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Classification and Spatio-Temporal Change Detection of Land Use/Land Cover Using Remote Sensing and Geographic Information System in the Manouba Region, NE Tunisia

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Abstract

Land use/land cover (LULC) mapping and change detection are fundamental aspects of remote sensing data application. Therefore, selecting an appropriate classifier approach is crucial for accurate classification and change assessment. In the first part of this study, the performance of machine learning classification algorithms was compared using Landsat 9 image (2023) of the Manouba government (Tunisia). Three different classification methods were applied: Maximum Likelihood Classification (MLC), Support Vector Machine (SVM), and Random Trees (RT). The classification aimed to identify five land use classes: urban area, vegetation, bare area, water and forest. A qualitative assessment was conducted using Overall Accuracy (OA) and the Kappa coefficient (K), derived from a confusion matrix. The results of the land cover classification demonstrated a high level of accuracy. The SVM method exhibited the best performance, with an overall accuracy of 93% and a kappa accuracy of 0.9. The ML method is the second-best classifier with an overall accuracy of 92% and a kappa accuracy of 0.88. The Random Trees method yielded the lowest accuracy among the three approaches, with an overall accuracy of 91% and a kappa accuracy of 0.87. The second part of the study focused on analyzing LULC changes in the study area. Based on the classification results, the SVM method was chosen to classify the Landsat 7 image acquired in 2000. LULC changes from 2000 to 2023 were investigated using change detection comparison. The findings indicate that over the last 23 years, vegetation land and urban areas in the study area have experienced significant increases of 31.94% and 5.47%, respectively. This study contributed to a better understanding of the classification process and dynamic LULC changes in the Manouba region. It provided valuable insights for decision-makers in planning land conservation and management.

Keywords

Remote Sensing, GIS, LULC, SVM, MLC, RT, Change Detection

1. Introduction

The world is currently undergoing swift and extensive transformations in land use, with the scale and intensity of LULC change surpassing those observed in the past [1]. In fact, humans have transformed nearly a third of the world's land in the last 60 years [2]. These changes play a pivotal role in regional socio-economic development [3] and can significantly impact the environment and natural resources. The changes can affect channel morphology and riverbank erosion [4], decrease groundwater flow [5] and influence temperature trends [6] [7].

LULC changes result from a multidimensional interaction among institutional and environmental dynamics [8] [9]. Described as forest degradation, agricultural intensification, globalization and urbanization [10] [11], these factors play a significant role in shaping the landscape.

Hence, it is crucial to use precise and effective tools for monitoring and managing LULC changes, especially when the population and economy are rapidly growing in developing countries [12]. Remote sensing and GIS technologies provide a potent approach for quantifying and analyzing such changes [13]. These technologies constitute a good alternative to conventional methods, offering data in a relatively short time and cost-efficient manner [14]. Many studies have demonstrated the efficiency of these technologies in understanding and managing dynamic landscapes in various applications, including urban planning [15] [16] [17], natural resource management [18] [19] and disaster risk assessment [20] [21].

Remote sensing technology has undergone rapid development, serving as a valuable and current information source for understanding the pattern, characteristics and development of an environment. Multispectral and multi-temporal satellite data have emerged as essential tools for estimating vegetation cover and detecting changes [22]. The rich archive and spectral resolution of satellite images are the most important reasons for their widespread use [14] [23].

A variety of techniques are applied to quantify changes. Attri *et al.* [24] classify them into two general types: (1) those based on spectral classification of the input data, such as post-classification comparison and direct two-date classification, and (2) those based on radiometric change between different acquisition dates. Post-classification comparison is extensively employed and boasts simplicity in comprehension. In this approach, two images obtained at distinct dates and separately classified are compared. Changes between the two times are represented through a change matrix, illustrating the pixel count for each class on both dates [24].

Precise classification is essential for accurate mapping and understanding of dynamic landscapes. The main objective of the classification system is to accurately identify the type of land cover present in a given area [25]. It is an important technique to assess the relationship between the environment and human activities [26]. In recent years, the integration of remote sensing data and machine learning (ML) techniques has gained increasing importance in automating land cover mapping, allowing for the accurate extraction of information from satellite imagery. These techniques have demonstrated their robustness in classifying homogeneous and heterogeneous land cover types [27]. Among these algorithms, Support Vector Machine (SVM) and Random Trees (RT) stand out as two of the most widely used ML classifiers [28]. SVM excels at capturing non-linear relationships within data, while RT is particularly effective at handling large, high-dimensional datasets. Another commonly employed classification method is the Maximum Likelihood Classifier (MLC), considered a standard classification algorithm [29]. MLC leverages statistical principles to make classification decisions. The choice of the appropriate classifier method is crucial to obtaining a good classification, which is essential for planners [30].

