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Modeling and predicting forest dynamics in Talassemtane National Park (Morocco) using cellular automata and artificial neural networks

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ABSTRACT

Predicting land use and land cover change is vital for managing forest dynamics, particularly in protected areas under human pressure. This study focuses on Talassemtane National Park in Morocco, utilizing advanced geospatial modeling techniques specifically, the QGIS MOLUSCE plugin and artificial neural networks to assess and forecast forest cover changes. Using historical Land use land cover maps (1995, 2000, 2005) and spatial variables such as slope, distance to buildings, distance to roads, and distance to water, the model was trained and validated, achieving an overall accuracy of 86% and Kappa coefficient of 71%. Predictive analysis indicates forest cover will decrease from 35,522 hectares in 2024 to 31,254 hectares by 2040, a 12% loss averaging 251 hectares annually. By 2040, forests are projected to cover only 48.4% of the park's area, down from 55% in 2024. The main drivers of forest loss include fires, illegal logging, agricultural expansion overgrazing, and infrastructure development, all exacerbated by climate change. These findings highlight the urgent need for targeted conservation strategies and sustainable land management practices. The methodology presented offers a scalable approach for other protected areas, providing valuable insight for policymakers and resource managers to mitigate forest loss and promote ecological resilience.

Keywords: LULC change, forest loss, Talassemtane National Park, cellular automata, ANN.

INTRODUCTION

The rate of deforestation worldwide is experiencing a worrying increase and is considered a key factor in climate change and global warming. Researchers around the world are closely monitoring the progress and working to implement solutions that identify this problem and provide decision-making tools to governments and non-governmental organizations. Globally, (Hansen et al., 2013) Present Global Forest Change 2000–2024. This product provides important information about tree cover loss and gain on the global scale. Also, the factors contributing to this deterioration have been widely debated (Curtis et al., 2018). Tyukavina et al. (2022) analyzed global trends in forest loss due to fire from 2001 to 2019, highlighting fire as a significant driver of deforestation worldwide. Regionally, Feng et al. (2022) reported a doubling of annual carbon forest loss over tropical regions in the early twenty-first century, emphasizing the increasing impact of deforestation on carbon emissions. Alaniz et al. (2022) examined the spatiotemporal patterns of forest carbon sinks and sources between 2000 and 2019, providing insights into how forests act as both carbon reservoirs and emitters over time. Hamunyela (2017) utilized multi-satellite observations for space-time monitoring of tropical forest changes, demonstrating the effectiveness of remote sensing in tracking deforestation and forest degradation. Chergui et al. (2018) found that socioeconomic factors significantly influence fire-regime variability in the Mediterranean

Basin, linking human activities to changes in fire patterns and forest loss. Chen et al. (2018) Mapped spatial and temporal changes in forests on Hainan Island (China) from 2007 to 2015 by integrating radar and optical satellite imagery, showcasing advanced methods for forest monitoring. Locally, several studies around the world have shed light on this phenomenon as well as the factors of degradation(Calderón-Caro et al., 2024; Duarte et al., 2020; Guria et al., 2024; Muteya et al., 2023; Sannier et al., 2016; Simou et al., 2024; Sims et al., 2025; Vieilledent et al., 2018; Zeng et al., 2018).In Morocco, so far there has been little data on the rate of deforestation except through the data provided globally (Knostmann and Rasoamanana, 2025). But research in the regions and localities of the kingdom is becoming increasingly abundant (Chergui et al., 2024; Ghazi et al., 2024; Mikesell, 1960; Simou et al., 2024).

LULC remains the most widely used process worldwide for assessing deforestation, particularly with the emergence of new classification techniques and the increased availability of satellite images (Alshari and Gawali, 2021; Ouchra and Belangour, 2021). LULC Change has made it possible to track changes in space and time. The evolution of change detection techniques has made it possible to overcome the constraints of the past (Chang et al., 2018; Lu et al., 2004). In addition, researchers have developed new techniques for assessing the accuracy of LULC maps (Congalton and Green, 2008; Kamusoko, 2022; Olofsson et al., 2013, 2014). Globally, several regional and local studies across different geographies have contributed valuable insights into LULC change, forest loss, and the drivers influencing these dynamics. Zeng et al. (2018) examined how expanding highland cropland in Southeast Asia has contributed to forest loss in the 21st century, highlighting regional agricultural encroachment and deforestation. Similarly, Guria et al. (2024) explored the factors driving forest cover change and assessed deforestation susceptibility in Northeast India by applying multicriteria decision-making models. In North Africa, Karmoude et al. (2025) focused on the efficient detection of Argan tree deforestation in Morocco using Sentinel-2 time series data and machine learning techniques, demonstrating the effectiveness of advanced remote sensing for monitoring specific tree species. Solano et al. (2014) examined the relationship between cannabis cultivation and deforestation in the Site of Bio Ecological Interest (SIBE) of Bouhachem, Morocco, highlighting the role of illicit agriculture in forest degradation. Elsewhere, Abuelaish and Olmedo (2016) used remote sensing and GIS models to simulate land use and land cover change scenarios in the Gaza Strip, demonstrating the utility of geospatial tools for forecasting and planning. Padma et al. (2022) simulated LULC dynamics around the Outer Ring Road in Southern India, utilizing Google Earth data and QGIS to analyze urban expansion and its environmental implications. The use of time series analysis for monitoring LULC change is illustrated by Kaur et al. (2023), who analyzed Earth observation data from 2001/2002 to 2021 with Google Earth Engine to detect changes in forest cover in the East Godavari Region, Andhra Pradesh, India. In Egypt, Mostaf et al. (2023) developed a Sentinel-2 satellite framework for remote sensing imagery, enabling the detection of land-cover change at different spatial and temporal scales. Finally, Jia et al. (2018) investigated the spatiotemporal patterns and characteristics of land-use change in China between 2010 and 2015, offering a comprehensive overview of rapid LULC transitions in one of the world's largest countries. These studies collectively demonstrate the diversity of methods and applications used to monitor, analyze, and predict LULC change and deforestation at local, regional, and national scales.

