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OBJECT-BASED APPROACHES FOR LAND USE-LAND COVER CLASSIFICATION USING HIGH RESOLUTION QUICK BIRD SATELLITE IMAGERY (A CASE STUDY: KERBELA, IRAQ)

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Abstract. Land Use / Land Cover (LULC) classification is considered one of the basic tasks that decision makers and map makers rely on to evaluate the infrastructure, using different types of satellite data, despite the large spectral difference or overlap in the spectra in the same land cover in addition to the problem of aberration and the degree of inclination of the images that may be negatively affect rating performance. The main objective of this study is to develop a working method for classifying the land cover using high-resolution satellite images using object based method. Maximum likelihood pixel based supervised as well as object approaches were examined on QuickBird satellite image in Karbala, Iraq. This study illustrated that use of textural data during the object image classification approach can considerably enhance land use classification performance. Moreover, the results showed higher overall accuracy (86.02%) in the o object based method than pixel based (79.06%) in urban extractions. The object based performed much more capabilities than pixel based.

Keywords: object-based approaches, maximum likelihood, quick bird, satellite imagery, LULC, processing.

Introduction

The essential aim in remote sensing application is extracting LULC feature such as urban areas which represent a center of social and economic development. Specific spectral sensor and spatial characteristics, enhanced image analysis techniques are vital to accurately characterize this complex spatial environment (Shareef & Hasan, 2020). Innovative concepts in image analysis and new data resources have the possible for successful map producing and analyzing of spatial LULC area. Remote sensing is crucial standard technology for LULC mapping via diverse classification techniques over broad scales (Cihlar, 2000; Kazemi et al., 2009). QuikBird and IKONOS data are accessible as a new high-spatial resolution satellite sensors. These data have important possible for digital imaging of the urban areas (Snehmani et al., 2017). The comparatively high-resolution data and wide swath allow for suitable coverage on a large-scale with resolution of small-scale farmland (Steinhausen et al., 2018). The typical procedure for producing LULC map requires data classification, and examines diverse factors (Shareef, Hassan, et al., 2020).

The use of traditional methods of analyzing images represents one of the most difficult procedures in obtaining information, extracting land features and producing thematic maps despite of using high resolution of the image data. On the other hand, high-resolution images are characterized by having a small number of pixels and high resolution through which the spatial contrast between areas can be detected (Pu & Bell, 2017).

However, the heterogeneity of the various objects such as roads, small cracks or shrinkages, and topography which is referring to the geometry of the targets will all resulting from the different spectral variations within homogenous LULC (Walter, 2004). Accordingly, obtaining classification information from this type of data requires directed classification that relies on unconventional methods that use pixel classification and which are mainly based on analyzing the image rather than on analyzing the objects in the image. (Liu & Xia, 2010). Object-based or object-oriented classification is relaying on object segmentation in an image for many objects which results from a homogeneous and precise map product with higher information about class or object class (Chen et al., 2009).

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Moreover, using object-based classification approaches must available details about context and spatial shape. Therefore, these approches have shown their potential in classifying the various types of close features with considering spatial complexity in image classification (Ding et al., 2018). On the otherhand, many studies have been studies the combination of diffirent high resolution optical and Radar sensor and their effectance of the landuse land cover classification (Shareef, Hassan, et al., 2020).

Although the integration of multispectral bands and SAR Synthetic Aperture Radar) data is promising for land application and LULC mapping, it remains rarely used (Joshi et al., 2016). Furthermore, many studies have confirmed the needing for more efficient and enhanising LULC mapping depending on the coupling of multispectral high resolution sensor for classifications the lands (Elatawneh et al., 2014; Sturari et al., 2017; Gibril et al., 2017).

Moreover, numerous researches aimed to evaluate the impact of speckle on LULC classification accuracy applied on fused radar or optical satellite images (Hasan et al., 2021).

