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1 Time-lapsing biodiversity: an open source
2 method for measuring diversity changes by
3 remote sensing

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32 **Abstract**

33 Understanding biodiversity changes in time is crucial to promptly
34 provide management practices against diversity loss. This is over-
35 all true when considering global scales, since human-induced global
36 change is expected to make significant changes on the Earth's biota.
37 Biodiversity management and planning is mainly based on field ob-
38 servations related to community diversity, considering different taxa.
39 However, such methods are time and cost demanding and does not
40 allow in most cases to get temporal replicates. In this view, remote
41 sensing can provide for a wide data coverage in a short period of time.
42 Recently, the use of Rao's Q diversity as a measure of spectral diversity
43 has been proposed in order to explicitly taking into account differences
44 in a neighborhood considering abundance and relative distance among
45 pixels. The aim of this paper was to extend such a measure over the
46 temporal dimension and to present an innovative approach to calculate
47 remotely sensed temporal diversity. We demonstrated that temporal
48 beta-diversity (spectral turnover) can be calculated pixel-wise in terms
49 of both slope and coefficient of variation and further plotted over the
50 whole matrix / image. From an ecological and operational point of
51 view, for prioritisation practices in biodiversity protection, temporal
52 variability could be beneficial in order to plan more efficient conser-
53 vation practices starting from spectral diversity hotspots in space and

54 time. In this paper we delivered a highly reproducible approach to cal-
55 culate spatio-temporal diversity in a robust and straightforward man-
56 ner. Since it is based on open source code, we expect that our method
57 will be further used by several researchers and landscape managers.

58 keywords: biodiversity; ecological informatics; Rao's Q diversity; remote
59 sensing; satellite imagery; temporal variability

60 **1 Introduction**

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

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

67 This is overall true when considering global scales, since human-induced
68 global change is expected to make significant changes on the Earth's biota
69 (Moreno et al., 2017). This is explicitly taken into account by the Sus-
70 tainable Development Goals of the United Nations ([https://www.un.org/
71 sustainabledevelopment/sustainable-development-goals/](https://www.un.org/sustainabledevelopment/sustainable-development-goals/)), with Goal
72 15 explicitly aiming to "halt biodiversity loss".

73 However, biodiversity management and planning is mainly based on field
74 observations related to community diversity, considering different taxa, under
75 the assumption of robust statistical sampling and proper methods of analysis
76 (e.g. Chiarucci et al. (2017)). Such a method is time and cost consuming
77 and does not allow in most cases to get temporal replicates.

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

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

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

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

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

112 The temporal dimension, coupled with spatial approaches, might help
113 inferring biodiversity change over large areas. While this has been widely
114 acknowledged in some ecological modelling practices, like in environmental

115 niche modelling (Feng and Papes, 2017), it has rarely been explicitly consid-
116 ered when dealing with remotely sensed diversity measurements, over wider
117 temporal scales. In this view, most of the research efforts have been de-
118 voted to phenology (He et al., 2009) without an explicit spatial approach to
119 measure spectral turnover in space and time.

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

126 2 Benchmark example

127 2.1 Algorithm development

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

$$Q = \sum \sum d_{ij} \times p_i \times p_j \quad (1)$$

130 where d_{ij} = pairwise distance between pixels attaining to reflectance val-

131 ues i and j , $p_i =$ relative abundance of pixels attaining to reflectance value
 132 i , and $p_j =$ relative abundance of pixels attaining to reflectance value j . As
 133 proposed by Rocchini et al. (2017), given an input 2D matrix (image)

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

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

$$M = \begin{pmatrix} P_{1,1} & P_{1,2} & P_{1,3} \\ P_{2,1} & P_{2,2} & P_{2,3} \\ P_{3,1} & P_{3,2} & P_{3,3} \end{pmatrix} \quad (3)$$

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

138 Rao's Q diversity value applied to remotely sensed images allows one to
 139 discriminate among environmental situations with low or high evenness, as
 140 the mostly used Shannon's H' does, but also including distance among pixel
 141 values. Given an image I , Figure 1 shows four different situations, starting

