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Application of the Maxent Model in Habitat Suitability Assessment for *Rosalia alpina* (Linnaeus, 1758) in Montenegro

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Abstract

This study applies the Maxent model to predict the potential habitat suitability of the endangered saproxylic beetle *Rosalia alpina* in Montenegro. The model identified temperature (TEMP) and near-surface relative humidity (NSRH) as the dominant predictors influencing the species' distribution, followed by vegetation type (VEG) and topographic variables such as slope (SLP) and aspect (ASP). The model achieved good predictive accuracy, with an average test AUC of 0.798 ± 0.012 across five replicates, confirming its robustness and reliability. The resulting potential habitat suitability map indicates that the central and north mountainous regions of Montenegro represent the most suitable areas, corresponding closely with known field observations. These findings highlight the importance of preserving structurally diverse deciduous forests and provide a valuable basis for spatially targeted conservation and sustainable forest management strategies for *R. alpina* in Montenegro. However, spatial overlap analysis showed that only about 18% of highly suitable (potential) habitats are located within nationally protected areas, and around 20% within the proposed Emerald network. This indicates that a considerable portion of potentially suitable habitats remain unprotected, emphasizing the need to strengthen and expand the existing conservation frameworks and to prioritize these areas for inclusion in the future Natura 2000 network, ensuring effective long-term protection of the species and its key forest habitats.

Keywords: *Rosalia alpina*, Maxent, conservation, biodiversity, Montenegro

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INTRODUCTION

The conservation of biodiversity is gaining critical importance in the face of rapid transformations in natural ecosystems, predominantly driven by anthropogenic influences. Among the most significant threats to species survival are habitat destruction, fragmentation, and the accelerating impacts of climate change (IPBES 2019).

Rosalia alpina (Linnaeus, 1758), commonly referred to as the Alpine longhorn beetle, stands out as one of Europe's most emblematic saproxylic beetle species. Due to its sensitivity to habitat conditions, it is widely recognized as a bioindicator of well-preserved deciduous forest ecosystems (Drag et al. 2011, Jugovic et al. 2022). Although classified as "Least Concern" (LC) on the IUCN Red List (Nieto and Alexander 2010), it is strictly protected under the EU Habitats Directive (Annexes II and IV, Council Directive 92/43/EEC). Despite this, ongoing declines in old-growth forest areas and reduced availability of deadwood are placing increasing pressure on the species (Ranius 2006, Seibold et al. 2016).

Interest in *R. alpina* dates back over two centuries, with its first formal description provided by Linnaeus (1758). Early studies in the 19th and early 20th centuries largely focused on its taxonomy and morphological features (Mulsant 1839, Reitter 1912). However, in the latter half of the 20th century, scientific attention shifted toward the species' ecological requirements, particularly its dependence on deadwood in mature deciduous forests (Campanaro et al. 2017). With the evolution of forest ecology and saproxylic entomology, *R. alpina* has been increasingly acknowledged as a key indicator of forest quality (Müller et al. 2008, Drag et al. 2011).

Species distribution modelling (SDM) has become a fundamental tool in biodiversity research, offering insights into potential species ranges by linking the observed occurrences with relevant environmental variables (Elith and Leathwick 2009). Within this framework, the Maximum Entropy (Maxent) model has emerged as one of the most robust and widely applied approaches (Phillips et al. 2006, Merow et al. 2013), particularly advantageous for assessing species that are rare, elusive, or otherwise difficult to detect, where only presence data are available (Elith et al. 2011). Since the late 2000s, Maxent has been increasingly utilized to model the distribution of saproxylic insects, responding to a growing need for precise spatial tools to inform conservation planning for rare species (Drag et al. 2011, Bosso et al. 2013). Its integration of occurrence data with ecologically meaningful predictors enables detailed spatial projections of potential habitat suitability, making it particularly useful in forestry and conservation contexts (Phillips et al. 2006).

This study aims to develop the first Maxent-based habitat suitability model for *R. alpina* in Montenegro, using verified field data and key environmental variables as predictors. The results are intended to support spatially informed conservation strategies and contribute to identifying core habitats for protection, especially in the context of Montenegro's ongoing efforts to establish the Natura 2000 ecological network.

