Project report 2018

Lidar data as indicators for forest biological diversity: a review

(Kan lidar data brukes som indikator på biologisk mangfold?: En litteratursammenstilling)

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Preface

The work presented in this report is the result of the project "Kan lidar data brukes som indikator på biologisk mangfold?: En litteratursammenstilling" (Lidar data as indicators for forest biological diversity: a review) with reference number 2018/7772. The project was funded by the Norwegian Environment Agency and conducted in autumn of 2018 by the Norwegian University of Life Sciences.

Sammendrag

Økosystemet skog har en variert sammensetning av livsformer, og majoriteten av jordas terrestriske arter lever her. Strukturell kompleksitet kan forklare den store variasjonen av biodiversitet i skog. Fjernmåling kan brukes på stor skala for kartlegging med høy oppløsning. En fjernmålingsteknikk kalt *light detection and ranging* (lidar) er effektiv for kartlegging av skogstruktur. Lidar trenger gjennom trekronene, og kan dermed gi tredimensjonale data om alle kronesjikt. Lidar kan også beskrive topografiske egenskaper i tillegg til skogens vertikale og horisontale variasjon. Lidar gir derfor pålitelige data for å karakterisere og klassifisere habitat. Målet med denne studien var å undersøke om biologisk diversitet kan karakteriseres ved hjelp av skogstruktur representert med informasjon fra lidar. Vi gjorde en litteratursammenstilling av 36 studier som brukte variabler ekstrahert fra lidardata for å enten predikere utbredelsen av biologisk diversitet i skog eller for å evaluere forholdet mellom disse. Vårt mål var å utføre en meta-analyse av dataene hentet ut fra studiene for å ekstrahere informasjon om potensielle lidarindikatorer for biologisk diversitet. For hver studie hentet vi ut kvantitative data om effekt- og utvalgsstørrelse. Vi hentet også ut informasjon angående responsvariabelen (målet på biologisk mangfold og studiens taksa) og modellens forklaringsvariabel (lidar og andre fjernmålingsvariabler, og andre miljøvariabler). De ekstraherte dataene ble satt sammen i en tabell for sammenligning. På grunn av begrenset kvantitativ informasjon og stor heterogenitet innenfor studietaksa, skogtype og modelleringsmetode så var det ikke mulig å utføre en meta-analyse. Vi utførte likevel en systematisk litteratursammenstilling av studiene for å komme med preliminære anbefalinger for lidarindikatorer relatert til biologisk mangfold. Tidligere studier på biologisk mangfold har funnet av vegetasjonsstruktur (vegetasjonshøyde – og tetthet) i tillegg til topografiske egenskaper (høyde over havet og helning) er viktig for å forklare tilstedeværelsen av forskjellige taksa. Disse egenskapene kan også bli fremstilt gjennom variabler uthentet fra lidardata, og slike variabler har blitt brukt i flere studier. Andre skogindikatorer fra en tidligere rapport om overvåkning av terrestriske økosystemer ble også evaluert av eksperter innenfor fjernmåling for å se om disse kan bli fremstilt gjennom lidardata. Basert på de 34 studiene og kunnskap om bruken av lidardata relatert til skog, kunne vi komme fram til anbefalinger med tanke på effektiv bruk av lidardata for bruk i studier av biologisk mangfold. Pulssensorer med diskrete returer virker til å være den mest relevante typen av lidardata. Dette er både på grunn av sensorens egenskaper og fordi denne typen sensor har mye data som allerede er tilgjengelig for bruk. Vi anbefaler en tostegs-tilnærming for å hente inn data hvor modellen først er kalibrert mot feltobservasjoner og så at modellen brukes mot et heldekkende lidardatasett. En forutsetning for denne tilnærmingen er at man har feltobservasjoner (grunnenhet) som kan brukes for kalibrering av en modell. Mobile arter trenger generelt større grunnenheter sammenlignet med stasjonære arter. Feltobservasjonene må posisjoneres for å forsikre at de har et romlig overlapp med fjernmålingsdataene. Forutsetningene for hvor nøyaktig posisjonene trenger å være avhenger av størrelsen på grunnenheten og hvilken type biologisk mangfold som skal kartlegges.

Utvidet sammendrag

Introduksjon

Omkring 80% av jordas terrestriske biodiversitet finnes I skog (Balvanera et al., 2014). I skogøkosystemer påvirker vegetasjonsstrukturen tilstedeværelsen og mengden av arter på lokal skala (Hunter and Hunter, 1999, Tews et al., 2004). Vegetasjonen og kompleksiteten i skog påvirker arters tilstedeværelse, mengde og adferd gjennom ulike mekanismer. Skogen kan påvirke tilgjengeligheten og diversiteten til ressurser og nisjer, ved at mikroklima blir påvirket, ved at hekkeplasser og leveområder for ulike arter blir formet, og at arter finner vern mot predatorer (MacArthur and MacArthur, 1961, Melin et al., 2014, Suggitt et al., 2011). Viktigheten av vegetasjon og habitatstruktur for opprettholdelse av biologisk diversitet i skog er anerkjent at flere og flere (Gustafsson et al., 2012, Noss, 1990, 1999). Mer strukturell kompleks skog har ofte høyere artsdiversitet enn skjøttet skog som er mindre kompleks (Ishii et al., 2004). Feltinventeringer er ressurskrevende, og også begrenset til arealet av feltflatene. Behovet for mer effektive metoder for karlegging av biologisk diversitet på stor skala er derfor tydelig.

Ulike typer fjernmåling har vist seg å være gode supplement til feltdata siden man ved bruk av slike data kan gjøre karlegging på landskapsnivå og helt opp til global skala. Metoder for karlegging av biologisk mangfold ved hjelp av fjernmåling kan enten være direkte eller indirekte (Turner et al., 2003). Direkte metoder kan identifisere taksa eller arealtyper direkte fra fjernmålingsdataene. Indirekte metoder bruker fjermålingsdata til å modellere fordelingen av biologisk diversitet. Optiske sensorer, lik de som sitter i Landsat satellittene, er nyttige til å gjøre analyser av den horisontale strukturen og vegetasjonstyper på grov romlig skala. Lidar kan imidlertid anvendes på landskapsnivå for å kartlegge både den horisontale og vertikale strukturen til vegetasjonen (Zolkos et al., 2013) og alder (Racine et al, 2014). Lidar kan også brukes på relativt grov romlig skala, noe som gjør dataene egnet til å gjøre analyser av trender og mønstre i fordelingen av det biologiske mangfoldet.

For å undersøke om det er en sammenheng mellom biologisk mangfold og strukturen av habitater i skog, karakterisert ved hjelp av lidar, brukte vi en meta-analyse tilnærming. Det finnes ingen tidligere litteratursammenstillingsstudier som har brukt meta-analyse for å analysere sammenhengen mellom skogstruktur representert ved variabler fra fjernmåling og biologisk mangfold.

Materialer og metode

Litteratursøket ble utført 19. september 2018 i databasen ISI Web of Science med denne kombinasjonen av søkekriterier:

> (Laser OR (lidar OR (light AND Detection AND Ranging)) OR (als OR (airborne AND laser AND scanning))) AND forest* AND (biodiversity OR diversity OR richness OR ecolog* OR species OR habitat).

Søket ble gjort under feltet "Topic", og de ble ikke lagt noen skranker med tanke på år eller språk. Søkeordene ble valgt slik at de var tilpasset oppdraget og slik at sannsynligheten for å utelate relevante studier ble minimert. Kombinasjonen av søkeord ble valgt med det formål å fange studier som har kvantifisert sammenhengen mellom miljøvariabler målt med lidar, og minst en av følgende:

1. Direkte mål på biologisk diversitet, enten for:
    a. en enkelt art («presence/absence» eller hyppighet)
    b. en taksonomisk eller funksjonell gruppe av arter

c. flere grupper med arter (taksonomisk eller funksjonell)
2. Indirekte mål på biologisk diversitet (habitat/vegetasjonsstruktur/død ved).

Søket resulterte I 1897 artikler. Antallet ble redusert I henhold til utvalgte kriterier ved en mer inngående sjekk av hver studie. 1)Tittel, sammendrag og nøkkelord ble undersøkt for å eliminere irrelevante studier. 2) Andre litteratursammenstillinger og studier skrevet på andre språk enn engelsk ble ikke inkludert i biblioteket av referanser. 3) Studier som bare hadde brukt terrestrisk lidar, og ikke fra satellitt eller fly, ble eliminert. Terrestrisk lidar kan ikke brukes til å lage utbredelseskart over store områder. Når titler, sammendrag og nøkkelord ble lest, klassifiserte vi samtidig studiene i tre ulike kategorier av biologisk diversitet; enkeltarter (ca. 100 studier), flere arter (gruppere kategori b) og c) over), og habitater (ca. 30 studier).

For studier der «habitat» var brukt som respons, valgte vi de som omhandlet habitater i skog, eller habitategenskaper som skogsuksesjoner eller død ved. Totalt fant vi 23 studier der vi kunne ekstrahere data. Studier der formålet var klassifisering av habitater i skog versus habitater i «ikke skog» ble ikke inkludert i denne litteratursammenstillingen. Vi ekstraherte følgende informasjon fra hver studie: responsvariabel (skogtype / skogegenskaper; inkludert død ved), forklaringsvariabler fra lidar, forklaringsvariabler fra andre typer fjernmåling, land, breddegrad, lengdegrad, utvalgsstørrelse, størrelsen på studieområdet og modelleringstilnærming (prediksjonsmodellering / annen statistisk modellering). For studiene som brukte prediksjonsmodellering, ekstraherte vi også mål på modellens tilpassing og kategoriserte dem som: eksellent, god, tilfredsstillende, dårlig, ingen sammenheng,

<u>Resultater og anbefalinger</u>

Totalt hentet vi ut informasjon fra 36 studier som hadde biologisk mangfold som responsvariabel og lidarvariabler som modellenes forklaringsvariabler. For de studiene som hadde habitat som responsvariabel ble det hentet ut informasjon fra 23 studier. Lokasjonen til studiene var spredt over hele kloden (Figur 4). Majoriteten av studiene var blitt utført i Nord-Amerika og Europa. Alle de sammenstilte studiene var blitt publisert i mellom år 2007 og 2018 hvor 60 % av studiene var blitt publisert etter 2015.

Det finnes ikke én måleenhet som kan kvantifiserer biologisk mangfold helt perfekt, og det finnes heller ikke en indikator som passer for alle mønstre. Muligheten til å utforske biologisk mangfold på forskjellige måter vil ikke kun hjelpe oss med å oppnå mer kunnskap om økosystemfunksjon, men også være med å løse på praktiske problemer som det å koble diversitet og økosystemtjenester med økologisk tilstand. Majoriteten av studiene som hadde relatert biologisk mangfold til lidarvariabler inkluderte kun informasjon om tilstedeværelsen og hvor vanlig artene var, og de fleste brukte artsrikdom med «presence only» som responsvariabel. Artsrikdom er den vanligste måleenheten for biologisk mangfold, men den inneholder ikke informasjon om hvor vanlig en art er. To områder med like mange arter trenger ikke å han noen arter til felles, og derfor ha to helt forskjellige samfunnssammensetninger. Få studier relaterer lidarvariabler til endringer i samfunnssammensetninger. I tillegg er det få studier som relaterer lidarvariabler til funksjonell diversitet. Dette er et klart kunnskapshull som burde fylles for at en skal kunne vurdere nyttigheten av lidar for å predikere økologisk tilstand.

I tillegg til mange forskjellige måter å måle biologisk mangfold for forskjellige taksonomiske grupper, skogtyper og geografiske regioner, så var det vanskelig å finne generelle mønstre mellom biologisk mangfold og lidarvariabler på grunn av det store antallet med mulige forklaringsvariabler. I prediksjonsmodellering er målet å maksimere prediksjonen og ikke nødvendigvis redusere antallet med forklaringsvariabler. Det kan derfor være urealistisk å finne én eller flere gode lidarindikatorer som kan predikere biologisk mangfold på generell basis. Ved å kombinere vår ekspertise innenfor fjernmåling og økologi med informasjon hentet ut fra litteratursammenstilling, har vi prøvd å komme med forslag til grupper med lidarvariabler som fanger økologiskrelevante aspekter av et skoghabitat. Hvilke egenskaper innenfor habitatet som er viktig vil avhenge av habitatkravene til den taksonomiske eller funksjonelle gruppen man ønsker å se på. I fremtiden så kan en meta-regresjonsanalyse basert på studier som ser på enkeltarter være mulig å gjennomføre. Dette vil mest sannsynlig bety at man må kontakte forfatterne bak studiene for å få tilgang til grunndataene. Dette er fordi mange av studiene hadde en høy variasjon innenfor statistiske modeller, og tilgangen til grunndataene vil la oss få hente ut den informasjonen som er nødvendig for å beregne effektstørrelse.

Litteratursammenstillingen viste at lidar har et stort potensial for prediksjonsmodellering av biologisk mangfold på en regional skala. Kalibrering av prediksjonsmodeller ved å bruke bakkesannheter som videre kan anvendes på beregningsceller over et areal er den mest pålitelige metoden. Lidardata kan også inneholde relevant strukturell informasjon som kan brukes uavhengig av kalibrering, men dette krever at indikatorene som brukes er nøye gjennomtenkt. Det er også viktig å huske at lidarsensorer også har noe å si for målemetodene og at disse også kan variere mellom skogtyper. Størrelsen og formen på bakkesannhetene må velges ut ifra hvilket fenomen som kartlegges. Generelt så vil mobile arter trenge større bakkeenheter enn stasjonære arter, og store enheter er mer nyttig for å kartlegge flere arter enn én art.

Vi anbefaler prediksjonsmodellering i henhold til en arealbasert metode. Med denne tilnærmingen er det relativt enkelt å få heldekkende «wall-to-wall» prediksjoner av biologisk mangfold og evaluere habitategenskaper over relativt store områder. Informasjon om habitategenskaper kan brukes til å forbedre utbredelsesmodellering av arter og organismegrupper basert på kjente forhold mellom arter og habitatpreferanser. Lidar og andre fjernmålingsmetoder kan brukes for å evaluere indikatorer for økologisk tilstand (Tabell 8). Faktorer som truer biologisk mangfold slik som veier, grøfter og flatehogst kan også detekteres (Tabell 9). Lidar er en stor datakilde for å evaluere biofysiske egenskaper til trær og vegetasjon, og også terrengets egenskaper. Kombinert med andre datakilder som gir spektral informasjon, så vil nytten av disse dataene være enorm.

Abstract

The forest ecosystem has a wide variation in life forms, and inhabit the majority of the Earth's terrestrial species. Structural complexity can explain this high amount of biological diversity. Remote sensing is applicable over broad scales to map areas in high resolution. One technique called light detection and ranging (lidar) can be applied to map the structure of the forest. Lidar can do this because of its capability to penetrate the forest canopy and therefore retrieve three-dimensional data representing all canopy layers. Lidar can both depict topographical features as well as vertical and horizontal variation of the forest. Thus, lidar can provide reliable data for characterizing- and classifying habitats. In this study, we aimed to see if the relationship between biological diversity and the forest structure could be characterized. We reviewed 36 studies that used a metric for biological diversity as a response variable and 23 studies with forest habitat types to assess the relationship between these and lidar-derived variables. Our main aim was to perform a meta-analysis of the data to extract information about potential lidar indicators of biological diversity. For each study, we extracted quantitative data on effect- and sample sizes. We also extracted information concerning the dependent variable (measure of biological diversity and study taxa or habitat type) and model predictor variables (lidar and other remote sensing variables, and other environmental variables). The extracted data was compiled into a table for comparison. Because of limited quantitative information and large heterogeneity within study taxa, forest type and modelling method it was not possible to perform a meta-analysis. We did however systematically review the studies to be able to come with preliminary recommendations for lidar indicators of biological diversity. Previous studies on biological diversity has found that vegetation structure (vegetation height and density) as well as topographic features (elevation and slope) to be important for explaining the presence of different taxa. These features can also be represented by variables extracted from lidar data, and such variables have been applied in multiple studies. Other forest ecosystem indicators extracted from a report on monitoring of terrestrial ecosystems were also evaluated to see if these could be extracted from lidar data. Based on the 36 reviewed studies and expert knowledge from the use of lidar data related to forest applications, we were able to make some recommendations with regard to efficient use of lidar data for biological diversity applications. Pulsed laser sensors with discrete returns seem to be the most relevant type of lidar data. This is both because of the sensor properties and that these are the most available data in terms of area coverage. We recommend a two-stage approach where a model is calibrated based on ground-truth observations in the first stage, and the model is applied on a wall-to-wall lidar dataset in the second stage. A prerequisite for this approach is that a basic unit is determined. The area of this unit must be determined so that it is relevant for the phenomenon that is being mapped. Mobile species generally requires larger basic units compared to stationary species. The ground-truth observations need to be positioned to secure that they spatially overlap with the remotely sensed lidar data. The requirements with regard to positioning accuracy will depend on the size of the basic unit and the specific measure of biological diversity in question.

Extended abstract

Introduction

Forests support about 80% of the World's terrestrial biodiversity (Balvanera et al., 2014). In forest ecosystems, vegetation structure affects the presence and abundance of species at local scales (Hunter and Hunter, 1999, Tews et al., 2004). Forest vegetation structure and its complexity influence species presence, abundance and behaviour through several mechanisms. It can affect the availability and diversity of resources and niches, modifying microclimatic conditions, and by providing breeding and roosting sites, concealment or shelter from predators (MacArthur and MacArthur, 1961, Melin et al., 2014, Suggitt et al., 2011). The importance of vegetation and habitat structure for the maintenance of biodiversity in forests is increasingly recognised (Gustafsson et al., 2012, Noss, 1990, 1999). More structural complex forests often have higher species diversity than less complex, managed forests (Ishii et al., 2004). Ground sampling is resource demanding in terms of time and cost, and also limited to the spatial scale of the survey plots. The need of more effective methods for broad-scale mapping of biological diversity is evident.

