Object-oriented Image Analysis for Monitoring Urban Expansion in the City of Riyadh, Saudi Arabia

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Riyadh is considered one of the fastest growing cities in the world. In the early seventeenth century, the city population was approximately one hundred thousand people. It has increased to almost five million. As a result, Riyadh's area has expanded as well. Remote sensing technology is considered an effective approach to monitor growth in urban areas. This study focuses on change detection in Riyadh city between the period 1994 and 2007 using object oriented classification techniques. Two multispectral Spot images have been used in this study. Image to image rectification was used to apply the geometric correction for these images. Object oriented classification relies on three steps: the first step is segmentation, the second one is creating clusters and the third one is classification rule. Post-classification change detection was applied to extract the change detection between the two classified images. The results show that urban expansion extended approximately 193.88 km^2 during the 14 years. The overall accuracy was 96.5% and 94.0% for the classified images 1994 and 2007, respectively.

Keywords— Riyadh, segmentation, object oriented classification, change detection, urban area expansion.

I. INTRODUCTION

RIYADH city has developed rapidly in recent years and is one of the big cities in the civilized world. The population in the seventeenth century was only about one hundred thousand people. This number has increased progressively and rapidly, reaching approximately five million at the present time. The growth rate in Riyadh reached 8% in previous years, and this figure is high compared to global growth rates [1].

The high growth rate has had a significant impact on planning and future development. Technical information is urgently required, however crude, to assist in planning future expansion of the city so as to avoid and benefit from mistakes in planning that have been made in the past.

Remote sensing technology provides high-precision information on growing urbanization at a reasonable cost. Urbanization is a term used to describe urban environmental changes due to human activities. It is one of the most challenging tasks, due to the rapid changes in land cover and land use that occur over short periods of time. Therefore, there is a significant need to study urban growth to extract up-to-date information. This informs urban decision-making and sustainable development. Unfortunately, up to date urban change information is either unavailable or unreliable in developing countries [2], [3]. Usually, available data in the third world from topographic maps and census data may be outdated and cannot be relied upon to identify future prospects.

Change detection in the urban area is a major source of data extraction and is used in planning urban areas, and therefore is not only of academic interest [4]. It must also be concerned with historical aspects in order to understand the dynamics of urban areas.

The main objective of this study was to identify changes in the city of Riyadh between the period 1994 and 2007 using two multi-spectral Spot satellite images. Each image was classified using an object-oriented classification techniques and a comparison then made to extract the changes that have taken place between the two periods (figure 1).

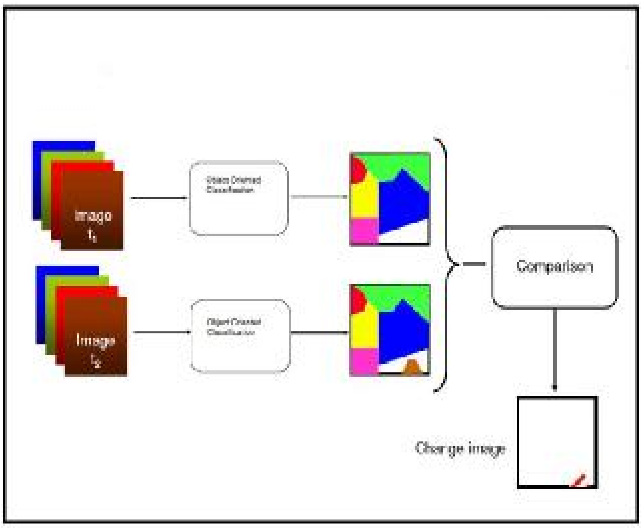

Fig.1. change detection procedure.
Each image classified separately using object oriented classification technique and then change image was achived using post-classification approach
(Adapted from Malthus 2007).

II. Object Oriented Classification Technique

During the last few decades, traditional pixel-based classification methods have been applied in various applications. This method depends only on spectral information and ignores additional information, resulting in 'salt-and-pepper' classified images due to the levels of noise. In order to reduce noise and produce a more homogenous pattern of classification, the object-oriented classification method has been employed [5-7]. This method takes into account other information, e.g. an object's texture, size and shape. With these parameters, it has been successfully applied in various applications [8-10].