A growing body of research demonstrates the application of advanced modeling techniques and open-source tools for monitoring, analyzing, and predicting LULC changes across diverse geographic regions. These studies provide valuable insights into both the patterns and drivers of LULC dynamics, supporting effective decision-making for sustainable land management. An in-depth analysis of land use and cover changes was conducted in a typical subtropical region of South Africa (Wang et al., 2023). This research also examined the underlying driving forces influencing these changes, providing valuable insights into the factors shaping LULC dynamics in the area. The QGIS MOLUSCE plugin was utilized to map and analyze LULC transformations in the Pakhal Lake region of Telangana (Amgoth et al., 2023). The study effectively captured the spatial patterns and trends of landscape changes over time. Open-source MOLUSCE tools enabled the monitoring and simulation of LULC changes in Ludhiana, Punjab (Dhiman et al., 2022). This comprehensive assessment aided in understanding the evolution of LULC in the region. Spatiotemporal change analysis and future LULC predictions for Linyi were performed using the QGIS MOLUSCE plugin in combination with remote sensing big data (Muhammad et al., 2022). This approach provided robust modeling of potential future scenarios and their implications. The QGIS MOLUSCE plugin was employed to simulate potential future LULC scenarios for the Bhavani basin in Tamil Nadu (Kamaraj and Rangarajan, 2022). This predictive modeling supported the evaluation of possible land cover transitions and their environmental impacts. Eshetie et al. (2023) applied artificial neural network (ANN) models to examine the impact of both past and projected future LULC changes on streamflow in the Upper Gilgel Abay watershed within the Abay Basin. This study demonstrates the utility of ANN approaches for integrating land cover dynamics with hydrological modeling, offering insights into how landscape transformation influences water resources. Atef et al. (2024) conducted a simulation study to assess future LULC changes in the El-Fayoum governorate, employing satellite data coupled with the CA-Markov model. This approach enabled scenario-based forecasts of land cover transitions, supporting land management and planning efforts. Jafarpour Ghalehteimouri et al. (2022) implemented integrated cellular automata Markov chain model-based scenarios to project spatial and decadal LULC changes (2019–2049) in the Zarriné-Rūd River Basin, Iran. Benchelha et al. (2022) modeled dynamic urban growth in Casablanca, Morocco, using cellular automata and geospatial techniques. The study "Future Scenarios of Land Use/Land Cover Based on a CA-Markov Simulation Model: Case of a Mediterranean Watershed in Morocco" applied this approach to simulate watershed-scale LULC changes (Islam et al., 2024).

This study aims to analyze and predict LULC changes within Talassemtane National Park, with a particular focus on forest loss and its underlying drivers. Using advanced modeling techniques such as cellular automata (CA) and artificial neural networks (ANNs), this research seeks to provide a comprehensive understanding of the spatial and temporal patterns of deforestation within the park.

MATERIALS AND METHODS

Study area

The Talassemtane National Park (TNP), which covers an area of 64000 hectares, is located in the Tangier, Tetouan, El Hoceima region (Figure 1). Created in 2004 by the Moroccan authorities to ensure the conservation of these remarkable ecosystems. The site, considered a biodiversity hotspot, is home to many endemic species, the most

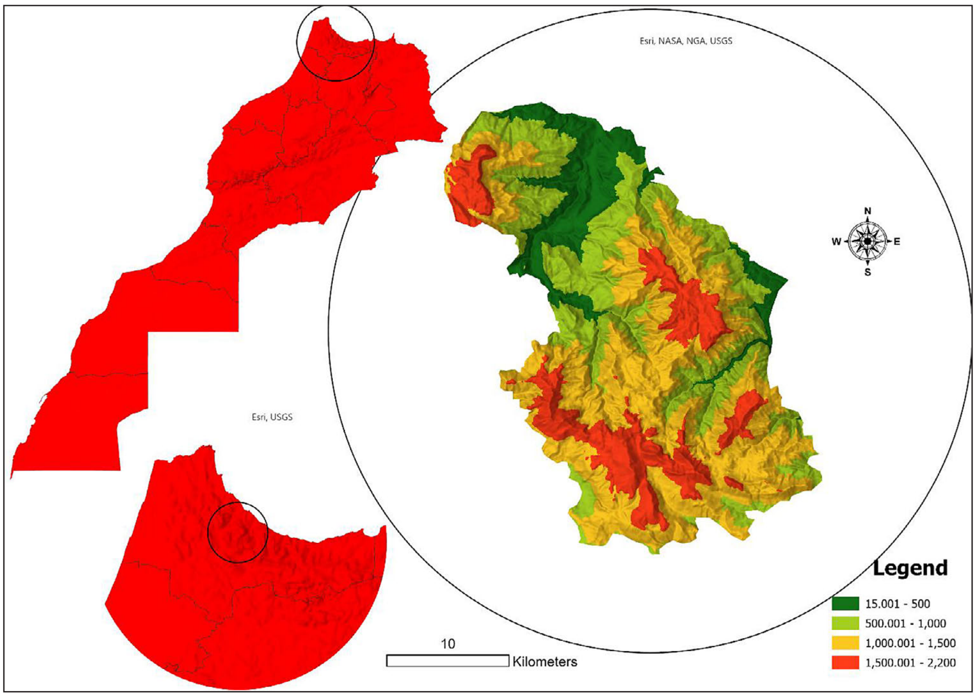

Figure 1. Geographic location of study area

remarkable of which is the fir tree *Abies marocana Trab*. (Aafi, 2000; Alaoui et al., 2025; Ben-Said, 2022; Ben-Said et al., 2020, 2022; Said et al., 2024). The TNP is part of the Mediterranean Intercontinental Biosphere Reserve established between Morocco and Spain (Seijo et al., 2023). Unfortunately, this area is subject to anthropozoogenic pressure, threatening the rare species still in the region (Said et al., 2024). Several recent studies have shown an alarming trend of degradation affecting the Park's natural stands (Chemchaoui et al., 2025; Lamrhari et al., 2025). The factors of degradation point to forest fires, illegal logging, land clearing for the extension of cropland, particularly cannabis, overgrazing (Boubekraoui et al., 2024; Boubekraoui et al., 2023; Chemchaoui et al., 2025).This degradation does not only concern the park but also affects the entire Rif region (Taïqui, 1997). the advanced degradation in the area calls on the authorities, Non-Governmental Organizations and the local community for urgent intervention and the adoption of practices that offer a balance between development and conservation (Boubekraoui et al., 2023; Derak et al., 2018, 2024).

Datasets

LULC maps from 1995 and 2000, produced in the previous study (Chemchaoui et al., 2025), were used as inputs in modules for land use change evaluation (MOLUSCE) (Figure 2 and 3). The spatial variables used were slope, distance to building, distance to road, and distance to water (Figure 4).