Despite the advantages in analyzing the images using the Object, the challenge remains in dealing with high-resolution satellite data, the size of the areas to be classified, the type of devices and the method of work used (Shareef, Ameen, & Ajaj, 2020). Dealing with large areas may require more images or an additional number that can be obtained by monogram images or can be compiled using mosaic techniques, which may require image radiometric or geometric processing to obtain the required accuracy (Degerickx et al., 2017) and then to minimize the distortion in features to supply a spectrally homogeneous image analysis (Li & Xiong, 2017).

This research aims to classify the QuickBird satellite image and extract LULC using two different classifications: pixel based maximum likelihood, and object based classification with respect to urban area. In addition, analysis and compare which method is more accurate and suitable for urban extraction based on accuracy assessment.

1. Area of study

The area studied herein is north part of Karbala city which is located in Alforat Al-awsat region, 88 km distance from Baghdad Iraq, with geographical coordinates of Latitude: 32.6167 Longitude: 44.0333 the coverage area is about 1094 hectares as is shown in Figure 1.

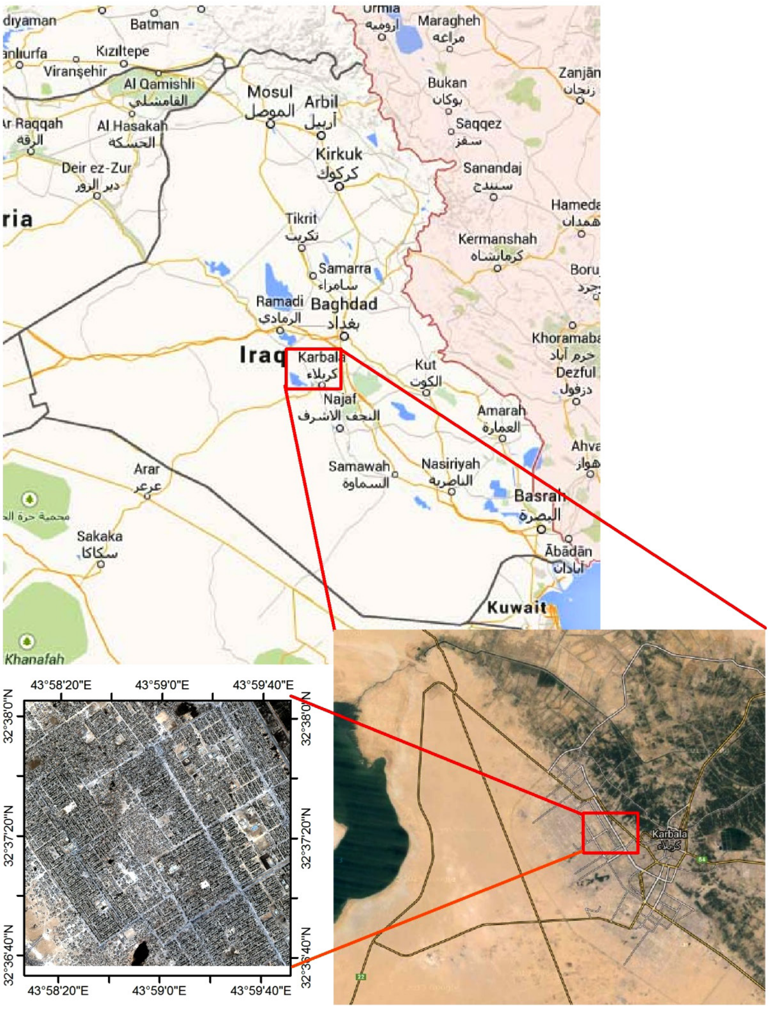

Figure 1. The study area

LULC classes of the are included bare land, road, urban and vegetation, as well as unclassified class. The predominant climate in Karbala city is the Local steppe climate, with limited rainfall throughout the year. The average temperature is about 25.6 °C and annual rains are about 364 mm. The mean precipitation is 0 mm in summer especially June, while the most maximum rainfall is in January, with a mean of 71 mm.