Many studies have proved that object-oriented classification is more accurate than traditional pixel-based classification, due to the reasons cited above. Reference [11] found that the object-oriented classification technique gave much more accuracy than results obtained using the pixel-based classification technique. Reference [12] compared different methods of change detection. In this study, the object-oriented classification technique gave more accurate change detection data than that obtained by traditional post-classification techniques. Object-oriented classification has also been applied to many studies monitoring urban change detection area. Reference [13] showed the ability of the object-oriented technique to update existing land-use databases using very high resolution orthophotos. Reference [14] determined urban expansion by applying a new object-based change detection approach. The first step in this study was to produce multi-scale objects from multi-temporal images depending on the spectrum, texture and context information. Then, potential change objects were extracted using the attributes of shape, structure and texture of each object. Reference [15] showed the ability of the post-classification approach in extracting change detection information from multi-temporal images by using object-oriented classification for each image independently.

1) *Segmentation*

Segmentation is the first and most important step in object-oriented classification. It is the process of fragmentation of an image into parts that do not overlap with each other [16]. As a result, an image is subdivided into separate regions. The segmenting process depends on the homogeneity of each pixel groups' neighbouring objects. The basic unit of segmentation is an object and not a single pixel [17]. There are several parameters controlling the degree of homogeneity of objects. These parameters are scale, colour, shape, compactness and smoothness. The scale parameter identifies the highest heterogeneity allowed for the objects. Therefore, a larger value for scale results in larger objects. Average object size is influenced indirectly by the scale parameter. Colour factor is considered the most important parameter to create meaningful objects. Shape factor helps to improve the quality of extracting objects. In addition, it helps to avoid a fractal shaping of objects in strongly textured data [16].

An analyst can control these parameters and change them to obtain the best segmentation results, since the values of these parameters depend on the available data and the purpose of the application as well.

Multi-resolution segmentation has two main approaches for image analysis. The first object is a semantic hierarchy in which small objects are aggregated into larger objects. The second approach is that a large object is split into smaller objects [16].

A multi-resolution segmentation technique therefore produces different levels of segmentation. These levels are known as a hierarchical network of image objects. Each level has its own parameters of segmentation and is produced by a single segmentation run. The information content of the image is essentially represented by this network [16].

The accuracy of segmentation is important because the performance of object-oriented classification is influenced by the accuracy of segmentation. The relationship of spectral and spatial properties of the image, the size and shape of the objects, and the land cover classes used are important factors contributing to the success of object-oriented classification. Human interpretation and correlation are the best way to evaluate the segmentation output. In addition, there are various methods for finding and measuring over- and under-segmentation of regions and the differences between the position of regions and boundaries.

2) *Image classification*

The segmentation process is followed by the classification process. Object-oriented classification has two basic methods for classifying images: the 'nearest neighbour' method (which depends on the training area) and the 'fuzzy membership' function. The nearest neighbour classifier is preferable when there are different feature order objects within classes. On the other hand, the fuzzy membership function is preferable when there are fewer number of feature objects in an image to discrete classes from each other [18].

The nearest neighbour classifier works with trainings area in multi-dimensional feature space, which means that it is similar in progress to a supervised classification method in the pixel-based classification technique. Therefore, an analyst has to determine the training areas and then classify the image according to these training areas. The classification process of primitive objects in this method depends on either the training units or segments of each class. The rest of the objects are classified to their nearest sample in each class. The spectral information of different image bands is used to describe the feature space of classes that are being classified. Object-oriented classification does not deal with single pixels but with meaningful objects: as a result, extra information such as texture, shape, and context attributes and topological relations between neighbours and other objects may be used after segmentation in the classification process, which generally leads to increased accuracy of classification. The advantage of this method is that there is no need to has based knowledge to describe feature space.

The membership function depends on the fuzzy sets of future objects. It depends on a mathematical approach to identify uncertain statements. The main idea of this method that it uses two continuous ranges of [0…1], where 0 means absolutely no (no membership) and 1 means absolutely yes (full membership). The rest of the values between 0 and 1 are more or less certain states of yes and no. To increase the accuracy of classes' classification in this method, the analyst has to play an important role as a knowledge-based system which can use the relevant information of objects in the classification process. In addition, the analyst can define a threshold for object in each class by using suitable attributes through fuzzy sets [16].

III. Chang Detection

Change detection is the process of extraction of change information between two or more digital images that are recorded over different times for the same scene. Therefore, to detect change information using multi-temporal images, the value of an image pixel or image object in image t1 is compared to the corresponding value of an image pixel or image object in image t2. Many different change detection techniques have been developed within the last 30 years, such as Multi-date Visual Composite Image change-detection, Image Differencing and Post-classification change detection.