Geoprocessing analysis using MOLUSCE plug in

The MOLUSCE is a dedicated plugin within QGIS used to achieve LULC change detection

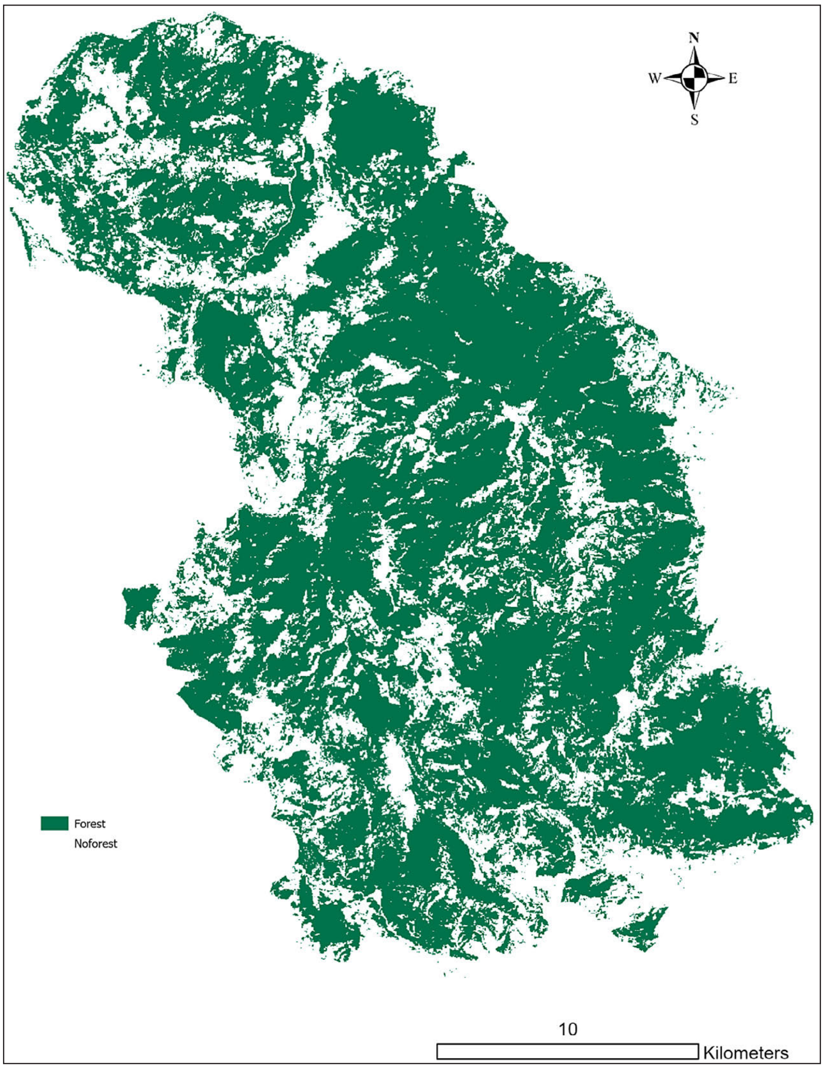

Figure 2. LULC of 1995 used as input in MOLUSCE (Chemchaoui et al., 2025)

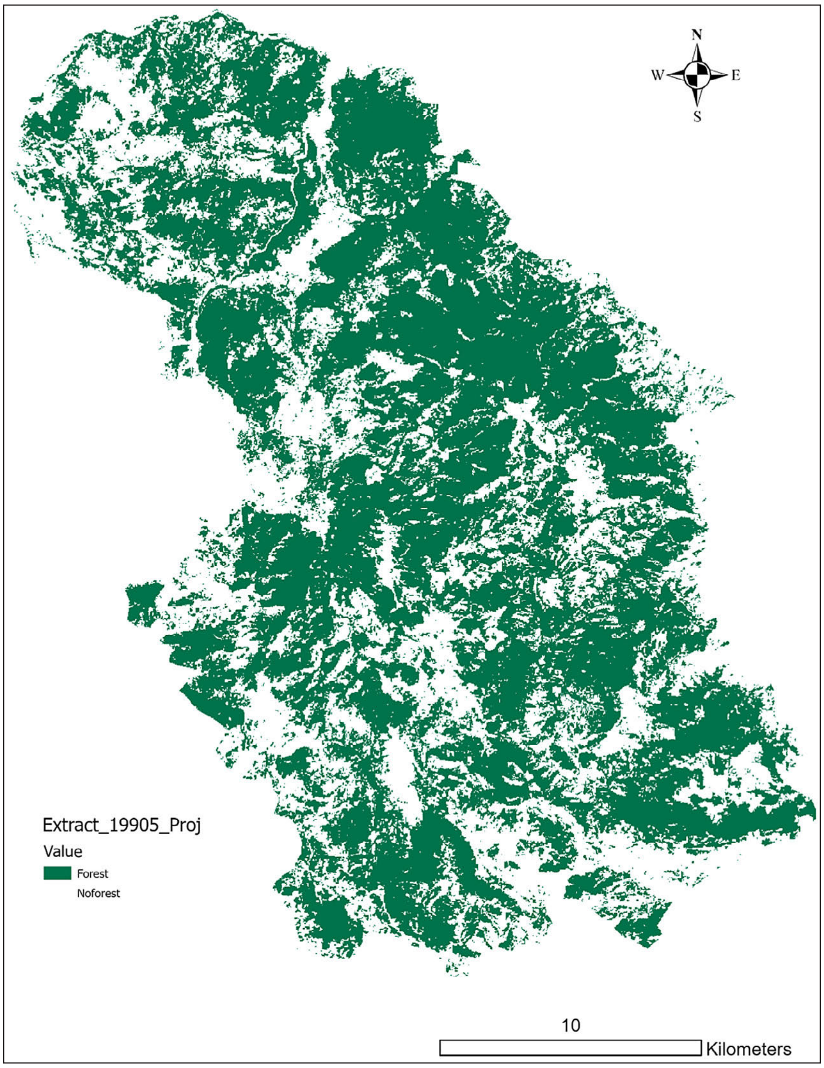

Figure 3. LULC of 2000 used as input in MOLUSCE (Chemchaoui et al., 2025)

and prediction. MOLUSCE enables users to analyze LULC transition potential and simulates future LULC changes. LULC 1995 used as initial LULC and 2000 as final LULC (Figure 5). First, we evaluate the correlation between the predictors using Pearson's correlation. Matrix provides a correlation value between spatial variables. A very high value indicates a high dependence relation between spatial variables, and it is recommended to exclude one of such predictors from the analysis (Figure 6). Area changes provide valuable information about class statistics and the transition matrix. Class statistics provide an area change per hecares and per percentage between two-year N and N+1. The second table indicates transitions of each class during the period between maps (Figure 7). Transition potential modeling is used to achieve prediction. An Artificial Neural Network or Multilayer Perceptron was used as a method. 1000 samples randomly selected were used to train neural network model (Figure 8).

