Assessing the Multi-Temporal Changes of Soil Salinity and Waterlogging in Ismailia City, Egypt.

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Abstract
In this study, multi-temporal changes in soil salinity and water logging in Ismailia City, Egypt were analysed based on classification results acquired using the pixel-based and object-based approaches. Landsat images from 1986, 2000 and 2006 were used to carry out the image classification and ground truth data were collected from reconnaissance surveys, geological maps, Google Earth and personal knowledge. In pixel-based analysis, supervised classification was performed using maximum likelihood as the classifier with ERDAS Imagine. On the other hand, object-oriented image analysis was evaluated through eCognition software using the feature tool as the basis for classification. Results of the classified images show that the object-oriented approach gave an overall accuracy of 95.9%, 96.1% and 96.1% which was slightly higher than the pixel-based analysis with overall accuracy of 82.26%, 82.14% and 83.21% respectively. Change detection techniques including Image ratioing, image differencing and change vector analysis were deployed and analyzed to depict the history of changes as well as the spatial distribution of changes between the period of study. Results show that the study area experienced a decrease of 22.15KM^2 and an increase of about 155.01 KM^2 in soil salinity and waterlogging yearly between 1986 and 2006, it was also observed that waterlogged areas decreased towards the northeast and increased towards the west, southwest and southeast part of the study area. These findings suggest that remote sensing is a useful tool to detect saline soils and waterlogged areas.

KEYWORDS: soil salinity, waterlogging, change detection, pixel-based analysis, object-based analysis.

INTRODUCTION

Waterlogging and soil salinity are generally caused by changes in the inputs, outputs and storage of water and salt by soils resulting from the lower use of annual crops and pastures which have replaced the native vegetation. Soil salinity is a natural disaster caused by different factors in addition to water logging. Waterlogging is said to be the presence of excess water in the root zone of plants resulting in poor gas exchange and anaerobic conditions (Moore and Mcfarlane, 1998). Soil salinity is the process of accumulation of excess salts in the root zone such that the potential yield of salt-sensitive crops and pastures is reduced by more than 10% (Ridd, 1998).

Soil salinization is the most common land degradation and land desertification process. It is mostly common in arid and semi-arid regions of the world National Commission on Agriculture [NCA](NCA, 1991), under severe climatic conditions, where precipitation is too low to maintain a regular percolation of rainwater through the soils, soluble salts accumulate in the soil further influencing the properties of the soil. Generally, this causes a decrease in soil productivity, limits the viability of crops, constrains agricultural productivity and in severe cases leads to the abandonment of agricultural soils (Lu *et al.,* 2001). Soil salinity is a severe environmental hazard as it leads to an increasing impact on crop yields and agricultural production (Ghassemi *et al.,*2000). It is said to have an effect in both dry and irrigated areas due to poor management of lands and expansion of the agricultural frontier into marginal dry lands which affects agricultural practice (Lu *et al.,* 2001).

Waterlogging and soil salinity are mostly associated with rising groundwater levels and discharge of saline groundwater, most saline land is also waterlogged. These conditions provide a transport mechanism for salt from deeper saline aquifers to the soil surface where concentration through evaporation results in salt accumulation on the soil surface and in the root crop zones and pastures. However, waterlogged soils do not always become salt-affected. Saline soils have been defined by (Mc Feeters, 1972; Mohamed, 2006) as soil measuring > 0.1% Sodium Chloride (NaCl) in loams and coarser soils and > 0.2% NaCl in clay loams and clays. (Flanders and Pereverz off, 2003) classified soils as saline using electrical conductivity measurements of a saturated extract of > 400msm-1 and/ or a terrain electrical conductivity of >50 msm-1 (measured with a geonics EM38 in the vertical position).

Change detection as a process of identifying differences in the state of an object or phenomenon by observing it at different times (Ridd, 1998), is commonly applied to detect changes in vegetation using geospatial technology, some of its application in vegetation studies includes deforestation, regeneration, selective logging, to mention but a few (Mahmoodzadeh, 2006). A comprehensive understanding of changes enables us to analyze the history of dynamic geospatial ecosystems and predict their future development. Monitoring is a key technique for discovering changes since it involves regular observation of the properties of entities over a particular period. Monitoring is aimed at identifying, understanding and controlling ongoing processes and changes occurring in an area. With growing concerns about environmental changes especially vegetation cover, detection of changes in the environment has become an important element to prevent damage on the vegetation cover.

The aim is to evaluate the use of a pixel-based and an object-based technique to map out, investigate and analyze the dynamics of water-logged areas and salt-affected soils between the years; 1984, 2000 and 2006, using remote sensing data and GIS techniques. The objectives are, to carry out a classification of waterlogging and soil salinity using the pixel-based technique, to carry out a classification of waterlogging and soil salinity using the object-oriented technique, to compare the overall accuracies of both techniques and to investigate changes that have occurred in the area using different change detection techniques.

THE STUDY AREA

The province of Ismailia is to the North East of Egypt between the Nile Delta and the Suez Canal, it is located between Latitude 30^o38^l N and $30^o38'$ N and between Longitude 32^o 12’ E and 32^o 20’ E. The province has a total land area of $3.255km^2$, the city is located along the Suez Canal and the Ismailia Channel. The soils of the area consist of desert loam and a sand deposit, which can also be characterized as Entisols that consist of heavy alluvial clay. The province is characterized by the occurrence of micro-depressions where waterlogging and salinity are natural phenomena. It has an average maximum temperature of about 36.7^oC mainly in summer while in winter the temperature is around 7.6^oC.The city receives no fewer than 7 millimeters of precipitation annually with most rainfall along the coast. Rainfall from April up to and including October is very low and uniform for the study area as a result the area during summer solely depends on irrigation farming.

