



**Detecting changes in essential ecosystem and biodiversity properties- towards a Biosphere
Atmosphere Change Index: BACI**

Deliverable 3.4: Synthesis dataset of biodiversity in plants and birds



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Contents

Overview and aims of D3.4	3
Temporal change in plants functional traits	3
Introduction	3
Methods	3
Data deliverable: maps of community weighted trait mean	6
Bird community dynamics	10
Introduction	10
Methods	11
Bird monitoring data	11
Analyses used to harmonise and synthesise the bird data	12
Data deliverable: maps of temporal beta diversity	13
References	15

Overview and aims of D3.4

The purpose of WP3 is to provide ground data that represent ecosystem-scale processes in a form that is useful for calibrating, validating and interpreting space data. The specific aims of deliverable D3.4 is to centralize data on the spatial distribution and temporal dynamics of bird and plant communities and harmonise the data into a format that allows the calibration, validation and interpretation of space data, particularly the data generated in other BACI WPs. Specifically, we have compiled, harmonized, and synthesized data on plant and bird communities and provide two spatially explicit data sets of temporal change at the scale of Europe: (1) community weighted plant functional trait mean, (2) bird community dynamics. While the plant data is potentially valuable for calibrating, validating and interpreting space data, the bird data is valuable for interpreting space data.

Temporal change in plants functional traits

Introduction

Plants cover a large proportion of Earth's terrestrial surface and therefore represent one of the main sources of variation in EO-derived variables. The majority of EO satellites since the 1970s have recorded spectral reflectance of visible and near-infrared wavelengths. Spectral reflectance in this range of the spectrum is highly sensitive to three broad vegetation attributes: three-dimensional vegetation structure, the biochemical composition of leaves and the physiological activity of those leaves. At large spatial scales and at coarse resolution, these attributes can be broadly classified into global biomes. However, within biomes and even within more narrowly defined vegetation types, there is substantial variation in the three-dimensional structure of individual canopies, in the biochemical composition and physiological functioning of leaves from different species, between individuals of the same species and even within canopies of a single individual. Representing these continuous gradients in vegetation structure and functioning by biomes (structure) or plant-functional types (functioning) hinders progress in two important research venues, which are both addressed in the BACI project. First, mapping and monitoring of biodiversity, functional diversity, and ecosystem stability. Second, biophysical change mapping and monitoring (Reichstein *et al.*, 2014) and the related earth system functioning, fluxes of energy and matter, and global climates. To an extent, this variation in plant structure and functioning can be quantified using plant functional traits. Therefore, we here provide data on continuous gradients in vegetation structure and functioning. Data expected to be of value for calibrating, validating and interpreting space data.

Methods

Vegetation survey data

We requested access to data from the sPlot data repository¹, an initiative started in 2013 by a consortium of scientists and hosted at the German iDiv research centre². sPlot integrates data from national and other large vegetation plot surveys. It is global in scope, but sampling is highly geographically biased with large parts of the world being poorly represented. Nonetheless, sampling density in Europe is high, with >900,000 plots in the sPlot version that we had access to (July 2016). For Europe, these vegetation plots largely coincide with data contained in more established repositories, such as the European Vegetation Archive (EVA), but sPlot distinguishes itself from other repositories by merging data on community composition (from vegetation plots) with data on plant

¹ <https://www.idiv.de/splot>

² <https://www.idiv.de>

functional traits. sPlot uses species mean trait values from the TRY database³. The version of TRY that was used in our version of sPlot contained data for 40,791 plant species and included 18 plant functional traits (Table 2).

Table 1 Plant functional traits from TRY included in this study.

Trait
Specific leaf area (SLA)
Plant height
Seed mass
Leaf dry matter content
Stem density
Leaf area
Leaf N per dry mass
Leaf P per dry mass
Leaf N per unit area
Leaf fresh mass
Leaf N/P ratio
Leaf C per dry mass
Leaf $\delta^{15}\text{N}$
Stem conduit density
Seed number per reproductive unit
Wood vessel length
Seed length
Dispersal unit length

Computing maps of community weighted trait means

By matching species in the community composition data with species names in TRY, we were able to calculate community weighted mean (CWM) trait values for each plot. It is important to recognise that not all species recorded in the plot surveys have an entry in TRY. In total, 62% of all recorded species had a record in TRY. However, it must be pointed out that this estimate may be inaccurate as the taxon was not always resolved to species level in the community data, but sometimes only to genus or family level. The percentage of species within each plot for which trait values are known is shown in Fig. 3a. In Fig. 3b species are weighted by their relative cover values. These figures show that in the majority of plots all species were represented in TRY and that the species that were represented in TRY account for the greatest portion of vegetation cover within these plots. We therefore conclude that the calculated CWM trait values should be good estimates for the vast majority of plots.

