Ann. For. Res. 67(2): 67-85, 2024
https://doi.org/10.15287/afr.2024.3596

ANNALS OF FOREST RESEARCH
www.afrjournal.org

Prioritizing conservation areas based on contributions to rarity and beta diversity in Mediterranean forest ecosystems in Türkiye

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Özkan K., Şentürk Ö., Arslan M., Negiy M.G., 2024. Prioritizing conservation areas based on contributions to rarity and beta diversity in Mediterranean forest ecosystems in Türkiye. Ann. For. Res. 67(2): 67-85.

Abstract The depletion of forest biodiversity arising from insufficient conservation of resources due to wood extraction, overgrazing, fire, and land use presents a significant challenge in the Mediterranean region. It becomes crucial to identify priority conservation areas for safeguarding biodiversity. We used plant species data taken from 800 plots in the Kuyucak mountain district, a typical Mediterranean forest ecosystem in Türkiye and maps of seven potential environmental predictors: elevation, aspect, slope, head index, topographical position index, landform characteristics, and bedrock geology. To assign priority areas for the conservation, local contribution to beta diversity (LCBD) and relative contribution to total rarity (RIRR) were examined with community metrics and environmental predictors, respectively. Correlation results showed that LCBD was positively related to rare species richness but negatively related to common species richness. RIRR was significantly associated with all the community metrics. According to the results of Random Forest regression models, elevation was the most important variable of LCBD, followed by slope, heat index, and pebblestone. For RIRR, the most contributed variables were elevation, heat index, limestone, and slope, respectively. The LCBD and RIRR Random Forest regression models were extrapolated along the Kuyucak mountain district, resulting in the creation of potential distribution maps for both LCBD and RIRR. Subsequently, from these maps, two distinct conservation value maps have been developed for the Kuyucak mountain district based on four conservation priority classes (Priority Class 1, Priority Class 2, Priority Class 3, and Priority Class 4): one employing a conservation cost approach and the other applying an ecology-centered approach. The results suggest that areas with elevated values of both LCBD and RIRR values are primarily situated below 1100 m on steep valley slopes, characterized by the presence of karstic limestone and intricate terrain. Compared to other areas, prioritizing the protection of such areas can provide greater benefits in contributing to ecological uniqueness.

Keywords: community rarity, conservation priority, ecological uniqueness, indicator species analysis, machine learning, species contributions to beta diversity.

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Manuscript: received March 18, 2024; revised September 24, 2024; accepted September 27, 2024.

Introduction

Biodiversity or biological diversity is the key to building sustainable development as it is directly linked to health, dynamism, and productivity of the ecosystems (Gao et al. 2021, Lin et al. 2022, Oliveira et al. 2022). Therefore, spatial distribution maps of biodiversity enable the most fundamental information layers of ecosystem-based management, an approach which considers the whole ecosystem, instead of managing target species. To determine spatial variations of biodiversity, majority of current management plans use distribution maps or models of alpha diversity (Lasram et al. 2015).

Alpha diversity refers to variety of species that can be measured at a specific site or location using various metrics. Among these metrics, the most widely recognized ones are species richness (Peet 1974), Simpson index (Simpson 1949), and Shannon's entropy (Shannon 1948). While species richness indicates the number of species present, the latter two combine measures of richness with abundance or incidence data (Liu et al. 2007, Abrams et al. 2021, Özkan et al. 2022). The metrics used for assessing alpha diversity can also be applied to measure gamma diversity. Gamma diversity characterizes species diversity across a district or region, spanning a larger area compared to a single site. Essentially, both diversity measures fall under the concept of inventory diversity, sharing similar characteristics while differing primarily in scale (Jurasinski et al. 2009, Zhang et al. 2014).

Beta diversity is denoted as the divergence in species composition among assemblages, communities, or sites (Whittaker 1960). Research on beta diversity has recently increased to better understand the foundations underlying species diversity distribution in natural ecosystems. However, it is more challenging to create biodiversity assessment and conservation strategies using beta diversity than alpha diversity (Ferrier et al. 2007, Zhang et al. 2014).

Beta diversity is defined through two approaches: a directional approach and a non-directional approach. To the best of our knowledge, only one directional approach has been proposed, attributed to Nekola and White (1999), hinging on the slope of similarity decay in species composition concerning spatial distance. Non-directional beta diversity indices have been suggested by multiple researchers. Among these, the most established one, introduced by Whittaker (1960), is the beta index of species richness as $\beta=\alpha/\gamma$, where α is the mean number of species within ecological units or study sites in the region, and γ is the total number of species in the region.

Other popular non-directional indices based on Shannon's entropy belong to additive ($H_\alpha+H_\beta=H_\gamma$) and multiplicative ($\exp(H_\alpha)\times\exp(H_\beta)=\exp(H\gamma)$) approaches that is identical with Whittaker's formula. Beta diversity is unity when all communities are identical and, it is equal to the number of communities when all N communities are completely distinct and equally weight (Jost 2007, Chao et al. 2012). In these approaches, all beta diversity measures are derived from alpha and gamma indices.

Magurran (1988) presented the option to compute beta diversity independently from gamma and average alpha, specifically through dissimilarity indices such as Sorensen, Jaccard, and Morisita. However, all those techniques cannot provide a beta diversity value for a community or site. As Ellison (2010) highlighted, it would be more practical to have a method for estimating beta diversity specifically for a community or site without needing prior alpha and gamma calculations. In this context, Legendre and De Cáceres (2013) introduced the concept of local contribution to beta diversity (LCBD). This method uses a site-by-species abundance or presence-absence data set to estimate the total variance within a community, which can be decomposed into contributions of individual sites and species to overall beta diversity. In essence, LCBD provides a value that represents beta diversity unique to each community, sampling plot, or location.

Based on the information presented so far, it seems that among the various components of diversity, beta diversity stands out as a crucial numerical indicator. It can support decision makers in identifying and prioritizing conservation areas and help guide effective management strategies However, beta diversity is not the sole criterion employed to evaluate the conservation value of living communities. Other supplementary criteria encompass rarity, naturalness, and threat of human interference (Margules & Usler 1981).

In comparison to naturalness and threat of human interference, rarity displays a closer link with beta diversity, as its core objective revolves around estimating the value of a community or site based on the presence of rare species at regional or global scales. Rarity is the fundamental facet of biodiversity (Le Bagousse-Pinguet et al. 2021, Riva & Mammola 2021). The rarer a species, the more valuable it is (Hall et al. 2008). This correlation stems from the heightened risk of extinction faced by rare species in contrast to common ones (Flather & Sieg 2007, Södersröm et al. 2007). As a result, localities rich in rare species bear greater significance in conservation strategies than those housing common species. Several indices have been proposed to estimate local rarity (Borges et al. 2000, Dennis et al. 2000, Palmer et al. 2002, Fattorini 2008, Hussain et al. 2008, Mendes et al. 2008, Leroy et al. 2012, Özkan 2016). Among these, the index of relative rarity (IRR), proposed by Lorey et al. (2012), is the most widely used, as it can be employed with various weighting methods considering a comprehensive species-by-site dataset.

