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RESEARCH ARTICLE

How to integrate remotely sensed data and biodiversity for ecosystem assessments at landscape scale

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Abstract
Context Biodiversity and ecosystem functioning underpins the delivery of all ecosystem services and should be accounted for in all decision-making related to the use of natural resources and areas. However, biodiversity and ecosystem services are often inadequately accounted for in land use management decisions.
Objective We studied a boreal forest ecosystem by linking citizen-science bird data with detailed information on forest characteristics from airborne laser scanning (ALS). In this paper, we describe this method, and evaluate how similar kinds of biological data sets combined with remote sensing can be used for ecosystem assessments at landscape scale.
Methods We analysed data for 41 boreal forest bird species and for 14 structural ALS-based forest parameters.
Results The results support the use of the selected method as a basis for quantifying spatially-explicit biodiversity indicators for ecosystem assessments, while suggestions for improvements are also reported. Finally, we evaluate the capacity of those indicators to describe biodiversity-ecosystem service relationships, for example with carbon trade-offs. The results showed clear distinctions between the different species as measured, for example, by above-ground forest biomass at the observation sites. We also assess how

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the available data sources can be developed to be compatible with the concept of essential biodiversity variables (EBV), which has been put forward as a solution to cover the most important aspects of biodiversity and ecosystem functioning.

Conclusions We suggest that EBVs should be integrated into environmental monitoring programmes in the future, and citizen science and remote sensing methods need to be an important part of them.

Keywords Ecosystem service · Habitat · LiDAR · Essential biodiversity variable · Citizen science · Forest

Introduction

There is a growing research interest in and societal need for ecosystem assessments on various scales, from global to national and landscape scales (e.g. MAES work on the EU Biodiversity strategy to 2020 at national and continental scales; IPBES global ecosystem assessment until 2018). In the ecosystem assessments, an integrated evaluation of both biodiversity and ecosystem services should be taken into account. Techniques of mapping and modelling ecosystem services have developed rapidly during recent years (e.g. Maes et al. 2011, 2012a, b), whilst parallel consideration of relevant biodiversity variables is not so often integrated into those analyses (Mace et al. 2012). Although biodiversity and ecosystem functioning enable the delivery of all ecosystem services, linkages between these are often difficult to show in practical terms and on a scale relevant for decision-making. Coupling ecosystem services with feasible biodiversity indicators that can be monitored over time remains a considerable practical challenge. Finding a relevant and comprehensive bundle of biodiversity indicators to estimate, for instance, the impact of land use change on ecosystem functioning and on ecosystem services is difficult. Rather than being spatially explicit, available indicators are most often derived from statistics on ongoing monitoring programmes on global, national, and sometimes on regional or municipal scales (for a spectrum from global to subnational indicators, see, for example, Secretariat of the Convention on Biological Diversity 2010; European Environment Agency 2010; Auvinen et al. 2010; Normander et al. 2012; City of Helsinki 2014). Furthermore, the majority of the potential biodiversity indicators are case-specific, meaning that they depend on the focused ecosystem type or taxa, and on the scale of observation.

Recent advances in applying remote sensing techniques and collecting large biological databases—often updated by citizen scientists—have improved the possibilities to develop spatial biodiversity indicators on a landscape scale, which could be monitored over time (GEO BON; Newton et al. 2009; Pereira et al. 2010; Coops et al. 2013). Earth Observation studies have often led to land cover data that is derived from satellite images (Gottschalk et al. 2005). An increasingly important field of remote sensing applications is wildlife habitat assessment and modelling (Clawges et al. 2008; McDermid et al. 2009; Tattoni et al. 2012; Melin et al. 2013). Birds have often been used as an indicator group in studies searching for structural and functional features that best describe the biodiversity values of landscapes (Dauber et al. 2003; Jeanneret et al. 2003; Jones et al. 2013; Zellweger et al. 2013, 2014; Morelli et al. 2014). The selection of a comprehensive set of biodiversity indicators to analyse trade-offs with ecosystem services is a necessity for the sustainable management of ecosystems.

The challenge of measuring biodiversity is concrete (see Magurran 2004): How should the different aspects of diversity, such as structural, functional, ecosystem, community, species, and genetic diversity, be quantified? Long-term monitoring of the state and trends of biodiversity and ecosystem services is crucial for applying scenarios, models, and management decisions to halting biodiversity loss, but lack of resources to do that work is a common problem. The concept of essential biodiversity variables (EBV) has emerged recently to cover the most important aspects of the biodiversity measures (Pereira et al. 2013). EBVs should fulfil the criteria of scalability, temporal sensitivity, feasibility, and relevance (Pereira et al. 2013). Examples of EBV classes could be genetic composition, species populations, species traits, community composition, ecosystem structure, and ecosystem function (Pereira et al. 2013). EBVs aim to provide a set of indicators that can be monitored based on remote sensing, repeated sampling programmes, or, for instance, citizen science. Citizen science engages volunteers to gather or process data to address scientific questions, and they have already been highly useful, for example, in studying bird population trends in relation to environmental changes, because of the popularity of bird watching (Tulloch et al. 2013; Sullivan et al. 2014).

EBVs could be determined, for instance, for certain ecosystem types. (Winter et al. 2011) selected 41 candidates for forest biodiversity variables, based on current ecological literature and expert opinion. The study revealed that, for example, bird species were ranked as an important variable, but feasibility of use was low. At the same time, variables of forest structure were not ranked as having such high importance, but the feasibility of obtaining that information from, for example, national forest inventory data was deemed relatively good. Lack of data is also a well-known problem for species inventory data for many taxonomic groups. For instance, in Finland, there are regions or smaller areas such as municipalities that have a high data coverage for vascular plant or breeding bird distribution, and where the distribution maps can be drawn in 1 km^2 grids (e.g. Ranta and Siitonen 1996; Tynjälä 2004). At the same time, in some other areas, species distributions, even in 10 km^2 grids, are uncertain. “Presence-only” type data carries with it the general problem of empty cells that makes the use of scattered data challenging, even in well-studied areas. We cannot guarantee that the empty cells are really empty or merely a result of less intensive observation efforts.

