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Using spectral diversity and heterogeneity measures to map habitat mosaics: An example from the Classical Karst

This is the final peer-reviewed author's accepted manuscript (postprint) of the following publication:

Published Version:

Pafumi E., Petruzzellis F., Castello M., Altobelli A., Maccherini S., Rocchini D., et al. (2023). Using spectral diversity and heterogeneity measures to map habitat mosaics: An example from the Classical Karst. APPLIED VEGETATION SCIENCE, 26(4), 1-14 [10.1111/avsc.12762].

Availability:

This version is available at: https://hdl.handle.net/11585/952760 since: 2024-01-11

Published:

DOI: http://doi.org/10.1111/avsc.12762

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APPLIED VEGETATION SCIENCE VOL. 26 ISSN 1654-109X

DOI: 10.1111/avsc.12762

The final published version is available online at:

https://dx.doi.org/10.1111/avsc.12762

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1	Using remote sensing to map natural habitats: an integrated approach
2	applied to the Classical Karst eco-mosaic
3	
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## 14 Abstract

15 Remote sensing is a well-established tool for habitat mapping, but its use is still challenging in heterogeneous landscape 16 mosaics. Novel approaches to improve classification performance include multi-temporal data and multiple remotely sensed 17 variables. In this study, an integrated approach was developed to map the natural habitats in Classical Karst eco-mosaic (NE 18 Italy), by quantifying the importance of Spectral Heterogeneity (SH) measures and providing a robust framework to include 19 multi-temporal remotely sensed data. 20 A collection of 12 monthly Sentinel-2 images was retrieved using the Google Earth Engine platform. Vegetation and SH indices 21 were computed and aggregated in four temporal configurations: (1) monthly layers of vegetation and SH indices; (2) seasonal 22 layers of vegetation and SH indices; yearly layers of multi-temporal SH indices computed (3) across the months, and (4) across 23 the seasons. For each temporal configuration, a Random Forest classification was performed, first with the complete set of 24 input layers and then with a subset obtained by Recursive Feature Elimination. Training and validation points were 25 independently extracted from field data. The maximum overall accuracy (OA = 0.72) was achieved with the seasonal temporal configuration, after the number of 26 27 habitats was reduced from 26 to 11. SH measures allowed to improve the accuracy of the classification and the spectral  $\beta$ -28 diversity was the most important variable in most cases. Spectral  $\alpha$ -diversity and Rao's Q, on the other side, had a low relative 29 importance, possibly due to the small spatial extent of the habitats. Regarding the inclusion of multi-temporal data, the 30 aggregation of monthly data in seasonal median composites proved to be the best approach, since it allowed to reduce the 31 number of input layers without losing accuracy. The approach developed in this study allows to improve habitat mapping in 32 complex landscapes in a cost- and time-effective way, suitable for monitoring applications.

33

34

## 35 Keywords:

- 36 Multi-temporal classification; Random Forest; Sentinel-2; Spectral diversity; Spectral heterogeneity; Vegetation indices
- 37
- 38

## 39 Highlights

- 40 Spectral heterogeneity measures increase the accuracy of image classifications.
- 41 The most important variable in most classifications is spectral  $\beta$ -diversity.
- 42 Spectral  $\beta$ -diversity mainly distinguishes woodlands, grasslands and pine forests.
- 43 Spectral  $\alpha$ -diversity and Rao's Q index have a lower importance.
- Aggregating data in seasonal composites is a reliable way to reduce dimensionality.
- 45

#### 46 **Abbreviations:**

- 47 BC Bray-Curtis dissimilarity 48 DT Decision Tree 49 GNDVI Green Normalized Difference Vegetation Index 50 I-0 Grassland encroachment level 0 (pure grassland) 51 I-1 Grassland encroachment level 1 52 I-2 Grassland encroachment level 2 53 IRECI Inverted Red Edge Chlorophyll Index LAI 54 Leaf Area Index 55 LiDAR Light Detection And Ranging 56 NDVI Normalized Difference Vegetation Index 57 NDWI Normalized Difference Water Index 58 NIR Near Infra-Red 59 OA **Overall Accuracy** 60 OOB Out Of Bag PA 61 Producer's accuracy 62 PCA Principal Component Analysis 63 PCoA Principal Coordinate Analysis 64 RF Random Forest 65 RFE **Recursive Feature Elimination** SH Spectral heterogeneity 66 SWIR Short Wave Infra-Red 67 UA 68 User's accuracy
- 69

## 70 **1. Introduction**

Mapping natural habitats is a fundamental step for the conservation of biodiversity. The Habitats Directive, for example, requires EU member states to conserve habitats and species "of community interest" and assess their conservation status every six years, by reporting on parameters such as habitat area, range, indicators of habitat quality and future previsions for habitat survival (European Commission, 2005). These reports require habitat mapping. However, habitat maps have traditionally been produced through time-consuming and costly field surveys, that make them unsuitable to regular updates. Thus, more cost- and time-effective monitoring strategies are required, and remote sensing has become an essential tool for this objective (Corbane et al., 2015).

Habitat mapping by remote sensing is generally carried out through the process of automatic image classification, in which all pixels in a remotely sensed image are categorized into classes of ground cover (Borra et al., 2019). Over time, many remote sensing data have become available, including multispectral and hyperspectral satellite images, and data from active sensors such as radar (Richards, 2013), while image processing tools have been improved, allowing to map a broad range of habitats, such as forests, grasslands, heathlands and wetlands (Corbane et al., 2015).

Despite the advances in this field, mapping some types of habitats remains a difficult task, especially in heterogeneous areas. Mosaics of natural and semi-natural grasslands, for example, are particularly challenging to map, due to the typical small spatial extent of the habitat patches, their spectral similarity, and the high spatial, structural and temporal variability of the vegetation (Corbane et al., 2015; Tarantino et al., 2021). This is complicated by the fact that boundaries between the patches are often not discrete (Rocchini et al., 2013b). Thus, innovative approaches should be tested (Schuster et al., 2015).

88 The use of multi-temporal data has been proven to facilitate the differentiation of habitats in areas with a seasonal variability (Rapinel et al., 2019; Schuster et al., 2015). This approach, indeed, accounts for phenological differences among vegetation 89 90 types, that can be the key to distinguish spectrally similar habitats, especially when the most appropriate dates are selected 91 (Senf et al., 2015). However, there are many possible ways to include the multi-temporal information in the classification 92 process. For example, Schuster et al. (2015) found that the accuracy of a classification in grassland habitats was increased by 93 the number of used images, but with differences according to the type of data source. Tarantino et al. (2021) compared the 94 effect of using a time series of a single vegetation index and a set of Sentinel-2 images and found that the first method 95 outperformed the latter. In another study, multiple Sentinel-2 seasonal composites were compared, and the highest accuracy 96 was achieved using the summer mean composite (Praticò et al., 2021).