In Türkiye, the Mediterranean region stands out as a reservoir of remarkable plant diversity, primarily due to the significant heterogeneity within its diverse habitats. This considerable diversity is rooted in the region's expansive elevational gradient and complex geological and geomorphological features (Médail & Quézel 1997, Özkan et al. 2010, Şekercioğlu et al. 2011, Koç et al. 2018). However, much of the Mediterranean region has been subjected to degradation, reflecting the complex interplay of anthropogenic and environmental pressures. The region's rich history of human settlement has led to extensive transformation through activities such as logging, burning, and overgrazing over centuries (Velmoere et al. 2003, Fontaine et al. 2007). These compounded impacts have been further exacerbated by ongoing climate change, amplifying the ecological challenges faced by the region's ecosystems. In this context, research focused on mapping potential distribution areas for community or site attributes, such as rarity and diversity, becomes crucial. By providing insights into the spatial distribution of critical ecological characteristics, these studies play a pivotal role in informing effective management, conservation, and restoration strategies tailored to the unique needs of Mediterranean ecosystems.

The goal of this study is to identify the priority conservation areas in the Kuyucak mountain district located in the Mediterranean Region, Türkiye, examining the variations in relative contribution to local rarity (RIRR) and local contribution to beta diversity (LCBD) in relation to environmental attributes and creating their distribution models.

Materials and Methods

Study area

The Kuyucak mountain district, located in the transition zone of the Mediterranean region, lies at 370 29’ 17’’ N latitude and 300 59’ 46’’ E longitude, covering an area of 984.5 km^2. Elevation ranges from 250 m to 2500 m a.s.l. (Fig. 1). The predominating parent materials include limestone, sandstone, pebblestone, ophiolite, dolomite are the predominating parent materials. Locally also basalt, chert, shale, travertine, and vulcanite are present.

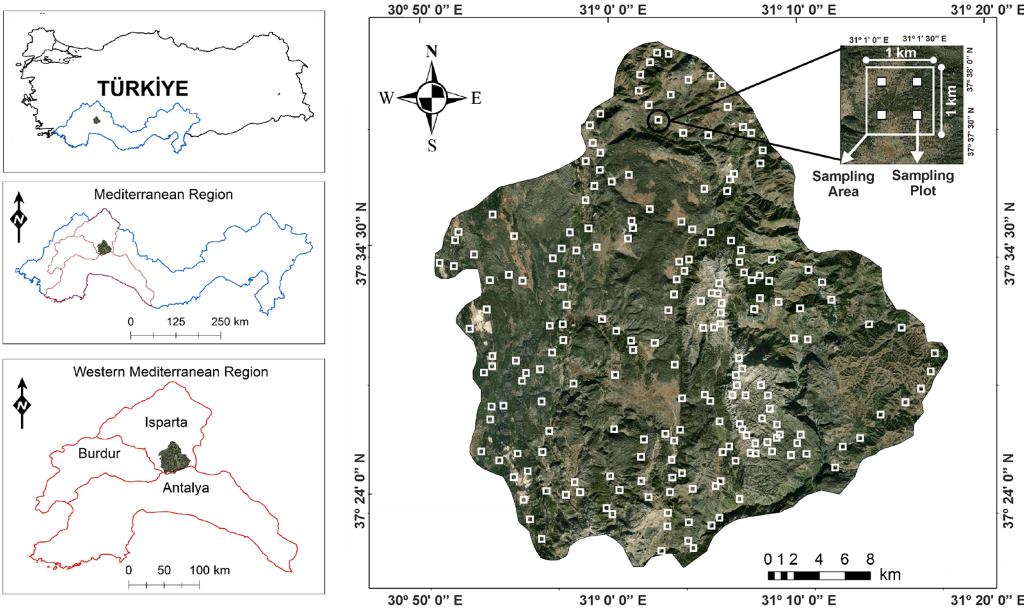

Figure 1 Locations of the sampling sites across the Kuyucak mountain district.

In the district, a transition climate prevails between the Mediterranean climate and continental climate, with an average annual rainfall of 950 mm. Heavy rains occur in November, December, January, and February, while the dry period extends from the beginning of June until the end of October. The most arid and hottest months are July and August. The mean annual temperature is 13.1^{0}C and the average relative humidity is 54% (Özkan & Gülsoy 2009).

The flora of the district is composed of 63 families, 225 genera and 478 species (Özçelik & Korkmaz 2002). The study area is covered by approximately 50% Mediterranean mountain forests, mainly composed of *Pinus brutia* var *brutia* (Brutian pine), *Pinus nigra* subsp. *pallasiana* (Crimean pine), *Ouercus* spp. (Oak), *Juniperus* spp. (juniper) and some relic stands of *Cedrus libani* (Lebanon cedar) (Özkan & Gülsoy 2009).

Research methods

Community and species metrics

The Kuyucak mountainous district is characterized by a diverse topography dominated by karstic features including canyons, dolines, uvalas, poljes, and lapies. Due to this intricate topography, significant variations in vegetation composition can occur even in areas that are geographically close to each other. Therefore, data were collected using a preferential sampling with nested plot selection approach. Two hundred sampling areas, each 1x1 km^2 in size, were selected to represent the district, avoiding disturbed areas and accounting for factors such as elevation, aspect, landform characteristics, and parent material. Within each sampling area, four 20x20 m plots were established to represent the overall vegetation. Perennial vascular plant species were recorded at each plot along with geo-referenced data.

Upon completing the field survey, we compiled a plot-by-species presence-absence (PS) dataset. From this dataset, we initially tabulated species frequency or incidence data (i.e., the number of plots occupied by the jth species, denoted as I_j) (see Table S1 in the Supplementary). Cluster analysis was conducted using Sørensen distance measure and a flexible beta linkage approach (with beta= –0.25) to define cluster groups in the PS dataset (McCune & Mefford, 1999). The clustering process started with a minimum of two and a maximum of eighteen groups. To determine the most informative number of clusters, we employed a multiresponse permutation procedures (MRPP) test using the Sørensen distance measure and a natural group weighting factor (Fontaine et al. 2007). The distinction between groups was assessed using a test statistic (*T*) and the chance-corrected within-group agreement (*A*). A high negative *T*-value indicates a greater degree of separation between the groups, while a low negative *T*-value suggests less separation. The optimal number of groups is associated with the lowest negative *T*-value. The *A*-value ranges between 0 and 1 and reflects the degree of homogeneity or heterogeneity within the groups. The ideal number of groups is characterized by a high *A*-value (Everhart et al. 2008, Brinkmann et al. 2009, Naftal et al. 2024).

Subsequently, we calculated the species specialization index (SSI_j) for each cluster group (see Table S2 in the Supplementary for SSI_j values) using the following formula:

$$B_{jk}=\frac{I_{jk}}{I_k} \qquad (1)$$

We calculated SSI as the coefficient of variation of those occurrence frequencies (standard deviation/average) for each species (Julliard et al. 2006, Leroy et al. 2014).

