

# Landscape Environmental Monitoring: Sample Based Versus Complete Mapping Approaches in Aerial Photographs

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## 1. Introduction

Unknown land use premises are to be expected due to changing conditions, e.g. shifting land use priorities, climate change, globalizing natural resource markets or new products in the natural resource sector. As a result the need is obvious for accurate, relevant and applicable landscape data to be used in cause-and-effect analysis concerning changes in environmental conditions (Ståhl et al., 2011).

The current land use strongly influence landscape structure (composition and configuration) and contribute to biodiversity loss (Hanski, 2005; Fischer and Lindenmayer, 2007). In order to consider current status and also to monitor trends within a landscape there is a need for reliable and continuous information as a basis for policy- and strategic – as well as operational decision making (Bunce et al., 2008). For this purpose, many countries have now established or are in the process of establishing monitoring programs that provide information on large spatial scale (e.g., regional and national levels), for instance, the National Inventory of Landscapes in Sweden (NILS) (Ståhl et al., 2011), the Norwegian 3Q (NIJOS, 2001), and similar programs in other countries, e.g., in Hungary (Takács and Molnár, 2009). A major concern in landscape monitoring at national scale is the large complexity and amount of data, and the consequently the labor need in data acquisition, database management as well as data analysis and interpretation.

Description and assessment of landscape conditions and changes require relevant, accurate and applicable landscape metrics, which are defined based on measurable attributes of landscape elements such as patches or boundaries. The suite of metrics must cover both the composition and configuration of the landscape to have potential to detect changes within a given landscape or when comparing different landscapes.

Calculation of landscape metrics is commonly conducted on completely mapped areas based on remotely sensed data. FRAGSTATS (McGarigal and Marks, 1995) is a frequently used software for this purpose. In mapping, homogenous areas are first delineated as polygons. Aerial photo interpretation is usually performed using a manual approach while some automated and computer-assisted approaches have recently become available (e.g., Blaschke, 2004). Important attributes in manual interpretation include tone, pattern, size and

shape (Morgan et al., 2010). The experience of the interpreters is critical and the results from manual interpretation are thus often more accurate than those from automated approaches. However, the manual approach may be time-consuming (Corona et al., 2004), subjective (interpreter-dependent) and considerable variation may occur between photo interpreters. The automated approach is sometimes unreliable, for instance, when land cover classes that are similar in terms of spectral reflectance should be separated (Wulder et al., 2008). In addition, overall time, including delineation and corrections may be large if an inappropriate automated approach is chosen.

Sample based approach is an interesting alternative to extract landscape data compared to complete mapping (Kleinn and Traub, 2003). The argument is that a sample survey takes less time; that it is possible to achieve more accurate result in a well-designed and well-executed sample survey; and that data can be acquired and analyzed more efficiently (Raj, 1968; Cochran, 1977). The efficiency and speed in delivering results is of particular interest in landscape-scale monitoring programs where stakeholders commonly are closely involved and expect outputs within reasonable time. Figure 1 shows examples of complete mapping and sample based approaches (point and line intersect sampling methods) over 1 km × 1 km aerial photo from NILS.

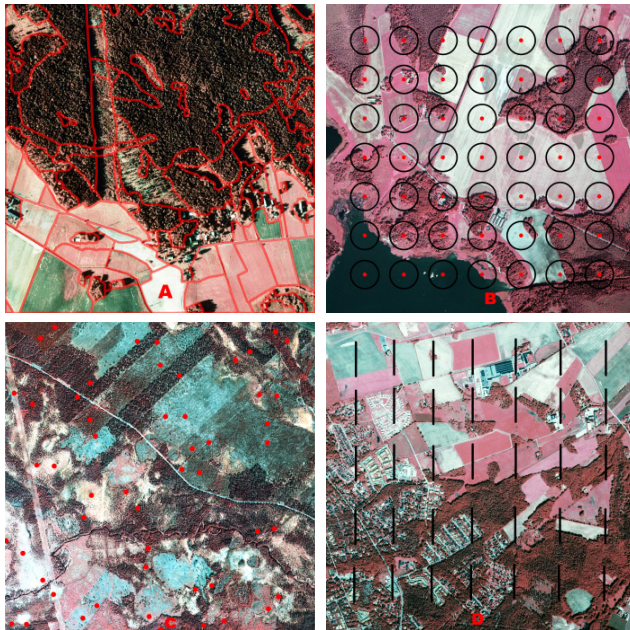


Fig. 1. Examples of complete mapping and sample based approaches to extract landscape metrics in 1 km × 1 km aerial photo. A) Complete mapping, B) systematic point sampling with fixed buffer (40 m), C) point pairs sampling, and D) systematic line intersect sampling.

