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Status and trend analysis in landscape pattern through field-based sampling data

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ABSTRACT
Traditionally, calculation of landscape metrics is commonly conducted on land cover/use maps of entire landscape which is created from remotely sensed data. An interesting approach, however, is to make use of sample data, without the use of wall-to-wall mapping. In the present review and case study, it is aimed to estimate three basic landscape metrics, namely Shannon's diversity (SH), forest edge length (E) and contagion (C) from field-based sampling data. It is also intended to estimate landscape change using time series datasets. Estimated variance (sampling error) was used to assess landscape metric estimators. For this purpose, sampling data from National Inventory in the Landscape of Sweden (NILS) is used. In this case study, the metrics are estimated with acceptable precision. In most cases, the estimated variance (sampling error) was less than 10 %. The largest sampling error was 28 % for forest edge length. We will be able to compare different landscape at a given time or a landscape over time using filed-based sampling data. Furthermore, in an ecological survey it may be possible to find a relationship between landscape pattern and ecological processes such as biodiversity. The methods applied in this study is very simple and there is no need for extra measurements.

Keywords: Landscape metrics; Forest fragmentation; Sampling methods; Ecological process.

INTRODUCTION
Human activities such as forest management in addition to natural disturbances such as fire and storms can cause landscape changes and forest fragmentation (Geri *et al.* 2010; Arroyo-Rodríguez *et al.* 2013). These changes may contribute to climate change and biodiversity loss when forested areas are converted to farmlands *(Copeland et al.* 1996; Hanski 2005; Shapiro *et al.* 2016; Fahrig *et al.* 2018). Lister *et al.* (2019) states that landscape fragmentation and forest loss have drawn interest in recent years due to increased focus on carbon monitoring and climate change mitigation. There is a need for reliable information regarding current status and also to monitor trends within a landscape. Hence, many countries have now established or are in the process of establishing sample-based monitoring programs that provide information on a national scale, for instance, the US EMAP (Hunsaker *et al.* 1994); the Norwegian monitoring program for agricultural landscapes in Norway (3Q); the Spanish rural landscape monitoring system (SISPARES); the Alberta Biodiversity and Monitoring Institute in Canada, land use inventory (IUTI, Corona *et al.* 2017) in Italy, and the Land Cover Trends Project in USA (Loveland *et al.* 2002). Landscape pattern is of primary importance for landscape ecologists because it is recognized that the pattern can affect many ecological processes (van Dorp *et al.* 1987; Turner 2005). The landscape ecologists attempt to understand pattern-process relationships; hence the pattern of landscape should be quantified first. Haines-Young (2005) states that landscape pattern can serve as a predictor variable in assessing ecological processes. Direct measurement of landscape pattern is difficult (Traub *et al*. 1999). Thus, to assess landscape conditions and changes require relevant, accurate and applicable landscape metrics (Ramezani *et al.* 2011), which are based on measurable attributes of landscape elements such as area, edge length, or number of patches. A patch is defined as a relatively homogenous area that differs from its surroundings (Forman 1995). Landscape pattern analysis through metrics provides useful information for many applications. For instance,

