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Forest fragmentation assessment using field-based sampling data from forest inventories

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ABSTRACT

Forest fragmentation has a relevant impact on biodiversity. An interesting alternative to estimate these indices is to use sampling data. This study aims to estimate aggregation index (AI) and the degree of clumping of forested landscape based on AI. The assessment was conducted using different point distances, inventory regions and cardinal directions. For this purpose, a dataset from one five-year periods (2007–2011) of the Swedish National Forest Inventory (NFI) was used. The estimation of AI from field-based inventory can give us a general picture of the current status of forest landscape. The results also show that the estimated AI is a distance dependent function. The corresponding estimated variance of the index is smaller for longer distances. The obtained results indicate that the estimated variance depends on both sample size and pair point distances. Estimated AI showed different values in different cardinal directions. To compare two regions or a given region over time, a given point distance should be used. The main advantage of the applied procedure is that a range of AI values can be produced rather than a single number. Furthermore, in field-based inventory, the obtained results are more reliable, because one works implicitly with a single forest definition only.

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NFI; sampling methods; forest landscape; environmental monitoring

Introduction

Forest fragmentation is a dynamic process where a large forest patch is broken into many small and isolated patches (Tolentino and Anciaes 2020). Forest fragmentation is also considered as a state of a forest landscape at a given time. Forest loss and forest fragmentation have received more attention in recent years due to recognition that fragmentation has a relevant impact on biodiversity and ecosystem services provided by forested landscapes (Shapiro et al. 2016; Lister et al. 2019). It is also found that climate change and fragmentation may have combined effect on habitat loss (Pyke 2004). Corona et al. (2018) states that there are not only effects of biodiversity and land management from climate change, but that there are also changes in biodiversity and ecosystem functioning that in turn affect climate change. Thus, landscape change monitoring is important and landscape indices are appropriate for such purposes (Lister et al. 2019). Landscape indices can deliver quantitative measurements of forest landscape dynamics which can provide a basis for decision making by politicians and policy makers (Ji et al. 2006).

Landscape indices are quantitative indices that describe both the composition and configuration aspects of landscape pattern. In particular, composition refers to a variety of land cover types and their proportions, whereas configuration refers to spatial distribution of land cover types in a landscape (McGarigal et al. 1995). Quantification of the configuration aspect of a landscape is important in landscape ecological surveys because ecological processes such as movements of organisms and natural disturbance regimes can be affected by geographic distribution of forest patches in a landscape. For this purpose, several configuration indices have been proposed and aggregation index (AI) is a typical example (He et al. 2000).

Sample-based approaches are a promising alternative to wall-to-wall approaches for estimating some landscape indices. These approaches are commonly conducted on remotely sensed data. For instance, Hunsaker et al. (1994), Hassett et al. (2011), and Ramezani and Grafström (2014) applied hexagon and square plots on satellite images; Ramezani et al. (2010) and Lister et al. (2019) used point grid on aerial photos; and Corona et al. (2004) and Ramezani and Holm (2011) used line interest sampling (LIS) method on aerial photos. It is also possible to estimate some currently used landscape indices from field-based inventories such as National Forest Inventories (NFIs; Kleinn 2000; Ramezani and Ramezani 2015), but this possibility has received less attention.

The NFIs have a long history in many countries (Axelsson et al. 2009), providing information on the status and trend of forests. The NFIs have usually been designed to assess coverage of different land cover types, growing stock, basal area and forest biodiversity (Chirici et al. 2012). In forest inventories, forest attributes recorded at sample plots can be used to

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Table 1. Information on six inventory regions: the total area; the size of tracts; number of circular subplots in one tract in permanent (*P*) and temporary (*T*) tracts.

		Tract size (km)		The number of tracts (circular subplots)	
Regions	Total area (km^2)	*P*	*T*	*P*	*T*
1	118,130.92	1.2	1.8	531 (8)	285 (12)
2-1	68,720.46	1.2	1.5	419 (8)	248 (12)
2-2	67,140.55	1.2	1.5	436 (8)	220 (12)
3	69,644.09	1	1.5	556 (8)	258 (12)
4	116,848.48	0.8	0.8×0.4	1185 (8)	1089 (6)
5	34,476.76	0.3	0.3×0.6	849 (4)	368 (6)

estimate biodiversity indicators, although information on the spatial distribution of sample plots is not normally used to derive such inferences. However, this type of information can be applied to understand the spatial structure and patterns of forest habitat patches (Corona et al. 2011).

