Multispectral and Panchromatic used Enhancement Resolution and Study Effective Enhancement on Supervised and Unsupervised Classification Land – Cover

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Abstract. The goal of the study is to support analysis Enhancement of Resolution and study effect on classification methods on bands spectral information of specific and quantitative approaches. In this study introduce a method to enhancement resolution Landsat 8 of combining the bands spectral of 30 meters resolution with panchromatic band 8 of 15 meters resolution, because of importance multispectral imagery to extracting land-cover. Classification methods used in this study to classify several land-covers recorded from OLI-8 imagery. Two methods of Data mining can be classified as either supervised or unsupervised. In supervised methods, there is a particular predefined target, that means the algorithm learn which values of the target are associated with which values of the predictor sample. K-nearest neighbors and maximum likelihood algorithms examine in this work as supervised methods. In other hand, no sample identified as target in unsupervised methods, the algorithm of data extraction searches for structure and patterns between all the variables, represented by Fuzzy C-mean clustering method as one of the unsupervised methods, NDVI vegetation index used to compare the results of classification method, the percent of dense vegetation in maximum likelihood method give a best results.

Keywords. Panchromatic Band, NDVI, Maximum likelihood and supervised Classification, Enhancement resolution.

1. Introduction
In Research of environment the applications of R.S meaningful tool, where R.S successful to extract land-cover map and classification of the spectral image [1, 2], monitoring and detection real time of deforestation [3, 4], guess production and vegetation area [5] and pollution monitoring [6].

Ehlers fusion method used to enhancement resolution to obtain land cover data by remote sensing and interpretation of imagery through merge high-resolution panchromatic band (15 meters) with bands-spectral imagery of 30 meters.

Image classification is usually applied in an optical pattern, object recognize, in medical applications and industrial processes [7]. Methods of classification (unsupervised, supervised) develop to give the solution of scientific problems [8], Fuzzy C-mean clustering method as one of unsupervised methods [9], where K-NN and MLC techniques an example of supervised classification [10, 11], which can be
divided into two-stage first: calibration depends on spectral signature of various bands obtain from training to known class labels, second: estimation class which applied to other un-known location.

2. Methodology

The study area was located in the northwest provinces of Iraq between Tikrit and Kirkuk, at 43.30°→43.45°E longitude, and 34.40°→34. 50°N latitude, datum WGS 84 and UTM projection, zone 38. The image is high quality and does not contain clouds, the study area is surrounded by wheat plantations 'Figure 1'.

![Image](image_url)

**Figure 1.** (a) Land use map of Iraq country lies between the geographic coordinates lat. 37.38°→28.5°N, and Long. 38.70°→48.75°E. (b) photomap of the study area.

The data of study area acquire from the free website (http://landsat.usgs.gov/landsat8.php) of OLI satellite for February (2014, 2015). OLI-8 consist of 11 bands, 1-7, 9 bands with spatial resolution 30 meters, band 8 (panchromatic ) is 15 meters resolution while bands 10, 11 with 100-meter spatial resolution. OLI - 8 presented on February 11, 2013, include two senses (Thermal Infrared, Operational Land Imager), the image produce from OLI- 8 of 16 bit (65536 gray level), and coverage study area every 16 days.

Ehlers fusion, image classification methods, true color composite image and panchromatic image of the study area (2014, 2015) was applied using Matlab 2013 and Erdas software 2014. 'Figure 2' show the true color image and panchromatic.
Figure 2. (a) True color composite image (size 1002×1202) pixels, spatial resolution 30 m resolution 30 m of the study area, (b) panchromatic image b8( size 2004×2404) resolution 15 m of the study area.