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metrics serve as tools in environmental monitoring programs *(Hunsaker et al. 1994; Frohn et al. 1996; Schuft et al.* 1999; Dramstad *et al.* 2002; Ståhl *et al.* 2011). They also act as the quantitative link between landscape pattern and ecological processes as well as species abundances (Krummel *et al.* 1987, Bunnell 1997). Landscape metrics allow for comparison between different regions or studies of time trends (Tinker *et al.* 1998; Ji *et al.* 2006), and also provide information useful for biodiversity assessment at the landscape level (Benitez-Malvido *et al*. 2003, Bebber *et al.* 2005), for analyzing fragmentation, and connectivity of landscape units *(Schumaker 1996; With et al.* 1997; Hargis *et al.* 1998). Calculation of landscape metrics is commonly conducted on wall-to-wall maps created from remotely sensed data. An interesting approach, however, is to make use of sample data, without the use of wall-to-wall mapping (Hunsaker *et al.* 1994, Kleinn 2000, Stehman *et al.* 2003, Corona *et al*. 2004, Ramezani *et al.* 2010, Hassett *et al.* 2011, Ramezani *et al.* 2013). The argument for using sampling data is concern for both the cost and precision of information obtained (for the areas included in the sample) and the possibility for finding synergic with ongoing sample-based surveys such as the National Forest Inventories (NFIs). Complete mapping is a time-consuming approach and satellite-based maps with high-resolution satellite images may be very expensive to produce (in large spatial scale such as national level). However, in sample-based approach less time is needed, and data can be captured and analyzed more efficiently. Corona *et al.* (2004) and Ramezani and Holm (2011) demonstrated that line intersect sampling (LIS) method can provide reliable information on linear features in the landscape and that it is more efficient than a traditional wall-to-wall mapping approach. The previous studies of landscape change assessment (trend analysis) by means of landscape metrics have usually been conducted using remotely sensed data i.e., aerial photos and or satellite images (Hunskar *et al.* 1994, Corona *et al.* 2004, Li 2008, Zengin *et al.* 2018, Lister *et al.* 2019). Kleinn (2000), however, demonstrated the possibility of deriving some currently used metrics or developing new metrics from field-based forest inventories as well. This allows trend analysis based on existing historical data such as National Forest Inventories (NFI) (e.g., Corona *et al.* 2011). The possibility of estimating metrics from field-based inventories has received less attention than conventional approach (i.e., on remotely sensed data). The reason might be that the field-based sample surveys are not designed for such a purpose. Despite the potential of extracting some landscape metrics from sampling data there are some limitations for such procedure. For instance, all landscape metrics cannot be estimated from sampling data and a set of metrics cannot be estimated unbiasedly. Furthermore, some metrics might be underestimated where plot boundaries truncate large patches (Hassett *et al.* 2012). In this review and case study, the overall objective is to quantify landscape pattern and assess landscape change over time (trend analysis) through large-scale field-based inventory. Specifically, it is intended to estimate the landscape metrics Shannon's diversity index (*SH*), the total forest edge length (*E*), and contagion (*C*). It is intended to compare inventory regions (strata) with different degree of landscape fragmentation in terms of the metrics. Variance of the estimators of the selected metrics is also estimated.

MATERIALS AND METHODS

Study area

In the present study, dataset from two five-year periods (2003-2007 and 2008-2012 i.e., with 5 years interval) of the National Inventory of Landscape in Sweden (NILS) was used (Ståhl et al. 2011). NILS program was launched in 2003 and was developed to monitor conditions and trends in land cover types, land use and biodiversity at multiple spatial scales (point, patch, landscape) as a basic input to national and international environmental frameworks and reporting schemes.

The program is accomplished by combining field-based inventory and remotely sensed data (photo plots, 5 km × 5 km). An inner square (1 km × 1 km) at the center of each photo plot 25- km^2 was mapped and interpreted, where according to the NILS protocol there were 27 land cover types. In this study, however, only dataset from field-based inventory was used. Sampling units in the field-based inventory of the NILS program was composed of a 1 km × 1 km square and in each 1-km^2 square there are 12 circular plots and 12 line transects, each 200 m long. The line transects and circular subplots are located along the sides of a 750 m × 750 m square inside the 1 km × 1 km (see Fig. 1). According to the NILS program, the country is divided into ten strata, which labeled from the south to the north. A total of 631 sample units are systematically distributed across the land base of Sweden, of which 20% are surveyed each year and each sampling unit is re-inventoried after 5 years. Sampling intensity decreases toward the north of the country. Table 1 provides information on the total area of NILS' ten strata and the number of square cluster plots (sample size) per stratum.

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Table 1. The total area of ten inventory regions (strata), the number of square cluster plots and the total number of circular subplots (square cluster plot × the number of circular subplot at each cluster, 12) within each stratum for a five-year rotation.

Strata	Total area (km^2)	Sample size (No. of square cluster plot)	No. of circular subplots
1	5655.84	9	108
2	10572.20	30	360
3	11290.85	26	312
4	29897.67	46	552
5	54251.88	62	744
6	32999.34	34	408
7	38660.23	36	432
8	73695.61	53	636
9	72223.79	54	648
10	80498.18	111	1332