³ <https://www.try-db.org>

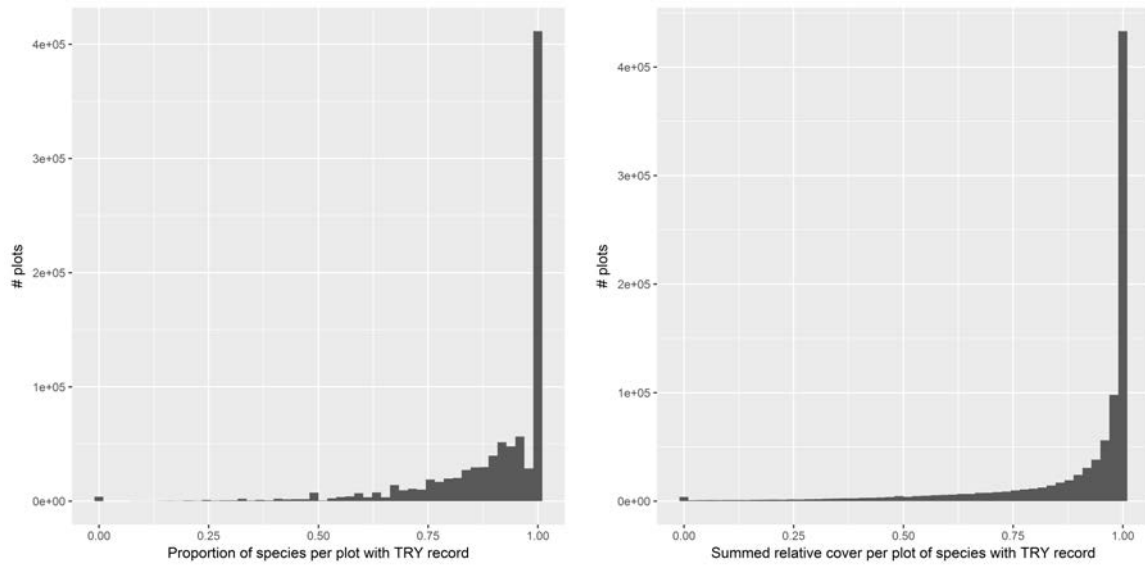


Figure 1 Representation of species in TRY. a) The number of vegetation plots as a function of proportion of species within each plot that is represented in TRY. b) As a), but weighted by each species' relative cover.

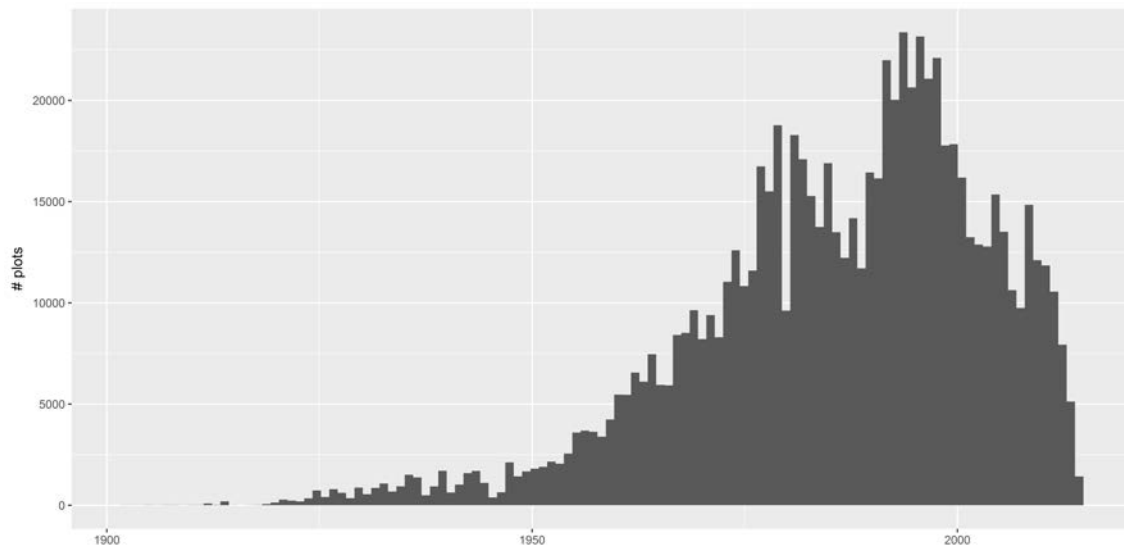


Figure 2 The number of plots in sPlot within the study area as a function of time

We calculated CWM values for all traits for all plots and then aggregated plots spatially into a 1/12 degree grid. This resolution is arbitrary, but is consistent with several long-term satellite products (e.g. the GIMMS AVHRR data). Moreover, this resolution is coarse enough to not have many empty grid cells in the more densely sampled areas while it is fine enough to detect spatial gradients in CWM trait values that coincide with environmental gradients. Maps of CWM trait values are shown in Fig. 5.

