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Random Forest (RF) and Artificial Neural Network (ANN) Algorithms for LULC Mapping

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K E Y W O R D S

Artificial neural network,
LULC Mapping,
Random forest.

A B S T R A C T

In this paper to make use of complementary potential in the mapping of LULC spatial data is acquired from LandSat 8 OLI sensor images are taken in 2019. They have been rectified, enhanced and then classified according to Random forest (RF) and artificial neural network (ANN) methods. Optical remote sensing images have been used to get information on the status of LULC classification, and extraction details. The classification of both satellite image types is used to extract features and to analyse LULC of the study area. The results of the classification showed that the artificial neural network method outperforms the random forest method. The required image processing has been made for Optical Remote Sensing Data to be used in LULC mapping, include the geometric correction, Image Enhancements, The overall accuracy when using the ANN methods 0.91 and the kappa accuracy was found 0.89 for the training data set. While the overall accuracy and the kappa accuracy of the test dataset were found 0.89 and 0.87 respectively.

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1. Introduction

Nowadays, with progress in remote sensing gathering technology and the increased call for remote sensing programs, high spatial decisions far off sensing, statistics are regularly turning into greater great [1]. The availability and accessibility of significant amounts of high-decision far off sensing information have created a venture for faraway sensing image class. As a result, Artificial Neural Network and

Random Forest techniques have emerged and compared according to their accuracy to address these issues. The thematic layer was created by using a supervised classification method that was through using the random forest (RF) and artificial neural network (ANN) algorithms. After using algorithms for the training areas and select the best algorithm based on the accuracy and acceptable the Kappa coefficients. The results of the classification showed the random forest and the artificial neural network showed the significance of the ANN method. Through those above methods, the area was classified into five distinct classes, namely buildings, water, agriculture, bare land, and wetland.
The objective of the study was as follows as:

- Update statistics of the region shown in Figure 1 using two extraordinary classification algorithms.
- Comparing two kind classification algorithm according to accuracy evaluation
- This paper ambitions to map the LULC for study vicinity the usage of different type strategies and comparing the outcomes. The produced LULC maps within the observed area will be used for analyses and map as a basis for strategic planning and management. Moreover, this examines affords help and guidance for making efficient and powerful selections by decision-makers. Classification is a way that relates things to a legitimate class. Through the procedure of sorts, each picture element is allocated to a certain or questionable class and as a result connected to the class pecking order. The yield of the class is a system of classified picture objects with one of a kind ascribes and explicit relations to their object in the brilliance chain of importance. Imagery type can be subdivided into supervised and unsupervised, or parametric and nonparametric, sub-pixel, and reliable with-field [2]. The parametric classifiers assume that a regularly dispersed dataset exists and that the measurable parameters, replicated from the tutoring tests are an agent. What's more, poor, non-delegate, or multimodal dispersion instruction tests can comparatively acquaint vulnerability with the image type procedure. Another basic snag of the parametric classifiers outcomes from the issue of incorporating otherworldly measurements with subordinate data. With nonparametric classifiers, the assumption of an ordinary dispersion of the dataset isn't constantly required [3]. No factual parameters are required to part photograph guidelines. Non-parametric classifiers are thus particularly appropriate for the fuse of non-otherworldly records in a class way [2]. Over about the end of two decades, the remote detecting network has embraced significant endeavours to sell the utilization of item-based absolutely age for land-cowl mapping [4-6]. Moreover, spatial choice relates to the most satisfying division scales and inspect the spot, and Random Forest (RF) proposes the charming presentation in the article fundamentally based sort. The locale based absolutely exactness evaluation technique can accomplish strong class generally speaking execution, and proposes a tough connection among precision and preparing set size, in the meantime, as the exactness of the factor-based methodology is more than likely to be unstable in light of joined things. What's more, the general precision points of interest from better spatial choice pics or rural areas wherein it moreover corresponds with the assortment of centred targets.

