Evaluation of Agroforestry Suitability in Tazekka National Park: A geospatial approach based on Google Earth Engine

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ABSTRACT

Climate change is having a major impact on the world's forests, compromising their health and resilience. Agroforestry, which consists of integrating trees into agricultural systems, appears to be a solution for strengthening this resilience. This study assesses the suitability of agroforestry in Tazekka National Park, Morocco, using its ecological features to explore the contribution of agroforestry to reducing the effects of climate change. Using Google Earth Engine (GEE), the Land Use and Land Cover (LULC) classification was generated by comparing two major machine learning algorithms: Support Vector Machine (SVM) and Random Forest (RF). The most accurate LULC classification, as determined by the algorithms, was integrated with various environmental variables such as rainfall, temperature, soil pH, soil texture, slope, vegetation indices (NDVI, NDWI), population density, erosion risk, and tree cover. These factors were incorporated into the analysis using Multi-Criteria Analysis (MCA) to calculate and generate a suitability index for agroforestry. The Analytical Hierarchy Process (AHP) was employed to assign weights to the variables based on their relative importance. The results of the LULC classification revealed that SVM outperformed RF, achieving an accuracy of 95.05% compared to 85.15% for RF. The final results produced a more accurate suitability map for agroforestry, effectively identifying areas with low, medium, and high suitability for agroforestry interventions. This research highlights the potential of agroforestry at the local level and proposes a strategic framework for sustainable land management in the face of climate change at regional and global levels.

1. Introduction

1.1 Introduction

Agroforestry is a sustainable land management system which combines trees, crops and or livestock in the same area of land in a way that the species are naturally complementary to each other and support the natural ecosystem and make the resources to be used in a sustainable manner (Slavin, T., 2024). It provides solutions to environmental problems such as deforestation, soil degradation and climate change while improving food security and enhancing the resilience of rural populations (FAO, 2017). Agroforestry is the integration of farming and forestry and is a sustainable land use approach for ecosystem rehabilitation and biodiversity conservation.

Beside the environmental advantages, agroforestry has a key role to play in socio-economic development. It helps in reducing poverty by enhancing the diversification of income sources for farmers by providing timber, fruit, and other non-timber forest products (Lal, 2001). It also offers employment in the tree management, product processing, and rural infrastructure development sectors. The adoption of agroforestry is in conformity with the UN Sustainable Development Goals (SDGs) which include those related to poverty (SDG 1), food security (SDG 2), climate action (SDG 13) and life on land (SDG 15) (FAO, 2021).

Assessing agroforestry suitability requires advanced spatial analysis tools such as Geographic Information Systems (GIS) and remote sensing. These technologies allow for the evaluation of environmental parameters like land use, soil quality, topography, and water availability (Corbeels et al., 2019). Multi-criteria analysis (MCA) further refines site selection by integrating ecological, economic, and social factors, enabling informed decision-making for agroforestry implementation (Malczewski, 2006).

Conducting comparative analyses in agroforestry suitability assessments is pivotal for refining methodologies across diverse environmental and socio-economic contexts. Such studies underscore the effectiveness of spatial analysis, remote sensing, and multi-criteria decision-making in optimizing agroforestry implementation. For instance, Mishra et al. (2023) conducted a GIS-based multi-criteria land suitability assessment in Uttarakhand, India, identifying 93.44 km² as highly suitable for agroforestry expansion. Similarly, in the Kashmir Valley of India, a study utilized the Analytic Hierarchy Process (AHP) and GIS to assess land suitability for mulberry-based agroforestry, aiming to achieve sustainable agriculture. In Rwanda's Musanze District, Ngwijabagabo et al. (2021) applied spatial analysis and mapping techniques, finding that 24.3% of the area was very suitable for agroforestry, with a strong correlation between suitability levels and tree survival rates. Additionally, a study in Fiji employed GIS and multi-criteria decision analysis for land suitability evaluation, facilitating multiple crop agroforestry planning. Collectively, these studies highlight the critical role of geospatial technologies and decision-support frameworks in advancing agroforestry suitability assessments.

Tazekka National Park in Morocco presents an ideal case study for agroforestry adoption. Spanning 13,737 hectares, it is home to diverse ecosystems, including cedar and holm oak forests, but faces significant challenges such as deforestation, soil erosion, and resource pressure from local communities. Traditional farming practices contribute to land degradation, making agroforestry a promising solution for ecological restoration and economic sustainability (Chellik, S., 2024).

This study aims to identify suitable agroforestry areas in Tazekka National Park to combat environmental degradation and socio-economic challenges. By integrating trees into agricultural landscapes, agroforestry restores soils, conserves water and stimulates biodiversity while supporting the livelihoods of rural populations. Despite the worldwide success of GIS and remote sensing in agroforestry planning, Morocco lacks comprehensive studies combining the two methods. This research fills this gap, using advanced spatial analysis for sustainable land-use planning and long-term ecological and economic resilience.

2. Materials and Methods

2.1 Study area

Tazekka National Park is located in the northernmost part of the Middle Atlas, near the city of Taza. The city of Taza is situated northeast of the park, approximately 21 km as the crow flies from the core of the park (Tazekka Cedar) and 46 km by road. The park is part of a remarkable tourist circuit with a total length of 76 km (secondary road No. 311), which starts from the city of Taza, passing near a series of natural attractions (waterfalls, caves, large wooded areas...). It allows travelers to cross particularly picturesque regions: including the classified douar of Sidi Majber, before rejoining the main road No. 1 at Sidi Abdellah, near Oued Amlil (Figure 1).

