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Research paper

Hybrid Machine Learning Approach to Model Cedar Forest Cover Changes in Morocco's Middle Atlas

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ABSTRACT

The Atlas cedar forests in the Moroccan Middle Atlas, particularly the Sidi M'Guild region, are undergoing rapid degradation due to increasing climatic stress and anthropogenic pressure. This study introduces a hybrid modelling approach integrating random forest (RF), cellular automata (CA) and Markov chains to simulate forest cover dynamics from 1990 to 2032. The model integrates remote sensing data from Landsat 4, 8 and Sentinel-2, bioclimatic variables (temperature, seasonality, rainfall of the driest quarter) and indicators of human influence (density of occupancy, proximity to forest edges). The results project a 91% decline in *Cedrus atlantica* and a 74% decline in juniper, contrasted with a 1,290% expansion of holm oak, indicating a major ecological shift to drought-tolerant hardwoods. The RF–AdaBoost classifier achieved 98% accuracy, and the RF–CA–Markov framework demonstrated strong predictive power (Kappa = 0.72). These results offer a solid tool to anticipate forest transitions and guide adaptive forest management strategies, aligned with Morocco's national reforestation efforts.

Keywords: Atlas cedar, Forest dynamics, Climate change, Random forest, Cellular automata, Sentinel, Landsat

The Middle Atlas forests of Morocco, particularly Sidi M'Guild, are key ecological zones supporting climate regulation, biodiversity, and rural livelihoods (Legdou *et al.,* 2022). Dominated by *Cedrus atlantica*, *Quercus rotundifolia*, and *Juniperus thurifera*, these forests are increasingly degraded due to climatic stress and human pressure. Recent decades have seen marked forest decline driven by temperature variability, reduced precipitation, overgrazing, and land expansion (Laaribya *et al.,* 2024).

Agrometeorological indicators are vital for understanding forest dynamics in semi-arid regions. Sharma *et al.,* (2018) demonstrated the role of temperature and rainfall patterns in shaping forest productivity in India's dry zones, supporting our use of climate-based predictors to model *Cedrus atlantica* decline and holm oak expansion.

As a keystone species, *Cedrus atlantica* is highly drought-sensitive, and its loss compromises carbon storage, soil stability, and water regulation (Alba-Sánchez *et al.,* 2025)relatively drought-tolerant but also highly sensitive to recurrent summer heat stress. Cedar forests have undergone a dramatic range contraction in recent decades. The development of effective conservation strategies requires long-term perspectives to understand how forests have responded to past disturbances. We present a multi-proxy, high-resolution analysis of a 122 cm-deep fossil record (Merj Lkhil; LKH. Remote sensing images like Landsat series and Sentinel-2 enable large-scale forest monitoring (Simou *et al.,* 2024). Machine learning (ML) classifiers such as Random Forest and AdaBoost enhance land-cover discrimination under complex topoclimatic conditions (Chafik *et al.,* 2020), while models like Markov Chains and Cellular Automata offer spatially explicit forest simulations (Beroho *et al.,* 2023). Although remote sensing and modelling have been widely used in Morocco, integrated frameworks remain scarce (Legdou *et al.,* 2020).

