing grain size influences the values of the landscape metrics calculated in FRAGSTATS.

Several studies have shown that landscape pattern is an important factor influencing nutrient and organic matter runoff from catchments (Stålnacke et al., 1999; Arheimer and Brandt, 2000; Steegen et al., 2001; Davenport et al., 2003; Buck et al., 2004). The composition of the landscape (land use/cover proportions) partly reflects human influence and, as many studies have shown, it can be used as a predictor for nutrient runoff from catchments (Steegen et al., 2001; Wickham et al., 2003; Davies and Neal, 2007; Poor and McDonnell, 2007). For example, if there is a high proportion of agricultural areas in the catchment, the nutrient runoff is higher due to more intensive fertilization. High levels of nutrient and organic matter loading can have adverse effects on both humans and aquatic ecosystems. In addition to land use proportions, however, the configuration of landscape pattern is also important, i.e. spatial arrangement of patches, especially riparian zones (Gergel, 2005). In the second part of the thesis I try to ascertain the relationships between landscape pattern and nutrient and organic matter runoff from catchments. I assume that nutrient and organic matter runoff from catchments is influenced by land use and landscape pattern.

Although FRAGSTATS enables one to calculate over a hundred landscape metrics, this popular software does not include indices on different spatial structure functions like correlograms and variograms, which are popular in geostatistics (Cressie, 1993). A classical estimator of spatial dependence is Moran's I, (1948) which has also been proposed as a spatial analogy of autocorrelation used in time series analysis (Taylor, 1977). Correlograms form when plotting autocorrelation values (in our case Moran's I) against distance classes (lag). Spatial correlograms have been used for the spatial analysis of several natural (Overmars et al., 2003; Camarero et al., 2006; Barbaro et al., 2007) and social phenomena (Zmyslony and Gagnon, 1998; Wheeler, 2001). In the third part of the current thesis I studied the spatial autocorrelation (Moran's I) of the Estonian soil map. Soil cover, as one of the most informative and integrative landscape factors, can be used for the analysis of landscape pattern. The relationship of soil properties to landscape character, as well as the relations of soil quality with characteristics of other landscape components, is one of the best studied issues in landscape research. Soils are organically related to topography, a fact that is well reflected in toposequent soil ordination in landscape transects and catenas (see Schimel et al., 1985, Imeson and Lavee, 1996; Sommer and Schlichting, 1997). A toposequent soil spectrum determines soil wetness and moisture conditions (Wang et al., 2002; Blyth et al., 2004), as well as the spatial distribution of plant communities (Phillips et al., 2003; Fu et al., 2004), and is closely related to landscape fragmentation (Shoshany, 2002).

If Moran's I is used on discrete soil data, there arises the problem of how to take into quantitative consideration the qualitative differences in neighbouring soil patches. Gradients of soil characteristics are needed to make soil maps that are usable in spatial autocorrelation analysis. The contrast of soil cover is one of the parameters which can be used for this purpose, although most soil contrast studies consider the vertical contrast of soil horizons in terms of texture differences (e.g., clay-sand contrast; see Phillips, 2004). In the current study carbonate content, soil water regime, and the depth of the groundwater table were taken into consideration in compiling the scale of contrast (see Lõhmus, 1984).

We also propose Moran's I correlograms and half-value distance lag as a new landscape metric that measures landscape pattern. Half-value distance lag also allows one to correlate Moran's I with FRAGSTATS metrics to detect whether some of the FRAGSTATS metrics indirectly measure spatial autocorrelation.

The main objectives of the current thesis are: 1) to determine the relationships between landscape metrics and nutrient and organic matter runoff in catchments, and how these relationships are affected by the scale dependence of landscape metrics; 2) to estimate spatial autocorrelation in Estonian landscapes by using correlograms calculated on the basis of the soil map of various landscape regions in Estonia.

2. DATA AND METHODS

2.1. Scale dependence of landscape metrics

In order to examine the influence of spatial resolution on landscape metrics, we tested different artificial and real landscapes. The grain size (pixel size) was systematically changed from 10 m to 1000 m. The landscape metrics were analyzed using the FRAGSTATS computer program (McGarigal and Marks, 1995). Many of the landscape metrics are correlated with each other (Griffith et al., 2000; Wu et al., 2002). Therefore we performed a correlation analysis and picked those landscape metrics that did not correlate significantly with the others (Uuemaa et al., 2005: Publication II). There was only one exception – Patch Density, which correlated with Edge Density, but is very often used. We used the following landscape metrics (Uuemaa et al., 2005: Publication II):

- Edge Density (ED);
- Patch Density (PD);
- Mean Shape Index (SHAPE_MN);
- Mean Euclidean Nearest Neighbour Index (ENN_MN);
- Contagion (CONTAG);
- Patch Richness Density (PRD); and
- Shannon's Diversity Index (SHDI).

For details and metrics formulae see McGarigal and Marks (1995).

We used eight artificial landscapes and three real landscapes (Uuemaa et al., 2005: Publication II). The land use data for the real landscapes was derived from the Estonian Basic Map (1:10 000), the Estonian Base Map (1:50 000) and the CORINE Land Cover Map (1:100 000) (Table 2). As at the time of the analysis the Basic Map was not available for all the catchments studied in the nutrient runoff analysis (only the Porijõgi River catchment was covered), we used two additional areas with considerably different landscape patterns – "South Estonia" and "Northeast Estonia" (Fig. 1) – for the landscape pattern analysis. The South Estonian landscape is fragmented and dominated by agricultural and urban areas, while the Northeast Estonian landscape is more homogenous and less influenced by human activities (Uuemaa et al., 2005: Publication II). The size of the study sites (Northeast Estonia and South Estonia; Fig. 1) was set at 15km×15km = 225 km^2. The Porijõgi catchment has natural boundaries and a size of 241km^2; a large part of it is located on the Otepää Heights, and the landscape is very fragmented and dominated by semi-natural grasslands and forests (Mander et al., 2000; Uuemaa et al., 2005: Publication II).

Table 2. Land use and land cover types in real landscapes and study catchments (Uuemaa et al., 2005: Publication II).

Basic Map 1:10,000	Base Map 1 :50,000	CORINE Land Cover Map 1:100,000	New classification of CORINE Land Cover Map
Lakes	Lakes	Lakes	Natural areas
Water courses	Water courses	Water courses	Natural areas
Forests	Agricultural land	Non-irrigated arable land	Agricultural land use
Small ponds	Urban	Urban	Urban land use
Young forests	Mine	Mine	Other
Cultivated grasslands	Dump site	Dump site	Other
Orchards	Fen	Inland marshes	Fens, bogs and mires
Fallow lands	Peat field	Bogs	Fens, bogs and mires
Buildings	Wetland	Deciduous forests	Natural areas
Graveyards	Airport	Green urban areas	Urban land use
Sparsely vegetated areas		Sport and Leisure facilities	Urban land use
Fens		Fruit trees and berry plantations	Agricultural land use
Arable lands		Pastures	Agricultural land use
Streets		Coniferous forest	Natural areas
Yards		Mixed forest	Natural areas
Natural grasslands		Natural grassland	Natural areas
Raised bogs		Moors and heath land	Natural areas
Recreational open space		Sparsely vegetated areas	Natural areas
Bushes		Bushes	Natural areas
Burnt woodland		Salt marshes	Fens, bogs and mires
Peat fields		Peat fields	Other

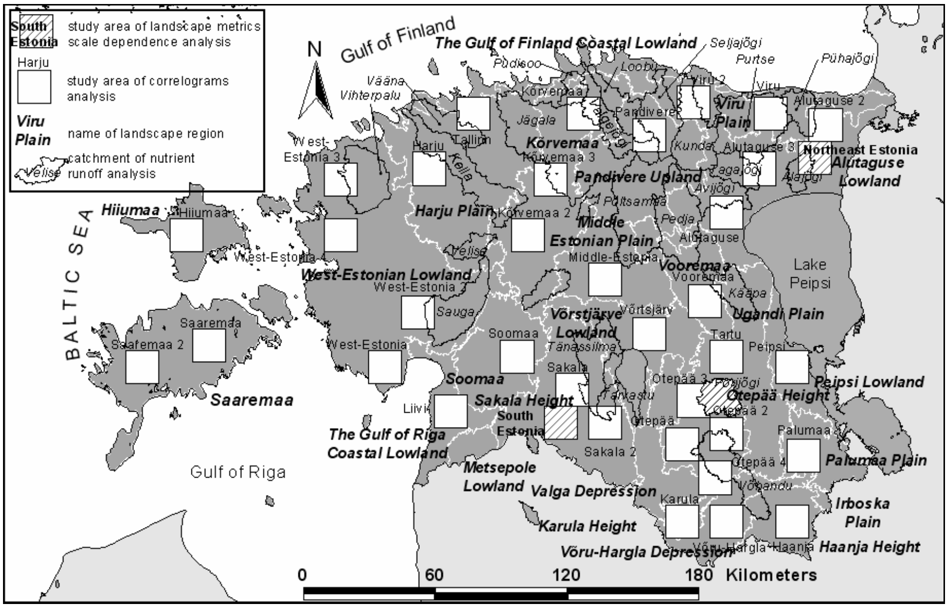

Figure 1. Study areas and landscape regions of Estonia. Landscape regions are colored grey with white borders.

