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Time-lapsing biodiversity: An open source method for measuring diversity changes by remote sensing

Duccio Rocchini [a, b, c, d, *], Matteo Marcantonio [e], Daniele Da Re [f], Gherardo Chirici [g], Marta Galluzzi [g], Jonathan Lenoir [h], Carlo Ricotta [i], Michele Torresani [j], Guy Ziv [k]

[a] *University of Trento, Center Agriculture Food Environment (C3A), Via E. Mach 1, 38010 S. Michele all'Adige, (TN), Italy*
[b] *University of Trento, Department of Cellular, Computational and Integrative Biology (CIBIO), Via Sommarive, 9, 38123 Povo, (TN), Italy*
[c] *Fondazione Edmund Mach, Research and Innovation Centre, Department of Biodiversity and Molecular Ecology, Via E. Mach 1, 38010 S. Michele all'Adige, (TN), Italy*
[d] *Czech University of Life Sciences Prague, Faculty of Environmental Sciences, Department of Applied Geoinformatics and Spatial Planning, Kamýcka 129, Praha, Suchdol 16500, Czech Republic*
[e] *Department of Pathology, Microbiology, and Immunology, School of Veterinary Medicine, University of California, Davis, USA*
[f] *Earth and Life Institute, Université catholique de Louvain, Place Louis Pasteur 3, 1348 Louvain-la-Neuve, Belgium*
[g] *geoLAB - Laboratory of Forest Geomatics, Department of Agricultural, Food and Forestry Systems, University of Florence, Via San Bonaventura, 13, 50145 Firenze, Italy*
[h] *UR "Ecologie et dynamique des systèmes anthropisées" (EDYSAN, UMR 7058 CNRS-UPJV), Université de Picardie Jules Verne, 1 Rue des Louvels, 80037 Amiens Cedex 1, France*
[i] *Department of Environmental Biology, University of Rome "La Sapienza", Rome 00185, Italy*
[j] *Free University of Bolzano/Bozen, Faculty of Science and Technology, Piazza Universitá/Universitätsplatz 1, 39100 Bolzano/Bozen, Italy*
[k] *School of Geography, University of Leeds, Leeds LS2 9JT, UK*

A R T I C L E I N F O

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A B S T R A C T

Understanding biodiversity changes in time is crucial to promptly provide management practices against diversity loss. This is overall true when considering global scales, since human-induced global change is expected to make significant changes on the Earth's biota. Biodiversity management and planning is mainly based on field observations related to community diversity, considering different taxa. However, such methods are time and cost demanding and does not allow in most cases to get temporal replicates. In this view, remote sensing can provide for a wide data coverage in a short period of time. Recently, the use of Rao's *Q* diversity as a measure of spectral diversity has been proposed in order to explicitly taking into account differences in a neighbourhood considering abundance and relative distance among pixels. The aim of this paper was to extend such a measure over the temporal dimension and to present an innovative approach to calculate remotely sensed temporal diversity. We demonstrated that temporal beta-diversity (spectral turnover) can be calculated pixel-wise in terms of both slope and coefficient of variation and further plotted over the whole matrix / image. From an ecological and operational point of view, for prioritisation practices in biodiversity protection, temporal variability could be beneficial in order to plan more efficient conservation practices starting from spectral diversity hotspots in space and time. In this paper we delivered a highly reproducible approach to calculate spatio-temporal diversity in a robust and straightforward manner. Since it is based on open source code, we expect that our method will be further used by several researchers and landscape managers.

1. Introduction

Understanding biodiversity changes in time is crucial to promptly provide management practices against diversity loss (Gaston, 2008).

This has been proven for various part of the globe, considering different biomes and habitat types like dry (Nagendra et al., 2010) and humid (Somers et al., 2015) tropical forests, savannas (Oldeland et al., 2010), grasslands (Feilhauer et al., 2013), among the others.

This is overall true when considering global scales, since human-induced global change is expected to make significant changes on the Earth's biota (Moreno et al., 2018). This is explicitly taken into account by the Sustainable Development Goals of the United Nations (https://

* Corresponding author at: University of Trento, Center Agriculture Food Environment (C3A), Via E. Mach 1, 38010 S. Michele all'Adige, (TN), Italy.
Email address: duccio.rocchini@unitn.it (D. Rocchini)

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www.un.org/sustainabledevelopment/sustainable-development-goals/), with Goal 15 explicitly aiming to "halt biodiversity loss".

