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

Deliverable 8.3: <u>Validation of European space data layers for biodiversity monitoring</u>

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Responsible of the deliverable	Signe Normand (Aarhus University) Phone: +4587154345 Email: signe.normand@bios.au.dk
Contributors:	Robert Buitenwerf[1], Jens-Christian Svenning[1], Signe Normand[1] [1] Aarhus University
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Introduction

Background

Essential ecosystem variables such as gross primary production (GPP) and net primary production (NPP) are strongly forced by environmental variables such as atmospheric CO_2 concentration, temperature, photosynthetically active radiation and vapour pressure deficit between leaf interior and atmosphere. These relationships are exploited by dynamic vegetation models and Earth system models to estimate ecosystem variables across large areas. However, essential ecosystem variables also depend strongly on the composition of plant communities. For example, GPP is simply the summed carbon that is assimilated by all plants in a community. Similarly, NPP is GPP minus all carbon respired by plants in the community. Since evolution and life history constrain physiological traits like maximum carbon assimilation rate, respiration rate and stomatal conductance (REF), the taxonomic composition and ecological history of plant communities are expected to be important predictors of essential ecosystem variables.

Vegetation modellers have dealt with this biological diversity by classifying species into broad functional types and assigning distinct physiological rates and trade-offs to each functional type. On the other hand, community ecologists have used species as the fundamental level of organisation to study relationships between diversity (i.e. species richness) and essential ecosystem variables, specifically primary productivity. These relationships have been an important study topic since the 1970s, and has resulted in a long-standing and vigorous debate among ecologists. The debate has generated a large number of hypothesises regarding the shape of the bivariate relationship and the underlying mechanisms that produce it. Interestingly, most hypotheses have also been supported by individual empirical datasets (Grace, et al. 2016). In a recent effort to bring some order to this chaos, a large empirical dataset with global extent was used to test competing hypotheses in a multivariate framework (Grace, et al. 2016). The study explained significantly more variance in species richness than any previous bivariate study, strongly suggesting that multiple interactions, including feedbacks, between driving and response variables need to be considered in order to understand the relationship between species richness and productivity. In turn, this suggests that several ecological mechanisms operating in concert ultimately determine the shape of the relationship.

One major finding by Grace et al. was that productivity increases linearly with species richness, suggesting a direct causal relationship between species richness and primary productivity. However, despite these advances in understanding the relationship between species richness and primary productivity, much remains unclear about how biodiversity and ecosystem functioning (e.g. essential ecosystem variables) affect each other in general. For example, nearly all terrestrial studies exploring the diversity productivity relationship focus on grasslands, where community dynamics are relatively fast and where above ground biomass can be measured easily and accurately by clipping. Little is known about other vegetation types (but see Musavi et al. (2017)). Furthermore, little is known about how diversity may affect other essential ecosystem variables, such as actual evapotranspiration (AET), water use efficiency or fire regimes. Productivity is a direct consequence of plant growth, which is a primary indicator of fitness for plants in nearly all communities. The ecological relevance of ecosystem variables like GPP and NPP is therefore immediately clear, but fitness consequences are less obvious for ecosystem variables such as AET.

Another feature of many studies is that biodiversity has primarily been represented by species richness. The species is an indicator of phylogenetic history, which constrains the spectrum of functional properties that a species can express. However, genetic diversity may be an unreliable indicator of functional properties, resulting in a possible mismatch between species richness and ecosystem functioning. One potential reason for such a mismatch is the concept of functional overlap,

or functional redundancy. If different taxa overlap in their functional properties, then taxonomically different communities may function equivalently. Quantifying the functional properties of taxa or communities directly, may therefore result in greater explanatory power when predicting ecosystem functioning, or vice versa.

A greater degree of functional overlap is also expected to increase the resilience of a community to perturbations, e.g. environmental shocks such as droughts. The hypothesis is that when certain species are negatively affected by a perturbation, other species with similar functional properties are able to substitute the lost processes and thus buffer the stability of ecosystem functioning.

Questions and hypotheses

In this study we therefore ask how the spatial distribution of taxonomic and functional diversity affects temporal dynamics in ecosystem functioning, where temporal dynamics are quantified as both directional change and as resilience. We hypothesise that, within vegetation types, productivity (LAI) increases with richness and that vegetation resilience also increases with richness.

Deliverable aims

The aim of this deliverable is to understand how data layers from EO satellites may be used for biodiversity monitoring across Europe. The logical first step in this process is to quantify the relationships between current spatial patterns of biodiversity and EO-derived data on ecosystem structure and functioning. To allow a temporal aspect to the analysis, we use EO data products that already have a substantial temporal extent.

