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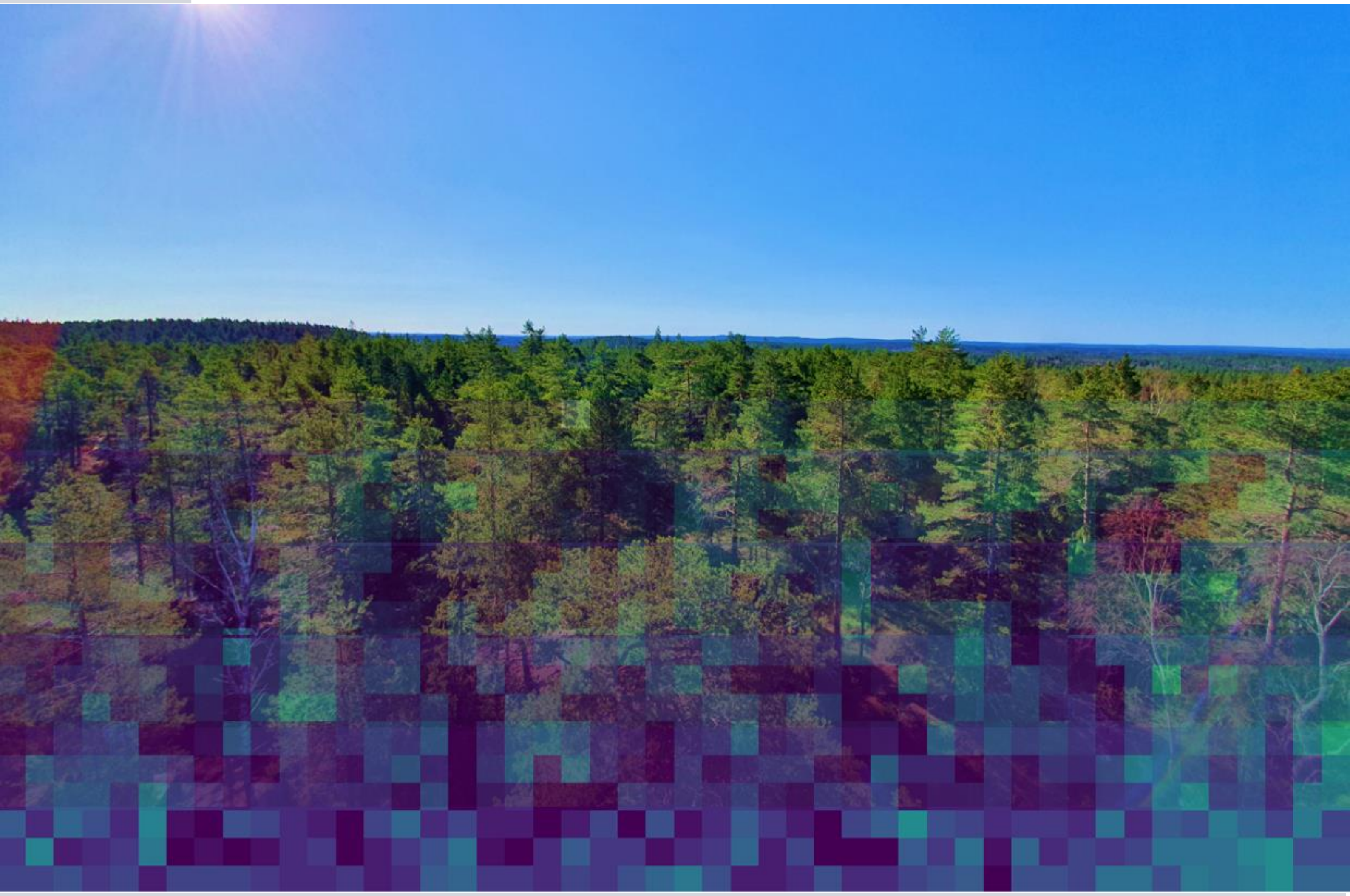
Landscape analysis of Old Natural Forest polygons identified from LiDAR data

Erik Framstad, Megan Nowell and Zander Venter



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Erik Framstad, Megan Nowell and Zander Venter

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Abstract

Framstad, E., Nowell, M. & Venter, Z. 2020. Landscape analysis of Old Natural Forest polygons identified from LiDAR data. NINA Report 1799. Norwegian Institute for Nature Research.

This report presents results from a landscape analysis of Old Natural Forest (ONF) polygons for Eastern Norway. The polygons were aggregated from pixels with assigned probabilities of being ONF, based on airborne LiDAR data and National Forest Inventory (NFI) data. Ten municipalities had <40% LiDAR cover. Polygons consisted of the pixels with highest probability of being ONFs, up to a threshold set by NFI data for each county. Polygons smaller than 0.5 ha were discarded. The aggregation procedure resulted in higher proportions of ONF area than set by the thresholds, marginally for most counties but substantially for Buskerud and Aust-Agder. 333 819 ONF polygons with a total area of 11 367 km^2 were extracted; these covered 22.6% of the available forest area with LiDAR data. Parts of Hedmark, Oppland, Vestfold, and Telemark had the highest density of ONF polygons. The ONF polygons varied considerably in size, although about 50% were smaller than 1 ha and only 67 polygons were larger than 500 ha.

Several spatial metrics were calculated, including basic polygon properties, polygon shape complexity and connectivity. Municipalities were used as landscape units and values aggregated to county level. Mean polygon size varied among counties, with Buskerud and Aust-Agder having the largest mean polygon sizes of 5.8 and 6.4 ha, respectively. Edge density reflects the number of polygons per forest area, and this was highest for Vestfold and Telemark. Total edge and total core area reflects the total ONF area and number of polygons. The four metrics for polygon shape complexity were closely correlated. Telemark and Vestfold had the most irregular ONF polygons on average, and Oslo and Akershus had the most regular. The four main connectivity metrics represent different aspects of connectivity and were not closely correlated. These metrics indicate that ONF polygons in Buskerud had the highest degree of connectivity. Aust-Agder had the lowest connectivity values for three of the four metrics.

If the extracted ONF polygons represent real old natural forest, we should expect other conservation values linked to such forest to occur more frequently in ONFs than in other forest. ONFs and forest in general differed only marginally in their cover of forest in protected areas. However, ONFs covered more of forest key biotopes (3%, 4%) than forest in general (1.8%). The ONFs also had a higher frequency of observations of forest-associated red-listed species of insects, lichens and fungi (5.4 observations per 10 km^2) than did forest in general (3.8 observations).

Old natural forest and clearcuts represent totally different forest stages. Nevertheless, 12.7% of the area of ONF polygons overlapped clearcuts classified from Landsat images. 7.5% of the area of ONFs were clearcuts made before the LiDAR data were collected, indicating inconsistencies in the methods of identifying ONFs or clearcuts. The locations of ONF polygons and clearcuts did not differ much with respect to distance to the nearest road or elevation, but ONFs tended to occur in somewhat steeper terrain.

These results are further discussed in terms of the influence from the methodology, including identification of ONF pixels from LiDAR data, the aggregation procedure, properties of the spatial metrics, and other aspects of the analyses. Using a narrower and more distinct definition for old natural forest may result in better targeting of old natural forest with high conservation values. A map of old natural forest patches could be part of the input data for the assessment of ecological condition in forests, but setting reference values for landscape level indicators would be challenging. Recommendations for improving the methodology include assessment of most appropriate definitions of old natural forest, possibilities for improving ground truth data, possible use of other remote sensing data sources, exploration of the effects of alternative steps in the aggregation procedure from pixels to polygons, and the use of photo and field validation of what extracted polygons actually cover.

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Sammendrag

Framstad, E., Nowell, M. & Venter, Z. 2020. Landskapsanalyse av polygoner av gammel naturskog identifisert fra LiDAR data. NINA Rapport 1799. Norsk institutt for naturforskning.

Denne rapporten presenterer resultater fra en landskapsanalyse av polygoner av gammel naturskog for Øst-Norge med Agder. Polygonene ble aggregert fra piksler med tildelte sannsynligheter for å være gammel naturskog, basert på data fra luftbåren LiDAR og Landsskogtakseringen. Ti kommuner hadde <40% dekningen av LiDAR-data. Polygonene besto av pikslene med størst sannsynlighet for å være gammel naturskog, opp til en terskel satt ved Landsskogtakseringens data for hvert fylke. Polygoner mindre enn 0,5 ha ble forkastet. Aggregeringsprosedyren resulterte i høyere andeler av gammel naturskog enn gitt ved terskelverdiene, marginalt for de fleste fylkene, men betydelig for Buskerud og Aust-Agder. Til sammen ble det avgrenset 333 819 polygoner av gammel naturskog med et totalareal på 11 367 km^2; disse dekket 22,6% av det tilgjengelige skogarealet med LiDAR-data. Tettheten av polygoner var høyest i deler av Hedmark, Oppland, Vestfold og Telemark. Polygonene varierte betydelig i størrelse, selv om ca. 50% var mindre enn 1 ha og bare 67 polygoner var større enn 500 ha.

Flere mål for polygonenes romlige egenskaper ble beregnet, inkludert polygonenes form og konnektivitet. Kommuner ble brukt som landskapsenheter, og verdier ble sammenstilt på fylkesnivå. Gjennomsnittlig polygonstørrelse varierte mellom fylkene, der Buskerud og Aust-Agder hadde de største gjennomsnittlige polygonene på henholdsvis 5,8 og 6,4 ha. Kanttettheten gjenspeiler antall polygoner per skogareal, og denne var høyest for Vestfold og Telemark. Total kantlengde og totalt kjerneareal reflekterer det totale arealet og antall polygoner. De fire målene for polygonform var nært korrelert. Telemark og Vestfold hadde de mest uregelmessige polygonene i gjennomsnitt, og Oslo og Akershus hadde de mest regelmessige. De fire viktigste konnektivitetsmålene representerer forskjellige aspekter ved konnektivitet og var ikke tett korrelert. Disse målene indikerer at polygoner i Buskerud hadde høyeste grad av konnektivitet. Aust-Agder hadde de laveste konnektivitetsverdiene for tre av de fire målene.

Hvis de avgrensete polygonene representerer faktisk gammel naturskog, bør vi forvente at andre naturverdier knyttet til slik skog forekommer hyppigere i polygonene enn i annen skog. Det var liten forskjell mellom polygonene og skog generelt i hvor mye de dekket av skog i verneområder. Imidlertid hadde polygonene klart høyere dekning av nøkkelbiotoper (3%, 4%) enn skog generelt (1,8%). Polygonene hadde også en høyere frekvens av observasjoner av skogtilknyttete rødlistearter av insekter, lav og sopp (5,4 observasjoner per 10 km^2) enn skog generelt (3,8 observasjoner).

Gammel naturskog og hogstflater representerer totalt ulike skogtilstander. Likevel overlappet 12,7% av polygonarealet hogstflater klassifisert fra Landsat data, og 7,5% av polygonarealet var hogd før LiDAR-dataene ble samlet inn. Dette tyder på avvik i metodene for å identifisere gammel naturskog eller hogstflater ved fjernmåling. Fordelingene av polygoner og hogstflater skilte seg ikke mye fra hverandre med hensyn til avstand til nærmeste vei eller høyde over havet, men polygonene forekomme i noe brattere terreng.

Disse resultatene er videre diskutert mot ulike sider av metodikken, som identifisering av gammel naturskog fra LiDAR-data, aggregeringsprosedyren, målene for romlige egenskaper og andre aspekter ved analysene. En snevrere og mer distinkt definisjon for gammel naturskog kan i større grad fange opp slik skog med høy forekomst av naturverdier. Et kart over gammel naturskog kan være del av relevant datagrunnlag for vurdering av økologisk tilstand i skog, men det vil være utfordrende å fastsette referanseverdier for indikatorer på landskapsnivå. Anbefalinger for å videreutvikle metodene omfatter vurdering av de mest egnete definisjonene for gammel naturskog, muligheter for å forbedre data for bakkesannheter, mulig bruk av andre fjernmålingsdata, avklaring av effektene av ulike valg i aggregeringsprosessen, og bruk av foto og feltvalidering for å sjekke hva ekstraherte polygoner faktisk dekker.

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Foreword

This report presents the results from a minor part of a larger project initiated by the Norwegian Environment Agency on the use of remote sensing data for the mapping and monitoring of forests. One of the tasks of the main project has been to calculate a probability of a given pixel being old natural forest, based on a specific definition of such forest and remote sensing data (in this case airborne LiDAR data). This report covers one part of the overall project, specifically the process of aggregating pixels (generated through a process not reported here) that are likely to be old natural forest into larger polygons. The resulting polygons are further analysed with respect to their spatial properties, overlap with other conservation interests associated with old natural forests, and relationships to clearcuts, distance to roads and terrain variables (elevation, slope). The results reported here should be seen as examples of how results from remote sensing-based mapping of forest properties may be explored. As the methods are still under development, the results should not be interpreted as representations of reality about old natural forest in Norway.

This main project has been led by Hans Ole Ørka at NMBU. Erik Framstad (NINA) has led the part of the project reported here. Zander Venter (NINA) has processed the data provided by the main project into polygons. Megan Nowell has conducted all the analyses of these polygons.

Tomas Holmern has been the contact person of the Environment Agency.

Oslo, April 2020

Erik Framstad

1 Introduction

Since 2015 The Norwegian Environment Agency (NEA) has initiated projects on the use of remote sensing data for mapping and monitoring of forests. A key aim of these projects has been to identify forest that satisfies criteria for being old natural forest with a minimum impact of modern forestry or other physical impacts from human activities. The Environment Agency published two tenders in 2017 and 2018 which were won by the Norwegian University of Life Sciences (NMBU) in cooperation with the company Science and Technology and NINA. Results from the first part of the work have been reported by Ørka et al. (2018a,b, 2019).

In this report we present the results of additional landscape analyses of old natural forest patches based on improved LiDAR data for most counties of Eastern Norway. We have employed the following definition of old natural forest (D7): *Forest that was identified as cutting class 5 in the 7th National Forest Inventory of 1994-1998 and still remain in that cutting class today*. Such forest has most likely not been harvested by clearcutting and therefore may have retained various structural properties characteristic of old natural forest (Storaunet & Rolstad 2015). According to the last National Forest Inventory such forest covered between 15 and 22% of the total forest areas in the counties of Eastern Norway[1] (**Table 1**), which constitutes the study area (cf. **Figure 1**).

The input data to the landscape analyses are maps of 15.8114 x 15.8114 m pixels with a specified probability of being old natural forest according to the D7 definition. These probabilities are based on extraction and interpretation of airborne LiDAR data from 2005-2018, according to a procedure described in Ørka et al. (2019). On the basis of these maps we have aggregated pixels into polygons of presumed old natural forest (ONF) (cf. chapt. 2) and performed the following analyses on the resulting polygons:

- Landscape patterns of the ONF polygons and their individual properties
- Overlaps between ONF polygons and other measures of forest conservation interest
- Relationships between ONF polygons, identified recent clearcuts, and their respective relationships to natural variation (terrain) and human impact (road network)

The results are discussed with respect to various methodological issues and their management implications. Recommendations are made for further development for the methodology.

[1] The pre-2020 county and municipality structure has been retained as a suitable resolution for presentation.

2 Methods

Input data

The basic input data for the analyses are 15.8114 x 15.8114 m pixels with specified probabilities of being old natural forest (ONF), according to the definition D7, i.e., forest plots that were classified as cutting class 5 in the 7th NFI and remain so today. The estimation procedure for the ONF pixel probabilities is described in Ørka et al. (2019). The estimation has been done separately for each county, and the resulting probabilities are not comparable across counties. The proportion of forest area classified from NFI data as ONF according to the D7 definition also varies among counties (**Table 1**). Hence, the selection of a set of pixels defined as ONF pixels is based on a ranking of pixel probabilities and selection of a proportion of high-ranking pixels approximately equal to the proportion of NFI-based ONF area for each county. These pixels are further aggregated into ONF polygons as described below.

Forest cover varies across the different counties, and not all municipalities within counties have full LiDAR cover. **Figure 1** illustrates the variation in forest cover and the gaps in LiDAR cover for the study area.

Table 1 *AR5 forest area (km^2), forest covered by LiDAR data (km^2), area of extracted old natural forest (ONF) polygons, ONF polygons as proportion of forest area with LiDAR cover, and the target proportion of ONF area according to the D7 definition based on NFI data, for each county of the study area.*

County	AR5 forest area (km^2)	Forest with LiDAR (km^2)	Area of ONF polygons (km^2)	ONF area as proportion (%) of forest w/LiDAR	ONF area as proportion (%) of forest from NFI data
Østfold	2 607	2 605	503	19.3	18.5
Oslo/Akershus	3 448	3 437	567	16.5	15.0
Hedmark	15 993	14 876	2 858	19.2	15.8
Oppland	9 451	8 466	1 652	19.5	19.0
Buskerud	7 784	4 777	1 682	35.2	19.7
Vestfold	1 426	1 426	251	17.6	15.8
Telemark	8 129	7 727	1 840	23.8	21.4
Aust-Agder	4 209	3 740	1 272	34.0	22.0
Vest-Agder	3 518	3 334	742	22.3	18.0
Total study area	**56 565**	**50 388**	**11 367**	**22.6**	**18.4**

ONF patch identification

To assess ONF spatial metrics, we needed to identify contiguous ONF forest patches. The aim was to convert the raw ONF probability pixel values into binary ONF presence/absence pixel values that were spatially connected as forest patches. The basic procedure is conducted in the following sequence on a per county basis:

1. Use a probability threshold to define ONF and non-ONF pixels.
2. Mask out all non-ONF pixels.
3. Identify connected pixel patches (2 or more connected pixels) and drop all pixels that are unconnected.
4. Calculate patch sizes and mask out patches less than 0.5 ha in size.

This procedure results in a raster map of contiguous ONF patches. However, depending on the probability threshold used in step (1), one can end up with a large variation in total ONF forest coverage for a given county. This area may deviate significantly from the proportional coverage defined by the NFI data and the forest area for each county based on N50 forest. Therefore, in order to create ONF patch rasters with total coverages that matched the NFI proportions, we iterated over steps (1)-(4) with a different probability threshold each time until the resulting map coverage matched the NFI proportion. The procedure was followed for each county and the resulting rasters mapped ONF forest patches where 1 was ONF and 0 was background. These were used in further processing steps to calculate spatial pattern metrics and overlap with areas of interest.

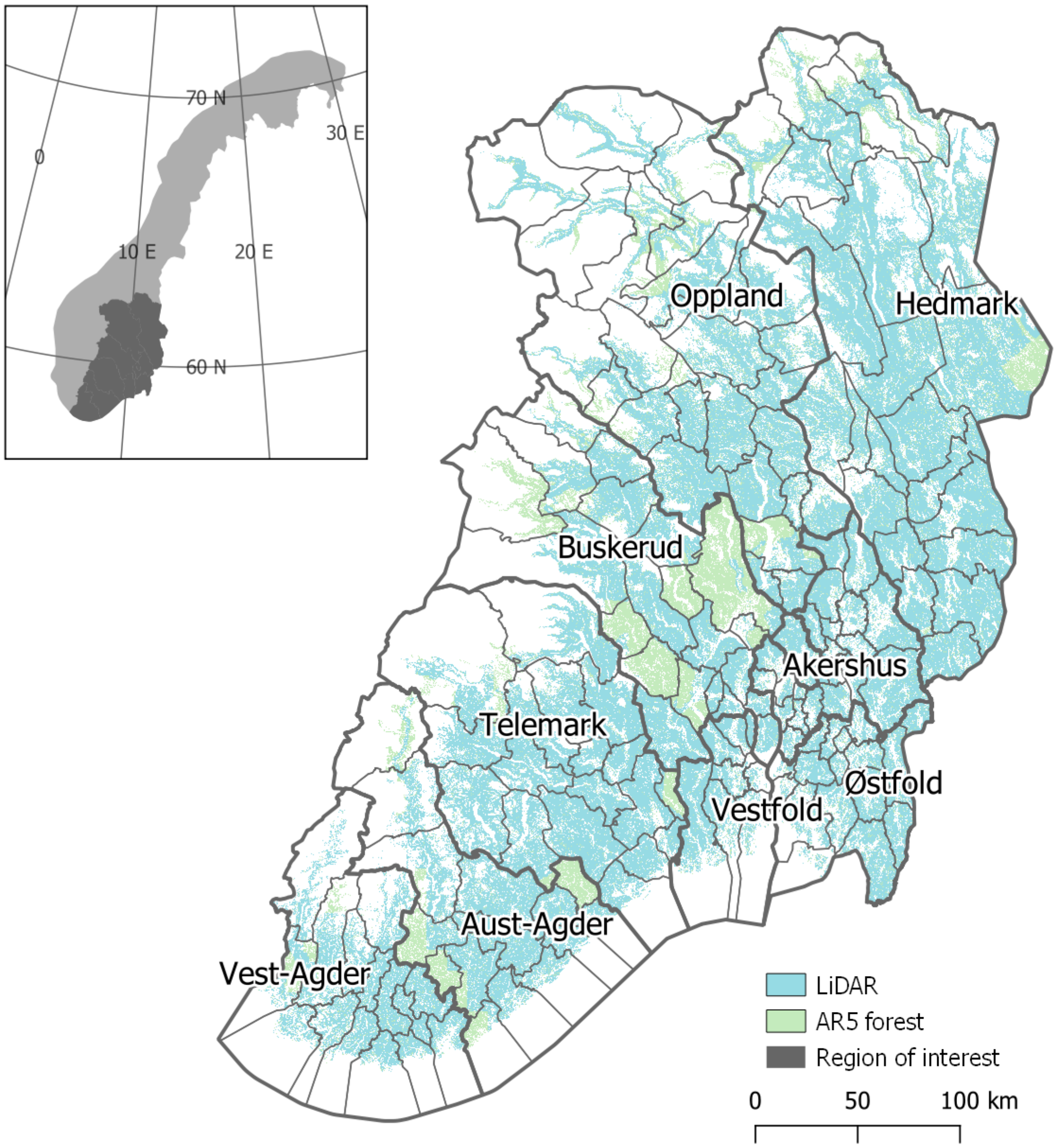

Figure 1 *Forest cover (based on AR5 data) and LiDAR cover for the study area. White space indicates areas not covered by AR5 forest.*

Data exploration and verification

The binary rasters were converted to polygons, and holes in the polygons smaller than 1000 m^2 were removed to reduce noise (**Figure 2**). These cleaned ONF polygons were assigned to municipalities based on the largest overlap. In other words, if a polygon overlapped the boundary between two municipalities, it would be assigned to the municipality where most of the polygon lay. This approach was chosen over splitting polygons to preserve the contiguity of polygons in the spatial pattern metrics and to avoid double counting.

