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PREDICTED HABITAT SUITABILITY OF SCOTS PINE IN ROMANIA

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Abstract: *Scots pine (Pinus sylvestris L.) forests cover around 28 million hectares in Europe, representing approximately 20% of the commercial forest area. Sudden environmental changes can cause the maladaptation of a species, a reduced fitness, and population decline. This study aimed to identify the main climatic drivers of Scots pine distribution in Europe and to model its current and future habitat suitability in Romania under two Shared Socioeconomic Pathways (SSPs) – SSP2-4.5 and SSP5-8.5, with a focus on projected range shifts. The climatic variables that had the highest relative importance were Annual Mean Temperature (BIO1) and Temperature Seasonality (BIO4). At present, more than 70% of Romania (187,000 km^2) represents areas with excellent climate suitability (above 80%) for Scots pine. By the end of the century, this area is predicted to diminish to 55,000 km^2 – 14,000 km^2 (22 – 6%), under SSP 2-4.5 and SSP 5-8.5, respectively. To provide forest managers and policymakers with reliable adaptation frameworks, it is essential to model climate-driven shifts in species distribution. Future modelling efforts should enhance predictive accuracy for Scots pine by integrating additional key environmental variables.*

Key words: *sdm, habitat suitability models, species distribution, Shared Socioeconomic Pathways, Pinus sylvestris.*

1. Introduction

Scots pine (*Pinus sylvestris* L.) is one of the most widespread tree species globally, covering around 143 million hectares (3.7% of the global forest area) [53]. In Europe, Scots pine forests represent around 20% of the commercial forest area, over 28 million hectares [39]. While the species was widespread during the last glaciation in the Carpathian region [56], its modern distribution across the Carpathian Mountains is characterised by fragmented and disjunct populations [51].

In Romania, natural Scots pine forests cover approximately 9,000 hectares and

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are mostly confined to glacial refugia [53].

Because of its dynamic ecological plasticity and its capacity to thrive in harsh environments, Scots pine plays a crucial role in both forestry and the timber industry [12].

Drought and the associated decline in groundwater levels due to climate change are the most discussed threats to Scots pine [12, 16]. Although Scots pine is generally considered a drought-resistant species, European pine forests have suffered extensive damage from the frequent and severe dry spells of recent years [16].

Nevertheless, given its specific habitat requirements, the species demonstrated a relatively high degree of resilience to the ongoing impacts of climate change [12]. In the Czech Republic, Scots pine had the highest resistance of the 12 studied tree species [59]. In Romania, Mihai et al. [41] showed that the warming process is more accentuated at the altitudinal limits (both upper and lower) of the species distributions, including the mixed deciduous species with *Pinus sylvestris* and other coniferous species.

Ecological niche models serve as essential tools for mapping suitable habitats [29], reconstructing historical ranges [61], and forecasting how species distributions might shift under various climate change projections [17, 47]. Because niche-related traits typically evolve at a slower pace than the environment changes, species may successfully track shifting habitats during periods of gradual transition; however, abrupt environmental shifts often lead to maladaptation, diminished fitness, and subsequent population decline [1, 48].

The objectives of this study were to: *i)* identify the climatic variables that influence the distribution of Scots pine in Europe; *ii)* predict potential areas with suitable climate conditions for this species in Romania under current conditions; *iii)* predict areas with potentially suitable climate conditions for this species under three future periods (2041-2060, 2061-2080, and 2081-2100) and two distinct shared socioeconomic pathways (SSPs) – 2-4.5 and 5-8.5; and *iv)* evaluate the range shifts.

2. Materials and Methods

The Harmonized Tree Species Occurrence Points for Europe dataset [33] was used to extract the presence points of *Pinus sylvestris*. Out of the 163,246 records, 572 were removed because they were flagged as country capitals (419) or country centroids (153).

The area of interest was Romania. However, the entire spatial extent of the data points (specifically encompassing the region between -17.799 and 39.971 longitude and 28.696 and 71.073 North latitude) was used to identify broad climatic drivers. The projections for Romania were afterwards cropped and analysed.

Due to the 10-minute resolution of the dataset, the study area extends beyond Romania’s borders; certain grid cells at the perimeter encompass geographic areas outside the country's political limits.