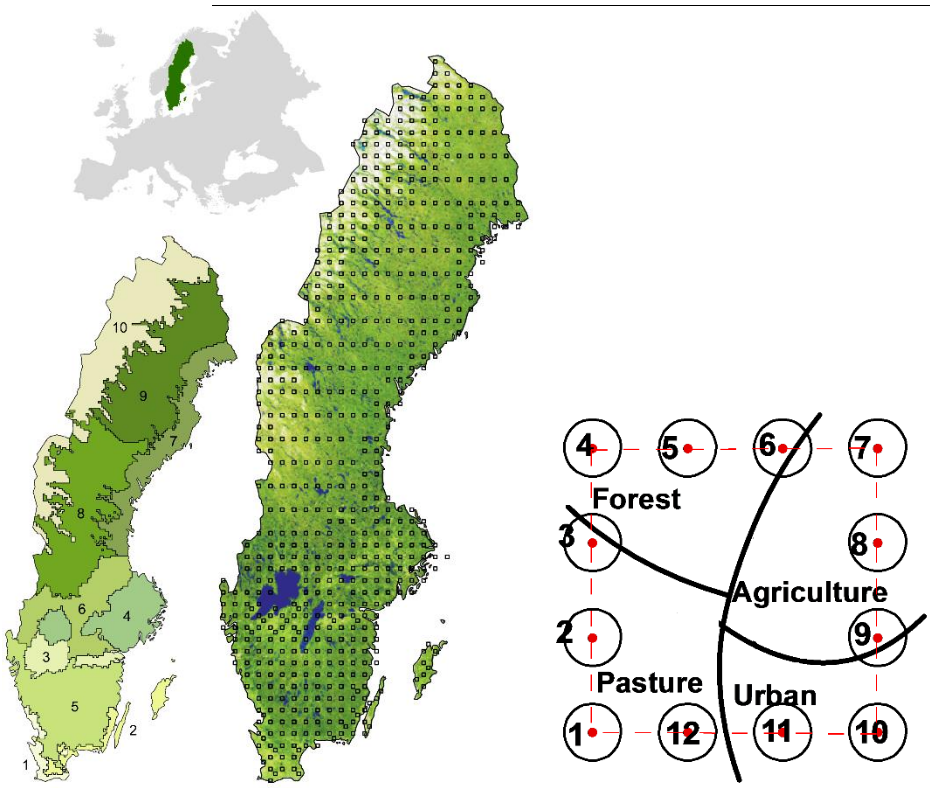

Fig. 1. Illustration of the systematic distribution of NILS sample square plots across Sweden, ten strata (left) (from Ståhl *et al.* 2011) and an example of one square plot with 12 circular subplots (right).

Landscape metrics

Landscape metrics are based on measurable attributes such as the number, size, or edge length of patches. To estimate the selected metrics, the patch attributes (components of metrics) should first be estimated using one of the sampling methods. Landscape pattern cannot be adequately described using a single metric, but instead requires a set of metrics (Riitters *et al*. 1995). The estimators, corresponding variance estimators, estimation methods, and ecological significance of the metrics in this study (Shannon's diversity (*SH*), total forest edge length (*E*), and contagion (*C*)) are briefly described in the following sections. Note that the estimation of *SH* and *C* was based on aggregating all plot data into a "pooled" sample, but *E* was computed for each individual cluster plot and then was taken the mean over all plots. Selected landscape metrics was estimated for ten strata separately.

Landscape diversity

Estimates of the area of different land cover types are relevant for nature conservation planning (McKendry 2002; Berndes *et al*. 2003). Landscape diversity is highly related to biodiversity, which may not be possible to measure directly in many circumstances. In this study, Shannon's diversity index was used to estimate landscape diversity. The index estimator, *SH*, is defined as:

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$$\widehat{SH} = -\frac{\sum_{j=1}^{s} \hat{p}_j . \ln(\hat{p}_j)}{\ln(s)} \quad \textbf{(1)}$$

where s is the total number of land cover types within the landscape and p_j is the area proportion of the j th land cover type which can be estimated unbiasedly by $\hat{p} = \frac{1}{n}\sum_{j=1}^{s} y_j$ and then inserted into Eq. 1 in order to estimate the *SH* index (where n is sample size and y_j is variable on interest). The resulting value of the index is between 0 and 1, where values close to 0 indicate a landscape dominated by one or a few land cover types, while values close to 1 indicate a landscape in which the land cover types present have roughly equal proportions. To estimate this index, it is necessary to know the land cover type for each sampling location. In this study, plot centers served as sampling locations and land cover type was taken from the NILS inventory, which is one of the over 200 variables recorded.

Variance estimation

In this study, data from a five-year period were used as only one sample. Hence, the jackknife estimator is considered to be straightforward technique for the estimation of the variance (Thompson 2002). This method also used by Kleinn (2000) and Lister et al. (2019). Using this method, one cluster plot is deleted from the sample, and a given metric is calculated. This is repeated for each plot in succession, and the estimator of the variance of a given metric is calculated as follows:

$$\hat{v}(\hat{y}) = \frac{n-1}{n}\sum_{i=1}^{n}(\hat{y}_i - \bar{y}_{jack})^2 \quad \textbf{(2)}$$

where $\hat{y}_i$ is the estimator when leaving square cluster plot *i* out and $\bar{y}_{jack} = \frac{1}{n}\sum_{i=1}^{n}\hat{y}_i$ and *n* is the number of square cluster plots. Note that with this technique it is assumed that observations are independent but as pointed out previously datasets are provided from a systematic sampling design. For such conditions, other variance estimators have been suggested and discussed deeply by Barabesi *et al.* (2015).