Since aerial photos are important source of data for many ongoing environmental monitoring programs such as NILS (Ståhl et al., 2011), there is an urgent need to investigate the possibilities and limitations of both mapping and sample based approaches for estimating landscape metrics. The overall objective of this chapter is to compare the

advantages and limitations of complete mapping versus sample based approaches for estimating landscape metrics Shannon's diversity, total edge length and contagion from aerial photos. The specific objectives are: (1) to compare point and line intersect sampling for selected metrics in terms of the level of detail and accuracy of data extracted, and the time needed (cost) to extract the data, (2) to compare sample based and complete mapping approaches in terms of time needed, and (3) to investigate statistical properties (bias and RMSE) of estimators of selected metrics using Monte-Carlo sampling simulation.

## 2. Material and methods

### 2.1 Study area

The data was collected from aerial photographs and land cover maps from the NILS program (Ståhl et al., 2011), which covers the whole of Sweden. NILS was developed to monitor conditions and trends in land cover classes, land use and biodiversity at multiple spatial scales (point, patch, landscape) as basic input to national and international environmental frameworks and reporting schemes. NILS was launched in 2003 and has developed a monitoring infrastructure that is applicable for many different purposes. The basic outline is to combine 3-D interpretation of CIR (Color Infra Red) aerial photos with field inventory on in total of 631 permanent sample plots (5 km × 5 km) across all terrestrial habitats and the land base of Sweden (see Fig. 2).

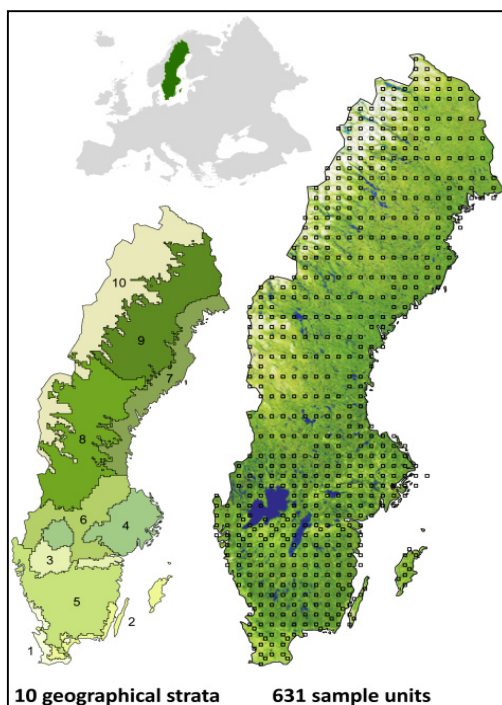


Fig. 2. Illustration of systematic distribution of 631 NILS 1 km × 1 km sample plot across Sweden with ten strata. The density of plots varies among the strata (Ståhl et al., 2011).

The present study is based on a detailed aerial photo interpretation of a central 1 km × 1 km square in the sample plot. Landscape data was extracted from 50 randomly selected NILS 1 km × 1 km sample plots distributed throughout Sweden. The aerial photo interpretation is carried out on aerial photos with a scale of 1:30 000. The aerial photographs in which interpretations were made had a ground resolution of 0.4 m. Polygon delineation is made using the interpretation program Summit Evolution from DAT/EM and ArcGIS from ESRI. According to the NILS' protocol, homogenous area delineated into polygons which are described with regard to land use, land cover class, as well as features related to trees, bushes, ground vegetation, and soils (Jansson et al., 2011; Ståhl et al., 2011).

## 2.2 Landscape metrics

Landscape metrics are defined based on measurable patch (landscape element) attributes where these attributes first should be estimated. In this study, point (dot grid) and line intersect sampling (LIS) methods were separately applied in (vector-based) land cover map from aerial photos for estimating three landscape metrics: Shannon's diversity, total edge length and contagion. Riitters et al. (1995) demonstrated that these metrics are among the most relevant metrics in landscape pattern analysis. Definition and estimators of the selected metrics are briefly described below.