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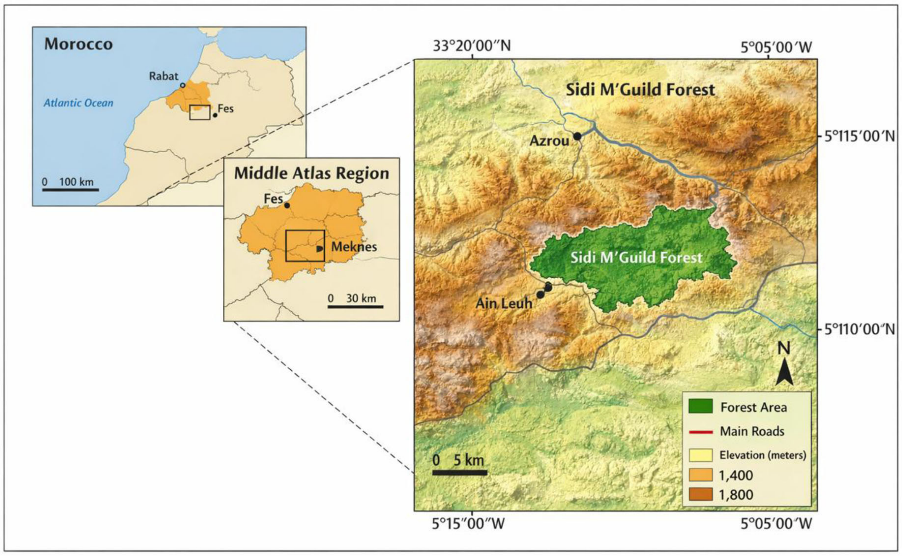

Fig. 1: Location of the Sidi M'Guild forest in the Middle Atlas, Morocco

Table 1: Datasets used for land cover modeling and environmental variable extraction

Data type	Source	Spatial resolution	Period	Main variables / Use
Landsat 4 TM / 8 OLI	USGS Earth Explorer	30 m	1990, 2004, 2018	Landsat 4 TM: Bands 1–5, 7 (Blue, Green, Red, NIR, SWIR1, SWIR2); Landsat 8 OLI: Bands 2–7 (Blue, Green, Red, NIR, SWIR1, SWIR2); NDVI, SAVI
Sentinel-2 MSI	ESA Copernicus	10–20 m	2018 (Jan–Nov)	Bands 2, 4, 8, 11, 12
DEM (SRTM)	NASA	30 m	—	Elevation, slope, aspect
WorldClim v2.1	WorldClim	1 km	1970–2000	BIO1–BIO19 bioclimatic vars
Moroccan Census 2014	HCP Morocco	—	2014	Settlement density and distance

This study fills that gap by applying a hybrid RF–CA–Markov model to simulate forest change (1990–2032), combining AI, climate data, and spatial modelling to inform forest vulnerability and guide reforestation strategies.

MATERIALS AND METHODS

Study Area

The study area, Sidi M'Guild Forest (29,000 ha), lies in the central Middle Atlas Mountains of Morocco (33°15′ to 33°30′ N; 5°00′ to 5°20′ W), within a UNESCO Biosphere Reserve (Fig. 1). This mountainous region (1,400–2,200 m a.s.l.) features Jurassic limestone and red clay basins (Mounir *et al.,* 2019) and experiences a cold sub-humid climate with 800–1,200 mm annual rainfall and strong seasonal temperature variation (Mokhtari *et al.,* 2014). The dominant species, *Cedrus atlantica*, *Quercus rotundifolia*, and *Juniperus thurifera* - are increasingly threatened by drought, overgrazing, and land-use pressure (Linares *et al.,* 2011; Rhanem, 2011).

Data Sources and Variables

To model spatio-temporal forest transitions, we used Landsat 4 TM/Landsat 8 OLI imagery (1990, 2004, 2018; 30 m, USGS), Sentinel-2 MSI (2018; four seasonal dates; 10 and 20 m), SRTM DEM (30 m) for topography, bioclimatic layers (BIO1–BIO19, WorldClim v2.1), anthropogenic data (settlement density, village proximity; census 2014), and forest edge distance from official boundaries (Table 1). All datasets were standardized to 30 m resolution and projected to WGS-84 / UTM zone 30N.