142 from the lowest diversity in the environment (Figure 1A), with pixels which
143 are similar to each other (low distance) and with one value dominating the
144 landscape (low evenness). On the contrary, Figure 1D represents the high-
145 est possible diversity with a high distance among pixels and a high evenness
146 (equidistribution of pixel values). While information theory based on Shan-
147 non's H' allows discriminating between extreme situations, it does not allow
148 discriminating diversity hotspots deriving from i) a high evenness of pixel
149 values but with a low distance among them (similar environments) and ii) a
150 high evenness of pixel values with a high distance among them (very different
151 environments). Since in environmental science and in remote sensing of en-
152 vironmental diversity the interest is pointed to the detection of strong differ-
153 ences among environment, i.e. diversity hotspots, the Rao's Q diversity seems
154 to perform better with respect to common information theory based calculus.
155 The mathematical calculation of Shannon's H' and Rao's Q values is provided
156 in Appendix 2, which is performed by the algorithm described in Rocchini et
157 al. (2017) and freely available under the GitHub flagship project at: <https://github.com/mattmar/spectralrao/blob/master/spectralrao.r>.

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

$$O_{t_0} = \begin{pmatrix} P_{1,1}t_0 & P_{1,2}t_0 & P_{1,3}t_0 & \dots & P_{1,n}t_0 \\ P_{2,1}t_0 & P_{2,2}t_0 & P_{2,3}t_0 & \dots & P_{2,n}t_0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ P_{m,1}t_0 & P_{m,2}t_0 & P_{m,3}t_0 & \dots & P_{m,n}t_0 \end{pmatrix} \quad (4)$$

$$O_{t_1} = \begin{pmatrix} P_{1,1}t_1 & P_{1,2}t_1 & P_{1,3}t_1 & \dots & P_{1,n}t_1 \\ P_{2,1}t_1 & P_{2,2}t_1 & P_{2,3}t_1 & \dots & P_{2,n}t_1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ P_{m,1}t_1 & P_{m,2}t_1 & P_{m,3}t_1 & \dots & P_{m,n}t_1 \end{pmatrix} \quad (5)$$

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

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

165 Let $Q_{P_0t_0}$ be the Rao's Q value at a given site (pixel P_0) in a certain mo-
166 ment (time t_0 , Figure 2). The $Q_{P_0t_x}$ value can be viewed in a linear time space
167 from t_0 to t_n . Once such values have been plotted, a locally weighted scatter-
168 plot smoothing (LOWESS) function, also referred to as LOESS (Cleveland

169 , 1979; Cleveland and Devlin, 1988), can be estimated, which reduces to a
170 linear function $y \sim x$ in case of linear variability. LOESS fits a function to a
171 subset of the data, generally splitting the explanatory variable and giving a
172 higher weight to points near the point where the response is being estimated.

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

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

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

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

200 Each pixel was projected in a temporal space according to Figure 2 from
201 2000 to 2016, and a LOESS function with automatic smoothing parameter
202 selection through bias-corrected Akaike information criterion (AICc) was fit-
203 ted relying on the r package `fANCOVA` (Wang, 2010), building a global set
204 of N functions where $N =$ number of pixels in the image. The mean slope
205 and the coefficient of variation along the temporal gradient of the LOESS
206 function was calculated for each pixel and further spatially plotted.

207 **2.2 Results**

208 Rao's Q temporal diversity considering LOESS mean slope (mean tempo-
209 ral diversity) and LOESS coefficient of variation (temporal turnover) showed
210 a discriminant pattern among different areas (Figure 4). Both measures
211 detected a higher temporal diversity in areas with higher landscape morpho-
212 logical complexity detected by the spatial Rao's Q (see Figure 3) with an
213 enhancement in the relative temporal beta-diversity (turnover) detected by
214 the coefficient of variation of the LOESS function.

215 Spatial Rao's Q showed a high value in Italy in topographically and eco-
216 logically complex mountain areas, including Alps and Appennines (central
217 italy) (Figure 3). However, once considering the temporal dimension, alpine
218 areas showed a higher relative value of Rao's Q temporal variation, consid-
219 ering both mean and turnover in temporal diversity (Figure 4). This pattern
220 has also been hypothesized, but never specifically tested until now, by Roc-
221 chini et al. (2011) who stressed the possibility of a higher variation in space
222 and time of top mountainous areas (in particular, Alps) which are expected
223 to show a high amount of ecologically contrasting traits, from agricultural
224 areas to conifers and broadleaf forests, to pastures, grasslands and bare rocks
225 (Pelorosso et al., 2011).