MATERIALS AND METHODS

To assess the potential distribution of *R. alpina* across Montenegro, a habitat suitability modelling approach was employed using the Maxent algorithm – Maximum Entropy Modelling (Phillips et al. 2006). This method is widely recognized as a commonly used approach in ecological modelling when only species presence data are available (Elith et al 2011). It operates on the principle of maximum entropy to estimate the most probable distribution of suitable habitats based on a set of environmental predictors and species occurrence data (Franklin 2010, Merow et al. 2013).

Presence data for *R. alpina* were collected during field surveys conducted as part of the establishment of the Natura 2000 network in Montenegro, between 2017 and 2024. These surveys covered a wide range of habitat types, primarily within mountainous and hilly forest ecosystems. A total of 451 georeferenced and validated occurrence records were used as input for the Maxent modelling. For the purpose of model training, the occurrence data were randomly split into two groups: 70% for model training (n = 316) and 30% for model testing (n = 135), ensuring an objective assessment of model performance and minimizing the risk of overfitting (Fielding and Bell 1997, Muscarella et al. 2014). The model was developed using the Maxent software platform v3.4.4, with adjusted settings for regularization and feature types The model used 10,192 background points in each of the five cross-validation replicates to estimate the Maxent distribution. Regularization values were set as follows: linear/quadratic/product = 0.050, categorical = 0.250, threshold = 1.000, and hinge = 0.500. The model employed hinge, product, linear, and quadratic feature types. Model evaluation was performed using five replicates with the cross-validation approach, including response curves and a jackknife test of variable importance.

We initially considered ten environmental predictors for the modelling (Table 1). Vegetation-related predictors were represented by Forest Type (FT) and NDVI. FT was derived from the CLC+ Backbone 2023 dataset, which provides harmonized land cover information at a 10 m spatial resolution based on Sentinel-2 satellite imagery for the reference year 2023 (Copernicus Land Monitoring Service, 2023). NDVI was calculated from MODIS satellite data at a 250 m resolution as the mean annual value for 2023, representing vegetation productivity and canopy density (Didan, 2015).

Climatic variables (TEMP, PREC, VPD, NSRH, and NSWS) were obtained from the CHELSA v2.1 database, which provides downscaled high-resolution (1 km) climate data derived from long-term climatological averages for 1981–2010 (Karger et al. 2017). Topographic parameters (ELEV, SLP, and ASP) were derived from the EU-DEM v1.1, which has a 25 m resolution and integrates SRTM and ASTER GDEM data (European Environment Agency 2016).

All predictor layers were reprojected to the WGS 84 coordinate system and resampled to a unified spatial resolution of 1 × 1 km to ensure spatial consistency and comparability. Prior to modelling, all environmental variables were examined for multicollinearity using the Variance Inflation Factor (VIF) and Tolerance (TOL) values computed in SPSS. This procedure was conducted to verify that the explanatory variables were not highly correlated with each other, as excessive multicollinearity can distort regression estimates.

For each variable, the Maxent algorithm calculated relative contribution, permutation importance, and response curves, allowing interpretation of the relationship between each predictor and the potential habitat suitability (Phillips et al. 2006, Yackulic et al. 2013). Model performance was evaluated using the Receiver Operating Characteristic (ROC) curve and its associated metric, the Area Under the Curve (AUC), which quantifies the model's ability to discriminate between suitable and unsuitable environmental conditions (Warren and Seifert 2011).

A jackknife test of variable importance was conducted to assess the independent contribution of each predictor and the reduction in explanatory power when excluded from the model. The ROC curve was also used to visualize the trade-off between sensitivity and specificity across different suitability thresholds. Based on the results, a continuous habitat suitability map was generated, with predicted suitability values ranging from 0 (unsuitable) to 1 (highly suitable). This continuous approach allows for a more nuanced interpretation of potential habitat suitability, without applying binary presence–absence thresholds (Liu et al. 2005, Jiménez-Valverde and Lobo 2007). Habitat suitability values were classified into five categories (very low, low, moderate, high, and very high suitability) using the Natural Breaks (Jenks) classification method.

Table 1 Environmental variables used in the model.