2.2. Landscape metrics as indicators of river water quality

In order to determine the relationships between landscape metrics and nutrient and organic matter runoff in catchments, we used the water quality data (BOD7 and CODKMnO4 values, total-N and total-P concentrations in water samples from closing weirs of studied rivers, mg l^{-1}) from the Estonian Environmental Monitoring Programme database. Fifty-seven catchments are included in the Environmental Monitoring Programme, but we were only able to use 24 (Fig. 1), because many catchments extended almost all the way to Russia or Latvia. As in the interests of interpretability we decided to use correlation and multiple regression analysis to detect relationships between water quality data and landscape metrics, we were not able to use more than one subcatchment of the catchment, or the data points would not have been independent.

The disadvantage of this data was its dependence on point pollution sources (towns, factories). However, the relation between biological oxygen demand (BOD7) and chemical oxygen demand (determined on the basis of potassium permanganate; CODKMnO4) helps to distinguish between anthropogenic (mostly point pollution) sources and natural/semi-natural sources of pollution (Uuemaa et al., 2007b: Publication I).

For landscape metrics calculation, we derived the land use and land cover maps of 24 catchments (Fig. 1) from the Estonian Base Map (1:50 000) and the CORINE Land Cover Map (1:100 000) (Table 2; Uuemaa et al., 2005: Publication II). Due to the computational limitations of FRAGSTATS, the spatial resolution for both maps was 30 m. To determine the initial relationships between water quality and landscape metrics, we used correlation analysis for both maps. The Estonian Base Map has less land cover types than the CORINE Land Cover Map, although the cartographical scale is larger, which may be one reason why the Base Map did not yield very good results. Therefore, in multiple regression analysis we used only the CORINE Land Cover Map.

In order to ascertain the relationships between land use and water quality, we reclassified CORINE land cover types into four general groups: (1) the proportion of natural areas (NA) (forests, grasslands); (2) the proportion of agricultural land use (ALU); (3) the proportion of fens, bogs and mires (FBM); and (4) the proportion of urban land use (ULU) (Table 2; Uuemaa et al., 2007b: Publication I). These land use proportions were used in the regression analysis. Mining lands, dump sites and peat bogs were classified as Other and were not used in the analysis. The Estonian Base Map did not need reclassification because it had basically the same land use types as the new classification in table 2.

The same landscape metrics were analyzed as in the scale dependence analysis. According to the Kolmogorov–Smirnov test for normality, in the case of the Estonian Base Map, none of the landscape metrics under consideration were normally distributed; therefore, the Spearman Rank Order Correlation was performed first. This analysis showed that the Estonian Base Map was not the best data for this analysis, because of its large level of generalization. Therefore stepwise multiple regression analysis was only used on the CORINE Land Cover Map. In the case of the CORINE Land Cover Map, all of the variables under consideration were normally distributed, except for one variable – total-P. Regressions were tested using an ANOVA test and the normality of residuals. A casewise plot of residuals was used to calculate the number of possible outliers. The regression models were validated through an examination of their predictability using an independent data set. In order to achieve this, we randomly selected four catchments out of 24 and performed stepwise multiple regression analysis on 20 catchments. A statistically significant regression model was found for every water quality parameter, and these models were validated on the four catchments that were initially left out of the analysis. The procedure was performed six times, and in each analysis we randomly selected four new catchments for the validation of the models. Repetitions were avoided, and therefore six different combinations were possible. For all predicted values, we calculated 95% prediction intervals using STATISTICA 6.0. The probability of entering variables into the stepwise regression model was set at $p<0.01$ and the probability of removing was set at $p<0.05$. For the statistical analysis of data, the computer program STATISTICA 6.0 was used. The level of significance of $\alpha=0.05$ was accepted in all cases.

2.3. Spatial correlograms and half-value distance lag as the new landscape metrics

In order to determine how soil correlograms describe the Estonian landscape pattern, we needed study areas that represent most of the Estonian landscape types, and therefore thirty-five new study areas were selected on the basis of Estonian landscape regions (Fig. 1). Landscape regions are geosystems that are determined by relief forms. Thus a region differs significantly from neighbouring areas by its geological structure (Arold, 2005). Landscape regions can be grouped into six general groups: 1) accumulative heights (Otepää Height, Haanja Height, Karula Height and Vooremaa); 2) uplands with a bedrock core (Pandivere Upland and Sakala Upland); 3) inter-upland depressions (Valga Depression and Võru-Hargla Depression); 4) plains (Harju Plain, Viru Plain, Middle Estonian Plain, Ugandi Plain, Palumaa Plain and Irboska Plain); 5) coastal lowlands and sea islands (The Gulf of Finland Coastal Lowland, West-Estonian Lowland, The Gulf of Riga Coastal Lowland, Saaremaa and Hiiumaa); 6) inland paludified lowlands (Alutaguse Lowland, Peipsi Lowland, Võrtsjärve Lowland, Kõrvemaa, Soomaa and Metsepole Lowlands).

From some landscape regions, more than one study areas were chosen, and from four smaller landscape regions none of the study areas were chosen. Land use was also taken into consideration in choosing study areas. Of 35 study areas there were sites dominated by agricultural land use, forests, bogs or urban areas. Study areas were formed according to soil map sheets, i.e. each study area consists of a 3×3 soil map sheet. Each study area was 15×15km.

Soil data was derived from the Estonian Soil Map (1: 10,000) converted into raster format using 10 m pixel size. We had to use reclassified soil data in order to take into quantitative consideration the qualitative differences in neighbouring soil patches (elementary soil units, i.e. polypedons). Soil types were reclassified so that new type numbers could be used as contrast indexes (Table 3). For reclassification, a field survey manual for Estonian soil mapping was used (Kokk et al., 1973). Carbonate content, soil water regime and the depth of the groundwater table were taken into consideration in compiling the scale of contrast (see Lõhmus, 1984). In the case of soil types M_i and M_j, their difference ($|i-j|$) shows the contrast between these types. For example, the difference between Planosols and Endoeutric Albeluvisols is the same grade as that between Molli-Histic Gleysols and Histi-Hyperdystric Gleysol (Table 3).

Table 3. Scale of soil contrast (Uuemaa et al., 2007a: Publication III).

No	Soil types	Soil symbols of WRB (2001) classification	Symbols in Estonian classification
1	Anthropic-, Urbic-, Spolic-, Regosols	RG	T
2	Rendzi-Lithic Leptosols, Rendzic Leptosols, Skeletic Leptosols, Hyperskeletic Leptosols, Rendzic Leptosols+Calcaric Regosols	LP	Kh'; Kh"; Kr; Kk; K
3	Eutric Arenosols, Albic Arenosols, Dystric Arenosols, Entic Podzols, Haplic Podzols	AR; PZ	L(k)I; L(k)II; L(k)III; LI; LII; LIII
4	Hyperskeleti-Gleyic Leptosols, Skeleti-Gleyic Leptosols, Skeleti-Gleyic Cambisols, Rendzi- Gleyic Leptosols+ Calcari-Gleyic Regosols, Endocalcaric Cambisols, Endocalcari-Gleyic Luvisols	LP; CM; LV	Kkg; Krg; Korg; Kg; Kog; KIg
5	Skeletic Cambisol, Endocalcaric Cambisols, Endocalcaric Luvisols	CM; LV	Kor; Ko; KI
6	Lithic-Gleyic Leptosols, Rendzi-Gleyic Leptosols, Calcari-Lithic Gleysols, Calcari-Abruptic Gleysols, Calcari-Histic Gleysols	LP; GL	Kh'g; Kh"g; Gh'; Gh"; Gh1
7	Planosols + Stagnic Luvisols + Phaeozems	PL; LV; PH	LP
8	Stagni-Gleyic Luvisols + Gleyic Planosols	PL; LV	LPg
9	Umbric Gleysols, Stagnic Gleysols	GL	LkG; LPG
10	Endoeutric Albeluvisols, Umbric Albeluvisols	AB	LkI; LkII; LkIII; E
11	Eutri-Gleyic Arenosols, Albi-Gleyic Arenosols, Dystri-Gleyic Arenosols, Endogleyic Podzols, Gleyic Podzols, Cumulic Podzols	ARg; PZg	L(k)Ig; L(k)IIg; L(k)IIIg; LIg; LIIg; LIIIg; Lsg; Ls
12	Skeleti-Calcaric Gleysols, Calcaric Gleysols, Skeleti-Mollic Gleysols, Mollic Gleysols, Eutric Gleysols	GL	Gr; Gkr; Gk; Gor; Go; GI
13	Molli-Histic Gleysols, Eutri-Histic Gleysols, Calcari-Histic Gleysols	GLh	Go1, GI1, Gr1
14	Hyposalic Regosols, Hyposali-Gleyic Fluvisols, Hyposalic-Histic Fluvisols, Haplic Fluvisols, Gleyic Fluvisols, Histic Fluvisols, Pachic+Cumulic Gleysols	RG; FL; FLh; GL	Ar; ArG; ArG1; Ag; AG; AG1; D; Dg; DG
15	Eutri-Sapric Histosols, Eutri-Fluvic Histosols, Hyposali-Fluvic Histosol	HS	M; AM; Mr
16	Gleyic-Histic Podzols	PZh	LG1
17	Fibric Histosols, Dystri-Fibric Histosols	HS	S; R

An AUTOCORR module in Idrisi Kilimanjaro was used to calculate Moran's I (Uuemaa et al., 2007a: Publication III). King's case autocorrelation was calculated for study areas when lag h=10, 20, 30, …, 100, 120, …,200, 300, 400, 500 and 1000m. Waterbodies and urban areas were masked out. We used the results to construct the graphs of $I(h)$, which are called correlograms.

