COMPARING PIXEL-BASED TO OBJECT-BASED IMAGE CLASSIFICATIONS FOR ASSESSING LULC CHANGE IN AN ARID ENVIRONMENT OF NORTHERN WEST SAUDI ARABIA

EMAN KHALED ALBALAWI

Assistant professor in Spatial Science
Department of Geography, Umm Al-Qura University,
Makkah, Saudi Arabia.
Correspondence: ekbalawi@uqu.edu.sa

COMPARING PIXEL-BASED TO OBJECT-BASED IMAGE CLASSIFICATIONS FOR ASSESSING LULC CHANGE IN AN ARID ENVIRONMENT OF NORTHERN WEST SAUDI ARABIA

EMAN KHALED ALBALAWI

Assistant professor in Spatial Science
Department of Geography, Umm Al-Qura University, Makkah, Saudi Arabia.
Correspondence: ekbalawi@uqu.edu.sa

1.1 Abstract

Land use and land cover (LULC) changes in many developing countries are inevitable. In Tabuk, a region northwest of Saudi Arabia, rapid urbanization and an agricultural evolution have led to dramatic changes in LULC over the last 30 years. Increasing land demand to meet food production desire has led to expanding these agricultural areas into previously undeveloped deserted or barren areas. This places immense pressure on valuable water reserves, therefore correctly defining irrigated or non-irrigated agricultural land is important to meet the need for intensive and sustainable agriculture development. The pixel-based image classification technique is often used to assess LULC changes (e.g., Maximum Likelihood Classification (MLC) and Support Vector Machine (SVM)). Object-based image analysis (OBIA) has also been widely used for LULC change detection. Therefore, the paper aims to compare the most common image classification methods for assessing LULC change in the agricultural arid of Tabuk using medium-resolution data from Landsat (1985-2015).

Based exclusively on overall accuracy assessments, there was no advantage to preferring one image analysis method over another for the purposes of assessing LULC changes in arid environments using medium spatial resolution imagery. Visual interpretation, however, shows that the OBIA provided more accurate and satisfying results. Both pixels-based and object-based results indicate their possible further applicability for assessing LULC changes and corresponding studies. The result suggests that OBIA has the potential to be an alternative method over pixel-based methods for assessing LULC information taken over the spatially mixed land cover of arid Saudi Arabia.

Keywords: Arid area, Land use change, Remote sensing, Image Classification, OBIA

مقارنة بين عمليات التصنيف المراقب (الموجة) وعملية التصنيف الهدفي لتقييم التغيرات في استعمالات الأراضي/ الغطاءات الأرضية في شمال غرب للمملكة العربية السعودية

ايمان خالد البلوي
أستاذ مساعد، علوم مكانية
قسم الجغرافيا، جامعة أم القرى، مكة المكرمة،
المملكة العربية السعودية
ekbalawi@uqu.edu.sa

الملخص:

تهدف هذه الدراسة إلى المقارنة بين طرق التصنيف التقليدية واسلوب التصنيف الهدفي Pixel المعتمدة على وحدة الخلية وذلك لتقييم استعمالات ،Object-Based Classification الاراضي وكشف التغيرات في الغطاءات الارضية لمدينة تبوك وضواحيها في شمال غرب المملكة العربية السعودية. واعتمدت هذه الدراسة على المنهج الوصفي التحليلي باستخدام بيانات القمر الصناعي لاندسات 7,5,8 للفترة ما بين عامي (2015-1985). وقد تم تصنيف استعمالات الاراضي باستخدام اسلوب التصنيف المراقب (Supervised Classification) بطريقة الاحتمالية العظمى Maximum Likelihood وطريقة آلة ناقلات الدعم Support Vector Machine في اسلوب التصنيف التقليدي ومقارنتها بطريقة خوارزمية التجزئة متعددة الوضوح Multi-resolution Segmentation لإنشاء أهداف الصورة في اسلوب التصنيف الهدفي (OBC) ولتقييم صحة التصنيف تم اجراء عملية التدقيق لمقارنة الصفوف الناتجة مع نقاط الضبط الأرضي باستخدام الدراسة الميدانية والصور العالية الدقة، وقد انتجت خرائط موضوعية باستخدام طرق التصنيف السابقة وجرى تقييم جودتها باستخدام اختبار الصحة الشاملة Overall Accuracy، ومعامل كابا Kappa Coefficient. وخلصت الدراسة الى ان اسلوب التصنيف الهدفي حقق صحة عالية في تقييم استعمالات الاراضي وكشف التغيرات في الغطاء الارضي مقارنة بأساليب التصنيف التقليدية القائمة على وحدة الخلية Pixel، وقد اوصت هذه الدراسة بضرورة تطوير المزيد من النماذج المساعدة على تحسين التصنيف وإمكانية تطبيقها لتقييم تغيرات استخدام الأراضي والغطاء الأرضي بوصفه أسلوبا فعال لدعم المخططين وصانعي القرار.

كلمات مفتاحية: المنطقة الجافة، تغيير استخدامات الأراضي، الاستشعار عن بعد، تصنيف الصور، تصنيفات الصور الهدفي

1.2 Introduction

Land cover is characterized by the physical and biological cover of the land surface (e.g., water, bare soil, and vegetation), whereas land use refers to human activities that affect the environment. Land use and land cover (LULC) change is a dynamic process that may have serious consequences for the ecosystem. There are several driving forces of change in LULC, and they can be used as key indicators to assess change in LULC over affected areas including urbanisation, agriculture land use, and hydrological process. Therefore, accurate identification of the LULC is important to quantify the impact on the environment and socio-economic development. Arid regions dependent on limited water resources are particularly vulnerable (Zhou et al. 2015). Mismanagement of fragile land in arid areas as seen in agricultural practices of intensive agriculture can lead to land degradation (including an increase in soil salinity), water and air pollution, and biodiversity (Rastgoo & Hasanfard, 2021). Land resources management and policy development for arid areas require an accurate assessment of LULC to improve land use efficiency and reduce environmental impacts when responding to the demands of an increasing population (Campbell and Wynne 2011).

Advances in remote sensing have allowed for easy and fast means to obtain relatively up–to–date and reliable information on LULC changes that can help the decision-making process to monitor environmental impacts (Campbell and Wynne 2011). Satellite remote sensing tools detect land changes through scientific evaluation of both natural and artificial forces that lead to a change in land cover. It is possible by correlating a direct land observation technique that shows these forces and actions at required times (Konecny 2014). Land use change can easily be identified from satellite imagery, with LULC being an effective indicator of change (Zhu and Woodcock 2014). However, assessing LULC change in arid areas has been an ongoing challenge due to the similarity of spectral reflectance of surface features (Ram and Kolarkar 1993). As a result, the separating pure pixel from the mixed pixel is difficult (Lu et al. 2010, Zhang et al. 2016). The detection of changes in vegetation cover can also be problematic in arid areas where the density of vegetation is extremely low and where harvested agricultural land is mixed with fallow areas (Fisher 1997, Bakr et al. 2010). The issue is rather complex as the boundaries of barren land, urban areas, and sparse vegetation cover in an arid environment are not physically defined.

Image classification can be of general two categories: supervised and unsupervised (Lillesand et al. 2014). The supervised pixel-based means the information about the ground type distribution in some areas of the image is used to initiate the classification process (Rees 1999). Choosing training data cautiously and prior knowledge by the analyst are the major factors influencing the success of a supervised pixel-based approach (Canty 2014 and Campbell 2002). Numerous techniques in the supervised classification process have been developed to assess variation in LULC including parametric classifiers maximum likelihood classification (MLC), and newly developed non-parametric classifier support vector machine (SVM) (Vapnik 1999). Support vector machine (SVM) is a non-parametric machine learning algorithm that provides an optimal separating hyperplane to find the optimal boundaries between classes (Megahed et al. 2015).