Different types of remote sensing have been found to be a good supplement for ground sampling as the methods can map areas from landscape to global scale. Approaches for mapping biological diversity using remote sensing can in general be either direct or indirect (Turner et al., 2003). Direct approaches can identify taxa or land cover types directly from the remote sensing data. Indirect approaches use remote sensing data to model the distribution of biological diversity. The structural complexity of a forest can be studied by multiple remote sensing techniques. Optical sensors like the ones carried by the Landsat satellites are useful in studying horizontal structure and vegetation types on a broad landscape scale. However, lidar (light detection and ranging) can be applied on landscape scale to map both horizontal and vertical vegetation structures (Bergen et al., 2009) in addition to other forest inventory attributes like aboveground biomass (Zolkos et al., 2013) and forest age (Racine et al, 2014). Lidar can also be used over broad extents, which makes it a good tool for examining patterns of biological diversity.

To assess if there is an association between biological diversity and forest habitat structures that could be characterized by lidar, we aimed to use a meta-analysis approach. No previous review studies on the subject have carried out a meta-analysis to assess the influence of habitat structure, quantified with lidar or other remote sensing techniques, and measures of biological diversity. No previous review studies on the subject have carried out a meta-analysis to assess the relationship between forest structure quantified by lidar and other remote sensing techniques and measures of biological diversity.

Material and methods

The literature search was conducted September 19th 2018 in the database ISI Web of Science with this combination of terms:

> (Laser OR (lidar OR (light AND Detection AND Ranging)) OR (als OR (airborne AND laser AND scanning))) AND forest* AND (biodiversity OR diversity OR richness OR ecolog* OR species OR habitat).

The search was performed under "Topic", and there were no restrictions with regard to year or language. The words in the search term were chosen to represent the review study and to minimize the probability of excluding relevant studies. Our combination of search terms were selected with the intention of capturing studies that have quantified the relationship between environmental variables – as quantified by lidar – and at least one of the following:

1) Direct measures of biological diversity, either for:

i) a single species (presence/absence or abundance)

ii) a taxonomic or functional group of species

iii) multiple groups (taxonomic of functional) of species

2) Indirect measures of biological diversity (habitat/vegetation structure/dead wood).

The search resulted in 1897 articles. This number of studies were further reduced according to certain criteria in a more detailed scrutiny of each study. 1) Title, abstract and keywords of each article were examined to remove irrelevant studies. 2) Review studies and studies written in other languages than English were not included in the filtered reference library. 3) Studies that only used ground-based lidar (terrestrial laser scanning; TLS) and not aerial or spaceborne lidar as their predictor data were excluded from the list. The rationale behind this is that TLS operate on a smaller scale, and the data from these systems cannot be used to make large-area distribution maps. When scanning the titles, abstracts and keywords of the papers, we also classified the papers into three main categories according to the type of biological diversity response variable reported; single species (ca. 100 papers), multiple species (pooling categories ii and iii) and "habitat" (ca. 30 papers).

For the papers using "habitat" as the response variable, we selected those that concerned different types of forest habitats or forest habitat attributes like forest successional stages or dead wood. In total, we found 23 papers that we could extract data from. Papers dealing with classification of forest versus non-forest habitats were not included in this review. We extracted the following information from each paper: response variable (forest type/forest attribute (including dead wood)), lidar predictors/explanatory variables, other remote sensing predictors/response variables, country, latitude, longitude, sample size, sample scale, study area size, and modelling approach (prediction modelling/other statistical modelling). For the prediction modelling papers, we also extracted the predictive power (PP) of the models and categorized them as either: excellent, good, fair, poor, bad, fail.

Results and recommendations

In total, we extracted information from 36 studies having biological diversity as the response variable lidar variables as model predictors. For those studies having habitat as a response variable, we extracted information from 23 studies. The spatial location of the studies is scattered across the globe (Figure 4). The majority of the studies have been carried out in North America and Europe. All the reviewed studies were published between 2007 and 2018 where 60 % of the studies were published after 2015.

There is no one metric that perfectly quantifies biological diversity, and there is no single index that will suit all needs. The ability to examine biological diversity in different ways, will not only help us gain better understanding of how ecosystems function, but also sheds light on issues of practical concern such as the link between diversity and ecosystem services and ecological state. However, the large majority of studies that have related biological diversity to lidar predictors include only information on the presence and abundance of species, and the majority use species richness with presence only as dependent variable. Species richness is the iconic measure of biological diversity, but it contains no information about the abundance of species. Two areas with exactly the same number of species may have no species in common and thus a completely different community composition. Studies relating lidar variables to changes in community composition are scarce. Furthermore, few studies have related lidar variables to measures of functional diversity. This is an important knowledge gap that should be filled in order to assess the usefulness of lidar to predict ecological state.

In addition to having many different measures of biological diversity from different taxonomic groups, forest types and geographic regions, a major challenge in trying to extract some general patterns about the relationship between biological diversity and lidar-derived variables, is the large number of candidate predictors. In prediction modelling, the aim is to maximise prediction and not necessary to restrict the number of predictors. It may not be realistic to find one or a few good lidar indicators that can predict biological diversity in general. We have tried to use our own expertise within remote sensing and ecology with the added insights from this literature review, to suggest groups of lidar variables that captures ecologically relevant aspects of the forest habitat. Which attributes of the habitat is important, will depend on the habitat requirements of the focal taxonomic or functional group. In the future, a meta-regression based in single-species models may possible. However, this will probably mean contacting authors to get access to original data. This is because many of the studies have a high heterogeneity of statistical models, and the access to the original data will let us get the needed information to calculate effect sizes.

The review of the literature showed that lidar has a great potential for predictive modelling of biological diversity on a regional scale. Calibration of predictive models using ground-truth observations, that can be applied to grid cells over an area is the most reliable approach. However, lidar data can also contain relevant structural information that can be used even without calibration. This strategy requires that the relevance of metrics calculated from the lidar data is carefully considered. It is also important to point out that the metrics that is derived from lidar are dependent on the specific lidar sensor that is used, and the specific acquisition parameters used in a particular mission (Næsset, 2009). The metrics derived from lidar will also tend to be different between forest types. The size and shape of the ground-truth plots must be chosen according to what phenomenon that is being mapped. In general, we can say that mobile species require larger basic units than stationary, and that large basic units are more useful for mapping multiple species than one single species.

Here we have recommended prediction modelling using an area-based approach. With such an approach, it is relatively straightforward to obtain wall-to-wall predictions of biological diversity measures and assess habitat features over relatively large areas. This information can be used to improve predictive distribution modelling of species and groups of organisms, based on known habitat-species relationships. Using lidar and other remote sensing to assess indicators of ecological state can also be carried out (Table 8). Factors that are threats to biological diversity, such as roads, ditches and clearfellings can also be detected (Table 9). Lidar is a powerful data source for assessing biophysical properties of trees and vegetation, and also physical properties of the terrain. Combined with other data sources that provide spectral information, the utility of the data is huge.

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Abbreviations

AIC:	Akaike information criterion
ATLAS:	Advanced Topographic Laser Altimeter System
BIC:	Bayesian information criterion
DSM:	Digital surface model
DTM:	Digital terrain model
GEDI:	Global Ecosystem Dynamics Investigation
GLAS:	Geoscience Laser Altimeter System
GLM:	Generalized linear models
GLONASS:	Global navigation satellite system
GNSS:	Global navigation satellite systems
GPS:	Global positioning system
ICESat:	Ice, Cloud and land Elevation Satellite
IMU:	Inertial measurement unit
Lidar:	light detection and ranging
nDSM:	Normalized digital surface model
NDVI:	Normalized difference vegetation index
NFI:	National forest inventory
RGB:	Red green blue
RMSE:	Root-mean-square error
RTK:	Real time kinematic
SAR:	Synthetic aperture radar
SE:	Standard error
TLS:	Terrestrial laser scanning
TWI:	Topographic wetness index

1 Introduction

Forests support about 80% of the World's terrestrial biodiversity (Balvanera et al., 2014). In forest ecosystems, vegetation structure affects the presence and abundance of species at local scales (Hunter and Hunter, 1999, Tews et al., 2004). Forest vegetation structure and its complexity influence species presence, abundance and behaviour through several mechanisms. It can affect the availability and diversity of resources and niches, modifying microclimatic conditions, and by providing breeding and roosting sites, concealment or shelter from predators (MacArthur and MacArthur, 1961, Melin et al., 2014, Suggitt et al., 2011). The importance of vegetation and habitat structure for the maintenance of biodiversity in forests is increasingly recognised (Gustafsson et al., 2012, Noss, 1990, 1999). More structural complex forests often have higher species diversity than less complex, managed forests (Ishii et al., 2004). A review on the structural complexity found that most studies found a positive relationship between habitat heterogeneity and animal species diversity (Tews et al., 2004). Traditionally, data for species distribution mapping has been based on ground surveys of where the species are registered in the field. However, ground sampling is resource demanding in terms of time and cost and limited to the spatial scale of the survey plots. The need of more effective methods for broad-scale mapping of biological diversity is evident. Making use of the recent advances in remote sensing in ecological studies may improve our knowledge about relationships between species and habitat structure (Simonson et al., 2014a, Davies and Asner, 2014).

Different types of remote sensing have been found to be a good supplement for ground sampling as the methods can map areas from landscape to global scale. Approaches for mapping biological diversity using remote sensing can in general be either direct or indirect (Turner et al., 2003). Direct approaches can identify taxa or land cover types directly from the remote sensing data. Indirect approaches use remote sensing data to model the distribution of biological diversity. The structural complexity of a forest can be studied by multiple remote sensing techniques. Optical sensors like the ones on the Landsat satellites are useful in studying horizontal structure and vegetation types on a broad landscape scale. However, lidar (light detection and ranging) can be applied on landscape scale to map both horizontal and vertical vegetation structures (Bergen et al., 2009) in addition to other forest inventory attributes like biomass (Zolkos et al., 2013) and forest age (Racine et al., 2014).

To assess if there is an association between biological diversity and forest habitat structures that could be characterized by lidar, we aimed to use a meta-analysis approach. Previous review articles on this subject have looked at animal diversity and lidar derived habitat structures (Simonson et al., 2014a, Davies and Asner, 2014) and given an overview of the indicators of biological diversity. No previous review studies on the subject have carried out a meta-analysis to assess the relationship between forest structure quantified by lidar and other remote sensing techniques and measures of biological diversity.

This report is divided into four chapters. In Chapter 2, we provide background information on lidar systems and present relevant variables for forest biological diversity that can be extracted from lidar data. In Chapter 3, we present the review of how lidar data has been used to study forest biological diversity. We also present our main findings and discuss the implications. In Chapter 4, we make general recommendations for biological diversity indicators. We also make recommendations for the acquirement of lidar data. Towards the end of Chapter 5, we summarize our findings and recommendations.

2 Lidar background

Lidar systems measure the distance between the laser sensor and the surface of a target. For the most common sensors, distance is measured by determining the time between a laser pulse is emitted, and an echo is returned to the sensor (Wehr and Lohr, 1999). Lidar is an active remote sensing technique, meaning that it does not depend on reflected sunlight, but actively emits light pulses that are reflected back to the sensor. The most frequently used sensors use near-infrared light, but sensors depending on light pulses of wavelengths such as shortwave-infrared and green also exists. This means that lidar can be operated without sunlight, contrary to so called passive techniques such as optical remote sensing that depend on an external source of light. The resulting dataset after a lidar survey is a cloud of echoes representing the three-dimensional coordinates (x,y,z) for the reflected laser pulses' location on the surface (Figure 1).

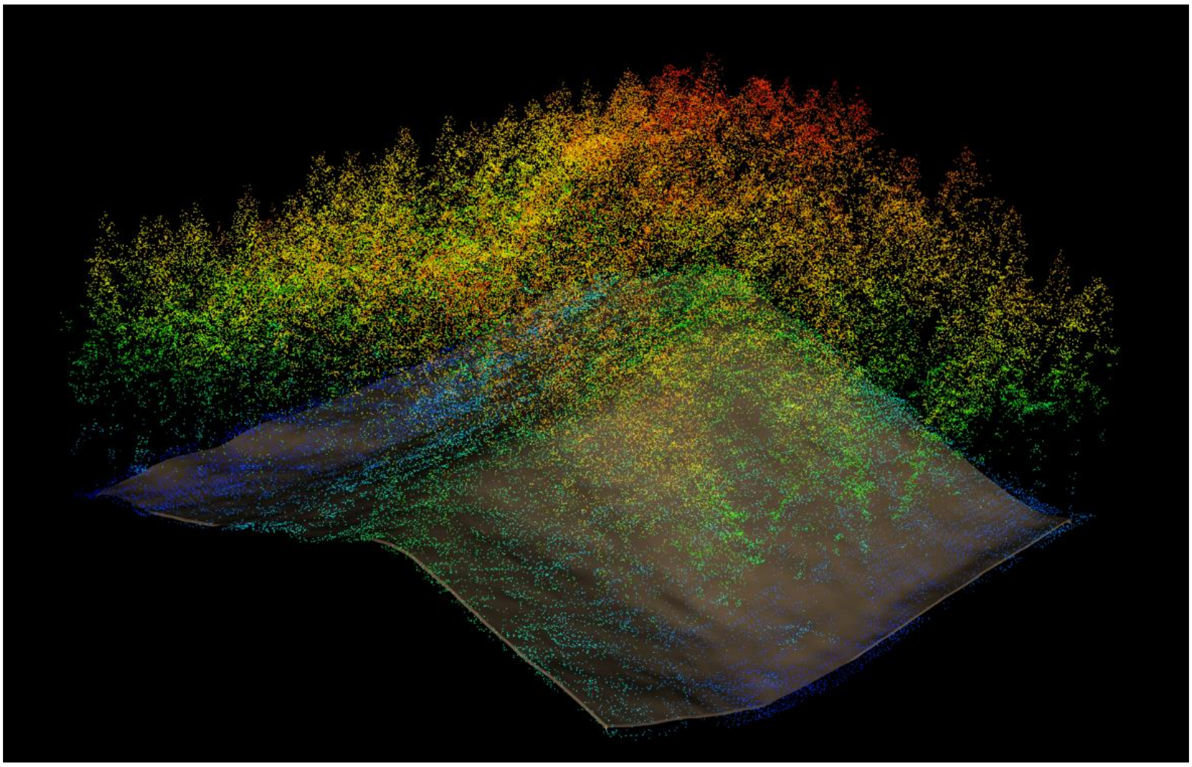

Figure 1 Three-dimensional locations of reflected laser pulses over a forest. The coloured points represent the vegetation and the grey plane beneath is the terrain model. The points are coloured according their height above the terrain model.

Lidar can mainly be applied on three different platforms: spaceborne, airborne and terrestrial. The platform used will affect the resolution of the data and the area that can be covered. Spaceborne lidar can normally have a global cover and output data with resolutions normally being over 30 m. Airborne lidar generally cover smaller areas typically up to 1,000 km^2 in each mission (Simonson et al., 2014b, Næsset, 2014), but have higher output resolutions. Terrestrial based lidar can also be used to measure vertical structures, but the techniques cannot be used for large-area measurements. Spaceborne and airborne lidar will therefore be focused on here.

2.1 Description of airborne and spaceborne lidar

All lidar sensors can mainly be divided into two groups: pulse methods and continuous wave. Pulse lasers emit short (4-10 nm) pulses, typically of near-infrared light. Continuous wave on the other hand, a sinusoidal signal is produced by a continuously emitting laser and the phase change is measured and converted into travel time (Wehr and Lohr, 1999). The wave will have different peaks based on the magnitude of returns returning at the same time. Between the two groups, the former group of lidar sensors are most commonly used, and will be focused on here.

With pulse lasers (Figure 2), the area enlightened by the pulse increases proportionally to the distance from the sensor, and by the time it hits an object beneath an airborne platform operated on a typical altitude, it leaves a footprint with a size of 15-25 cm. These systems are classified as small-footprint systems (Figure 2c). The pulse sensors can further be divided into two types; 1) sensors that are capable of capturing one or more echoes from the returning pulse, referred to as discrete-return lidar, and 2) sensors that record the entire energy distribution of the returning pulse, referred to as full-waveform recording lidar (Figure 2a and b). If the space beneath the footprint is composed of more than one layer, for example a tree where permeable branches are distributed over a certain distance along the travel trajectory of the pulse, the energy of one specific pulse is returned over a range of distance from the sensor. For discrete pulse systems that register an echo when the returning pulse energy exceed a certain threshold, this will result in multiple echoes from the same pulse. When it comes to measuring vertical structures in forests with these systems, the first and last echoes are especially important, as it is those that are used to make the digital surface model (DSM) and the digital terrain model (DTM), respectively.

There are in general two ways that laser data can be sampled, which is either by profiling or scanning. Profiling lasers are aimed in one specific direction, which often will be towards the earth from an aircraft or a satellite (Campbell and Wynne, 2011). When the laser platform is moving, the laser will create a single track of laser echoes (Figure 2d). Scanning lasers use a mechanism to distribute the pulses also perpendicular to the flight direction, for example an oscillating mirror or a rotating polygon mirror (Figure 2c; Campbell and Wynne, 2011). The more or less continuous pattern of reflected laser pulses can be used to create images of the scanned terrain and surface. The first instruments that were designed were profiling lasers and were useful for determining the terrain before laser scanners were developed. However, profiling have limitations when it comes to acquiring information about large areas to map the terrain and surface (Toth and Petrie, 2018), although large-area applications are demonstrated (Nelson et al., 2005).