Recent advances in earth observation technologies have supported land-cover-based ecosystem trait, structure, and service mapping on global, regional, and local scales. The European CORINE Land Cover (CLC2000) database in a 25 m grid can help in coarse assessments of some biophysical characteristics of the environment (Vihervaara et al. 2010), but it cannot provide accurate information on local species assemblages and biotope types that form the basis of ecosystem service supply. More detailed tools, such as airborne laser scanning (ALS), are needed (Hill and Thomson 2005; Pesonen et al. 2008; Vehmas et al. 2009; Asner et al. 2012; Vihervaara et al. 2012; Pippuri et al. 2012, 2013). ALS has revolutionized the ways to measure forest structure in 3D. It uses Light Detection and Ranging (LiDAR) to make distance measurements, namely the distance between the sensor and a target. In ALS, a scanning LiDAR device collects echoes (i.e. 3D points) from an area beneath an aeroplane or helicopter. Several parallel flight lines are flown to obtain wall-to-wall coverage in the target area. ALS data are used mainly for terrain modelling, urban reconstruction, and forest inventory, but it is well suited to the study of all kinds of phenomena that can benefit from a 3D description of the environment.

The applications of ALS for ecology have been developed over the last decade (Coops et al. 2010; Flaherty 2012; Palminteri et al. 2012; Lone et al. 2014). The underlying principle in these studies is as follows: the 3D structure of vegetation affects the suitability of the habitat for a species, and ALS provides information about this structure. Birds are used as indicators with reference to species-specific functional traits such as migration strategy, size, breeding time, and foraging preferences (cf. Green and Elmberg 2014). Birds are also vulnerable to environmental changes, including global climate change and land use (Barbet-Massin et al. 2012), and they can function as robust indicators of the ecological condition of their habitats, as they integrate the effects of abiotic stressors acting on species at lower trophic levels (O’Connell et al. 2000; DeLuca et al. 2004; Green and Elmberg 2014). Relationships between habitat quality, vegetation structure, and birds have been studied using ALS data, but in many studies, only a few species and structural parameters (e.g. canopy height) have been analysed, and the studies have covered relatively small areas (Hill et al. 2004; Bradbury et al. 2005; Graf et al. 2009). However, more recent work (e.g. Coops et al. 2010; Jung et al. 2012; Palminteri et al. 2012; Zellweger et al. 2013) has been increasing the numbers and types of species studied, and especially the types of structural variables that can be derived from ALS data.

Birds are considered a good indicator group because they are conspicuous, their ecology is well-known, they have diverse preferences for different habitats, and observation methods for them are well-developed (Koskimies 1989; O’Connell et al. 2000, 2007; Carignan and Villard 2002; Arzel et al. 2015). However, due to a lack of spatially accurate data on their occurrence over extensive areas, it has been difficult to use birds as biodiversity indicators on a landscape scale (see, however, Luoto et al. 2004). Citizen science may improve this situation remarkably, as these data sets can cover wide areas with sufficient data coverage.

In this paper, we describe a method based on the two important components of defining EBVs, namely remote sensing (in particular ALS) and a large citizen-

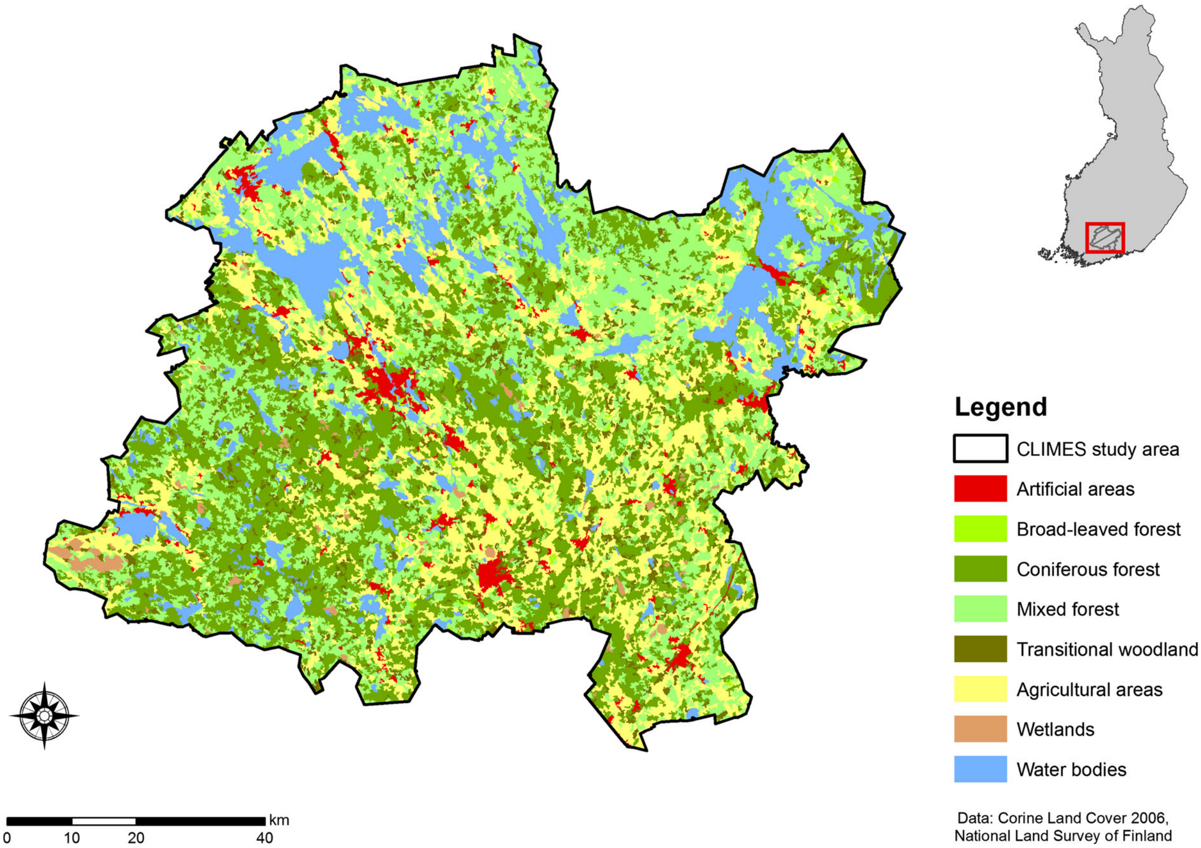

Fig. 1 The study area is situated in Southern Finland, where typical boreal forest characterises the area

science database (bird observation data). These can be used in preparing spatially explicit and temporally monitored landscape scale biodiversity indicators for forest ecosystems, and for further trade-off analysis with other ecosystem services. The specified objectives of this investigation are the following:

(1) Define potential data sources for structural and functional biodiversity and ecosystem structure data, and develop a methodology for how biodiversity indicators can be used in analysing trade-offs with ecosystem services.
(2) Test the feasibility and applicability of species data (bird observation sites) and ecosystem structure data (ALS) in a forest ecosystem, Southern Finland.
(3) Recommend how the EBV concept could be integrated into environmental monitoring programmes in the future.