An object-based image analysis (OBIA) has been developed and gained popularity (Walter 2004) as it generates a cluster of pixels to create objects in the image according to their spectral similarity, with the integration of expert knowledge and feature space optimization, making the classification more accurate (Platt and Rapoza 2008). The main difference between pixel-based and object-based (OBIA) is that the entire characteristics of an object in the image including spatial, textural, and spectral information are used in the OBIA, unlike pixel-based depends on spectral information of individual pixels. The OBIA also considers the object size, color, shape, and compactness during the segmentation process which can minimize the noise in the classified image (Myint et al. 2011, Bhaskaran et al. 2010). A high-resolution image is preferred in the OBIA approach; however, several LULC change studies have applied it on medium resolution with very satisfactory results (Whiteside et al. 2011).

Since the 1970s, moderate Landsat imagery has been the most common sensor used to understand LULC change as they are free and consistent. Landsat data are a valuable source of data for an understanding pattern of land use in the past and present, and through modeling to simulate potential future impacts (Turner et al. 2015). The selection of an appropriate classification method is fundamental for extracting reliable information from satellite data, especially in an arid environment. Exploring the different techniques used to evaluate LULC and the associated problems is required for arid areas to ensure the most robust analysis is employed.

Over the last three decades, increased oil revenues in Saudi Arabia have resulted in major changes in LULC due to rapid growth in the urban population. Agriculture sectors have been considered the backbone of the national economy to generate self-sufficiency and decrease dependency on an oil-based economy (Al-Shayaa et al. 2012). Agricultural areas in Saudi Arabia (e.g. Tabuk) are groundwater-dependent ecosystems and have been under ongoing stress due to highly vulnerable to land degradation and water depletion (Al-Ahmadi 2009). Increasing demand for irrigation requirements for the increased area of agriculture places immense pressure on valuable water reserves, therefore correctly defining irrigated or non-irrigated agricultural land is important to meet the need for intensive and sustainable agriculture development.

The paper aims to compare the most common image classification methods for assessing LULC change in the agricultural arid of Tabuk using Landsat data (from 1985 to 2015). The Maximum Likelihood Classification (MLC), Support vector machine and was the chosen method for supervised classification to be compared to object-based classification.

1.3 Study area

The study area as defined for this paper covers an area of approximately 4 212 km2 in the north-western of Saudi Arabia within the Tabuk region, located between 28˚23` to 28˚39`N and 36˚35` to 36˚57`E at an average altitude of 600-800 m above mean sea level (Fig. 1). The Tabuk region has an area of 131 100 km2 and corresponds to about 6% of the total area for Saudi Arabia with a population of 890 922 (CDSI, 2016).

Tabuk region is considered arid with an annual average rainfall of 40 mm, mostly occurring between November and January with snowfalls every 2-3 years. The mean daily minimum and maximum temperatures are 15° C and 30° C, respectively. The predominant land cover in Tabuk is semi-desert grazing land about 78.5%. 16.8% of the area of the total region is cultivable (agricultural irrigation), and shrubs cover 4 %. 5% of the land use of the study area is urban land (Vijayan et al., 2013).

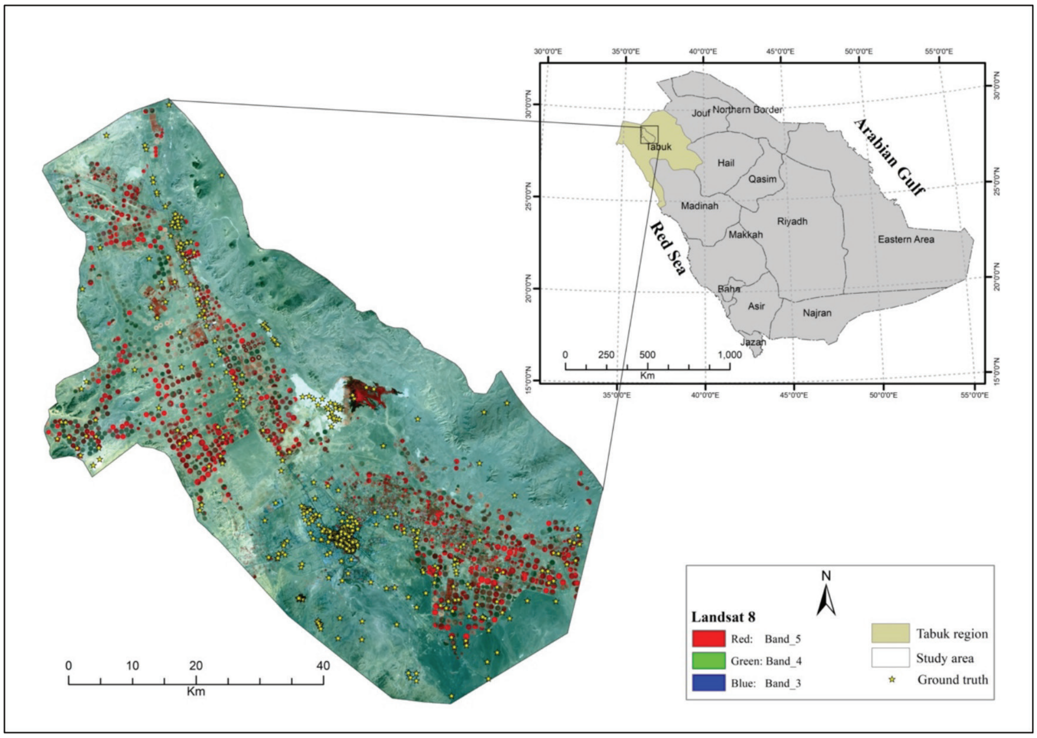


Figure 1 The location of the study area with ground truth data

1.4 Methods

1.4.1 Image Acquisition and preparation

Landsat Thematic Mapper (TM), Enhanced Thematic Mapper plus (ETM+), and Operational Land Imager (OLI) (path 173 and row 40) for 1985, 1990, 1995, 2000, 2005, 2009, and 2015 were acquired and sourced from United States Geological Survey (USGS), Earth Explore site. Images were selected during March and April of any given year to provide uniformity when detecting and assessing LULC change, and only those with minimal cloud cover were selected. The research intended to use 5 years intervals and consistent data, however, the data for the year 2010 was lacking in the same period, thus 2009 was considered instead.

A field survey was conducted from December 2015 to January 2016 to obtain the ground truth data (a total of 488 GPS coordinates), with a hand-held global positioning system Garmin (GPS) with accuracy ±5 m. A combination of the dataset including SPOT S5 with 2.5 m resolution was provided by King Abdul-Aziz City for Science and Technology (KACST), for 2005, 2008, 2010, and 2015. The General Authority for Survey and Geospatial Information (GASI) provides access to topographic and cadastral maps 1: 25,000. The map was constructed based on an aerial photograph taken in 1981 and updated in 2009 from various Saudi Arabia Ministries sources and ground field surveys. Topographical map Joint Operations Graphic (JOG) 1:250,000 for 1994 was acquired freely from USGS.

1.4.2 Image pre-processing

Landsat images acquired at different periods contain varying amounts of haze and dust in the atmosphere (Chavez 1996). Therefore, before any change detection procedure can be applied geometric and atmospheric correction is required on raw imageries.

Landsat satellite images obtained at level 1 product are geometrically corrected and rectified to the Universal Transverse Mercator (UTM) coordinate system (zone 37). Also, base and warp pre-processing image-to-image registration technique were used (Jin 2018). This technique aligned the images and generated automatic tie points between the base image (Landsat ETM+ of 2000) and the warped image (Landsat TM of 1985). About 50 ground control points (GCPs) were used with the nearest neighbourhood method for resampling. The Root Mean Square Error (RMS) was 0.46. Other Landsat images were corrected through an "image-to-image" rectification method based on the 2000 georeferenced image. The total RMS error of fewer than 0.5 pixels was generated for all six images (1985,1990, 1995,2005, 2009, and 2015).