In a variety of studies, the post-classification change detection technique is generally considered the most suitable technique to extract the change information from two or more digital images [11], [19]. In this approach, multi-temporal images for the same scene are classified independently and then compared to extract the change information [20]. The main advantage of this technique is that data normalization for atmospheric and sensor differences between the different times is generally not required [21]. Another advantage is that it can be effectively used when data are available from similar or comparable satellite sensors. This advantage has helped many studies to examine change detection over a long period of time when one type of remotely sensed data is not available.

Since each image is classified independently, the accuracy of the post-classification technique is influenced by the accuracy of classification. As a result, high classification accuracy leads to high accuracy of change detection.

IV. Accuracy Assessment

Remote sensing data accuracy assessment concerns two main aspects: positional accuracy and thematic accuracy. Positional accuracy refers to the accuracy of a geometrically rectified image, while thematic accuracy refers to the accuracy of classification [22]. An accuracy assessment can be done by determining a confusion matrix. This finds the relationships between the mapped class label and that observed on the ground or reference data for a sample of cases at specific locations. The overall accuracy can be determined by dividing the number of correctly classified pixels by the total number of reference pixels. Overall accuracy is considered as the most suitable method for calculating accuracy assessment [23]. The Kappa coefficient of agreement can be used to improve the overall accuracy. It expresses the proportionate reduction in error generated by a classifier compared with the error of a completely random classification [12].

Sampling design is a very important task in accuracy assessment. The most common designs are sample random sampling (SRS), systematic sampling, cluster sampling and stratified sampling. In this study, accuracy assessment was calculated using eCognition software; a spate multi-spectral SPOT image was used as reference data.

V. Study Area and Data Set

Riyadh is the capital city of Saudi Arabia and located in the centre of the country (figure 2). It lies on latitude 34º to 38º north and longitude 46º to 43º east, at 600 m above sea level [1]. The climate in Riyadh is dry and hot in the summer and cold with irregular rains in the winter. The temperature reaches 42˚ C in the summer, with average humidity of 19%. In the winter season, it decreases to 11˚ C with average humidity of 23%. Riyadh has a low rate of rainfall during the year.

Fig.2. Location of the study area. [1]

In less than a half century, Riyadh has evolved from a small town with an area of a few square kilometres to become a sprawling city. This study applied on around 1373 km^2 of Riyadh area. Its area is high compared to other cities around the world: for example, Riyadh's area is equivalent to three times that of Singapore' area [1]. In addition, the population in Riyadh has increased sharply — in the seventeenth century, the population was almost one hundred thousand people: this number has increased gradually to 3,116,773 in 199٤ and to 4,260,000 in 2004 [24]. At the moment five million people are estimated to be living in Riyadh. The increase in area of the city and in the number of population reflects the rapid growth in the city. The annual rate of growth has not dropped below 8% in the last few years. This percentage is considered a high growth rate compared to global urban growth rates. One of the most important reasons leading to this increase is migration from other cities in the country, being responsible for approximately 50% of the increase in population in the city [1].

Three digital images were used in this project. The first was a multi-spectral SPOT 2 image with spatial resolution of 10 m recorded on 05/02/1994 (Figure 3). This image had been obtained by merging a 20 m multi-spectral image with a 10 m panchromatic image to obtain a multi-spectral image with a spatial resolution of 10 m. The second image was a multi-spectral SPOT 5 image with a spatial resolution of 10 m recorded on 23/08/2007 (Figure 4). The third image was a multi-spectral SPOT image with spatial resolution of 10 m recorded in 2001. This latter image was used to apply the geometric correction for the other images using an image-to-image rectified technique. It was also used as reference data to calculate the accuracy assessment for the classified images.

The ERDAS IMAGINE 9.0 and eCognition 4.0 software were used in this study. The ERDAS IMAGINE 9.0 software was used to apply the geometric correction for the images. ECognition software is the first commercial classification package for using the object-oriented technique. It was produced by Defininės. In this study, eCognition 4 was used to classify the two images from 1994 and 2007 respectively [16].

VI. Methodology

A. Data Pre-processing

In order to apply the change detection technique and to obtain accurate data from the digital images, the images must first be rectified [25-27]. An image-to-image geo-referencing method was applied in this study for correcting the two images from 1994 and 2007. The multi-spectral SPOT image recorded in 2001 was used as reference data. The Root Mean Square (RMS) of transformation was less than one on the two corrected images. It was around 7 m and around 8.5 m on the 1994 and 2007 corrected images, respectively. A second order polynomial was used and nearest neighbour re-sampling applied.

