Deriving landscape metrics from sample data

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Cover: Non-delineated aerial photograph (upper left), dot grid layer (upper right), the corresponding polygon delineated map (bottom left), and the formula for the unconditional contagion function (bottom right).
(Aerial photo: from NILS)

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Abstract

This thesis focuses on the efficiency of using sampling methods to derive landscape metrics. It also explores what sampling methods are to be preferred for different metrics and how metrics in some cases can be redefined to better suit a sample-based data collection framework.

In paper I, a review was conducted to assess previous research in the area of sample-based assessment of landscape metrics. It was found that only rather few studies have been conducted, but these indicate that data acquisition through sampling appears to be a promising alternative to traditional wall-to-wall mapping.

In papers II and III, point and line intersect sampling (LIS) methods were used to estimate the metrics Shannon's diversity and edge density. Monte-Carlo simulation was employed to investigate the statistical properties in terms of bias and root mean square error (RMSE) of the metrics estimators for different sampling designs. Further, the cost (time needed) of data collection using wall-to-wall mapping and sampling was studied. Both bias and RMSE decreased with increasing sample size, to magnitudes small enough to make sampling a competitive alternative to wall-to-wall mapping. As is commonly the case in sampling, systematic designs were found to be superior to simple random designs. In the case of LIS, longer line transects were superior to short ones and a straight line was more efficient than the other configurations considered.

Papers IV and V address the contagion metric. In paper IV a new definition of the metric for vector data was developed. The definition is distance dependent and also forms a basis for estimating the contagion metric from point sampling data. It was found that a simple negative exponential function could be used as a good proxy function for the unconditional contagion while no such proxy function was found for the conditional contagion metric. The proxy function for the unconditional contagion was found to be strongly related to the area proportion of different land cover types (Shannon's diversity) and to the rate of change of the contagion value over different distances. In paper V sampling simulation was performed to evaluate the properties of estimators for different point sampling designs and distances between point pairs. For the unconditional contagion, the sizes of bias and RMSE were fairly small for sample sizes that could be expected in practice, while the conditional contagion was found to require large sample sizes or otherwise the accuracy of the estimates would be poor. A general conclusion from the studies are that sample-based approaches to landscape metrics estimation are promising for several, but not all, of the metrics commonly applied in landscape ecology. Further, by slightly redefining the definitions for some metrics, it is possible to make them better suited for a sample-based data acquisition framework.

Keywords: point sampling, line intersect sampling, Shannon's diversity, edge density, contagion, landscape metrics, landscape pattern analysis, bias, root mean square error, Monte-Carlo simulation

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Dedication

To ***Maryam*** and ***Alireza***

Contents

List of Publications

This thesis is based on the work contained in the following papers, referred to by Roman numerals in the text:

I Habib Ramezani, Anna Allard, Sören Holm, and Göran Ståhl. (2010). A review of sampling based approaches for estimating landscape metrics (Manuscript).

II Habib Ramezani, Sören Holm, Anna Allard, and Göran Ståhl. (2010). Monitoring landscape metrics by point sampling: accuracy in estimating Shannon's diversity and edge density. *Environmental Monitoring and Assessment* 164:403-421.

III Habib Ramezani and Sören Holm (2009). Sample based estimation of landscape metrics; accuracy of line intersect sampling for estimating edge density and Shannon's diversity index. *Environmental and Ecological Statistics (in press)*

IV Habib Ramezani and Sören Holm. (2010). A distance dependent contagion functions for vector-based data (Submitted).

V Habib Ramezani and Sören Holm. (2010). Estimating a distance dependent contagion function using point grid data (Manuscript).

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1 Introduction

1.1 Background

Human activities such as forest management and farming, along with natural events such as fire, storms, and floods have caused widespread land use changes and landscape fragmentation. Loss of biodiversity may be a consequence of such changes (Lindborg and Eriksson, 2004; Hanski, 2005). Landscape changes may also contribute to climate change when forested area is converted to farmlands (Copeland et al., 1996; Stohlgren et al., 1998; Pyke, 2004). The current patterns of landscapes are the result of interactions of physical, biological, and social factors (Milne, 1991). Landscapes therefore are dynamic systems, which change over time. In order to manage landscapes in sustainable ways and monitor the development there is a need for reliable information. Hence, many countries have now established or are in the process of establishing monitoring programs that provide landscape information, for instance, the Norwegian 3Q Monitoring Program (NIJOS, 2001) and the National Inventory of Landscapes in Sweden (NILS)(Ståhl et al., 2010).

Landscape structure is of primary interest for landscape ecologists since a fundamental assumption is that the structure of landscapes significantly affects many ecological processes (Risser et al., 1984; van Dorp and Opdam, 1987; Turner, 1989; Turner, 1991; Pickett and Cadenasso, 1995; Kie et al., 2002; Turner, 2005a). Landscape ecology attempts to understand such pattern-process relationships (Fortin and Agrawal, 2005; Turner, 2005b; Leitão et al., 2006) and Haines-Young (2005) states that landscape structure can be treated as a predictor variable in assessing many ecological processes. Influence of landscape structure on ecological processes, especially on plant species, has been studied by several authors (Harrison et al., 2001;

Hernandez-Stefanoni and Ponce-Hernandez, 2004; Hernandez-Stefanoni, 2005, 2006; Kumar et al., 2006; Hernandez-Stefanoni and Dupuy, 2008)

There are several definitions of the landscape concept (Farina, 2006). For instance, Forman (1995) has defined landscape as a heterogeneous land area composed of a cluster of interacting ecosystems that is repeated in similar form throughout; landscape is defined by Green (1996) as a particular configuration of topography, vegetation cover, land use which delimits some rationality of natural and cultural processes; Haber (2004) has defined landscape as a piece of land which we perceive comprehensively around us, without looking closely at single components. Relevant landscape sizes differ for different organisms and there is no unique size for a landscape. Rather, the size of a landscape depends on what phenomena are considered (McGarigal and Marks, 1995).

There are two general model approach of landscape structure; the patch-mosaic model (Forman, 1995) and the gradient-based model (McGarigal and Cushman, 2005; McGarigal et al., 2009). Under the patch-mosaic model, landscape structure is as a mosaic of patches (landscape elements); a patch is defined as a homogeneous area that differs from its surroundings. With this model, discrete boundaries (edges) constitute borders between different land cover/use types. The model is frequently used in landscape pattern analysis and meta-population modeling is a typical example of this model in ecological research. Unlike the former model the gradient-based model assesses landscape properties to change continuously over space, i.e., there are no explicit boundaries between patches. The patch-mosaic model is widely applied in practice since landscape structure can be simplified and represented by categorical maps, e.g., land cover/use maps, and the model is a basis for many frequently applied software such as FRAGSTATS (McGarigal and Marks, 1995).

For research, monitoring, and management there is a need for methods that describe landscape structure in meaningful ways. Whereas direct measurement of landscape structure is difficult (Traub and Kleinn, 1999), quantification of landscape structure by means of landscape metrics has become a common approach in landscape surveys (e.g., O'Neill et al., 1988; Turner and Ruscher, 1988; McGarigal and Marks, 1995; Gustafson, 1998). In such procedures, patches (landscape units) are treated as the basic elements for calculating metrics based on measurable patch attributes such as size, number, length of borders between patches (edge length), and space among patches. The metrics can capture both composition and configuration aspects of landscape structure. Composition refers to the abundance of different types of land cover/use types. Configuration refers to how these types are geographically arranged within the landscape.

Landscape structure analysis through metrics provides useful information for many applications. For instance, metrics serve as tools in environmental monitoring programs (Hunsaker et al., 1994; Frohn et al., 1996; Sachs et al., 1998; Chuvieco, 1999; Schuft et al., 1999; NIJOS, 2001; Ståhl et al., 2010). They also act as the quantitative linkage between landscape structure and ecological processes as well as species abundances (Krummel et al., 1987; Bunnell, 1997). Landscape metrics allow for comparisons between different regions or studies of time trends (Tinker et al., 1998; Ji et al., 2006). They provide information useful for biodiversity assessment at the landscape level (Benitez-Malvido and Martinez-Ramos, 2003; Bebber et al., 2005), for analyzing fragmentation, and connectivity of landscape units (Schumaker, 1996; With et al., 1997; Hargis et al., 1998).

Despite the widespread utilization of landscape metrics they have some limitations. For instance, a single metric cannot capture all aspects of landscape structure (Turner, 2005b) and a metric may have the same numerical value for different structures (Tischendorf, 2001). Landscape metrics often are sensitive to thematic resolution (number of land cover types) (Bailey et al., 2007) and spatial scale (i.e., pixel size and extent) (Turner et al., 2001), and classification errors (Hess, 1994; Wagner and Fortin, 2005; Hoechstetter et al., 2008). Interpretation of some metrics is often difficult (Gustafson, 1998) and qualitative changes in landscapes may not be recognized by the metrics (Wickham et al., 1997; Turner et al., 2001).

Quantification of landscape structure through metrics is commonly conducted on land cover/use maps of entire landscapes, i.e., wall-to-wall mapping, which are frequently based on remotely sensed data (e.g., O'Neill et al., 1988; Hunsaker et al., 1994; Wu et al., 2002; Li et al., 2005). This has been simplified by recent advances in computer processing and geographic information system (GIS). To derive landscape metrics from mapped data of entire landscapes, software such as FRAGSTATS (McGarigal and Marks, 1995) and The Patch Analyst (Elkie et al., 1999) are commonly applied. In some cases, however, complete land cover maps may not be available. Furthermore, land cover/use maps based on low or medium-resolution satellite images (e.g., Landsat TM and SPOT) may have low overall accuracy (Fang et al., 2006). Although high spatial resolution satellite imagery, for instance, QuikBrid and IKONOS, can provide detailed information there are also constraints in using these data sources. Restrictions, include a large amount of data to store, costs (Wulder et al., 2004; Lu and Weng, 2007; Gardner et al., 2008), and cloudy conditions, in particular in mountainous areas (Ihse, 2007).

As mentioned earlier, wall-to-wall land cover/use maps are frequently employed in landscape ecological surveys. However, it should be noted that land cover and land use refer to different characteristics of the landscape. Whereas land cover describes natural and man-made features that can be observed on a landscape, land use refers to how people use the land. Land cover maps are often made by remotely sensed data such as satellite imagery and aerial photographs. Land use maps, however, cannot be extracted from remote sensing data since the interpretation of land use from remotely sensed data can be problematic. Hence, there is a need for reference data like field survey.

In the commonly applied wall-to-wall mapping approach to quantify landscape structure, at the first step all potential polygons are delineated on remotely sensed data. Manual or automated delineation methods are used for this purpose. The former method is not only time-consuming (Corona et al., 2004) but it is also a subjective method. The latter one is often associated with problems such as merging two dissimilar adjacent polygons into one, or conversely, dividing a large polygon to two small ones (Wulder et al., 2008). In addition, overall time (for delineation and correction) may be large if an inappropriate automated technique is chosen. However, an alternative to the wall-to-wall mapping approach would be to use sample data. It is known from many different areas of application that sample data, rather than census data, would often be preferred when all relevant aspects of planning, data acquisition, and estimation are simultaneously considered.

