

Spatial modelling and prediction of natural regeneration of *Tetraclinis articulata* using geomatics and machine learning in the Korifla Forest of Morocco

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ABSTRACT

The natural regeneration of *Tetraclinis articulata* represents a vital role in the conservation of semi-arid Mediterranean forest ecosystems. This study aims to characterize and model its spatial dynamics in the forest of Korifla (Morocco) from 48 plots of land, described by 41 explanatory variables integrating spectral data Sentinel-2, topographic, climatic and pedological. Factor analysis of mixed data (AFDM) shows that the first two axes explain 46.4% of total variability, mainly according to soil-topographic and water-structural gradients. The Random Forest (RF) model performed best for shoots (AUC = 0.951) than for shoots regeneration (AUC = 0.803); for this reason, it was selected to map the probability of natural regeneration. Random Forest mapping, based on field measurements, reveals a predominance of regeneration by shoots, with a high potential (> 0.66) of 70.01%, compared to 22.40% for seedlings. Currently, the RF mapping indicates a very high potential (> 0.8) of 43.49% for regeneration by shoots, compared to only 2.63% for regeneration by seedling. The climate projection for 2040 based on the SSP2-4.5 scenario indicates a predominance of regeneration by shoots is high (> 0.6) over 82.91% of the area, while regeneration by seedlings is minimal (24.07%). Furthermore, projections based on changes in the NDVI and GCI indicate relative stability of the predicted probability of the regeneration potential between 2036 and 2046, For regeneration by seedling, the very high potential (> 0.8) remains almost stable, decreasing from 2.32% in 2036 to 2.43% in 2046. These results highlight the value of combining field data, remote sensing and machine learning to support the conservation and sustainable management of *T. articulata*.

Keywords: natural regeneration, spatial modelling, machine learning, geomatics, remote sensing, *Tetraclinis articulata*, Korifla Forest.

INTRODUCTION

Forests are fundamental ecosystems for controlling biogeochemical cycles, preserving biodiversity and providing vital ecosystem services to humanity (FAO, 2020; Kelly & Ray, 2023). Natural regeneration is considered to be one of the most

important processes by which forest ecosystems renew themselves through the germination and growth of young plants, thereby ensuring the sustainability of forest ecosystems and their ability to survive (Cerioni et al., 2024). Maintaining this environmental sustainability is a priority in the Mediterranean basin, which is characterized by variable

climatic conditions and strong human pressure (Duche & Toutchkov, 2018; Mallard et al., 2024).

Among Mediterranean forest ecosystems, *Tetraclinis articulata* woodlands, dominated by *Tetraclinis articulata* (Vahl) Mast., constitute ecosystems of high ecological and heritage value (Esteve-Selma et al., 2017). The thuja is a conifer, endemic to the western Mediterranean region, has a geographical distribution mainly centered in the Maghreb, with the largest extent occurring in Morocco, where it covers approximately 607,900 hectares (El Mechri et al., 2024). Its ecological importance extends beyond its silvicultural value: it contributes to soil stabilization, water regulation within watersheds, and provides a preferred habitat for numerous associated species in semi-arid ecosystems (Zahir et al., 2020; Zemrani et al., 2023). However, despite being classified as Least Concern at the global scale, some subpopulations, particularly those in Malta and Spain, are classified as Endangered or Critically Endangered (García-Castaño et al., 2021).

Natural regeneration is regarded as an important indicator of the development of forest stands and their long-term viability (Dallahi et al., 2017). Its success depends on numerous biotic and abiotic factors, including water availability, soil depth, topographic exposure, vegetation structure, and grazing pressure, which constitute key determinants of seedling establishment success (Fennane, 1988; Irifi & Tribak, 2024; Rozas et al., 2021). Regeneration of *Tetraclinis articulata* may occur naturally through seedling recruitment or stump sprouting, or artificially through direct seeding or planting. It is worth noting that thuja is one of the few conifers capable of producing stump sprouts (Esteve-Selma et al., 2017). The absence of effective natural regeneration significantly accelerates the decline of *Tetraclinis articulata* woodland ecosystems, resulting in structural imbalances within forest stands (Hadjadj Aoul et al., 2009). In particular, summer drought and rainfall variability are major limiting factors, directly affecting the germination, survival and growth of young seedlings (Benamara et al., 2026; Dallahi et al., 2017; El Mechri et al., 2024).

Given this complexity, traditional methods for assessing forest regeneration have significant limitations. Conventional field inventories, whilst providing accurate data on seedlings, are labour-intensive, costly and logistically challenging to carry out over large areas (Aguirre-Gutiérrez et al., 2026). Ground-based remote sensing techniques,

such as laser scanning, struggle to detect plants less than 1.30 m in height with sufficient accuracy (Liang et al., 2016). These methodological constraints limit our ability to effectively monitor regeneration dynamics at the landscape scale.

The emergence of remote sensing and geomatics offers promising prospects for overcoming these limitations. Images acquired by Landsat, Sentinel satellites or other sensors enable the extraction of numerous vegetation indices (NDVI, EVI, SAVI, NDMI, etc.) which provide information on the state of vegetation cover, the vigour of stands and the environmental conditions influencing regeneration (Oikonomou et al., 2025; Stevens-Rumann & Morgan, 2019). The integration of these spatial data into a geomatics environment facilitates the multi-criteria analysis of ecological factors at different spatial and temporal scales (Witzmann et al., 2025).

At the same time, the contribution of machine learning is revolutionising the prediction of regeneration processes (Perbet, 2025). Several algorithms, notably random forests (RF) and extreme Gradient Boosting (XGBoost), have demonstrated their superiority in modelling post-fire plant dynamics through the integration of meteorological and environmental factors (Taha et al., 2024). These multivariate models outperform traditional univariate approaches by capturing the complexity of ecological interactions and providing accurate predictions of regeneration trajectories (Gass & Hülsmann, 2026; Vivian et al., 2026; Wudel et al., 2026).

Furthermore, the integration of climate projections based on SSP scenarios also enables the assessment of the spatial sensitivity of conditions favourable to regeneration in the face of future environmental changes. The SSP2-4.5 scenario, corresponding to an intermediate emissions pathway, is in particular a relevant benchmark for exploring potential changes in temperature and rainfall conditions in the medium term. Integrating these future climate data into predictive models makes it possible to identify areas that are likely to maintain, improve, or lose favorable conditions for the presence of *Tetraclinis articulata* stump sprouts, thereby contributing to improved anticipation of conservation challenges in Mediterranean ecosystems (Madrigal-González et al., 2018; Mechergui et al., 2025).

In this context, this study propose an integrated framework to characterize and predict the spatial dynamics of natural regeneration of *Tetraclinis*

articulata in the Korifla forest, through: (i) the integration of field surveys with Sentinel-2 data and topographic, climatic, and pedological variables; (ii) the explicit distinction between regeneration by seed and stump sprouts; (iii) the selection of variables and the application of the Random Forest model to predict their spatial probability; (iv) the spatial validation of predictions to limit the risks of overfitting and spatial autocorrelation; and (v) the projection of regeneration potential according to future climatic conditions and vegetation dynamics. This approach aims to provide a robust spatial basis for the monitoring, conservation, and adaptive management of thuja stands in the face of environmental changes.

METHODOLOGY

Study area

The Korifla forest, which spans up to 15,140 hectares in the communes of Brachoua, Sidi Yahya Zaer, Oum Azza, and Marchouch in the Rabat-Salé-Kénitra region, is dominated by *Tetraclinis articulata*, which occupies approximately 10,436 hectares of the forest (Figure 1).