However, in the study area, little work has been done to quantify the LULC changes. Initially, an assessment of the performance of various LULC classification methods was conducted. This involved evaluating and comparing the effectiveness of these classifiers in LULC mapping within the Manouba region. Subsequently, a quantitative analysis of LULC changes from 2000 to 2023 was carried out using multi-temporal Landsat imagery.

This study contributes to evaluating the magnitude of the transformation in the region over 23 years, identifying the major driving forces and their impact on LULC changes. It helps bridge the information gap necessary for planners and policymakers.

2. Materials and Methods

2.1. Study Area

The study area, Manoubacity, is located in the North East of Tunisia. It covers the coordinates of 36˚48'28"N, 10˚06'04"E (**Figure 1**). The city has an area of 1137 km^2 and its population was 420,445 according to the 2020 census survey [31]. The governorate of Manouba is characterized by a heterogeneous and highly varied topographic surface: plains and hills nestled between ranges of mountains that dominate them to the north, southwest, and a portion of the east of the governorate. However, the plains and hills constitute the dominant topographic features in the area (almost 75%) [32]. Agriculture and industry remain the dominant sectors in the governorate's economy.

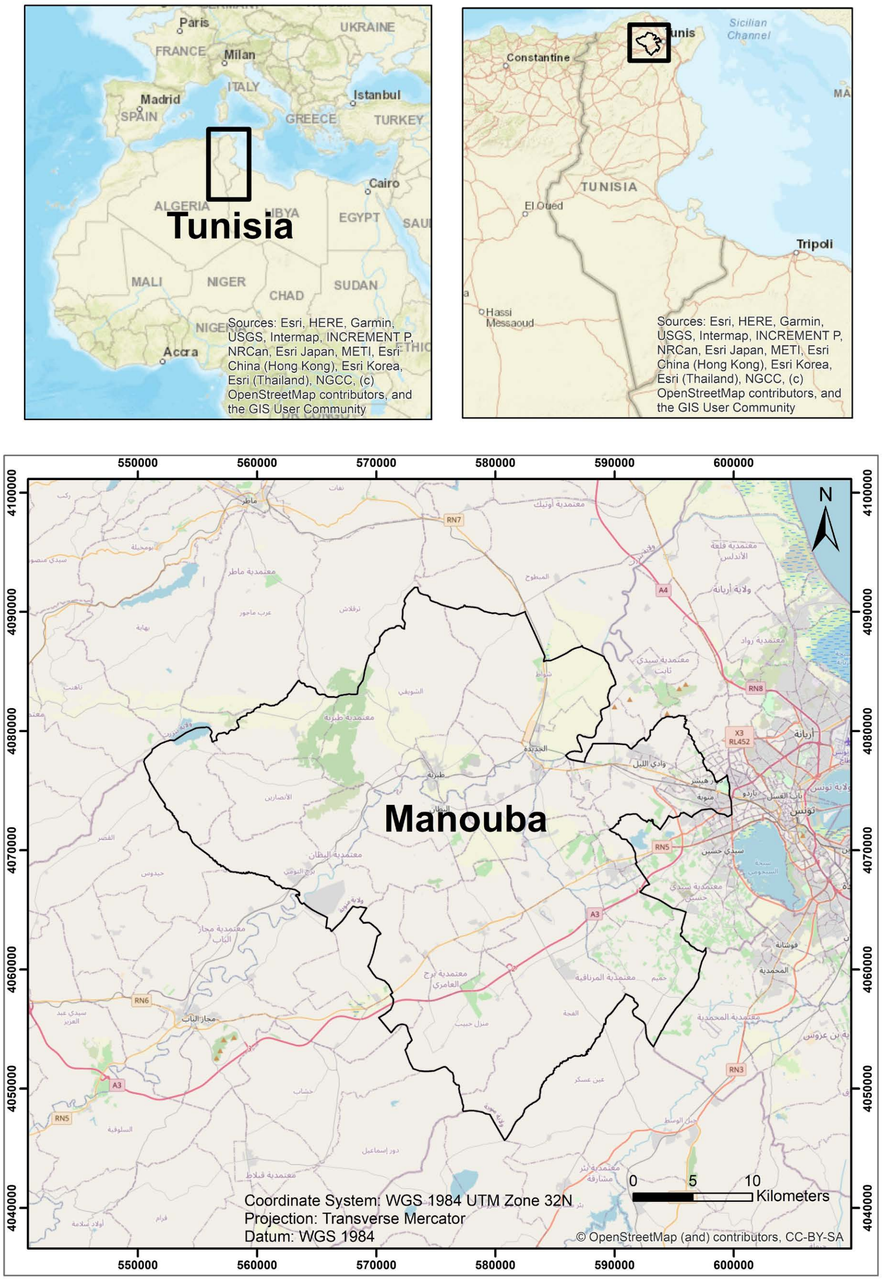

Figure 1. Location of the study area.