The above issues are the main motivations for exploring the usability of sampling methods in landscape metrics estimation as an alternative to the common wall-to-wall based approaches. Generally, in sample surveys, data are collected at low cost and sampling may also provide more accurate results, since assessments can be carefully conducted at a small number of sampling units such as points, lines, or plots (Freese, 1962; Raj, 1968; Cochran, 1977). Moreover, sample surveys can cover large areas and more variables can be assessed (Sorensen et al., 2002). Several studies are emerging where the potential of using this type of data for landscape metrics estimation is investigated (Hunsaker et al., 1994; Kleinn, 2000; Kleinn and Traub, 2003; Corona et al., 2004). For instance, Corona et al. (2004) found that some characteristics of landscapes can be estimated at low cost and that the results in general will be accurate, provided that the sample sizes are large enough. Kleinn (2000) demonstrated that landscape metrics can be derived from field-based forest inventory, allowing the use of existing data from large scale monitoring programs. Issues of data acquisition and accuracy assessment become more critical in landscape ecology (Wu and Hobbs, 2002) due to landscape ecological surveys being conducted at large scale (e.g., regional and national levels). Danielsen et al. (2003) point out that large scale monitoring programs are costly and are often terminated to budget limitation.

1.2 Overview of patch-mosaic-based landscape metrics

Landscape metrics were first used in the 1980s to describe landscape structure. These metrics have been developed for patch, class, and landscape levels (McGarigal and Marks, 1995). While patch level metrics are computed for every patch in the landscape, class and landscape level metrics are calculated for individual land cover/use types and all patches in the pattern are considered. It is important to note that landscape level is limited by the size of the landscape (King, 2005) and this property can be varied depending on ecological processes or organisms under investigated. We consider some important metrics of both composition and configuration that are commonly used in the quantification of landscape structure. It should be noted that not all landscape metrics can easily be classified into either of the categories. For example, mean patch size and patch density of a particular land cover/use type reflect both the amount of a land cover/use type present (composition) and its spatial distribution (configuration) (McGarigal and Marks, 1995). However, these two general categories are frequently accepted and often applied by landscape ecologists.

1.2.1 Composition metrics

These metrics refer to the variety and abundance of different land cover types within a landscape, but disregard the spatial character and position of patches in the landscape. Metrics of this group are often applicable at landscape level. Below, some commonly applied examples are described.

Proportion (p) of a certain land cover/use type in a landscape is fundamental composition metric and is defined as

$$p_i = \frac{a_i}{A} \qquad (1)$$

where a_i is the area of land cover/use category *i* and *A* is the total area of the landscape. The proportion is often correlated with aspects of pattern such as patch size, length of edge, and the number of patches in a landscape (Gustafson and Parker, 1992; Turner et al., 2001).

Shannon's diversity index (H) refers to both the number of land cover/use types and their proportions in a landscape. The index is defined as

$$H = -\frac{\sum_{i=1}^{s} p_i \cdot \ln p_i}{\ln(s)} \qquad (2)$$

where *s* is the total number of land/use types in the classification system or the number present. The index value ranges between 0 and 1. A high value shows that land cover types present have roughly equal proportion whereas a low value indicates that the landscape is dominated by one land cover type.

Simpson's diversity index (S) (McGarigal and Marks, 1995; Herzog and Lausch, 2001) is an alternative to Shannon's diversity. The index is defined as

$$S = 1 - \sum_{i=1}^{s} p_i^{\,2} \qquad (3)$$

Its value ranges between 0 and 1. A high value indicates that the number of land cover types is high and that they have roughly equal proportion whereas a low value indicates that the landscape is dominated by a single land cover type. This index, unlike Shannon's diversity, is more sensitive to rare cover/use types.

Total core area (TCA) (McGarigal and Marks, 1995) is the interior area of a given land cover type after a user-specified edge buffer is eliminated. It is defined as

$$TCA = \sum_{k=1}^{n} c_k \qquad (4)$$

where c_k is the core area of the k th patch of a certain land cover/use type, and *n* is the number of patches. The value of *TCA* is ≥ 0.

Edge density (ED) refers to the amount of edge length per unit area. An edge is defined as the border between two different land cover types. Edge density is a robust metric and can be applied as a measure of fragmentation (Li et al., 1993; Saura and Martinez-Millan, 2001). ED is defined as

$$ED = \frac{e}{A} \tag{5}$$

where e is the total edge length and A is total area. In a highly fragmented landscape there are more edges and response to these changes depending on the species under consideration. Edge length is an image resolution-dependent metric. In high resolution images the total edge lengths tend to be longer compared to those in coarse resolution images.

1.2.2 Configuration Metrics

This group of metrics refers to spatial character and position, arrangement or orientation of patches within a certain class or the whole landscape. Some important metrics of this group are considered below.

Contagion (C) was first proposed by O'Neill et al. (1988) and later by several authors (e.g., Turner, 1989; Turner et al., 1989; Turner, 1990; Graham et al., 1991; Gustafson and Parker, 1992) as a measure of clumping or aggregation of patches. This index is highly correlated with indices of diversity and dominance (Riitters et al., 1995; Cain et al., 1997); it is defined as

$$C = 1 + \frac{\sum_{i=1}^{s}\sum_{j=1}^{s} p_{ij} \cdot \ln p_{ij}}{2 \cdot \ln(s)} \tag{6}$$

where p_{ij} is the probability that two randomly chosen adjacent pixels belong to land cover type i and j, respectively, that is, $p_{ij} = p_i \cdot p_{j/i}$ and s is the number of land cover types in the system or in the landscape. Values for contagion range from 0 to 1. A high contagion value is characteristic of a landscape with few large continuous patches, while a low value of C indicates a fragmented landscape with many small patches. Although contagion is not defined as a measure of fragmentation, it is indirectly related to fragmentation (Moilanen and Nieminen, 2002). For instance, Hargis et al. (1998) found that there is a substantial negative correlation between contagion and edge density metrics.

Heterogeneity index (Hix) was developed by the monitoring program 3Q in Norway (Fjellstad et al., 2001). The index is defined as

$$Hix = 1 - \frac{\sum_{i=1}^{n} \sum_{\substack{j=1 \\ i \neq j}}^{n} w_{ij} \cdot c_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \qquad (7)$$

where w_{ij} is a binary weight set to 1 if *i* and *j* are neighbours, otherwise 0; and c_{ij} is the binary similarity index set to 1 if *i* and *j* are identical, otherwise 0. *Hix* is 1 in a heterogeneous landscape where no two neighbouring points have the same class and 0 indicates a homogeneous landscape.

Mean perimeter-area ratio (MPAR) is the sum of each patch perimeter/area ratio divided by number of patches. It was proposed by Mandelbrot (1977) as mean to compute a fractal dimension of natural planar shapes and is defined as

$$MPAR = \frac{\sum_{k=1}^{n} (p_k / a_k)}{n} \qquad (8)$$

where p_k and a_k are perimeter and area of the kth patch, respectively. Perimeter to area ratio is mathematically easy to calculate; however, it is relatively insensitive to differences in patch shape.

Mean shape index (MSI) is the sum of the patch perimeter divided by the square root of patch area for each patch in the landscape, adjusted by a constant for a circular standard (vector) or square standard (raster), and divided by the number of patches. On raster-based data it is defined as

$$MSI = \frac{\sum_{k=1}^{n} (p_k / 4\sqrt{a_k})}{n} \qquad (9)$$

when all patches are square (grids) the value of *MSI* is equal to one. Shape indices have been applied in wildlife research (Diamond, 1975) and timber management planning (Baskent and Jordan, 1995).

Area weighted mean shape index (AWMSHI) (Saura and Martinez-Millan, 2001) is intended, similar to *MSI,* to measure complexity of patch shape but in *AWMSHI* patch area is used as a weighting factor since larger patches have more effect on landscape structure (Li et al., 1993; Schumaker, 1996).

Square pixel (SqP) was introduced by Frohn (1998) as an alternative to fractal dimension for quantifying shape complexity. It considers the perimeter-area relationship for a raster format data set. SqP is defined as

$$SqP = 1 - \frac{4\sqrt{A}}{E} \tag{10}$$

where A is the total area of the landscape and E is the total edge length. Value of SqP ranges from 0 to 1.

Patch cohesion (PC) index was developed by Schumaker (1996) to quantify the connectivity of patches of the same land cover/use type (class). It is defined as

$$PC = \left[1 - \frac{\sum_{i=1}^{n} p_i}{\sum_{i=1}^{n}(p_i \cdot \sqrt{a_i})}\right] \cdot \left[1 - \frac{1}{\sqrt{A}}\right]^{-1} \tag{11}$$

where a_i and p_i are the area and perimeter of patches of the class i, respectively. Its value ranges between 0 and 1. A low value shows that patches of given class are isolated while a high value (close to 1) indicates a single patch for a given class. Schumaker (1996) found *PC* to be more relevant than other metrics in surveys of animal population dispersal.

Proximity index (PROX) (Gustafson and Parker, 1992; Gustafson and Parker, 1994) is the sum of the ratio between area and nearest neighbor edge-to-edge distance for all patches within a predefined buffer distance around a patch. *PROX* is defined as

$$PROX = \sum_{i=1}^{n}\left(\frac{a_i}{d_i}\right) \tag{12}$$

where a_i is patch area and d_i is distance to the nearest patch of the same land cover type. Different forms of this metric have been developed, for instance, by Hokit et al. (1999) and Hanski (1999). From a biological perspective, this metric reflects the number of habitat sources that are adjacent to a patch as a function of their sizes and distances (Bender et al., 2003).

1.3 Gradient-model based landscape metrics

The gradient landscape model is only recently introduced and not many studies are reported. In a gradient model, environmental properties change continuously and landscape heterogeneity is represented as a surface. The metrics reported so far have focused on the topography and less on patch-based metrics. One advantage is that the model contains topographic characteristics such as slope and elevation, which play a critical role in ecosystem functioning and structuring (Hoechstetter et al., 2008). This model is beginning to emerge in landscape structure analysis and McGarigal (2005) states that in such procedures a primary concern is to develop relevant metrics. For this purpose, techniques such as surface metrology, fractal analysis, and wavelet analysis have been proposed by McGarigal (2005). These techniques were first developed and applied in physical science for describing three-dimensional structures. The techniques have recently been applied in landscape structure analysis (Hoechstetter et al., 2008; McGarigal et al., 2009) for complete mapping. Similar to the patch-mosaic model, both non-spatial and spatial metrics can be defined for the gradient landscape model.

1.4 Advantages and disadvantages of the two landscape structure models

Although the patch-mosaic model has weaknesses in the representation of spatial heterogeneity of landscape, the model has many applications, for instance, in human-dominated landscapes where sharp borders have been produced by human activities. In the patch-mosaic model the number of land cover types to be represented and the smallest patch sizes are arbitrary (subjectively) determined. As mentioned earlier, an alternative to the patch-mosaic model is the gradient-based model where the landscape can sometimes be more realistically represented. The gradient-based model appears to be appropriate to describe landscape structure where patch boundaries cannot be defined well, such as for a savanna landscape (Price et al., 2009) or where topographic features of land need to be considered (Hoechstetter et al., 2008). In addition, this model, unlike the patch-based, doesn't suffer from patch delineation errors. In both models there is a need for a set of metrics in order to capture all aspects of landscape structure and the choice of appropriate model depends on the landscape and the ecological processes or species under consideration.

