EEET ECOLOGICAL ENGINEERING & ENVIRONMENTAL TECHNOLOGY

Ecological Engineering & Environmental Technology 2023, 24(9), 161–169
https://doi.org/10.12912/27197050/173211
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Received: 2023.09.30
Accepted: 2023.10.25
Published: 2023.11.15

Land Use and Land Cover Analysis Using Geomatics Techniques in Amara City

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ABSTRACT

The remote sensing technique is crucial for creating maps showing land use and land cover from a procedure known as image classification. For the process of image classification to be successful, many aspects must be taken into consideration; one of these factors is the availability of high-quality Landsat images. This study aims to classify and map the studied area's land use and cover using remote sensing and geographic information system techniques. This study is divided into two parts: part one focuses on classifying land use and land cover, while part two evaluates how accurate the classification is. Several classification methods are compared for their efficacy in this study. Some image classification methods have shown promising results when used to remote sensing data. An efficient classifier is necessary for extracting data from remote-sensing images. The maximum likelihood classification was the most effective classifier in our study. In this study, the Maximum Likelihood classification accuracy has achieved an overall accuracy of 91% and an overall kappa accuracy of 86.83%. This study provides essential data for planners and decision-makers to design sustainable environments.

Keywords: remote sensing, GIS, supervised classification, land use land cover.

INTRODUCTION

Remote sensing, especially satellites, provides a wealth of data to investigate environmental factors' temporal and spatial variability. Remotely sensed imaging is used for surveillance, mapping products for military and civilian use, environmental damage assessment, land use monitoring, radiation monitoring, soil assessment, and urban planning (Falih and Saedi, 2020). In general, remote sensing can offer crucial coverage, mapping, and classification of land-cover elements. These features include vegetation, soil, water, and forests. Creating a classification map of the distinguishable or significant characteristics or classes of land cover types in a scene is a crucial application of remotely sensed data (Jasinski, 1996). Information on LULC is necessary for policy formulation, commerce, and administration of government programs. Since they contain spatial information, the data are essential for both the preservation of the environment and spatial planning. The categorization of land use is necessary since it provides data that can be utilized as input for modelling, mainly modelling that is concerned with the environment. For example, models that deal with climate change and policy developments require data that can be obtained through land use classification (Disperati and Virdis, 2015). As a result, the integrated LULC grants provide an all-encompassing method for comprehending the behaviour and interactions of geo-biophysical and socioeconomic systems (Moran et al., 2004). Combining Remote Sensing with GIS analysis is a common practice to obtain more valuable data regarding land cover.

Although occasionally used interchangeably, the phrases "land use" and "land cover" are distinct. The difference between LULC can be summarised as follows: land use relates to how the

Land is utilized, whereas land cover refers to the things found on the earth's surface. Examples of the many land cover classes are snow, water, grassland, and bare soil. Land uses include agricultural Land, urban areas, recreation areas, and wildlife management areas (Talukdar et al., 2020). Aerial photographs and images obtained from the Landsat satellite are typically utilized to evaluate the distribution of land cover and to bring existing geospatial information up to date. Recent years have seen a meteoric rise in the significance of remote sensing in the GIS field due to advancements in image processing and remote sensing software (Merchant and Narumalani, 2009).

Accuracy assessment is an essential step in analyzing data from remote sensing. It determines the output data's information value as seen by the user. The classification image's overall accuracy is assessed by comparing the classifications made for each pixel to the exact land cover conditions identified from the related ground truth data. Errors of omission are a measurement that determines how accurately different forms of real-world land cover can be detected, and they are used to determine the accuracy of production. Errors of commission are used to evaluate the user's accuracy, which is the likelihood that a classified pixel will match the land cover type of the real-world site it is connected with (Campbell and Wynne, 2011). The kappa coefficient and error matrix are standard metrics for assessing image classification accuracy.

This study employed RS and GIS techniques to classify and map the LULC of the studied area. In addition, an accuracy assessment was also performed to learn how to interpret the classification's value and how well the classification operations were executed.