Owing to its significant ecological, socio-economic and environmental value, this forest is an area of major interest and includes a Site of Biological and Ecological Interest (SIBE) covering an area of approximately 2000 ha. Vegetation cover is dominated by *Tetraclinis articulata* woodlands, which account for 70.2% of the forest area (10,633.1 ha), including 10,436.1 ha of pure stands and 197 ha of mixed stands. Cork oak (*Quercus suber*) stands remain limited, covering 185.6 ha. Reforested areas cover 2,961 ha (19.5% of the forest) and are mainly composed of Aleppo pine (*Pinus halepensis*), complemented by Turkish pine (*Pinus brutia*), as well as plantations established for the artificial regeneration of thuja and, to a lesser extent, cork oak. Other land-cover types include secondary formations, non-forested areas, shrublands, agricultural land, poplar plantations, as well as daya wetlands, built-up areas, and nursery areas. From a bioclimatic perspective, the forest is situated in the semi-arid zone with a temperate winter, characterized by variable rainfall. The average annual rainfall recorded at Rommani is approximately 528 mm, with the dry season lasting for nearly six months. There is also a considerable

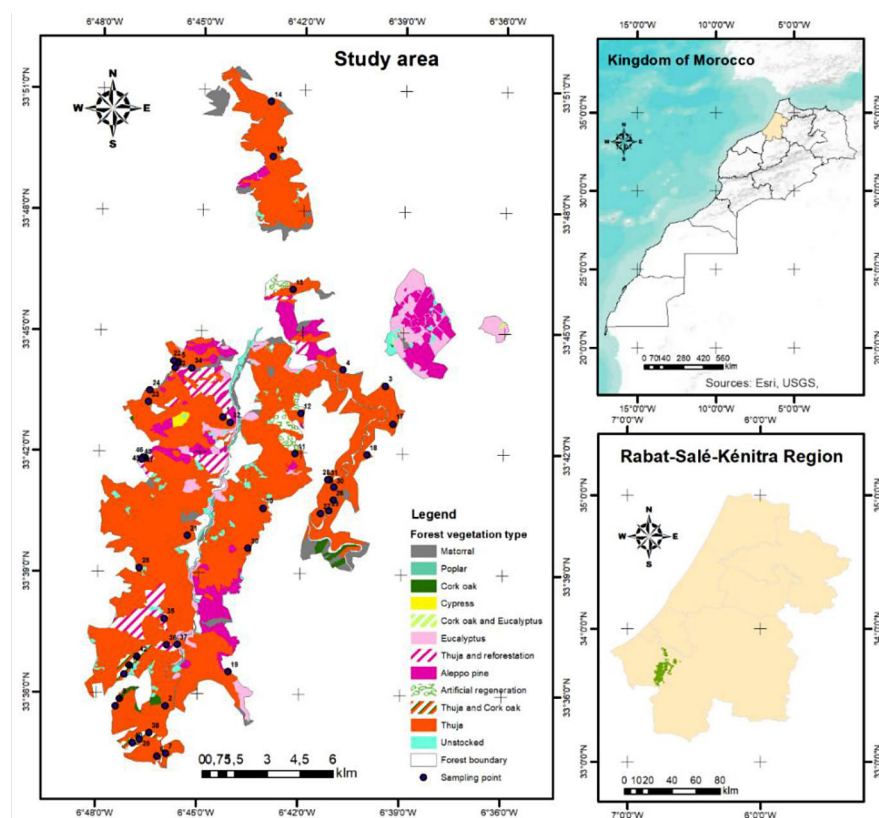


Figure 1. Location of the study area

temperature range in the climate, with temperatures reaching up to 37 °C at the Rommani station. All these climatic conditions pose a challenge to the natural regeneration of forests, and more specifically to that of the Berber thuja.

Sampling procedure

The collection of the land sample was carried out by defining 20 × 20 m (400 m²) squares. The observations recorded within each plot were subsequently extrapolated to a per-hectare basis to facilitate comparisons among sampling sites. In addition, 20-m-long linear transects were established to characterize selected vegetation attributes and natural regeneration parameters, measured in March and April (Spring) 2018.

Within each sampling plot, all factors potentially influencing natural regeneration, either directly or indirectly, were systematically recorded using a standardized field data sheet (Table 1). The collected variables were classified into five major categories:

- Situational characteristics: topographic situation, exposure and slope.
- Stand structure: percentage of tree, shrub (including *Cistus* spp.), and herbaceous cover; percentage of bare soil; number of stems (shoots) per coppice stool; mean number of stems per stool; and total number of stump sprouts;
- Natural regeneration characteristics: number of seedlings by height class (used as an indicator of age), seedling position relative to the existing vegetation (seed trees, shrubs, sub-shrubs, etc.), and fruit presence;
- Soil characteristics: substrate type, degree of soil penetration and cohesion, soil moisture percentage, and presence of litter;
- Disturbance factors: grazing, erosion, and various anthropogenic disturbances and forest-related offences.

A total of 48 plots were surveyed and distributed throughout the study area to capture the variability in ecological conditions and forest stand characteristics.

Measured variables and data preparation

The database comprised 48 field surveys characterized by 41 explanatory variables, grouped into five categories (Figure 2):

- Vegetation variables derived from field measurements, describing stand structure and natural regeneration;
- Topographic factors including elevation, aspect and slope, are calculated based on the digital elevation model (DEM) <https://search.asf.alaska.edu/#/?zoom=9.144&center=-6.574,33.414&dataset=ALOS> ;
- Climatic variables obtained from WorldClim (Bio1, Bio5, Bio6, Bio12, Bio15, Bio18, and Bio19) <https://www.worldclim.org/data/index.html> ;
- Soil variables extracted from SoilGrids (sand, clay, silt, organic carbon, nitrogen, pH, bulk density, cation exchange capacity, coarse fragments, and organic carbon density) <https://soilgrids.org/> ;
- Disturbance variables, represented by grazing and erosion.

All datasets were compiled and preprocessed within the RStudio environment (Posit team, 2025). The different data sources were harmonized to construct a common data matrix linking field observations with the environmental predictors used in the statistical analyses and predictive modeling.

Remote sensing data

The remote sensing data used was derived from Sentinel-2 multispectral images from the Copernicus program (Drusch et al., 2012), selected for their spatial resolution (10 to 20 m), their spectral richness and their ability to characterize the spatial variations of the vegetation cover. The image series were processed in Google Earth Engine (GEE) (Gorelick et al., 2017) <https://developers.google.com/earth-engine/datasets?hl=fr>. This processing consisted in filtering the images affected by cloud cover, selecting the appropriate spectral bands and extracting the values corresponding to the sampling plots.

Several spectral indices related to vegetation condition, photosynthetic activity, water content and water stress were calculated from the Sentinel-2 bands, including NDVI, SAVI, NDWI, MSI, PSRI, NDRE, CVI, TVI, GCI, EVI and LAI (Table 2). The B3, B4, B5, B8, B11 and B12 bands were used according to the requirements of each index. After that, the spectral results were combined with field information and environmental data to assess the spatial

Table 1. Factors assumed to exert a direct or indirect influence on the natural regeneration of *Tetraclinis articulata*, recorded within each sampling plot

Variable	Code	Unit
Number of seedlings	NSd	Number
Seedling height	SH	cm
Seedling condition	SC	1. Under coppice / 2. Between shrubs / 3. Open area (gap)
Fruit	Fruit	1. Absent / 2. Abundant
Number of shoots	Nrejets	Number
Number of crown	Ncrown	Number
Number of twig	Ntwig	Number
Substrate	Substrate	1. Well-developed soil / 2. Poorly developed soil / 3. Raw mineral substrate
Aspect	Aspect	1. Shaded / 2. Sunny (south-facing)
Slope	Slope	1. < 20% / 2. > 20%
Topographic position	Tposition	1. Upstream / 2. Midstream / 3. Downstream
Tree cover	TreeC	%
Shrub cover	ShrubC	%
Cistus cover	CistC	%
Herbaceous cover	HerbaceousC	%
Bare soil	BS	%
Tree litter cover	TLC	%
Shrub litter cover	SLC	%
Moisture	Moisture	%
Penetration resistance (kg/cm ²)	Penetration	kg/cm ²
Soil cohesion (kg/cm ²)	Scohesion	kg/cm ²
Erosion	Erosion	1. Low / 2. Moderate / 3. High
Grazing	Grazing	1. Absent / 2. Present / 3. Intensive

conditions related to natural regeneration of *Tetraclinis articulata*. A diachronic analysis of Landsat satellite images acquired on average in April between 1990 and 2026 was carried out in order to describe the spatio-temporal evolution of the vegetation cover. The NDVI and GCI indices were determined based on the appropriate spectral bands, then compared for different dates to identify trends in vegetation dynamics and vitality.

Statistical analysis and variable selection

An exploratory data analysis was conducted to identify the main patterns, structures, and trends within the field survey data. The number of shoots has been considered quantitative indicator of the dynamics of natural regeneration. To investigate regeneration gradients in the statistical analyses, this variable was categorized into three classes according to the levels observed across the sampling plots. Quantitative environmental variables were also discretized into three classes

based on quantiles when required to examine associations among variables.

A factorial analysis of the mixed data (FAMD) was then carried out in order to explore simultaneously the relationships between quantitative and qualitative variables and to characterize the structure of plots according to their environmental conditions and their level of regeneration. The statistical analyses were performed using the FactoMineR (Lê et al., 2008), factoextra (Irnawati et al., 2020), Hmisc (Jr et al., 2026), and ggplot2 (Sumner, 2024) packages in R. The spatial analyses and predictive modeling were conducted using terra (v1.7-71), sf (v1.0-15), randomForest (v4.7-1.1), tidyterra (v0.5.0), and patchwork (v1.2.0). To ensure reproducibility, a fixed random seed was used (set.seed(42)).