METHODS AND TECHNIQUES

Different methods and techniques were used to carry out the assessment of waterlogging and soil salinity in Ismailia city. Applied digital image processing techniques that involved data manipulation such as best band selection, image contrast stretch, pixel-based classification of land use/land cover based on spectral reflectance using maximum likelihood classifier, object-based classification of land use /land cover through image segmentation were used. The image was classified into four classes namely; saline soils, non-saline soils, vegetation and water. Finally, analysis of the change detection techniques included; image ratio, image differencing and change vector analysis.

Supervised Classification

ERDAS Imagine software for digital image processing was used for the pixel-based classification. The three images were classified into four different land cover types (saline soils, non-saline soils, water and vegetation), Ancillary information about the study area was acquired through field visitation, a geological map, coupled with prior knowledge of the area, and training sites were selected. Training samples were selected for each of the four different land cover types by delimiting polygons around representative sites, using the pixels enclosed by these polygons, spectral signatures were derived for the respective classes. A spectral signature is considered to be satisfactory when confusion among land covers to be mapped is minimal (Goossens et al., 1993), for each classification, the Spectral Reflectance of different land cover classes was first collected to check the possibility of differentiating them from other land cover types. Finally, supervised classification analysis was performed using maximum likelihood as the classifier and an accuracy assessment of the classification result was conducted.

Object-Based Classification

An object-based approach using eCognition software was used to conduct the classification of the three Landsat images. The images were first segmented into objects using the homogeneity criterion (scale, shape and colour). A scale parameter of 120 was used for the segmentation which produces very different sizes of objects. This was chosen because it got the most accurately represented features of the land cover types. One disadvantage of multi-resolution segmentation was that it was time-consuming and also process-intensive (computer constraints). Still, its main advantage was that it provided the most suitable features for classification. The homogeneity criterion was a combination of shape (which splits up into smoothness and compactness) and colour (spectral values). By applying different scale parameters, the user can create hierarchical image objects (Definiens, 2001).

The next step after segmentation was image object classification, here, the basic step is to find a feature rule set and a threshold to represent the image object of interest (Definiens, 2001). The images were classified into two major classes (superclass) otherwise known as the first hierarchy, these classes were soil classes and others. These super classes were further divided into sub-classes at the second hierarchy where soil classes were split into saline and non-saline classes using the mean layer brightness as a rule set to separate between the two types of soils.

On the other hand, the other class was further divided into water and vegetation using Land and Water Mask (LWM) as the rule set to separate between land and water. Land and water masks are important variables in classifying all types of water bodies, with LWM water values usually ranging between 0 and 50 (Definiens, 2001).

LWM = (Mean layer 5) / (Mean layer 2) * 100

The combination of the rule sets and the threshold on each class, form the basis of the classification. Finally, accuracy assessment of the object-based classification was measured based on the error matrix using the Training and Test Area (TTA) mask.

Change Detection Analysis

Image Ratioing

The three Landsat images were used for the Normalized Difference Water Index (NDWI), this was chosen because the research was aimed at identifying waterlogged areas and saline soils; The Normalized Difference Water Index (NDWI) ratio is a key factor in extracting information on saline soils and water (Ding et al, 2011).

NDWI = (G – NIR) / (G + NIR)

Where G is the digital number of the green band (b2) and

NIR is the digital number of the near-infrared band (b4).

Image Differencing

The resultant images obtained from the NDWI ratio were used for image differencing to calculate the area and percentage rate of changes that have occurred between the three images (2000 from 1986 and 2006 from 2000). Two change maps were compiled to display the specific nature of the changes and percentage area.

RESULTSAND DISCUSSION

Pixel-Based Classification Analysis

Following the supervised classification method, the images were classified into five classes (saline soils, non-saline, water, vegetation and others). Waterlogged and salt-affected areas were identified as well as their spatial distribution, and the resultant maps were exported to Arc GIS for mapping. (Figures 1, 2, and 3) shows the different classes produced from the supervised classification.