However, biodiversity management and planning is mainly based on field observations related to community diversity, considering different taxa, under the assumption of robust statistical sampling and proper methods of analysis (e.g. Chiarucci et al., 2009). Such a method is time and cost consuming and does not allow in most cases to get temporal replicates.

This led to the urgent need of developing worldwide research and stakeholders networks to face climate and biodiversity change at global scale, like the Global Climate Observing System (GCOS, https://public.wmo.int/), the Intergovernmental Panel on Climate Change (IPCC, http://www.ipcc.ch/) or the Group on Earth Observations - Biodiversity Observation Network (GEO BON, https://geobon.org/). Essential Climate Variables (ECVs) and the Essential Biodiversity Variables (EBVs, see Pereira et al., 2013) were thus the main outputs of such networks, as proxies of Earth global change in space and time.

In this framework, remote sensing has been proposed as a straightforward operational tool providing a wide data coverage in a short period of time (Rocchini and Di Rita, 2005; Skidmore et al., 2015), helping to save costs and time. Furthermore, measures of diversity from remotely sensed vs. field data showed a positive relationship, leading to consider remote sensing diversity as a direct proxy of the variation of biodiversity in space (Gillespie et al., 2008; Lausch et al., 2016).

Most of the remote sensing-based measures of spectral diversity have been widely based on i) the spatial variability of pixel values by measuring pairwise distances in a spectral space (Feret and Asner, 2014; Somers et al., 2015) or on ii) measures of relative abundance of values based on information theory (Ricotta, 2005).

Recently, Rocchini et al. (2017) proposed the use of Rao's Q diversity as a measure of spectral diversity which explicitly takes into account differences in a neighbourhood relying on abundance and relative distance among pixels, extending for the first time to 2D-matrices (satellite images) the measure firstly proposed by Rao (1982).

This might allow the so called continuous field mapping which in most cases has been applied to land cover classification (Mathys et al., 2009) but it is also a valuable tool for diversity mapping over wide geographical regions, mainly based on moving window methods. Basically, starting from the spectral mixing space of a satellite image, one can measure the continuous variability of pixel values in space by local-based measures, which maximise the contrast in spectral diversity highlighting hotspots of diversity, mainly related to transition zones in space (Small, 2005).

The temporal dimension, coupled with spatial approaches, might help inferring biodiversity change over large areas. While this has been widely acknowledged in some ecological modelling practices, like in environmental niche modelling (Feng and Papes, 2017), it has rarely been explicitly considered when dealing with remotely sensed diversity measurements, over wider temporal scales. In this view, most of the research efforts have been devoted to phenology (He et al., 2009) without an explicit spatial approach to measure spectral turnover in space and time.

The aim of this paper is to present an innovative approach to calculate the temporal change of remotely sensed diversity. We will first introduce the theoretical background of the diversity calculation in time and then provide an empirical example based on MODIS data, by also providing the complete R code (Appendix 1 or https://gitlab.com/danidr/temporal_rs_biodiversity/blob/master/RocchiniEtAl_2019_slopes.R).

2. Benchmark example

2.1. Algorithm development

Rao's Q diversity explicitly considers both relative abundance and spectral distances among pixel reflectance values as:

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

where d_{ij} = pairwise distance between pixels attaining to reflectance values i and j, p_i = relative abundance of pixels attaining to reflectance value i, and p_j = relative abundance of pixels attaining to reflectance value j. As proposed by Rocchini et al. (2017), given an input 2D matrix (image)

$$I = \begin{pmatrix} P_{1,1} & P_{1,2} & P_{1,3} & \dots & P_{1,n} \\ P_{2,1} & P_{2,2} & P_{2,3} & \dots & P_{2,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ P_{m,1} & P_{m,2} & P_{m,3} & \dots & P_{m,n} \end{pmatrix} \tag{2}$$

where P = input pixel, Rao's Q can be calculated by a moving window (spatial kernel or 2D matrix)

$$M = \begin{pmatrix} P_{1,1} & P_{1,2} & P_{1,3} \\ P_{2,1} & P_{2,2} & P_{2,3} \\ P_{3,1} & P_{3,2} & P_{3,3} \end{pmatrix} \tag{3}$$

using $n \times n$ pixels in a neighbourhood of a given site (pixel) by returning an output map of local alpha-diversity hotspots.

