Assessing land cover for Bahar Al-Najaf using maximum likelihood (ML) and artificial neural network (ANN) algorithms

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Abstract. Change information of the earth’s surface is becoming more and more important in monitoring the local, regional and global resources and environment. In this paper, two algorithms maximum likelihood (ML) and artificial neural network (ANN) have been applied for a change detection at the Baher Al-Najaf from 2016 to 2020 and using two satellite imagery Landsat and sentinel. The accuracy assessment of these algorithms was based on the confusion matrix such as overall accuracy, and the kappa index were calculated for each created map. It was found (ANN) classifier is the better than (ML) classifier. As well as two different experiments were conducted to analyze the network depth and optimization of ANN classifier, and the results showed that the proposed classifier achieves higher overall accuracy and kappa index with pansharpening image. Finally, this study proved (ANN) classifier ability to extract useful high-level features in the classification process.

1. Introduction
Change information of the earth’s surface is becoming more and more important in monitoring the local, regional and global resources and environment. Whereas, Remote sensing images are attractive data sources to derive land cover information using image classifications [1]. The large collection of past and present remote sensing imagery makes it possible to analyze spatiotemporal pattern of environmental elements and impact of human activities in past decades. Research has been widely reported on methodology of remote sensing change detection and monitoring. In recent years, a great progress technological has been reported by researchers with various imagery and algorithms. Over the past years, researchers have put forward large numbers of change detection techniques of remote sensing image and summarized or classified them from different viewpoints (e.g., Singh, 1989; Lu et al., 2004). Iraqi lakes also had a large side of the monitoring where it was used satellite images from the Sentinel 2B by ESA (European Space Agency) were used to classify the land cover of Al-Hawizeh marsh/Iraq-Iran border. Three classification methods were used aimed at comparing their accuracy, using multispectral satellite images with a spatial resolution of 10 m. The classification process was performed using three different algorithms, namely: Maximum Likelihood Classification (MLC), Artificial Neural Networks (ANN), and Support Vector Machine (SVM) [1]. We also note 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 (ANN) methods [2]. Several change detection techniques have been introduced in recent decades for the extraction of water features and others features from satellite
imagery. For examples, Alesheikh et al., 2007 was used method based on the combination of histogram thresholding and band ratio techniques on Urmia Lake coastline whereas, the 20th largest and the second hyper saline lake in the world [3]. Ghosh et al. 2011 was used Two fuzzy clustering algorithms, namely fuzzy c-means (FCM) and Gustafson-Kessel clustering (GKC) algorithms as well as used two other optimization techniques, genetic algorithm (GA) and simulated annealing (SA) have been used for land use and land cover change detection in the western Nile delta of Egypt. And the results are compared with those of existing Markov random field (MRF) and neural network-based algorithms and found to be superior. The proposed technique is less time consuming and unlike MRF does not require any a priori knowledge of distributions of changed and unchanged pixels [4].

Moreover, Hegazy et al., 2015 was attempted to assess the land use change detection by using GIS in Mansoura and Talkha from 1985 to 2010. Change detection analysis shows that built-up area has been increased from 28 to 255 km² by more than 30% and agricultural land reduced by 33%. Future prediction is done by using the Markov chain analysis. Information on urban growth, land use and land cover change study are very useful to local government and urban planners for the betterment of future plans of sustainable development of the city [5]. Abdl-Kawy et al., 2011 was provided recent and historical land use/cover (LULC) maps for the western Nile delta of Egypt using the integration of supervised maximum likelihood classification and visual interpretation of remote sensing data. In this study, a supervised classification was applied to four Landsat images collected over time (1984, 1999, 2005, and 2009) that provided recent and historical LULC conditions for the western Nile delta [6].