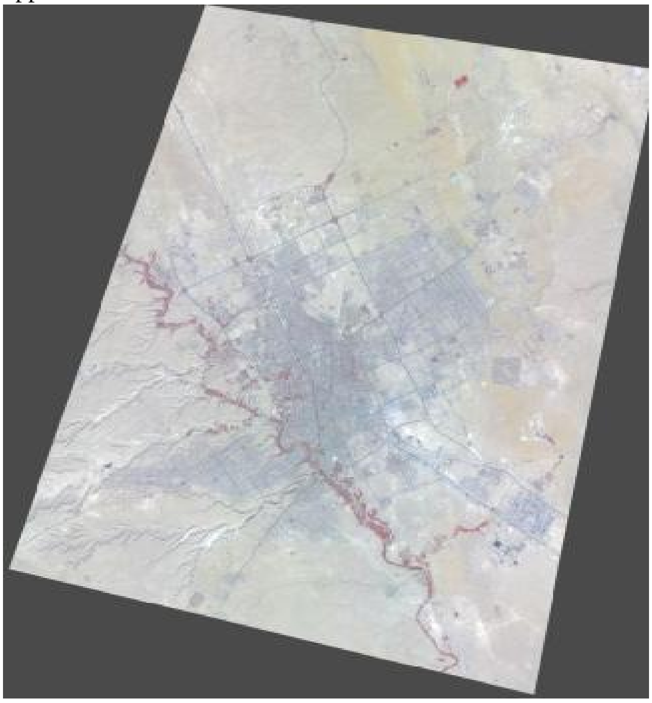

Fig.3. Multispectral SPOT 2 IMAGE with resolution of 10 m recorded in 1994.

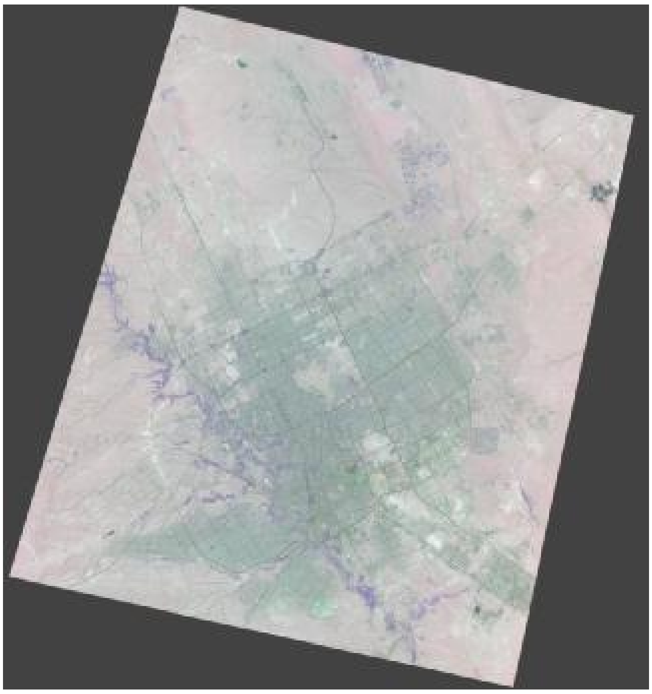

Fig.4. Multispectral SPOT 5 IMAGE with resolution of 10 m recorded in 2007.

B. Segmentation

The segmentation process can be created in different levels that are known as a class hierarchy. Each level has its own parameters. The classification process depends on the class hierarchy. In this study, the class hierarchy was applied at two levels. At the higher level (level 2), the scale parameter was 35, which is considered high because the purpose was only to distinguish between the urban and non-urban areas in the city. The shape and compactness values were 0.5 and 0.5, respectively (Figure 5). The non-urban areas were more obvious outside of the city. At the smaller level (level 1), the scale parameter was 10. The shape and compactness values were 0.3 and 0.5, respectively. There are many unused areas inside the city, and some of these did not appear at the level 2 — the aim of the level 1 was to highlight these areas. As a result, the unused areas were now more obvious and easily recognized, as shown in Figure 6. After the segmentation of the two images, two segmentation images with two levels for each were obtained.

Fig.5. Example of segmentiation view with scale parameter of 35, shape factor of 0.5 and compactness of 0.5 (level 2).

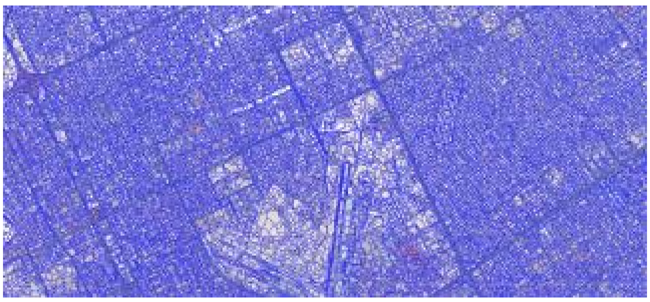

Fig.6. Example of segmentiation view with scale parameter of 10, shape factor of 0.3 and compactness of 0.5 (level 1).