This study aims to estimate the degree of clumping of forested landscape in terms of aggregation index (AI) from field-based forest inventory, (e.g. National Forest Inventory, NFI). It also aims to investigate the performance of AI in terms of the estimated variance in different point distances.

Material and methods

Material

Data from the Swedish National Forest Inventory (NFI) were used in this study. The NFI was initiated in the 1920s where the sampling design was a strip survey (Axelsson et al. 2009). From the 1950s, a cluster plot design (tract) was introduced into the Swedish NFI. The NFI divides the country into six inventory regions with the sampling intensity decreasing towards the north of the country. Tracts were systematically distributed over each region, and their locations were temporary (changing over inventory cycles). From the 1980s and onwards, the NFI's sampling design has essentially been the same as today, with permanently located tracts introduced at that time. Circular subplots in tracts have radius 10 and 7 m in permanent and temporary tracts, respectively. In the Swedish NFI, about 20% of the total number of tracts is measured each year and the re-measurement interval is thus every five years. In the present study, to estimate AI, a dataset from one five-year periods (2007–2011) of the NFI was used. The tract size, the number of tracts in different inventory regions and the number of circular subplots in each tract for both permanent and temporary tracts are summarized in Table 1.

Aggregation index (AI)

This index was originally designed for raster data, in which landscapes are divided into grids of square cells (He et al. 2000). The original raster-based version considers the four immediate neighbors. More recently, however, a point aggregation index (*AI*) has been developed by Lister et al. (2019). According to Lister et al. (2019), the point aggregation index estimator can be defined as

$$\widehat{AI} = \frac{\sum_{i}^{m} \sum_{j,j \neq i}^{m} \hat{F}_{ij}}{\sum_{i}^{m} \sum_{j,j \neq i}^{m} \hat{N}_{ij}} \tag{1}$$

where $\hat{F}_{ij}$ is the number of forest-forest point adjacencies at distance d, $\hat{N}_{ij}$ is the total number of point adjacencies between forest and any other land cover type at distance d