Although a new generation of satellites, particularly the Sentinel missions, are likely to substantially improve our capability to quantify ecosystem variables from space, direct observation of biodiversity from EO data is likely to require greater spectral resolution (imaging spectroscopy, i.e. hyperspectral) and improved measures of the three-dimensional structure of vegetation (e.g. estimated using lidar) (Jetz, et al. 2016). We therefore focus on a better understanding of the bi-directional relationships between spatial patterns of biodiversity and temporal change in ecosystem variables.

Methods

LAI data

To quantify vegetation dynamics we used LAI derived from the MODIS sensor on NASA's Terra satellite. LAI for broadleaved vegetation can be interpreted as the one-sided leaf area (m^2) per ground area (m^2) and as half the total leaf area per ground area for needle-leaved vegetation (Myneni et al. 2015). LAI therefore contains information on both the structure of vegetation (e.g. broadleaved vs conifer forest) and productivity (e.g. dense vs sparse canopies). The LAI product is provided as 8-day composite images at 500 m resolution (Myneni, Knyazikhin and Park 2015). Quality assessments for each pixel allow further sub-setting and masking of poor quality data.

In this study we use monthly LAI time-series as the vegetation response. Monthly time-series were constructed from the original 8-day time-series by weighted averaging. LAI time-series were cleaned of records with sub-optimal quality. Months with very low LAI (<0.5) were omitted from the analysis.

Climate data

We used time-series of three environmental variables as predictors, all taken or calculated from CRU data version 4.00, which provides monthly climate variables in 0.5° grids. We used mean temperature, percent cloud cover and an aridity index, which we calculated as potential evapotranspiration - precipitation. Temperature and moisture availability are fundamental drivers of plant physiological activity and cloud cover is used as a proxy for incoming photosynthetic radiation. Months with temperatures below 0° C were omitted from the analysis.

LAI resilience

To quantify vegetation resilience we adapted the method developed by (Seddon, et al. 2016). The method aims to quantify the sensitivity of vegetation change, in our study LAI, to changes in climate variables. There are two major parts to this analysis, which is performed for each LAI pixel and is done separately for each month of the year.

First, vegetation anomalies are calculated by subtracting the long-term mean. The same is done for climate variables. By dividing the vegetation anomalies by the climate anomalies, a sensitivity score is generated. For example, a large vegetation anomaly that coincides with a small climate anomaly suggests that the vegetation is highly sensitive to fluctuations in that climate variable. However, in this example it is also possible that the large vegetation anomaly is not related at all to the small climate anomaly. To account for this possibility, the overall effects of climate variables on vegetation in an area are used to weight the sensitivity scores.

To generate these weights, climate variables are z-scaled and rotated using a PCA. The principal components are used as the predictor variables in a linear regression, where vegetation (here LAI) is the response variable. Climate variables are rotated with PCA before the regression with vegetation to remove potential collinearity between the predictor variables. Following Seddon et al. (2016), we also included a 1-month lag effect (AR1) to account for possible memory effects. PCs with significant slopes are identified and transformed back to the units of the original variables, by multiplying the slopes with the variable loadings on the significant PCs. The resulting values are summed for each climate variable, which then indicate the contribution of each climate variable to explaining variance in the vegetation response variable. These are used to weight the sensitivity score.

The above steps are performed separately for each month. Monthly weights are averaged for each climate variable, to attain a single value that indicates the effect (weight) of a climate variable on vegetation throughout the year.

Lastly, the vegetation sensitivities to individual climate variables are multiplied by their respective weight. As a final summary, the weighted sensitivities to all climate variables are summed to yield a single vegetation sensitivity index (VSI). The reciprocal of VSI can be interpreted as resilience.

Modifications

One potential issue in the approach described above is the z-scaling of predictor variables before PCA. Scaling is necessary to achieve equal importance of variables with different units, but PCA maximises the amount of explained variance in the original variables: first in PC 1, then in PC 2 and so on. In the subsequent PC regression, this can lead to a situation where PCs with small eigenvalues, i.e. PCs that capture little of the variance in the original predictor variables, are strong and significant predictors of the response variable (LAI). This situation may be undesirable, as it results in a low overall amount of explained variance in the response variable. We therefore explored "Y-aware scaling" of predictor variables before performing the PCA and principal components regression, which can significantly increase the amount of explained variance in a PC regression (Zumel 2016, Mount and Zumel 2017). Instead of scaling predictor variables by their own standard deviation (z-scaling), predictor variables are expressed in the units of the response variable (hence "y-aware"). This is easily achieved by fitting a linear regression between predictor and response and multiplying the predictor values by the slope of that regression. The y-scaled predictor variables are also centred on zero. These Y-scaled predictor variables are then used in the PCA and subsequent PC regression, from where the analysis steps are identical to those described above for z-scaled variables.

