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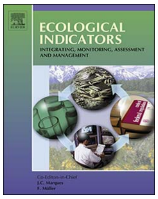

Brief article

Remotely sensed spatial heterogeneity as an exploratory tool for taxonomic and functional diversity study

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ABSTRACT

Assessing biodiversity from field-based data is difficult for a number of practical reasons: (i) establishing the total number of sampling units to be investigated and the sampling design (e.g. systematic, random, stratified) can be difficult; (ii) the choice of the sampling design can affect the results; and (iii) defining the focal population of interest can be challenging. Satellite remote sensing is one of the most cost-effective and comprehensive approaches to identify biodiversity hotspots and predict changes in species composition. This is because, in contrast to field-based methods, it allows for complete spatial coverages of the Earth's surface under study over a short period of time. Furthermore, satellite remote sensing provides repeated measures, thus making it possible to study temporal changes in biodiversity. While taxonomic diversity measures have long been established, problems arising from abundance related measures have not been yet disentangled. Moreover, little has been done to account for functional diversity besides taxonomic diversity measures. The aim of this manuscript is to propose robust measures of remotely sensed heterogeneity to perform exploratory analysis for the detection of hotspots of taxonomic and functional diversity of plant species.

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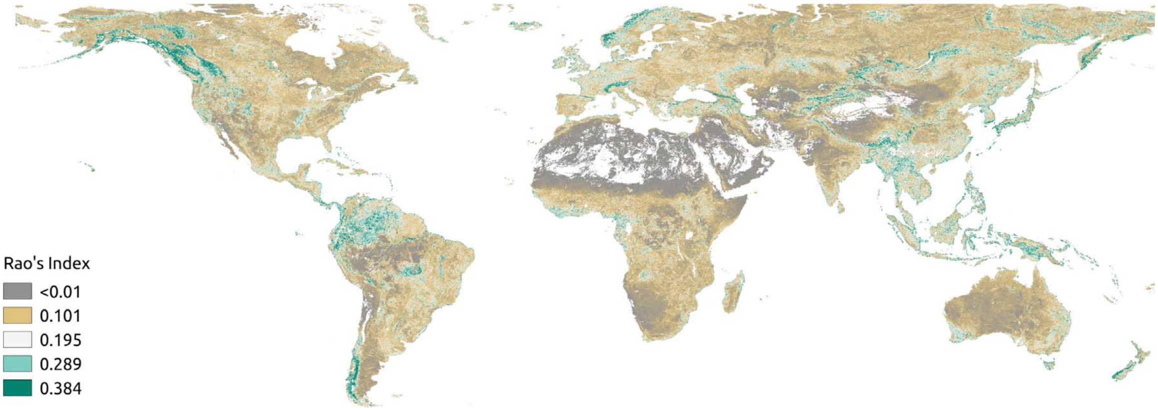


Fig. 1. Rao's quadratic diversity metric applied to an NDVI map of the world (date 2016-06-06, http://land.copernicus.eu/global/products/ndvi), resampled at 2 km resolution with a moving window of 5 pixels. As far as we know, this is the first application of Rao's *Q* metric to satellite data covering the whole world. The complete R code is provided in Appendix 1.

1. Introduction

The assessment of biodiversity for a conservation purpose is difficult to undertake via field survey (Palmer, 1995). Species richness is the simplest, most intuitive and most frequently used measure for characterizing the diversity of an assemblage (Chiarucci et al., 2012; Chao and Chiu, 2016). In nearly all biodiversity studies, however, the compilation of complete species census and inventories often requires extraordinary efforts and is an almost unattainable goal in practical applications. There are undiscovered species in almost every taxonomic survey or species inventory (Palmer, 1995). Consequently, a simple count of species (observed richness) in a sample underestimates the true species richness (observed plus undetected), with the magnitude of the negative bias possibly substantial. In addition, empirical richness strongly depends on sampling effort and thus also depends on sample completeness. Statistically sound sampling of biodiversity requires several assumptions to be fulfilled in order to allow reproducibility and credible estimation. The crucial assumption is a random sampling design, i.e. the random spatial distribution of samples based on standardised statistical sampling procedures, which generally hampers rapid sampling mainly due to logistic problems. In fact, complex ecosystems might not be systematically surveyed or temporarily monitored by conventional biodiversity surveys because of high costs, challenges to access the sampling sites or the lack of historical data (Roy and Tomar, 2000).

