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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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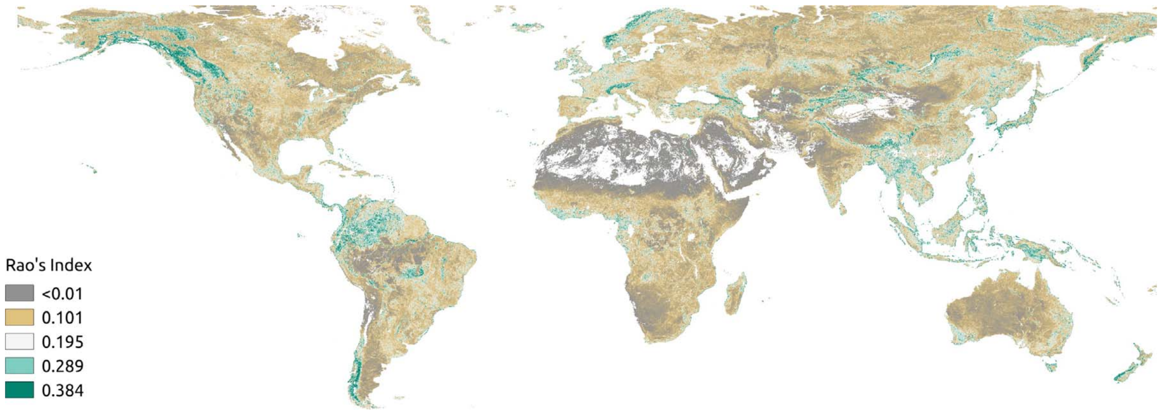

Fig. 1. Rao's quadratic diversity metric applied to an NDVI map of the world (date 2016-06-06, http://land.copernicus.eu/global/products/ndvi), resampled at 2 km resolution with a moving window of 5 pixels. As far as we know, this is the first application of Rao's *Q* metric to satellite data covering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

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

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

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