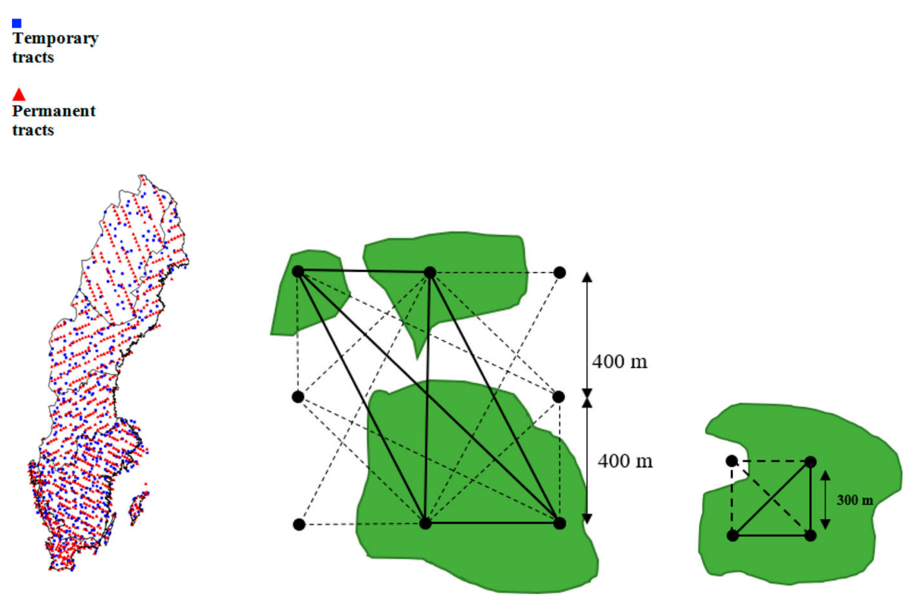

Figure 1. Regional division (*left*) and an illustration of permanent tract from inventory region 4 (800×800 m) (*middle*) and permanent tract from inventory region 5 (300×300 m) (*right*) with different circular subplots from the Swedish National Forest Inventory (NFI). Black dots show subplot centers (sampling location). All possible point pairs between two adjacent points at different distances are illustrated with solid and dashed lines. The solid lines show adjacencies between forest-forest land cover type and dashed lines show adjacencies between forest-non forest land cover types. Green polygons show forest patches, whereas white background shows other (non-forest) land cover types in the landscape. As an example, using Equation (1), with a point distance 400 m, $N_{ij} = 6$, $F_{ij} = 2$ and thus, *AI* is equal 0.333. For point distance 800 m, $N_{ij} = 5$, $F_{ij} = 1$, *AI* is equal 0.200. In inventory region 5 for point distance 300 m, $N_{ij} = 4$, $F_{ij} = 2$ and thus, *AI* is equal 0.5, for point distance 424 m, $N_{ij} = 2$, $F_{ij} = 1$ and thus, *AI* is equal 0.5.

Table 2. Land cover types are recognized in the Swedish National Forest Inventory (NFI).

No.	Land cover types
1	Productive forest land
2	Natural pasture
3	Arable land
4	Mire
5	Mountain
6	Mountain coniferous forest
7	Road and rail
8	Power line in productive forest land
9	Built-up land
10	Another mark
11	Fresh water
12	Saltwater

(including forest) in the estimation area. To calculate $\hat{F}_{ij}$, an $i \times j$ ($i = j = 1 \ldots m$ points in the estimation area) adjacency matrix with binary elements (1 = a forested point adjacent to another forested point, 0 otherwise) and, $\hat{N}_{ij}$, an $i \times j$ adjacency matrix with binary elements (1 = a forested point adjacent to any point type, 0 otherwise) was made. i and j refer to land cover types. *AI* has values in the range of 0–1, so that a high value represents a landscape with highly aggregated forest patches, whereas a low value represents a landscape with highly disaggregated (fragmented) forest patches. An example of the calculation of *AI* is presented in Figure 1.

To estimate *AI*, it is necessary to know the land cover type for each sampling location. In this study, circular subplot centers in tracts served as sampling locations. All possible circular subplot centers at distance d are treated as point pairs. For instance, for a permanent tract in inventory region 4 with 8 circular subplots, there are five distinct distances.

In the Swedish NFI, 12 land cover types are distinguished (see Table 2) and for the purpose of our study, we consider the two types forest/non-forest only. In the present study, different inventory regions and different spatial scales are investigated. The degree of clumping is compared in different cardinal directions; east–west, north–south, northwest–southeast and northeast-southwest.