From this point of view, remote sensing is an efficient tool allowing to cover large areas over a short period of time, hence providing key information on the spatio-temporal variation of biodiversity.

This is overall true (from a biodiversity conservation viewpoint), considering the fact that recent Life Cycle Impact Assessment (LCIA) studies acknowledged the importance of understanding the human induced cause–effect mechanisms shaping the decline or improvement of biodiversity and thus the provision of biodiversity-related ecosystem services (Moran et al., 2016).

Recently, Souza et al. (2015) explicitly observed that landscape-oriented approaches to evaluate biodiversity loss in a LCIA context are still lacking (Scheiner et al., 2000; Dungan et al., 2002). Changing the focus from individuals to communities, entire ecosystems and biomes might represent a key concept to a correct and widely usable LCIA model.

The aim of this paper is to propose novel approaches using remote sensing to perform exploratory analysis for the detection of hotspots of taxonomic and functional diversity of plant species. The complete R code (R Core Team, 2017) used to implement all the presented algorithms is available in Appendix 1.

2. Heterogeneity measurement from remote sensing and the relationship with taxonomic diversity

According to the spectral variation hypothesis (Palmer et al., 2002) the larger the spectral heterogeneity the higher will be the niche availability for different organisms to survive. Hence, the higher the spectral variability of an environment the higher might be its biodiversity. Such a hypothesis has been widely tested with taxonomic data (Rocchini, 2007; Rocchini et al., 2016; Schmeller et al., 2017) and often resulted in a positive statistical relationship although the link does not always hold true (Schmidtlein and Fassnacht, 2017).

The variability over space is generally tested relying on a local calculation of heterogeneity based on a moving window in a satellite image and connecting it to human-related and ecological/geographical drivers shaping biodiversity in the field.

For instance, spectral heterogeneity measurements, based on the calculation of indices of variability of neighboring pixels in an image have been recently proposed as a possible solution to support the assessment of land use impacts on biodiversity (Rugani and Rocchini, 2017). Such approaches might help detecting the geographical location of hotspots of diversity and their temporal changes in a straightforward manner. Fig. 1 shows as an example the Rao's quadratic diversity in two dimensions over the world, theoretically depicted by Rocchini et al. (2017), calculated from Normalized Difference Vegetation Index (hereafter NDVI) based on Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data. As far as we know, this is the first application of Rao's *Q* metric to satellite data covering the whole world. The complete R code is available in Appendix 1.

Given a certain number of reflectance values in a portion of a remotely sensed image (usually a moving window of $n \times n$ pixels), such metric is defined as the expected difference in reflectance values between two pixels drawn randomly with replacement from the set of pixels:

$$Q = \sum \sum d_{\mathrm{ij}} \times p_i \times p_j \tag{1}$$

where d_{ij} is the spectral distance between pixel i and j and p_i is the relative proportion of pixel i (i.e. in a window of n x n pixels $p_i = 1/n^2$). The spectral distance d_{ij} can be calculated either for a single band or in a multispectral system, thus allowing to consider more than one band at a time (Rocchini et al., 2017). If Q is calculated for a single band, the resulting value can be directly related to the variance of the reflectance values within the considered set of pixels, a well-known metric for summarizing the spatial complexity of remotely sensed images (Rocchini et al., 2010). Rao's *Q* metric weights the distance among pixel values in a spectral space and their evenness. In practice, higher diversity in this example is related to the relative distance of NDVI spectral values and to relative evenness in the distribution of such