2. Methodology

2.1. Data and materials

In this study, the data used is the high spatial resolution and multi spectral QuickBird 0.6 meter spatial resolution along with three spectral bands which collected in September 2016 covering the Karbala city in middle part of Iraq as shown in Figure 2. The schematic of research methodology illustrate in Figure 3.

2.2. Preprocessing (atmospheric and radiometric correction)

Atmospheric correction is vital for image processing when detecting the presence of targets using a reference spectral library. Atmospheric correction also offers limited assistances when using in-scene derived signatures for target detection. In this study, the Dark Object Subtraction Atmospheric Correction method has been used in order to remove some atmospheric attenuation from QuickBird image. Also, radiometric distortions must be corrected that result from sensor's response and atmospheric conditions such as fog or aerosols in order to obtain the real irradiance or reflectance.

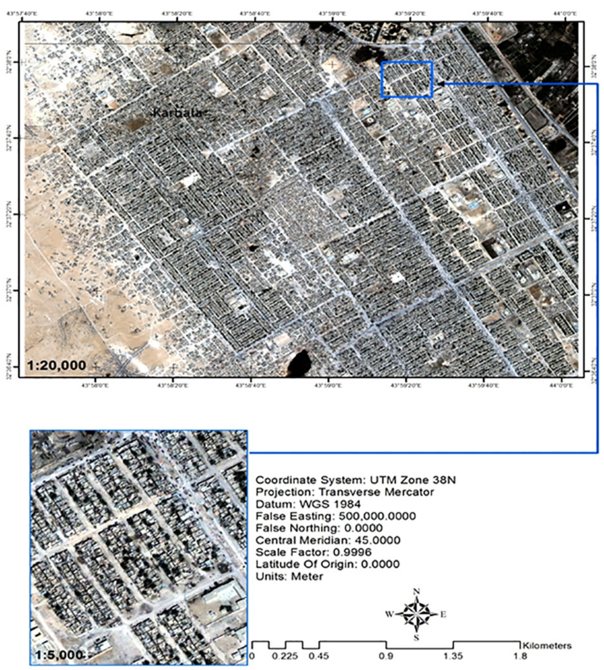

Figure 2. The QuickBird satellite image

2.3. Processing

Object Based Classification: It is more challenging to use conventional digital image analysis procedures to extract thematic information from these new data because of higher spatial resolution. High spatial resolution (2.5–0.6 m) sensors characterize urban land cover objects in comparatively few adjacent pixels considering the spatial heterogeneity of urban areas.

Rule based classified method was applied as categorized system with Level I classes. Four classes for image classification was defined in this study. Although spatial resolution of QuickBird allows us to go further to level 2, this city has the homogeneous pattern in land use and different of classes were limited.

Moreover, we could not identify different types of residential area due to lack of ancillary data along with in situ ground control points. Table 1 shows descriptions of classes adopted.

Image segmentation is the first process in object-oriented analysis with rule based. It derives significant image objects (e.g. vegetation patches, streets) depended on their spectral and textural properties.

By giving a spatial resolution of 0.6 m representative separable land cover objects (built up structures) are symbolized by several pixels. The segmentation was implemented by equally weighting of all three bands using the following parameters: Scale Level 50, Merge Level 30; Smoothness 0.4/Compactness 0.5. Image segmentation result of the study area is shown in Figure 4.

Table 1. Explanations of classes

S/N	Land cover	Description (s)	Color
1	Built up areas or urban	This class contains continuous and discontinuous urban commercial, industrial and fabric.	Red
2	Bare land/ Open	Barren soil, desert area without plants and unstructured lands.	Yellow
3	Areas of Vegetation	This involves green urban areas, irrigated land, non-irrigated arable land, scrubs and palm cover.	Green
4	Road	Asphalts, unpaved roads and transportation	Gray

In this study, the image classification is depended on user defined a rule based algorithm which implements class assignment depended on wave length measures. Also, rule based feature space involved layer value main (layer and max brightness) and geometry (shape and based on polygons) has been nominated as features for image classification. Textural mean of variety of spectral measurements have been applied and land use classes in different reflectance was extracted as shown in Figure 5.