3. Ehlers fusion

The algorithm of Ehlers Fusion is merging of two images different in spatial resolution to create a new image with new properties. Fusion differentiated into three ways: scale of pixel, acknowledge and feature [12]. Pixel scale fusion algorithm is often used in image pansharpening [13]. These methods depend on a group of arithmetic processing (PCA, Fourier Transform, HIS, wavelet transform,) [14]. The algorithm of Ehlers Fusion implemented by steps:

1. Multispectral image transformation in intensity hue saturation.
2. Apply Fast Fourier Transform (FFT) and low-pass filter in the result of step 1.
3. Apply (FFT) and high pass filter in the panchromatic image.
4. Apply inverse FFT and the results are combining.
5. Inverse intensity hue saturation transformation apply to output a fused color (RGB) image.

The algorithm implements for three bands till all bands are fused with the panchromatic band. The result of fusion is presented in ‘Figure 3’.
Figure 3. Pansharpened image True Color Composite (size 2004×2404) resolution 15 m of the study area (Feb. 2015)

4. Green Vegetation Index
One vegetation indicator for dense vegetation assessment is called Normalized Difference Vegetation Index (NDVI), the range of NDVI (0.2 – 0.8) for healthy plants. NDVI is calculated on a per-pixel basis as the difference between the reflectance of red band and reflectance of near infrared band from an image:

\[ NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} \]  

(1)

Where \( \rho \) represent the reflectance, the result show in figure (4) and percentage of dense vegetation from land cover show in table (1).

Table 1. Percentage of dense vegetation from NDVI method.

| Year | Percentage area% |
|------|------------------|
| 2014 | 14.53            |
| 2015 | 14.28            |
5. Unsupervised classification

Fuzzy c-mean clustering FCM method is widely applied to dividing data into homogeneous classes with respect to some given criterion. This algorithm presented by [9]. Which based on minimizing an object function \( J_q \) as follow:

\[
J_q = \sum_{i=1}^{n} \sum_{j=1}^{m} u_{ij}^q d(x_i, \theta_j)
\]  

(2)

Where \( d \) is the distance between the center of clusters \( \theta_j \) and data \( x_i \), \( u \) is fuzzy membership of data \( x_i \) to cluster with center \( \theta_j \) and \( u \) calculated from the equation 3:

\[
u_{ij} \in [0, 1], \sum_{j=1}^{m} u_{ij} = 1 \quad \& \quad 0 < \sum_{j=1}^{m} u_{ij} < n
\]

(3)

The \( u_{ij} \) function and center \( \theta_j \) of each cluster are calculated from:

\[
u_{ij} = \left( \frac{\sum_{k=1}^{m} u_{ik}^q d(x_i, \theta_j)}{\sum_{k=1}^{m} u_{ik}^q d(x_i, \theta_k)} \right)^{\frac{2}{q-1}}
\]  

\[\theta_j = \frac{\sum_{i=1}^{n} u_{ij}^q x_i}{\sum_{i=1}^{n} u_{ij}^q}
\]

(4) \hspace{1cm} (5)

The object function of FCM optimize by frequent update of the \( u_{ij} \) function and centers \( \theta_j \) of clusters till the different between two iteration is smaller than a threshold, the results of method show in Figure 5 and percentage of each class of land cover show in Table 2, where the accuracy calculated depend on dense vegetation percent from NDVI method.

**Figure 4.** Normalized Difference Vegetation Index (NDVI), (a) 2014, (b) 2015.
| Year | Name class | Percentage classes of original Resolution | Percentage classes of Enhanced Resolution |
|------|------------|------------------------------------------|--------------------------------------------|
|      |            | Percentage area% | Accuracy | Percentage area% | Accuracy |
| 2014 | Water      | 3.1%           | 3.3%     | 2.6%           | 2.8%     |
|      | Wet Soil   | 22.7%          | 24.9%    | 23.2%          | 24.4%    |
|      | Dry Soil   | 16.3%          | 16.5%    | 16.2%          | 16.2%    |
|      | Dense Vegetation | 15.3% | 94.7% | 15.4% | 94.01% |
|      | Wet Vegetation | 16.6% | 16.0% | 16.0% | 16.0% |
|      | Dry Vegetation | 26.1% | 23.9% | 23.9% | 23.9% |
| 2015 | Water      | 1.6%           | 1.8%     | 1.6%           | 1.8%     |
|      | Wet Soil   | 24.6%          | 25.2%    | 24.6%          | 25.2%    |
|      | Dry Soil   | 18.6%          | 17.8%    | 18.6%          | 17.8%    |
|      | Dense Vegetation | 12.2% | 85.43% | 11.9% | 83.33% |
|      | Wet Vegetation | 17.2% | 18.2% | 18.2% | 18.2% |
|      | Dry Vegetation | 25.8% | 25.1% | 25.1% | 25.1% |