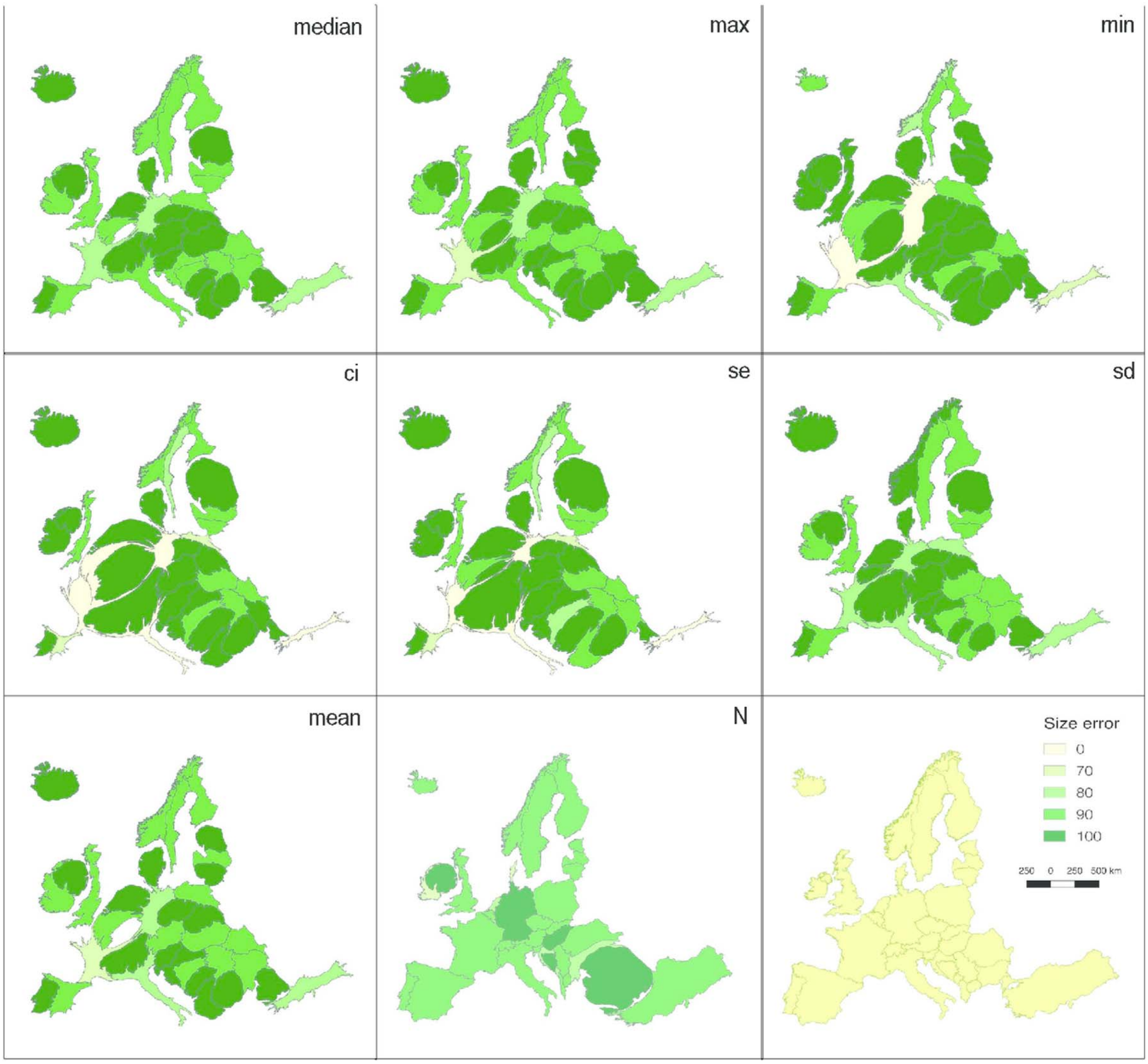


Fig. 2. Cartograms showing univariate statistics of the Rao's *Q* metric in Europe, distorting the shape of units (in this case, as an example, countries) depending on the relative value of the index. ci = confidence interval at 95%, se = standard error, sd = standard deviation. The free software ScapeToad (https://scapetoad.choros.ch/) was used to generate the cartograms.

values.