1.5 Scale

Landscape heterogeneity is scale-dependent (Quattrochi and Pelletier, 1990). This means that the representation of a landscape may be heterogeneous at one scale but homogenous at another. Spatial scale has three components; extent, grain, and minimum mapping unit (MMU). Extent is defined as the total area to be studied and grain is the smallest recognizable feature (Turner et al., 2001). MMU is defined as the smallest area that will be mapped as a discrete unit (Fassnacht et al., 2006). Several studies have been conducted on the characteristics of landscape structure with changing spatial scale. Saura (2004) showed that patch density, edge length, and mean patch size metrics are sensitive to spatial resolution (grain), hence it is recommended that landscape metrics derived from maps with different resolution should not be compared. Saura (2002) demonstrated that metrics of mean patch size and number of patches are very sensitive to the MMU. Turner et al. (1989) showed that rare (small) land cover types can be lost as grain become bigger and that values of contagion metrics increase with increasing extent. It is recognized that there is close relationship between scale and classification systems (Loveland et al., 2005). Saura and Martinez-Millan (2001) found that shape complexity metrics such as the mean shape index is sensitive to spatial extent.

1.6 Classification

In large scale ecological surveys, categorical maps (e.g., land cover/use maps) based on remote sensing are often used as a basis for the analysis (Kumar et al., 2006). Since any map derived from remotely sensed data can be associated with classification error, then any subsequent analysis, for instance landscape structure quantification, will depend on these errors (Gergel, 2007). Several surveys have been conducted to evaluate the impact of this error on metric values (Hess and Bay, 1997; Brown et al., 2000; Shao et al., 2001; Shao and Wu, 2004; Langford et al., 2006; Shao and Wu, 2008). A general conclusion is that landscape metrics can accurately be derived only from categorical maps with high accuracy.

Accuracy of categorical maps is commonly assessed in an error matrix. With this matrix, misclassifications between different categories are assessed. Accuracy is expressed in terms of user's, producer's, and overall accuracies. The error matrix can also represent commission errors (error of inclusion) and omission error (errors of exclusion). A commission error is defined an as area into a class when it does not belong to that class and an omission error is excluding that area from the class to which it belongs. A detailed description of the error matrix and its potential applications can be found in Congalton and Green (1999).

2 Data acquisition approaches

Since landscape surveys usually deal with large areas (e.g., regional or national levels) data acquisition is a main concern. For example, Kumar et al. (2006) state that due to economic and time restrictions only a small fraction of any landscape is measurable. The required data to assess landscape structure can be obtained from a variety of sources, including field sampling, topographic maps, aerial photos, and satellite images. As has been pointed out, remote sensing systems are frequently used sources of data (Gergel and Turner, 2002). Different remote sensing systems and three sampling approaches, frequently used in forestry and ecological surveys, are briefly described below.

2.1 Remote sensing

Remote sensing is defined as a technique of obtaining information about objects under investigation without contact with these subjects (Schreuder et al., 2004; Lillesand et al., 2008). Since remotely sensed data can be collected in multiple spatial and temporal scales it is an important data source for landscape ecology application. Remotely sensed data along with geographical information systems (GIS) has facilitated many studies of landscape structure (e.g., Iverson et al., 1989; Roughgarden et al., 1991; Narumalani et al., 2004; Yang and Liu, 2005). These tools can provide information on size, number, type, and space between patches in a landscape. Passive and active sensors are two commonly used remote sensing systems. They can be mounted on either air-borne or space-borne platforms.

2.1.1 Passive sensors

This group of sensors detects energy (sunlight) that is reflected by the objects on the earth. Passive sensors are dependent on weather and light conditions (Aronoff, 2005). Aerial photographs and optical satellite images are two typical examples of this group, which are frequently applied in landscape structure surveys.

Satellite images

Satellite imagery is considered a very useful tool in landscape research, since it provides a digital mosaic of the spatial arrangement of land cover types in a landscape. Data from the Landsat and SPOT satellites have been adopted in ecological studies (O'Neill et al., 1988; Wu et al., 1997; Turner et al., 2001; Cardille et al., 2005; Ferraz et al., 2005; Yemefack et al., 2006). Another satellite-based data source is QuickBird, which provides images with high spatial resolution (0.61m) (Lillesand et al., 2008). Satellite-based maps are consistent with tools such as FRAGSTATS, which was established for landscape pattern analysis through landscape metrics (McGarigal and Marks, 1995). A rapid technological advance, increasing spatial resolution, good coverage, increased access to satellite images, the ability to electronically store data, and high temporal resolution have contributed to the widespread use of satellite data in natural resource monitoring programs.

Aerial photography

Aerial photos are acquired from aircraft flying at altitudes typically ranging from 500-10000 (m) and generally collect data at finer spatial resolution than satellites. Due to the high spatial resolution, some landscape characteristics, such as edges (i.e., border between two different land cover types), can be accurately recorded (Naesset, 1998) and also leads to detecting detailed information of forest patches (Holmgren et al., 1997). Aerial photographs have been used in national environmental monitoring programs (NIJOS, 2001; Ståhl et al., 2010) and it is a frequently used source of information for mapping and other applications, such as forest inventory (Hall, 2003). Interpretation of aerial photo data is usually performed using manual methods, although some automated and computer-assisted approaches are nowadays also available (Wulder et al., 2008). With manual methods, criteria of tone, pattern, size, shape, and location are used. The results from manual interpretation are often more accurate than those from an automated approach that often uses mathematical algorithm (Loveland et al., 2005).

In mapping, homogenous areas are first delineated as polygons and then these polygons are interpreted and classified into predefined categories. Manual polygon delineation is slow and costly (Corona et al., 2004), and skilled and experienced photo interpreters are required. Leckie et al. (2003) say, however, that time needed for manual interpretation can considerably be reduced through advanced digital image processing. As long as manual interpretation is based on subjective criteria, the result may vary from one interpreter to another (Kadmon and Harari-Kremer, 1999).

2.1.2 Active sensor

This kind of sensors generates and emits energy and measures the response. Examples of sources of this kind are LIDAR (Light Detection and Ranging) and imaging radar (Radio Detection and Ranging). Such systems can provide three-dimensional information of points on the ground (Naesset et al., 2004). One advantage of active sensors is that they can be operated in many different conditions; generated energy can penetrate forest canopy, and smoke. The LIDAR system lately has become as useful technique in forest inventory applications. The LIDAR appears to be superior to photogrammetric and other remote sensing systems in assessing growing stock and tree height (Magnusson and Fransson, 2010). The system can also provide accurate three-dimensional maps (Lefsky et al., 2002), which can be important data for landscape pattern analysis.

2.2 Field inventory

Despite significant advances in remote sensing, field-based inventory still is a widely used approach, for instance, in natural resource management, ecological surveys, and monitoring programs such as National Inventory of Landscape in Sweden (NILS) (Ståhl et al., 2010). The reasons are that more detailed and reliable information can be obtained. Field inventory can be performed subjectively and/ or objectively and due to cost and operational restrictions it can normally only be used on a sampling basis. Below three frequently used sampling methods are briefly described.

2.2.1 Point sampling

Point sampling is a well-known method for estimating some population parameters (e.g., areas) on aerial photographs, maps or directly in the field. In point sampling, data are assessed at the sampling location. Tools such as the global positioning system (GPS) device or a compass and tape enable point sampling in field surveys. Kleinn (2000) demonstrated the possibility of measuring some patch attributes and deriving some landscape metric using a grid of points from field-based forest inventory. In general, estimation with a systematic dot grid in comparison to random sampling yields more precise results (De Vries, 1986).

2.2.2 Line intersect sampling (LIS)

In line intersect sampling observations are conducted along survey lines and objects are sampled when intersected by the line. The method is an efficient and common procedure for surveying linear features such as logging residues, edge lengths, ditches, and roads (Matérn, 1964; Warren and Olsen, 1964; Van Wagner, 1968; Brown, 1971; Schuerholz, 1974; Hansen, 1985; Schreuder et al., 1993; Ringvall, 2000; Dahm, 2001; Corona et al., 2004; Eiden et al., 2005). However, it has many other applications, for instance, it can be used in estimating the areas of two-dimensional objects such as polygons, and the total number of objects (e.g., Battles et al., 1996; Gregoire and Valentine, 2008). In the estimation of total length of linear features, the method relies on the counting of intersections between survey lines and polygon borders (edge). LIS can be implemented either with single straight lines or multiple-segmented transects such as the L-shape as used in Canada, square transects as in NILS (Ståhl et al., 2010), and Y-shape transects as used by the U.S. Forest Service and the National Forest Inventory of Switzerland (Affleck et al., 2005). In many cases, LIS is a cost-efficient alternative to complete assessment (Corona et al., 2004). Efficiency, in term of precision, of line transect configuration depends on the pattern of population elements. In a simulation study, Hazard and Pickford (1986) demonstrated that a multiple-segmented line transect was preferred due to increase of precision in populations where the elements tend to be oriented in the same direction.

2.2.3 Fixed-area plot sampling

This sampling method is a widely used field-based approach in natural resources and environmental surveys (Lindgren, 1984; DeVries, 1986; Schreuder et al., 1993; Levesque, 1996; Thompson, 2002; Dengler, 2008; Dengler and Boch, 2008). This method has also been conducted on raster-based land cover maps in order to estimate some landscape metrics (Hunsaker et al., 1994); further, it has been the dominant method in timber oriented inventories. Depending on the survey objective, the shape of the sample plot may vary. A circular shape is often used in field surveys, although other plot shapes, such as squares or rectangles, may be used (Köhl et al., 2006). For instance, in plant species diversity assessment squares or rectangles shapes are preferred (Keeley and Fotheringham, 2005). Fixed-area plot sampling can be used for all kind of objects such as two-dimensional objects (like polygons), linear features (like felled trees and edges), and particularly when objects are represented by points (standing trees) (Schreuder and Gregoire, 1995). For the purpose of natural resources, a nested-plot design is frequently applied where plots with the same shape but different sizes are often established at each sampling location (Ponce-Hernandez, 2004; Gregoire and Valentine, 2008). The fixed-area method has different advantages, for instance, Schreuder et al. (1987) found that the method is more efficient, in terms of accuracy, for tree density than point and horizontal-line sampling methods. Paulo et al. (2005) demonstrated that fixed-area plot is preferable for estimating non-timber production like cork. The method is recommended in continuous forest inventory and monitoring programs since growth can readily be assessed over time (Scott, 1998).

2.3 Combination of remote sensing and field methods

A combination of field-based inventory methods and remotely sensed data are frequently applied in practice. This combination is termed multi (e.g., two)–stage or two phase sampling design (DeVries, 1986; Schreuder et al., 1993; Corona and Fattorini, 2006). In such procedures the first stage typically is a sample of remotely sensed data (e.g., aerial photos), and in the second stage one or more field sampling methods described previously can be used within each first stage sampling unit (Ståhl et al., 2010). For instance, line intersect sampling was conducted on sampled aerial photos by several authors (Hansen, 1985; Eiden et al., 2005; Esseen et al., 2006) to assess linear features in the landscape. LIS was also applied on aerial photos to estimate area of gaps in a forest landscape. Hunsaker et al. (1994) applied large plot sampling on satellite-based land cover maps in estimating landscape metrics. The advantage of this type of sampling design, particularly in a large scale survey, is that it may provide estimates of a given precision at less cost (Freese, 1962).

