Relating spatial pattern of forest cover to accessibility

1 Abstract

Urban planning for optimal provision of recreational forests is not only concerned with how much space is needed, but equally with how this could be arranged in the landscape in order to make these forests accessible to many potential visitors. The present study sought to establish relationships between the spatial pattern of forest cover and these forests' accessibility - either on foot or by bike - for short walks. This question was approached in an experimental way using landscape structure metrics.

A factor analysis identified the common axes of spatial pattern. The first five factors explained 82.2 % of the variation of the original data set. The first factor is related to forested area and number of forest patches, the second is related to shape complexity. The third factor quantifies contiguity, and the fourth measures the clumpiness of forests. The fifth refers to variability in forest shape. Only the factors related to forested area - shape complexity and clumpiness - show a significant correlation with recreational provision. A higher forest coverage and more forests should thus lead to a higher provision for short walking trips. However, when a small afforestation budget is available, high shape complexity, low forest contiguity and a high landscape shape index (LSI) should take priority. Shape indices make the most important contribution to single out patterns that offer recreation possibilities to a high number of people. The findings show the potential of using landscape structure metrics for modelling of forest recreational provision.

2 Keywords

landscape configuration, recreational provision, regional scale, landscape metrics

3 Introduction

Over the 20^{th} century, large parts of the world have become strongly urbanized and forests are increasingly recognized as vital elements for keeping urban dwellers in touch with nature (Konijnendijk et al., 2005). In various countries across Europe (e.g. United Kingdom, Denmark, the Netherlands, Belgium), this has prompted decision makers to adopt ambitious policies for increasing the forest cover (Van Herzele et al., 2005).

Remarkably, these afforestation strategies - especially apparent in heavily urbanized regions of Western Europe - have shown to be particularly effective at the national and regional scale (Van Herzele et al., 2005; Van Herzele, 2006). To make valid projections of the outcome of such afforestation policies, their effects on outdoor recreational provision should be evaluated. For this, the wider scale - covering an area of several square kilometers - is being considered as the most appropriate (Zhang, 2004; Konijnendijk, 2004; Konijnendijk and Randrup, 2004). Scaling up from a locus-based to a broader landscape scale - which is further referred to as the regional scale - is likely to facilitate the formulation of alternatives for recreation planning.

One of the few cases in which the effect of afforestation on recreational provision has been assessed on a regional scale is that of possible forest locations near Antwerp, Belgium (Van Herzele et al., 2005). In this study, a GIS-based working method was applied to evaluate seven alternative locations for the creation of a new forest. Accessibility, defined as the number of people living near enough to visit this future forest on a regular basis, was calculated using a hierarchical system of standards, which links distance from the home to forest size (Van Herzele and Wiedemann, 2003). The study used a fixed afforestation 'budget' of 300 ha, to be realized in one single forest unit. However, even the best location could supply the demand for forest recreation only partially. This observation prompted a need for further research to verify whether a well considered spatial arrangement dividing the afforestation 'budget' in terms of hectares over smaller units would benefit more urban dwellers. If so, a more efficient solution could be obtained by creating spatial patterns that provide a high number of people with short walking trips in relation to the land area that is set aside for forest. The ability to quantify this pattern is a prerequisite to monitor the recreational provision on a regional scale and offer alternative scenarios for spatial planning.

In this paper, we aim to make a first step to establish relationships between accessibility and measures of spatial pattern on a regional scale. Flanders (northern autonomous part of Belgium - $13,522km^2$) is selected as study area, as it features a very high degree of urbanization. According to UN (2004), 98 % of the flemish population is living in urban areas. This situation is combined with a relatively low forest cover (about 11 %). Before elaborating on the case study, we clarify the main concepts used, and their integration within the study approach.

3.1 Recreational provision assessed by accessibility

Accessibility refers to the ability of using transportation facilities to reach desired locations at suitable times (Geertman and Van Eck, 1995). Most measures of accessibility incorporate the distance between a person and his or her destination, as well as the utility of this location. Some of the best known measures are based on the 'potential model' (Geertman and Van Eck, 1995; Horner, 2004; Liu and Zhu, 2004; Stanilov, 2003; Talen and Anselin, 1998; Zhang, 2004). The concept of potential is closely related to gravity, where the attraction of object a on object b is directly related with the mass of object a and inversely related with the distance between these two objects. Several software packages have implemented this concept, such as FlowMap ($http://flowmap.geog.uu.nl$), LADSS, and LocNet (Kammeier, 1999).