97 Image classification outcomes can also be improved by the integration of ancillary data, that modern classification algorithms 98 are able to handle (Wulder et al., 2018). Topographic features such as slope and aspect are often relevant, since they influence 99 the distribution of natural communities on fine scales (Bhatt et al., 2022). Data on vegetation structure derived from active 99 sensors like LiDAR (Light Detection And Ranging) can also facilitate habitat mapping, as demonstrated for example for a 91 semi-arid region of Brazil by da Silveira et al. (2018) and for non-forest Natura 2000 habitats in Poland by Osińska-Skotak et 92 al. (2021). However, some of the greatest improvements in image classifications are achieved when texture information is included, as was highlighted in a recent meta-analysis (Khatami et al., 2016). Image texture metrics measure the spatial
arrangement and variation of pixel values, and thus provide valuable information on the homogeneity of areas (Haralick et al.,
1973). For this reason, they can facilitate the differentiation of spectrally similar habitats (e.g. Bhatt et al., 2022).

106 The spatial variability of the remotely sensed signal is also the basis for the assessment of plant biodiversity from remote 107 sensing (Rocchini et al., 2010a). The so-called spectral diversity, or spectral heterogeneity, has been directly related to 108 environmental heterogeneity by the Spectral Variation Hypothesis (Palmer et al., 2002; 2000). Moreover, spectral heterogeneity 109 can be considered a proxy for species diversity (Rocchini et al., 2010a), because environmentally heterogeneous areas have a 110 large number of niches available and are expected to host a high species diversity (Stein et al., 2014). The relationship between 111 spectral heterogeneity and species diversity has proved to be sensitive to many factors (Wang and Gamon, 2019), like spatial 112 scale (Oldeland et al., 2010; Wang et al., 2018), spectral resolution (Rossi et al., 2021) and temporal scale (Fauvel et al., 2020), 113 thus it cannot be considered universally valid (Fassnacht et al., 2022). However, spectral heterogeneity can be useful regardless 114 of its relation with taxonomic diversity, since it encompasses also a functional and a phylogenetic dimension of biodiversity 115 (Wang and Gamon, 2019).

116 Many indices have been proposed as measures of spectral heterogeneity (Wang and Gamon, 2019). The most traditional ones 117 include metrics of variability of single wavebands or vegetation indices such as NDVI (Gillespie, 2005; Levin et al., 2007), 118 and metrics that condense full-spectrum variability, such as the distance from spectral centroid (e.g. Palmer et al., 2002; 119 Rocchini, 2007). Recently, two novel approaches have emerged to estimate spectral heterogeneity. The first one relies on 120 information theory: diversity indices based on information theory are computed from spectral data, generally by applying the 121 moving window approach (Rocchini et al., 2013a). The most common of these indices is Shannon entropy (Shannon, 1948), 122 computed by considering the relative abundance and richness of reflectance values. However, indices that consider also the 123 spectral distance among pixel values have some advantages, as was recently highlighted by Thouverai et al. (2021). Rao's 124 quadratic entropy has been proposed for this reason and proved to perform well in natural areas (Rocchini et al., 2021a).

125 The second novel and powerful approach to estimate spectral heterogeneity is based on "spectral species", i.e. spectral types 126 considered as proxies for biological species (Féret and Asner, 2014). Following this approach, each pixel of the image is 127 assigned to a spectral species, generally through unsupervised k-means clustering, thanks to the fact that pixels from the same 128 species tend to converge to the same cluster (Féret and Asner, 2014). The spatial variation in spectral species is then used to infer metrics of  $\alpha$ - and  $\beta$ -diversity (Féret and Boissieu, 2020). So far, the spectral species method has been applied to tropical 129 130 forests, based on very high-resolution airborne imaging spectroscopy (Féret and Asner, 2014), to low-resolution MODIS 131 images of the entire Europe (Rocchini et al., 2021c), and recently also to Sentinel-2 data (Féret and Boissieu, 2020) to assess 132 biodiversity changes in secondary forests (Chraibi et al., 2021) and to estimate plant diversity in an ecological network (Liccari 133 et al., 2022).

In this light, measures of spectral heterogeneity have the potential to improve habitat mapping frameworks. Indeed, when vegetation types share similar spectral reflectance characteristics, considering additional levels of information may facilitate their differentiation (e.g. Bhatt et al., 2022). The variability of taxonomic, functional and phylogenetic traits, as expressed by 137 spectral heterogeneity (Wang and Gamon, 2019), may be such a type of information. Thus, including spectral heterogeneity 138 measures in image classification procedures could increase their robustness and accuracy, especially in complex landscape 139 mosaics. However, very few studies have tried to incorporate these measures (e.g. Marzialetti et al., 2020).

140 Interestingly, both Rao's entropy and spectral species-based metrics can be assessed in the temporal dimension. If a multi-

temporal stack is provided as input instead of a multi-spectral image, in fact, temporal diversity will be computed (Marzialetti

- 142 et al., 2020). This spectral temporal diversity will likely be useful to assess biodiversity, since differences in phenology can be
- 143 important to estimate plant diversity (Fauvel et al., 2020).

144 Moving forward from these premises, the aim of this study was to test and discuss an integrated approach to map a complex

145 mosaic of natural and semi-natural habitats through remote sensing, using the Classical Karst as case study. Specifically, the 146 main objectives were:

147 1) quantify the importance of measures of spectral heterogeneity for habitat classification;

148 2) provide a robust framework to include multi-temporal remotely sensed data for habitat classification.

To achieve these goals, multiple sets of remote sensing derived variables, namely vegetation indices and spectral heterogeneity indices, along with their variation over one year, were computed based on a series of Sentinel-2 images covering the period March 2021 - February 2022. These variables were aggregated in four temporal configurations, for which separate classifications were performed. Classification accuracies were compared to find the most reliable approach.

153

### 154 **2. Materials and methods**

#### 155 **2.1. Study area**

The study was carried out in the Italian part of the Classical Karst, a limestone plateau, with altitudes ranging from 0 to 600 m, located in the provinces of Trieste and Gorizia within Friuli-Venezia Giulia region (NE Italy; Fig. 1). Seven different territorial disjunct patches were considered, that cover a total surface of 60 ha and are involved in a restoration project called "Ecomosaico del Carso" (Appendix). These areas are partially included in two Natura 2000 sites: the special area of conservation "Carso Triestino e Goriziano" (IT3340006) and the special protection area "Aree carsiche della Venezia Giulia" (IT3341002).