Materials and methods

Test area of Vanajavesi catchment, southern Finland

Our study area is located in the Lake Vanajavesi catchment (8,391 km^2, of which our study area covered 3,000 km^2) in southern Finland (Fig. 1). The area represents typical boreal forests with adjacent mires, lakes, and small rivers, and agricultural areas. The major parts of the forests are managed for economic purposes. The final study area was selected on the basis of ALS data and bird observation data availability, coverage of which is also illustrated on the map (Fig. 2). The area has been intensively studied for other forest-based ecosystem services, such as carbon sequestration and stocks, nutrient retention, hydrology, and aerial N deposit (Holmberg et al. 2015). For this reason, it is an interesting case area to develop the EBV concept for forest biodiversity for more specified trade-off analysis in future.

Bird data for indicator species

Description of different bird data sets

In our analyses, we concentrated on bird species breeding in forests and woodlands. We took into account only species with a possible indicator value for valuable forest patches. Thus, we included species of conservation concern, such as the European Union's Birds Directive species (Annex I) and red-listed species in Finland (for further classifications, see Virkkala et al. 2013), species preferring old-growth or mature forests, and species of herb-rich, lush, and deciduous forests (Virkkala et al. 1994, Väisänen et al. 1998). We also included species occurring in boreal agricultural-forest mosaics or breeding in shoreline woods (such as the kestrel *Falco tinnunculus* and the hobby *F. subbuteo*). All of the 41 bird species included in our analyses breed regularly in wooded habitats (see Fig. 2; Appendix 1).

We used observation data of these 41 bird species from two different data sources:

(1) Ringing data of our study species, ringed either as a nestling or as an adult breeding in 2006–2012 (Finnish Museum of Natural History's database; referred to in this paper as "FMNH"). A brood was regarded as just one observation. All of the ringing records included in our analysis contain exact coordinates of the ringing site.

(2) Bird observation data from 2006–2012 recorded in the Tiira database maintained by BirdLife Finland (referred to in this paper as "Tiira"). We included only those observations of our study species that were recorded during the breeding season, which was defined specifically for each species. Ringing and Tiira database observations were reported at a 1 × 1 m resolution, but the resolution achieved in practice was likely to be considerably worse. However, these data had to be analysed further to be comparable with the other bird data. In a large number of the Tiira observations, only the observer's location is reported. Here we only used observations with both the observer's and the bird's location reported. We calculated the average and maximum distances of an observer and a bird specifically for each species. We then reflected these distances against our own experience of the observability of the species. Because the Tiira database is known to include a small portion of false locations, we excluded those observations where the distance between the observer and the bird was too big, by setting maximum allowed distances specifically for each species. After excluding outliers in this manner, we then used a 75 % fractile of the remaining observations as a distance ($DIST_{0.75}$) from the observer to more specifically connect the observation to certain forest patch(es) (see Appendix 1). These 75 % fractiles represent "inaccuracy" of the observation: the further away from the observer a bird species was recorded, the more "inaccurate" the location of the observation site was in relation to the habitat variables measured.

In addition, applicability of the data from the Finnish Breeding Bird Atlas carried out in 2006–2010 (Valkama et al. 2011; referred to in this paper as "Atlas") was checked.

Preparation of bird data

We combined the two datasets of bird observations and chose to use only the most accurate bird locations (accuracy 100 m or less). Points that were inside water courses or urban areas according to the Topographic database (National Land Survey of Finland) were excluded. Since we wanted to assess our observation data within forests, we set a limit of 2 m of vegetation height to exclude the points that are in agricultural areas or recently clear-cut areas. In our final dataset, we ended up with 2,875 bird observation points in total: 2,112 points from the Tiira database and 763 from the FMNH ringing dataset. Bird Atlas points ended up being too coarse for our purpose.

In our study, we compared bird observation sites with randomly selected sites. These random points represent the study area, being the distribution of a particular metric in the whole study area. The number of randomly selected points was equal to the number of observations. We included only random points that