Some plot surveys predate 1900, but the majority of plots were surveyed after 1950 (Fig. 4). For our product we only used data between 1970 and 2010, which coincides with the satellite era. This period contains 69% of data points within the study area. To provide the opportunity for temporal

analyses, especially with satellite data, we split the data up by decade i.e. four decades from 1970 to 2010. Again, the choice of decadal time steps is somewhat arbitrary, but the sparsity of the data does not allow much smaller time steps. As an example, Fig. 7 shows decadal time steps in plant height, but these data are available for all 18 traits.

Finally, we recognise that changes in plant community composition and the associated CWM of trait values may result from abrupt shifts in human land-use change, rather than from gradual change driven by slower processes such as climatic change, nitrogen deposition or increased atmospheric CO₂. To accommodate the separation of these driving processes, it is necessary to quantify compositional turnover within a particular land-use or land cover type. However, reliable land cover maps at sufficiently high resolution are only available for approximately the past 20 years. We therefore used a subset of the sPlot data, 2001 to 2010, and intersected it with the 2006 Corine land cover map to estimate CWM trait values per 1/12 degree grid cell, for each of nine broad semi-natural land cover classes from the Corine map. Fig. 8 shows the example for plant height over the period 2001-2010 in the nine selected semi-natural land cover types.

Data deliverable: maps of community weighted trait mean

We produced 234 spatial layers, quantifying the temporal dynamics of 18 plant functional traits during the satellite era. For all 18 traits there are four decadal time steps (1970s-2000s) and for the 2000s the data has been split up by land cover type. These data quantify biodiversity change at a functional level and are thus valuable independently. Furthermore, the observed trends in plant functional composition may be reflected in Earth observation variables. Such potential links with space data will be explored in D8.5.

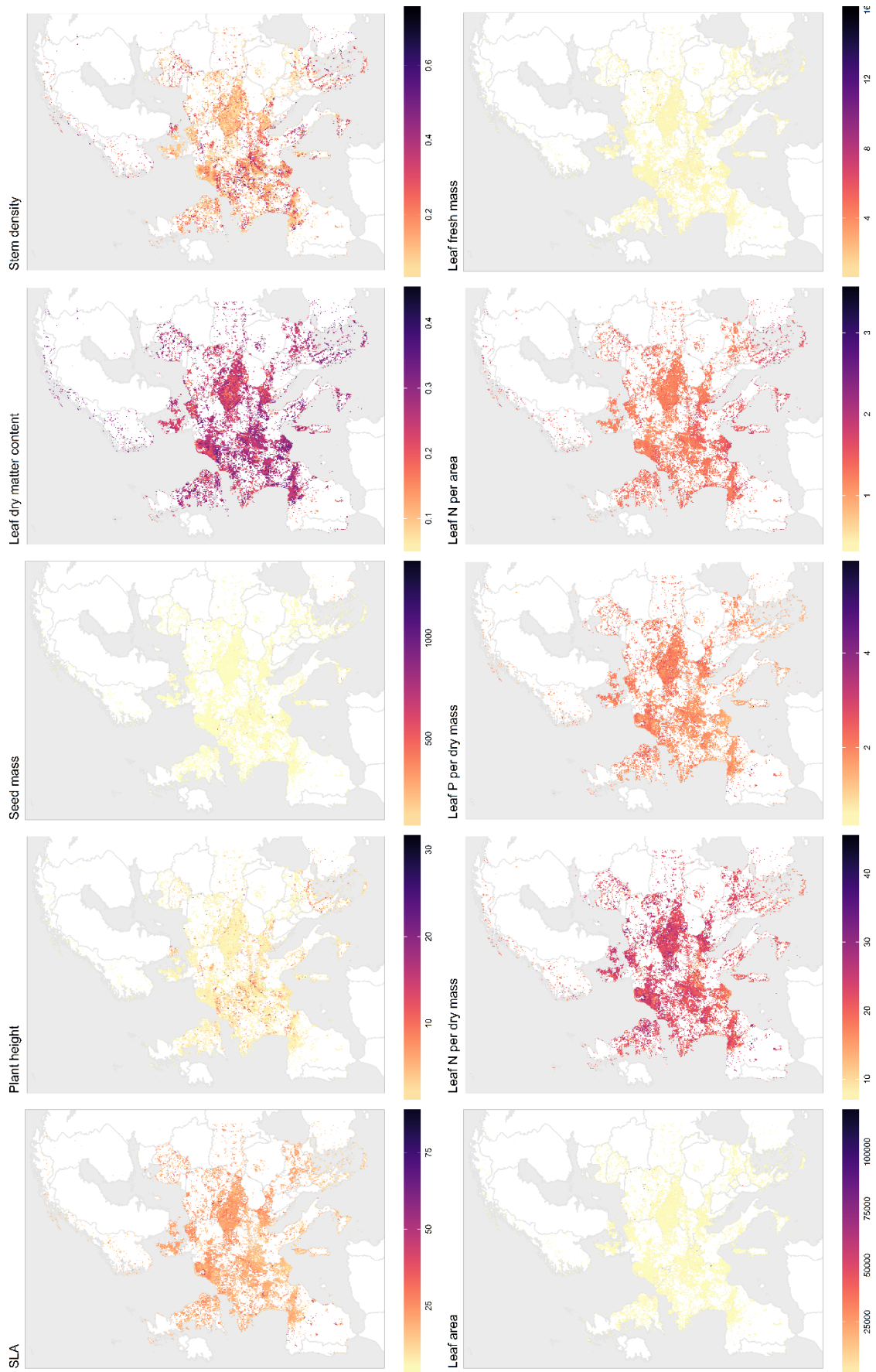


Figure 3 Community weighted trait values. Grid resolution is 1/12 degree.