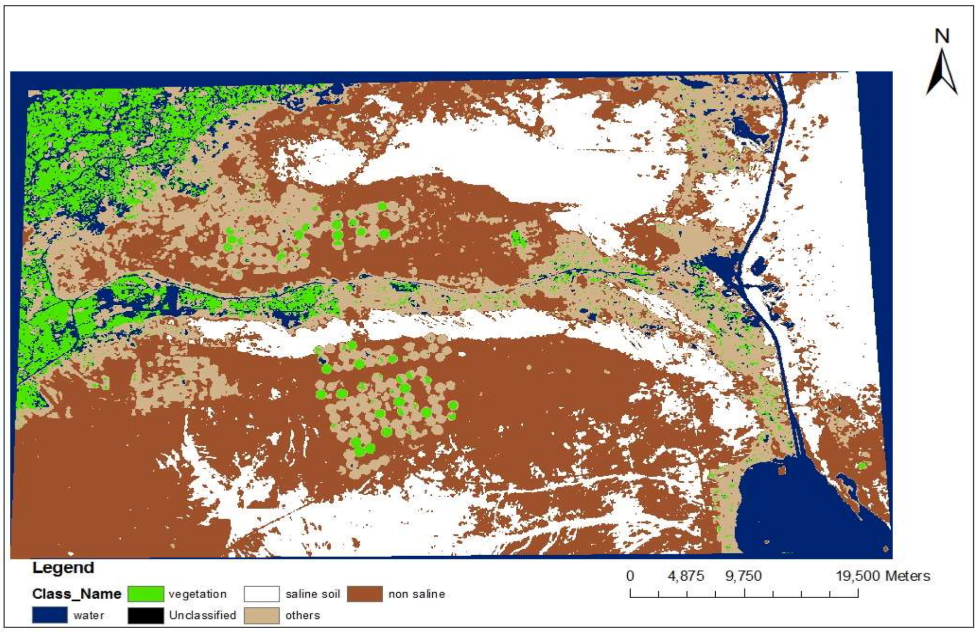


Figure 1: Classification Result of the 1986 Image.

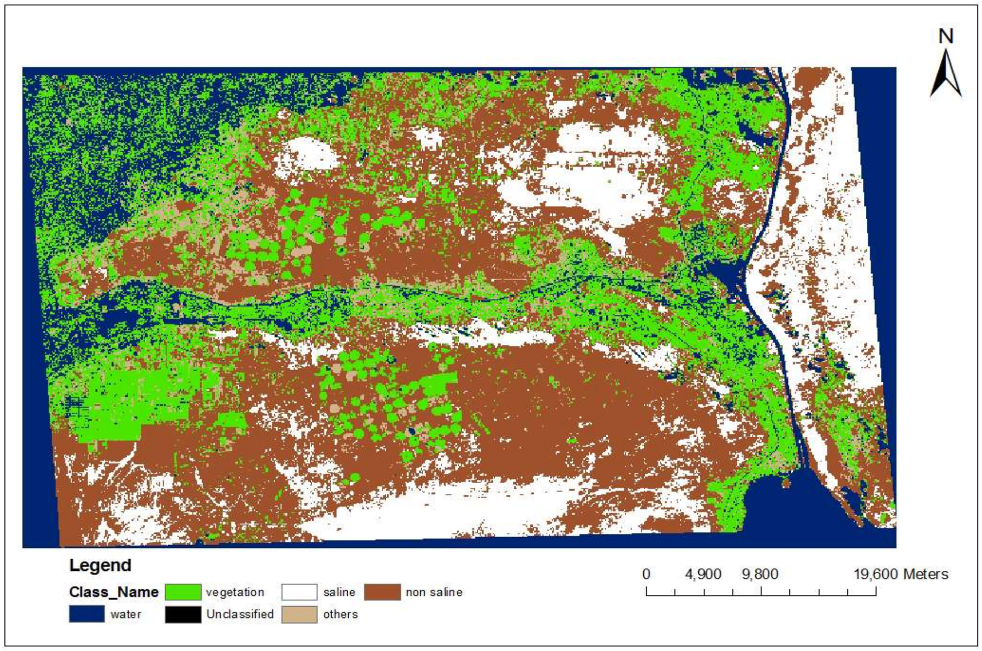


Figure 2: Classification Result of the 2000 Image

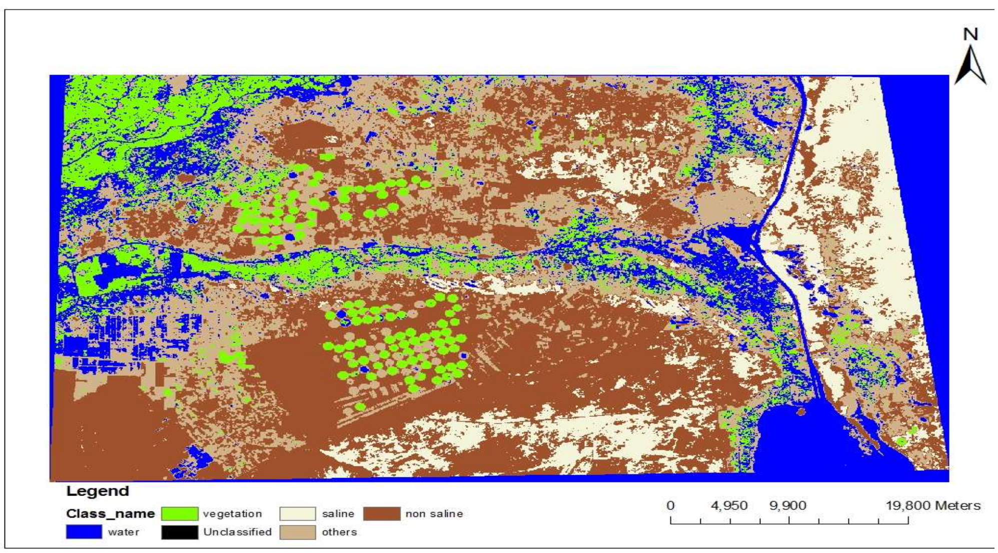


Figure 3: Classification Result of the 2006 Image

Areas affected by salinity and waterloggingwere calculated. In 1986, salt affected soils cover an area of 89941.8 (Ha) and waterlogged areas cover 44282.4 (Ha). In 2000, water logged areas increased to 60536.5 (Ha) and salt affected areas decreased to 57769.5 (Ha), waterlogged areas increase further in 2006 to 62680.4 (Ha) while salt affected soils decrease to an area of 41048.8 (Ha). Figure 4 shows a chart of the increase and decrease in soil salinity and waterlogging between the three images.