We investigated the soil correlograms of the test areas and found these to be quite regular. In order to compare Moran's I correlograms from different study areas, we introduced a simple characteristic of the half-value distance lag: $h_{I=0.5}$ – the distance lag where Moran's I drops below 0.5. The value of Moran's I may range from –1 to +1, but in our study areas the value only fell below 0 few times in cases of 1000m lag. Shortridge (2007) also found that "…While the theoretical range of I extends from roughly –1 to 1 for a raster map, in practice possible I values are much more restricted. The nature of the restriction is due to the rigid cell framework, which defines contiguity, as well as the relative proportions of ones to zeros in the binary raster. Unequal proportions of ones and zeros can result in minimal I values considerably larger than –1, and in many cases considerably larger than 0. Implications for the use of I on raster maps are considered, as is the potential relevance of negative spatial autocorrelation and its measurement." Therefore we chose the half-value within the positive scale. We also correlate FRAGSTATS metrics with $h_{I=0.5}$ in order to detect whether some of the FRAGSTATS metrics indirectly measure spatial autocorrelation.

In addition to those landscape metrics that we used in scale dependence and nutrient runoff analysis, we tried to select those FRAGSTATS metrics that would most likely reflect or explain the behaviour of Moran's I. The selection was based on the formulas and definitions of FRAGSTATS metrics. Metrics that were added to the analysis were: Mean Area Distribution (AREA_MN), Contrast-Weighted Edge Density (CWED) and Percentage of Like Adjacencies (PLADJ). For details and metrics formulae see McGarigal and Marks (1995). Only PRD that was used in scale dependence and nutrient runoff analysis was left out of the correlograms analysis, because SHDI very accurately reflects the number of land cover types.

According to the Kolmogorov-Smirnov test for normality, most of the variables under consideration were not normally distributed. Therefore we calculated Spearman ρ for relationships between $h_{I=0.5}$ and FRAGSTATS metrics, and the significance of differences was analysed using the non-parametric Kruskal-Wallis test. For the statistical analysis of data, the computer programs *STATISTICA 6.0* and *Microsoft Excel 2000* were used. The level of significance of α = 0.05 was accepted in all cases.

3. RESULTS AND DISCUSSION

3.1. Scale dependence of landscape metrics

3.1.1. Artificial landscapes

The behaviour of many metrics has not yet been evaluated (McGarigal et al., 2002), and the analysis of artificial landscapes is one way to achieve a better understand not only of the scale dependence of landscape metrics but also of their behaviour. Since Gardner et al. (1987) introduced the concept of neutral models into landscape ecology, many have used them to investigate the behaviour of landscape metrics (Hargis et al., 1998; Li et al., 2005). In the current study the analysis of artificial landscapes helped to clarify the behaviour of landscape metrics and explain their scale dependence.

The results showed that the value of PD does not change much before the grain size exceeds patch size. PD is very sensitive to the existence of small patches. However, the orientation of patches is also important in changing grain size. Orientation affects the connectedness of the patches, especially in the case of long and narrow patches. ED responses to changing grain size were similar to PD. This indicates that ED is mostly influenced by the same factors (size and number of patches) as PD. There are, however, some exceptions. When large and very complex patches dominate in the landscape structure, then PD is low but ED is high. In that case the PD does not decrease as much with increasing grain size as ED.

With increasing grain size, values of SHAPE_MN started to approach 1.0, because the more grain size increases, the more the patches begin to consist of only one pixel. The decrease in the value of SHAPE_MN is more rapid if the landscape consists of small patches.

The values of ENN_MN generally increase linearly with increasing grain size, because it measures distance (m) to the nearest neighbouring patch of the same type, based on shortest edge-to-edge distance, computed from cell center to cell center (McGarigal et al., 2002). However, if patches start to break apart into smaller patches with increasing grain size, then the value of ENN_MN may decrease.

As the calculation of CONTAG is based on pixel adjacency proportions, it is very dependent on grain size (Li and Reynolds, 1993; Riitters et al., 1996; Ricotta et al., 2003). Given a particular patch mosaic, a smaller grain size will result in a proportional increase in like adjacencies and in an increase in the values of CONTAG. An analysis of artificial landscapes showed that CONTAG mostly decreases with increasing grain size. If, however, there are many small patches in a landscape structure and they begin to disappear with increasing grain size, then the value of CONTAG may increase. The reason for this is that

CONTAG also depends on the composition of the landscape. Therefore CONTAG does not always reflect the clumpiness of spatial patterns (He et al., 2000).

The behaviour of PRD and SHDI was similar as the grain size increased. Both metrics began to fluctuate as the number of patch types changed. Values of diversity metrics, especially PRD, are mostly determined by the number of patch types present in the landscape (McGarigal et al., 2002; Wu et al., 2002). Therefore their response to changing grain size depends on how the number of patch types varies in the landscape.

3.1.2. Real landscapes

Values of ED and PD decreased logarithmically with increasing grain size, and they had predictable responses across the different landscapes (Fig. 2). According to Wu et al. (2002), this is characteristic to Type I. However, Wu et al. (2002) found that these two metrics decreased in their values with power-law relationship, but the response to the increase in grain size was generally the same. Furthermore, our results also showed that the decrease in ED and PD depended on the configuration of the landscape. If the landscape pattern was very complex, then the decrease in the ED and PD was very rapid, and vice versa. Therefore the difference between landscapes disappears at some resolution. In our study it was approximately 400m.

There was also the difference between values of ED and PD calculated on maps with different map scales (Fig. 2). At 400–500m the maps with different scale had almost the same values of PD and ED. Values of metrics calculated on large scale maps decrease more rapidly with changing grain size than values of metrics calculated on small scale maps. Topographic scale (generalization, classification) seems to have a significant effect on values of landscape metrics.

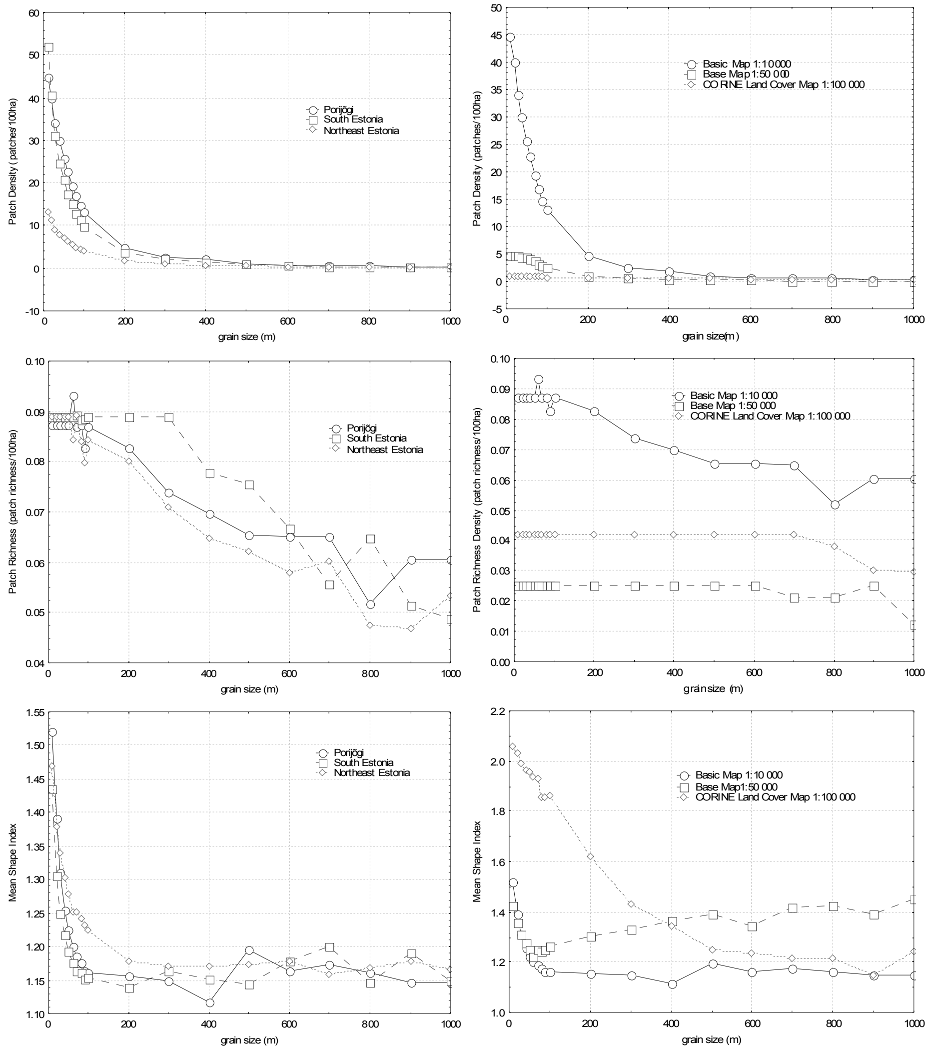

Figure 2. Effects of changing grain size on Type I (above), Type II (middle) and Type III (below) at different map scales in Porijõgi catchment (right) and landscape metrics in different study areas calculated on the Estonian Basic Map (left) (Uuemaa et al., 2005: Publication II)

Diversity metrics PRD and SHDI decreased in a staircase-like fashion with increasing pixel size and, according to Wu et al. (2002), they belonged to Type II (Fig. 2). As PRD directly measures the number of patch types present in the landscape (McGarigal et al., 2002), it fluctuated as patch types appeared or disappeared in the landscape structure. The decrease in SHDI was not as obvious, because SHDI also depends on evenness. PRD and SHDI also showed some increases in their values. This is explained by the influence of the aggregation method used. We used the central-point method. With the central-point method, patch types are not eliminated permanently, i.e. patch types can reappear after elimination. If the majority rule is used, then there should not be increases in values of diversity metrics with increasing grain size. PRD and SHDI decreased stepwise at all map scales, but the dissimilarity between maps remained. Therefore diversity metrics depend mostly on classification scheme and not so much on generalization.