Code	Variable	Source	Unit
TEMP	Mean Annual Temperature	CHELSA v2.1 (Karger et al. 2017)	°C
PREC	Annual Precipitation	CHELSA v2.1 (Karger et al. 2017)	mm · year $^{-1}$
VPD	Vapor Pressure Deficit	CHELSA v2.1 (Karger et al. 2017)	kPa
NSRH	Near Surface Relative Humidity	CHELSA v2.1 (Karger et al. 2017)	%
NSWS	Near Surface Wind Speed	CHELSA v2.1 (Karger et al. 2017)	m · s $^{-1}$
ELEV	Elevation	EU-DEM v1.1 (EEA 2021)	m a.s.l. (meters above sea level)
SLP	Slope	EU-DEM v1.1 (EEA 2021)	° (degrees)
ASP	Aspect	EU-DEM v1.1 (EEA 2021)	° (degrees, 0–360°)
VT	Vegetation Type	CLC+ Backbone 2023 (Copernicus Land Monitoring Service 2023)	Categorical (land cover class)
NDVI	Normalized Difference Vegetation Index	MODIS (Didan 2015)	Unitless (–1 to +1)

RESULTS AND DISCUSSION

As a result of the multicollinearity analysis (Table 2), vapor pressure deficit (VPD) and elevation (ELEV) were excluded from further analysis due to their strong intercorrelations with other climatic and topographic variables. The exclusion criterion was set at VIF > 5 and TOL < 0.2. The final set of eight environmental predictors retained for modelling showed acceptable VIF and TOL values, confirming the absence of significant multicollinearity and ensuring statistical independence among variables. The relative contribution and permutation importance of ecological variables are presented in Table 3. In Figure 1, the marginal response curves of the Maxent model are presented for individual environmental variables. In Figure 2, the response curves of the Maxent model based on individual variables are shown.

The Maxent model identified TEMP and NSRH (Phillips et al. 2006, Elith et al. 2011, Merow et al. 2013) as the dominant predictors influencing the potential distribution of *R. alpina* (Bosso et al. 2013, Campanaro et al. 2017). TEMP had the highest contribution (39.5%) and permutation importance (48%), showing a clear unimodal response (Figure 2). Suitability increased above 2°C, peaked at 8–9°C, and sharply declined beyond 12°C, indicating the species' preference for cool, humid montane environments (Seibold et al. 2016, Castro et al. 2019).

NSRH (26.3%, 19.1%) showed a strong positive relationship with habitat suitability, reflecting the species' dependence on moist, shaded deciduous forests (Jurc et al. 2008, Müller et al. 2008, Bouget et al. 2013, Micó Balaguer et al. 2013, Horák et al. 2019) with suitable microclimatic and substrate conditions. VT, derived from CLC+ Backbone (2023), contributed 13.2%, with the highest suitability for broadleaved deciduous forests (class 3), while coniferous (class 2) and low woody vegetation (class 5) showed much lower suitability (Figures 2 and 3).

In line with the known ecological traits of *R. alpina*, whose life cycle is strictly confined to forest ecosystems, the results clearly highlight the importance of VT—particularly the presence of beech forests—in determining the potential distribution of this species in Montenegro (Drag et al. 2011). This saproxylic, xylophagous beetle favours well-preserved, moist, mesophilic forests with complex wood structure and trees at various stages of decomposition (Buse et al. 2008, Horák et al. 2019).

Topographic variables SLP (9.3%) and ASP (5.7%) had moderate influence, indicating preference for north- and east-facing (Szujecki 1987, Seibold et al. 2016), moderately inclined slopes that retain higher humidity and stable temperatures. Other predictors, PREC (4.4%), NDVI (1.2%), and NSWS (0.5%), had minor effects on habitat suitability. Overall, the response curves confirm that *R. alpina* (Bosso et al. 2013, Campanaro et al. 2017) distribution is mainly driven by TEMP and NSRH, in combination with VT and topographic factors (SLP, ASP), defining the most suitable habitats in humid, mid-elevation deciduous forest zones. The jackknife test (Phillips and Dudík 2008, Elith et al. 2011) (Figure 3) confirmed that TEMP and NSRH provided the highest training gain, test gain, and AUC (Fielding and Bell 1997, Lobo et al. 2008) when used individually, and their exclusion caused the largest reduction in model performance.

The ROC curve (Figure 4), averaged over the replicate runs, demonstrates the overall accuracy of the Maxent model. The average test AUC (Fielding and Bell 1997, Lobo et al. 2008) of 0.798 with a standard deviation of 0.012 indicates good model performance and high stability across replicates. This suggests that the model effectively distinguishes suitable from unsuitable potential habitats for *R. alpina* (Bosso et al. 2013, Campanaro et al. 2017), with consistent results between runs. The use of predicted area to define specificity (Liu et al. 2005, Jiménez-Valverde and Lobo 2007) follows the standard Maxent approach.