161 Land cover is characterized by a fine mosaic of natural and semi-natural habitats, created by the long-lasting human presence in the region. The main vegetation types are grassland, downy oak woodland and black pine plantation. Karst grassland is an 162 163 extremely species-rich gramineous herbaceous formation that evolved with the millenary action of grazing and is now being 164 replaced by shrublands and woodlands due to pasture abandonment. Downy oak woodlands are expanding in abandoned 165 pastures and cover 70% of the Karst nowadays. Black pine has been planted since the mid 19th century for reforestation purposes 166 and from then on has spontaneously expanded creating species-poor pine forests (Poldini, 2009, 1989). Many conservation 167 projects are being developed in recent years to maintain and restore Karst grassland (Marin and Altobelli, 2021), that is also a 168 habitat of community interest (code 62A0 "Eastern sub-Mediterranean dry grasslands (Scorzoneratalia villosae)" in Annex I 169 of the Habitat Directive; European Commission, 1992).

- 170 The climate is transitional between Mediterranean and continental (Poldini, 1989). The average rainfall is 1200 mm/year, and
- the mean annual temperature is 12.5°C, although there are large differences due to elevation and slope exposure (OSMER,
- 172 2015). The dry and cold Bora from NE contributes to desiccation and soil erosion (Poldini, 1989).
- 173

#### 174 **2.2. Field data collection**

Field surveys were carried out between March and May 2022. Habitats present in the intervention areas of "Ecomosaico del Carso" project were identified on the field. In a first phase, habitats were identified as vegetation types with a high level of detail, in most cases as associations, according to the phytosociological types described for Classical Karst by Poldini (1989; 2009). In a second phase, habitats were defined on the basis of their structural-physiognomic and ecological characteristics, and some of the previous classes were aggregated into coarser classes. The two classifications account respectively for 26 and 11 habitat classes. Specifically, for the first classification process, different classes of grassland were distinguished according to the following criteria:

182 1) type of grassland: thermophilous, mesophilous, on flysch;

- degree of felting (i.e., presence of *Sesleria autumnalis*): pure grassland (no *S. autumnalis*), first degradation stage
  (few patches of *S. autumnalis*), second degradation stage (mosaic with ca. 50% grassland elements and 50% *S. autumnalis*), third degradation stage (felted grassland, completely covered by *S. autumnalis*);
- 3) stage of vegetational succession: no bushes (zero encroachment level, I-0), few bushes with low height (ca < 1.5 m)</li>
  and widely spaced (first encroachment level, I-1), medium height bushes (ca 3-4 m) relatively close to each other
  (second encroachment level, I-2).

189 In the second classification, only the last criterion was considered, while shrublands, initially differentiated according to the 190 vegetation type, were aggregated into a single class. The two classes of downy oak woodland - namely, a young class with low 191 height individuals, and a mature class with individuals higher than 6 m - were also merged. Groves with Ailanthus altissima 192 and Robinia pseudoacacia were aggregated into an invasive alien species class, while sessile oak woodlands, black pine 193 plantations, hay meadows and pasture-grasslands were kept as separate classes. Finally, a grassland-woodland mosaic was 194 defined as a dynamic stage with patches of grassland and well-spaced patches of woodland. The complete list of habitat classes 195 considered in this study is in Table A2. Two areas were excluded from the analysis since vegetation could not be classified 196 according to the defined scheme: area n.17, where vegetation was cut before field surveys, and a portion of area n.6, where a 197 fire occurred on 14/08/2021.

The habitats present in the study areas were manually mapped based on field collected data using QGIS 3.16.14 software (QGIS Development Team, 2022). Maps of vegetation height derived from LiDAR data were used as a base for polygon drawing. LiDAR RAFVG survey has been conducted in Friuli-Venezia Giulia region in the years 2017-2020 by aerial means. LiDAR point clouds, that have an average density of 16 points/m<sup>2</sup>, were downloaded from Eagle FVG portal (https://eaglefvg.regione.fvg.it). Each point includes a classification field (1 – unclassified, 2 – ground, 3 – low vegetation, 4 – medium vegetation, 5 – high vegetation): points belonging to "Ground" class were extracted and interpolated to create a plan,

- then the distance of the vegetation points from the plan was computed and maps of vegetation height were produced.
- 205 Elaboration was performed in CloudCompare 2.11.1 (Cloud Compare, 2021).
- 206

#### 207 **2.3. Satellite data collection and processing**

- 208 The workflow applied to manage satellite data and to derive input variables for classification is represented in Fig. 2. First, 209 Sentinel-2 images were retrieved using Google Earth Engine platform (Gorelick et al., 2017). The Sentinel-2 level-2A image 210 collection ("COPERNICUS/S2 SR HARMONIZED") was filtered by date (from 2021-03-01 to 2022-02-28), by area (the 211 Trieste and Gorizia Karst) and by cloud coverage (cloudy pixel percentage < 50%). The less cloudy image of each month was 212 manually selected, to produce a collection of 12 monthly images covering a whole year. 213 Then, the 12 Sentinel-2 images were divided into four seasonal groups: spring (March 2021-May 2021), summer (June 2021-August 2021), autumn (September 2021-November 2021), and winter (December 2021-February 2022). Each group was 214 215 reduced to a single image by computing the median of each spectral band, so that, at each location in the output image, the
- 216 pixel value of a band is the median of all pixel values of that band in the input group.
- 217

#### 218 **2.4. Vegetation indices**

- Vegetation indices were preferred over the original Sentinel-2 spectral bands as inputs for the classification because they allow to reduce the dimensionality of the dataset while being more strongly related to the temporal variation of vegetation (Coppin et al., 2004). Four vegetation indices were derived from each Sentinel-2 image (Table 1): Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Normalized Difference Water Index (NDWI) and Inverted Red Edge Chlorophyll Index (IRECI).
- NDVI (Rouse et al., 1975) includes the red and NIR bands, respectively sensitive to chlorophyll content and leaf structure. It has been proven to be correlated to biomass, LAI and photosynthetic activity (Gamon et al., 1995). GNDVI is an alternative to NDVI, with the green band instead of the red band, that has been proposed to avoid saturation in case of high chlorophyll
- 227 content (Gitelson et al., 1996). NDWI, including the NIR and SWIR bands, is sensitive to water content and can be useful in
- 228 assessing vegetation water status (Chen et al., 2005). Finally, IRECI uses Sentinel-2 red and red-edge bands and is very sensitive
- to LAI parameter and canopy chlorophyll content (Frampton et al., 2013).
- 230 These indices were computed from each image in the monthly dataset and then aggregated into seasonal median composites,
- following the same procedure used for Sentinel-2 reflectance bands. These operations were performed in Google Earth Engine.