It was established on July 11, 1950, initially covered 680 hectares, preserving the Atlas cedar forest (Cedrus atlantica) atop the 1,981-meter Tazekka massif. It reflects the historical range of Moroccan cedars, similar to those in the Middle Atlas and Rif. Given that forest ecosystems require larger areas for ecological stability, the park's expansion was proposed in 1993. The extension to 12,700 hectares was officially approved on October 8, 2004, bringing the park to its current 13,737 hectares, encompassing both natural habitats and local villages while maintaining the cedar forest as its ecological core (Saadi, k,. 2023).

· Latitude: Approximately 34° 25' N
· Longitude: Approximately 4° 05' W
· Altitude: Varies from 600 to 1,981 meters above MSL.

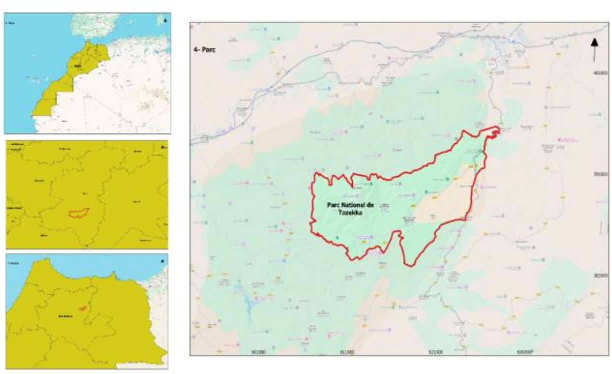


Figure 1. Geographical location of Tazekka National Park: (1): In relation to the country - (2): In relation to the region - (3): In relation to the province - (4): Current boundary of Tazekka National Park

2.2 Method

This study identifies optimal agroforestry zones in Tazekka National Park using geospatial analysis in Google Earth Engine (GEE). An AHP-based multi-criteria evaluation was applied to 11 environmental and socio-economic factors, including land use, climate, soil properties, vegetation indices, and infrastructure.
Data preprocessing involved integrating raster and vector layers into GEE, followed by normalization on a 0–1 scale to ensure comparability across variables. Suitability was assessed based on weighted factors, with uniform weights at first and then different weights according to the importance of each variable. The final suitability index, calculated by combining the normalized and weighted values, was classified into five categories ranging from "very low" to "very high" suitability.

Validation using Random Forest and Support Vector Machine, along with zonal statistics and variance mapping, confirmed model reliability. The resulting suitability map provides a robust tool for sustainable agroforestry planning, balancing ecological conservation with rural development. GEE ensures scalability and reproducibility for dynamic land-use assessments.(Figure 2)

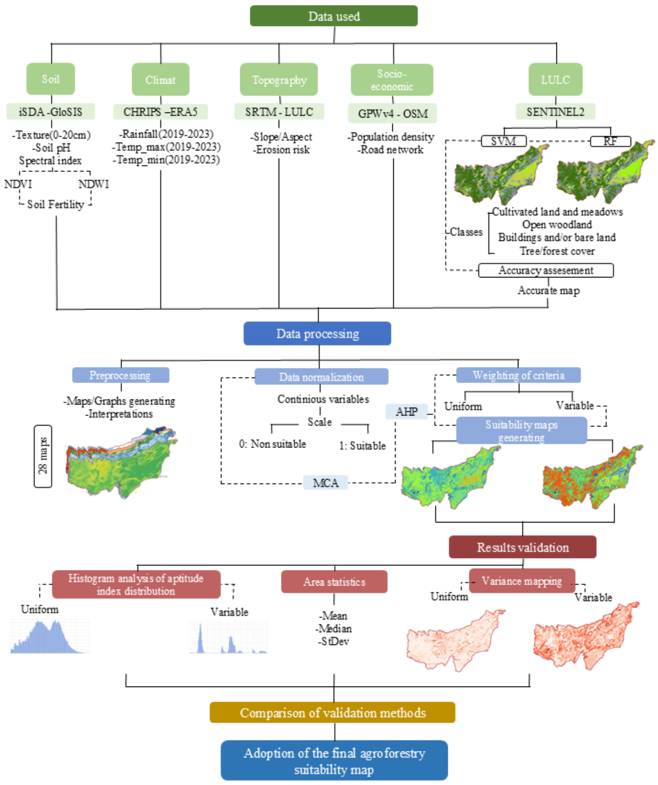


Figure 2. Methodology Flowchart

2.3 Data used

Our comprehensive agroforestry suitability assessment of Tazekka National Park integrated 11 distinct spatial datasets: land use/land cover maps, annual precipitation records (2019-2023), temperature extremes, soil texture and pH measurements, vegetation indices (NDVI and NDWI), tree cover percentages, population density figures, road network data, soil erosion estimates, and topographical parameters (slope and aspect). These datasets, categorized into four key domains (soil, climate, topography, and socioeconomics) (Table 1).

Criteria	Variable	Unit	Data Source
Soil	Texture		iSDA
	Ph	-log(H^+)	GloSIS
	NDVI		COPERNICUS/S2_SR
	NDWI		COPERNICUS/S2_SR
Climat	Rainfall	mm	CHIRPS
	Min Temp	°C	ERA5-Land
	Max Temp		
Topography	Erosion		LULC
	Aspect and slope	° (dégrée)	SRTM
Socioeconomic	Population Density	Hab/km^2	GPWv4
	Road Network		OSM

Table 1. Data list

2.3.1 Annual precipitations records

Precipitation is a key factor in agroforestry management, influencing water availability, crop productivity, and ecosystem health. This study uses CHIRPS data for 5 years from 2019 to 2023 to provide insights for optimizing irrigation, ensuring water availability, and mitigating drought risks (Morales, I,. 2023). Integrating precipitation data into agroforestry planning enhances resource efficiency, soil moisture retention, and ecosystem resilience.