Indicator species analysis (IndVal) was conducted to define the indicator species of the cluster groups (Dufrêne & Legendre 1997, Bakker 2008).

$$\mathrm{IndVal}_{jk}=A_{jk}\times B_{jk}\times 100 \qquad (2)$$

For the IndVal, A_{jk} (specificity) is calculated as follows:

$$A_{jk}=\frac{I_{jk}}{I_j} \qquad (3)$$

In Equations 1-3, B_{jk} is the occurrence frequency of species j in cluster group *k*, I_{jk} is the number of plots in cluster group *k* occupied by species *j*, I_k is the number of plots in each cluster group k, and I_j is the total number of plots occupied by species *j*.

Non-metric multidimensional scaling (NMDS) was employed to investigate indirect gradients influencing species distribution. NMDS was performed on the vegetation data using the Sørensen distance measure, with three starting dimensions and an instability criterion of 10^{-5} (McCune & Mefford 1999). The dimensions were determined after 500 iterations of the data. The ordination's stress value was utilized to evaluate the reliability of the NMDS, where a stress value under 20% (or 0.2) signifies good data conformity (Clarke 1993). Continuous environmental variables that do not show high correlations with each other, along with all categorical environmental variables, were related to the ordination axes of the NMDS. The continuous environmental variables used in the NMDS are the same as those described for Random Forest regression (RFR) in Section 2.2.4. Explanations regarding the selection of continuous variables for the RFR are also provided in that section.

Lastly, we defined the species richness (S_i), rare species richness (RS_i) and abundant (common) species richness (AS_i) for each plot. Here RS_i refers to an incidence rate of 1% or less while AS_i corresponds to an incidence rate of 5% or higher. Cluster analysis, MRPP, IndVal and NMDS were conducted using PC-ORD 4.0 for Windows (McCune & Mefford 1999).

Rarity and beta diversity metrics

We calculated local rarity of the *i*th plot, denoted as IRR_i using the metrics proposed by Dapporto and Dennis (2008), Leroy et al. (2012). The formula for IRR_i is given by:

$$\mathrm{IRR}_i=\frac{(\sum w_j/S)\ \text{-}w_{min}}{w_{max\text{-}w}\text{-}w_{min}} \qquad (4)$$

In the equation S represents the species richness in the ith plot. The weight of the jth species, denoted as w_j, is given by $1\text{-}(I_j/I_{max})$, where I_j is the occurrence of species j and I_{max} is the maximum occurrence (i.e., occurrence of the most widespread species). The minimum weight, w_{min}, is assigned to the species with the maximum occurrence in the PS dataset, while the highest weight, w_{max}, is assigned to the species with lowest occurrence of the PS dataset. The calculations for IRR_i were conducted using the Rarity version 1.3-6 package (Leroy 2013). For each plot i, relative contribution to total rarity, denoted as RIRR_i was computed as follows:

$$\mathrm{RIRR}_i=\frac{\mathrm{IRR}_i}{\sum \mathrm{IRR}_i} \quad (5)$$

where the sum of RIRR_i values for all plots ($\sum_i \mathrm{RIRR}_i$) is to equal 1.

Species and local contributions to β-diversity (SCBD and LCBD, respectively) were calculated using the approach of Legendre and De Cáceres (2013). PS dataset was initially transformed as follows:

$$y'_{ij}=\sqrt{(}y_{ij}/y_{i+} \quad (6)$$

where $y_{i+}=\sum_{j=1}^{p} y_{ij}=\mathrm{S}_i$ and y_{ij} represents the dataset containing occurrence values of p species (column vectors $y_1, y_2, \ldots, y_p$ of Y) observed in n plots (row vectors $x_1, x_2, \ldots, x_n$ of Y). We then calculated SCBD values for each species (SCBD_j) and LCBD values for each plot (LCBD_i) using the following formulates.

$$\mathrm{SCBD}_j=\mathrm{SS}_j/\mathrm{SS}_{\mathrm{Total}} \quad (7)$$

$$\mathrm{LCBD}_i=\mathrm{SS}_i/\mathrm{SS}_{\mathrm{Total}} \quad (8)$$

where $\mathrm{SS}_j=\sum_{i=1}^{n} s_{ij}$ and $\mathrm{SS}_i=\sum_{j=1}^{p} s_{ij}$. s_{ij} and $\mathrm{SS}_{\mathrm{Total}}$ were computed as follows:

$$s_{ij}=(\mathrm{y}'_{ij}-\bar{y}_j)^2 \quad (9)$$

$$\mathrm{SS}_{Total}=\sum_{i=1}^{\mathrm{n}}\sum_{j=1}^{p} s_{ij} \quad (10)$$

s_{ij} creates the matrix composed of squared differences from column average. $\mathrm{SS}_{\mathrm{Total}}$, the sum of the squared deviations from the column means of whole-transformed matrix, forms the basis of $\mathrm{BD}_{\mathrm{Total}}$ which is the index of beta diversity.

$$\mathrm{BD}_{\mathrm{Total}}=\mathrm{SS}_{\mathrm{Total}}/(n-1) \quad (11)$$

It is important to note that $\sum_j \mathrm{SCBD}_j=\sum_i \mathrm{LCBD}_i=1$. The calculations of SCBD_j and LCBD_i were executed using the 'adespatial' package within the R software program (Dray et al. 2012, Dray et al. 2017).

All the computed metrics including I_j, SSI_j, S_i, RS_i, AS_i, RIRR_i, SCBD_j and LCBD_i derived from PS dataset were compiled and stored in an excel file for use subsequent utilization in later stages of the analysis.

Environmental predictors

Elevation (ELEV) and bedrock geology (ROCK) maps were provided by OGM (General Directory of Forestry) and MTA (General Directorate of Mineral Research and Exploration). While the elevation map has a resolution of 30x30 m, the bedrock geology map used in the study was derived from a pre-existing geology map of the Mediterranean region with a resolution of 100x100 m. Therefore, all the maps were resampled at a resolution of 100 m by 100 m grids by using nearest neighbor interpolation as simplest technique for assigning pixel values to the new grid. Slope (SLOP) and aspect (ASPT) were derived from the elevation-built function provided by ArcGIS. The topographic position index (TPI) and landform category (LFC) maps were derived from elevation map by "Topographical Tools" into the ArcGIS extensions (Jennes 2006). Additionally, the heat index (HI) was calculated for each grid using the following equations:

$$\mathrm{HI}=\cos(\mathrm{aspect}-202.5^0)\times \tan(\text{slope inclination angle}) \quad (12)$$

In the HI equation, 202.5^0 represents the SSW aspect and is assumed to be the highest heat load on slopes facing southwest (Zelený

& Chytrý 2007).

The resampled bedrock map was composed of 7 main classes: limestone (LIME), sandstone (SAND), pebblestone (PEBB), ophiolitic (OPHI), dolomite (DOLO), alluvium (ALLU) and a combined group containing basalts, chert, shale, travertine, and vulcanite (COMB). Landform types were composed of 8 classes: canyons, deeply incised streams (CANY), midslope drainage and shallow valleys (MDSV), upland drainages, headwaters (UDHE), U-shaped valleys (USVA), upper slopes, mesas, plain small, open slopes (USME), local ridges/hills in valley (LRHV), midslope ridges, small hills in plains (MRSH) and, mountain tops or high ridges (MTHR).