C. Object Oriented Classification

Two object-oriented classification methods were used in this study. Each method has its own strategy for the classification process. The membership function method was applied to extract the urban and non-urban areas with higher scale parameter values. The nearest neighbour method was applied with smaller values of the scale parameter to extract more classes from the images. In order to detect information changes in Riyadh city between the periods 199٤ and 2007, the classification process was focused only on the difference between urban and non-urban areas in the two images. The urban area class contained all kinds of buildings in the city, roads, and any type of vegetation in the image (parks, gardens, etc.). In other words, anything that is made by human activity was classified as urban area. Gardens and parks within the city, and also some trees planted in various parts of the city (for cosmetic purposes) were classified as urban area in the level 2, but in the level 1 a vegetation class was created as a child class from urban area.

After level 2 had been segmented with a scale parameter of 35, the fuzzy classification method was applied depending on the mean of the spectral value of each object, using band 3 in the first image (1994) and band 4 in the second image (2007). We used two different continuous ranges to identify the urban and non-urban area classes. As a result, the classification of level 2 was applied depending on these two ranges. Figures 7 and 8 show the classification results of urban and non urban areas in the city for the two 1994 and 2007 images, respectively.

Some of unused areas inside the city did not appear in this level. Therefore, the level 1 segmentation was created with a smaller scale parameter of 10. In this level, the urban area class was divided into two child classes: used area and a vegetation class. Used area contained all kinds of buildings and roads and the vegetation class included all types of agriculture in the city such as parks and gardens. The nearest neighbour classification method was used with an appropriate number of training samples chosen for each class in the images. Since the images used in this study are medium resolution at 10 metres, some objects in the segmentation images contained more than one type of class.

Samples which have more than one type of class are known in eCognition as critical samples. This problem may cause errors in the classification process, because the nearest neighbour classification depends on the selected sample. To avoid this problem we tried different values of parameters until we obtained the best image segmentation result. The parameter values were 0.3 and 0.5 for shape and compactness factors, respectively. After the classification process, the classified image was slightly different from the original image, which meant that there was a need for further improvement. This further improvement can be easily done by adding other samples, or adding other samples if there is a need for that, and then classification repeated. These processes were repeated until we obtain classified images that were almost similar to the original images (Figures 9 and 10).

Some objects are classified as urban area but in fact they are non-urban area: for example, shadow areas outside the city are classified as urban area because these objects have the same properties as roads (such as shape and colour). Most of these shadow areas were outside the city, so we reduced their influence by clipping these areas from the images.

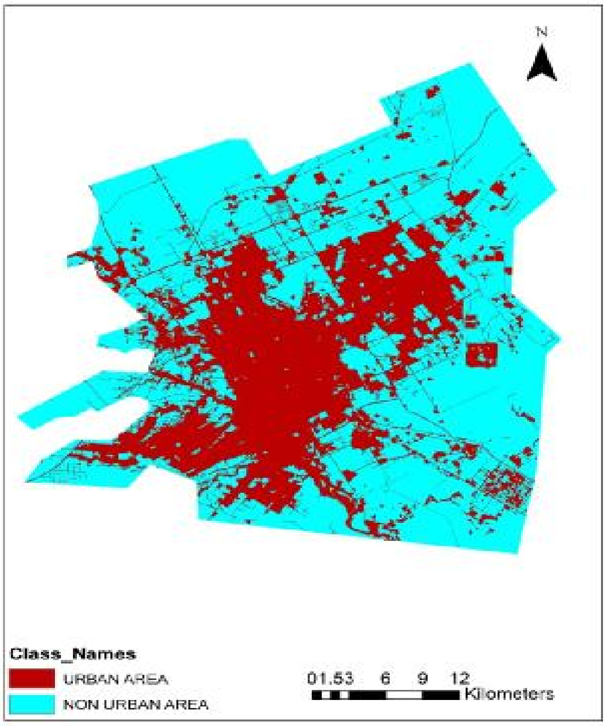

Fig.7. Classified image of 1994 with scale parameter of 35, shape factor of 0.5 and compactness of 0.5 (level 2). The classification method achived using the membership function.