Climate data for the 1970-2000 period, at a 10-minute resolution, were extracted using the *worldclim_global* function from the *geodata* R package [34], from the WorldClim2 dataset [24]. The bioclimatic variables capture key environmental dimensions by measuring annual trends (such as mean temperature and total precipitation), seasonal variations (including annual temperature and rainfall ranges), and limiting ecological extremes. The extremes are highlighted by factors like the temperature of the warmest and coldest months, or precipitation levels during the wettest and driest quarters – with a quarter defined as a three-month period [24]. Bradie and Leung [10] reviewed over 2,000 species distribution and ecological niche modelling studies across nearly 1,900 species, identifying WorldClim's 19 BIOCLIM variables as the most frequently utilised predictors [8]. The 1970-2000 period captures the "climate envelope" that allowed the current young and middle-aged generations to establish.

The 19 climatic variables (BIO1-19) were checked for collinearity, and those with collinearity problems (highly correlated) were excluded from the analysis, using the *vifstep* command (Variance Inflation Factor and test for multicollinearity) from the *usdm* R package [42]. Multicollinearity induces instability in model coefficients, leading to high variance across different samples [3, 15].

For three future periods, 2041-2060, 2061-2080, and 2081-2100, the remaining seven climatic variables, which were not collinear, were extracted from the following six climate models: ACCESS-CM2 [21], EC-Earth3-Veg [23], HadGEM3-GC31-LL [60], IPSL-CM6A-LR [9], MIROC6 [55], and MPI-ESM1-2-HR [30], a subset of the 10 used by Alexandru et al. for the modelling of the habitat suitability of *Larix decidua* Mill. [2].

Two Shared Socioeconomic Pathways (SSPs) – 2-45 (middle of the road) and 5 8.5 (Fossil-fuelled development) were analysed. The two SSPs are updates to the RCP4.5 and RCP8.5 scenarios [57].

The *sdmData* command from the *sdm* R package [43] was used to create an sdmdata object that held the species records and the climate data (the explanatory variables), as well as 1,000 background records (pseudo-absences) generated with the *gRandom* method.

The *sdm* command from the *sdm* R package [43] was used to fit and evaluate the distribution models for *Pinus sylvestris*. The following four modelling methods were used: generalised linear model (GLM) [40], boosted regression trees (BRT) [26], random forests (RF) [11] and flexible discriminant analysis (FDA) [32]. They are commonly used for SDM ensembling [44, 49]. A generalised linear model (GLM) differs from a standard general linear model in one major way: it allows the analysis of a response variable that does not follow a normal (Gaussian) distribution - this means the ability to model data that comes in the form of counts or binary outcomes using distribution families like Poisson or Binomial [28, 49]. Random Forest (RF) is a highly popular, top-performing machine learning algorithm built on a collection of individual decision trees; to build these decision trees, the algorithm generates each tree independently using a bootstrap sample – a subset of the data selected entirely at random with replacement [49]. Boosted Regression Trees (BRT) is another ensemble technique that uses multiple decision trees, but it operates differently than Random Forest – instead of building trees independently, BRT creates them sequentially, meaning each new tree is specifically designed to correct the errors made by the one before it [38]. Flexible Discriminant Analysis (FDA) is a classification technique that extends standard linear regression into a mixture of models. It works by using optimal scoring to adjust the regression weights for better linear separation between classes, while relying on multivariate adaptive regression splines (MARS) to map out a flexible, nonlinear decision boundary [31].

The modelling methods were replicated through partitioning using the bootstrapping and the subsampling techniques, three times for each technique, resulting in 24 models. For the subsampling technique, 30% of the data was randomly selected. The performances of the methods were assessed using the True Skill Statistic (TSS) [37] and the Area Under the Receiver Operating Characteristic Curve (AUC) [5].

The relative variable importance of the climatic variables was averaged for all 24 models, based on correlation and AUC metric (*getVarImp* command from the *sdm* R package). We have generated and plotted the ecological niche for the climatic variables with the highest relative variable importance.

The *ensemble* function from the *sdm* R package was used to create a consensus of predictions of the 24 models, using True Skill Statistic (TSS) [37] as the evaluation metric and the optimum threshold criterion that maximises both sensitivity and specificity for the weighted averaging procedure. This resulted in a raster object in which the predicted probability of occurrence was represented in each pixel. We have also run the *ensemble* function for the three future periods, under both SSPs.