SHAPE_MN, ENN_MN and CONTAG belonged to Type III, and they did not exhibit predictable responses to changing grain size (Fig. 2), although as said before, the two latter are directly dependent on grain size. SHAPE_MN and CONTAG decreased and ENN_MN increased quite monotonically until 200–300m, and then their values began to fluctuate. Behaviour at different map scales was similar, and as in the case of Type II metrics, the dissimilarity between maps did not disappear.

Wickham and Riitters (1995) found that landscape metrics should not be dramatically affected by the change in pixel size up to 80 m. We, on the contrary, found that metrics that belonged to Type I and III were most sensitive to the scale between 10–100m pixel size. Type II metrics (diversity metrics) are indeed relatively insensitive to pixel size until 200–300m resolution, because rare patch types then begin to disappear. However, the results may vary depending on actual landscape pattern and specific metrics.

Thus I can conclude that landscape metrics' dependence on grain size influences the relationships between the pattern and the process. In our study the 30m grain size is most likely optimal for the CORINE Land Cover Map and the Estonian Base Map for nutrient runoff analysis. For both maps there was no significant change in the values of landscape metrics from 10m to 30m grain size. Furthermore, the data for CORINE Land Cover Data is originally obtained at 30m resolution, and therefore there is no need for smaller grain size. However if we would have had the opportunity to use the Estonian Basic Map in nutrient runoff analysis, the 10m grain size would have been better than 30m, because the values of landscape metrics changed significantly from 10m to 30m. In addition, the difference between the different study areas decreased.

6

3.2. Landscape metrics as indicators of river water quality

3.2.1. BOD_7

Correlation analysis showed that high PD and ED values result in lower values of BOD_7 (Fig. 3; Uuemaa et al., 2005: Publication II), which indicated the ability of a heterogeneous landscape to retain more organic matter. However, these results should be considered with care, because three catchments (the Pühajõgi, Purtse and Vääna) have a very high proportion of urban areas, which is probably the main reason why the values of BOD_7 are very high (Fig. 3). If these three catchments are left out of the analysis, then the relationships are not statistically significant. Nevertheless, the trend that organic matter runoff is lower from landscapes with complex pattern can still be seen in Fig. 3. Regressions of FRAGSTATS landscape metrics and land use proportions explained up to 82% of the observed variation in BOD7, and the percentage of outliers was relatively low (Table 4). All of the regressions showed significant ANOVA tests. ULU and PD had the highest β values in most of the regression equations, which means that they contribute most to the prediction of BOD_7 values. ULU correlated positively and PD negatively with BOD_7 (Fig. 3). Therefore lower amounts of BOD_7 are washed out of the catchments with fragmented landscape pattern and low ULU. The importance of ULU in regression equations is easily explained by the fact that high values of BOD_7 are usually caused by point pollution sources (Qualls and Richardson, 2003; Shanmugam et al., 2007) and indicate insufficient wastewater treatment, which is still a problem in North Estonian rivers (Fig. 3; Keskkonnaülevaade, 2005).

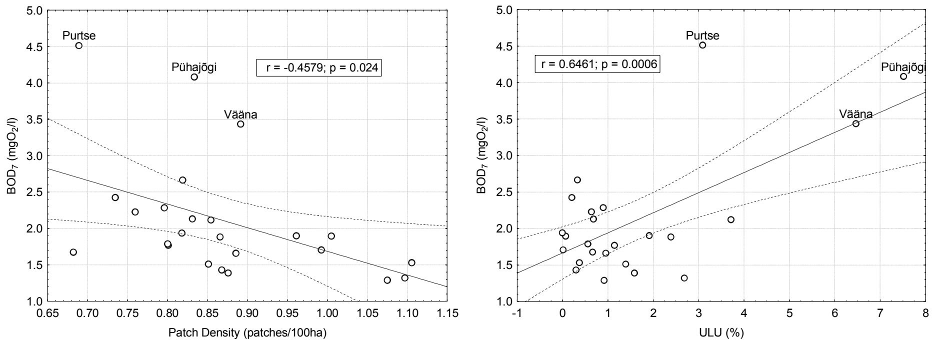

Figure 3. Relationships of Patch Density (PD) with BOD_7 in the left (all catchments) and the proportion of urban land use (ULU) in the right (all catchments). The solid line is the linear regression equation, and the dashed lines indicate the 95% confidence intervals.

Model validation showed that the difference between predicted and measured values of BOD_7 were small. Only in case of Purtse and Pudisoo catchments did the observed value not fall within the 95% prediction intervals (Table 5; Uuemaa et al., 2007: Publication I). The *V* model underestimates the value of BOD_7 for the Purtse catchment, because there are lots of factories. For Pudisoo, the *VI* model calculated a higher value than measured (Table 5), because there is high FBM, which has a relatively high β value (Table 4; Uuemaa et al., 2007b: Publication I).

3.2.2. COD_{KMnO4}

Different regression equations explained up to 94% of the variation in COD_{KMnO4} values, and all the regressions were statistically significant (Table 4). For COD_{KMnO4}, the most important predictors were SHAPE_MN and CONTAG, which had the highest β values (Table 4). SHAPE_MN correlated positively and CONTAG negatively with COD_{KMnO4} (Uuemaa et al., 2005: Publication II; Uuemaa et al., 2007b: Publication I), which refers to the fact that higher amounts of humic and fluvic acids are washed out from more fragmented landscapes (high values of SHAPE_MN and low values of CONTAG). It is, however, more likely that SHAPE_MN and CONTAG are correlated with COD_{KMnO4}, because SHAPE_MN is also positively correlated with NA and CONTAG is positively correlated with ALU (Figure 4; Uuemaa et al., 2005: Publication II), and it is well known that that organic matter losses are higher from natural areas, swamps, fens and bogs (Figure 4; Behrendt et al., 2002; Uuemaa et al., 2005: Publication II).

Table 4. Regression equations and main statistics for water quality characteristics (Uuemaa et al., 2007b: Publication I)

No. of random selection	Regression equation	R^2	p	Outliers %	β
I	BOD_7= –3.48PD + 0.25 ULU + 4.7	0.50	<0.01	10%	PD β = –0.52; ULU β =0.52
II	BOD_7= 0.21ED – 7.68PD + 1.3SHDI+0.35ULU –1.86	0.76	<0.01	5%	ED β = 0.78; PD β = –1.0; SHDI β =0.30; ULU β = 0.83
III	BOD_7= 0.18ED – 7.87PD + 1.65SHDI + 0.32 ULU – 1.15	0.82	<0.01	0%	ED β = 0.61; PD β = –1.0; SHDI β = 0.35; ULU β = 0.74
IV	BOD_7= 0.23ED – 8.28PD+ 1.46SHDI + 0.37ULU – 2.57	0.74	<0.01	0%	ED β = 0.94; PD β = –1.2; SHDI β = 0.34; ULU β = 0.77
V	BOD_7= 4.78SHAPE_MN + 0.35ULU – 7.98	0.74	<0.01	0%	SHAPE_MN β = 0.51; ULU β = 1.06
VI	BOD_7= 0.12CONTAG– 0.32NA – 0.37ALU – 0.36FBM + 27.55	0.77	<0.01	5%	CONTAG β = 0.34; NA β = –3.8; ALU β = –4.6; FBM β =–2.0
I	COD_{KMnO4} = 64.52SHAPE_MN – 0.87CONTAG – 58.93	0.86	<0.01	0%	SHAPE_MN β = 0.75; CONTAG β = –0.37
II	COD_{KMnO4} = – 0.80ED + 54.25SHAPE_MN – 1.83CONTAG – 9.74 SHDI + 66.35	0.87	<0.01	0%	ED β = –0.45; SHAPE_MN β = 0.64; CONTAG β = –0.79;SHDI β = –0.33
III	COD_{KMnO4} = 56.71SHAPE_MN+2.84NA + 2.7ALU + 3.1FBM +3.97ULU–377.7	0.86	<0.01	0%	SHAPE_MN β = 0.75; NA β = 6.81; ALU β = 7.20; FBM β = 2.60; ULU β = 1.40
IV	COD_{KMnO4} = –0.7ED + 63.93SHAPE_MN – 1.26CONTAG + PRD 87.55 – 12.49	0.89	<0.01	0%	ED β = –0.43; SHAPE_MN β = 0.72; CONTAG β = –0.61; PRD β = 0.32
V	COD_{KMnO4} = –0.64ED + 47.52SHAPE_MN – 1.75CONTAG –13.37SHDI + 0.146FBM + 0.9ULU +70.69	0.94	<0.01	5%	ED β = –0.32; SHAPE_MN β = 0.57; CONTAG β = –0.64; SHDI β = –0.35; FBM β = 0.36; ULU β = 0.30
VI	COD_{KMnO4} = 1.49ED –48.86PD –1.02CONTAG – 0.31NA – 0.41ALU +94.38	0.87	<0.01	0%	ED β = 0.89; PD β =–1.1; CONTAG β = –0.44; NA β = –0.59; ALU β = –0.81