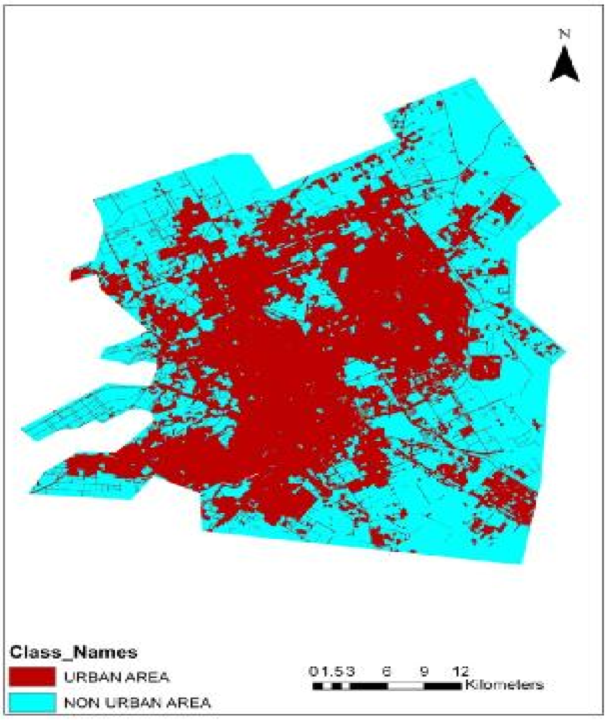

Fig.8. Classified image of 2007 with scale parameter of 35, shape factor of 0.5 and compactness of 0.5 (level 2). The classification method was achived using the membership function.

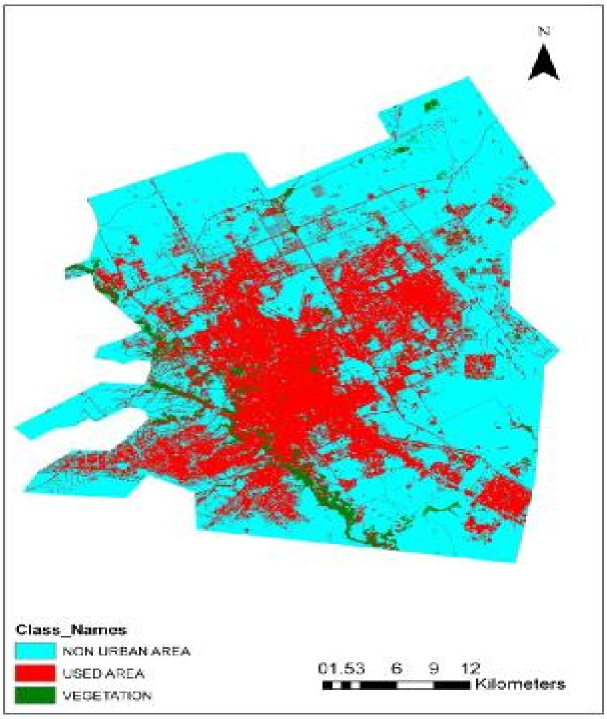

Fig.9. Classified image of 1994 with scale parameter of 10, shape factor of 0.3 and compactness of 0.5 (level 1). The classification method was achived by nearestneibour classification method.

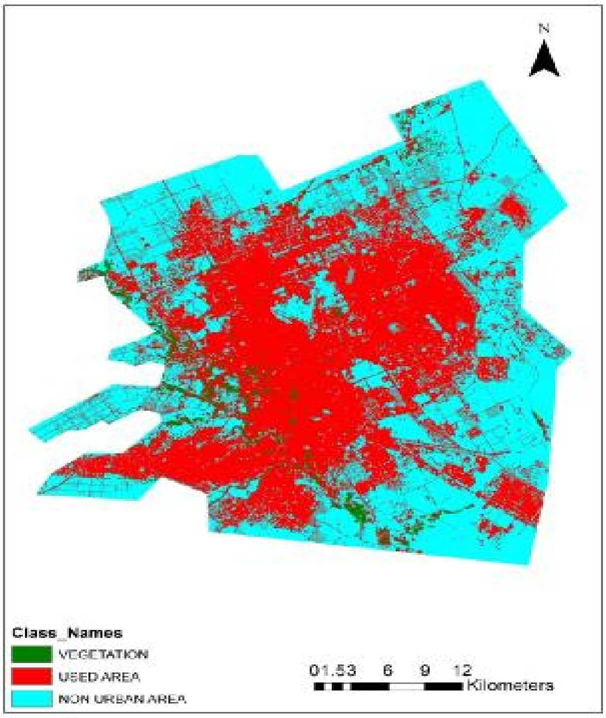

Fig.10. Classified image of 2007 with scale parameter of 10, shape factor of 0.3 and compactness of 0.5 (level1). The classification method was achived by nearestneigbour classification method.