Rao's Q diversity value applied to remotely sensed images allows one to discriminate among environmental situations with low or high evenness, as the mostly used Shannon's H' does, but also including distance among pixel vaues. Given an image I, Fig. 1 shows four different situations, starting from the lowest diversity in the environment (Fig. 1A), with pixels which are similar to each other (low distance) and with one value dominating the landscape(low evenness). On the contrary, Fig. 1D represents the highest possible diversity with a high distance among pixels and a high evenness (equidistribution of pixel values). While information theory based on Shannon's H' allows discriminating between extreme situations, it does not allow discriminating diversity hotspots deriving from i) a high evenness of pixel values but with a low distance among them (similar environments) and ii) a high evenness of pixel values with a high distance among them (very different environments). Since in environmental science and in remote sensing of environmental diversity the interest is pointed to the detection of strong differences among environment, i.e. diversity hotpots, the Rao's Q diversity seems to perform better with respect to common information theory based calculus. The mathematical calculation of Shannon's H' and Rao's Q values is provided in Appendix 2, which is performed by the algorithm described in Rocchini et al. (2017) and freely available under the GitHub flagship project at: https://github.com/mattmar/spectralrao/blob/master/spectralrao.r.

In general, the output Rao's Q diversity map is derived at a certain time t_0, based on the date of the original input image being used. In this paper, we are aiming at summarizing different output maps derived in different times as:

$$O_{t0} = \begin{pmatrix} P_{1,1}t0 & P_{1,2}t0 & P_{1,3}t0 & \dots & P_{1,n}t0 \\ P_{2,1}t0 & P_{2,2}t0 & P_{2,3}t0 & \dots & P_{2,n}t0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ P_{m,1}t0 & P_{m,2}t0 & P_{m,3}t0 & \dots & P_{m,n}t0 \end{pmatrix} \tag{4}$$

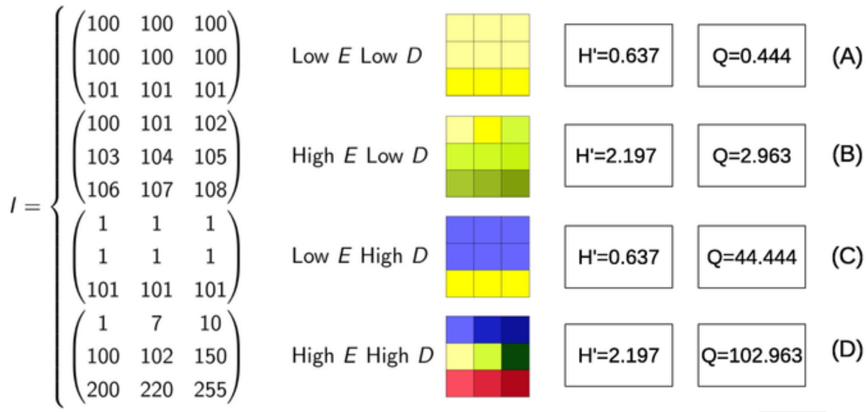

Fig. 1. Synthetic example showing four different environmental situations and their relative Shannon's H' and Rao's Q indices. (A) Lower diversity in terms of both evenness and distance among pixel values; (B) and (C) intermediate situations; (D) higher diversity in terms of both evenness and distance among pixel values. Refer to the main text for additional information and to Appendix 2 for the mathematical calculation.

$$O_{t1} = \begin{pmatrix} P_{1,1}t1 & P_{1,2}t1 & P_{1,3}t1 & \dots & P_{1,n}t1 \\ P_{2,1}t1 & P_{2,2}t1 & P_{2,3}t1 & \dots & P_{2,n}t1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ P_{m,1}t1 & P_{m,2}t1 & P_{m,3}t1 & \dots & P_{m,n}t1 \end{pmatrix} \quad (5)$$

$$O_{tn} = \begin{pmatrix} P_{1,1}tn & P_{1,2}tn & P_{1,3}tn & \dots & P_{1,n}tn \\ P_{2,1}tn & P_{2,2}tn & P_{2,3}tn & \dots & P_{2,n}tn \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ P_{m,1}tn & P_{m,2}tn & P_{m,3}tn & \dots & P_{m,n}tn \end{pmatrix} \quad (6)$$

In other words, the present manuscript seeks to find a method to account for the change in time of Rao's Q diversity.