On the other hands, Sharma et al., 2018 was used change detection analysis for Nepal-2015 earthquake induced landslides through satellite images of different dates could be gathered which facilitated analysis on development of landslide with time. This study also revealed that the trending geological faults have controlled the landslide occurrence in specially in Ramche area and along the Bagmati river valley [7]. As for Classification of SAR data is used to compensate for the lack of authoritative map data for decision support planning purposes. Land use/landcover mapping of the study area has been performed using multi-sensor (SAR, optical) data in combination with object-oriented classification. The results have been evaluated on the basis of an accuracy assessment with a reference to substantial ground truth. The Cosmo-SkyMed image has been classified before and after the fusion with LandSat 7, and the results have been compared according to an accuracy assessment. An overall classification accuracy of 92% and 86.50% has been accomplished [8]. And we also see in the study that was conducted to monitor the agricultural drought in the Middle Euphrates area, Iraq during the period from 1988 to 2018. Multispectral Landsat TM, ETM+, and OLI images were used. The images dated 1988, 1993, 2000, 2005, 2010, and 2018, A computerized drought monitoring was adopted using ERDAS Imagine 2015, ENVI 3.2, and ArcGIS 10.5 environments to process and analysis the data [9].

In this paper, the two algorithms (ML) and (ANN) were applied for change detection at the Baher Al-Najaf from 2016 to 2020 and using two satellite imagery Landsat and sentinel. The accuracy assessment of these algorithms was based on the confusion matrix such as overall accuracy, and the kappa index were calculated for each created map.

2. Data and methodology

2.1. Study area

The study area is located in Baher Al-Najaf, Iraq (Figure 1). It is a governorate in southern Iraq. The geographic coordinates of this area are 32° 00' 00" N, 44° 32' 00" E. The subset area occupies an area of 311.41 km². This area was selected for this research to study the change detection from 2016 to 2020s on the Baher Al-Najaf.
Figure 1. The study area boundary.

2.2. Data and pre-processing
Figures 2 and 3 show the Landsat 8 and Sentinel images respectively were used in this study after proceeding these images. The former data was used for it contains several spectral bands (coastal: 0.43 to 0.45mm, blue: 0.45 to 0.51mm, green: 0.53 to 0.59mm, red: 0.64 to 0.67mm, NIR: 0.85 to 0.88mm, SWIR 1: 1.57 to 1.65mm, SWIR 2: 2.11 to 2.29mm, cirrus: 1.36 to 1.38mm, TIRS 1: 10.60 to 11.19mm, and TIRS 2: 11.50 to 12.51mm, panchromatic band 0.50 to 0.68mm). These bands allow calculating vegetation and water and other spectral indices such as NDVI and NDBI. The latter, radar data was used for its advantages in vegetation and water mapping. Other advantages for radar images include free-cloud images, sensitive to soil moisture, and efficient data for water extraction. The ground truth data was created from the Field visits to the study area. Overall, 70 samples of water and 30 samples for others class were collected. The ground truth data was used to train the models (70%) and to test the accuracy of the model with the remaining 30% samples. The images were geometrically collected with collected ground control points (GCPs) from obvious locations. The transformation was applied using a second-order transformation. Then, nearest neighbour resampling approaches were applied, in which the related root mean square error (RMSE) was 1.13 pixels. Instead, for radar data, a second-order transformation and cubic resampling were applied. The estimated RMSE was 1.28 pixels. After correcting both the Landsat and Sentinel images, they were projected to the WGS84 UTM 38N. The geometric calibration of the images was very important prior sensor integration. The Landsat image was converted into a radiance image. The digital numbers of the image were converted into meaningful radiance values. Atmospheric correction was applied using dark object subtraction method. However, the Sentinel image was calibrated to sigma-nought during radiometric correction. The speckle noises in the image were reduced using enhanced Lee filter with a kernel size of (3 x 3). Finally, we are using the pan sharpen algorithm to integrate the Landsat with Sentinel satellites as shown in Figure 4.
3. Methodology
This section describes the methodology developed in the current research to detect water bodies area in an integrated Landsat OLI and Sentinel satellite images. The spectral index development, mapping water bodies areas using random forest method, and the accuracy assessment are explained.