2.3.2 Temperature extremes

Minimum and maximum temperatures are key determinants of plant growth, climate adaptation, and risk management in agroforestry. This study leverages five years (2019–2023) of high-resolution ERA5-Land reanalysis data to analyze temperature variability (Muños Sabater, J,. 2021). These insights aid in optimizing plant selection, mitigating thermal stress, and enhancing climate resilience in agroforestry systems.

2.3.3 Soil texture

Soil texture influences water retention, nutrient availability, and plant growth in agroforestry systems. This study utilizes USDA soil texture classifications for depths of 0–20 cm and 20–50 cm, derived from iSDA's machine learning models trained on over 100,000 soil samples with 30 m resolution. These insights support soil fertility management, water optimization, and sustainable land use in agroforestry (USDA, 2011).

2.3.4 pH measurements

Soil pH regulates nutrient availability and plant health, shaping agroforestry productivity (Khaled, F,. 2023). This study uses OpenLandMap soil pH data (measured in water) at six depths (0–200 cm) with a 250 m resolution. As a key soil chemistry indicator, pH influences nutrient uptake and ecosystem balance, guiding soil amendments and sustainable land management.

2.3.5 Vegetation indices (NDVI and NDWI)

The Normalized Difference Vegetation Index (NDVI) assesses vegetation health and density, aiding agroforestry suitability analysis. Derived from Sentinel-2 imagery, it identifies vegetation cover and ecosystem vitality (Lasaponara, R., 2022). Similarly, the Normalized Difference Water Index (NDWI) detects water bodies, supporting water resource management by tracking water availability and mitigating flood risks for sustainable land use (Du, Y., 2016).

2.3.6 Tree cover percentages

Tree cover percentage data helps assess vegetation density and forest extent, vital for agroforestry suitability. It guides land-use planning, ensuring optimal conditions for both ecological health and agricultural productivity while supporting sustainable agroforestry and forest conservation (FAO, 2020).

2.3.7 Soil erosion estimates

The erosion risk map highlights areas vulnerable to soil erosion, crucial for sustainable land management. For Tazekka National Park, an integrated approach combined multiple datasets: precipitation data (R factor), SRTM elevation data (LS factor), Sentinel-2 NDVI (C factor), and reclassified LULC data (K factor). These factors, along with a constant P factor, were multiplied to generate the final erosion risk map (Elnashar, M., 2021). This analysis aids in soil conservation, guiding agroforestry planning and interventions to reduce land degradation and ecosystem deterioration.

2.3.8 Topographical parameters (slope and aspect)

Slope and aspect data, derived from SRTM, describe terrain inclination and orientation, critical for erosion and water management in agroforestry. Slope affects runoff, soil retention, and land stability, guiding agroforestry practices. Additionally, terrain steepness impacts accessibility, influencing the feasibility of agroforestry interventions and project implementation (Geopard, 2019).

2.3.9 Population density

Population density data, sourced from GPWv4 (2000-2020), offers insights into human distribution and its impact on natural resources. With a 30-arc-second resolution (~1 km), this data is crucial for assessing resource pressure and guiding sustainable development strategies, ensuring a balance between human needs and environmental conservation (Liu, L., 2024).

2.3.10 Road network

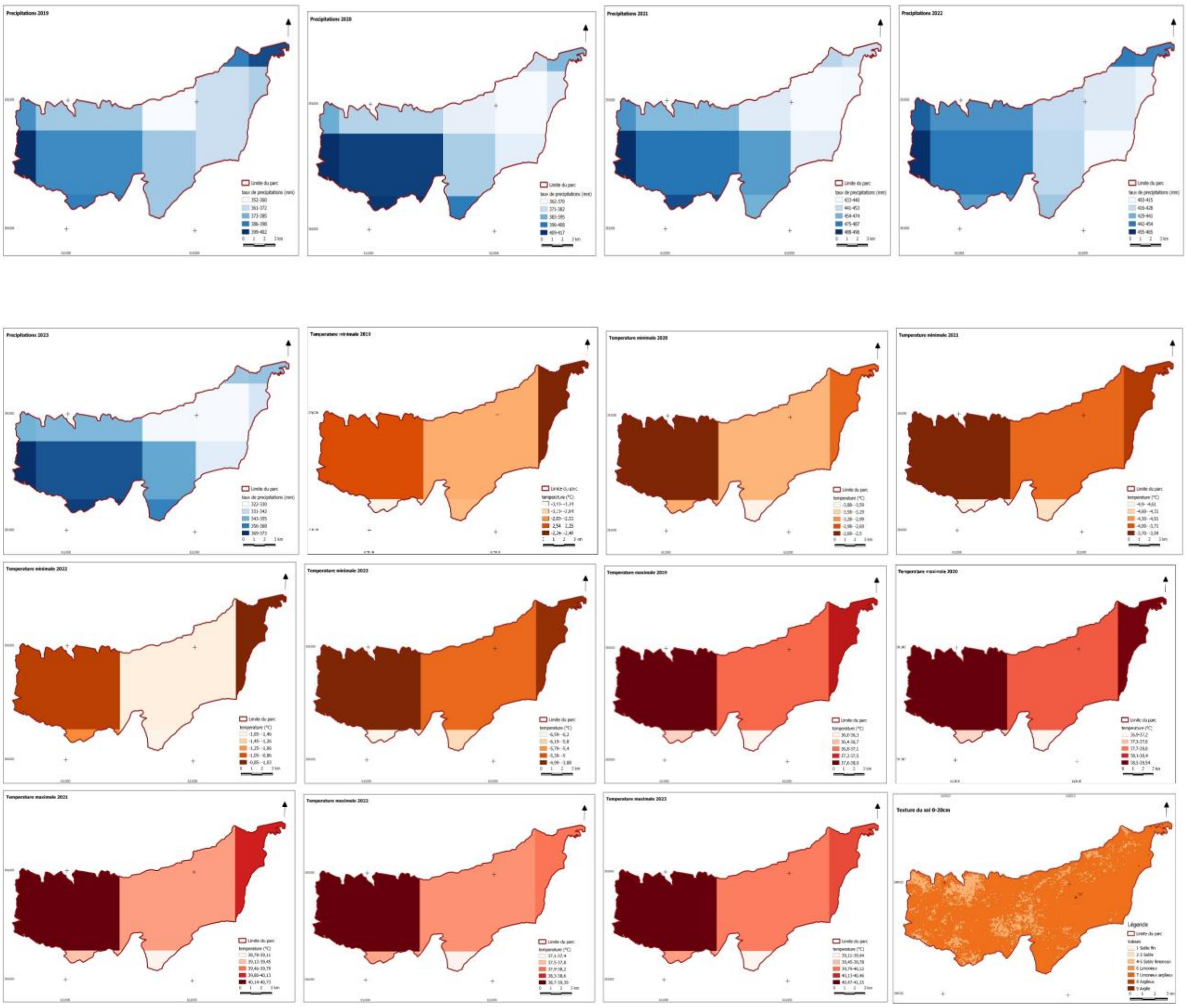
Road network data, sourced from OpenStreetMap (OSM), provide valuable insights into transportation infrastructure. These data influence not only access to study sites but also the management of natural resources in the region, facilitating efficient planning and resource distribution (Hosseini, R., 2025).