The potential model can be applied to recreation forests and calibrated using data on average travel distance derived from socioeconomic research. Numerous recreation studies in Flanders and elsewhere have concluded that travel distance from home is the single most determinant factor for the use of a recreational space (for an overview, see Van Herzele and Wiedemann (2003); Grahn and Stigsdotter (2003) or Roovers et al. (2002)). In addition, the maximum distance people are willing to travel differs according to the attributes of the recreational space. In this respect, the size of the forest is a determinant factor for recreational use in terms of frequency, duration, and travel distance (Van Herzele et al., 2005).

3.2 Relating spatial pattern of forest cover to accessibility

Landscape monitoring, focussing on spatial pattern, also defined as landscape structure, rapidly evolved during the last decades, combining remote sensing and geographic information systems (GIS) (Forman and Godron, 1986; Turner and Gardner, 1991; Farina, 2000; Luck and Wu, 2002; Turner et al., 2003). Statistical measures to quantify composition and configuration of a landscape are called landscape metrics or pattern indices (McGarigal and Marks, 1994). In the field of landscape ecology, a comprehensive set of landscape indices has been developed (Hulshoff, 1995; Riitters et al., 1995). These are considered as useful tools to monitor the natural environment (Forman and Godron, 1986; O'Neill et al., 1988; Baskent and Jordan, 1995; Trani and Giles, 1999; Farina, 2000; Imbernon and Branthomme, 2001). Metrics of landscape composition are not spatially explicit. They measure what is present and their relative areal proportions, without reference to its location in the landscape. Configuration refers to the relative spatial arrangement of forests in the landscape (Turner et al., 2001).

4 Research questions

The objective of this paper is to explore the relationship between the spatial structure of a forested landscape, as assessed by pattern metrics, and the number of people that could use these forests for short walking trips, as determined by accessibility. The following questions are answered:

(1) Which measures of spatial pattern are correlated with forest accessibility on a regional scale?

(2) Which of these metrics are independent of the amount of forest ?

(3) Which pattern metrics can single out forest patterns that contribute to efficient land use, by providing the maximum number of people with forest recreation, combined with the minimum land area set aside for forest ?

This paper seeks to determine which metrics, if any, are most appropriate in models assessing the provision of forest recreation on a regional scale.

5 Material and Methods

5.1 Study Area

The study area of Flanders (see figure 1) comprises $13,522 km^2$ and features a modest forest cover (146,000 ha or ca. 11% forest cover) (Leyman and Vandekerkhove, 2003). High land pressure is caused, amongst others, by high population density, amounting to 443 inhabitants per km^2 (NIS, 2004).

[insert figure 1 here]

5.2 Data and Software

Artificial maps with random spatial patterns can be generated by random processes (Turner et al., 2001). However, this technique is cumbersome, while the existing spatial pattern of forest cover is readily available in digital format and performs better in capturing all pattern characteristics of actual landscape patterns (Gustafson and Parker, 1992; Baldwin et al., 2004; Li and Wu, 2004).

To obtain a spectrum of spatial patterns, the forest map of Flanders (with a spatial accuracy of 10 m (OC GIS-Vlaanderen, 2001a) was subdivided into 135 coverages corresponding to the geographic extent of equally sized hexagons, as shown in figure 2. These hexagonal coverages were the basis for all pattern metric calculations and were chosen as calculating units because of their regular and compact shape. These coverages were considered as just one possible sample of future and past landscape patterns in Flanders.

Spatial population data was available per neighborhood, defined by the digital administrative boundaries of *statistical sectors* and was acquired from the National Statistics Institute (NIS, 2001). Flanders counts 10,826 statistical sectors. These are the size of a small number of building blocks and represent a more or less homogeneous quarter in social respect (Pelfrene et al., 1998).

[insert figure 2 here]

Pattern metrics on a regional scale were determined for each hexagon, using ESRI′s ArcView 3.1 and Fragstats 3.3 (McGarigal and Marks, 1994).