Pre-processing and Index Calculation

Standard corrections included radiometric and atmospheric correction (DOS), image co-registration, and masking of clouds using Fmask. Sentinel-2 bands were resampled to 30 m. Two vegetation indices were calculated to enhance forest discrimination:

$$\mathrm{NDVI} = \frac{\mathrm{NIR-RED}}{\mathrm{NIR+RED}}\,; \quad \mathrm{SAVI} = \frac{(\mathrm{NIR-RED})}{(\mathrm{NIR+RED+L})} X\,(1+L)$$

where *L=0.5 (canopy cover factor)*

These indices were used to enhance vegetation discrimination and reduce soil background effects. These indices were used to enhance vegetation discrimination and reduce soil background effects. In the SAVI formula, *L* represents the canopy background adjustment factor (set to 0.5 for intermediate vegetation cover). (El Mhamdı *et al.,* 2023; El Moussaoui *et al.,* 2024)land

Table 2: Performance metrics for tested classifiers

Classifier	Overall Accuracy (%)	Kappa	Strengths	Weaknesses
Random Forest (RF)	95	0.89	High robustness, non-parametric	Slight over-classification of mixed stands
AdaBoost (ADA)	91	0.84	Efficient boosting of weak learners	Sensitive to noise
RF–ADA ensemble	98	0.92	Combines stability + precision	Computationally heavier
LDA	80	0.73	Performs well on linear boundaries	Limited in complex landscapes
SVM	37	0.25	Handles high dimensions	Poor generalization here
KNN	39	0.28	Simple, transparent	Affected by imbalance

use studies, and geological or other applications. A variety of DEMs, such as the Advanced Space Thermal Emission Radiometer (ASTER GDEM.

Supervised Classification

Five machine learning algorithms—Random Forest (RF), AdaBoost (ADA), Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and Linear Discriminant Analysis (LDA)—were evaluated using field-based training data. Forest cover was classified into pure (Ca, Qr, Jt) and mixed vegetation types (e.g., CaQrJt).

Training and testing samples were collected during field surveys conducted in spring–summer 2018, coinciding with the Sentinel-2 acquisition period (January–November 2018). A total of 477 ground-truth points were recorded across the study area using GPS, covering all seven vegetation classes (Ca, Qr, Jt, CaQr, CaQrJt, QrJt, CaJt) and non-forest areas (V). Points were distributed proportionally to class extent (Ca: 31, CaQr: 112, Qr: 30, CaQrJt: 59, Jt: 76, QrJt: 75, CaJt: 36, V: 58), with a minimum of 30 samples per class to ensure adequate representation of rare classes. Samples were randomly split into 70% for training (334 points) and 30% for testing (143 points). Field observations were conducted in coordination with the Moroccan Forest Administration, using official forest inventory maps as reference.

Variable Selection

To limit multicollinearity, predictors with strong correlations ($|r| > 0.8$) were removed using Pearson correlation analysis (Mei *et al.,* 2022). The final model retained five variables: temperature seasonality (BIO4), precipitation of the driest quarter (BIO17), distance to settlements, settlement density, and distance to forest edge.

Forest Transition Modeling

Forest dynamics were simulated using a hybrid framework (Asif *et al.,* 2023) combining Markov Chains to estimate transition probabilities (1990–2004) (Kamusoko *et al.,* 2013), Random Forest regression to model spatial transition likelihoods, and Cellular Automata to account for neighborhood effects (Grinand *et al.,* 2020) The model was iterated 1,000 times to ensure stable results.

RESULTS AND DISCUSSION

Model Validation and Projection

The RF–CA–Markov model was validated by comparing simulated and observed forest maps for 2018. Based on the validated model, forest cover was projected to 2032 using a single Markov transition step (2018–2032), calibrated from the 1990–2004 and 2004–2018 periods under the assumption of stationary transition processes (Merhej *et al.,* 2025).

Classification Accuracy and Forest Mapping Performance

Classification of multi-temporal Landsat TM/OLI and Sentinel-2 MSI imagery using five machine learning algorithms showed varying performance. The RF–AdaBoost ensemble achieved the highest accuracy (98%) and Kappa (0.92), outperforming Random Forest (95%) and LDA (80%), while SVM and KNN underperformed (≤40%) due to spectral overlap and class imbalance (Table 2). These results highlight RF–AdaBoost's robustness in classifying complex forest types in mountainous areas. The final map identified seven vegetation classes: pure stands of *Cedrus atlantica* (Ca), *Quercus rotundifolia* (Qr), *Juniperus thurifera* (Jt), their mixed types, and non-forest areas (V). Incorporating NDVI, SAVI, and topographic variables enhanced class separability.