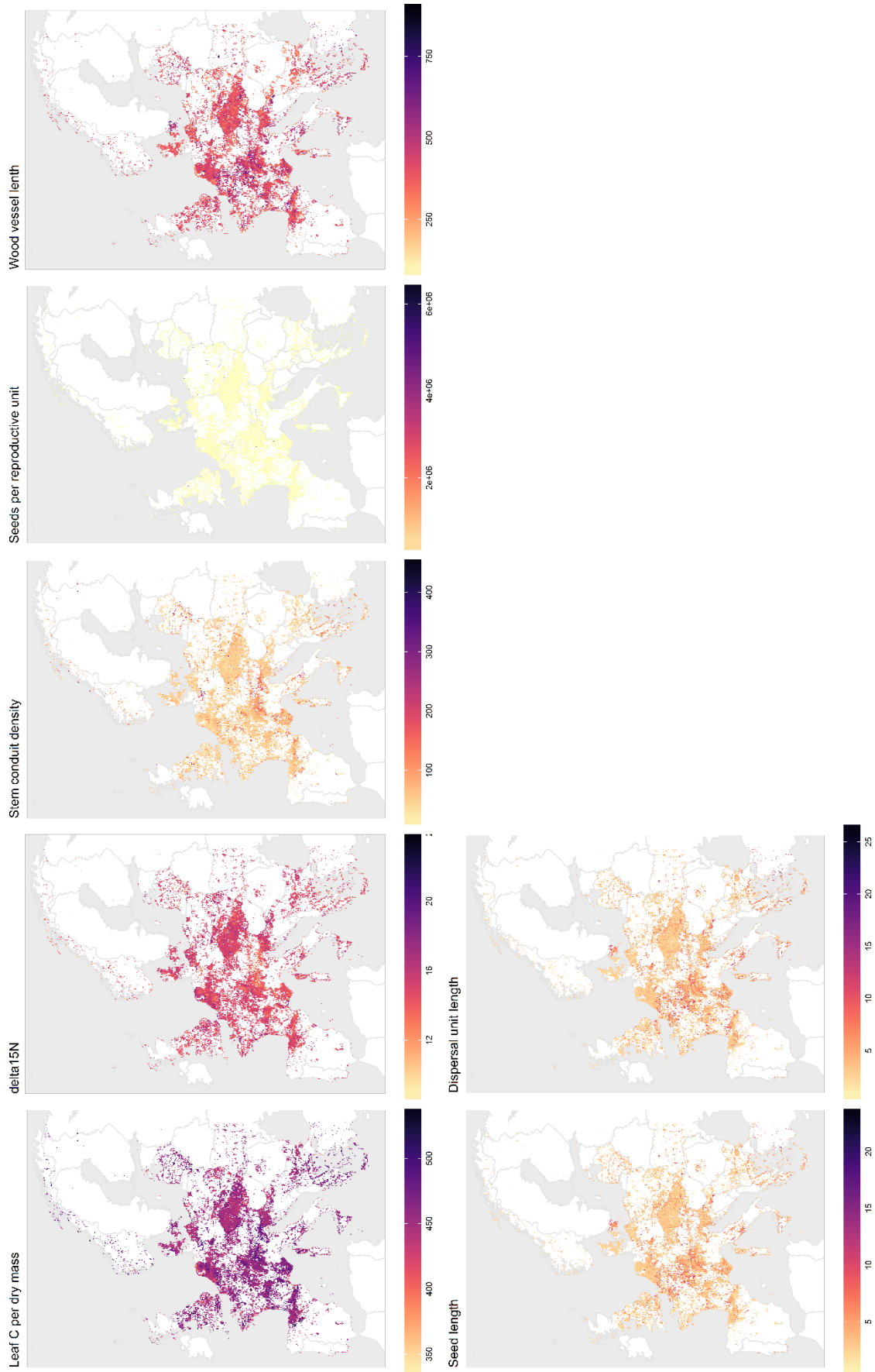


Figure 4 Community weighted trait values. Grid resolution is 1/12 degree.