2) Maximum Likelihood image classification: There are several reasons to use QuickBird satellite images in this research. These reasons include: it have very high spatial resolution (0.6 meter), an outstanding price-quality ratio and good spectral (three bands from visible to the infrared specter).

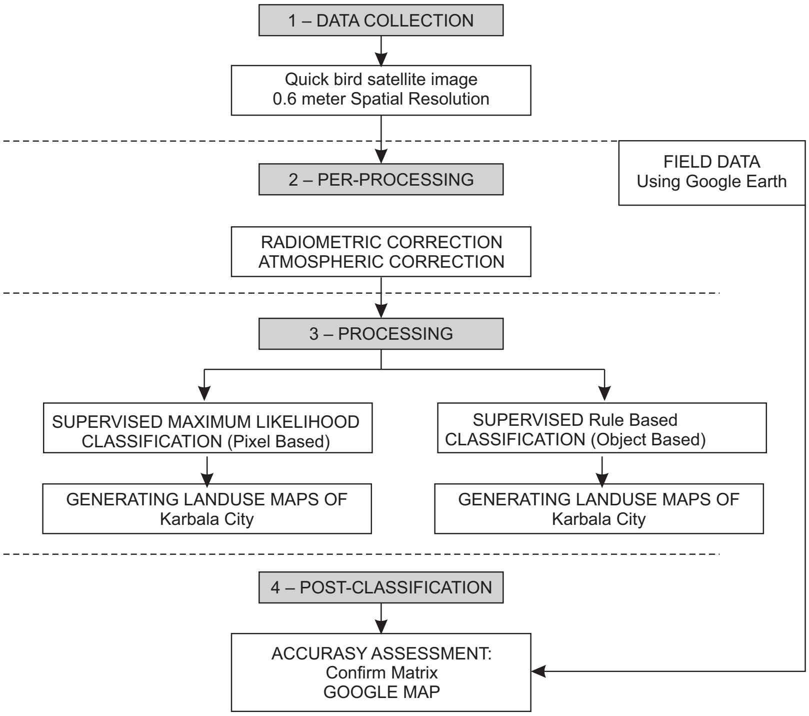

Figure 3. The schematic of research methodology

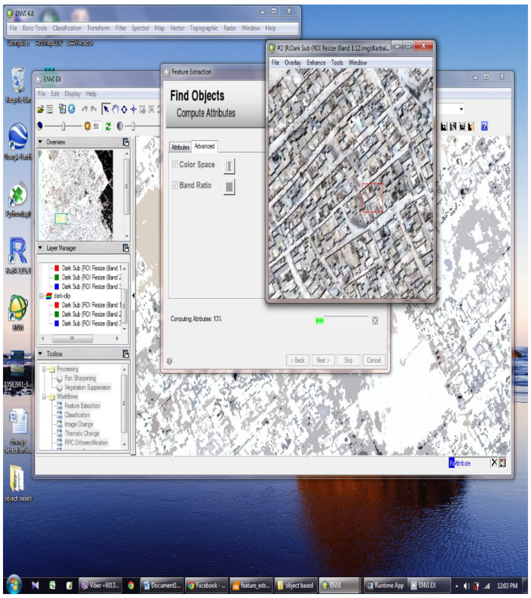

Figure 4. Image segmentation of the study area

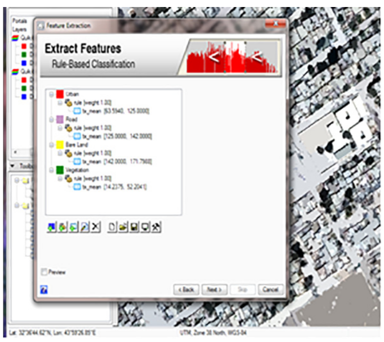

Figure 5. Extract feature based on the reflectance of textural mean

One high resolution and multispectral scene of Quick-Bird have been applied for this study. It was acquired on September of 2016. First the scene was sub sat by a part of Karbala city. Then were geo-referenced to WGS1984 coordinate system. Having implemented the preprocessing on image such as radiometric correction and Atmospheric correction, it classified to 4 different classes according to the Anderson scheme using pixel based Maximum Likelihood method. The images are shown in Figure 4. The same number class were extracted as Rule based approach (Urban, Road, Vegetation and Bare Lands). There was sufficient number of training site for each Land use class which applied on image by using ENVI 4.8 software.