STUDY AREA

The study area map was derived from a map of the Maysan province. Its administrative center is the city of Amarah, and it is composed of six districts. The area falls under latitude 32°N and longitude 47° E. The overall area covered by the study is 16,072 km^2. Figure 1 depicts the geographical location that was used for the research.

MATERIALS AND METHODS

Accuracy assessment of LULC analysis are the two topics this research covers. According to the methodology shown in Figure 2.

Land use/land cover (LULC) classification

Image pre-processing

Satellite images were acquired from the Landsat 8 OLI/TIS on July 18, 2022., and were used for the classification procedure and study of the various LULC classes. These images (path 166, rows 38). The Landsat images were downloaded using the USGS Earth Explorer, found at (https://earthexplorer.usgs.gov/) (Eastman, 2003). The

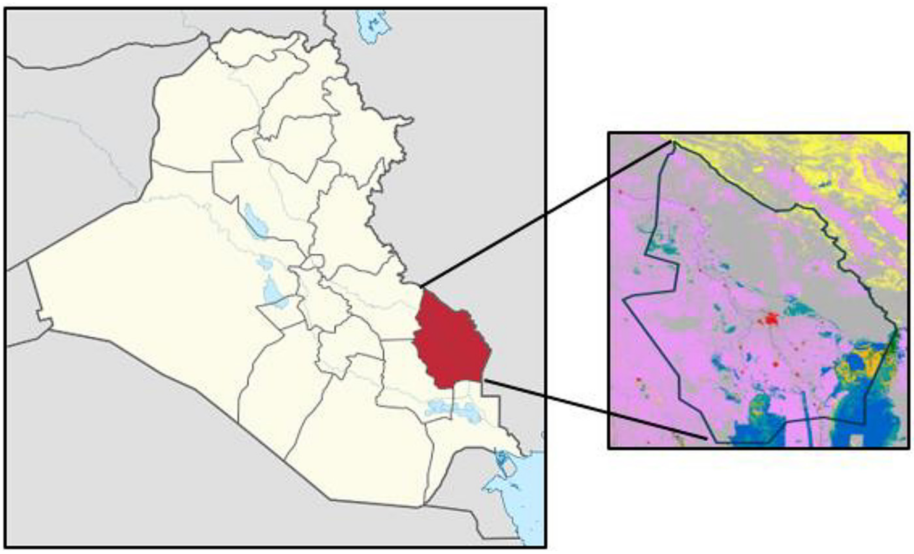

Figure 1. Map of the study area

WGS 84 datum and the UTM Zone 38 North were utilized to georeference each Landsat.

Layer stacking and georeferencing were just two examples of extensive pre-processing. ENVI 5.3 software was then used to process the image. Each band's satellite image was stacked in ENVI 5.3 using the layer-stacked function. After that, using ENVI 5.3 software, the study area from the stacked satellite image was clipped.

Supervised classification

After the user has developed the spectral signatures of different categories, such as urban and forest, the user then assigns the cover type to each pixel in the image based on the cover type to which that pixel's spectral signature is most comparable using supervised classification (Kadhum et al., 2023). Supervised classification is utilized most frequently in quantitatively assessing the image data acquired by remote sensing (Richards and Jia, 2006). The Landsat Image, ESA-Worldcover, and Google Earth were used to decide the training locations (Figure 3). The fundamental operations for supervised classification were as follows:

- Defining training sites – when doing a supervised classification, the initial step that has to be done is to establish training sites for every class of land cover.