Based on the threshold that maximises specificity *max(se+sp)* (the rate of instances of absence correctly predicted as absences) and sensitivity (the rate of instances of presence correctly predicted as presences) [35], the predicted probability of occurrence was classified as suitable/unsuitable data (1 or 0) for both current and future periods. That facilitated the analysis of the predicted shifts in the habitat suitability of Scots pine. The shifts were defined as follows: unsuitable (unsuitable in the present and in the future); expansion (unsuitable in the present, but suitable in the future); contraction (suitable in the present, but unsuitable in the future); and stable (suitable in the present and in the future), as presented in Table 1.

The habitat suitability was also classified based on the limits proposed by Brown and Griscom [13]: unsuitable (less than 0.20), poor (0.21-0.40), fair (0.41-0.60), good (0.61-0.80), and excellent (above 0.81).

The shifts classification Table 1

Present classification	Future classification	Shift classification
Unsuitable	Unsuitable	Unsuitable
	Suitable	Expansion
Suitable	Unsuitable	Contraction
	Suitable	Stable

3. Results

3.1. Climate Variables and Model Performance

Seven climate variables showed no collinearity issues and were retained in the analysis (Table 2). The maximum correlation among them was between Annual Mean Temperature (BIO1) and Precipitation of Warmest Quarter (BIO18) (r= -0.782). BIO1-Annual Mean Temperature had the highest relative variable importance, based on both Correlation and Area Under the Curve (AUC) metrics (Figure 1). All climatic variables present a bell-shaped response curve (Figure 2).

Climatic variables, descriptions, and the Variance Inflation Factors (VIFs) Table 2

Variables	Description	VIF
BIO1	Annual mean temperature	7.648
BIO2	Mean diurnal range (Mean of monthly (max temp - min temp))	4.160
BIO4	Temperature seasonality (standard deviation ×100)	2.899
BIO8	Mean temperature of wettest quarter	2.595
BIO15	Precipitation seasonality (Coefficient of variation)	1.897
BIO18	Precipitation of warmest quarter	4.970
BIO19	Precipitation of coldest quarter	2.779