### 2.2.1 Shannon's diversity index (H)

This metric refers to both the number of land cover classes and their proportions in a landscape. The index value ranges between 0 and 1. A high value shows that land cover classes present have roughly equal proportion whereas a low value indicates that the landscape is dominated by one land cover class. The index,  $H$ , is defined as

$$H = - \frac{\sum_{j=1}^s p_j \cdot \ln(p_j)}{\ln(s)} \quad (1)$$

where  $p_j$  is the area proportion of the  $j$  th land cover class and  $s$  is the total number of land cover classes considered (assumed to be known). For  $p_j = 0$ ,  $p_j \cdot \ln(p_j)$  is set to zero. The estimator  $\hat{H}$  of  $H$  is obtained by letting the estimator  $\hat{p}_j$  for land cover class  $j$  in Eq. 2 (for point sampling) and in Eq. 3 (for line intersect sampling) take the place of  $p_j$  in formula (1). With point sampling,  $p_j$  is estimated without bias by

$$\hat{p}_j = \frac{1}{n} \sum_{i=1}^n y_i \quad (2)$$

where  $y_i$  takes the value 1 if the  $i$  th sampling point falls in certain class and 0 otherwise and  $n$  is the sample size (total number of points).

With the line intersect sampling (LIS) method (Gregoire and Valentine, 2008),  $p_j$  can unbiasedly be estimated by

$$\hat{p}_j = \frac{A}{L} \cdot \sum_{i=1}^n l_{ij} \quad (3)$$

where  $l_{ij}$  is the intersection length of the  $j$  th land cover class with sampling line  $i$ ,  $L$  is the total length of all line transects, and  $A$  is the total area.

**2.2.2 Total edge length (E)**

This metric refers to the amount of edge within landscape. An edge is defined as the border between two different land cover classes. Edge length is a robust metric and can be used as a measure of landscape fragmenattion (Saura and Martinez-Millan, 2001). In a highly fragmented landscape there are more edges and response to those depends on the species under consideration (Ries et al., 2004). The length is relevant for both biodiversity monitoring and sustainable forest magament.

Ramezani et al. (2010) demonstrated that total edge length in the landscape can be estimated using point sampling in aerial photographs without direct length measurement. In such procedure, estimation of the length is based on area proportion of a buffer around patch borders. In Fig. 3 is shown a rectangular buffer around patch border for simulation application. The proportion of sampling points within the buffer can be employed for estimating the buffer area and, hence, the edge length. In practice, however, if a photo interpreter observed a point within distance  $d$  from a potential edge, this would be recorded. Figure 2 shows a circular buffer (with fixed radius 40 m) around sampling points on non-delineated aerial photograph for estimating edge length in practice.

According to Ramezani et al. (2010), the buffer area  $B_j$  inside the landscape with area  $A$ , can be estimated without bias, for a given land cover class by

$$\hat{B}_j = \hat{p}_j \cdot A \tag{4}$$

where  $\hat{p}_j$  is the estimator (1) of the buffer area proportion. The length  $E_j$  of the edge of the land cover class  $j$  is then estimated by

$$\hat{E}_j = \frac{\hat{B}_j}{2d} = \hat{p}_j \cdot \frac{A}{2d} \tag{5}$$

where  $d$  is buffer width (m) in one side.

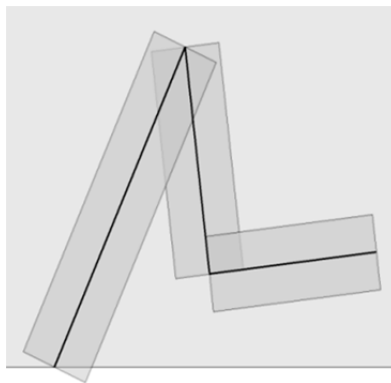


Fig. 3. Illustration of rectangular buffer with fixed width created in both sides of patch border for estimating edge length for simulation application (from Ramezani et al., 2010)

In the LIS method, the estimation of total edge length is based on the method of Matérn (1964). The edge length can unbiasedly be estimated by simply counting the number of intersections between patch border and the line transects. According to Matérn (1964), the total edge length estimator  $\hat{E}$  (m ha<sup>-1</sup>), using multiple sampling lines of equals length, is given by

$$\hat{E} = \frac{10000 \cdot \pi \cdot m}{2 \cdot n \cdot l} \quad (6)$$

where  $m$  is the total number of intersections,  $n$  is the sample size (number of lines) and  $l$  is the length of the sampling line (m).