In general, in sample surveys a small fraction of the target population is sampled for the estimation of population parameters such as total and mean. The survey can be conducted objectively and/or subjectively. Whereas the latter is usually surveyor-dependent (Ståhl, 1992) the former one relies on statistical theory and thus it is possible to estimate the precision of estimates.

For a given parameter there may be several sampling strategies (sampling design and type of estimator) and from a statistical point of view the strategy with low variance and an unbiased estimate is preferable. Variance refers to the mean squared deviation of all possible estimates and expected values, and unbiasedness means that the difference between true and expected values is zero (Raj, 1968; Wonnacott and Wonnacott, 1990). Monte-Carlo simulation is an appropriate approach to assess statistical performance of estimators. The simulation has frequently been applied to study the statistical performance of sample based estimators of parameters of relevance for the management and monitoring of natural resources (e.g., Ståhl, 1998; Kleinn and Vilcko, 2006). Units of sampling such as points, lines and plots can be distributed systematically and or completely at random over the area of interest.

Sample survey has several advantages, for instance, it takes less time than a complete census; it is possible to achieve more accurate results using highly trained staff, careful supervision, and a in well-designed and executed sample survey; data can be acquired and analyzed faster, in particular at large scales such as a National Forest Inventory (NFI) (Raj, 1968; Cochran, 1977).

3 Objectives

The main objective of this thesis was to investigate the efficiency of using sampling methods to derive landscape metrics. Further, it was to be explored what sampling methods are preferable, in terms of cost and accuracy, for selected landscape metric. These metrics have been used in several studies and found to be of ecological relevance. Thus, this thesis focuses on sampling properties of selected metric estimators without assessing the ecological significance of the metrics. In the different studies the specific objectives were:

- In paper *I* the objective was to review previous literature about sample-based assessment of landscape metrics.
- In papers *II-III* the statistical performance (in terms of RMSE and bias) of Shannon's diversity and edge length/density estimators were evaluated. Two basic sampling methods, point sampling and line intersect sampling (LIS), were applied.
- In paper IV the main objective was to develop a new definition of contagion for vector-based data. Also, the properties of the new definition were investigated.
- In paper V the objective was to assess statistical properties (RMSE and bias) of the contagion estimators for different point sampling designs.

4 Summary of papers

4.1 Material and methods

4.1.1 Paper I

This literature review was carried out in order to assess previous experiences of advantages and disadvantages of sampling based approaches for assessing landscape metrics. Papers published in international journals indexed by Web of Knowledge (WoK) were searched for. The search criteria were "landscape metrics", "sampling methods", and "quantifying landscape pattern" in the title, abstract, and key words in the papers. The search was also conducted in the reference lists of available papers. The review largely encompasses papers from the two past decades; the first paper on sample based assessment of landscape metrics was published in the 1990's. Much attention has been paid to point, line intersect, and plot sampling methods. Findings of previous studies and some theoretical assessment are given in the result section.

4.1.2 Paper II-III

In the sampling experiment studies (i.e., in papers II, III and V) in order to assess statistical properties of metric estimators a large number of samples were taken on already delineated maps. Sampling simulation (Monte-Carlo) was performed for different combinations of factors depending on selected metric and the sampling method employed. Below details of the combinations are described.

In studies II and III the objective was to examine statistical properties (RMSE and bias) of Shannon's diversity and edge length/density estimators. In these studies, 50 $1km^2$ already delineated quadrats from NILS, the National Inventory of Landscape in Sweden, were used. The landscapes quadrats were distributed across Sweden and were selected from different landscapes (see Fig. 1). Both true and estimated values of these metrics were calculated through a computer program which was written (in FORTRAN) specifically for this purpose. A study about time required to measure patch attributes was conducted on a few randomly selected, non-delineated (raw) aerial photographs. For this purpose a skilled photo interpreter from the NILS program was employed. These quadrates were used in papers II to V.

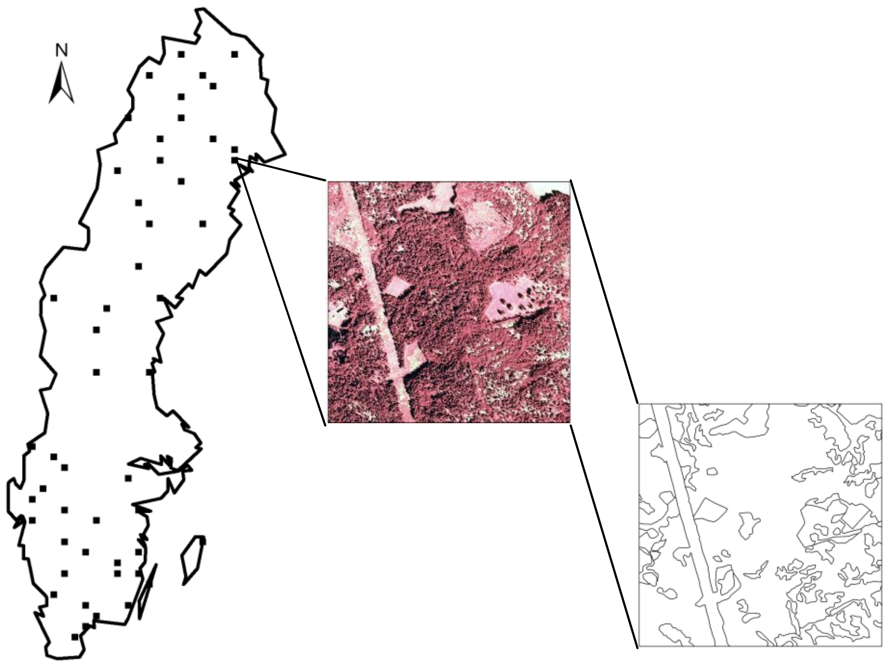


Figure 1. Illustration of distribution of 50 NILS's quadrates and an example of 1 km^2 aerial photograph and corresponding delineated map.

In the case of point sampling (*paper II*), for both metrics, sampling simulation was conducted for all combinations of four sample sizes (49, 100, 225, and 400), two sampling designs (random and systematic), and two classification systems (7 and 20 classes). In addition, for edge length, simulations were implemented for five (virtual) buffer widths (5, 10, 20, 40, and 80 m) where the width of the buffer generated around patches was used as a means for measuring edge length. The classification systems with two levels are described in Table 1.

Table1. *Classes according to the two different classification systems (with 7 and 20 classes)*

Level 1 (Seven classes)	Level 2 (Twenty classes)
1- Forest	1-1- Coniferous-Dense
	1-2- Coniferous-Sparse
	1-3- Deciduous-Dense
	1-4- Deciduous-Sparse
	1-5- Mixed-Forest- Dense
	1-6- Mixed-Forest- Sparse
2- Urban	2-1- Housing-Areas
	2-2- Urban-Green-Areas
	2-3- Urban-Forest
3- Cultivated fields	3-1- Crop fields
	3-2- Grassland
4- Wetlands	4-1- Bog
	4-2- Fen
	4-3- Mixed-Wetland
5- Water	5-1- Open-Water 5-2- Water-Vegetation
6- Pasture	6-1- Open- Pasture
	6-2- Pasture-Sparse-Trees
	6-3- Wooded-Pasture
7- Other land	7- 1- Other land

The estimator of Shannon's diversity index, H , was

$$\hat{H} = -\frac{\sum_{j=1}^{s} \hat{p}_j \cdot \ln(\hat{p}_j)}{\ln(s)} \tag{13}$$

where *s* is the total number of land cover types considered (assumed to be known) and

$\hat{p}_j = \frac{1}{n}\sum_{i=1}^{n} y_i$ is the estimator of area proportion of the jth land cover type; y_i takes the value 1 if the *i*th sampling point falls in the jth land cover type and 0 otherwise.

To estimate the edge length of a certain land cover type or total edge length, rectangular (virtual) buffers with fixed width *d* were generated around patch borders on both sides (Fig. 2). The proportion of sampling points within the buffer area can be utilized for edge length estimation, as shown below. If a sampling point was located within distance *d* from an edge, then this was recorded together with the land cover type of the patch on the other side of the boundary.

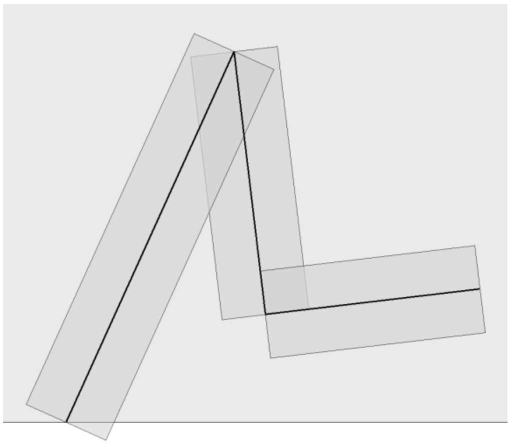


Figure 2. Patch borders and generated buffer on both sides. This layout illustrates the method used for the estimation of edge length and edge density.

For a given land cover type j, the buffer area B_j inside area A, can be estimated by

$$\hat{B}_j = \hat{p}_j \cdot A \qquad (14)$$

where $\hat{p}_j$ is the estimator of the buffer area proportion. The length L_j of the edge of the land cover type j is then estimated by

$$\hat{L}_j = \frac{\hat{B}_j}{2d} = \hat{p}_j \cdot \frac{A}{2d} \qquad (15)$$

The estimator $\hat{L}_j$ underestimates the true length since parts of rectangles close to the map border are outside the map, and no sampling point will fall there. In order to eliminate or reduce the bias three methods were used; i) Richardson extrapolation (Freese, 1962), ii) Reflection method (Schreuder et al., 2004), and iii) External buffer zone (Gregoire and Valentine, 2008).

In the LIS case (*paper III*) sampling simulation was conducted for all combinations of five line intersect configurations (Fig. 3), two sampling designs (random and systematic), two classification schemes (7 and 20 classes), four sample sizes (16, 25, 49, and 100), two transect orientations (fixed and random), and three different lengths of the total sampling lines per configuration (37.5, 75, and 150 m).

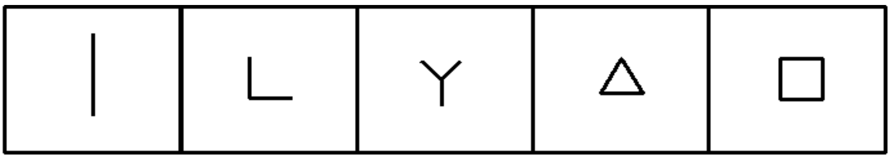


Figure 3. Illustration of the five line transect configurations applied in this study

For LIS, estimation of Shannon's diversity was based on the proportion of the length of line transects within a certain land cover type to total length of all line transects. The edge length estimation was based on the method of Matérn (1964) where edge length can be estimated without bias by simply counting the number of intersections between patch borders and line transects.

According to Matérn (1964), the total edge length estimator $\hat{T}$ (m ha^{-1}), using multiple sampling lines of equal lengths, is given by

$$\hat{T} = \frac{10000 \cdot \pi \cdot m}{2 \cdot n \cdot l} \qquad (16)$$

where *m* is the number of intersections, *n* is the number of sampling lines, and *l* is total sampling line length.