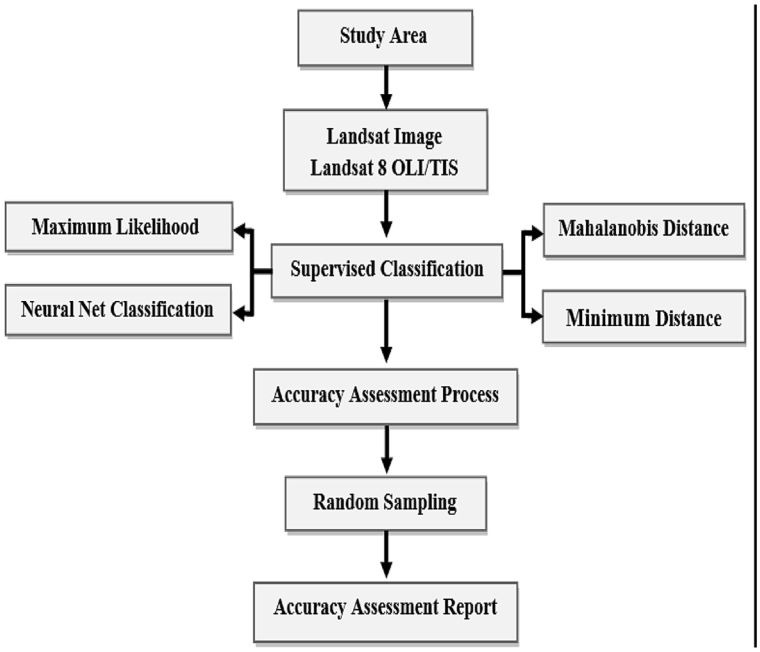

Figure 2. Schematic of methodological workflow

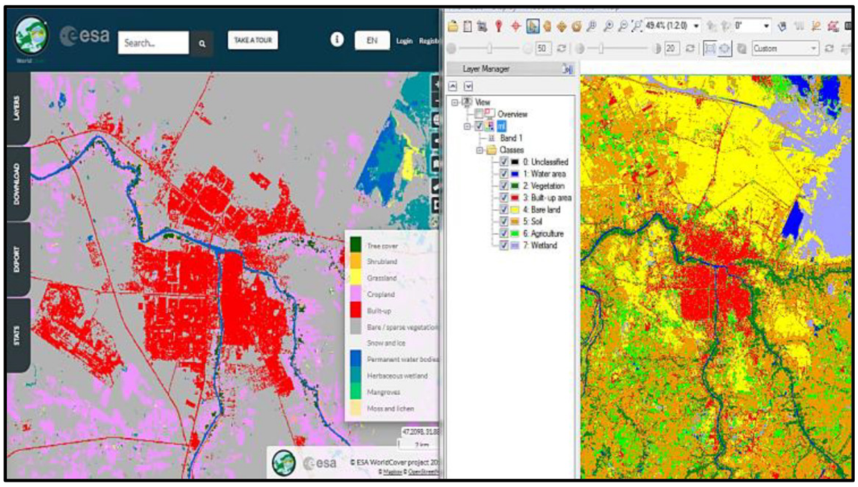

Figure 3. Landsat image (ENVI 5.3 software) and Esa-World cover were used to locate suitable training sites

- Classification of the image – following established training classes, supervised classification has been used. Seven categories were used to categorize the image: water area, vegetation, built up areas, soil, bare land, and wetland.

Methods

This study's goals included classifying and mapping the study area's land use and cover using multispectral data and performing an accuracy assessment of the various classification algorithms to evaluate the effectiveness of the classification processes. It is implemented with ENVI 5.3.

Maximum likelihood classification

Supervised maximum likelihood classification (MLC) has been employed to analyze remotely sensed images. The categorization process used a Landsat image. Based on Bayes' categorization, MLC assigns pixels to classes depending on their likelihood of falling into a specific category. The essential MLC component that may be extracted from training data is the mean vector and covariance metrics. According to classification data, MLC is a reliable technique with very low odds of misclassification. "Figure 4" displays the image with the (MLC) classification.

Neural network classification

An artificial neural network (ANN) with several layers is used for non-linear categorization. This model employs the conventional back propagation technique for supervised learning; in addition to that, it consists of at least one hidden layer, one layer of output data, and one layer of input data. Learning occurs when the node weights are adjusted so that there is as minimal of a gap as possible between the activation of the output node and the output. Recursive weight modification is used once the fault has been back-propagated through the network (Atkinson & Tatnall, 1997). Figure 5 displays the classified image.