Figure 4: Areas Affected by Soil Salinity and Waterlogging Between the years 1986, 2000 and 2006

Accuracy Assessment Result of the Pixel Based Classification

During the supervised classification of salt affected soils and waterlogging, producer's accuracy, user's accuracies and overall accuracies were calculated with error matrixes. KHAT values from Kappa coefficients were also derived in order to evaluate the quality of each classification. From the 1986 image, 82.86% of the

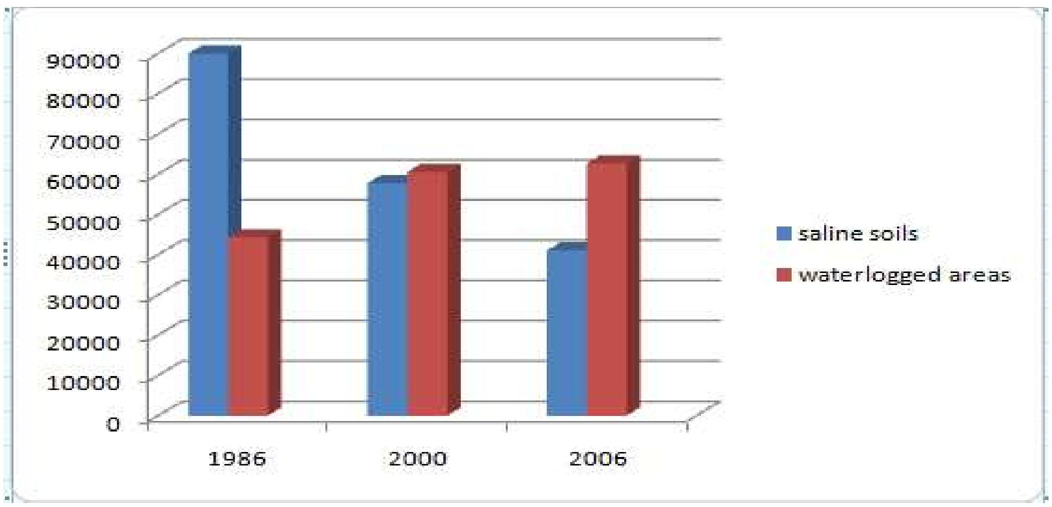


image area was correctly classified, the producer's accuracy was 87.02%, and the user's accuracy was 83.12%. The Kappa value of the accuracy result was 0.766, which means that the classification process avoided 76.6% of the errors that a random classification would generate. The values of accuracy assessment results obtained for each class from the three images are shown in Table 1.

Table 1: Accuracy Assessment of the Classified Images of 1986, 2000 and 2006

Years	Producers Accuracy (%)	Users Accuracy (%)	Overall Accuracy (%)	Khat Value
1986	87.02	83.122	82.86	0.766
2000	82.46	81.33	82.14	0.758
2006	86.01	80.55	83.21	0.776

Object Based Classification

The object-based classification results through segmentation of the image was achieved, the images were classified into four classes; saline soils, non-saline soils, vegetation and water. The classified images were exported to Arc GIS for mapping. Figures 5, 6, and 7 shows the resultant maps of the object-based analysis.