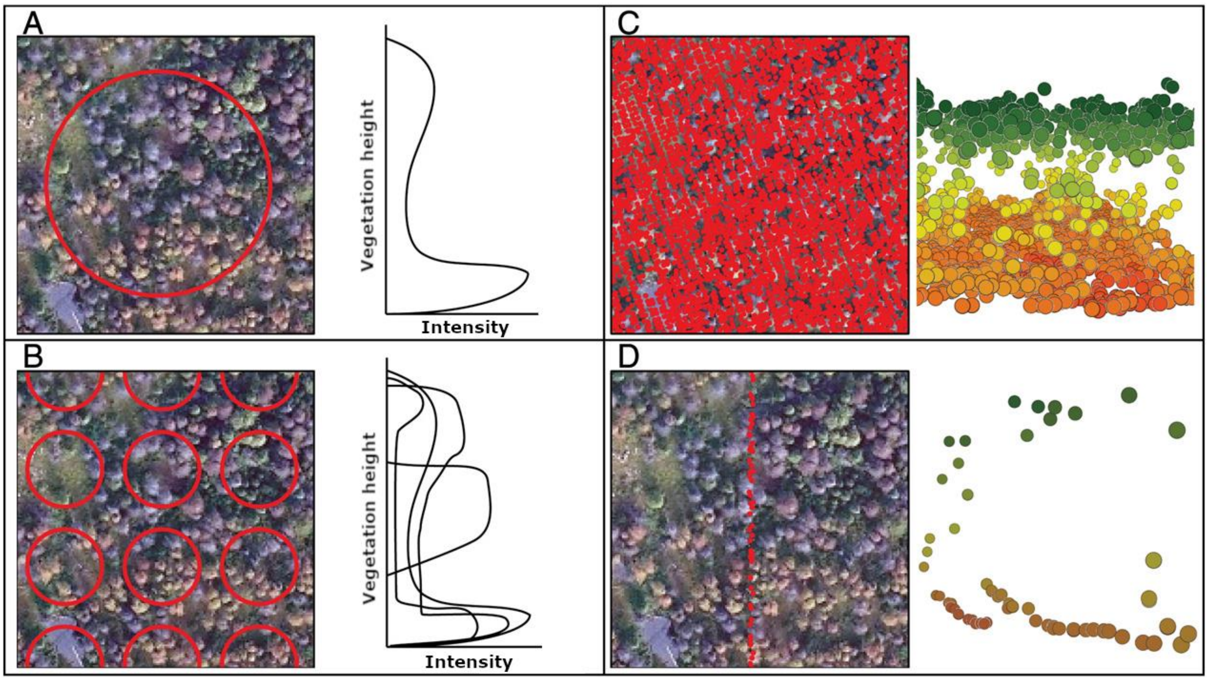

Figure 2 Differences between discrete-return and full-waveform recording lidar sensors with differing footprint sizes. A) Spaceborne and full-waveform lidar with large footprint (ca. 60 m in diameter). B) Airborne and waveform lidar with multiple large footprints (ca. 20 m in diameter). C) Discrete-return scanning lidar with small footprints. D) Discrete-return profiling lidar with small footprints. Adapted Wulder et al. (2012).

Airborne lidar are mainly based on two components: the laser scanner and a GPS/IMU system (Beraldin et al., 2010). The laser scanner includes transmitter and receiver units for measuring the distance between the aircraft and the surface, and a scanning mechanism that is used to scan the surface in a specific pattern. The GPS/IMU system allows one to reconstruct the flight path as it measures the position and orientation of the laser system. The laser platform also includes a control and data recording unit, which is in control of the whole system and stores the data recorded from the scanner and GPS/IMU. At last, an operator laptop is used to communicate with the control and data recording unit so that the survey can be monitored.

An object's reflectivity depends on the wavelength that the laser has, and one specific system will therefore be more or less suited for scanning a certain type of object depending on its reflectivity. Laser systems for terrestrial applications use wavelengths between 800 nm and 1550 nm depending on which surface that the lasers are applied on (Beraldin et al., 2010). Airborne laser systems often use wavelengths between 900-1064 nm for terrain data acquisition (Lefsky et al., 2002). This wavelength is also useful for vegetation studies as vegetation reflectance also is high within this spectrum.

When surveying the area and acquiring lidar data, no interpretation of the area is being done. To be able to get information about the terrain and surface in the surveyed area, the data has to be filtered and classified. The filtering classifies the lidar echoes as either terrain or surface based on some algorithm. Often, the lowest echoes are assumed to represent the terrain and not vegetation and other objects. By interpolating between these different echoes it is possible to make a digital terrain model (DTM), which represents the topography of the study area. The echoes that are classified as vegetation echoes, are used to construct a digital surface model (DSM). Outliers can also be present in the lidar data when for example the laser hits a bird far above the terrain. These echoes has to be filtered out so that they do not create information about the surface that does not exist in reality.

Spaceborne lidars use satellites orbiting the Earth as their platform for studying the surface on the planet. Spaceborne remote sensing is more commonly performed by optical imagery sensors like Landsat or Quickbird, but also with active radar sensors like synthetic aperture radar (SAR; Gillespie et al., 2008). All spaceborne laser sensors like the Geoscience Laser Altimeter System (GLAS) on Ice, Cloud and land Elevation Satellite (ICESat) have waveform lasers with large footprints and use profiling to acquire information about the area below (Toth and Petrie, 2018). Because of great flying altitudes and speeds for spaceborne platforms, only laser profiling of the earth can be performed, and laser scanning from satellites has not yet been done (Toth and Petrie, 2018). The GLAS instrument was operational from 20 February 2003 to 11 October 2009 and recording waveform information in a 70 m footprint, separated by 170 m along track (Abshire et al., 2005). These footprints were remeasured every 8 days during the mission. The GLAS information has been used to map and monitor vegetation (Nelson et al., 2009). The new instrument carried by ICESat-2 was launched in September 2018 one of the objectives is to measure heights and estimate carbon storage in vegetation. The Advanced Topographic Laser Altimeter System (ATLAS) instrument on ICESat has one beam that is split into three paired beams spaced 3 km apart and 90 m between the beam pair. The footprints are 17 m and overlap in along the track direction. The latest lidar instrument in space is Global Ecosystem Dynamics Investigation (GEDI) that was mounted on the international space station 5 December 2018. GEDI is specifically designed for mapping and monitoring vegetation. The footprint size of the GEDI instrument is 25 m and it has tree beams split into a total of 8 ground tracks spaced ~600 m apart with an along-track spacing of 60 m (Stavros et al., 2017).

2.2 Data fusion

Lidar can be combined with other types of remote sensing to create datasets with additional information. Data fusion are generally done to improve prediction of continuous and categorical variables (Zhang et al., 2009).

Optical data is often used together with lidar-derived data. The fusion can create complementary information on the spectral and spatial structure of a forest. The combination of optical and lidar data can give better classifications of land cover types (Yang et al., 2015), tree species (Vauhkonen et al., 2014) and prediction of forest canopy height (Hudak et al., 2002) than can be done with either of the two data sources independently. High-resolution spectral (hyperspectral) data can be combined with lidar for better tree species classification (Dalponte et al., 2012, Naidoo et al., 2012). Texture measurements derived from optical data can also be used to better estimate horizontal vegetation structures together with lidar (Zhang et al., 2009).

Another remote sensing type of data that can be fused with lidar is radar. Radar is an active remote sensing technique, but uses microwave wavelengths and not visual and near-infrared wavelengths like lidar. Microwave radar techniques are similar to laser techniques as both can transmit wavelengths within a narrow range and receive the returning energy to map the surface. However, radar techniques use a different type of wavelength, which is not as high in energy as lidar (Wehr and Lohr, 1999). Because of this, lidar does more accurate measurements compared to radar. The combination of lidar and radar has also given mixed results in how the prediction models improve when the data is fused (Kaasalainen et al., 2015).

2.4 Lidar variables relevant to forest biological diversity

Forest structure is the three-dimensional arrangement of layers in a forest, normally divided into vertical and horizontal layers (Franklin & Van Pelt, 2004). This arrangement includes old and young trees, shrubs, ground vegetation and dead wood (McCleary & Mowat, 2002). The relationship between this three-dimensional structure and habitats for organisms has been recognised for decades (Macarthur and Macarthur, 1961). Because lidar is a useful tool within forestry applications for characterizing forest structure, ecologically related studies have also applied lidar for assessing species habitats (Hill et al., 2014). Lidar can also be used over broad extents, which makes it a good tool for examining relationships between lidar-derived variables and patterns of biological diversity. Here, we will give an overview of lidar-derived variables that may be relevant for forest biological diversity.

2.4.1 Topography

Topography is the shape and features of the terrain, and is represented by the DTM produced from lidar data. Multiple metrics can be calculated from the DTM, and the most common ones are elevation, slope and aspect. Elevation is the height of the terrain relative to the sea level. Slope is the steepness of the terrain. Aspect is the compass direction of the terrain.

The topography of an area can have local effects on species diversity. For plants, topography can alter their growing conditions and thus lead to different species patterns (Katovai et al., 2015), but also animals can be affected (Zhou et al., 2015). Elevation has long been considered an important variable for biological diversity (Lomolino, 2001). The aspect of the terrain may also have strong effects on biological diversity as it may determine the amount of sun radiation the area receives (Mccune and Keon, 2002). The interaction between slope and aspect has been found to have a significant effect on plant species richness with warmer slopes having more species (Badano et al., 2005). Soil moisture is also a factor that may affect local biological diversity. It can be represented in many ways through different topographic indices, but topographic wetness index (TWI) is one of the most common types. TWI uses the slope to measure the local drainage and hydrological paths (Beven and Kirkby, 1979). For plant species abundance, TWI explained 30 % of the variance (Zinko et al., 2005). In addition to elevation, slope, aspect, sun radiation and TWI there are a number of potential topographical variables that can be computed from a lidar derived terrain model depending on the objective (Szypula, 2017).

2.4.2 Vegetation structure

The vegetation structure of a habitat is its morphology and how the habitat is constructed. For a forest, the structure will often be more heterogeneous and have higher complexity where it has multiple layers of vegetation and varies in openness and closedness (Rutten et al., 2015). For lidar data, the structure metrics can be calculated from echoes that are classified as being part of the surface (DSM) and not the terrain (DTM). Forest vegetation structure can mainly be divided into two categories based on the forest's three-dimensional form: vertical structures and horizontal structures.

The vertical structures are the variations of the vertical profile of the forest. The different metrics for vertical structures often work on different layers of the forest (canopy, mid-story and understory). The heights of the different layers can be calculated and represented as height percentiles (Næsset, 2002).

Variation of heights can also have a positive effect on biological diversity as tree size variation create a multi-layered forest, which increase structural complexity. The density of the different layers relate to the penetration rates of the laser pulses. The density of the different layers can be calculated as the proportion of pulses above certain heights (Næsset, 2002) and this measure often can be represented as the density of leaves above that height (Magnussen and Boudewyn, 1998).

Horizontal structures can be defined as spatial variations in the horizontal profile. Different indices can be calculated from lidar data as horizontal structures. Gaps are openings and closures of the forest canopy (St-Onge et al., 2014). From these gaps different edge metrics can also be calculated, where the outline of the gaps represent edges. Patchiness is the horizontal variation of density of different height classes (Roth, 1976). It is often calculated as Shannon Diversity using canopy height and density. Intensity metrics represent the relative strength of the reflected light compared with the emitted light (Song, 2002). Because different objects have different reflectance, the intensity will differ between objects. In that way intensity could be useful in classifying different land covers (Yan et al., 2015).

Although lidar is very useful for detecting and predicting mass and structural properties of the vegetation, it also has its limitations especially for low and/or sparse vegetation. There are mainly three reasons. 1) Point density: Most trees and other vegetation have little surface area in the top. This means that point data with a certain spacing between the echoes, do not have 100 % probability of hitting the top of every individual of vegetation. 2) Penetration rate: For a lidar pulse to trigger an echo, the returning energy needs to exceed a certain threshold. Even if a pulse hits exactly at the very pinnacle of a tree, the mass of the treetop is usually not substantial enough so that an echo is triggered. 3) Errors in the DTM: The automatic algorithms that is used for classification of echoes into terrain and vegetation echoes are not perfect. This means that echoes from vegetation that is very low and close to the terrain can sometimes be classified as ground echoes (Sithole and Vosselman, 2003). Because of these three main reasons, the raw lidar heights are often systematically lower than the true height (Næsset 2004). Næsset & Nelson (2007) and Thieme et al. (2011) showed this in their studies of pioneer tree detection in the forest tundra ecotone.

2.4.3 Classification of habitat

The physical environment of where organisms reside is normally defined to be the habitat of that organism. Detecting the habitat of an organism is important for understanding which requirements an organism has in order to live in an environment. It is also important for monitoring the species if a specific habitat is already known to be important for the survival of the species. Specific tree species can make up habitats for specific species, and tree species recognition by remote sensing is well-studied (Fassnacht et al., 2016). Species that are depending on older forests are often negatively affected by forest management (Paillet et al., 2010), and lidar has been found to be able to detect old-growth natural forests from managed forests (Sverdrup-Thygeson et al. 2016). Dead and decaying trees are important for biological diversity in forest ecosystems (Stokland et al., 2012, Sverdrup-Thygeson et al., 2016). During their decomposition, dead trees offer habitats for thousands of species, and today there are between 400 000 and 1 million wood-inhabiting species in the world, in particular insects and fungi (Stokland et al., 2012). Lidar has been found to detect both standing and laying dead wood in a forest (Pesonen et al., 2008, Martinuzzi et al., 2009).

2.5 Strengths and weaknesses with airborne lidar compared to other techniques

Because of the many applications of lidar, it is important to state that the technique has both strengths and weaknesses. Table 1 summarizes the benefits and the drawbacks of using airborne lidar as previously mentioned in the chapter.

One of the often mentioned drawbacks with lidar is the high costs of acquiring data. However, data acquisition cost should be evaluated also with regard to the value of the information derived. This is might be more difficult in assessing biodiversity than in assessing other natural resources like timber (Eid et al., 2004). However, during the last decade, national programs for acquiring data has been initialized in several countries including Denmark, Finland, Norway and Sweden. In Denmark and Sweden repeated flights are planned and conducted. The data is also mostly open and freely available making the use of this data easier in the assessment of biodiversity. In Norway, the national lidar scanning campaign is planned to finalize in 2022, but already much of the forested areas is covered with lidar. All lidar projects in the national scanning is available through www.hoydedata.no. In addition, some historical datasets are published here. However, for older public and private acquisitions information might be available from the mapping authorities, municipalities and forest associations.

Table 1 Strengths and weaknesses with using the airborne lidar.

Strengths	**Weaknesses**
● Active sensor, which means that data can be acquired any time of day. ● Acquired data is also consistent irrespective of sun angle. ● Large area coverage ● High resolution, three-dimensional point data with high precision. The data can be adapted to any spatial scale. ● Represents vertical and horizontal structures ● Can be used to model the terrain features ● Can be combined with other data sources ● Easy to adapt area of basic observation unit	● Acquisitions can be hampered by weather conditions (rain, fog) ● Penetrates low vegetation - difficult to detect short vegetation close to the ground ● Difficult to derive an accurate representation of the terrain if the canopy is extremely dense. An inaccurate terrain model will result in less accurate vegetation heights.

3 Review

3.1 Material and methods

3.1.1 Study selection

The literature search was conducted September 19th 2018 in the database ISI Web of Science with this combination of terms:

> (Laser OR (lidar OR (light AND Detection AND Ranging)) OR (als OR (airborne AND laser AND scanning))) AND forest* AND (biodiversity OR diversity OR richness OR ecolog* OR species OR habitat).

The search was performed under "Topic", and there were no restrictions with regard to year or language. The words in the search term were chosen to represent the review study and to minimize the probability of excluding relevant studies. The first part of the search term reflect the remote sensing that we considered to be relevant for the review. The second and third part reflect that we wanted to include studies from forest ecosystems that analysed biological diversity within forests. Our combination of search terms were selected with the intention of capturing studies that have quantified the relationship between environmental variables – as quantified by lidar – and at least one of the following:

1) Direct measures of biological diversity, either for:

   i) a single species (presence/absence or abundance)

   ii) a taxonomic or functional group of species

   iii) multiple groups (taxonomic of functional) of species

2) Indirect measures of biological diversity (habitat/vegetation structure/dead wood).

Biological diversity can be measured and characterized in many different ways (Magurran and McGill, 2011). Studies that use one or more groups of species as the biological diversity response variable, typically use various biological diversity indices (e.g., species richness, Simpson's diversity, Shannon diversity), aiming to reduce the often complex details of the relative abundance of species in a defined area or ecosystem to a single number.

The search resulted in 1897 articles. This number of studies were further reduced according to certain criteria in a more detailed scrutiny of each study. 1) Title, abstract and keywords of each article were examined to remove irrelevant studies. 2) Review studies and studies written in other languages than English were not included in the filtered reference library. 3) Studies that only used ground-based lidar (terrestrial laser scanning; TLS) and not aerial or spaceborne lidar as their predictor data were excluded from the list. The rationale behind this is that TLS operate on a smaller scale, and the data from these systems cannot be used to make large-area distribution maps.

When scanning the titles, abstracts and keywords of the papers, we also classified the papers into three main categories according to the type of biological diversity response variable reported; single species (ca. 100 papers), multiple species (pooling categories ii and iii) and "habitat" (ca. 30 papers).

It was not possible within the available period to extract quantitative information from all the studies. Therefore, we first prioritized the papers with multiple species response variables, as this is a more direct measure of biological diversity than "habitat" response variables. Single species – although they contribute to biological diversity – contribute less to the total diversity than multiple species, and these papers were not reviewed. The ca. 30 papers with "habitat" as response variables were reviewed after we had completed the review of the papers with multiple species response variables, following a slightly simpler procedure of data extraction and data compilation (see 3.1.4).