Mahalanobis distance classification

Unlike minimum distance classification, the covariance matrix is employed in Mahalanobis distance classification. The Mahalanobis distance algorithm works under the assumption that the

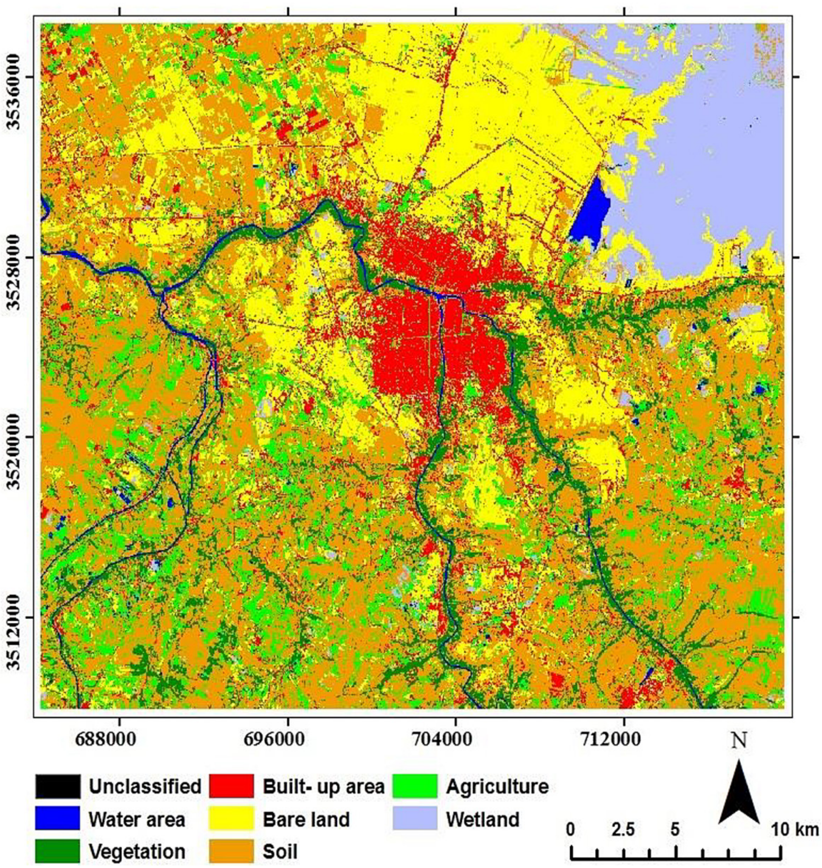

Figure 4. Maximum likelhood classification.

histograms of the bands usually have distributed data (Perumal and Bhaskaran, 2010). In Figure 6, the classified image is displayed.

Minimum distance classification

The minimal distance choice rule defines the spectral distance between the measurement vector for the candidate pixel and the mean vector for each sample, which is the foundation for this decision-making process. The class with the least spectral distance is subsequently given the candidate pixel's assignment (Perumal and Bhaskaran, 2010). In Figure 7, the classified image is displayed.

CLASSIFICATION ACCURACY ASSESSMENT

The image classification process requires an assessment of the level of accuracy achieved. The objective of the accuracy assessment is to determine, quantitatively, the level of success achieved in sampling the relevant land cover categories using the pixels. In addition, the primary focus for the accuracy of assessment pixel selection was placed on regions easily distinguishable in both Landsat high-resolution pictures. The confusion matrix can produce results that can be used for accuracy assessment (Rwanga and Ndambuki, 2017). A quantitative comparison of the relationship between the photos that have been categorized and the reference data, which may include a field survey, a high-resolution digital map, or thematic maps, is performed via confusion matrices. After the confusion matrix has been created, the overall accuracy, the producer and the user accuracies, omission and commission mistakes, and the Kappa statistics can be written out as given in Equation 1.