Table 4. Continuation

No. of random selection	Regression equation	R^2	p	Outliers %	β
I	N-Total = 0.46ULU+1.83	0.49	<0.01	0%	ULU β = 0.7
II	N-Total = – 0.2ED +11.11SHAPE_MN – 0.34CONTAG+ 0.67NA + 0.74ALU + 0.63FBM +0.98ULU – 60.06	0.81	<0.01	0%	ED β = –0.59; SHAPE_MN β = 0.69; CONTAG β = –0.76; NA β = 7.74; ALU β = 9.97; FBM β = 2.77; ULU β = 1.79
III	N-Total = 0.37ULU + 1.92	0.46	<0.01	0%	ULU β = 0.68
IV	N-Total = –0.17ED + 0.02ALU + 8.0	0.48	<0.01	0%	ED β = – 0.58; ALU β = 0.41
V	N-Total = 0.4ULU + 1.97	0.50	<0.01	0%	ULU β =0.709
VI	N-Total = 0.34ULU + 1.89	0.49	<0.01	0%	ULU β = 0.7
I	P-Total = –0.05ED + 1.3PD + 1.71SHAPE_MN + 1.86PRD+0.006ALU – 2.62	0.80	<0.01	0%	ED β=-2.1; PD β=2.13; SHAPE_MN β=1.72; PRD β= 0.55; ALU β=1.29
II	P-Total = – 0.00035ENN_MN + 0.06ULU + 0.24	0.66	<0.01	5%	ENN_MN β= – 0.40; ULU β= 0.96
III	P-Total = –0.0003ENN_MN+0.058ULU+0.21	0.64	<0.01	5%	ENN_MN β= –0.35; ULU β= 0.91
IV	P-Total = 0.065ULU – 0.0068	0.74	<0.01	15%	ULU β= 0.86
V	P-Total = 0.051ULU + 0.01	0.63	<0.01	5%	ULU β = 0.79
VI	P-Total = 0.043ULU+ 0.0086	0.55	<0.01	10%	ULU β = 0.75

Table 5. Results of model estimation. Results where the predicted value did not fall within the 95% prediction intervals are in bold (Uuemaa et al., 2007b: Publication I)

		BOD_7			COD_{KMnO4}			Total-N			Total-P		
No of random selection	Catchment name	Predicted	Measured	Residual	Predicted	Measured	Residual	Predicted	Measured	Residual	Predicted	Measured	Residual
I	Kunda	1.97	2.13	0.16	14.45	11.66	–2.79	2.15	3.07	0.92	**0.14**	**0.035**	**–0.105**
I	Pühajõgi	3.67	4.08	0.41	11.86	14.06	2.2	5.29	4.04	–1.25	**0.099**	**0.57**	**0.471**
I	Tänassilma	0.93	1.53	0.6	**23**	**12.93**	**–10.07**	2	1.87	–0.13	0.14	0.085	–0.055
I	Võhandu	1.85	1.66	0.19	**15.13**	**8.09**	**–7.04**	2.27	0.86	–1.41	0.072	0.037	–0.035
II	Põltsamaa	2.09	1.51	–0.58	14.38	9.57	–4.81	3.09	3.1	0.01	0.085	0.035	–0.05
II	Avijõgi	2.1	2.23	0.13	21.37	16.16	–5.21	3.6	3.33	–0.27	–0.0036	0.026	0.0296
II	Saarjõgi	2.17	1.94	–0.23	26.34	23.25	–3.09	3.64	1.48	–2.16	0.037	0.03	–0.007
II	Loobu	1.09	1.29	0.2	11.49	11.28	–0.21	2.6	2.18	–0.42	**–0.055**	**0.053**	**0.108**
III	Jägala	2.57	1.77	–0.8	17.43	14.99	–2.44	2.34	2.4	0.06	0.01	0.051	0.041
III	Pedja	2.42	1.68	–0.74	11.54	13.29	1.75	2.16	2.83	0.67	–0.01	0.036	0.046
III	Sauga	2.66	2.29	–0.37	**6.05**	**26.77**	**20.72**	2.25	1.63	–0.62	0.056	0.076	0.02
III	Velise	1.1	1.71	0.61	15.42	15.05	–0.37	1.92	1.32	–0.6	0.05	0.021	–0.029
IV	Alajõgi	2.64	2.43	–0.21	23.98	24.42	0.44	1.72	2.39	0.67	0.067	0.037	–0.03
IV	Keila	1.89	1.9	0.01	7.74	12.65	4.91	2.57	3.38	0.81	0.12	0.09	–0.03
IV	Vääna	3.74	3.44	–0.3	11.47	14.83	3.36	**2.89**	**4.77**	**1.88**	**0.41**	**0.1**	**–0.31**
IV	Vihterpalu	2.47	1.79	–0.68	22.85	25.03	2.18	1.93	1.87	–0.06	0.03	0.036	0.006
V	Kääpa	1.78	1.9	0.12	**11.42**	**17.851**	**6.431**	2	1.82	–0.18	0.014	0.04	0.026
V	Porijõgi	1.64	1.43	–0.21	6.95	8.64	1.69	2.09	1.58	–0.51	0.025	0.056	0.031
V	Purtse	**2.73**	**4.51**	**1.78**	19.52	19	–0.52	3.19	2.52	–0.67	0.17	0.029	–0.141
V	Valgejõgi	2.02	1.32	–0.7	**16.59**	**11.1**	**–5.49**	3.03	1.65	–1.38	0.15	0.042	–0.108
VI	Pudisoo	**2.78**	**1.39**	**–1.39**	12.73	14.16	1.43	2.43	1.77	–0.66	0.077	0.08	0.003
VI	Seljajõgi	1.66	2.12	0.45	**1.07**	**8.63**	**7.56**	**3.14**	**5.01**	**1.87**	**0.17**	**0.35**	**0.18**
VI	Tagajõgi	2.3	2.66	0.36	22.49	26.3	3.81	2.0	2.5	0.5	0.023	0.047	0.024
VI	Tarvastu	1.35	1.88	0.53	9.16	8.94	–0.22	2.69	3.01	0.32	0.11	0.069	0.041

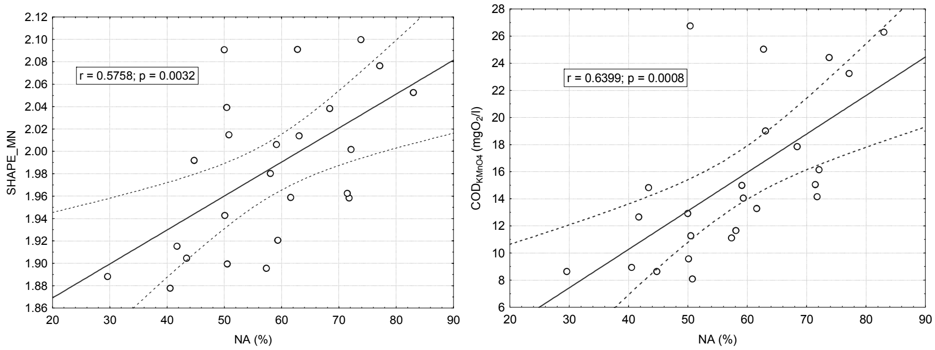

Figure 4. Relationships between natural areas (NA) and Mean Shape Index (SHAPE_MN) in the left (all catchments) and with COD_{KMnO4} in the right (all catchments). The solid line is the linear regression equation and the dashed lines indicate the 95% confidence intervals.