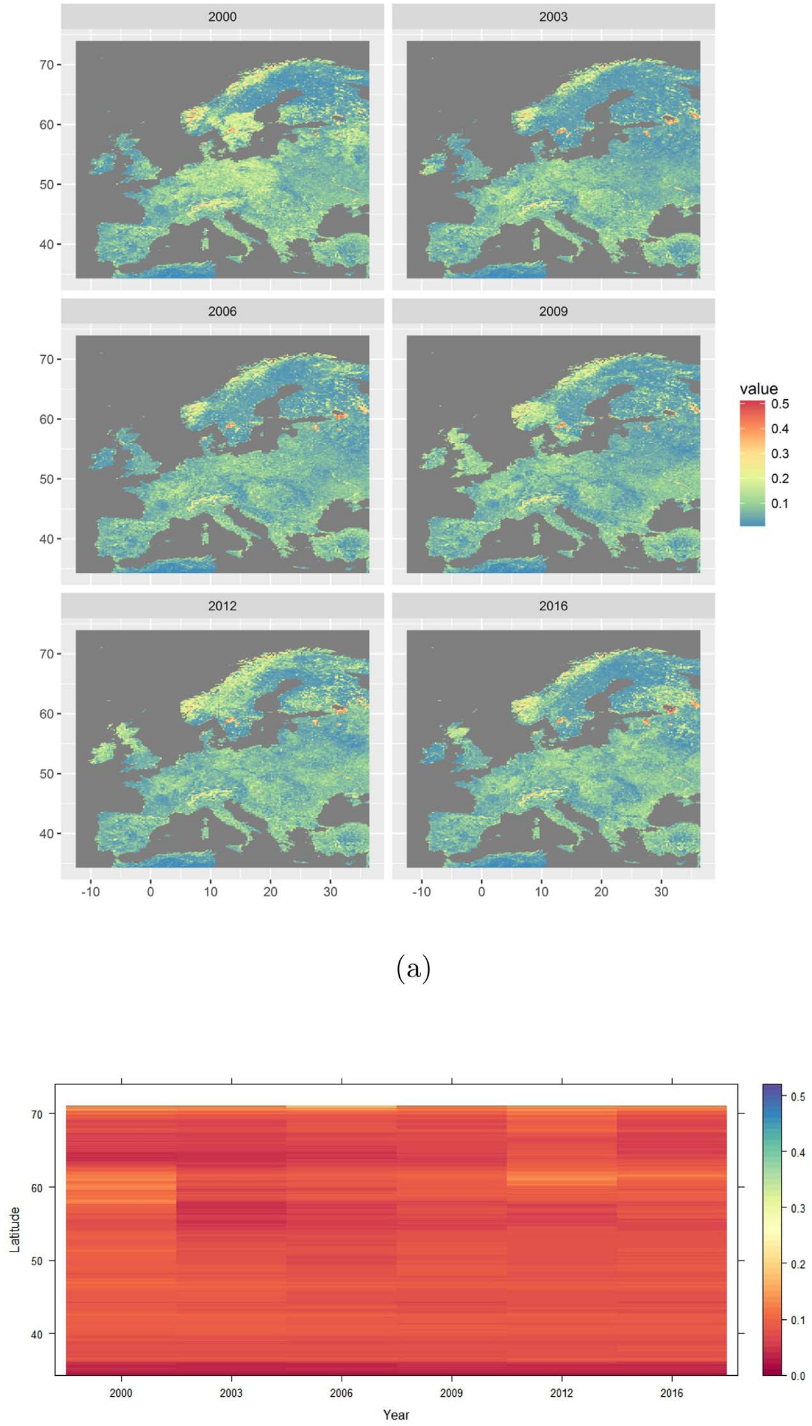
Once applied at large spatial scales, Rao's quadratic diversity might reveal differences among different countries, areas, habitats or land use types to be potentially linked to related ecosystem services.

In this view, the use of cartograms (Fig. 2, Gastner and Newman, 2004) can help to show the differences among units (in this case, different countries are shown, as an example) in terms of Rao's *Q*, by distorting each unit depending on the relative value of the entropy index reported in Fig. 1 (restricted to Europe in Fig. 2).