After training, the model predicts using a cellular automata simulation. A single iteration was used for the 2005 LULC prediction (Figure 9). The 2005 LULC produced in the previous study was used as a reference map, and the simulated LULC was used to achieve an accuracy assessment of the model. The MOLUSCE plug-in provides percentage of correctness and the Kappa index (Figure 10).

Change detection technique

Categorical change analysis was performed in GEE using a Java script to identify changes between two land cover maps (Figure 7). A transition matrix (Figure 8) further details of these changes.

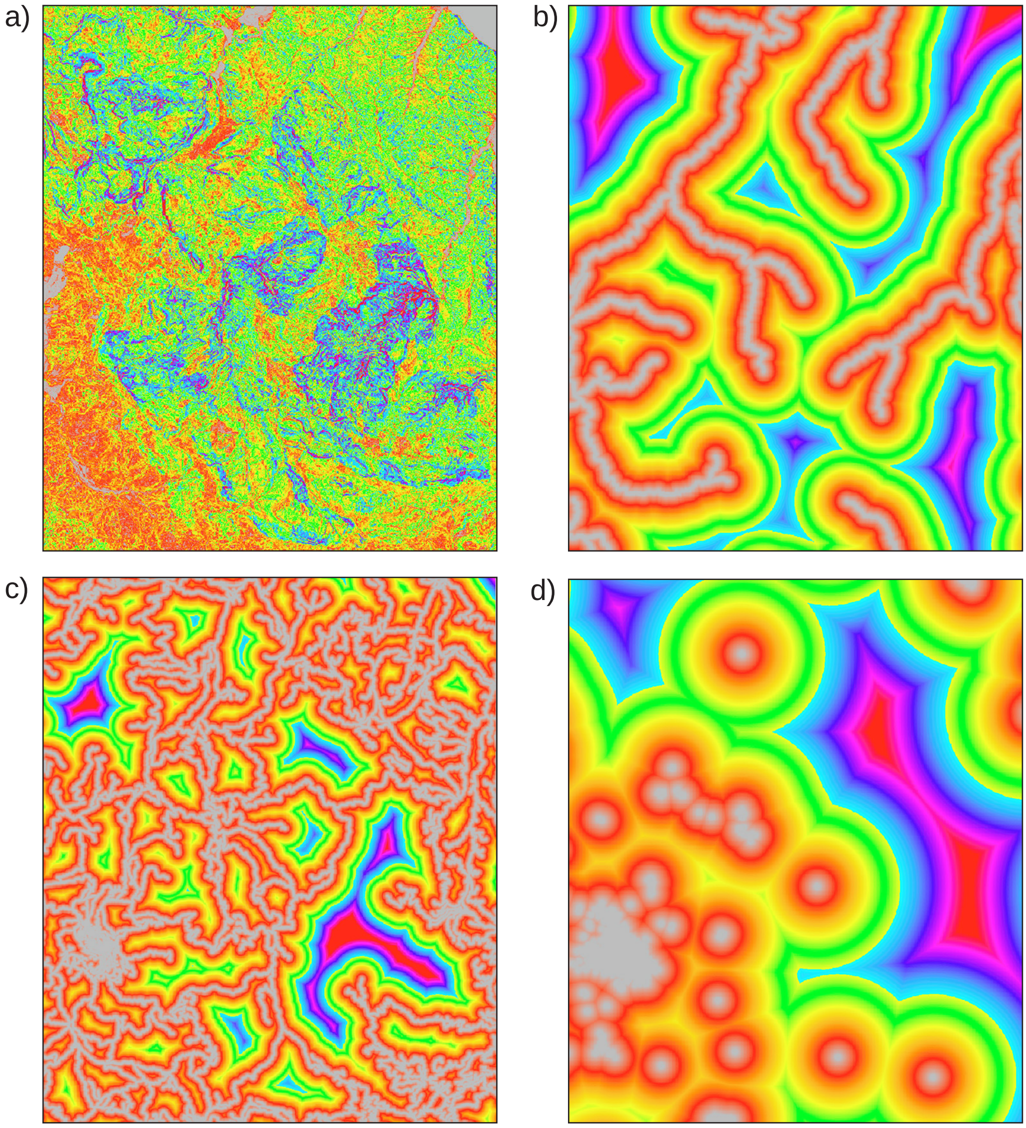

Figure 4. Spatial variables used in the analysis: a) slope; b) distance to water; c) distance to road; d) distance to building