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_i + Xx_{+1}\right)}{N^2 - \sum_{i=1}^{r}\left(x_{ii} Xx_{+1}\right)} \quad (1)$$

where: N – total observations, r – the number of columns and rows in the error matrix (pixels), $X{+i}$ – marginal column I total, $Xi+$ = marginal row I total, and Xii = observation in column I and row I Perfect agreement is indicated by a Kappa coefficient

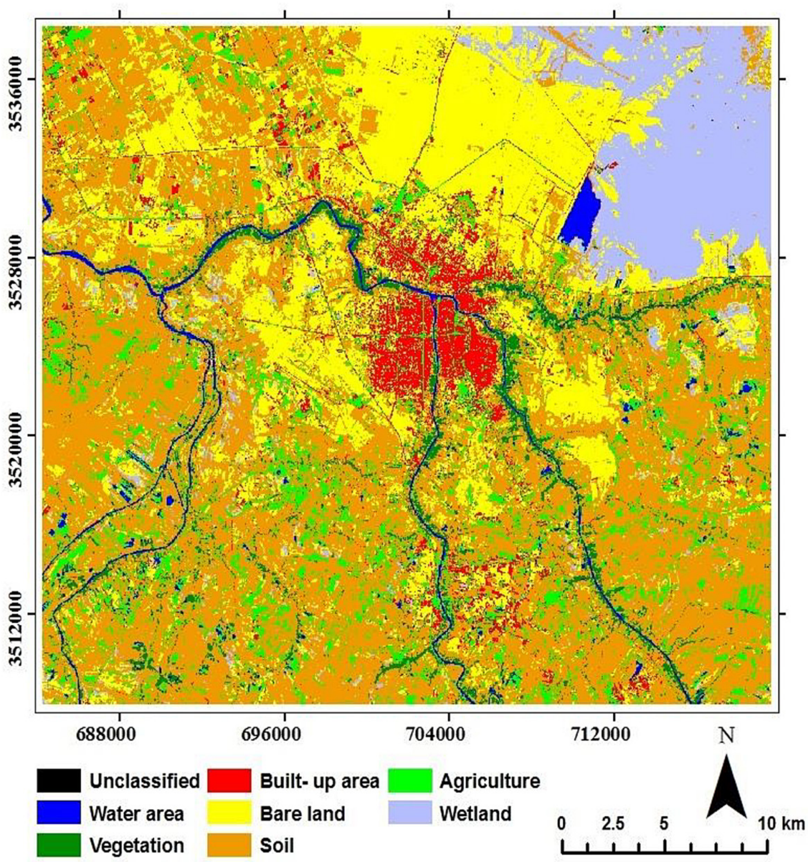

Figure 5. Neural network classification

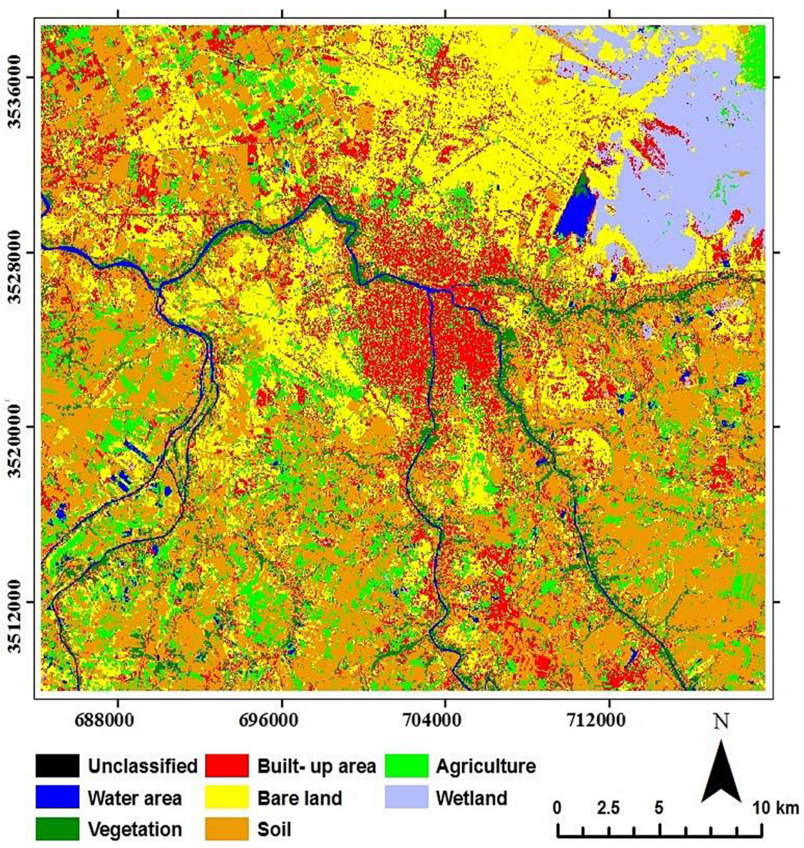

Figure 6. Mahalanobis distance classification

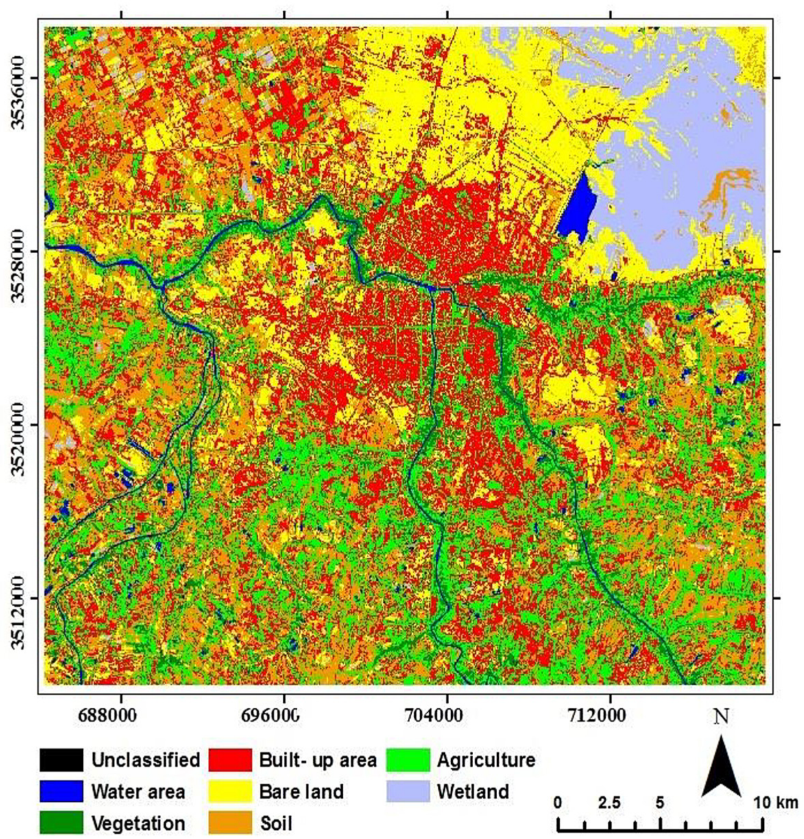

Figure 7. Minimum distance classification

of 1. Table 1 reproduces the widely used category of the Kappa statistic (Rwanga and Ndambuki, 2017).