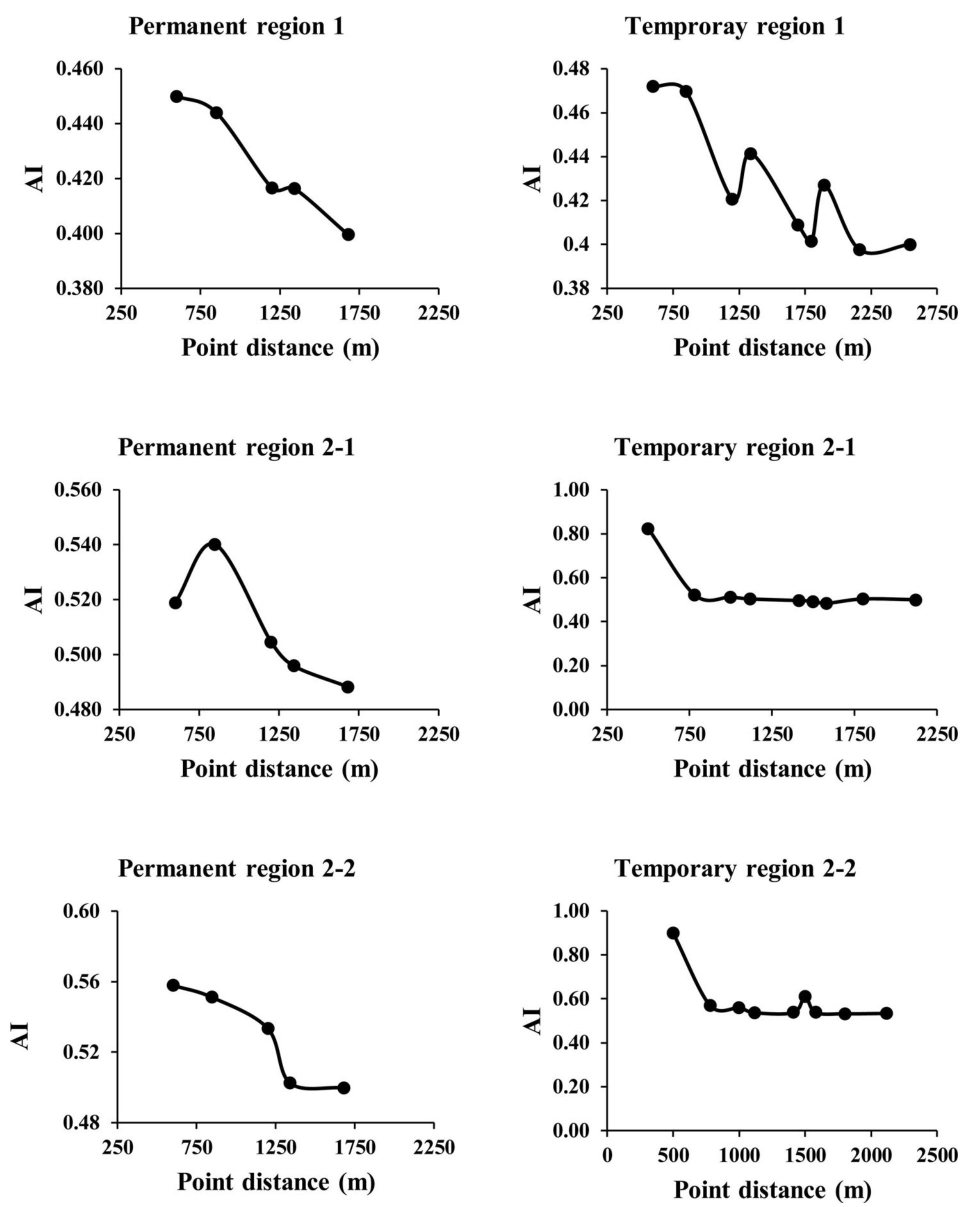

Figure 2. Relationship between point distance and estimated value of *AI* for six inventory regions. For permanent and temporary tracts.