2.3.11 Land use/Land Cover maps

LULC (Land Use/Land Cover) data describe land use types and coverage, crucial for understanding the current and future impacts of agroforestry practices (Santoso, T., 2024). This data helps identify coverage types, plan land use, and assess environmental impacts, supporting sustainable land management and agroforestry planning.

2.4 Data preprocessing

Data preprocessing is a critical step in the preparation of geospatial data for analysis, particularly when working with environmental variables in Google Earth Engine (GEE). In this phase, 28 raster maps are created for each relevant variable, utilizing specific codes in GEE. These maps represent various environmental parameters that are crucial for understanding the suitability of land for agroforestry. The creation of these raster maps involves extracting, processing, and transforming raw satellite data into a consistent format that can be used in subsequent analysis. These maps will serve as the foundational input for the final suitability mapping analysis, where they will be combined to identify optimal locations for agroforestry based on various ecological and environmental factors. This preprocessing ensures that all variables are standardized and ready for in-depth spatial analysis, enabling informed decision-making in land-use planning. (Figure3).



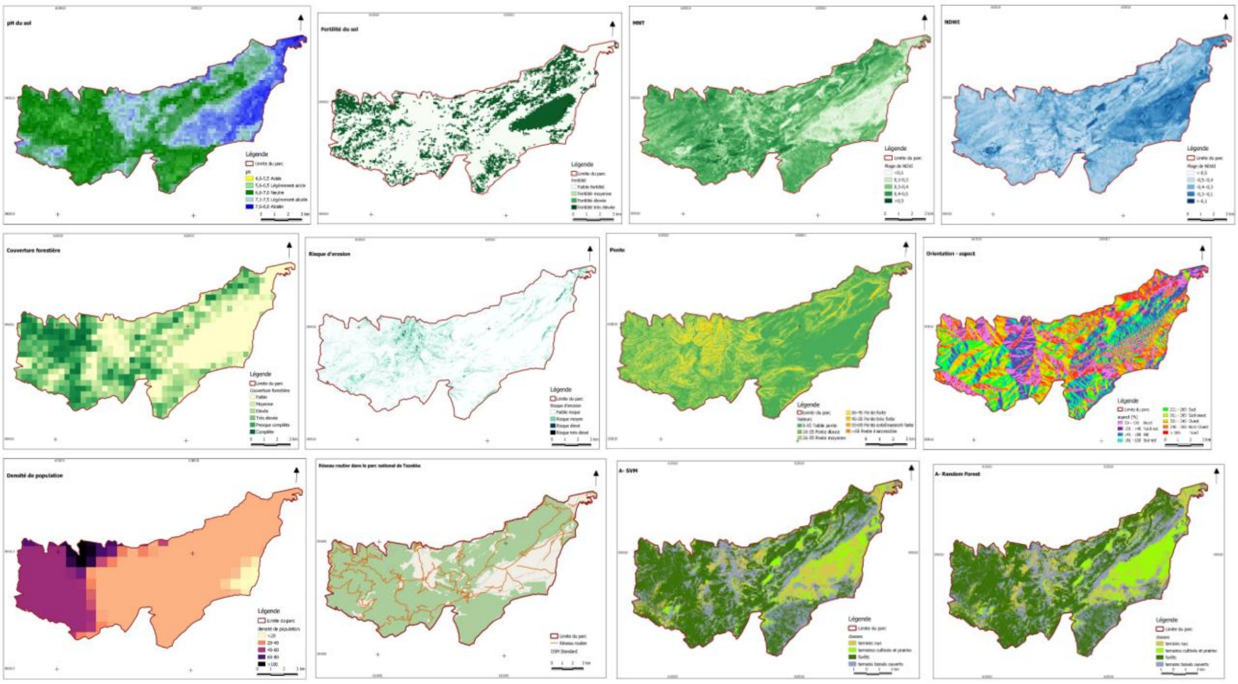


Figure 3. Generated maps using GEE: from top left: Annual Rainfall accumulations of 2019 - Annual Rainfall accumulations of 2020 - Annual Rainfall accumulations of 2021 - Annual Rainfall accumulations of 2022 - Annual Rainfall accumulations of 2023 - Annual Rainfall accumulations of 2019 – Annual minimum Temperature of 2019 - Annual Minimum Temperature of 2020 - Annual Minimum Temperature of 2021 - Annual Minimum Temperature of 2022 - Annual Minimum Temperature of 2023 – Annual Maximum Temperature of 2019 - Annual Maximum Temperature of 2020 - Annual Maximum Temperature of 2021 - Annual Maximum Temperature of 2022 - Annual Maximum Temperature of 2023 – Soil Texture (0-20cm) – Soil pH level – Fertility level - NDVI – NDWI – Tree cover – Erosion Risk – Slope – Aspect – Population density – Road network – LULC(SVM) – LULC (RF)

2.5 Methods and algorithms used in GEE

2.5.1 Supervised classification

Supervised classification is a machine learning technique that uses labeled data to create predictive models for classifying unlabeled datasets, particularly in GIS and remote sensing. It analyzes variables like vegetation, land use, slope, temperature, and soil texture to assess agroforestry suitability, segmenting areas based on their capacity for integrating trees, crops, and livestock. Popular algorithms include Random Forest (RF) and Support Vector Machine (SVM), both of which excel at handling large, diverse datasets and producing accurate maps for agroforestry planning (Kasahun, M., 2024).

- **Random Forest (RF)**

Random Forest is a classifier consisting of multiple tree classifiers, each casting a vote for the most frequent class based on input data. It operates on independent, identically distributed random vectors (Van der Aalst, 2016).

- **Support Vector Machine (SVM)**

SVM is a classification algorithm that finds the optimal hyperplane to separate data classes by maximizing the margin between them. It uses support vectors to define this hyperplane (Liu et al., 2021). For nonlinear data, SVM employs kernel functions, like the Radial Basis Function (RBF), to project data into higher dimensions for linear separation and complex relationship modeling.