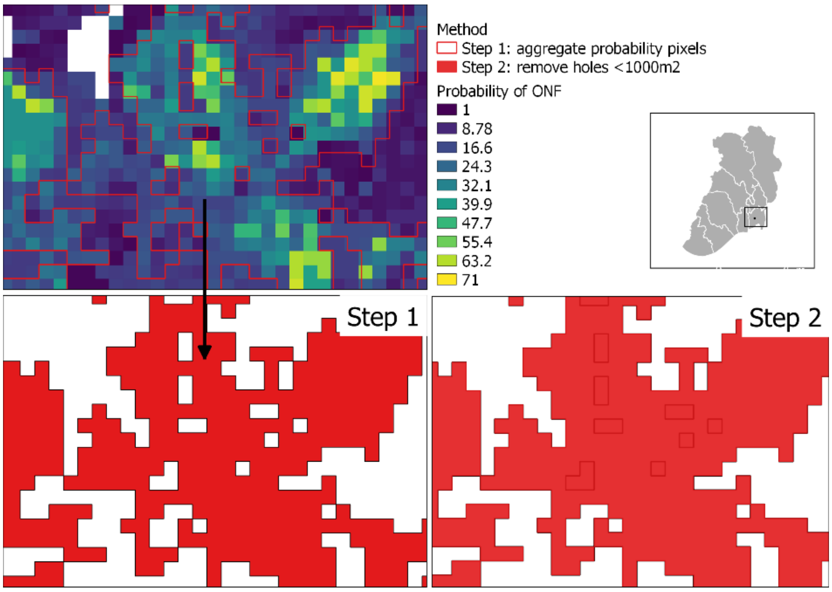

Figure 2 *Pixels were aggregated based on the probability of being old natural forest in step 1. In step 2, holes <1000m^2 were removed from ONF polygons. ONF probabilities are given on a scale from 0 to 100. White areas in the upper left panel are other land categories than forest.*

Gaps in the LiDAR data where forest was present, but LiDAR data was not available when processing the probability maps, were also identified and quantified for each municipality. Ten municipalities had LiDAR cover below 40%: Flesberg, Hol, Hole, Krødsherad, Ringerike, Rollag, and Øvre Eiker in Buskerud, Siljan in Telemark, and Gjerstad and Bykle in Aust-Agder. Per county overall LiDAR coverage of AR5 forest was lowest in Buskerud (61%) and Aust-Agder (89%), but at least 90% in all other counties. As a result of the lower LiDAR cover, the extracted ONF polygons (based on N50 forest) represent a much higher proportion of forest with LiDAR cover for Buskerud and Aust-Agder than the target value based on the NFI data. Low LiDAR cover may also result in spurious results for some spatial metrics, particularly for municipalities with the lowest LiDAR cover, where potential neighbouring ONF polygons have not been identified due to lacking data.

Spatial pattern metrics

Spatial pattern metrics were calculated for ONF polygons as a way to quantify patch composition, core and edge, shape complexity and patch connectivity. The landscapeMetrics package in R was used to calculate the metrics at class level based on FRAGSTATS algorithms (Hesselbarth et al 2019, McGarigal 2015). As this study focused on a single class of forest (i.e. ONF), municipalities were treated as landscape units such that metrics could be compared. A full explanation of the metrics is available in **Appendix 1**.

- The metrics representing patch composition included total ONF polygon (class) area (CA), number of patches (NP) and mean patch size (MPS). These describe the size distribution of the ONF. Total edge (TE) and the edge density (ED) were calculated based on the perimeter of patches. The core area (CORE) was identified as the area of the ONF patch 10 m from the edge. This is an important aspect of habitat patches for species requiring habitat conditions typical of the interior of patches.
- Shape complexity, i.e., the irregularity of the patch shape, was quantified using the shape index (SHAPE), the perimeter:area ratio (PARA), and fractal dimension (FRAC). The mean of the contiguity index (CONT) was also calculated as a measure of the spatial connectedness of the raster cells within a patch, thereby describing patch boundary configuration. The complexity of a shape may be used as an indicator of the 'naturalness' of the patch, whether the patch is artificially regular (square) or very irregular due to fragmentation.

- Various aggregation metrics were calculated at the landscape level to measure aspects of connectivity or fragmentation of the patches within each municipality. These include the Euclidean nearest neighbour mean and range (ENNmn, ENNra), the proximity index (PROX), the connectance index (CONN), and the cohesion index (COHES). ENNmn gives the average of the closest distance between all neighbouring patches, measured from edge to edge. PROX sums the areas of all patches within a specified distance (here 500 m), weighted by the inverse squared distance between these patches. CONN gives a measure of connectivity based on the number of connections between all patches within a specified distance (here 500 m), as the proportion (%) of the number of possible connections between all patches in the landscape (here each municipality). COHES measures the connectedness of patches and increases as the patches become more clumped or aggregated.

ONF overlap with areas of conservation interest
The overlap of ONF polygons with areas of conservation interest, included the overlap with red-listed forest species, nature reserves and national parks, the Naturbase forest key biotopes (Nature type) and mapping of habitats for red-listed species in forests (MiS). The species data were obtained from the Artsdatabanken and consisted of all observations of red-listed insects, lichens and fungi between 1995 and 2016. A spatial join in ArcMap (ESRI Inc.) was used to count the number of observations in each ONF patch and for the forest (i.e., forest with LiDAR cover) in each municipality. The overlap between ONF patches and the protected areas, forest Nature type and MiS forest key biotopes was calculated using the intersection tool in ArcMap. Similarly, the area of all forest (forest with LiDAR cover) overlapping these ecologically important areas was also calculated.

Risk of harvesting
Accessibility and terrain play an important role in the selection of harvest sites. For this reason, we explored the distance of ONF polygons to the nearest road, the average slope of the patch and the elevation as factors that may determine the risk of an ONF polygon being harvested. A 10 m digital terrain model was downloaded from Høydedata (Kartverket 2020) and slope calculated using the GDAL slope tool in QGIS (QGIS developers team). The average slope and elevation were calculated for each patch using the zonal statistics tool in ArcMap Spatial Analyst extension (ESRI Inc. 2020). Road data (Elveg 2.0) were acquired from the Norwegian Mapping Authority (Kartverket 2020). The Euclidean distance from each polygon to the nearest road was calculated using the Near tool in ArcMap (ESRI Inc.)

Data on harvested areas was obtained from analyses of Landsat 4-8 for the period 1985-2019 (Ørka et al. 2019). The accessibility and terrain variables were calculated for harvest sites. Next we performed an overlay of harvest sites and ONF patches and calculated the area of overlap and year of harvest. This allowed us to evaluate the ONF classification and to see which ONF patches were actually harvested after the LiDAR data used to detect ONF were acquired.

3 Landscape ecological patterns of old natural forest polygons

The process of aggregating pixels with probabilities above a set threshold into old natural forest polygons (ONF) resulted in more than 333 000 polygons scattered over the study area where we had LiDAR data. **Figure 3** shows the distribution of ONF polygons within 1x1 km pixels for the study area. It is apparent that the density of ONF polygons is highest in parts of Hedmark, Oppland, Vestfold, and Telemark. **Figure 4** shows a detailed example of what such ONF polygons may look like in a local landscape.

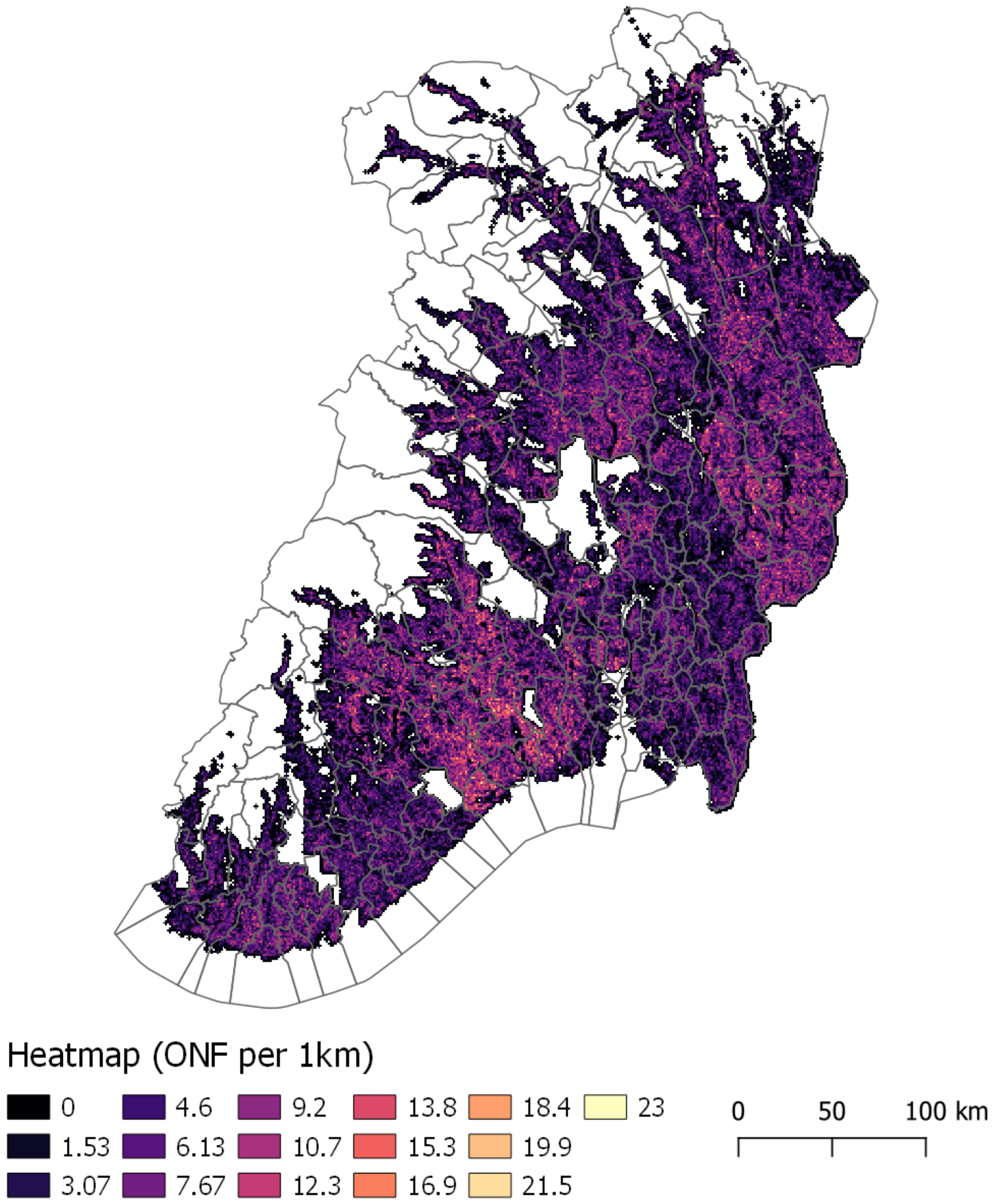

Figure 3 *Map of the study area with the number of old natural forest (ONF) polygons per 1x1 km square. Area without LiDAR cover does not have any ONFs.*

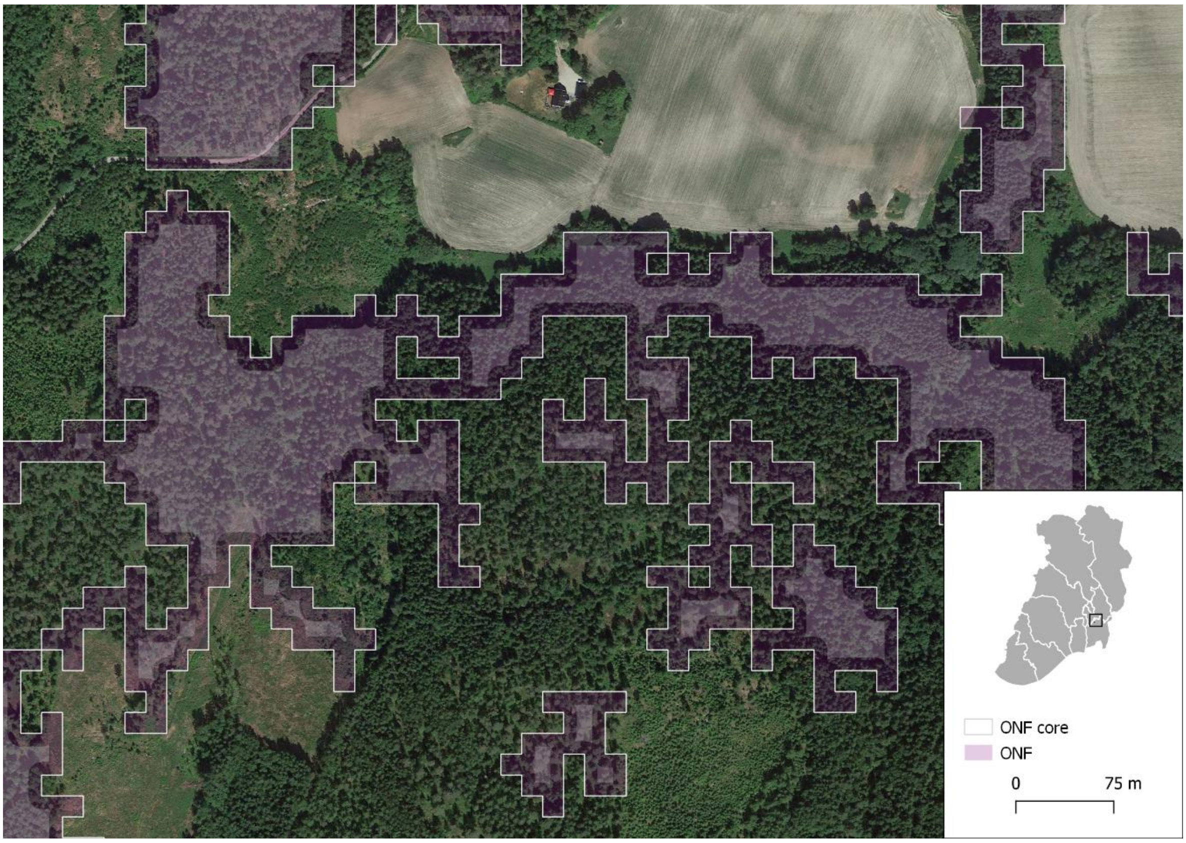

Figure 4 *Example of old natural forest (ONF) polygons in a local landscape. A boundary 10 m wide is indicated to show the interior core area.*

The potential value of such forest patches to biodiversity associated with old natural forest depends on patches being sufficiently large and having a shape that does not result in a large proportion of patch area close to the patch edge. The degree of connectivity between old forest patches is also a key landscape property of high potential significance for biodiversity associated with old natural forest (cf. Framstad et al. 2018a). Hence, we have calculated a range of metrics (cf. chapt. 2 and **Appendix 1**) to describe various landscape properties of the individual ONF polygons and their connectivity. To make the results accessible we present total or average values for these metrics per county and municipality.

3.1 Number, size, edge and core of ONF polygons

The total area of extracted ONF polygons varies between counties, mainly due to the differences in forest area for the various counties (**Table 1**) and the extraction procedure. As the extraction of ONF polygons was based on adapting the target proportions to the area of N50 forest per county, the ONF polygons constitute a rather large proportion of forest with LiDAR data for Buskerud and Aust-Agder (which had the lowest such cover). The size distribution of the ONF polygons (**Figure 5**) indicates that close to 50% of the polygons are between 0.5 and 1 ha (remember that aggregated pixels <0.5 ha were discarded). For most of the counties, less than 6% of ONF polygons were >10 ha, the exception being Aust-Agder with 9% of ONF polygons >10 ha. Of the 67 ONF polygons larger than 500 ha, 29 occurred in Buskerud and 16 in Aust-Agder, with the rest in Hedmark (8), Telemark (6), Oppland (5), Vest-Agder (2) and Akershus (1).

The values of the spatial metrics at county level are presented in **Table 2**. **Figures 6, 8** and **9** illustrate the variation in several of these spatial metrics at the municipal level.

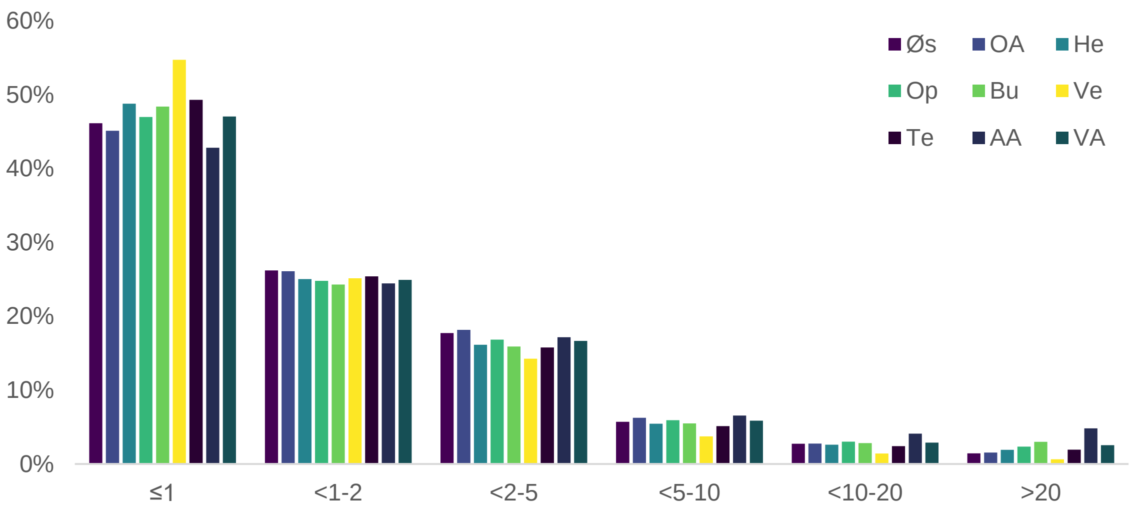

Figure 5 *Size distribution for extracted ONF polygons. Classes are given in ha. Only polygons of at least 0.5 ha are included. The counties are Øs Østfold, OA Oslo and Akershus, He Hedmark, Op Oppland, Bu Buskerud, Ve Vestfold, Te Telemark, AA Aust-Agder, and VA Vest-Agder.*

Table 2 *Spatial metrics for the derived ONF polygons, per county. CA is the total area (km^2) of all ONF polygons, CA-% is the proportion of polygon area to LiDAR forest area (cf. Table 1), NP is the number of polygons, NP/km^2 is the number of ONF polygons per km^2 of forest, MPS is the mean polygons size (ha), ED is the mean edge density (m/ha), TE is the total edge length (km) of all polygons, CORE is the total core area (km^2) of all polygons, SHAPE is the Shape Index, PARA is the Perimeter:Area Ratio, FRAC is the Fractal Dimension, CONTIG is the Contiguity Index, PROX is the Proximity Index, ENNmn is the mean Euclidean Nearest Neighbour (m), CONN is the Connectance Index, COHES is the Cohesion Index, all as totals or means per county (see chapt. 2).*

	Spatial configuration							
County	**CA**	**CA-%**	**NP**	**NP/km^2**	**MPS**	**ED**	**TE**	**CORE**
Østfold	503	19.3	19 232	7.38	2.61	587	29 521	242
Akershus	515	16.3	19 100	6.05	2.70	522	26 903	271
Oslo	52	18.4	1 823	6.48	2.84	520	2 698	31
Hedmark	2 858	19.2	97 904	6.58	2.92	645	184 441	774
Oppland	1 652	19.5	48 952	5.78	3.37	601	99 210	302
Buskerud	1 682	35.2	29 118	6.10	5.78	515	86 590	1 235
Vestfold	251	17.6	13 557	9.51	1.85	783	19 661	82
Telemark	1 840	23.8	62 798	8.13	2.93	758	139 400	625
Aust-Agder	1 272	34.0	19 841	5.31	6.41	481	61 214	719
Vest-Agder	742	22.3	21 494	6.45	3.45	581	43 144	361
	Shape complexity					**Connectivity**		
County	**SHAPE**	**PARA**	**FRAC**	**CONTIG**	**ENNmn**	**PROX**	**CONN**	**COHES**
Østfold	2.485	0.077	1.169	0.659	100	114	2.79	96.51
Akershus	2.198	0.070	1.147	0.689	95	55	0.43	94.75
Oslo	2.241	0.070	1.149	0.688	92	42	3.47	94.50
Hedmark	2.853	0.084	1.188	0.630	113	197	0.38	95.32
Oppland	2.823	0.082	1.186	0.641	97	163	1.05	96.93
Buskerud	2.728	0.079	1.174	0.649	57	2 851	3.16	98.50
Vestfold	2.826	0.091	1.195	0.600	79	75	1.36	95.73
Telemark	3.247	0.091	1.205	0.602	75	580	0.17	98.08
Aust-Agder	2.855	0.076	1.178	0.666	542	1 650	0.09	93.94
Vest-Agder	2.738	0.080	1.181	0.647	84	235	0.05	97.61