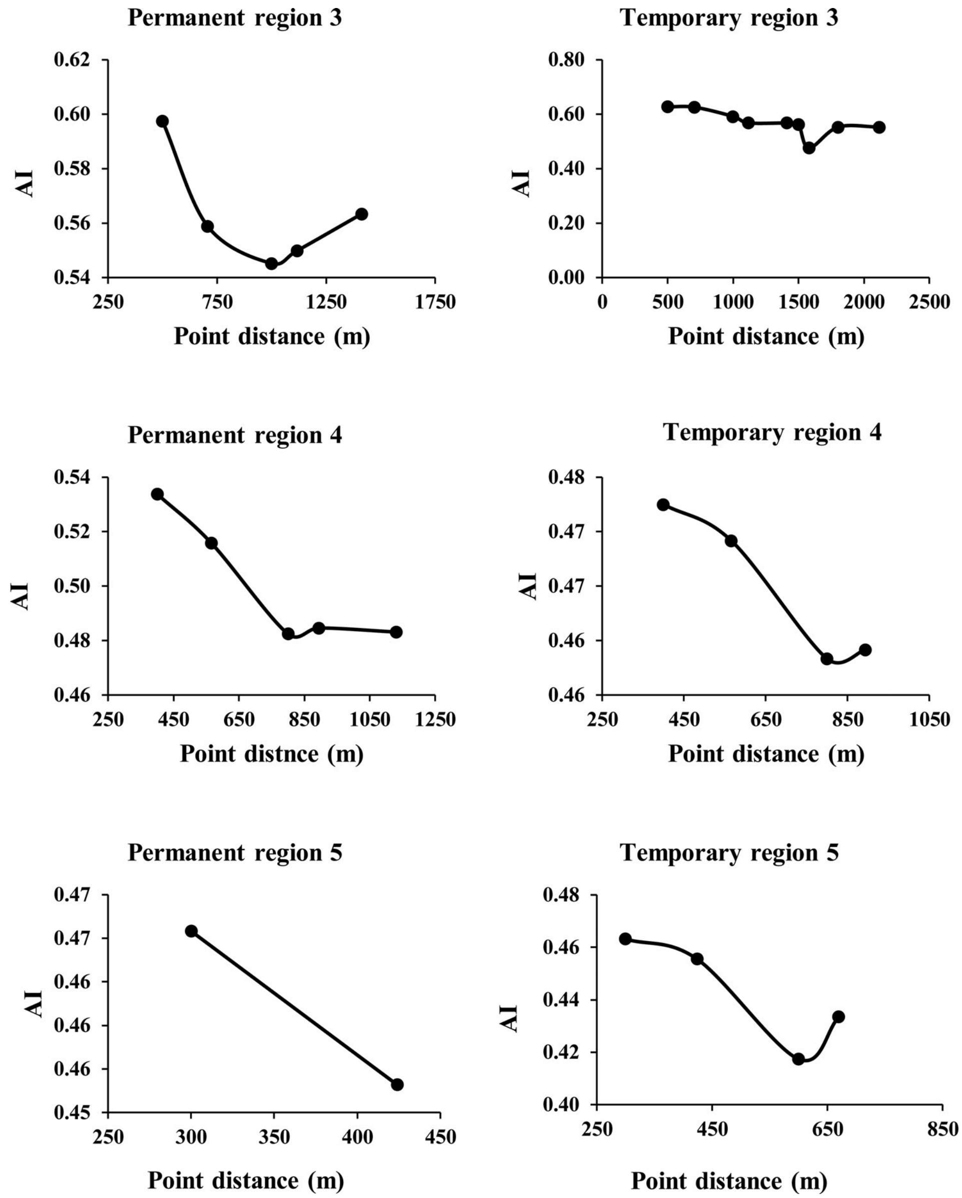

Figure 2. *Continued*

Variance estimation

In the present study, the variance was used to assess statistical performance of the *AI* estimator. To estimate the variance of the *AI* estimator, the sample of *n* tracts is treated as a population itself. In such a situation, the jackknife estimator is a straightforward procedure for the estimation of variance (Thompson 2002). The jackknife estimator was also used by Kleinn (2000) and Lister et al. (2019). Using the jackknife estimator, one tract at a time is systematically removed from the sample and then *AI* is calculated. This is repeated for each tract in succession. According to Thompson (2002), the jackknife estimator of the variance is

$$\hat{v}(\widehat{AI}) = \frac{n-1}{n}\sum_{i=1}^{n}(\widehat{AI}_i - \overline{AI}_{jack.})^2 \quad (2)$$

where $\widehat{AI}_i$ is the estimator when leaving tract *i* out and $\overline{AI}_{jack.} = \frac{1}{n}\sum_{i=1}^{n}\widehat{AI}_i$ and *n* is the number of tracts. Note that with this technique it is assumed that observations had independently been selected, but as pointed out previously datasets are provided from a systematic sampling design and are not independently selected.

Results

The *AI* was estimated for six inventory regions, at different point distances. The relationship between *AI* and point distance for different inventory regions using permanent and temporary tracts is shown in Figure 2. As our results show, in most cases, the value of the *AI* decreases with increasing point distance, and it can be explained by positive spatial autocorrelation. It is difficult to compare different inventory regions, because *AI* is distance dependent function and point distances are various in different inventory regions.

However, inventory regions 2-1 and 2-2 have similar tract size and point distances *d*. As the result shows, *AI* estimator has almost similar behaver.

The estimated *AI* in different cardinal directions for six inventory regions and using permanent and temporary tracts is presented in Figure 3. The estimated *AI* has different values in different cardinal directions. This dissimilarity of *AI* in different directions can be explained by diverse spatial distribution of forest landscape in different directions.