Values of COD_{KMnO4} most likely do not depend directly on landscape configuration, because landscape metrics reflect the catchments' land use, and COD_{KMnO4} had the strongest relationships with land use proportions (Uuemaa et al., 2005: Publication II). Therefore the model validation results (Table 5) were also not so good, because many predictors in COD_{KMnO4} regression equations did not have direct relationships with $COD_{KMnO4.}$ In the case of Tänassilma and Võhandu catchments, for example, the *I* model strongly overestimated COD_{KMnO4} values (Table 5), because they both have a very complex landscape pattern (high value of SHAPE_MN) (Uuemaa et al., 2007: Publication I), but not as high a proportion of FBM and NA, which are mostly the source of humic and fulvic acids. Regression model *III* very greatly underestimates the COD_{KMnO4} value for the Sauga catchment (Table 5), which has a very high FBM (Uuemaa et al., 2007: Publication I). However, ALU and NA have the highest β values apart from FBM. The *V* regression model gives a higher COD_{KMnO4} value for Valgejõgi. There is strong groundwater input in the Valgejõgi catchment, which probably dilutes the concentration of COD_{KMnO4}. Furthermore, the seasonality in the values of COD $_{KMnO4}$ and nutrients that is caused by rainy periods (Karakoç et al., 2003; Torrecilla et al., 2004; Nõges et al., 2007) may also influence the relationships between water quality data and landscape metrics (Buck et al., 2004), because we used averaged concentrations per year. The *V* model also underestimates the COD_{KMnO4} value for Kääpa catchment, because it has a very low ULU, which is not an important source for humic and fulvic acids, but is included in the model as a predictor for COD_{KMnO4}. Model *VI* underestimates the COD_{KMnO4} value for the Seljajõgi catchment (Table 5), because it has high ALU (Uuemaa et al., 2007b: Publication I) that has high β values, although NA is a more important source for humic and fulvic acids. However, Zeilhofer et al., 2006 found that COD_{KMnO4} concentrations increased significantly, receiving loads from sub-basins under intensive agricultural use where the main source of the COD_{KMnO4} is organic fertilizers. But as in Estonia, agricultural land use intensity decreased significantly in the 1990s, when most of the humic and fulvic acids were washed out of natural areas and fens.

3.2.3. Total-N

Regression equations did not explain the very high percent of the observed variation of total-N, but all of the regressions were significant, and the percent of outliers was zero in all cases (Table 4). The most important predictor for total-N was ULU. Fig. 5 shows that the close correlation between ULU and total-N (Uuemaa et al., 2005; 2007b: Publications II, I) is mainly caused by three catchments that have a very high ULU and also total-N. This confirms the results of Ahearn et al. (2005) who found that population density and nitrate-N loadings are related when waste water treatment plants are not built in the catchments. This indicates the insufficient wastewater treatment in the catchments, which is a critical problem in catchments that belong to the Gulf of Finland basin (Keskkonnaülevaade, 2005). Usually a very good positive correlation is found between total-N and the proportion of agricultural land use (Arheimer and Liden, 2000; Meynendonckx et al., 2006), because agriculture is one of the main sources of nitrogen. However, our results did not give significant correlations with ALU, probably because the substantial decrease in the use of fertilizers and livestock production has caused a reduction of nitrogen in river water in recent decades in Estonia since the collapse of the Soviet Union (Iital et al., 2003).

FRAGSTATS landscape metrics were only predictors for total-N in two regression equations, and ED seemed to be the most important of these. ED correlated negatively with total-N (Fig. 5 and Uuemaa et al., 2005: Publication II), i.e. lower amounts of nitrogen are washed out of catchments with a more complex landscape pattern. Although ED also correlated negatively with ULU, the relationship between ED and total-N seems to be causal (Uuemaa et al., 2005: Publication II).

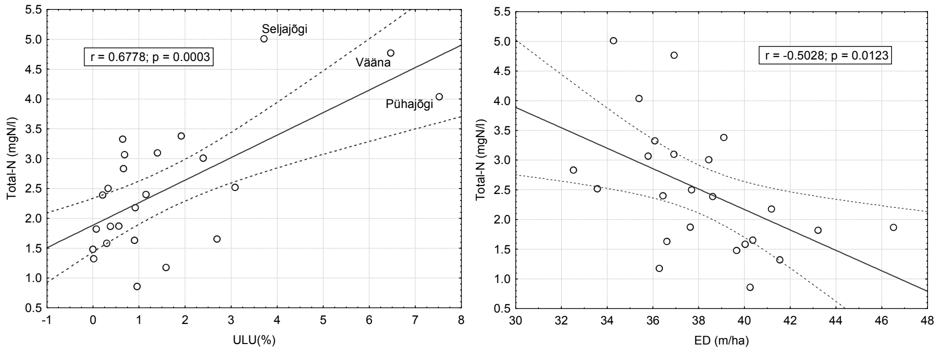

Figure 5. The relationship between the proportion of urban land use (ULU) and total-N (all catchments) in the left, and the relationship between Edge Density (ED) and total-N (all catchments) in the right. The solid line is the linear regression equation, and the dashed lines indicate the 95% confidence intervals.

The results of model estimation were good (Table 5). Only two values of total-N did not fall between the 95% prediction intervals. Model *IV* underestimates nitrogen runoff from Vääna catchment, and model *VI* from Seljajõgi catchment. In both catchments, the high loads of nitrogen come from point source pollution (high ULU), but in Seljajõgi catchment there is also considerably high ALU (Uuemaa et al., 2007: Publication I). Regression equation *IV* does not take into account ULU, but there are several towns in the Vääna catchment. Therefore the model underestimates the value of total-N. Model *VI* gives a lower total-N value than that measured, because it does not take into account ALU, which is very high in the Seljajõgi catchment (Uuemaa et al., 2007b: Publication I). This shows that both ALU and ULU should probably be taken into consideration as predictors for total-N runoff from Estonian catchments, but landscape pattern also has an influence on total-N values.

3.2.4. Total-P

For total-P the most important predictor was ULU (Table 4). All regressions were significant but the percentage of outliers was relatively high, probably because values of total-P were not normally distributed. Outliers may artificially increase the value of a correlation coefficient, which is probably the case with the close correlation between total-P and ULU, which is caused by two catchments (Seljajõgi and Pühajõgi) that have very high values of ULU and total-P (Uuemaa et al., 2007b: Publication I). If these two catchments are left out of the analysis, there is no relationship between ULU and total-P. This points to the problem with phosphorus removal from wastewater from industries and towns (Sliva and Williams, 2001). The insufficiency of wastewater plants was a critical problem ten years ago (these analyses were performed with water quality data from the years 1996–1998) in Northeast Estonian catchments. By the year 2005 the value of total-P in the Pühajõgi catchment has decreased fivefold due to the modernization of agricultural production, the construction and renovation of waste water treatment plants and structured legislative drafting. However, the concentrations of total-P are still near the critical level (0.1 mg P/l) for avoiding eutrophication in rivers (Keskkonnaülevaade, 2005). FRAGSTATS landscape metrics were not very important predictors for total-P (Table 4; Uuemaa et al., 2005: Publication II) because phosphorus probably mainly comes from point-pollution sources.

The results of model estimation were not very good (Table 5). The difference between measured and predicted total-P values were quite significant considering the actual total-P values. Regression model *I* heavily underestimated the total-P value for the Pühajõgi catchment, because in that equation ULU is not included as a predictor for total-P, but there is high ULU (7.5%) in the Pühajõgi catchment. In the case of the Kunda catchment, the ED is relatively low, and in the regression equation the β value for ED is very high. In regression model *II*, the Loobu catchment has a high ENN_MN value that causes a very low predicted value of Total-P. Model *IV* overestimates the value of total-P for the Vääna catchment. The ULU is high in the Vääna catchment, but most of the wastewater coming from Tallinn (part of Tallinn belongs to Vääna catchment) is routed to the wastewater management plant and then discharged to the sea. Therefore relationships between total-P and ULU may lead to incorrect conclusions, as the wastewater plants where the drainage is routed may not be in the same basin (Ahearn et al., 2005).

I can conclusively say that that land use proportions are the most important predictors for water quality. For BOD_7, total-N and total-P, the proportion of urban areas was the most significant predictor, because in these study catchments organic matter, nitrogen and phosphorus runoff is strongly influenced by point-pollution sources. The relationships between water quality parameters and land use proportions can also reveal problems with wastewater treatment in catchments. Johnson et al. 1997 also found that human-influenced land cover types are positively related to N and P in surface waters, and Boyer et al., 2002 found that input of total-N is positively correlated with the proportion of agricultural areas and negatively with the proportion of forests. However, relationships between land use proportions and water quality should be considered carefully, because the proportions of land use types are not independent (King et al., 2005), since the increasing in the proportion of one type necessarily results in a decrease in the proportion of one or more other types (Van Sickle, 2003). In this study, land use proportions also correlated with several FRAGSTATS landscape metrics, and therefore in the case of some FRAGSTATS landscape metrics, it was difficult to determine whether the relationships between water quality data and FRAGSTATS landscape metrics were causal or not. Nevertheless, landscape pattern played a significant role in predicting the values of water quality in catchments. Therefore these relationships should be taken into account in land-use planning in watersheds. Although regression equations used in this study should not be used in other catchments, the methods can be applied anywhere in Europe because of the availability of the CORINE Land Cover Map.

3.3. Spatial correlograms and half-value distance lag as the new landscape metrics

The correlograms for the study areas were quite different (Fig. 6). The general tendency was that heights and uplands had very abrupt correlograms, and lowlands and plains had more slanting correlograms. Therefore the values of $h_{I=0.5}$ were also significantly lower in the case of heights and uplands than in the case of all other landscape regions. All six study areas from heights (except Vooremaa) had a value of $h_{I=0.5}$ of less than 100m (Fig. 7), i.e. the spatial autocorrelation is very low. Vooremaa probably has higher values of $h_{I=0.5}$ because it is not a typical accumulative height. It is actually a drumlin field formed during the last glaciation that is 90–100m higher than the surrounding areas and is thus conditionally considered as a height.

