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A Framework for Improving Urban Land Cover Using Object and Pixel-Based Techniques via Remotely Sensed Data

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ABSTRACT

Recently, the advancement of remote sensing technology played a key role in urban land/cover mapping, planning, tourism, and environmental management. Images with a high spatial resolution for urban classification are widely used. Despite the high spectral resolution of the image, spectral confusion happens among different land covers. Furthermore, the shadow problem also causes poor results in the classification based on traditional per-pixel spectral approaches. This study looks at ways of improving the classification of urban land cover using QuickBird images. Maximum likelihood (ML) pixel-based supervised as well as Rule-based object-based approaches were examined on high-resolution QuickBird satellite images in Karbala City, Iraq. This study indicates that the use of textural attributes during the rule-based classification procedure can significantly improve land-use classification performance. Furthermore, the results show that rule-based results are highly effective in improving classification accuracy than pixel-based. The results of this study provide further clarity and insight into the implementation of using the object-based approach with various classifiers for the extended study. In addition, the finding demonstrated the integration of high-resolution QuickBird data and a set of attributes derived from the visible bands and geometric rule set resulted in superior class separability, thus higher classification accuracies in mapping complex urban environments.

INTRODUCTION

The application of remote sensing technology is a major target for urban areas as centers of economic urban planning, and environmental and development of social (Banzhaf et al. 2009, Noori et al. 2019a). The spatial and spectral heterogeneity in an urban environment that usually involves structures built up (buildup area and roads), much vegetation (parks, gardens, crops, and agricultural areas), bare land area, and water causes problems common to remote sensing in detailed and accurate urban areas. Due to the urban spatial heterogeneity, high spatial resolution sensors (2.5 m) reflect urban cover artifacts in relatively few adjacent pixels (Sertel & Alganci 2016). Therefore the classification of the urban land cover from this kind of data could use an object-oriented image analysis instead of a pixel-based (Ma et al. 2017). Classification based on image segmentation will lead to a more homogeneous and reliable mapping product with a higher level of detail (Darwish et al. 2003).

The spectral resolution of satellite sensors such as QuickBird is relatively limited. Because of the complexities of the urban area, the separation of built-up and unbuilt material, roofs and roads, and various roof styles have unique limitations (Herold et al. 2003, Ruiz Hernandez & Shi 2018). Additional information about spatial shape and context should thus be included in the image classification (Mezaal et al. 2019). Object-based techniques have shown their potential to take spatial complexity into account when classifying images (Bruce 2008, Song et al. 2018, Mahmoud et al. 2021).

Supervised and unsupervised spectral-based methods have been applied in the fields of resource survey, forecast, environment evaluation, forest monitoring, and weather (Tehrany et al. 2014, Wang et al. 2004). Numerous studies on the use of multispectral data for land usage classification have been carried out since the launch of the Landsat satellite (Forkuor et al. 2018). Multi-spectral classification approaches used in many of these studies assigned a pixel class mark dependent only on its spectral characteristics (Belgiu & Csillik 2018).

The implementation of high spatial dates and object-based strategies for big urban areas is a major challenge (Sameen et al. 2017, Hashim et al. 2022). The coverage of these large areas typically requires many separately acquired images and reflects a high spectral range within the class variation of different land cover types. To provide a highly homogenous image data set, geometric distortions and radiometric differences between images must be minimized.

Most methods are multi-spectral and dependent on pixels based (Noori et al. 2019b). Due to the presence of miscellaneous pixels, induced via low spatial sensor resolutions, many existing classificatory fail to produce high precision performance (Castillejo-González et al. 2009). Therefore, the object-based technique is needed.

The object-oriented analytical method (OOA) is an analysis method that explores the requirements from the class and object perspective of the problem domain vocabulary (Kohli et al. 2013, Mahmoud et al. 2021). In the OOA, many concepts and strategies for the management of complexity, such as abstraction, encapsulation, inheritance, the association have been compiled. The OOA methodology is used in the design and management field of object-based spatial data modeling to upkeep object-based analysis for land/ use and land cover classification in residential zones (Hussain et al. 2013).

The implementation of object-oriented approaches is a method to map specific land uses (Bhaskaran et al. 2010). This technique takes into account the pixel group and geometric qualities of objects in the image. The images are divided into uniform regions based on the spectral and spatial characteristics of neighboring pixels. In this project, therefore, an objective-oriented procedure was used to avoid the problem of mixed pixels.

