Detection of Temporal Changes of Eastern Coast of Saudi Arabia for Better Natural Resources Management

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Three different data sets of images used to obtain the land cover changes in this study: Multi-Spectral Scanner (MSS) acquired in 1973, Landsat-5 Thematic Mapper (TM) acquired in 1990 and Landsat-8 Operational Land Imager (OLI) acquired 2013 consequently. For each data set, three Landsat scenes mosaicked to cover the whole study area. Supervised classification implemented to classify the area into six major land cover classes using two different classification algorithms. A total number of 400 points evenly distributed over the designated study area used in classification accuracy assessment. Kappa statistics obtained to specify the most appropriate classification algorithms in term of accuracy assessments. The results indicated that the rapid imbalance changes occurred among three land’s cover classes urban area, surrounding desert and sedimentation. Human impacts in the form of sedimentation process practiced constantly on the Eastern Coast of Saudi Arabia, besides the loss of vegetation cover over the last four decades.

[Keywords: Accuracy Assessment, Classification, Human Impacts, Remote Sensing Data, Sedimentation, Urbanization]

Introduction

Monitoring of land cover changes is the keystone strategy for better natural resources management. Land cover changes on a local scale cannot satisfy the national demands to monitor the global environmental changes1,2. Therefore, the use remote sensing data in the form of multi-spectral images is becoming the fundamental tool to detect environmental changes 3.

Change detection techniques are specifically based on two or more temporal imageries comparison 4, 5, 6. There are two principal methods to detect anomalies in satellite images: a) pixel-to-pixel comparison and b) post-classification comparison6, 7, 8. The main improvement of the post classification method over the pixel-by-pixel classification is that the former is based on comparing two or more separately classified temporal images 9, 10, 11, 12.

There are several classification algorithms that employs post classification method but Maximum Likelihood (ML) and Support Vector Machine (SVM) are the most successful algorithms in term of classifications accuracy assessment8, 13, 14, 15. Assessing the pattern and the magnitude of Land Use Land Cover changes is critical to project the future of natural resources management16, 17.

Satellite images as a source of remote sensing data, combined with Geographic Information Systems (GIS) has been extensively practiced and acknowledged as an influential and operational approach in detecting of Land Use Land Cover changes 8, 14, 18. Coastal cities in Saudi Arabia have experienced a major development process including the alteration of Land Use Land Cover 4, 19. Both of eastern and western coast of Saudi Arabia witnessed a temporal changes20, 21, 22, the current study will focus on the eastern coast due it the rapid development actions took place in Ras Tarout area.

The aim of this study is to detect the changes occurred in Ras Tarout land cover types over a period of four decades. Therefore, investigating trends and rates of land cover alteration are essential for the management planner in order to...
perform rational land and natural resources management plans.

**Materials and Methods**

Study area located in the eastern province of the Kingdom of Saudi Arabia, within Longitudes of 50° and 50° 13'N and Latitudes 26° 11' and 26° 27'E approximately (Figure 1). The area located in an arid environment where is the precipitation is very low (3.52 mm/year). However, the area may receive a longer falls as heavy local showers, and some places receive significantly more precipitation than the general average. In the case of longer rain, vegetation cover grows as growing period is prolonged. Moreover, in sandy areas, if the infiltration exceeds a depth of 10 cm, soil seals moisture in surface layers where herbage grows for a longer period.

![Figure 1. Location of the study area](image)

Tarout Island is the center for all other islands located in the Tarout Bay, which was known as the Gulf of Quepos. The Gulf is called the Gulf of Tarout related to the Tarout mother island where the foot of history started. Tarout Island includes several villages in addition to the ten scattered neighborhoods small villages strewn about Tarout Bay. Tarout is not a small island, maximum length reaches (10 km) and almost maximum width is (6 km) with nearly fifty thousand inhabitants. A very small village located in the study area called, “Al-Zour” used to have a very great importance in the past. However, its importance has diminished or has now ended completely. The village located on the island's tail from the north and surrounded by water from the east and north. In West Al-Zour, a small stream aqueous river located and the water present in it during the tidal, and this small a river slot from the north, where the intervention of sea water loaded with fish and heading south. The island is a trees breed growth in the region and those trees are evergreen and grow in the mud and have a pleasant smell while known locally as (Crimea) shall not exceed the height of this tree more than two meters, the island located west of Tarout bay in the region known as (Umalshajar Island). There are some few important islands are also buried with the development of the region, which are part of the history of the area of natural limits. Temporary sand dunes are flooded by seawater during tide and show during the islands becomes dry sand as most of the Tarout Bay regions are of shallow land. There are other small islands insignificant strewn in Tarout Bay and others on the road from Ras Tanura to Dammam beach.