Table 2 Results of multicollinearity analysis.

Variable	TOL	VIF
VT	0.943	1.060
NDVI	0.699	1.430
TEMP	0.021	47.013
PREC	0.739	1.353
VPD	0.024	42.114
NSRH	0.289	3.465
NSWS	0.488	2.051
ELEV	0.024	41.568
SLP	0.786	1.272
ASP	0.913	1.095

Table 3 Relative contribution and permutation importance of ecological variables.

Variable	Percent contribution (%)	Permutation importance (%)
TEMP	39.5	48
NSRH	26.3	19.1
VT	13.2	4.4
SLP	9.3	10.3
ASP	5.7	3.2
PREC	4.4	7.3
NDVI	1.2	6.8
NSWS	0.5	0.9

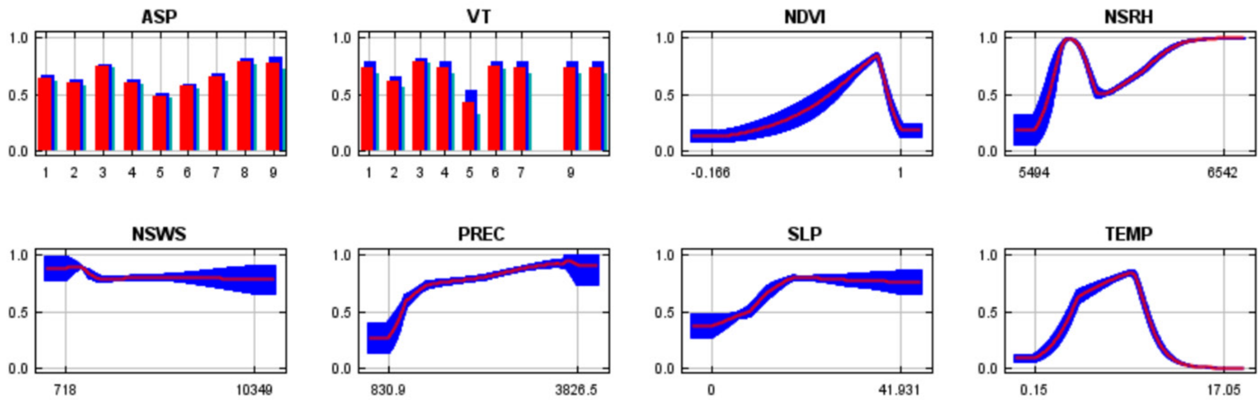

Figure 1 Marginal response curves for environmental variables in the Maxent model.

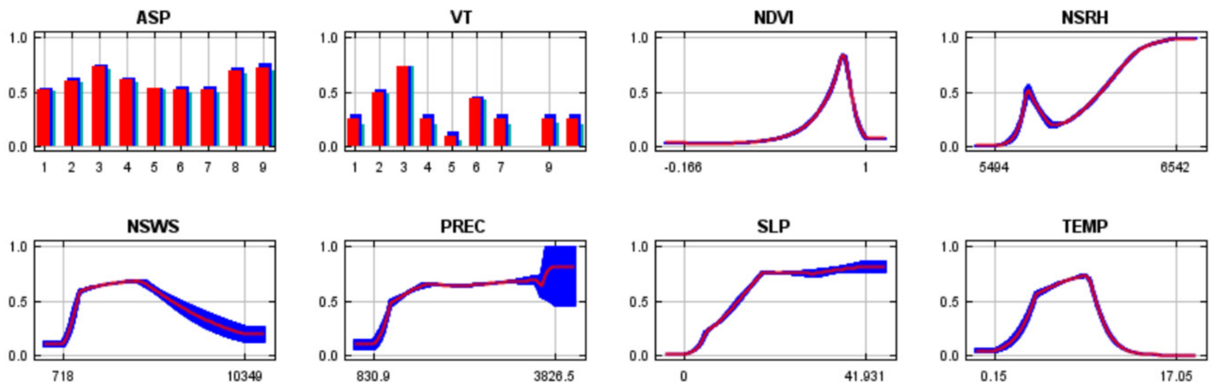

Figure 2 Maxent model response curves based on individual variables.