#### 233 **2.5. Metrics of spectral heterogeneity and diversity**

- Rao's quadratic entropy (Rao's Q; Rao, 1982) is a diversity index that considers both relative abundances of pixel values ( $p_i$ ,
- 235  $p_i$ ) and spectral distances among them  $(d_{ij})$ :

236 
$$Q = \sum_{i=1}^{N} \sum_{j=1}^{N} d_{ij} \times p_i \times p$$



240 Then, Rao's Q was computed also in the multi-temporal dimension, by setting a "multidimension" method. In this case, the 241 distances among pixel values are calculated considering more than one layer. For each vegetation index, two layers of multi-242 temporal Rao's Q were produced, one from the stack of 12 monthly images and the other from the stack of 4 seasonal 243 composites.

244 Spectral  $\alpha$ - and  $\beta$ -diversity metrics were calculated following the spectral species concept proposed by Féret and Asner (2014), using the R package biodivMapR (Féret and Boissieu, 2020). The used algorithm includes several steps: first, the multi-245 246 spectral images are filtered to remove irrelevant pixels (non-vegetated, shady, or cloudy). Then, a principal component analysis (PCA) is performed, and the relevant principal components (PCs) are manually selected based on visual analysis. Spectral 247 248 species mapping is based on k-means clustering. A subset of pixels is randomly extracted from the image and used to define k 249 clusters (i.e., "spectral species"). The number of clusters was set to 20 in this study as it was suggested as the optimal for 250 moderately diverse temperate sites (Féret and Boissieu, 2020). Then, clustering is applied to the whole image, so that each 251 pixel is assigned to a cluster. Finally,  $\alpha$ - and  $\beta$ -diversity maps are produced, basing on the distribution of spectral species in 252 the window size, that was set to 3x3 pixels in this case, since habitat patches were small. Shannon index was chosen as indicator 253 of  $\alpha$ -diversity, while  $\beta$ -diversity was derived from a pairwise Bray-Curtis (BC; Bray and Curtis, 1957) dissimilarity matrix 254 obtained from the spectral species map. The BC matrix was then subjected to an ordination (Principal Coordinate Analysis, 255 PCoA) to project it into a 3-dimensional space and obtain a visual representation of the results (larger BC dissimilarity between 256 pixels corresponds to larger color differences in the RGB space).

257 This algorithm was applied on each Sentinel-2 monthly and seasonal image, to obtain maps of  $\alpha$ - and  $\beta$ -diversity for each 258 month and season. Then, this procedure was applied on a multi-temporal level, using stacks of vegetation indices covering a 259 whole year as input. For each vegetation index, a stack of 12 layers (each corresponding to a month) and then a stack of 4 layers 260 (each corresponding to a season) were used as input. In this way, two sets of multi-temporal  $\alpha$ - and  $\beta$ -diversity maps were 261 obtained for each vegetation index, one based on monthly values (multi-temporal monthly) and the other based on seasonal 262 values (multi-temporal seasonal).

263

#### 2.6. Satellite image classification 264

265 The remote sensing variables produced through the processing steps outlined before were aggregated in four temporal 266 configurations, as listed in Table 2, that were used as input for distinct classifications.

Reference data for image classification were derived from field surveys. Training points were randomly extracted from a set of training areas selected on the field, outside the polygons of "Ecomosaico del Carso" project when possible, and mapped by acquiring their GPS location. Validation points, on the other hand, were randomly launched in the whole set of polygons created in QGIS after excluding the training areas. Through this procedure, training and validation points can be considered as independent.

272 Image classification was performed using a Random Forest (RF) classification algorithm. Random Forest (Breiman, 2001) is 273 an ensemble machine-learning classifier that builds a large number of decision trees (DTs), each based on a random subset of 274 the training data and of the predictor variables. The training data not used to build the model (i.e., the out-of-bag data, OOB) 275 are used to evaluate the model performance. The results of the different DT models are then averaged to assign each pixel to a 276 class. In this way, the overall result is more reliable than the one obtained from an individual DT and is less affected by 277 correlation among predictors (Maxwell et al., 2018). The relative importance of the predictor variables is computed using the 278 OOB data, by systematically comparing the performance of the DTs that include specific variables and of those that do not: 279 variables with high importance have a positive effect on the prediction accuracy (Breiman, 2001).

For each temporal configuration, two alternative pathways were followed. In one case, the whole set of variables was used as input for the classification. In the other case, a subset of variables was extracted through Recursive Feature Elimination (RFE; (Guyon et al., 2002). RFE is a common feature selection algorithm based on backward elimination, that uses a RF classifier to determine variables permutation importance and remove the less important variables. The importance measures are updated after each deletion, making the method suitable also to highly correlated variables (Gregorutti et al., 2017).

In this study, RF classification was performed using R caret package (Kuhn, 2021). Training data were randomly partitioned into a training and a testing set, with respectively 80% and 20% of the data. The *mtry* parameter (the number of randomly selected predictors used at each node) was optimized through a 5-fold cross-validation, while the relative importance of variables was calculated with *varImp* function.

289 The accuracy of each classification procedure was evaluated using a set of validation points independent from the training data. 290 A confusion matrix was computed, and the proportion of correctly classified pixels (overall accuracy, OA) was derived. OA is 291 preferable to other common metrics such as the Kappa coefficient because it is easier to understand and more suited for 292 comparisons (Foody, 2004). Performances for individual classes were also assessed by considering User's accuracy (UA) and Producer's accuracy (PA). For a given class i, UA is the proportion of pixels classified as i that have reference class i, while 293 294 PA is the proportion of pixels of reference class *i* that are classified as *i* (Borra et al., 2019). Both metrics vary between 0 and 1. The significance of differences in classification accuracy among the different pathways was tested with McNemar's test, as 295 296 suggested by Foody (2004).

After the classifications were performed as described above and the best input configuration was identified, another classification was carried out using only vegetation indices as input, to assess the effect of excluding spectral heterogeneity on the results.