226 3 Discussion

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

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

242 Our method represents a powerful approach to estimate remotely sensed
243 beta-diversity in time, at large spatial extents. Once coupled with hierar-
244 chical methods to also account for different scales of diversities, e.g. with
245 Bayesian hierarchical modelling (Zhang et al., 2014), our approach might

246 represent a benchmark for modelling the variability in space and time of
247 diversity at multiple spatial scales. It is far beyond the aim of this paper
248 to test the sensitivity of the method to different spatial grains and spectral
249 resolutions, but since it is based on pixel distances and relative abundance
250 we expect that it can be applied to any kind of multi- or hyper-volumes like
251 multi- or hyper-spectral images at different spatial and spectral resolutions
252 from high (e.g. Quickbird, Ikonos) to medium (e.g. Sentinel-2 or Landsat
253 data) and low grains (like MODIS data in our case).

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

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

266 There are intrinsic difficulties related to the estimate of biodiversity changes

267 in time (temporal beta-diversity) mainly related to the sampling replication
268 in the same location with the same sampling protocol. Permanent plots
269 arranged in networks like the Long Term Ecosystem Research in Europe
270 (LTER, <http://www.lter-europe.net/>) have been explicitly implemented to
271 solve the problem. However, they represent sporadic and spatially scattered
272 locations in local areas. Once zones with high spatial and temporal variabil-
273 ity have been detected, the attained information could be a powerful tool for
274 guiding field based surveys of species diversity (Rocchini et al., 2005). This
275 is overall true when considering ancillary models specifically dedicated to the
276 development of efficient sampling designs, based on e.g. sampling optimisa-
277 tion based on synthetic maps (Schweiger et al., 2015) or on virtual species
278 sets (Garzon-Lopez et al., 2016).

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

286 In this paper, the continuous variability of spectral pixel values, coupled
287 with the temporal dimension provided for additional information on the vari-

288 ation of ecosystems, allowing a better detection of highly diverse spot in space
289 and in time, considering different time spans t_0, t_1, \dots, t_n . Strictly speaking,
290 including temporal variation in the analysis of diversity from remote sensing
291 might provide additional information to spatial kernels measured at t_0 .

292 Obviously, the variability of the spectral signal is not the only proxy
293 of diversity, and in some cases (e.g. in urban areas) a high environmental
294 variability is not necessarily related to a high amount of biodiversity in the
295 field (Ricotta et al., 2010). However, in case of natural and seminatural ar-
296 eas, spectral variability might represent one of the main proxies of diversity
297 (Skidmore et al., 2015; Schmeller et al., 2017). Hence, in order to measure
298 spatial and temporal changes in diversity, it could be coupled with additional
299 variables such as: i) climatic predictors (Zellweger et al., 2019), ii) soil prop-
300 erties (Tuomisto et al., 2003), iii) topographical complexity (Badgley et al.,
301 2017). Furthermore, in this manuscript we made use of a spectral index like
302 the inter-annual NDVI as an example dataset to calculate spatial heterogene-
303 ity, as in Oindo and Skidmore (2002) or Gillespie (2005) and more recently
304 Feilhauer et al. (2012), by deriving the Rao's Q diversity on a continuous
305 data matrix to monitor heterogeneity changes through time, although the
306 annual inter-variation of productivity could be related to several factors, and
307 not just to niche-based diversity changes. We refer to the debate between
308 Krishnaswamy et al. (2009) and Rocchini (2009) about problems related to

309 alpha- and beta-diversity measurement from NDVI.

310 4 Conclusion

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

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

320 The open source code provided will guarantee the robustness and repro-
321 ducibility of the method. In fact, we are expecting that such a code will be
322 used by other researchers to further develop additional algorithms on tem-
323 poral variability measurement from satellite images.

324 From an ecological and operational point of view, for species inventory-
325 ing maximisation in biodiversity protection, advocated by the Sustainable
326 Development Goal 15 ("halt biodiversity loss") and scientifically proposed by
327 Rocchini et al. (2005) and more recently reviewed by Schmeller et al. (2017),

328 the temporal variability, together with the spatial one, could be beneficial in
329 order to plan more efficient conservation practices starting with those diver-
330 sity hotspots detected in space and time by remote sensing techniques.