In both papers *II* and *III* the statistical properties of the estimators were extracted using a large number of independently simulated samples (i.e., Monte-Carlo simulation). The expected value was estimated by the mean over simulations

$$\hat{E}(\hat{Y}) = \frac{1}{M}\sum_{i=1}^{M}\hat{Y}_i \qquad (17)$$

where $\hat{Y}_i$ is the estimated value of the i th simulation and *M* is the number of simulations. The root mean square error, RMSE, was estimated by

$$R\hat{M}SE = \sqrt{\sum_{i=1}^{M}(\hat{Y}_i - Y)^2 / M} \qquad (18)$$

where *Y* is the true value.

In the line intersect sampling case (*paper III*) the following mixed model was used to study the rate of decrease of RMSE with increasing sample size and/or line length

$$z_{ijk} = \mu + c_i + \alpha \ln(n_j) + \beta \ln(l_k) + \lambda u_{jk} + e_{ijk} \qquad (19)$$

Here z_{ijk} is the logarithm of the RMSE for quadrate *i*, sample size *j*, and line length *k*; n_j and l_k are sample size and length; $u_{jk} = (\ln(n_j) - m_n)(\ln(l_k) - m_l)$ where m_n and m_l are the means of $\ln(n_j)$ and $\ln(l_k)$ over the data set; c_i is a random quadrate effect and e_{ijk} is a random error. In paper II a similar model was used.

4.1.3 Paper IV

In this study the aim was to develop new contagion metric which could be applied on vector-based or sample data as opposed to raster-based maps. Both unconditional and conditional definitions of the contagion were considered. The vector-based unconditional contagion metric is defined as

$$C_u(d) = 1 + \frac{\sum_{i=1}^{s}\sum_{j=1}^{s} p_{ij}(d)\cdot \ln(p_{ij}(d))}{2\ln(s)} \quad (20)$$

where p_{ij} is the probability that two randomly chosen points at distance *d* belongs to the classes *i* and *j*, and *s* is the number of land cover types considered or the number of classes present.

The conditional contagion metric is defined as

$$C_c = 1 + \frac{\sum_{i=1}^{s}\sum_{j=1}^{s} p_{j/i}(d)\cdot \ln(p_{j/i}(d))}{s\ln(s)} \quad (21)$$

where the conditional probability $p_{j/i}(d)$ equals $p_{ij}(d)/p_i(d)$, where $p_i(d) = \sum_{j=1}^{s} p_{ij}(d)$. Conditional probability is the probability that the "second point" in a randomly chosen pair of points at distance *d* belongs to class *j*, given that the "first" point belongs to class *i*. Both contagion formulas above (Eqs 20 and 21) are derived from the existing raster-based definitions but are functions of the distance *d* between points.

To calculate contagion for each map a sample of first points was laid out systematically in each polygon, with random start. The number of points in the polygons was based on polygon area. With the point as centre of a circle with radius *d*, the relative lengths of the circumference within all polygons were determined. The mean of all such relative lengths over the systematic sample estimates the local p_{ij} s for the given polygon, and the final global p_{ij} was determined by weighting overall all polygons of class *i*. The study was conducted on 50 vector-based maps of real landscapes and some simulated ones. Point pairs with nine distances 2, 5, 10, 20, 30, 60, 100, 150, and 250 meters were used to assess the statistical behavior of the contagion estimators. Also a non-linear regression analysis was employed to develop an empirical model for the unconditional contagion function.

4.1.4 Paper V

In this study the aim was to assess the statistical properties (RMSE and bias) of the contagion estimators using point sampling. Monte-Carlo sampling simulation was applied. Similar to papers II and III this study was conducted on the 50 $1km^2$ quadrates from NILS (National Inventory of Landscape in Sweden), for which true values where calculated in paper IV. Estimated values of these metrics were calculated through a computer program, which was written in FORTRAN specifically for this purpose.

The contagion functions are those defined by Eqs (20) and (21) in paper IV. The probabilities $p_{ij}(d)$ and $p_{j/i}(d)$ are estimated from a sample of randomly chosen point pairs at distance *d* in the landscape; $p_{ij}(d)$ is estimated by the frequency of points in classes *i* and *j* and $p_{j/i}(d)$ is estimated according to its definition. The estimators $\hat{p}_{ij}(d)$ and $\hat{p}_{j/i}(d)$ are inserted into the defining expressions (20) and (21) to obtain estimators $\hat{C}_u(d)$ and $\hat{C}_c(d)$ of the contagion functions.

Sampling simulation was performed for all combinations of five sample sizes (25, 49, 100, 225, and 400), two sampling designs (random and systematic), the two classification systems (7 and 20 classes), and nine point distances (2, 5, 10, 20, 30, 60, 100, 150, and 250). Estimates were calculated for all classes in the system (7 and 20) and for the number of classes present in the landscape, and with unconditional and conditional contagion definitions. Figure 4 shows an example of the random distribution of point pairs on NILS map.

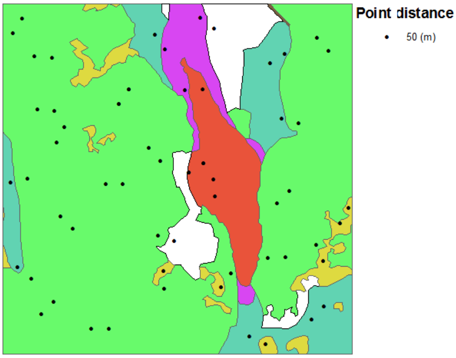


Figure 4. Illustration of random distribution of point pairs on a 1 km^2 NILS vector-based map

4.2 Results and discussion

4.2.1 Paper I

The literature review revealed that derivation of landscape metrics through sampling data has potential advantages and disadvantages. Advantages include, for instance, that some metrics can be extracted at a low cost; that there is the possibility of using existing data materials from ongoing large scale inventories such as National Forest Inventories (NFI); and that there is the possibility of providing more reliable information of landscape structure and to estimate metrics through very careful assessments of a small number of sampling units such as lines in comparison to traditional polygon delineation approach. Disadvantages include that some metrics cannot be estimated; that some metrics may be estimated with bias, particularly ratio-based metrics for patch attributes; and that sample-based assessments require new skills for the practitioner. In general, the review done for Paper I indicates that sampling data seem to be a promising alternative to wall-to-wall mapping. However, very few relevant papers were found, with the reason being that wall-to-wall mapping is the predominantly used data source in the calculation of landscape metrics.

Further studies are needed for the following areas: (i) optimization of sample based inventories from the point of view of landscape metric estimation, (ii) comparisons of different sampling based approaches and wall-to-wall based approaches, where all relevant error sources and costs are included, and (iii) further studies to evaluate if metrics can be redefined to better suit sampling based assessments. Table 2 provides the estimators and type of estimate of a set of metrics using three sampling methods. In general in sample survey, landscape metrics can unbiasedly be estimated when their components can be estimated without bias. In some cases, however, the metric estimator may still be biased despite the components are estimated without bias, for instance, metrics which are a ratio of the components.

Table 2. *Estimators of landscape metrics*

Definition	Name of metric	Sampling methods	Estimator	Property
$p_i = \frac{a_i}{A}$	Proportion	D, L, P	$\hat{p}_i = \frac{\hat{a}_i}{A}$	Unbiased
$PD = \frac{n}{A}$	Patch density	D,P	$\hat{P}D = \frac{\hat{n}}{A}$	Unbiased
		L		–
$ED = \frac{e}{A}$	Edge density	L, P	$\hat{E}D = \frac{\hat{e}}{A}$	Unbiased
		D	$\hat{E}D = \frac{\hat{e}}{A}$	Unbiased under certain assumption
$MSI = \frac{1}{4} \cdot \frac{\sum_{i=1}^{n}\left(\frac{l_i}{\sqrt{a_i}}\right)}{n}$	Mean shape index	D, L, P	$M\hat{S}I = \frac{1}{4} \cdot \frac{\sum_{i=1}^{n}\left(\frac{\hat{l}_i}{\sqrt{\hat{a}_i}}\right)}{\hat{n}}$	Almost Unbiased
$MPAR = \frac{\sum_{i=1}^{n}(\frac{l_i}{a_i})}{n}$	Mean perimeter-area ratio	D, L , P	$M\hat{P}AR = \frac{\sum_{i=1}^{n}(\frac{\hat{l}_i}{\hat{a}_i})}{\hat{n}}$	Almost Unbiased
$MFD = \frac{2}{n}\sum_{i=1}^{n}\frac{\ln(l_i)}{\ln(a_i)}$	Mean fractal dimension	D, L, P	$M\hat{F}D = \frac{2}{n}\sum_{i=1}^{n}\frac{\ln(\hat{l}_i)}{\ln(\hat{a}_i)}$	Almost Unbiased

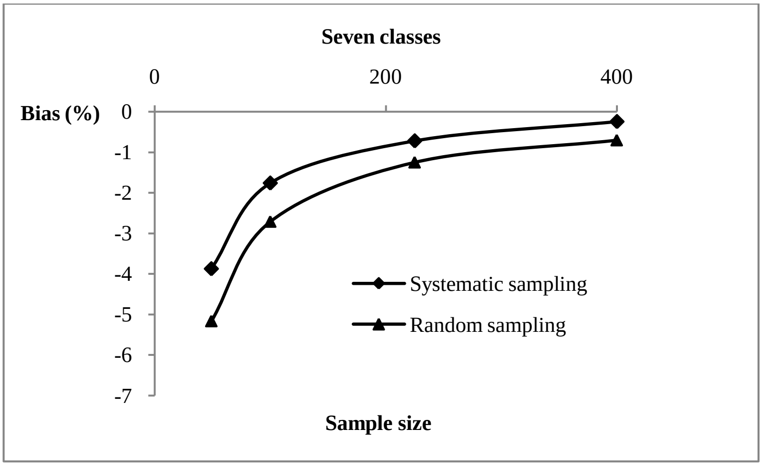
Table 2. *Continued*

Definition	Name of metric	Sampling methods	Estimator	Property
$MPS = \frac{\sum_{i=1}^{n} a_i}{n}$	Mean patch size	D, L, P	$M\hat{P}S = \frac{\sum_{i=1}^{n} \hat{a}_i}{\hat{n}}$	Almost Unbiased
$H = -\frac{\sum_{i=1}^{s} p_i \ln p_i}{\ln(s)}$	Shannon's diversity	D, L, P	$\hat{H} = -\frac{\sum_{i=1}^{s} \hat{p}_i \ln \hat{p}_i}{\ln(s)}$	Biased (even if $\hat{p}_i$ unbiased)
$D = \frac{\ln s + \sum_{i=1}^{s} p_i \ln p_i}{\ln(s)}$	Dominance	D, L, P	$\hat{D} = \frac{\ln s + \sum_{i=1}^{s} \hat{p}_i \ln \hat{p}_i}{\ln(s)}$	Biased (even if $\hat{p}_i$ unbiased)
$C = 1 + \frac{\sum_{i=1}^{s}\sum_{j=1}^{s} p_{ij} \ln p_{ij}}{2\ln(s)}$	Contagion	D, L, P	$\hat{C} = 1 + \frac{\sum_{i=1}^{s}\sum_{j=1}^{s} \hat{p}_{ij} \ln \hat{p}_{ij}}{2\ln(s)}$	Biased
$LPI = \frac{\max_i (a_i)}{A}100$	Largest patch index	D, L, P	$L\hat{P}I = \frac{\max_i (\hat{a}_i)}{A}100$	–

Note: D = Dot grid, L = Line intersect sampling, P = Plot sampling

4.2.2 Paper II

The RMSE and bias of Shannon's diversity for different sample sizes and for two sampling designs is given in Figure 5. Both RMSE and bias decreased with increasing sample size and systematic sampling design showed less RMSE and bias than did random sampling.