Using multitemporal remotely-sensed imagery, such a map might prove useful to detect abrupt changes, referred to as "catastrophic regime shifts", which can lead to an alteration in the provision of ecosystem services, such as water provision (Guttal and Jayaprakash, 2009). An example is provided in Fig. 3 in which MODIS tiles (NDVI, 16-days product, June, Appendix 1) have been used to calculate Rao's *Q* at a spatial resolution of 1 km. Care might be taken considering the first years after the launch of the Terra MODIS satellite (launched December 18th 1999), in which calibration was still in process but provisional data were acquired (e.g. year 2000). As pointed out by Rocchini et al. (2017) variations at large spatial scales (large extent) are mainly due to the variability of climatic conditions, e.g. the high variability at higher latitudes (Fig. 3a and b), while local scale variability could be related to processes like local management practices, urban spread, agricultural land conversion or disturbance. Rao's *Q* applied over multiple dates (also potentially including different seasons) might help detecting local to global scale changes in heterogeneity. In fact, the approach is generic and applicable to different datasets at all scales, from local to global, and at different resolutions (grain, sensu Dungan et al., 2002). In order to allow reproducible experiments using the proposed metric, we also provide a multitemporal Rao's Q diversity set (together with the R data project based on the code of Appendix 1) from 2000 to 2016 using MODIS data with a resampled spatial grain of 5 km (Appendix 2; data at higher resolution are available upon request).

Furthermore, the so-called global disparities and habitat losses might be also detected once applying proper diversity measures at global spatial scales. Major disparities between habitat loss and conservation lead some areas of the world to be more sensible to environmental change. In such a case, measuring diversity from satellites can help to anticipate habitat loss, providing useful tools to further improve management actions (Hoekstra et al., 2005).

The spectral variation approach has been observed to be complementary to the current state-of-the-art practice in LCIA of land use on biodiversity, where characterization models are mainly based on the consideration of species–area relationships (De Schryver et al., 2010; de Baan et al., 2013; Elshout et al., 2014; Chaudhary et al., 2015; Verones et al., 2015). Assessing spectral heterogeneity seems also a complementary approach to the study of (Human Appropriation of) Net Primary Production ((HA)NPP, Haberl et al., 2014). Indeed, detecting



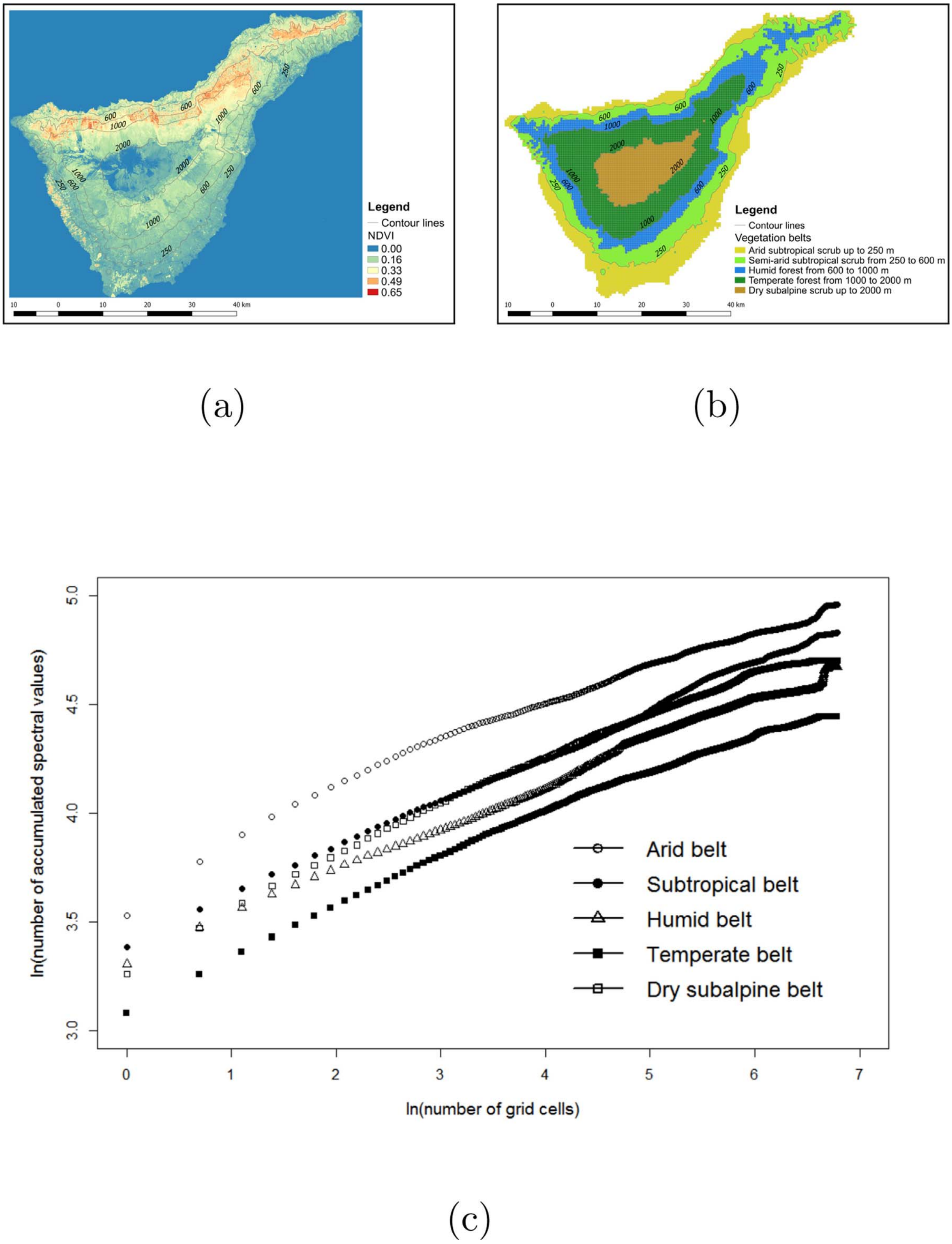
(a)