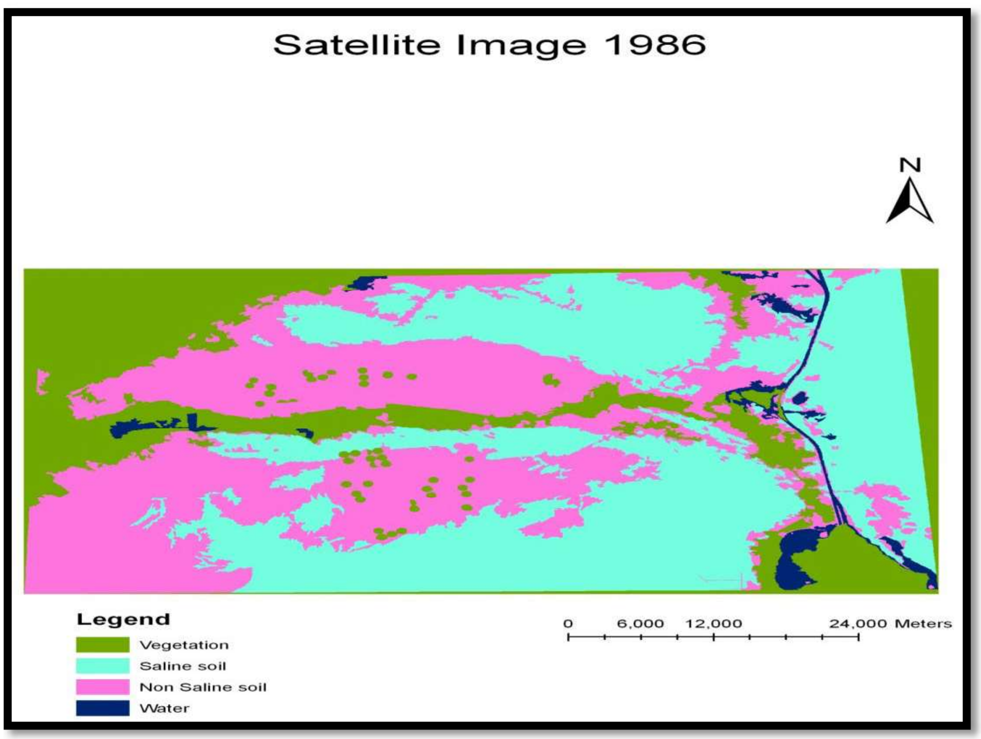


Figure 5: Object Based Classification Result of the 1986 Image

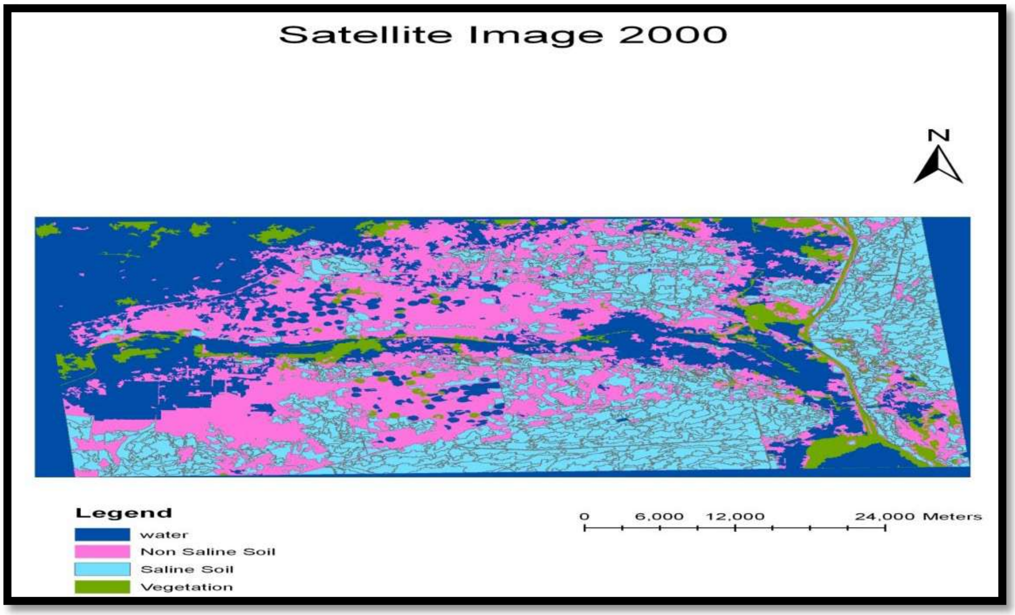


Figure 6: Object Based Classification Result of the 2000 Image

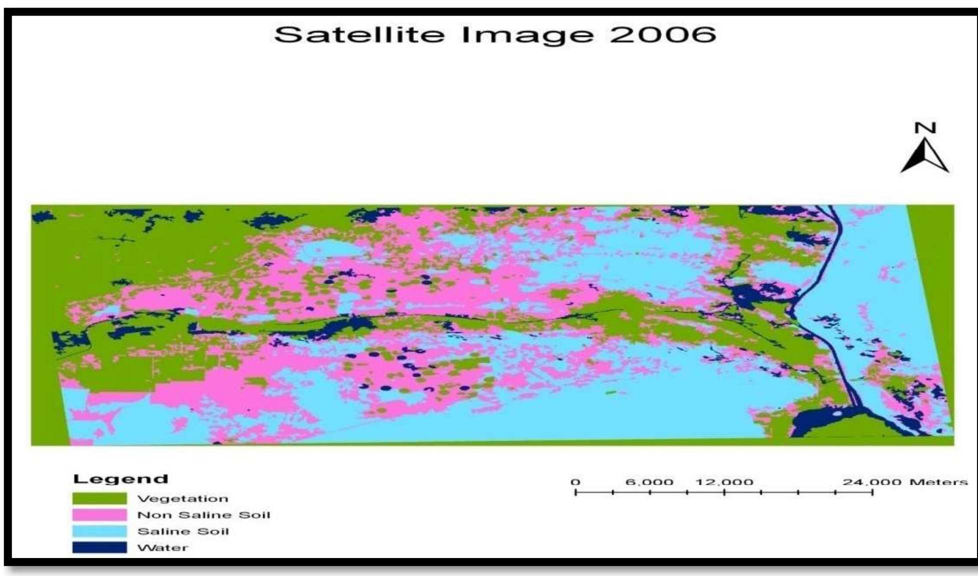


Figure 7: Object-Based Classification Result of the 2006 Image

Accuracy Assessment Result of the Object-Based Classification

Overall classification accuracy of the object-based classification for the three images is presented in Table 2

Table 2: Accuracy Assessment of the Object-Based Classification

Years	Producers Accuracy (%)	Users Accuracy (%)	Overall Accuracy (%)	KIA (%)
1986	94.6	96.7	95.9	94.4
2000	94.3	96.4	96.1	94.4
2006	95.4	97.6	96.1	94.4

Image Ratioing

To detect the salt-affected soils and water-logged areas, the Normalized Difference Water Index (NDWI) imagerationing technique was used. This technique often brings out information on water and vegetation cover. Figures 8, 9 and 10show the resultant maps of NDWI.