3.1. Maximum likelihood classification
Maximum likelihood classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless you select a probability threshold, all pixels are classified. Each pixel is assigned to the class that has the highest probability (that is, the maximum likelihood). If the highest probability is smaller than a threshold you specify, the pixel remains unclassified.

ENVI implements maximum likelihood classification by calculating the following discriminant functions for each pixel in the image (Richards, 1999):

\[ g_i(x) = \ln p(w_i) - \frac{1}{2} \ln |\Sigma_i| - \frac{1}{2} (x - m_i)^T \Sigma_i^{-1} (x - m_i) \]  \hspace{1cm} (1)

Where:

\[ i = \text{class} \]
\[ x = n\text{-dimensional data (where } n \text{ is the number of bands)} \]
\[ p(\omega_i) = \text{probability that class } \omega_i \text{ occurs in the image and is assumed the same for all classes} \]
\[ |\Sigma_i| = \text{determinant of the covariance matrix of the data in class } \omega_i \]
\[ \Sigma_i^{-1} = \text{its inverse matrix} \]
\[ m_i = \text{mean vector} \]
Figure 3. The map of the Sentinel (from 2016-2020) images.

Figure 4. The pansharpening image (Landsat with Sentinel) (from 2016-2020) images.
Table 1. The characteristics of the datasets.

| Dataset      | Parameter     | Characteristics |
|--------------|---------------|-----------------|
| Landsat OLI  | Path/Raw      | 168/38          |
|              | Date          | 2016-01-24      |
|              |               | 2017-01-10      |
|              |               | 2018-01-29      |
|              |               | 2019-01-16      |
|              |               | 2020-01-03      |
|              | Cloud Cover (%)| 0, 1, 0, 2, 0   |
|              | Spatial       | Resolution: 30 m|
|              | Date          | 2016-02-14      |
|              |               | 2017-02-18      |
|              |               | 2018-02-18      |
| Sentinel     | Date          | 2019-02-18      |
|              |               | 2020-02-23      |
|              | Polarization  | HV              |
|              | Spatial       | Resolution: 10 m|

3.2. Artificial neural network classification

In machine learning, NN is a family of statistical, and biological learning models. It is a multilayer perceptron which consists of a system of simple interconnected neurons or nodes. The model represents a nonlinear mapping between some inputs and outputs. Neurons are usually organized into layers with full or random connections between successive layers [10]. Conceptually, there are three types of layers: input, hidden, and output layers that receive process and present the results, respectively. The nodes are connected by numeric weights and output signals, which are a function of the sum of the inputs to the node modified by a simple activation function [11]. What has attracted the research fraternity the most in NN is the possibility of learning. The most common learning algorithm for NN is the back propagation, which was developed by (Werbos) in 1974 and rediscovered independently by Rumelhart and Parker (1980) and (Priddy & Keller, 2005)[12]. It is an iterative gradient algorithm designed to minimize the error function as shown in Equation 2. Despite the success of NN in remote sensing applications, a significant limitation of this model is the fact that their computational complexity is quite high and it has a drawback of overlearning [13].

\[
E = \frac{1}{2} \sum_{i=1}^{L} (d_j - o_j^M)^2
\]

(2)

where, \(d_j\) and \(o_j^M\) represent the desired output and current response of the node “j” in the output layer, respectively, and “L” is the number of nodes in the output layer. In an iterative method, corrections to weight parameters are computed and added to the previous values as illustrated in Equation 3:

\[
\begin{align*}
\Delta w_{ij} &= -\mu \frac{\partial E}{\partial w_{ij}} \\
\Delta w_{ij}(t+1) &= \Delta w_{ij}(t) + \alpha \Delta w_{ij}(t)
\end{align*}
\]

(3)
where, $w_{ij}$ is weight parameter between node i and j, $\Delta$ a positive constant that controls the amount of adjustment and is called learning rate, $\alpha$ a momentum factor that can take on values between 0 and 1 and “t” denotes the iteration number. The parameter $\alpha$ can be called smoothing or stabilizing factor as it smoothest the rapid changes between the weights [14].