RESULTS AND DISCUSSIONS

According to several research findings, the LULC classes' areas do not correspond to one another in any classification methods. The application of four different approaches classified the image, and the findings from investigating these approaches demonstrate variation. The region that is part of the definition of any given land-use class by one classifier does not precisely correspond to the area that is part of the definition of the same land-use class by a different classifier. Table 2 contains several other accuracy-evaluating parameters

Table 1. Rating of Kappa statistics

No	Statistics kappa	Degree of agreement
1	0.00–0.20	Slight
2	0.21–0.40	Fair
3	0.41–0.60	Temperate
4	0.61–0.80	Essential
5	0.81–1.00	Almost ideal

Table 2. Implementation of Overall Accuracy and Kappa Coefficient for different classification methods

Class	Maximum likehood classification		Neural network Classification		Mahalanobis distance classification		Minimum distance classification	
	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy
Water area	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Vegetation	100.0	100.0	99.6	100.0	97.9	99.6	100.0	100.0
Built- up area	87.1	86.6	67.2	90.4	73.3	45.3	88.7	42.3
Soil	73.1	83.0	80.8	78.3	70.7	88.4	44.9	75.3
Bare land	93.9	89.6	94.4	87.9	84.1	84.4	76.5	83.1
Wetland	96.1	98.5	94.6	98.2	84.5	99.9	84.2	94.5
Overall accuracy	91.00%		89.65%		81.55%		76.28%	
Kappa coefficient	0.8683		0.8474		0.7352		0.6631	

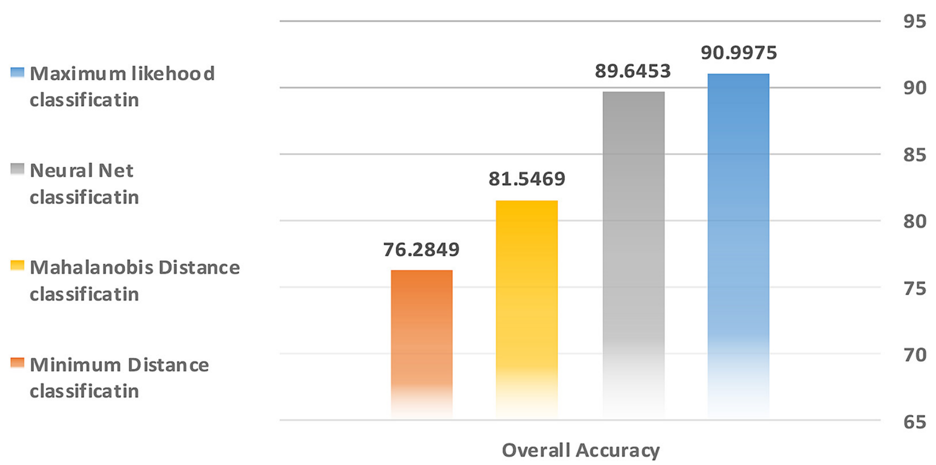

Figure 8. Overall accuracy for different classification methods

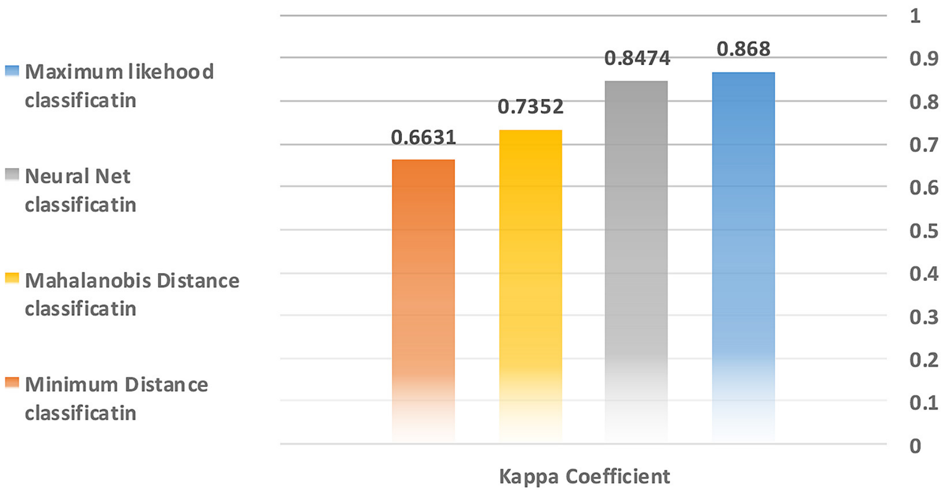

Figure 9. Kappa coefficient for different classification method

Confusion Matrix:

Overall Accuracy = (12625/13874) 90.9975%
Kappa Coefficient = 0.8683

Ground Truth (Pixels)

Class	Water test	Vegetatin tes	Built- up are	Soil test	Bare land tes
Unclassified	0	0	0	0	0
Water area	158	0	0	0	0
Vegetation	0	238	0	0	0
Built- up are	0	0	1364	38	174
Soil	0	0	29	1408	170
Bare land	0	0	169	473	5945
Wetland	0	0	4	7	44
Total	158	238	1566	1926	6333

Ground Truth (Pixels)

Class	Wetland test	Total
Unclassified	0	0
Water area	0	158
Vegetation	0	238
Built- up are	0	1576
Soil	89	1696
Bare land	52	6639
Wetland	3512	3567
Total	3653	13874

Ground Truth (Percent)

Class	Water test	Vegetatin tes	Built- up are	Soil test	Bare land tes
Unclassified	0.00	0.00	0.00	0.00	0.00
Water area	100.00	0.00	0.00	0.00	0.00
Vegetation	0.00	100.00	0.00	0.00	0.00
Built- up are	0.00	0.00	87.10	1.97	2.75
Soil	0.00	0.00	1.85	73.10	2.68
Bare land	0.00	0.00	10.79	24.56	93.87
Wetland	0.00	0.00	0.26	0.36	0.69
Total	100.00	100.00	100.00	100.00	100.00

Ground Truth (Percent)

Class	Wetland test	Total
Unclassified	0.00	0.00
Water area	0.00	1.14
Vegetation	0.00	1.72
Built- up are	0.00	11.36
Soil	2.44	12.22
Bare land	1.42	47.85
Wetland	96.14	25.71

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Water area	0.00	0.00	0/158	0/158
Vegetation	0.00	0.00	0/238	0/238
Built- up are	13.45	12.90	212/1576	202/1566
Soil	16.98	26.90	288/1696	518/1926
Bare land	10.45	6.13	694/6639	388/6333
Wetland	1.54	3.86	55/3567	141/3653

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Water area	100.00	100.00	158/158	158/158
Vegetation	100.00	100.00	238/238	238/238
Built- up are	87.10	86.55	1364/1566	1364/1576
Soil	73.10	83.02	1408/1926	1408/1696
Bare land	93.87	89.55	5945/6333	5945/6639
Wetland	96.14	98.46	3512/3653	3512/3567

Figure 10. Confusion matrix obtained from the ENVI software

that have been computed and summarized. Additionally, the accuracy of a classified image must be evaluated. Using an error matrix, an accuracy assessment was done in this study. The classification accuracy Maximum Likelihood classifier has achieved an overall accuracy of 91% and an overall kappa accuracy of 86.83% (Figures 8, 9). The kappa coefficient was determined to be substantial, and as a result, the classified image has been deemed appropriate for additional study. There have been many attempts to classify land uses using machine learning techniques, but so far, the results of these models have not been thoroughly evaluated. In this article, we used four different machine-learning methods to determine which one can generate the most accurate LULC map.

CONCLUSIONS

Image classification is a technique that can be used in remote sensing to create maps of land use/land cover. The performance of different classifiers was examined in this research, and it was discovered that the Maximum Likelihood classifier outperformed even the most sophisticated classifiers. This precise yet straightforward classifier demonstrates the value of considering the link between the data set and classifier for successful image classification. In addition, there is also a noticeable increase in the amount of Land that is covered by built-up areas. However, the amount of Land used for agriculture, areas of water, and areas of forests has decreased. The findings of this study make it abundantly evident that population growth and the associated development activities have a substantial impact on LU/LC change. The use of classifiers has to be improved by completing more research to broaden the scope of their application.

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