MONITORING FOREST DEGRADATION OVER FOUR DECADES USING REMOTE SENSING AND MACHINE LEARNING CLASSIFICATION ALGORITHMS IN BOUSKOURA, MOROCCO

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ABSTRACT:

A large portion of Morocco's forest ecosystem is being damaged by human activity and climate change, which makes it crucial for the country to monitor forest dynamics and develop measures to counter these effects. The objective of this study was to determine how the forest cover has changed over the past four decades in Bouskoura forest, Morocco. Based on Remote Sensing (RS), Geographic Information System (GIS) and machine learning algorithms. Throughout the process, Spatial data such as Landsat 5 TM, Sentinel-2B, and spectral indices, including NDVI, NDWI, NDBI, and MSAVI2 were used to train/validate Random forest (RF), support vector machine (SVM), and K-nearest neighbor (KNN) classifiers. By comparing the performance of the three classifiers for all four periods, the RF method was the most effective with an overall accuracy of 0.99 and kappa coefficient of 0.99 for 1991, 2001 and 2011, and an overall accuracy of 0.99 and kappa coefficient of 0.98 for 2021 . Therefore, the RF was selected as a method of examining time variations. The results indicated that forests covered an area of 20,41 km^2 in 1991 which has decreased to 18,96 km^2 in 2021, a loss of 1,45 km^2 (7.10%) in four decades. The highest forest loss was 2,69 km^2 during 1991-2001, 2,12 km^2 during 2001-2011, 1,40 km^2 during 2011-2021. And the highest forest gain was found to be 3,75 km^2 during 2011-2021, 0,61 km^2 during 2001-2011, 0,43 km^2 during 1991-2001. Recent declines in forest degradation attest to the benefits of initiatives to conserve the environment taken by the country.

1. INTRODUCTION

Geographically, Morocco sits between the Atlantic Ocean and the Mediterranean Sea on the west and the Sahara on the east, which together provide a wealth of diverse forest ecosystems with a total area of 9 million hectares, including 5,8 million forested, or 8% of the country (Said et al., 2010). In addition to protecting the environment and fighting desertification, forest management in Morocco contributes to rural socio economic development (Said et al., 2010). While sustained efforts are made to conserve and develop forests resources, forest ecosystems face a variety of restrictions related to socioeconomic conditions typical of rural poor economic order and climate related to aridity and climate change (Said et al., 2010). Consequently, negative consequences result (loss of water resources, soil erosion, desertification, etc.) at local, regional and national levels (Said et al., 2010).

Forest degradation refers to a long-term reduction in trees due to natural or anthropogenic causes (Geist and Lambin, 2001). World-wide, it is caused by a complex combination of socioeconomic factors, such as population and population growth, agricultural expansion, and wood extraction in developing countries (Allen and Barnes, 1985). Furthermore, economic, political, technological, and cultural factors are responsible for forest degradation (Geist and Lambin, 2001). Many severe problems are caused by forest degradation, including biodiversity loss, soil erosion, water cycle changes, and potential global effects (Fearnside, 1995). With less forest cover, less water will be returned to the soil, and the inland areas could be more prone to drought (D'Almeida et al., 2007). When tropical forests are destroyed, an enormous amount of carbon dioxide stored by the vegetation is released to the atmosphere which accelerates global warming (Fearnside and Laurance, 2004).Forest degradation is the second largest source of carbon emissions after fossil fuels, making it a major concern today (Le Quéré et al., 2009).

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Remote sensing can be used to monitor forest change, This method can provide an accurate and practical way to determine the number of trees lost, the correlation between human disturbance and forest clearing, and the effectiveness of forest policy regulation (Fuller, 2006), Which can be addressed through earth observation satellite data and decisions support tools such as Geographic Information System (Yeh, 2002). Furthermore, rapid global change requires understanding of temporal ecosystem dynamics, which in conjunction with remote sensing techniques can help control and prevent further forest degradation (Manning et al., 2009).

Remote sensing-based approaches for classification are commonly used to monitor changes, and many algorithms have been developed for solving complex classification problems (Meyer et al., 2018). This includes random forest (RF), support vector machine (SVM), K-nearest neighbor (KNN), artificial neural networks (ANNs), and decision trees (DTs), These algorithms are also known as machine learning algorithms, A data-driven approach that examines the relationships between predictors and responses (Breiman, 2001).There have been many studies investigating the use of machine learning for monitoring tasks and mapping land cover (Yu et al., 2018).