5.3 *Description of the GIS-based accessibility model*

To assess the accessibility of forested landscapes, the greenspace monitoring tool was applied (Van Herzele and Wiedemann, 2003; Van Herzele et al., 2005) and programmed in ArcView 3.1 using AVENUE. It is a straightforward method that determines the recreational provision in a region, using the attractiveness of each greenspace, based on its size and specific attributes for recreation. In this study, the tool was used in a simplified way, because extra information concerning amenity was not available. We preferred this model to other models, since it has been especially developed for the evaluation of outdoor recreational provision.

The greenspace monitoring tool is based on the concept of accessibility as developed by Geertman and Van Eck (1995). Attraction of each forest site is linked to its area and expressed as a maximum distance people are willing to travel for a visit to this forest. This maximum distance delimits an attraction zone, henceforth referred to as catchment. The recreational value of the forest was expressed as the number of people living in the catchment. This relationship (see Table 1) was based on the standards proposed by the Flemish forest administration (Van Herzele et al., 2000). Mobility research in the Netherlands has indicated that trips for leisure often cover short distances, and walking and cycling are dominant modes of transport (Dieleman et al., 2002). To none of the forests a distance larger than 5 km was allocated, which is considered the maximum distance that will be covered on foot or by bike (Van Herzele et al., 2000; Dieleman et al., 2002).

[Insert Table 1 here]

For each forest fragment the attraction distance was calculated and the associated catchment area was delineated. Per hexagon the area proportion within a catchment was calculated. Each sector was consecutively clipped using the catchment lines. The population of partial sectors was calculated using the area proportion of the original statistical sector surface. The sum of all persons having access to forest recreation was expressed as a percentage of the population living within the hexagonal sample unit.

5.4 Description of the spatial pattern

To quantify the spatial pattern, 19 commonly used pattern indices were calculated (see Table 2). Landscape *composition* is described by the total forested area (TA) and the number of forest patches (NP) . Spatial *configuration* collects different groups of metrics, referred to as *contagion*, *patch-based metrics*, *connectivity* and *proximity*. The first, *contagion* of forest patches, is assessed by the following metrics: PLADJ, DIVISION, MESH, SPLIT, AI.

[insert Table 2 here]

Patch-based metrics comprise a second group. Once area and perimeter of each forest are determined, these can be summarized (as in LSI) or frequency distributions can be drafted. *Shape complexity* is quantified through PARA, SHAPE, FRAC, CONTIG and GYRATE. Per sample unit the mean (.MN) and median value (.MD), as well as the standard deviation (.SD) and the coefficient of variation (.CV) were recorded. *Connectivity* is assessed by LPI, CONNECT and COHESION. Finally *proximity* - the degree to which patches are isolated - is quantified using PROX and ENN.

Full description and calculation of these indices are provided by McGarigal and Marks (1994) and Turner et al. (2001).

5.5 Relating spatial pattern of forest cover to accessibility

5.5.1 Correlation between accessibility and pattern metrics

Using Spearman correlation analysis the correlation between accessibility and each of the pattern metrics was tested for significance.

5.5.2 Assessing independent groups of pattern metrics

Using principle component analysis (PCA), the pattern metrics were grouped into a small number of independent components. In order to facilitate the interpretation of the components, a Varimax rotation was applied. For a detailed description of this technique, we refer to Riitters et al. (1995). The PCA scores of all hexagons were then tested for correlation with the recreation accessibility data from the GIS model, using a simple linear least square model and Spearman rank correlation coefficient. This procedure was also adopted by Honnay et al. (2003) to investigate the biological meaning of landscape structure metrics, and determine which indices should be used in ecological monitoring.

5.5.3 Efficiency in recreational provision

Discriminant analysis tests whether a set of variables (pattern metrics) is able to correctly classify the hexagons into groups. The discriminating power of the respective variables is relative to the coefficients of these variables in the discriminant function (Mather, 1976; Buys, 2003). This technique was applied to determine which metrics indicate differences between groups. It requires a division of the hexagons into groups, according to their effectiveness in providing access to recreation.

To obtain these groups, the landscapes, representing the hexagons and their spatial forest patterns, were ranked according to the criteria of optimization, which are to maximize accessibility (Objective 2) with a minimum forest area (Objective 1). According to pareto-logic, landscape x is dominated by (or worse than) landscape y if landscape y scores better on both objectives. For this, landscape y should have a higher accessibility, whilst containing a lower - or equal - forest cover. In figure 3, a hypothetic example is given. Objective 2, accessibility, should be maximized and objective 1, forest cover, should be minimized. Landscape b is dominated by landscape c, since landscape c has both a higher accessibility and a lower forest cover. Landscape a scores better on the first objective than landscape b, but scores worse on the second objective. Landscapes a and b are considered not comparable, since neither one dominates the other.