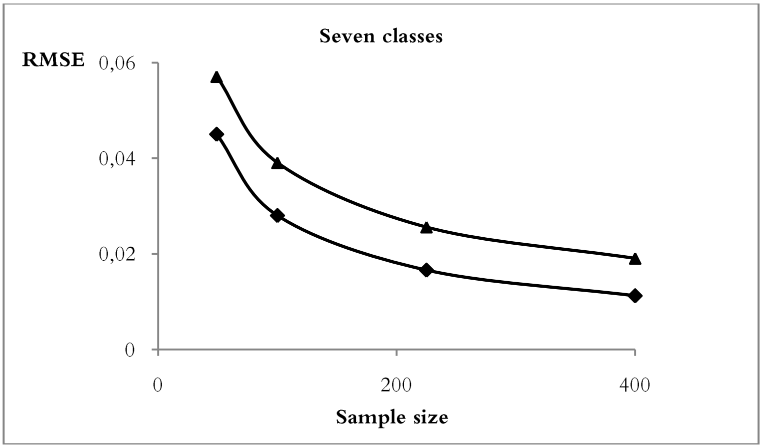
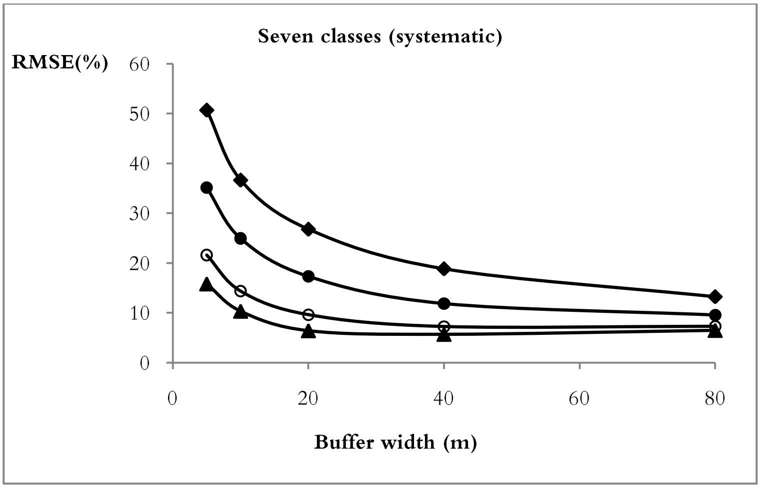


Figure 5. An example of relationships between bias (top) and RMSE (bottom) of Shannon's diversity estimator for different samples sizes.

Similar to Shannon's diversity, the RMSE of the edge length estimator, at a given buffer width decreased as sample size increased and buffer width increased. This resulted in larger bias due to the increased impact of boundary conditions. This effect was shown to be independent of sample size (Fig. 6).



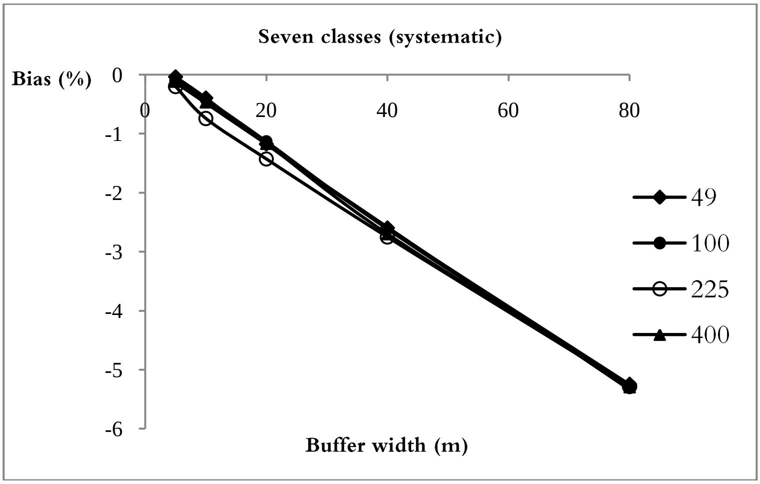


Figure 6. An example of relationships between RMSE (top) and bias (bottom) of the total edge length estimator and buffer width with different samples sizes.

A low accuracy of edge length estimates was obtained in highly fragmented landscapes where the patches had complex shapes. In contrast, high accuracy was obtained in landscapes comprising polygons with simple shapes. The estimators of both metrics produced negative bias. For

Shannon's diversity the bias is due to the nonlinearity in the definition of the estimator. In the case of edge length and density, estimators in theory should provide estimates without bias, although practical concerns introduce boundary-induced bias. In Figure 7 is shown bias of corrected and uncorrected estimators of the total edge density.

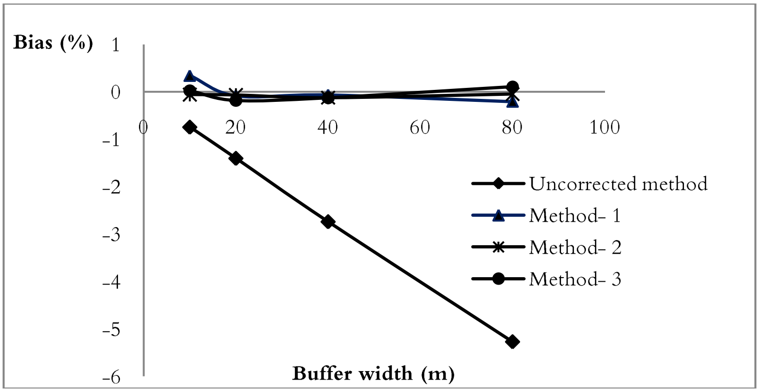


Figure 7. A comparison of bias of the total edge density estimator between the uncorrected method and the three correction methods with different buffer widths.

RMSE vs. cost (time needed to measure patch attributes from aerial photographs) of total edge density, for different buffer widths, is given in Figure 8. The RMSE decreased with increasing buffer width at a given cost. This was true for Shannon's diversity and edge density per certain land cover type estimators.

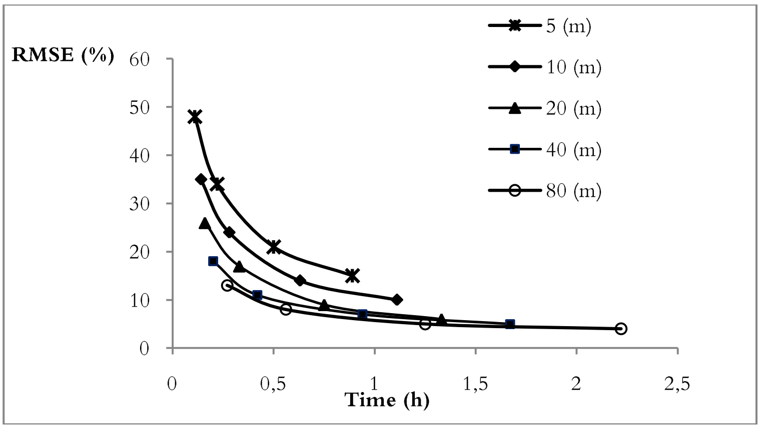


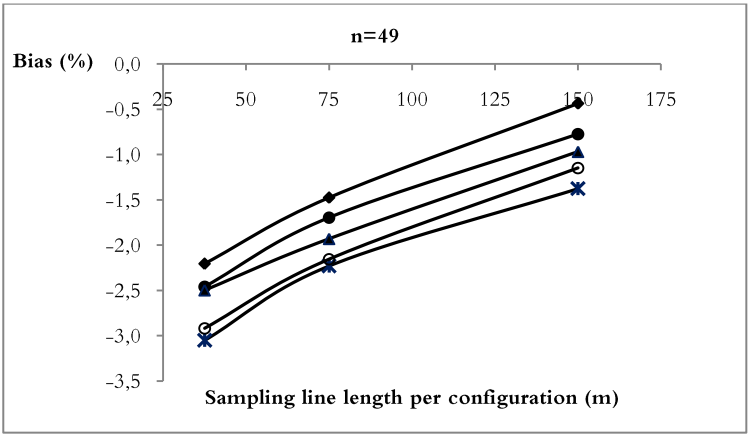
Figure 8. Relationship between time (cost) and the RMSE of the total edge density estimator.

Point sampling can be conducted with high accuracy at a reasonable cost for both metrics. In the case of edge length, the cost was a function of sample size and buffer width, whereas in the case of Shannon's diversity it was just a function of sample size. Times needed were largely dependent on landscape complexity and wide buffer widths were found to be more efficient than narrow ones in estimating edge density.

This sampling method can readily be applied over remote sensing data and in field-based forest inventory (Kleinn, 2000). Furthermore, it is recognized that a given landscape metric can be estimated through several sampling methods such as line intersect sampling (LIS) and plot sampling (Hunsaker et al., 1994; Corona et al., 2004). The efficiency of the sampling method depends on the selected metric.

4.2.3 Paper III

An example of relative RMSE and bias of Shannon's diversity estimator for different sampling line lengths and configurations is illustrated in Fig. 9. The magnitude of RMSE and bias decreased when the number and/or length of lines per configuration was increased.



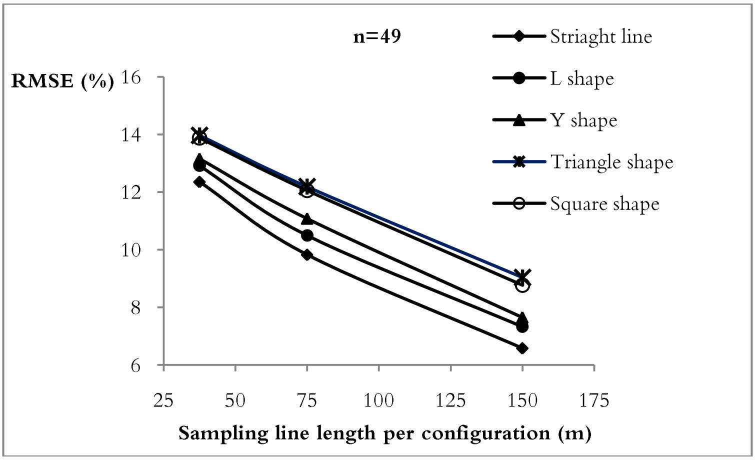
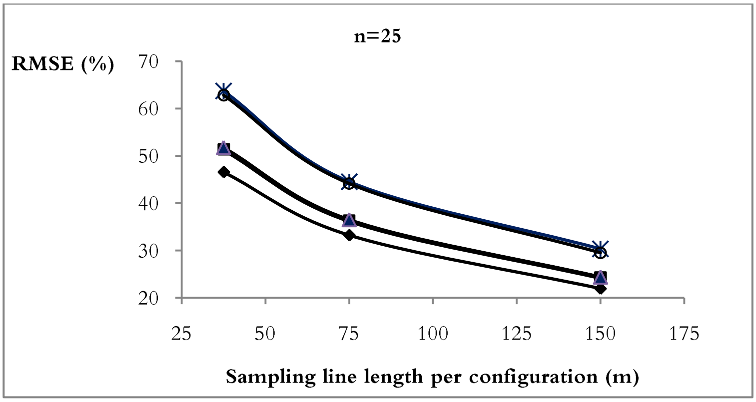


Figure 9. Relative bias (top) and RMSE (bottom) of the Shannon's diversity estimator for different sampling line lengths and transect configurations in the systematic sampling design, for sample size 49.