The nominated class involved urban (residential area, main building), vegetation, bare land and road (asphalted, main and minor networks).

3. Results and discussion

In this research, two methods of image classifications have been applied and illustrated different results for feature extractions.

The results of rule based classification revealed that land use comprised approximately 1094 hectares. These land uses have been classified in high accuracy in comparing with other land uses in this study area because of spectral variability of urban and road. Table 2 is illustrated land use Rule based classification results for the study area.

According to this results, urban with 418.15 hectare is involved maximum area in comparing with other land uses and Vegetation (green and agricultural lands) with almost 100 hectares is involved minimum area in this area of study. Figure 6 shows object based classification map for the study area.

Table 2. Land use area using object based classification

Land use	Area (m^2)	Area (ha)	Percentage
Bare Land	2 507 777.8	250.77	22.93
Road	2 867 484.6	286.75	26.22
Urban	4 181 496.5	418.15	38.22
Vegetation	998 873.82	99.89	9.13
unclassified	382 196.14	38.22	3.49

The result of Maximum Likelihood showed different area for each land use classes, however total area of entire study are the same aproximately 1094 hectares. Table 3 is illustrated the results of land use Maximum Likelihood classification method for the study area.

Table 3. Land use area using maximum likelihood classification

Land use	Area (m^2)	Area (ha)	Percentage
Bare Land	1 853 207.68	185.32	16.94
Road	2 398 698.97	239.87	21.93
Urban	5 601 570.18	560.16	51.21
Vegetation	1 084 352.03	108.43	9.914

According to this results urban with 560.16 hectare (51%) is involved maximum area in comparing with other land uses while Vegetation (green and agricultural lands) with almost 108.43 (10%) hectares is comprised minim area in this study area. Road and Bare Land have almost 22 and 17 percentages respectively. Figure 7 shows the maximum Likelihood classification map for the study area,it should be mentiond that the assessement of classification is using overall accuracy or Kappa coefficient.