Let $Q_{P_0t_0}$ be the Rao's Q value at a given site (pixel P_0) in a certain moment (time t_0, Fig. 2). The $Q_{P_0t_x}$ value can be viewed in a linear time space from t_0 to t_n. Once such values have been plotted, a locally weighted scatterplot smoothing (LOWESS) function, also referred to as LOESS (Cleveland, 1979; Cleveland and Devlin, 1988), can be estimated, which reduces to a linear function $y \sim x$ in case of linear variability. LOESS fits a function to a subset of the data, generally splitting the explanatory variable and giving a higher weight to points near the point where the response is being estimated.

The mean slope (trend) of the LOESS is expected to represent the change of Rao's Q diversity in time. In order to get a pixel-wise approximation of the slope we extracted the derivative of the Rao's Q diversity smoothed temporal function at each t_i, computing the $\triangle y/\triangle x$. Then, the descriptive statistics over the whole time series were calculated, giving information on the smoothed function trend.

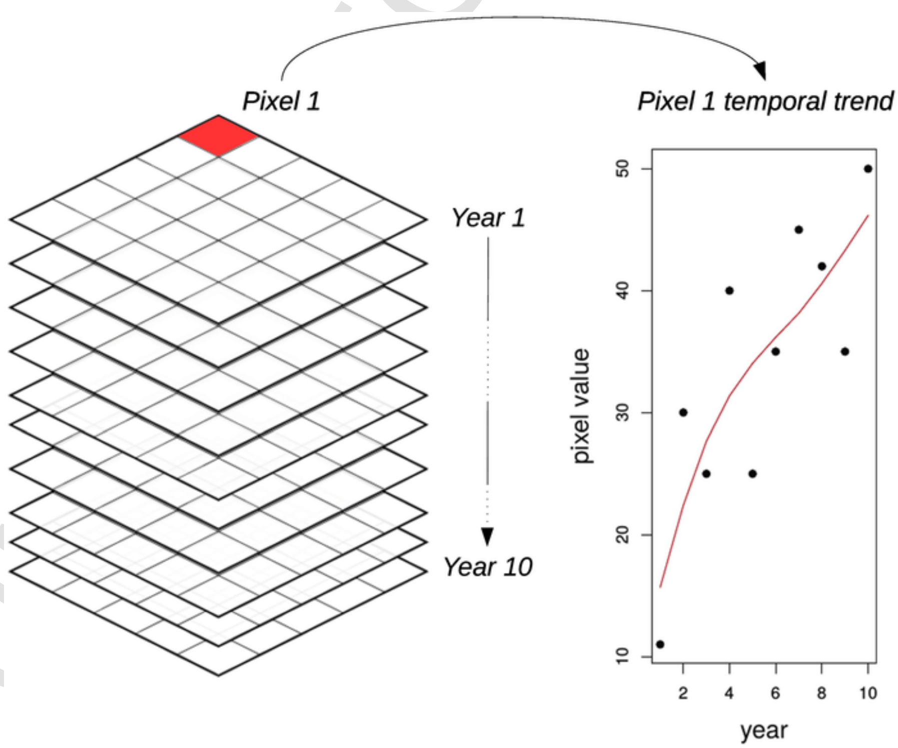

Fig. 2. The Rao's value $Q_{P_0t_0}$ at a given site (pixel P_0) in a certain moment (time t_0) can be plotted on a time scale. Once all the values from $Q_{P_0t_0}$ to $Q_{P_0t_n}$ have been plotted, a smooth LOESS function canbe estimated and its slope (trend) of coefficient of variation would represent the mean variation of Q in time and its temporal turnover.

As a proxy of the variation of the Rao's *Q* diversity values over the whole time series, a temporal coefficient of variation index (CV) was computed following Hijmans (2004). This index, expressed as a percentage, is the ratio between the standard deviation and the mean of all the Rao's *Q* diversity values. Larger percentages represent a higher spectral-turnover, providing a beta-diversity quantification.