[Insert fig 3 here]

Dominated landscapes score worse on one of the two objectives, when compared with at least one other landscape, while doing similar or worse for the other objective. Non-dominated sample units form the so-called *pareto-front* and represent land use configurations that cannot be improved for both objectives simultaneously. The forest patterns of these landscapes are given rank "1". Rank "2" was assigned to hexagons that were dominated by only one other landscape and rank "3" was given to all other sample units. The closer a landscape is situated to the pareto-front, the more efficient the spatial forest pattern is with respect to accessibility to recreation. These groups were used to detect differences in landscape configuration, regardless of the percentage of forest cover.

6 Results

6.1 *Correlation between pattern metrics and accessibility*

In Table 3, Spearman correlations between accessibility and pattern metrics are listed. Not surprisingly, accessibility is highly correlated with forest composition, described by TA ($r = 0.91$) and NP ($r = 0.75$). Contagion and connectivity have an intermediate influence on accessibility; the highest correlation in this group is with MESH ($r = 0.66$). Regarding distribution of forest size, it is the variation ($r = 0.65$ for AREA.CV and $r = 0.64$ for AREA.SD), which is correlated. In the group describing the distribution of forest shape, several metrics have a significant correlation with accessibility, although none of these is high. The summarizing LSI is nonetheless rather well correlated ($r = 0.72$). Finally, forest isolation, quantified by ENN.MN and ENN.SD, is negatively correlated with accessibility ($r = -0.79$ for ENN.MN; $r = -0.81$ for ENN.SD).

[Insert Table 3 here]

6.2 *Distinguishing configuration from composition*

Principal component analysis shows that the first 5 components explain $82,2\%$ of the original data set. In Table 4, the factor loadings are listed, expressing the correlation between a factor and the original variables after Varimax rotation.

Each variable is assigned to the factor for which the correlation is highest. The pattern metrics are ranked according to decreasing correlation.

Clearly, the factors in landscape pattern in Flanders do not completely coincide with the pattern aspects as defined by Turner et al. (2001). The first factor is highly correlated with area.sd, prox.sd, gyrate.cv, mesh, prox.mn, area.cv, gyrate.sd, ta, cohesion, area.mn, pladj, ai, prox.md and shape.cv. These variables are strongly determined by the total area of forest cover.

[Insert Table 4 here]

Variables associated with the second factor are: shape.mn, frac.mn, shape-.md, gyrate.md, frac.md, gyrate.mn, area.md, shape.sd, frac.sd and enn.cv. These are all indices that describe patch shape. As the values of these indices increase, the patches become more irregular in shape.

The third factor can be interpreted as a supplementary factor connected with forest shape, since it is correlated with contig.mn, para.mn, contig.md, para.md, ai and frac.cv . The factor has its highest, albeit negative, correlation (- 0.81) with contig.mn. This pattern index assesses the spatial connectedness of a patch, which is related to both patch size and patch shape.

The fourth factor can be interpreted as a component measuring the clumpiness of the landscape. Variables correlated with this factor are: lsi, division, lpi,

NP, SPLIT, ENN.SD, ENN.MN, CONNECT, ENN.MD and PROX.CV. The number of patches, their size and geographical distribution have an important influence on these indices. Many indices using the distances between two neighboring forest patches are linked to this factor.

Since the fifth factor contains solely standard deviations and coefficients of variation of shape indices, it is interpreted as a factor describing variability of shape complexity. Correlated indices are: CONTIG.SD, PARA.CV, PARA.SD and CONTIG.CV.

Table 5 shows the Spearman correlations between the forest accessibility and the pattern indices that are selected for their high correlation with the respective factors. The aspects of landscape configuration which are important for accessibility, are described by AREA.SD (0.64), SHAPE.MN (0.29), CONTIG.MN (0.03), LSI (0.72) and CONTIG.SD (0.16). Correlation with the first factor is meaningful, as was expected. From the other factors, only the fourth one (LSI) yields a correlation coefficient that can be considered important.

6.3 Efficiency in recreational provision

For the discriminant analysis, we use the three groups as obtained from pareto-ranking. Group 1 contains non-dominated landscapes; the hexagons in group 2 are dominated by only 1 other landscape, and all other landscapes are in group 3.