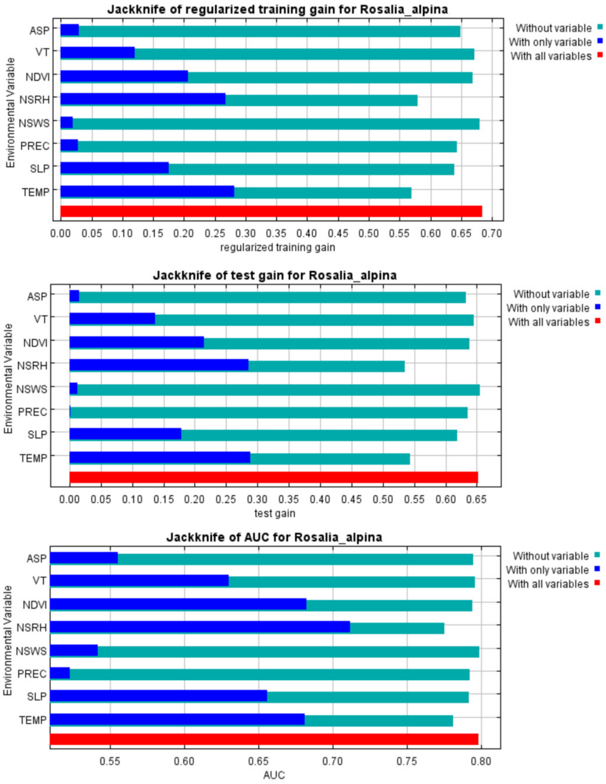

Figure 3 Jackknife analysis results.

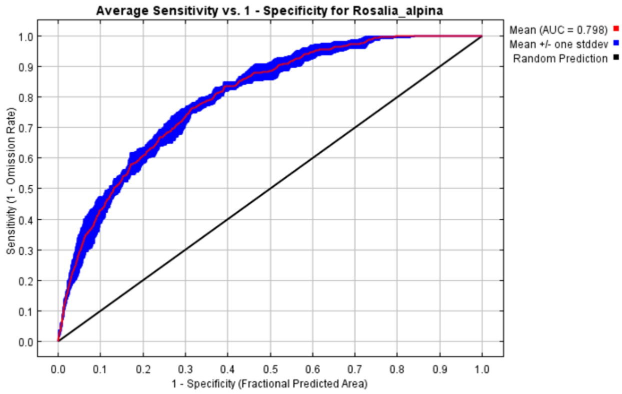

Figure 4 ROC AUC curve for training and testing samples.

The displayed potential habitat suitability map (Figure 5) represents the spatial projection of the Maxent model results for the potential distribution of *R. alpina* in Montenegro. The map is classified into five suitability categories – Very Low, Low, Moderate, High and Very High – based on Natural Breaks (Jenks) classification of probability values. These categories facilitate easier interpretation and help identify spatial conservation priorities.

Based on the resulting distribution map, it is evident that the central and north regions of Montenegro are classified as moderately to highly suitable. These areas correspond closely with the majority of field presence data, both training points and testing points (Figure 5). They encompass mountain ranges such as Bjelasica, Komovi, Prokletije, Visitor, and Zeletin, as well as the edges of Sinjajevina, higher zones of the Morača mountains, the coastal mountains of Orjen and Lovćen, and areas surrounding Durmitor, all of which are recognized habitats of this saproxylic species (Drag et al. 2011, Bosso et al. 2013, Campanaro et al. 2017).

Table 4 presents the percentage of total area and the distribution of test data points across each habitat suitability class. The largest portion of Montenegro's territory (32.66%) falls within the Very Low suitability category, where only four test points were identified, which supports the model's prediction that low habitat suitability in these areas are located in areas of low predicted suitability. Combined, the Very Low and Low categories account for 57.31% of the territory but include just 12 test points, indicating that these regions are largely unsuitable or only marginally suitable for the species. Areas of moderate habitat suitability cover 19.19% of Montenegro's territory, with 23 test points identified, indicating a balanced representation of this suitability level within the study area. In contrast, the High and Very High suitability classes, which together cover 23.51% of the territory, contain 100 test points in total, confirming the strong correspondence between modeled suitability and observed occurrences. This spatial agreement between model predictions and field data further supports the reliability of the model performance, which is consistent with the AUC results (Fielding and Bell 1997, Phillips and Dudík 2008, Elith et al. 2011). These high and very high suitability areas are therefore of critical importance for conservation planning since they represent zones with a high probability of species presence and ecological stability (Guisan and Zimmermann 2000, Nakládal et al. 2022). When the High and Very High suitability zones (classes 4 and 5) were spatially (Figure 5) overlaid with the network of nationally protected areas, only about 18% of potential habitats were found to be under protection. Within the boundaries of proposed Emerald sites, the coverage of High and Very High suitability areas slightly increased to just over 20%, highlighting a notable gap in effective habitat conservation. The remaining potentially suitable habitats (classes 4 and 5) lie outside formally protected zones, emphasizing their role as potentially suitable and ecologically valuable areas that should be prioritized for future inclusion in conservation frameworks to ensure the long-term survival of the species (Nieto and Alexander 2010, IPBES 2019, European Commission 2020).