Most of the plains and lowlands had values of $h_{I=0.5}$ higher than 200m, and in case of uplands and depressions the value of $h_{I=0.5}$ was between 100m and 200m. According to the correlograms and $h_{I=0.5}$, the spatial autocorrelation in heights and uplands is significantly lower than in all other landscape regions.

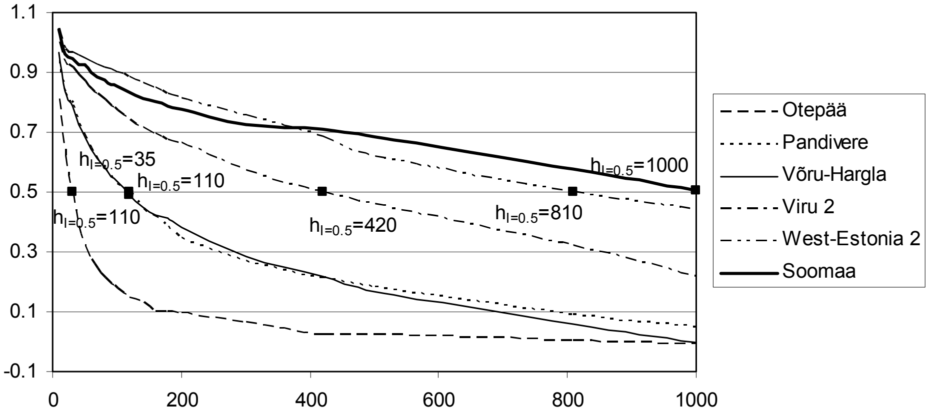

Figure 6. Correlograms of study areas from different landscape regions. Typical examples were chosen from each landscape region: Otepää – heights; Pandivere – uplands; Võru-Hargla – depressions; Viru 2 – plains; Soomaa – inland paludified lowlands; and West Estonia 2 – coastal lowlands and sea islands.

In some FRAGSTATS landscape metrics values (PD and ED) there was a relatively large interval where none of the study areas were presented (Fig. 8). Heights have PD values higher than 40, and all of the other landscape regions have PD values lower than 25. Therefore there is a very clear distinction between heights and the rest of the landscape regions. There are no landscapes with a definite complexity of landscape structure (25<PD<45 and 165<ED<225; Uuemaa et al., 2007a: Publication III). Aunap et al. (2006) performed a similar analysis on land use data, and also found that the landscape pattern in heights and uplands is more fragmented (smaller patches) than in lowlands and plains.

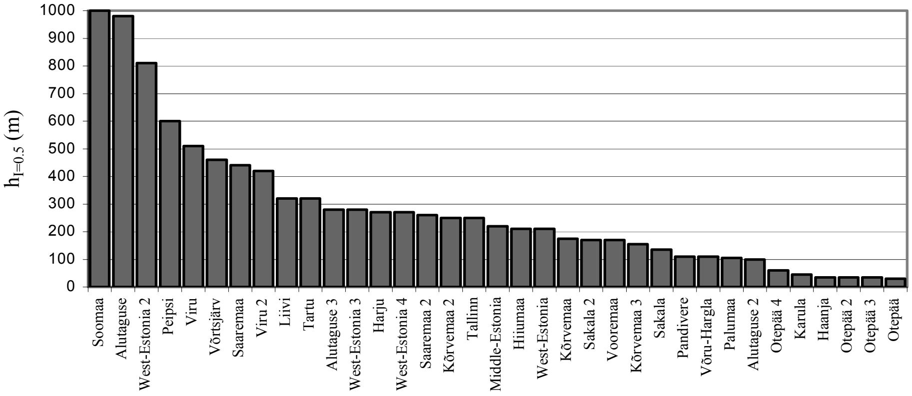

Figure 7. Values of $h_{I=0.5}$ of all study areas (Uuemaa et al., 2007a: Publication III).

We also correlated several FRAGSTATS landscape metrics with $h_{I=0.5}$ in order to detect whether some of the FRAGSTATS metrics indirectly measure spatial autocorrelation. All calculated FRAGSTATS landscape metrics correlated significantly with $h_{I=0.5}$. As expected, the PD, ED and CWED had a very strong negative and AREA_MN and PLADJ a positive relationship with $h_{I=0.5}$ (Spearman ρ>0.8). This indicates the higher spatial autocorrelation in landscapes with large patches and low edge density and contrast of edges, i.e. very fragmented landscapes have low spatial autocorrelation (Uuemaa et al., 2007a: Publication III). Moran's I relationship with mean patch size is also detected by Overmars et al. (2003). This relationship is also easily explained, as there are more pixels aggregated in larger patches, and Moran's I describes the degree to which values in any pixel will be similar to the pixels surrounding it; the large patches have a high autocorrelation.

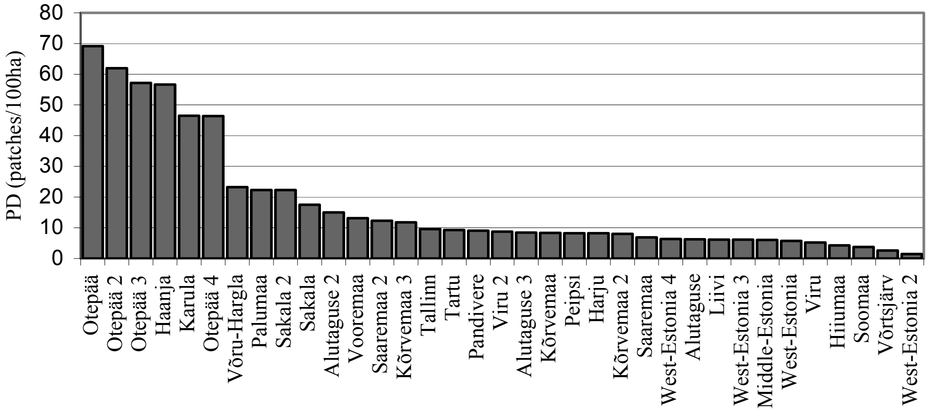

Figure 8. Values of the Patch Density (FRAGSTATS) of all study areas (Uuemaa et al., 2007a: Publication III).

We tested how the correlograms of soil describe Estonian landscapes, and found them to be quite characteristic to different landscape regions. I was, however, unable to find many studies that use Moran's I for detecting spatial autocorrelation in soils or land use/cover. The most probable reason for this is that land use/cover and soil maps are usually categorical i.e. qualitative data (Table 1), and it is difficult to create an ordinal scale for soils or land use/cover (Uuemaa et al., 2007a: Publication III). One possibility for calculating spatial autocorrelation for land use is to use quantitative remote sensing data. For example, Read and Lam (2002) used unclassified remote sensing data to calculate Moran's I and landscape metrics for detecting land cover changes in remote sensing data, and found that Moran's I is good for the distinguishing of differing degrees of spatial complexity represented by land-cover types, and Southworth et al. (2004) used vegetation index (NDVI) in calculating Moran's I for the investigation of land use changes in the western Honduras region.

In order to create an ordinal scale of contrast, we reclassified soil types on the basis of the authors' expert knowledge (Table 2). Nevertheless, the distribution of soils in toposequent transects (catenas) determines the logic of this ordering (see Sommer and Schlichting, 1997). The main soil types and forest site types in Estonia are also logical-statistically ordered in two crossing catenas (Lõhmus, 1984; Uuemaa et al., 2007a: Publication III), which support our assumptions concerning the scale of soil contrast.

It is obvious that the results of all spatial analyses are scale–dependent, and the scale-dependence of FRAGSTATS metrics has been shown by several authors (Wu et al., 2002; Uuemaa et al., 2005: Publication II; Buyantuyev and Wu, 2007). Moreover, Qi and Wu (1996) demonstrate that Moran's I is also dependent on grain size, and that changing the scale affects the amount of autocorrelation found in the landscape pattern. Fortin (1999) pointed out that the intensity of spatial autocorrelation increases with quadrant size and reaches a plateau at a certain distance (200–225 m). In our study, correlograms showed that even though Moran's I decreases (spatial autocorrelation is decreasing) with increasing lag, the different landscapes are still comparable. Even when the lag was 1000 m, the difference between landscapes with high and low spatial autocorrelation was considerable, which is not the case with FRAGSTATS metrics, where the difference between landscapes disappears at approximately 400m (Uuemaa et al., 2005: Publication II). Furthermore, I could even say that correlograms and $h_{I=0.5}$ seem to be better than FRAGSTATS landscape metrics for determining or/and describing differences between landscapes if one is uncertain about the optimal scale for certain analysis or due to different limitations uses larger than optimal grain size. We have been working at a scale that can be considered medium-range. If one works with more detailed maps or high resolution satellite images or, on the other hand, with large-scale material representing much larger territories, the relationships between the FRAGSTATS metrics and the autocorrelation parameters can differ (see Legendre and Fortin 1989). However, for practical landscape research and planning purposes, the medium scale is the most commonly used scale.