Summarizing, the average slope of the LOESS curve is expected to represent the amount of mean diversity along a temporal trend, while its coefficient of variation would represent the temporal turnover in the spectral Rao's *Q*. Temporal diversity can thus be calculated pixel-wise in terms of both slope and coefficient of variation and further plotted over the whole matrix/image.

In order to implement an empirical example of the method being proposed, we made use of the free set of Rao's *Q* data based on MODIS NDVI images at a resolution of 5 km provided in Rocchini et al. (2018). A sketch of the original MODIS NDVI input set is provided in Appendix 3. In order to rely on a high complexity landscape we decided to focus on the Italian peninsula, which guarantees a high ecological gradient from the sea to high mountain alps (until 4000 m). Based on the open source code provided in Appendix 1, the method can be straightforwardly extended to other areas, habitats, or biomes. The final stack of layers consisted of 17 Rao's *Q* images gathered from 2000 to 2016 in June (Fig. 3).

Each pixel was projected in a temporal space according to Fig. 2 from 2000 to 2016, and a LOESS function with automatic smoothing parameter selection through bias-corrected Akaike information criterion (AICc) was fitted relying on the r package `fANCOVA` (Wang, 2010), building a global set of N functions where N = number of pixels in the image. The mean slope and the coefficient of variation along the temporal gradient of the LOESS function was calculated for each pixel and further spatially plotted.

2.2. Results

Rao's *Q* temporal diversity considering LOESS mean slope (mean temporal diversity) and LOESS coefficient of variation (temporal turnover) showed a discriminant pattern among different areas (Fig. 4). Both measures detected a higher temporal diversity in areas with higher landscape morphological complexity detected by the spatial Rao's *Q* (see Fig. 3) with an enhancement in the relative temporal beta-diversity (turnover) detected by the coefficient of variation of the LOESS function.

Spatial Rao's *Q* showed a high value in Italy in topographically and ecologically complex mountain areas, including Alps and Appennines (central Italy) (Fig. 3). However, once considering the temporal dimension, alpine areas showed a higher relative value of Rao's *Q* temporal variation, considering both mean and turnover in temporal diversity (Fig. 4). This pattern has also been hypothesized, but never specifically tested until now, by Rocchini et al. (2011) who stressed the possibility of a higher variation in space and time of top mountainous areas (in particular, Alps) which are expected to show a high amount of ecologically con-

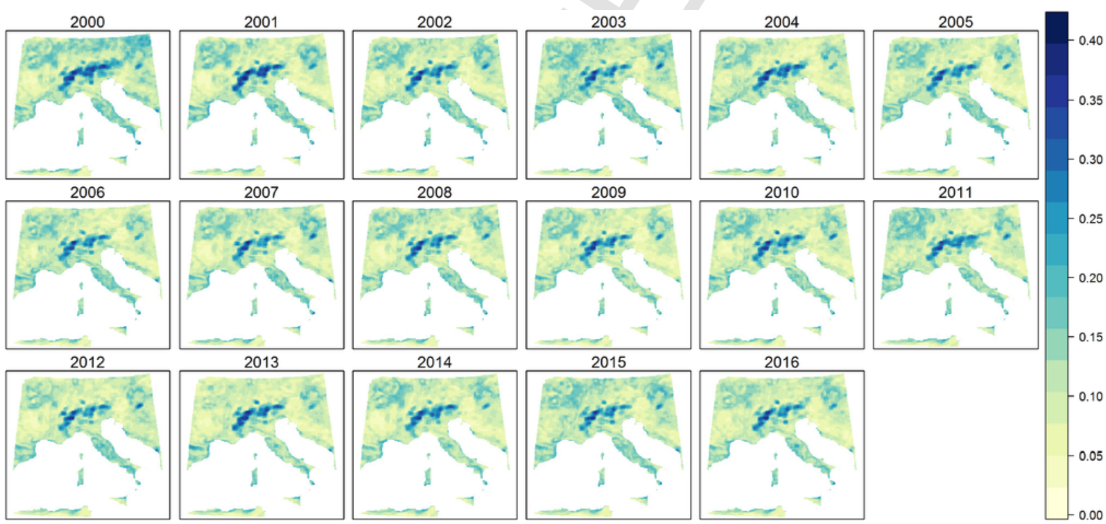

Fig. 3. Spatial representation of the free set of Rao's Q data based on MODIS NDVI images at a resolution of 5 km provided by Rocchini et al. (2017). The final stack of layers consists of 17 Rao's *Q* images gathered from 2000 to 2016 in June.