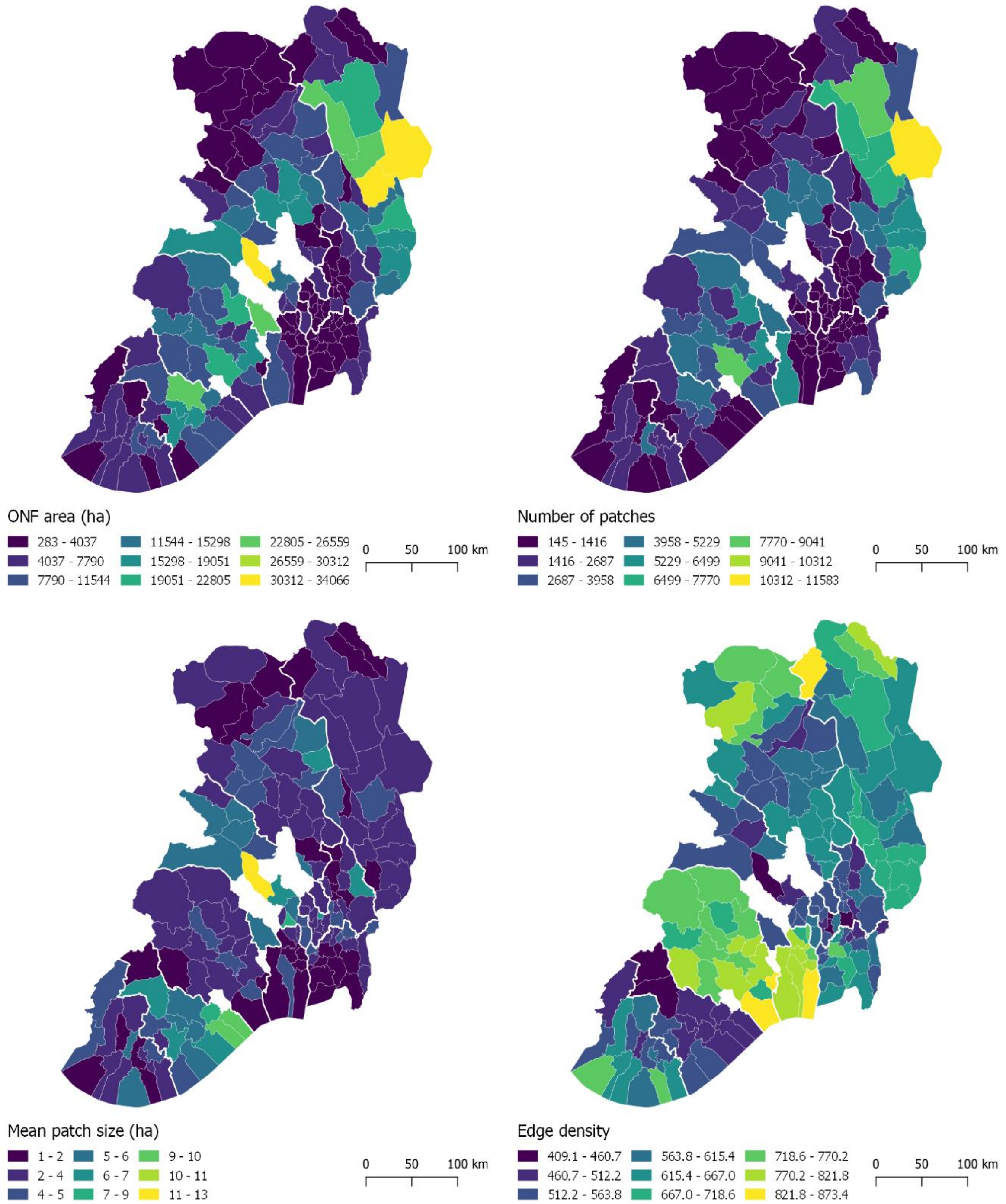

***Figure 6** Basic spatial metrics for municipalities: Total old natural forest (ONF) polygon area, total number of ONF polygons, mean ONF polygon size, and edge density of polygons. Municipalities with low LiDAR cover are excluded. See appendix 1 for explanation of spatial metrics.*

The number of ONF polygons per county mainly reflects the total ONF area of the respective counties, being highest for Hedmark and Telemark (**Table 2**). Buskerud and Aust-Agder have far fewer ONF polygons than their total polygon area should indicate (respectively, 56 284 and 42 843), if they had followed the same relationship as the other counties (cf. above). However, if we look at the number of polygons per forest area (with LiDAR cover), Vestfold and Telemark have the highest number (9.5 and 8.1), with Aust-Agder the lowest (5.3).

The mean polygon size (MPS) also indicates that there are some differences (**Table 2**): The MPS for Buskerud (5.8 ha) and Aust-Agder (6.4 ha) are considerably larger than the MPS for the other counties (1.9–3.4 ha), consistent with Buskerud and Aust-Agder having rather fewer polygons relative to their total ONF polygon area (cf. above). If Buskerud and Aust-Agder had the same relationship between total ONF area and number of ONF polygons as the other counties, they would both have had MPS values around 3 ha. This is partly a consequence of the higher proportion of ONF polygons relative to the area of forest with LiDAR coverage for these counties. As the total area of ONF polygons increases, the aggregation procedure will result in a higher proportion of larger polygons. These counties might still have some large ONF polygons irrespective of this scaling issue, although it is difficult to assess to what extent.

Edge density (ED) measures the amount of ONF polygon perimeter per unit of forest area in the county (or municipality). Vestfold and Telemark have higher values than the other counties. ED reflects about the same property for ONF polygons as the number of polygons per forest area (NP/km^2): the more polygons per unit area, the higher the edge density. Total edge (TE) is a measure of total perimeter length within the county, and as such closely reflects both total polygon area and number of polygons.

The core area of habitat patches is an important property for organisms associated with the interior of such patches, although the sensitivity to impacts from the surroundings will vary a lot among species. Due to the small size of most ONF polygons, we have defined the core area of polygons to be area 10 m from the edge, although this is generally too close to the edge to maintain real interior habitat properties. The CORE metric sums up the total core area for all patches, and as such it reflects the total polygon area and the number of polygons. Buskerud and Aust-Agder deviate somewhat from the main pattern, as they tend to have relatively more core area than expected, given their total polygon area or number of polygons (cf. above).

These spatial metrics also vary a lot for individual municipalities (**Figure 6, Appendix 2**), reflecting both the amount of forest area and the number and area of ONF polygons. Among individual municipalities, Sigdal (in Buskerud) has both the largest total ONF polygon area (34 066 ha), the largest total core area (19 847 ha), and overall the two largest polygons (14 493 ha and 7 966 ha). As Sigdal has relatively few polygons (2718), it has by far the highest mean polygon size (12.5 ha). This contrasts with Trysil (in Hedmark) which has the third most total polygon area (31 763 ha), but many more polygons (11 583) and therefore relatively less total core area (13 853 ha) and lower mean polygon size (2.7 ha). The contrasts between Sigdal and Trysil may be seen from the maps of these municipalities (**Figure 7**). Note that Sigdal's large ONF polygons also partly overlap the municipal boundary, thus somewhat artificially raising the total polygon area for this municipality.

Based on the values of the metrics for individual municipalities, it is apparent that several of the metrics are closely correlated (**Table 3**). For the basic polygon metrics, there are significant positive correlations between total polygon area (CA) and number (NP) per municipality, as well as between total polygon area and mean polygon size (MPS). There are also significant positive correlations between these three metrics and total edge (TE) and total core area (CORE) and between these two metrics. On the other hand, the correlations between edge density (ED) and MPS and CORE are negative. The direction and strength of these relationships are as expected from the basic properties of these metrics.

3.2 Shape complexity of ONF polygons

Four metrics describe various aspects of the shape of polygons: The Shape Index (SHAPE) which relates polygon perimeter to a square of similar area, the Perimeter:Area Ratio (PARA), which is not invariant with size, the Fractal Dimension (FRAC) which measures the complexity

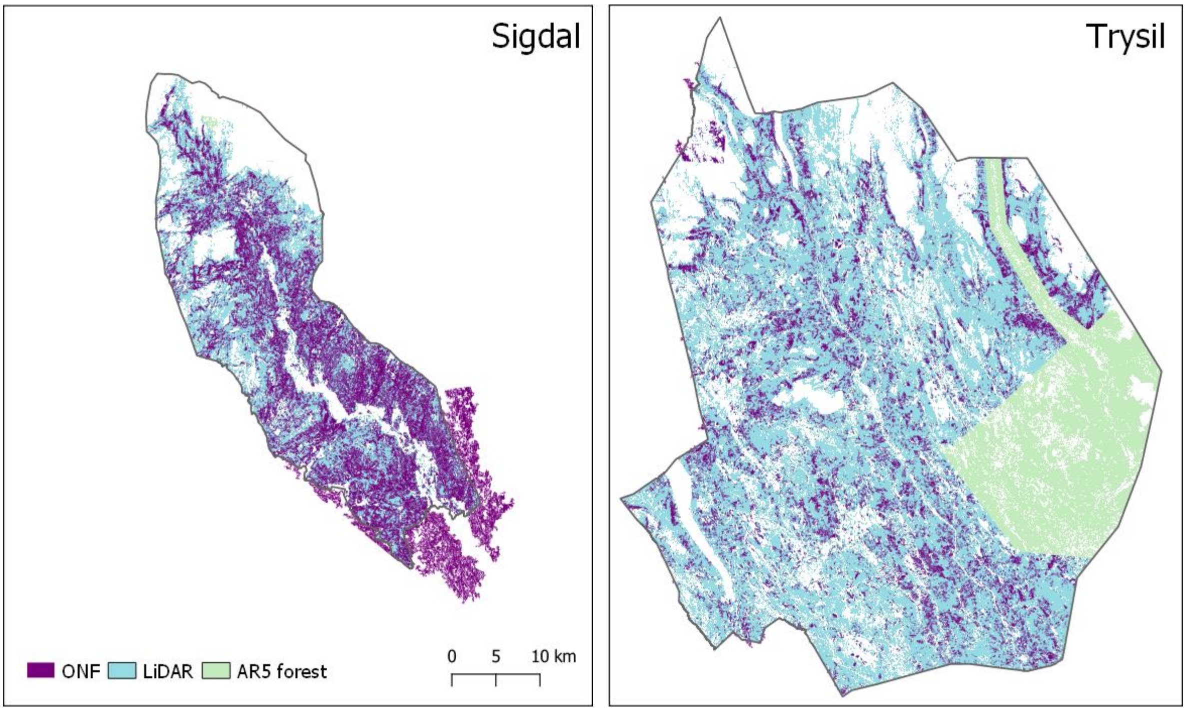

***Figure 7** Maps of Sigdal (Buskerud) and Trysil (Hedmark) municipalities. Note the lack of LiDAR cover for parts of Trysil. White space indicates non-forest area.*

of the polygon perimeter, and the Contiguity Index (CONTIG) which represents the internal contiguity of pixels within a polygon (cf. **Appendix 1** for further descriptions). SHAPE, PARA and FRAC all indicate patches with more irregular shapes for higher values of these metrics, whereas CONTIG is positively related to patches with more regular shape. They are all closely related. **Table 2** shows mean values for these metrics at the county level, and **Figure 8** illustrates the variation in these metrics for municipalities. Some of the municipality level metrics show clear clustering by county, suggesting that the shape of the ONF polygons partly depends on the total area of ONF polygons per county.

Telemark has the highest values for SHAPE, PARA and FRAC and the second lowest for CONTIG, indicating that its ONF polygons overall tend to be somewhat more irregular in shape compared to polygons of other counties. Akershus has the lowest values for SHAPE, PARA and FRAC and the highest for CONTIG, indicating that ONF polygons here are somewhat more regular. To give an impression of what various values of SHAPE may mean in terms of shape irregularity, a square will have value 1, whereas a rectangle where the long side is 14 times the short side will have value 2 and a rectangle where the long side is 34 times the short side will have value 3. Akershus has a SHAPE value of 2.2, whereas Telemark has a value of 3.2. Hence, in both cases their polygons are quite irregular, although considerably more so for Telemark.

Although there are strong correlations between all shape complexity metrics (**Table 3**), and the patterns are quite consistent for all these metrics at the county level (cf. above), the ranking of municipalities differs somewhat for the individual metrics. All municipalities had average SHAPE values above 2, and most counties had some municipalities with SHAPE values above 3. In Telemark, all municipalities had SHAPE values above 3, and Nome had the highest value (3.488) overall. Gjerdrum in Oslo and Akershus had the lowest SHAPE value (2.048), being the only municipality with adequate LiDAR coverage and a value below 2.1. Municipalities in Telemark and Vestfold had consistently high values for the Perimeter:Area Ratio (PARA), with the highest values for the coastal municipalities Kragerø (0.097) and Færder (0.095). The lowest PARA values

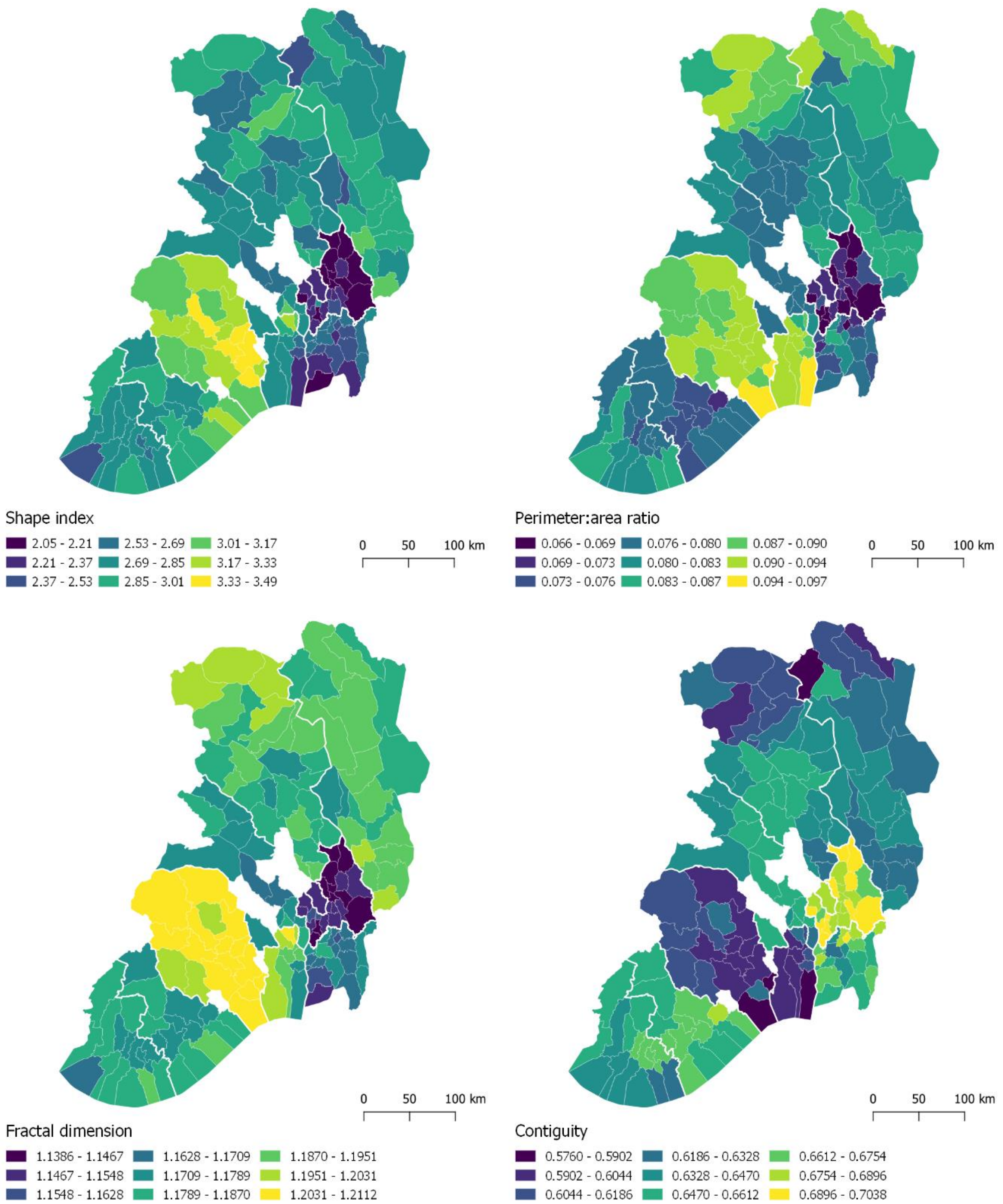

***Figure 8** Shape complexity metrics for municipalities: The Shape Index, the Perimeter:Area ration, the Fractal Dimension, the Contiguity Index. Larger values of the three first metrics indicate more irregularly shaped ONF polygons, whereas larger values for Perimeter:Area Ration indicate more regular ONF polygons. Municipalities with low LiDAR cover are excluded. See Appendix 1 for explanation of metrics.*

(<0.070) occurred for several municipalities in Oslo and Akershus. The Fractal Dimension (FRAC) values for municipalities tend to follow the pattern of the other metrics, with municipalities in Telemark and Vestfold with highest values (Porsgrunn 1.211 and Sande 1.204). All municipalities in Telemark except Hjartdal had FRAC values above 1.200. Again, Oslo and Akershus had the lowest FRAC values, with several municipalities with values below 1.150. As noted above, the

Contiguity Index (CONTIG) has higher values for more regularly shaped patches, but otherwise it follows the patterns of the other metrics. Again Telemark and Vestfold have the most irregular ONF polygons, with the lowest CONTIG values for Kragerø (0,576) and Færder (0.581), whereas Oslo and Akershus have the overall highest CONTIG values, highest for Oppegård with 0,706.

3.3 Connectivity of ONF polygons

Here we consider the physical connectivity represented by the ONF polygons as physical patches in two-dimensional space, with Euclidean distances, and not the functional connectivity linked to organisms' dispersal or ecosystem processes in real landscapes. Physical connectivity depends on both the closeness of the various patches, their sizes, and how they are distributed in space as clumped or dispersed entities. Several metrics have been calculated to describe aspects of connectivity between ONF polygons. **Table 2** shows values of these connectivity metrics at the county level, and **Figure 9** illustrates the variation among municipalities.

The simplest of these metrics is probably the Euclidean Nearest Neighbour (ENN), represented by the mean ENN for counties or municipalities. The higher the ENNmn value, the less connected are the ONF polygons. To represent a measure of the variation in ENN values within a county, we have also calculated ENN range (ENNra; not shown in **Table 2**). A more relevant measure of true connectivity is the Proximity Index (PROX), as this takes into account both the distances to neighbouring patches within a specified neighbourhood (here 500 m), and the area of these patches. The Proximity Index will have high values when neighbouring patches are large and close by. The Connectance Index (CONN) measures the number of possible connections between patches within a specified neighbourhood (here 500 m), as a proportion (%) of all possible connections for patches within a landscape (here county or municipality). CONN has a high value when many of the patches in the landscape are clumped within the specified neighbourhood. Note that the Connectance Index is sensitive to differences in the total number of patches in the defined landscape, as this is the basis against which the connections within the specified neighbourhood are compared. The Cohesion Index measures the physical connectedness of the patches in the landscape (as a percentage), increasing as patches cover more of the landscape and/or become more aggregated.