Biodiversity

We used taxonomic and functional diversity as estimated by Ordonez and Svenning (2016). These estimates are based on range maps for angiosperm 2702 species from the Atlas Florae Europaeae[1] (AFE). The AFE distribution maps are grids with a resolution of approximately 50×50 km.

Taxonomic diversity was estimated as species richness. Functional diversity was quantified using functional richness i.e. the multi-dimensional range of trait values within a community (Mason, et al. 2005) and functional dispersion, which is a measure of the multi-dimensional variance in trait values within a community (Laliberté and Legendre 2010). These measures were based on four functional traits: specific leaf area (SLA; cm^2 g^{-1}), seed mass (mg), maximum stem height (m) and wood density for woody species and stem specific density for non-woody species (kg m^{-3}).

Trait data was collated from several sources and gaps in the data were imputed using a Multivariate Imputation Chained Equations procedure (Ordonez and Svenning 2016). Traits were $\log_{10}$ transformed and normalised (mean = 0, SD = 1) before calculating diversity metrics.

Since it can be argued that LAI from EO data primarily quantifies differences between woody vegetation types, we also used a second set of diversity maps that includes only woody species >1.5 m (both angiosperm and gymnosperm). For the woody-only data leaf area (m^2) was used as an additional trait variable. The woody-only maps have not yet been published.

Spatial diversity in land cover

The 50×50 km grid cells of the AFE data provided an opportunity to classify the diversity of land cover types within each of those cells. For land cover data we used nine (see Fig. 6) semi-natural vegetation types from the 2006 Corine land cover map, which is a spatial grid with 100×100 m cells. We calculated the relative abundance of each land cover type and used that to calculate Simpson's diversity index: $1/\sum_{i=1}^{S} p^2$, where p is the relative abundance of species i.

Results and Discussion

In preparing the data layers described above, we investigated a large number of potential interactions between the seven different measured of diversity (species richness, functional richness, functional dispersion: for both angiosperms and woody species, and land cover diversity), temporal LAI change and eight different measures of LAI resilience (total VSI, VSI for temperature, aridity and cloudiness, for both z-scaled and y-aware scaled variables. In the following section we report a subset of these results and add some preliminary interpretation.

LAI resilience

Vegetation sensitivity (VSI) to climate variables showed a spatially aggregated pattern (Fig. 1), with areas of high VSI throughout Europe. Particularly parts of Scandinavia, the Alps and south-eastern Spain show high VSI.

Figures 2 and 3 show that our y-aware scaling of the climate variables in the calculation of climate weights (PC regression) results in markedly different VSI patterns than the z-scaled variables by Seddon et al. (2016). The units are not directly comparable, but the y-aware scaling appears to produce ecologically more realistic results, with generally greater vegetation sensitivity to aridity in in southern Europe, where vegetation is typically water limited in summer. The y-aware scaling also results in lower vegetation sensitivity in northern Scandinavia (Fig. 3) compared to the z-scaled approach (Fig. 2), where vegetation is not typically water limited. Although further comparisons are required to determine the relative advantages and disadvantages of either method, our modification to vegetation sensitivity index calculation looks promising.

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[1] https://www.luomus.fi/en/atlas-florae-europaeae-afe-distribution-vascular-plants-europe

Diversity

Maps of functional richness and dispersion for angiosperms are presented in Ordonez and Svenning (2016). In Figures 4 and 5 we show the spatial patterns of functional richness and dispersion for woody species > 1.5 m. Functional richness can mostly be summarised as increasing along a north to south gradient, with higher richness in mountainous areas and warm oceanic climates superimposed. The Functional dispersion map is more complex.

Vegetation change, resilience and Diversity

Taking LAI pixels (500×500 m) as observation units, the relationship between the total VSI score and the functional richness of tree communities differed substantially between vegetation types (Fig. 6). For example, in broad-leaved forest VSI increases briefly at low functional richness, but then declined with increasing functional richness. This suggests that LAI in the functionally most diverse tree communities is the least sensitive to climatic fluctuations. This is what may be expected from theory, when species within a community show overlap in their functional attributes. Similar patterns were found for other forest types, but non-forest vegetation types showed less clear patterns.