From the filtered reference library, the full text was examined to find studies for data extraction that fulfilled these criteria:

1. Had forest as the studied habitat or as one of the habitats that were examined
2. Used aerial or spaceborne lidar or lidar and other remote sensing indicators as predictor variables
3. Had one or more measures of biological diversity as the dependent (response) variable(s).
4. Reported quantitative information on effect size - i.e. on the strength and direction of the relationship (e.g. R^2, r, parameter estimates, variable importance, etc.) between biological diversity and lidar predictors

The final reference library consisted of 36 studies that were further used for data extraction and meta-database compilation.

3.1.2 Data extraction, categorization and compilation

Although we suspected that the 36 studies would not provide sufficient data for an analysis, we proceeded to designing a meta-database, following the procedure described in Koricheva et al. (2013). For each study, we extracted and tabulated quantitative data on effect sizes – i.e. the magnitude and direction of relationships(s) between the dependent biological diversity variable(s) and predictors (lidar, other remote sensing, and other environmental predictors). We also included study identity, sample size(s) and information that coded each study for variables, which we had reason to believe, could affect the outcome of each study, or whose possible influence on effect size we wished to investigate. This included study design, taxonomic information on the studied species, geographic location of the studied population, size of the study area, habitat (forest) type and lidar sampling methodology. We also extracted information on type of dependent variable (measures of biological diversity) and relevant subgroups, as well as model predictors (lidar and other remote sensing variables, other environmental variables; Table 2).

Because our initial searches and selected search terms generated a large number of matches, we were optimistic about getting enough data for a meta-analysis. However, after screening of the literature it became clear that we did not have enough data. During the process of extracting quantitative information from the individual papers, we also realized that in order to carry out a meta-analysis of studies using lidar variables to describe or predict biological diversity patterns, there are also some methodological challenges that needs to be dealt with, which are not described in the meta-analysis literature (see Discussion).

Table 2 Information extracted from each study. Not all studies had every type of information listed.

Study	– First author – Publication year – Study title
Study area	– Country – Geographic region name – Latitude and longitude (mid-point of geographic region if these were not listed) – Size of study area – Habitat type
Study unit (ecological data)	– Taxonomic group(s) and sub-groups – Biological diversity metric(s) – Sample size (number of survey plots, etc.) – Number of species in the study – Number of individuals sampled in the study – Study year and time of year for data sampling in field – Sampling system (systematic, stratified random, random) – Data source (research, national data)
Lidar data	– Study year and time of year for data sampling – Sensor type – Pulse density / return density – Flying height – Scan angle – Data source (research, national) – GNSS type and accuracy
Other remote sensing	– Study year and time of year for data sampling – Type (sensor type, Landsat 5 TM, Quickbird, SPOT-5) – Spatial scale – Data source (research, other)
Effect size and model info	– Model type (GLM, Pearson's etc.) – Model (which variables it included etc.) – Model significance – Model intercept + SE – Model quality (AIC, BIC or R^2) – Effect size measures (R^2, r, parameter estimates, variance explained) and associated variance
Model variables	– Model response (dependent) variable (species richness, species diversity etc.) – Model predictor variable name – Predictor variable class (See Table 3 concerning predictor variables) – Predictor variable class category (See Table 3 concerning predictor variables) – Predictor model estimate + SE – Predictor model estimate significance – Pearson's correlation coefficient r
Model validation	– Validation model type (K-fold cross validation, leave one out validation) – Validation model parameter type (RMSE, R^2) – Validation model parameter estimate

We decided to continue the data extraction from all the 36 papers and complete the database, even though the magnitude did not support a meta-analysis. The rationale for completing the time-consuming process of extracting and compiling data from the original papers, rather than jumping directly to writing a narrative review, was that we wanted to identify the knowledge gaps, to guide future studies/recommendations.

When extracting data from original papers, we searched the main text, tables and figures, as well as any supplementary information. Meta-analysis is based on expressing the outcome of each study on a common scale. This measure of outcome, which we here define as an effect size, includes information on the direction and magnitude of an effect of interest (e.g., biological diversity) from each study. When the association between two continuous variables is of interest, such as between biological diversity and a continuous predictor, Pearson's correlation coefficient, *r*, is commonly used as an effect size measure in ecological meta-analyses (e.g. Koricheva et al., 2013). Effect size is simply a way of quantifying the strength and sign of a relationship between two variables, without confounding this with sample size. In original research studies, regression – or multiple regression – techniques are often used to assess the relationship between one or more lidar-variables and biological diversity. In theory, essentially the same approach could be used with meta-analysis, except that the predictors (e.g. lidar-variables) are at the level of the study rather than the level of the study subject, and the biological diversity response is the effect size in the studies rather than subject scores. This approach is called a meta-regression. Meta-regressions use weighting based on the precision of the estimate of the effect: larger studies with higher precision are weighted more heavily than smaller and/or more variable.

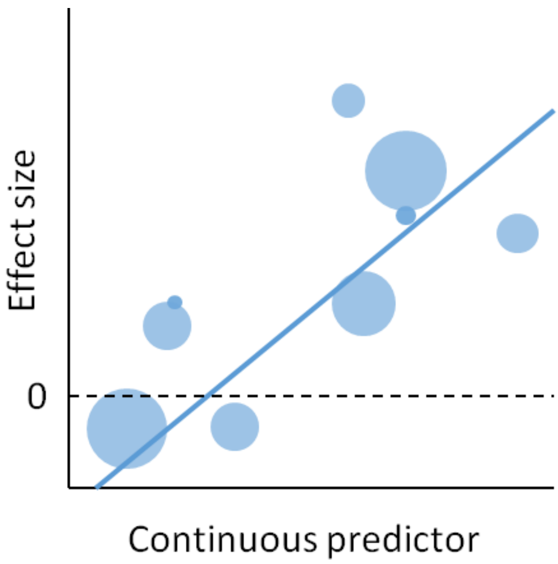

Figure 3 A hypothetical 'bubble' plot showing a line predicted from a meta-regression analysis; the sizes of the bubbles reflect the sample sizes of the individual studies (adapted from Gurevitch et al. 2018). This type of plot may be used to assess the influence of continuous predictors (also called moderators; see Koricheva et al., 2013).

We endeavoured to extract effects sizes from all the 36 studies. Ideally, one should choose an appropriate effect size and moderators (predictors) before the data extraction process starts (Koricheva et al., 2013). However, our initial screening of the papers revealed that the reporting of effects sizes and predictors varied a lot between papers. Therefore, we took a broader approach and tabulated all the information that we could find about effects sizes (any measures of the magnitude and sign of the association between biological diversity and predictors (lidar predictors, other remotes sensing predictors and other environmental predictors), sample sizes and the variance of the effect sizes.

In addition to common problems in meta-analysis, such as lack of information about sample size and/or the variance of the effect size, we found it challenging that the association between biological diversity and predictors were quantified in many different ways (i.e., different statistical models and test statistics), with a plethora of predictors. Compared to traditional, typically field based or climate predictors, the number of candidate lidar and other remote sensing variables is large. Some studies use single lidar variables as predictors, whereas others group lidar variables into composite predictors that describe some hypothesized important attribute of the habitat. However, there is little consistency among papers with respect to how this grouping of lidar variables is carried out. Furthermore, for lidar variables, or groups of lidar variables, which are not included as predictors in the published models, it is often not clear whether they were explored and found to be unimportant or not explored at all. Although multiple alternative models are often reported in the same paper (see supplementary material Table A1), it is often not clear what the difference in explanatory or predictive power is between the alternative models, which makes is difficult to infer the benefit of including lidar and other remote sensing variables as predictors. Another important challenge when assessing the association between biological diversity and (lidar) predictors is that usually only the influence of the predictors – conditional on the other predictors in the model – are reported, i.e. not single-variable or variable-group ‘effects’ on biological diversity.

The challenges described above were discovered relatively early in the process. It took us longer to realize that one of the reasons why there was so much variation among the studies in effect size measures is that they differ fundamentally with respect to the overall modelling approach; some studies have conducted explanatory/descriptive modelling, whereas others have carried out prediction modelling approaches (see Discussion). In hindsight, we realize that this should have been systematically scored in the meta-database, but this was not done.

In order to detect some general patterns with respect to the association between biological diversity and lidar predictors, we categorized the lidar variables used in different studies and models into five groups that correspond to different ecologically relevant features of the vegetation structure and four groups that reflect important topographic features (Table 3).

Table 3 Predictor variable categories used in the data compilation

Lidar vegetation structure	
Height	The height of the forest. Canopy height, understory height, mid-story height etc.
Var	Variation of lidar echo height distribution
Density	Measures describing the density of the forest (crown coverage, layers, number of stems)
Intensity	Variables computed from the recorded intensity of lidar echoes.
Horizontal	Variables computed to describe horizontal patterns (gaps, patches etc. often computed from nDSM)
Lidar topography	
Elevation	Elevation of the sample
Slope	Slope of the sample
Aspect	Compass direction of slope
Wetness	The wetness of the area based upon the slope of the DTM
Climate	
Temperature	All temperature based variables
Precipitation	All precipitation based variables
Solar radiation	All solar radiation variables
Plant	All variables that were related to plants and was not sampled by remote sensing. Can be tree classes, number of species etc.
Soil	Variables within here could be pH, soil moisture etc.
Other remote sensing (Optical)	Invariably spectral. NDVI, other measurements of wavelengths

3.1.3 Data exploration and analysis

In primary studies, we need an appropriately large ratio of *subjects* to covariates (predictors) in order for the analysis to be meaningful. Likewise, in meta-analysis we need an appropriately large ratio of studies to predictors. The use of meta-regression, especially with multiple predictors, is not a recommended option when the number of studies is small (Borenstein et al., 2011). In primary studies, some have recommended a ratio of at least ten subjects for each covariate, which would correspond to ten studies for each predictor in meta-regression (Borenstein et al., 2011). From this, and the description of the meta-database in previous sections, it is clear that a meta-regression was not a good option.

Based on the meta-database spreadsheet, we compiled the 36 reviewed studies in a table (supplementary Table A1), in which we included multiple types of information. These were geographic location, forest habitat type, size of study area, study design, lidar methodology (sampling season, lidar campaign, sensor type, pulse density, return density), species group, biological diversity measure and broad categories of model predictors (lidar vegetation structure, lidar topography, other remote sensing, other environmental variables).

In an attempt to detect some general patterns about which lidar variables that can be used to model or map biological diversity, we focused on studies that have used biological diversity of birds as dependent variable (Table 4). The rationale for focusing on birds is that this was the taxon, for which we found the largest number of studies (16 of 36). In addition, field-based studies of birds have revealed that the three-dimensional arrangement of the habitat strongly influences bird habitat use (Macarthur and Macarthur, 1961, Brokaw and Lent, 1999). For forest-dwelling birds, the three-dimensional structural complexity of the forest (i.e., canopy height, stem density and tree species composition), influences the presence of single bird species as well as bird richness (Macarthur and Macarthur, 1961, Karr and Roth, 1971, Willson, 1974, Holmes and Robinson, 1981, Peck, 1989).

3.1.4 Data extraction and data compilation - studies using "habitat" as response variable

For the papers using "habitat" as the response variable, we selected those that concerned different types of forest habitats or forest habitat attributes like forest successional stages or dead wood. In total, we found 23 papers that we could extract data from (Table 5). Papers dealing with classification of forest versus non-forest habitats were not included in this review. Based on our experience from reviewing the 36 papers using multiple species response variables (see above), we decided to reduce the level of detail in the data extraction when reviewing the "habitat" papers. We also decided to score all papers with respect to whether they reported results from prediction models or not. We extracted the following information from each paper: response variable (forest type/forest attribute (including dead wood)), lidar predictors/explanatory variables, other remote sensing predictors/response variables, country, latitude, longitude, sample size, sample scale, study area size, and modelling approach (prediction modelling/other statistical modelling). For the prediction modelling papers, we also extracted the predictive power (PP) of the models and categorized them as either: excellent, good, fair, poor, bad, fail. The categories were adapted from the recommendations of Swets (1988) on interpreting range values. The interval values between 0 and 1 and categories are here: excellent PP > 0.9; good 0.9 < PP > 0.8; fair 0.8 < PP > 0.7; poor 0.7 < PP > 0.6; bad 0.6 < PP > 0.5; fail PP < 0.5.

3.2 Results

In total, we extracted information from 36 studies having biological diversity as the response variable and 23 habitat studies that had lidar variables as model predictors. The spatial location of the studies is scattered across the globe (Figure 4). The majority of the studies have been carried out in North America and Europe.

For the biological diversity studies, mobile mid and stationary taxa were most commonly used as response variables with 14 and 13 studies, respectively (Figure 5a). Studies looking at forest types were most common when studying forest habitats (17 studies) and five studies had dead wood as the habitat. All the reviewed studies were published between 2007 and 2018 where 60 % of the studies were published between 2015-2018 (Figure 5b).

3.2.1 Biological diversity studies

The 36 reviewed studies - which used one of more measures of biological diversity as response variable - spanned a broad range of geographic locations, spatial scales, forest types and taxonomic groups (Figure 4; supplementary material A1). The majority of the studies used species richness as dependent variable (i.e., measure of biological diversity; see the column "BiolDivMetric" in supplementary material A1).

Of the 36 studies that were reviewed, 16 assessed the association between bird diversity and lidar predictors, and 14 of these used species richness of birds as dependent variable (Table 4). Sample size and number of species in the bird communities varied among studies. The capability of lidar and other predictors to explain variation in bird species richness/diversity was modelled in many different ways and with many different predictors. Lidar-derived vegetation structure variables quantifying tree density and mean tree height occurred in many of the models. Some models also included variables quantifying variability in tree height, and a few included horizontal tree cover. The lidar "topography" variables elevation and slope occurred in many of the models. Only three of the bird studies report the use of predictors derived from other types of remotely sensed data (optical).

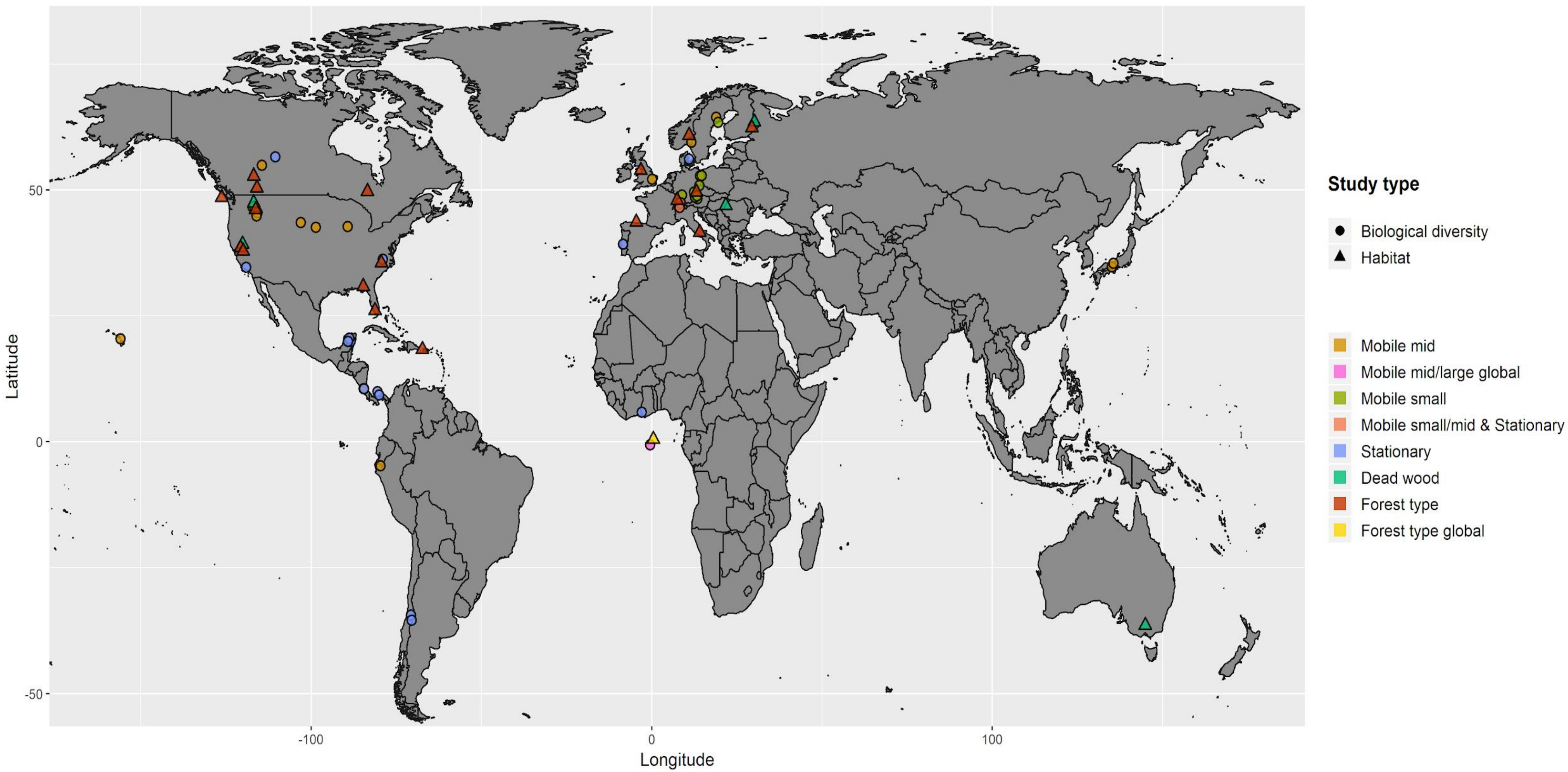

Figure 4 Location of biological diversity (circles) and habitat (triangles) studies using lidar variables as predictors. The biological diversity studies are categorized by mobility and size. The category "Mobile large" represent mammals. "Mobile mid" are birds, bats and amphibians. "Mobile small" are insects, spiders and snails. "Stationary" species represent vascular plants, bryophytes, lichens and fungi. Habitat studies are categorized by studies looking at specific forest types and studies examining dead wood with lidar. The term "global" behind two of the categories represent studies using global data. Multiple studies had the same geographical coordinates, and the point localities are therefore adjusted so that each point is viewable on the map.