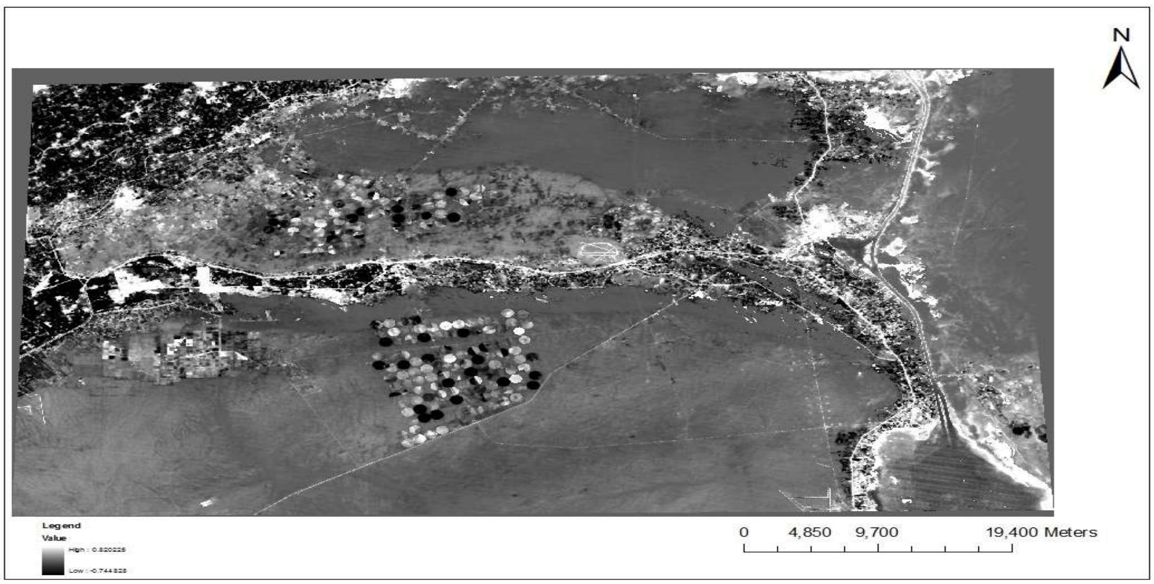


Figure 8: NDWI Map of the 1986 Image

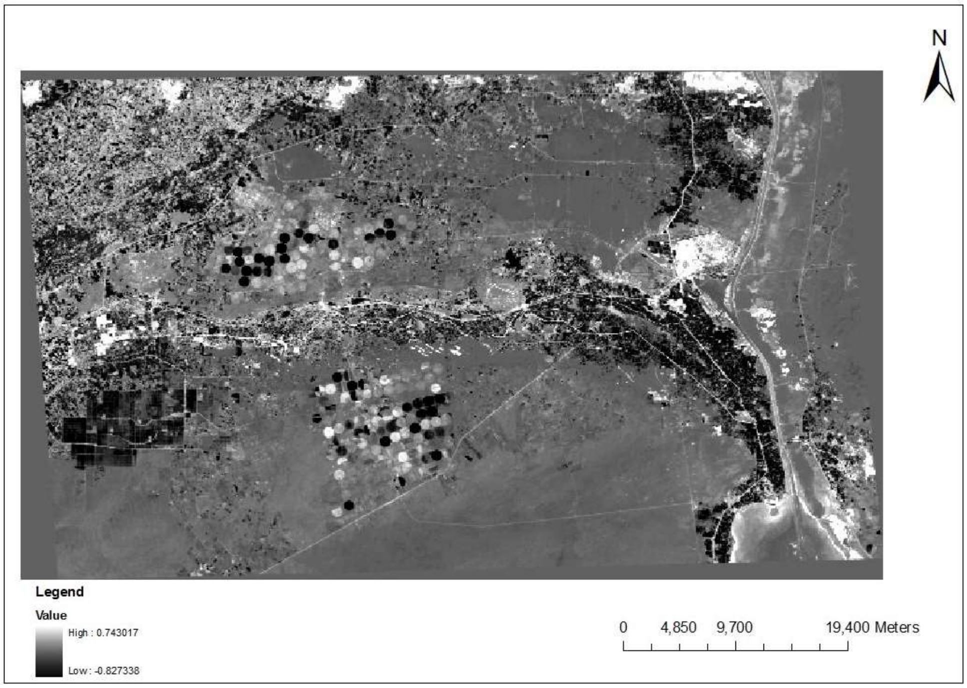


Figure 9: NDWI Map of 2000 Image

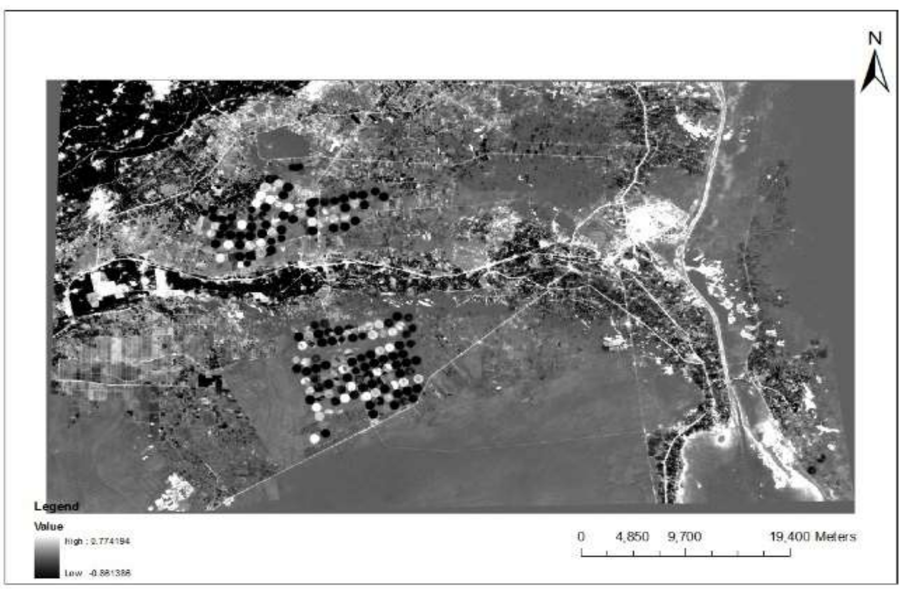
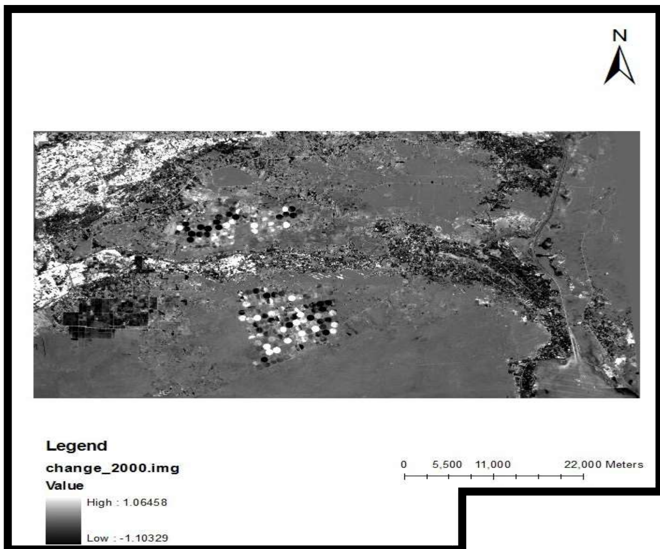


Figure 10: NDWI Map of the 2006 Image

Changes in Soil Salinity and Waterlogging

The three resultant maps from the Normalized Difference Water Index (NDWI) above were used to calculate the changes that occurred between the period 1986 to 2000 and 2000 to 2006 through image differencing. Figure 11 and 12 shows the resultant maps between the two periods.



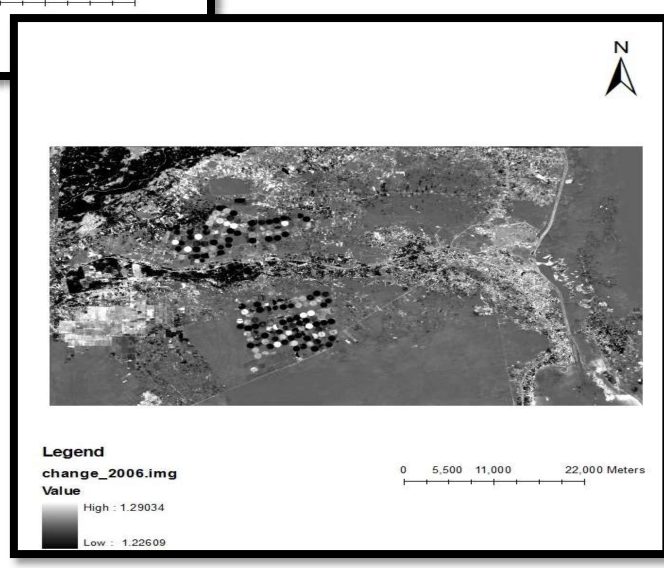


Figure 11: Image Differencing Between 1986 and 2000 ImagesFigure 12: Image Differencing Between 2000 and 2006 Images.

The image differencing resultant maps above produces the amount in hectares of areas that increased and decreased between the two dates. Between 1986 and 2000, there has been a decrease of in soil salinity amounting to an area of 47365.3 (Ha) and an increase of 49531.9 (Ha). On the other hand, between 2000 and 2006 there was a decrease of 44317.4 (Ha) of the total area and an increase of 62954.9 (Ha).

Spatial Distribution of Waterlogged Areas
Each of the three original images of 1986, 2000 and 2006 were used to digitize the waterlogged areas on each image. This was done by creating a new shape file in Arc GIS. It was performed in order to show the direction of the waterlogged areas, the three digitized vector layers were overlaid to show the spatial distribution and direction of waterlogged areas. Figure 13 shows the resultant map of the vector analysis.