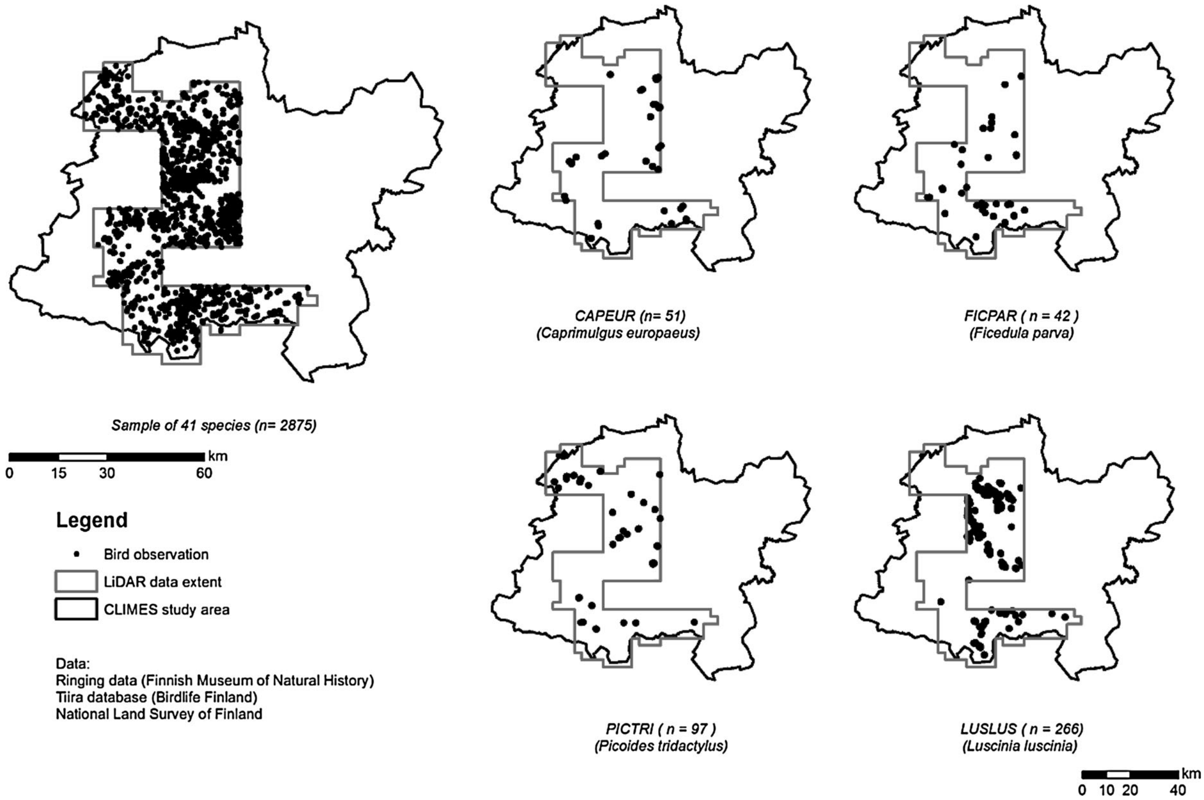

Fig. 2 Data extent of ALS data and observation sites of the four study species: Eurasian nightjar (*Caprimulgus europaeus*), red-breasted flycatcher (*Ficedula parva*), three-toed woodpecker (*Picoides tridactylus*), and thrush nightingale (*Luscinia luscinia*) (see 2.2 Bird data for indicator species)

were situated in forest land, using a similar method as for the preparation of original bird observation data. Thus, for comparison, a sample of 2,875 random points was generated for the study area.

In our analysis, we used a 50 m buffer around each observation and random site—area that is big enough to represent the forest characteristics around the observation point, but small enough not to lose the uniqueness of the site. Furthermore, the resulting 0.8 hectare area reflects quite well the average forest patch size of the study area. Forest patches are generally quite small in southern Finland, due to private forest ownership, intensive forestry, and other land uses.

We ran two analyses. First, we compared all indicator species with random sites, and then we selected specific indicator species preferring certain forest habitats, such as old-growth coniferous forests (the three-toed woodpecker *Picoides tridactylus* and the red-breasted flycatcher *Ficedula parva*; see e.g. Virkkala and Rajasärkkä 2006, Pakkala et al. 2014), lush and deciduous forests (the thrush nightingale *Luscinia luscinia*), or pine-dominated forests (the Eurasian nightjar *Caprimulgus europaeus*) (see Väisänen et al. 1998, Valkama et al. 2011). The 75 % fractile in the distance between the observer and the bird was 28 and 50 m for the three-toed woodpecker and the red-breasted flycatcher (Appendix 1), respectively, showing that the birds were observed at a rather close distance, and thus the birds' observation site is exact in relation to the habitat composition measured. On the other hand, the 75 % fractile of both the thrush nightingale and the Eurasian nightjar was >200 m between the observer and the bird (Appendix 1), because these bird species could be observed at a longer distance, thus increasing the inaccuracy of the exact observation site in these species (Fig. 2).

Airborne laser scanning data for ecosystem structure

ALS data and field measurements were used to predict metrics, i.e. structural parameters, linked to species occurrence. The field data of 249 sample plots were collected in the summers of 2007 and 2008. The sample plots of 9 m in radius were distributed over forest stands with different development stages and dominant tree species. A differential global positioning system (DGPS) was used to determine the position of the centre of each plot. Diameter at breast height (DBH) was measured, and tree species determined for each tree. Tree height by tree species was also measured, and Näslund's (1937) height model was used to predict the height of the rest of the trees. Forest attributes including volume (V), above ground biomass (AGB), basal area weighted mean diameter (DGM), dominant height (Hdom), tree species proportions, and forest structure attributes were calculated for each plot. Stem volume was predicted using models by Laasasenaho (1982), and above ground biomass using a model by Repola et al. (2007). Tree species proportions and dominant tree species in terms of volume were computed for plots. Following Valbuena et al. (2014), the forest structure attributes selected were: the Gini coefficient (GC; Glasser 1962), Lorenz asymmetry (LA; Damgaard and Weiner 2000), and the proportions of number of stems (NSLM) and basal area (BALM) larger than mean (Gove 2004). In the context of a forest ecosystem, the GC assesses the degree of tree size inequality, whereas LA evaluates the balance between overstory and understory, and hence the development of natural regeneration (Valbuena et al. 2013a). Furthermore, Valbuena et al. (2013b) detected the importance of considering the components of LA: NSLM and BALM, describing separately the shares of number of trees and basal area that are stocked above the DGM. Gove (2004) described the importance of BALM with regards to analysing diameter distributions of differing shape, so that BALM can be employed to distinguish a Gaussian from an exponential distribution, which may be otherwise be similar in light or other attributes (Valbuena et al. 2014).

ALS data were collected in May–June 2008 using an Optech ALTM GEMINI laser-scanning system. The area was measured from an altitude of 2,000 m above ground level, using a half angle of 20°. This resulted in a swath width of 1,450 m and a nominal sampling density of about 0.5 measurements per square metre. A digital terrain model (DTM) was generated from the ALS data. First, laser points were classified as ground points, and other points as explained in Axelsson (2000). A DTM raster with a cell size of 2 m was then interpolated by Delaunay triangulation (Fowler and Little 1979). Finally, the orthometric heights of ALS echoes (Z) were converted to above ground heights (dZ) by subtracting the DTM at the corresponding location. First, echoes were used to construct the canopy height model (CHM), which was interpolated to a grid of 1 m by taking a maximum height (dZ) within a radius of 2 m from the centre of a pixel.