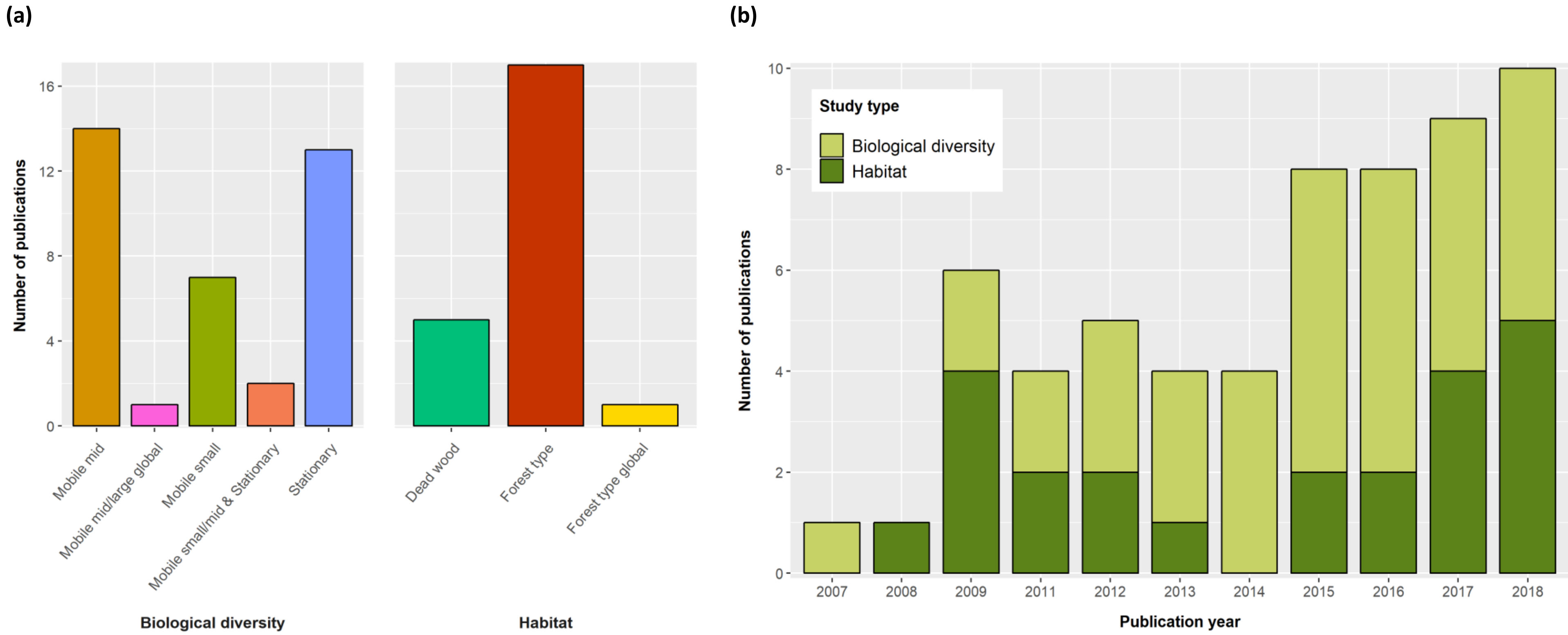

Figure 5 Number of publications per study type and year. **(a)** Number of publications per study type and their categories. The term "global" behind two of the categories represent studies using global data. **(b)** Temporal trends for biological diversity and habitat studies. The bars represent the total number of publications per year divided into the two study types

Table 4 Studies that have quantified the relationship between **biological diversity of birds** and one or more lidar predictors. Response is the biological diversity measure (dependent variable). Many of the studies also include models for sub-groups of birds (typically various foraging or nesting guilds), but only relationships for the whole bird community in each study are listed here. Under predictors, the different models that were listed in each study are separated with the symbol "**;**". Optical = spectral remote sensing predictors. Effects size type and size for the relationships between the dependent variable and the model predictors are not shown, because effect size type varied among studies (i.e., *r*, variable importance, parameter estimates, R^2), and the figures are not comparable among studies, due to different effects size types and modelling approaches used (predictive/explanatory/descriptive).

Habitat	Response	Predictors (**LIDAR VEGETATION**, **LIDAR TOPOGRAPHY**, climate, **Optical**)	Country	Sample size	Reference
Boreal	Species richness	**DENSITY**	Norway	148 plots, 25 species	Eldegard et al. (2014)
Boreal	Species richness	**DENSITY**; **HEIGHT**	Sweden	47 plots	Lindberg et al. (2015)
Mixed	Species richness	**DENSITY** **;** **HEIGHT** **;** **HORIZONTAL** **;** **VAR**	Germany	50 plots	Renner et al., (2018)
Mixed habitat[3]	Species richness	Aspect **;** Aspect + **SLOPE** + Soil **;** Aspect + **SLOPE** + Soil + **HEIGHT** / **DENSITY** / **VAR** **;** **DENSITY** **;** **HEIGHT** / **DENSITY** / **VAR** **;** Precipitation **;** Solar radiation **;** Temperature **;** Temperature + Precipitation + Solar radiation **;** Temperature + Precipitation + Solar radiation + **ASPECT** + **SLOPE** + Soil **;** Temperature + Precipitation + Solar radiation + **ASPECT** + **SLOPE** + Soil + **HEIGHT** / **DENSITY** / **VAR** **;** Temperature + Precipitation + Solar radiation + **HEIGHT** / **DENSITY** / **VAR**	Switzerland	520 plots, 92 species	Zellweger et al. (2016)
Mixed habitat[3]	Beta diversity	**ASPECT** **;** **HEIGHT** **;** Precipitation **;** **SLOPE** **;** Soil **;** Temperature **;** **VAR**		520 plots, 144 species	Zellweger et al. (2017)
Mixed[1]	Species richness	**DENSITY** **;** **HEIGHT** **;** **VAR** **;** Precipitation **;** Temperature	Canada	1656 sites	Coops et al. (2016)

Table 4 cont.

Habitat	Response	Predictors (LIDAR VEGETATION, LIDAR TOPOGRAPHY, climate, Optical)	Country	Sample size	Reference
Multiple	Species richness	HEIGHT ; Optical ; Precipitation ; Temperature	USA & Canada	118 plots, 56 species	Lesak et al. (2011)
Mixed conifer	Species richness	DENSITY ; DENSITY + HORIZONTAL + Optical ; DENSITY + Optical ; ELEVATION ; HEIGHT + DENSITY ; HEIGHT + DENSITY + HORIZONTAL + SLOPE + ELEVATION + Optical ; HEIGHT + DENSITY + Optical ; HEIGHT + DENSITY + SLOPE + ELEVATION + HORIZONTAL ; HEIGHT + DENSITY + SLOPE + ELEVATION + Optical ; HORIZONTAL ; Optical ; SLOPE SLOPE + ELEVATION ; VAR	USA	164 plots, 65 species	Vogeler et al. (2014)
Mixed conifer[2]	Species richness	DENSITY ; HEIGHT ; Plant ; Plant + HEIGHT ; Plant + HEIGHT + DENSITY ; Plant + VAR ; VAR		130 plots	Swift et al., (2017)
Mixed	Species diversity	DENSITY		51 plots, 43 species	Clawges et al. (2008)
Mixed	Species richness	DENSITY ; HEIGHT ; VAR		118 plots, 56 species	Lesak et al. (2011)
Decidious	Shannon diversity	DENSITY ; HORIZONTAL	England	28 species	Melin et al. (2018)
	Species richness	DENSITY ; HORIZONTAL			
Evergreen [4]	Species diversity	DENSITY ; Ground Height ; HEIGHT ; VAR	Japan	13 plots	Sasaki et al. (2016)

Table 4 cont.

Habitat	Response	Predictors (LIDAR VEGETATION, LIDAR TOPOGRAPHY, climate, Optical)	Country	Sample size	Reference
	Species richness	DENSITY ; Ground Height ; HEIGHT ; VAR			
Evergreen [5]	Bird community	DENSITY ; ELEVATION ; HEIGHT ; HEIGHT + DENSITY ; Optical	Ecuador	30 plots, 147 species	Wallis et al. (2016)
	Phylo-diversity	DENSITY ; ELEVATION ; HEIGHT ; HEIGHT + DENSITY ; Optical ; SLOPE			
	Shannon diversity	HEIGHT + DENSITY		30 plots, 147 species	
Kipuka	Species richness	HEIGHT ; VAR ; Optical		18 plots, 11 species	Flaspohler et al. (2010)
Multiple	Species richness	HEIGHT ; Plant ; Precipitation ; Temperature	Global	12904 plots	Roll et al. (2015)

[1]Coniferous forest, deciduous forest, mixed forest, grassland, and shrubland; [2]Aspen, mixed aspen-conifer, and conifer forest; [3]2/3 other & 1/3 forest (Forest: 43 % coniferous, 33 % mixed, 24 % broadleaved); [4]Evergreen broad-leaved forest; [5]Evergreen lower and upper montane forest

Table 5 Compilation of studies that have used lidar variables or lidar in combination with spectral remote sensing (RS) variables to predict forest habitat types or forest habitat attributes. Variables in bold are remote sensing variables. Lidar predictors (see Table 3 for explanation) are shown in colours: green = lidar vegetation structure, brown = lidar topography. Optical (in red) = spectral remote sensing predictors. The predictive power (PP) of each prediction model ranging between 0 and 1 is indicated as Excellent (PP > 0.9), Good (0.9 < PP > 0.8), Fair (0.8 < PP > 0.7), Poor (0.7 < PP > 0.6), Bad (0.6 < PP > 0.5) or Fail (PP < 0.5). -- indicates no reported predictions.

Forest type/attribute (response)	Other RS	Predictors	Prediction	Reference
6 classes of successional stages	No	**density** + **height**	Excellent	Falowski et al. 2009
7 classes of successional stages	No	**density** + **height**	Excellent	Falowski et al. 2009
Open stem exclusion	No	**density** + **height**	Excellent	Falowski et al. 2009
Stand initation	No	**density** + **height**	Excellent	Falowski et al. 2009
Young multistory	No	**density** + **height**	Excellent	Falowski et al. 2009
Mature multistory	No	**density** + **height**	Excellent	Falowski et al. 2009
Stand initation	No	**density** + **height**	Excellent	Falowski et al. 2009
Young multistory	No	**density** + **height**	Excellent	Falowski et al. 2009
Old multistory	No	**density** + **height**	Excellent	Falowski et al. 2009
Short, open canopy stand	No	**var** + **density**	Excellent	Guo et al. 2017
Tall, dense canopy cover stand	No	**var** + **density**	Excellent	Guo et al. 2017
Very tall, closed canopy stand	No	**var** + **density**	Excellent	Guo et al. 2017
Semi-evergreen forest	Landsat ETM+	**slope** + **wetness** + solar radiation	Excellent	Martinuzzi et al. 2012
Forest	Landsat ETM+	**slope** + **elevation** + distance to coast + **var** + **density** + **height** + **wetness**	Excellent	Martinuzzi et al. 2012
Scrub forest	Landsat ETM+	**slope** + **elevation** + distance to coast + **var** + **density** + **height** + **wetness**	Excellent	Martinuzzi et al. 2012
Semi-deciduous forest	Landsat ETM+	**slope** + **elevation** + distance to coast + **var** + **density** + **height** + **wetness**	Excellent	Martinuzzi et al. 2012
Semi-evergreen forest	Landsat ETM+	**slope** + **elevation** + distance to coast + **var** + **density** + **height** + **wetness**	Excellent	Martinuzzi et al. 2012
Mesquite forest	Landsat ETM+	**slope** + **elevation** + distance to coast + **var** + **density** + **height** + **wetness**	Excellent	Martinuzzi et al. 2012
Broadleaved trees	Quickbird	**optical** + **topography** + **height** + **var** + **intensity**	Excellent	Onojeghuo et al. 2017
Coniferous trees	Eagle MNF	**optical** + **topography** + **height** + **var** + **intensity**	Excellent	Onojeghuo et al. 2017
Old near-natural boreal	No	**var** + **horizontal**	Excellent	Sverdrup-Thygeson et al. 2016
Stand initiation	Leica ADS-40	**height** + **optical**	Excellent	Zhang et al. 2017
Young multistory	Leica ADS-41	**height** + **optical**	Excellent	Zhang et al. 2017
Old growth	Leica ADS-43	**height** + **optical**	Excellent	Zhang et al. 2017

Table 5 cont.

Forest type/attribute (response)	Other RS	Predictors	Prediction	Reference
Quercus spp.	Landsat 8 OLI	slope + **height** + **optical** + temperature + precipitation	Good	Álvarez-Martínez et al. 2017
Luzulo-Fagetum beech	No	**height + var + density + elevation + solar radiation**	Good	Bässler et al. 2011
Understory initiation	No	**density + height**	Good	Falowski et al. 2009
Old multistory	No	**density + height**	Good	Falowski et al. 2009
Open stem exclusion	No	**density + height**	Good	Falowski et al. 2009
Understory initiation	No	**density + height**	Good	Falowski et al. 2009
Scrub forest	Landsat ETM+	**var + height + density + horizontal**	Good	Martinuzzi et al. 2012
Mesquite forest	Landsat ETM+	**slope + wetness + solar radiation**	Good	Martinuzzi et al. 2012
Forest	Landsat ETM+	**slope + density + var + height + wetness + horizontal**	Good	Martinuzzi et al. 2012
Scrub forest	Landsat ETM+	**slope + density + var + height + wetness + horizontal**	Good	Martinuzzi et al. 2012
Semi-deciduous forest	Landsat ETM+	**slope + density + var + height + wetness + horizontal**	Good	Martinuzzi et al. 2012
Dwarf forest	Landsat ETM+	**slope + density + var + height + wetness + horizontal**	Good	Martinuzzi et al. 2012
Semi-evergreen forest	Landsat ETM+	**slope + density + var + height + wetness + horizontal**	Good	Martinuzzi et al. 2012
Mesquite forest	Landsat ETM+	**slope + density + var + height + wetness + horizontal**	Good	Martinuzzi et al. 2012
Forest	Landsat ETM+	**slope + var + density + wetness + height** + **optical** + **horizontal**	Good	Martinuzzi et al. 2012
Scrub forest	Landsat ETM+	**slope + var + density + wetness + height** + **optical** + **horizontal**	Good	Martinuzzi et al. 2012
Semi-deciduous forest	Landsat ETM+	**slope + var + density + wetness + height** + **optical** + **horizontal**	Good	Martinuzzi et al. 2012
Dwarf forest	Landsat ETM+	**slope + var + density + wetness + height** + **optical** + **horizontal**	Good	Martinuzzi et al. 2012
Semi-evergreen forest	Landsat ETM+	**slope + var + density + wetness + height** + **optical** + **horizontal**	Good	Martinuzzi et al. 2012
Mesquite forest	Landsat ETM+	**slope + var + density + wetness + height** + **optical** + **horizontal**	Good	Martinuzzi et al. 2012
Dwarf forest	Landsat ETM+	**slope** + **elevation** + distance to coast + **var** + **density** + **height** + **wetness**	Good	Martinuzzi et al. 2012
Old near-natural boreal	No	**horizontal**	Good	Sverdrup-Thygeson et al. 2016
Old near-natural boreal	No	**var + horizontal**	Good	Sverdrup-Thygeson et al. 2016
Old near-natural boreal	No	**var + height + density**	Good	Sverdrup-Thygeson et al. 2016
Old near-natural boreal	No	**horizontal**	Good	Sverdrup-Thygeson et al. 2016

Table 5 cont

Forest type/attribute (response)	Other RS	Predictors	Prediction	Reference
Vascular plant community composition	hyperspectral G-LiHT	Composite remotely sensed predictors derived by ordination techniques	Good-Fair	Hakkenberg et al. 2018
Sub-Atlantic & medio-European oak/oak-hornbeam	Landsat 8 OLI	solar radiation + **height** + precipitation + aspect + **optical** + elevation + slope	Fair	Álvarez-Martínez et al. 2017
Galicio-Portuguese oak (*Quercus* spp.)	Landsat 8 OLI	**height** + precipitation + **optical** + temperature + elevation	Fair	Álvarez-Martínez et al. 2017
Acidophilous *Picea*	No	**height + var + density + elevation + solar radiation**	Fair	Bässler et al. 2011
Closed stem exclusion	No	**density + height**	Fair	Falowski et al. 2009
Short, medium canopy cover stand	No	**var + density**	Fair	Guo et al. 2017
Very short, dense canopy cover stand	No	**var + density**	Fair	Guo et al. 2017
Very tall, complex stand	No	**var + density**	Fair	Guo et al. 2017
Short, closed canopy stand	No	**var + density**	Fair	Guo et al. 2017
Semi-deciduous forest	Landsat ETM+	**var + height + density + horizontal**	Fair	Martinuzzi et al. 2012
Semi-evergreen forest	Landsat ETM+	**var + height + density + horizontal**	Fair	Martinuzzi et al. 2012
Semi-deciduous forest	Landsat ETM+	**slope + wetness + solar radiation**	Fair	Martinuzzi et al. 2012
Coniferous trees	Quickbird	**optical** + **topography** **+ height + var + intensity**	Poor/Fair/Bad	Onojeghuo et al. 2017
Broadleaved trees	Eagle MNF	**optical** + **topography** **+ height + var + intensity**	Fair/Poor/Bad	Onojeghuo et al. 2017
Seven forest vegetation types	multispectral aerial imagery		Fair	Su et al. 2016
Old near-natural boreal	No	**density + height + var**	Fair	Sverdrup-Thygeson et al. 2016
Understory Reinitation	Leica ADS-42	**height** + **optical**	Fair	Zhang et al. 2017
Mature multistory	No	**density + height**	Poor	Falowski et al. 2009
Understory shrub cover (pres/abs)	No	**density + slope * aspect**	Poor	Martinuzzi et al. 2009
Forest	Landsat ETM+	**var + height + density + horizontal**	Poor	Martinuzzi et al. 2012
Four forest vegetation types	multispectral aerial imagery		Poor	Su et al. 2016
Atlantic acidophilous beech	Landsat 8 OLI	**height** + elevation + temperature + aspect + **optical** + precipitation + solar radiation	Bad	Álvarez-Martínez et al. 2017
Castanea sativa	Landsat 8 OLI	**height** + **optical** + elevation + temperature + wetness + precipitation	Bad	Álvarez-Martínez et al. 2017

Table 5 cont.