D. *Accuracy Assessment*

Accuracy assessment is the process of determining the agreement between the selected reference material and the classified data. For this purpose, a multi-spectral SPOT image recorded in 2001 with a resolution of 10 m was used as reference data to calculate the accuracy of the classification process. In this study, we only used classified images with level 1 (scale parameter was 10) to calculate the accuracy assessment.

ECognition software has different methods to calculate the accuracy assessment: in this study, an error matrix based on the TTA Mask method was used. This method uses test areas from reference material to calculate the error matrix. The first step of this method is to create a TTA mask that contains test areas. Then this mask is loaded in eCognition software to determine the agreement between the test areas in this mask and the classified image. Two TTA masks were created from the reference image: the first TTA mask had 200 samples; all of these samples were the same and did not change between the two images (1994 and 2001). The second TTA mask also had 200 samples; they also had the corresponding positions, and did not change between the two images (2001 and 2007). All of these samples were selected randomly, and then these masks were loaded in eCognition to determine the classification accuracy of the two images (1994 and 2007). The error matrix was generated as shown in Tables I and II. These tables include producer's accuracy and user's accuracy. Table III contains the overall accuracy and kappa statistic for each image.

Table I
Accuracy results for classified SPOT image of 1994 (Level 1) from object oriented image analysis

Class Name	Producer's Accuracy (%)	User's Accuracy (%)	Kappa Statistic
Non Urban Area	96.3	98.8	0.91
Used Area	96.6	90.8	0.95
Vegetation Area	97.9	99.0	0.98

Table II
Accuracy results for classified SPOT image of 2007 (Level 1) from object oriented image analysis

Class Name	Producer's Accuracy (%)	User's Accuracy (%)	Kappa Statistic
Non Urban Area	93.0	97.1	0.84
Used Area	93.9	85.4	0.91
Vegetation Area	98.5	100	0.98

Table III
Overall accuracy and Kappa values for object oriented classification results images (level 1)

Accuracy Statistics	SPOT Image 1994	SPOT Image 2007
Overall Accuracy (%)	96.5	94.0
Overall Kappa Statistic	0.93	0.89

E. *Change Detection*

To obtain the change detection between the two classified images, the confusion matrix was created from the result of the object-oriented classifications. Table IV shows the result of the classified changes in terms of land area of classes. Table V reports the percentage change for each class. Classified images of 1994 and 2007 were then overlaid to generate the change image using the ERDAS IMAGINE software.

The results of extend areas and the rate of change between the two periods 1994 and 2007 are reported in Tables IV and V. The used area increased sharply, from 449.30 km^2 in 1994 to 643.18 km^2 in 2007. Table V shows the percentage of objects' statistics for each class in the classified image. Used areas were representing around 48.52% from the sum of the whole area in the classified image of 1994. This percentage reached to representing 60.31% on the classified image of 2007. On the other hand, non urban area on classified image was representing around 47.47%. This percentage decreased to 37.07% on the classified image of 2007. As a result, the expansion of used area increased by approximately 193.88 km^2 in only 14 years. This increase is considered a high rate of expansion, but is equivalent to the increases of population in the Riyadh area in the same period. The vegetation area in 1994 was 40.85 km^2 representing 4.02%, but these numbers decreased to 30.73km^2 representing 2.62% in the classified image of 2007. The reasons behind this are the change of some vegetation area to used area in 2007 and some changes to unused area in 2007. Most of the vegetation area is parks, private farms on the outskirts of the city and trees planted along the roadsides.

The change detection image was created using the ERDAS IMGAINE software (Figure 11). This image shows the information change in each class between the two periods. The most extension of urban area took place to the north and east sides of the city. The used area expansion is shown in red and the used area in 199٤ is shown in blue. In the south-eastern and west sides there was expansion in the used area, but by a smaller percentage in comparison to the north side of the city. In addition, some unused areas inside the city in 1994 changed to development areas in 2007. The decreases in used area from 199٤ to 2007 are shown in yellow. Some of the vegetation areas in 199٤ changed to used area in 2007 — these areas are shown in light green. Despite the expansion which occurred on the outskirts of the city, a lot of unused area within the city did not change or develop during the two periods.

As we know, the change detection image was created from the two classified images. As a result, the accuracy of this image depends on the accuracy of the classification images.