**Table 2.** Percentage classes of Enhanced Resolution and original band using FCM method.

**Figure 5.** (a) FCM Classification of Original OLI Bands Composite(size 1002×1202), (b) Pansharpened image True Color Composite(size 2004×2404), first row (2014), second row (2015).
6. Supervised classification

6.1. K-Nearest Neighbor Algorithm
The K-nearest neighbor method program is one of the most celebrated classification algorithms used for expecting the class of a sample with unspecified class based on its neighbor records class [15], it’s an exemplify of instance-based learning, in which the set of data is stored as training data, so that a classification for unclassified sample may be found merely by comparing it to the closest records in the training set [16]. The steps of the algorithm as follows:

1. The distance between of input sample and training samples are calculated.
2. Depending on distance select the K-nearest neighbor to arrange the training samples.
3. The class which has the majority of the k-nearest neighbors is used.

The important parameter in K-nearest neighbor method is K value, its proper value depends on the data apportionment [16], the results of method shown in Figure 6 and percentage of each class of land cover shown in the Table 3.

| Year | Name class     | Percentage classes of original Resolution | Percentage classes of Enhanced Resolution |
|------|----------------|-------------------------------------------|-------------------------------------------|
|      |                | Percentage area%                          | Accuracy                                  | Percentage area%                          | Accuracy                                  |
| 2014 | Water          | 2.9%                                      | 3.0%                                      |                                           |                                           |
|      | Wet Soil       | 19.1%                                     | 19.4%                                     |                                           |                                           |
|      | Dry Soil       | 22.2%                                     | 20.7%                                     |                                           |                                           |
|      | Dense Vegetation| 16.4%                                     | 87.13%                                    | 17.8%                                     | 77.49%                                    |
|      | Wet Vegetation | 14.5%                                     | 14.0%                                     |                                           |                                           |
|      | Dry Vegetation | 24.8%                                     | 25.2%                                     |                                           |                                           |
| 2015 | Water          | 1.7%                                      | 2.0%                                      |                                           |                                           |
|      | Wet Soil       | 14.9%                                     | 2.0%                                      |                                           |                                           |
|      | Dry Soil       | 25.3%                                     | 23.2%                                     |                                           |                                           |
|      | Dense Vegetation| 15.2%                                     | 93.55%                                    | 16.7%                                     | 83.05%                                    |
|      | Wet Vegetation | 21.4%                                     | 21.7%                                     |                                           |                                           |
|      | Dry Vegetation | 21.0%                                     | 19.4%                                     |                                           |                                           |
Figure 6. (a) The K-nearest neighbor Classification of Original OLI Bands Composite (size 1002 × 1202), (b) Pansharpened image True Color Composite (size 2004 × 2404), first row (2014), second row (2015).