331 Attempts have been made to measure the spatial sensitivity of the rela-
332 tion between species and spectral diversity (Wang et al., 2018) which might
333 impact further management practices if disregarded. However, as far as we
334 know, nothing has been done to project it also in time. Our method repre-
335 sents a potential benchmark for applying such a variation measurement in
336 time, which could be extended i) not only to other types of sensors in satel-
337 lite images but to every kind of 2D matrices including species-plot arrays,
338 ii) to other methods such as the measure of spatial and temporal autocorre-
339 lation (Guelat and Kery, 2008), iii) to additional ecospace (sensu Dick and
340 Laflamme (2018)) by fuzzy modelling.

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553 abundance. *Environmental and Ecological Statistics*, 21: 611-625.

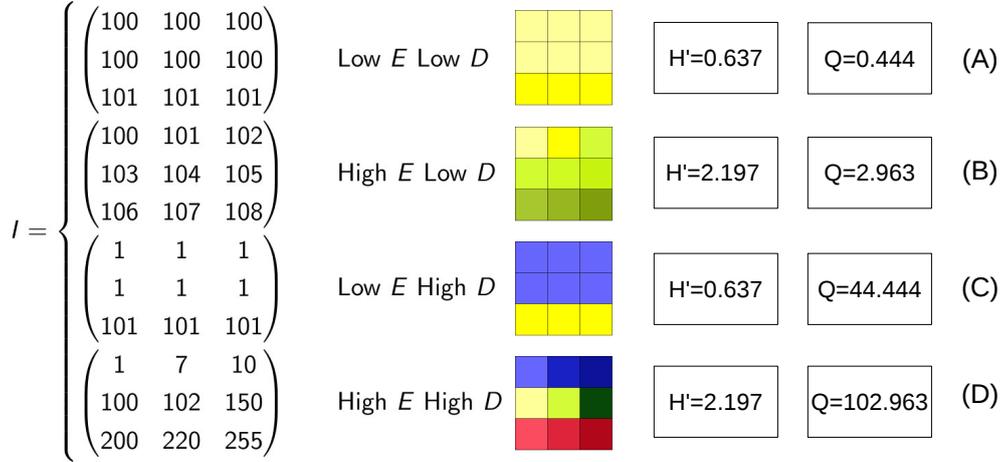


Figure 1: Synthetic example showing four different environmental situations and their relative Shannon's H' and Rao's Q indices. (A) Lower diversity in terms of both evenness and distance among pixel values; (B) and (C) intermediate situations; (D) higher diversity in terms of both evenness and distance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

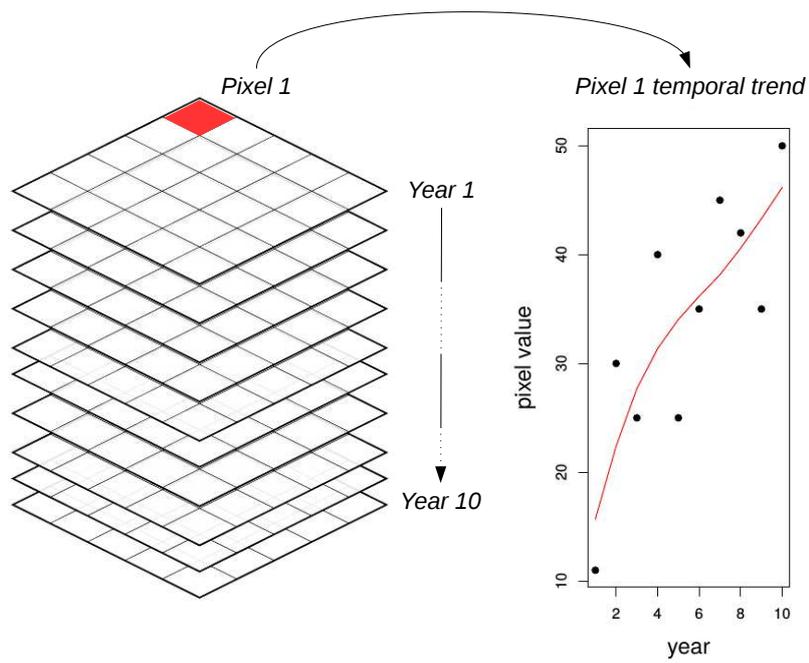


Figure 2: The Rao's value $Q_{P_0 t_0}$ at a given site (pixel P_0) in a certain moment (time t_0) can be plotted on a time scale. Once all the values from $Q_{P_0 t_0}$ to $Q_{P_0 t_n}$ have been plotted, a smooth LOESS function can be estimated and its slope (trend) of coefficient of variation would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