Spatial modeling of natural regeneration

Spatial modeling was conducted using data derived from field surveys and the various environmental and biophysical layers covering the

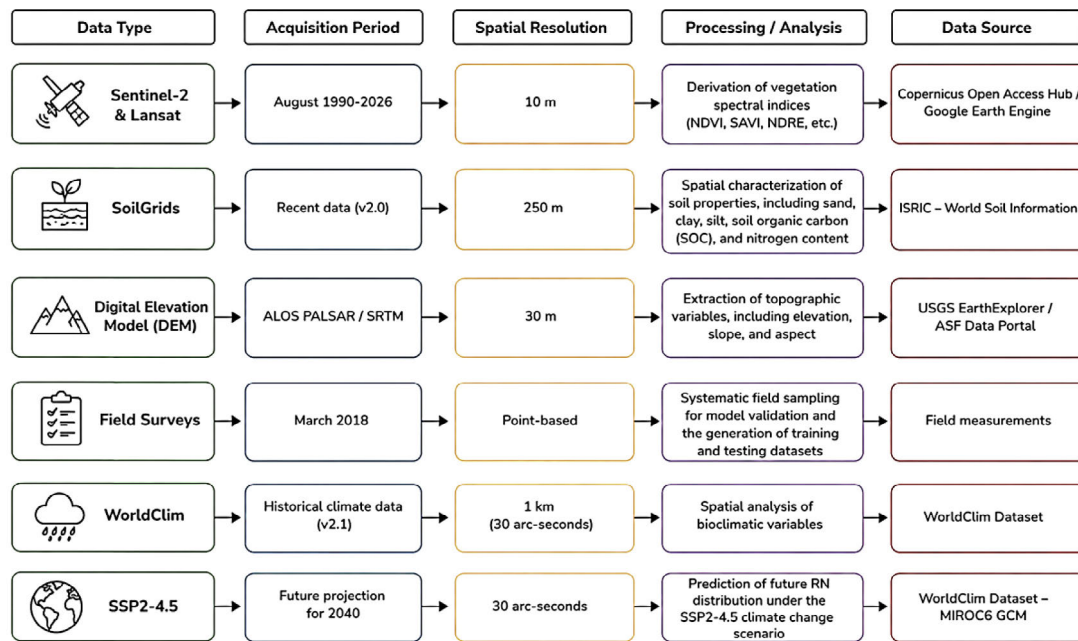


Figure 2. Description of the datasets used for the analysis

Table 2. Spectral and biophysical indices used to characterize vegetation and canopy condition from Sentinel-2 data

Biophysical theme	Index	Main parameter	Equation	Reference
Vegetation vigor	NDVI	Vegetation vigor, canopy density and green biomass	$NDVI = (B_{08} - B_{04}) / (B_{08} + B_{04})$ (1)	(Ma et al., 2023; Maimouni et al., 2011)
	SAVI	Reduction of soil background effects in sparsely vegetated areas	$SAVI = (B_{08} - B_{04})(1 + L) / (B_{08} + B_{04} + L)$ (2)	(Huete, 1988)
Vegetation water content	NDWI	Assessment of vegetation water availability and moisture levels	$NDWI = (B_{08} - B_{11}) / (B_{08} + B_{11})$ (3)	(Gao, 1996)
Water stress	MSI	Vegetation water stress and drought conditions	$MSI = B_{11} / B_{08}$ (4)	(Zhang & Zhou, 2019)
Physiological stress / senescence	PSRI	Leaf senescence and physiological stress	$PSRI = (B_{04} - B_{02}) / B_{06}$ (5)	(Anderegg et al., 2020; Avetisyan, 2021)
Chlorophyll / physiological activity	NDRE	Chlorophyll content and early vegetation stress	$NDRE = (B_{08} - B_{05}) / (B_{08} + B_{05})$ (6)	(Liu & Zhu, 2024),
	CVI	Chlorophyll concentration and photosynthetic activity	$CVI = (B_{08} \times B_{04}) / B_{03}^2$ (7)	(Vincini et al., 2008)
	TVI	Vegetation structure and chlorophyll content	$TVI = 0.5[120(B_{08} - B_{03}) - 200(B_{04} - B_{03})]$ (8)	(Ma et al., 2023; Yan et al., 2025)
	GCI	Chlorophyll concentration and vegetation condition	$GCI = B_{08} / B_{03} - 1$ (9)	(Pagot et al., 2026)
Biomass / productivity	EVI	Vegetation biomass and productivity, reducing atmospheric and soil effects	$EVI = 2.3 = (B_{08} - B_{04}) / (B_{08} + 6B_{04} - 7.5B_{02} + 1)$ (10)	(El Mazi et al., 2026)
Canopy structure / productivity	LAI	Canopy structure and leaf area density	Sentinel-2 biophysical product; no single analytical equation	(Chatterjee et al., 2025)

Note: B_{02} , B_{03} , B_{04} , B_{05} , B_{06} , B_{08} and B_{11} refer to the Sentinel-2 spectral bands. L is the ground adjustment factor used in the SAVI index, generally set at 0.5 for moderate vegetation cover. All equations have been calculated using Sentinel-2 surface reflectance bands.

Korifla Forest. The number of shoots and of seedling recorded in each sampling plot was used as the reference measure of natural regeneration. For spatial modeling purposes, the number of

shoots and of seedling was transformed into a binary occurrence variable to enable the application of classification algorithms. Plots with no shoots were coded as 0 (absence), whereas plots with at

least one shoot were coded as 1 (presence). This transformation makes it possible to estimate the spatial probability of the presence of shoot according to environmental conditions, without seeking to directly predict their abundance.

The explanatory variables include Sentinel-2 spectral indices (NDVI, SAVI, NDWI, MSI, PSRI, NDRE, CVI, TVI, GCI, EVI and LAI), topographical variables (such as elevation, aspect and slope), climatic variables from WorldClim, and soil variables derived from Soil grids dataset.

Two machine learning algorithms were used: Random Forest (RF) (Salman et al., 2024), XG-Boost (Ndiaye et al., 2025). The RF model, which demonstrated the best classification performance for regeneration by shoots and by seedling, was chosen to map the probability of the naturel regeneration, while both algorithms were used to assess the robustness of the environmental variables' significance.

Model validation and evaluation

To evaluate the model's performance, a five-block spatial cross-validation was applied to the 48 observations to limit overfitting and spatial autocorrelation. The blocks were generated using the blockCV package (Valavi et al., 2018), with each iteration using four blocks for training and one independent block for validation. Performance was evaluated using sensitivity, specificity, accuracy, Kappa, precision, F1 score (Sujon et al., 2025), and AUC (Meroua, 2025), along with its 95% confidence interval. The final Random Forest models, trained on the entire dataset, were then used to generate continuous probability maps of regeneration via seeding and shoots.

Predictive mapping of natural regeneration

The model achieving the best performance during validation was applied to the environmental and biophysical raster layers covering the entire Korifla Forest to estimate, on a pixel-by-pixel basis (Thenkabail, 2018), the probability of *Tetraclinis articulata* naturel regeneration (shoot, seedling) occurrence under current environmental conditions. The resulting map provides a continuous probability gradient, allowing the identification of areas that are more or less favorable to natural regeneration. To assess future dynamics, the model was applied to project NDVI and GCI values, derived from their spatiotemporal

evolution between 1990 and 2026, in order to estimate shoot and seedling occurrence probabilities for the 2036 and 2046 horizons. Comparing the resulting maps makes it possible to identify changes in regeneration potential associated with changes in vegetation-cover dynamics. Finally, the model was applied to projected environmental variables under the SSP2-4.5 scenario (the reference period 1970–2000, with a native resolution of 30 arcseconds) for the 2040 horizon to assess potential changes in the spatial distribution of areas favorable to natural regeneration.

RESULTS

Environmental variables and structural parameters of natural regeneration based on field measurement

The analysis of ecological and structural parameters across different vegetation strata reveals a high degree of heterogeneity in site conditions, which influences the natural regeneration of Barbary's thuja (*Tetraclinis articulata*) in the Korifla forest (Figure 3). The results show that regeneration is closely linked to vegetation cover characteristics, soil properties and environmental disturbances. The "High regeneration" class has the highest number of shoots (14 shoots), together with the presence of seedling regeneration (1.3) and young seedlings (12 cm). The regeneration class featured a substantial tree canopy (53%) and a dense shrub layer (58%), along with established leaf litter (26% for trees and 21% for shrubs), which helped retain soil moisture (15%). and favorable conditions for the establishment and development of young individuals. Moderate regeneration is observed at sites where soil compaction is greater (3 to 4 kg/cm²) and the proportion of bare soil increases, which limits the establishment of young plants despite the presence of vegetative regeneration. Conversely, low regeneration is mainly associated with unfavorable ecological conditions, characterized by rocky or poorly developed soils, more pronounced erosion and high grazing pressure.