In this project the main focus is to show the change of Bouskoura forest over the last 4 decades to help prevent forest degradation using GIS and RS coupled with machine learning methods which are Random forest (RF), support vector machine (SVM), and K-nearest neighbor (KNN) classifiers.

The central objective of this project is to comprehensively analyze and illustrate the transformation of the Bouskoura forest over the course of the past four decades. This is driven by the goal of forest conservation and the prevention of forest degradation. To achieve this, the project use a multidisciplinary approach that combines Geographic Information Systems (GIS) and Remote Sensing (RS) technologies, coupled with machine learning methods, namely the Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) classifiers.

2. METHOD

2.1 Study Area

Bouskoura forest is Located about twenty kilometers south of Casablanca in the central-western part of Morocco, between 33° 26 56 latitude north, 7° 38 55 longitude west, the forest of Bouskoura is spread on a surface area of 2992 acres. There are mainly eucalyptus trees growing here, making it one of Casablanca's green lungs (Figure 1).
On the weekend and bank holidays, locals flock to Bouskoura forest to have lunch with friends or workout with their colleagues in the forest. When visiting Bouskoura during the week, introverts are almost guaranteed to find it calm and peaceful (Yasmine, 2017).

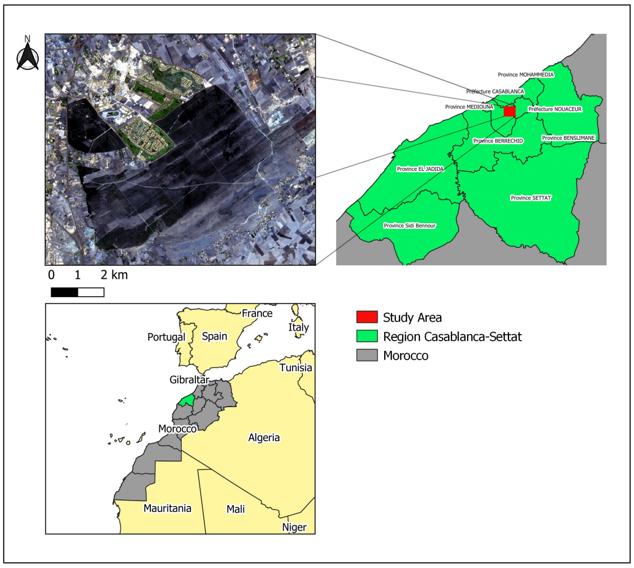

Figure 1: Study area location

2.2 Methodology

In order to monitor forest degradation over the last four decades the study follows four main steps (Figure 2):
The process started with collecting data Spatial data were collected from USGS such as Landsat 5 TM, Sentinel-2B.
Secondly, In data preparation spatial data was utilized to calculate the spectral indices including NDVI, NDWI, NDBI, and MSAVI2, and extracted the ground truth data of four decades.
Thirdly, Random forest (RF), support vector machine (SVM), and K-nearest neighbor (KNN) classifiers were used to create a supervised classification of 1991, 2001, 2011 and 2021 periods.
Lastly, based on the difference between two time periods, the gain and loss of forest cover has been calculated and displayed.

2.3 Collecting data

From NASA's Landsat and the ESA's Sentinel satellites, the multispectral bands R, G, B, Nir, and Swir1 and Swir2 were collected

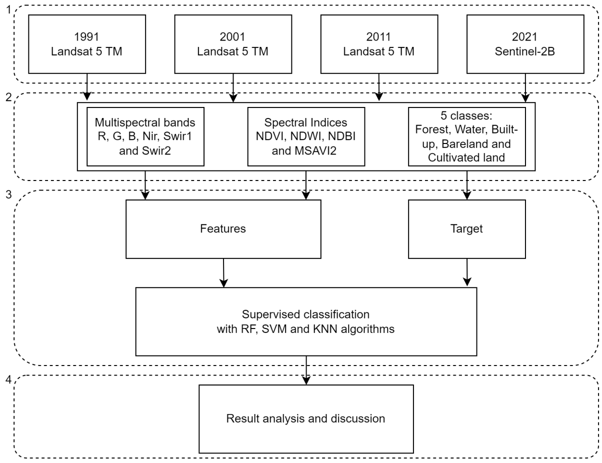

Figure 2: The study's methodology

for the purpose of determining forest cover change.
Sentinel-2B data were used in the analysis of the year 2021, and Landsat 5 TM were used for three periods (1991, 2001 and 2011) (Table 1).