300 All classifications and accuracy assessment analyses were performed in R software (R Core Team, 2022).

## 302 **3. Results**

#### 303 **3.1. Accuracy of image classification**

The values of overall accuracy (OA) and Kappa obtained from the RF classifications are presented in Table 3. The OA was significantly higher when 11 habitat classes were considered of 26 (p-value < 0.05; Fig. 3a), while there was no significant difference when the number of input variables was reduced through RFE (Fig. 3b). The use of different temporal configurations only had a slight effect on accuracy (Fig. 3c): in particular, there were no significant differences between the monthly and the seasonal configurations, while there were significant differences between each configuration and its respective multi-temporal version (p-value < 0.05).

An OA higher than 70% was achieved only with the monthly and the seasonal configurations, considering 11 habitat classes. For each of these configurations, an additional classification was performed after removing spectral heterogeneity layers (i.e., with only vegetation indices). In both cases, the resulting accuracy was significantly lower (0.65 vs. 0.72 for the seasonal configuration, p-value < 0.05; 0.69 vs. 0.73 for the monthly configuration, p-value < 0.05).

The classifications that achieved an OA > 70% did not differ significantly among them. Thus, the seasonal configuration was chosen as the best one based on a simplicity criterion, since it had a lower number of predictors, especially after RFE (34 predictors). This classification will be referred to as the "best classification" and explored in the next paragraphs, while the results of the other classifications are reported in the Appendix.

318 The habitat map resulting from the best classification is represented in Fig. 4. The most common habitat inside the study areas, 319 as resulting from field surveys, is downy oak woodland (27.94%), followed by grasslands at successional stages I-2 (20.95%) 320 and I-1 (11.97%). In the best RF classified map, on the other hand, grassland I-2 (24.80%) is more common than downy oak 321 woodland (21.70%), and is followed by shrubland (16.10%), grassland-woodland mosaic (13.38%) and grassland I-1 (12.89%). 322 The confusion matrix for the best classification is reported in Table 4. The rows of the matrix represent the results obtained 323 from the classification, while the columns represent the validation data used as reference; the diagonal contains the correctly 324 classified pixels. Class-specific accuracy parameters derived from the confusion matrix are reported in Table 5. 325 Black pine plantation was the class for which the best results were achieved considering both Producer's accuracy (PA = 0.88) and User's accuracy (UA = 0.92), followed by downy oak woodland (PA = 0.74, UA = 0.86). Among the grassland classes, 326

pure grassland and grassland I-1 achieved relatively high UA (respectively 0.80 and 0.78) and PA (respectively 0.71 and 0.68),

and most of the errors occurred with grassland-I2 and downy oak woodland. For grassland I-2, PA was relatively low (0.64)

- because some pixels were misclassified as grassland-woodland mosaic, while the UA (0.69) was mainly affected by some
- pixels belonging to grassland-1 and downy oak woodland. For shrublands, higher values were obtained for PA (0.57) than for
- 331 UA (0.21), since many pixels classified as shrubland belonged to grassland I-2 and downy oak woodland. A similar result was
- found for hay meadow (PA = 0.71, UA = 0.59), that was mainly confused with grassland I-2. For pasture-grassland, UA (1.00)
- 333 was higher than PA (0.13), and most pixels were misclassified as hay meadow. For grassland-woodland mosaic, both UA and

- PA were quite low (0.28 and 0.72), and most of the errors occurred for pixels that either belonged to or were misclassified as grasslands and downy oak woodlands. The lowest values of accuracy were obtained for sessile oak woodlands (UA = 0.36, PA = 0.27), that were mainly confused with downy oak woodlands, and for invasive species groves, for which all validation pixels were misclassified as shrublands, downy oak woodlands or grassland-I1 (UA = 0.00, PA = 0.00).
- 338

#### 339 **3.2. Variable importance**

340 The relative importance of the variables used as input for the best classification is shown in Fig. 5. The most important variable,

- 341 present in every RF model, is the PCo2 of the  $\beta$ -diversity computed from the autumn composite (100.00%). Other important
- 342 variables are, in order, PCo1 of the winter  $\beta$ -diversity (94.19%), PCo1 of the autumn  $\beta$ -diversity (88.93%), GNDVI and IRECI
- of the summer (respectively 79.39% and 72.29%).

In the other classifications, the most important variable is almost always a  $\beta$ -diversity, with the only exception of the monthly classification with 11 classes, in which vegetation indices are at the first places. The relative importance of  $\alpha$ -diversity and Rao's Q indices is low in all the classifications: the maximum values are respectively 42.56% for  $\alpha$ -diversity (in the monthly 26-classes classification) and 64.91% for Rao's Q (in the monthly 11-classes classification). A detailed description of the input variables is presented in the Appendix.

349

### 350 **4. Discussion**

#### 351 **4.1. Accuracy of image classification**

352 In this study, multiple RF classifications were performed to test different combinations of vegetation and spectral heterogeneity 353 indices, using as study area a complex mosaic of habitats in Classical Karst. The small spatial extent of the habitat patches, 354 combined with their spectral similarity and the high variability of vegetation, make this type of landscape particularly challenging to map from remote sensing (Corbane et al., 2015; Tarantino et al., 2021). The maximum overall accuracy achieved 355 in this study was thus relatively low (0.73 for the 11-class classifications and 0.65 for the 26-class classifications). However, 356 357 other studies using similar types of data did not achieve much higher levels of accuracy. For example, Rapinel et al. (2019) 358 managed to map seven wet grassland plant communities with an accuracy of 0.78, by using Sentinel-2 time series and a SVM 359 classifier. Tarantino et al. (2021) achieved an accuracy of 0.95, by using a SVM classifier and a set of input variables that 360 included multi-seasonal Sentinel-2 images, a time series of MSAVI index and a DTM. However, they only mapped four 361 Mediterranean grassland types. Bhatt et al. (2022), that used very high-resolution imagery (60 cm) to map nine heterogeneous 362 habitats going from forests to open water, only reached a maximum accuracy of 0.79.

Moreover, some additional factors increased the complexity of the classification in the present work. Firstly, the analyzed areas are distributed over a relatively wide region (the Italian part of the Classical Karst), where the differences in altitude and substrate composition increase intra-habitat variability (Poldini, 1989). Villoslada et al. (2020) found that the spectral heterogeneity of the training samples can affect the accuracy of the classification, and that generally homogeneous classes are

367 more accurately mapped. The results observed for Classical Karst seem in line with this finding, since the best performances 368 were observed for the most spectrally homogeneous habitats, namely black pine plantations and downy oak woodlands. Finally, 369 most habitat patches in the study area had a small spatial scale, thus the proportion of mixed pixels was probably high, and this 370 complicated habitat class separation (Rocchini et al., 2013b). The lowest class-specific accuracy, indeed, was found for invasive 371 alien species groves, that were present in the smallest areas. Mapping invasive alien species from remote sensing is generally 372 a challenging task, and the most promising results have been obtained using hyperspectral instead of multispectral imagery, to 373 facilitate the differentiation of target species from others (He et al., 2011; Rocchini et al., 2015). For these reasons, the accuracy 374 achieved in this study can be considered relatively high.