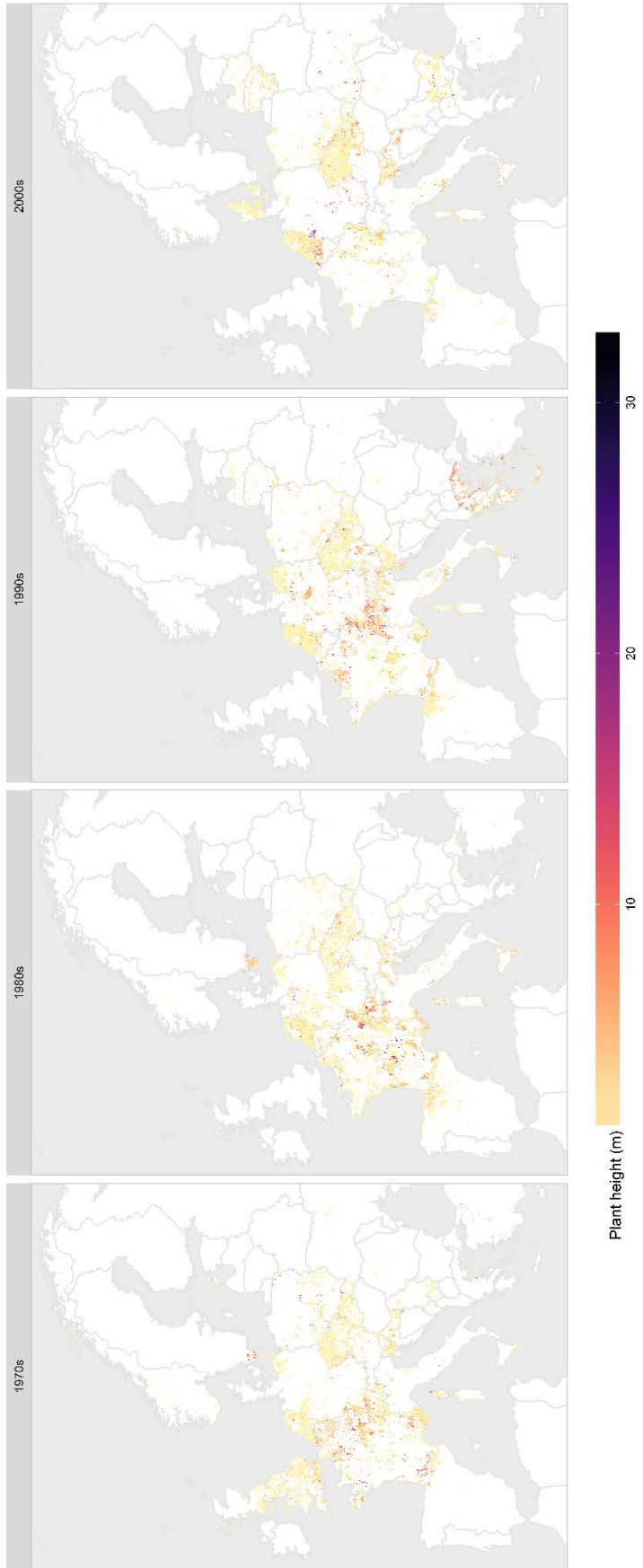


Figure 5 CWM plant height per decade. The maps have a resolution of 1/12 degree.