These factors significantly reduce the natural regeneration: QsTa: Cork oak and thuja; RbEuTa: Reforestation of eucalyptus and thuja; RbPhTa: Reforestation of pine and thuja; Ta1: Dense thuja; Ta2: Medium-dense thuja; Ta2fa: Low to medium

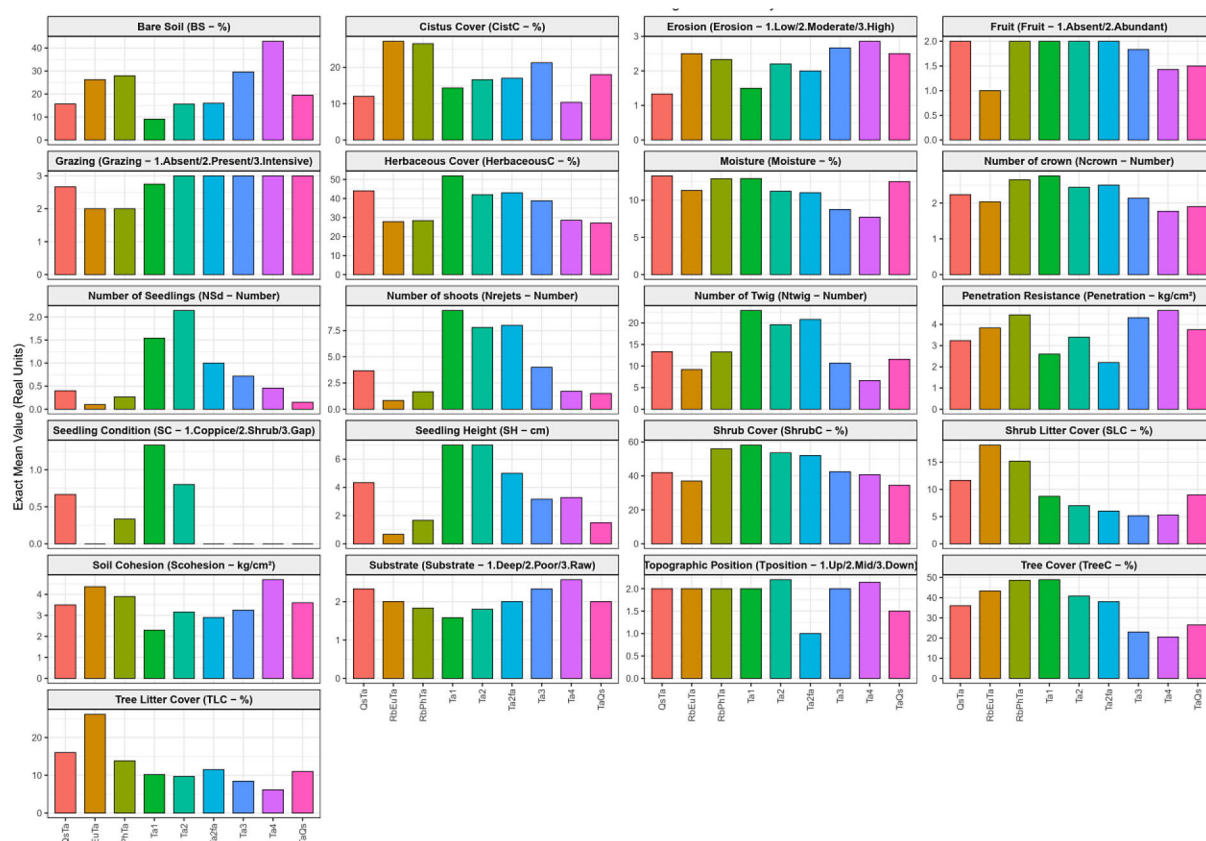


Figure 3. Exact average values of ecological and structural variables per plot (plant strata) in a 400 m² quadrat

density thuja; Ta3: Low density thuja; Ta4: Very low-density thuja; TaQs: Thuja and cork oak

Structure and typology of plots according to regeneration dynamics

Factor analysis and explained inertia

The factor analysis and explained inertia (FAMD) analysis summarized the variability of

all environmental variables into a small number of factor axes. The distribution of eigenvalues highlights a gradual decrease in the inertia explained by the factor axes (Figure 4), with the first two dimensions accounting for the majority of the variation (46.4%). This configuration reflects the existence of major ecological gradients structuring the environmental conditions of the study area. The selected axes thus provide a comprehensive representation of the variability in the

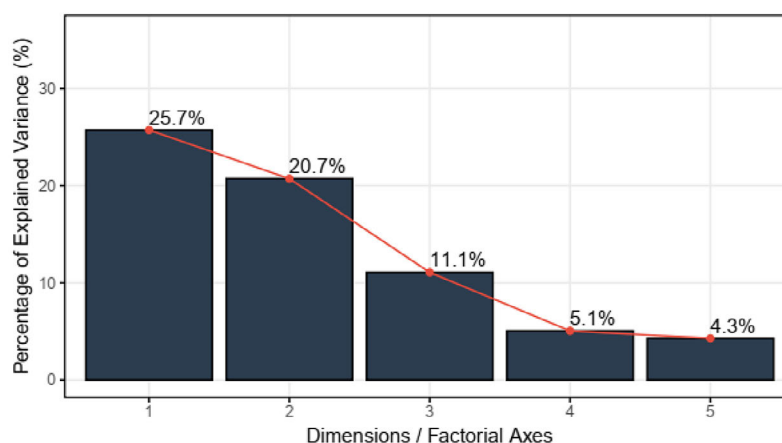


Figure 4. Percentage of explained inertia by axis (48 variables)

remote-sensing, topographical, climatic and soil variables used in the modelling, which captures the main environmental gradients influencing the natural regeneration of *Tetraclinis articulata*.

Typology of sampling plots based on regeneration dynamics

The typological analysis of the sampling plots reveals three distinct levels of natural regeneration of *Tetraclinis articulata*, assessed on the basis of the number of shoots recorded in 400 m² plots (Figure 5). High levels of natural regeneration (8 to 14 shoots) are mainly observed in dense (Ta1) and moderately dense (Ta2) thuja stands, where canopy conditions appear to favour the maintenance of an active regeneration process. Conversely, moderate regeneration (8 to 4 shoots) characterises low-density thuja stands (Ta3) as well as mixed stands combining thuja with cork oak, eucalyptus or pine (TaQs, RbEuTa), reflecting ecological conditions less favourable to the establishment of young trees. Finally, low natural regeneration (fewer than 4 shoots) is observed in very open thuja stands (Ta4) and in mixed replantings of thuja with pine or eucalyptus (RbEuTa, RbPhTa). The latter showed virtually no regeneration from seed during field observations, suggesting that these stands offer conditions that are not conducive to the natural regeneration of *Tetraclinis articulata*.

Variables driving the natural regeneration of *Tetraclinis articulata*

The AFDM reveals a structure among the 48 variables, with the first two dimensions explaining 46.4% of the variance (Dim 1: 25.7%;

Dim 2: 20.7%). Dim 1 is primarily associated with vegetation indices (NDVI, LAI, SAVI, NDRE), while Dimension 2 is more closely linked to forest structure and microhabitat conditions (Number of Twigs (Ntwig), Number of Crowns (Ncrown), Tree Cover (TreeC), Shrub Cover (ShrubC), Bare Soil (BS)). The other variables, particularly topographic and bioclimatic factors, contribute less significantly to this factor plan. Nevertheless, their integration into geospatial machine learning models remains essential to account for their complex interactions and predicted spatial suitability of regeneration of *Tetraclinis articulata* at the macroecological scale, particularly in the context of climate change (Figure 6).

Variable importance and determinants of regeneration

The analysis of predictor importance identified the main environmental factors governing the dynamics of natural regeneration of *Tetraclinis articulata* in the Korifla Forest, taking into account the two components of regeneration: seedlings and shoots. The relative importance of the variables was assessed using Random Forest (average reduction in the Gini index) and XGBoost (relative gain) models, as shown in Figures 7 and 8.