Table 3 presents estimated variance of *AI* for six inventory regions and different point distances. It is expected the estimated variance should be smaller for shorter point distances with a larger sample size. However, the obtained results indicate that the estimated variance tended to decrease with increasing point distances. This means that, the estimated variance depends on both sample size and point distances *d*. In a few point distances, however, the increase in *AI* value occurs for longer distances and the estimated variance is small for longer distances. The reason is that the number of observations is limited in such distances, and this number should strongly affect the estimated variance.

Discussion

The estimation of *AI* from field-based inventory can give us a general picture of the current status of forest landscape. Furthermore, estimation procedure of *AI* is very simple and can also provide information on landscape development over time (trend analysis). Fortunately time series NFI datasets are available in many countries.

This study shows the possibility of assessing forest fragmentation in terms of aggregation index (*AI*) through sample based NFIs, although NFIs are not initially designed for such purpose. The main advantages are that (1) the procedure can be applied where raster-based land cover/use maps of the entire forest landscape are not available and (2) that it produces a range of values, rather than a single number or index value information on forested landscape. Our findings show that historical field-based forest inventory has the potential for assessing landscape change over time. Historical NFI data are available in many countries and for a long time period (Tomppo et al. 2009).

Generally, the estimated *AI* value decreases with increasing point distances and our finding is consistent with Lister et al. (2019), where point aggregation index was applied on aerial photographs to assess forest fragmentation. This phenomenon can be explained by positive spatial autocorrelation, where dissimilarity of land cover class occurs with larger distances. Our findings also show that the decrease in estimated variance occurs over longer distances, despite the number of observations being limited when considering such distances. It can be explained by a larger variation, in

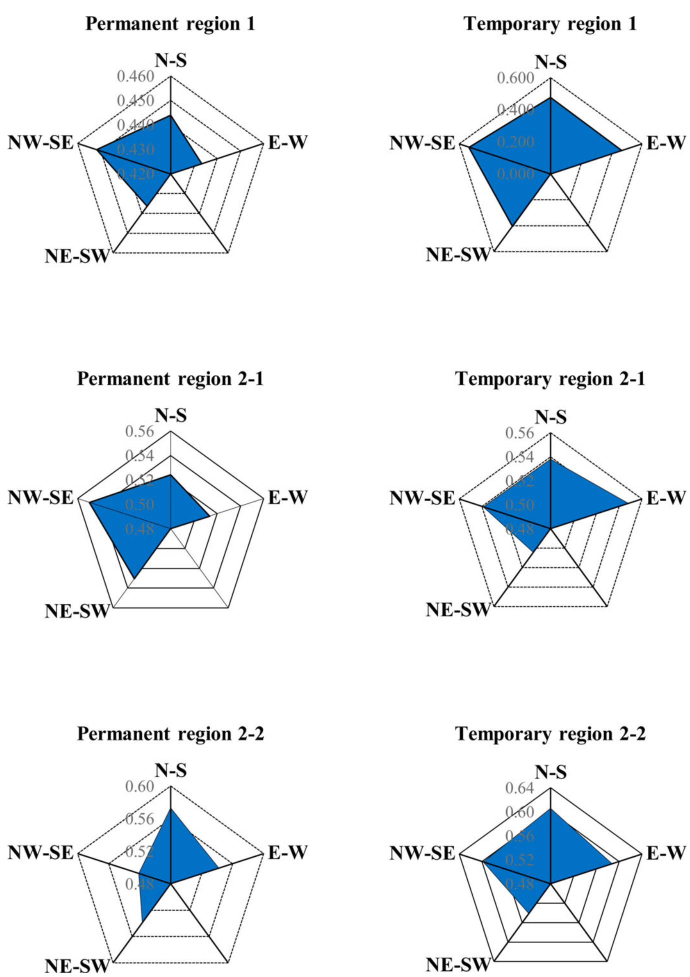

Figure 3. Estimate value of *AI* for different directions, for two time periods, and for six inventory regions. For permanent and temporary tracts.