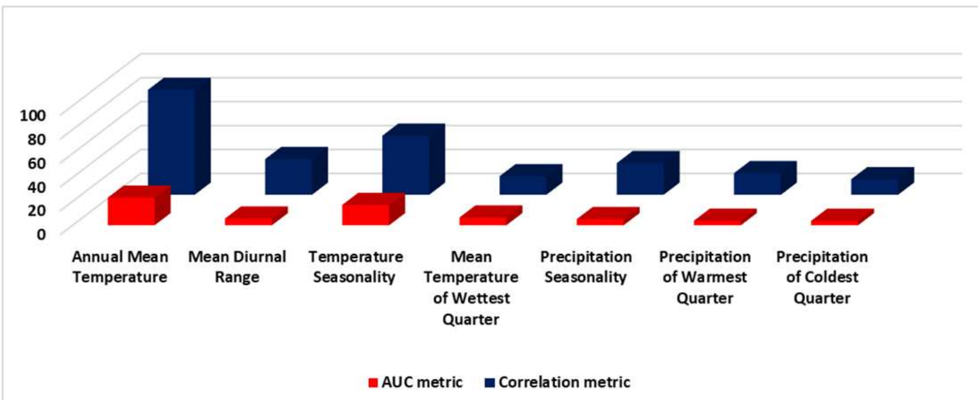

Fig. 1. *Relative variable importance of the climatic variables*

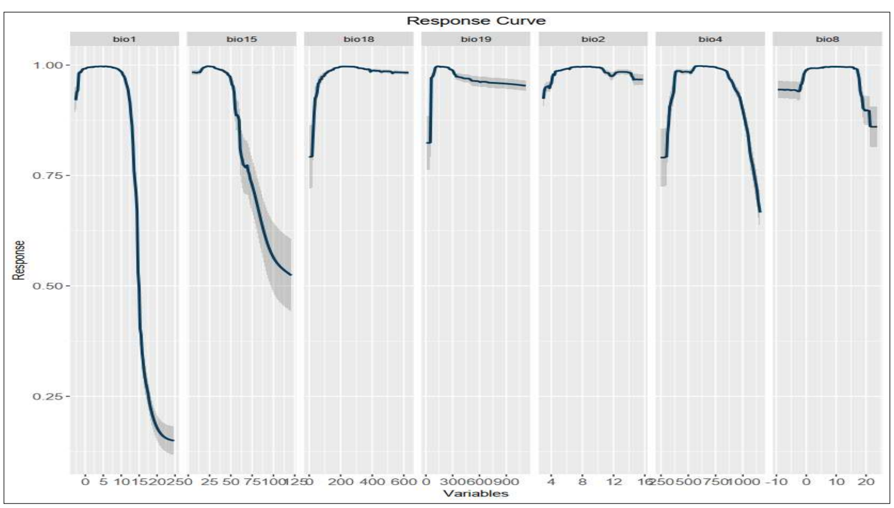

Fig. 2. *The response curves of the climatic variables*

The performance of the models ranged from fair to excellent (0.71 to 0.90), based on the mean AUC; and from fair to substantial, based on the True Skill Statistic (TSS) (Table 3). The Random Forest (RF) model had the highest performance.

Model mean performance Table 3

Methods	Name of the method	AUC	COR	TSS	Deviance
GLM	Generalised Linear Models	0.72	0.45	0.44	0.07
BRT	Boosted Regression Trees	0.71	0.48	0.39	0.06
RF	Random Forest	0.90	0.55	0.71	0.05
FDA	Flexible Discriminant Analysis	0.71	0.39	0.40	0.08

3.2. Habitat Suitability based on the Threshold

The maximum threshold, which maximises sensitivity and specificity, was 0.98045. Based on it, the current potential habitat suitability (Figure 3) was converted to 0s or 1s (Figure 4), and future changes were assessed (Figure 5).

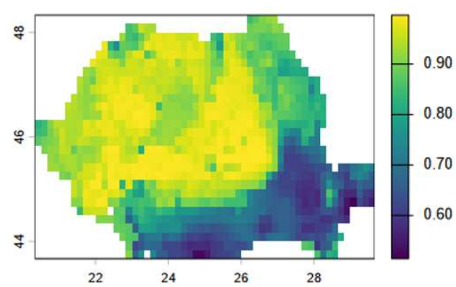

Fig. 3. *The current potential habitat suitability of Scots pine in Romania*

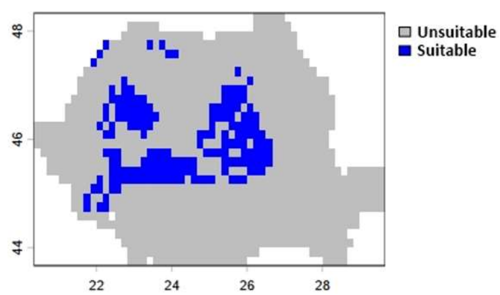

Fig. 4. *The current potential habitat suitability of Scots pine in Romania based on the 0.98045 threshold*

The current climate conditions in Romania indicate that around 16% of the country (approximately 40,000 km^2) is bioclimatically suitable for Scots pine (above the 0.98045 threshold – Figure 4). Analysing the two SSPs and the three periods, at least 32,000 km^2 are predicted to experience climate shifts that will no longer meet the suitability threshold (contraction areas). For the period 2081-2100, under SSP5-8.5, the entire studied area is predicted to become climatically unsuitable, falling below the 0.98045 threshold (Figure 5).

Except for the period 2081-2100, under SSP5-8.5, there will be some new areas with suitable climate conditions (expansion areas), between 0.2-1.5% of the analysed area (400 to 3,800 km^2), mostly in the Făgăraș and Maramureșului Mountains, the highest and the northernmost parts of the Carpathian Mountains in Romania, respectively.