### 2.2.3 Contagion (C)

Contagion metric was first proposed by O'Neill et al. (1988) as a measure of clumping of patches. Values for contagion range from 0 to 1. A high contagion value indicates a landscape with few large patches whereas a low value indicates a fragmented landscape with many small patches. Contagion metric is highly related to metrics of diversity and dominance and can also provide information on landscape fragmentation. This metric is originally defined and calculated on raster based map (O'Neill et al., 1988; Li and Reynolds, 1993).

Recently, however, a new (vector-based) contagion metric has been developed by Ramezani and Holm (2011a), which is adapted for point sampling. The new version is distance-dependent and allows estimating contagion metric using point sampling (point pairs).

According to Ramezani and Holm (2011a), for a given distance  $d$  the (unconditional) contagion estimator is defined as

$$\hat{C}(d) = 1 + \frac{\sum_{i=1}^s \sum_{j=1}^s \hat{p}_{ij}(d) \cdot \ln(\hat{p}_{ij}(d))}{2 \ln(s)} \quad (7)$$

where the  $p_{ij}(d)$  (unconditional probability) is estimated by the relative frequency of points in land cover classes  $i$  and  $j$ . The estimator  $\hat{p}_{ij}(d)$  is then inserted into the Eq. 7 to obtain estimator of  $\hat{C}(d)$  the unconditional contagion function and  $s$  is the number of observed land cover classes in sampling.

A vector based contagion metric has been developed by Wickham et al (1996), which is defined based on the proportion of edge length between land cover classes  $i$  and  $j$  to total edge length within landscape. This definition (i.e., Eq. 8) is more adapted to the LIS method. According to Wickham et al (1996), contagion estimator can be written

$$\hat{C} = - \frac{\sum_i \sum_{i \neq j} \hat{p}_{ij} \cdot \ln(\hat{p}_{ij})}{\ln(0.5(s^2 - s))} \quad (8)$$

Similar to point based contagion (Eq. 7), component  $\hat{p}_{ij}$  should be estimated and then inserted into Eq. 8. The estimator  $\hat{p}_{ij} (= \hat{E}_{ij} / \hat{E}_i)$  is the proportion of the estimator of edge length between land cover classes  $i$  and  $j$  ( $\hat{E}_{ij}$ ) to the estimator of total edge length ( $\hat{E}_i$ )

within landscape. Both  $\hat{E}_{ij}$  and  $\hat{E}_i$  can unbiasedly be estimated by Eq. 6. In contrast to Eq. 7, a value of 1 from Eq. 8 indicates a fragmented landscape with many small patches.

### 2.2.4 Monte-Carlo sampling simulation

In this study, Monte-Carlo sampling simulation was used to assess statistical performance (bias and RMSE) of estimators of the selected metric. Bias (or systematic error) is the difference between the expected value of the estimator and the true value. RMSE is the square root of the expected squared deviation between the estimator and the true value.

In point sampling, simulation was conducted for four sample sizes (49, 100, 225, and 400) for both Shannon's diversity and total edge length and five buffer widths (5, 10, 20, 40, and 80 m) for total edge length. In line intersect sampling, simulation was conducted for four sample sizes (16, 25, 49, and 100), three line transect length (37.5, 75, and 150 m), and five transect configurations (Straight line, L, Y, Triangle, and Square shapes). In point pairs sampling (i.e., using Eq.7) simulation was conducted for nine point distances (2, 5, 10, 20, 30, 60, 100, 150, and 250 m) and five sample sizes (25, 49, 100, 225, and 400). Systematic and simple random sampling designs were employed for all cases above.

## 3. Results

In this study, the statistical properties (RMSE and bias) of the estimators of the selected metrics were investigated for different sampling combinations. But some major results are presented here. In general, a systematic sampling design resulted in smaller RMSE and bias compared to simple random design, for all combinations.