Fig. 2 (a) presents the forest-cover map for 2018 generated using the RF–AdaBoost model. Atlas cedar dominates higher elevations and northern slopes, whereas holm oak and mixed stands prevail at lower altitudes and near settlements, illustrating the influence of topoclimatic gradients and human activities on forest structure.

Temporal Dynamics of Forest Cover (1990 – 2018)

Comparison of classified maps from 1990, 2004, and 2018 shows significant shifts in forest composition. Atlas cedar declined sharply from 8,975.9 ha to 2,007.9 ha (−77.6%), while juniper slightly decreased (−3.1%). In contrast, holm oak expanded by over 400%, largely replacing degraded cedar stands (Table 3).

Fig. 2 (b) shows forest-cover change from 1990 to 2018. Cedar decline is concentrated on southern slopes and accessible areas near Aïn Leuh, while holm oak expands mainly over former cedar zones, indicating species replacement rather than overall forest gain.

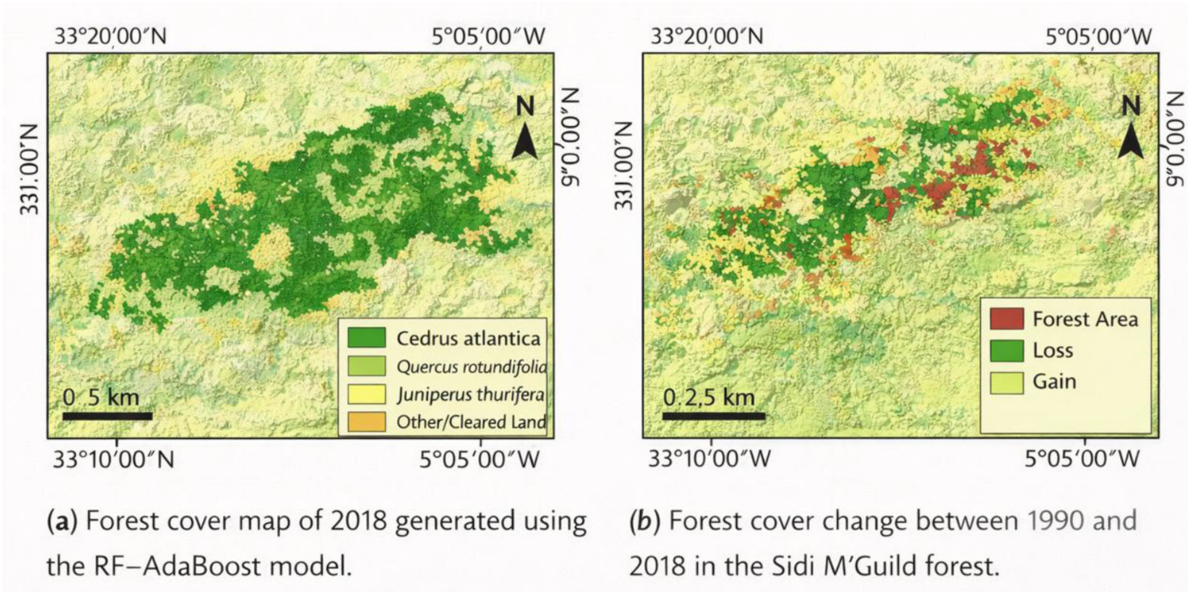

Fig. 2: Classified Forest cover map of the Sidi M'Guild Forest (Middle Atlas, Morocco) for 2018 generated using the RF–ADA ensemble model