Total forest edge length (E)

Forest edge refers to a border between forest and non-forest lands or between different categories of forest; in a fragmented landscape, the total forest edge length tends to be large (Lister *et al.* 2005). The edge of forest can have important effects on biodiversity and forest regeneration (Murcia, 1995, Laurance *et al.* 2000, Harper *et al.* 2011). This quantity can be estimated in different ways, but the method of Matérn (1964) (i.e., line intersect sampling, LIS) is the most common approach where a simple count is made of the intersections between the line sampling transect and any forest boundary. However, such information (the number of intersections) is not available from NILS. Hence, in this study, we use a buffer zone approach (Kleinn 2000), which is briefly described in the following subsection.

Buffer zone approach

This approach is introduced in detail in Kleinn (2000). Using this approach, simply counting the intersection of the cluster plot with forest boundaries, it is possible to estimate the perimeter length of forest patches. Using this approach, when all twelve centers of subplots of a certain square cluster plot do not fall into forest or non-forest land, this means that the square plot crosses the forest boundary. The total forest edge is estimated by

$$\hat{E} = \frac{\pi \cdot A}{4 \cdot l}\hat{p} \quad \textbf{(3)}$$

where $\hat{p}$ is the proportion of square cluster plots intersecting forest boundaries, *l* is the side length of the square cluster plot (0.75 km) and *A* is the total area (km^2) of the inventory region (stratum). According to Cochran (1977), the corresponding variance estimator is

$$\hat{v}(\hat{E}) = (\frac{\pi \cdot A}{4 \cdot l})^2 \cdot \frac{\hat{p}(1-\hat{p})}{n-1} \quad \textbf{(4)}$$

Contagion metric (C)

The contagion metric is a commonly used landscape metric for measuring landscape fragmentation (e.g., Hunsaker *et al.* 1994, Hassett *et al.* 2011). The value of contagion ranges from 0 to 1, so that a low value indicates a highly fragmented landscape whereas a high value indicates an aggregated landscape. This metric belongs to the configuration category (McGarigal *et al.* 1995) which describes geographical distribution of land cover types

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in a landscape. Contagion was originally defined on raster based data (Li *et al.* 1993). Recently, however, a new contagion metric has been developed by Ramezani and Holm (2012) where the metric is defined using point-based data. The new contagion estimator is defined as

$$C(d) = 1 + \frac{\sum_{i=1}^{s}\sum_{j=1}^{s} p_{ij}(d) \cdot ln\, p_{ij}(d)}{2 \cdot ln(s)} \qquad \textbf{(5)}$$

where $p_{ij}$is the relative frequency of point pairs for land cover types *i* and *j* in distance *d* and *s* is the number of land cover types in the landscape (where, *s* equals 27 according to the NILS protocol).
To estimate this metric, we need the information of the land cover type for each in sampling locations (here subplot centers). In order to estimate the variance of contagion metric, Eq. 2 was used for the same reason as Shannon's diversity index.

Landscape change (trend analysis)
The information captured from trend analysis can be employed to anticipate future changes in the landscape. It also provides a baseline towards re-establishing a landscape where intensive changes have occurred. Knowledge about past processes within the landscape coupled with how the landscape is expected to change in the future can give land managers better information needed to plan resource management. Trend analysis surveys have usually been conducted on land cover/ land use maps (Li 2008). However, in this study, field-based sampling data from NILS was used. Trend analysis was used to identify the rate of land cover change and the location where the changes occurred. A natural change estimator as estimated landscape change is

$$\hat{\Delta} y = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}(t_2) - \hat{y}(t_1)) \qquad \textbf{(6)}$$

where $\hat{y}(t_1)$ and $\hat{y}(t_2)$ are the estimator of metric of interest at times t_1 and t_2, respectively.