### 3.1 Shannon's diversity index

In point sampling, both RMSE and bias of Shannon's diversity estimator tended to decrease with increasing sample size in both sampling designs. In Fig. 4 is shown the relationship between bias and sample size of Shannon's diversity estimator in systematic and random sampling designs.

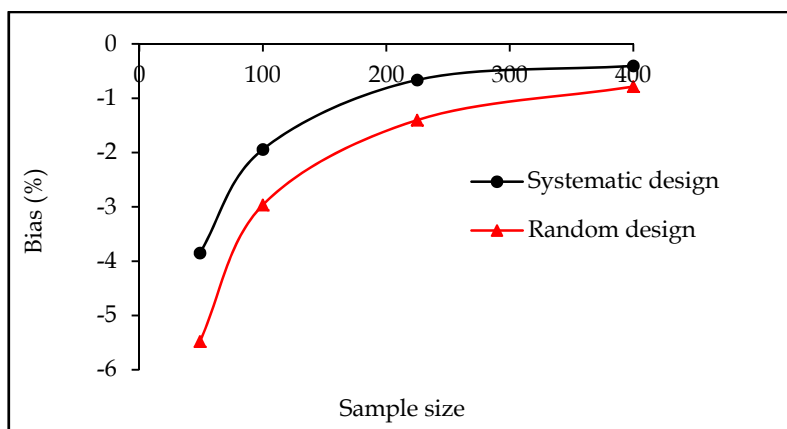


Fig. 4. The relationship between bias and sample size of Shannon's diversity estimator using point sampling method in systematic and random sampling designs (from Ramezani et al., 2010).

In line intersect sampling, similar to point sampling, both RMSE and bias of Shannon's estimator tended to decrease with increasing sample size and line length. The longer line transect (here 150 m) resulted in lower RMSE and bias than shorter one (here 37.5 m), for a given sample size. We found a small and negative bias for the estimator in both point and the LIS methods. The magnitude of bias tended to decrease both with increasing sample size and line transects length. Straight line configuration resulted in lower RMSE and bias than other configurations.

### 3.2 Total edge length

In point sampling, the magnitude of RMSE of estimator is highly related to buffer width, for a given sample size and a wide buffer resulted in lower RMSE than narrow one. The edge length estimator had bias since parts of buffer close to the map border were outside the map. Bias of estimator tended to increase with increasing buffer width whereas it was independent on sample size. To eliminate or reduce the bias of estimator three corrected methods were suggested which have been discussed in detilas in Ramezani et al. (2010).

In LIS, the magnitude of RMSE of estimator is dependent on the length of the line transect, for a given sample size and the longer transect resulted in lower RMSE than short one. Furthermore, straight line configuration resulted in lower RMSE compared to other configurations (e.g., L and square shape). In Fig. 5 is shown the relationship between relative RMSE and sampling line lengths of total edge length estimator.

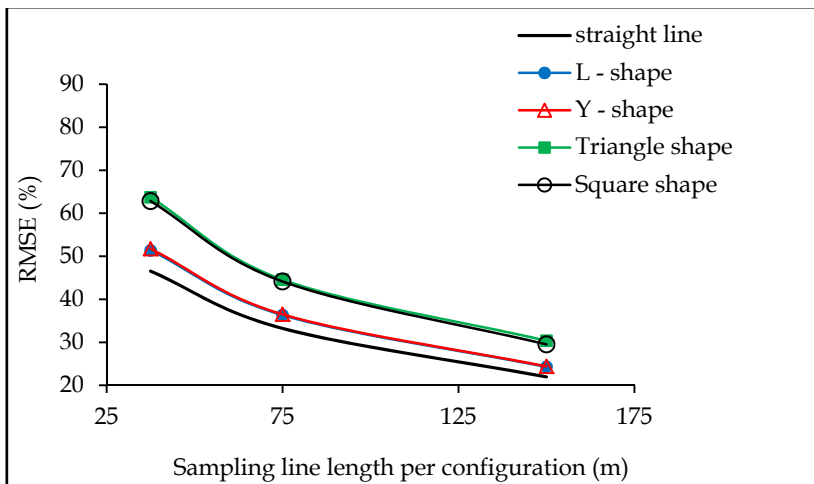


Fig. 5. Relative RMSE of total edge length estimator for different sampling line lengths and configurations of line intersect sampling, for a given sample size (from Ramezani and Holm, 2011c).