Taking AFE pixels (50×50 km) as observation units, a strong positive relationship was found between the richness of woody species and temporal LAI change between 2000 and 2016 (Fig. 7). It is possible more diverse communities allow for greater temporal LAI change to be attained, but it is also possible that more diverse areas are most subject to change in other drivers of LAI, such as climate or land use. Such potential interactions stress the need to calculate variables like VSI, which take environmental drivers of change into account.

Finally, it needs to be acknowledged that the traits on which our functional diversity metrics were based are not likely to capture all relevant aspects of plant physiology and functioning that affect LAI of a community. Leaf area, stem height and SLA are likely to be informative traits, but they do not fully capture relative growth rates or shade (in)tolerance, which are both likely to be important predictors of LAI change in a community.

Conclusions

Preliminary analysis indicate that the data may provide novel opportunities to quantify interactions between biodiversity and ecosystem functioning. To advance both the data and the ideas presented here we intend to develop this work for publication. We intend to use relevant variables generated by WP 2, 4 and 5 when they become available. The generated data layers will be available, both internally to BACI and publicly.
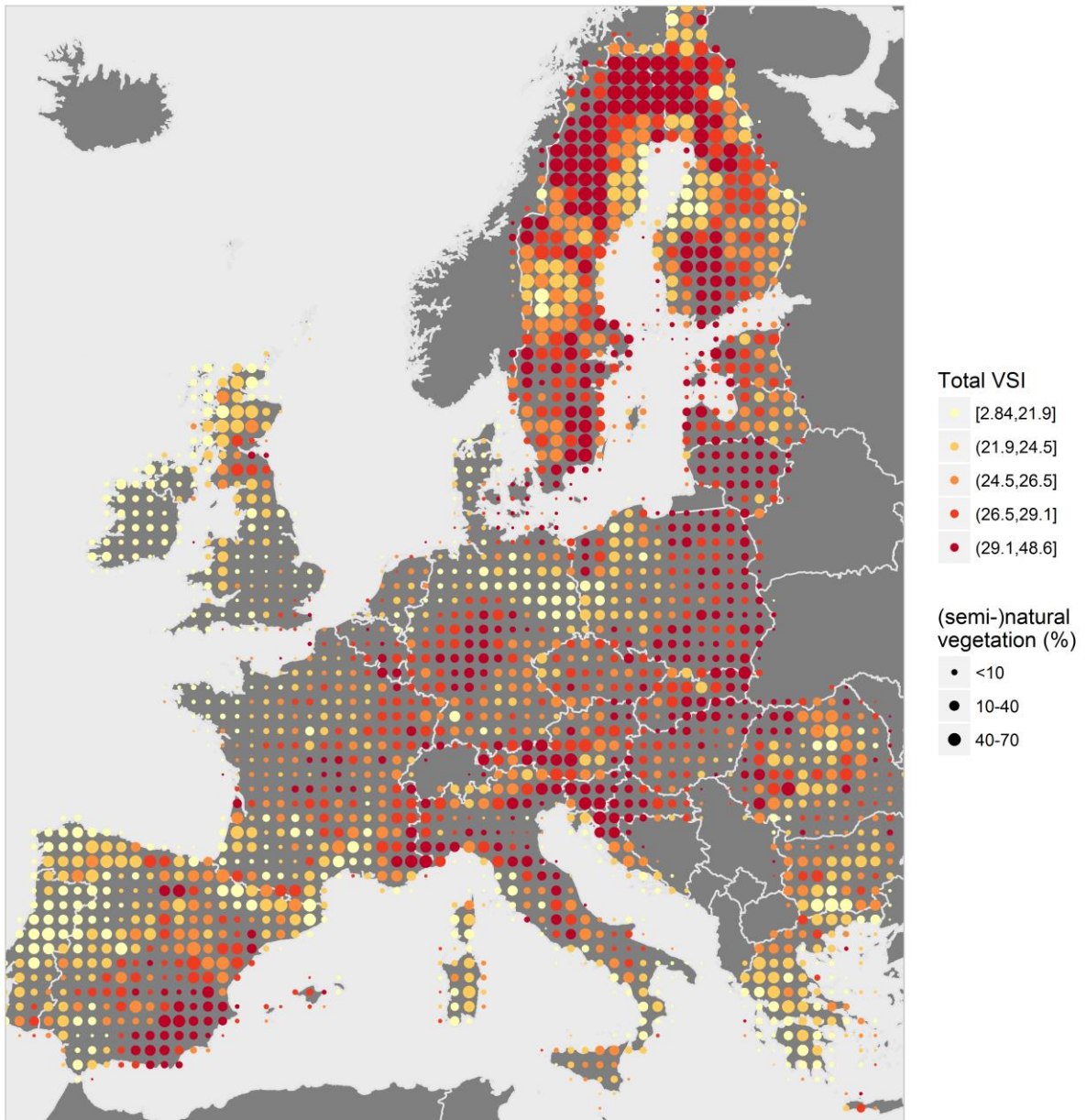
Figure 1: Vegetation (LAI) sensitivity to the combined effects of temperature, aridity and cloud cover.
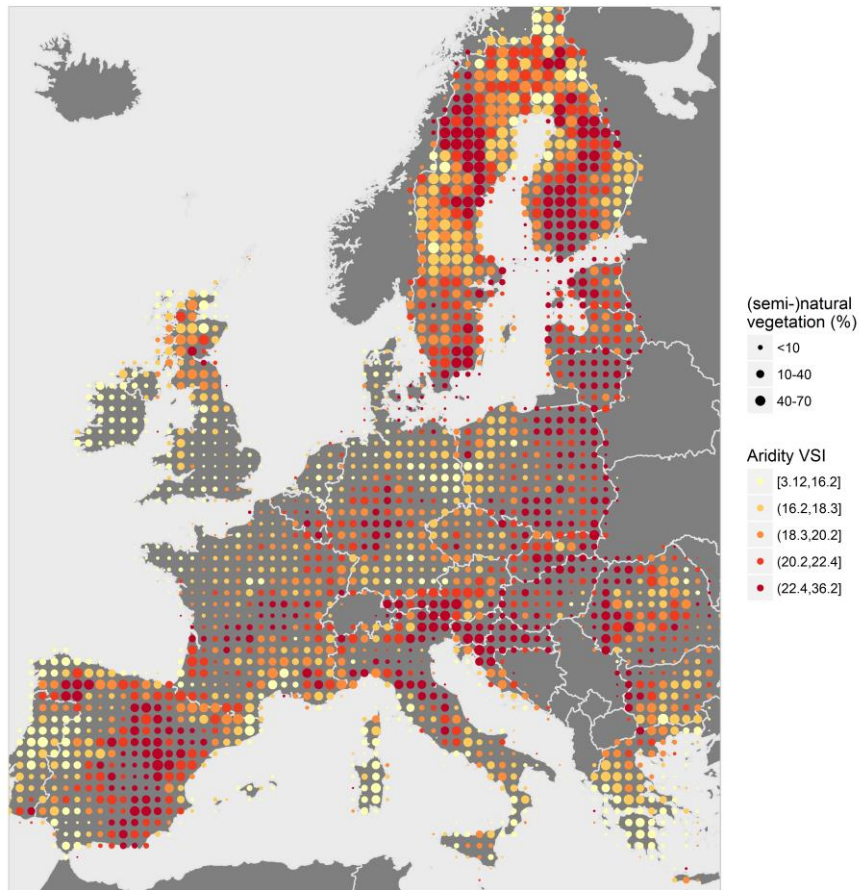
Figure 2: Vegetation (LAI) sensitivity to aridity. The VSI index was calculated using z-scaled climate variables (see text for explanation).
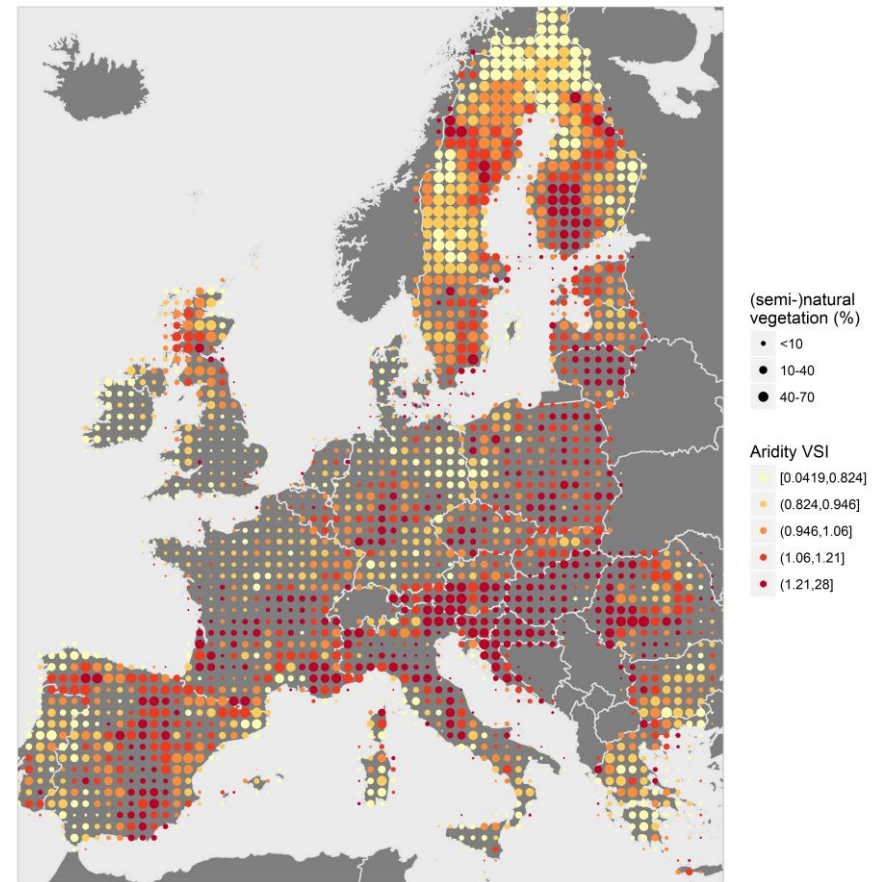