An example of relative RMSE of total edge length and edge density of the forest class estimators for different sampling line lengths and configurations is shown in Fig. 10. The magnitude of RMSE decreased with increasing number and/or length of lines per configuration.



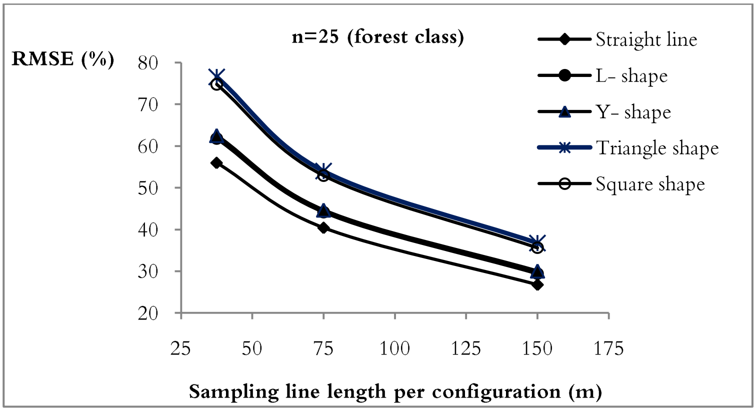


Figure 10. Relative RMSE of the total edge length (top) and edge density of forest class (bottom) estimators for different sampling line lengths and transect configurations in the systematic sampling design, for sample size 25.

For both metrics the systematic sampling design was superior to the random one with respect to RMSE. In all combinations considered, the straight line configuration resulted in the lowest RMSE and bias. The reason is that the straight line has the least compact form and thus avoids the negative effects of spatial auto-correlation. The random orientation of line transects gave slightly lower RMSE than the fixed one and this was true for all five configurations, three different sampling line lengths and four sample sizes. The small difference between random and fixed orientations is due to a systematic trend in some landscapes. The results of a statistical model for RMSE demonstrated that the effect of line length is larger for both designs for the two edge parameters than for Shannon's diversity. For the sampling strategy used there is no bias in the edge length estimator, but in practice, where only parts of lines within the image are considered, the corresponding estimator is ratio type and will have some bias. However, this bias is negligible when the study area is large in relation to sampling line length.

The RMSE vs. time (cost) of total edge density estimator is given in Figure 11. The magnitude of RMSE decreased with increasing cost, and with a given sampling budget longer sampling lines resulted in lower RMSE.

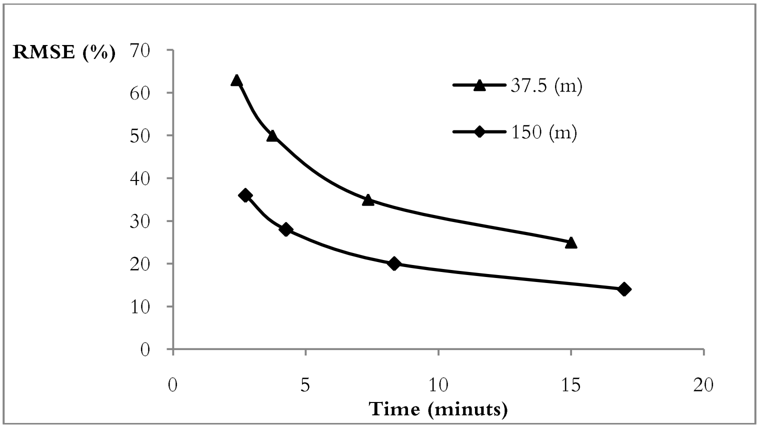


Figure 11. Relationships between cost and RMSE of the edge density estimator for the forest class for two sampling line lengths (37.5 and 150 m).

The time study revealed no large differences in interpreting time between short and long line lengths, which favors the latter alternative with respect to cost-efficiency. In the case of Shannon's diversity, for a given sampling budget, there was no difference between short and long lines. Efficiency, in term of cost-accuracy, of point and line intersect sampling methods was compared for the total edge length estimator. The result shows that to obtain a given RMSE LIS is the cost-efficient alternative.

Corona et al (2004) found that to estimate the total edge length LIS is more efficient than the traditional polygon delineation approach. It is recognized that a single sampling method is not efficient for all metrics. For instance, point sampling appears to be more efficient to estimate area of land cover types and thus Shannon's diversity (Ramezani et al., 2010). LIS also have been found to be an efficient method to assess population parameters of sparse populations (Ringvall and Ståhl, 1999) and to estimate area proportion of two-dimensional objects such as polygons (Gregoire and Valentine, 2008).

4.2.4 Paper IV

The results focus on the behavior of the contagion function and are based both on theoretical findings and empirical values and comparison between them.

Mathematical properties

(a) Unconditional contagion can be rewritten as

$$C_u(d) = 1 + \frac{\sum_{i=1}^{s} p_i(d)\ln(p_i(d))}{2\ln(s)} + \frac{\sum_{i=1}^{s} p_i(d)\sum_{j=1}^{s} p_{j/i}(d)\ln(p_{j/i}(d))}{2\ln(s)}$$

and the conditional contagion as

$$C_c(d) = 1 + \frac{\sum_{i=1}^{s}(1/s)\sum_{j=1}^{s} p_{j/i}(d)\ln(p_{j/i}(d))}{\ln(s)}$$

Hence the inner sums of the double sum have equal weights ($1/s$) for the conditional contagion, while the small classes have small weights ($p_i(d)$) for the unconditional.

(b) When the distance *d* tends to 0, for unconditional contagion we get

$$C_u(d) \to 1 + \frac{\sum_{i=1}^{s} a_i \ln(a_i)}{2\ln(s)} = 1 - H/2$$

where H is Shannon's diversity index. In the case of conditional contagion we get

$$C_c(d) \to 1$$

(c) For long distances and under the unconditional definition we get, assuming long distance independence,

$$C_u(d) \approx 1 + \frac{\sum_{i=1}^{s} p_i(d)\ln(p_i(d))}{\ln(s)}$$

Under the conditional definition we get

$$C_c(d) \approx 1 + \frac{r}{s} \cdot \frac{\sum_{i=1}^{s} p_i(d)\ln(p_i(d))}{\ln(s)}$$

Comparison between theoretical and empirical values

Comparisons were made between theoretical (items (b) – (c)) and empirical contagion values. The agreements were in general very good as shown in Table 3.

Table 3. *Difference between empirical and theoretical values for conditional and unconditional contagion for small and large distances d for the two classification systems. Figures show mean values of absolute values of the differences for the 50 maps. Numbers in parentheses show the number of positive differences of the expression given within the absolute sign. H is Shannon's diversity index, s is the number of classes (7 or 20) and r is the number of classes actually present. Extrapolation means that the empirical values for 2 and 5 meters were used for a linear extrapolation to* $d = 0$.

		7 classes	20 classes
		$\lvert (1-H/2)-C_u(d) \rvert$	
Short distance ($d \to 0$)	$d = 0.05$	0.0006 (50)	0.0007 (50)
	$d = 2$	0.0170 (50)	0.0201 (50)
	Extrapolation	0.0048 (47)	0.0048 (50)
		$\lvert 1-C_c(d) \rvert$	
Short distance ($d \to 0$)	$d = 0.05$	0.0016 (50)	0.0010 (50)
	$d = 2$	0.0486 (50)	0.0319 (50)
	Extrapolation	0.0160 (49)	0.0093 (50)
		$\lvert C_u(d)-(1-H) \rvert$	
Long distance ($d \to \infty$)	$d = 250$	0.0137 (47)	0.0152 (47)
		$\lvert C_c(d)-(1-r \cdot H/s) \rvert$	
Long distance ($d \to \infty$)	$d = 250$	0.0227 (34)	0.0230 (40)

The values indicate that the 2 and 250 meters distances are small and large enough to cover the range of values of the contagion functions. The nine distances used to calculate the contagion should thus be sufficient. For long distances *d* the empirical result also supports the assumption in item (c) of long distance independence.

A proxy function for the unconditional contagion function

For all the landscapes studied, the unconditional contagion function was a convex and decreasing function of distance (within the range studied). It was found that the relationship between the contagion function value and distance *d* could be described by $C_u(d) \approx f(d)$, where

$$f(d) = c + a \cdot e^{-b \cdot d}$$

The fit of the model was good. Figure 12 shows two examples for the 7 class classification system, one for a landscape with average standard deviation around the function and the other landscape with the highest standard deviation among the 50 studied.

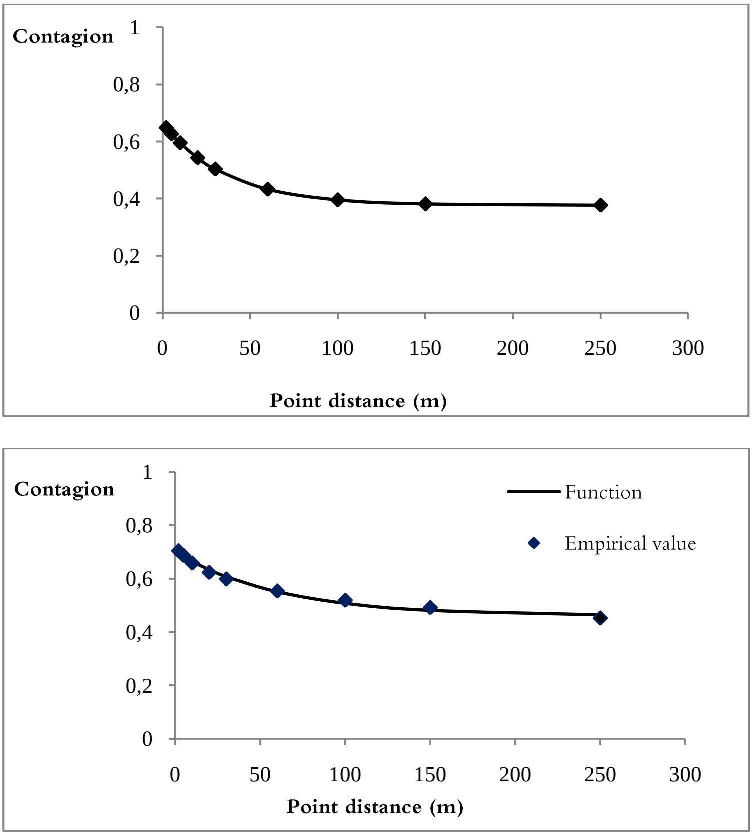
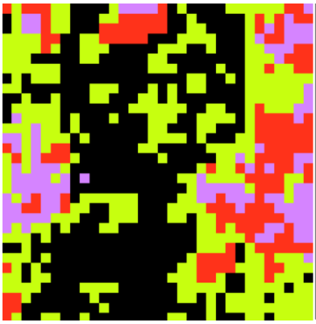


Figure 12. Illustration of two contagion functions with average (top) and highest (bottom) standard deviation around the function for the 7 class classification system.