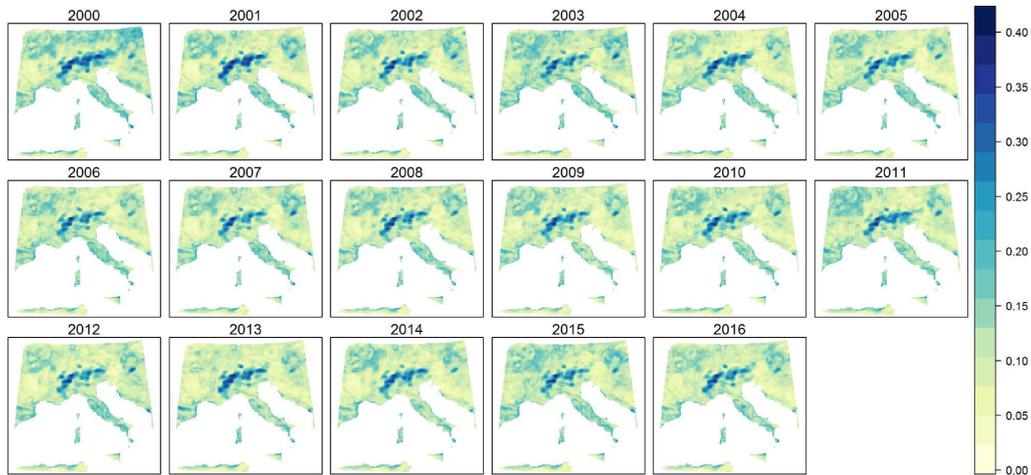


Figure 3: Spatial representation of the free set of Rao's Q data based on MODIS NDVI images at a resolution of 5km provided by Rocchini et al. (2017). The final stack of layers consists of 17 Rao's Q images gathered from 2000 to 2016 in June.

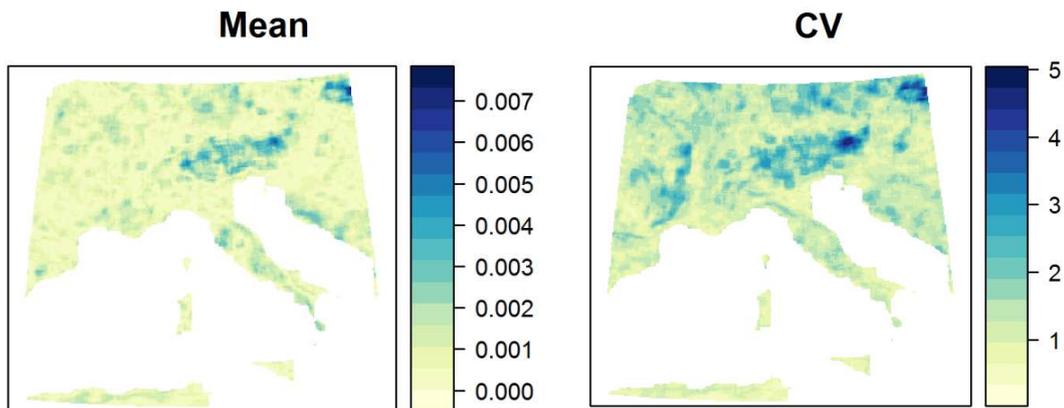


Figure 4: Rao's Q temporal diversity considering LOESS mean slope (mean temporal diversity) and LOESS coefficient of variation (temporal turnover). Both measures detected a higher temporal diversity in areas with higher landscape morphological complexity detected by the spatial Rao's Q .