4. CONCLUSIONS

In recent decades many landscape metrics have been developed and widely used. One of the essential research topics for landscape ecology is how to relate these landscape metrics to ecological processes and how the scale-dependence of spatial pattern affects relations between landscape metrics and ecological processes. This dissertation focuses on finding how commonly used landscape metrics respond to changing grain size and how this affects relationships between landscape metrics and nutrient and organic matter runoff in catchments.

The responses of landscape metrics to changing grain size varied significantly among landscape metrics and across landscapes. This is mainly because of different factors that affect the behaviour of landscape metrics. Values of Edge Density (ED) and Patch Density (PD) decreased rapidly with increasing grain size. The reason for this is the simplification of edges and elimination of small patches. Landscapes of complex configuration have a greater decrease in their Edge Density and Patch Density values, reaching the same value as homogenous landscapes i.e. at some point of spatial resolution the difference between landscapes disappears. Mean Euclidean Nearest Neighbour Distance (ENN_MN) and Contagion (CONTAG) are directly dependent on grain size; therefore, they should be used and interpreted carefully in the case of changing grain size. Diversity metrics (PRD and SHDI) decreased in a staircase-like fashion with increasing grain size, because their value depends on the number of patch types, and SHDI is also influenced by the distribution of patches in the landscape. We found that for the CORINE Land Cover Map, 30m pixel size is optimal for analyzing the relationships between landscape metrics and water quality data.

Land use proved to be the most important predictor for water quality, but landscape structure also played a significant role in predicting the values of water quality in catchments. For BOD_7, total-P and total-N, the proportion of urban land use (ULU) was evidently the most significant predictor, because in catchments that belong to the Gulf of Finland basin, organic matter, nitrogen and phosphorus runoff is strongly influenced by point-pollution sources. The close relationships between ULU and water quality data also pointed to the problem with waste water treatment in many Estonian catchments. In addition to ULU, ED seemed to play an important role in predicting values of total-N. Lower amounts of total-N are washed out of catchments with complex landscape patterns. For BOD_7, PD was also an important predictor. Catchments with fragmented landscape patterns have lower organic matter runoff. Landscape configuration plays an important role in organic matter and nutrient runoff from catchments.

Landscape metrics are easily computed with different software, and if scale is taken into consideration, then they can effectively be used as indicators for the land-water relationship, which is important from the point of view of watershed planning and management. Although the regression models used in this study can only be used on these specific catchments, they still provide information about the role of land use and landscape configuration in river water quality.

In addition to FRAGSTATS landscape metrics, we also used spatial correlograms of soil cover characterizing the spatial pattern of Estonian landscapes. We also proposed the distance (lag) of spatial correlograms at which the Moran's I value reaches 50% of the maximal value ($h_{I\,=\,0.5}$) in the positive scale as a new landscape metric for the characterization of landscape pattern. We found a positive spatial autocorrelation in the soil data. Soil correlograms for different landscape regions differed significantly. Landscapes with flat topography (lowlands and plains) mostly have slanting spatial correlograms and high $h_{I\,=\,0.5}$ value i.e. high spatial autocorrelation. Hilly landscape types (heights and uplands) have rapidly decreasing spatial correlograms and low $h_{I\,=\,0.5}$ values, i.e. low spatial autocorrelation. We could find a representative spatial correlogram for each landscape region in Estonia. As the spatial autocorrelation for different landscapes was still considerably different, even in the case of 1000m lag, then correlograms and $h_{I\,=\,0.5}$ are good for the description of landscape pattern if the optimal scale for certain analysis is not known. However, there is a need for further analysis of the behaviour of Moran's I on real land use/cover because the spatial autocorrelation of landscape pattern may differ due to urban areas.

SUMMARY IN ESTONIAN

Maastikuindeksid jõgede veekvaliteedi ja maastikumustri indikaatorina

Maastikumustri hindamiseks on välja töötatud väga palju erinevaid maastikuindekseid. Tänapäeval on maastikuökoloogia üheks oluliseks uurimisülesandeks leida, kuidas saab maastikuindekseid seostada ökoloogiliste protsessidega. Kuna kõik ruumianalüüsi tulemused sh ka maastikuindeksite väärtused sõltuvad skaalast, siis avaldab see mõju ökoloogiliste protsesside ja maastikumusti vaheliste seoste analüüsi tulemustele.

Käesolevas töö eesmärgiks oli 1) leida kas ja kuidas maastikumuster mõjutab toitainete ja orgaaniliste ainete väljakannet valglatest ning kuidas neid seoseid mõjutab maastikuindeksite sõltumine piksli suurusest ; 2) hinnata ruumilist autokorrelatsiooni Eesti maastikel kasutades muldkattele arvutatud korrelogramme.

Maakasutuse/katte andmetena kasutati Eesti Põhikaarti (1 : 10 000), Eesti Baaskaarti (1 : 50 000) ning *CORINE*'i maakatte kaarti (1 : 100 000). Maastikuindeksid arvutati *Fragstats*-is ja ruumilise lahutuse analüüsis korreleeriti neid piksli suurusega ning indikaatorite analüüsis väljakande andmetega. Töös kasutati väljakande andmetena Eesti jõgede riikliku hüdrokeemilise seire andmeid. Korrelogrammide arvutamiseks kasutati Eesti mullakaarti (1 : 10 000). Eesti maastikurajoonide järgi valiti 35 uurimisala, millele arvutati Morani I erinevate laagide (h=10, 20, 30, …, 100, 120, …,200, 300, 400, 500 ja1000m) korral.

Tulemused näitasid, et maastikuindeksid sõltuvad piksli suurusest erinevalt. Eraldiste tiheduse (PD) ja servatiheduse (ED) väärtused langesid ühtlaselt piksli suurenedes, sest väiksesed eraldised hakkavad maastikust kaduma ning servad muutuvad siledamaks. Samuti täheldati keerukama maastiku mustriga alade puhul nende indeksite väärtuste kiiremat langust kui homogeensema maastiku mustriga aladel. Leiti, et keskmine lähima naabri kaugus (ENN_MN) ja koonduvus (CONTAG) sõltuvad otseselt piksli suurusest ja on seega väga tundlikud ruumilise lahutuse muutmisele. Mitmekesisuse indeksite (Shannoni mitmekesisuse indeks – SHDI ja eritüübiliste eraldiste tihedus – PRD) väärtused seevastu muutusid alles siis, kui erinevate maakasutuse/katte tüüpide arv maastikus hakkas vähenema. Kokkuvõttes leiti, et CORINE Maakatte kaardi jaoks on 30 m piksli suurus optimaalne analüüsimaks maastikuindeksite ja veekvaliteedi näitajate vahelisi seoseid.

BHT_7, $N_{üld}$ ja $P_{üld}$ jaoks oli kõige olulisem faktor linnade osakaal valglas. Tõenäoliselt oli põhjuseks asjaolu, et Kirde-Eesti jõgede veekvaliteet on väga palju mõjutatud punktreostusallikate poolt. Samas viitab tugev toitainete ja orgaaniliste ainete väljakande seos linnade osakaaluga puudulikule reovete puhastusele. Lisaks linnade osakaalule oli BHT_7 jaoks oluliseks näitajaks ka eraldiste tihedus (PD), mis viitas sellele, et keerukama maastiku mustriga

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valglatest on orgaaniliste ainete väljakanne väiksem. $N_{üld}$ puhul viitas sarnasele tendentsile servatihedus (ED). Seega võib öelda, et orgaaniliste ainete ja toitainete väljakanne valglast on mõjutatud nii maakasutuse kui ka maastikuindeksite poolt. Kuigi antud töös kasutatud regressiooni mudeleid ei saa kasutada teistes valglates, saab antud meetodeid rakendada igalpool mujal Euroopas tänu CORINE maakatte kaardi olemasolule.

Eesti maastike iseloomustamiseks kasutati Morani I korrelogramme nind pakuti välja ka uus maastiku mustrit iseloomustav näitaja — korrelogrammide poolestuskaugus ($h_{I=0.5}$) kui ruumilise autokorrelatsiooni laag, mille puhul Morani I väärtus jõuab 50%-ni maksimumväärtusest positiivses skaalas. Maastikurajoonide jaoks arvutatud korrelogrammid erinesid üksteisest oluliselt. Madaliku alade puhul Morani I väärtus langes aeglaselt ning $h_{I=0.5}$ väärtus oli väga kõrge so ruumiline autokorrelatsioon oli kõrge. Samas künklikel aladel langesid autokorrelatsiooni väärtused laagi kasvades väga kiiresti ning $h_{I=0.5}$ väärtused olid madalad. Kõikide Eesti maastikurajoonide jaoks leiti iseloomulik mullakaardile arvutatud korrelogramm. Korrelogramme ja $h_{I=0.5}$ on maastikumustri hindamisel otstarbekas kasutada siis, kui optimaalne piksli suurus antud uurimuse jaoks ei ole täpselt teada, sest erinevad maastikumustrid jäävad võrreldavaks ka 1000m laagi korral.

Maastikuindekseid saab edukalt kasutada maastikumustrite hindamiseks ja iseloomustamiseks. Tänu nende indikatsiooniväärtusele jõgede veekvaliteedi osas on neid võimalik kasutada ka valglate veemajanduskavade koostamisel.

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