Several height, density, and intensity metrics were calculated from the ALS data. All metrics were computed separately for first (prefix f) and last (prefix l) echoes. The principle of the area-based method was used here (Næsset 2002). The first step was to calculate the height distributions for each sample plot and grid cell (see the grid approach below). Weighted height percentiles 1, 5, 10, 20,… 80, 90, 95, 99 (h1,…, h99) were computed, and the corresponding densities (p1,…, p99) were calculated for the respective percentiles. Height percentiles were calculated by summing the heights at above ground level. For example, the metric h50 is the height at which 50 % of the cumulative height has accumulated, and p50 is the number of laser hits below h50 divided by all the laser hits on the plot or grid cell. In addition, the mean and standard deviation of heights, and the proportion of vegetation hits versus ground hits using a threshold of 0.5 m (veg), were calculated. The following intensity features were also computed: mean (f/l_iavg), standard deviation (f/l_istd), and percentiles 10, 30, 50, 70, and 90 (e.g. f/l_i90). Intensity is the echo strength of the laser pulse that generated the point. It is related to the reflectivity of the object struck by the laser pulse.

Regression models for V, AGB, DGM, and Hdom, and beta regression models for tree species proportions and forest structure variables GC, LA, BALM, and NSLM were constructed using ALS metrics as predictor variables. The maximum number of variables in the models was fixed at three, to avoid overfitting. A subset of ALS metrics was determined by testing all possible combinations of the three metrics. Different transformations were also tested, and the final model forms were decided based on residual plots, RMSE (root mean squared error), and bias and significance tests of the alternative model candidates. Selected variables and the error rates of the

Table 1 Predictor variables selected for the models and their error rates (absolute and relative RMSEs)

Predictor variable	Metrics	RMSE	RMSE-%	Bias
AGB (ton/ha)	f_havg, f_p0, l_havg	26.3	25.7	−0.00
V (m^3/ha)	f_havg, l_havg, l_p90	50.1	25.4	−0.00
Hdom (m)	f_h90	2.1	10.9	−0.00
DGM (cm)	l_h60, f_p95, f_h80	2.60	12.7	−0.00
Pine (%)	l_havg, f_h90, l_h40	26.0	–	0.15
Spruce (%)	l_havg, f_p90, f_p5	23.0	–	0.98
Deciduous (%)	f_iavg, f_istd, f_p90	12	–	−1.91
GC	f_h5, l_h5, l_h80	0.09	24.5	<0.01
LA	l_h40, f_istd, f_p1	0.07	11.3	<0.01
BALM	f_i90, l_h5, l_h50	0.08	10.8	<−0.01
NSLM	f_p1, f_p80, l_h5	0.07	16.9	0.68

The prefix f/l indicates that metrics are calculated from first or last echoes. Some models are biased because the used beta regression is inherently biased

Table 2 Forest structure parameters (maps) based on ALS

Map	Explanation
DTM	Digital terrain model (m)
CHM	Canopy height model (m)
f_veg	Proportion of vegetation hits (%)
AGB (ton/ha)	Above ground biomass of trees (ton/ha)
V (m3/ha)	Volume of trees (m^3/ha)
Hdom (m)	Dominant height of trees (m)
DGM (cm)	Basal area weighted mean diameter (cm)
Pine (%)	Proportion of pine (%)
Spruce (%)	Proportion of spruce (%)
Deciduous (%)	Proportion of deciduous (%)
GC	Gini coefficient
LA	Lorenz asymmetry
BALM	Basal area larger then mean
NSLM	Proportion of number of stems

models are shown in Table 1. Error rates are in line with earlier studies (e.g. Næsset et al. 2004; Packalen et al. 2009; Valbuena et al. 2013b).

The study area was overlaid with a grid of 15 × 15 m cells, which approximately corresponds to the size of the plots. The models constructed with sample plot data were used to predict values for each grid cell, where the tree height was more than 5 m (value of metrics h95 > 5 m). Minimum and maximum values for the predictions were also fixed to keep predictions within reasonable limits. In the case of tree species proportions, predictions were scaled to sum up one. Finally, grids were converted to raster maps. All the layers used in subsequent analyses are shown in Table 2.

Combining and analysing bird observation and ALS data

First, we created a circular buffer of 50 m around all bird locations (41 species) (Fig. 3.). Then we extracted the histograms of forest structure parameters (Table 2) from the buffered zone. The same was done for random locations representing population, and for the four selected bird species. Differences between bird observation locations and random sites were statistically tested separately for the pooled data and the four bird species, using Chi squared and Kolmogorov-Smirnov tests. The bird species observation sites were related to the structural parameters of ecosystems and presented as distribution curves (Fig. 4; Appendix 2). Finally, we assessed the applicability of the overall method for ecosystem assessment, and discussed how it could be improved and applied in the future. The flow chart of the overall processing is presented in Fig. 3.

Results

Comparison of bird data with forest structure

Our principal aim was to test the method for linking species data with ecosystem structure. The results are illustrated in relation to six structural parameters in Fig. 4. We show distribution curves for the Eurasian nightjar, the red-breasted flycatcher, the thrush nightingale, the three-toed woodpecker, and all 41 species observations, as well as random points compared with DGM, dominant height of trees, proportion of tree species, and LA. The result curves for the rest of the structural parameters are not included in the demonstration, but they are shown in Appendix 2. Due to the high number of observations, all the tested curves