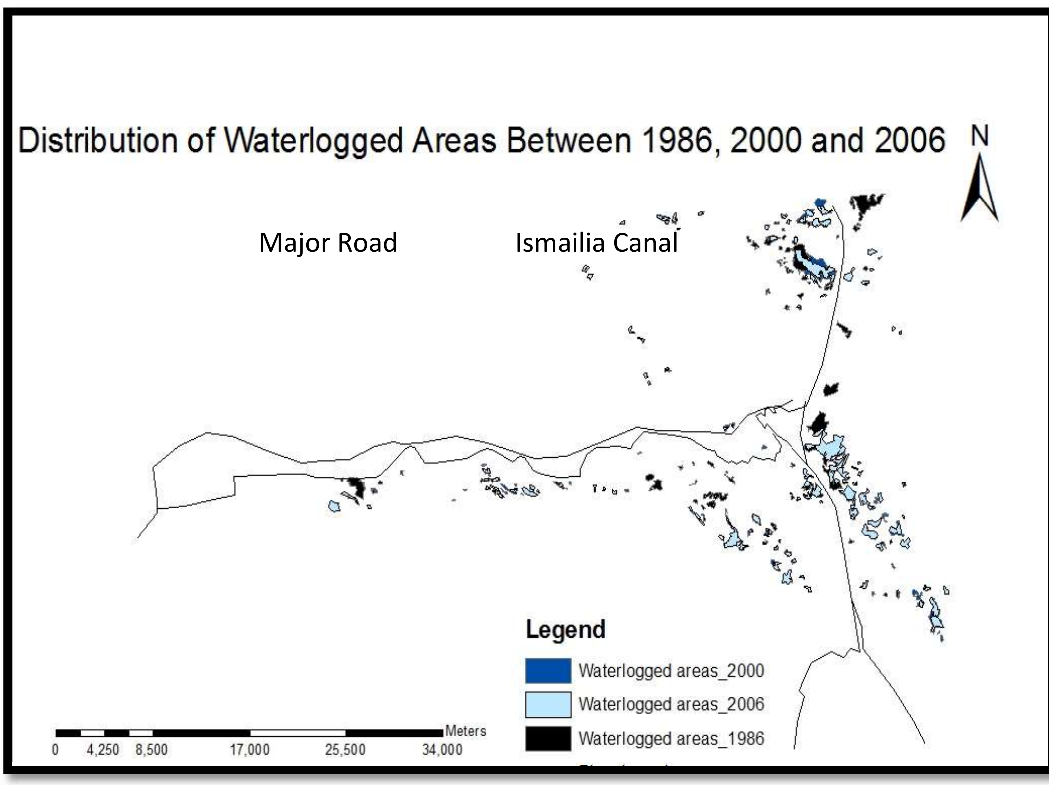


Figure 13: Distribution of Waterlogged Areas Between 1986, 2000 and 2006

Suez Canal

Comparison Between the Pixel-Based and the Object-Based Classification Results

Both pixel-based and object-based classifications prove to be powerful tools in detecting saline soils and waterlogged areas, the accuracy assessment results of both methods showed that there was a slight difference between the overall accuracy of both methods. The pixel-based classification gave an overall accuracy of 82.86% on the 1986 image while the object-based classification of the same year gave an overall accuracy of 95.9 % on the 2000 image, the pixel-based overall accuracy was 82.14% while that of the object-based was 96.01% and then finally, on the 2006 image, the pixel-based gave an overall accuracy of 83.21% and the object-based overall accuracy was 96.1%. From the results presented, it can be seen that the object-based classification is slightly higher than the pixel-based classification. This is similar to studies of (Dingle and King, 2009; Cleve et al, 2008; Zinck, 2000) where they each compared the accuracy of the pixel-based and the object-based classification for change detection in vegetation cover types using high-resolution photography and Landsat images, they each found that the object-based analysis gave a higher accuracy value than the pixel-based classification

On the other hand, contrary to what (Cleve et al, 2008) obtained in their analysis, where they found the object-based classification gives much higher accuracy results as compared with the pixel-based classification, they also found that the object-based classification was the most accurate method to discriminate between different land cover types.

CONCLUSION

In this study, Landsat images from 1986, 2000 and 2006 were used to depict the history of changes in soil salinity and waterlogging in Ismailia City, Egypt. A comparison between the pixel-based classification using spectral analysis and an object-based classification through image segmentation was conducted. Image ratioing, image differencing and change vector analysis, as change detection techniques were used to analyze the rate of change, the percentage rate as well as the spatial distribution and direction of change that have occurred in the area.
Results showed that the overall accuracy of the pixel-based classification on the three images was 82.26%, 82.14% and 83.21%, while the overall accuracy of the object-based classification was 95.09%, 96.14% and 96.10% respectively which shows that the object-based analysis was slightly higher than the pixel-based classification results, although the object-based classification did not perfectly classify the land cover types, it failed to separate water from vegetation despite

using different rule sets in separating both features. This could be due to imperfection in the use of eCognition software package,It can also be emphasized that the object-based analysis was more computationally intensive than the pixel-based technique, while the pixel-based technique was relatively straight forward and easy to perform, the object-based analysis was more complex to construct (Mthuthuzeli, 2008), the development of the knowledge base analysis43 depends highly on an experts input and background knowledge of the images to classify.Object-based analysis usually gives a better result with high-resolution imagery such as IKONOS and often provides an accurate classification if applied to study features of an urban area such as house roofing or different sizes of trees (Baatz et al., 2000).

Results of the change detection analysis showed that the study area experienced an increase in the amount of surface waterlogging between 1986 and 2006 while there was a decrease in soil salinity, the rate of change showed that an area of 22.15 square kilometres experienced a decrease yearly between 1986 and 2006 in soil salinity and waterlogging, and 155.01 square kilometers of land increases yearly. The distribution of waterlogged areas showed that the problem occurs along the Ismailia Canal and Suez Canal, but is mostly concentrated along the Suez Canal, it was noticed that the direction of change in the distribution of waterlogged areas decreased towards the northeast but seriously increased towards the southeast, southwest and western direction of the study area.

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