4. Accuracy assessment

Based on error matrix analysis, Overall Accuracy (OA) and a Kappa (K) analysis are used to get the classification accuracy assessment. OA was computed by dividing the total correct (sum of the major diagonal) by the total number of pixels in the error matrix. On the other hand, the Kappa analysis is a discrete multivariate technique used in accuracy assessments [15]. Kappa analysis yields K statistic that is a measure of agreement or accuracy [16]. K statistic was computed as:

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

(4)

where $r$ is the number of rows in the matrix, $x_{ii}$ is the number of observations in row i and column i, $x_i+$ and $x_{+i}$ are the marginal totals for row i and column i respectively and $N$ is the total number of pixels.

5. Results and discussion

This section presents the main findings which shows the results of Maximum likelihood (ML) and ANN classifier, the sensitivity analysis on the hyper-parameters of the best algorithm and the change detection between images from 2016 to 2020.

5.1. Results of maximum likelihood

The ML classifier with best configuration of the hyper-parameters as found via the sensitivity analysis was used to classify the Landsat scene into two land cover classes (i.e., water and others) as shown in Figures 5 and 6. The OA and K accuracy of ML on the images was found to be (78.51, 0.55), (79.12, 0.59), (80.94, 0.55) and (80.71, 0.59) respectively for 2016, 2017, 2018, 2019 and 2020 as shown the figure 7. On the other hand, the OA and K accuracy ML classifier on the Landsat and sentinel satellites were (88.41, 0.75), (89.71, 0.77), (84.35, 0.68), (88.47, 0.52) and (88.26, 0.74) for 2016, 2017, 2018, 2019 and 2020 respectively as indicated Figure 8. whereas, was found the higher accuracy of ML classifier on Landsat with sentinel is more than Landsat imagery. Figures 5 and 6 show the maps from 2016 to 2020 which are producing from ML algorithm on Landsat imagery and pansharpening image (Landsat with Sentinel). From these figures, it was found that the best overall accuracy and the kappa in 2017 which was 89.71 and the 0.77 respectively.
Figure 5. The classification map using the maximum likelihood classification method on Landsat image.

Figure 6. The classification map using the maximum likelihood classification method on pansharpening image.
Figure 7. The overall accuracy and kappa coefficient of maximum likelihood classification method on Landsat image.

Figure 8. The overall accuracy and kappa coefficient of maximum likelihood classification method on pansharpening image.

5.2. Results of artificial neural network
On this study, the proposed algorithm which is ANN classifier with best configuration of the hyper-parameters as found via the sensitivity analysis was used to classify the Landsat scene into two land cover classes (i.e., water and others). Figure 9 shows the OA and K accuracy of ANN on the Landsat images was found to be (91.84, 0.80), (90.43, 0.77), (91.89, 0.80), (91.34, 0.78) and (90.43, 0.77) respectively for 2016, 2017, 2018, 2019 and 2020. On the other hand, the OA and K accuracy ML classifier on the Landsat and sentinel satellites were (94.29, 0.85), (91.52, 0.68), (99.57, 0.85), (93.49, 0.76) and (95.56, 0.83) for 2016, 2017, 2018, 2019 and 2020 respectively as in Figure 10. Whereas, it was found that a high accuracy of ANN classifier on Landsat with sentinel is more than Landsat
imagery. So, Figures 11 and 12 show the maps from 2016 to 2020 which are producing from ANN algorithm on Landsat imagery and pansharpening image (Landsat with Sentinel). From these figures we were found the best overall accuracy and the kappa on 2018 which was 99.57, and 0.85 respectively.

**Figure 9.** The overall accuracy and kappa coefficient of artificial neural network classification method Landsat image.

**Figure 10.** The overall accuracy and kappa coefficient of artificial neural network classification method on pansharpening image.
Discussion
This section reveals that the results obtained from the ANN with pansharpening image is better than others, therefore this section discusses the sensitivity analysis of ANN classifier such as networks.
depth and optimization algorithm analysis. As well as we are taken the pansharpening 2018. Figure 13 shows the overall accuracy and kappa coefficient and others index of the confusion matrix analysis of ANN method.