Data analysis

We employed Pearson correlation to examine the relationships between $SCBD_j$ and both I_j and SSI_j as well as to investigate the associations of $LCBD_i$ with S_i, RS_i and AS_i. Additionally, we explored the connections between the community response data ($LCBD_i$ and $RIRR_i$) and discrete environmental variables through Spearman correlation, while also examining their relationships with continuous environmental variables using Pearson correlation.

We employed Random Forest regression (RFR) to analyze the patterns of $LCBD_i$ and $RIRR_i$. We opted for RFR as our modeling tool due to its popularity as a machine learning algorithm for both classification and regression problems. Introduced by Breiman (2001), RFR is based on model aggregation concepts. It has been frequently used for modeling species distribution with binary and continuous data. Before conducting the RFR analysis, to mitigate multicollinearity, we conducted a Pearson correlation between continuous environmental variables and excluded highly correlated variables (r>0.60) (Pozzobom et al. 2020). In cases of correlation between two variables, we retained the variable that contributed most to the RF models of $LCBD_i$ and $RIRR_i$. The performances of the RFR models were evaluated using root mean square error (RMSE) and mean absolute error (MAE), two common metrics to measure accuracy for continuous variables. Enhanced model performance is indicated by lower RMSE or MAE (Aertsen et al. 2010, Karunasingha 2022). The variables' predictive power from the RFR model is visually represented, showing the ranking of each variable's importance in the prediction process. Variables with greater importance are major contributors to the outcome, significantly affecting the resulting values (Islam et al. 2023). For correlation analysis, we utilized the Paleontological Statistics (PAST) software version 1.89 (Hammer et al. 2001). The modeling and prediction of $LCBD_i$ and $RIRR_i$ were accomplished using the caret package within the R environment (Kuhn 2023).

Results

A total of 103 species were identified across 800 sampling plots (Table S1). Through clustering, the sample plots were categorized into four distinct groups (labeled as I, II, III, and IV), yielding a highly informative arrangement with substantial separation between these groups (MRPP T = -324.660) and a significant internal coherence within each group (MRPP A = 0.258) The number of sampling plots in Group I to Group IV were 347, 217, 127, and 109, respectively (for the cluster dendrogram, see Fig. S1 in the Supplementary). A total of 59 species demonstrated significant associations (p<0.01) with the cluster groups based on the findings of the indicator species analysis. The count of indicator plant species (p<0.01) in Group I to Group IV were 9, 7, 6, and 37, respectively (see Table S2 in the Supplementary for the outcomes of Indicator Species Analysis, $IndVal_{jk}$). Group I is characterized by *Pinus nigra* subsp. *pallasiana*, *Juniperus oxycedrus* subsp. *oxycedrus*, *Teucrium polium* subsp. *polium*, *Cotoneaster nummularius*, and *Cedrus libani*. Group II is distinguished by prominent indicator species such as *Quercus cerris*, *Styrax officinalis*, *Crataegus orientalis* var. *orientalis*, *Cistus salviifolius*, and *Quercus ithaburensis* subsp. *macrolepis*. Group III comprises indicator species like *Acantholimon confertiflorum*, *Origanum onites*, *Astragalus angustifolius* subsp. *angustifolius*, *Berberis crataegina*, and *Juniperus excelsa* subsp. *excelsa*. Group IV includes *Quercus coccifera*, *Pistacia terebinthus* subsp. *palaestina*, *Pinus brutia* var. *brutia*, *Phillyrea latifolia*, and *Daphne sericea.*

A stable NMDS ordination was achieved with a final stress of 17.19% for the three-dimensional solution. The NMDS axes together account for 80.7% of the variance. Axis 1 captures 42.4% of this variance, while Axis 2 accounts for 21.5%, and Axis 3 covers 16.8%. ELEV exhibits the strongest correlation with Axis 1 (r=-0.828). This is followed by MTHR (r=-0.258) and CANY (r=0.242). The environmental predictors with the highest correlation with Axis 2 are SAND (r=0.521) and LIME (r=-0.493) (see Table S3 in the Supplementary for the correlation results of the environmental predictors).

The groups defined by the cluster analysis and the MRPP test are meaningfully distributed along the first two axes of the ordination diagram. This is because, in general, sample plots from the same group are positioned closer to each other than to sample plots from different groups. Sample plots of Group IV are predominantly clustered in the lower right quadrant of the ordination diagram. A significant portion of the sample plots of Group II is located in the middle and upper regions of the diagram. All sample plots of Group III are located in a narrow section in the lower left corner of the ordination diagram. Across the ordination diagram, the only group that occupies the largest area, shows the most heterogeneous distribution, and comes into contact with all other groups is Group I. However, a large portion of the sample plots belonging to this group is also positioned in the lower left quadrant where the sample plots of Group III are located (Fig. 2).

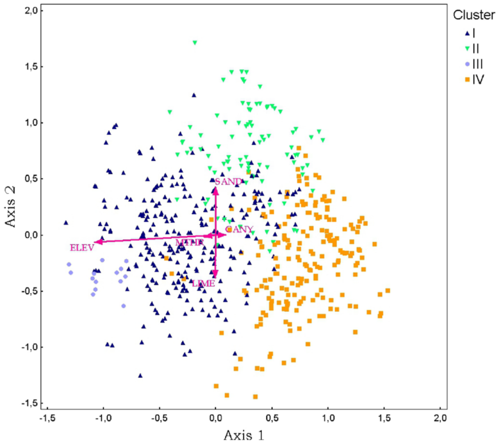

Figure 2 NMDS ordination of 800 sampling plots in the Kuyucak mountain district, Mediterranean Region, Türkiye. Sampling plots are labelled according to four groups produced by cluster analysis and MRPP test.

Twelve species exhibit the highest correlation (r>0.4) with the first axis of the NMDS ordination (Table S3), all of which are identified as indicator species for Group II, Group III, and Group IV. These include *Styrax officinalis* (r=0.529) and *Cistus salviifolius* (r=0.401) as indicator species for Group II; *Acantholimon confertiflorum* (r=-0.608), *Astragalus angustifolius* subsp. *angustifolius* (r=-0.665), *Berberis crataegina* (r=-0.723), and *Juniperus excelsa* subsp. *excelsa* (r=-0.423) for Group III; and *Quercus coccifera* (r=0.659), *Pistacia terebinthus* subsp. *palaestina* (r=0.602), *Pinus brutia* var. *brutia* (r=0.725), *Phillyrea latifolia* (r=0.505), *Daphne sericea* (r=0.423), and *Fontanesia phillyraeoides* (r=0.428) for Group IV (Table S3). None of the Group I indicator species exhibit a significant correlation with Axis 1. A possible reason for this may be the more heterogeneous distribution of sample plots belonging to this group along the NMDS ordination axes compared to the sample plots of the other groups. Only one indicator species from Group I, *Pinus nigra* subsp. *pallasiana*, is correlated with the second axis (r=0.468). Additional species significantly correlated with the second axis include *Quercus cerris* (r=0.640) as well as *Juniperus excelsa* subsp. *excelsa* (r=-0.619), which is also correlated with the first axis and serves as an indicator for Group III, and *Styrax officinalis* (r=0.461), which is also correlated with the first axis and serves as an indicator for Group II.