Spectral heterogeneity measures had an important role in improving the capacity of classifying habitats from satellite data. The classifications performed without spectral heterogeneity measures (maximum OA = 0.69) were significantly less accurate than the others (maximum OA = 0.73), and the resulting maps also had a noisier aspect. Spectral heterogeneity is mainly investigated nowadays for its relationship with species richness, that has been tested in many environments (Wang and Gamon, 2019), but it has rarely been used as an additional level of information for the classification of habitats. The results obtained in this study suggest that image classification frameworks could benefit from the inclusion of spectral heterogeneity measures, although with caution about which type of metric is being used, as will be discussed below.

382 The most important variables in almost all the classifications were metrics of spectral  $\beta$ -diversity. In this study, the spectral  $\beta$ -383 diversity was referred to the pairwise Bray-Curtis dissimilarity computed from the distribution of spectral species, as defined 384 by Féret and Asner (2014). Spectral species are distinct spectral entities, that can be considered as proxies for individual plant 385 species only with very high-resolution remote sensing data (Féret and Asner, 2014). In case of coarser spatial resolutions, such 386 as the ones used in this study, spectral species can be related to higher levels of biological organization, such as plant 387 communities or habitats (Rocchini et al., 2021c). Although both  $\alpha$ - and  $\beta$ -diversity in this study were based on the spectral 388 species approach, the latter was far more important than the former for habitat classification. This can be explained considering 389 what these metrics represent:  $\alpha$ -diversity measures the diversity within a single community, while  $\beta$ -diversity represents the 390 degree of differentiation between communities, or their compositional dissimilarity (Whittaker, 1960). Different habitats can 391 share a similar  $\alpha$ -diversity despite having different species; on the other hand,  $\beta$ -diversity allows more easily to differentiate 392 habitats based on their dissimilarity. Here, the values of spectral  $\beta$ -diversity projected in the PCoA space clearly separated the three main groups of habitats present in Karst eco-mosaic: habitats dominated by woody deciduous plants (woodlands and 393 394 shrublands), habitats dominated by herbaceous plants (grasslands and meadows) and habitats dominated by evergreens (pine 395 forests).

The use of metrics based on the spectral species approach has some additional advantages. One of the first steps in the algorithm, indeed, is a PCA (Féret and Asner, 2014), that is one of the most widely used methods in image classifications to reduce feature dimensionality while maximizing spectral separability (Richards, 2013). Then, a k-means clustering is performed to distinguish and map the so-called spectral species. To some extent, this procedure is equivalent to a hybrid classification approach, in which an unsupervised classification is carried out before the application of supervised algorithms, to identify the main groups 401 of pixels basing only on their spectral similarity (Borra et al., 2019). Usually, this step is applied to choose appropriate classes 402 and guide the collection of training samples (e.g. Lane et al., 2014). This procedure has some advantages: the full spectral 403 information of satellite is exploited (Baldeck and Asner, 2013), and spectrally extreme pixels do not unproportionally affect 404 the results, but are simply grouped into separate classes (Fassnacht et al., 2022). Moreover, the computation of spectral  $\beta$ -405 diversity requires another ordination (a PCoA), that further maximizes the separation of groups of similar pixels.

406 Moreover, the relationship between spectral and species diversity can be different for  $\alpha$ - and  $\beta$ - components. In many studies, 407 the estimation of  $\alpha$ -diversity from remote required very high-resolution data (e.g. 1 m<sup>2</sup> in Wang et al. 2016a). In this study, for example, the spectral  $\alpha$ -diversity was similar in black pine plantations and pasture-grasslands, although they have very different 408 409 species richnesses (Poldini, 1989). A study by Fassnacht et al. (2022) also pointed out that, at the spatial resolution of Sentinel-410 2 images, intensively used agricultural patches can show higher spectral diversity compared to species-rich grasslands. For  $\beta$ -411 diversity, on the other hand, a good agreement between spectral and field-based metrics was obtained also at relative coarse 412 spatial resolution (e.g. Rocchini et al., 2010b), although few studies focused on this component of biodiversity (Wang & Gamon 413 2019). For example, Rocchini et al. (2010) found that the relation between field and spectral  $\beta$ -diversity is even greater at larger grain sizes (20x50 m instead of 10x10 m). In another study (Hoffmann et al., 2019), most of the  $\beta$ -diversity of different plant 414 415 communities distributed along an elevational gradient could be explained using Sentinel-2 data with 10 m spatial resolution. 416 Thus, the link between species and spectral diversity seems to be generally stronger for  $\beta$ - than for  $\alpha$ -diversity.

417 The other spectral heterogeneity index considered in this study, spectral Rao'Q, had a low relative importance in all the 418 classifications. This index is a measure of the heterogeneity of a pixel with respect to its surroundings (Thouverai et al., 2021), 419 and has been proven to match species diversity in natural areas but not in agricultural lands with high heterogeneity (Rocchini 420 et al., 2021b). In this study, the lowest Rao's Q values were found for black pine plantations and downy oak woodlands, that 421 do host a low species diversity, while the highest values were found for pasture-grasslands and pure grasslands, that are speciesrich habitats (Poldini, 2009). However, high values of Rao were found also for invasive species groves, thus the relation 422 423 between spectral Rao's Q and species diversity was not clear. One possible reason is related to the spatial extent of the habitat 424 patches: in this study, Rao's O was computed with moving windows of 3x3 pixels (900 m<sup>2</sup>), thus, the habitats present in smaller 425 patches were more likely to border with other habitats inside this window, resulting in higher spectral heterogeneity (i.e., high 426 Rao's Q values). Using remote sensing data with higher spatial resolutions would probably improve this aspect.

427 However, the approach used to calculate Rao's Q may itself be a problem, since it highlights the differences among close 428 pixels, and thus maximizes the noise, instead of minimizing it. Therefore, while the Rao's Q index can be used to estimate 429 species diversity in some cases (Rocchini et al., 2021b), it might be less useful in the context of habitat mapping.