Table IV
Sum area for each class change matrix in Riyadh from 1994 to 2007 (km^2) (level 1)

Class Name	1994 (km^2)	2007 (km^2)	2007-1994 (km^2)
Non Urban Area	883.17	699.25	-183.92
Used Area	449.30	643.18	+193.88
Vegetation Area	40.85	30.74	-10.12

Table V
Objects' statistics for each class of classifed images (level 1) of 1994 to 2007 (%)

Class Name	1994 (%)	2007 (%)	2007-1994 (%)
Non Urban Area	47.47	37.07	-10.4
Used Area	48.52	60.31	+11.79
Vegetation Area	4.02	2.62	-1.40

VII. Conclusion

This paper monitored the urban expansion of Riyadh between the dates of 1994 and 2007. Post-classification change detection techniques were used to identify the differences between the two classified images. The images were classified using the object-oriented classification approach. Each image was classified separately on two levels. The level 2 had a scale parameter with 35 and shape and compactness factors of 0.5 and 0.5, respectively. The aim of level 2 was only to distinguish between the non-urban and urban areas. The membership function method was used to classify this level depending on the mean of spectral values of objects in band 3 one of the 1994 image and in band 4 of the 2007 image. Level 1 has a smaller scale parameter of 10 m and shape and compactness factors of 0.3 and 0.5, respectively. The urban areas are divided into two child classes: used area and vegetation area. The nearest neighbour technique was used to classify the image on this level. Two masks were created to calculate the classification accuracy using a multi-spectral SPOT image recorded in 2001. Many training samples were chosen for doing the accuracy assessment: the overall accuracy of the first classified image was 96.5% with kappa of 0.93 and the second classified image was 94% with kappa of 0.89. A confusion matrix was calculated to identify the change detection between the two classified images. The change detection image was achieved using ERDAS IMAGINE software.

This paper found that used area increased by approximately 193.88 km^2 between the dates 1994 and 2007. Riyadh has expanded much more on the north and east sides than on the south and west sides of the city. Some of the non-urban areas were developed between these periods. On the other hand, large areas inside the city were not developed.

Object oriented classification techniques are considered more reliable than that pixel based classification techniques because they take in account the other information from the image like shape, size and colour. As many researchers proved that object oriented classification techniques give more accurate results than that pixel based classification techniques, also this study gave a high accuracy of classified images using object oriented techniques. In order to avoid the complexity of urban areas, high resolution images should be used and LIDAR data to improve classification accuracy and subdivided classes.

Monitoring the rapid changes in land cover and land use is not a simple task but remote sensing technologies have helped to obtain high-precision information on growing urbanization. This information is used to study planning future expansion cities.

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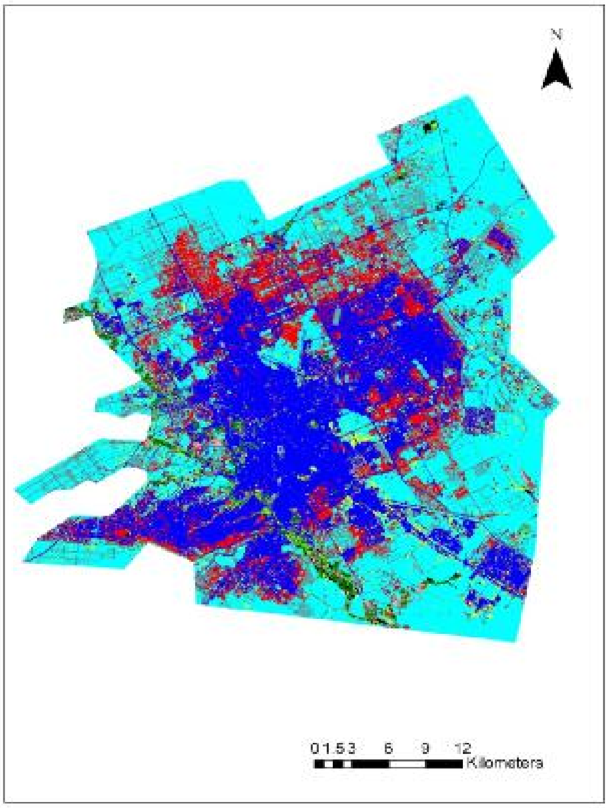

Legend

- Non urban area
- Used area in 1994
- Increase used area
- Decrease used area
- Vegetation to used area
- Vegetation to non urban area
- Change in vegetation area
- Vegetation area only in 2007
- Used area to vegetation

Fig.11. Post-classification change detection image between the dates 1994 and 2007.

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