![Table 2](image)

**Figure 13.** Overall accuracy, kappa coefficient and others index of the confusion matrix analysis on artificial neural network classification method.

### 6.1. Network depth analysis

This experiment was conducted to determine the effect of network depth in the sense of hidden layers. We examined several network depths ranging from 1 to 3 hidden layers with fixed number of neurons (i.e., 5). The evaluation was based on OA and K metrics measured on training and testing datasets. The summary of the results is shown in table 2. The results indicate that the depth of the network is not necessary to improve the accuracy of the classification map based on the training and testing samples. The best accuracies were achieved with only a two hidden layer. On the training dataset, OA and K were 99.57 and 0.85, respectively. On the other hand, on the testing dataset, the classifier performed was achieved OA of 97.24 and K of 0.95. Since the results show that there are no specific patterns in the performance of ANN with different depth configurations, it is important to search through different depths for data of different environments.

| Experiment No. | Hidden Layers | OA Training | OA Testing | K Training | K Testing |
|----------------|---------------|-------------|------------|------------|-----------|
| 1              | 1             | 89.61       | 85.52      | 0.80       | 0.82      |
| 2              | 2             | **99.57**   | **97.24**  | **0.85**   | **0.95**  |
| 3              | 3             | 90.63       | 83.47      | 0.88       | 0.79      |

### 6.2. Optimization Algorithm Analysis

Optimizations of neural networks play a significant role in its overall performance and generalization. There are several ways and algorithms developed for such purposes including gradient and non-
gradient based methods such as stochastic gradient descent (SGD), ADAM, and LBFGS. Table 3 summarizes the result of an experiment conducted to determine the suitable algorithm for optimizing ANN classifier to classify the pansharpening image into the pre-defined classes. The results indicate that LBFGS is more suitable than the other methods for the land cover mapping in our work. ANN classifier with this optimization method achieved an OA of 99.57 and 97.24, using the training and testing datasets, respectively. The same classifier achieved a K of 0.85 and 0.95, for the training and testing datasets, respectively. So, the analysis shows that the standard SGD performs better than ADAM and SGD.

Table 3. The results of the optimization algorithm analysis.

| Experiment No. | Solver | OA Training | OA Testing | K Training | K Testing |
|----------------|--------|-------------|------------|------------|-----------|
| 1              | SGD    | 90.35       | 89.64      | 0.88       | 0.87      |
| 2              | ADAM   | 95.33       | 92.24      | 0.94       | 0.90      |
| 3              | LBFGS  | **99.57**   | **97.24**  | **0.85**   | **0.95**  |

6.3. Surface water change detection using the proposed method (ANN)
The performance of ANN classifier with default and best hyper-parameters were found the better than ML classifier, so the statistical of the area results based on the ANN with pansharpening image and the figure is showing the Baher Al-Najaf area was increase or decrease between 2016 to 2020. Whereas the area of Baher Al-Najaf was 82.351 km² in 2016, and it was been 88.594 km² in 2017, while in 2018 was increased about 2.104 km² (90.498 km²), 109.72 km² in 2019 and in 2020 was 116.164 km² as shown Figure 14.

![Figure 14](image_url)

Figure 14. The area of Baher Al-Najaf from 2016 to 2020 based on the artificial neural network classification method on pansharpening image.

7. Conclusion
This research examines a construction of neural networks via sensitivity analysis for land cover mapping using Landsat OLI and Sentinel satellites. Two different experiments were conducted to analyze the network depth and optimization of the network the classifier. Based on the best results achieved in these experiments, an ANN classifier was constructed and used to perform land cover mapping. As well as the results showed that the proposed classifier achieves with pansharpening
image is better results compared with ML method using identical training sites (2016-2020). This is likely due in part to the ANN's ability to extract useful high-level features in the classification process. Beside the results of this work, showing the Baher Al-Najaf area was increase about 33.813 km² from 2016 to 2020.

8. References

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