(b)

Fig. 3. Multi spatio-temporal comparison of Rao index on NDVI images: (a) spatial pattern of heterogeneity at European scale and (b) temporal–latitude profile of Rao's *Q* index with an increase of heterogeneity between 60° and 70° (i.e. mainly in the Scandinavian region), principally due to the variability related to temporary snow cover. Once data on different phenological seasons are attained, different patterns are also expected.

heterogeneity through the processing of remotely sensed imagery allows to capture possible changes associated with plant species diversity loss or gain over time and at various spatial resolutions and extents, while (HA)NPP indicators can provide a quantitative measure of the impact associated with spatial variability patterns.

In some cases, the heterogeneity measured from space might be directly related to human-based processes, like urban spread, which seem to affect both ecosystem functioning and the provision of ecosystem services (Tratalos et al., 2007). As an example, Fig. 4 represents the number of accumulated spectral values once increasing the extent of analysis (sampling effort), attained by calculating a rarefaction curve on the spectral values of a Landsat 8 image (pixel resolution = 30 m) in the Tenerife island (Canary Islands) as in Rocchini et al. (2011). After (i) superimposing a grid of 500 × 500 m on the Landsat 8 image and (ii) extracting the first principal component (Appendix 1), the amount of spectral values accumulated by increasing the extent (number of grid cells) was calculated as:



(a)

(b)

(c)

Fig. 4. Applying rarefaction techniques to a Landsat 8 image might reveal the diversity of different land use classes which can be related to human-based processes. As an example, in Tenerife (a), human-related land use, mainly related to urban spread, is concentrated in the arid coastal (vegetation) belt at low elevations (b). This leads to a higher spectral heterogeneity caused by a mixed anthropic–natural landscape which is described by a higher number of accumulated spectral values (c).

$$E(S) = S - \frac{\sum_{i=1}^{S}\binom{N-N_i}{n}}{\binom{N}{n}} \tag{2}$$

where S = total number of spectral values, N_i = number of grid cells in which the spectral value i is found, n = number of randomly chosen grid cells. Reader is referred to Shinozaki (1963) and Kobayashi (1974) for the original formulation of the rarefaction curve algorithm, and to Ugland et al. (2003) and Chiarucci et al. (2008, 2009) for a critique on its application to ecological data (species rarefaction), and further to Rocchini et al. (2011) for its application to remote sensing data (spectral rarefaction). In this example, human-related land use, mainly related to urban spread, is concentrated in the arid coastal (vegetation) belt at low elevations (Fernandez-Palacios and Nicolás, 1995), leading