The negative correlation of Axis I with elevation (ELEV) and canyons (CANY), alongside the positive correlation with mountain tops or high ridges (MTHR), indicates that the indicator species of Groups II and IV (*Styrax officinalis*, *Cistus salviifolius*, *Quercus coccifera*, *Pistacia terebinthus* subsp. *palaestina*, *Pinus brutia* var. *brutia*, *Phillyrea latifolia*, *Daphne sericea*, and *Fontanesia phillyraeoides*) are more commonly found in lower elevations within the Kuyucak mountain district, particularly in canyons or deeply incised streams characterized by concave topography. In contrast, the indicator species of Group III (*Acantholimon confertiflorum*, *Astragalus angustifolius* subsp. *angustifolius*, *Berberis crataegina*, and *Juniperus excelsa* subsp. *excelsa*) are more prevalent in higher elevations and areas with steep ridges characterized by convex topography. The positive correlation of SAND and the negative correlation of LIME with Axis II indicate that the parent material also plays a role in the distribution of species in the Kuyucak mountain district. Species that show a strong positive correlation with Axis II, such as *Quercus cerris*, *Pinus nigra* subsp. *pallasiana*, and *Styrax officinalis*, are generally common in areas with sandstone bedrock, while *Juniperus excelsa* subsp. *excelsa* is more prevalent in areas with limestone bedrock.

The value of SS_{Total} (eqn10) was 540.755, and the corresponding value of BD_{Total} (eqn 11) was 0.677. The range of $SCBD_j$ spanned from 8.030×10^{-5} to 5.953×10^{-2} (Table S1), with a mean $SCBD_j$ of 9.708×10^{-3}.Twenty-five of the 103 species contributed to beta diversity above the average value (refer to Fig. 2), comprising 83.3% of the total beta diversity. Among these species, the top three species (*Berberis crataegina*, *Astragalus angustifolius* subsp. *angustifolius* and *Juniperus exelsa* subsp. *excelsa*) contributing the most to beta diversity are found in approximately half of the sample plots. *Juniperus oxycedrus* subsp. *oxycedrus* has the highest occurrence value and ranks fifth in terms of its contribution to beta diversity. The species contributing the least to beta diversity among these 25 species are *Origanum minutiflorum*, *Phlomis grandiflora* var. *grandiflora*, *Colutea cilicica* and *Cedrus libani*, with their occurrence values ranging from 50 to 91 (Fig. 3, Table S1).

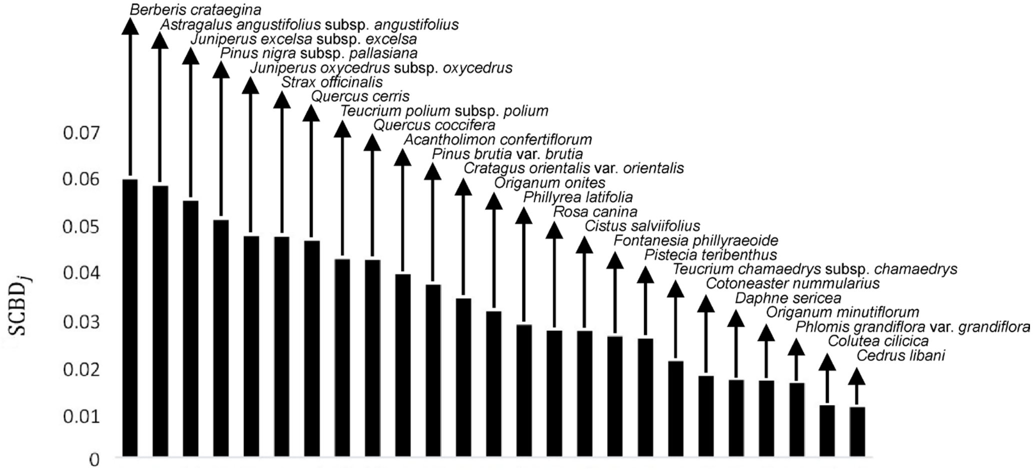

Figure 3 $SCBD_j$ values of the species exceeding the average $SCBD_j$ value.

Notably, SCBD$_j$ exhibited statistically significant positive associations with I$_j$, while showing negative associations with SSI$_j$. *Berberis crataegina* and *Astragalus angustifolius* subsp. *angustifolius*, with values of 399 and 382 respectively, contribute the most to the positive relationship between SCBD$_j$ and I$_j$. These species have the highest SCBD$_j$ values, which are 0.0595 and 0.0580. On the other hand, *Juniperus oxycedrus* L. subsp. *oxycedrus*, with the highest I$_j$ value of 542, weakens the positive relationship between SCBD$_j$ and I$_j$, as its SCBD$_j$ value is 0.0473 (Table S1). This situation implies that very frequently occurring species or species with an occurrence value greater than 50% do not contribute to SCBD$_j$. The main role in the negative relationship between SCBD$_j$ and SSI$_j$ is played by species that are found in a single cluster and have a rare distribution. Specifically, there are 44 species in a single cluster, and their SSI$_j$ values are 200. Among these 44 species, the I$_j$ values of 34 species are below 10. Additionally, the average SSI$_j$ value of all species is 160.11, and among the species that contribute above the average to beta diversity (Fig. 3), only the values of *Cedrus libani* and *Acantholimon confertiflorum* exceed the average SSI$_j$ value.

The LCBD$_i$ values ranged from 2.027×10^{-3} and 6.883×10^{-4}, while the range for RIRR$_i$ values extended from 2.085×10^{-3} and 4.005×10^{-4} (Table S3). Regarding the relationships, LCBD$_i$ exhibited a strong positive correlation with RS$_i$, a weak positive correlation with S$_i$, and a strong negative correlation with AS$_i$ (Table 1). A significant positive relationship was observed between LCBD$_i$ and RIRR$_i$ (r=0.748) (Fig. 4), indicating a parallel trend in the relationships of LCBD$_i$ and RIRR$_i$ with environmental predictors.

Table 1 Pearson correlation results of SCBD$_j$ and LCBD$_i$ with species and community metrics. Asterisks show the level of significance for each variable (*0.05, **0.01, ***0.001).

Species metrics (n=103)	SCBD$_j$	
I$_j$	0.956***	
SSI$_j$	-0.707***	
Community metrics (n=800)	LCBD$_i$	RIRR$_i$
S$_i$	0.078*	0.649***
RS$_i$	0.286***	0.431***
AS$_i$	-0.238***	0.388***

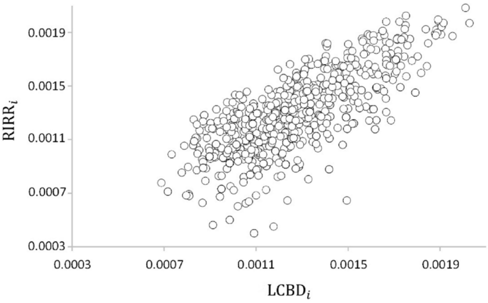

Figure 4 Scatterplot depicting the relationship between LCBD$_i$ versus RIRR$_i$.