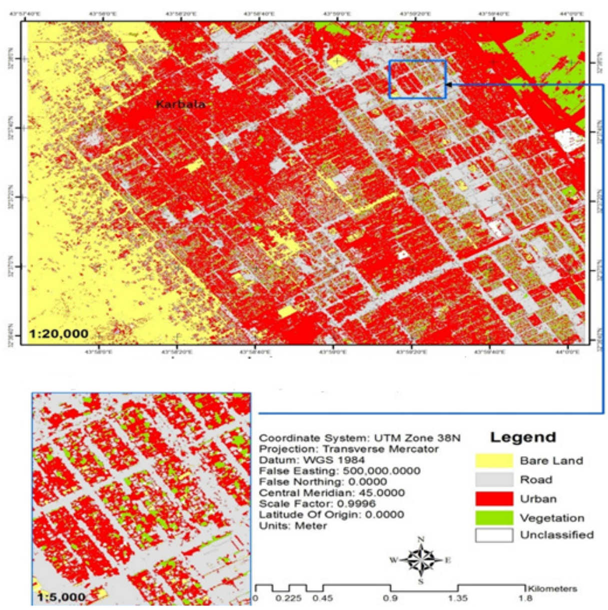

Figure 6. Object based classification map

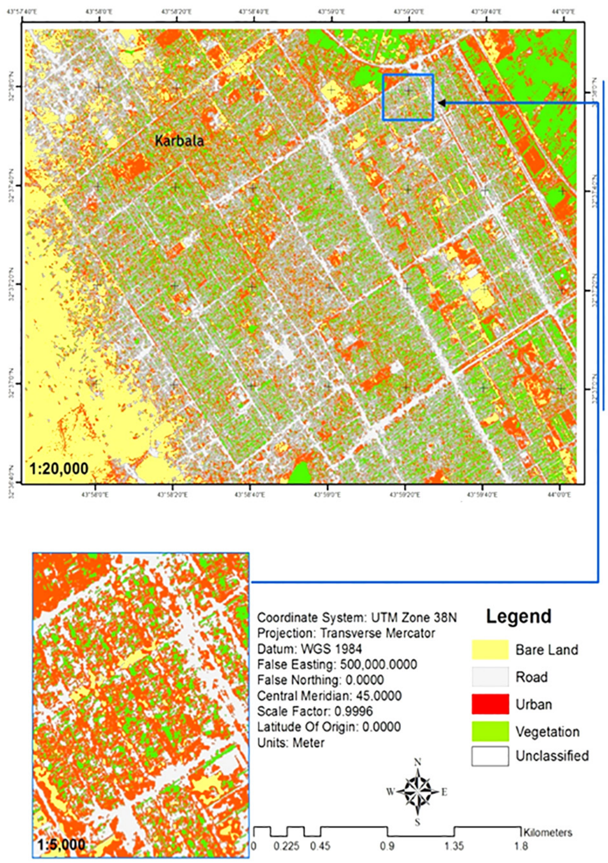

Figure 7. Maximum Likelihood classification map

Accuracy assessment is an integral part of any image classification because it used different classification methods may classify pixels or group of pixels to wrong classes. Error matrix is a standard method to represent classification accuracy.

Overall producer's and user's accuracy were determined in this research for analyzing of Maximum likelihood by using the confusion matrix as shown in Table 4 while for assessment of object based method 190 sample testing for all land use class were performed from Google Map as shown in Table 5. Also, Kappa coefficient was calculated where the Kappa statistics is a discrete multivariate procedure used in accuracy assessment. Tables 4 and 5 are shown Maximum likelihood accuracy assessment using confusion matrix and object based method using sampling of Google Earth to validate the classification of two used methods.

Table 4. Maximum likelihood accuracy assessment using confusion matrix

Land use classes	Producer accuracy (%)	User accuracy (%)	Producer accuracy (pixels)	User accuracy (pixels)
Bare Land	77.4	74.26	79 117/102 213	79 117/106 535
Road	60.55	84.09	56 952/94 051	56 952/60 528

End of Table 4

Land use classes	Producer accuracy (%)	User accuracy (%)	Producer accuracy (pixels)	User accuracy (pixels)
Urban	92.38	26.9	12 757/13 809	12 757/47 418
Vegetation	95.68	99.92	99 382/103 872	99 382/99 464
Overall Accuracy			(248 208/313 945)	79.06%
Kappa Coefficient			0.78	

Table 5. Object based accuracy assessment using sampling of google earth

land use classes	User accuracy (%)	User accuracy (pixels)
Bare Land	89.85	44/50
Road	70.24	21/30
Urban	80.31	48/60
Vegetation	93.56	47/50
Overall Accuracy		86.02%
Kappa Coefficient		0.82

Conclusions

In this study, two types of image classification were applied on high resolution satellite image (QuickBird) on a part of Karbala city in Iraq. Two set of Land use with four classes were generated. The results showed higher overall accuracy (86.02%) with 0.82 kappa coefficient using the object based classification method while the overall accuracy were (79.06%) with 0.78 kappa coefficient using pixel based classification. Object based classification using the object base approach was not only more accurate in general, but also specially for urban and road classes which normally hard to make a distinguish, had a great capability to extract features. So it is recommended for future studies to use object based classification on high resolution satellite images like quick Bird particularly for residential area extraction.

It is recommended that Iraq should inspire its personnel funding toward the high resolution satellite images and relegated techniques by conducting more researches focus on the use of modern GIS and Remote sensing applications to get accurate digital data because traditional methods are not useful and expensive and need to much time.

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