The ONF polygons in Aust-Agder have a mean nearest neighbour (ENNmn) of 542 m, indicating that these polygons are placed considerably farther apart on average than the ONF polygons in other counties (with ENNmn values of 57–113 m) (**Table 2**). The range for ENN values in Aust-Agder is 2559 m, indicating that the high ENNmn value probably is not due to a few very distant nearest neighbours but rather that many ONF polygons are widely distributed. This contrasts with Buskerud which has the lowest ENNmn value of 57 m with a similar range for ENN values (2613 m). This indicates that ONF polygons tend to be quite clumped. The Proximity Index PROX has very high values for both Buskerud and Aust-Agder, compared to the other counties. This is most likely an effect of the higher proportion of ONF polygon area to forest area with LiDAR, resulting in much larger mean polygon sizes (MPS) for Buskerud and Aust-Agder and therefore much more polygon area within the specified neighbourhood of 500 m (in spite of Aust-Agder having more distant polygons, cf. the high ENNmn value). The smaller counties Oslo, Akershus, and Vestfold have the smallest PROX values, indicating that their ONF polygons are rather small and scattered. The Connectance Index (CONN) has a relatively high value for Buskerud (3.16%) compared to other counties, and is consistent with a high PROX value, indicating rather well-connected ONF polygons. A high value for Oslo (3.47%) is in contrast to a low value for PROX and may rather reflect the small size and therefore fewer possible connections for this county. Aust-Agder and Vest-Agder have the smallest CONN values, something that does not fit particularly well with the other connectivity metrics. Finally, Buskerud has the highest value (98.5) for the Cohension Index (COHES), something that is consistent with Buskerud's high values for PROX and CONN and the low ENNmn value. Aust-Agder has the lowest COHES value, and this is consistent with its low value for CONN and high value for ENNmn, but not with its high value

Table 3 *Pearson correlations between spatial metrics for ONF polygons in municipalities. The metrics are groups by theme: basic polygon characteristics, shape complexity and connectivity metrics. Values significant at p<0.01 are in bold. All municipalities are included irrespective of the degree of LiDAR coverage, except for Hol in Buskerud which did not have any ONF polygons. There are only minor differences in correlation values when the municipalities with low LiDAR cover are excluded. See Table 1 and Appendix 1 for explanation of metrics.*

	ca	**np**	**mps**	**ed**	**te**	**core**	**shape**	**para**	**frac**	**contig**	**prox**	**enn_mn**	**conn**	**cohes**
ca		**0,865**	**0,365**	-0,055	**0,973**	**0,972**	**0,414**	0,187	**0,326**	-0,181	**0,412**	**-0,280**	-0,141	**0,445**
np			-0,040	0,199	**0,935**	**0,748**	**0,402**	**0,325**	**0,409**	**-0,319**	0,061	**-0,244**	-0,140	**0,278**
mps				**-0,591**	**0,225**	**0,484**	**0,252**	**-0,264**	-0,014	**0,270**	**0,570**	**-0,208**	-0,016	**0,559**
ed					0,106	**-0,216**	**0,325**	**0,846**	**0,588**	**-0,851**	-0,204	0,062	0,026	**-0,318**
te						**0,890**	**0,483**	**0,308**	**0,427**	**-0,301**	**0,289**	**-0,276**	-0,125	**0,403**
core							**0,320**	0,053	0,205	-0,047	**0,510**	**-0,268**	-0,151	**0,461**
shape								**0,671**	**0,923**	**-0,652**	0,080	**-0,320**	0,053	**0,592**
para									**0,870**	**-0,999**	-0,033	-0,095	-0,003	0,071
frac										**-0,854**	-0,017	**-0,251**	0,025	**0,372**
contig											0,027	0,103	0,000	-0,064
prox												-0,099	-0,053	**0,269**
enn_mn													0,045	**-0,543**
conn														**-0,264**
cohes														

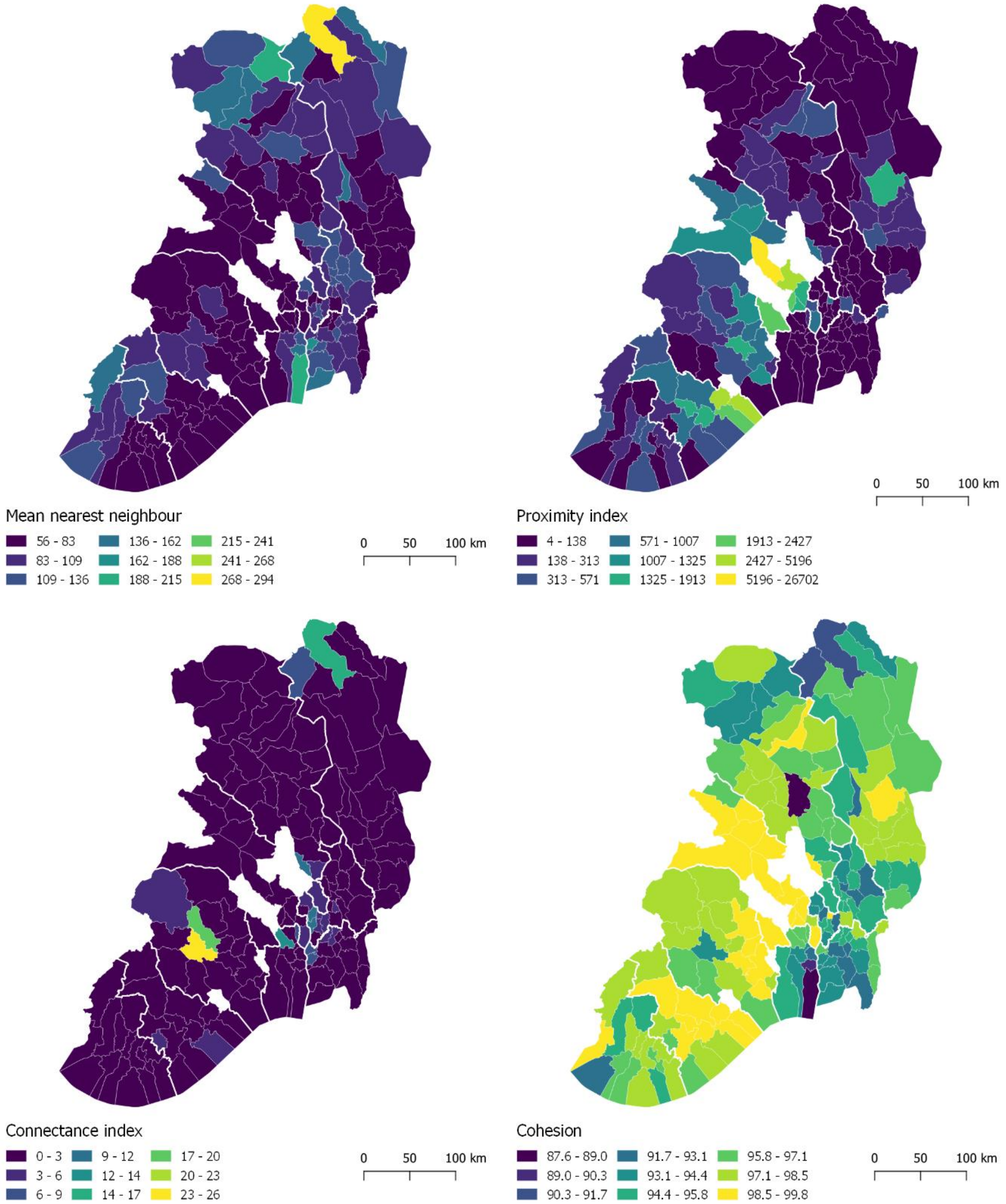

Figure 9 *Connectivity metrics for municipalities: Mean Nearest Neighbour, the Proximity Index, the Connectance Index, and the Cohesion Index. Higher values of Mean Nearest Neighbour indicates more isolated ONF polygons, whereas higher values of the other metrics indicate more aggregated or connected polygons. Municipalities with low LiDAR cover are excluded. See Appendix 1 for explanation of metrics.*

for the Proximity Index. Based on these metrics, ONF polygons in Buskerud seem to have the best connectivity, whereas it is less clear where the ONF polygons tend to be most fragmented or isolated. However, the ONF polygons of Aust-Agder rank as most fragmented by three of four metrics. Note that the low LiDAR cover of some municipalities in Buskerud and Aust-Agder may strongly influence particularly the Mean Nearest Neighbour values.

Based on the values of the connectivity metrics for ONF polygons at the municipality level, it is apparent that these metrics have fewer and somewhat weaker correlations to each other and to the non-connectivity metrics than most of the other metrics. This is particularly the case for the Connectance Index which has no significant correlations to other metrics. This was also found by Wang et al. (2014) who conclude that the Connectance Index is a reliable measure of fragmentation that is not dependent on patch size. The Cohesion Index in contrast has quite a few significant although not very strong correlations. This pattern is probably a reflection of the more complex properties represented by the connectivity metrics.

At the municipal level, the Mean Nearest Neighbour (ENNmn) has its highest values for quite varied municipalities (when we ignore municipalities with low LiDAR cover): Tynset (294 m), Dovre (210 m), Færder (198 m), and Rygge (178 m), i.e. mountain, coastal and lowland municipalities where ONF polygons may be expected to be fairly isolated. Municipalities with low ENNmn values (<60 m) are mostly rather lowland municipalities with more forest cover, as well as a couple of coastal municipalities. Values for the Proximity Index are highest for Sigdal (29 702), Modum (5196), and Vegårshei (2970), well forested municipalities with many to several ONF polygons and large mean polygon sizes. Municipalities with low PROX values (<20) are coastal, agricultural or mountain municipalities with relatively small mean polygon sizes. The five municipalities (Kviteseid, Seljord, Tynset, Holmestrand, Nesodden) with values above 10% for the Connectance Index are varied and with few commonalities for other spatial metrics. The five municipalities (Rendalen, Nordre Land, Kongsvinger, Trysil, Elverum) with CONN values below 0.20% are more typically forested municipalities with quite a lot of total ONF polygon area. The 11 municipalities with the values above 99% for the Cohesion Index include several of the municipalities from Buskerud and Aust-Agder with high values also for the Proximity Index. Three municipalities (Færder, Tønsberg, Nordre Land) had Cohesion Index values below 90% (and adequate LiDAR cover), partly consistent with their values for some of the other connectivity metrics.

3.4 Management implications of results for spatial metrics

The basic assumptions behind these analyses are that the D7 definition gives a meaningful representation of old natural forest (ONF) properties and that the classification procedure is able to identify and rank ONF pixels correctly with respect to these ONF properties (to the extent that they are reflected in the NFI data used for calibration). Based on these assumptions we may draw some conclusions from the results on the spatial metrics for the ONF polygons:

- The ONF polygons are widely distributed across the forest in the study area, and most of the polygons are quite small: Almost 50% are <1 ha and only 67 polygons are >500 ha. This implies that it will be difficult to use the whole set of polygons directly as a basis for identifying forest of high conservation value. Some additional sorting of the polygons will be needed, e.g. by identifying particularly high local concentrations of polygons (cf. **Figure 3**) or by investigating the largest polygons (e.g. polygons >100 ha).
- Another apparent characteristic of the ONF polygons is the quite irregular shape of most of them (cf. example in **Figure 4**). This indicates that many polygons have a limited core area and that they are likely to be quite exposed to influences from changes in their immediate surroundings. Only the largest or most regular polygons are likely to be able to maintain intact core areas. In a management context it will be necessary to consider not only a given polygon in isolation but also the surrounding area, either as a buffer zone with special management considerations or as area combined with the ONF polygon.
- The connectivity metrics in this report represent statistics for all ONF polygons within a specified landscape, here counties or municipalities. These metrics can be used to assess the level of connectivity of ONF polygons for counties or municipalities, but they are not useful for indicating where ONF polygons are well connected or fragmented within each county or municipality. Other connectivity metrics may be calculated for individual patches (and their neighbourhoods) and may provide a measure of connectivity variation within a county.

4 Measures of forest conservation interest in old natural forest polygons

To the extent that our extracted old natural forest (ONF) polygons actually represent areas of old natural forest, we would expect these polygons to cover a significant proportion of various natural values associated with old natural forest. Such natural forest characteristics have to a great extent been the main basis for the selection of protected areas such as forest nature reserves (Framstad et al. 2017), and they have also been important criteria for other protected areas with substantial proportions of forest area (e.g. other nature reserves and national parks). Properties associated with biodiversity in natural forests are also important criteria for the identification of forest key biotopes, whether based on the MiS approach (Gjerde & Baumann 2002) or the procedure for mapping of important Nature types for biodiversity (DN 2007). Finally, the recorded occurrence of forest-associated red-listed species will also provide an indication of concentrations of natural forest properties relevant for the quality of the habitat of such species. The key question here is whether the identified ONF polygons cover a greater proportion of such natural forest properties than does forest in general. If that is the case, this may indicate that the ONF polygons actually represent old natural forest and not just random patches of forest.

Note that when we refer to forest in general, we mean forest area for which we have LiDAR coverage. This is the basis for our extraction of the ONF polygons and should therefore be the basis for our comparison of other conservation interests for these ONF polygons relative to forest in general.

4.1 Old natural forest polygons and protected areas

The main objectives for Norway's protected areas, such as nature reserves and national parks, are to protect a representative selection of Norway's nature, particularly areas with little modern impact from human activities, and areas that preserve threatened species and nature types. This implies that forest nature reserves in particular, as well as many other nature reserves and national parks with forest, have a higher proportion of old forest and natural forest characteristics than can be found in the general forest landscape (Framstad et al. 2017). Hence, if our ONF polygons really represent old natural forest, we should expect the ONF polygons to cover a higher proportion of forest protected area than do forests in general.

The proportion of all forest that occurs within nature reserves and national parks for the various counties is shown as the yellow columns in **Figure 10A**, whereas the proportion of ONF polygons that occurs within these protected areas is shown as the green columns. It is apparent that the proportion of ONF polygons occurring within protected areas is considerably higher than the proportion for forest in general for some counties (Oslo and Akershus, Buskerud, Vest-Agder), whereas it is marginally higher for Østfold, Vestfold, and Telemark, and lower for Hedmark, Oppland and Aust-Agder. Overall the ONF polygons have about the same proportion (4.05%) of their area in protected areas as forest in general (4.00%). Incidentally, Framstad et al. (2017) reported that the proportion of forest in nature reserves and national parks, based on NFI data, was 3.5% for these counties. Since that report was published, additional forest reserves have been established.

The ONF polygons cover a rather large proportion (16-35%) of the forest area (with LiDAR cover) for the counties of our study area (cf. **Table 1**). It may also be of interest to see to what extent ONF polygons cover protected areas, compared to the share of forest they cover. **Figure 10B** shows that the ONF polygons cover a substantially higher proportion of protected areas in some counties (Oslo and Akershus, Buskerud, Vest-Agder) than they cover of forest in general, but for all counties together the ONFs cover about the same proportions of protected areas and forest in general. The pattern for the various counties is quite similar to that exhibited in **Figure 10A**.

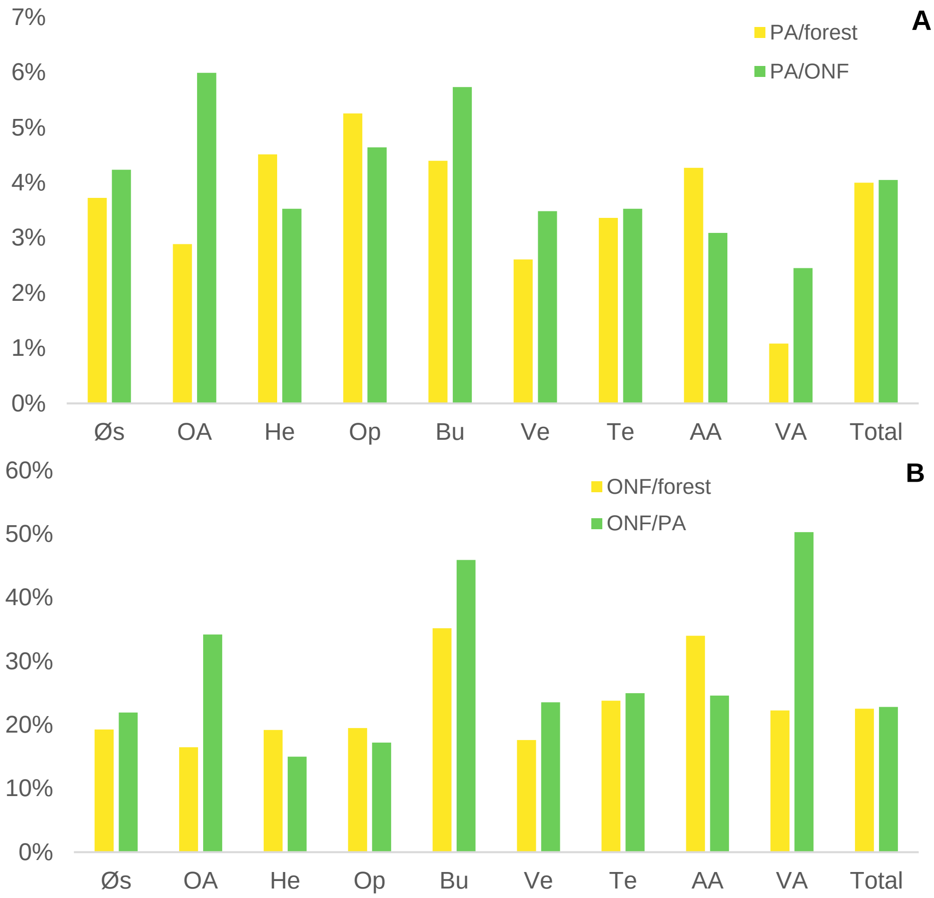

Figure 10 A: *Proportion of forest with LiDAR cover (PA/forest) and ONF polygons (PA/ONF) covered by forest in national parks and nature reserves, for the various counties in the study area.* ***B:*** *Proportion of national parks and nature reserves (ONF/PA) and forest in general (ONF/forest) covered by ONF polygons. The counties are identified as Øs Østfold, OA Oslo and Akershus, He Hedmark, Op Oppland, Bu Buskerud, Ve Vestfold, Te Telemark, AA Aust-Agder, VA Vest-Agder.*

Although some counties show that ONF polygons occur to a higher degree in protected areas than in forest in general, this is not the case for the majority of counties. Hence, it is not a clear or consistent indication that ONF polygons overall tend to 'target' forest in protected areas to a greater extent than forest in general. The overall pattern is rather that ONF polygons tend to be rather like forest in general with respect to overlap with protected areas.

4.2 Old natural forest polygons and forest key biotopes

The aim of the mapping of forest key biotopes has been to identify and delimit forest areas that have a particular value for forest biodiversity, either as habitat for red-listed species (MiS) or for biodiversity in more general terms (Nature types) (cf. Gjerde & Baumann 2002, DN 2007). Hence, if our ONF polygons really represent old natural forest, we should expect that the proportion of forest key biotopes identified through MiS and mapping of Nature types should be higher in the ONF polygons than in forest in general. Here we have considered all categories of MiS key biotopes and all categories of forest Nature types. Some of these categories have less relevance as indicators of old natural forest, as they are more closely associated with natural site properties of value to biodiversity, such as special terrain features or high availability of calcium. Nevertheless, the most frequent categories of these key biotopes are relevant, such as the ones linked to dead wood or old trees (>66% of gross MiS area for our study area). Note also that we have summed the areas of the various MiS categories although these may overlap. The data used here therefore represent gross area of the various MiS categories per county. The forest Nature types also include some forest types more associated with rich or special site conditions than old forest, although the latter make up more than 60% of the total area of forest Nature types.

Note that survey efforts for forest Nature types in particular may be skewed in favour of forest with high perceived conservation values, i.e., often old natural forest. Hence, results for ONFs may to some extent reflect an higher survey effort in forest covered by ONFs than in other forest. This is less likely to be the case for surveys of MiS patches, as these surveys tend to be more systematic (cf. Brandrud & Sverdrup-Thygeson 2008).

Figures 11A and **11C** show that our ONF polygons cover forest key biotopes to a greater degree than these key biotopes occur in forest in general, varying from 44% to 200% more, depending on the county and whether it is MiS or forest Nature types. The overlap of ONF polygons with MiS tends to be a bit higher (just over 4% for all counties) than with Nature types (just over 3%), although MiS and forest Nature types both cover about 1.8% of forest in general. The maximum cover of forest key biotopes by ONF polygons is around 8% (MiS in Vestfold, Nature types in Oslo and Akershus).

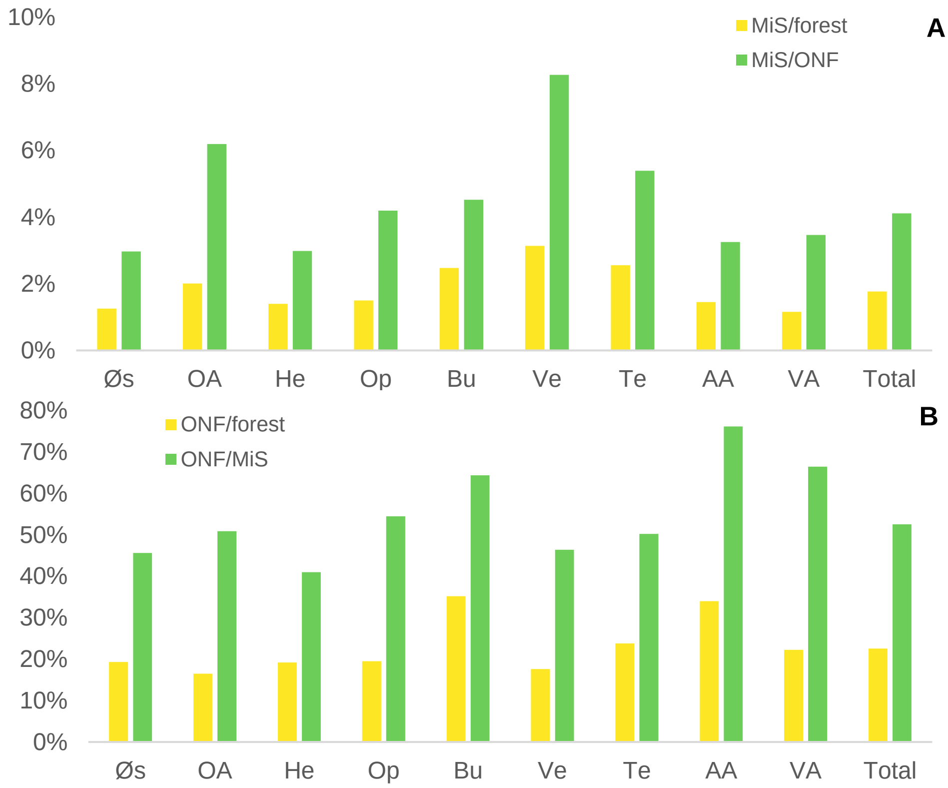

Figure 11 A: *Proportion of forest with LiDAR cover (MiS/forest) and ONF polygons (MiS/ONF) covered by forest key biotopes mapped as MiS patches, for the various counties in the study area.* ***B:*** *Proportion of forest key biotopes mapped as MiS patches (ONF/MiS) and forest in general (ONF/forest) covered by ONF polygons. (See Figure 11 C, D below)*

Figure 11 C: *Proportion of forest with LiDAR cover (Nature type/forest) and ONF polygons (Nature type/ONF) covered by forest key biotopes mapped as forest Nature types according to DN (2007), for the various counties in the study area.* ***D:*** *Proportion of forest key biotopes mapped as forest Nature types according to DN (2007) (ONF/Nature type) and forest in general (ONF/forest) covered by ONF polygons. See Figure 10 for county symbols.*

The ONF polygons cover a much larger proportion of forest key biotopes, 52.6% for MiS and 39.6% for Nature types, than the ONF polygons' share of forest in general (22.6%), for all counties combined (**Figures 11B, D**). The ONFs cover the largest proportion of forest key biotopes in Aust-Agder (MiS 76%, Nature types 51%) and the lowest proportion in Hedmark (MiS 41%, Nature types 33%), although the greatest deviation is found for Oslo and Akershus, where ONFs cover key biotopes about 3 times more than forest in general.

The results in **Figure 11** are based on all categories of MiS and forest Nature types, respectively. A breakdown of the results by individual MiS and forest Nature type categories for the whole study area gives essentially the same picture (**Figure 12**). We see that the ONF polygons tend to have a substantially higher proportion than forest in general for virtually all of these forest key biotope categories. It is also apparent that categories associated with old forest dominate.

In summary, the ONF polygons tend to overlap with forest key biotopes to a greater extent than forest in general. This pattern applies to virtually all categories of such forest key biotopes. If the forest key biotopes reflect characteristics of old natural forest, this indicates that also ONF polygons reflect such characteristics, and to a greater degree than forest in national parks and nature reserves.