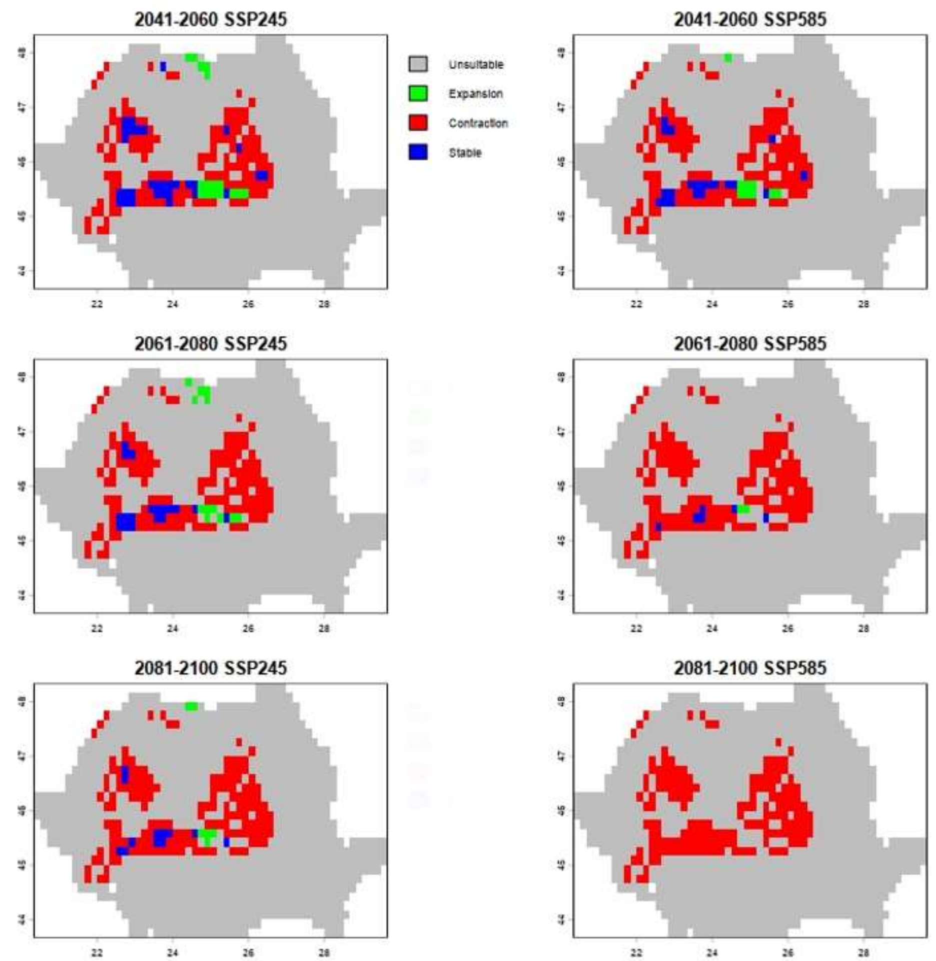

Fig. 5. *Predicted changes of habitat suitability for Scots pine in Romania, based on the 0.98045 threshold, for three periods and two Shared Socioeconomic Pathways (SSPs)*

3.3. Habitat Based on the Levels of Suitability

Based on the levels of suitability, more than 70% of Romania (187,000 km^2) represents areas with climate conditions corresponding to the excellent habitat suitability (above 80%) for Scots pine (Figure 6). By 2081-2100, this area is predicted to reduce to 22% - 6% (55,000-14,000 km^2), based on SSP 2-4.5 and SSP 5-8.5, respectively (Figure 7).

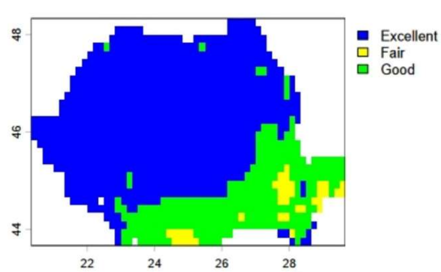

Fig. 6. *The current levels of potential habitat suitability of Scots pine in Romania*