Figure 3: Vegetation (LAI) sensitivity to aridity. The VSI index was calculated using y-aware scaled climate variables (see text for explanation).
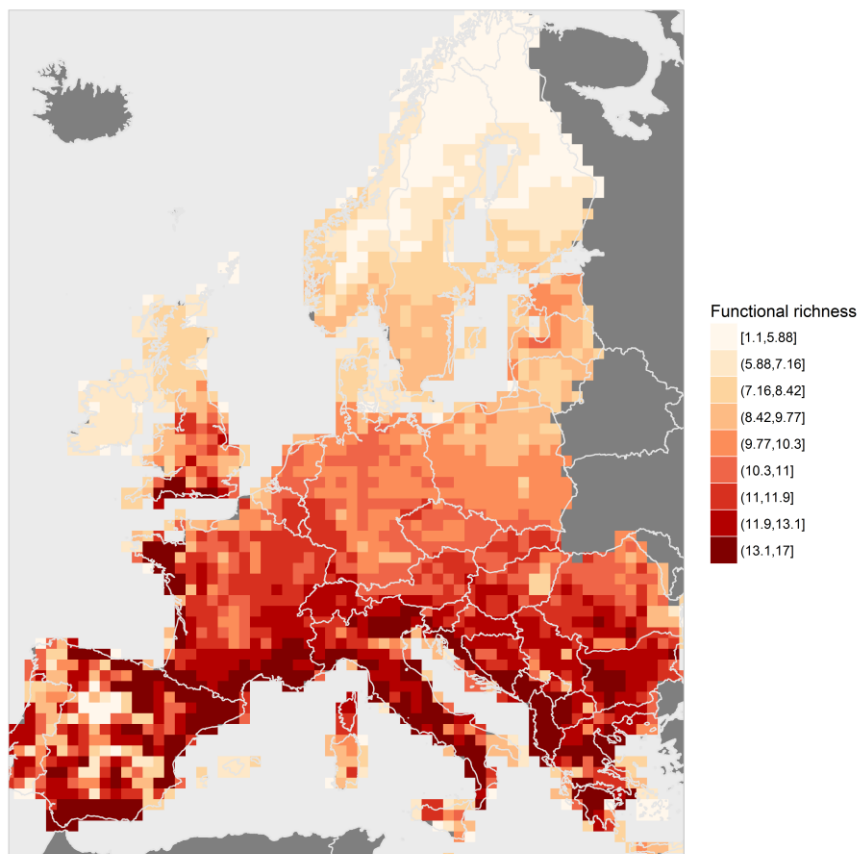
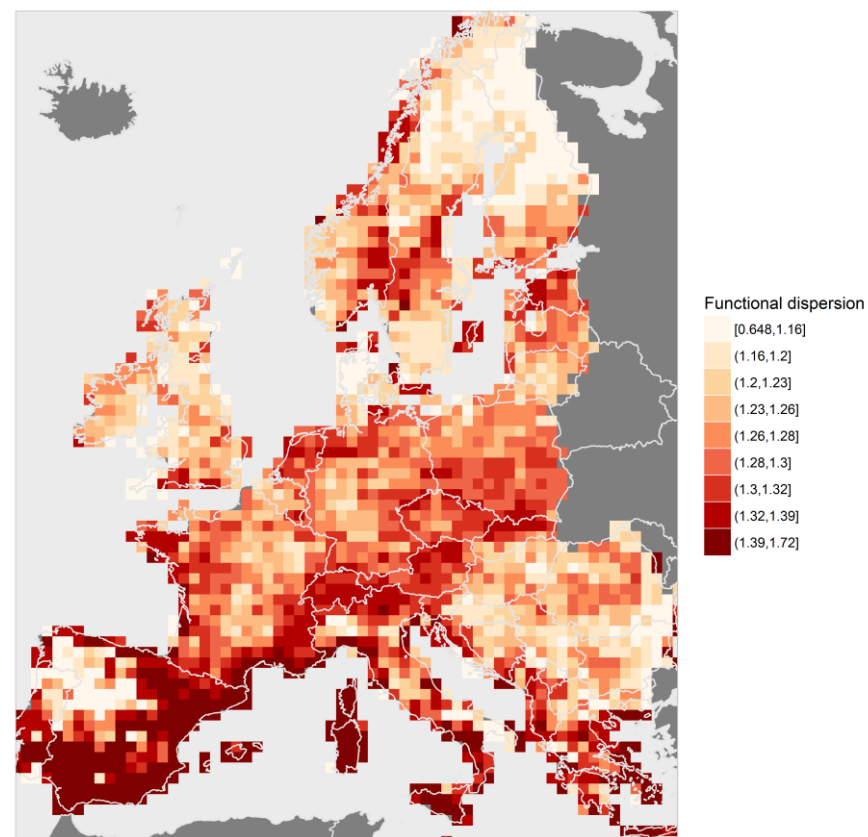Figure 4: Functional richness of woody species.