6.2 Supervised Maximum Likelihood Classification Image
The popular method used to classify Landsat imageries is Maximum Likelihood Classification (MLC) which applied in this study as one of the supervised methods. The algorithm depends on predefined 6 classes as training (Dense Vegetation, Wet Vegetation, Dry Vegetation, Water, Wet Soil, and Dry Soil), the steps of implementing the method as follow:
1. Six types of land cover specified in the study area as training classes set.
2. The pixels are selected from each training classes using the information of land cover for the study area.
3. Mean vector and covariance matrix are evaluated for each class.
4. Jeffries-Matusita (JM) distance used to measure the class separability of normal distribution for two training classes by the following [17]:
   \[ J_{ij} = \sqrt{2(1 - e^{-\alpha})} \]  
   (6)

Where \( \alpha \) is the Bhattacharyya distance is defined as:
\[ \alpha = \frac{1}{8} \left( \mu_i - \mu_j \right)^T \left[ \frac{C_i + C_j}{2} \right]^{-1} \left( \mu_i - \mu_j \right) + \frac{1}{2} \ln \left[ \frac{\sqrt{C_i \cdot C_j}}{|C_i|} \right] \]  

(7)

\( \mu \) is the means of vector and \( C \) is covariance matrices, \( J_{ij} \) ranges from 0 to 2.0, where \( J_{ij} > 1.9 \) indicates good separability of classes.

Moderate separability for \( 1.0 \leq J_{ij} \leq 1.9 \) and poor separability for \( J_{ij} < 1.0 \).

5. The last step, classified each pixel in the image into one of the six land cover types.

The results of method classification (MLC) show in figure (7) and percentage of each class of land cover shown in the Table 4.

Table 4. Percentage classes of Enhanced Resolution and original band using Maximum Likelihood Classification method.

| Year | Name class      | Percentage classes of original Resolution | Percentage classes of Enhanced Resolution |
|------|-----------------|------------------------------------------|------------------------------------------|
|      | Percentage area | Accuracy | Percentage area | Accuracy |
| 2014 | Water           | 0.7%     | 0.8%           |           |
|      | Wet Soil        | 29.2%    | 23.7%          |           |
|      | Dry Soil        | 7%       | 4.2%           |           |
|      | Dense Vegetation| 15.7%    | 91.94%         | 15.1%     | 96.07% |
|      | Wet Vegetation  | 18.2%    | 9.1%           |           |
|      | Dry Vegetation  | 29.0%    | 46.9%          |           |
| 2015 | Water           | 0.7%     | 0.9%           |           |
|      | Wet Soil        | 23.5%    | 19.6%          |           |
|      | Dry Soil        | 1.6%     | 4.0%           |           |
|      | Dense Vegetation| 14.6%    | 97.7%          | 14.8%     | 96.35% |
|      | Wet Vegetation  | 20.8%    | 18.0%          |           |
|      | Dry Vegetation  | 38.1%    | 42.8%          |           |
Figure 7. (a) The Maximum Likelihood Classification of Original OLI Bands Composite(size 1002×1202), (b) Pansharpened image True Color Composite(size 2004×2404), First row (2014), Second row(2015).

7. Conclusion
The possibility of merging multi - spectral bands with a panchromatic band made OLI - 8 it has been a good spatial resolution to detect and classification Land - cover. Properties of Land – cover can be extracted effectively with image classification, the first problem we have encountered was the lack of accurate records issued by the Iraqi Ministry of Agriculture for the true percent of the study area (Because of the occupation ISIS parts of the study area). For this purpose, the research team has
compared the result of Normalized difference vegetation index (NDVI) with methods classification to install the percentage of land cover and make sure the data was correct.

The results showed that supervised classification (MLC) is the most powerful methods when accurate training data is provided where the percentage of dense vegetative areas give a very good accuracy, that means the MLC method is useful in the classification of homogeneous areas. While the result of KNN method smaller than MLC with lower accuracy, it is due to the fact that the study area has an overlap between different species.

FCM method takes a long time to classify image depend on the number of iterations to minimizing an object function, we conclude that FCM method being useful in the classification of overlapping areas when getting a suitable number of iteration.

Ehlers fusion was applied as Enhancement method in this study is good for monitoring changes in land cover and is considered an important way to improve the accuracy of land sat 8 images.

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