During a discriminant analysis, a multiple ANOVA is performed, testing for the equality of means of the indicated groups. The value of Wilks Lambda 0.1750 (p=0.00) indicates that the groups are separable on the basis of the values of the pattern indices. The pairwise comparison in Table 6 shows significant differences in the multivariate means of all three groups.

[Insert Table 6]

A univariate ANOVA is performed. Significant univariate differences are recorded between group 1 and 3 for the following variables: GYRATE.MD, ENN.MN and ENN.MD. Groups 2 and 3 are significantly different regarding FRAC.SD and FRAC.CV. None of the univariate means were statistically different for groups 1 and 2. None of the variables, associated with the factors of forest pattern, as determined in section 6.2, are significantly different for the three groups. Only a few pattern indices feature a significant difference for the specified groups. Hence, the results are not shown here.

Two discriminant functions are drawn. The canonical coefficients of these discriminant functions can be found in Table 7. These are sorted according to decreasing coefficients. For the first discrimination function, FRAC.MN, CONTIG.SD, FRAC.SD and CONTIG.MN have high coefficients. The coefficients for the other pattern metrics quickly drop to zero. In the second discriminant function, FRAC.SD and CONTIG.SD obtain rather high coefficient values as well. CONTIG.SD and CONTIG.MN also describe main aspects of landscape pattern (cfr. section 6.2) and are not directly correlated with forest accessibility. As is apparent from Table 4, FRAC.MN is correlated (0.89) with the second factor of forest pattern, and can be regarded as more or less equivalent to SHAPE.MN. FRAC.SD is not very well correlated with the factors of landscape pattern (0.60 for the second factor).

When performing a cross-validation through iteration, each observation is systematically dropped, the discriminant function is re-estimated, and the excluded observation is classified. This leave-one-out technique reports a classification error of 14.93 %. Keeping in mind that the results are only used for the detection of differences between groups and not for absolute prediction of which group a landscape will belong to, this error is considered acceptable.

7 Discussion and Conclusions

Urban planning for optimal provision of recreational forests is not only concerned with how much space is needed, but equally with how this could be spatially arranged in the landscape in order to make these forests accessible to many potential visitors. In this context, the present study sought to establish significant relationships between the spatial pattern of forest cover and forest accessibility for short walks.

The main originality of the study resides in the use of landscape structure metrics in the context of recreation planning. Existing research into spatial structure predominantly focuses on the use of pattern metrics for ecological monitoring (e.g. Honnay et al. (2003)). More specifically, the goal of this paper was to determine the utility of a given set of pattern metrics in planning for the creation of new forests.

Given the experimental nature of the study, the results are valuable as practical knowledge for the construction of models for recreation assessment. The results show that accessibility for short walks is related to the spatial pattern of forest cover. First and foremost, forested area and the number of forests have an effect on the provision of forests for short walks. The correlation is respectively 0.91 and 0.75. Metrics describing forest connectivity and forest shape have a lower influence on accessibility and a negative correlation is found between accessibility and forest isolation. These correlations between accessibility and pattern metrics indicate that nearly all aspects of spatial pattern have an influence on the recreational provision under investigation. Moreover, high correlation amongst pattern metrics suggest that when metrics are selected only on the criterion of high correlation with accessibility, the selected subset would provide redundant information.

Factor analysis, commonly performed for the selection of a subset of pattern metrics, yields five factors of spatial pattern. The first factor is related to forested area; the second factor indicates shape complexity of forest patches. The third factor quantifies contiguity. The fourth factor measures the clumpiness of forests. The fifth factor contains metrics referring to variability in forest shape. Only the first, the second and the fourth factor have a significant correlation with recreational provision. The correlation coefficient with the second factor is low but still significant. Contagion, expressed by MESH, seems to be a useful pattern metric based on its correlation with accessibility. Factor analysis, however, indicates that this metric describes the same component of spatial pattern as expressed by forested area or patch size distribution. Similarly, an increasing number of forest patches entails a decreasing forest isolation. Only forest contiguity, making up 2 of the 5 factors of the spatial pattern, is not significantly correlated with recreational provision.

This leads to the logical conclusion that a higher forest coverage and more forests will indeed increase recreational provision. However, when a small afforestation budget is available, high shape complexity, low forest contiguity and a high landscape shape index (LSI) warrant special attention.