2. Methods and Materials

I. Data

In this study, datasets from Landsat OLI (multispectral and thermal bands) are used (Figure 1). The Landsat OLI multispectral bands were utilised to create the land use and land cover map of the region using the random forest and neural network approaches. The description of these datasets is given in Table 1. The Landsat OLI image was pre-processed before using it for LULC mapping. This included radiometric calibration, geometric correction, atmospheric correction, and spatial subset. They helped to reduce the malfunction errors and reduce the noise from the images. It also helped to co-register the images correctly and remove the sunlight effects from the image. The digital numbers of the imagery were changed over into radiance esteems (radiometric adjustment) utilizing the addition and counterbalance esteems recovered from the metadata document of the information. Second, the radiance esteems were standardized and changed over into surface reflectance. This progression was urgent as it evacuated the varieties because of environmental conditions and the bidirectional reflectance distribution function (BRDF). From that point onward, the imagery was geometrically adjusted and co-enlisted to guarantee correspondent with one another and the ground truth information, which were gathered from Google Earth. Finally, the QUAC atmospheric correction algorithm was used to convert the radiance to reflectance and retrieve the spectral reflectance of the image. Finally, the images were subset to cover only the area of interest.

Table 1. Description of the datasets used in the current research.

Parameter	Landsat OLI
Acquisition date	2019-03-05
Cloud cover (%)	2.3%
Spatial Resolution (m)	30
Usage	LULC, Surface Temperature

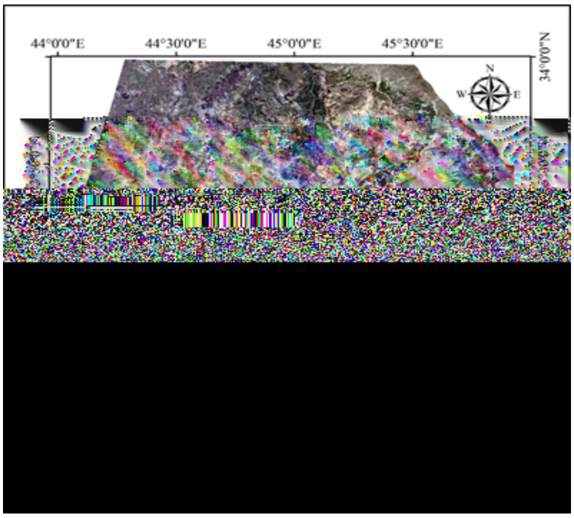
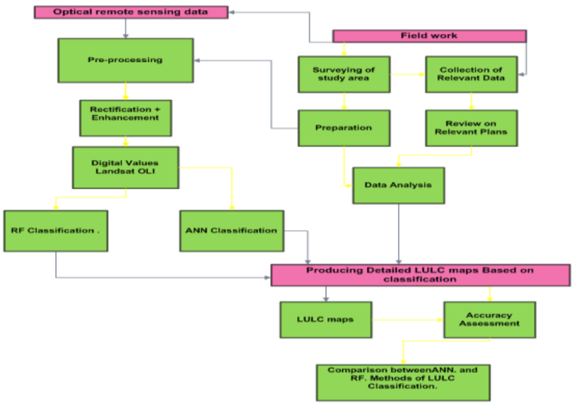


Figure. 1: Landsat OLI image

II. Land use and landcover

This method is one of the significant factors for desertification mapping. The thematic layer was created by using a supervised classification method that was carried out with the random forest (RF) using Weka software and artificial neural network (ANN) using a python script. After using algorithms for the training areas and select the best algorithm based on the accuracy and acceptable Kappa coefficients LULC classes were identified. The results of the classification showed the random forest and the artificial neural network methods as shown in the figure 3 and 4. Through those above methods, the area was classified into five distinct classes, namely buildings, water, agriculture, bare land, and wetland. For more information, as shown flowchart 1 below.



Flowchart 1

3. Study Area

The study area is located between 44° – 46° longitudes and 32° – 34° 30' latitudes (Figure 2). It covers a large part (30,545.25 km^2) of Iraq, including Diyala, Baghdad, Wasit, Al Anbar, Karbala, and Babylon provinces.