554 Appendix 1 - R code

```
555 ##### 1
556 ## R CODE FOR APPLYING THE APPROACH PRESENTED IN:
557 ## Rocchini, D., Marcantonio, M., Da Re, D., Chirici, G., 3
558 Galluzzi, M., Lenoir, J., Ricotta, C., Torresani, M., Ziv, G.
559 (2019). Time-lapsing biodiversity: an open source method for
560 measuring diversity changes by remote sensing. Remote
561 Sensing of Environment.
562 #####
563 5
564 ## Set working directory and load libraries
565 setwd("/home/TemporalAlfaDiv/") 7
566 library(raster)
567 library(parallel) 9
568 library(fANCOVA) # To automatically select loess smoothing
569 parameters select using aicc
570 library(ggplot2) 11
571 library(rasterVis)
572 library(plyr) 13
573 library(RColorBrewer)
574 library(gtable) 15
575 library(grid)
```

```

576 library(gridExtra) 17
577 library(ggpubr)
578 19
579 ##### 1. Load data #####
580 load("/home/TemporalAlfaDiv/all_raoQ_5km.RData") 21
581 rao_stack<-stack(rao2000_5km, rao2001_5km ,rao2002_5km ,rao2003_5
582 km ,rao2004_5km ,rao2005_5km,
583 rao2006_5km, rao2007_5km, rao2008_5km, rao2009_5 23
584 km, rao2010_5km, rao2011_5km,
585 rao2012_5km, rao2013_5km, rao2014_5km, rao2015_5
586 km, rao2016_5km)
587 25
588 s<-as.list(rao_stack)
589 27
590 ##Cut on Italy
591 s_red<-mclapply(s, function(x) {y=crop(x, extent(0,20,36,50)); 29
592 return(y)},mc.cores=detectCores())
593
594 ##Derive values from raster and put them in a 3D array 31
595 rao<-mclapply(s_red,trim,mc.cores=8)
596 raoV<-mclapply(rao,getValues, mc.cores=8) 33
597 raoA<-array(as.numeric(unlist(raoV)), dim=c(336, 275, 17))
598 35
599 ##### 2. Apply loess on the time series #####

```

```

600 #Loess smoothing parameters are automatically selected using aicc 37
601 #The derivative of a function is dy/dx, which can be approximated
602     by  $\hat{\Delta}y/\hat{\Delta}x$ , that is, "change in y over change in x". This
603     can be written in R using diff function
604 #in order to get an approximation to the derivative of the 39
605     function at each x
606
607 stats<-c("mean","min","max") 41
608 xl<-seq(2000:2016)
609 outl <- rep( list(matrix(nrow=336, ncol=275)),3 ) 43
610 prd <- array( as.numeric(NA), dim=c(336, 275, 17) )
611 45
612 for (r in 1:336) {
613     options(warn=-1) 47
614     for (c in 1:275) {
615         if(any(is.na(raoA[r,c,]))) { 49
616             next()
617         } else { 51
618             prd[r,c,]<-predict(loess.as(seq(1:17), raoA[r,c,], criterion
619             = c("aicc"), degree=1, plot = F))
620             for (s in 1:3) { 53
621                 outl[[s]][r,c]<-sapply(list(diff(prd[r,c,])/diff(xl)),get
622                 (stats[s]),na.rm=T)
623             } 55

```

```

624     }
625 }
626     options(warn=0)
627 }
628
629 ##Make an output raster map
630 raoTslopes <- stack(s_red[[1]], s_red[[1]], s_red[[1]])
631
632 ##Add mean, min and max matrices
633 raoTslopes_out <- stack(lapply(1:3, function(x) {
634     values(raoTslopes[[x]])<-as.numeric(outl[[x]]);
635     names(raoTslopes[[x]])<-c("mean", "min", "max")[x];
636     return(raoTslopes[[x]])
637 })))
638
639 plot(raoTslopes_out)
640
641 ## Compute coefficient of variation
642 rao_stack_it<-crop(rao_stack, extent(0,20,36,50))
643 rao_stack_it<-stack(rao_stack_it)
644 rao_mean<-calc(rao_stack_it, mean)
645 rao_sd<-calc(rao_stack_it, sd)
646 rao_CV<-((rao_sd)/(1+rao_mean))*100
647 names(rao_CV)<-"rao_CV"