### 3.3 Contagion

Point based contagion (i.e., Eq. 7) is a distance-dependent function that delivers a contagion value that decreased with increasing point distance. The rate of decrease of the contagion value was faster in a fragmented landscape compared to a more homogenous landscape. Examples of such landscapes are shown in Fig. 6. The contagion estimator was biased even



if its component (i.e.,  $p_{ij}(d)$ ) was estimated without bias. The sources of bias discussed in details in Ramezani and Holm (2011b).

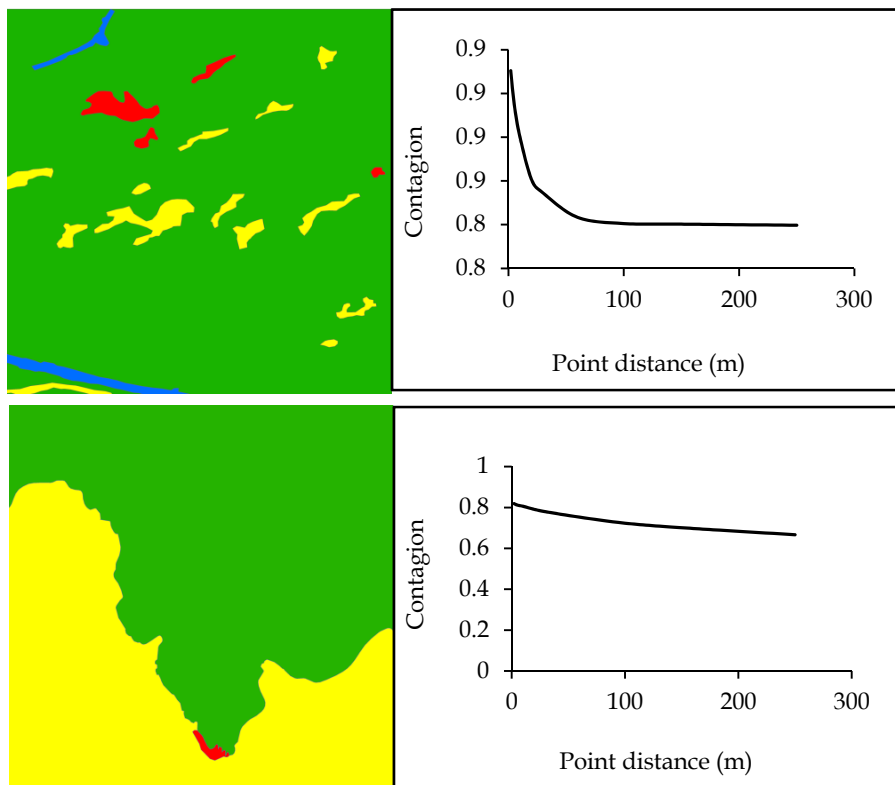


Fig. 6. Example of two landscapes with different degree of fragmentation and their corresponding contagion function (Eq. 7). Top: a high fragmented landscape (four land cover class and nineteen patches) with large rate of decrease of the contagion function. Bottom: a homogenous landscape (three land cover class and three patches) with a small rate of decrease in the contagion function.

In line intersect sampling, both RMSE and bias of the contagion estimator (Eq.8) tended to decrease with increasing sample size and line transects length. Straight line configuration resulted in lower RMSE and bias than other configurations. We found a small and negative bias for the contagion estimator despite its components (i.e.,  $\hat{E}_{ij}$  and  $\hat{E}_t$ ) can be estimated without bias. The relative RMSE and bias of the contagion estimator through line intersect sampling (LIS) method (Eq.8) is shown in Fig. 7. Note that the two contagion estimators differ as they are based on different equations (i.e., Eqs.7 and 8).

A comparison was also made for variability in terms of range and mean in sample based estimates of Shannon’s diversity, edge length and contagion metrics for sample sizes 16 and 100. In Table 1 is provided an example for line intersects sampling method, systematic sampling design, straight line configuration and line length 37.5 m.