When analyzing the performance of both classifiers, SVM demonstrated a higher level of precision than RF. According to the confusion matrix analysis, the overall accuracy for SVM was 92.21%, slightly surpassing RF's 91.61%. The Kappa index for SVM was 0.896, reflecting better agreement between predicted and actual classifications compared to RF's 0.888. Although RF performed well with land categories like cultivated land (90.7% accuracy), SVM excelled, especially in classifying forests (100% accuracy). Additionally, SVM showed slightly better classification precision for built-up areas (97.4% accuracy) compared to RF. While RF was strong in classifying agricultural areas, SVM's superior performance in forest and built-up area classifications makes it the more precise choice overall.

2.5.2 Multicriteria analysis

Multi-criteria analysis is a method used to combine various evaluation criteria to obtain an integrated measure of an area's suitability (Mushtaq et al., 2024). This approach is essential for agroforestry suitability assessment as it considers a range of environmental and socio-economic factors.

- **Weighting of criteria**

Weighting of criteria is a crucial component of multi-criteria analysis, reflecting the relative importance of each factor in evaluating agroforestry suitability. Weights can be determined by experts or using quantitative methods like the Analytical Hierarchy Process (AHP), and these weights directly impact the final suitability score (Topuz et al., 2023). The suitability score

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is calculated by multiplying normalized values of criteria by their respective weights, creating a composite score that integrates multiple factors into a single suitability index, thereby facilitating informed decision-making.

Suitability Formula (Suitablity index)

Composite Score: $S = \sum_{i=1}^{n} \omega_i \cdot C_i$

where S = overall suitability score
ωi = weight assigned to criterion *i*
Ci = normalized value of criterion *i*
n = total number of criteria considered

This formula calculates a composite score by weighting and normalizing criteria, commonly used in multi-criteria decision systems for agroforestry suitability assessments. It integrates individual criterion contributions for an overall evaluation (Schepaschenko et al., 2011).

- **Data Normalization**

Data normalization ensures comparability of criteria with different scales and units by transforming values onto a uniform scale (0 to 1), using methods like min-max or z-score normalization. This ensures a fair and balanced evaluation (GeeksforGeeks, n.d.).

Min-Max Normalization Formula:

Transformation : $C_{norm} = \frac{C - C_{min}}{C_{max} - C_{min}}$

where *Cnorm* = normalized value
C = original value
Cmin = minimum value of the criterion
Cmax = maximum value of the criterion

The Min-Max normalization method scales data to a common range (usually 0 to 1), allowing for fair comparison of diverse criteria. It is commonly applied in multi-criteria assessments, like agroforestry suitability analysis, to ensure all variables contribute equally to the decision process (GeeksforGeeks, n.d).

- **Analytic Hierarchy Process (AHP)**

The Analytic Hierarchy Process (AHP) is a decision-making method that structures complex problems by organizing criteria in a hierarchy. It is used in agroforestry suitability assessments to weight factors like soil quality, climate, and accessibility. AHP involves defining the problem, creating a hierarchy, making pairwise comparisons of criteria on a 1-9 scale, and calculating weights using eigenvalue methods, with the largest eigenvalue (λmax) determining the relative importance of each criterion (Kahsay, A., 2024).

$$\lambda_{max} = \sum \omega_i$$

where *λmax* = the maximum eigenvalue of the matrix,
ωi = the weight of each criterion.