To minimise atmosphere effects, atmospheric correction techniques have been used including radiometric calibration to convert the digital numbers (DN) to top-of-atmosphere (TOA) reflectance (Chavez 1996). Dark-object subtraction method (DOS) was used to correct Landsat imageries for atmospheric scattering, followed by subset image and image registration (pixel by pixel). The study area was masked using the image-subsetting technique.

1.4.3 Image Classification

The land cover types for the study site were identified by local field knowledge and high-resolution images for the Tabuk study area. The land use and land cover (LULC) classification scheme (Anderson 1976) was adapted to define four LULC classes (Table 1). Four main classes were identified in this study: barren land, urban areas, agricultural land, and water (Figure 2).

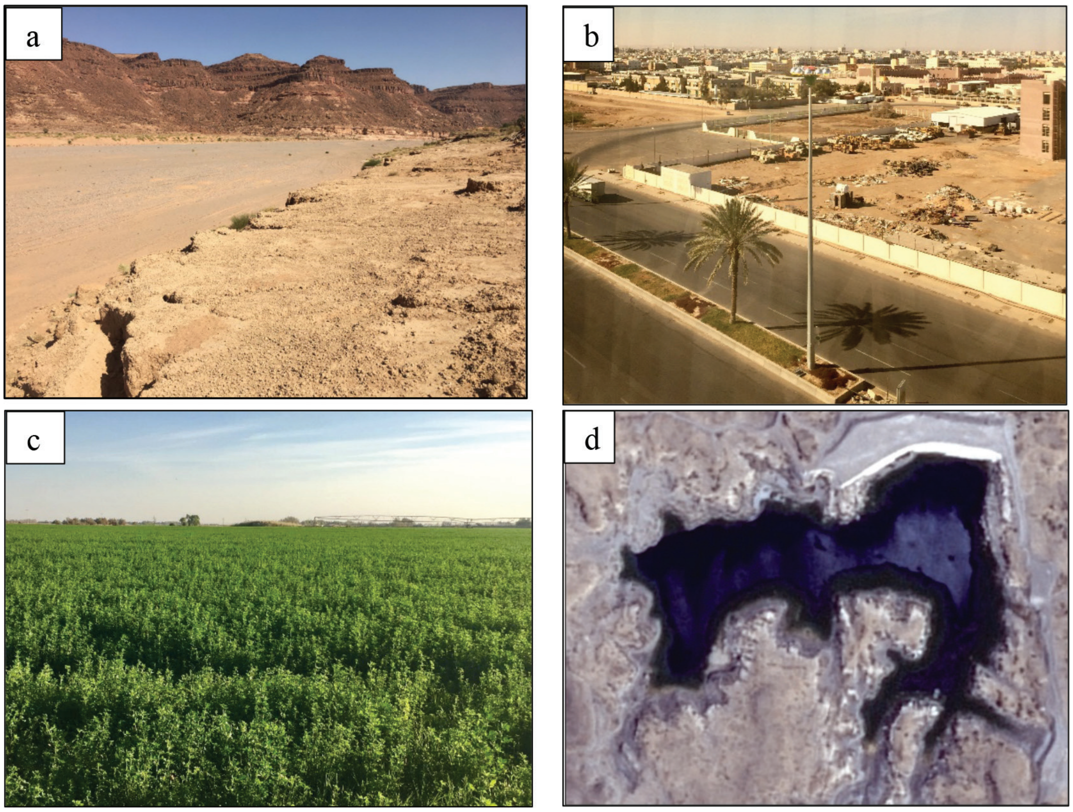


Figure 2 Photographs and screenshot showing examples of some of the classes used of the study area, a) barren land, b) urban, c) agriculture, and d) water.

Table 1. Land use/cover classification scheme (adapted from Anderson 1976)

Code	Class	Description
1	Barren land	Bare exposed rock, desert sand, mountain, dry salt flats, and mixed bare land
2	Urban areas	Residential, settlements; and transportation infrastructure commercial, and industrial areas.
3	Agricultural land	Cropland and pasture fields, greenhouses, fallow, and harvested lands
4	Water	Ponds and a small lake

1.4.4 Supervised technique

1.4.4.1 The maximum likelihood classification (MLC)

The MLC estimates means and variances of the LULC types to establish the probability of each pixel (Campbell 2002). Supervised classification requires training data sets to perform the classification which is the most important requirement as the algorithm depends on the spectral reflectance of individual pixels (Lillesand et al. 2014). The Regions of Interest (ROI) were cautiously selected to determine the training samples, with the aid of available reference data, e.g., high-resolution images, aerial photography, and field data for 2005, 2009, and 2015. The topographical maps were used for 1985,1990, 1995, and 2000 during the training stage. False colour composite (bands 3, 4, 5, and 7) on the imageries were also used. This composite help in assigning the feature in an agriculture class and making it easier to see individual agriculture features. The spectral characteristics of the study area are diverse and complex, such that each type of LULC requires > 3000 pure pixels. The number of training samples has a significant impact on obtaining the most accurate classification results. To reduce the amount of the 'salt and pepper effect' and to enhance the appearance of the thematic MLC classified maps, the majority tool (Lillesand and Kiefer 1999) was applied. In ArcGIS, a majority filter with eight neighbourhoods was used and a half-replacement threshold was chosen so that the pixel value within the neighbourhood was replaced with the majority value.

1.4.42 Support vector machine (SVM)

The important step to perform SVM is parameter selection. A Kernel can be chosen only by trial-and-error method on the data set and would enhance SVM's performance (Figure 3). Several runs with different parameters were applied to the SVM model field to choose a specific kernel for obtaining an appropriate function and scale. In this study, previously created ROIs during the supervised MLC classifier were used to classify the image into LULC types. SVM considers a spectral discrimination technique that finds a linear separating hyperplane by defining the decision boundaries between classes. There are no clearly defined boundaries between different land cover classes in arid areas thus, sometime data may not be linearly separable.

The parameters utilised for the SVM classifier for all images were: Kernel type as Radial basis function (RBF), gamma (γ) in kernel function as = 0.007, Penalty Parameter was 150, Pyramid levels set as zero value, and classification probability threshold of 0.05. The kernel function and parameter values were selected based on the classification accuracy results by testing the performance of each model.

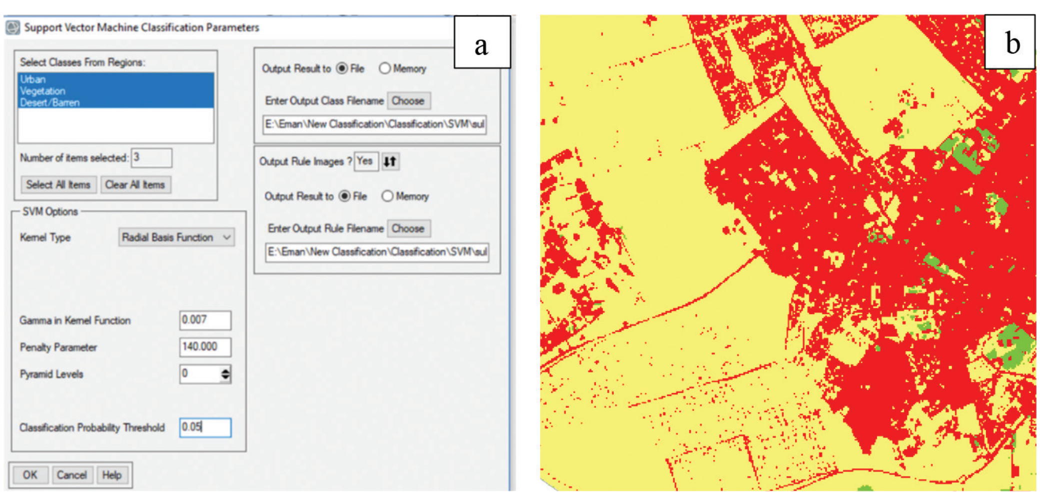


Figure 3 (a) An example of the parameters used in the process of SVM (error and trial phase), and (b) is the outcome, the colours represent: red is for urban areas, green is for the agricultural area, yellow is for the barren area,