No	Type	Date	Resolution
1	Landsat 5 TM	1991-08-13	30 m
2	Landsat 5 TM	2001-08-24	30 m
3	Landsat 5 TM	2011-08-04	30 m
4	Sentinel-2B	2021-07-15	10 m

Table 1: Spatial data used in the study

2.4 Preparing data

2.4.1 Spectral Indices

Landsat and Sentinel multispectral data were used to calculate spectral indices using equations, spectral indices such:

NDVI Normalized Difference Vegetation Index is one of the most commonly used vegetation indices for ecological research (Pettorelli, 2013). (Rouse et al., 1973) developed this method to estimate biomass. Taking into account the red and near infrared bands (RED and NIR) (Equation 1) (Pettorelli, 2013).

$$\frac{NIR - Red}{NIR + Red} \tag{1}$$

NDWI Normalized Difference Water Index developed by (McFeeters, 1996) this satellite-derived system uses short wave infrared (SWIR) and NIR channels to derive an index that reflects changes in both water content (absorbing SWIR radiation) and spongy mesophyll content of vegetation canopies (Gao, 1996) (Equation 2) (Gao, 1996).

$$\frac{Green - NIR}{Green + NIR} \tag{2}$$

NDBI Normalized Difference Built-Up Index was used to extract Built-up from remote sensing imagery, which exploits the unique spectral characteristic of built-up areas and other land cover types (Zha et al., 2003). Through the integration of Otsu's method, the NDBI was used to automate the process of mapping built-up areas (Zha et al., 2003). Based on the near-infrared band (NIR) and shortwave infrared band 1 (SWIR1), the NDBI was calculated as follows (Zha et al., 2003) (Equation 3) (Zha et al., 2003).

$$\frac{SWIR - NIR}{SWIR + NIR} \tag{3}$$

MSAVI2 Modified Soil Adjusted Vegetation Index 2 means the soil-adjusted vegetation index tries to overcome some of the NDVI limitations in areas where soil is exposed (Qi et al., 1994). The MSAVI algorithm has been used in numerous range land studies, often as a complement to field data on vegetation cover (Qi et al., 1994) (Equation 4) (Qi et al., 1994).

$$\frac{2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - Red)}}{2} \tag{4}$$

2.4.2 Ground truth data Ground truth samples were created with the help QGIS and multispectral bands Nir, R and G (Figure 3).

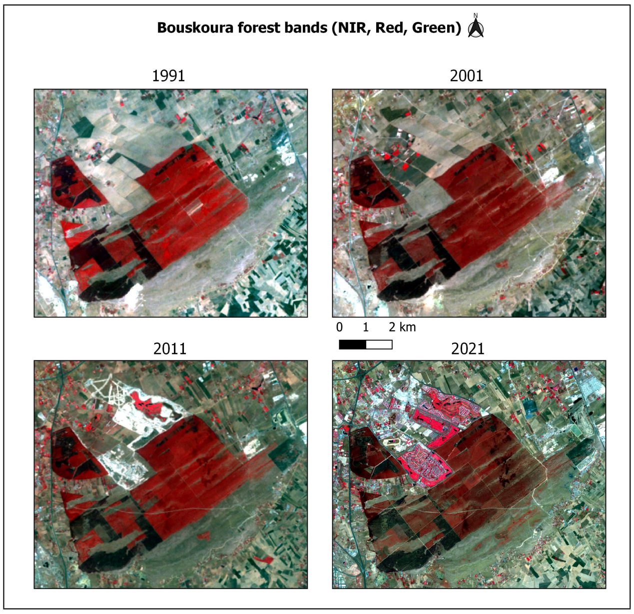

Figure 3: Color Infrared of the study area

2.5 Machine learning algorithms

2.5.1 Preprocessing Data The data was transformed to a CSV file where each period have features which are the Spatial data and the Spectral Indices and a target which is called Class which have 5 classes (1: Forest, 2: Water, 3: Built-Up, 4: Bareland, 5: Cultivated land). The data will serve as training material for machine learning algorithms such as Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN).