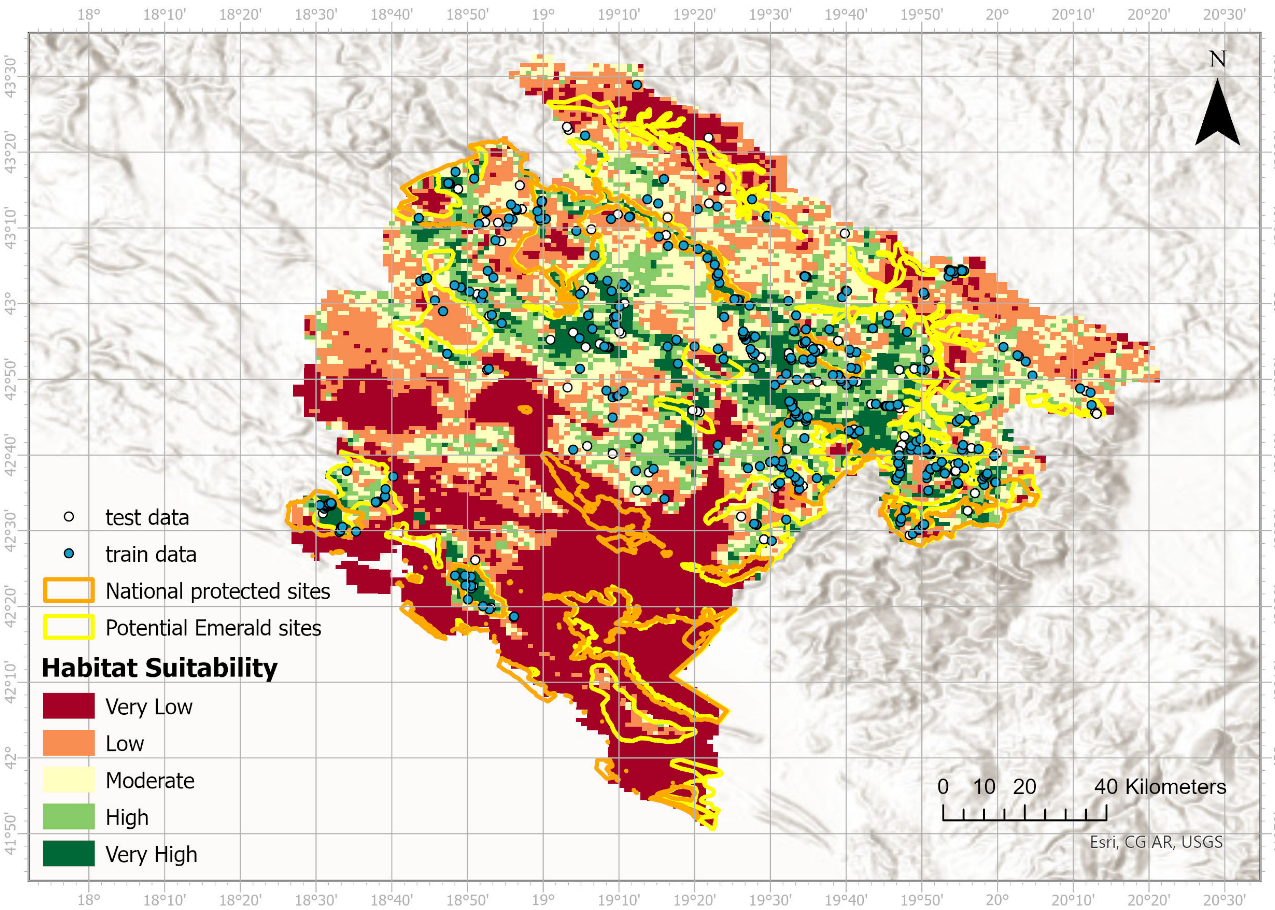

Figure 5 Habitat suitability map for *R. alpina*, overlaid with nationally protected areas and potential Emerald sites. The prediction represents the mean of five replicate runs.