Table 3: Evolution of forest cover classes between 1990 and 2018

Forest Class	1990 (ha)	2004 (ha)	2018 (ha)	Change 1990–2018 (%)
Ca (Atlas cedar)	8 975.9	2 171.3	2 007.9	−77.6
CaQr (Cedar + Holm oak)	8 482.1	9 141.9	7 138.6	−19.8
Qr (Holm oak)	44.4	551.9	233.1	+425.0
CaQrJt (Cedar + Holm oak + Juniper)	4 034.5	3 184.8	3 758.6	−6.8
Jt (Juniper)	5 010.8	3 491.3	4 854.9	−3.1
QrJt (Holm oak + Juniper)	2 208.0	5 986.7	4 803.0	+54.0
CaJt (Cedar + Juniper)	2 208.0	2 405.7	2 282.9	+3.4
V (Non-forest)	1.0	1 822.9	3 677.6	+100 ×

Table 4. Validation statistics for RF–CA model

Metric	Value	Interpretation
Overall Correctness	73 %	Good spatial fit
Kappa (Cohen)	0.72	Strong agreement
Kappa Histogram	0.97	Excellent frequency match
Kappa Location	0.70	Accurate spatial localization

Model Calibration, Validation, and Predictive Performance

The RF–CA model was calibrated using 1990–2004 transitions and validated against the 2018 forest map. As shown in Table 4, the simulation reached 73% overall accuracy and a Kappa of 0.72, reflecting strong spatial agreement. A high Kappa histogram score (0.97) further confirms close class proportion matching.

The most influential predictors were temperature seasonality (BIO4), precipitation of the driest quarter (BIO17), settlement density, distance to settlements, and proximity to forest edge.

Forest Cover Projection for 2032

Forest cover simulation for 2032 projects major compositional shifts. Atlas cedar and juniper are expected to decline by 91.5% and 74.4%, respectively, while holm oak may expand by over 1,200% compared to 2018 (Table 5), indicating a strong trend toward thermophilous hardwood dominance.

Fig. 3 presents the predicted forest-cover distribution for 2032 obtained using the RF–CA hybrid model. Coniferous stands are largely restricted to high-elevation refugia, whereas holm oak and mixed hardwood formations dominate large portions of the central and southern slopes, reflecting increasing climatic stress and anthropogenic disturbance.

Interpretation of Model Behavior and Ecological Implications

The model outputs emphasize the combined impact of climatic variability and human pressure on forest trajectories. High temperature seasonality and prolonged droughts limit cedar regeneration, while proximity to settlements and grazing pressure accelerate degradation. Fig. 4 compares classification performance metrics (accuracy, precision, recall, and F1-score) for all tested

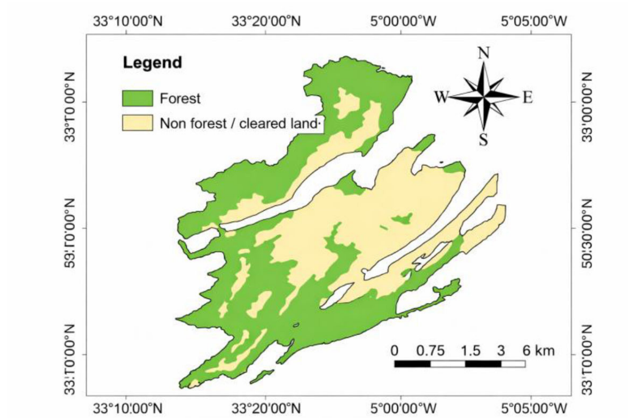

Fig. 3: Predicted forest-cover distribution for 2032 obtained using the RF–CA hybrid model.

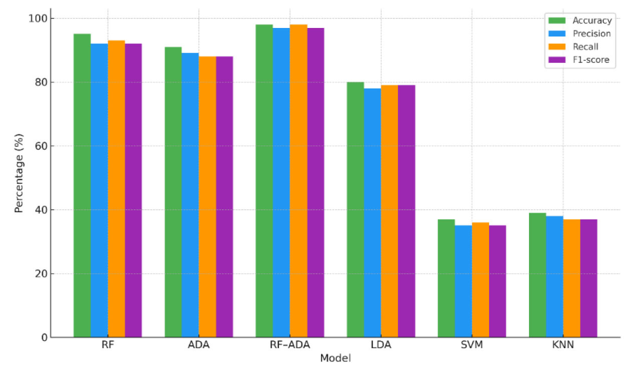

Fig. 4: Classification performance metrics (Accuracy, Precision, Recall, F1-score) for the six tested algorithms.