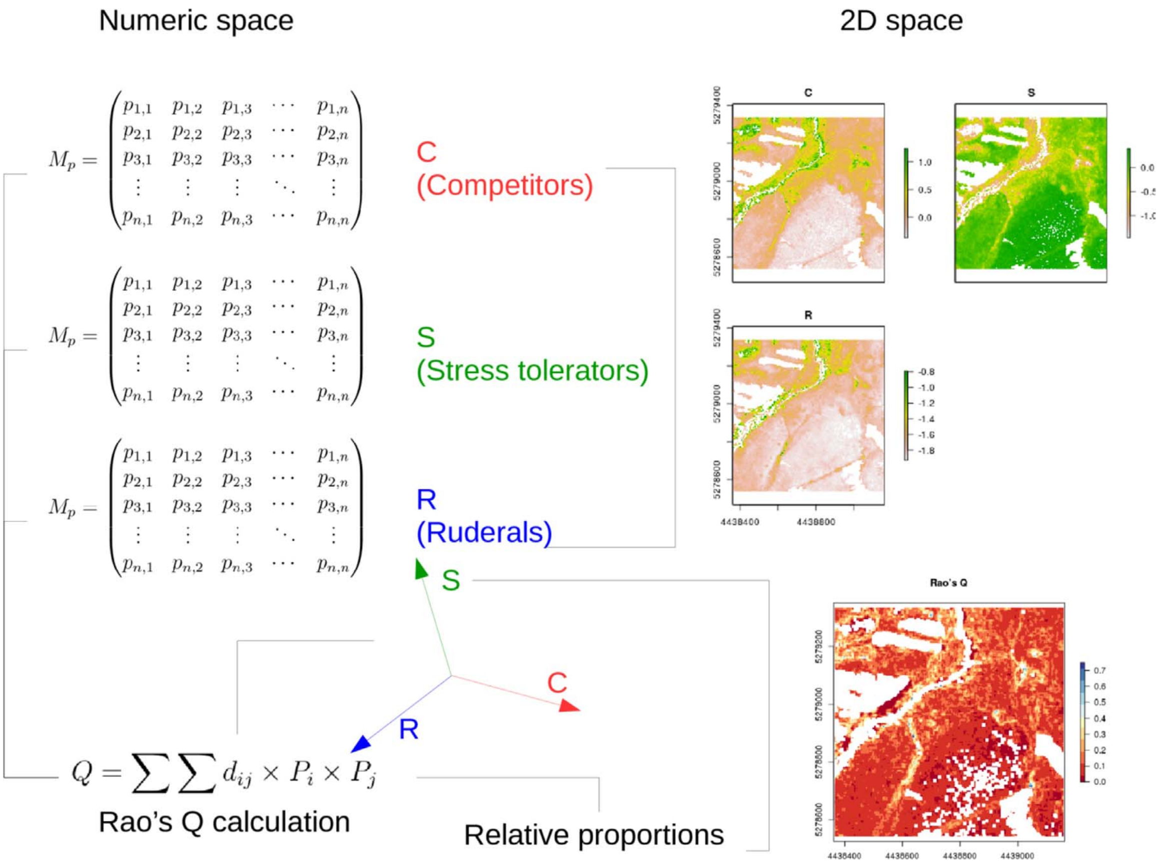


Fig. 5. Rao's *Q* calculated on a set of C (competitive species), S (stress-tolerative species), R (ruderal species) score maps (derived from Schmidtlein et al. (2012)) to estimate the diversity of functional types probability in space. In the numeric space (left), the C, S, R maps can be viewed as score matrices in two dimensions; in the Rao's *Q* formula the distance between such scores is used together with their relative abundance.

to a higher spectral heterogeneity caused by a mixed anthropic–natural landscape which is described by a higher number of accumulated spectral values.

3. The importance of estimating functional diversity

Beside taxonomic diversity, the combination of different traits is generally investigated by remote sensing to find indirect measures of functional diversity from a remote sensing perspective (Schmidtlein et al., 2012; Kattenborn et al., 2017).

The underlying assumption for the use of taxonomic diversity as a proxy of general biodiversity of an area is that the taxa are equally distinct from one another, disregarding the fact that communities are composed by species with different evolutionary history and a diverse array of ecological functions. More recently, the concept of functional diversity has received considerable attention because it captures information on species functional traits, which is absent in traditional measures of species diversity (Violle et al., 2007; Bartha, 2008; Lavorel et al., 2008; Ricotta et al., 2014). Functional traits are morphological, physiological, and phenological attributes, which impact individual fitness via their effects on growth, reproduction and survival.