Forest type/attribute (response)	Other RS	Predictors	Prediction	Reference
Quercus suber	Landsat 8 OLI	precipitation + **height** + **optical** + slope + precipitation + solar radiation + elevation	Bad	Álvarez-Martínez et al. 2017
Bog woodland	No	**height + var + density + elevation + solar radiation**	Bad	Bässler et al. 2011
Mesquite forest	Landsat ETM+	**var + height + density + horizontal**	Bad	Martinuzzi et al. 2012
Forest	Landsat ETM+	**slope + wetness + solar radiation**	Bad	Martinuzzi et al. 2012
Dwarf forest	Landsat ETM+	**slope + wetness + solar radiation**	Bad	Martinuzzi et al. 2012
Medio-European limestone beech	Landsat 8 OLI	**height** + temperature + precipitation + **optical** + aspect	Fail	Álvarez-Martínez et al. 2017
Alluvial: *Alnus glutinosa & Fraxinus excelsior*	Landsat 8 OLI	**height** + wetness + temperature + elevation + wetness + slope	Fail	Álvarez-Martínez et al. 2017
Iberian oak (*Quercus* spp.)	Landsat 8 OLI	**height** + temperature + precipitation + slope + elevation + **optical** + aspect	Fail	Álvarez-Martínez et al. 2017
Salix alba & Populus alba galleries	Landsat 8 OLI	wetness + elevation + **height** + **optical** + precipitation + aspect + slope	Fail	Álvarez-Martínez et al. 2017
Ilex aquifolium	Landsat 8 OLI	**height** + wetness + solar radiation + temperature + **optical** + slope	Fail	Álvarez-Martínez et al. 2017
Asperulo-Fagetum beech	No	**height + var + density + elevation + solar radiation**	Fail	Bässler et al. 2011
Very tall, open canopy stand	No	**var + density**	Fail	Guo et al. 2017
Dwarf forest	Landsat ETM+	**var + height + density + horizontal**	Fail	Martinuzzi et al. 2012
Scrub forest	Landsat ETM+	**slope + wetness + solar radiation**	Fail	Martinuzzi et al. 2012
9 wildlife tree classes	No	**var**	--	Bater et al. 2009
Measure of vertical forest structure	No	Not explicitely stated	Prediction maps	Dees et al. 2012
Forest structural diversity	No	**height**	Fair-Poor	Mura et al. 2015
Classification of grizzly bear habitat	multispectral images	**height** + **density** + **optical**	Fair classification of habitat	Nijland et al. 2015
Giant trees (rainforest)	No	**height** + **density** + global scale climate data	--	Scheffer et al. 2018
spatially explicit ecological condition model (ECM)	No	--	--	Trager et al. 2018
Boreal forest stands with high herbaceous plant diversity	No	**height** + **intensity**	Intermediate–high classification accuracy	Vehmas et al. 2009
Seven plant communities	WV2	**topography**	--	Wendelberger et al. 2018
Dead standing Eucalyptus		**var** + **horizontal**	Methodological	Miltiadou et al. 2018

Table 5 cont.

Forest type/attribute (response)	Other RS	Predictors	Prediction	Reference
Downed trees	No	**topography**	Fair	Mücke et al. 2013
Downed logs			Fair	Blanchard et al. 2011
Snags > 15 cm diameter	No	forest succession **+ wetness + height + topography**	Fair	Martinuzzi et al. 2009
Snags > 25 cm diameter	No	forest succession + **aspect + wetness + height** + **topography + density** + **elevation**	Fair	Martinuzzi et al. 2009
Snags > 30 cm diameter	No	forest succession + **density** + **height** + **aspect** + **topography**	Fair	Martinuzzi et al. 2009
Coarse woody debris (CWD); downed dead wood & standing dead wood	No	**height + intensity**	Fair-Poor	Pesonen et al. 2008
Snags > 15 cm diameter	No	**height**	Bad	Martinuzzi et al. 2009
Snags > 30 cm diameter	No	**topography + height**	Bad	Martinuzzi et al. 2009
Snags > 25 cm diameter	No	**height**	Fail	Martinuzzi et al. 2009

3.3 Discussion

There is no one metric that perfectly quantifies biological diversity, and there is no single index that will suit all needs. The ability to examine biological diversity in different ways, will not only help us gain better understanding of how ecosystems function, but also sheds light on issues of practical concern such as the link between diversity and ecosystem services and ecological state. However, the large majority of studies that have related biological diversity to lidar predictors include only information on the presence and abundance of species, and the majority use species richness (presence only) as dependent variable. Species richness is the iconic measure of biological diversity, but it contains no information about the abundance of species. Two areas with exactly the same number of species may have no species in common and thus a completely different community composition. Studies relating lidar variables (i.e., proxies for habitat) to changes in community composition are scarce. Furthermore, few studies have related lidar variables to measures of functional diversity. This is an important knowledge gap that should be filled in order to assess the usefulness of lidar to predict ecological state.

Another challenge when trying to infer general patterns from the studies in our literature search is that the distribution of taxonomic groups is heavily skewed (Fig. 4, Table 4). In addition, often a functionally constricted group of species has been studied, which should not be used as a surrogate of a higher taxonomic group, as this may lead to exaggerated taxonomic generalizations (see Halme et al., 2010).

It is common that original papers have to be excluded from a meta-analysis because information about effects size, or about sample size and/or the variance of the effects size, is missing (Borenstein et al., 2011). Sometimes converting among effect size measures is possible, but often effect sizes from different studies are not comparable. In the literature review process, we realized just that with effect size metrics that were based on completely different modelling approaches. Two main types of statistical modelling are common in ecological studies; explanatory and predictive. Explaining and predicting are different, but conflation between explanation and prediction is common in the literature. Models of high explanatory power do not necessarily have high predictive power.

In explanatory modelling, statistical models are applied to data in order to test causal hypotheses. In such models, a set of underlying factors that are measured by variables X are assumed to cause an underlying effect, measured by variable Y. In contrast, predictive modelling is the process of applying a statistical model or data mining algorithm to data for the purpose of predicting new or future observations where the goal is to predict the output value (Y) for new observations given their input values (X). This includes spatial prediction and temporal forecasting. A predictive model is any method that produces predictions, regardless of its underlying approach: Bayesian or frequentist, parametric or nonparametric, data mining algorithm or statistical model, and so on. A third type of modelling, which is much used in non-experimental studies, is descriptive modelling. This type of modelling is aimed at summarizing or representing the data structure in a compact manner. Unlike explanatory modelling, in descriptive modelling the reliance on an underlying causal theory is absent or incorporated in a less formal way. However, unlike predictive modelling, descriptive modelling is not aimed at prediction. Fitting a regression model can be descriptive if it is used for capturing the association between the dependent and independent variables rather than for causal inference or for prediction. Our literature search was not aimed at differentiating between descriptive and predictive modelling approaches. Studies that have used descriptive modelling approaches do typically not state explicitly what type of modelling approach has been used. This was confusing when we tried to extract comparable effect sizes. This dawned upon us rather late in the process of constructing the meta-database, and we did not score the modelling approach systematically. This should be done in future studies.

As documented in the literature research and initial screening of the hits, there are many articles concerning the descriptive/prediction modelling of single species (~100 articles). These studies typically use presence/absence data to explain or predict the distribution of individual species. These were not included in this literature review (i.e. quantitative information was not extracted and compiled in a meta-database) due to time constraints. It may be possible to do a meta-regression based on these papers, at least if there is a sufficient number of prediction modelling studies on single species. The single-species studies that were found in the literature search, but not reviewed in this report also include 11 studies, in which individuals animals from a single species have been tagged with GPS-transmitters, to understand animal movements and habitat use (e.g. Ciuti et al., 2018, Garabedian et al., 2017, Melin et al., 2016, Lone et al., 2014a).

In addition to having many different measures of biological diversity from different taxonomic groups, forest types and geographic regions, a major challenge in trying to extract some general patterns about the relationship between biological diversity and lidar-derived variables, is the large number of candidate predictors. In prediction modelling, the aim is to maximise prediction and not necessary to restrict the number of lidar predictors. In explanatory/descriptive modelling, which is very common in ecological studies, the overall goal is to understand the system, and often aim to reduce number of predictors (explanatory variables). It may not be realistic to find one or a few good lidar indicators that can predict biological diversity in general. In the chapter 3.2 Results and in chapter 4 Recommendations, we have tried to use our own expertise - with the added insights from this literature review - to suggest *groups* of lidar variables that captures ecologically relevant aspects of the forest habitat. Which attributes of the habitat is important, will depend on the habitat requirements of the focal taxonomic or functional group. For example, forest birds and dead wood-associated fungi will have very different habitats requirements.

As compared to the studies with the response variable being a direct measure of biological diversity, a larger proportion of the studies using forest habitat as response were prediction models. Reviewing the literature, we found several studies showing that lidar variables can give excellent or good predictions of forest habitats, but also many studies where this was not the case. The analysis of species–environment relationship has always been a central issue in ecology. Habitat suitability models are widely used to quantify species-environment relationships and to predict species occurrence and/or density at un-surveyed locations (Welsh et al., 1996, Martin et al., 2005, Heinanen et al., 2008). Habitat suitability models are useful in conservation and wildlife management because they can identify species distributions and abundances in a spatially explicit way and can support planning and decision making, especially over large areas (Guisan and Zimmermann, 2000, Guisan et al., 2013).

There are two common ways to build habitat suitability models; either 1) based on literature review and expert opinion, or – if presence-absence data or abundance is available for the species in the study area – then 2) empirical statistical models can be created by relating the species occurrence data to habitat factors. However, habitat suitability models are often based on digital maps that describe the environment at a human scale and hence miss ecological structures and features that are important for wildlife (Tattoni et al., 2012). Furthermore, predictors that have known impacts on the species of interest are measured at the site level but are not available over the large areas at which the models need to be applied. Lidar data can fill this gap by providing useful information not only on the spatial extent of habitat types but also information on the vertical height. The advantage of lidar derived variables lays also in the availability at a large scale, instead of just in the survey sites.

4 Recommendations

In this chapter, we present recommendations based on the literature review. First, we discuss the main findings from the review on potential indicators of biological diversity. We then present expert opinion recommendations for lidar-based indicators. Second, we discuss lidar approaches used in the reviewed literature and recommendations about data sampling protocols using lidar.

4.1 Indicators of biological diversity recommendations

The main aim of the conducted review was to identify indicators of forest biological diversity that could be derived from lidar data together with other remote sensing techniques. The limited and highly heterogeneous quantitative information from the literature review did not allow for a meta-analysis, and compilation of the results in tables did not reveal clear patterns that could support recommendations about lidar-based indicators. Based on the review results, our recommendations of lidar indicators at this stage are preliminary. However, there were some pinpoints from the reviewed studies to which indicators that could potentially be used to predict biological diversity on taxa to habitat level.

4.1.1 Forest structure and topography

Based on the predictor groups in Table 3, we combined the project group members' knowledge about remote sensing and ecology to define ecologically relevant groups of lidar variables. These groups were based on ecological knowledge of what forest attributes influence forest biological diversity. The predictor groups, or rough indicators, for forest structure are forest density, tree height and variability in tree height, i.e as suggested to be derived from lidar in a forest structural habitat index (Coops et al., 2016). In addition, topography variables such as elevation, slope, aspect and wetness, which are known to be ecologically important, can be derived from lidar. Including optical data can give additional information about tree species composition (Dalponte et al., 2012, Naidoo et al., 2012). The main advantage of lidar compared to other remote sensing techniques is the three-dimensional quantification of the habitat. Forests are three-dimensional vegetation structures, and groups of species like birds and bats are known to respond strongly to forest structure.

4.1.2 Prediction modelling of habitat; indirect prediction of the distribution of organisms, or indirect prediction of ecological state

Lidar and other remote sensing data allows assessing habitat features over large areas (Graf et al., 2009). This can be used to improve habitat suitability models and hence improve predictive distribution modelling of species and groups of organisms. For many species and groups of organisms, the question is not whether lidar or other remote sensing data are useful or not, but whether the scientists and managers have the necessary competence for identifying the ecologically relevant lidar and other remote sensing predictors. There are considerable methodological challenges related to downloading remote sensing data, data management and preparing comprehensible predictors for ecologists. A close collaboration is required between remote sensing experts and ecologists with limited knowledge about the lidar data acquisition and data management and also systems for dealing with data storage of big datasets and data accessibility.

In addition to assessment of habitat features, lidar and other remote sensing can be used also to derive indicators of ecological state. We applied an expert opinion approach, where we made use of our existing knowledge about the relationship between lidar and forest structure to suggest lidar-based indicators that correspond to field-based existing and proposed indicators of ecological state in the ANO system ("arealrepresentativ naturovervåking"; Evju et al., 2018, Nybø et al., 2018). In Evju et al. (2018) for the Tables 1 and 3, field-based indicators for current monitoring programmes and future programmes are listed. For these forest ecosystem related indicators, we provide expert opinions about the potential for using airborne lidar to assess the indicators (Tables 6 and 7). The potential is ranked "HIGH", "INTERMEDIATE" or "LOW". The category "HIGH" is used when lidar is the primary data source for assessment of the indicator, and when little is gained by introducing other data to the assessment. This is typically related to indicators related to biophysical properties (height, biomass etc.) If the assessment of the indicator benefits greatly from fusion between lidar and for example optical data, we have used the category "INTERMEDIATE", and when lidar data explain very little or no variation of the indicator in question, we have used the category "LOW".

Table 6 Field-based indicators that are relevant for assessing ecological state, and which are already included in an existing area representative monitoring programme; the National Forest Inventory (NFI), with ca. 13 000 permanent plots in forest ecosystems or tree-covered areas in Norway. We have used an expert opinion approach to suggest corresponding lidar indicators. For each of the field-based indicators, we have categorized the potential for assessing the same indicator by use of lidar i as HIGH, INTERMEDIATE or LOW. The field-based indicators are the same as the forest ecosystems indicators listed in Table 1 in Evju et al. 2018 for.

Existing field-based indicator	**Eksisterende indikator (Norwegian)**	**Monitoring programme**	**Potential for lidar-based indicator**	**Reference for lidar indicator**
Biomass of trees	Biomasse av trær	NFI	HIGH	Næsset and Gobakken, 2008
Amount of dead wood (standing dead wood)	Mengde stående død ved	NFI	HIGH	Pesonen et al., 2008, Martinuzzi et al., 2009
Amount of old-growth natural forest	Mengde gammel naturskog	NFI	HIGH - INTERMEDIATE	Sverdrup-Thygeson et al., 2016
Amount of biologically old forest	Mengde biologisk gammel skog	NFI	HIGH - INTERMEDIATE	Sverdrup-Thygeson et al., 2016

Table 6 cont.

Existing field-based indicator	Eksisterende indikator (Norwegian)	Monitoring programme	Potential for lidar-based indicator	Reference for lidar indicator
Amount of rowan, aspen and goat willow	Mengde av rogn, osp og selje	NFI	INTERMEDIATE (biomass of young trees)	Økseter et al., 2015
Tree species composition	Treslagsfordeling	NFI	INTERMEDIATE (leaf-off data for deciduous tree species)	Ørka et al., 2009
Amount of large/old/hollow deciduous trees	Mengde store/gamle / hule løvtrær	NFI	INTERMEDIATE (large trees)	Saynajoki et al., 2008 Korhonen et al., 2016 Maltamo et al., 2015
Dead wood, total (m3/ha)	Mengde død ved totalt (m3/ha)	NFI	INTERMEDIATE	Pesonen et al., 2008, Martinuzzi et al., 2009
Dead wood, coarse (diameter >30 cm) (logs, standing) (m3/ha)	Mengde grov (>30 cm i diameter) død ved (liggende, stående) (m3/ha)	NFI	INTERMEDIATE	
Age distribution of trees	Trærnes aldersfordeling	NFI	INTERMEDIATE (with bi-temporal lidar data)	
Amount of dead wood (fallen dead wood)	Mengde liggende død ved	NFI	INTERMEDIATE-LOW	Pesonen et al., 2008, Martinuzzi et al., 2009
Bilberry cover	Dekning av blåbær	NFI	LOW	
Dead wood, diameter >20 cm, on areas in early succession phase (m3/ha)	Mengde død ved >20 cm i diameter på areal i tidlig suksesjonsfase (m3/ha)	NFI	LOW	
Decomposed dead wood (logs) (m3/ha)	Mengde mye nedbrutt (liggende) død ved (m3/ha)	NFI	LOW	Bater et al., 2009

Table 7 Field-based indicators that are relevant for assessing ecological state, which have been recommended for the proposed system for 'Area Representative Mapping and Monitoring of Nature Types' (see Table 3 in Evju et al., 2018), with associated spatial scale (size) of sample plots. We have used an expert opinion approach to suggest if lidar can be used to assess these indicators. For each of the field-based indicators, we have categorized the potential for assessing the same indicator by use of lidar as HIGH, INTERMEDIATE or LOW.