When compared to RIRR$_i$, LCBD$_i$ showed statistically significant associations with a greater number of environmental predictors. The environmental variables that exhibited significant relationships with LCBD$_i$ and RIRR$_i$ are ELEV, SLOPE, TPI, LIME, PEBB, and DOLO. Additionally, LCBD$_i$ demonstrated significantly negative relationships with ASPT, HI, USME, and LRHV, along with significantly positive relationships with SAND and COMB. On the other hand, only CANY and MTHR emerged as environmental variables that showed significant relationships with RIRR$_i$ but not with LCBD$_i$ (Table 2).

Table 2 Pearson and Spearman correlation results of LCBD$_i$ and RIRR$_i$ with environmental variables (n=800). Asterisks show the level of significance for each variable (*0.05, **0.01, ***0.001).

Environmental data		
Continuous data		
ELEV	-0.291***	-0.469***
ASPT	-0.110**	-0.032
SLOP	0.140***	0.137***
HI	-0.109**	-0.041
TPI	-0.099*	-0.236***
Categorical data		
ROCK(LIME)	0.114**	0.109**
ROCK(PEBB)	-0.207***	-0.072*
ROCK(OPHI)	0.037	0.066
ROCK(ALLU)	-0.019	0.057
ROCK(DOLO)	-0.101**	-0.233***
ROCK(SAND)	0.075*	0.046
ROCK(COMB)	0.075*	0.009
LFC(CANY)	0.067	0.149***
LFC(MDSV)	0.050	0.048
LFC(UDHE)	0.029	-0.060
LFC(USVA)	-0.011	-0.050
LFC(USME)	-0.080*	-0.066
LFC(LRHV)	-0.121***	-0.056
LFC(MRSH)	-0.010	-0.046
LFC(MTHR)	-0.020	-0.088*

The results of Pearson correlation tests conducted between each pair of continuous environmental predictors are presented in Table 3.

Table 3 Pearson correlation results of the continuous environmental variables (n=800). Bold fonts show correlation coefficients greater than 0.6.

	ELEV	ASPT	SLOP	HI
ASPT	-0.079			
SLOP	0.085	-0.044		
HI	0.047	**0.608**	0.088	
TPI	**0.835**	-0.092	0.080	0.019

The subsequent variables, namely ASPC and TPI were excluded from the RFR analyses. In other words, RFR models for $LCBD_i$ and $RIRR_i$ were developed using ELEV, SLOPE, HI as continuous environmental predictors, along with ROCK and LFC as categorical environmental predictors.

For $LCBD_i$ and $RIRR_i$, RFR with 500 trees was run using 10-fold cross validation. Both RFR models exhibited high predictive performances (RMSE= 1.830×10^{-4} and MAE=1.428×10^{-4} for $LCBD_i$ and RMSE=1.950×10^{-4} and MAE=1.470×10^{-4} for $RIRR_i$). The performance of the RFR regression model for $LCBD_i$ was slightly superior to that of the RFR regression model for $RIRR_i$, as indicated by the RMSE and MAE results. ELEV was the most significant predictor of $LCBD_i$ (importance=90.952), followed by SLOP (36.414), HI (35.854) and ROCK(PEBB) (35.125) (Fig. 4a1). The local maximum of $LCBD_i$ occurred at approximately ELEV=400 m, SLOP=35 and HI=0.75. The partial dependence plots indicated that increases as ELEV and HI decrease while SLOP increases. Lower $LCBD_i$ values were observed in areas dominated by ROCK(PEBB) (Fig. 5b1-e1).

For $RIRR_i$, the most contributed predictors were ELEV (importance=104.095), HI (37.521), ROCK(LIME) (33.580) and SLOP (32.176), respectively (Fig. 5a2). The local maximum of $RIRR_i$ for ELEV (~400 m), and SLOP (~30) were very close to those of $LCBD_i$. For HI, the local maximum was ~0.88. Like $LCBD_i$, the increase of $RIRR_i$ occurred with decreasing ELEV and increasing SLOP. However, the relationship between $RIRR_i$ and HI were non-linear. Higher $RIRR_i$ values were in areas dominated by ROCK(LIME).

As a result, Random Forest Regression models of $LCBD_i$ and $RIRR_i$ were applied to a total of 98,450 pixels at a resolution of 100x100 m covering the Kuyucak mountain district, resulting in the predictive distribution maps shown in Fig. 6a and 6b. $LCBD_i$ and , $RIRR_i$ were subsequently referred to as $LCBD_{pv}$ and $RIRR_{pv}$, based on the pixel values that make up their distribution maps. There are significant similarities as well as notable differences between the maps of $LCBD_{pv}$ and $RIRR_{pv}$. The most significant similarities are observed in pixels where the $LCBD_{pv}$ and $RIRR_{pv}$ values are high. The areas with the highest $LCBD_{pv}$ and $RIRR_{pv}$ values are generally steep valley slopes, characterized by complex terrain and karstic limestone, located at elevations below 1100 m. The most significant differences between the $LCBD_{pv}$ and $RIRR_{pv}$ maps are observed in areas of the district that are above 1100 m in elevation. Generally, between elevations of 1100 and 1300 m, $RIRR_{pv}$ values are higher than $LCBD_{pv}$ values, while in areas above 1300 m, $LCBD_{pv}$ values are higher than $RIRR_{pv}$ values (Fig. 6a and 6b).

In forest ecosystems, developing conservation plans that account for economic costs is essential for the success of conservation practices. This need for economically viable strategies highlights the differences between the conservation cost approach and the ecology-centered approach, which vary significantly in their focus when defining priority conservation areas. Conservation cost approach prioritizes areas based on the economic feasibility of conservation efforts. It aims to maximize biodiversity outcomes while minimizing financial expenditures, emphasizing cost-effectiveness and resource allocation.

Ecology-centered approach focuses on the intrinsic ecological value of areas, prioritizing habitats and ecosystems based on their biodiversity, habitat quality, and