**Image classification process**

First, all scenes in each temporal data set have been geometrically corrected to a reference image of known geographic coordinate system (UTM N 36, WGS_84 datum). Second, an adequate radiometric correction technique based on image regression was implemented to minimize or eliminate the effects of dissimilar dates of acquisition. Third, a simple atmospheric correction according to Yuan et al. to identify dark object subtraction was performed as:

\[
L_A = DN \ast G_{rescale} + B_{rescale}
\]

Eq. 1

Where

\[G_{rescale} \text{ and } B_{rescale}\] are the channel specific rescaling gain and bias factors

According to Song et al. equation, the calculation of the path radiance \((L_p)\) based on identify dark object subtraction is:

\[
L_p = \frac{DN_{min} \ast G_{rescale} + B_{rescale} - 0.001 \left[ E_0 \cos(\Theta_0) T_z + E_{down}\right] T_r}{\pi}
\]

Eq. 2

Where

\(\Theta_0\) is the solar zenith angle
\(E_0\) is the solar spectral radiance
\(T_z\) is the atmospheric transmittance from the sun to ground surface
\(T_r\) is the atmospheric transmittance from ground surface to sensor
\(E_{down}\) is the down-welling spectral irradiance

Song et al. assumed that \(T_z\) and \(T_r\) are equal to 1.0 and \(E_{down}\) is equal to zero, therefore, the atmospheric correction equation can be reformulated as:

\[
L_p = \frac{DN_{min} \ast G_{rescale} + B_{rescale} - 0.001 \left[ E_{sun} \cos(\Theta_0)\right]}{\pi d^2}
\]

Eq. 3

Where

\(E_{sun}\) is the exoatmospheric solar irradiance
\(d\) is the sun-earth distance

**Supervised classification**

Classification is the practice of assigning unknown pixels into individual categories of data,
based on uninformed/informed training data set. If pixel fulfills certain criterion/criteria, then the pixel is assigned to a category that corresponds to those criteria\textsuperscript{29}. Classification process based on unsupervised and/or supervised classification through a distinguish patterns in the data. Training sets are the process of identifying the criterion/criteria by which these patterns are distinguished\textsuperscript{30}. In the current study, six different supervised classification algorithms are used.

Supervised signature extractions with six different classification algorithms were performed to select the optimum classification algorithm. The different classification algorithms according to Richards\textsuperscript{31} are:

**Mahalanobis Distance**: a deterministic distance classifier that uses statistics for each assigned categories based on the following equation:

\[ \|x - y\| \Sigma_1^{-1} - 1 = (x - y)^T \Sigma_1^{-1}(x - y) \]  \text{Eq.4}

\( \Sigma_1^{-1} \) considered as a stretching factor on the space

**Minimum Distance**: uses the mean vectors of each end member and calculates the Euclidean distance from each unknown pixel to the mean vector for each class based on the following equation:

\[ d(x, y) = \sqrt{\sum_{i=1}^{d} (x_i - \mu_i)^2} \]  \text{Eq. 5}

Where

- \( L_i \) is the label found in the dataset
- \( \mu \) is the mean
- \( x \) is the distance between each unlabeled sample vector need to be classified

Maximum Likelihood: uses the statistics for each class in each band as a normally distributed function and computes the likelihood of a given pixel belongs to a specific category based on the following equation:

\[ g_i(x) = \frac{1}{2} \ln(p(\omega_i)) + \frac{1}{2} \ln|\Sigma_i| - \frac{1}{2} (x - \mu_i)^T \Sigma_i^{-1} (x - \mu_i) \]  \text{Eq. 6}

Where

- \( i = \text{class} \)
- \( x = \text{n-dimensional data (where n is the number of bands)} \)
- \( p(\omega_i) = \text{probability that class } \omega_i \text{ occurs in the image and is assumed the same for all classes} \)
- \( |\Sigma_i| = \text{determinant of the covariance matrix of the data in class } \omega_i \)
- \( \Sigma_i^{-1} = \text{its inverse matrix} \)

Artificial Neural Networks: uses standard back propagation for supervised learning based on the following equation of Okwuashi et al.\textsuperscript{32}:

\[ \text{net}_i = (x, t) = \sum_i W_{ij} S_i(x, t) \]  \text{Eq. 7}

Where

- \( S_i(x, t) \) denotes the site attributes given by variable (neuron) \( i \)
- \( W_{ij} \) is the weight of the input from neuron \( i \) to neuron \( j \)