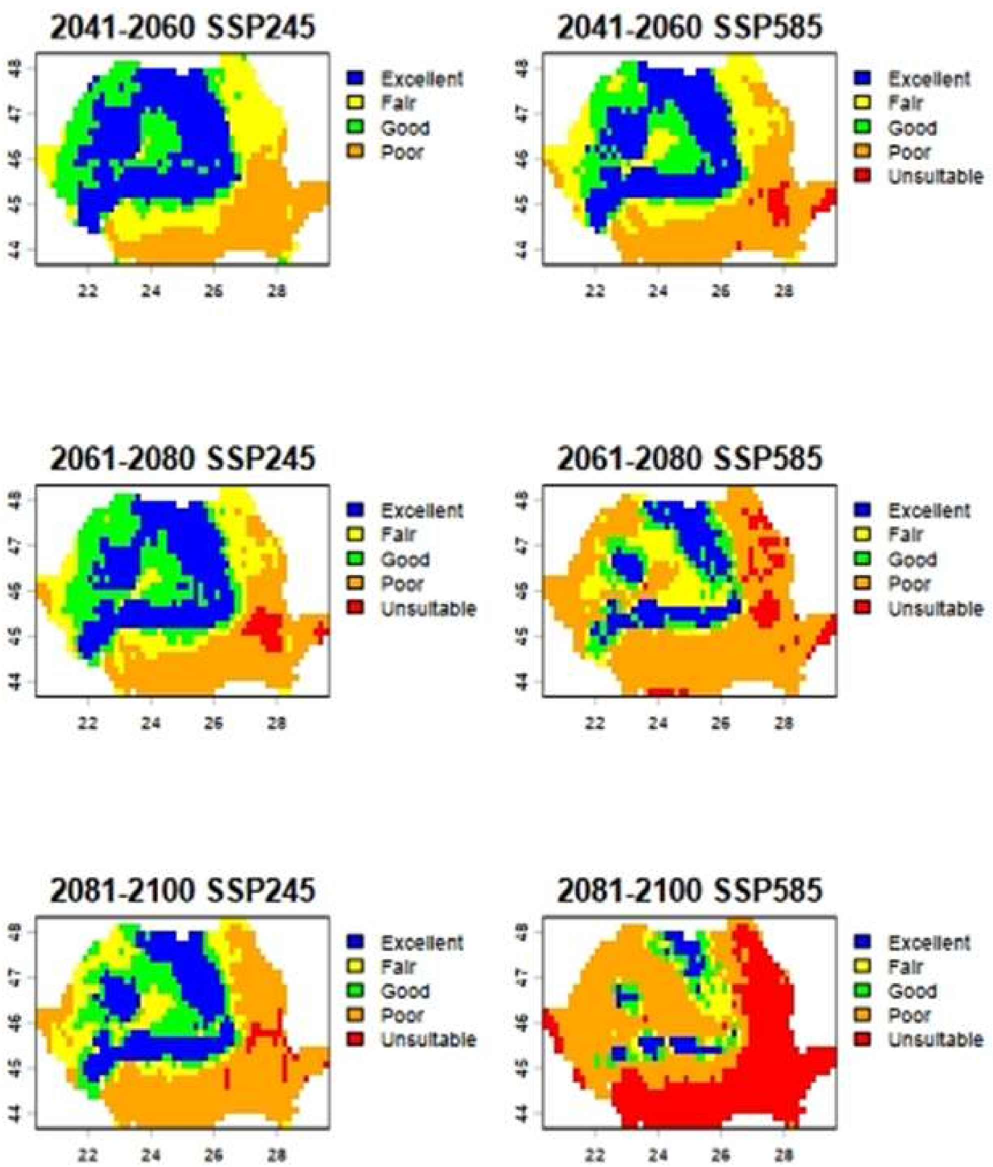

Fig. 7. *Predicted levels of habitat suitability of Scots pine in Romania for three periods and two Shared Socioeconomic Pathways (SSPs)*

The entire Carpathian Mountains are predicted to have excellent climate conditions for Scots pine, for all periods and both SSPs, except 2081-2100 SSP5-8.5, where the central part of the Orientals, the Moldavian-Transylvanian Carpathians, is predicted to have a fair habitat suitability. These suggest that the Scots pine habitat will retreat to higher altitudes.

Under SSP2-4.5, some unsuitable areas in the 2061-2080 period are predicted to slightly improve the climate conditions, the habitat suitability changing to the poor category in the 2081-2100 period: Braila, Buzau, south-east of Vrancea, south of Galati and east of Tulcea counties, areas that are under cold-semi arid climate, according to the Köppen-Geiger classification [45].

Some areas are predicted to be unsuitable for this species, having unsuitable climate conditions, starting with the 2041-2060 period for SSP 5-8.5, or 2061-2080, for SSP 2-4.5. For SSP 5-8.5 and the period 2081-2100, the unsuitable area is around 40% (around 100,000 km^2 – Figure 8).