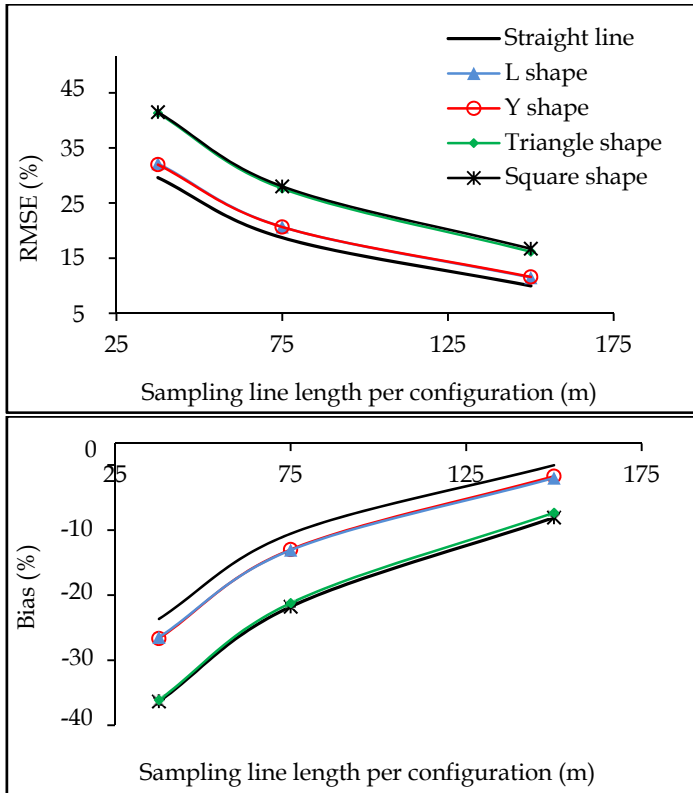


Fig. 7. Relative RMSE (top) and bias (bottom) of contagion estimator (Eq. 8) for different sampling line lengths and configurations, a sample 49 and systematic sampling design

Landscape metrics	Sample size	
	16	100
Shannon' diversity	0.398 (0.019-0.747)	0.423 (0.026-0.784)
Contagion <sup>a</sup>	0.188 (0.006-0.478)	0.407 (0.226-0.758)
Total edge length (m ha <sup>-1</sup> )	92.2 (12.2-197.6)	92.1 (10.5-194.6)

<sup>a</sup> according to Eq.8

Table 1. Variability (mean) in sample based estimates of Shannon’s diversity, edge length and contagion in fifty random landscapes (NILS plots) in Sweden for sample sizes 16 and 100. Data collected using line intersects sampling method, systematic sampling design, straight line configuration and 37.5 m length of sampling lines. Ranges are given in parentheses.

**3.4 Time study (cost needed for data collection)**

A time study was conducted on non-delineated aerial photos from NILS employing an experienced photo interpreter. The results of the time study for Shannon’s diversity and total edge length are summarized in Tables 2 and 3.

Method	Time needed (h)
Complete mapping	3.5
Point sampling (number of points)	
9	0.4
100	0.8
225	1.9
400	3.3

Table 2. Average time consumption of data collection on five NILS plots for point sampling and complete mapping for deriving the Shannon’s index (from Ramezani et al. (2010))

Sampling method	Time needed (min)	
	Edge length estimator	Shannon’ s diversity estimator
Point sampling	25 <sup>a</sup>	28.3
LIS	18.3 <sup>b</sup>	60 <sup>b</sup>

<sup>a</sup> (buffer 40 (m))

<sup>b</sup> (line 150 (m))

Table 3. Average time needed for point and line intersect sampling (LIS) methods for deriving Shannon’s diversity and total edge length. For sample size 100 (number of point and lines)

The time needed to collect data was highly related to landscape complexity and the classification system applied. We also found that in a coarse classification system the time needed was less than in a more detailed system. This issue becomes more serious in complete mapping approaches where all potential polygons should be delineated. Furthermore, time was also dependent on sampling method the chosen. With a point sampling method less time was needed for estimating Shannon’s diversity compared with other metrics. With line intersect sampling; it was more time efficient to use edge-related metrics. For a given sample size, the time depended on the length of line transect (in LIS) and the buffer width (in point sampling). With the former method it is indicated that the time is independent on line configuration in the aerial photo.