	B1	B2	B3	B4	B5	B7	NDVI	NDWI	NDBI	MSAVI2	Class
0	0.0407	0.0382	0.0478	0.0691	0.0747	0.0574	0.182207	-0.287978	0.038943	0.038747	4.0
1	0.0420	0.0399	0.0519	0.0712	0.0840	0.0622	0.156783	-0.281728	0.082474	0.034852	4.0
...	...	...	...	...	...	...	...	...	...	...	...
103818	0.0440	0.0453	0.0585	0.0732	0.0826	0.0631	0.111617	-0.235443	0.060334	0.026246	4.0
103819	0.0432	0.0417	0.0544	0.0691	0.0806	0.0603	0.119028	-0.247292	0.076820	0.026445	4.0

Table 2: (A) 1991 Dataset

	B1	B2	B3	B4	B5	B7	NDVI	NDWI	NDBI	MSAVI2	Class
0	0.0386	0.0352	0.0473	0.0623	0.0883	0.0738	0.136861	-0.277949	0.027341	0.027341	4.0
1	0.0381	0.0343	0.0490	0.0613	0.0877	0.0756	0.111514	-0.282427	0.177181	0.022359	4.0
...	...	...	...	...	...	...	...	...	...	...	...
103818	0.0353	0.0304	0.0351	0.0481	0.0733	0.0587	0.156250	-0.225478	0.207578	0.207578	4.0
103819	0.0413	0.0381	0.0457	0.0603	0.0752	0.0615	0.137736	-0.225610	0.109963	0.026693	4.0

Table 2: (B) 2001 Dataset

	B1	B2	B3	B4	B5	B7	NDVI	NDWI	NDBI	MSAVI2	Class
0	0.0400	0.0370	0.0464	0.0705	0.0787	0.0547	0.206159	-0.311628	0.054960	0.043935	4.0
1	0.0400	0.0388	0.0494	0.0676	0.0899	0.0698	0.155556	-0.270677	0.141587	0.033026	4.0
...	...	...	...	...	...	...	...	...	...	...	...
103818	0.0426	0.0415	0.0533	0.0696	0.0880	0.0627	0.132628	-0.252925	0.116751	0.029374	4.0
103819	0.0422	0.0425	0.0525	0.0705	0.0886	0.0636	0.146341	-0.247788	0.113765	0.032476	4.0

Table 2: (C) 2011 Dataset

	B2	B3	B4	B8	B11	B12	NDVI	NDWI	NDBI	MSAVI2	Class
0	0.1450	0.1362	0.2016	0.2712	0.2712	0.2759	0.201426	-0.303220	0.162446	0.096256	4.0
1	0.1418	0.1376	0.1962	0.2631	0.3934	0.2949	0.229833	-0.299580	0.198477	0.093382	4.0
...	...	...	...	...	...	...	...	...	...	...	...
933508	0.2023	0.1792	0.2835	0.3484	0.4168	0.2944	0.158379	-0.265299	0.089388	0.080297	4.0
933509	0.1932	0.1715	0.2724	0.3477	0.4168	0.2944	0.177784	-0.285635	0.090386	0.094045	4.0

Table 2: (D) 2021 Dataset

2.5.2 Random forest An independent random vector sample is used to create each classifier in the random forest classifier, to classify the input vector, each tree votes for the most popular class (Breiman, 1999). Random forest classifiers consist of randomly selecting features or combining features at each node to build a tree. Using the bagging method, N random replacement examples are drawn to generate the training dataset, where N is the size of the original training set (Breiman, 1996), was used for each feature/feature combination selected. In the forest, examples (pixels) are classified by taking the class that has received the most votes from all trees (Breiman, 1999).

2.5.3 Support Vector Machines The purpose of SVMs is to determine the location of decision boundaries that produce the best separation of classes, based on statistical learning theory (Vapnik et al., 1995). SVMs select the linear decision boundary that leaves the greatest margin between two classes in a two-class pattern recognition problem where classes are linearly separable. Basically, margin is the sum of the distances from the nearest points of the two classes to the hyperplane (Vapnik et al., 1995). By using quadratic programming (QP) optimization techniques, this problem of maximizing the margin can be solved. Calculation of the margin is based on data points that are closest to the hyperplane. As a result, these data points are known as 'support vectors', and are always small in number (Vapnik et al., 1995).

2.5.4 K-Nearest Neighbours The KNN algorithm is based on instance-based learning, and all the training samples need to be kept for classification purposes (Cover and Hart, 1967). During classification, each test sample is compared to its K neighboring training samples, To derive the class label prediction, neighbors are generally defined according to the Euclidean distance metric, and the decision is made by majority vote among neighbor samples (Hastie et al., 2009).