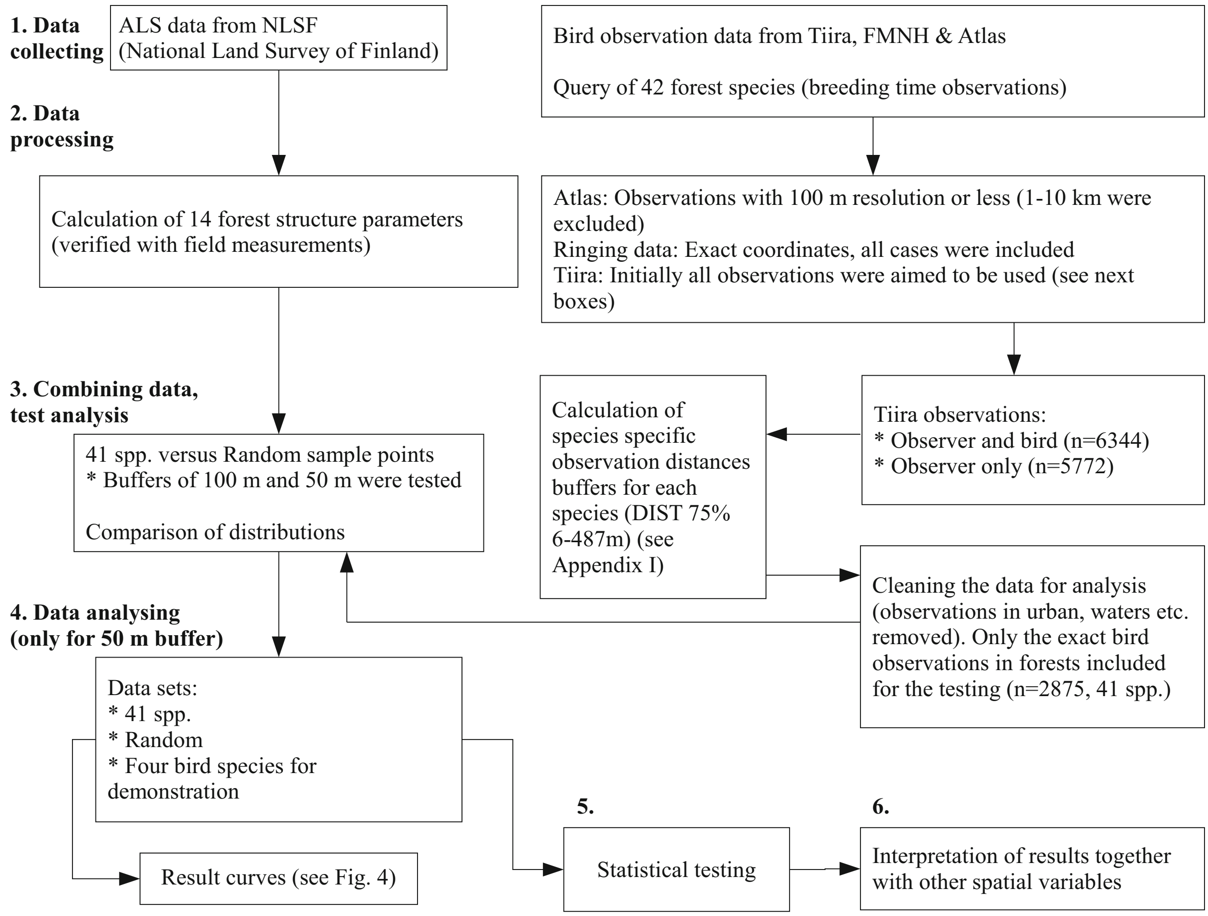

Fig. 3 Work flow illustrating the data preparation, processing, and analysis

differed statistically significantly from the population (random). The results illustrate that, for instance, the red-breasted flycatcher and three-toed woodpecker were related to a higher value of DGM, higher trees, and a higher proportion of Norway spruce than other compared species and random points. The thrush nightingale preferred a higher proportion of deciduous trees, and the Eurasian nightjar that of Scots pine. The Lorenz asymmetry value was lower for the thrush nightingale, indicating that it occurred in structurally multilayered forests. The thrush nightingale also occurred in sites with a higher proportion of Scots pine than random sites.

Biodiversity data and selection of EBVs for ecosystem service assessments

Another aim of this study was to assess how the available data sets could be used in defining essential biodiversity variables for ecosystem assessments on landscape scale. The method described in this paper could cover the EBV classes at least for species populations, functional traits, or behavioural patterns in assemblages, and measures of ecosystem structure as a pre-requisite for biodiversity indicators. It is possible to find an optimal hand, meaning a priority set of indicators for ecosystem assessments. This presents a way forward, to improve knowledge on the relationship of different EBVs to various ecosystem services, such as the relation of bird species to above-ground biomass (Fig. 5) and thus to carbon sequestration and storage, for example. We found that, for example, the red-breasted flycatcher and three-toed woodpecker had the highest proportion of frequency in sites with a biomass of more than 200 tons per hectare. After scanning data for different species, it is possible to find prioritised indicator species for several ecosystem services (cf. Holmberg et al. 2015), but that requires much more investigation.