To corroborate these conclusions, the forest patterns available were divided into groups. To ensure that the groups were not dependent on the quantity of forested area, pareto logic was used. Univariate ANOVA showed that metrics having different means for the defined groups are variables related to forest shape (GYRATE.MN, FRAC.SD and FRAC.CV) and isolation (ENN.MN and ENN.MD). These variables show a significant Pearson correlation with accessibility. They are allotted to the first, second and fourth factor in the PCA, but do not show a very high correlation with their respective factor.

Consequently, a discriminant analysis was performed on these groups. The results show that the pattern metrics are able to classify the forest configurations into the given groups with an accuracy of 85.07 %, based on shape indices alone (FRAC.MN, FRAC.SD, CONTIG.MN and CONTIG.SD). These variables are not correlated with accessibility, but show high correlations with the factors two, three and five. Despite the small divergence in outcome between the factor analysis and discriminant analysis, this analysis confirms the importance of shape and contiguity when a higher recreational provision is sought without a substantial enlargement of the forested area.

The findings of this study confirm that possibilities exist for the use of pattern metrics in the modelling of forest recreation. At the same time it indicates issues for further investigation. First and foremost, the relationships between spatial pattern and recreational provision should be verified in other geographical regions. Secondly, it should be tested whether these relations equally apply to longer forest recreation (e.g. hiking, ..), where accessibility by car is more important.

Finally, models for recreational provision, based on pattern metrics, should be developed. The following variables are assumed to yield good results for short forest recreation : forested area, number of forest features, shape metrics such as fractal dimension (FRAC) or contiguity (CONTIG) and nearest neighbor distances (ENN). Since the relationships between pattern metrics and species richness have been studied intensively, other objectives - such as maximizing biodiversity - and ancillary data - such as road networks - can be included in the model.

8 Acknowledgements

The authors would like to express their gratitude towards the colleagues in the Laboratory for Forest Management and Spatial Information Techniques, Department of Forest and Water Management in the University of Ghent. We would like to thank the anonymous reviewers for their constructive remarks.

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9 Tables

Table 1
Relation between the minimum area of forest and the maximum distance that will be covered for a recreation experience (after Van Herzele et al., 2000)

Maximum distance (m)	Minimal area (ha)
150	–
400	1
800	10
1600	30
3200	60
5000	200

Table 2
Acronyms of the pattern metrics

Abbreviation	Full name (units)
.MN	mean value of the preceding pattern index
.MD	median value of the preceding pattern index
.SD	standard deviation of the preceding pattern index
.CV	coefficient of variation of the preceding pattern index
TA	Total Area (ha)
NP	Number of Patches (-)
PLADJ	Percentage of Like Adjacencies (%)
DIVISION	Landscape Division Index (Proportion)
MESH	Effective Mesh Size (ha)
SPLIT	Splitting Index (-)
AI	Aggregation Index (%)
LSI	Landscape Shape Index (-)
AREA	Area (ha)
PARA	Perimeter-Area Ratio (-)
SHAPE	Shape Index (-)
FRAC	Fractal Dimension Index (-)
CONTIG	Contiguity Index (-)
GYRATE	Radius of Gyration (m)
LPI	Largest Patch Index (%)
CONNECT	Connectance Index (%)
COHESION	Patch Cohesion Index (-)
PROX	Proximity Index (-)
ENN	Euclidean Nearest-Neighbor Distance (m)

Table 3
Spearman correlations between accessibility and the pattern metrics
* $0.01 < P \leq 0.05$; **$P \leq 0.01$