3. RESULTS

3.1 Validation Results

The validation of the land cover classification was performed using two key metrics: Cohen's Kappa and overall accuracy, as detailed in Table 3. To provide a more comprehensive evaluation, confusion matrices were generated for each of the four time periods (as displayed in Figures 4 (A, B, C, D)). These validation results unequivocally establish the random forest (RF) algorithm as the most accurate classifier, a conclusion supported by the associated confusion matrices. For all four time periods, the RF algorithm consistently achieved the highest level of overall accuracy, registering an impressive 0.99 accuracy score for each period.

Periods	Metrics	RF	SVM	KNN	Periods	Metrics	RF	SVM	KNN
1991	Overall accuracy	0.99	0.97	0.98	2011	Overall accuracy	0.99	0.94	0.98
	Kappa	0.99	0.92	0.97		Kappa	0.99	0.89	0.96
	Precision	1.00	0.94	0.98		Precision	1.00	0.91	0.96
	Recall	1.00	0.99	0.99		Recall	1.00	0.97	0.97
	F1-score	1.00	0.96	0.99		F1-score	1.00	0.94	0.97
2001	Overall accuracy	0.99	0.96	0.98	2021	Overall accuracy	0.99	0.94	0.98
	Kappa	0.99	0.91	0.96		Kappa	0.98	0.90	0.96
	Precision	1.00	0.93	0.97		Precision	1.00	0.96	0.98
	Recall	1.00	0.99	0.99		Recall	1.00	0.98	0.99
	F1-score	1.00	0.96	0.98		F1-score	1.00	0.97	0.99