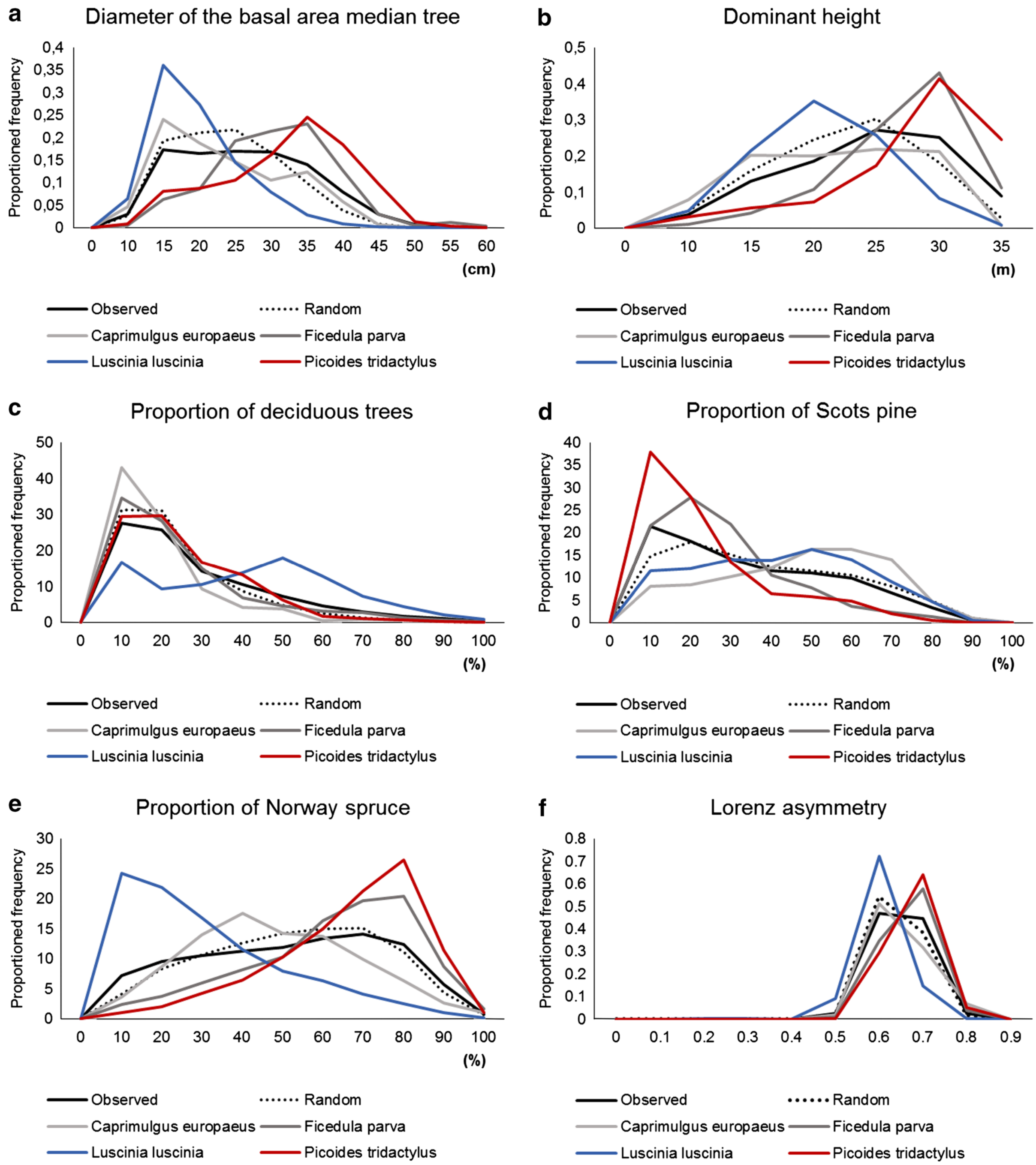

Fig. 4 Bird observations in relation to six ALS-based forest structure parameters. The "observed" curve shows all 41 species observations

The applicability of the method should also be studied in different circumstances with varying data sets, including taxa other than birds. There are also other data sources in many countries, such as for butterflies and vascular plants, often collected and updated by citizen scientists. Remotely sensed structural data can be provided for wider areas from many sources, such as satellite images and aerial

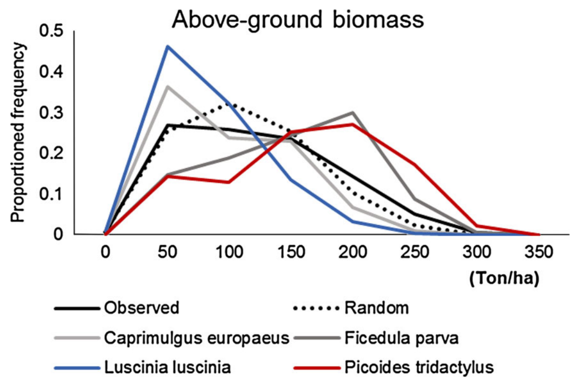

Fig. 5 An example showing different bird species occurrence in relation to adjacent carbon storage

photographs, but ALS is an especially promising data source due to its ability to describe the exact 3D structure of ecosystems.

Discussion

Opportunities and uncertainties in integrating species and remote sensing data

Our principal aim was to develop and test methodology on how available species data sets and the latest remote sensing products, such as ALS data, could be applied to define EBVs for forest ecosystems, particularly describing detailed structural variables. ALS data has previously been used to define landscape structure indicators in comparison with bird occurrence data (Zellweger et al. 2013, 2014). Our work demonstrates that available bird databases, together with remote sensing, are good sources of information for defining EBVs. EBVs can be seen as raw material for more specified biodiversity indicators. Selecting different classes of EBVs based on species data (e.g. bird populations, functional traits), and applying remote sensing data from freely available sources, can improve the mapping and modelling of different aspects of biodiversity indicators and their interdependencies. Based on the method used in this paper, it is possible to assess correlations of certain species groups with selected ecosystem services for which spatially explicit monitored or modelled data is available, or can be derived from remote sensing parameters. We demonstrated that for four bird species, in relation to carbon sequestration and storage, but further work is needed to focus this theme profoundly. However, this approach can be used in spatially explicit mapping of biodiversity and ecosystem services for ecosystem assessments at landscape scale.

Modelling of habitat preferences for many taxa has been done, especially based on field observation and habitat inventories (e.g. Similä et al. 2006; Heino 2010). In some cases, remote sensing products such as satellite images and aerial photographs have also been employed (e.g. Luoto et al. 2004). However, only spectral information is observed with imaging sensors, although the 3D structure of the ecosystem is often a more relevant measure (Valbuena et al. 2014). Therefore, satellite image-based predictions of ecosystem structure parameters are usually substantially less accurate than ALS-based predictions. ALS has been used to model, for example, the habitat preference of great tits (*Parus major*), based on the canopy height model (Hill et al. 2004), the occurrence and activity of bats (Jung et al. 2012), the distribution of arthropods (Müller and Brandl 2009; Vierling et al. 2011), and the foraging areas of moose (*Alces alces*) (Melin et al. 2013). Besides simple height or density parameters, indices such as GC, LA, BALM, and NSLM, which describe the forest layer structure, have also been developed, but seldom used to explain the biodiversity response to them (Valbuena et al. 2013a, b). Our results indicate that those might also reveal species-specific differences, and their use should be studied more.

Citizen-science atlas data has been used to model species distributions (Sadoti et al. 2013). However, there have been few, if any, attempts to link citizen science-based large spatial data sets of observations with multiple ALS-based parameters. ALS data has been used to explain bird observations, but often birds have been counted during the study and the focused study areas have often been relatively small, varying from hectares to square kilometres (e.g. Hinsley et al. 2008; Jones et al. 2013), while in comparison, our focus area was some magnitudes wider in size. In Switzerland, a database of the Ornithological Institute and nationally available LiDAR were used to calculate horizontal and vertical structural heterogeneity, to model the occurrence of four bird species, including the three-toed woodpecker, in 1 km^2 grids for an area of 21,620 km^2 (Zellweger et al. 2013). Structural characteristics obtained by remote sensing were found to be promising for developing species and habitat distribution models, which is also supported by our experiences. We used ALS-based parameters to evaluate the occurrence of birds as surrogates of overall biodiversity values on observation sites at landscape scale, and despite some difficulties with the preparation of data (Fig. 3), the developed methodology revealed many interesting outcomes, which we discuss in detail next.