```

```

648
649  raoTslopes_out<-stack(raoTslopes_out, rao_CV) 81
650  plot(raoTslopes_out)
651 83
652  ##save rasters
653  stackSave(raoTslopes_out, "raoTslopes") 85
654
655  ##### 3. plot ##### 87
656
657  ##plot parameters 89
658  pal<-brewer.pal(9, "YlGnBu")
659  myTheme <- rasterTheme(region = pal) 91
660
661  utm32n<-" +proj=utm +zone=32 +ellps=WGS84 +datum=WGS84 +units=m + 93
662    no_defs +towgs84=0,0,0"
663  crs(raoTslopes_out)<-"+proj=longlat +datum=WGS84 +no_defs +ellps=
664    WGS84 +towgs84=0,0,0"
665  raoTslopes_out<-projectRaster(raoTslopes_out, crs=utm32n) 95
666  p1<-levelplot(abs(raoTslopes_out[[1]]), main= "Mean", scales=
667    list(draw=FALSE), contour = FALSE, margin = FALSE, par.
668    settings = myTheme, ylab= "", xlab= "")
669  p2<-levelplot(raoTslopes_out[[2]], main= "Min", scales=list(draw 97
670    =FALSE), contour = FALSE, margin = FALSE, par.settings =
671    myTheme, ylab= "", xlab= "")

```

```

672 p3<-levelplot(raoTslopes_out[[3]], main= "Max", scales=list(
673   draw=FALSE), contour = FALSE, margin = FALSE, par.settings =
674   myTheme, ylab= "", xlab= "")
675 p4<-levelplot(abs(raoTslopes_out[[4]]), main= "CV", scales=list 99
676   (draw=FALSE), contour = FALSE, margin = FALSE, par.settings
677   = myTheme, ylab= "", xlab= "")
678
679 grid.arrange(p1,p2,p3,p4, nrow=2) 101
680 ggsave("raoRslopes.tiff", height=8, width=12, units="in", dpi
681   =300, plot= pp, path = "/home/TemporalAlfaDiv/img/")
682 103
683 ##### Appendix: MODIS NDVI #####
684 load("/home/TemporalAlfaDiv/all_NDVI_5km.RData") 105
685 ndvi_stack<-stack(raster(NDVI_07_2000_5km),raster(NDVI_07_2001_5
686   km), raster(NDVI_07_2002_5km), raster(NDVI_07_2003_5km),
687   raster(NDVI_07_2004_5km), raster(NDVI_07_2005_5 107
688   km), raster(NDVI_07_2006_5km), raster(NDVI_07_2007_5km),
689   raster(NDVI_07_2008_5km), raster(NDVI_07_2009_5
690   km), raster(NDVI_07_2010_5km), raster(NDVI_07_2011_5km),
691   raster(NDVI_07_2012_5km), raster(NDVI_07_2013_5km), raster(
692   NDVI_07_2014_5km), raster(NDVI_07_2015_5km),raster(NDVI_07_
693   2016_5km))
694 109
695 crs(ndvi_stack)<-"+proj=longlat +datum=WGS84 +no_defs +ellps=

```

```

696     WGS84 +towgs84=0,0,0"
697 ndvi_stack<-crop(ndvi_stack, extent(0,20,36,50)) 111
698 ndvi_stack<-projectRaster(ndvi_stack, crs=utm32n)
699 annual_ndvi<-as.character(2000:2016) 113
700 rastNam<-as.character(2000:2016)
701 115
702 ##Time-series plot
703 mapTheme <- rasterTheme(region=brewer.pal(8,"Greens")) 117
704 p12<-levelplot(ndvi_stack, xlab="", ylab="", scales=list(draw=
705     FALSE),names.attr=rastNam,
706     layout=c(6, 3), contour = FALSE, margin = FALSE, 119
707     par.settings = mapTheme, main= "NDVI 2000-2016")
708
709 tiff("img/ndvi2000-2016_GreenTheme.tiff", height = 10, width = 121
710     13, res=300,units="in")
711 p12
712 dev.off() 123

```

713 **Appendix 2 - Synthetic example of Rao's Q di-**
714 **versity index calculation**

715 We provide a mathematical example of the calculation of Shannon's H' and
716 Rao's Q diversity indices based on the synthetic examples provided in Figure
717 1. We will apply such indices to the input image (matrix) I with the highest
718 diversity (Figure 1D). The calculation can then be translated to any matrix.