The results of this study show that some spectral heterogeneity metrics might be more useful than others in the context of habitat mapping. The relationship between spectral and species diversity is still not clear in many cases, but, as pointed out by Fassnacht et al. (2022), these measures can be useful regardless of their link with actual species diversity, since they allow to exploit the main strength of remote sensing: measures can be repeated over time, to capture habitat specific variations and

434 monitor landscape evolution.

#### 436 **4.2. Importance of vegetation indices**

437 Vegetation indices were the most important variables after  $\beta$ -diversity metrics in all the monthly and seasonal classifications. 438 In particular, summer GNDVI, summer IRECI and autumn NDVI were the most important vegetation indices in the best 439 classification. NDVI, with its variant GNDVI, is the most commonly used index and has been found useful in many studies 440 (e.g. Schuster et al., 2015).

- 441 IRECI is the only index considered in this study that includes the Red Edge Sentinel-2 bands and has a strong linear relationship 442 with canopy chlorophyll content and LAI (Frampton et al., 2013). The results presented here seem to confirm this relationship. Indeed, the temporal variation of IRECI follows the expected seasonal changes of canopy chlorophyll content, with an increase 443 in spring, a maximum in summer and a decrease in autumn (Gara et al., 2019). In summer, the highest values were found for 444 445 downy oak woodlands, in agreement with the fact that broadleaves species have a higher chlorophyll content compared to 446 conifers (Li et al., 2018). Conversely, in winter IRECI was relatively high only for the evergreens black pine plantations. 447 Moreover, the differences of IRECI among habitats might also reflect the variation of LAI across ecosystems: mean LAI 448 generally increases from grasslands  $(1.7 \pm 1.2)$  and shrublands  $(2.1 \pm 1.6)$ , to temperate deciduous broadleaves  $(5.1 \pm 1.6)$  and 449 evergreen needleleaves ( $5.5 \pm 3.4$ ) forests (Asner et al., 2003). Optical traits like chlorophyll content can improve the estimation and mapping of species composition over space, as demonstrated by Feilhauer et al. (2017) in semi-natural temperate 450 grasslands. Although IRECI itself has not been tested much in the context of habitat mapping, other indices using the Red Edge 451 spectrum have been shown to be useful for this purpose. For example, Schuster et al. (2012) found that the Red Edge channel 452 453 of the RapidEye satellite had a positive influence on the overall accuracy of a land cover classification in a mosaic of natural 454 and agricultural areas in Germany, especially for the bush vegetation and dry grassland classes. In another study, Alpine 455 grasslands were distinguished from shrublands relying on the Sentinel-2 Red Edge bands, by detecting the seasonal anthocyanin accumulation in the shrub species (Bayle et al., 2019). A Red Edge-based index was also found to be more useful than NDVI 456 457 to map plant communities in coastal meadows (Villoslada et al., 2020). These examples are in line with the results of this study, 458 that confirm the role of the Red Edge spectrum for the distinction of habitats.
- 459

#### 460 **4.3. Inclusion of multi-temporal data**

The aggregation of monthly data in seasonal composites using the median statistical operator allowed to reduce the number of input layers without losing information. The levels of accuracy achieved with the monthly and the seasonal temporal configurations, indeed, were not significantly different, while the number of input layers was reduced from 144 to 48. This method of reducing data dimensionality can be complemented with variable selection through RFE, that did not have a significant effect on accuracy. The use of seasonal composites for habitat mapping is known to be useful because it reduces the problem of cloudy images but maintains the advantage given by multi-temporal data (Kollert et al., 2021). In a recent work by (Praticò et al., 2021), the mean turned out to produce slightly better results than other statistical operators such as the median. In this study the median was chosen because it is less sensitive to outliers and is generally the most common way to perform
 image reduction (Kollert et al., 2021), but other statistical operators could be investigated.

The multi-temporal configurations generally led to worse results than the other configurations, as was evident both from the accuracy values (mean OA = 0.59 for 26 classes and 0.65 for 11 classes) and from the visual assessment of the classified maps. The temporal Rao's Q computed for different vegetation indices over a year was successfully used by Marzialetti et al. (2020) to map coastal dune habitats, but also the mean, the 10<sup>th</sup> and the 90<sup>th</sup> percentiles of vegetation indices were included in that case. In this study, only temporal heterogeneity layers were used as input in the multi-temporal configurations, and this may have reduced the capacity of distinguishing habitats. Including other measures that summarize the annual variation of vegetation indices could be a possible improvement.

477 The most relevant seasons for distinguishing vegetation types in Karst eco-mosaic were summer, autumn and winter, as was 478 found by comparing the most important variables for the seasonal classifications. Spring, however, appeared among the most 479 important variables in some classifications, and the month of May was important in multiple monthly classifications. This 480 suggests that there is not one single period better than the others, and that multiple seasons should be considered. The advantage 481 of using multi-temporal data for habitat classification has been proven in many cases, because data from different seasons 482 provide different information (e.g. Feilhauer et al., 2013; Rapinel et al., 2019; Schuster et al., 2015). For example, Soubry and 483 Guo (2021) found that the best season to distinguish shrubs in grasslands changed according to the spectral bands considered. 484 In spring the most important bands were the red and blue bands, because the peak in growth was reached by shrubs but not by grasses; in summer a good separation was achieved only in the NIR region, due to the differences in leaf structures typical of 485 486 woody and herbaceous plants; in autumn the most important bands were the SWIR and red, related to greenness and moisture. 487 In the case of Karst eco-mosaic, autumn and winter generally allowed to distinguish evergreens from deciduous plants, while 488 in summer there was the greatest separation among the different deciduous habitats especially with the NDVI and IRECI 489 indices.

490

### 491 Conclusion

In this study, novel spectral heterogeneity indices were tested in a multi-temporal classification framework, and their potential
to improve habitat mapping in complex landscapes was demonstrated, using the Classical Karst as testing area.

The aim of the study was generally achieved, but several improvements could be made. For example, different remote sensing data sources could be used, including hyperspectral sensors, active sensors such as LiDAR and radar, or sensors with very high spatial resolutions (Nagendra et al., 2013). In this way, the estimation of spectral heterogeneity could be improved. Moreover, input variables have been combined in a limited number of ways in this study and testing other configurations can possibly produce better results.

- 499 The framework presented here was applied to some areas of Classical Karst, but could be extended to test its validity on a
- 500 larger scale. This approach based on remote sensing cannot replace field work and requires field data for training and validation,
- 501 though it can be a valid tool to map habitats in a cost- and time-effective way that is very well suitable for monitoring purposes.