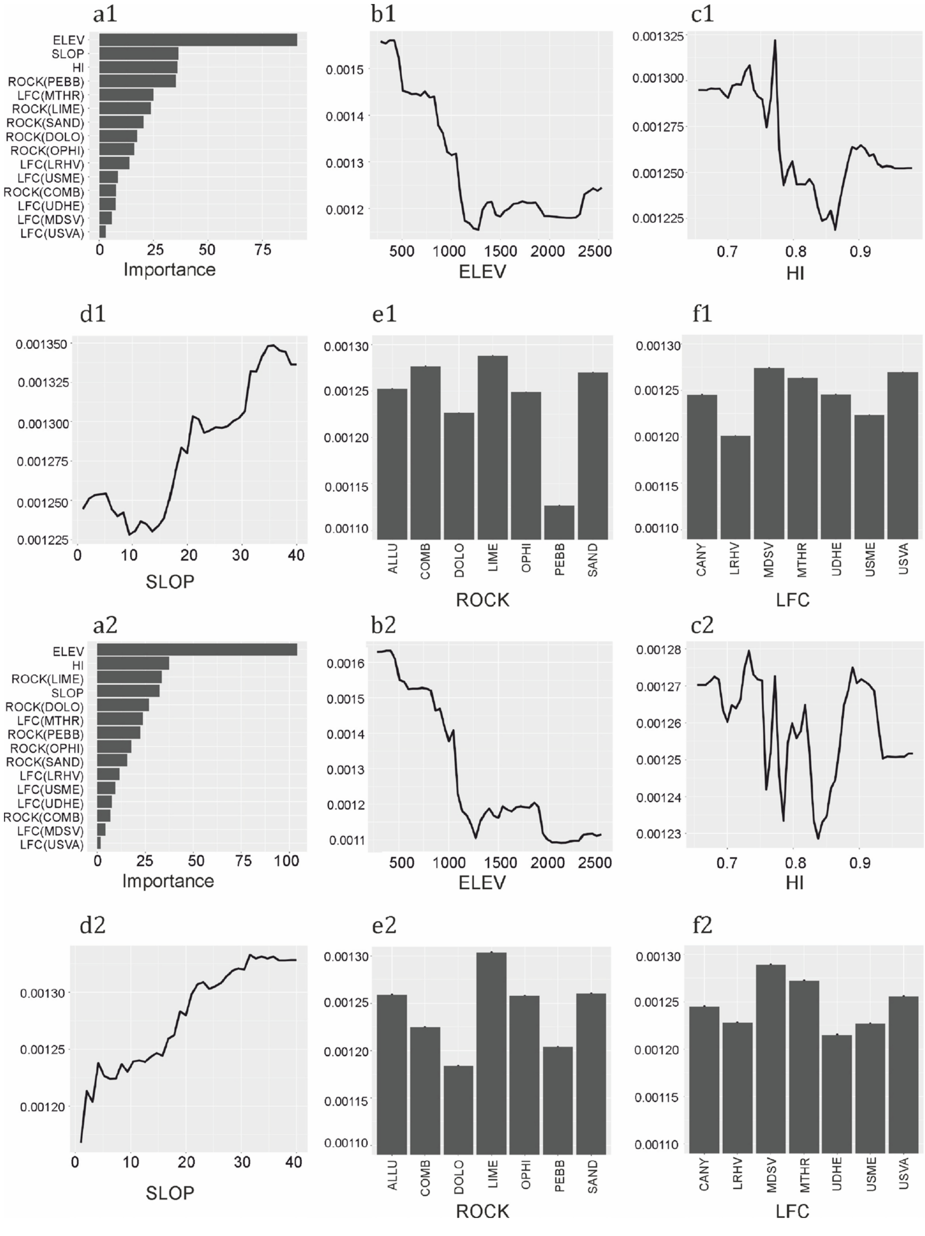

Figure 5 Relative importance of predictors of $LCBD_i$ (a1) and $RIRR_i$ (a2). Partial dependence plots for RFR of $LCBD_i$ (b1-f1) and $RIRR_i$ (b2-f2).

ecological functions, irrespective of economic considerations. While an ecology-centered approach is advantageous for ensuring ecosystem sustainability, relying exclusively on this approach can lead to significant financial implications. To address this challenge in the Kuyucak mountain district, two distinct conservation value maps have been created based on four conservation priority classes (Priority Class 1 > 0.0016, Priority Class 2 (0.0013-0.0016), Priority Class 3 (0.0010-0.0013), and Priority Class

4 < 0.0010), taking into account the RMSE values of the provided RF regression models for LCBD$_i$ and RIRR$_i$. One map employs a conservation cost approach, represented by $\min(\mathrm{LCBD}_{pv},\mathrm{RIRR}_{pv})$, while the other utilizes an ecology-centered approach, represented by $\max(\mathrm{LCBD}_{pv},\mathrm{RIRR}_{pv})$ (see Figures 6c and 6d). In this context, $\min(\mathrm{LCBD}_{pv},\mathrm{RIRR}_{pv})$ signifies the lowest value among the Local Contribution to Beta Diversity (LCBD) and Relative Importance of Rare Species (RIRR) for the same pixel, whereas $\max(\mathrm{LCBD}_{pv},\mathrm{RIRR}_{pv})$ denotes the highest value. In other words, the smallest value among the LCBD and RIRR values for a given pixel is expressed as $\min(\mathrm{LCBD}_{pv},\mathrm{RIRR}_{pv})$, while the largest value is expressed as $\max(\mathrm{LCBD}_{pv},\mathrm{RIRR}_{pv})$. Consequently, the maps are referred to as the minConVal map (indicating conservation value based on minimum pixel values) and the maxConVal map (indicating conservation value based on maximum pixel values).

In Figures 6c and 6d, the areas exhibiting the highest conservation value are represented in the color red. When determining the area to be conserved in the Kuyucak mountain district, decision-makers can use either of these two maps or a composite map derived from them while considering conservation costs. This dual mapping approach provides the necessary information for decision-makers to achieve a balance between ecological integrity and economic feasibility.

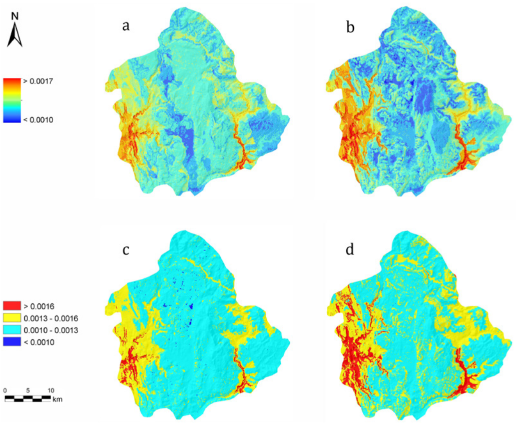

Figure 6 Predictive distribution maps of LCBD$_{pv}$ (a) and RIRR$_{pv}$ (b), along with the minConVal map (c) and the maxConVal maps (d).

Discussion

We used data from perennial plant species to derive our response variables (i.e., SCBD$_j$, LCBD$_i$, and RIRR$_i$). This approach was chosen because, as Irl et al. (2017) noted, data from perennial species can be obtained more quickly, easily, and cost-effectively compared to annual species. Furthermore, the long lifespan of perennial species makes them valuable indicators for assessing the impact of environmental factors on biodiversity. In contrast, annual species are less reliable indicators due to their short lifespans and susceptibility to transient climatic events (Duarte et al. 2024).

SCBD quantifies the relative contribution of a species to total beta diversity and provides insight into identifying species with significant variations across the study district or region (Legendre & De Cáceres 2013). Our findings reveal that SCBD$_j$ is positively correlated with species incidence, meaning that species significantly influencing beta diversity are more frequently encountered. This observation aligns with previous research (Heino & Grönroos 2017, Vilmi et al. 2017, de Paiva et al. 2021). Species exhibiting the highest SCBD$_j$ values (e.g., *Berberis crataegina*, *Astragalus angustifolius* subsp. *angustifolius*, *Juniperus excelsa* subsp. *excelsa*, *Pinus nigra* subsp. *pallasiana*, *Juniperus oxycedrus* subsp. *oxycedrus*, *Styrax officinalis*, *Quercus cerris*, *Teucrium polium* subsp. *polium*, and *Quercus coccifera*) also demonstrated intermediate occurrence (ranging from 246 to 542 plots), consistent with observations by Heino and Grönroos (2017), Szabó et al. (2019).