In both models, micro-environmental characteristics and canopy structure (Number of Twig, aspect, OCD, Bio05) demonstrated the highest predictive power and relative gain regarding seedling regeneration, indicating that initial seedling establishment relies heavily on protective shade and thermal and edaphic micro-conditions. Conversely, herbaceous cover and soil surface

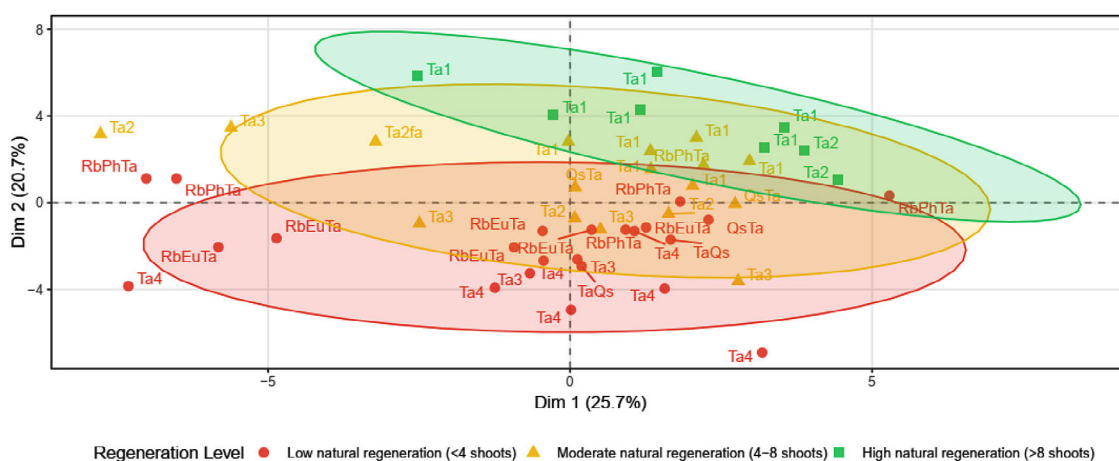


Figure 5. Typology of sampling plots for regeneration dynamics (48 variables)

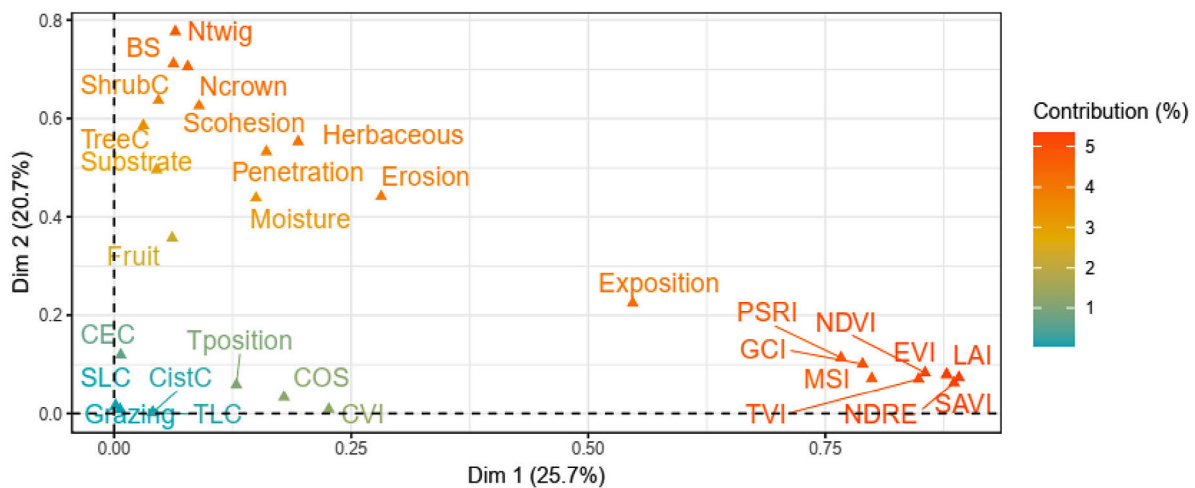


Figure 6. Variables driving tetraclinis articulata natural regeneration (48 variables)

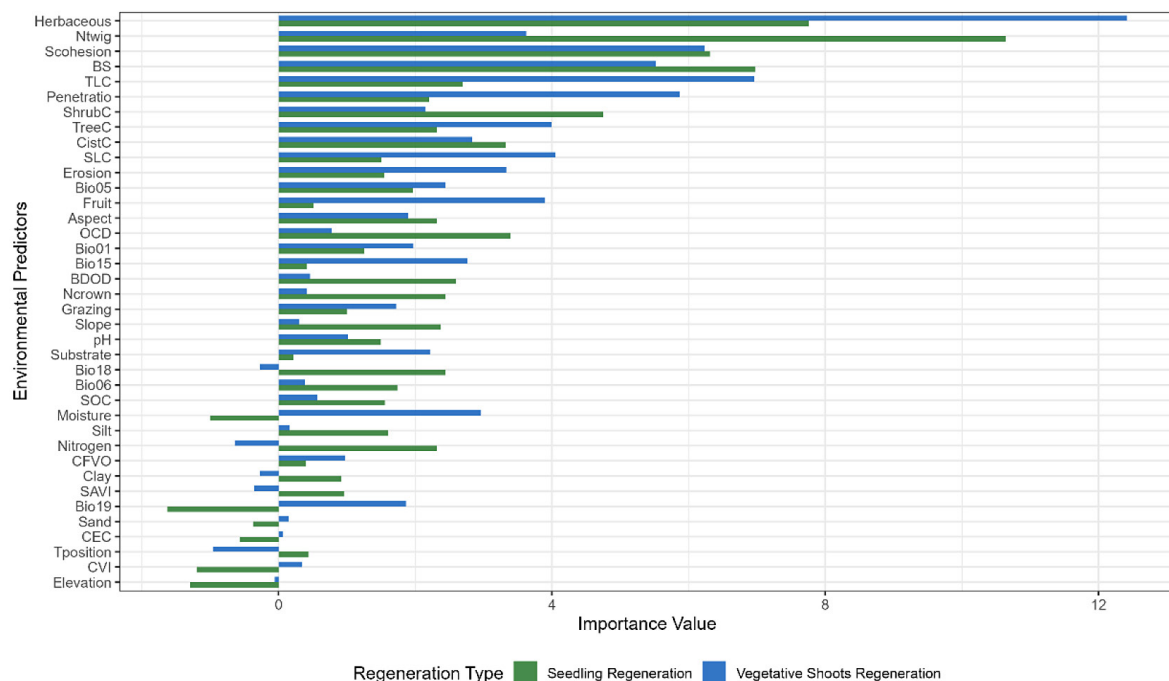


Figure 7. Variables importance ranking (Random Forest)

properties (Herbaceous Cover, Bare Soil, Soil Cohesion, Penetration Resistance) proved predominantly important for predicting vegetative shoot regeneration, reflecting the dependence of stump sprouts on herbaceous competition and substrate physical stability. The strong agreement between the importance rankings from Random Forest (Figure 7) and the relative gains from XG-Boost (Figure 8); marked by the overwhelming dominance of Herbaceous Cover and Number of Twig, confirms the robustness of the key factors identified and validates the non-linear variable selection process.

Validation of Predictive Models for the two types of natural regeneration

The Random Forest models showed good discriminatory ability for both regeneration pathways, with higher performance for shoot regeneration (AUC = 0.951) than for shoots regeneration (AUC = 0.803). Seedling prediction exhibited a more balanced trade-off between sensitivity (0.696) and specificity (0.800), whereas shoot prediction achieved very high sensitivity (1) at the expense of lower specificity (0.364). Overall accuracy and F1-scores were satisfactory for both

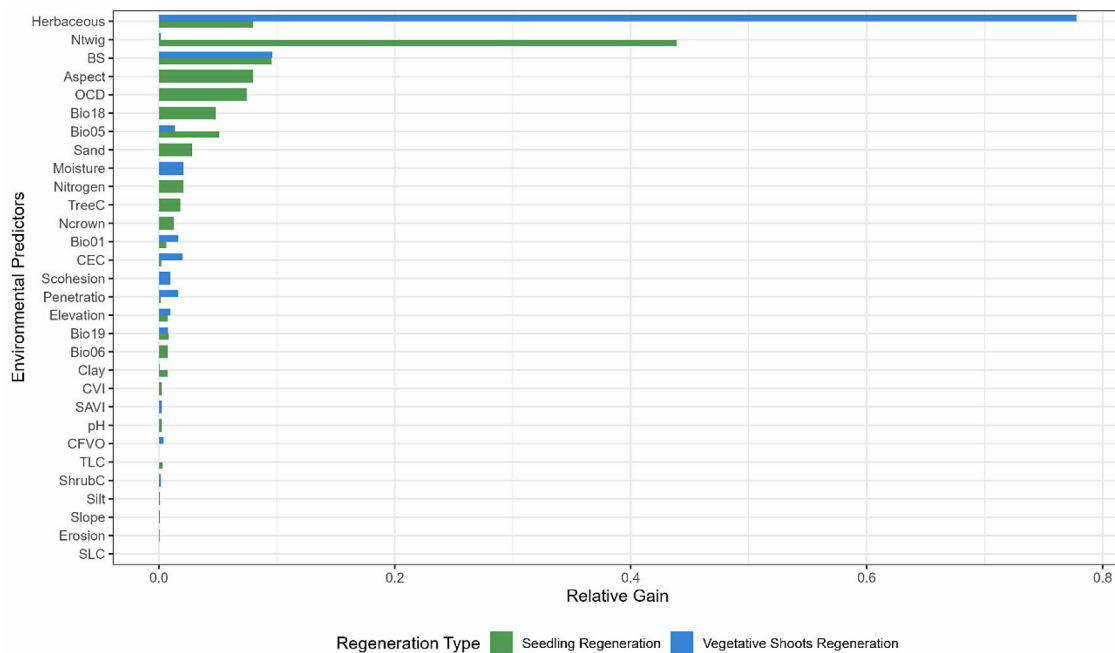


Figure 8. Relative feature importance in XGBoost model

models (0.727 and 0.914, respectively), supporting their use for spatial prediction under the spatial block cross-validation framework (Table 3).