In the present study, the same sampling units (cluster plots) and the same numbers of cluster plots were used at occasion's t_1 and t_2. Hence, according to Gergoire and Valentine (2008) corresponding variance estimator of change, Δy, is as

$$\hat{v}[\hat{\Delta} y] = \hat{v}[\hat{y}(t_2)] + \hat{v}[\hat{y}(t_1)] - 2\hat{C}[\hat{y}(t_2), \hat{y}(t_1)] \qquad \textbf{(7)}$$

where $\hat{v}[\hat{y}(t_1)]$ and $\hat{v}[\hat{y}(t_2)]$ were estimated by Eqs. 2 and 4 for a given metric at times $t_1$and t_2 and $\hat{C}[\hat{y}(t_2), \hat{y}(t_1)] = \frac{1}{n(n-1)}\sum_{i=1}^{n}[\hat{y}(t_2) - \bar{\hat{y}}(t_2)].[\hat{y}(t_1) - \bar{\hat{y}}(t_1)]$ is the covariance between the two estimators. As long as the same cluster plots were measured at both t_1 and at t_2 the variance of $\hat{\Delta} y$ is expected to be smaller. In other word, $\hat{\Delta} y$ is expected to be more precise estimator of Δy.

RESULTS AND DISCUSSION
The estimated value of Shannon's diversity (*SH*) and its corresponding covariance are presented in Table 2. As expected, strata 1 in the south and 10 in the north showed the largest and smallest *SH* value, respectively. A higher human population in the south (stratum 1) resulted in a high fragmented landscape with many small patches. However, stratum 10 in the north is the mountain region, which is covered by a few large and natural patch types. These two strata indicated the largest variance (low precision) because the sampling intensity was small in both strata. This was true for both time period t_1 and t_2. The total forest edge length (*E*) and its corresponding variance are presented in Table 3. The total forest edge was estimated with moderate precision in most cases because sample size was not enough large for this purpose. The largest variance was observed in stratum 1 in the south. Forest edge density was large and small in the south and north of Sweden, respectively. For instance, it was 800 m km^{-1} in stratum 1 and 500 m km^{-1} in stratum 10. A higher density of forest edge in the south can be explained by a more clear-cut and small-scale forestry in comparison to the north. The estimated contagion metric for different point distances and two time periods is shown in Fig. 2. The values of contagion tended to decrease for longer distances because for longer distances dissimilarity of land cover types tends to increase.

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Table 2. Estimated Shannon's diversity (*SH*) in ten strata and corresponding variance for time periods t_1 and t_2.

Strata	t_1		t_2		$\hat{\Delta}(SH)$	$\hat{v}(\hat{\Delta})$
	$\widehat{SH}$	$\hat{v}(\widehat{SH})$	$\widehat{SH}$	$\hat{v}(\widehat{SH})$		
1	0.6932	0.0055	0.6744	0.0051	-0.0188	0.0058
2	0.6909	0.0017	0.6585	0.0014	-0.0324	0.0024
3	0.6132	0.0017	0.6146	0.0016	0.0014	0.0019
4	0.5682	0.0010	0.5921	0.0010	0.0239	0.0015
5	0.4753	0.0006	0.5921	0.0006	0.1168	0.0009
6	0.4147	0.0010	0.4334	0.0011	0.0187	0.0018
7	0.3737	0.0007	0.3595	0.0007	-0.0142	0.0011
8	0.3535	0.0004	0.3393	0.0004	-0.0142	0.0055
9	0.3997	0.0004	0.3697	0.0004	-0.0300	0.0061
10	0.1016	0.0002	0.0814	0.0001	-0.0202	0.0022

Table 3. Estimated the total forest edge length (*E*) in ten strata and corresponding variance for time periods t_1 and t_2.

Strata	t_1		t_2		$\hat{\Delta}(E)$	$\hat{v}(\hat{\Delta})$
	$\hat{E}$ (Km)	$\hat{v}(\hat{E})$	$\hat{E}$ (Km)	$\hat{v}(\hat{E})$		
1	4606	7.5×10^5	4606	7.5×10^5	0	1.4×10^6
2	8484	7.5×10^5	3320	8.8×10^5	-5164	1.6×10^6
3	9545	8.6×10^5	9545	8.6×10^5	0	1.7×10^6
4	22449	4.4×10^6	25170	3.4×10^6	2721	1.4×10^7
5	42130	1.1×10^6	42130	1.1×10^6	0	1.5×10^7
6	27428	5.9×10^6	26412	6.5×10^6	-1016	1.9×10^7
7	28100	9.9×10^6	28100	9.9×10^6	0	1.8×10^7
8	52393	2.4×10^6	45117	2.7×10^6	-7277	1.2×10^7
9	62995	1.4×10^6	60195	1.7×10^6	-2800	1×10^7
10	37953	1.6×10^6	34916	1.5×10^6	-3036	1.8×10^7