2.2. Data

In the recent years, satellite imageries, such as Landsat data, have been used worldwide in studies concerning LULC changes across multiple spatial and temporal scales [33] [34] [35] [36]. In this research, we utilized Landsat 7 and Landsat 9 satellite imagery acquired on November 20, 2000, and April 10, 2023, respectively. The data were accessed through the United States Geological Survey (USGS). Multiband images were generated using ArcGIS. The study area encompasses various land use types, with the classification system consisting of five categories: urban, vegetation, bare area, water, and forest. ArcGIS software was employed for various stages of satellite image processing.

3. Methodology

In this paper, the methodology has three main steps: image classification, accuracy evaluation and change detection (Figure 2).

3.1. Image Classification

The use of the supervised classification involved the collection of training samples for LULC classes. This stage is the most crucial and difficult part of the supervised classification process [37].

Using visual interpretation, training areas were delineated using polygons for each class and classification was conducted using the SVM, ML, and RT classifiers.

- Support vector machines (SVM)

The SVM algorithm is a supervised machine learning classifier. It is used to resolve different problems related to regression and classifications [38]. The SVM model uses support vectors for the optimal identification of the separation hyperplane, by maximizing the boundaries between classes [39] [40] [41].

- Random Trees (RT)

A decision tree classifier is a non-parametric classifier that does not require

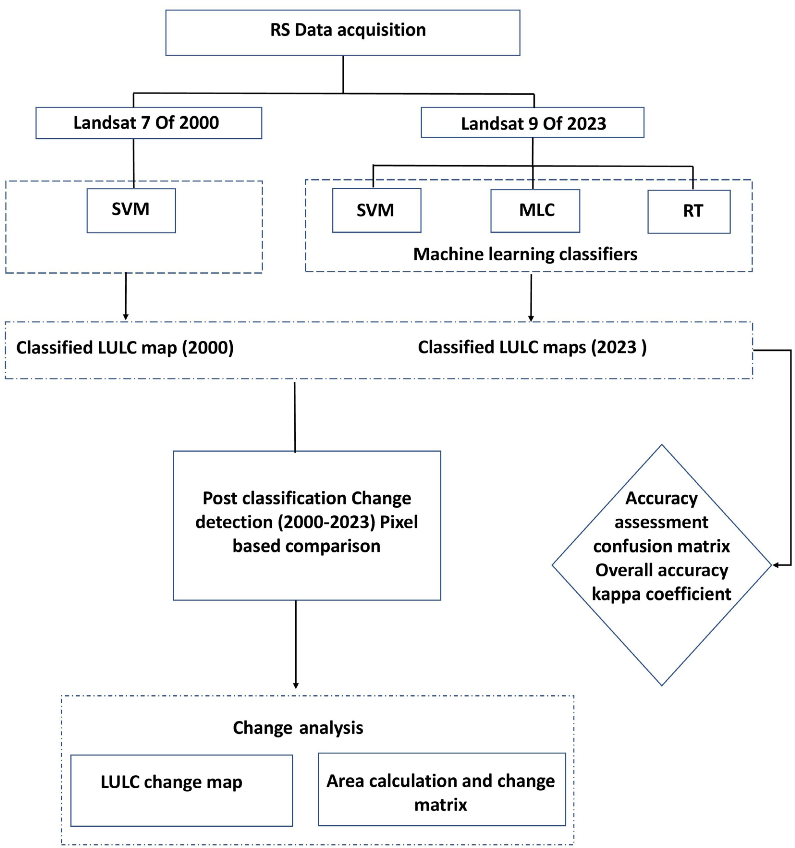

Figure 2. Methodological workflow chart.

any a priori statistical assumptions to be made regarding the distribution of data. The algorithm uses a random subset of predictors at each node to create individual decision trees. This randomness helps reduce overfitting and improves the model's generalization [42].

- Maximum likelihood classifier (MLC).

It is a supervised classification method. It assumes that the radiometric values within each class conform to a normal distribution, enabling the characterization of each class through a probability function defined by its mean vector and variance-covariance matrix [43].