Mapping of natural regeneration potential

Spatial distribution of natural regeneration observed from field surveys

The natural regeneration of *Tetraclinis articulata* exhibits marked spatial heterogeneity, with stump sprouts predominating over seedlings (Figure 9). The regeneration potential via stump sprouts is very high (> 0.66) across 70.01% of the forest area, compared to 22.40% for seedlings, whereas low potential (< 0.33) applies to only 1.66% of the area for sprouts, compared to 14.06% for seedlings. The highest levels of regeneration are mainly located in the eastern part of the massif, particularly near the Oued El Machrae, as well as on lower slopes, in ravines, and in more favorable areas. Conversely, regeneration is low on the plateau and in the southwestern part, where rocky and limestone substrates

predominate. Several areas also lack natural regeneration, reflecting a high degree of spatial heterogeneity in stand renewal.

Current state of regeneration potential predicted by the Random Forest model

The predictive mapping generated by the Random Forest model highlights a generally favorable current potential for natural regeneration in the Korifla Forest (Figure 10).

However, regeneration by seedling growth remains very low (less than 0.2) in the southern part of the forest (2 %), dominated by cork oak, while it shows higher potential in certain northern areas, particularly near the SIBE and close to the SMBA dam. In contrast, regeneration by stump shoots (more than 0.6) is widespread and covers most of the forest (78.86%), with particularly high potential on slopes and in valleys. The combination of these two regeneration modes thus reveals a favorable overall regeneration potential across much of the study area, underscoring the importance of vegetative regeneration in the renewal of

Table 3. Performance of Random Forest models for the two types of natural regeneration using spatial block cross-validation

Regeneration	N	Sensitivity	Specificity	Accuracy	Kappa	Precision	F1	AUC
Seedling	48	0.696	0.8	0.75	0.497	0.762	0.727	0.803
Shoots	48	1	0.364	0.854	0.468	0.841	0.914	0.951

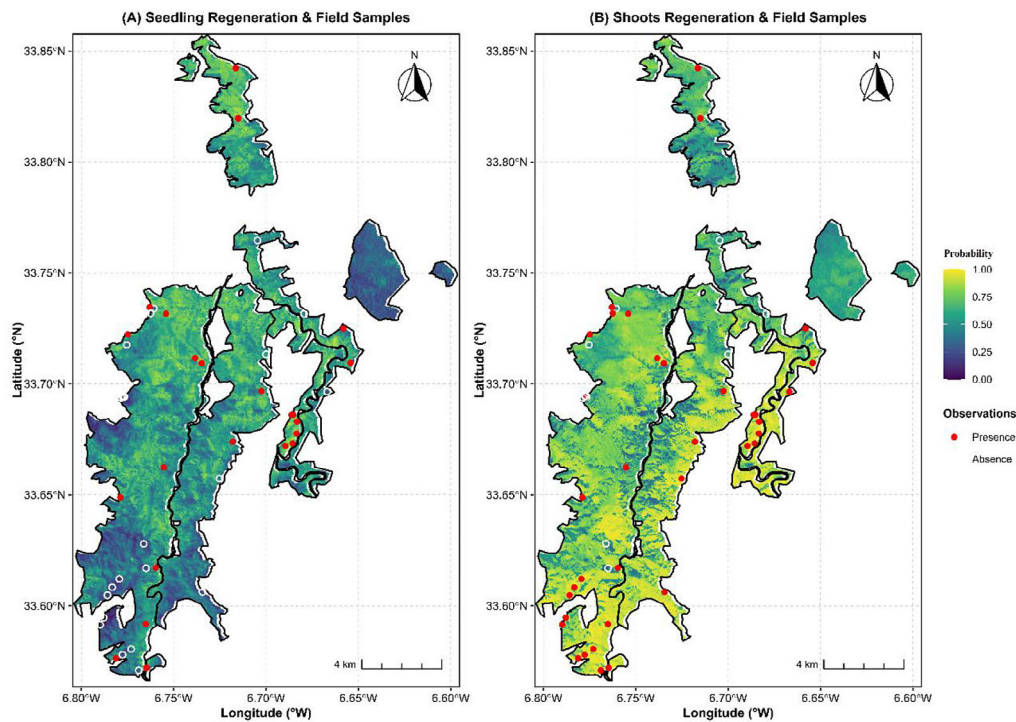


Figure 9. Spatial distribution of *Tetraclinis articulata* regeneration by seedling (A) and shoots (B) based on field measurements and the RF model

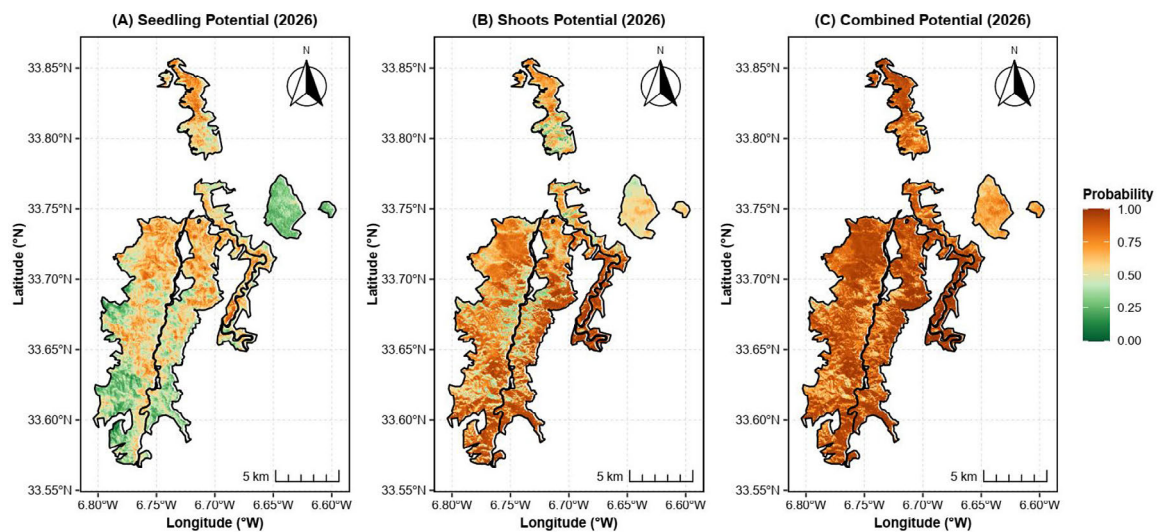


Figure 10. Spatial distribution of the current regeneration potential of *Tetraclinis articulata* by seeding (A) and shoots (B) and combined (C) predicted by the RF model

Tetraclinis articulata. This distribution is consistent with the favorable conditions, which may be linked to the exceptionally wet nature of this year, which improved water conditions and promoted vegetation growth and regeneration dynamics.

Future projection under climate change

The projection according to the SSP2-4.5 scenario to 2040 highlights a clear predominance of

the predicted probability of occurrence of regeneration by stump sprouts (Figure 11), with an average probability of 0.744 compared to 0.495 for seedlings. The regeneration potential by shoots is high (> 0.6) over 82.91% of the area, while regeneration by seedlings is minimal (24.07%). The projection thus suggests that the capacity of *Tetraclinis articulata* to maintain itself is primarily ensured by vegetative regeneration. Conversely, the relatively low contribution of seedlings reflects a

limitation of sexual renewal under the projected climatic conditions. These results therefore highlight the major role of stump sprouts in the future persistence of stands and suggest an increased vulnerability of regeneration by seeding to future climatic conditions.

Prediction of regeneration potential according to NDVI and GCI dynamics

The prospective analysis of the NDVI and GCI indices between 2036 and 2046 highlights a continuous increase in plant vigor in the Korifla forest (figure12). The area associated with very high NDVI values (> 0.70) increases from 7.40% to 12.90%, while very high GCI (>4) experiences a significant doubling, rising from 1.88% to 5.84%. The stability of the moderate classes and the dominance of the high classes reflect a densification of the forest canopy.” These prospective trajectories serve as key explanatory variables for anticipating areas favorable to the natural regeneration of *Tetraclinis articulata*.