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## 703 **Table Captions**

- 704 **Table 1:** List of vegetation indices used for the analysis.
- 705 **Table 2:** Input variables configurations used for image classification.
- 706 **Table 3:** Overall accuracy (OA) and Kappa values obtained from the different classification pathways.
- 707 **Table 4:** Confusion matrix for the best classification (seasonal classification performed with 11 classes). The rows represent
- the results obtained from the classification, while the columns represent the reference data. The values on the matrix diagonal
- are the correctly classified pixels. Habitats are abbreviated as follows: Shrubland (Shr), Downy oak woodland (DOW), Sessile
- oak woodland (SOW), Invasive alien species (IAS), Pure grassland (Gr\_10), Grassland at successional stage 1 (Gr\_11),
- 711 Grassland at successional stage 2 (Gr\_12), Grassland-woodland mosaic, Black pine plantation, Hay meadow, Pasture-grassland.
- 712 Table 5: Class-specific accuracy parameters (UA: user's accuracy, PA: producer's accuracy) obtained for the seasonal
- 713 classification performed with 11 classes. Accuracy was assessed using independent validation data.

## **Tables**

### **Table 1**

Index	Formula	Reference
NDVI	$(NIR_{(B8)} - Red_{(B4)})/(NIR_{(B8)} + Red_{(B4)})$	Rouse et al., 1975
GNDVI	$(NIR_{(B8)} - Green_{(B3)})/(NIR_{(B8)} + Green_{(B3)})$	Gitelson et al., 1996
NDWI	$(NIR_{(B8)} - SWIR_{(B11)}) / (NIR_{(B8)} + SWIR_{(B11)})$	Chen et al., 2005
IRECI	$\left( (\text{RedEdge}_{(B7)} - \text{Red}_{(B4)}) / ((\text{RedEdge}_{(B5)} / \text{RedEdge}_{(B6)}) \right) \times 10000$	Frampton et al., 2013

#### **Table 1**

Temporal	Input variables	Number of
configuration		input layers
Monthly	Vegetation indices: 4 layers per month (NDVI, GNDVI, NDWI, IRECI)	144
	Rao's Q: 4 layers per month (NDVI, GNDVI, NDWI, IRECI)	
	$\alpha$ -diversity: 1 layer per month	
	$\beta$ -diversity (first 3 PCoA axes): 3 layers per month	
Seasonal	Vegetation indices: 4 layers per season (NDVI, GNDVI, NDWI, IRECI)	48
	Rao's Q: 4 layers per season (NDVI, GNDVI, NDWI, IRECI)	
	$\alpha$ -diversity: 1 layer per season	
	$\beta$ -diversity (first 3 PCoA axes): 3 layers per season	
Multi-temporal	Multi-temporal Rao's Q: 4 layers per year (NDVI, GNDVI, NDWI, IRECI)	20
monthly	Multi-temporal $\alpha$ -diversity: 4 layers per year (NDVI, GNDVI, NDWI, IRECI)	
	Multi-temporal $\beta$ -diversity (first 3 PCoA axes): 3x4 layers per year	
Multi-temporal	Multi-temporal Rao's Q: 4 layers per year (NDVI, GNDVI, NDWI, IRECI)	20
seasonal	Multi-temporal $\alpha$ -diversity: 4 layers per year (NDVI, GNDVI, NDWI, IRECI)	
	Multi-temporal $\beta$ -diversity (first 3 PCoA axes): 3x4 layers per year	

722	Table	3

$N^\circ$ of classes	Input configuration	$N^{\circ}$ of predictors	OA	Kappa 723
26	Monthly	144	0.65	0.58
	+ RFE	48	0.63	0.56
	Seasonal	48	0.63	0.56
	+ RFE	46	0.62	0.54
	Multi-temporal monthly	20	0.62	0.54
	+ RFE	20	0.61	0.53
	Multi-temporal seasonal	20	0.57	0.50
	+ RFE	20	0.58	0.51
11	Monthly	144	0.73	0.65
	+ RFE	100	0.73	0.65
	only vegetation indices	48	0.69	0.59
	Seasonal	48	0.72	0.64
	+ RFE	34	0.72	0.64
	only vegetation indices	16	0.65	0.56
	Multi-temporal monthly	20	0.66	0.57
	+ RFE	14	0.67	0.57
	Multi-temporal seasonal	20	0.64	0.55
	+ RFE	17	0.64	0.55

	Shr	DOW	SOW	IAS	Gr_I0	Gr_I1	Gr_I2	GWM	BPP	HM	PG
Shr	8	6		2		2	20		1		
DOW	2	156	10	1			1	1	9	1	
SOW		7	4								
IAS		4		0			1		1		
Gr_I0		2		1	12						
Gr_I1	1					21	5				
Gr_I2	1	5	1		3	7	51	3		2	1
GWM	1	22			2	1	2	13	4	1	
BPP	1	7						1	107		
HM		1								10	6
PG											1

#### **Table 5**

Class	UA	PA
Shrubland	0.21	0.57
Downy oak woodland	0.86	0.74
Sessile oak woodland	0.36	0.27
Invasive species	0.00	0.00
Grassland I0	0.80	0.71
Grassland I1	0.78	0.68
Grassland I2	0.69	0.64
Grassland-woodland mosaic	0.28	0.72
Black pine plantation	0.92	0.88
Hay meadow	0.59	0.71
Pasture-grassland	1.00	0.13

## 732 **Figure Captions**

- **Figure 1:** Location of the study area, represented on the Sentinel-2 median composite of summer 2021.
- Figure 2: Workflow synthesizing the approach used to map natural habitats through a Random Forest classification and
- 735 multiple combinations of input layers (vegetation and spectral heterogeneity indices).
- 736 **Figure 3:** Comparison of the overall accuracy achieved by considering different numbers of habitat classes (a), by performing
- or not a variable selection step through RFE (b), and by using different input variables configurations (c).
- 738 Figure 4: Habitat map resulting from the RF classification based on seasonal layers of vegetation and spectral heterogeneity
- range range
- the amount of input layers. A total of 11 habitat classes was considered, based on structural-physiognomic and ecological
- characteristics. The areas are located in Monfalcone (a), Case Coisce (b), Opicina (c), Aurisina (d), San Lorenzo (e), San
- 742 Giuseppe (f) and Bagnoli (g).
- 743 Figure 5: Relative importance of the variables used as input for the seasonal classifications with 11 classes. Classifications
- were performed with the whole set of input variables (a) and with a subset obtained by RFE (b). Only the first 20 variables are
- shown.
- 746

## **Figures**

## 748 Figure 1



















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