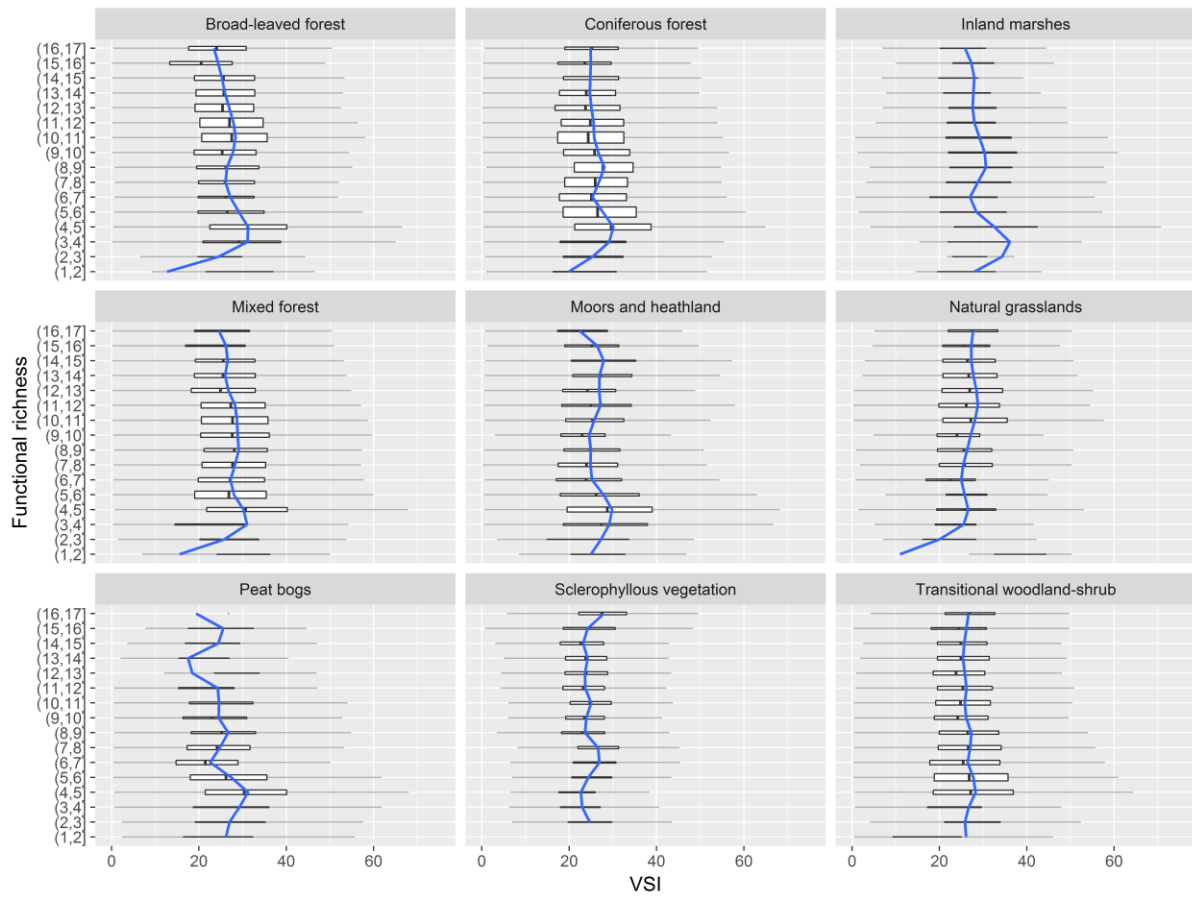Figure 5: Functional dispersion of woody species.