The results obtained from NMDS indicate that the vegetation groups are significantly separated from one another. With the exception of *Quercus cerris*, all species exhibiting the strongest correlations with the first and second NMDS axes also serve as indicator species for the vegetation groups identified through cluster analysis. The most influential environmental factor in differentiating species or vegetation groups is elevation. These results for the Kuyucak mountain district are consistent with studies conducted by Kavgacı et al. (2021), Özkan (2014), and Fountain et al. (2007) on vegetation-environment relationships in the Mediterranean region.

Most indicator species from vegetation groups contribute significantly to beta diversity. For instance, *Berberis crataegina*, *Astragalus angustifolius* subsp. *angustifolius*, and *Origanum onites*—characteristic species of the Group III along with *Juniperus oxycedrus* subsp. *oxycedrus*, an accompanying species of the Group I, are among the most influential contributors to beta diversity. These species are also present in the other communities, leading to generally lower SSI_j values. Therefore, it is not surprising that $SCBD_j$ exhibits a negative correlation with SSI_j.

Local Contribution to Beta Diversity (LCBD) measures the ecological uniqueness of species assemblages or sites (Heino & Grönroos 2017, Yao et al. 2021). Our study demonstrates a weak correlation between $LCBD_i$ and S_i (r = 0.078), suggesting that the association between unique species compositions and higher species richness is not substantial. This finding contrasts with the results reported by Kong et al. (2017), Landeiro et al. (2018), Pearman et al. (2020) and Camara et al. (2022), who identified significant positive relationships between $LCBD_i$ and S_i. Additionally, it diverges from the negative associations observed in studies by Legendre and De Cáceres (2013), Da Silva and Hernández (2014), Heino et al. (2017), Heino and Grönroos (2017), Pajunen et al. (2017), Ngor et al. (2018), Heino and Alahuhta (2019), Tan et al. (2019), Brito et al. (2020), Borges et al. (2020), Dubois et al. (2020), Dansereau et al. (2021), Santos et al. (2021) and Hill et al. (2022). The weak relationship between $LCBD_i$ and S_i may be attributed to the use of presence-absence data rather than species abundance data in the calculation of $LCBD_i$, the fact that the species contributing most to $LCBD_i$ have different habitat preferences, or the environments in which these species occur exhibit a wide variation in species richness.

We observed a positive association between $LCBD_i$ and the number of rare species (RS_i), while it displayed a negative association with the number of abundant species (AS_i). These findings align with Qiao et al. (2015), who conducted a study in the Badagongshan National Nature Reserve, Hunan Province, Central China. Another relevant metric for identifying priority conservation areas is the Index of Relative Rarity (IRR_i) (Dapporto & Dennis 2008, Leroy et al. 2012). In our study, we employed the Relative Contribution to Total Rarity, denoted as $RIRR_i$. $RIRR_i$ exhibited a stronger correlation with RS_i compared to AS_i. $RIRR_i$ and $LCBD_i$ display contrasting relationships with abundant species richness (AS_i), as AS_i is positively correlated with $RIRR_i$ but negatively correlated with $LCBD_i$. Overall, these relationships underscore the significant role of rare species in $LCBD_i$ and $RIRR_i$, with rare species contributing more significantly to $LCBD_i$ than to $RIRR_i$.

Numerous studies across different biological communities have indicated correlations between local contribution to beta diversity and various environmental factors, including latitude, elevation, environmental heterogeneity, water chemistry, soil characteristics, and geology in aquatic ecosystems (Kong et al. 2017, Vilmi et al. 2017, Szabó et al. 2019, Leão et al. 2020, Camara et al. 2022, Gavioli et al. 2022, Xia et al. 2022), and elevation, slope, convexity, aspect, precipitation seasonality, soil pH, and soil organic matter in terrestrial ecosystems (Tan et al. 2019, Santos et al. 2021, Yao et al. 2021). Similarly, our results demonstrated positive associations between $LCBD_i$ and several environmental variables (SLOP, ROCK(LIME), ROCK(SAND), and ROCK(COMB)), as well as negative associations with others (ELEV, ASPT, RI, HI, TPI, ROCK(PEBB), ROCK(ALLU), ROCK(DOLO), LFC(USME), and LFC(LRHV)). $RIRR_i$, conceptually similar to $LCBD_i$, also exhibited connections with environmental factors but employed a distinct approach and simpler formulation to rank priority conservation sites based on species occurrence values (Dapporto & Dennis 2008, Leroy et al. 2012). Although there were differences in $LCBD_i$ and $RIRR_i$ values for the same plots, we did not observe explicit contrasts in their primary driving variables (ELEV, SLOPE, TPI, ROCK(LIME), ROCK(PEBB), and ROCK(DOLO)). As a result, the distribution maps produced by the Random Forest Regression (RFR) model for the elevated values of both metrics proved to be very similar. In the Kuyucak mountain district, areas with elevated $LCBD_i$ and $RIRR_i$ values are primarily found in steep valley slopes below 1100 m, characterized by complex terrain and karstic limestone, predominantly within the termo- and meso-Mediterranean vegetation belt. Preserving such areas is crucial as they contribute significantly to ecological uniqueness.

Conclusions

The expenses associated with conservation vary in accordance with the size of the areas intended for protection. When compared to smaller-scale forest areas, the costs of protection, along with the time and labor needed for such efforts, tend to be notably higher in larger-scale forest areas. To enhance ecological assessment, restoration initiatives, and conservation planning in the Kuyucak mountain district, we have expanded our analysis beyond the distribution maps derived from $LCBD_{pv}$ and $RIRR_{pv}$.

Specifically, we generated distribution maps considering the conservation cost approach (Fig. 6c) and the ecology-centered approach (Fig. 6d). The conservation cost approach emphasizes economic efficiency and cost-effectiveness in prioritizing conservation areas, while the ecology-centered approach focuses on ecological integrity and biodiversity preservation. These approaches can complement each other, providing a more comprehensive framework for conservation planning.

This pioneering study represents the first endeavor in geospatial modeling and mapping of conservation value distribution for Mediterranean forest ecosystems in Türkiye. Its findings have the potential to serve as a foundational reference for future studies pursuing similar objectives in distinct districts or regions.

Conflict of interest

The authors declare that they have no conflict of interest.

Acknowledgments

This study was funded by the Scientific and Technological Research Council of Turkey (TÜBİTAK) under Project No: 113O495. We sincerely appreciate the insightful and constructive suggestions provided by the anonymous reviewers, which have significantly enhanced this work. Our heartfelt thanks go to Akın KIRAÇ, Tunahan ÇINAR, and Uysal Utku TURHAN, Şükran OĞUZOĞLU for their indispensable help in data collection during the fieldwork.

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