Aspect	Metric	r	
composition	TA	0.91	**
composition	NP	0.75	**
contagion	DIVISION	0.17	
contagion	MESH	0.66	**
contagion	SPLIT	0.17	
contagion	AI	0.43	**
contagion	PLADJ	0.51	**
connectivity	LPI	-0.15	
connectivity	CONNECT	-0.45	**
connectivity	COHESION	0.47	**
patch size distribution	AREA.MN	0.54	**
patch size distribution	AREA.MD	0.10	
patch size distribution	AREA.SD	0.64	**
patch size distribution	AREA.CV	0.65	**
patch based configuration	LSI	0.72	**
patch shape	SHAPE.MN	0.29	**
patch shape	SHAPE.MD	0.08	
patch shape	SHAPE.SD	0.37	**
patch shape	SHAPE.CV	0.38	**
patch shape	FRAC.MN	0.14	
patch shape	FRAC.MD	0.19	
patch shape	FRAC.SD	0.20	
patch shape	FRAC.CV	0.21	*
patch shape	PARA.MN	-0.04	
patch shape	PARA.MD	-0.06	
patch shape	PARA.SD	0.16	
patch shape	PARA.CV	0.21	*
patch shape	CONTIG.MN	0.03	
patch shape	CONTIG.MD	0.18	
patch shape	CONTIG.SD	0.16	
patch shape	CONTIG.CV	0.15	
patch shape	GYRATE.MN	0.32	**
patch shape	GYRATE.MD	0.11	
patch shape	GYRATE.SD	0.48	**
patch shape	GYRATE.CV	0.52	**
patch isolation	PROX.MN	0.67	**
patch isolation	PROX.MD	0.80	**
patch isolation	PROX.SD	0.66	**
patch isolation	PROX.CV	0.01	
patch isolation	ENN.MN	-0.79	**
patch isolation	ENN.MD	-0.63	**
patch isolation	ENN.SD	-0.81	**
patch isolation	ENN.CV	-0.33	**

Table 4
Factor loadings for the factors after VARIMAX rotation
The first 5 factors explain 82% of the variance of the original data set

Factor	Pattern metrics	r
1	AREA.SD	0.94
1	PROX.SD	0.90
1	GYRATE.CV	0.90
1	MESH	0.90
1	PROX.MN	0.87
1	AREA.CV	0.87
1	GYRATE.SD	0.86
1	TA	0.83
1	COHESION	0.76
1	AREA.MN	0.74
1	PLADJ	0.68
1	PROX.MN	0.62
1	SHAPE.CV	0.57
2	SHAPE.MN	0.93
2	FRAC.MN	0.89
2	SHAPE.MD	0.88
2	GYRATE.MD	0.82
2	FRAC.MD	0.80
2	GYRATE.MN	0.78
2	AREA.MD	0.65
2	SHAPE.SD	0.61
2	FRAC.SD	0.60
2	ENN.CV	0.31
3	CONTIG.MN	-0.81
3	PARA.MN	0.78
3	CONTIG.MD	-0.74
3	PARA.MD	0.73
3	AI	-0.67
3	FRAC.CV	0.59
4	LSI	0.91
4	DIVISION	0.84
4	LPI	-0.82
4	NP	0.81
4	SPLIT	0.66
4	ENN.SD	-0.65
4	ENN.MN	-0.60
4	CONNECT	-0.56
4	ENN.MD	-0.37
4	PROX.CV	0.29
5	CONTIG.SD	0.95
5	PARA.CV	0.95
5	PARA.SD	0.95
5	CONTIG.CV	0.93

Table 5
Spearman correlation coefficients between the selected variable representing a factor and forest accessibility

Factor	Variable	r
F1	AREA.SD	0.64 **
F2	SHAPE.MN	0.29 **
F3	CONTIG.MN	0.03
F4	LSI	0.72 **
F5	CONTIG.SD	0.16

Table 6
Multiple ANOVA for the three groups

	F	df1	df2	p
Wilks lambda				
0.175	2.721	88	176	0.00 *
Hotelling's T pairwise comparison				
1-2	3.142	44	88	0.00 *
1-3	2.612	44	88	0.00 *
2-3	2.926	44	88	0.00 *