And then in order to check the consistency of judgments, the Consistency Ratio (CR) is used. A CR less than 0.1 is generally considered acceptable. The CR is calculated as follows:

$$CR = \frac{CI}{RI}$$

where *CI* = the Consistency Index, calculated as:

$$CI = \lambda_{max} - n(n-1)$$

RI = the Random Index, which depends on the matrix size. Final results are synthesized, and the weights are calculated to obtain a global score that evaluates agroforestry suitability, helping make informed decisions about the most suitable areas for agroforestry. (Table 2)

Var N°	Factor		Weight
1	Rainfall		0.08
2	Temperature		0.08
3	Slope		0.08
4	Soil texture		0.08
5	Tree cover		0.08
6	Erosion risk		0.08
7	NDWI		0.08
8	NDVI		0.08
9	Population density		0.05
10	pH		0.05
11	LULC	Cultivated land and meadows	0.40
		Open woodlands	0.10
		Buildings and/or bare lands	-0.40

Table 2. Estimated weight for each variable

3. Results and Discussion

3.1 Agroforestry suitability napping

Agroforestry, combining agriculture and tree management, requires a thorough analysis of environmental factors to identify suitable areas. We mapped agroforestry suitability by considering soil texture and fertility, pH, slope, population density, erosion, vegetation cover, and other climatic and geophysical elements. Each factor plays a vital role in assessing land suitability for sustainable agroforestry systems. For instance, well-drained, fertile soils promote tree and crop growth, while steep slopes and erosion-prone areas present challenges. Our mapping approach, using remote sensing and geospatial tools like GEE, integrated data from multiple sources to generate accurate agroforestry suitability maps, highlighting optimal zones and how environmental factors influence land suitability. These results serve as a valuable resource for decision-makers and land managers to support sustainable natural resource management. For the analysis, we normalized variables like slope, NDVI, soil texture, forest cover, precipitation, temperature, erosion risk, population density, pH, and NDWI to a scale from 0 to 1 to ensure consistency across factors. In weighting the factors, we first applied equal weights to all variables for an initial suitability map. However, recognizing local variations, we later adjusted the weights based on each factor's relative importance—soil quality and population density received higher weights, while erosion and slope were less influential in certain areas. This approach resulted in a more accurate suitability map, identifying low, medium, and high suitability zones for agroforestry

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interventions. The weights assigned were designed to reflect the relative importance of each factor, with cultivated and pasture lands receiving the highest weight (0.40), while buildings were assigned a negative weight (-0.40), as they reduce available land for agroforestry. (Figure 4)

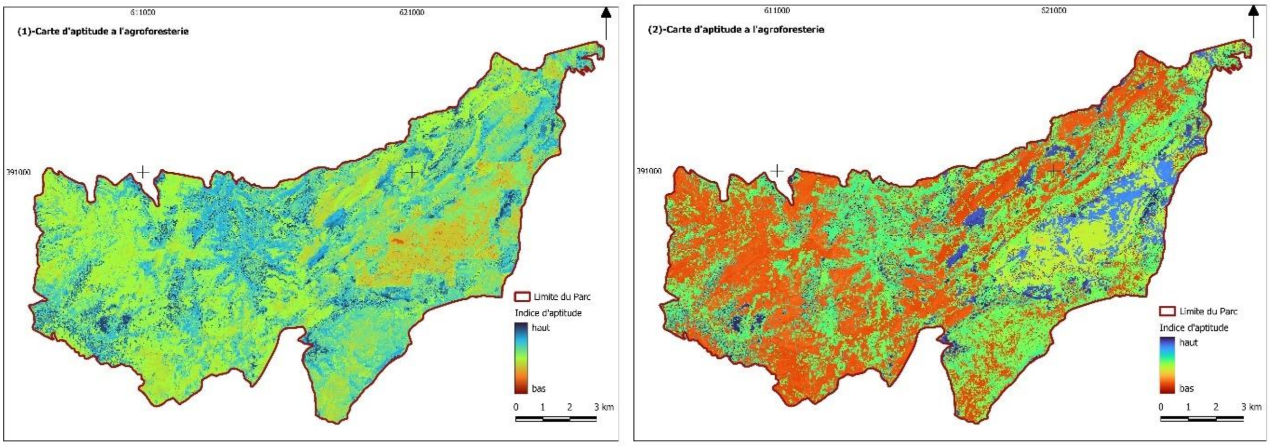

Figure 4. Suitability maps for agroforestry in Tazekka National Park - (1): with uniform weights - (2): with variable weights

3.2 Results validation

By comparing two methods of spatial analysis of suitability for agroforestry, we found significant differences in accuracy and local relevance. The first approach, which applied equal weights to all variables, produced a uniform suitability map, oversimplifying the region and neglecting critical factors such as slope, soil texture, and population density. This approach failed to capture the complexity of the landscape and its suitability for agroforestry.

On the other hand, the second approach, which applied differentiated weightings to the variables, produced a much more nuanced and realistic assessment. It effectively highlighted areas of varying suitability—high, medium, and low—by incorporating local conditions into the analysis. This approach better reflects the various environmental and socio-economic factors that influence the success of agroforestry.

Given the lack of local data on agroforestry, direct validation was not possible. Instead, alternative methods such as suitability index distribution, zonal statistics, and variance mapping were employed to assess model reliability. The first approach showed little variability, while the second displayed a much wider range of suitability, aligning more closely with actual land conditions.