Projections based on NDVI and GCI dynamics between 1990 and 2026 show strong stability of the predicted probability of the regeneration potential between 2036 and 2046 (Figure 13). For regeneration by seeding, the very high potential (> 0.8) remains almost stable, decreasing from 2.32% in 2036 to 2.43% in 2046. For regeneration by shoots, it also remains high, at 40.73% in 2036 versus 41.08% in 2046, confirming the predominance of suckers in future projections. These results demonstrate a high degree of suitability in future potential and suggest the continuation of

conditions favorable to the regeneration of *Tetraclinis articulata*, with a predominant contribution from vegetative regeneration.

DISCUSSION

Spatial heterogeneity of regeneration

The spatial distribution of natural regeneration of *Tetraclinis articulata* highlights a strong degree of heterogeneity within the Korifla forest. This heterogeneity suggests that the occurrence of root and stump sprouts is associated with a combination of site, topographic, edaphic, hydrological, and vegetation-cover structural factors, whose relative importance varies spatially across the forest (Dallahi et al., 2017; Hadjadj Aoul et al., 2009). This interpretation is consistent with studies conducted on Moroccan thuja forests, which show that natural regeneration is particularly favored in areas characterized by relatively high elevations, cooler exposures, relatively deep soils, and low grazing pressure (Irifi & Tribak, 2024). Field analyses show that areas with higher tree cover (53%) and shrub cover (58%) are also characterized by a greater occurrence of sprouts. This association may reflect a facilitative effect of vegetation cover, potentially creating more favorable microenvironmental conditions for the persistence of vegetative regeneration, particularly through the reduction of direct radiation and water losses (Cohen et al., 2025). However, these mechanisms cannot be considered directly demonstrated by our spatial approach and would

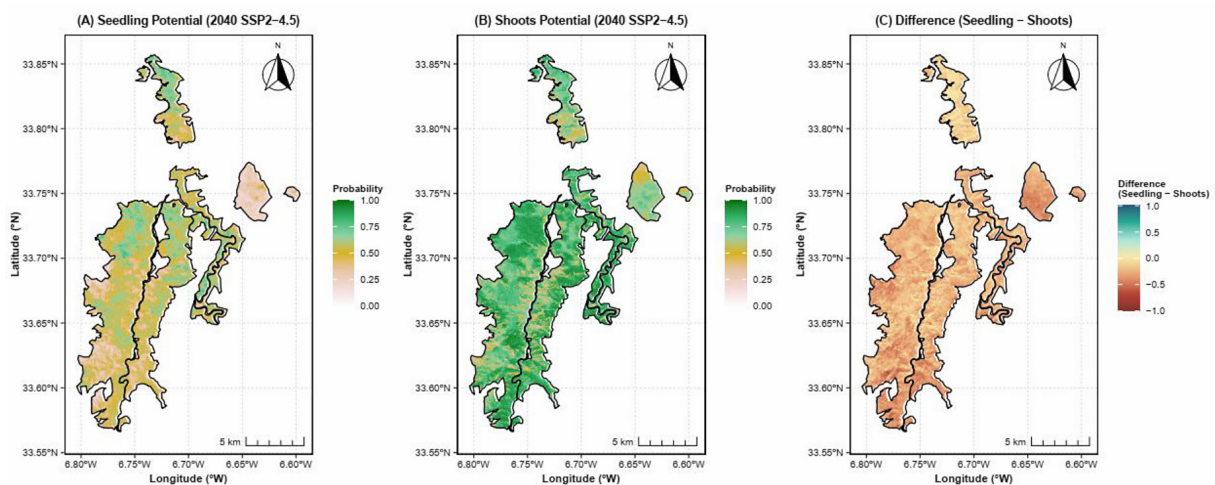


Figure 11. Probability of regeneration presence of *Tetraclinis articulata* under current conditions and projected for 2040 under the SSP2-4.5 scenario using the RF model

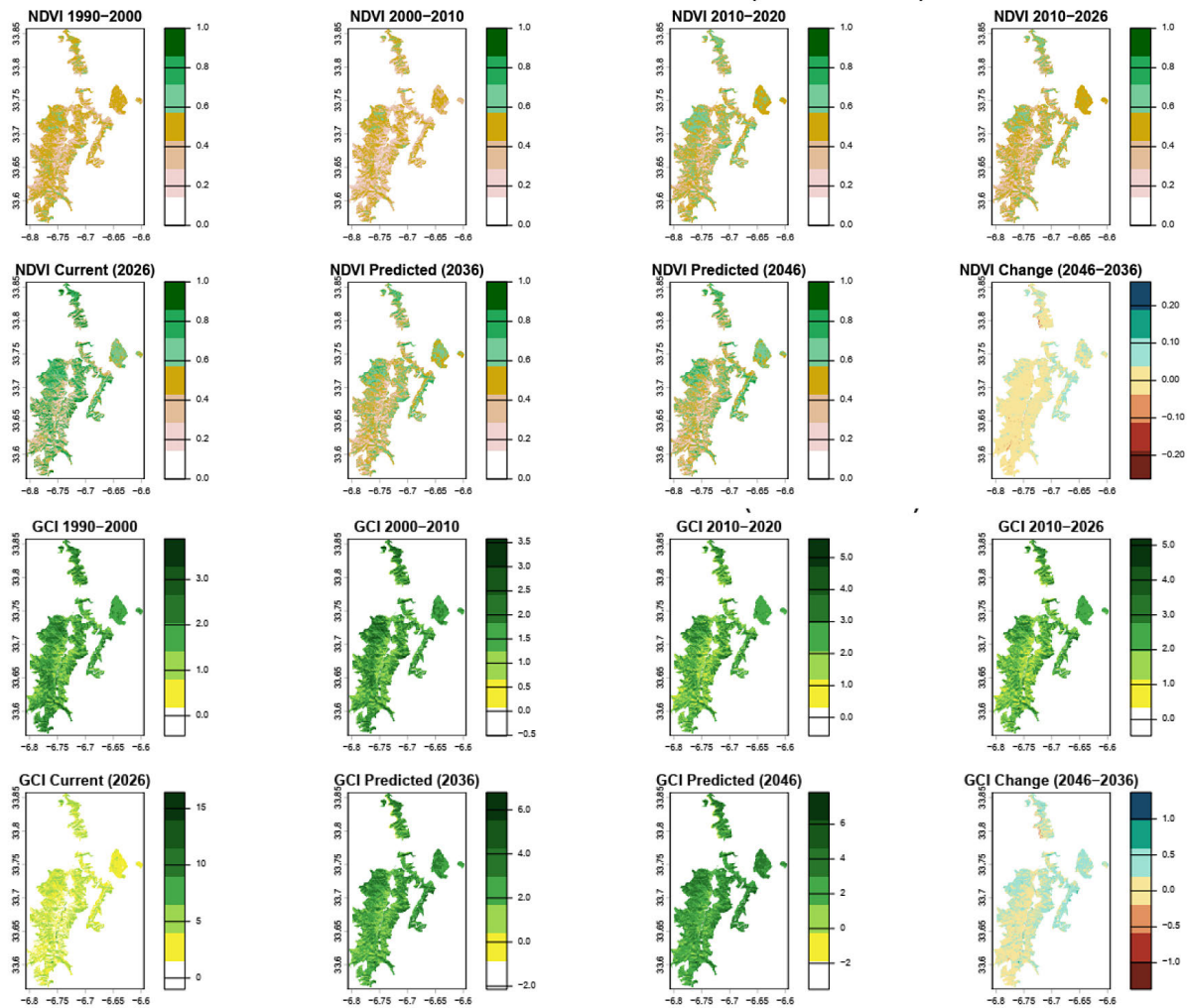


Figure 12. Dynamics of vegetation indices and future predictions

require complementary microclimatic measurements. The spatial distribution of Sentinel-2 indices highlights strong heterogeneity in vegetation vigor and water status, consistent with the spatial variability in regeneration observed in the field (Zsigmond et al., 2026).

Typology and factorial structuring of plots according to regeneration dynamics

The analysis of environmental variables and the typology of plots obtained using Multiple Factor Analysis for Mixed Data confirms a spatial organization of regeneration, as this method is well suited to mixed ecological datasets (Pagès, 2014). This spatial organization can be interpreted through the concept of “safe sites”, whereby certain local configurations provide more favorable environmental conditions for the persistence and expression of regeneration, particularly in

semi-arid environments (Stammel et al., 2006). This structuring rather emphasizes the importance of edaphic and hydrological conditions in the spatial occurrence of sprouts (Dallahi et al., 2017; El Haddadi et al., 2022), in agreement with studies highlighting the role of local environmental conditions in thuja regeneration (Zemrani et al., 2023) and (Nichols et al., 2020).