Simulated landscapes with extreme cases were generated and the fit of the proxy function for the unconditional contagion was fairly good even for these landscapes. In Figure 13, a simulated landscape, treated as vector based, with its unconditional contagion and proxy function is shown.



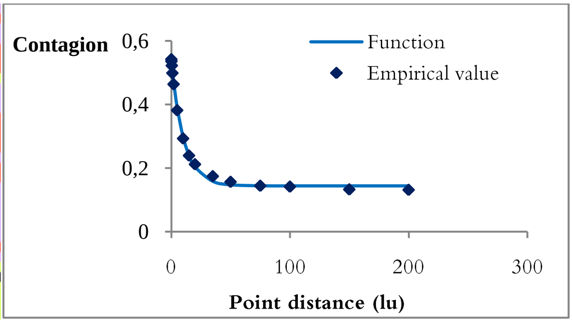


Figure 13. Illustration of a simulated landscape and its unconditional contagion values and proxy functions.

In general, the proposed metric can be used to quantify landscape structure. Thus, there is no need for raster-based maps. Two main conclusions are: 1) the unconditional contagion cannot be interpreted without considering the Shannon's diversity and 2) the parameter *b*, "rate of contagion change", of the proxy function provides, for unconditional contagion, most of the information about the spatial distribution or fragmentation. For conditional contagion no simple proxy function was found. For some landscapes the function had a minimum value while for other it decreased monotonically. By a visual inspection of the landscapes it was found that the former type occurred for landscapes with one dominating and several small fragmented classes. This is in line with mathematical property (a) above, saying that small classes are as important as large ones for the conditional contagion. For unconditional contagion the contribution of the small classes is negligible.

In contrast to Wickham et al. (1996), by using the proposed version of contagion there is no need to delineate borders between polygons, which in turn can avoid potential errors in polygon delineation.

The definition of the contagion functions, with point pairs, bears some resemblance with concepts in geostatistics, i.e., spatial autocorrelation (e.g., Cressie, 1993). However, in our case the observations are categorical variables (on a nominal scale) and not continuously varying over the landscape.

The method developed here also provides a basis for sampling-based estimation of contagion metrics. Metric estimation from sample data is recognized as a cost efficient alternative to wall-to-wall mapping approach (Corona et al., 2004; Ramezani et al., 2010) and it also is possible to derive some metrics from field-based inventories as was demonstrated by Kleinn (2000).

4.2.5 Paper V

In this study the aim was to investigate the statistical properties of the contagion estimator. Comparison of contagion estimators in simple random and systematic sampling showed that the systematic design resulted in slightly smaller RMSE and bias. Figure 14 shows bias and RMSE of the unconditional estimator for a point pair distance of 20 m and the data with 7 classes.

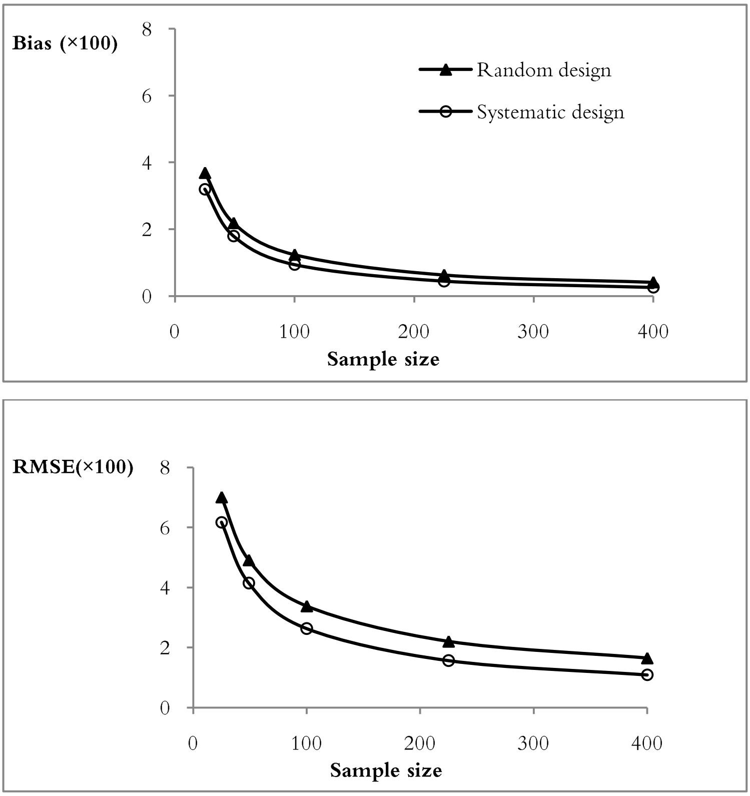
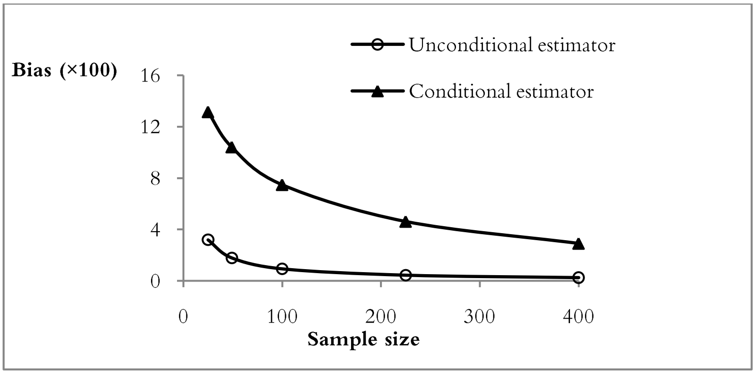


Figure 14. Bias (top) and RMSE (bottom) of the estimator of unconditional contagion using a 20 m point distance, average over the 50 landscapes using the 7 classes system, and all classes (s=7).

Both contagion estimators were biased. Bias and RMSE of the conditional estimator were much larger than for the unconditional estimator. In Figure 15 is shown the relationship between bias (left) and

RMSE (right) and sample size for the unconditional and conditional estimators, for point distance 20 m, and for all classes.



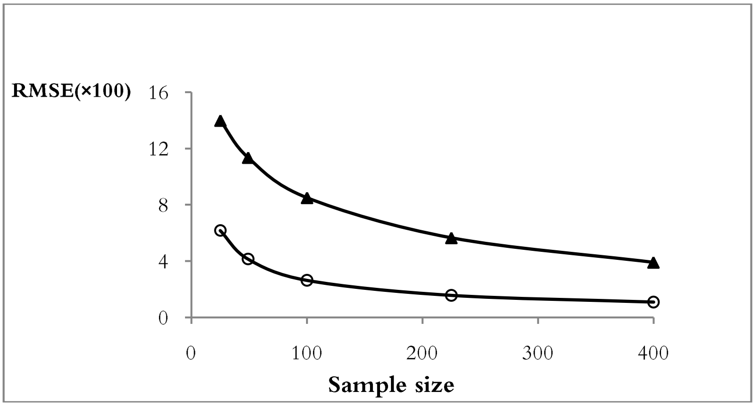


Figure 15. Relationship between the bias (top) and RMSE (bottom) with sample size of the contagion estimators, for point distance 20 m, the 7 classes system, and all classes (s=7).

The reason for the large bias of the estimator of conditional contagion is that, in contrast to unconditional contagion, both small and large classes have equal weight in its definition and also in its estimator. Hence, missing a small class, with small area proportion, affects the conditional contagion much more than the unconditional (Ramezani and Holm, 2010).

In a sample survey, statistical properties of contagion were assessed by Hunsaker et al. (1994). However, the study was conducted on raster-based map using (hexagonal) plot sampling and due to a different definition a direct comparison is not possible. In contrast to the vector version of Wickham et al. (1996), with the new vector version there is no need to delineate borders between polygons.

The results show that the contagion estimators are biased. Bias from sampling can be explained by ratio estimators $\hat{p}_{ij}(d)$ and $\hat{p}_{j/i}(d)$ and also the number $\hat{r}$ of classes observed in the sample. The bias is fairly small for reasonable large sample sizes.

5 Conclusions and recommendations

This thesis addresses the use of probability sampling methods for assessing landscape metrics. A main conclusion is that many metrics can be estimated with high accuracy at sample sizes that would be affordable in practice. However, it is also clear that for some metrics, e.g. conditional contagion, very large sample sizes would be needed in order to obtain reliable results. Also, due to the definition of some metrics, they cannot be estimated based on sample data. In general, a prerequisite for unbiased metric estimation is that the components of metrics, such as size, number, and edge length of landscape units, can be estimated without bias. However, this is a necessary but not sufficient condition since in metrics such as Shannon's diversity and contagion, non-linear transformations of the components imply that the metrics will be biasedly estimated although the individual components are not.

The review study (Paper I) showed that sample-based assessment of landscape metrics is a field where research studies have commenced only rather recently and to this date relatively few studies exist. However, most of these studies indicate that sampling is a cost-efficient alternative to traditional wall-to-wall mapping.

In studies II and III the statistical properties of estimators of the Shannon diversity index and edge length are investigated by using point and LIS sampling methods. Both methods were found to be cost-efficient alternatives to wall-to-wall mapping. Further, it was found that systematic sampling designs are more efficient than simple random designs. In LIS, long line transects and straight line configurations gave the best results. The results are consistent with findings in previous studies.

In study IV a new definition of the contagion metric was developed in order to meet vector format data; the definition is a function of point distances. A proxy function for the unconditional contagion metric, with point distance as independent variable, was proposed and demonstrated to work well in all kinds of landscapes. Through this function, a landscape can be characterized through two parameters: one related to area proportions of different land cover types and the other related to spatial arrangement over cover types. The proposed contagion definition can be used as a basis for sample based estimation of contagion.

In study V, sampling simulation was applied to assess contagion according to the new definition. This was found to work well for unconditional contagion, while for conditional contagion very low accuracy was obtained for sample sizes that would be relevant in practice.

In sample-based assessments of landscape metrics the efficiency of a given sampling method depends on what metrics are estimated. For instance, point sampling appears to be efficient for metrics involving area proportions, such as Shannon diversity, and LIS appears to be efficient for edge–dependent metrics, such as edge density. Thus, in sample-based approaches to landscape metrics estimation it is likely that several sampling methods should be combined in order to set up cost-efficient data acquisition schemes.

In studies IV and V the contagion metric was slightly redefined so that it would suit a sample based framework. Similar adjustments of the definitions should be possible in other cases as well.

Since sample based assessment of landscape metrics is a new and promising approach, further studies would be motivated. Important topics include:

- Further evaluation of statistical properties of sample based estimators of landscape metrics.
- Further comparison of cost-accuracy relationships when using wall-to-wall mapping and sampling, considering also potential classification and delineation errors.
- Further studies to develop metrics that are suitable to estimate from sample data (without sacrificing ecological meaning).
- Further studies to investigate the possibility of estimating currently used metrics or to develop new metrics from existing sample based field inventories, such as national forest inventories.
- Further studies to test whether landscape metrics from sample data are sensitive enough to detect landscape changes over time.

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