\( \text{net}(x, t) \) is the signal received for neuron \( j \) of cell \( x \) at time \( t \)

Parallelepiped: uses parallelepiped dimensions and the standard deviation threshold from the mean of each selected category in two bands based on the following equation:

\[ \frac{(x-\mu_A)^2}{(k\sigma_A)^2} + \frac{(x-\mu_B)^2}{(k\sigma_B)^2} = 1 \]  \text{Eq. 8}

Where

- \( \sigma_A \) and \( \sigma_B \) are standard deviation of selected pixels in band A and band B
- \( \mu_A \) and \( \mu_B \) are average of selected pixels in band A and B
- \( K \) is adjustable for altering the size of parallelepiped

Support vector machine (SVM): distinguishes the categories upon margin maximization of a decision surface between the categories based on sigmoidal function equation:

\[ K(x_i, x_j) = \tanh(gx_i^{T}x_j + r) \]  \text{Eq. 9}

Where:

- \( g \) is the gamma term in the kernel function for all kernel types except linear
- \( r \) is the bias term in the kernel function for the polynomial and sigmoid kernels.

Based on the calculation of the Optimum Index Factor (OIF), six classes were assigned to describe the LULC in each data set, the LULC classes are Sea, Sediment, Vegetation, Bare land, Desert and Urban areas.

A total number of 400 training sites were selected in each data set and a total number of 300 points of ground truth data for validation were collected during March 2014, the points were for the major LULC demonstration in the study area. The 400 training sites were divided based on class’s separability and proportionally to the total area of each class per data set according to the following table:
Table 1: Total number of the training and validation points per class

<table>
<thead>
<tr>
<th>Class name</th>
<th>Total number of the training points</th>
<th>Total number of the validation points</th>
<th>Training points percentage per class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sea</td>
<td>84</td>
<td>74</td>
<td>20 %</td>
</tr>
<tr>
<td>Sediment</td>
<td>65</td>
<td>45</td>
<td>15 %</td>
</tr>
<tr>
<td>Vegetation</td>
<td>37</td>
<td>24</td>
<td>8 %</td>
</tr>
<tr>
<td>Bare land</td>
<td>81</td>
<td>57</td>
<td>19 %</td>
</tr>
<tr>
<td>Desert</td>
<td>53</td>
<td>36</td>
<td>12 %</td>
</tr>
<tr>
<td>Urban</td>
<td>80</td>
<td>64</td>
<td>19 %</td>
</tr>
</tbody>
</table>

**Classification accuracy assessment**

The final step in the digital image analysis is the assessment of the accuracy of the computer derived classification results. Producers, users and Overall accuracy were derived from a Matrix. These results often articulated in plane form, known as a confusion matrix. The Kappa examination is the distinct multivariate method used in accuracy assessment to specify statically whether one error matrix is significantly different to another. The accuracy assessment was carried out following to estimate \( K_{\text{hat}} \) for different the employed classification algorithms:

\[
K_{\text{hat}} = \frac{\sum_{i=1}^{r} x_{ij} - \sum_{i=1}^{r} (x_{ij} \times x_{ji})}{N^2 - \sum_{i=1}^{r} (x_{ij} \times x_{ji})}
\]

Eq. 10

Where

- \( r \) is a number of rows in the error matrix;
- \( x_{ij} \) is a number of observations in row \( i \) and column \( j \) (the diagonal cells);
- \( x_{i+} \) is total observations of row \( i \);
- \( x_{+j} \) is total observations of column \( j \);
- \( N \) is total of observations in the matrix.

**Post classification Comparison**

Post Classification techniques are used principally to classify images decision rules, to compute category statistics and to estimate majority or minority analysis to the three different temporal classification images. Mas\textsuperscript{16} developed, then Coppin et al.\textsuperscript{9} improved techniques well know now as the Post-Classification Comparison (PCC), PCC used in a current research study to spatially detect changes which occurred after classifying the temporal images separately from the three time periods 1973, 1990 and 2013 as it illustrated in Figure 2. Each temporal date set of images was adequately classified. The temporal classified images were compared and analyzed in order to detect spatially the temporal LULC changes\textsuperscript{10,36,37}.