Table 5: Predicted forest cover change between 2018 and 2032

Class	Observed 2018 (ha)	Predicted 2032 (ha)	Δ (%)
Ca (Atlas cedar)	2 007.9	170.8	−91.5
CaQr (Cedar + Holm oak)	7 138.6	9 145.0	+28.1
Qr (Holm oak)	233.1	3 249.5	+1 294.0
CaQrJt (Cedar + Holm oak + Juniper)	3 758.6	8 444.6	+124.7
Jt (Juniper)	4 854.9	1 243.6	−74.4
QrJt (Holm oak + Juniper)	4 803.0	2 405.5	−49.9
CaJt (Cedar + Juniper)	2 282.9	1 254.5	−45.1
V (Non-forest)	3 677.6	2 881.4	−21.6

algorithms. The RF–AdaBoost ensemble consistently exhibits the highest performance, confirming its suitability for forest-cover discrimination in complex mountainous environments. The numerical values corresponding to Fig. 4 are reported in Table 6.

Fig. 5 shows the relationship between observed and simulated forest-area values for 2018. The strong linear agreement ($R^2 \approx 0.9$) confirms the reliability of the RF–CA model in reproducing observed forest distributions.

Fig. 6 presents the variable importance derived from the Random Forest model. Temperature seasonality (BIO4) and distance to settlements emerge as the most influential predictors, followed by precipitation of the driest quarter (BIO17) and landscape fragmentation indicators.

The Pearson correlation matrix of the five retained explanatory variables (Table 7) confirms the absence of strong correlations ($|r| > 0.8$), ensuring minimal multicollinearity and robust model calibration.

This study highlights an ongoing ecological transformation in the Sidi M'Guild forest (Middle Atlas). By 2032, *Cedrus atlantica* (−91%) and juniper (−74%) are projected to decline sharply, reflecting conifers' vulnerability to climate stress and anthropogenic pressure. These patterns mirror broader Mediterranean trends, where warming and land-use intensification accelerate mesic species retreat. The massive expansion of holm oak (*Quercus ilex*, +1290%) exemplifies ecological substitution, as thermophilous hardwoods replace declining conifers.

Spatial analysis revealed topographic structuring of degradation: cedar persists on high-altitude, north-facing slopes with cooler microclimates, while deforestation dominates low-elevation, south-facing areas near villages and grazing paths—consistent with land degradation models in similar contexts.

Methodologically, the hybrid model (RF, AdaBoost, CA, Markov Chains) showed strong predictive power (98% accuracy, Kappa = 0.72), comparable to recent AI-based land change models. Its strength lies in integrating environmental drivers (e.g., temperature seasonality, proximity to edges) while the CA module captures spatial contagion effects.

Ecologically, *Cedrus atlantica* loss entails a regime shift toward xerophytic, structurally simpler ecosystems, as seen elsewhere in the Mediterranean. From a management perspective, north-facing slopes above 1,900 m emerge as priority zones for restoration, alongside buffer zones near settlements—recommendations aligned with adaptive planning in Morocco and similar biomes.

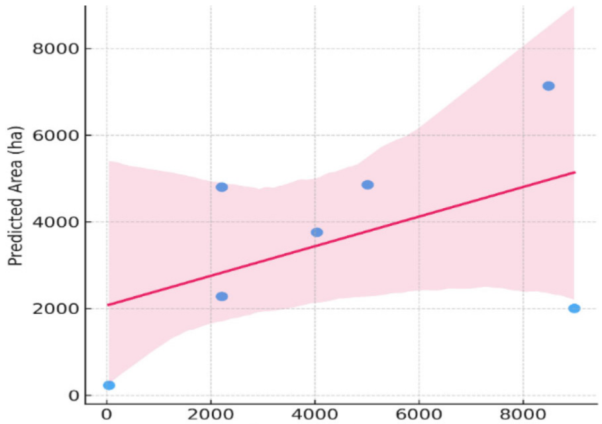

Fig. 5: Observed vs. predicted forest-area values (ha) for 2018 (RF–CA model).