3.2. Accuracy Evaluation

Assessing the outcomes of a classification is a crucial step within the classification process. In this work, a quantitative accuracy assessment based on sampling strategies was employed. First, we created a shapefile test data with 2000 points. The stratified sampling method was used. This technique permits obtaining the sample data with high efficiency [44]. The accuracy assessment is carried out with the help of a confusion matrix. It is calculated by obtaining a sample from a particular class of a classified map and then the actual class is validated from the field [45]. Finally, the classification accuracy of each algorithm was evaluated using overall accuracy and the kappa coefficient, derived from the confusion matrix.

3.3. LULC Change Detection

Change detection is used when someone is interested in identifying alterations that have occurred in a specific region, provided that satellite data covering that area can be easily obtained [46]. To conduct effective change detection research, information such as area change, change rate, and spatial distribution of changed types should be provided [24]. In this context, the Modules for Land-Use Change Simulation (MOLUSCE), a plugin inside QGIS, was utilized to estimate spatiotemporal changes. This tool supports LULC change analysis and it has been effectively employed by various researchers due to its efficiency [47] [48] [49]. The initial (2000) and the last generated (2023) LULC maps were used to obtain information on LULC dynamics in terms of pattern and conversion rate.

4. Results and Discussion

4.1. LULC Classification and Validation

The LULC classification process involves the use of SVM, ML and RT classifiers (**Figure 3**). The results indicate that the highest coverage of built-up land is achieved by MLC (10.7%), followed by RT and SVM classifiers (9.8% for both). The maximum coverage of vegetation land was classified using the RTC (64.08%) and SVM (62.99%) methods, while the lowest coverage was obtained with MLC (59.12%). Water coverage was nearly evenly distributed across all

SVM confusion matrix

ClassValue	C_1	C_2	C_3	C_4	C_5	Total	U_Accuracy	Kappa
C_1	820	7	10	0	1	838	0.978520286	0
C_2	14	500	9	0	6	529	0.945179584	0
C_3	52	9	346	0	0	407	0.85012285	0
C_4	0	0	0	10	0	10	1	0
C_5	3	20	5	0	190	218	0.871559633	0
Total	889	536	370	10	197	2002	0	0
P_Accuracy	0.922384702	0.932835821	0.935135135	1	0.964467005	0	0.932067932	0
Kappa	0	0	0	0	0	0	0	0.902265814

MLC confusion matrix

ClassValue	C_1	C_2	C_3	C_4	C_5	Total	U_Accuracy	Kappa
C_1	814	1	31	0	0	846	0.962174941	0
C_2	13	499	4	0	6	522	0.955938697	0
C_3	55	14	329	0	0	398	0.826633166	0
C_4	0	0	0	10	0	10	1	0
C_5	7	22	6	0	191	226	0.845132743	0
Total	889	536	370	10	197	2002	0	0
P_Accuracy	0.915635546	0.930970149	0.889189189	1	0.969543147	0	0.920579421	0
Kappa	0	0	0	0	0	0	0	0.88567133

RT confusion matrix

ClassValue	C_1	C_2	C_3	C_4	C_5	Total	U_Accuracy	Kappa
C_1	811	2	35	0	0	848	0.956367925	0
C_2	15	500	5	0	9	529	0.945179584	0
C_3	55	15	324	0	0	394	0.822335025	0
C_4	0	0	0	10	0	10	1	0
C_5	8	19	6	0	188	221	0.850678733	0
Total	889	536	370	10	197	2002	0	0
P_Accuracy	0.912260967	0.932835821	0.875675676	1	0.954314721	0	0.915584416	0
Kappa	0	0	0	0	0	0	0	0.878346927

C_1 : Urban area **C_2 :** Vegetation **C_3 :** Bare area **C_4 :** Water **C_5 :** Forest

Figure 3. Kappa coefficient and overall accuracy for SVM, ML and RT classifiers.

classifiers (0.05). The results reveal a difference in the percentage of forest distribution, with 9.38% for SVM, 8.92% for RT and 7.45% for MLC. For the bare area class, the ML classifier (22.67%) exhibited the highest coverage. Each algorithm's classification accuracy is evaluated using a confusion matrix. The same dataset is employed for accuracy assessment across all cases. The evaluation includes overall accuracy, user accuracy, producer accuracy and the kappa coefficient (**Figure 4**).

The results show that land cover classification from the SVM method produces a LULC map with an overall accuracy value of 93.20% and a kappa coefficient value of 0.9. The ML method generates a LULC map with an overall accuracy value of 92% and a kappa coefficient value of 0.88. Lastly, land cover classification using the RT method yields a LULC map with an overall accuracy of 91.55% and a kappa coefficient of 0.87. The results derived from the classifications and validation samples reveal that the SVM technique correctly classifies a higher number of points (1866 out of 2000 test points) compared to the ML and RT classifiers, which correctly classify 1844 and 1833 points, respectively.