Table 3: Classification report

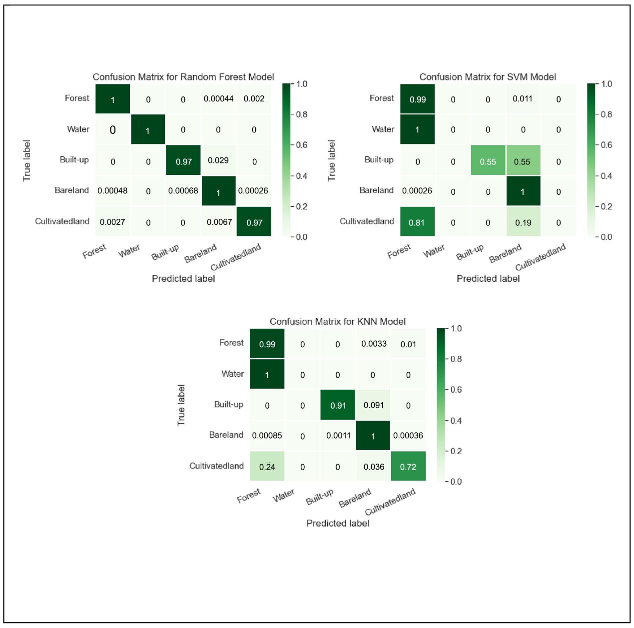

Figure 4: (A) Confusion Matrix 1991

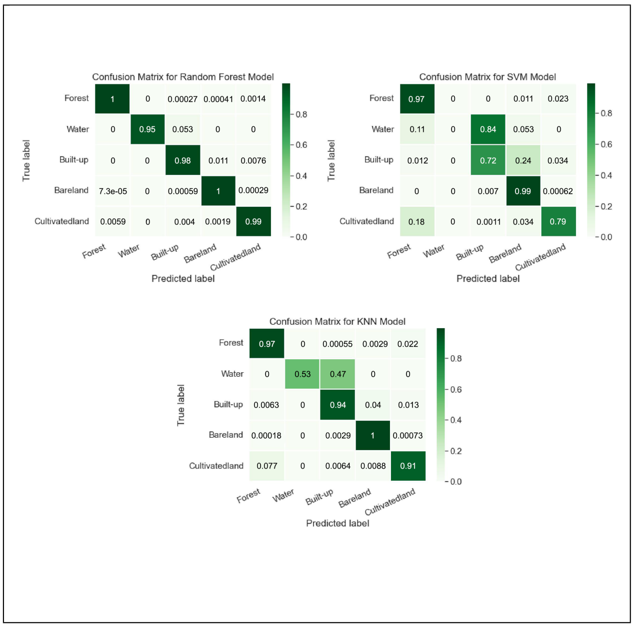

Figure 4: (C) Confusion Matrix 2011

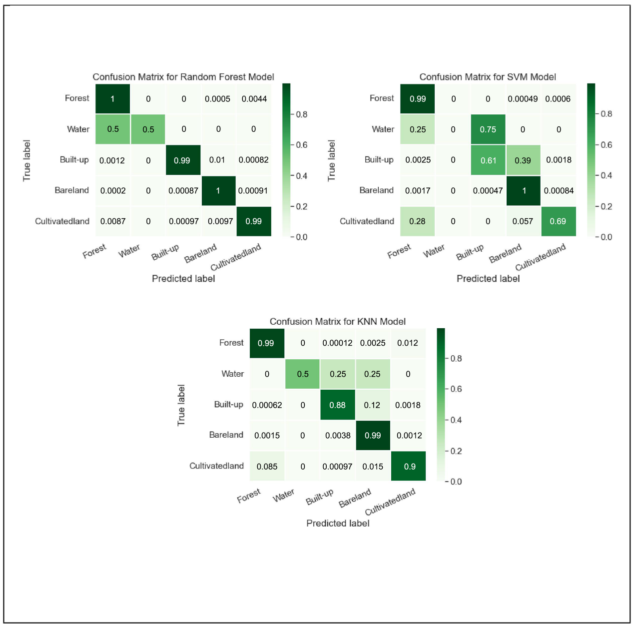

Figure 4: (B) Confusion Matrix 2001

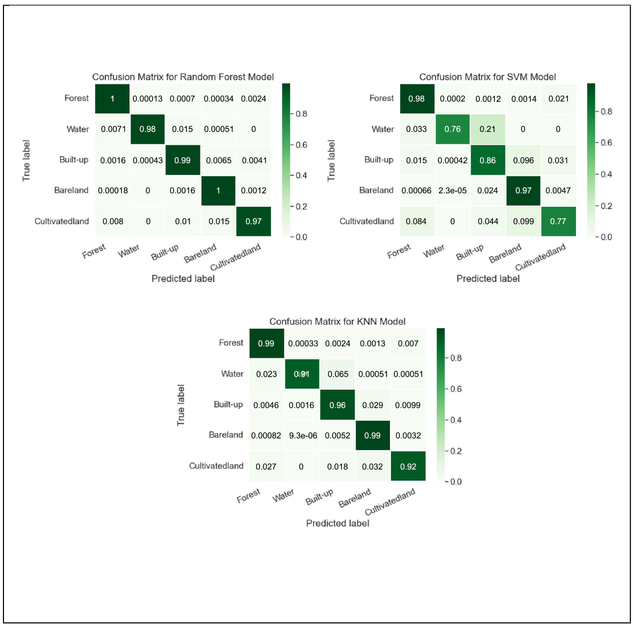

Figure 4: (D) Confusion Matrix 2021

Moreover, Cohen's Kappa coefficients were calculated and found to range between 0.98 and 0.99 for all time periods.
In addition to Cohen's Kappa, other important metrics were computed to further assess the classification performance. These metrics include precision, recall, and the F1-score. These measures are particularly valuable when dealing with problems involving imbalanced binary classification. Precision, for instance, quantifies the percentage of correctly classified forest instances, providing insight into the algorithm's ability to accurately identify forested areas.

3.1.1 Setting up the models In the study, machine learning models were optimized with specific settings: Random Forest with 300 trees, a maximum depth of 20, and 30% feature selection; SVM using a radial basis function kernel, C=10, and a slack variable of 0.5; and KNN with K=15, using Euclidean distance and distance-based weighting. All models incorporated feature scaling and class weight adjustments, with SMOTE applied in KNN for class imbalance. These settings were carefully chosen to suit the dataset's characteristics and the study's objectives, ensuring an effective and robust analysis.