The second method (Figure 4 (2)), which utilizes variable weighting, offers a more precise, nuanced, and contextually relevant depiction of agroforestry suitability. This approach facilitates better decision-making and enhances planning by identifying areas that are most suitable for successful agroforestry interventions, ensuring effective allocation of resources.

3.3 Discussion

The study at Tazekka National Park uses Multi-Criteria Analysis (MCA) and Google Earth Engine (GEE) to find the most suitable agroforestry zones. It combined classification methods like Random Forest (RF) and Support Vector Machine (SVM) with a variety of environmental factors, such as temperature, precipitation, slope, soil properties, and vegetation indices. Outstanding accuracy ratings of 92.21% for SVM and 91.61% for RF were achieved with this combined approach. To increase the validity and applicability of the findings, the study did, however, also point out a number of limitations that need to be investigated.

Since the results mostly depended on indirect remote sensing data, the lack of field validation is a major drawback that could lead to errors when compared to actual ground conditions. Furthermore, the satellite imagery's resolution was inadequate to adequately depict fine-scale topography differences, including small-scale ridges or depressions, or to capture vital water resources concealed beneath thick tree canopies. Additionally, crucial soil characteristics like permeability and drainage depth were not included, which affected the precision of water retention evaluations and might have resulted in overestimations or underestimations of the land's suitability for agroforestry.

The failure to include land policy issues, which are essential to the viability and deployment of agroforestry systems, is another significant drawback. The study's recommendations might not be entirely feasible or sustainable in practice if local land management laws and policies are not taken into account.

Although MCA was successful in combining different agroforestry suitability criteria, it might be greatly improved by adding more advanced artificial intelligence (AI) methods like neural networks and data envelope analysis (DEA). These techniques could improve the impartiality and accuracy of the suitability evaluation by offering greater insights into intricate, nonlinear interactions between environmental variables.

Long-term monitoring of important environmental and land-use variables will be crucial to adjust to the difficulties presented by climatic variability and guarantee their resilience by so improving agroforestry plans. Future studies in this field should combine more thorough soil data covering important factors like permeability and drainage depth with on-site validation, higher-resolution images from sources including the Mohammed VI satellite, LiDAR, and drones. Including land policy analysis will also offer a more all-encompassing method of agroforestry design, therefore guaranteeing that plans are both socially feasible and ecologically sustainable.

4. Conclusion

The agroforestry suitability analysis in Tazekka National Park highlighted the critical role of variable weighting in result accuracy. Initially, assigning equal weights to all variables led to imprecise assessments, underestimating or overestimating key areas. Adjusting the weights significantly improved accuracy, revealing the dominant influence of factors like rainfall, temperature, and slope in identifying optimal agroforestry zones. These findings emphasize the need for tailored approaches that consider local environmental complexities. The results provide valuable insights for sustainable park management, helping balance conservation with local livelihoods by promoting agroforestry systems that enhance biodiversity, prevent soil erosion, and support rural communities. Integrating this research into long-term strategies can strengthen ecosystem resilience against climate change and land degradation. Beyond Tazekka, this study serves as a model for regional agroforestry planning, encouraging data-driven decision-making to address soil degradation, biodiversity loss, and food security challenges. By promoting agroforestry, communities can diversify incomes, improve food security, and enhance environmental sustainability. Ultimately, this research lays the groundwork for practical, scalable agroforestry solutions, fostering ecological and economic sustainability while informing broader natural resource management initiatives.

References

Corbeels, M., Marchão, R. L., Neto, M. S., Ferreira, E. G., Madari, B. E., Scopel, E., & Brito, O. R. (2019). *Evidence of limited carbon sequestration in soils under no-tillage systems in the Cerrado of Brazil. Scientific Reports*, 9(1), 1-13.

Chellik, S., Dbiba, Y., Mansouri, I., Squalli, W., Achiban, H., el Agy, A., & Zidane, L. (2024). Characterization of Natural Ecosystems, Biodiversity, Socioeconomic and Infrastructures for Sustainable Tourism in the National Park of Tazekka in Taza Province (Morocco). *Ecological Engineering & Environmental Technology*, *25*(5), 167–178. https://doi.org/10.12912/27197050/184225

Du, Y., Zhang, Y., Ling, F., Wang, Q., Li, W., & Li, X. (2016). Water Bodies' Mapping from Sentinel-2 Imagery with Modified Normalized Difference Water Index at 10-m Spatial Resolution Produced by Sharpening the SWIR Band. *Remote Sensing*, *8*(4), 354. https://doi.org/10.3390/rs8040354

Elnashar, M. M., El-Gohary, A., & El-Baz, F. K. (2021). Assessment of Soil Erosion by RUSLE Model using Remote Sensing and GIS: A case study of El-Minia Region, Egypt. *Agriculture*, 13(1), 35. https://doi.org/10.3390/agriculture13010035

FAO. (2017). *Agroforestry for landscape restoration: Exploring the potential of agroforestry to enhance the sustainability and resilience of degraded landscapes*.

FAO. (2021). *Agroforestry and Sustainable Development Goals.*

FAO. (2020). *Global Forest Resources Assessment 2020: Main Report*. Food and Agriculture Organization of the United Nations. https://www.fao.org/forest-resources-assessment/en/

Fleischmann, J., Birkel, C., Blechinger, P., & Platzer, W. J. (2021). Land suitability evaluation for multiple crop agroforestry planning using GIS and multi-criteria decision analysis: A case study in Fiji. *ResearchGate*.