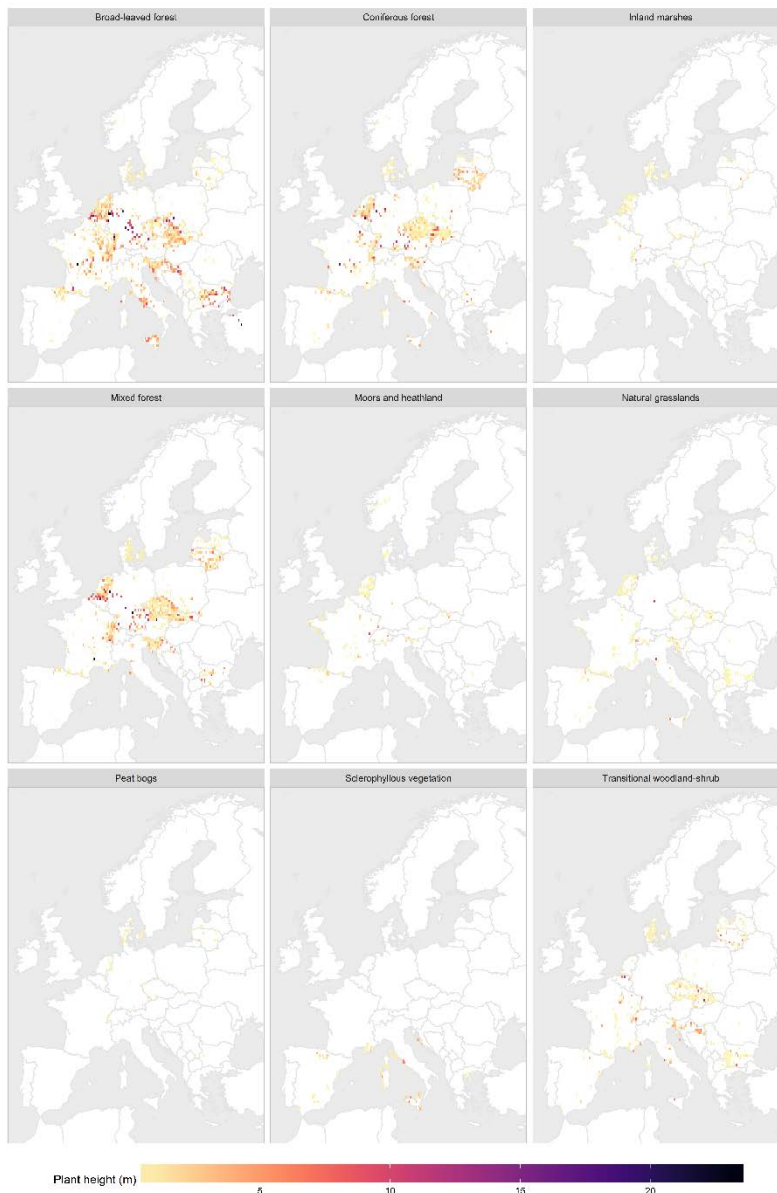


Figure 6 CWM plant height during the 2000s in nine semi-natural vegetation types. Land cover types were taken from the Corine land cover map. The data have a resolution of 1/12 degree but for clarity the resolution for the plotted maps was aggregated to 0.25 degree.

Bird community dynamics

Introduction

Unlike plant communities, bird communities do not affect Earth Observation (EO) variables by their physical presence, structure and composition. In other words, bird communities are generally not directly observable from space, at least not with the spatial resolution of the sensors currently exploited in BACI (e.g. Sentinel). Nevertheless, spatiotemporal dynamics of bird populations and communities may serve as indicators of environmental change that can be detected using EO. The primary reason for this is that the population dynamics of many bird species is tightly linked to land cover and human land-use. As such, bird population dynamics and community dynamics may be used to interpret anomalies detected in space data. On the other hand, it is difficult to use bird

population and community dynamics for validating and calibrating space data, as there are many other variables that affect bird population dynamics. Examples of important drivers of bird population dynamics that are not readily observed from space include human hunting pressure, disease and the soil and surface water concentrations of certain toxins, e.g. heavy metals. However, the population and community dynamics of different bird species may not respond to the environmental perturbations immediately. These possible lags effects additionally, challenges the use of bird population and community dynamics as indicators of environmental change using EO variables. With these challenges and opportunities in mind, we have aimed at synthesising a data set that is both novel and useful.

Methods

Bird monitoring data

The data harmonised and synthesised focusses on Europe, as bird monitoring programs in several European countries have collected high-quality survey data, often over considerable periods. These data have not been aggregated previously, which is in sharp contrast with e.g. the North American Breeding Bird Survey that has been publicly available and has thus been explored and analysed in many scientific studies and publications. The fragmented nature of European bird survey data, plus the fact that in many countries there is no official protocol by which to apply for access to the data, makes gaining access particularly challenging. Nonetheless, we gained access to data from six countries/regions: Sweden, Denmark, Poland, the UK, France and Catalonia. Of these, Sweden, Denmark and Catalonia cover BACI focus areas. The data we gain access to is unique, but also challenging to harmonize. Survey methods vary by country. There are differences in sampling design (i.e. how sampling sites are chosen and which sites are surveyed each year), the area of each sampling site, sampling duration, whether surveys are conducted in plots or along transects, etc. The details are summarised in Table 1 and Figure 1.

Table 2 Description of sampling schemes for different bird monitoring programs in different countries.

	Sampling unit	Extent?	Obs. unit	Obs. units / Sampl. unit	Obs. unit dim.	Duration / obs. unit	Surveys yr ⁻¹	Time span
Sweden	Transect	8 km	Transect section	8	1000×200 m	30-40 min km ⁻¹	1	2000-2015
Denmark	Transect		Point	10-20	200 m radius	5 min	1	2000-2016
Poland	Grid cell	1×1 km	Transect section	10	200×200 m	40 min km ⁻¹	2	2000-2015
England	Grid cell	1×1 km	Transect section	10	200×200 m	60 min km ⁻¹	2	
France	Grid cell	2×2 km	Point	10	200 m radius	5 × 2 min	2	2001-2015
Catalonia	Transect	3 km	Transect section	6	500×200 m	30-40 min km ⁻¹	2	2002-2015