3.2 Classification Results & Forest Change

The classification of land cover using machine learning algorithms was carried out in the years 1991, 2001, 2011, and 2021. The outcomes of these analyses were subjected to metrics examination, and it was determined that the random forest algorithm consistently delivered the highest accuracy in land cover classification.
Forest changes over time can be assessed by examining the differences in forest cover between two consecutive time intervals. This analysis provides valuable insights into the dynamics of forest ecosystems.
In the context of our study, Figure 5 represent these changes, with purple areas denoting forest loss and blue areas indicating forest gain.
During the initial period from 1991 to 2001, the rate of forest loss was notably high, measuring 2.69 square kilometers. This amount equated to approximately 13.18% of the total forest cover during that time frame.This significant loss underscores the challenges faced by the forested regions during this period.
In the subsequent decade, from 2001 to 2011, there was a noticeable improvement in the forest's condition, as the rate of forest loss decreased. The estimated forest loss during this period amounted to 2.12 square kilometers, equivalent to 11.68% of the total forest cover. This decline in forest degradation reflects positive conservation efforts and possibly changing land use practices.
Moving on to the third period, from 2011 to 2021, the forest degradation rate continued to decrease. The forest loss during this time was estimated to be 1.40 square kilometers, accounting for 8.42% of the total forest cover. This downward trend in forest loss highlights ongoing conservation efforts and potentially improved forest management strategies.
Interestingly, over the course of these three periods, there was a noticeable increase in forest gain. Specifically, between 2011 and 2021, the forest gain was estimated to be 3.75 square kilometers, representing 19.78% of the total forest cover. This positive trend in forest gain is a significant development, indicating potential ecological restoration or afforestation initiatives that deserve further exploration.
The analysis of forest changes over time reveals both challenges and encouraging signs for forest ecosystems. While forest loss has been a concern, particularly in the earlier periods, the decrease in degradation rates and the notable increase in forest gain, especially in the most recent decade, demonstrate the potential for positive conservation outcomes and the importance of ongoing monitoring and sustainable forest management practices.

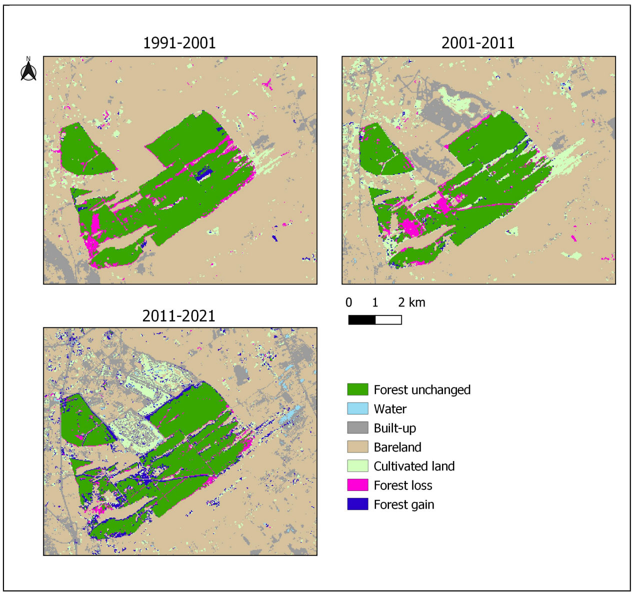

Figure 5: Forest change

4. DISCUSSION&CONCLUSION

4.1 Discussion

In this study, the forest degradation dynamics were mapped for a specific area within the Bouskoura forest, located in the country of Morocco. Utilizing state-of-the-art machine learning algorithms, particularly the random forest algorithm, the results obtained were not only satisfactory but also deeply intriguing. The methodology involved an analysis of multi-temporal satellite datasets derived from renowned missions such as Landsat and Sentinel. These invaluable datasets were thoughtfully categorized into five land cover classes, allowing for a more comprehensive examination of the landcover change. Consequently, the resulting land cover maps, which captured the period of the years 1991, 2001, 2011, and 2021, proved to be an absolute useful information, offering profound insights into the dynamic shifts taking place.
The effect of human growth is the main cause of forest degradation rate by observing the result it is obvious that when built-up started increasing, the forest degradation started increasing too. However, Using with the help of machine learning algorithms monitoring changes of forests, urban planing, climate and more would be efficient and highly accurate. Machine learning, remote sensing and gis, can be play a big part into helping countries overcome a lot of challenges.
The forest change identified from the results revealed that Morocco is overcoming the challenges of forest degradation in Bouskoura forest.

4.2 Conclusion

For the period 1991-2021, land cover analyses were conducted in Bouskora forest to map the dynamics of forest degradation. Using machine learning to classify multispectral satellite imagery.

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Maps produced from the output classification were highly accurate with the help of radom forest classifier for the forest cover, Forest loss and gain trends were accurately computed, and results were compared to other similar studies. Based on the experimental results, the implemented approach can provide high classification accuracy for future works. Providing decision makers with the necessary information to design and implement proper regulations to protect forests can be very helpful.

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