4.2. LULC Change Detection

The primary objective of the change detection technique is to identify alterations in two or more images of identical sites captured at different periods [50]. Consequently, a second image was required to assess and detect changes. We opted for a study duration of 23 years and based on the classification results, the SVM method was selected to classify the Landsat 7 image acquired in 2000 (**Figure 5**).

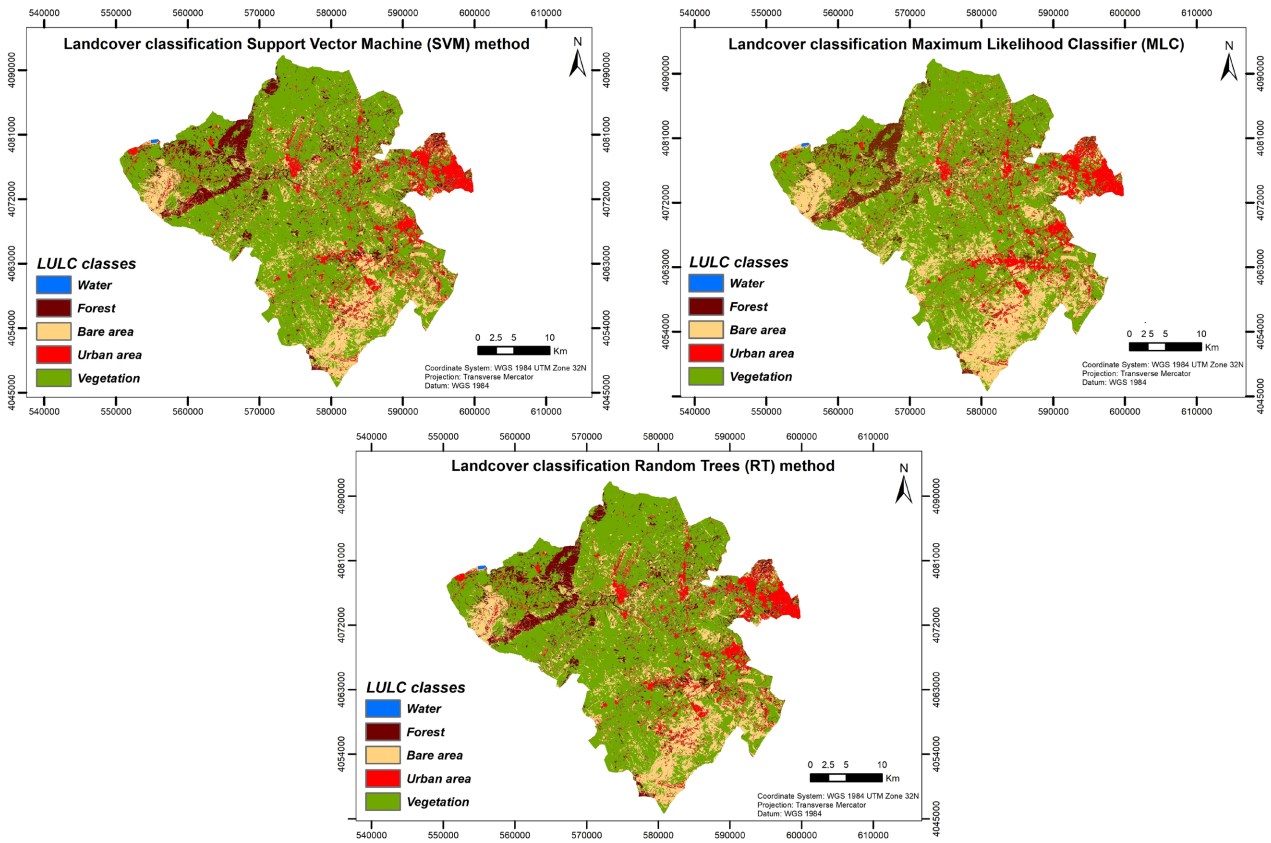

Figure 4. Comparison of LULC classification of the study area for the year 2023 based on the SVM, MLC and RT models.