It was true for all ten strata. For the shortest point distance 250 m, the largest contagion value observed in stratum 10 (0.81, an aggregated landscape), whereas for the same distance the smallest contagion value observed in stratum 2 (0.52, a highly fragmented landscape). In most cases, the estimated contagion values in t_2 were smaller than t_1. It can be interpreted that the landscape became more fragmented in terms of contagion metric. Estimated variance of the contagion metric for different point distances and for ten strata is presented in Table 4. The estimated variance in stratum 10 in the north with aggregated landscape was smaller than strata 1 in the south with highly fragmented landscape. The estimation of selected landscape metrics from field-based inventory can give us not only a general picture of the current status of landscape pattern but they can also provide information on landscape development over time (trend analysis). Trend analysis in landscape pattern and forest type pattern may be a highly informative support with respect to climate change issues, and operational guidelines to adapt to it (Kolström *et al.* 2011). The proposed sample-based metrics can also be used to assess the forest landscape pattern and their dynamics within forest ecosystems (Barbati *et al.* 2007). In most cases, the metrics are estimated with reasonable precision and the estimation procedure is simple although the NILS program has not been designed to estimate landscape metrics. In some cases, however, the estimates, due to low sampling intensity, are associated with large variance (low precision). The estimates can be improved in different ways, including 1) to combine NILS's datasets with other data sources, for instance, the National Forest Inventory in Sweden (NFI), where the Swedish NFI has the same design as NILS, that is, square cluster plots (Fridman *et al.* 2014); 2) to combine remote sensing data (e.g., photo plot) and field-based data and using linear or logistic regression techniques; and 3) to combine different sampling methods such as point sampling and line intersect sampling (LIS). In the case of using LIS, virtual lines between subplots can be served as line transect. Note that in the case of the combination with other data sources, the datasets should be harmonized because different classification schemes might be used in different surveys. The number of land cover type within a landscape is a main component of some landscape metrics. In this study, for the Shannon's diversity, the number of land cover types in classification system (here 27) has been used for denominator component (ln(s)) of the estimator. In a sample survey, however, it is likely to miss one or more land cover types particularly uncommon (small in size) ones in the sample plots. It becomes more serious when the sample size is not enough large and or when using a detailed classification system. One way to overcome this problem is to use the number of land cover types actually present in the landscape for ln(s).

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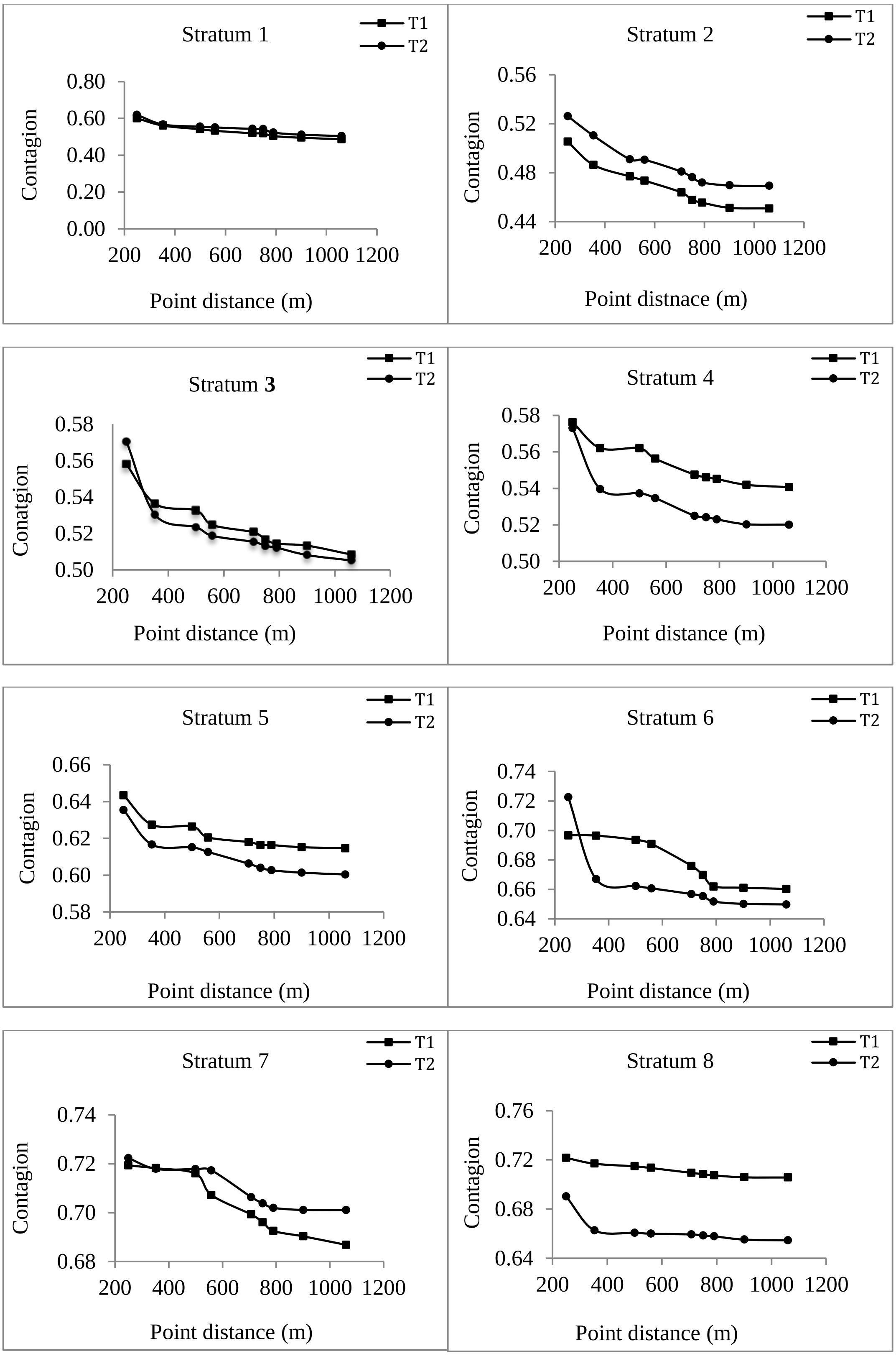