719 Let $I = \begin{pmatrix} 1 & 7 & 10 \\ 100 & 102 & 150 \\ 200 & 220 & 255 \end{pmatrix}$ be the input image on which the calcula-
720 tion is applied. Shannon's H' turns out to be $H' = -\sum p \times \ln(p)$ where
721 p =proportion of each pixel value. Since p is $\frac{1}{9}$, in this case, hence $H' =$
722 $9 \times 0.11 \times \ln(0.11) = 2.197$.

723 Rao's Q diversity adds to such abundance-based calculation the distances
724 among pixel values as $Q = \sum \sum d_{ij} \times p_i \times p_j$. A distance matrix is first cal-
725 culated, returning $N \times N$ distances, where N =number of input pixels (in
726 this case 9), as:

$$\begin{matrix}
727 & D_i = & \begin{pmatrix}
0 & 6 & 9 & 99 & 101 & 149 & 199 & 219 & 254 \\
6 & 0 & 3 & 93 & 95 & 143 & 193 & 213 & 248 \\
9 & 3 & 0 & 90 & 92 & 140 & 190 & 210 & 245 \\
99 & 93 & 90 & 0 & 2 & 50 & 100 & 120 & 155 \\
101 & 95 & 92 & 2 & 0 & 48 & 98 & 118 & 153 \\
149 & 143 & 140 & 50 & 48 & 0 & 50 & 70 & 105 \\
199 & 193 & 190 & 100 & 98 & 50 & 0 & 20 & 55 \\
219 & 213 & 210 & 120 & 118 & 70 & 20 & 0 & 35 \\
254 & 248 & 245 & 155 & 153 & 105 & 55 & 35 & 0
\end{pmatrix} \\
728 & &
\end{matrix}$$

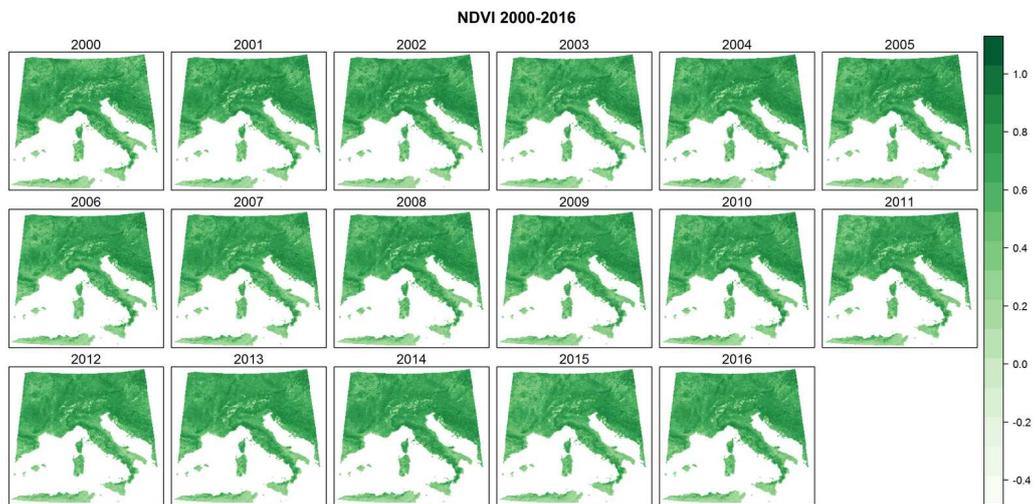
729 According to the Rao's Q formula, each pairwise distance between the
730 i th and the j th pixel in the image is then multiplied by their proportions p_i
731 and p_j , hence by $\frac{1}{9} \times \frac{1}{9} = \frac{1}{81} = 0.0123$.

732 Extracting all these terms and applying the sum as in Equation 1 will
733 lead to a final value of $Q = 102.963$, as in Figure 1D.

734 In the additional Supplementary Material we also provide a spreadsheet
735 with the calculation of Shannon's H' and Rao's Q indices for the four envi-
736 ronmental situations reported in Figure 1.

737 Appendix 3 - Sketch of the original NDVI values

738 used to calculate Rao's Q



This graph represents the sketch of NDVI maps from which the Rao's Q diversity has been derived and provided for free by Rocchini et al. (2018).