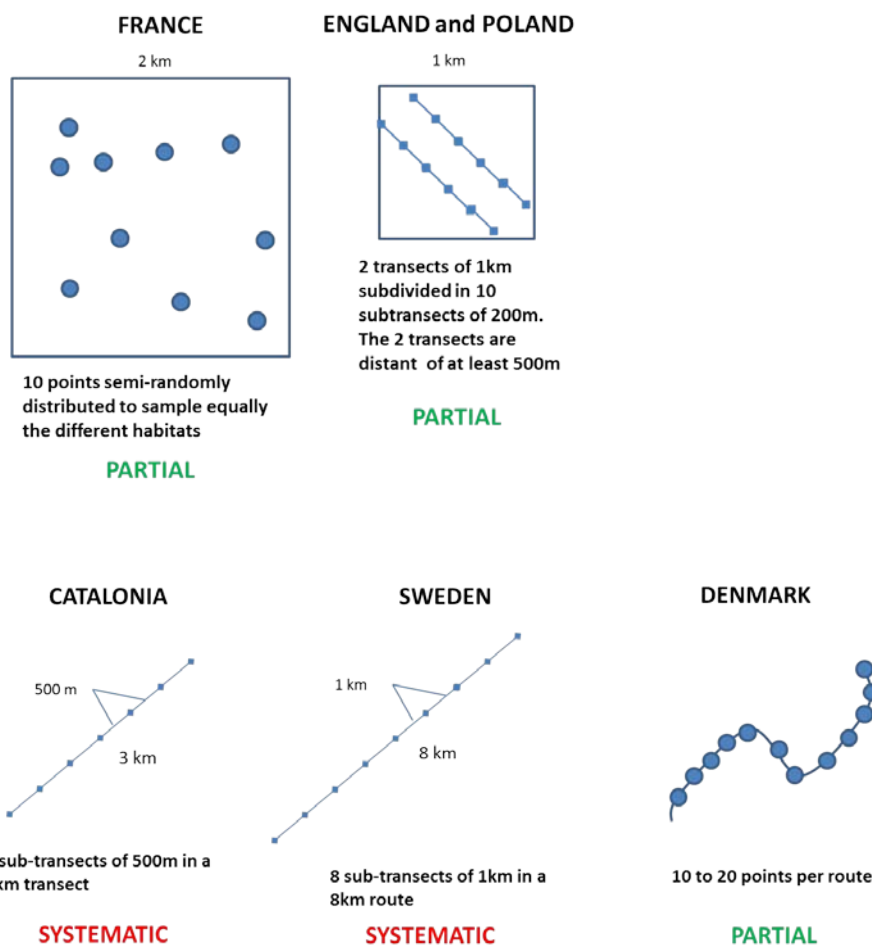


Figure 7 Graphical representation of the sampling schemes summarised in Table 1.

Analyses used to harmonise and synthesise the bird data

Since survey methods differed significantly between countries, it is unlikely that abundance estimates can be harmonised in a meaningful way. Major error would result from uncertainty in the sampling area of transect-based methods, variation in observer skill, variation in detectability of different species, variation in detectability of birds in different vegetation types (e.g. dense forest vs. open pasture) and variation in detectability with weather conditions. To avoid spurious comparisons, we therefore focus on presence/absence data. Although some of the the same points listed above may apply to presence/absence data, we assume perfect detection in order to make comparisons between sites and between countries. Perfect detection is a reasonable assumption when skilled observers follow strict sampling protocols, such as described above.

Community composition varies spatially as various traits and processes affect species ranges, including environmental tolerances or preferences, dispersal, biotic interactions such as competition and so on. To quantify the dissimilarity among biological communities we use beta diversity, which has been explored extensively in the literature. Beta diversity is generally defined as the ratio between regional (gamma) and local (alpha) diversity (Whittaker, 1960). However, communities can differ in different ways. Principally, there may be a difference in species richness but one community is a subset of the other, communities may differ in composition but not in the number of species (richness), or both composition and richness may differ. A multitude of indices to estimate

beta diversity have been developed to address these different types of community dissimilarity, many of which are based on one of several distances (or dissimilarity) metrics. Here we adopt the approach of (Baselga & Leprieur, 2015) , who estimate overall beta diversity but also partition overall beta diversity into a nestedness component (one community is a subset of another community) and a turnover component (communities differ in composition, but not in richness).

The concept of beta diversity can be extended to temporal change. Instead of estimating differences in composition between communities in different geographic locations, it is possible to quantify differences in community composition at the same locations but at different times.

For each pair of subsequent years, for each site, we calculated overall temporal beta diversity, the nestedness component of beta diversity and the turnover component of beta diversity. Then, for each pair of subsequent years, we up-scaled the site-specific beta diversity estimates to 0.5×0.5 degree grid cells, by averaging beta diversity estimates of all sites within a grid cell. This yielded time series of all three beta diversity estimates from 2001 to 2015.

Data deliverable: maps of temporal beta diversity

The time series of the three beta diversity metrics from 2001 to 2015 are made available. The year-to-year dissimilarities are summarised in Fig. 2, where temporal beta diversity indices were averaged over all years of the time series. The maps show strong latitudinal gradients of temporal beta diversity and both of its components, with higher temporal change at higher latitudes.