Determinants of regeneration: the contribution of machine learning

The Random Forest model enables the identification of the environmental variables that make the strongest predictive contribution to the presence of saplings, including soil water availability and vegetation cover structure. This result is consistent with (Vanwalleghe et al., 2009). Furthermore, the variable importance profiles obtained with Random Forest and XGBoost highlight

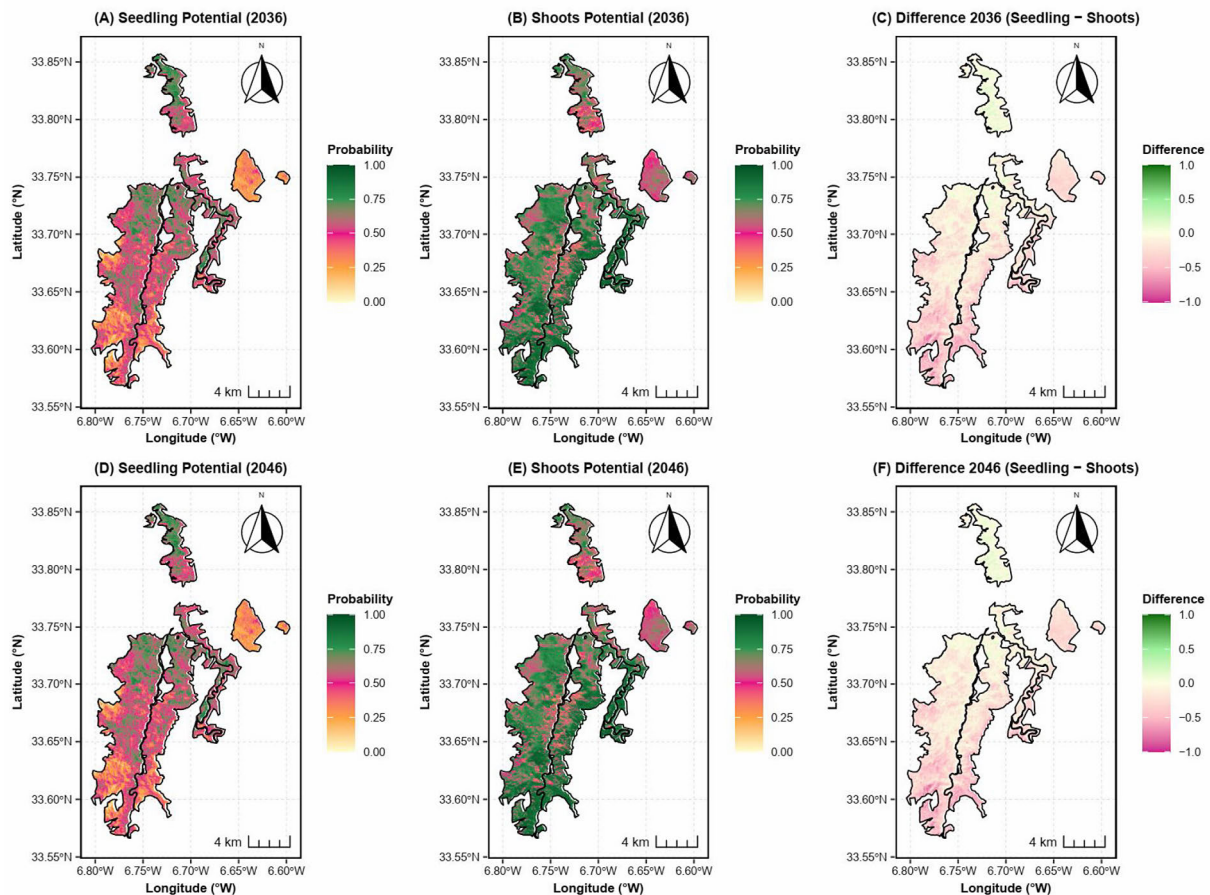


Figure 13. Predicted regeneration probability for 2036 and 2046 on the evolution of NDVI and GCI (1990–2026)

non-linear relationships between certain predictors and the probability of occurrence, indicating that the environmental conditions associated with favorable natural regeneration do not necessarily follow simple linear relationships.

Model performance and spatial mapping of regeneration potential

The performance results of Random Forest indicate a very good ability to distinguish sites of the natural regeneration, and (Zhao et al., 2023) found similar results. This situation highlights the importance of local conditions in the establishment of young seedlings (Acevedo-Limón et al., 2024) and supports the role of environmental factors in forest regeneration (Lloret et al., 2011). The agreement between the predicted probabilities and the observed distribution of shoots confirms the effectiveness of this approach in identifying environmental conditions favourable to regeneration. However, whilst this mapping provides information on the current potential for

shoots occurrence, it does not, on its own, allow for a direct prediction of the future success of thuja regeneration. But constitutes a decision-support tool for forest management, making it possible to identify areas that should be preserved as well as those requiring enhanced monitoring or restoration actions (Zhao et al., 2023).

Integrated response of natural regeneration to environmental change: contribution of climate projections and vegetation-cover dynamics

The model projection according to the SSP2-4.5 scenario for the 2040 horizon (2021–2040 period) revealed a suitability and spatial dominance of high potential (> 0.66) natural regeneration by shoots in 82.91% of the forest area. In the Mediterranean context, where increasing temperatures and declining water availability constitute major vulnerability factors for forest ecosystems (Koulelis et al., 2026; Madrigal-González et al., 2018), this

heterogeneity could become more pronounced over longer time horizons (Intergovernmental Panel on Climate Change (IPCC), 2023). However, projections based on trends in NDVI and GCI indices between 1990 and 2026 showed that the proportion of very high NDVI values (> 0.60) increased from 19.33% to 27.16%, while the proportion of high GCI (> 4) values increased from 1.88% to 5.84%. These indices thus reflected the overall response of vegetation cover to environmental conditions. In particular, the NDVI is recognised as a relevant indicator of changes in vegetation productivity and dynamics in response to environmental variations (Pettorelli et al., 2005). This stability may be explained by the inertia of topographic and edaphic factors, whereas climate change progressively affects vegetation-cover conditions. This interpretation is particularly relevant for *T. articulata*, for which annual rainfall, average temperature, and precipitation availability during the driest month play a major role in shaping the future configuration of its distribution range (Mechergui et al., 2025; Touaf et al., 2026).

Areas that are currently favorable and projected to remain stable or experience an increase could therefore constitute priority sectors for the conservation of natural regeneration, whereas areas showing a decline should be subject to enhanced monitoring. Such an approach would make it possible to integrate climate projections into thuja conservation planning and to anticipate future changes in its regeneration potential.

Limitations and uncertainties of the modelling approach

Despite the high performance achieved, the interpretation of the results should take into account several limitations inherent to spatial modelling. First, converting the number of sprouts observed in the field into a binary variable (absence = 0; presence = 1) makes it possible to model the probability of sprout occurrence but does not retain information regarding their abundance. Thus, two plots containing one sprout and several dozen sprouts, respectively, are considered to belong to the same presence class. The model therefore primarily provides information on the environmental conditions favorable to the occurrence of vegetative regeneration rather than on its intensity.

Second, despite the diversity of environmental variables incorporated into the model, some

ecological processes that may influence sprout dynamics remain difficult to represent spatially, particularly biotic interactions, local seed availability, fine-scale stand structure, and certain forms of anthropogenic disturbance. These factors may account for part of the variability that remains unexplained by the predictors used.

Third, despite the use of spatial block cross-validation, some spatial dependence between observations may persist, particularly with a limited sample size ($n = 48$). High performance (AUC, F1) should therefore be interpreted with caution, as estimates conditional on the sampling design and the spatial structure of the study area.

Finally, projections for the 2040 horizon are based on a specific climate scenario (SSP2-4.5) and on the available future climate data. They should consequently be regarded as a representation of the potential spatial response of environmental conditions favorable to sprout occurrence, rather than as a deterministic prediction of future regeneration dynamics. The uncertainty associated with the climate scenario, climate models, and assumptions of stationarity in the relationships between environmental conditions and sprout occurrence should be taken into account when interpreting future maps.

CONCLUSIONS

This study characterized and modelled the spatial distribution of vegetative regeneration of *Tetraclinis articulata* in the Korifla forest by integrating field observations, remote sensing, environmental variables, and machine learning. Field surveys based on the number of shoots revealed strong spatial heterogeneity in regeneration, associated in particular with hydrological and edaphic conditions, vegetation-cover structure, and topographic characteristics.

The Random Forest model demonstrated a very high ability to distinguish between sites with and without saplings. Analysis of the variables' contributions particularly highlights the importance of soil water availability and vegetation cover structure in determining the probability of saplings being present. The resulting map thus enables the spatial identification of areas with conditions favourable to natural regeneration.

The projection to 2040 under the SSP2-4.5 scenario, shows relative stability of the predicted probability of the regeneration in regeneration

potential, however, these results suggest a spatially differentiated response to environmental changes.

Thus, the integration of field data, geomatics and machine learning provides a useful tool for mapping, monitoring and guiding the conservation of natural thuja regeneration. Areas with a high and stable probability of sapling occurrence can, in particular, be considered priorities for conservation, whilst areas showing a decline warrant closer monitoring.

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