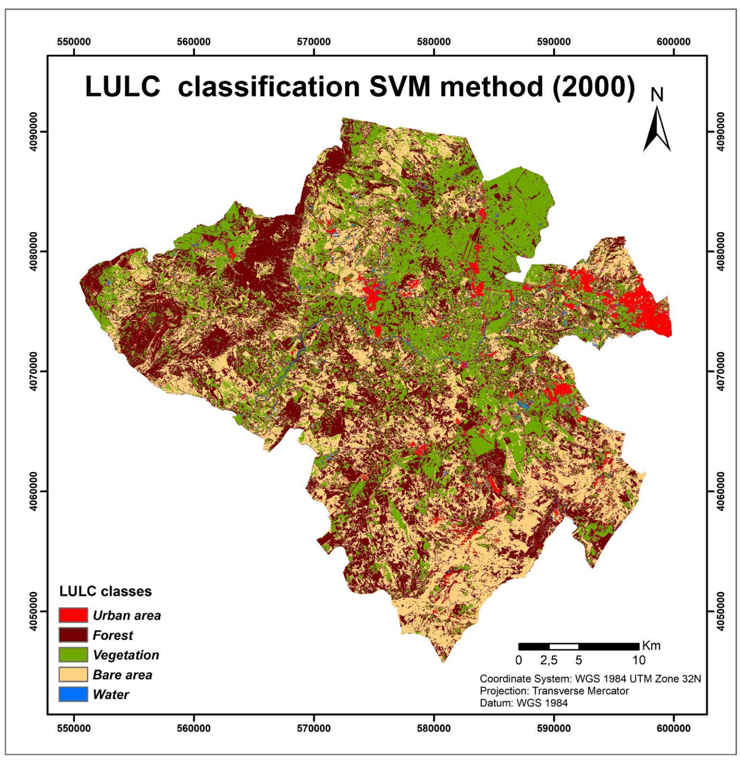

Figure 5. LULC classification result using SVM method for the year 2000.

The percentages of classified areas are as follows: urban area (4.42%), forest (32.86%), vegetation (31.06%), bare land (30.25%) and water (1.4%). Forest was identified as the dominant type of land use, followed by vegetation areas, while the least classified was the water body. The MOLUSCE plugin incorporates the LULC maps for the years 2000 and 2023 to generate a cross-tabulation analysis. The changes from a specific category to another land cover category and their respective areas over the assessed period were calculated on a pixel-by-pixel basis (**Table 1**). Consequently, a new thematic layer was produced from the two five-class maps, encompassing various combinations of 'from-to' change classes (**Figure 6**). This LULC change map indicates the spatial dynamic variations in the LULC pattern during the study period. The results from 2000 to 2023 show a notable expansion in the urban area and vegetation surface. The vegetated area was 35289.09 hectares in 2000, experiencing an increase to 71575.83 hectares in 2023. The urban area saw growth from 5,025.87 hectares in 2000 to 11,239.92 hectares in 2023. Conversely, there was a reduction in forested areas, with these regions decreasing from 37,335.24 hectares to 10,656.27 hectares in 2023. The water bodies also exhibited a decline, shrinking from 1,594.08 hectares to 51.48 hectares in 2023. The bare area witnessed a decrease from 34,377.30 hectares in 2000 to 20,098.08 hectares in 2023 (**Figure 7**).

4.3. Discussion

The paper aimed to investigate the effectiveness of various classification methods in mapping and evaluating LULC changes using remote sensing and GIS. This involved the application of supervised classification techniques and LULC detection.

In the first section, classification procedures were applied to Landsat 9 using different methods, including SVM, ML, and RT classifiers. It's noteworthy that our findings align with existing research in the literature. Several studies have also highlighted the performance of SVM in LULC classification [51]. The obtained classification results indicate variations in the areas of LULC classes. It's important to highlight that the selection of a classifier influences the accuracy of LULC data classification in satellite imagery. Nevertheless, some researchers

Table 1. Summary of Landsat classification area statistics for 2000 and 2023.

	2000		2023		2000-2023	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Difference (ha)	Difference (%)
Urban area	5025.87	4.42	11239.92	9.89	6214.05	5.47
Forest	37335.24	32.86	10656.27	9.38	−26678.97	−23.48
Vegetation	35289.09	31.06	71575.83	62.99	36286.74	31.94
Bare area	34377.30	30.26	20098.08	17.69	−14279.22	−12.57
Water	1594.08	1.40	51.48	0.05	−1542.60	−1.36