#### 4. Discussion

This study addresses the potential of sampling data for estimating some landscape metrics in remote sensing data (aerial photo). Sample based approach appears to be a very promising alternative to complete mapping approach both in terms of time needed (cost) and data quality (Kleinn and Traub, 2003; Corona et al., 2004; Esseen et al., 2006). However, some metrics may not be estimated from sample data regardless of chosen sampling method since currently used landscape metrics are defined based on mapped data. To describe landscape patterns accurately, a set of landscape metrics is needed since all aspect of landscape composition and configuration cannot be captured through a single metric. On the other hand, all metrics cannot be extracted using a single sampling method. Thus, in a sample based approach a combination of different sampling methods is needed, for instance, a combination of point and line intersect sampling. In such combined design, the

start, mid and end points of line transects can be treated as grid of points which is preferred for estimating area proportions of different land cover classes within a landscape and thus Shannon's diversity. It would also be effective in terms of cost if several metrics could simultaneously be derived from a single sampling method.

From a statistical point of view unbiasedness is a desirable property of an estimator. In sample based assessment of landscape metrics, attributes (metrics components) such as the number, size, and edge length of patches must unbiasedly be estimated (Traub and Kleinn, 1999) if an unbiased estimate is needed. However, this is a necessary but not sufficient conditions (Ramezani, 2010). For instance, in the case of Shannon' diversity, there is still bias despite its component i.e., area proportions of land cover classes can be estimated without bias through both point and line intersect sampling methods (Ramezani et al., 2010; Ramezani and Holm, 2011c). The bias is due to non-linear transformation, which also generally is the case for other metrics with non-linear expression such as contagion. Bias of selected metric estimators is very small if the sample size is large and the magnitude of bias depends jointly on type of selected metric, the sampling method, and the complexity of the landscape structure. To achieve an acceptable precision in a complex landscape there is a need for a larger sample size compared to the homogenous landscape.

The landscape metrics used in this study are based on a patch-mosaic model where sharp borders are assumed between patches. In such procedure, as noted by Gustafson (1998) the patch definition is subjective and depends on criterion such as the smallest unit that will be mapped (minimum mapping units, MMU). This becomes more challenging in a highly fragmented landscape where smaller patches than predefined MMU are neglected. Even though these patches constitute a small proportion (area) of the landscape, they contribute significantly to the overall diversity of that landscape; including biodiversity where other type organisms may occupy these patches habitats. However, in sample based approach which can be conducted in non-delineated aerial photos, there is no need to predefine minimum patch size and even very small patches can be included in the monitoring system. Furthermore, point sampling appears to be in consistent with gradient based model of landscape (McGarigal and Cushman, 2005) where landscape properties change gradually and continuously in space and where no subjective sharp border need to be assumed between patches.

Polygon delineation errors are common in manual mapping process. It can be assumed that this error can be eliminated when sampling methods are used for estimating some landscape metrics. As a result, obtained information and subsequent analysis is more reliable than for traditional manual polygon delineation. As an example, for estimating the metrics Shannon's diversity and contagion using point sampling, no mapped data are needed and assessment is only concentrated on sampling locations. This is also true for the LIS, for instance, the total length estimation of linear features within a landscape is to be based on simply counting the interactions between lines transect and a potential patch border. Consequently, assessment is conducted along line transect which, thus, considerable reduce the polygon delineation error.

It is clear, however, that a sample based approach cannot compete with a complete mapping approach, in particular when high quality mapped data is available. With the mapping approach a suite of metrics can be calculated for patch, class, and landscape levels whereas in sample based approach a limited number of metrics on landscape level can often be estimated.

## 5. Conclusion

A sample based approach can be used complementary to complete mapping approach, and adds a number of advantages, including 1) the possibility to extract metrics at low cost 2) applicable in case of lacking categorical map of entire landscape 3) the possibility in some case to obtain more reliable information and 4) the possibility of estimating some metrics from ongoing field-based inventory such as national forest inventories (NFI). In some cases, there is a need to slightly redefine currently used landscape metrics or develop new metrics to meet sample data. There is obviously plenty of room for further studies into this topic since sample based assessment of landscape metrics is a new approach in landscape ecological surveys.

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