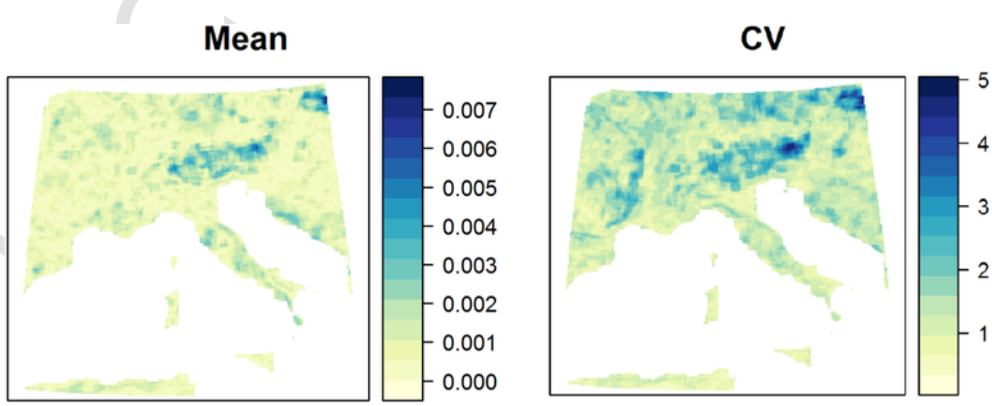

Fig. 4. Rao's *Q* temporal diversity considering LOESS mean slope (mean temporal diversity) and LOESS coefficient of variation (temporal turnover). Both measures detected a higher temporal diversity in areas with higher landscape morphological complexity detected by the spatial Rao's *Q*.

trasting traits, from agricultural areas to conifers and broadleaf forests, to pastures, grasslands and bare rocks (Pelorosso et al., 2011).

3. Discussion

Estimating values of diversity over an area given a sample is crucial for a number of different ecological tasks (Granger et al., 2015). Remote sensing certainly represents a powerful tool for getting estimated diversity values in a 2D surface. Extending on Ricotta (2008), who calculated community beta-diversity starting from species presence/absence scores, in this paper we propose to substitute such scores with pixel based values, being such values diversity measures (like the Rao's *Q* scores) or original reflectances in a satellite image, by further redistributing them in a new time-system to carry out a LOESS based calculation of diversity changes.

In this view, the variability of diversity over space has been investigated at different spatial scales and with different approaches (refer to Rocchini et al., 2010 for a review). As stressed by Leitao et al. (2015), it might be crucial to find methods readily available to deal with time series data, in order to potentially account for the time axis in the analysis of beta-diversity change.

Our method represents a powerful approach to estimate remotely sensed beta-diversity in time, at large spatial extents. Once coupled with hierarchical methods to also account for different scales of diversities, e.g. with Bayesian hierarchical modelling (Zhang et al., 2014), our approach might represent a benchmark for modelling the variability in space and time of diversity at multiple spatial scales. It is far beyond the aim of this paper to test the sensitivity of the method to different spatial grains and spectral resolutions, but since it is based on pixel distances and relative abundance we expect that it can be applied to any kind of multi- or hyper-volumes like multi- or hyper-spectral images at different spatial and spectral resolutions from high (e.g. Quickbird, Ikonos) to medium (e.g. Sentinel-2 or Landsat data) and low grains (like MODIS data in our case).

Furthermore, our method might help measuring not only spatial variations in beta-diversity to be related directly to the effect of ecosystem dynamics (Wang and Loreau, 2014), but also supply a synthesis of temporal variations in beta-diversity thus implicitly incorporating such dynamics.

In some cases, spatial non-stationarity has been advocated as one of the major problems when the variability of a certain variable is non-uniform in space (Osborne et al., 2007). In our case, we would promote our approach to also account for potential anomalies, or simply spots of diversity variation in time, when measuring beta-diversity from satellites. As an example, Mathys et al. (2009) proved that, when dealing with land cover continuous variability over space, adding spectral diversity derived from remotely sensed images could improve modelling performance.