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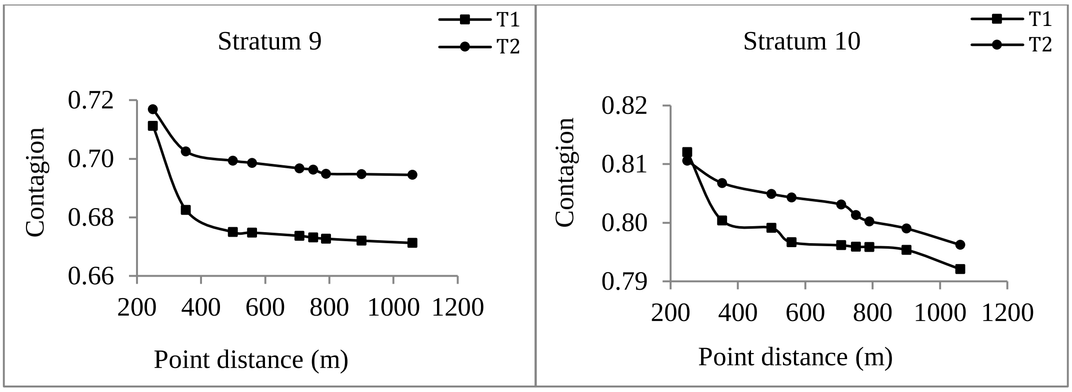

Fig. 2. Estimated contagion value in ten strata for time periods t_1 and t_2.

Table 4. Estimated variance of contagion estimator for ten strata, different point distances and for t_1 and t_2.

Strata	Point distance (m)	$\hat{v}$	
		t_1	t_2
Stratum 1			
	250	17.3	15.9
	353	9.8	9
	500	13.5	13.8
	559	13.2	12
	707	9.3	8.6
	750	14	14.4
	790	15.2	14.4
	901	11.8	11.8
	1060	10.3	9.8
Stratum 2			
	250	11.9	13.2
	353	7	7.8
	500	8.9	10.8
	559	9.7	10.1
	707	7	7.8
	750	9.9	11
	790	10.1	12.2
	901	9	10.6
	1060	8	9.2
Stratum 3			
	250	11.3	9.6
	353	7.5	5.3
	500	10.2	8.7
	559	9	6.6
	707	7.2	4.8
	750	9.7	8.6
	790	11.5	9.2
	901	9.7	7
	1060	8.8	6.8
Stratum 4			
	250	12.6	12.8
	353	7	8.1
	500	11.1	10.7
	559	9.7	10.5
	707	7.3	8
	750	11.2	11.2
	790	12.2	11.6
	901	9.9	10.1
	1060	8.2	8.3