1.4.5 Object-Based image analysis (OBIA)

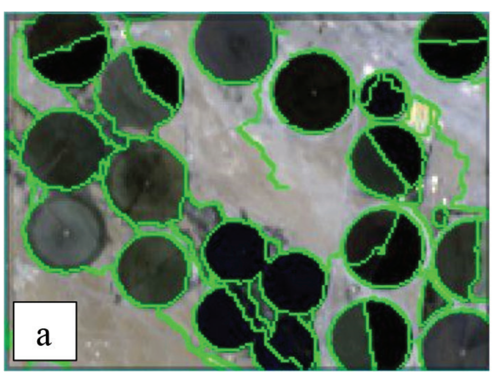
In this approach, similar spectral, spatial, and texture features of each Landsat imagery were divided into segments in the feature extraction tool. Several attempts were made to find the most appropriate OBIA scale that is appropriate for the study area and can represent the smallest feature of objects. The parameters were selected based on preliminary classification analysis of data.

As a result, for this study, the Edge segmentation method was chosen at a scale level of 10 (on a scale from 0 to 100). This method draws lines along the strongest intensity gradients, making it an effective edge detector (ENVI). The Full Lambda Schedule merging method at the level of 97 (on a scale from 0 to 100) was chosen to combine adjacent segments when the merging value increased merge and for texture kernel size 3 was used to perform. the segmentation processes (Figure 4).

To train areas for classifying Landsat imagery, around 100 polygon samples were distributed randomly through the image and assigned to each LULC type with the aid of the reference data. K Nearest Neighbor (KNN) supervised classification algorithm was then selected. The threshold value was 10 which means segments that have less than 10 percent confidence in each class are set to "unclassified. The neighbor's value was 3. A higher value considers more neighbors when choosing a target class and should reduce noisy or irrelevant features. The output result file is saved and exported as a vector file to be used in GIS tools for eliminating and merging unclassified polygons. The same classification parameters were applied to all other images. The same segmentation, merge and classification parameters were applied to other images.

1.4.6 Accuracy Assessment

An error matrix was utilized to measure the degree of closeness of the outputs (thematic maps) to the true values, including overall accuracy, producer's accuracy, user's accuracy, and kappa coefficient (Lu et al. 2004). A combination of high-resolution imagery and ancillary data was utilized to improve the classification results (Foody 2002, Lu and Weng 2007). A topographical map was used to validate the LULC map of 1985. Ground truth points and the high-resolution image was used to validate the LULC map of 2015. For other years, around 500 points distributed randomly were identified in SPOT images for 2005, 2008, and 2010 and attributed to the four LULC types in the study area to assess the accuracy of the classified LULC maps for 2005 and 2009 years. Reference data were not available for 1990,



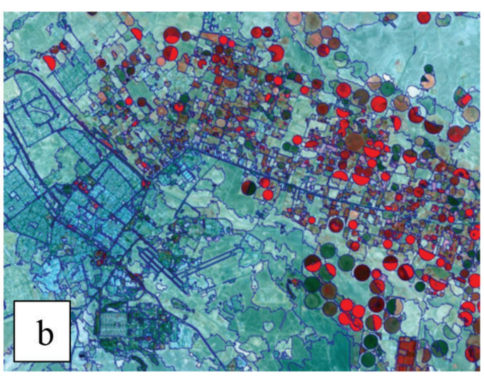


Figure 4 (a)screenshot of OBAI showing segmentation parameters used (scale level of 10 and merge level 97), (b) a section of the study area for 2015 image showing image segments after segmentation parameters were selected for the study site.

1995, and 2000, therefore, the areas where they do not experience substantial change i.e., barren (unchanged areas) used as references for the LULC 2000 based on the 2005 maps.

Minor adjustments were done in obvious land cover changes such as barren land to cropland and vice versa using the high-resolution map, topographic maps, and personal knowledge. The same process was applied to LULC maps of 1990 and 1995, by using the LULC map of 2009 as a reference (Zhou et al. 2008). The agreement between the classified results and reference data was calculated using Kappa Coefficient (Congalton 1991):

$$K = \frac{N\sum_{i=1}^{k} xii - \sum_{i=1}^{k}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{k}(x_{i+} \times x_{+i})} \quad (1)$$

Where:

k is the number of rows in the error matrix.

xii is the number of observations in row i and column i,

xi+ and x+i are the marginal totals of row k and column i; and

N is the number of observations in the matrix.

1.5 Results

1.5.1 Interpreting image classifications

The figure displays Pixel-based (MLC and SVM) and object-based image analysis was evaluated using multi-year Landsat satellite images to find the best method that can be suited for assessing LULC change in the arid environment. Pixel-based and object-based classifications are used to capture spatial and temporal LULC types in arid Tabuk with adequate overall accuracies. When the visual inspection was performed, the LULC-type maps using OBIA and SVM were devoid of mixed pixels. The SVM and OBIA thematic maps showed slightly similar interpretations and presented smoother and neater maps. MLC appeared to have the least clarity (Figures 5 & 6 producing a salt-and-pepper effect from the noise that could not be filtered out (Figure 5).

Urban area and agricultural land are the main land use in Tabuk. In this regard, the performance of MLC, SVM, and OBIA classifiers for urban and agricultural land for 1985 and 2015 years are presented in Figures 5 and 6. An over-estimation and under-estimation were observed in urban areas using MLC and SVM classifiers respectively (Figure 4). Whereas OBIA performed consistently more accurate depictions in the urban class. A mixed class between urban and water class also occurred using the MLC classifier and between urban and barren using the SVM classifier. Figure 4 revealed that using OBIA improved the spatial delineation between urban and barren land, where small objects (i.e., network well segmented) were provided.