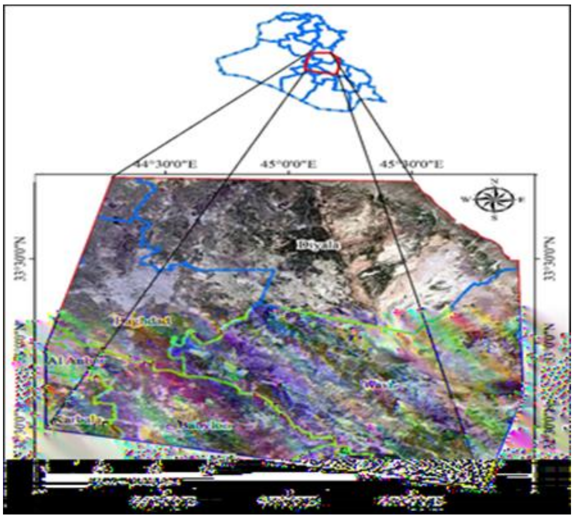


Figure2: Study area

4. Results and Discussion

I. LULC Mapping

LULC thematic layer was created by a supervised classification method using the random forest and neural network algorithms. The training areas were resolved by field considers and adequate Kappa coefficients. The results of the classification showed that the artificial neural network method outperforms the random forest method, thus, the former method was selected in this research. The area was classified into five distinct classes, namely building, water, agriculture, bare land, and wetland as shown in figures 3 and 4, and tables 2 and 3 explain the accuracy for image classification through an artificial neural network (ANN) and random forest (RF) methods.

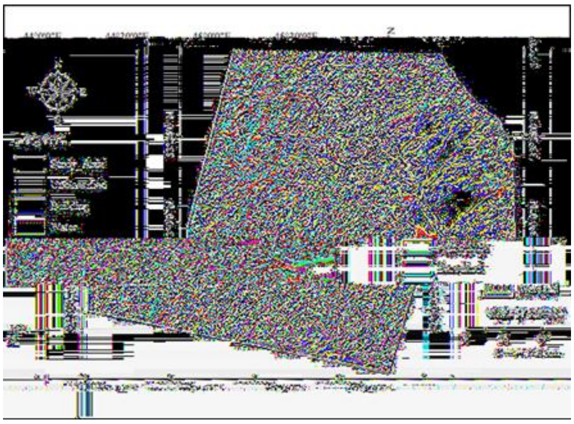


Figure 3: The LULC map producing by ANN model

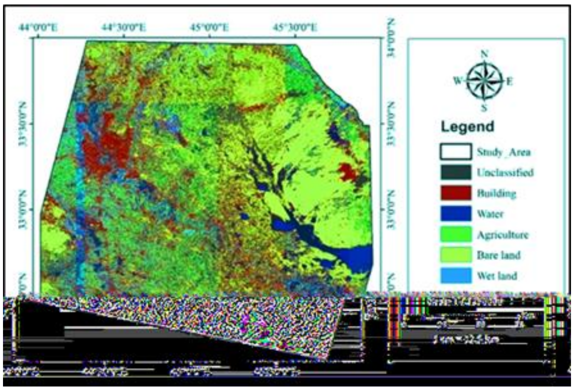


Figure 4: The LULC map producing by RF model

II. Accuracy Assessment

The overall accuracy when using the ANN methods 0.91 and the kappa accuracy were found 0.89 for the training dataset. While the overall accuracy and the kappa accuracy of the test dataset were found 0.89 and 0.87 respectively. As well as, the best accuracy achieved, when using 35 the hidden layers as given in Tables 2 and 3.

Table (2) The accuracy of ANN and RF classifiers.

Classifier	Overall accuracy		kappa accuracy	
	Training	Testing	Training	Testing
ANN Model	**0.91**	**0.89**	**0.89**	**0.87**
RF Model	0.85	0.81	0.82	0.78

Table (3) the results of hidden Layers for ANN.

Experiment No.	Hidden Layers	Overall accuracy		kappa accuracy	
		Training	Testing	Training	Testing
1	10	0.53	0.51	0.52	0.51
2	15	0.58	0.56	0.55	0.53
3	25	0.63	0.60	0.61	0.58
4	30	0.75	0.72	0.73	0.70
5	**35**	**0.91**	**0.89**	**0.89**	**0.87**
6	40	0.76	0.74	0.75	0.72
7	45	0.62	0.57	0.60	0.54
8	50	0.56	0.52	0.54	0.49

5. Conclusion

The study was triggered with the aid of the recognition of supervised classification of LULC mapping. The potential of ANN and RF techniques with Optical Remote Sensing Data for LULC mapping was evaluated. They carried out distinct type of classification techniques applied to data giving excessive accuracy. The accurate evaluation of category isn't always better to depend upon which category strategies used. Due to ANN classifications rely upon both the spectral records and the spatial statistics contained in digital images it turned into the satisfying strategies to classify an image in comparison to RF technique.

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