There are intrinsic difficulties related to the estimate of biodiversity changes in time (temporal beta-diversity) mainly related to the sampling replication in the same location with the same sampling protocol. Permanent plots arranged in networks like the Long Term Ecosystem Research in Europe (LTER, http://www.lter-europe.net/) have been explicitly implemented to solve the problem. However, they represent sporadic and spatially scattered locations in local areas. Once zones with high spatial and temporal variability have been detected, the attained information could be a powerful tool for guiding field based surveys of species diversity (Rocchini et al., 2005). This is overall true when considering ancillary models specifically dedicated to the development of efficient sampling designs, based on e.g. sampling optimisation based on synthetic maps (Schweiger et al., 2015) or on virtual species sets (Garzon-Lopez et al., 2016).

Landscape metrics (e.g., patch area and connectivity) have been widely used as tools for identification of areas with higher biodiversity, but they mostly refers to categorical maps such as land cover (Katayama et al., 2014; Morelli et al., 2018). However, land cover maps are generally an oversimplification of habitat variability (Amici et al., 2017) and should be used with care to avoid the underestimation of the continuous ecological variability over the landscape (Austin, 1987; Palmer et al., 2002; Rocchini, 2007).

In this paper, the continuous variability of spectral pixel values, coupled with the temporal dimension provided for additional information on the variation of ecosystems, allowing a better detection of highly diverse spot in space and in time, considering different time spans *t*0, *t*1, …, *t*n. Strictly speaking, including temporal variation in the analysis of diversity from remote sensing might provide additional information to spatial kernels measured at *t*0.

Obviously, the variability of the spectral signal is not the only proxy of diversity, and in some cases (e.g. in urban areas) a high environmental variability is not necessarily related to a high amount of biodiversity in the field (Ricotta et al., 2010). However, in case of natural and seminatural areas, spectral variability might represent one of the main proxies of diversity (Schmeller et al., 2017; Skidmore et al., 2015). Hence, in order to measure spatial and temporal changes in diversity, it could be coupled with additional variables such as: i) climatic predictors (Zellweger et al., 2019), ii) soil properties (Tuomisto et al., 2003), iii) topographical complexity (Badgley et al., 2017). Furthermore, in this manuscript we made use of a spectral index like the inter-annual NDVI as an example dataset to calculate spatial heterogeneity, as in Oindo and Skidmore (2002) or Gillespie (2005) and more recently Feilhauer et al. (2012), by deriving the Rao's *Q* diversity on a continuous data matrix to monitor heterogeneity changes through time, although the annual inter-variation of productivity could be related to several factors, and not just to niche-based diversity changes. We refer to the debate between Krishnaswamy et al. (2009) and Rocchini (2009) about problems related to alpha- and beta-diversity measurement from NDVI.

4. Conclusion

In this paper, we presented a robust and reproducible approach to estimate the temporal ecosystems' beta-diversity based on a locally weighted scatterplot smoothing. We applied it to the spatial Rao's Q diversity proposed by Rocchini et al. (2017), but the method could be ported to any spatial diversity measure made in a spectral space.

Being based on open source coding, we expect a high reproducibility of the proposed approach, and stimulate researchers to test it in different habitats, by varying spatial grains and extents and potentially making use of different sensors.

The open source code provided will guarantee the robustness and reproducibility of the method. In fact, we are expecting that such a code will be used by other researchers to further develop additional algorithms on temporal variability measurement from satellite images.

From an ecological and operational point of view, for species inventorying maximisation in biodiversity protection, advocated by the Sustainable Development Goal 15 ("halt biodiversity loss") and scientifically proposed by Rocchini et al. (2005) and more recently reviewed by Schmeller et al. (2017), the temporal variability, together with the spatial one, could be beneficial in order to plan more efficient conservation practices starting with those diversity hotspots detected in space and time by remote sensing techniques.

Attempts have been made to measure the spatial sensitivity of the relation between species and spectral diversity (Wang et al., 2018) which might impact further management practices if disregarded. However, as far as we know, nothing has been done to project it also in time. Our method represents a potential benchmark for applying such a variation measurement in time, which could be extended i) not only to other types of sensors in satellite images but to every kind of 2D matrices including species-plot arrays, ii) to other methods such as the measure of spatial and temporal autocorrelation (Guelat and Kery, 2018), iii) to additional ecospaces (sensu Dick and Laflamme, 2018) by fuzzy modelling.

Uncited references

Ewald et al., 2018
Rocchini et al., 2015

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2019.05.011.

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