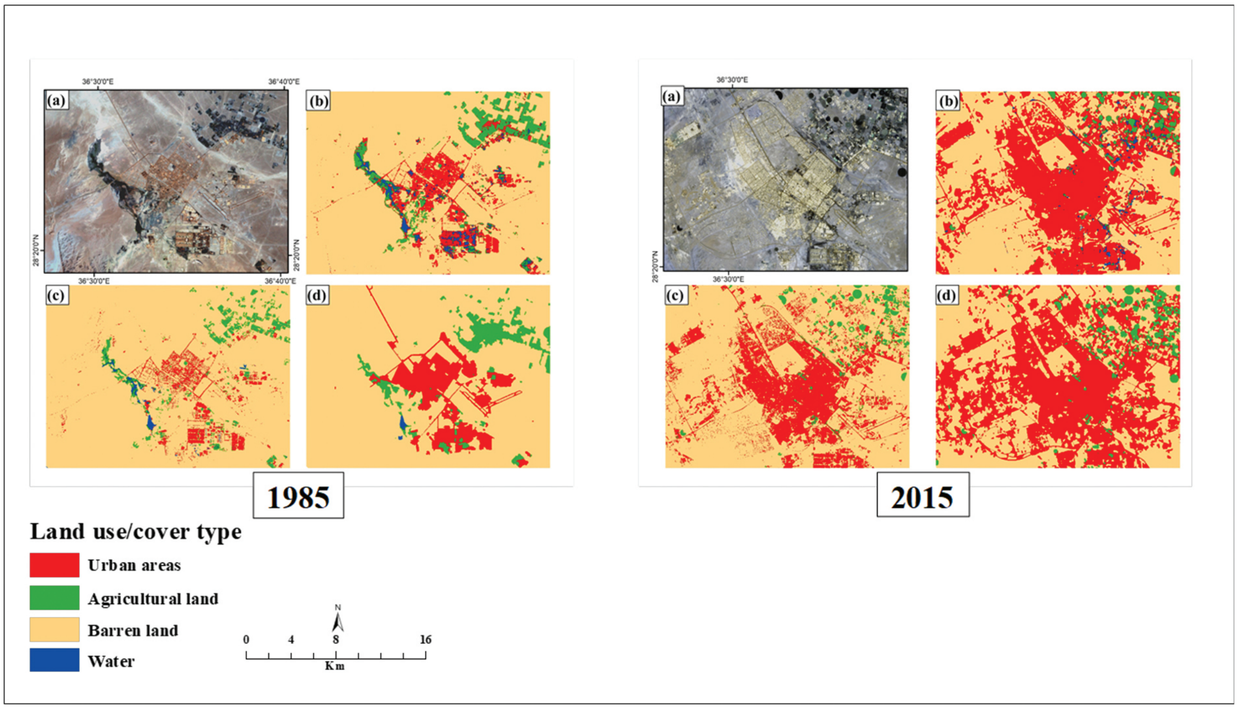


Figure 5 Comparison of pixel-based and object-based methods, (a) Landsat image showing the urban area in the study site (b) MLC (c) SVM (d) OBIA classification

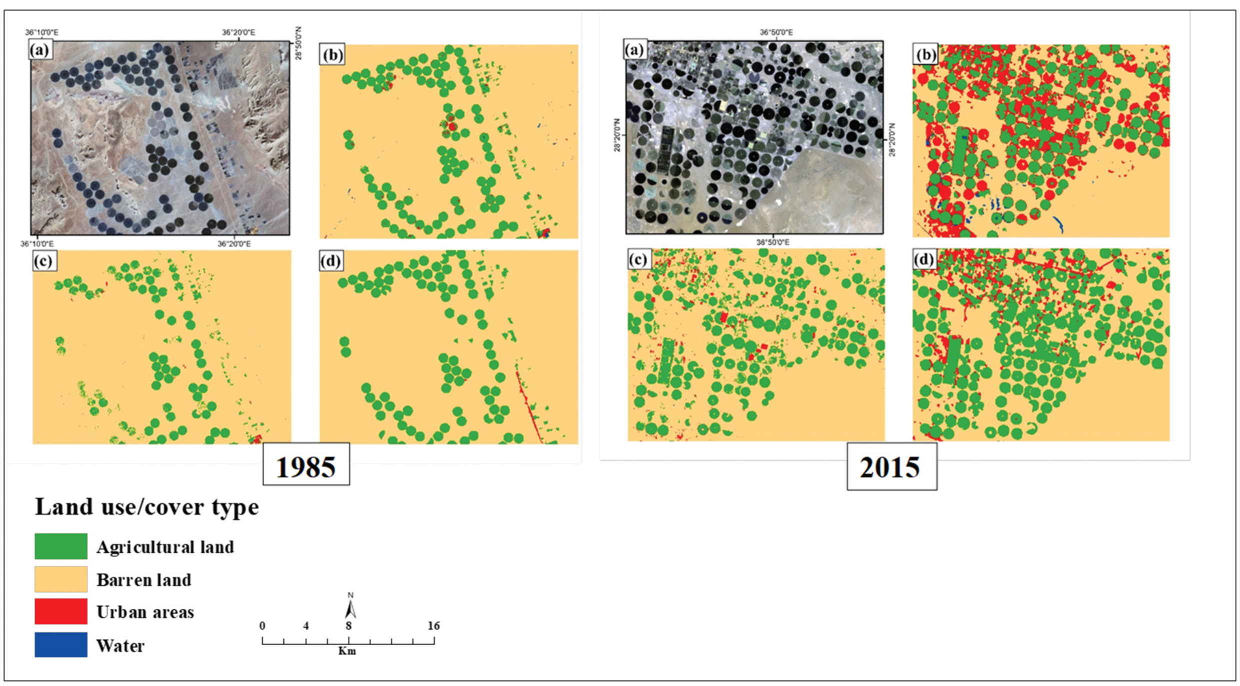


Figure 6 Comparison of pixel-based and object-based methods, (a) Landsat image showing the agricultural area in the study site (b) MLC (c) SVM (d) OBIA classification

Agricultural land (including healthy/irrigated crops) produced distinct spectral reflectance in the near-infrared bands and was easy to identify by all three methods (Figure 6). However, there are many agricultural areas mapped as barren land and urban areas using SVM and MLC respectively. Agricultural misclassification in supervised classification occurred mainly in harvested crops where the growth is poor. As a result, some agricultural areas are spectrally similar to urban and other agricultural areas are spectrally similar to barren areas (Figure 6). For assessing agricultural land, the maximum likelihood classification was the least reliable classifier specifically in the harvested land. Figure 5 shows the improvement and the capability of OBIA to eliminate the possibility of misclassification in agricultural land with complex boundary structures. The utilization of the spatial characteristics i.e., textures and spectral reflectance in OBIA was beneficial for consistent and accurate agriculture identification (Figure 5&6). The study results confirm that OBIA results are satisfactory using 30-m image resolution.

1.5.2 The classification accuracy results

The results of the accuracy assessment for the supervised classification MLC, SVM, and OBIA were compared (Table 2 and Figure 7). The validation of the classification results proved that OBIA produced more reliable and accurate LULC maps since all overall accuracies were higher than 93% and the kappa coefficient was higher than 90% (Table 2). There was a high agreement between ground truth/reference data and classified data obtained from OBIA. A slightly similar result is achieved using MLC with overall accuracies of land-use maps were ranged from 91 to 95 %, and for Kappa ranged from 0.87 to 0.92%. According to Anderson (1976), the results of OBIA and MLC considered a good level of accuracy which should be at least 85%. While the accuracy of the SVM-supervised classification was > 81%, with a Kappa was > 0.72 % (Table 2). There was little difference in overall accuracies for all methods tested.

Table 2 Summary of classification accuracy and kappa coefficient for three methods

Year	Overall accuracy (%)			Kappa coefficient		
	MLC	SVM	OBIA	MLC	SVM	OBIA
1985	95	91	94	0.91	0.85	0.91
1990	93	93	97	0.89	0.89	0.96
1995	94	91	94	0.91	0.85	0.91
2000	95	93	95	0.92	0.88	0.93
2005	93	93	96	0.89	0.89	0.94
2009	94	93	97	0.91	0.89	0.95
2015	91	85	93	0.87	0.74	0.90

A comparison of the individual accuracy level in terms of producer and user accuracies of each class. The classes with the highest accuracy were barren land and agricultural land in three classification techniques, whereas the urban class was the lowest accuracy, especially in the producer's results. Despite the supervised MLC and SVM classification produced maps with agricultural class are close to the ground truth data, based on visual interpretation, there are many agricultural lands inaccurately classified into urban and barren respectively. The result specifies that no significant advantage of SVM for this binary class separation in term of metrics analysis, but visual inspection of the SVM classified images were much clearer than MLC. Water class gave the lowest value and was poorly performed at a percentage of 50 % among the four LULC types using OBIA (Figure 8).

Comparison between ground truth (for the year 2015) and reference points using three methods are presented (Figure 7). The result shows that the OBIA classifier assigned most of the agricultural land and urban reference points correctly follows by the MLC classifier. In contrast, the SVM classifier assigned the lowest number of agricultural land and urban reference points (Figure 7).