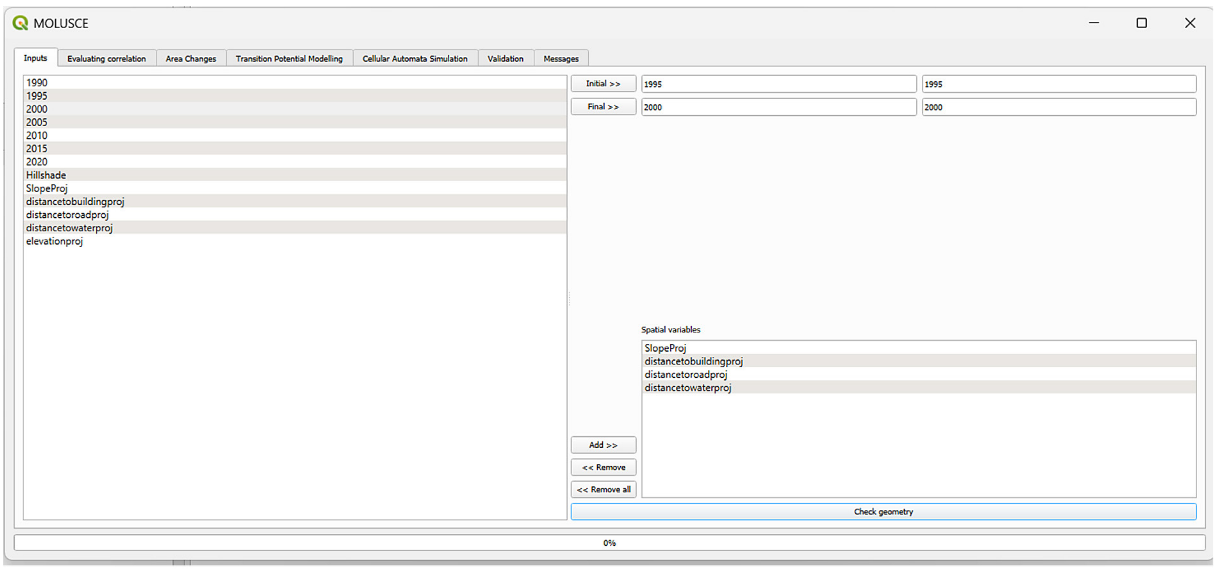

Figure 5. Inputs and spatial drivers used to achieve prediction

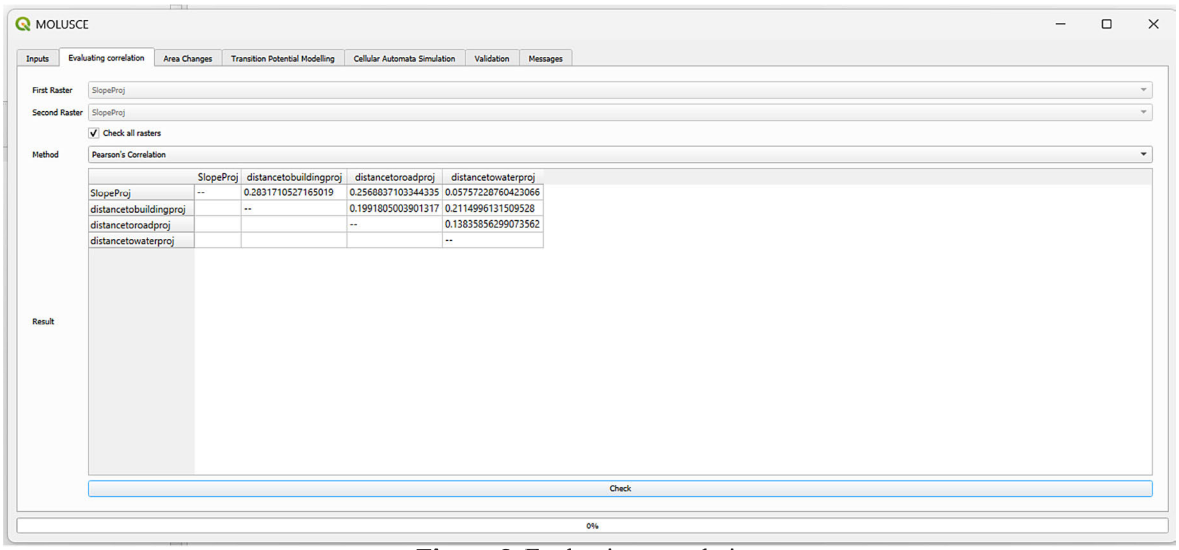

Figure 6. Evaluating correlation

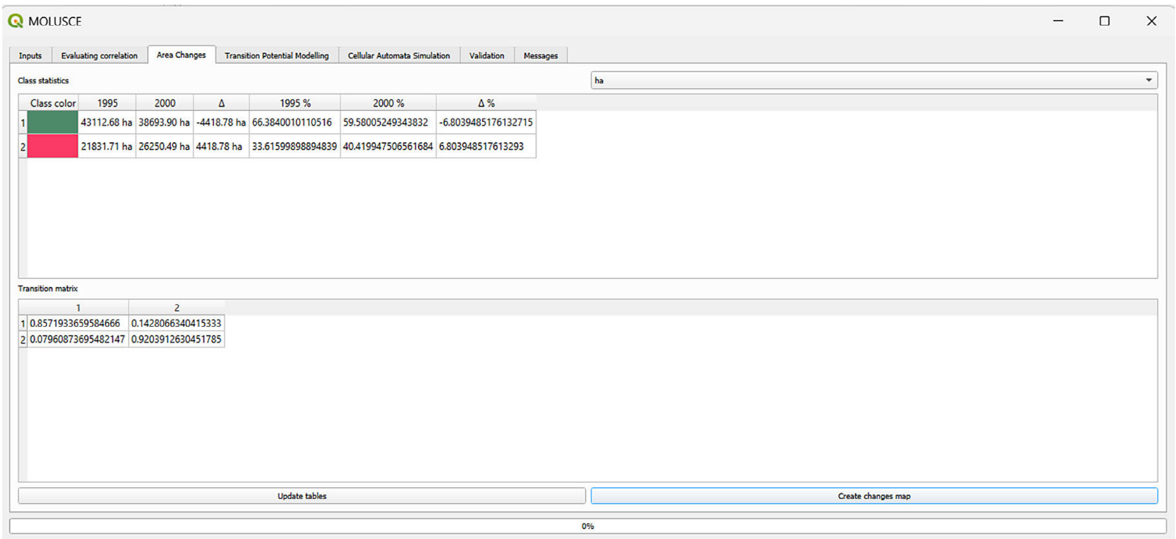

Figure 7. Area changes

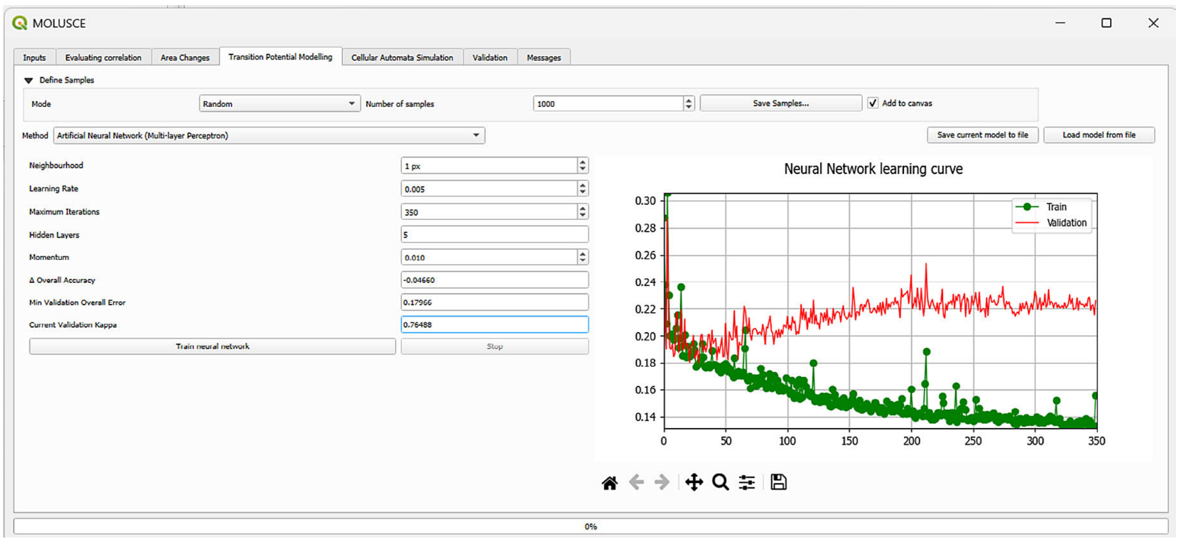

Figure 8. Transition potential modeling

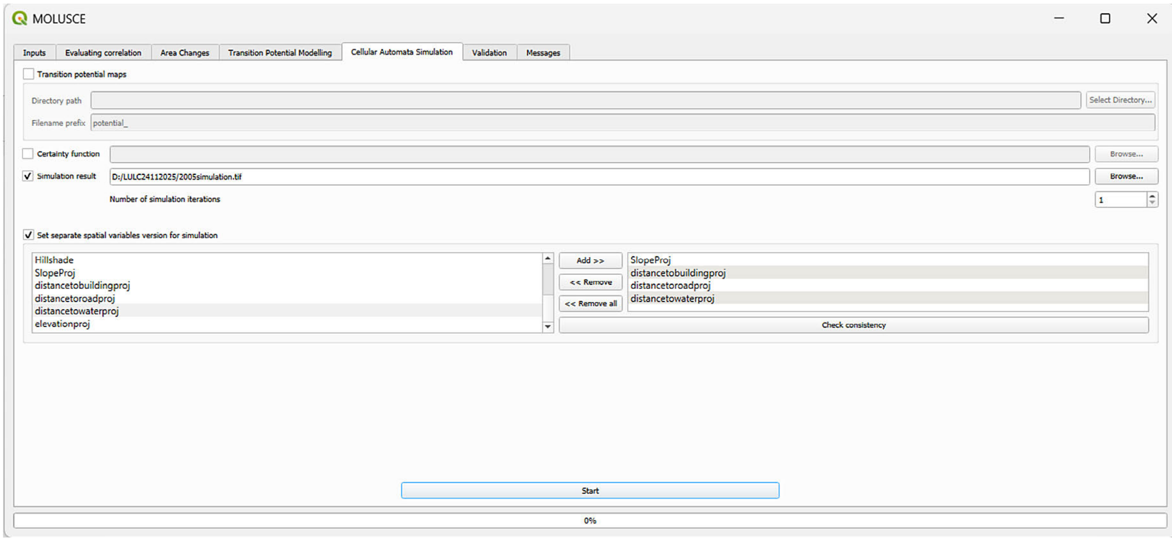

Figure 9. Cellular automata simulation

RESULTS

LULC prediction

2005 LULC simulated

Predicting 2005 LULC serves both to train the model and validate the simulation. Figure 11 shows the prediction results. According to the validation result shown in Figure 10, the model achieves an overall accuracy of 86%, indicating that most predicted pixels matched the classified date. Furthermore, the model produced a Cohen's Kappa coefficient of 71%, which reflects a substantial level of agreement between the predicted and classified LULC classes.

LULC 2040 predicted

Using the previously trained model, we predicted LULC for 2040 (Figure 12). Compared to Chemchaoui et al. (2025), forest cover is projected to decrease from 35,522 hectares in 2024 to 31,254 hectares in 2040 – a loss of 4,286 hectares, representing a 12% decline or 251 hectares per year.

Change detection analysis

Change detection analysis showed a total change of 21.7% of the total change area between 2024 and 2040 (Figures 13 and 14). The transition matrix from Google Earth Engine showed