Figure 6: The relationship between climate sensitivity of vegetation and functional richness. VSI is vegetation (LAI) sensitivity to the combined effects of temperature, aridity and cloud cover. Functional richness is for woody species >1.5 m only.
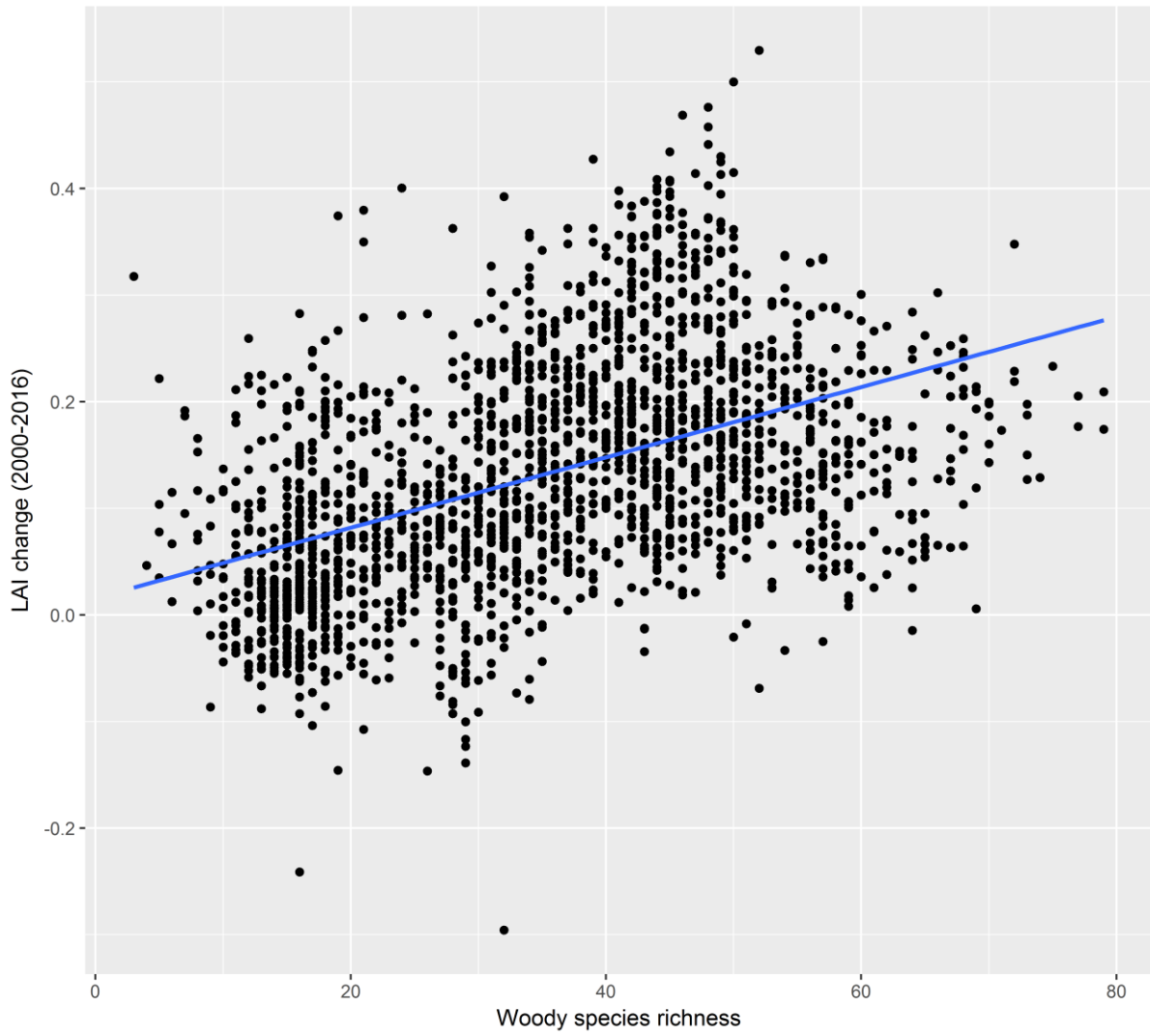
Figure 7: Temporal LAI change is greater in communities with more woody species.

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