GeeksforGeeks. (n.d.). Data Normalization in Data Mining. Retrieved March 12, 2025, from https://www.geeksforgeeks.org/data-normalization-in-data-mining/

Geopard. (2019). Topography and Relief Analytics for Agricultural Fields. Geopard Technologies. Retrieved from https://geopard.tech/blog/topography-and-relief-analytics-for-agricultural-fields/

Hosseini, R., Tong, D., Lim, S., Sohn, G., & Gidófalvi, G. (2025). A framework for performance analysis of OpenStreetMap data in navigation applications: the case of a well-developed road network in Australia. *Annals of GIS*, 1–18. https://doi.org/10.1080/19475683.2025.2468184

Kahsay, A. Application of Fuzzy Analytical Hierarchy Process in Land Suitability Evaluation for Faba Bean Crop. *Agric Res* (2024). https://doi.org/10.1007/s40003-024-00812-9

Kamal, S., Khalid, A., Amal, E. K., Lahcen, Z., Jamila, D., & Nadia, B. (2023). *Diversity of the Bryoflora of the Tazekka National Park, North-East Morocco* (pp. 645–672). https://doi.org/10.1007/978-3-031-35248-5_58

Kasahun M, Legesse A. Machine learning for urban land use/ cover mapping: Comparison of artificial neural network, random forest and support vector machine, a case study of Dilla town. *Heliyon*. 2024 Oct 12;10(20):e39146.

Khaled, F., & Sayed, A. (2023). Soil pH and its influence on nutrient availability and plant health. *International Journal of Advanced Chemistry Research*, *5*(2), 68–70. https://doi.org/10.33545/26646781.2023.v5.i2a.204

Lal, R. (2001). Soil degradation by erosion. *Land Degradation & Development*, 12(6), 519–539

Lasaponara, R., Abate, N., Fattore, C., Aromando, A., Cardettini, G., & Di Fonzo, M. (2022). On the Use of Sentinel-2 NDVI Time Series and Google Earth Engine to Detect Land-Use/Land-Cover Changes in Fire-Affected Areas. *Remote Sensing*, *14*(19), 4723. https://doi.org/10.3390/rs14194723

Liu, L., Cao, X., Li, S. et al. A 31-year (1990–2020) global gridded population dataset generated by cluster analysis and statistical learning. *Sci Data* 11, 124 (2024). https://doi.org/10.1038/s41597-024-02913-0

Liu, J., Xiong, J., Cheng, W., Li, Y., Cao, Y., He, Y., 2021. Assessment of Flood Susceptibility Using Support Vector Machine in the Belt and Road Region 1–37.

Malczewski, J. (2006). GIS-based multicriteria decision analysis: a survey of the literature. *International Journal of Geographical Information Science*.

Mishra, D. K., Kumar, U., & Arunachalam, K. (2023). GIS-based multi-criteria land suitability assessment for potential agroforestry area expansion in Uttarakhand. *Indian Journal of Agroforestry*, *24*(2).

Morales, J. A., & Morales, R. E. (2023). Potential of the CHIRPS Database for Extreme Precipitation Risk Studies: Assessment in the State of Jalisco (Mexico). *International Journal of Sustainable Development and Planning*, *18*(3), 637-646.

Mushtaq, R., Yadav, R.K., Fayaz Fayaz, A. *et al.* Multi-criteria land suitability assessment for mulberry-based agroforestry using AHP and GIS approach in Anantnag district of the Kashmir valley, India, to achieve sustainable agriculture. *Environ Dev Sustain* **26**, 28293–28315 (2024). https://doi.org/10.1007/s10668-023-03812-x

Muñoz Sabater, J. (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, *13*(9), 4349–4383.

Ngwijabagabo, H., Niyonzima, T., Nyandwi, E., Hirwa, H., Nishyirimbere, A., Mwizerwa, F., Hategekimana, G., Barifashe, T., & Uwera, D. (2021). Spatial suitability analysis and mapping of agroforestry areas: Case study of Musanze District in Northern Province of Rwanda. *Rwanda Journal of Engineering, Science, Technology and Environment*, *4*(1).

Santos, J. C., Silva, R. M., & Almeida, C. D. (2021). Assessment of land suitability for agroforestry in the Brazilian Amazon using remote sensing and GIS. *Journal of Environmental Management*, *282*.

SantosoT., DarmawanA., & HilmantoR. (2024). Agroforestry Land Use Land Cover Area Classification Using Decision Tree Algorithm . *Jurnal Manajemen Hutan Tropika*, *30*(3), 399. https://doi.org/10.7226/jtfm.30.3.399

Schepaschenko, Dmitry & Mccallum, Ian & Shvidenko, Anatoly & Fritz, Steffen & Kraxner, Florian & Obersteiner, Michael. (2011). A new hybrid land cover dataset for Russia: A methodology for integrating statistics, remote sensing and in situ information. Journal of Land Use Science. 6. 245–259.

Slavin, T., 2024: *Can the bioeconomy help save the Amazon from deforestation?* Reuters, December 18, 2024.

Topuz, M., Deniz, M. Application of GIS and AHP for land use suitability analysis: case of Demirci district (Turkey). *Humanit Soc Sci Commun* **10**, 115 (2023). https://doi.org/10.1057/s41599-023-01609-x

USDA Natural Resources Conservation Service. (2011). Soil Quality Indicators: Available Water Capacity. *United States Department of Agriculture*.

Van der Aalst, W., 2016. Process mining: Data science in action. Process Min. Data Sci. Action 1–467. https://doi.org/10.1007/978-3-662-49851-4