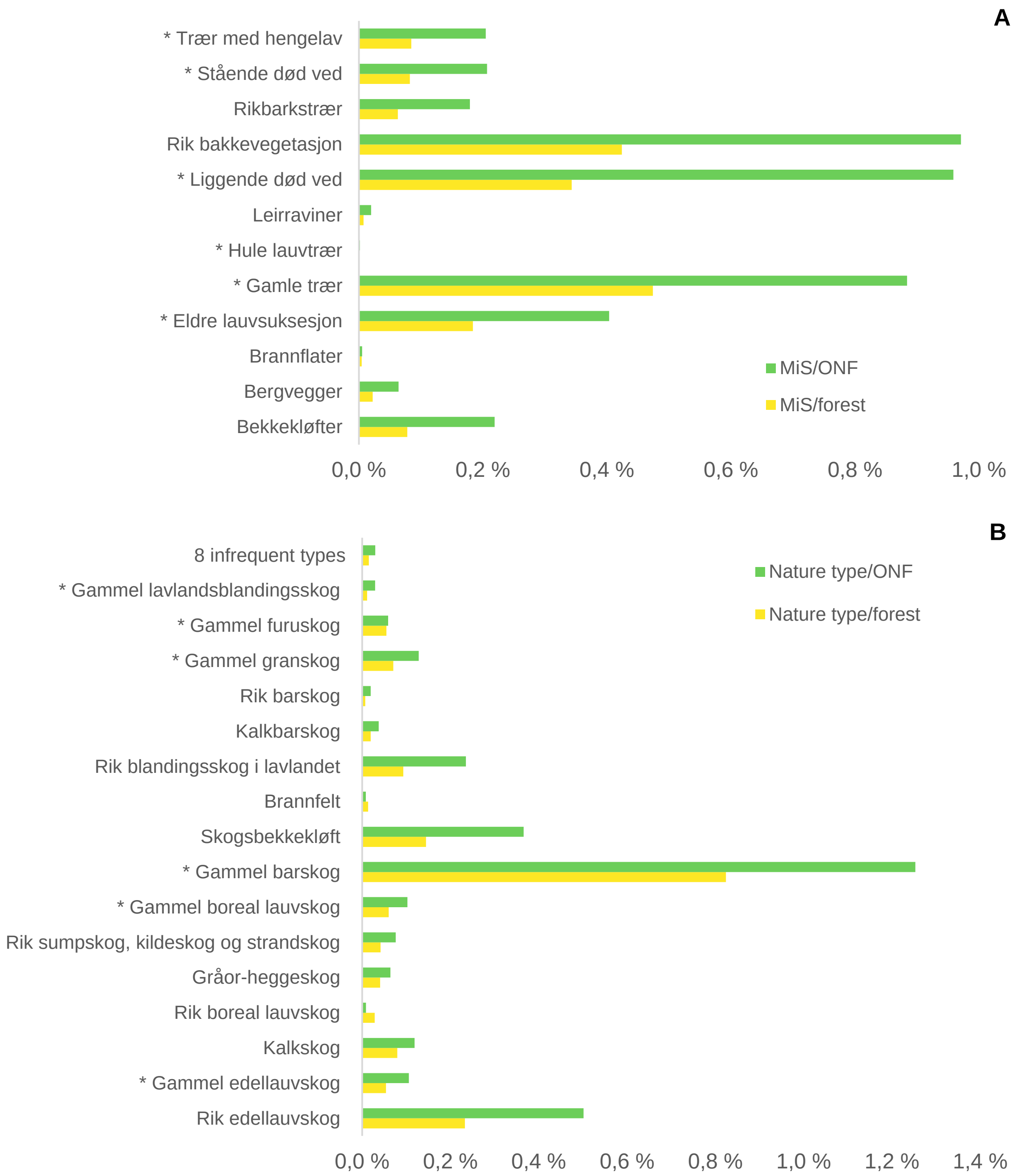

Figure 12 *Proportions of forest with LiDAR cover and ONF polygons covered by forest key biotopes, mapped as the various types of MiS categories (**A**) and as forest Nature types (**B**), for the whole study area. * indicates categories of MiS and forest Nature types associated with old forest where structural features may be relevant for detection by LiDAR.*

4.3 Old natural forest polygons and red-listed forest species

Red-listed forest species are among the key indicators of forest conservation value. Many of them are closely associated with old natural forest. Here we have selected such species from the taxonomic groups fungi, lichens and insects. These groups have a large number of species, and their association to natural forest properties has been well studied. If our ONF polygons represent forest with a high degree of old natural forest characteristics, we should expect the

ONF polygons to have a considerably higher proportion of records of such species than forest in general per unit area (provided the location information for the species observations is accurate enough).

The surveys for red-listed species in forests have not been evenly distributed over all forest areas or counties. There has probably been a higher survey effort in potential old natural forest than in forest in general. The survey effort may also have been lower in remote areas. Hence, in the comparison of recorded species for ONF polygons versus forest in general, results for ONF polygons may to some extent be an artefact of higher survey efforts in old natural forests.

Figure 13 illustrates the variation in number of species observations across the counties of the study area, in forest in general and in our ONF polygons. For the whole study area the ONF polygons appear to have about twice as high density of red-listed forest-associated species as forest in general. There is a higher density of observations in ONF polygons for most counties, highest for Oppland, Vestfold, and Buskerud, and lowest for Hedmark and Vest-Agder. For both Oslo and Akershus and Oppland the observation density for ONF polygons is more than twice as high as for forest in general. Hence, overall it appears that the ONF polygons represent forest characteristics that correlate with the habitat requirements of red-listed forest-associated species of insects, lichens and fungi.

The distribution of observations of different species groups also differed between the counties and between the ONF polygons and forest in general. Overall, lichens had the highest proportion of observations in both ONF polygons and forest, with 54% in the ONFs and 46% in general forest. The proportion of observations of insects was only 12% in the ONFs, against 26% in forest (although the density of observations of insects is about the same). The distribution of these species groups varied even more between the counties (**Figure 14**). In Oppland a very high proportion of the observations are of lichens (both for ONFs and forest in general), whereas observations of fungi make up a high proportion in Telemark and Oslo and Akershus, especially in the ONFs. Insects make up a high proportion of observations in Østfold and Vestfold, as well as in Vest-Agder for forest in general (but not for ONFs).

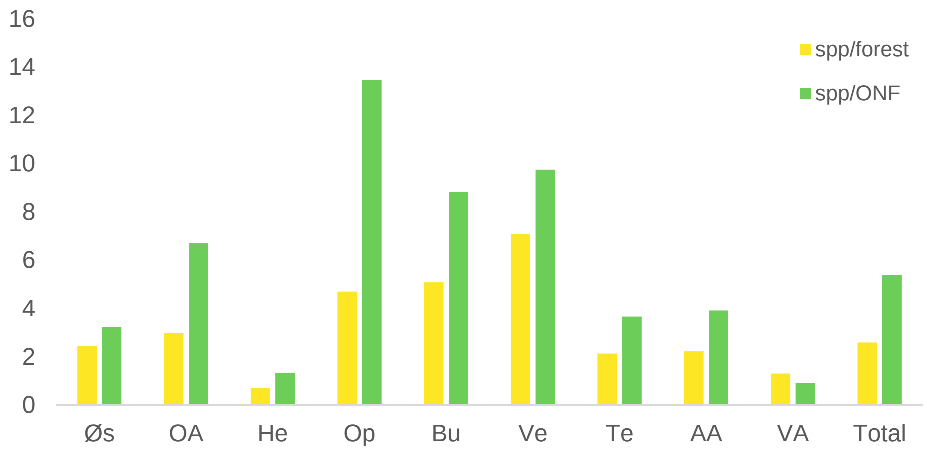

Figure 13 *Number of observations of forest-associated species of insects, lichens and fungi per 10 km^2 of forest with LiDAR cover (spp/forest) and for the ONF polygons (spp/ONF), for the various counties in the study area. See Figure 10 for county symbols.*

***Figure 14** Proportion of observations of red-listed forest-associated insects, lichens and fungi for the ONF polygons and for forest in general. **A:** Species observations in ONF polygons. **B:** Species observations in forest in general. See Figure 10 for county symbols.*

4.4 Management implications of ONF polygons' relations to forest conservation values

The purpose of this chapter is to see how well ONF polygons cover protected areas, forest key biotopes and forest-related red-listed species compared to forest in general. Such conservation interests are often rather strongly related to old natural forest characteristics. A high degree of overlap for ONFs should therefore indicate that ONFs represent such old natural forest characteristics better than forest in general. Hence, the results in this chapter use the locations of forest in protected areas, forest key biotopes and forest-related red-listed species to inform us if ONF polygons seem to represent old natural forest better than forest in general. We could ask the reversed question of whether the location of ONFs may indicate where we may find conservation values associated with forest protected areas or forest key biotopes, or suitable habitat for forest-associated red-listed species:

- The results do not indicate that ONFs are an effective way to find potential sites for forest reserves. There is little difference in overlap between ONFs and forest in protected areas compared to the overlap between forest in protected areas and forest in general.
- ONFs cover forest key biotopes to a considerably higher degree (1.8-2.3 times) than does forest in general. Hence, the chance of finding such forest key biotopes appears to be about twice as high if one searches ONF polygons rather than forest in general.
- Also for forest-associated red-listed species, it seems that searching for such species in ONFs rather than forest in general would double the potential success rate, as the density of observations is about twice as high in ONF polygons (although skewed survey effort may have contributed to the higher species frequency in ONF polygons). However, the density of observations of these species is still only just over 5 per 10 km^2. For both forest key biotopes and red-listed species, it is likely that experienced surveyors will increase their chances of success more by using more target indicators than the location of ONF polygons.

5 Old natural forest polygons, clearcuts, and relations to terrain and human impact

Forest identified as old natural forest from the classification of LiDAR data should obviously differ from forest identified as recent clearcuts. Hence, there should be no overlap between our identified old natural forest (ONF) polygons and clearcuts, unless forest was harvested after the recording of the LiDAR data used in the analyses. If the ONF polygons overlap with older clearcuts, this indicates a problem with the classification of the LiDAR data, with the aggregation procedure of pixels into ONF polygons, or with the classification of the clearcuts.

The general spatial relationship between our ONF polygons and identified clearcuts is of more ecological significance. If the ONF polygons actually represent old natural forest, then clearcuts that occur close to these ONF polygons could compromise the old forest qualities of these ONF polygons. Hence, it is relevant to explore how close the nearest clearcuts are to ONF polygons, even when they are not overlapping.

Where we find remaining old natural forest, will probably depend both on natural characteristics of the landscape, such as terrain, and the closeness to available infrastructure, in particular roads. These characteristics of natural variation and human impact will also be important for the location of forestry operations (cf. Granhus et al. 2014). However, we should expect that ONF polygons and clearcuts differ in their response to terrain characteristics (especially slope) and closeness to roads, i.e., that terrain slope and elevation, as well as closeness to roads should help to separate ONF polygons from clearcuts. Here we have made a first descriptive analysis of these relationships. A more complete statistical analysis is beyond the scope of this report.

5.1 Old natural forest polygons and their relation to clearcuts

Overlap between ONF polygons and clearcuts

We have done an overlay analysis of our extracted ONF polygons against identified clearcuts (for 1985-2019). Here we have distinguished between clearcuts that occurred before and after the recording of the LiDAR data which is the basis for our identification and delimitation of ONF polygons. Overall there are 333 819 ONF polygons with a total area of 11 367 km^2 in the study area (cf. data per county in **Table 2**). The overlay analysis showed that overall 12.7% of the ONF area overlapped with clearcuts. This varied between counties as shown in **Figure 15A**, with more than 15% of ONF area overlapping with clearcuts in Østfold, Oslo and Akershus, and Hedmark.

Overall, 7.5% of ONF area overlapped with clearcuts that were made before the LiDAR data were recorded. This also varied among counties, with at least 8% of total ONF area in Hedmark, Oslo and Akershus, Østfold, and Vestfold harvested before LiDAR data were recorded. In Hedmark, Buskerud, Vestfold, Telemark, and Aust-Agder more than 50% of the overlap between ONF area and clearcuts occurred before LiDAR data were recorded (**Figure 15B**). As pointed out above, overlap between ONF area and clearcuts made before LiDAR data were recorded, indicates that there may be problems either with the classification of ONF pixels from LiDAR data, the aggregation of these pixels into ONF polygons, or with the classification of clearcuts.

Distance between ONF polygons and clearcuts

Although direct overlap between ONF polygons and clearcuts is the most drastic effect of forest harvesting on old forest, harvesting close to old forest patches can also reduce the old forest qualities. Both the distance to neighbouring harvesting sites and the area harvested in the immediate neighbourhood of old forest polygons will be of importance. However, here we have only looked at the distance between ONF polygons and the nearest harvesting site. The average distance between ONF polygons and the nearest clearcut site for the entire study area is 126 m. These average distances vary between counties, being lowest for Østfold, Oslo and Akershus, and Vestfold, and larger for Aust-Agder and Vest-Agder (**Figure 16A**). These patterns seem

Figure 15 *Degree of overlap between old natural forest (ONF) polygons and clearcuts, before and after the recording of LiDAR data which formed the basis for identification of ONF polygons.* ***A:*** *The proportion of total ONF area that overlaps with clearcuts.* ***B:*** *The relative proportions of overlapping clearcuts before and after recording of the LiDAR data. See Figure 10 for county symbols.*

consistent with differences in natural conditions like terrain and forest cover, as with established forestry practices with most intensive forestry in the central counties of Eastern Norway.

We get a more detailed picture of the distances from the ONF polygons and the nearest clearcut sites in **Figure 16B**. The vast majority (61.5%) of all ONF polygons are less than 50 m from the nearest clearcut. The differences between the counties are about as expected: The counties of central Eastern Norway with accessible forests and well developed forestry, also have the highest proportion of ONF polygons less than 50 m from clearcuts. The counties to the southwest tend to have a larger proportion of ONF polygons more distant from the nearest clearcut. This is particularly the case for Vest-Agder, with 17% of ONF polygons more than 500 m from clearcuts. Overall there are more than 5750 ONF polygons more than 1 km from the nearest clearcut, more than 1300 of these in each of Hedmark and Telemark, but with the highest proportion of all ONF polygons >1 km from cleacuts in Aust-Agder and Vest-Agder (3.8% and 4.0%). Only 17 ONF polygons are more than 4 km from the nearest clearcut, and 13 of these are in Oslo.

Note that results above on distances between ONF polygons and clearcuts are based on the number of ONF polygons, irrespective of their area. If we look at the distribution of ONF polygon area by distance classes (**Figure 16C**), a much larger proportion is found a short distance from clearcuts. For most counties 77–98% of the ONF area is less than 50 m from the nearest clearcut. Only Vest-Agder has a lower share (67%). This is mainly a result of the fact that large ONF polygons by necessity will end up near some clearcut. On the other hand, large ONF polygons will be less sensitive to neighbouring clearcuts than small ONF polygons, since they have much more core area and therefore are more robust against any negative influences from the surroundings.

***Figure 16 A:** Mean distances between ONF polygons and the nearest harvesting site for various counties. **B:** Proportion of ONF polygons at different distances from the nearest harvesting site in various counties. **C:** Proportion of ONF polygon area at different distances from the nearest harvesting site in various counties. See Figure 10 for county symbols.*

5.2 How do terrain and roads relate to old forest polygons and clearcuts?

Above we have seen that old natural forest (ONF) polygons and timber harvesting sites very often are located close together, and that 12.7% of the area of ONF polygons even overlap with clearcuts. Nevertheless, it is widely acknowledged that the economic viability of forest operations depends on the accessibility of harvestable forests, both with respect to terrain properties like elevation and slope and the availability of access roads (e.g. Granhus et al. 2014). Remaining old natural forest should therefore be expected to occur at higher elevation, on steeper slopes and farther from roads than clearcuts. Based on a GIS analysis of the location of ONF polygons and clearcuts with respect to elevation, slope and distance to the nearest road, we have compared to what extent ONF polygons and clearcuts differ in their positions for these aspects of terrain and human infrastructure.

Terrain variables

From **Figure 17A** it is apparent that ONF polygons and clearcuts do not differ very much in their mean elevations for various counties. Overall, the ONF polygons tend to occur a little higher, with an overall mean elevation of 392 m asl, versus 389 m for cleacuts. There is some variation among the counties, with ONF polygons occurring a little higher in Hedmark, Buskerud, Telemark, and Aust-Agder. The relative difference between ONF polygons and clearcuts is greatest for the 600-899 m elevation class where the ONF polygons are about 5 percentage points more frequent than clearcuts (**Figure 17B**). The distribution on elevation classes for ONF polygons and clearcuts vary considerably among the counties, as a reflection of their general topographic variation. Hedmark, Oppland, Buskerud, and Telemark have the highest proportion above 600 m. However, this pattern is quite similar for ONF polygons and clearcuts, and we therefore do not present these details here.

The mean slope of ONF polygons differs a bit more from the mean slope of clearcuts (**Figure 18A**) than does elevation. The overall mean slope is 13.3 degrees for ONF polygons and 10.1 degree for clearcuts, with ONF polygons having consistently higher mean slope for all counties. There is a higher frequency for ONF polygons than clearcuts in all steepness classes above 10 degrees (**Figure 18B**). As for elevation, there is considerable variation in steepness among the counties, both for ONF polygons and clearcuts. The frequency on steepness classes per county is fairly similar for ONF polygons and clearcuts, but ONF polygons have especially higher frequencies for classes steeper than 20 degrees for Vestfold, Telemark, and Vest-Agder.

Overall, the position of ONF polygons with respect to the terrain variables elevation and slope does not deviate very much from the position of clearcuts. The ONFs tend to have a slightly higher elevation for some counties and a somewhat steeper slope but the general distributions are quite similar.

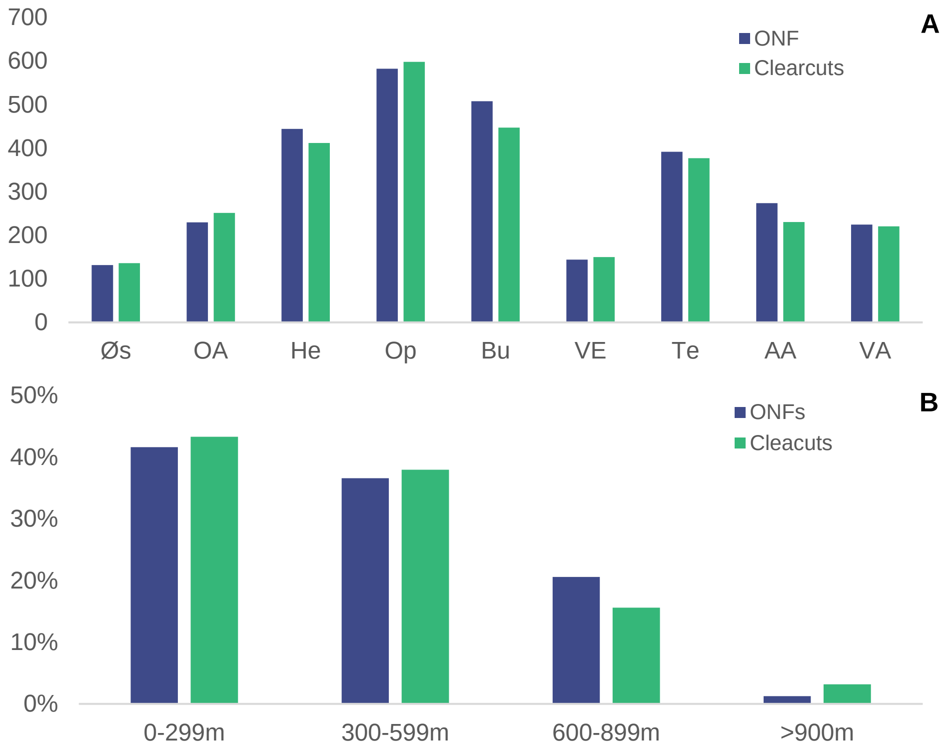

Figure 17 A: *Mean elevation for ONF polygons and clearcuts in the various counties. Mean elevations for ONFs and clearcuts are significantly different for all counties.* ***B:*** *Overall distribution of ONF polygons and clearcuts on elevation classes.*

Figure 18 A: *Mean slope for ONF polygons and clearcuts in the various counties. Mean slopes for ONFs and clearcuts are significantly different for all counties.* ***B:*** *Overall distribution of ONF polygons and clearcuts on steepness classes.*

Distance to roads
The overall mean distance from ONF polygons to the nearest road is 252 m. The overall comparable distance for clearcuts is somewhat shorter, 223 m. However, the mean distance from roads varies with county (**Figure 19A**). On average, the ONFs are more distant from roads than are clearcuts particularly for Hedmark, Telemark, and Aust-Agder, whereas they are closer for Oppland, Østfold, and Oslo and Akershus. The distribution of distances to the nearest road is very skewed for both ONF polygons and clearcuts (**Figure 19B**), with 38% of ONFs and 32% of clearcuts less than 50 m from the nearest road. On the other hand, 16% of the ONFs are at least 500 m from the nearest road, against 11% for clearcuts. Although the mean distance to the nearest road is somewhat further for ONF polygons than for clearcut, particularly for some counties, the distributions of distances to the nearest roads are quite similar.