Distribution curves of all 41 species observations indicated a slight emphasis on forests with greater height and density, thus indicating properties more typical of older forest than the random data set shows. However, there was no big difference between the two data sets. This was probably due to the heterogeneity of analysed bird species: there are many functional differences between species, and habitat preference patterns vary, for instance, in relation to dominating tree species. Instead of using data for all 41 species, it would be better to select one or a few species for which the response to environmental characters is more specified, when aiming to detect forests of certain characteristic-referring anticipated biodiversity values. In our results, the red-breasted flycatcher, for example, seems to prefer spruce forests of more than 30 m high, which indicates old forests with a possibly fairly natural state in the observation sites. The red-breasted flycatcher and the three-toed woodpecker prefer mature and old-growth forests (see Virkkala and Rajasärkkä 2006; Roberge et al. 2008; Pakkala et al. 2014), and thus they occur in habitats with large trees (particularly spruces), measured here also as high above-ground biomass. The occurrence of the thrush nightingale on the sites with a higher proportion of Scots pine than random sites is quite an unexpected result for deciduous forest-edge dwelling species. However, in the study region, herb-rich pine-dominated esker forests are common (Heikkinen 1991) and also suitable for the thrush nightingale. The result might also be partly due to the error in the original data source locations, following the higher observation distance (254 m of 75 % fractile).

Observation distance also affects the usability of certain species as an indicator of ecosystem structural properties. The Eurasian nightjar had a relatively high proportion of spruce forest in its occurrence buffer, although the nightjar is known to prefer pine-dominated forests (Väisänen et al. 1998, Valkama et al. 2011). This might be due to uncertain positioning of the observations in the original data sources (especially Tiira). The 75 % fractile of observation distances for the Eurasian nightjar was 234 m. A longer distance between the observer and the bird increases the risk of making a mistake when locating the observation on a map. In contrast, the detection distance was much less in the case of the red-breasted flycatcher and three-toed woodpecker (50 and 28 m, respectively), indicating that ALS data provide quite accurate indicators of the surrounding forest parameters for these species.

Methodological improvements and future options

We were encouraged by the usability of bird observation data as a species database for the analysis. However, we identified several opportunities for improving either the quantity or sensitivity of the census data. We used only the most detailed observations, while the vast majority of the observations lack exact bird coordinates in the Tiira database, and the Atlas databases contain quite a rough spatial resolution from 100 m up to 10 km. Observations including information on the bird's location cover many areas quite well in Southern Finland, where many people are observing birds. Because the results of the combined bird and forest structure data sets describe the relevant ecological characters, as expected, the data sources used in this study can be used similarly in future investigations. This is also encouraging for citizen scientists, whose work can thus support future ecosystem assessments. However, it is recommendable that exact bird locations should be reported, for example, in Tiira and Atlas mapping, to improve the data quality in future studies. Unfortunately, there are many remote areas where the observation density is much lower, and if the method could be improved so that observer only data could also be used, for example using buffering as described in Fig. 3 and Appendix 1, the number of observations would increase remarkably. Secondly, the analysis could also cover bird species from other biotopes, such as agricultural environments, wetlands, and mires. Widening the scope to other species groups and taxa would bring much more information about the functioning of the entire ecosystem. From that point of view, vascular plants and insects would be valuable groups for further analysis. For instance, there are active volunteer associations observing butterflies and moths, as well as bats, nowadays in Finland. In Sweden, so-called Artdatanbanken ("species data banks") cover plenty of observations from ordinary people. An obvious future path for deepening the results of this paper will go towards species-specific habitat modelling, which has been done in many studies already (e.g. Bradbury et al. 2005; Järvinen 2010; Tattoni et al. 2012), but seldom based on observation material from large databases. Remote sensing data, especially ALS, could be used more efficiently outside the forest ecosystems in characterising, for example, mire vegetation patterns. More work is also needed to find out which parameters predictable with ALS are the most useful in terms of biodiversity, for instance in relations to functional traits of certain taxa. Climate change is an important issue to take into account in future studies, because, for example, functional properties in a community may change due to changes in species composition. Long time series might also enable the application of the used data for observing the responses of species to climate change (see, e.g., Brommer et al. 2012; Virkkala and Lehikoinen 2014; Virkkala et al. 2014). Phenological variation could also be an interesting additional functional vegetation characteristic, which could rather easily be added to the analysis that we did (Coops et al. 2013).

Essential biodiversity variables for ecosystem assessments

We estimate that our approach offers a good starting point for searching for a balanced combination of ecosystem-specific and spatially explicit biodiversity indicators, which are urgently needed for emerging studies of ecosystem service trade-offs. There is evidence, for example, that conservation of high carbon storage and biodiversity might have mutual benefits (Thomas et al. 2013). In addition, in our case, observation sites for all the 41 species had slightly higher values in relation to above-ground biomass than random sites, which supports this presupposition. Unfortunately, we did not yet have the opportunity to test our results with other parallel ecosystem services, such as soil carbon budgets, nitrogen deposits, and retention, which have been quantified for the study area (Holmberg et al. 2015).

Related to the determination of EBVs in boreal forest ecosystems, we can provide measures for several EBV classes using the methods and data described in this paper—at least for species populations, species traits, community composition, and ecosystem structure, if using the divisions of Pereira et al. (2013). The missing elements still include genetic composition and ecosystem function; while for the latter, the approach presented by Holmberg et al. (2015) could bring solutions in future ecosystem assessments. Even though the presented examples of EBV classes are very rough, we believe that integrating them into environmental monitoring programmes is possible, and can be done following, at least partially, the methods described in this paper. However, more elaboration is needed before the optimal set of biodiversity indicators can be selected for assessing the relationships between ecosystem functioning and ecosystems' capacity to deliver ecosystem services.

Conclusions

Ecosystem assessments are dependent on qualified, spatially and temporally comprehensive data. Such data are often collected either in various national or regional monitoring schemes, or, to a greater extent, by volunteer citizen scientists. Recent developments in remote sensing and availability of ALS data provide the possibility to cover and map large areas, and to get detailed information on habitat structure in a cost-efficient manner. This paper describes a method by which those two components of modern landscape ecological research, meaning remote sensing and a large citizen-science database, can be combined for ecosystem assessments.

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