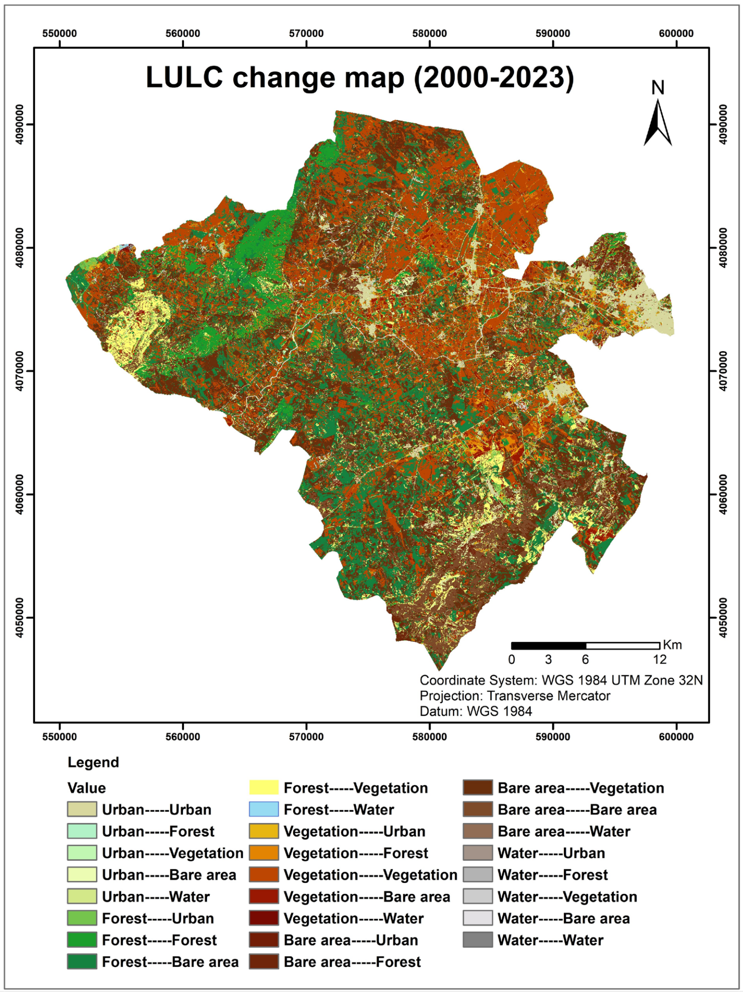

Figure 6. Change detection of LULC in study area from 2000 to 2023.

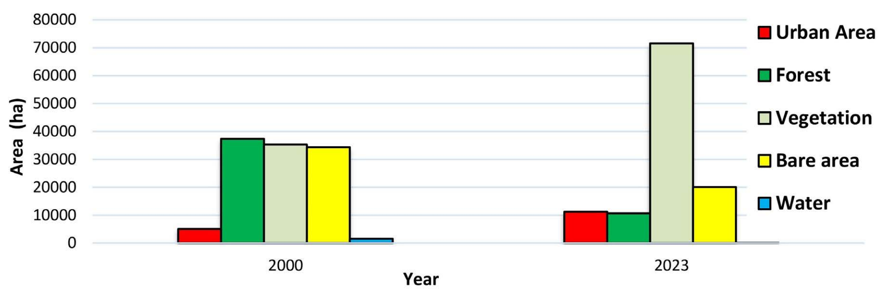

Figure 7. LULC Change dynamics in the study landscape (ha).

have demonstrated the accuracy of LULC classification not only with the classifier but also with space and time [52]. Remote sensing classification is indeed a complex process that necessitates the consideration of numerous factors [29].

In the second part of the research, we were interested in evaluating the LULC changes. The results pointed out that, during the last 23 years, urban area and vegetation classes increased by 5.46% and 31.93%, respectively, while forest, bare area, and water body decreased by 23.48%, 12.56%, and 1.35%, respectively

(**Figure 8**). The most significant loss is depicted in forest classes. A total of 26678.97 hectares of forest disappeared. Of this area, 65% was converted to vegetation, 15% to bare area, and 5% to urban area. Furthermore, the bare area decreased from 34377.30 hectares in 2000 to 20098.08 hectares in 2023, reflecting an average change of −12.56%. Sixty percent and 9% of this area were converted to vegetation and urban areas, respectively. It is apparent that large urban areas appeared (6214.05 ha). The conversion to this class occurred from various land cover types, particularly from water bodies (31%). Findings from 2000 to 2023 reveal a significant expansion in both vegetation and urban areas, juxtaposed with a reduction in the forest, bare area and water bodies.

The forest emerged as the largest contributor to the change from 2000-2023, with a significant conversion of major areas into vegetation classes, likely attributed to the extensive growth of agricultural practices. In fact, the governorate of Manouba is the leading producer of pears, accounting for 33% of the national production and it also leads in artichokes, contributing 26% to the national output. Moreover, it boasts over one million and twenty-six thousand olive trees planted, with 91% of them in productive condition [53]. Indeed, olive growing represents Tunisia's primary agricultural activity and its socio-economic role holds crucial significance. The least pronounced LULC modifications occurred in the western and southern regions, where the slope is relatively higher compared to other sectors. Notably, the original urban zones (western and central parts) expanded through the transformation of neighboring areas into residential spaces. These alterations are closely linked to escalating human activities and industrial expansion. The findings indicate that both physical and socioeconomic factors exerted a substantial influence on landscape patterns.