5.3 Management implications of ONF polygons' relations to pressures

The results in this chapter indicate that there are only small differences between the location of ONF polygons relative to that of clearcuts. This pertains to the physical proximity of ONF polygons and clearcuts, as well to their respective distances from roads and locations along elevation gradients. They only differ somewhat in steepness. The essence is that the ONF polygons and the clearcuts are widely distributed across essentially all forested parts of the study area, at a medium and coarse spatial scale. Only at a very fine scale do they differ somewhat, e.g. with respect to slope. The implications for environmental management can be summed up as follows:

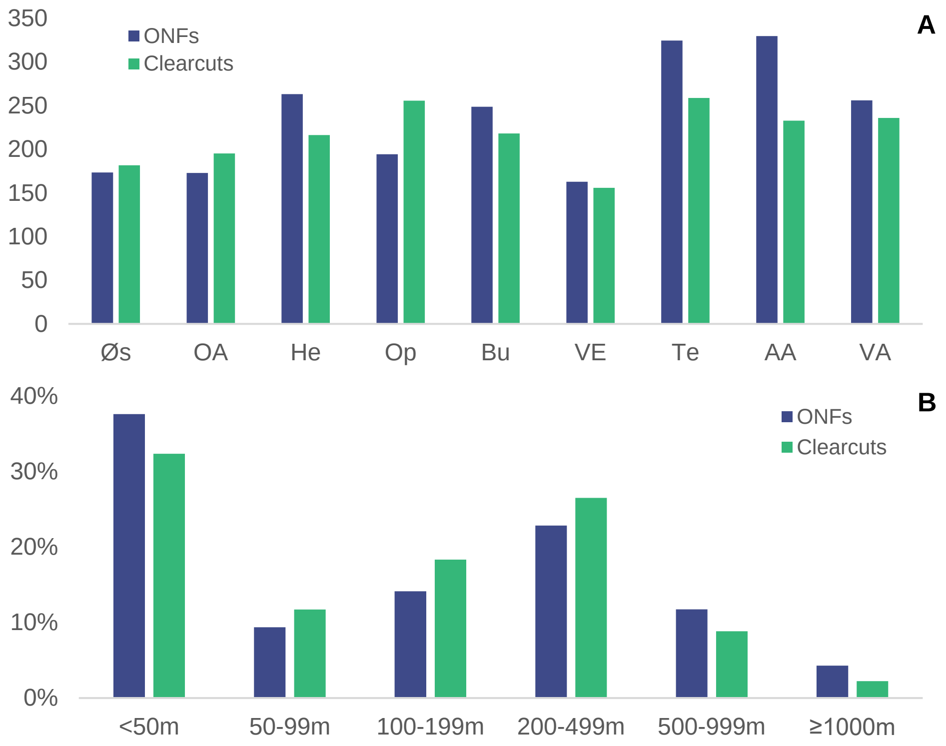

***Figure 19 A:** Mean distance from ONF polygons and clearcuts to the nearest road. Mean distances for ONFs and clearcuts are significantly different for all counties. **B:** Distribution of ONFs and clearcuts by classes of distances from the nearest road.*

- An overwhelming proportion of the ONF polygons are located at elevations, under terrain conditions, and sufficiently close to roads (<1000 m) to be easily accessible for forest harvesting. Being (presumably) mature forest, the ONFs will also be attractive for harvesting. This is also reflected in the physical proximity of most ONF polygons and clearcuts. Hence, it should be no surprise that many of the identified ONF polygons have been harvested since the recording of the LiDAR data used to identify the ONF pixels on which these analyses are based.
- Rather few, if any, ONF polygons are so inaccessible that they may be 'naturally protected'. Only 39 ONF polygons are >5 km from the nearest road and 28 of these are in north-eastern Hedmark and the rest in inner parts of Telemark and Agder. Hence, virtually all ONFs will sooner or later be harvested, unless legal restrictions are applied.
- Overlap between ONFs and clearcuts made before the LiDAR data were recorded is a clear indication of errors in the methods, either related to the classification methods for ONF pixels or clearcuts, or to the aggregation procedure of ONF polygons. Hence, these results should be interpreted with care, as the methods need to be further developed.

6 Discussion

The results presented in this report should be seen as examples of the sort of analyses that can be made on the basis of a set of polygons aggregated from pixels with specified environmental properties. The underlying data and the methods have not yet been verified to an extent where the results can be seen as representing the reality of forests of Eastern Norway. Hence, we will not discuss the results in depth here, but will instead reflect on various aspects of the data and the methods.

6.1 How well do these data and methods capture reality in forests?

Do the data represent what we expect?
The data used in this report are based on pixels with estimates of being old natural forest according to a specific definition (D7): *Forest that was identified as cutting class 5 (i.e. forest old enough to be ready for cutting) in the mid-1990s and still remain in that class today*. As forest in cutting class 5 in the mid-1990s would most likely be more than 50 years old, it is assumed that previous harvesting of such forest would almost exclusively have been by selective logging. Selective logging will preserve more of the structural characteristics of natural forest than harvesting by clearcutting. However, forest structure after selective logging will still vary considerably with growing conditions and other factors. The fact that forest satisfying the D7 definition constitutes as much as 15-22% of all forest area in the counties of our study area, based on data from the National Forest Inventory (cf. **Table 1**), also implies that the structure of such forest will vary considerably.

Given the character and extent of forest satisfying the D7 definition, the training set based on NFI data used to calibrate the estimation of probabilities of pixels satisfying this definition, is likely to be quite variable. It is therefore relevant to ask how well pixels with a high probability of being old natural forest actually cover such forest. It is not part of this project to do an analysis of this, but we provide some examples indicating that there are at least some mismatches that warrant further investigation.

Old natural forest (ONF) polygons were visually inspected using the Google Imagery basemap and a shapefile of the location of powerlines. Several counties showed that ONF polygons overlapped powerlines, which is a result of misclassification in the LiDAR data (**Figure 20**). The pylons may look like tall trees in the LiDAR point clouds, resulting in these areas being classified as old natural forest. We recommend that future studies mask out powerlines and other very tall structures (ex. Radio towers) in the classification methodology.

A recorded overlap of 7.5% between the area of old clearcuts (made before the LiDAR data were recorded) and the area of ONF polygons (**Figure 21**) is another indication that further exploration should be done of the classification of pixels based on remote sensing data. Here it is possible that LiDAR data were misclassified as ONF for forest that was already harvested. However, it is also possible that the analyses of Landsat data misclassified intact forest as clearcuts, or that the two methods classify mosaics with trees differently.

The extent of overlap between ONF polygons and non-forest areas like powerlines, clearcuts or possibly other areas with low tree cover should be analysed in more detail. If the extent is low enough, it may be considered acceptable errors in the classification. Nevertheless, field validation seems to be needed.

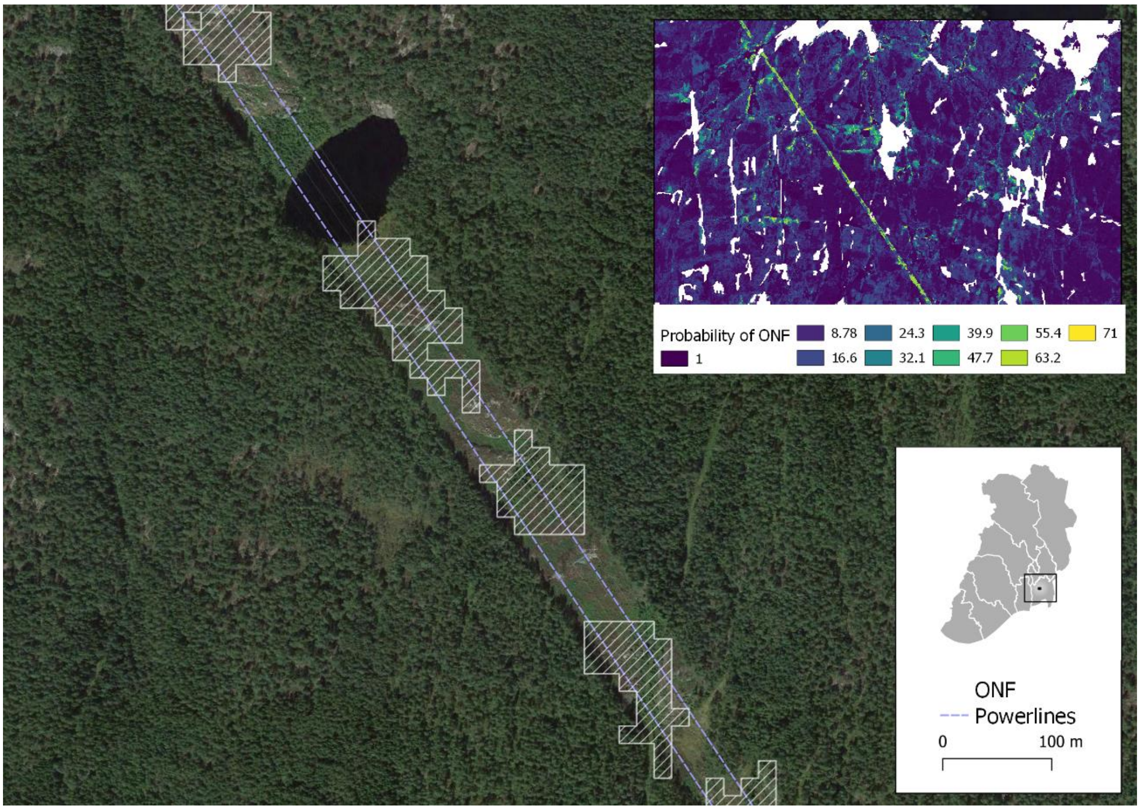

Figure 20 *An overlap between ONF polygons and cleared areas along powerlines was found in some counties.*

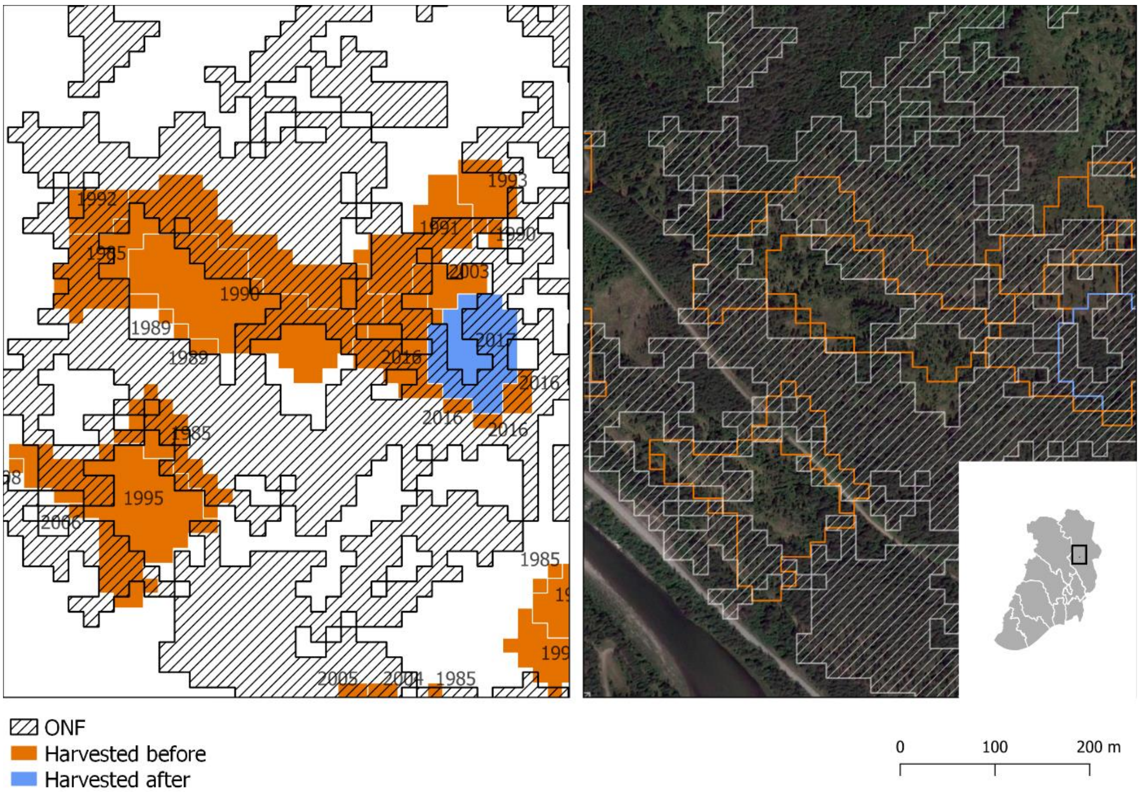

Figure 21 *In 7.5% of the cases, ONF polygons (cross-hatch) overlapped areas that had already been harvested. The year of harvest is given in the left-hand panel.*

Another challenge in using LiDAR data for such analyses of old natural forest, is that the LiDAR data rapidly become obsolete. After only a few years, more than 5% of identified ONF polygon area in our data set had already been harvest by new clearcuts. With the dynamic nature of forestry operations, frequently repeated mapping (by any method) or some form of reliable modelling will be needed to provide a realistic picture of the location and extent of old forest. Other sources of remote sensing data, such as Landsat or Sentinel 2, combined with LiDAR data hold much potential for mapping structural properties of vegetation with the added advantage of frequent updates (Lang et al. 2019).

What kind of forest is captured by the aggregation procedure?
Our aggregation of pixels into old natural forest (ONF) polygons was based on (1) selecting the pixels with the highest probability of being ONF, and (2) aggregating these through an iterative process until the area of the ONFs reached a target value given by the NFI data (after polygons <0.5 ha were discarded). The aggregation also incorporated lacunae <1000 m^2 into the ONF polygons. The target for ONF area per county was initially based on the N50 forest area for that county, i.e., the total ONF polygon area per county aimed to reach the same proportion of N50 forest as the NFI data specified for that county. However, since forest with LiDAR cover was the basis for identifying ONF pixels, the target area for ONFs based on N50 forest resulted in overshooting the target values for all counties when referred to forest area with LiDAR cover. This overshoot was marginal for most counties (<4.3 percentage points), but substantial for Buskerud (15.5 percentage points) and Aust-Agder (12.0 percentage points) where LiDAR cover of N50 forest was 59% and 69%, respectively. The consequence is that the ONF polygons for Buskerud and Aust-Agder includes considerably more area than intended.

When total ONF polygon area in a landscape increases as a proportion of available forest (here forest with LiDAR cover), the aggregation procedure will result in a higher proportion of larger polygons. This will particularly affect several of the spatial metrics, which tend to be sensitive to the total patch area within a landscape (Wang et al. 2014). In our case, this has implications for the interpretation of the spatial metrics for the ONFs in Buskerud and Aust-Agder compared to other counties. Some of the more striking patterns of the spatial metrics will reflect the higher proportion of ONF polygon area for Buskerud and Aust-Agder. In the counties with sufficient LiDAR coverage, and therefore an effective lower proportion of ONF area, the spatial metrics captured different properties for the configuration of ONF polygons in the landscape. Note that the spatial metrics also reflect differences in the layout of the ONF polygons that are less dependent on total ONF polygon area. It should be noted that the results in this report illustrate possible analyses and some of sensitivities of the methods, rather than giving a realistic description of forests of Eastern Norway.

How does LiDAR data influence differences between ONFs and forest in general?
The results indicate that there is little difference between ONF polygons and forest in general when it comes to cover of forest in protected areas (nature reserves and national parks). If we look at nature reserves only, which have more productive and well-developed forests than national parks, the overall cover of nature reserves for ONFs (3.8%) is a little higher than the cover for forest in general (3.5%). Nevertheless, ONF polygons do not seem to cover forest in protected areas much better than forest in general. On the other hand, the ONF polygons cover forest key biotopes based on MiS (4.1%) and forest Nature types (3.1%) to a greater extent than forest in general (1.8%). ONF polygons also seem to cover observations of red-listed forest-associated species to a greater extent than forest in general, with 5.4 observations per 10 km^2 of ONF area versus 2.6 for forest in general.

If we assume that forest in protected areas, forest key biotopes, as well as forest-associated red-listed species all should have or be associated with forest properties characteristic of old natural forest, we may ask if the method of identifying such old natural forest may be biased against one or more of these types of forest conservation interests. Protected areas are generally designated on the basis of a range of conservation interests (Framstad et al. 2017), although the selection of forest nature reserves in particular is heavily dependent on old natural forest characteristics, in addition to more general biodiversity properties (Framstad et al. 2018b). Hence, forest in protected areas may not have sufficiently distinct forest structural characteristics to be recorded effectively as ONF by LiDAR data. Several of the dominant categories of forest key biotopes associated with dead wood and old trees (making up >60 % of the area of such biotopes), as well as some of the other forest key biotope categories, are more likely to have specific structural characteristics recorded by LiDAR. Many of the forest-associated red-listed species of insects, lichens and fungi are associated with dead wood and old trees, i.e., structural features of old natural forests that may be explicitly recorded by LiDAR.

6.2 Would other old natural forest definitions be better?

Above we have seen that the D7 definition of old natural forest covers a rather large part of available forest area in our study area, 15-22% per county as judged by the NFI data. Several other definitions of old natural forest may be possible (cf. Ørka et al. 2018b). As part of their assessment of protected forest, Framstad et al. (2017) compared forest in protected areas with forest in general for three different definitions of old forest: cutting class 5, stand age above 120 years, and 'biologically old forest'. The latter modifies the stand age limit for old forest by the tree species (spruce, pine, deciduous[2]) and growing conditions (low, medium, high/very high productivity). The proportions of such old forest in forest in general and in protected areas in our study area, compared to the proportions of forest by the D7 definition for NFI data and our ONF polygons, are shown in **Figure 22**. As expected, the D7 definition of old natural forest covers only about half as much area as forest in cutting class 5 (which also includes old forest previously harvested by clearcutting). The proportion of ONF area is rather similar to the proportion of forest >120 years old in forest in general. It is apparent from **Figure 22** that 'biologically old forest' represents a smaller proportion of the forest area than the two other old forest variables, and that the proportion of 'biologically old forest' in protected areas compared to forest in general is relatively higher than for the other old forest categories. Hence, 'biologically old forest' may be a

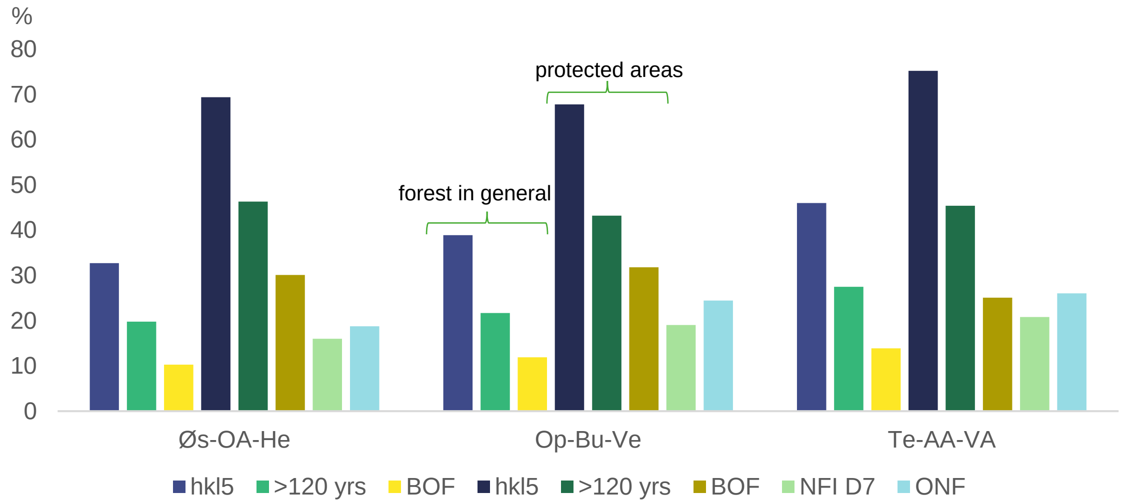

Figure 22 *The proportion of forest area covered by forest in cutting class 5 (hkl5), with stand age >120 years, and by 'biological old forest' (BOF; cf. text for explanation) in forest in general and in protected areas, compared to the proportion of forest area covered by old natural forest according to the D7 definition (NFI D7) and our ONF polygons, in different regions of our study area (cf. Figure 10 for county symbols). Data for hkl5, >120 yrs, and BOF are from Framstad et al. (2017).*

[2] Note that the age limit for old deciduous trees is probably set too high, as boreal deciduous tree species like birch, aspen and alder dominate and have lower maximum ages that temperate deciduous trees.

better candidate than D7 for old natural forest with high conservation value. Whether LiDAR data will be well suited to identify 'biologically old forest' remains to be seen.

Ørka et al. (2018b) analysed forest polygons for several different definitions of old natural forest for forest in Oslo and Akershus. Data from Landsat 8, Sentinel 2 and LiDAR were used as input for extraction of ONF polygons and analyses of the landscape characteristics of these polygons and their cover of various conservation values. The data and the aggregation procedure used in 2018 were not the same as those used for this report, but the basic approach was similar. Hence, it may be instructive to compare some of the results from the analyses in 2018 to the current analyses for Oslo and Akershus. Here we have selected results for the definitions D1 (the NFI definition of old natural forest), D2 (forest stand age ≥140 years), and D4 (the 25% of stands with the most varied size distribution in cutting class 5), in addition to definition D7. Note that the different definitions of old natural forest differ from each other in two main respects: The estimation of the probability of a pixel being old natural forest is based on data from NFI plots which satisfy the respective definitions and therefore differ in their characteristics. Also, the threshold values according to the NFI data range from 1% for D1 to 15% for D7 (**Table 4**).

In spite of the differences in input data and aggregation methods, one main pattern stands out: The higher the threshold value and the more widespread the cover of ONF polygons, the less distinct are the ONF polygons in terms of their cover of various conservation values. This may be modified somewhat by the ability of the data and the method to identify areas that satisfy the particular characteristics of the various definitions and how well these characteristics coincide with the various conservation values.

For most of the spatial metrics the main pattern is governed by the total ONF area and how this is distributed on number of ONF polygons. There is a rather close positive relationship between total ONF area and the number of polygons, but this relationship is not linear. As the polygon area increases, the proportion of large polygons increases. The distance between neighbouring polygons is similarly reduced. Other spatial metrics, such as the Shape Index, have less clear relationships to the total ONF area or the number of polygons. These patterns may, of course, also be modified by the actual layout of polygons in space. The analyses based on the D1 definition, for instance, did seem to produce more relevant polygon patterns (cf. discussion in Ørka et al. 2018b).

Table 4 *Comparison of some metrics from analyses of old natural forest polygons in Oslo and Akershus based on various old natural forest (ONF) definitions and LiDAR data. See Ørka et al. (2018b) for details of methods and results for definitions D1, D2, D4.*

	D1	D2	D4	D7
Spatial metrics				
Proportion of forest area according to NFI	1.0%	3.0%	6.5%	15.0%
Proportion of forest covered by ONFs	0.8%	3.0%	10.1%	16.5%
Total ONF area (km^2)	34.6	129.7	440.0	566.9
Number of ONF polygons	2 351	9 680	18 286	20 923
Number of ONF polygons per km^2	0.68	2.81	5.30	6.09
Mean polygon size MPS (ha)	1.47	1.34	2.41	2.71
Edge density ED (m/ha)	599	678	562	522
Mean Shape Index	2.06	2.21	2.40	2.21
Mean Nearest Neighbour distance (m)	514	337	286	95
Cover of conservation values				
Protected areas (% of ONF area)*	24.7%	9.5%	8.1%	6.0%
MiS key biotopes (% of ONF area)	11.0%	5.1%	3.6%	6.2%
Forest Nature types (% of ONF area)	28.2%	10.3%	7.4%	7.9%
Records of red-listed species per km^2	2.25	0.95	0.69	0.67

* Note that in 2018 all protected area was used, although only protected area overlapping with forest was counted, whereas in this report only forested protected area was used.