3.4. The Ecological Niche

The ecological niches described by BIO1 (Annual Mean Temperature) with BIO18 (Precipitation of Warmest Quarter – Figure 9) and with BIO2 (Mean Diurnal Range – Figure 10) indicate that the best conditions for Scots pine occur in areas where the Annual Mean Temperature is below 13.5°C.

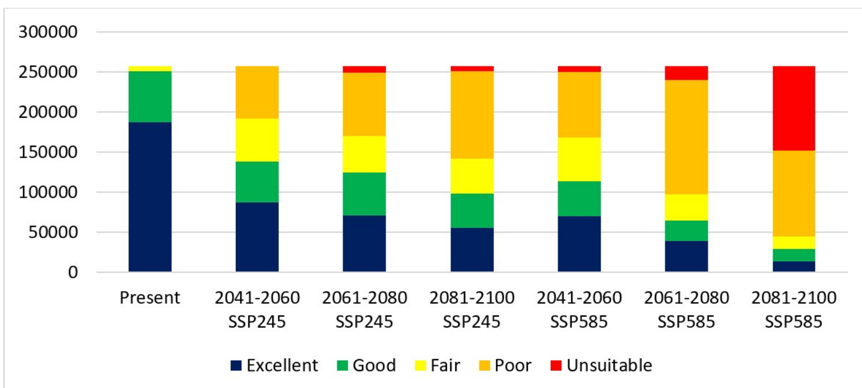

Fig. 8. *The areas of current potential and future predicted levels of habitat suitability of Scots pine in Romania for three periods and two Shared Socioeconomic Pathways (SSPs)*

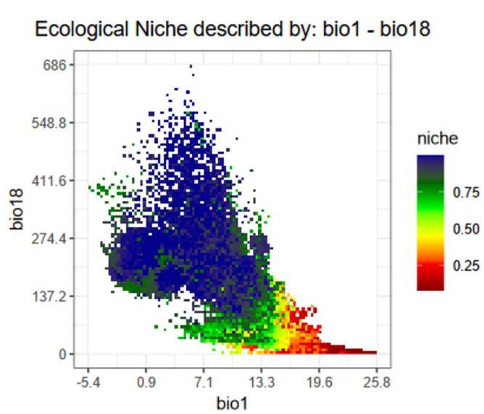

Fig. 9. *Ecological niche described by BIO1 (Annual Mean Temperature) and BIO18 (Precipitation of Warmest Quarter)*

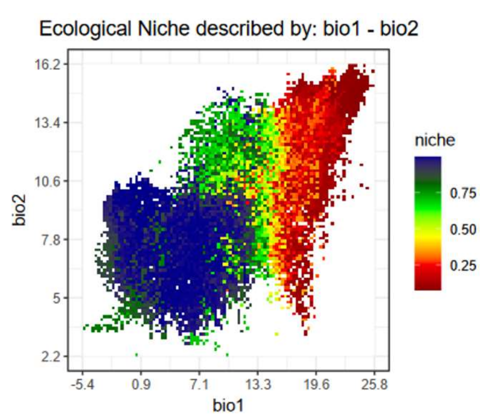

Fig. 10. *Ecological niche described by BIO1 (Annual Mean Temperature) and BIO2 (Mean Diurnal Range)*

4. Discussion

In this study, the potential current and future habitat suitability of Scots pine in Romania, as well as the potential range shifts, were assessed based on climatic variables.

By predicting where species can thrive, species distribution models enable forest managers to better prepare for landscape-scale changes in species ranges [25]. This makes them a cornerstone of modern reforestation, supporting both assisted migration and broader ecological restoration goals [4, 58].

BIO1-Annual mean temperature and BIO4-Temperature Seasonality had the highest relative variable importance, on AUC and correlation metrics. Our results are consistent with the study by Cetin et al. [18] indicating that the species distribution is significantly influenced by temperature patterns. High temperatures during spring and summer and low precipitation during the growing season led to a reduction in Scots pine radial growth [52]. High annual mean temperatures combined with periods of low precipitation were found to test the resistance of pine forest ecosystems in Transylvania [19].

Under SSP3-7.0, the annual mean temperature is projected to slightly increase for the 2041-2070 and 2071-2100 periods (compared with the 1981-2010 reference period) in the Romanian Carpathians and Subcarpathians [7].