**Figure 2. Thematic Change Detection Workflow**

**Results and Discussion**

Supervised classification using different classification algorithms were performed. Graphical and statistical analyzes of feature selection were piloted taken into consideration all of the visible and near infrared bands. Table 2 shows the summary classification results in term of accuracy and Kappa statistics of each classification algorithm.

Support Vector Machine showed better classification results than the rest of classification algorithms in principle. The result of the classification algorithm, both of overall accuracies and kappa statistics were increased gradually from MMS 1973 toward Landsat OLI- 8 acquired in 2013. This could be explained due to the fact that the date acquisition of the third data set (Landsat OLI-8 acquired in 2013) is relatively closer to the date of the training and validation points’ collection and also prove the adequacy of the SVM classifier over the rest classifier in complex areas\textsuperscript{4,19}.

Post Classification Comparison is demonstrated in Figures 3 – 8 and explains the thematic changes occurred in different LULC classes that exist in the study area.
Changes in LULC in term of percentages between the year 1973 and 1990 are demonstrated in Figure 3. A strong loss in bare land and sea total area were encountered by the expansion of both the urban area and sedimentation process. According to Figure 4, the expansion of the urban areas was toward the bare land, while the expansion of sedimentation was toward the sea. LULC changes that occurred between the year 1990 and 2013 (Figure 5), revealed by an additional loss in the total area of the bare land in addition to a decrease in the sea came along with the increase of sedimented areas (Figure 6). The final stage of change detection demonstrated in Figure 7, the total area of urbanization was approximately increased by only 18.3 % over two four decades which is rather similar to the increase of the sedimented areas (12 %), the expansion of urban areas was observed to be against the bare land and vegetation cover. A slight decrease in desert and vegetation total area was observed (Figure 8).

Figures 9 – 11 shows the contribution of each LULC classes of the three different data sets to the total cover of the study area. Dataset acquired in 1973 considered as a reference point to the current changes in LULC of the Tarout Bay. Figure 9 demonstrates the ratios among the six different land cover classes, where the sea computed to be more than a half of the total area (52 %) and bare land and desert are almost the other half (40 %). In the year 1990, the noticeable expansion of both urban areas and sedimented areas were directed against the total area of the sea and bare land. Slight decrease state in the total area of desert and vegetation were mapped (Figure 10). The final changes in the year 2013 demonstrate a further loss in the total area of the bare land and sea in accordance with vegetation cover land decreases, a remarkable increase in urban areas as well as sedimented areas. The total area of the desert state remains the same (Figure 11).

The expansion took place toward the sea and the surrounding bare land. This fact is related to the extensive human impacts. Continuing process of shallow land sedimentation has its negative effects on natural vegetation cover and coastal habitat existing in area. The drying of the wetlands and shallow lands for industrial purposes represents a new natural resource hazard added to other environmental hazards that may threaten the Tarout Bay during the coming years. The result contextually reports the lack of rational natural resources management in the designated study area.

![Figure 3. Post-classification changes from the year 1973 till the year 1990](image3)

![Figure 4. Thematic change detection map temporal resolution of 1973-1990](image4)
Figure 5. Post-classification changes from the year 1990 till the year 2013

Figure 6. Thematic change detection map temporal resolution of 1990-2013

Figure 7. Post-classification changes from the year 1973 till the year 2013

Figure 8. Thematic change detection map temporal resolution of 1973-2013

Figure 9. Land Use Land Cover classes’ percentage in 1973

Figure 10. Land Use Land Cover classes’ percentage in 1990
Conclusion

Post Classification Comparison method was performed in the current study using six different supervised classification algorithms. Six Land Use Land Cover classes were produced and only two main classes (urban area, sediments) have increased significantly in the study area. The urban class has been increased almost 19% during the period 1973–2013. Meanwhile, sediments have also increased by almost the same percentage (12%), regardless the proportional area of each class. The desert class has decreased due to human intervention. Sedimentation deposits are remarkably noticed along the shoreline of the study area.

The use of remote sensing data in term multispectral and multi-temporal imageries provides a cost-effective tool to obtain meaningful information for better understanding and monitoring land change patterns and developments. Knowledge of GIS delivers an interactive environment of loading, examining, and envisaging digital data compulsory for change detection database developments.

Consequently, the findings of the study strongly propose adoption of new policies to be taken into consideration for adjacent areas that may directly or indirectly influence by the land cover changes of the study area. For instance, the urban expansion should be strongly prohibited over the vegetation cover and the deposits of the sediment towards the shoreline should be wisely selected to peruse an effective management plan.

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References