It appears from these results that old natural forest definitions which comprise a rather large proportion (perhaps >10%) of available forest area tend to represent forest in general rather than forest with particular conservation values. In addition, some old natural forest definitions do not seem to be well targeted to fit characteristics that we generally associate with old natural forest. It still remains to test both the most appropriate old natural forest definitions and the most suitable data and methods to identify old forest polygons.

6.3 Locations of ONFs and clearcuts are quite similar

ONF polygons represent a fundamentally different forest state than clearcuts. Hence, it is surprising that there is so little difference in where they are located. There is virtually no difference in elevation, but ONFs tend to occur in a bit steeper terrain. Although the mean distance from roads is a little longer for ONFs than for clearcuts, the distributions on distance classes overlap extensively. There is also a significant direct overlap, with 12.7% of ONF area overlapping with clearcuts. The wide distribution of both ONF polygons and clearcuts and the high degree of similarity of their locations reflect that they are both covering virtually the full range of forest locations within the study area. Whatever distinction there is among them does not manifest itself at a spatial scale that matters with respect to our representation of roads or terrain variables.

The management implications of this are limited (cf. chapt. 5.3):

- The great majority of identified ONF polygons are easily accessible to forest harvesting, provided they are not already protected or have timber volumes that are too low to be economically relevant for harvesting. Hence, should these ONF polygons have important conservation values, only legal restrictions or environmental measures in forestry will secure these values.
- However, as we have seen in chapter 4, the ONF polygons do not cover a particularly high frequency of conservation values in the form of forest key biotopes or records of red-listed forest species. Although the identified ONF polygons, particularly the larger ones, might be considered a useful starting point for mapping such conservation values, there are probably more effective approaches to such mapping. That is particularly the case since we do not have a good documentation of what kind of forest the ONF polygons really cover.

6.4 RS-based old natural forest and forest ecological condition

In the recently proposed system for assessing the ecological condition of major ecosystems in Norway (Nybø & Evju 2017), ecological condition should be assessed against a reference condition based on the structure, function and productivity of ecosystems mainly under natural dynamics[3] and with minimal modern human impact. The assessments of ecological condition were proposed for rather large areas like counties or regions, and for broadly defined ecosystems. Condition could also be assessed for more detailed categories of ecosystems if they differed in their ecological characteristics and if data for relevant indicators had appropriate spatial resolution. Nybø & Evju (2017) proposed that the assessment of ecosystem condition should be based on a set of indicators that represented seven main features of ecosystems. Values of these indicators should be based on data that are representative for the region under assessment. In one of the two main approaches to the assessment of ecosystem condition, the index approach (Nybø et al. 2019), it should be possible to set values for the indicators under reference conditions, as a basis for scaling and comparing indicators measured in different units. Finally, in the index approach, it should also be possible to give indicators a value for a lower limit for good ecosystem condition. In the alternative scientific panel approach (Jepsen et al. 2019), substantial time series for indicator values are essential (although not strictly required) to assess whether changes in indicators can be judged to show significant directional change and be related to

[3] The specification for semi-natural ecosystems included traditional management.

human pressures. Long time series for indicator values will be an advantage for the index approach as well, to judge interannual variability in indicator values.

In Nybø & Evju (2017) various indicators were proposed for forests. These included the amount or proportion of forest area covered by, respectively, natural forest and 'biologically old forest' (cf. above), as well as the connectivity of 'biologically old forest' and the mean size of forest polygons. During further work to make the proposed system operational (Nybø et al. 2018), the two latter indicators were left out. In a pilot test of the system for Trøndelag (Nybø et al. 2019), only the indicator for the proportion of forest area covered by 'biologically old forest' was implemented, based on data from the National Forest Inventory. In the proposal for full-scale implementation of the system for assessment of ecological condition for forests (Nybø et al. unpubl.), a few additional indicators will be assessed for implementation in the assessment for forests.

So far two types of old and/or natural forest indicators have been proposed for assessment of ecological condition in forests, mean values for the proportion for forest area covered by specific types of old/natural forest, and landscape level indicators like the connectivity of 'biologically old forest' and the size of forest polygons. In the project reported here, we consider a specific definition (D7) for old natural forest. Previously, we have considered other such definitions (Ørka et al. 2018b). A selection of these definitions of old natural forest could be relevant to include in the system for assessment of ecological condition in forests. However, it would probably be better to source the data for the mean values of these indicators directly from the empirical data of the NFI, rather than going through the estimation and aggregation procedures required to derive ONF polygons, where some errors will be introduced. When it comes to landscape level indicators like the connectivity of 'biologically old forest', however, we do not have such empirical data available. The current approach of modelling the distribution of ONF polygons would be very relevant as a data source for such landscape level indicators. Various old natural forest definitions may be applied, although one should probably select definitions with a clearer relationship to forest conservation values than appears to be the case for definition D7. This definition also has another drawback: The amount of forest based on the D7 definition can never increase, as it is linked to the forest stands which were in cutting class 5 in the mid-1990s. These forest stands will gradually be harvested or decimated by natural disturbances, and the D7 definition does not include a mechanism for inclusion of new forest stands, although such a mechanism can be imagined. For any definition of old natural forest, it would also be reassuring to have better verification of what kind of forest the extracted ONF polygons actually represent.

Irrespective of the old natural forest definition applied, another major challenge in the assessment of ecological condition, at least under the index approach, is related to the need to set reference values for each of the indicators (and a limit value for good ecological condition). For some of the indicators that represent mean values for a region, such reference values may be set based on data from reference areas with minimum human impact, knowledge of indicator values for reference conditions in the recent past, or some form of mechanistic modelling underpinned by selected data (cf. Jakobsson et al. in prep.). To derive relevant connectivity measures for old natural forest, or forest in general, under reference conditions, some form of modelling to derive a reference landscape with spatially explicit old forest patches would be needed. This is obviously not a simple task, and one which would be based on many untestable assumptions. An alternative could be to apply the scientific panel approach for assessment of ecological condition. However, here rather long time series would be essential to judge whether observed values represent directional changes, deviations from some base level, or simply interannual variation. Long data series are lacking for most indicators, and would be quite complex to derive for landscape level indicators like connectivity.

6.5 Conclusions and recommendations

The results from this project illustrate some of the challenges involved in landscape analysis of forest patches, or land patches in general. Most landscapes are complex and it is difficult to capture essential properties of landscape structure with a general battery of indicators. Landscape analysis should have a specific purpose and specifically adapted indicators to reflect this purpose.

The results for the spatial metrics in particular also highlight the need to consider the proportion that the selected patch types cover of the total area, and to see this in context of the aggregation process of individual pixels into larger patches or polygons. These factors will affect the size distribution of patches as well as their landscape connectivity, even if the underlying pattern of environmental variation is the same.

In general, the identified ONF polygons do not differ very much from forest in general. ONF polygons have consistently higher coverage of forest key biotopes and of records of forest-associated red-listed species, but there is little difference in the cover of protected areas. There is also little difference between ONF polygons and clearcuts in their location relative to roads, elevation or slope. There are some possible reasons for this:

- The D7 definition for old natural forest may be too expansive and indistinct to allow a meaningful classification of old natural forest. Covering 15-22% of the forest area (according to the NFI data), and even more as a consequence of our aggregation procedure, such forest covers a large part of forest in general and therefore probably does not have very distinct properties compared to forest in general.
- The method for classifying old natural forest pixels may not be able to distinguish such forest well enough from forest in general. This may depend on both the nature of the LiDAR data, the training set of pixels with known characteristics, and the classification procedure.

In this project we have taken a theoretical approach to the analysis of the extracted old natural forest (ONF) polygons, assuming that the identified pixels truly represent occurrences of old natural forest (at least to the same extent as the NFI plots according to the same ONF definition). Above we have pointed to a few cases where it seems relevant to question how well the classification of ONF pixels and the aggregation of these into polygons actually represent old natural forest in any ecologically meaningful sense.

Recommendations for improved identification of old natural forest
To improve the process of identifying ecologically meaningful areas of old natural forest several steps may be needed:

- Indicators of old natural forest and delimitation of areas of such forest may be done in several different ways, and any one of these possible approaches may not give results that are optimal for all possible purposes. Hence, a clarification of the main purpose for the future use of such results would make it easier to select meaningful definitions for old natural forest and to design a process for identifying and delimiting areas of such forest.
- There is a clear need to assess the various ONF definitions in order to develop criteria for selection of suitable ONF definitions for different purposes. Such an assessment should consider which characteristics of old natural forest the various definitions cover and whether such characteristics are likely to be sufficiently distinct from forest in general to allow a clear classification of relevant pixels. It should also consider how well these old natural forest characteristics may be identified by potential remote sensing data, in order to classify pixels as well as possible.
- The technical aspects of the estimation of probabilities of pixels being old natural forest based on remote sensing data are beyond the scope of this report. However, the various definitions of old natural forest differ in the proportion of forest that they cover. A county-based estimation procedure may result in very few available NFI plots for calibration of the models for some old forest definitions and some counties. For instance, there were only four NFI plots in Oslo and Akershus satisfying the D1 definition and there were none in Østfold. Hence, a more robust training set for the estimation of old natural forest probabilities, e.g., by using the whole study area or several counties, may improve the results. However, we acknowledge that there may be other technical considerations that make this less suitable.

- If the resulting maps of ONF pixel probabilities shall reflect the current status of old natural forest, data that are updated regularly will be needed as input. As far as we know, there are no definite plans for regular repeated updates of country-wide LiDAR data. Hence, other available and frequently updated remote sensing data sources such as the Sentinel 1 and 2 data provided under the Copernicus program may be needed.
- Different aspects of the aggregation procedure may result in rather different total ONF area and shape and distribution of ONF polygons. These pertain to the set thresholds, rules for aggregating pixels, any rules for smoothing of pixel boundaries etc. These different aspects should be further explored with the aim of selecting a standard and optimal procedure for extracting ONF polygons.
- A major obstacle to make active use of the resulting ONF pixel or polygon maps in management and research is the uncertainty of what kind of forest the ONF pixels and polygons actually cover, i.e., whether the ONF pixels and polygons represent what we expect from the selected old natural forest definition. A cost-effective evaluation could be made on the basis of updated aerial photographs, e.g., by manual inspection of a representative sample of locations across the study area. Field verification of a selected sub-set of these locations may help to clarify if the interpretation of aerial photographs is correct or represents particular problems. A specific protocol for such a verification process should be adapted to the selected old natural forest definition and the characteristics of such forest.

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Appendix 1 Spatial metrics employed for analysis of ONF polygons

From McGarigal & Marks (1995), appendix 3, and McGarigal (2015).

Symbol	Metric	Explanation	Unit
CA	Total class area	Sum of area of all patches belonging to a specific class, here total ONF polygon area.	ha
NP	Number of patches	Number of patches of a given class, here number of ONF polygons.	none
MPS	Mean patch size	Mean size of patches of a given class, here mean size of ONF polygons.	ha
TE	Total edge	Sum of the edge (perimeter) of all patches of a given class, here the sum of perimeters of all ONF polygons per county or municipality.	km
ED	Edge density	Sum of the edge of all patches of a given class divided by the total landscape area, here the sum of perimeters of all ONF polygons within a county or a municipality, divided by forest area with LiDAR data of that county or municipality.	m/ha
CORE	Core area	Area (m^2) within the patch that is further than the specified edge distance (10 m) from the patch perimeter	ha
SHAPE	Shape index	Shape index of patches of a given class, here ONF polygons, calculated as the patch perimeter divided by (4 * the square root of patch area). The value increases from 1 for a perfectly regular patch (square) to an unbounded value for increasingly irregular shapes.	none
PARA	Perimeter:area ratio	Perimeter to area ratio for patches of a given class, here ONF polygons.	none
FRAC	Fractal dimension	Fractal dimension of a patch, here ONF polygon, is 2 * ln (0.25 * patch perimeter) divided by ln (patch area). Value between 1 and 2, where higher values indicate more irregular shapes.	none
CONTIG	Contiguity index	Average contiguity value of pixels in a patch, here ONF polygon, minus 1, divided by the sum of template values (13) minus 1 (values between 0 and 1). (cf McGarigal 2015, p 106)	none
ENNmn	Euclidean nearest neighbour – mean	Average Euclidean distance between a patch of a given class and its closest neighbour based on edge to edge distance, within a landscape, here ONF polygons per municipality.	m
PROX	Proximity index	Sum of patch area (m^2) divided by the nearest edge-to-edge distance squared (m^2) between the patch and the focal patch of all patches of the corresponding patch type whose edges are within a specified distance (m) of the focal patch, here a ONF polygons within 500 m.	none
CONNECT	Connectance index	Number of functional joinings between all patches of the corresponding patch type (sum of c_{ijk} where $c_{ijk} = 0$ if patch j and k are not within the specified distance of each other and $c_{ijk} = 1$ if patch j and k are within the specified distance), divided by the total number of possible joinings between all patches of the corresponding patch type, multiplied by 100 to convert to a percentage (values between 0 and 100). Calculated here for ONF polygons per municipality with a 500 m distance criterion.	none
COHES	Cohesion index	1 minus the sum of patch perimeter (measures as pixels) divided by the sum of patch perimeter times the square root of patch area (measures as pixels) for all patches in the landscape, divided by 1 minus 1 over the square root of the total number of pixels in the landscape, multiplied by 100 to convert to a percentage (values between 0 and 100). Calculated here for ONF polygons per municipality.	none

Appendix 2 Some characteristics of ONF polygons per municipality

Data for forest cover (AR5 forest and forest with LiDAR cover) and spatial metrics for the old natural forest (ONF) polygons for the municipalities of the study area. There were no polygons or data for Hol municipality. See Appendix 1 for explanation of the spatial metrics, including their units of measurement.

					lidar	Spatial metrics													
county	nr	municipality	forest km^2	lidar km^2	cover %	ca	np	mps	ed	te	core	shape	para	frac	contig	enn_mn	prox	conn	cohes
Øs	101	Halden	465.4	465.2	100	5438	2808	1.94	641	3487	2 388	2.350	0.078	1.164	0.657	104.40	21.37	0.28	92.77
Øs	104	Moss	35.3	35.2	100	1242	322	3.86	542	673	641	2.638	0.075	1.171	0.667	99.23	122.76	6.77	96.97
Øs	105	Sarpsborg	239.9	239.7	100	2961	1673	1.77	690	2042	1 189	2.420	0.082	1.172	0.639	108.91	21.32	0.43	92.63
Øs	106	Fredrikstad	139.1	139.0	100	2299	1106	2.08	611	1404	1 063	2.284	0.075	1.158	0.669	109.98	26.29	0.66	93.46
Øs	111	Hvaler	34.1	34.1	100	444	255	1.74	655	291	189	2.191	0.077	1.152	0.656	147.97	18.78	2.01	93.52
Øs	118	Aremark	234.4	234.2	100	5670	1742	3.25	559	3169	2 846	2.609	0.075	1.172	0.668	76.44	111.55	0.60	96.67
Øs	119	Marker	288.5	288.3	100	6646	2166	3.07	571	3794	3 284	2.598	0.077	1.173	0.659	81.73	71.42	0.45	95.82
Øs	121	Rømskog	137.6	137.5	100	4908	1090	4.50	500	2452	2 706	2.693	0.071	1.171	0.685	65.99	447.27	2.43	97.75
Øs	122	Trøgstad	106.7	106.5	100	3471	859	4.04	499	1733	1 922	2.632	0.072	1.171	0.681	85.36	173.15	2.20	97.22
Øs	123	Spydeberg	81.7	81.7	100	2442	780	3.13	560	1367	1 228	2.588	0.073	1.170	0.677	76.97	52.94	3.68	94.93
Øs	124	Askim	25.7	25.7	100	1110	288	3.85	485	538	626	2.445	0.069	1.162	0.694	87.95	59.02	2.51	95.72
Øs	125	Eidsberg	128.0	127.8	100	2659	971	2.74	555	1476	1 353	2.441	0.074	1.165	0.671	107.77	38.74	0.77	94.98
Øs	127	Skiptvet	52.9	52.8	100	736	410	1.80	652	480	318	2.361	0.081	1.168	0.643	114.27	17.74	1.58	92.66
Øs	128	Rakkestad	270.9	270.7	100	3880	1886	2.06	633	2454	1 731	2.382	0.079	1.167	0.651	101.20	22.74	0.41	93.21
Øs	135	Råde	53.5	53.4	100	999	443	2.26	623	623	453	2.456	0.077	1.169	0.661	119.21	28.89	1.54	94.29
Øs	136	Rygge	25.4	25.4	100	981	304	3.23	556	545	494	2.556	0.071	1.165	0.686	178.22	30.99	6.61	93.14
Øs	137	Våler	190.6	190.6	100	2243	1261	1.78	727	1631	832	2.573	0.085	1.182	0.626	96.33	23.58	0.65	92.73
Øs	138	Hobøl	97.6	97.5	100	2131	865	2.46	638	1360	943	2.614	0.081	1.177	0.644	73.91	50.54	4.53	94.79
OA	211	Vestby	78.8	77.9	99	1943	721	2.69	522	1013	1 034	2.218	0.068	1.147	0.697	83.52	46.52	1.34	94.40
OA	213	Ski	101.5	101.5	100	2150	898	2.39	566	1216	1 066	2.259	0.070	1.153	0.687	91.23	30.16	3.18	92.82
OA	214	Ås	46.4	46.4	100	1299	373	3.48	454	590	766	2.177	0.066	1.143	0.703	125.55	78.76	3.24	95.01
OA	215	Frogn	57.2	57.3	100	1508	436	3.46	498	751	829	2.323	0.068	1.152	0.696	89.78	51.98	9.12	94.42
OA	216	Nesodden	43.6	43.7	100	1015	384	2.64	559	567	509	2.305	0.073	1.156	0.674	81.25	53.80	10.19	93.00
OA	217	Oppegård	22.4	22.3	100	1074	145	7.41	435	467	645	2.742	0.066	1.159	0.704	76.03	1006.72	5.48	98.69
OA	219	Bærum	121.2	121.1	100	2249	901	2.50	554	1247	1 137	2.234	0.072	1.151	0.677	114.82	32.09	4.43	93.91
OA	220	Asker	54.4	54.4	100	1133	451	2.51	532	603	593	2.191	0.069	1.149	0.692	99.13	31.36	1.64	93.89
OA	221	Aurskog-Høland	697.4	697.3	100	9396	3706	2.54	523	4914	5 000	2.144	0.069	1.143	0.691	102.62	30.52	1.50	94.46
OA	226	Sørum	110.2	110.3	100	1582	758	2.09	570	902	782	2.122	0.071	1.144	0.683	113.21	20.13	0.81	92.90
OA	227	Fet	94.0	94.0	100	2309	740	3.12	508	1173	1 253	2.319	0.067	1.154	0.698	84.14	54.68	1.19	95.03