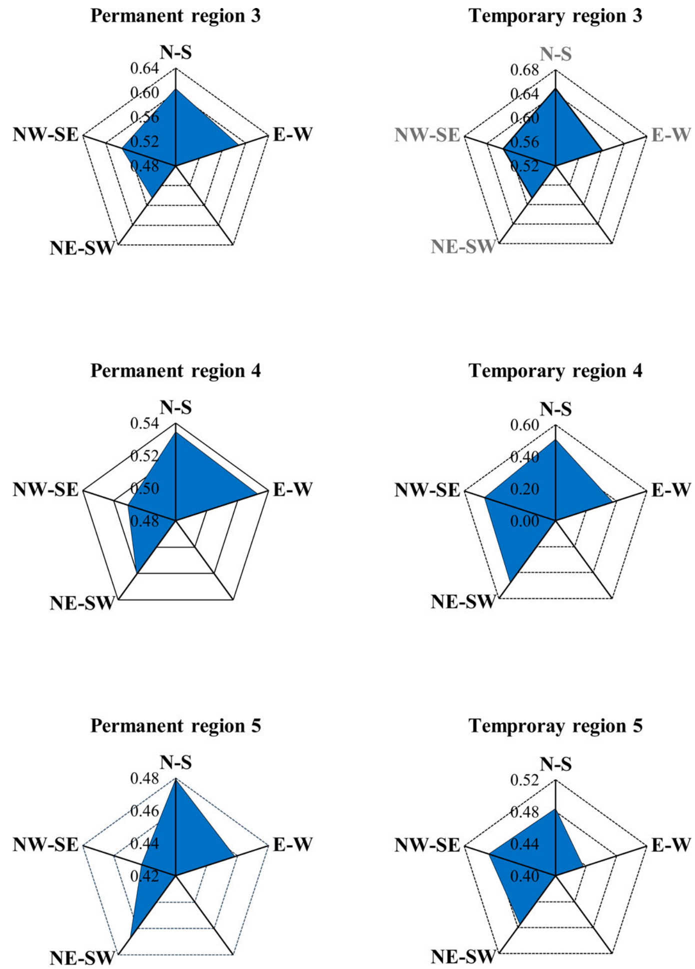

Figure 3 *Continued*

terms of cardinal directions, of pair points for shorter distances.

The *AI* showed a similar performance as a point-based contagion index from Ramezani and Holm (2014). Both *AI* and contagion quantify the degree of fragmentation, but in contrast to contagion, *AI* is calculated for a certain land cover type such as forest land cover type. Both indices can be estimated without delineating patch borders. As a result, not only polygon delineation error can be eliminated but also the procedure applied in this study can accommodate both the general model approaches to landscape structure, i.e. the patch-mosaic model (Forman 1995) and the gradient-based model (McGarigal et al. 2005) where landscape is viewed as continuous with no hard borders assumed between patches. Furthermore, in field-based inventory, the obtained results are more reliable, because one works implicitly with a single forest definition only.

A landscape has various aspects (composition and configuration) and thus it is not practical to measure and quantify all aspects of it using only a single index like *AI*. An alternative is to combine *AI* with other landscape indices such as contagion (Ramezani and Ramezani 2015) and forest edge length (Kleinn et al. 2011, Ramezani 2017), which can be estimated from the same dataset.

Our findings show (Figure 3) that the estimated *AI* has different values in different cardinal directions. This means that human activity or natural disturbance is various in different directions. In other words, landscape development and the degree of forest fragmentation is not the same in all directions.

In this study, the lowest *AI* value ($AI = 0.410$), was estimated for inventory region five in southern Sweden, using a point distance of 600 m. This lower value of *AI* can be explained by higher human activity and land-use conversion. The findings of this study are consistent with Ramezani (2017), who used the Swedish NFI for the estimation of the total forest edge length as another forest fragmentation index. The highest forest edge density was also found in this inventory region. Note that a given point distance should be used where it is aimed to compare two regions or a given region over time, because point aggregation index (*AI*) applied in this study is distance dependent.

In this study, we have used the variance for assessing statistical performance of AI estimator (Equation 1). However, *AI* similar to contagion is specified as a ratio between two random variables. A ratio estimator is applied when both the numerator and the denominator are estimated. Thus, a small bias will always be obtained (e.g. Thompson 2002). However, Ramezani et al. (2010) and Ramezani and Holm

Table 3. Estimated variance of *AI* for six inventory regions, for all possible point distances (*AI* values and sample sizes are presented in parentheses).