There is an increasing body of literature demonstrating that functional diversity tends to correlate more strongly than traditional species diversity with ecosystem functions such as productivity (Loreau, 2000; Petchey et al., 2004; Hooper et al., 2005; Cardoso et al., 2014), resilience to perturbations (Moretti and Legg, 2009; Mori et al., 2013), or regulation of biogeochemical fluxes (Waldbusser et al., 2004; Legendre and Rivkin, 2005). Functional diversity might also be a tool for predicting the functional consequences of human-induced biotic change (Ricotta and Bacaro, 2012).

The observed relationships between functional diversity and ecosystem functioning raise the question of how to measure functional diversity in meaningful ways. One of the most established systems for plant functional types is the strategy types proposed by Grime (1974, 1977). The CSR plant strategy type system categorizes plants according to their abilities to compete for resources (C strategists), tolerate stress (S strategists) and survive disturbance (R strategists), recognizing the interplay of plant functional types, plant functional traits and ecosystem functions (Schweiger et al., 2016).

However, as for species inventories, field measurements of plant functional traits are costly, time-consuming and notoriously difficult to acquire, especially in remote areas. In contrast, plant functional types can be deduced from botanical inventories (releve data) and corresponding trait databases, which are more widely available than plant functional trait measurement.

Recently, increasing efforts have been devoted in assessing existing links between plant species spectral signatures (Asner and Martin, 2008) and plant community functional diversity. Imaging spectroscopy could enable modeling and predicting plant functional types at the vegetation community scale with high accuracy and greater consistency than plant life/growth forms (Schmidtlein et al., 2012; Schweiger et al., 2016; Kattenborn et al., in press). Based on these results, it can be affirmed that remote sensing methods mainly proposed for estimating biodiversity at the taxonomic level could even be related to the variation of community functional characteristics: in other words, the spectral signature of plant functional types is preserved in the vegetation community's spectral response.

Using remotely sensed spectral heterogeneity might lead to an estimate of functional diversity. As an example, the previously mentioned Rao's *Q* has been extensively used in functional diversity applications (Botta-Dukat, 2005; Ricotta et al., 2014; Marcantonio et al., 2014). Functional ecologists make use of a wide set of functional traits (plants functional characteristics) to assess the diversity of natural systems. Rao's *Q* has been shown to be a valid candidate to summarize them in a single diversity value (Botta-Dukat, 2005).

In Fig. 5 we applied the Rao's *Q* measure to a set of C (competitive species), S (stress-tolerative species), R (ruderal species) scores reported in Schmidtlein et al. (2012). Seeing the probability of a plant species to belong to a certain functional group as a numeric array, or a 2D matrix, the Rao's *Q* might be applied to calculate the diversity of functional types probability in space (and time).

4. Conclusion and outlook

When assessing impacts associated with land use, biodiversity loss in terms of species richness and vulnerability is explicitly considered to have an intrinsic value for the ecosystem quality, while ecosystem services are reflected to have rather an instrumental value.

However, heterogeneity measurements can only capture spatial variability at different scales of complexity. Therefore, in the absence of field data it is difficult if not impossible to find the best solution to assess other functional biodiversity related issues, such as vulnerability resilience and recoverability of species or ecosystems.

This said, the use of remotely-sensed diversity might prove useful since in most cases satellite imagery is directly related to variables connected to ecosystem services. As an example, NDVI, which has been used to measure diversity from space in a number of papers (Gillespie, 2005; He and Zhang, 2009) is directly linked to the photosynthetic activity of the vegetation and thus indirectly to vegetation biomass (Krishnaswamy et al., 2009).

It might be clear that ecosystems biodiversity provides ecosystem services which also regulate human livelihood, like, as previously stated, water and carbon cycle regulation or soil erosion prevention. In this sense, remote sensing and the analysis of satellite data provide spatial models which are crucial for assessing the current (and predicting the future) conditions of habitats (Newton et al., 2009).

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ecolind.2017.09.055.

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