					lidar	Spatial metrics													
county	**nr**	**municipality**	**forest km^2**	**lidar km^2**	**cover %**	**ca**	**np**	**mps**	**ed**	**te**	**core**	**shape**	**para**	**frac**	**contig**	**enn_mn**	**prox**	**conn**	**cohes**
OA	228	Rælingen	42.4	42.4	100	838	306	2.74	531	445	439	2.319	0.069	1.154	0.689	82.91	53.04	3.23	94.53
OA	229	Enebakk	149.8	149.4	100	5260	1123	4.68	454	2385	3 088	2.397	0.069	1.154	0.689	66.85	391.79	0.95	98.32
OA	230	Lørenskog	46.3	46.3	100	879	235	3.74	537	472	455	2.295	0.072	1.153	0.679	92.35	51.02	2.62	95.37
OA	231	Skedsmo	30.1	30.1	100	531	229	2.32	554	294	268	2.163	0.070	1.146	0.685	133.63	26.56	2.43	94.46
OA	233	Nittedal	140.2	139.7	100	2137	822	2.60	527	1125	1 129	2.158	0.068	1.144	0.697	102.78	44.14	0.94	94.70
OA	234	Gjerdrum	45.8	45.7	100	563	266	2.12	546	307	289	2.048	0.070	1.139	0.686	130.84	15.58	1.96	92.78
OA	235	Ullensaker	116.8	115.2	99	2419	780	3.10	487	1177	1 361	2.224	0.067	1.148	0.700	112.98	36.71	0.79	94.80
OA	236	Nes	402.8	402.0	100	4315	622	6.94	597	2575	2 039	2.168	0.073	1.149	0.674	118.09	22.42	0.32	92.85
OA	237	Eidsvoll	290.2	290.1	100	4458	1604	2.78	507	2262	2 427	2.178	0.068	1.145	0.696	98.78	39.94	0.44	94.73
OA	238	Nannestad	240.7	240.6	100	2306	1032	2.23	544	1254	1 190	2.101	0.071	1.142	0.682	130.78	21.27	0.57	93.66
OA	239	Hurdal	233.2	228.0	98	2144	932	2.30	539	1156	1 113	2.107	0.068	1.142	0.696	116.37	23.13	0.67	93.19
OA	301	Oslo	281.9	281.4	100	5201	1825	2.85	520	2705	2 774	2.243	0.070	1.149	0.688	91.77	42.34	3.47	94.50
He	402	Kongsvinger	795.5	794.7	100	15946	6839	2.33	690	11010	6 339	2.821	0.085	1.190	0.627	74.13	70.27	0.18	95.52
He	403	Hamar	183.7	183.3	100	1574	954	1.65	701	1103	621	2.389	0.085	1.172	0.625	138.49	20.66	0.66	92.96
He	412	Ringsaker	646.3	644.0	100	10228	2243	4.56	662	6770	4 321	2.571	0.082	1.178	0.637	91.28	43.95	1.81	94.90
He	415	Løten	254.0	253.7	100	5458	1864	2.93	635	3465	2 408	2.793	0.082	1.184	0.639	90.67	189.59	0.56	97.49
He	417	Stange	466.5	466.3	100	11715	4164	2.81	676	7917	4 759	2.954	0.085	1.192	0.624	76.54	188.73	0.33	97.27
He	418	Nord-Odal	407.9	407.7	100	12131	4079	2.97	705	8549	4 623	3.154	0.086	1.199	0.621	58.91	341.13	0.42	97.98
He	419	Sør-Odal	364.8	354.5	97	7753	3413	2.27	716	5549	2 925	2.892	0.087	1.194	0.619	71.84	78.70	0.39	95.73
He	420	Eidskog	495.3	495.3	100	14715	5075	2.90	678	9974	5 940	3.069	0.083	1.197	0.635	59.76	168.39	0.30	96.77
He	423	Grue	628.1	627.8	100	15507	5688	2.73	676	10476	6 331	2.929	0.086	1.193	0.623	72.68	196.93	0.24	97.36
He	425	Åsnes	791.3	790.9	100	21203	6371	3.33	610	12940	9 770	2.908	0.083	1.189	0.633	73.49	238.80	0.20	97.62
He	426	Våler	522.7	522.3	100	13653	4158	3.28	636	8681	5 976	2.883	0.083	1.186	0.636	78.87	292.13	0.28	98.07
He	427	Elverum	954.1	953.7	100	32017	7127	4.49	575	18425	15 562	2.938	0.083	1.187	0.635	71.39	1912.98	0.19	99.21
He	428	Trysil	2084.4	1707.1	82	31763	11583	2.74	642	20402	13 853	2.769	0.084	1.185	0.631	88.95	94.92	0.18	96.69
He	429	Åmot	1022.5	1019.5	100	24158	7487	3.23	619	14950	10 963	2.909	0.083	1.189	0.637	74.20	197.59	0.35	97.40
He	430	Stor-Elvdal	1382.3	1371.5	99	23833	6707	3.55	613	14598	10 903	2.930	0.082	1.189	0.639	100.40	137.55	1.63	94.76
He	432	Rendalen	1670.4	1624.7	97	21443	8822	2.43	685	14680	8 623	2.793	0.086	1.189	0.623	91.61	88.09	0.12	96.46
He	434	Engerdal	994.2	949.6	96	9608	3491	2.75	634	6094	4 251	2.751	0.085	1.185	0.629	126.40	78.20	0.21	96.84
He	436	Tolga	414.8	247.5	60	1209	623	1.94	756	914	419	2.822	0.088	1.193	0.613	94.67	43.79	1.70	94.52
He	437	Tynset	748.5	603.0	81	5490	2311	2.38	705	3869	2 118	2.866	0.087	1.193	0.618	293.99	39.54	16.88	90.56
He	438	Alvdal	423.1	409.9	97	5428	1723	3.15	600	3256	2 545	2.770	0.078	1.182	0.656	77.00	101.63	0.60	96.59
He	439	Folldal	358.4	212.2	59	370	304	1.22	853	316	103	2.473	0.093	1.183	0.590	157.78	11.71	5.89	90.44
He	441	Os	384.0	236.7	62	624	413	1.51	809	505	192	2.584	0.092	1.184	0.598	143.33	22.98	1.60	93.71
Op	501	Lillehammer	307.4	307.5	100	8765	2334	3.76	569	4988	4 323	2.811	0.080	1.183	0.648	74.58	183.84	2.93	97.51
Op	502	Gjøvik	450.4	450.2	100	12157	4312	2.82	641	7788	5 287	2.794	0.080	1.184	0.646	70.14	98.22	0.56	96.17

county	nr	municipality	forest km²	lidar km²	lidar cover %	ca	np	mps	ed	te	core	shape	para	frac	contig	enn_mn	prox	conn	cohes
						Spatial metrics													
Op	511	Dovre	219.0	144.4	66	764	385	1.99	757	578	265	2.844	0.089	1.196	0.610	209.98	39.32	1.96	94.24
Op	512	Lesja	311.2	300.3	97	2187	885	2.47	735	1606	789	2.921	0.090	1.196	0.605	109.86	107.97	0.98	97.60
Op	513	Skjåk	245.3	225.0	92	2174	784	2.77	655	1424	924	2.956	0.086	1.199	0.625	106.03	49.58	2.79	95.29
Op	514	Lom	195.0	160.3	82	749	477	1.57	821	615	224	2.659	0.092	1.189	0.597	136.22	24.56	1.37	93.36
Op	515	Vågå	299.9	188.9	63	950	562	1.69	766	728	324	2.606	0.090	1.186	0.606	154.34	22.81	1.13	93.10
Op	516	Nord-Fron	520.6	435.1	84	7063	1541	4.58	549	3879	3 600	3.026	0.084	1.194	0.631	78.58	312.55	0.64	98.12
Op	517	Sel	347.9	194.9	56	3034	1103	2.75	663	2012	1 272	2.950	0.089	1.197	0.612	97.58	74.53	0.81	96.48
Op	519	Sør-Fron	312.2	302.2	97	5073	1282	3.96	497	2521	2 803	2.988	0.082	1.188	0.640	100.52	411.95	0.93	98.57
Op	520	Ringebu	557.0	556.2	100	9537	1802	5.29	527	5024	5 032	2.936	0.083	1.188	0.637	97.14	570.96	1.29	98.16
Op	521	Øyer	294.6	294.3	100	4222	641	6.59	573	2417	2 084	2.748	0.083	1.185	0.634	97.36	116.89	1.36	96.63
Op	522	Gausdal	612.1	610.0	100	8069	2671	3.02	579	4672	3 935	2.623	0.079	1.177	0.652	116.67	92.72	1.78	96.77
Op	528	Østre Toten	308.3	308.3	100	6873	2599	2.64	645	4432	2 970	2.738	0.082	1.184	0.638	85.11	78.66	0.41	96.18
Op	529	Vestre Toten	137.0	137.0	100	3705	1320	2.81	639	2369	1 618	2.794	0.081	1.187	0.644	76.90	78.04	0.76	95.77
Op	532	Jevnaker	157.5	149.0	95	5810	1109	5.24	532	3090	3 029	2.922	0.083	1.188	0.635	68.25	807.01	9.29	98.69
Op	533	Lunner	217.3	217.1	100	5940	1985	2.99	658	3911	2 494	2.968	0.085	1.194	0.627	99.97	188.67	3.92	96.66
Op	534	Gran	507.2	228.8	45	3788	1655	2.29	661	2504	1 596	2.622	0.084	1.182	0.628	112.62	40.82	1.03	95.00
Op	536	Søndre Land	555.1	554.9	100	15601	4872	3.20	646	10081	6 699	2.948	0.083	1.191	0.636	66.77	174.19	2.62	96.74
Op	538	Nordre Land	684.8	684.6	100	16803	4989	3.37	600	10085	7 851	2.818	0.079	1.184	0.653	71.34	131.06	0.12	88.15
Op	540	Sør-Aurdal	782.8	780.9	100	16743	5130	3.26	616	10317	7 599	2.780	0.079	1.180	0.652	78.12	263.57	0.22	97.73
Op	541	Etnedal	332.7	332.1	100	6596	1829	3.61	564	3718	3 284	2.678	0.078	1.177	0.658	86.55	218.18	0.52	97.57
Op	542	Nord-Aurdal	474.9	404.7	85	9955	2340	4.25	549	5460	5 073	2.842	0.078	1.183	0.660	76.08	281.76	0.45	97.87
Op	543	Vestre Slidre	206.6	159.6	77	3737	848	4.41	547	2043	1 910	2.972	0.081	1.190	0.644	78.54	292.45	2.46	97.54
Op	544	Øystre Slidre	227.8	190.8	84	3768	906	4.16	563	2124	1 873	2.984	0.080	1.191	0.651	82.83	162.33	2.32	97.41
Op	545	Vang	186.5	149.3	80	1290	433	2.98	639	825	562	2.808	0.083	1.185	0.636	107.76	94.26	1.79	96.51
Bu	602	Drammen	92.0	91.9	100	4617	605	7.63	514	2374	2 442	3.009	0.079	1.181	0.649	60.24	1561.77	2.15	99.21
Bu	604	Kongsberg	621.8	616.3	99	23281	4545	5.12	530	12340	12 058	2.755	0.079	1.175	0.651	56.68	2315.98	0.71	98.95
Bu	605	Ringerike	1189.8	133.2	11	6235	885	7.05	435	2713	3 750	2.889	0.076	1.178	0.660	60.83	628.74	5.36	98.07
Bu	612	Hole	99.1	24.2	24	620	149	4.16	478	296	350	2.400	0.069	1.156	0.690	144.55	62.03	3.09	96.49
Bu	615	Flå	443.3	414.5	94	11531	2867	4.02	571	6582	5 598	2.707	0.079	1.174	0.651	64.77	735.59	0.42	98.49
Bu	616	Nes	529.9	493.7	93	14689	2668	5.51	496	7292	8 041	2.724	0.079	1.173	0.649	70.99	1254.33	0.44	99.05
Bu	617	Gol	331.0	331.1	100	10009	2035	4.92	527	5274	5 215	2.707	0.079	1.173	0.648	69.94	965.78	0.60	98.86
Bu	618	Hemsedal	180.0	114.5	64	1412	543	2.60	635	896	615	2.575	0.081	1.174	0.639	118.39	77.02	1.36	96.02
Bu	619	Ål	365.8	268.5	73	6966	1426	4.88	538	3751	3 557	2.794	0.080	1.179	0.645	69.48	866.55	0.82	98.80
Bu	620	Hol	367.8	3.1	1														
Bu	621	Sigdal	604.5	594.9	98	34066	2718	12.53	448	15272	19 847	2.660	0.078	1.167	0.654	62.02	26701.69	0.44	99.84
Bu	622	Krødsherad	279.1	8.8	3	45	31	1.45	691	31	18	2.062	0.074	1.144	0.671	584.17	3.40	2.53	88.94

					lidar	Spatial metrics													
county	nr	municipality	forest km^2	lidar km^2	cover %	ca	np	mps	ed	te	core	shape	para	frac	contig	enn_mn	prox	conn	cohes
Bu	623	Modum	376.0	375.9	100	13874	2006	6.92	494	6853	7 584	2.682	0.077	1.170	0.655	75.03	5195.66	0.55	99.61
Bu	624	Øvre Eiker	332.6	105.4	32	3690	1000	3.69	576	2126	1 774	2.725	0.077	1.176	0.660	75.47	161.17	50.52	89.10
Bu	625	Nedre Eiker	90.8	89.6	99	4223	1252	3.37	539	2275	2 143	2.768	0.080	1.171	0.645	72.14	2427.03	1.97	99.38
Bu	626	Lier	209.9	209.9	100	8377	1538	5.45	529	4428	4 348	2.727	0.079	1.171	0.649	65.80	1456.79	0.83	99.07
Bu	627	Røyken	77.4	77.4	100	2866	720	3.98	604	1732	1 306	2.812	0.078	1.175	0.652	62.12	536.37	1.82	98.23
Bu	628	Hurum	126.2	126.2	100	4833	1220	3.96	604	2919	2 205	2.777	0.083	1.179	0.630	56.86	660.98	4.58	98.75
Bu	631	Flesberg	434.8	19.7	5	297	81	3.67	587	175	140	2.653	0.076	1.164	0.663	156.14	206.55	7.55	97.95
Bu	632	Rollag	333.6	31.2	9	334	112	2.99	541	181	172	2.335	0.075	1.157	0.668	252.50	34.52	2.79	95.62
Bu	633	Nore og Uvdal	698.2	646.7	93	16447	3328	4.94	552	9081	8 207	2.813	0.080	1.177	0.644	67.94	1220.81	0.37	98.92
Ve	701	Horten	30.2	30.2	100	508	283	1.79	727	369	190	2.669	0.087	1.190	0.616	121.70	14.63	2.50	92.79
Ve	704	Tønsberg	35.3	35.3	100	418	321	1.30	786	329	139	2.432	0.089	1.178	0.610	145.07	9.61	1.93	89.88
Ve	710	Sandefjord	249.5	249.3	100	4202	1022	4.11	800	3362	1 324	2.723	0.091	1.192	0.602	88.42	28.73	0.40	93.14
Ve	711	Svelvik	44.9	44.9	100	1254	483	2.60	736	922	452	3.102	0.089	1.201	0.609	59.65	143.03	7.19	96.72
Ve	712	Larvik	589.1	588.6	100	9722	5622	1.73	806	7832	3 011	2.837	0.092	1.197	0.595	82.08	48.32	0.22	94.68
Ve	713	Sande	125.5	125.5	100	3719	1205	3.09	701	2607	1 432	3.274	0.086	1.204	0.623	73.06	132.18	2.69	96.55
Ve	715	Holmestrand	179.8	179.8	100	3112	1622	1.92	798	2482	979	2.946	0.093	1.200	0.592	71.82	86.10	12.32	96.38
Ve	716	Re	126.0	126.0	100	1930	1148	1.68	783	1510	635	2.701	0.091	1.192	0.603	106.07	22.78	0.77	93.19
Ve	729	Færder	46.0	46.1	100	283	268	1.06	872	247	76	2.318	0.095	1.176	0.581	197.82	3.93	1.71	87.62
Te	805	Porsgrunn	124.5	124.4	100	3558	1651	2.16	830	2953	1 015	3.320	0.095	1.211	0.587	59.88	279.87	1.18	97.45
Te	806	Skien	610.0	609.9	100	18142	6292	2.88	780	14151	5 811	3.362	0.093	1.209	0.594	61.62	803.89	0.30	98.73
Te	807	Notodden	653.9	653.8	100	19458	5570	3.49	745	14504	6 727	3.303	0.092	1.205	0.597	66.41	1304.16	0.66	98.95
Te	811	Siljan	182.1	48.8	27	1280	556	2.30	810	1036	383	3.409	0.093	1.211	0.596	58.37	152.08	2.81	96.39
Te	814	Bamble	249.5	249.4	100	9103	2209	4.12	692	6297	3 515	3.452	0.087	1.205	0.619	57.14	1325.14	0.84	98.85
Te	815	Kragerø	247.1	247.1	100	5253	2951	1.78	873	4588	1 333	3.137	0.097	1.209	0.576	64.16	134.11	0.58	96.84
Te	817	Drangedal	876.4	876.3	100	21018	8070	2.60	789	16580	6 596	3.294	0.092	1.209	0.597	64.27	372.18	0.21	98.06
Te	819	Nome	332.3	332.3	100	10782	2884	3.74	738	7955	3 782	3.488	0.092	1.209	0.599	63.58	1514.90	0.58	99.12
Te	821	Bø	190.7	190.7	100	5085	1916	2.65	790	4018	1 595	3.239	0.093	1.208	0.594	64.09	527.38	0.84	98.45
Te	822	Sauherad	240.8	240.7	100	7397	2374	3.12	773	5717	2 405	3.366	0.092	1.206	0.599	64.21	812.21	0.72	98.69
Te	826	Tinn	632.4	604.1	96	12648	4290	2.95	752	9517	4 327	3.238	0.091	1.205	0.603	73.99	494.60	0.34	98.35
Te	827	Hjartdal	440.3	440.3	100	8745	2617	3.34	711	6216	3 270	3.142	0.087	1.199	0.619	87.17	281.96	2.80	97.63
Te	828	Seljord	407.4	407.3	100	11023	2966	3.72	719	7927	4 036	3.356	0.089	1.205	0.611	61.13	460.37	19.35	97.47
Te	829	Kviteseid	500.7	500.6	100	12529	4127	3.04	745	9337	4 354	3.268	0.091	1.206	0.603	86.13	241.84	25.88	93.52
Te	830	Nissedal	599.1	555.6	93	8703	3596	2.42	766	6665	2 896	3.081	0.089	1.201	0.610	89.58	109.26	0.65	96.51
Te	831	Fyresdal	724.5	724.2	100	9877	4551	2.17	786	7761	3 155	3.035	0.091	1.202	0.605	91.98	78.04	0.23	95.95
Te	833	Tokke	544.5	529.6	97	13074	3809	3.43	706	9236	4 926	3.264	0.088	1.204	0.616	80.59	279.10	2.19	98.02
Te	834	Vinje	572.7	392.2	68	6703	2369	2.83	738	4944	2 375	3.167	0.089	1.204	0.611	66.63	278.76	4.30	97.59

county	nr	municipality	forest km²	lidar km²	lidar cover %	Spatial metrics ca	np	mps	ed	te	core	shape	para	frac	contig	enn_mn	prox	conn	cohes
AA	901	Risør	155.9	155.9	100	7467	769	9.71	473	3530	4 232	3.087	0.077	1.180	0.661	59.80	2710.12	1.39	99.38
AA	904	Grimstad	214.4	214.4	100	8299	1562	5.31	515	4276	4 436	2.871	0.077	1.181	0.661	71.17	449.54	2.56	97.29
AA	906	Arendal	192.0	191.9	100	8753	1282	6.83	501	4390	4 771	3.155	0.078	1.188	0.656	74.74	420.86	4.37	98.15
AA	911	Gjerstad	272.8	4.1	1	41	32	1.28	703	29	16	1.972	0.075	1.139	0.674	523.36	1.69	4.44	86.96
AA	912	Vegårshei	289.3	289.3	100	14230	1698	8.38	465	6616	8 181	2.980	0.073	1.176	0.680	56.28	2970.12	0.80	99.33
AA	914	Tvedestrand	176.6	176.5	100	7655	797	9.61	490	3754	4 225	3.235	0.079	1.184	0.656	68.51	2218.82	1.35	99.23
AA	919	Froland	523.7	523.5	100	17550	2956	5.94	490	8595	9 752	2.824	0.074	1.176	0.675	63.18	1878.02	0.99	98.62
AA	926	Lillesand	48.5	48.5	100	1640	380	4.32	543	891	838	2.878	0.075	1.184	0.668	68.57	119.25	2.78	97.10
AA	928	Birkenes	424.8	424.7	100	15901	2469	6.44	479	7611	8 975	2.865	0.075	1.176	0.669	64.57	790.89	0.46	98.65
AA	929	Åmli	818.9	818.8	100	24687	4236	5.83	470	11593	14 175	2.730	0.075	1.173	0.669	70.86	964.54	0.62	98.71
AA	935	Iveland	27.9	27.9	100	879	308	2.86	552	486	444	2.708	0.075	1.175	0.668	60.61	111.23	4.58	95.95
AA	937	Evje og Hornnes	166.1	166.1	100	4616	1002	4.61	519	2394	2 461	2.841	0.079	1.182	0.654	85.65	312.95	1.04	98.03
AA	938	Bygland	399.8	398.2	100	10450	1548	6.75	453	4729	6 155	2.868	0.079	1.182	0.651	113.60	743.81	0.51	98.74
AA	940	Valle	286.0	244.3	85	4328	2186	1.98	409	1770	2 716	2.747	0.077	1.178	0.660	107.65	509.63	1.18	98.46
AA	941	Bykle	212.3	55.8	26	1067	253	4.22	516	550	573	2.795	0.077	1.180	0.665	790.90	69.42	1.90	90.57
VA	1001	Kristiansand	196.2	196.2	100	4348	1505	2.89	650	2828	1 850	2.715	0.084	1.182	0.628	82.64	222.18	0.68	97.58
VA	1002	Mandal	169.3	169.3	100	5082	829	6.13	599	3044	2 365	2.908	0.082	1.187	0.638	66.41	475.17	0.96	98.22
VA	1003	Farsund	137.8	137.7	100	1500	927	1.62	724	1086	559	2.380	0.083	1.169	0.633	121.71	17.54	0.74	92.17
VA	1004	Flekkefjord	333.6	195.8	59	5345	1129	4.73	527	2815	2 805	2.798	0.080	1.182	0.647	92.19	488.77	0.71	98.48
VA	1014	Vennesla	301.2	301.0	100	8650	2292	3.77	555	4800	4 349	2.733	0.077	1.178	0.661	69.27	238.77	0.51	97.60
VA	1017	Songdalen	172.1	172.1	100	4562	1422	3.21	592	2703	2 154	2.687	0.077	1.177	0.662	68.39	120.05	0.80	96.52
VA	1018	Søgne	116.3	116.3	100	2064	965	2.14	721	1488	767	2.784	0.086	1.189	0.622	76.91	69.43	1.20	95.16
VA	1021	Marnardal	322.3	322.4	100	10249	4708	2.18	522	5348	5 431	2.766	0.077	1.177	0.663	67.25	377.18	0.53	98.16
VA	1026	Åseral	252.1	252.0	100	3237	1011	3.20	581	1882	1 561	2.736	0.078	1.182	0.659	115.69	63.45	0.73	95.63
VA	1027	Audnedal	196.6	196.6	100	6312	1218	5.18	506	3197	3 422	2.816	0.076	1.178	0.666	69.54	414.37	0.85	98.17
VA	1029	Lindesnes	216.0	216.0	100	4706	1822	2.58	659	3103	1 975	2.773	0.083	1.186	0.638	77.03	95.83	0.62	95.98
VA	1032	Lyngdal	229.1	229.0	100	5562	1861	2.99	616	3429	2 524	2.708	0.082	1.181	0.639	83.27	149.26	0.56	97.03
VA	1034	Hægebostad	219.4	219.4	100	4203	2605	1.61	536	2251	2 183	2.754	0.079	1.178	0.654	96.64	214.44	0.91	97.67
VA	1037	Kvinesdal	431.8	386.1	89	5303	2092	2.53	653	3460	2 257	2.696	0.083	1.184	0.634	106.90	74.89	0.42	95.66
VA	1046	Sirdal	224.3	224.0	100	3412	703	4.85	501	1710	1 870	2.864	0.079	1.185	0.652	145.74	244.33	1.01	98.11

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NINA Report

The Norwegian Institute for Nature Research, NINA,
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Cooperation and expertise for a sustainable future