The delivered data provide interesting patterns of temporal change in bird communities. Although this work is primarily about delivering data, not interpreting data, the patterns of temporal change in bird communities that emerged call for further inspection and exploration. Overall temporal beta diversity and both the nestedness and turnover components of beta diversity were substantially higher in Sweden than in the other countries. Climate change at these high latitudes, particularly in the form of warming, has been large relative to the more temperate regions covered by the rest of this dataset. A potential relationship with the observed changes in bird communities should therefore be explored. However, other kinds of strong ecological change that affect vegetation have also been recorded in northern Scandinavia, including increased reindeer grazing (den Herder *et al.*, 2008; Cohen *et al.*, 2013) and outbreaks of geometrid moths (Hagen *et al.*, 2007; Jepsen *et al.*, 2009). These types of changes are likely to be captured by the BACI-Index and we will explore relationships between bird community change and the BACI-Index under D8.5.

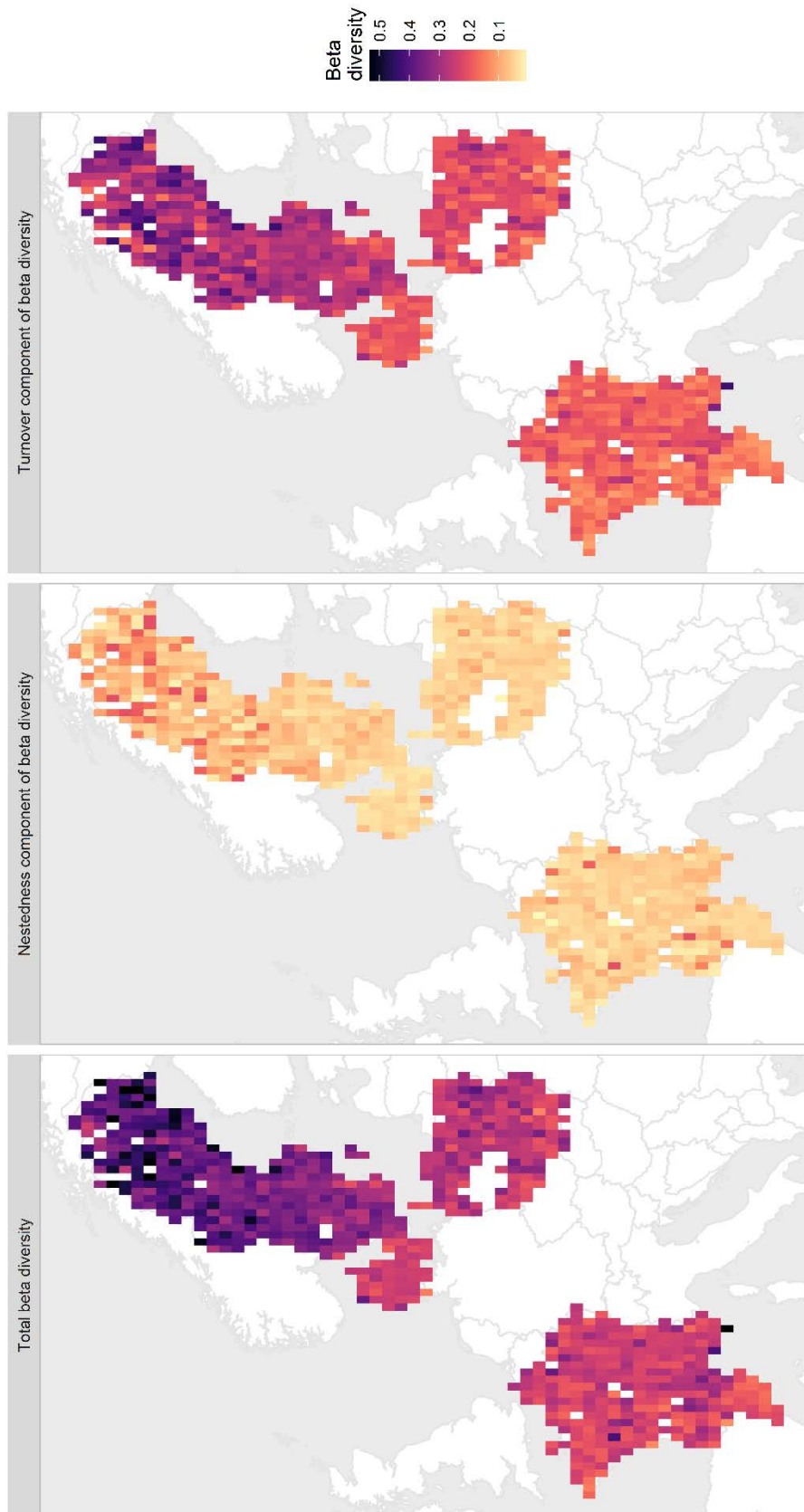


Figure 8 Temporal beta diversity of bird communities between 2001 and 2015. The maps show dissimilarity between subsequent pairs of years, averaged over all years of the time series. Plot-scale measurements were aggregated by averaging to 0.5 degree grid cells.

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