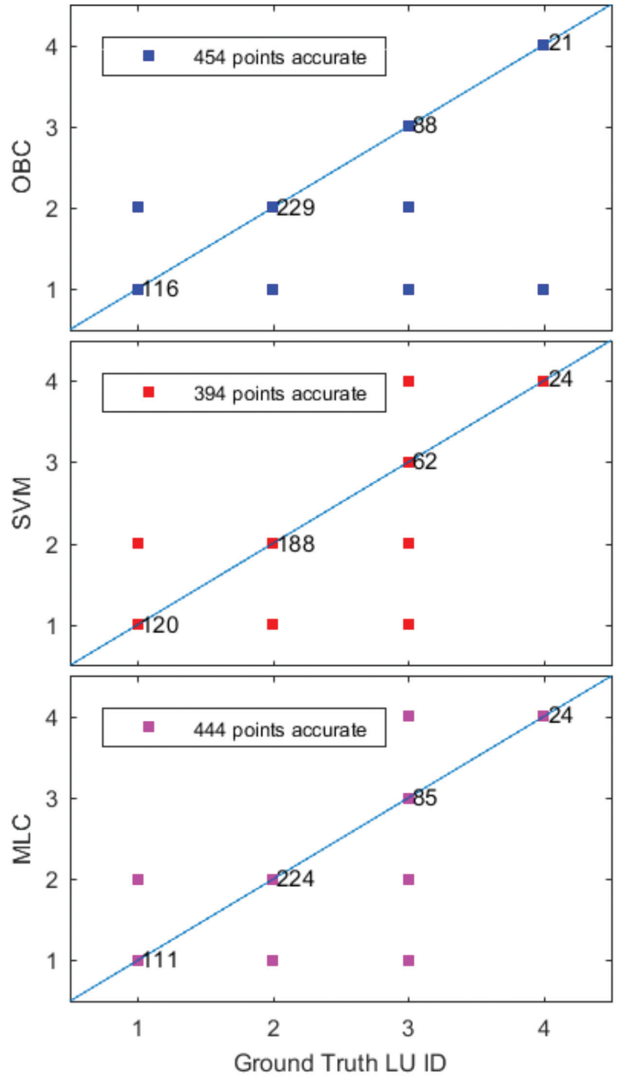


Figure 7 488-points ground truth points analysed in the 1-in-1 line for 2015 ground truth data, shows OBIA had the most accurate points assigned to agricultural and urban classes.

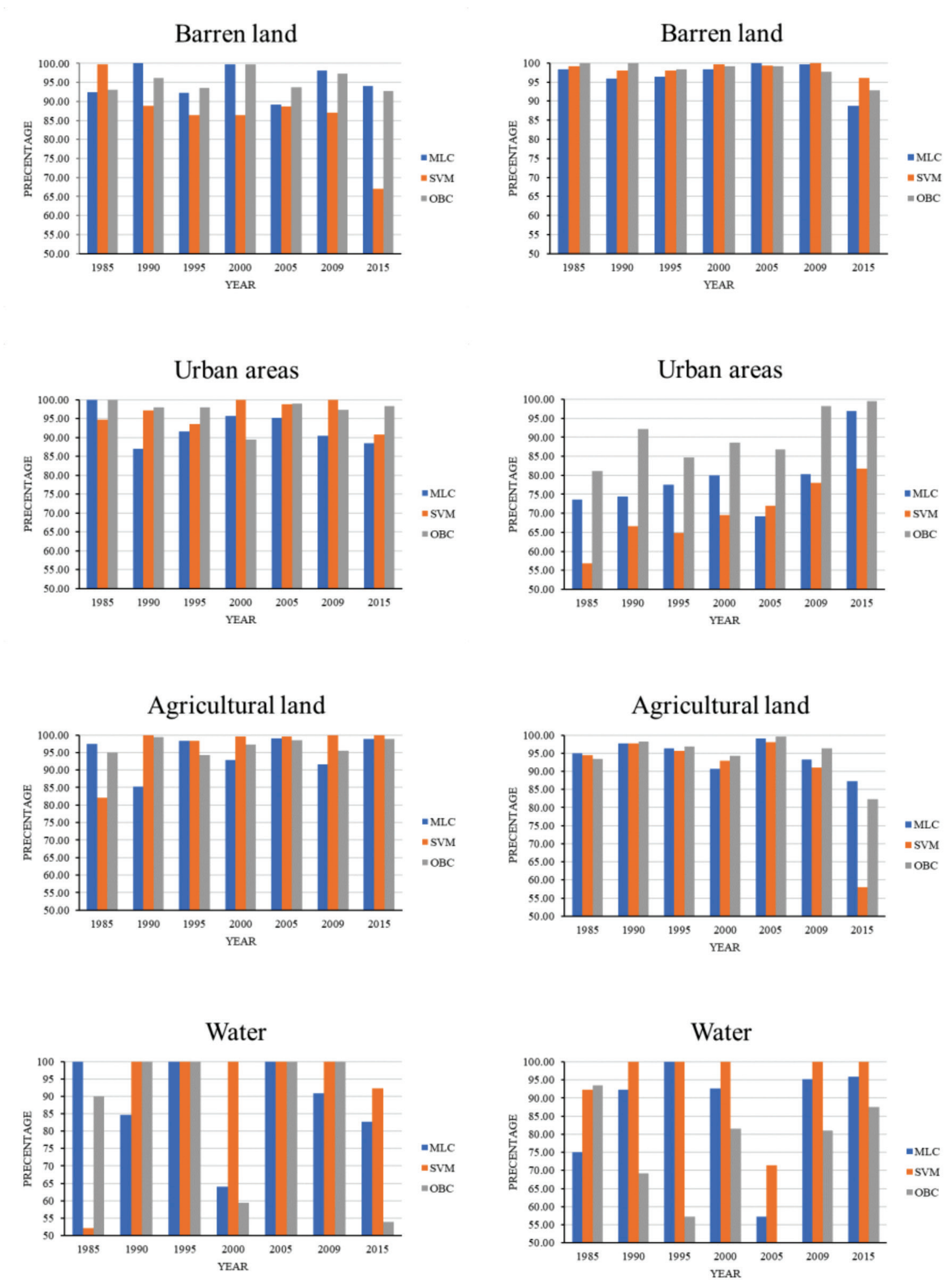


Figure 8 Comparison of the user's accuracy (left panel) and producer's accuracy (right panel) of three classification methods

From all the above comparisons and results obtained, the strengths and weaknesses of each method used in this arid case study are summarized below:

Table 3 Comparisons of the strengths and weaknesses of MLC, SVM and OBIA methods used.

Method	Strengths	Weaknesses
The maximum likelihood (MLC)	• Ideally with medium spatial resolution imagery • The analyst has control of LULC selection to determine training sample • Consider the mean, variability of brightness values in each class.	• Probability-based method • Long-time computation • Prior knowledge • A large number of training sample for optimality • Spectral classes and spatial information often misleading (mixed pixel), or overclassify with value have spectral similarities • Additional steps required
Support vector machine (SVM)	• Optimal separating hyperplane by creating linear discrimination • Reduce the noise of mix pixel	• Time-consuming to tune Kernel parameters • Not all data is linearly separable
Object-based image analysis (OBIA)	• Utilize the spatial and spectral information entirely • Cluster pixels with common values • Improve the accuracy Maps devoid of salt & pepper effects	• Determine Segmentation scale and training objects • A small object can be lost • Require high-resolution image for an accurate result
The main improvements using Object-based image analysis over supervised classification are marked as: • LULC change is assessed consistently and accurately through time. •Agricultural land and urban areas are distinguished clearly as separate classes.		