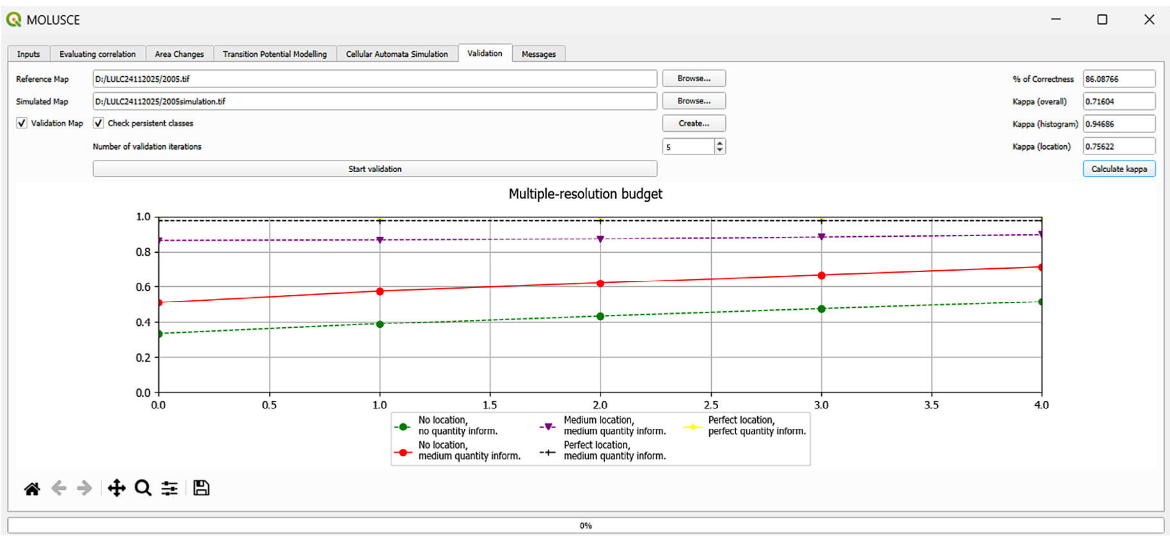

Figure 10. Validation

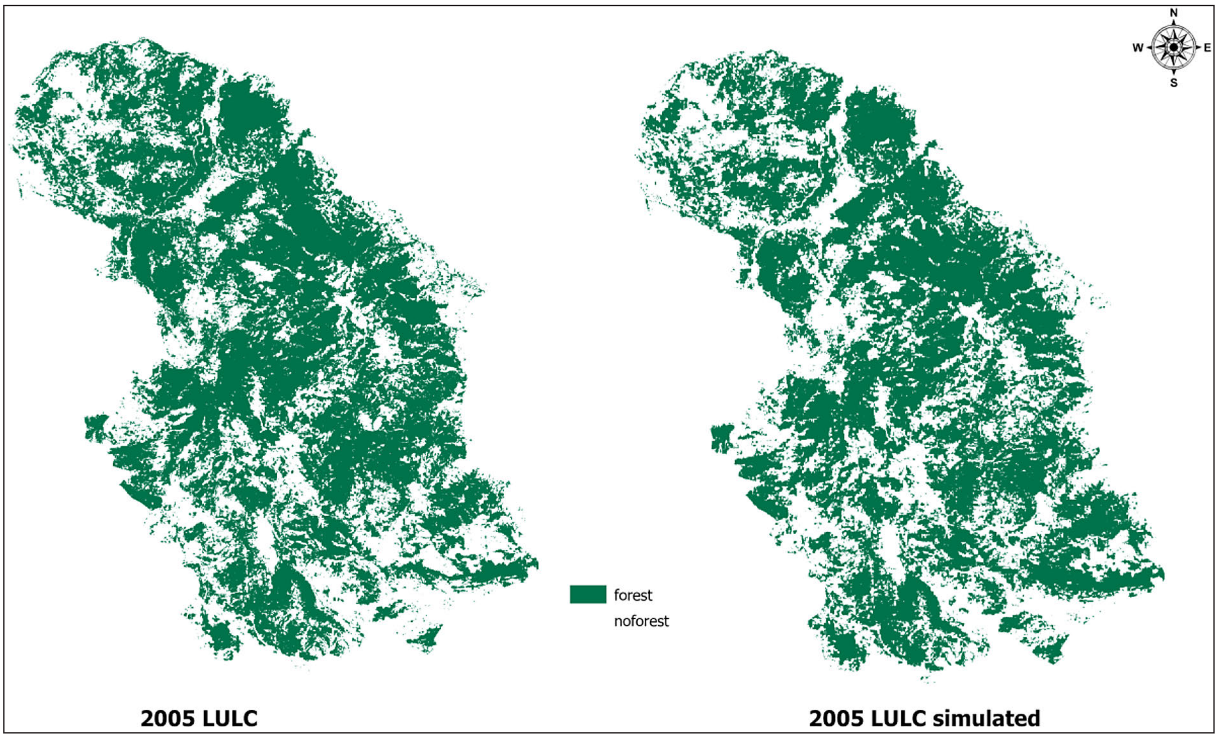

Figure 11. 2005 LULC classified and simulated

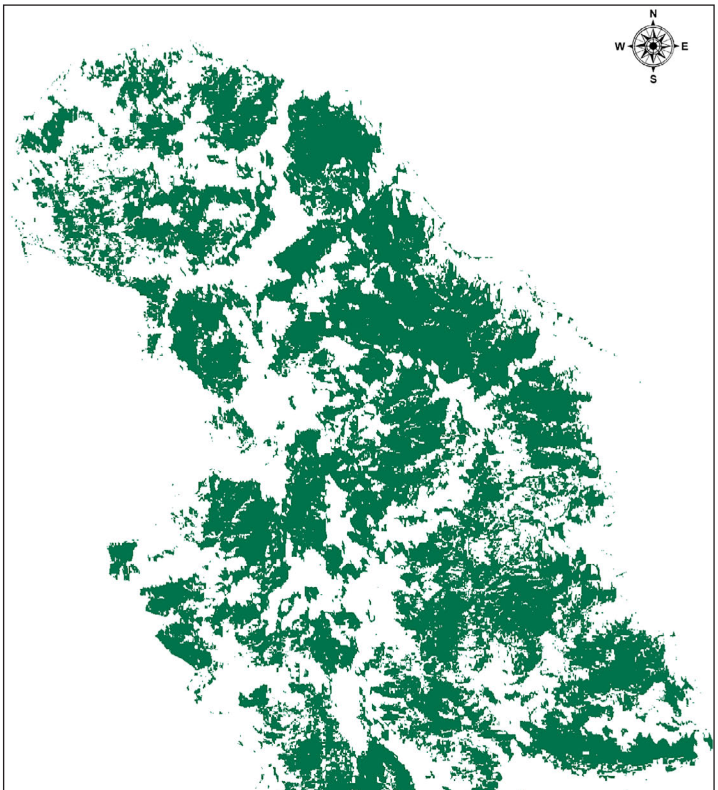

Figure 12. 2040 LULC simulated

that forest cover in TNP accounts for 48.4% of the park's total area (Table 1).

DISCUSSION

This study focuses on modeling and predicting LULC changes to assess forest dynamics in TNP, Morocco, using the QGIS MOLUSCE plugin and artificial neural networks (ANN). The model forecasts a substantial regression in forest cover from 35,522 hectares in 2024 to 31,254 hectares by 2040. The park lost 4.286 hectares of forest—12% of its area—at an average of 251 hectares per year. The study also projects that by 2040, 21.7% of the park will experience land cover change. The transition matrix highlights areas of forest loss, forest gain, and stable non-forest zones. The predictive model achieved an overall accuracy of 86% and a Kappa coefficient of 71%, indicating substantial agreement between predicted and observed LULC classes. The use of

Table 1. Transition matrix result

Parameter		2040 simulated	
		Forest (hectares)	No forest (hectares)
2024 classified	Forest (hectares)	25863	8648
	No forest (hectares)	5391	24734