Field survey	Feltregistrering	Spatial scale 1 m2	Spatial scale 250 m2	Comment in Evju et al. (2018; in Norwegian)	Potential for lidar	Reference for lidar
Tree layer (cover)	Dekning tresjikt		X	Vedvekster med høyde > 2 m: % dekning	HIGH	Korhonen et al., 2011
Tree layer (height)	Høyde tresjikt[1]		X	Vedvekster med høyde > 2 m: høyde (cm)	HIGH	Næsset, 2002
Shrub layer (cover)	Dekning busksjikt	X	X	Vedvekster med høyde 0,8−2 m: % dekning	INTERMEDIATE	Martinuzzi et al., 2009
Shrub layer (height)	Høyde busksjikt[1]	X	X	Vedvekster med høyde 0,8−2 m: høyde (cm)	INTERMEDIATE	Lindberg et al., 2012
Ground cover	Dekning bunnsjikt	X		Bunnsjiktet deles inn i tre grupper: lav, moser og torvmoser, og % dekning registreres for hver gruppe.	INTERMEDIATE	
Field layer (cover)	Dekning feltsjikt	X		Urter og vedvekster < 0,8 m: % dekning	LOW	
Field layer (height)	Høyde feltsjikt[1]	X		Urter og vedvekster < 0,8 m: høyde (cm)	LOW	
Vascular plants (richness and cover)	Mengde av karplanter	X		Alle karplanter innenfor en 1 x 1 m2 rute registreres med mengde, som % dekning.	LOW	Ceballos et al., 2015
Cover of single species	Dekning av enartsbestander[2]		X	Karplanter definert som «problemarter» - dekning (%).	LOW	Hauglin and Ørka, 2016
Litter cover	Dekning strøsjikt	X		Dødt organisk materiale: % dekning	LOW	

[1] the definition of field-, shrub- and tree layer follows NiN-mapping «Natur i Norge» (NiN) (Halvorsen, 2016).

[2] For example Sitka spruce

Nybø et al. (2018) suggested a set of field-based indicators to operationalize "fagsystem for økologisk tilstand for terrestriske økosystemer" (Figure 7 and Table 3 in Nybø et al. 2018). In Table 8, we have listed the field-based ecological indicators, which could potentially be assessed with lidar or other remote sensing techniques. Please note that there is some overlap in indicators/variables between Tables 6 and 7, and Table 8. Before any lidar or other remote sensing data acquisition is operationalized, experts in remote sensing of forest ecosystems should be involved to give practical, hands-on advice on the data acquisition and data management protocols.

Table 8 Indicators of ecological state in forest ecosystems, based on Table 3 in Nybø et al. 2018. We have included the indicators that are considered as possible to quantify with lidar and other remote sensing. Existing data indicate if the indicator is under surveillance (Yes) or if the indicator can be developed from National Forest Inventory data (NFI). Which ecological property each indicator is related to is either: Pr- Primary production, Ma- distribution of biomass in different trophic levels, Fu- functional groups within trophic levels, Vi- functionally important species and biophysical structures, La- landscape ecological patterns, Bi- biological diversity, Ab- abiotic factors. NDVI (Normalized Difference Vegetation Index) is an index showing photosynthetic activity (greening) and is one of the most widely used vegetation indices. The index for a given area can be calculated from satellite data, aerial photography or by measurements at ground level, depending on the relevant spatial scale. ROS = rogn, osp, *Salix* spp.

Forest	Existing data	Ecological property	Potential for lidar (and relevant supporting data)	Reference
Species				
Amount of rowan, aspen and goat willow	Yes	Fu, Vi, Bi	INTERMEDIATE (Optical for classification)	Økseter et al., 2015
Structure				
Area affected by forest fire	NFI	Bi	LOW (Optical for classification)	Chen, 2017, Veraverbeke et al., 2018
Area affected by insect attack	NFI	Bi	LOW (Optical for classification)	Lange and Solberg, 2008
Amount of dead wood	Yes	Vi	INTERMEDIATE	Pesonen et al., 2008, Martinuzzi et al., 2009
Age distribution of trees	NFI	Fu, Bi	INTERMEDIATE	Breidenbach et al., 2008
Area of biologically old forest	Yes	Vi, Bi	HIGH - INTERMEDIATE	Sverdrup-Thygeson et al., 2016
Area of old-growth natural forest	Yes	Vi, Bi	HIGH - INTERMEDIATE	Sverdrup-Thygeson et al., 2016
Amount of large/old/hollow deciduous trees	NFI	Vi, Bi	INTERMEDIATE (large trees)	Saynajoki et al., 2008 Korhonen et al., 2016
Size of forest	Yes	La	HIGH	
Forest area unaffected by management	Yes	La	INTERMEDIATE	Valbuena et al. (2016)
Other				
NDVI	Yes	Pr	LOW (optical)	Trier et al., 2018
Biomass of trees	NFI	Ma	HIGH	Næsset & Gobakken, 2008

4.1.3 Detection of factors affecting biological diversity

Human land use has transformed ecosystems across the planet and is currently causing an unprecedented reduction in biodiversity (Ellis et al., 2013, Dirzo et al., 2014). Climate change and pollution are other examples of factors that affect biological diversity. Generally, the threats to biological diversity can be categorized in 1) deforestation and habitat loss, 2) invasive species, 3) climate change, 4) pollution, and 5) overexploitation (Millenium ecosystem assessment, 2005).

In forestry, a network of roads are necessary for transporting timber from the forest and to a saw mill. Roads can affect biological diversity directly by increasing mortality of animals through traffic and indirectly by habitat fragmentation (Coffin, 2007). Both roads and ditches are regular line shapes that stand out from the rest of the landscape, and are clearly visible on a DTM made from lidar point data (e.g. Korpela et al., 2009). Automatic algorithms applied to the DTM can recognize these patterns. Azizi et al. (2014) and Li et al. (2015) detected road from airborne lidar by using both the height and intensity information from the echoes to distinguish road-reflected echoes from other terrain surfaces. Similarly, ditches can be detected with lidar. Roelens et al. (2018) used the height information and intensity from lidar together with spectral information from aerial images to map ditches over different land types. Passalacqua et al. (2012) even differentiated between natural waterways and manmade structures using curvature analysis. Different GIS-software have inbuilt algorithms that delineate features in the DTM such as drainage basins and watersheds (Maidment, 2002).

While both roads and ditches are semi-permanent features detectable from the DTM because of their shape and reflectance that stand out from the surroundings, clearfellings have to greater extent a temporal characteristic. Clearfelling have been the predominant harvest method in Norway since 1950. Ecologically speaking, clearfellings are dramatic interventions in the natural forest dynamics because most of the trees are removed, and the change in solar radiation on the remaining vegetation is immense. With multi-temporal lidar data, large changes in vegetation height over an area can easily be detected, and areas clear-felled between two lidar campaigns can therefore be classified. Using an area-based approach that operate on grid cells, the change in echo height calculated as the difference between the values of for example the 90th height percentile of the vegetation echoes for two different points in time, would be a reliable indicator of harvested grid cells. With the height change information on each grid cell, height change maps could be made, and with a certain cut-off value height difference, harvested areas could be detected. Satellite data could also be used to classify harvest (White et al., 2017). A recent study by Ørka et al. (2018) used multi-temporal data from Landsat and Sentinel-2 with Google Earth Engine to detect harvested areas. With satellite data, classification could be done more frequently and covering larger areas than with lidar data.

Introduced species could be a threat to biological diversity. Hauglin and Ørka (2016) combined orthophotos, Landsat images and lidar data to distinguish between, Norway spruce and Sitka spruce. Since lidar mainly provides height information, distinguishing between tree species of similar shapes often benefits greatly from the addition of spectral information (Asner et al., 2008).

With multi-temporal lidar data, estimates of forest growth rates can be produced (Noordermeer et al., 2018). Because the relationship between forest growth and forest age is non-linear, growth rate normal curves are developed. These growth curves enable the growth rate of a specific forest area to be classified into a *site index*. In Norway, the site index system is labelled H40, and a certain value in this system represents the potential height of a tree at 40 years of age. However, with climate change, growth rates could change. Noordermeer et al. (2018) showed that bi-temporal lidar data could be used to estimate site index, and with repeated estimates it is possible to monitor growth rates and thereby effects of a changing climate and possibly also pollution (N-deposition). Hyperspectral data can also be used to classify forest productivity (Kandare et al., 2017) because trees growing on soils of different productivity have different reflectance. Multi-temporal lidar data have also been applied to detect pioneer trees in the treeline ecotone (Næsset and Nelson, 2007. It has been shown that trees as small as 1 m of height can be detected with high accuracy (Thieme et al., 2011). Still there is no operational system for monitoring the treeline using lidar, but currently there are efforts being made in ongoing research projects in Norway to make this a reality.

Table 9 Relevant information to extract from different remotely sensed data for detection and classification of threats to biological diversity. For each of the factors, we have given relevant information than can be extracted from remote sensing data and categorized the potential as HIGH, INTERMEDIATE or LOW by using an expert opinion approach.

Factor	Relevant information from remote sensing	Potential for lidar	Reference
Deforestation and habitat loss			
Roads	Lidar (echo height, DTM, intensity)	HIGH	Azizi et al., 2014 Li et al., 2015
Ditches	Lidar (echo height, DTM, intensity)	HIGH	Passalacua et al., 2012, Roelens et al., 2018
Clearfelling	Lidar (change in echo heights), Satellite image (spectral)	HIGH	Ørka et al., 2018
Introduced species			
Alien tree species	Orthophoto (RGB) Satellite image (spectral) Lidar (echo heights)	LOW	Asner et al., 2008 Hauglin & Ørka, 2016
Climate change and pollution			
Increased growth	Hyperspectral images (spectral) Lidar (change in echo heights)	HIGH	Kandare et al., 2017 Noordermeer et al., 2018
Changes in treeline	Lidar (change in echo heights)	INTERMEDIATE	Næsset & Nelson, 2007 Thieme et al., 2017

4.1.4 Carbon storage

In addition to biological diversity, forest carbon storage is considered one of the main ecosystem services provided by forest ecosystems (Gamfeldt et al., 2013). However, the relationship between the two is not clear, and studies have found differing results. To assess the relationship a systematic review to explore the empirical evidence for the hypothesised relationship between forest carbon stocks and biological diversity was not carried out here. However, we did a search to find relevant studies, and the main findings from these studies are presented here.

On global scale, Strassburg et al. (2009) found a very strong relationship between animal species richness and terrestrial carbon storage. On more local scales, most studies that have examined the relationship between biological diversity and carbon storage have been conducted in tropical or temperate forests with different outcomes. One study in Spanish temperate forests used 54 000 Spanish forest inventory plots with sizes between 0.03 - 0.16 (circular plots with radius between 5 - 25 m), and they found a strong positive relationship between diversity and carbon storage (Ruiz-Benito et al., 2014). Another study found a significant positive relationship between neotropical aboveground carbon storage and species richness / diversity for 1975 0.1 ha plots (Poorter et al., 2015). This relationship was however not apparent for the 294 plots on 1 ha scale (Poorter et al., 2015). The same was found for global tropical forests where there were either a weak or no biodiversity-carbon relationship for 360 1 ha plots (Sullivan et al., 2017). Another study done on temperate forests in Europe found a weak positive relationship between above-ground live carbon stocks and biodiversity using 352 plots between 20 and 40 ha (Sabatini et al., 2018). The incongruence between studies in tropical and temperate forests may suggest a scale-dependency when it comes to detecting a relationship between biological diversity and carbon storage. Scale-dependency of the diversity-carbon relationship was examined in a study that used global forest plots of different sizes (Chisholm et al., 2013). For 0.04 ha plots there were a positive relationship, but for the larger plots with sizes of 0.25 ha and 1 ha there were mixed results (Chisholm et al., 2013). In the study they argued that plot sizes bigger than 0.1 ha may show mixed results meaning that the effects on the diversity-carbon relationship are coming from local variation (Chisholm et al., 2013).

For boreal forests, few studies have examined the relationship between biological diversity and carbon storage, and in our search only two studies were found. Using a nation-wide dataset from the national forest inventory in Sweden, Gamfeldt et al. (2013) found that the relationship between tree species richness and tree biomass production (kg m^{-2} $year^{-1}$) was positively hump-shaped when taking into account the influence of climate, soil nutrients and forest age. On average, biomass production at the average forest age was ca. 50% greater with five tree species than with only one species. Also, soil carbon storage and understory plant species richness increased with tree species richness (Gamfeldt et al. 2013). Similarly, using nation and state-wide datasets from Spain and Quebec, Lecina-Diaz et al. (2018) found that forest tree carbon stocks were positively related to both bird species richness, tree species richness and overall biological diversity in boreal forest, in both geographic regions. This positive relationship was also found for all the subclimates investigated in the study; boreal, temperate, humid Mediterranean and steppe (Lecina-Diaz et al. 2018). Forest carbon stocks were also positively related to the forest stand variables density and structural diversity (Lecina-Diaz et al. 2018). What the two studies also had in common were broad-scale data sets with many small plots: 127 000 plots in total with sizes ranging from 0.003 - 0.016 ha and 4500 tracts with a size of 0.13 - 0.25 ha for Lecina-Diaz et al. (2018) and Gamfeldt et al. (2013), respectively. The same strong positive relationship was found for the studies for tropical and temperate forests that had plots smaller than 0.16 ha.

4.2 Lidar recommendations

In this section, we give some recommendations with regard to which lidar systems that are most relevant for assessments of biological diversity. We also provide details related to carrying out practical assessments using lidar for biological diversity, biomass and carbon. Towards the end of the section, we inform about the acquirements and costs of lidar data.

4.2.1 Relevant lidar systems for mapping biological diversity

The strongest benefit of lidar data over forest areas is the capability of describing both the vertical- and horizontal structures and the tree biomass, and properties of the terrain. In most cases where biological diversity is modelled by means of lidar data, we take advantage of the relationship between forest structure as depicted by lidar and the measure of biological diversity. Both pulse and continuous waveform lidar systems are particularly useful for retrieving area-based structural information about forests.

With the discrete return pulse systems, the vertical structure of tree canopies are effectively depicted by means the point clouds (height measurements of the canopy) over an area of interest. Combining point clouds from several echo categories (first, second,…, last) returned from the vegetation can provide very detailed depictions of the vegetation structure. Even only using the first echoes can in most cases provide a sufficient representation of the vertical canopy structure. However, studies that have used lidar data to detect trees in the alpine tree line (Næsset and Nelson, 2007, Thieme et al., 2011) have shown that solitary trees that are shorter than 1 m often have too little surface area and too little mass to trigger an echo from a laser pulse. This, however, might be different in forests with a denser layer of short trees that have more mass in total. In a study by Ørka et al. (2016), it was shown that tree height as low as 0.5 m could be detected using lidar data with a point density of 0.7 pm^{-2} in a planted regeneration forest. As explained in Chapter 2, the vertical distribution of the laser echoes can be represented by height values at different percentiles of the height distribution of echoes. The horizontal distribution of the vegetation can also be precisely depicted using the point cloud. Gaps and degree of fragmentation over an area can easily be modelled (St-Onge and Vepakomma, 2012), and also the texture or roughness of the canopy (Renner et al., 2018). Variables that represent cumulative proportional canopy densities can also be calculated as a proxy for canopy density (Næsset, 2002) and horizontal heterogeneity can be assessed by the heterogeneity of different lidar metrics over an area (Bergen et al., 2009). Lidar data can also be segmented into bins in certain height layers of the canopy.

The sensors that are most frequently used in studies of biological diversity are discrete pulse sensors operated from airborne platforms (fixed-wing aircrafts or helicopters; supplementary material table A1). There are differences within the sensor categories, like for example with regard to capabilities of pulse repetition frequencies and pulse distribution system. However, there are no indications that one system is better than other systems. Furthermore, the studies that we have reviewed have applied a wide range of different point densities. Typical point densities for commercial projects where lidar data is collected for multiple purposes in Norway (Geovekst) are 1-2 points per square meter. In the reviewed studies the per square meter point densities range from 0.5 (Simonson et al., 2012) to 500 (Renner et al., 2018). The usefulness and need for higher point densities compared to what is typical will depend on the purpose. However, for most applications a vegetation structure represented by typical point densities (1-2 p m^{-2}) seem sufficient. The fact that data from discrete return systems are most common, is also an argument for recommending data from this type of sensors. There are many different types of applications that require lidar point data, like for example forest inventory, topographic mapping, and planning of new roads. Because of the high number of applications, synergies can be taken advantage of if they all use the same type of sensor. Currently, a project is ongoing, where Norway is being scanned with lidar (point density of 2 pm^{-2}) for the purpose of developing a new DTM for Norway. According to plan, the scanning of 230 000 km^2 will be completed in 2020, and the data will be free for all users.

4.2.2 Protocol for sampling of data: remote sensing and ground truths

Procedures based on a combination of ground-truth and lidar

Applications where lidar is used for prediction of vegetation properties usually follow a two-stage procedure. The first stage involves calibrating an empirical model between corresponding field and lidar metrics. The field observations must be related to a defined area or a *basic unit*, for example a circular or square area unit. The field observations must be positioned, typically using global navigation satellite systems (GNSS) to ensure that the field observations spatially overlap with the remotely sensed data. Spatial overlap is a key requirement for effective use of remotely sensed data calibrated with ground truth information. In the second stage, the empirical model developed using the pairwise ground-truth and lidar observations is applied to raster cells over the entire area where lidar data is available. For this to be possible, the lidar metrics selected as explanatory variables for the empirical model must be available for each raster cell. Cell predictions can subsequently be summed or averaged for larger area units.