The habitat suitability modelling results for *R. alpina* carry significant implications for the species' long-term conservation in Montenegro. Areas identified as highly suitable habitats can serve as a foundation for guiding conservation efforts, including targeted monitoring, the preservation of existing forests, and potentially the establishment of new protected areas aimed at mitigating threats to saproxylic species (Nieto and Alexander 2010). This finding aligns with observations from field and taxonomic studies (Drag et al. 2011, Bouget et al. 2013, Castro et al. 2019).

Given the saproxylic nature of the species and its dependence on old, often decaying trees, the preservation of mature forest stands and natural wood decay processes is a key conservation measure (Buse et al. 2008, Micó Balaguer et al. 2013). As emphasized by Bouget et al. (2013), the removal of deadwood and the homogenization of forest structures significantly impact saproxylic beetle populations, with R. alpina being particularly sensitive.

The results of our model highlight the need to integrate the conservation of this species into forest management plans, especially in regions not currently under formal protection, but identified by the model as suitable habitats (Jurc et al. 2008). This approach aligns with the EU Biodiversity Strategy, which underscores the importance of spatially targeted conservation actions (European Commission 2020). In many cases, potentially suitable habitats are excluded from conservation zones due to the lack of proper management and protection measures (Bosso et al. 2013).

Furthermore, the model can serve as a tool to assess the impact of planned forestry and infrastructure activities (e.g., logging, road construction) on the species' habitats, the

Table 4 Habitat suitability classes for *R. alpina*.

Class	Habitat suitability classes	Percentage of total area (%)	Number of test points
1	Very Low	32.66	4
2	Low	24.65	8
3	Moderate	19.19	23
4	High	13.86	35
5	Very High	9.65	65
Total		100.00	135

threats which were previously identified as major factors contributing to its decline (Campanaro et al. 2017).

In addition, the identified key localities can be used to raise public awareness and support educational initiatives which focus on the importance of saproxylic species and their role in forest ecosystem functioning. As Ranius and Jansson (2002) note, public understanding and support for the ecological role of deadwood are often crucial for the success of conservation measures. As a consequence, extensive areas where the species persists may remain outside formal nature reserves due to inadequate protection and management.

CONCLUSIONS

The potential habitat suitability modelling results for R. alpina highlight the importance of beech forests in higher elevation zones of Montenegro as key areas for the conservation of this endangered saproxylic species (Bouget et al. 2013, Micó Balaguer et al. 2013, Horák et al. 2019). The most significant ecological predictors in our model were TEMP and NSRH, which align with findings from similar studies conducted in the mountainous regions of Europe (Drag et al. 2011, Jugovic et al. 2022), confirming the consistency of the species' ecological requirements across its range (Bosso et al. 2013, Campanaro et al. 2017).

The application of the Maxent model proved to be a methodologically sound and conservation-relevant approach, demonstrating high accuracy and strong predictive performance (Phillips et al. 2006, Elith et al. 2011, Warren and Seifert 2011, Merow et al. 2013, Muscarella et al. 2014). The identified high-suitability areas provide a valuable basis for planning targeted conservation measures. Additionally, the results emphasize the need to preserve structurally complex, old-growth forest habitats with abundant deadwood, which are crucial for maintaining viable populations of this species (Ranius and Fahrig 2006, Buse et al. 2008, Jurc et al. 2008, Nakládal et al. 2022).

Spatial overlap analysis showed that only about 18% of highly suitable habitats are currently located within nationally protected areas, while coverage within the proposed Emerald network slightly increases to just over 20%. This indicates that a significant portion of potentially suitable habitats remains outside formal protection frameworks, highlighting the need to expand the existing conservation networks. These areas should be considered for future inclusion in the Natura 2000 network, ensuring coherent protection of R. alpina habitats at both national and international levels and supporting long-term species conservation in Montenegro.

It should be noted that the accuracy and reliability of the results depend significantly on the quality of the input geospatial data and the availability of detailed habitat information. Limitations such as the spatial resolution of predictor layers, potential errors in vegetation maps, and incomplete field data coverage may influence model precision. Moreover, integrating climate change scenarios into habitat suitability modelling would allow for projections of potential shifts in the species' distribution under global warming, thus improving long-term conservation planning.

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