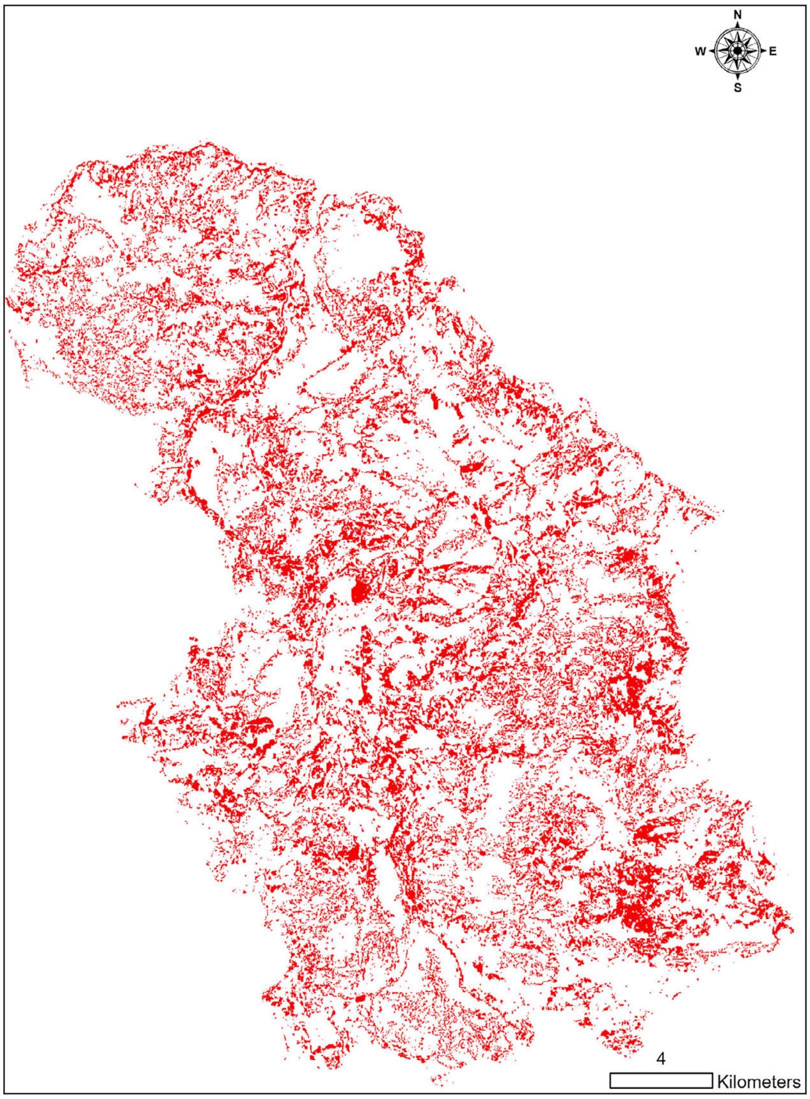

Figure 13. Change detection analysis result 2024–2040

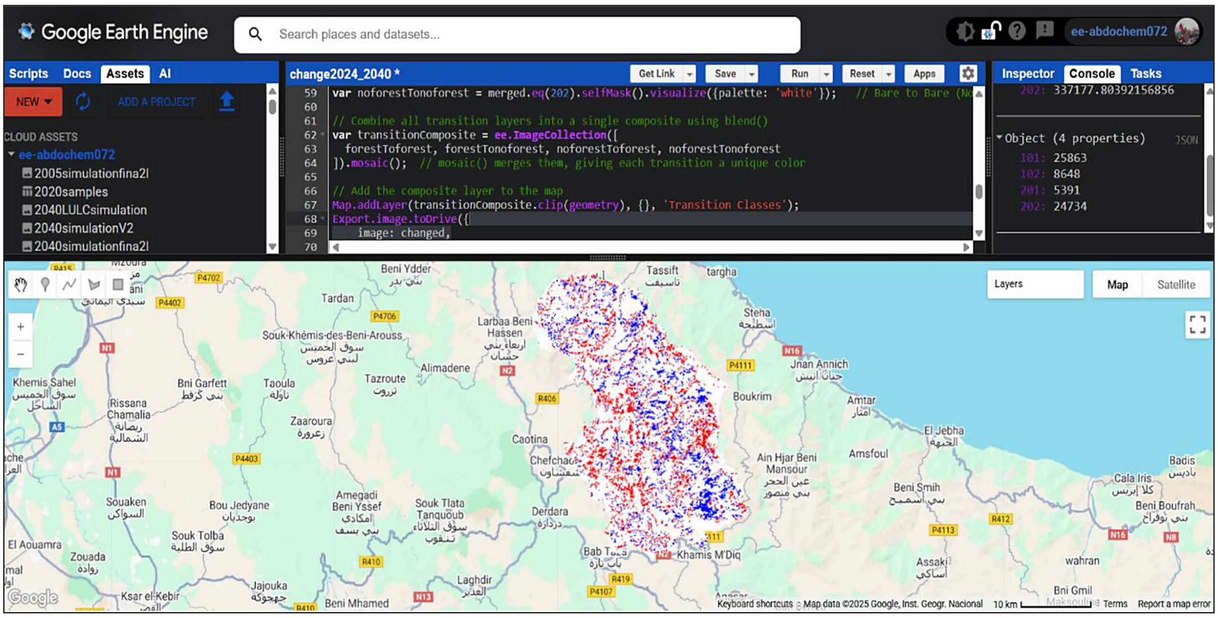

Figure 14. Differentiate tree cover loss (red) from gain (blue)

historical LULC maps (1995, 2000, 2005) and spatial variables (slope, distance to buildings, distance to roads, and distance to water) provided a robust foundation for training the ANN and simulating future scenarios.

The results of this study are consistent with those found in other studies in the region. Recent research has verified ongoing forest degradation in Morocco. The findings of this study revealed that forests were the only category exhibiting a declining trend, underscoring the critical state of forest ecosystems in Morocco (Ben-said et al., 2025). Another key finding is that forest decline is primarily caused by population growth, agricultural and urban expansion, overgrazing, and wood harvesting (Ben-said, 2025). These adverse factors seem to be further intensified by the rising frequency of drought conditions linked to climate change (Ben-said, 2025). Apart from the efforts made by the authorities in charge of forests in Morocco, the rate of degradation has persisted and even doubled over the past five years (Knostmann and Rasoamanana, 2025). Recent Global Forest Change data (2001–2020) shows that Tanger Tetuán Al Hoceima lost an estimated 36,865 hectares of forest cover (Boubekraoui et al., 2024; Boubekraoui et al., 2023). Furthermore, a total of 27 deforestation fronts were identified across this region, distributed evenly among provinces and prefectures (Boubekraoui et al., 2023). The study found that deforestation is driven by direct causes – such as infrastructure and agricultural expansion, wood extraction, and other factors – and indirect causes, including demographic, economic, technological, policy, institutional, and cultural influences (Boubekraoui et al., 2024; Boubekraoui et al., 2023). A study found that the park's forests, which covered 43,600 hectares (67% of its area) in 1990, lost over 18% of their cover, averaging a decline of 240 hectares per year (Chemchaoui et al., 2025). The main limitation was distinguishing between permanent conversion and temporary loss.

CONCLUSIONS

This study provides a comprehensive assessment of forest dynamics in the TNP using advanced geospatial modeling techniques, in particular the MOLUSCE QGIS plugin and artificial neural networks (ANNs). Predictive analysis reveals a worrying trend. The forest cover in the park is expected to decrease from 35,522 hectares in 2024 to 31,254 hectares by 2040, representing a loss of 12% at an average rate of 251 hectares per year. By 2040, forests will cover only 48.4% of the park's area, up from 55% in 2024. The model demonstrated strong predictive performance, achieving an overall accuracy of 86% and a Kappa coefficient of 71%. The main drivers of forest loss are anthropogenic pressures such as fires, illegal logging, agricultural expansion, overgrazing, and infrastructure development compounded by climate change. These findings underscore the urgency of targeted conservation strategies and sustainable land management practices. The study's methodology proposes a scalable approach for other protected areas facing similar threats, providing valuable information for policymakers and resource managers to mitigate forest loss and promote ecological resilience.

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