1.6 Discussion

Three image classification techniques commonly used for determining the change in arid and semi-arid areas have been compared to determine the best approach for the study area. Two supervised image classification techniques (MLC and SVM), and object-based image analysis (OBIA), were assessed to determine their effectiveness in producing LULC maps representative of the Tabuk area. Results from the different image classification techniques allow a comparison between the different methodologies and highlight the advantages and disadvantages, weaknesses, and strengths of the individual methods. Urbanization and agricultural land use appeared to be the main drivers of the changes observed. The accurate identification of these two classes is important in quantifying the impact on the environment and socio-economic development, however, the spectral signatures of these classes are not distinct or well-defined. The results suggest that the OBIA technique provides LULC maps that best represent the changing status of the area. The main advantage of this particular method is the ability to detect image objects having similar spatial, textural, and spectral characteristics; features that enhance the appearance of the classified image. The well-defined boundary of the agriculture class, including the different crop growth stages, was identified clearly without being adversely affected by similarities in the reflectance of other areas such as barren land or adjacent urban areas. This finding aligns with other studies which have been conducted on agricultural land and urban areas in arid areas (Li et al., 2016, Galletti and Myint, 2014, Kux and Souza, 2012, Myint et al. 2011).

Object and pixel-based classifications have shown good suitability for assessing LULC in arid areas when using medium-resolution imagery. Additional information, including ancillary data, knowledge of the study area, and careful selection of well-defined training samples (object and pixel), have improved the accuracy assessment results of the three image classifications (Campbell 2002, Foddy and Mathur 2004; Jensen 2004; Yang 2011). The overall accuracy results do not appear very useful in detecting minor accuracy differences (Lillesand et al. 2004, Congalton and Green 2009). The differences were obvious, however, when visually comparing the image classifications. Similar findings have also been reported previously (Goodin et al., 2015; Alqurashi and Kumar 2014, Al-Bilbisi and Makhamreh 2010), These studies found that OBIA generally outperformed the supervised classification methods, though the differences were not felt to be significant.

Well-irrigated agricultural land could be readily identified using both the OBIA and MLC classifiers due to the large amount of infrared radiation reflectance recorded in the images (Albalawi and Kumar 2013, Rouse et al. 1974). When viewing the results from the MLC classifier for areas near agricultural land boundaries, the probability of an agriculture pixel having a value close to an urban class value occurred most frequently in those agricultural areas which had been harvested, as well as in areas of sparse vegetation. A visual assessment of the results indicated that MLC performed poorly in classifying urban areas, even when using an adequate number of training samples (>3000 pixels) and with a majority, filter applied. The MLC, because it is a parametric classifier, uses only spectral information in the classification process, and this impacts the final result. Urban areas on MLC maps were overestimated, with many barren areas being classified as urban due to "salt and pepper" effects arising during processing. This salt and pepper effect had also been observed in other studies conducted in arid regions (El-Kawy et al. 2011, Shalaby and Tateishi 2007). This suggests that the misclassification of urban land and barren land is common when using an MLC pixel-based classification. It appears that using this method would tend to produce misleading results in regions having large areas of both urban land use and barren land (Lillesand et al. 2004). This is the case in the Tabuk study area, which does have substantial areas of barren land.

Although the SVM did separate the LULC in the study area and displayed a clear linear separation in the decision margins, some agricultural land was still identified as barren land (see Figure 3-3). As agricultural cropland, specially harvested or non-well-irrigated cropland, can demonstrate similar spectral and temporal responses, thus was difficult to separate these two classes using SVM and assess and map the conversions reliably on alone remote sensing data. If additional data, including irrigated land parcels, soil, and crop types, were to become available, it is also possible that further work using SVM techniques could provide a clearer result. The use of this additional data, where available, has shown to be of great benefit in other studies (Löw et al. 2015; Kraemer et al. 2015; Zheng, 2015). The current study focus, however, was to evaluate the three image classification techniques, specifically using medium-resolution satellite imagery, to ensure accurate LULC detection. The performance of the SVM indicates that not all data in arid areas is linearly separable, due to the similarity of the spectral characteristics of LULC. Urban areas appear underestimated and can be misclassified as barren land, especially in developing areas on the periphery of the city. A possible explanation for this is that the SVM is not finding the optimal hyperplane of the feature space. The SVM accuracy assessment results also indicate a poorer performance when compared to OBIA and MLC. The main disadvantage of using SVM is that the results are strongly influenced by user-defined input parameters, the setup of which can be time-consuming. The selection and use of suitable parameters to train the SVM classifier are very important, as this can have a significant impact on the results (Mountrakis et al. 2011).

The accuracy results and a visual interpretation of the images show the limitations of OBIA when using Landsat imagery to target the water class. This is due to the spatial image resolution (30-m) and the low percentage of water class represented in the study area (i.e., the size of the objects). For example, the small size of the water class within surrounding barren areas in this study resulted in this region being merged into a single polygon. In general, OBIA classification techniques perform best when using high spatial resolution images and so errors can be expected when using lower resolution images (Laliberte et al., 2004, Wang et al., 2018). For similar reasons, misclassifications also occur in barren/urban classes using the MLC classifier, even though these classes do have sufficient spectral differences (Ng et al. 2016). Under and overestimation of urban areas, using both MLC and SVM, indicate that the urban class is a difficult class to classify, primarily due to its spectral similarity to other classes found in this arid environment.

A significant amount of time was required to process the dataset. This included selecting the parameters (for SVM) and training data (for MLC). Methods that require prior knowledge of the study area (such as those using supervised classification algorithms) are significantly disadvantaged. The assessment of LULC in the study area also proved to be challenging due to the spectral similarities between the classes. Great care needs to be taken in choosing a classification method. Misclassifications resulting from the OBIA image classifier process could be overcome by using high-resolution imagery rather than the moderate-resolution imagery used in this study, however, access to high-resolution imagery over long periods and the high cost makes this problematic. The use of current, cost-effective (free), medium-resolution imagery in association with the use of OBIA classifications does provide data and a technique that can be used to successfully determine LULC patterns without the need for additional expert analysis and computational time. The use of remote sensing data and the selection of the most appropriate image classification method requires some thought, as most land use modeling is very sensitive to land use/cover classification accuracy. Both pixels-based and object-based results indicate their possible further applicability for assessing LULC changes and corresponding studies. The result, however, suggests that OBIA has the potential to be an alternative method over pixel-based methods for assessing LULC information from medium-resolution satellite imagery.

1.7 Conclusion

Detecting LULC change accurately is of great importance for the effective management and planning of natural resources. Satellite remote sensing image classification techniques have been compared for detecting LULC change from 1985 to 2015 in an arid area of Saudi Arabia. Detecting LULC change in an arid environment proved to be a problem because of spectral similarities between the classes, and care needs to be taken when choosing a classification method.

Based exclusively on overall accuracy assessments, there was no advantage to preferring one image analysis method over another to assess LULC changes in arid environments using medium spatial resolution imagery. Visual interpretation, however, shows that the OBIA provided more accurate and satisfying results. Mixed pixels and 'salt and pepper effects' in supervised classification were avoided using OBIA. Such an accurate detection of LULC changes can be used to simulate future LULC changes to achieve sustainable development. Accurate prediction of the spatial and temporal change of LULC could protect valuable natural resources from irreversible damage such as desertification, as well as enable planners to assess agriculture or urban growth.

1.8 References:

1- Abd El-Kawy, O. R., Rød, J. K., Ismail, H. A., & Suliman, A. S. (2011). Land use and land cover change detection in the western Nile delta of Egypt using remote sensing data. *Applied geography,* 31(2), 483-494.

2- Albalawi, E. K., & Kumar, L. (2013). Using remote sensing technology to detect, model and map desertification: a review. *J Food Agric Environ, 11*, 791-797.

3- Al-Ahmadi, M. E. (2009). Hydrogeology of the Saq Aquifer Northwest of Tabuk, Northern Saudi Arabia. *Journal of King Abdulaziz University: Earth Sciences,* 20, 51-66.

4- Al-Bilbisi, H., and Makhamreh, Z. 2010. A comparison of pixel-based and object-based classification approaches in arid and semi-arid areas of Dead Sea region using Landsat imagery, DIRASAT: Human and Social Sciences, 37 (3): 649-659.