The area in Romania where the current climate conditions correspond to a potential habitat suitability above 0.60 (excellent and good) is around 97%. A larger potential distribution than the current one was also observed in the Iberian Peninsula [27]. Under SSP5-8.5 for the 2061-2080 period, it is projected to decrease to 25%, and to 11% for the 2081-2100 period. Other studies revealed that *Pinus sylvestris* was predicted to have more than 50% of its current distribution in Europe threatened under a pessimistic scenario (RCP8.5) for the period 2061-2080 [22, 36], but exhibited the most resilient distribution among other major European species (*Fagus sylvatica, Quercus petraea, Picea abies*) [36]. In the Caucasus region, Scots pine is predicted to lose more than 90% of its current distribution by the end of the century [20]. In northeastern Germany, the results of Bauwe et al. indicate that changing climatic conditions were not the primary direct driver of future risks for Scots pine [6].

The Moldavian-Transylvanian Carpathians and the Curvature Carpathians (Central and Southern groups of the Oriental Carpathians) are the most affected areas based on the levels of habitat suitability, while the Maramureș and Bucovina Mountains will have climate conditions corresponding to the excellent habitat suitability (above 0.80), but not above the 0.98045 threshold.

In Romania, at least 14,000 km^2 are predicted to have climate conditions corresponding to an excellent habitat suitability for Scots pine (above 0.80) and, except for the 2081-2100 period, under SSS5-8.5, at least 1,900 km^2 (stable + expansion areas) are predicted to have climate conditions corresponding to a habitat suitability above 0.98045.

Under SSP2-4.5, the climate conditions are predicted to improve in new areas, the habitat suitability exceeding the 0.98045 threshold, such as the Făgăraș and Maramureș Mountains. Under SSP2-4.5, some unsuitable areas in the 2061-2080 period are predicted to have slightly better climate conditions, the habitat suitability advancing to the poor category in the 2081-2100 period: Braila, Buzau, south-east of Vrancea, south of Galati, and east of Tulcea counties, areas that are under cold-semi arid climate, according to Ontel et al. [45].

The entire Carpathian Mountains are predicted to have climate conditions corresponding to an excellent habitat suitability for Scots pine, for all periods and both SSPs, except 2081-2100 SSP5-8.5, where the central part of the Orientals is predicted to have a fair habitat suitability. These suggest that the Scots pine habitat will retreat to higher altitudes.

Under SSP 5-8.5 for the period 2081-2100, based on the threshold, the projected climate conditions for Romania indicate that the entire country will be unsuitable for Scots pine. For the same period and the same scenario, around 212,000 km^2 (around 83% of the studied area) are predicted to have climate conditions corresponding to poor or unsuitable habitat suitability (below 0.40).

Romanian forestry has been preoccupied with the conservation of genetic resources for more than half a century [50]. In Romania, 22 Forest Genetic Resources were designated for Scots pine in 2011 (only five preserved in situ – [14, 46], around 300 ha, while there were 4,000 ha for this species in 1975 [50].

In the study conducted by Șofletea et al. [54], based on the sampling of native populations, the Eastern and Southern Carpathian populations possess high within-population diversity in spite of the recent fragmentation and reduction of the Scots pine natural distribution range in Romania.

Therefore, the conservation strategy of Scots pine genetic resources in the Romanian Carpathians should not rely exclusively on in situ conservation stands, but also on ex situ conservation and assisted migration.

5. Conclusions

Based on climatic variables, the current and future potential habitat suitability of Scots pine was modelled for Romania.

The most important climate variables that influence the distribution of Scots pine were BIO1-Annual Mean Temperature and BIO4-Temperature Seasonality.

Under SSP 5-8.5 (Fossil-fuelled development) for the 2081-2100 period, the area with climate conditions corresponding to excellent habitat suitability is predicted to be the Western, Central, and Northern parts of the Carpathian Mountains, covering 5.5% of the country (around 14,000 km^2), but no area is above the 0.98045 threshold.

A pronounced altitudinal shift is expected, emphasising the role of the Carpathians as a potential climatic refuge for the species.

Projecting the impacts of climate change on species distribution may facilitate the design of more effective forest management strategies for mitigation and adaptation.

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