Since measurements done by lidar can accurately depict forest structure, information from lidar can be used even without ground calibration. By using ecological knowledge of habitat preferences for a particular species with regard to forest structure, lidar metrics can be used directly to map habitat quality for that species (Hill et al., 2014). For example, certain bird species prefer multi-layered forests (Mathys et al., 2006), and these can be mapped using information from the height distribution of lidar point data. Although such an approach can prove useful for certain species and for the purpose of management, the combination with field observations of either presence/absence or number of individuals is usually necessary. This is especially important if the purpose is to expand ecological knowledge about a specific species (Hill et al., 2014). Many lidar-derived indicators of biological diversity can be found in the reviewed literature. However, it is important to point out that the metrics that is derived from lidar are dependent on the specific lidar sensor that is used, and the specific acquisition parameters used in a particular mission (e.g., Næsset, 2009). Therefore, by using a relationship between certain measures of biological diversity obtained in an experimental study or operational application, the results might be systematically different if these relationships are used elsewhere. The metrics derived from lidar, will also tend to be different between forest types, given a certain “true” structural property. For example, the lidar metrics will differ between a spruce forest and a pine forest with the same biomass, tree height distribution, etc.

Shape and size of ground truth plots - general comments

Ground truth plots can have different forms and sizes, and these can affect the data in different ways. In the case of the circular plot, the positioning can be carried out in the centre, and the area and extent will be defined by the circle's radius. Circles are the most effective shape for reasonably sized plots in terms of both positioning and controlling the area of field measurements. However, using circles for large field plots may be an issue. It is difficult to be exact with regard to what is considered a large plot (Van Laar and Akça, 2007), but plots over 500 m^2 can be an issue when using circles. Controlling the perimeter of larger circular plots can be difficult if the vegetation is dense and the terrain is rugged or steep. However, using range finders based on laser or ultrasound, as compared to a surveyors tape, might simplify the work.

For large field plots, rectangular transects may be a better alternative. Positioning of quadrilateral plots requires that each corner is positioned. An alternative could also be that one or more positioned corners are combined with the orientation and length of the sides to calculate the position of the remaining corners. However, this strategy requires that the orientation can be accurately determined and that the positioning of the corners is accurate. Usually, the plot establishment is carried out using a compass and a surveyors tape, and it is hard to secure that the angles become exactly 90 degrees. Thus, in some cases it might be necessary to position each corner using satellite navigation equipment.

There are other issues related to plot shape and size. Edge-effects from the plots could be an issue. In a forest, there will always be elements outside the plot that affect the growth and properties of the trees within the plot (Monserud and Ek, 1974, Radtke and Burkhart, 1998). However, when using lidar data to retrieve structural properties from a sample plot, outside trees are important for other reasons (Næsset et al., 2015). For example, an outside-plot tree can extend its branches over the plot, and an inside-plot tree can extend branches beyond the perimeter of the plot. Thus, borderline trees will be only partly depicted by the lidar data. A circular shape has the smallest possible edge-to-area ratio, and will therefore be less affected by edge effects compared to squares. By also increasing the plot size, the edge-to-area ratio reduces. Another issue is the capability to capture spatial variation within the plots. It has to be considered what is an expedient spatial scale for capturing the relevant structural variation to explain the presence or magnitude of one or more species in question. Intuitively large plots capture more spatial variation. Maleki and Kiviste (2015) tested the effect of both plot size and shape with regard to estimating structural indices in a birch forest. They found that more variability was captured with increasing size, and the effect of shape was less pronounced.

Positioning accuracy

The position accuracy of the data is important, and the required level of accuracy depends on several factors. Large plots will partly mitigate inaccurate positions since the relative overlapping area between field and lidar data increases with plot size, given a certain positioning error (Gobakken and Næsset, 2009). However, an acceptable positioning error will also to some degree depend on what is modelled. In general, the requirement for positioning accuracy become more important with increasing dependency between the phenomenon that is being modelled, predicted or estimated, and the 3D structural properties of the vegetation and terrain as measured with lidar. Modelling the biomass of trees typically requires field observations of 200 m^2 with a position accuracy <0.5m. However, for habitat modelling of mobile species it may be expedient with larger field observations (Lone et al., 2014a, Lone et al., 2014b, Vierling et al., 2011), and consequently the positioning accuracy requirement may be less strict. If the vegetation structure significantly changes over short distances, the positioning accuracy needs to be high. This is especially evident if the plots also are small.

When high accuracy is needed (1 cm to 1 m) the use of survey grade GNSS equipment is recommended. With this, the position observations are corrected by means of data from a base station. Such corrections can be carried out in real-time (real-time kinematic; RTK) or be post-processed. While the former method is effective in relatively open forests, it requires a continuous connection (radio link or telephone) between the rover receiver and the base station. The rover receiver is the GNSS-unit used to measure the position of the field plot. The base station is a second receiver that continuously measures the positioning error due to ionospheric and atmospheric noise. The latter method using post-processing is a better choice in denser forests with regard to accuracy, but longer measurement time is needed on each plot compared to the use of RTK. An advantage of having accurate positions, is that ground-truth observations easily can be relocated. This enables the establishment of time-series and studies of change.

In cases where lower positioning accuracy is acceptable (1 m to 20 m), handheld devices can be used. Many of these devices have functionality where consecutive position measurements can be averaged. If averaging is carried out for a considerable time (approximately 30 min), the accuracy can sometimes be down to 1 m, but one should not expect accuracies <3 m under forest canopy. Many devices calculate a measure of accuracy that can be observed by the user in real time during the averaging. The measure is calculated the variation between single measurements. However, this measure is not by any means the true accuracy. Devices that observe two or more satellite systems (Global Positioning System (GPS), Global Navigation Satellite System (GLONASS), Galileo, Beidou-2) are preferable, especially since the satellite coverage of the GPS-system is not optimal for Norway.

<u>Ground-truth observations for biological diversity application</u>

The size of the basic unit to apply in a lidar-based survey of habitat quality or distribution of a certain species depends on several factors, both in terms of the properties of the lidar data, and in terms of what is an expedient spatial scale for the phenomenon that is observed on the ground.

In terms of the lidar data, the area has to be large enough so that the lidar metrics can be calculated. Most of the metrics that are supposed to capture structural variation requires several echoes. In principle, you need only two echoes to represent variation, but in practice, the most typical metrics does not make sense with less than 10 echoes. With typical point densities (1-2 p m^{-2}), this means that a basic unit need to be larger than 10 m^2. In principle, there is no upper limit.

There is also the issue of what is an expedient spatial scale for the ground observations. For a mobile species, there is a trade-off between what could be considered the territory of that species, and the level of detail that is necessary in a management perspective (Rechsteiner et al., 2017). For example, the expedient basic unit for birds might be different from that for arthropods. In the study by Rechsteiner et al. (2017), they used a basic unit of 125 m by 125 m. The mapping of not only the presence or magnitude of a certain species, but rather species richness (Currie, 1991), basic units of one square kilometre might be expedient (Zellweger et al., 2016). The recording of the actual ground-truth value of species richness for such large basic units are usually carried out by means of sampling, for example by observations of occurrence along transects. A much smaller unit was used in the study by Vierling et al. (2011), where they predicted the distribution of spiders. In the study, they used a basic unit of 1000 m^2. Their field observations were based on spider traps, and were carried out in the centre of circular plots with radii 17.84 m.

Compared to mobile species, the basic units used for mapping stationary species are typically smaller. For example, Ceballos et al. (2015) used basic units of 225 m^2 (15 m by 15 m) for estimating vascular plant richness, and Simonson et al. (2012) used 314 m^2 circular plots to model plant species composition in a Mediterranean oak forest. Furthermore for the vegetation structure dead wood, Bater et al. (2009) used rectangular plots of 625 m^2 and 900 m^2 to estimate the distribution.

The area of the unit for which lidar data is extracted might be different from the area of the basic unit that is used for the ground-truth observations. In the study by Zellweger et al. (2016), the ground-truth observations were carried out for 1 km^2, but lidar metrics were calculated for 20 m by 20 m pixels. Subsequently, the lidar pixels were upscaled to the area of the basic unit.

The ground-truth measurements will vary greatly depending on the application of the observations. Both counts and registrations of presence / absence are common. For some species, such as plants, it could be expedient to count the number or measure the biomass for a certain area. For other species, such as birds, it is more relevant to observe presence of a species or count the number of individuals per species from a given point, but still an area of the basic unit has to be defined. For example, Eldegard et al. (2014) counted different bird species by both visual and audio within a radius of 50 meters, and hence regarded a practical distance for determining if an observation was outside or inside the plot perimeter. Additional measurements on a plot, such as measuring the properties of the trees within the basic unit surrounding a point observation (e.g. Vierling et al. 2011), is usually only done in experimental studies where the explanatory power of field and remotely sensed data is compared.

It is well documented in the literature that the occurrence and abundance of single tree species, as well as forest habitat structure and tree species composition, can be directly inferred from lidar, or lidar in combination with other remote sensing techniques (Trier et al., 2018). The ability of lidar and other remote sensing techniques to capture important aspects of the habitat has been assessed by comparing the remote sensing data with data from field sampling plots. Thanks to thorough ground truthing in many previous studies, we can now use lidar and other remote sensing data to quantify habitat for many taxonomic groups over large areas, without additional field sampling of the habitat. These habitat data can be related to spatially explicit measures of biological diversity or single species. These relationships can in turn be used to predict biodiversity patterns and species occurrences in unsurveyed areas. However, it is important to field validate the predictions to improve the prediction maps.

When sampling data on biological diversity or single species, ecologists have to decide on the spatial extent and configuration of the field sampling, typically by some kind of field sampling plots. Recommendations about relevant spatial scales will depend on the organism in question, and is beyond the scope of this report. As is the question about whether additional habitat data should be measured in the field sampling plots. In general, a higher resolution of the lidar data (points per m^2) is required for species that have habitats that extend over small geographical areas, in order to get a strong relationship between the biodiversity response and lidar data. For larger species, spatial scale of the sampling plots is of less concern. Indeed, one of the major advantages of using remote sensing to quantify habitat is to avoid the scale sampling problem (Bisonette, 2017). On the contrary, using remote sensing data opens up new possibilities for exploring scale-dependence in ecology. For movement studies of animals that are large enough to equip with GPS transmitters, spatial extent and configuration of field sampling plots is not relevant. Here, the GPS positions of animals and buffers of varying size around each position is used to explore animal-habitat relationships with for example resource selection functions (Boyce et al., 2002), using spatially explicit habitat data derived from lidar.

Monitoring

If lidar data is available for a certain area at multiple points in time, monitoring can be carried out. As an example, St-Onge and Vepakomma (2012) used a bi-temporal lidar dataset from a mixed forest in Quebec, Canada, to detect canopy gaps that had occurred between the first and second measurement. Change has also been modelled for tree height (Hyyppä et al., 2003), leaf area index (Solberg et al., 2006) and biomass (Næsset et al., 2013). Thus, these studies, and several others show that change in forest structure, and hence indirectly the change in biological diversity, can be monitored. As indicated before, lidar data is collected regularly in Norway to serve many purposes, and the interval between each scanning is approximately 10-15 years. For such time intervals, data are already available for certain areas.

Using lidar to assess biomass and carbon stocks

As previously discussed, lidar is particularly suitable for predicting biomass. The study by Næsset and Gobakken (2008) showed that lidar could provide both above and belowground area-based estimates of biomass. In the review article by Zolkos et al. (2013), the accuracy of estimating aboveground biomass from lidar was found to be better compared with other remote sensing sensors. It is important to point out that while aboveground biomass is directly associated with the properties of the lidar point cloud, the predictability of belowground biomass relies on the allometric relationship between above and below ground biomass. More specifically, since the lidar echoes is reflected from the aboveground biomass only, the belowground has to be modelled by means of input variables representing the properties of the aboveground biomass.

Furthermore, change in area-based biomass can also be estimated. Næsset et al. (2013) showed that lidar assisted wall-to-wall estimation of change could be carried out with an efficiency up to 40 times better compared to relying on just a field-based survey. Using lidar for obtaining estimates of biomass, usually follow the same two-stage procedure as mentioned earlier. The procedure relies on that field observations of trees are carried out so that biomass can be calculated using allometric functions, so that ground truths can be established. Models can then be developed and predictions of biomass over a grid of wall-to-wall prediction cells can be made. These predictions of biomass can then be converted to carbon using fixed biomass to carbon ratios, which are very stable (Penman et al., 2003). As mentioned, belowground biomass and carbon can then be estimated from the aboveground estimates. However, for large scale assessment of soil carbon as opposed to belowground carbon in tree roots, a system such as the National Forest Inventory (NFI) is most expedient. The carbon fixed in the soil could be measured by means of samples from the plots of the NFI, which would enable estimation of the total amount of carbon per area unit. The carbon measurements could also be related to different soil types, so that with a soil type map stratified estimates could be provided. The Swedish NFI measures carbon on their field plot (Fridman and Nilsson, 2017), while in Norway soil carbon is estimated using the model Yasso (Liski et al., 2005). The latter method uses tree and climate data to estimate carbon stock, and it can also be used to simulate change in carbon stock over time.

Application of models is always associated with errors, so also with the Yasso model. The relationship between soil carbon and the aboveground conditions are still uncertain and there is still research going on to bridge this knowledge gap. The role of mycorrhiza-fungi seems to be especially important (Kløvstad 2019a,b)

4.2.3 Acquirement of data and costs

The equipment that is needed for collecting airborne lidar data is substantial and a big investment. Each user of the data must therefore in most cases purchase the data from a commercial vendor. Before the data can be used for a purpose such as mapping biological diversity, an initial processing is needed. In the processing, each echo is classified according to if it was reflected from the terrain or the vegetation. The ground echoes is then used to construct a digital terrain model (DTM). This model represent ground echoes subtracted from the vegetation echoes so that each of the vegetation echoes get a height relative to the ground surface and not to relative to the Earth ellipsoid. All processing steps are usually provided by the vendor, and the product that is offered to the customer comprise positioned height measurements of the vegetation and the terrain. Further use of these data requires knowledge in the use of geographic information system (GIS) tools and statistical software. There is also a need for statistical and mathematical competence, both to further process the lidar echoes into variables that can be used as input in statistical models, but also to fit appropriate models of the phenomenon of interest.

The cost of purchasing lidar data are dependent on many factors. First, there are always fixed costs related to getting the aircraft in the air and planning the operation. Thus, the per area unit cost will depend on the total area for which the lidar data is collected. Another factor is the point density where higher point densities result in higher costs. There are several ways of controlling the point density by varying the pulse repetition frequency, swath width, and flying altitude. In commercial, multi-purpose lidar campaigns in Norway, the cost per hectare is approximately 2- 5 NOK.

5 Conclusion

In the review of studies looking at lidar and biological diversity, a surprisingly high number of studies from the list of hits from the literature search had to be discarded. This was due to lack of relevant quantitative information within the studies, and in the end we did not have enough data to carry out a meta-regression. Thus, we are not able to answer all the questions in the announcement. Apart from the important documentation of a need for more primary studies, the process has clarified some important challenges that need to be overcome in future projects.

Using lidar for predicting biological diversity over broad spatial scales requires prediction modelling. It is important that the modelling approach (descriptive or predictive) is explicitly stated, and literature reviews should include modelling approach and not only the type of statistical model as a covariate in the meta-database. Typically, a large number of lidar and other remote sensing variables are listed in all the studies. To understand the system, we recommend grouping the lidar-derived variables into ecologically relevant categories that capture habitat attributes. In addition to species richness, biological diversity measurements should be expanded to including other metrics of taxonomic and functional community composition. In the future, it may be possible to do a meta-regression based in single-species models. However, this will probably mean contacting authors to get access to original data. This is because many of the studies have a high heterogeneity of statistical models, and the access to the original data will let us get the needed information to calculate effect sizes.

The review of the literature did however show that lidar has a great potential for predictive modelling of biological diversity on a regional scale. Calibration of predictive models using ground-truth observations, that can be applied to grid cells over an area is the most reliable approach. However, lidar data can also contain relevant structural information that can be used even without calibration. This strategy requires that the relevance of metrics calculated from the lidar data is carefully considered. It is also important to point out that the metrics that is derived from lidar are dependent on the specific lidar sensor that is used, and the specific acquisition parameters used in a particular mission (Næsset, 2009). Therefore, by using a relationship between certain measures of biological diversity obtained in an experimental study or operational application, the results will likely have systematically errors if these relationships are used elsewhere. The metrics derived from lidar will also tend to be different between forest types. The use of ground-truth plots is therefore recommended.

The size and shape of the ground-truth plots must be chosen according to what phenomenon that is being mapped, and what might be considered a good management unit. In general, we can say that mobile species require larger basic units than stationary, and that large basic units are more useful for mapping multiple species than one single species. The positioning of the ground-truth plots can in many cases be carried out with handheld GPS-receivers. However, survey grade receivers might be needed if the vegetation structure changes significantly over short distances and/or the phenomenon that is being mapped is extremely sensitive to changes in vegetation structure.

Here we have recommended prediction modelling using an area-based approach. With such an approach, it is relatively straightforward to obtain wall-to-wall predictions of biological diversity measures over relatively large areas. Lidar data is usually collected over the forested part of Norway with 10-15 years interval for the purpose of forest inventories, and sometimes even more frequently.

Currently, there is an ongoing national laser scanning which provide very large coverage of data in the years of this mission. The normal yearly coverage is not this extensive.

Monitoring of biological diversity using lidar is possible, at least indirectly through assessing habitat features. Lidar allows assessing habitat features over broad spatial scales. This information can be used to improve predictive distribution modelling of species and groups of organisms, based on known habitat-species relationships. Using lidar and other remote sensing to assess indicators of ecological state can also be carried out. For example, monitoring studies of ecosystem properties (e.g., biomass) that is dependent on vegetation structure, have proven to be efficient. Factors that are threats to biological diversity, such as roads, ditches and clearfellings can also be detected. Lidar is a powerful data source for assessing biophysical properties of trees and vegetation, and also physical properties of the terrain. Combined with other data sources that provide spectral information, the utility of the data is huge.

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