The paper emphasizes the role of remote sensing data, GIS and ML classification algorithms. Indeed, the cost-effectiveness of employing remote sensing technology and the advancements in computing techniques make it more feasible for developing countries [54]. These technologies permitted the classification of LULC in the governorate of Manouba, producing accurate data that was used

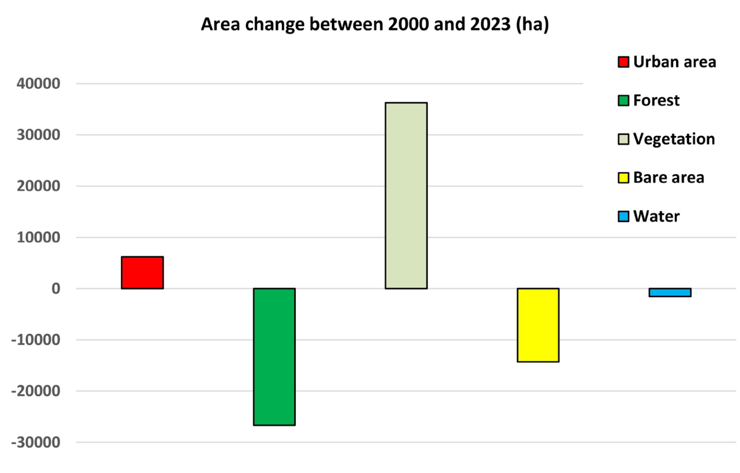

Figure 8. Rate of LULC change (2000-2023) in the study area.

to detect, evaluate, and understand the dynamics of LULC changes. This generated information can be instrumental in decision-making and environmental management, rendering them essential in today's world [55].

5. Conclusion

This paper underscores the effectiveness of GIS and remote sensing techniques. It provides insights into the comparative performance of these classification methods. Supervised classification procedures were applied to Landsat 9 (2023) using different methods, including SVM, ML, and RT classifiers. Our analysis was based on classification and validation samples. The results show five LULC classes in the Manouba region, namely, urban area, vegetation, bare area, water and forest. A spatial matrix analysis was adopted to evaluate the accuracy of the different classifiers. All the classification methods employed in our study have produced favorable results. The SVM method emerged as the top-performing classifier, achieving an overall accuracy of 93% and a kappa coefficient of 0.9. Following this, the ML method secured the second position among the classifiers, demonstrating an overall accuracy of 92% and a kappa coefficient of 0.88. The RT method exhibited the lowest accuracy among the three approaches, with an overall accuracy of 91% and a kappa coefficient of 0.87. Based on the classification results, we applied the SVM method to produce the 2000 LULC map. The MOLUSCE plugin compares classification outcomes from 2000 with those from 2023, generating a LULC change map. The examination of LULC changes explores the spatial dynamic variations in the LULC pattern throughout the study period. Of the LULC classes, urban areas and vegetation had shown progressive expansion. The 31% and 4.42% of vegetation and urban sectors of Manouba region in 2000 expanded to 62.99% and 9.89% in 2023, respectively, while the 32.8%, 30.2%, and 1.4% of the forest, bare area, and water body in 2000 decreased to 9.37%, 17.68% and 0.04 % in 2023, respectively. The results show a great loss in the case of forest and bare land by −23.48% and −12.56% respectively. The research highlights a notable rise in vegetation cover. Conversely, there has been a consistent decline in water quantities due to the reduction in annual rainfall. A phenomenon of deforestation has also been observed in the study area, with the disappearance of 26678.97 ha of forest. The dynamics of LULC change can be explained by various factors, including physical, socioeconomic activities, and climatic elements, all of which may influence landscape patterns. The findings will serve as a valuable resource for understanding the dynamic transformations in land utilization over 23 years and LULC driving factors in the study area. It constitutes an important tool for regional environmental management and planning. This paper has demonstrated the importance of LULC change analysis in monitoring, which can be applicable to other regions with comparable conditions.

However, the integration of additional data, including topographic and socio-economic factors, is expected to provide us with a more comprehensive understanding of LULC dynamics and the driving factors of change. Additionally, we plan to explore other advanced machine learning techniques to enhance the accuracy and efficiency of LULC classification and prediction, with the aim of improving the results of our current study.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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