Inventory regions	Temporary tracts: Point distance (sample size)	Temporary tracts: Variance (×1000)	Permanent tracts: Point distance (sample size)	Permanent tracts: Variance (×1000)
Region 1				
	600 (3420)	12 (0.472)	600 (4248)	10 (0.450)
	848 (1140)	8 (0.470)	848 (2124)	7 (0.444)
	1200 (2280)	10 (0.421)	1200 (3186)	9 (0.417)
	1341 (2280)	10 (0.441)	1341 (4248)	9 (0.416)
	1697 (1140)	7 (0.409)	1679 (1026)	4 (0.400)
	1800 (2280)	10 (0.401)		
	1897 (2280)	10 (0.427)		
	2163 (2280)	9 (0.398)		
	2546 (570)	4 (0.400)		
Region 2-1				
	500 (2976)	7 (0.822)	600 (3352)	7 (0.518)
	707 (992)	5 (0.521)	848 (1676)	7 (0.540)
	1000 (1984)	6 (0.511)	1200 (2514)	6 (0.504)
	1188 (1488)	7 (0.503)	1341 (3352)	6 (0.495)
	1414 (992)	5 (0.495)	1679 (838)	2 (0.488)
	1500 (1984)	5 (0.492)		
	1581 (1984)	6 (0.483)		
	1803 (1984)	5 (0.503)		
	2121 (496)	2 (0.499)		
Region 2-2				
	500 (2640)	9 (0.899)	600 (3488)	7 (0.557)
	707 (880)	5 (0.568)	848 (1744)	7 (0.551)
	1000 (1760)	8 (0.558)	1200 (2616)	6 (0.533)
	1188 (1760)	8 (0.536)	1341 (3488)	7 (0.502)
	1414 (880)	5 (0.537)	1679 (872)	2 (0.499)
	1500 (1760)	7 (0.610)		
	1581 (1760)	7 (0.537)		
	1803 (1760)	6 (0.531)		
	2121 (440)	3 (0.533)		
Region 3				
	500 (3096)	9 (0.627)	500 (4448)	9 (0.597)
	707 (1032)	4 (0.625)	707 (2224)	7 (0.558)
	1000 (2064)	8 (0.591)	1000 (3336)	7 (0.545)
	1118 (2064)	8 (0.568)	1118 (4448)	8 (0.549)
	1414 (1032)	5 (0.567)	1414 (1112)	3 (0.563)
	1500 (2064)	6 (0.561)		
	1581 (2064)	6 (0.476)		
	1803 (2064)	5 (0.552)		
	2121 (516)	3 (0.553)		
Region 4				
	400 (7623)	10 (0.456)	400 (9480)	10 (0.533)
	566 (4356)	6 (0.472)	566 (4740)	7 (0.515)
	800 (2178)	2 (0.476)	800 (7110)	8 (0.482)
	894 (2178)	3 (0.464)	894 (9480)	9 (0.484)
			1131 (2370)	3 (0.483)
Region 5				
	300 (2208)	11 (0.463)	300 (3396)	7 (0.468)
	424 (1472)	7 (0.455)	424 (1698)	3 (0.454)
	600 (736)	3 (0.417)		
	670 (736)	3 (0.433)		

(2014) in a simulation study demonstrated that the bias of the nonlinear indices such as contagion and Shannon's diversity tended to decrease with increasing sample size. In other words, the bias is negligible with a large sample size, as the case of this study. In the present study, it is impossible to estimate the bias because of the lack of a reference (true) value for *AI*.

Landscape ecological surveys can have the aim to explore relationships between landscape patterns and ecological processes such as forest biodiversity. Thus, it is clearly beneficial to sample characteristics belonging to different aspects of forest ecosystems at the same sample points and at the same time so that the information for different attributes can be related to each other (Motz et al. 2010). Sterba (2008) states that simultaneous assessment of both forest spatial and biodiversity related variables clearly enables forest monitoring with comparatively little additional cost, as opposed to the considerable costs of designing and implementing separate biodiversity inventories. A similar study can be conducted on other land cover types such as wetlands. The historical NFI data set is available in many countries, thus enabling trend analyses in forested landscapes over time.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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