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Table 4. Continued

Strata	**Point distance (m)**	$\hat{v}$	
Stratum 5		t_1	t_2
	250	11	10.3
	353	7	6.7
	500	9.5	9.2
	559	9	8.5
	707	7.1	6.9
	750	9	8.7
	790	9.7	9.7
	901	9	8.2
	1060	7.8	7.3
Stratum 6			
	250	9.5	10.9
	353	6.8	7
	500	8.2	9.4
	559	9.7	8.6
	707	7.6	6.7
	750	7.9	9
	790	8.4	9.7
	901	7.9	8.7
	1060	7.8	8.1
Stratum 7			
	250	9.4	9.9
	353	7.5	8.2
	500	8.5	9
	559	8.1	9.6
	707	7.8	7.6
	750	8.3	8.7
	790	9.1	8.9
	901	7.6	8.2
	1060	8.1	8.2
Stratum 8			
	250	8.8	12.1
	353	7.4	10
	500	8.2	11.2
	559	8.7	11
	707	7.3	10
	750	7.7	10.6
	790	8.7	11.5
	901	7.7	10.8
	1060	7.6	9.8

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Table 4. Continued

Strata	Point distance (m)	$\hat{v}$	
Stratum 9		t_1	t_2
	250	10.5	8.1
	353	7.2	6.5
	500	9.7	7.6
	559	9.1	8.5
	707	7.2	6.7
	750	9.1	7.6
	790	9.4	8
	901	8.2	6.4
	1060	7.9	7.3
Stratum 10			
	250	9.5	9.1
	353	7.8	6.9
	500	9	8.3
	559	7.9	7.7
	707	7.2	7.2
	750	8.5	8.2
	790	8.8	8.6
	901	8.2	7.6
	1060	7.5	7.3

In such procedure, however, the estimator might not be sensitive to differentiate landscapes with different patterns, as demonstrated by Ramezani *et al.* (2011). Like *SH*, *C* is also sensitive to land cover types missing. Wickham *et al.* (1997) found that contagion is the most sensitive metric to land cover types missing. The estimated variance of contagion estimator in stratum 10 in the north is smaller than stratum 1 in the south. Such difference can be explained by the degree of landscape fragmentation. In other words, the landscape pattern in stratum 10 is more aggregated (homogenous) than stratum 1. A similar result was found by Ramezani and Ramezani (2015), when data from national forest inventory (NFI) was used. However, direct comparison is impossible because the country is divided into inventory regions differently. In most cases, our results show that *SH* and *C* are estimated with acceptable precision (sampling error smaller than 10 %), but from analytical point of view both *SH* and *C* have bias estimators (Fattorini *et al.* 2017, Corona *et al.* 2018).

For the case of *SH*, the reason is that the estimator has non-linear definition although its component (i.e., p_j) can be estimated without bias. Ramezani (2019) applied NFI datasets to estimate *SH*, so that estimated SH showed the same behaver with high precision due to a large sample size. For the case of *C* as demonstrated by Ramezani and Holm (2014) there are several causes for bias: 1) the contagion metric for the same reason as Shannon's diversity has non-linear definition and 2) the estimator $\hat{p}_{ij\,(d)}$ in Eq. 5 is a ratio estimator and thus has a certain bias. In the case of using a large sample size, the bias can be reduced (Hassett *et al.* 2012) for both metrics, but sample size is fixed for this study. In the present study, forest edge length estimation using buffer zone approach has been based on considering all subplots. An alternative could be to observe just four subplots in the corner, but this procedure may be resulted in low precision.

The reason is that some information would be missed. By this study, it is impossible to explore which procedure is more reliable due to the lack of true value of the total forest edge length. However, it would be of interest to perform a sampling simulation for this purpose. In theory, using Eq. 3 the total forest edge length can be estimated without bias. However, in reality it might not be so because two adjacent forest patches might be very close to each other.

In such situation, the imaginary buffer around the forest patches will be overlapped. Kleinn (2000) demonstrated that the statistical efficiency of buffer zone approach depends on buffer width and thus it is expected that more plots will cross the forest boundary when using a large plot. In such situation, the estimated variance tends to decrease.

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CONCLUSION

We can use all three landscape metrics in monitoring program where the aim is to measure important biodiversity metrics regarding the forest landscape pattern. It is clearly beneficial to sample characteristics belonging to different aspects of ecosystems at the same sample points and at the same time so that the information for different attributes can be related to each other. For instance, this would allow relating the biodiversity dynamics of forest natural regeneration as usually measured by NFI plots to changes in landscape metrics as assessed by field measurements in the same plots (Corona *et al.* 2011).

The NILS program has been designed to collect data regarding biodiversity and vegetation on landscape level. Our result shows that other landscape metrics can also be estimated from NILS's dataset. In future, thus, we might be able to find a relationship between landscape pattern (as a predictor variable) and ecological processes across different spatial scales, ecosystems, and habitats. Furthermore, we will be able to compare different inventory regions at a given time. The results obtained show that the estimation of some currently used metrics from field-based sampling data is very simple.

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