5-Al-Shayaa, M. S., Baig, M. B., & Straquadine, G. S. (2012). Agricultural extension in the Kingdom of Saudi Arabia: Difficult present and demanding future. J. Anim. Plant Sci, 22(1), 239-246.

6- Alqurashi, A. F., & Kumar, L. (2014). Land Use and Land Cover Change Detection in the Saudi Arabian Desert Cities of Makkah and Al-Taif Using Satellite Data. Advances in Remote Sensing, 3(03), 106.

7- Anderson, J. R. (1976). A land use and land cover classification system for use with remote sensor data (Vol. 964): US Government Printing Office.

8- Bhaskaran, S., Paramananda, S., & Ramnarayan, M. (2010). Per-pixel and object-oriented classification methods for mapping urban features using Ikonos satellite data. Applied geography, 30(4), 650-665.

9- Campbell, J. B. (2002). Introduction to Remote Sensing. New York: The Guilford Press; 3 edition.

10- Campbell, & Wynne. (2011). Introduction to remote sensing: Guilford Press.

11- Canty, M. J. (2014). Image analysis, classification and change detection in remote sensing: with algorithms for ENVI/IDL and Python: CRC Press.

12- Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment, 37(1), 35-46.

13- Congalton, R.G. and Green, K. (2009) Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. 2nd Edition, Lewis Publishers, Boca Raton.

14- Chavez, P.S., Jr. 1996. Image-based atmospheric corrections–revisited and improved. Photogrammetric Engineering and Remote Sensing 62(9): pp.1025-1036.

15- Foody, G.M. and Mathur, A. (2004) A Relative Evaluation of Multiclass Image Classification by Support Vector Machines. IEEE Transactions on Geoscience and Remote Sensing, 42, 1335-1343. http://dx.doi.org/10.1109/TGRS.2004.82725

16- Foody, G. M. (2002). Status of land cover classification accuracy assessment. Remote Sensing of Environment, 80(1), 185-201.

17- Galletti, C. S., & Myint, S. W. (2014). Land-use mapping in a mixed urban-agricultural arid landscape using object-based image analysis: A case study from Maricopa, Arizona. Remote Sensing, 6(7), 6089-6110.

18- Goodin, D. G., Anibas, K. L., & Bezymennyi, M. (2015). Mapping land cover and land use from object-based classification: an example from a complex agricultural landscape. International Journal of Remote Sensing, 36(18), 4702-4723.

19- Kraemer, R., Prishchepov, A. V., Müller, D., Kuemmerle, T., Radeloff, V. C., Dara, A., & Frühauf, M. (2015). Long-term agricultural land-cover change and potential for cropland expansion in the former Virgin Lands area of Kazakhstan. *Environmental Research Letters,* 10(5), 054012.

20- Jensen. (2004). Digital change detection. Introductory digital image processing: A remote sensing perspective, 467-494

21- Kux, H., & Souza, U. D. (2012). Object-based image analysis of WORLDVIEW-2 satellite data for the classification of mangrove areas in the city of São Luís, Maranhão State, Brazil. ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences, 1, 95-100.

22- Laliberte, A. S., Rango, A., Havstad, K. M., Paris, J. F., Beck, R. F., McNeely, R., & Gonzalez, A. L. (2004). Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. Remote sensing of Environment, 93(1-2), 198-210. ISO 690

23- Lu, D., Hetrick, S., Moran, E., & Li, G. (2010). Detection of urban expansion in an urban-rural landscape with multitemporal QuickBird images. Journal of applied remote sensing, 4(041880), 041880.

24- Li, M., Zang, S., Zhang, B., Li, S., & Wu, C. (2014). A review of remote sensing image classification techniques: The role of spatial-contextual information. European Journal of Remote Sensing, 47, 389-411.

25- Lillesand T. M. and Kiefer R. W., “Remote Sensing and Image Interpretation,” John Willey and Sons, New York, 1999.

26- Lillesand, T., Kiefer, R. W., & Chipman, J. (2014). Remote sensing and image interpretation. New York: John Wiley & Sons.

27- Löw, F., Fliemann, E., Abdullaev, I., Conrad, C., & Lamers, J. P. A. (2015). Mapping abandoned agricultural land in Kyzyl-Orda, Kazakhstan using satellite remote sensing. Applied geography, 62, 377-390.

28- Lu, D., Mausel, P., Brondizio, E., &

Moran, E. (2004). Change detection techniques. International Journal of Remote Sensing, 25(12), 2365-2401.

29- Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing, 28(5), 823-870.

30- Mountrakis, G., Im, J. and Ogole, C. (2011) Support Vector Machines in Remote Sensing: A Review. ISPRS Journal of Photogrammetry and Remote Sensing, 66, 247-259. http://dx.doi.org/10.1016/j.isprsjprs.2010.11.001

31- Myint, S. W., Gober, P., Brazel, A., Grossman-Clarke, S., & Weng, Q. (2011). Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery. Remote Sensing of Environment, 115(5), 1145-1161.

32- Ram, B., & Kolarkar, A. (1993). Remote sensing application in monitoring land-use changes in arid Rajasthan. International Journal of Remote Sensing, 14(17), 3191-3200.

33- Rastgoo, M., & Hasanfard, A. (2021). Desertification in Agricultural Lands: Approaches to Mitigation. In Deserts and Desertification. IntechOpen.

34- Rouse Jr, J. W., Haas, R. H., Deering, D. W., Schell, J. A., & Harlan, J. C. (1974). *Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation* (No. E75-10354).

35- Shalaby, A. and Tateishi, R. (2007) Remote Sensing and GIS for Mapping and Monitoring LC and Land-Use Changes in the Northwestern Coastal Zone of Egypt. Applied Geography, 27, 28-41.

36- The General Authority for Statistics. (2015). Population and housing census. https://www.stats.gov.sa/en/13.Retrieved 2015

37- Turner, W., Rondinini, C., Pettorelli, N., Mora, B., Leidner, A. K., Szantoi, Z., Herold, M. (2015). Free and open-access satellite data are key to biodiversity conservation. *Biological Conservation, 182,* 173-176.

38- USGS. (2015). Landsat data. Accessed December 2015 from https://earthexplorer.usgs.gov/

39- Vapnik, V. N. (1999). An overview of statistical learning theory. Neural Networks, IEEE Transactions on, 10(5), 988-999.

40- Vijayan, L., & AlTalhi, F. A. (2015). Significance of Meteorological Parameters in the Implementation of Agriculture Engineering Practices in and Around Tabuk Region, KSA. International Journal of Applied Science and Technology, 3(5), 53-65.

41- Walter, V. (2004). Object-based classification of remote sensing data for change detection. ISPRS Journal of Photogrammetry and Remote Sensing, 58(3), 225-238.

42- Wang, X., Liu, S., Du, P., Liang, H., Xia, J., & Li, Y. (2018). Object-based change detection in urban areas from high spatial resolution images based on multiple features and ensemble learning. *Remote Sensing,* 10(2), 276.

43- Whiteside T.G., Boggs G.S. and Maier S.W . (2011) Comparing object- based and pixel- based classifications for mapping savannas, *International Journal of Applied Earth Observation and Geoinformation,* 13(6), 884 – 893.

44- Zhang, Z., Li, N., Wang, X., Liu, F., & Yang, L. (2016). A comparative study of urban expansion in Beijing, Tianjin and Tangshan from the 1970s to 2013. Remote Sensing, 8(6), 496.

45- Zhu, Z.; Woodcock, C.E. Continuous change detection and classification of land cover using all available Landsat data. Remote Sens. Environ. 2014, 144, 152–171.

46- Zheng, B., Myint, S. W., Thenkabail, P. S., & Aggarwal, R. M. (2015). A support vector machine to identify irrigated crop types using time-series Landsat NDVI data. International Journal of Applied Earth Observation and Geoinformation, 34, 103-112.