Table 7
Canonic coefficients for the two discriminant functions

Pattern metric	First discriminant function	Second discriminant function
FRAC.SD	326.07	-2171.81
CONTIG.SD	369.88	1154.52
FRAC.MN	-592.17	-103.27
CONTIG.MN	300.09	-223.58
FRAC.MD	90.36	-67.19
SHAPE.MN	45.86	27.37
SHAPE.SD	-38.76	5.22
FRAC.CV	-2.70	22.59
CONTIG.MD	-17.19	2.98
PLADJ	-5.83	8.99
AI	3.45	-9.86
CONTIG.CV	-1.92	-9.06
SHAPE.MD	-4.54	5.39
DIVISION	-2.01	0.90
COHESION	1.65	-0.05
AREA.MD	0.75	0.94
PARA.CV	-0.39	-0.45
SHAPE.CV	0.42	-0.25
CONNECT	-0.17	0.17
PD	-0.21	-0.05
LSI	-0.10	-0.12
AREA.SD	0.16	0.05
AREA.MN	-0.15	0.04
GYRATE.MN	0.08	-0.05
PARA.MN	0.08	-0.05
GYRATE.MD	-0.08	0.01
PARA.SD	0.02	0.06
GYRATE.SD	-0.02	-0.03
GYRATE.CV	0.00	0.05
LPI	0.00	0.04
SPLIT	-0.01	-0.03
AREA.CV	-0.01	-0.01
ENN.CV	0.02	0.00
ENN.MD	-0.01	0.01
ENN.SD	0.00	0.01
NP	0.00	0.01
MESH	0.00	-0.01
PROX.MD	0.00	-0.01
PARA.MD	0.00	0.00
ENN.MN	0.00	0.00
PROX.CV	0.00	0.00
PROX.MN	0.00	0.00
PROX.SD	0.00	0.00
TA	0.00	0.00

10 Figure captions

Figure 1 : Location of the study area in Belgium

Figure 2 : The Flanders region of Belgium overlayed with the hexagons used as sample units

The grey shades are forests.

Figure 3: Illustration of the pareto-rank logic

Landscape b is dominated by landscape c, since landscape c has both a lower value for objective one (that should be minimized) and a higher value for objective two (that should be maximized).

Landscape a scores better on the first objective than landscape b, but scores worse on the second objective. Landscapes a and b are considered not comparable, since neither one dominates the other.

11 Figures

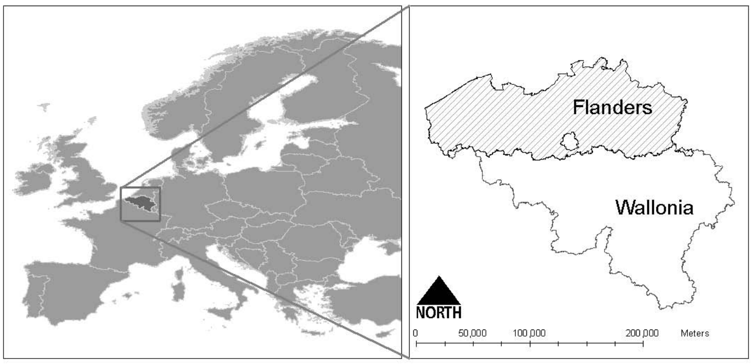

Fig. 1.

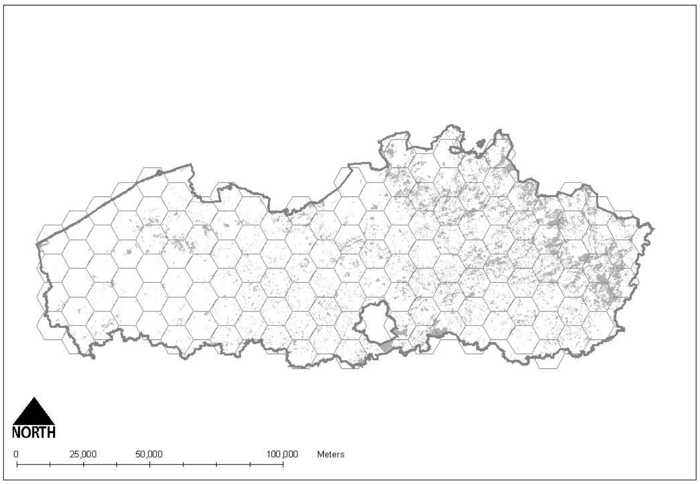

Fig. 2.

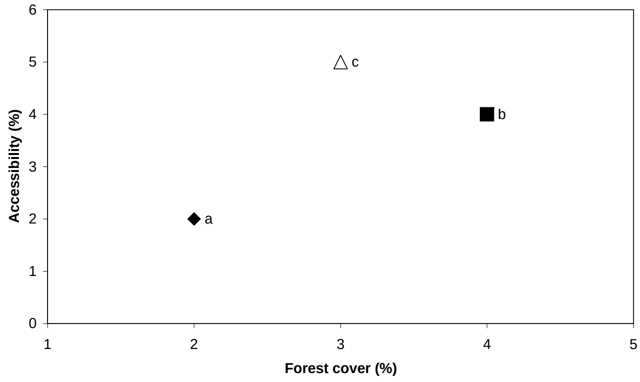

Fig. 3.