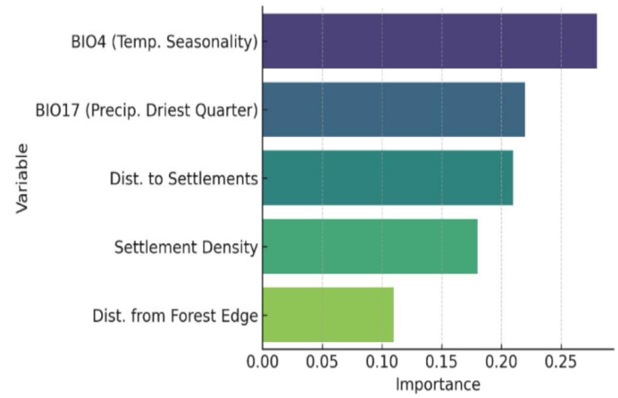

Fig. 6: Variable importance scores from the Random Forest model for the five

Table 6: Performance metrics of the tested classifiers.

Classifier	Accuracy (%)	Precision	Recall	F1-score
RF	95	0.94	0.93	0.93
ADA	91	0.89	0.88	0.88
RF–ADA	98	0.97	0.96	0.96
LDA	80	0.78	0.75	0.76
SVM	37	0.35	0.33	0.34
KNN	39	0.37	0.35	0.36

Table 7: Pearson correlation matrix of the five retained explanatory variables.

Variable	Temperature seasonality (BIO4)	Precipitation of driest quarter (BIO17)	Distance to settlements	Settlement density	Distance to forest edge
Temperature seasonality (BIO4)	1.00	−0.42	−0.31	0.28	−0.35
Precipitation of driest quarter (BIO17)	−0.42	1.00	0.26	−0.22	0.18
Distance to settlements	−0.31	0.26	1.00	0.61	−0.54
Settlement density	0.28	−0.22	0.61	1.00	−0.49
Distance to forest edge	−0.35	0.18	−0.54	−0.49	1.00

CONCLUSION

This research presents a reproducible, data-driven framework for ecological forecasting in semi-arid forests by integrating AI and spatial modeling. The hybrid RF–CA–Markov model captures forest transition dynamics and offers actionable guidance for conservation.

Ecologically, the study confirms a shift from cedar-dominated to hardwood-dominated communities, driven by climate trends and human proximity. Persistence of *Cedrus atlantica* in high-elevation refugia underscores the need for targeted reforestation, controlled grazing, and efficient silviculture.

Methodologically, this framework opens avenues for integrating deep learning (CNN, LSTM) and climate scenarios to enhance forecasts. At the policy level, it supports Morocco's Forest Strategy 2020–2030 and the UN Decade on Ecosystem Restoration, offering an advanced tool for sustainable forest management.

Safeguarding *Cedrus atlantica* means preserving the ecological and cultural legacy of the Middle Atlas—now at the crossroads of environmental resilience and technological innovation.

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Authors contributions: **Anass Legdou**: Conceptualization, methodology, data collection, remote sensing, machine learning, interpretation, visualization, and drafting; **Ayoub Souileh:** ML implementation, statistical analysis, model validation, and result interpretation; **Aouatif Amine:** Methodology supervision, algorithm optimization, model framework review, and manuscript revision; **Said Lahssini**: Forest ecology expertise, field data analysis, validation of assumptions, and input to discussion; **Bouchra Nassih:** Data curation, GIS processing, literature review, and manuscript editing.

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