The most important difference between pixel and object-based examines is linked to the improvement of results performance by using an object-based approach (Tehrany et al. 2014). Many studies have approved that object-based methods are accurate (Duro et al. 2012, Esetlili et al. 2018, Myint et al. 2011, Weih & Riggan 2010, Yan et al. 2006, Zhang & Jia 2014). In contrast, Adam et al. (2016) and Nugroho et al. (2017) mentioned that the pixel-based approach is slightly better than the object-based approach in the classification of land use land cover.

Therefore, the objective of this study is to examine pixel and object-based using QuickBird images of Karbala province in Iraq to classify a complex urban area. The pixel and object-based classification are implemented by ENVI software. Also, the performance of evaluations of two approaches was validated to know which one is most appropriate for urban land use. Finally, a comparison was conducted between these two approaches.

STUDY AREA AND DATA

Karbala city is placed between 3611461 to 3608525 X and 402565 to 406282 Y. The region covers an area of 1994.0 hectares and is situated in the northern part of the Iraqi city of Karbala (Mohammed et al. 2018). The province is situated

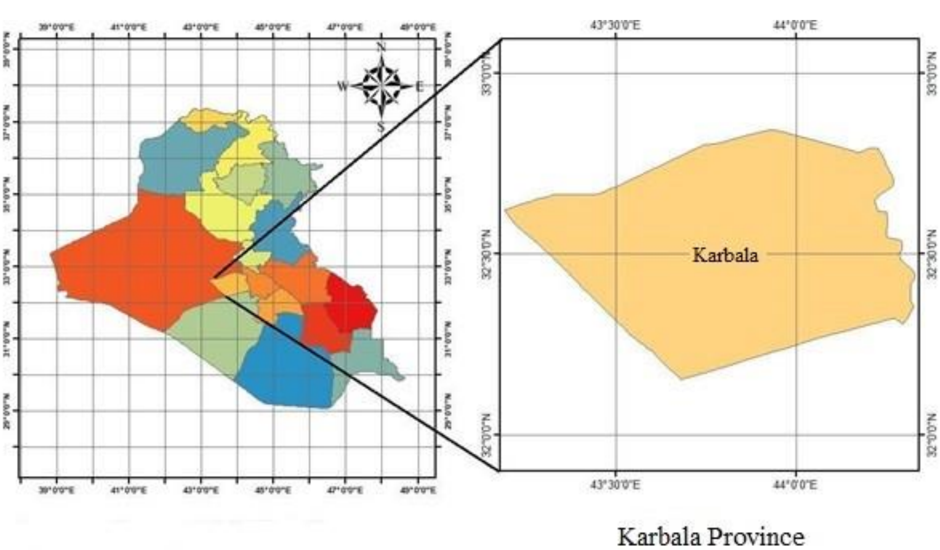

Fig. 1: Location map of the study area.

Fig. 2: The QuickBird satellite image.

in the Alluvial plain, in the sedimentary plane, and in the western plateau, where the warm desert climate prevails. It is located in the center of Iraq and near the capital of Iraq, Baghdad. Yearly precipitation ranges from 50 to 200 mm, and the bulk of the rainfall is from October to April. The temperature varies greatly between day and night, summer and winter, reaching an average of 45-50°C. The study area is shown in Fig. 1.

In this study, the data used are the high spatial resolution and multi-spectral (0.6 meters) spatial resolution QuickBird and the spectral three bands which covered the city of Karbala (Fig. 2).

MATERIALS AND METHODS

Digitally classified is a study of machine perception that defines pixels based on their numerical properties and because of their ability in the region calculation to count pixels. Preprocessing techniques have been applied to correct the atmospheric and radiometric of the image. Furthermore, two types of classification have been used to classify land-use types in the study area which are object-based and pixel-based. The results are quantified statistically and spatially to determine pattern continuity following classification methods applied to these data. Finally, an accuracy assessment has been applied to compare both classification types and approve which classification method is a performance for this specific data. Fig. 3. shows the overall methodology of this study.

Preprocessing

Atmospheric Correction

Remote sensing involves the passage of solar radiation through the atmosphere before the system is collected. This

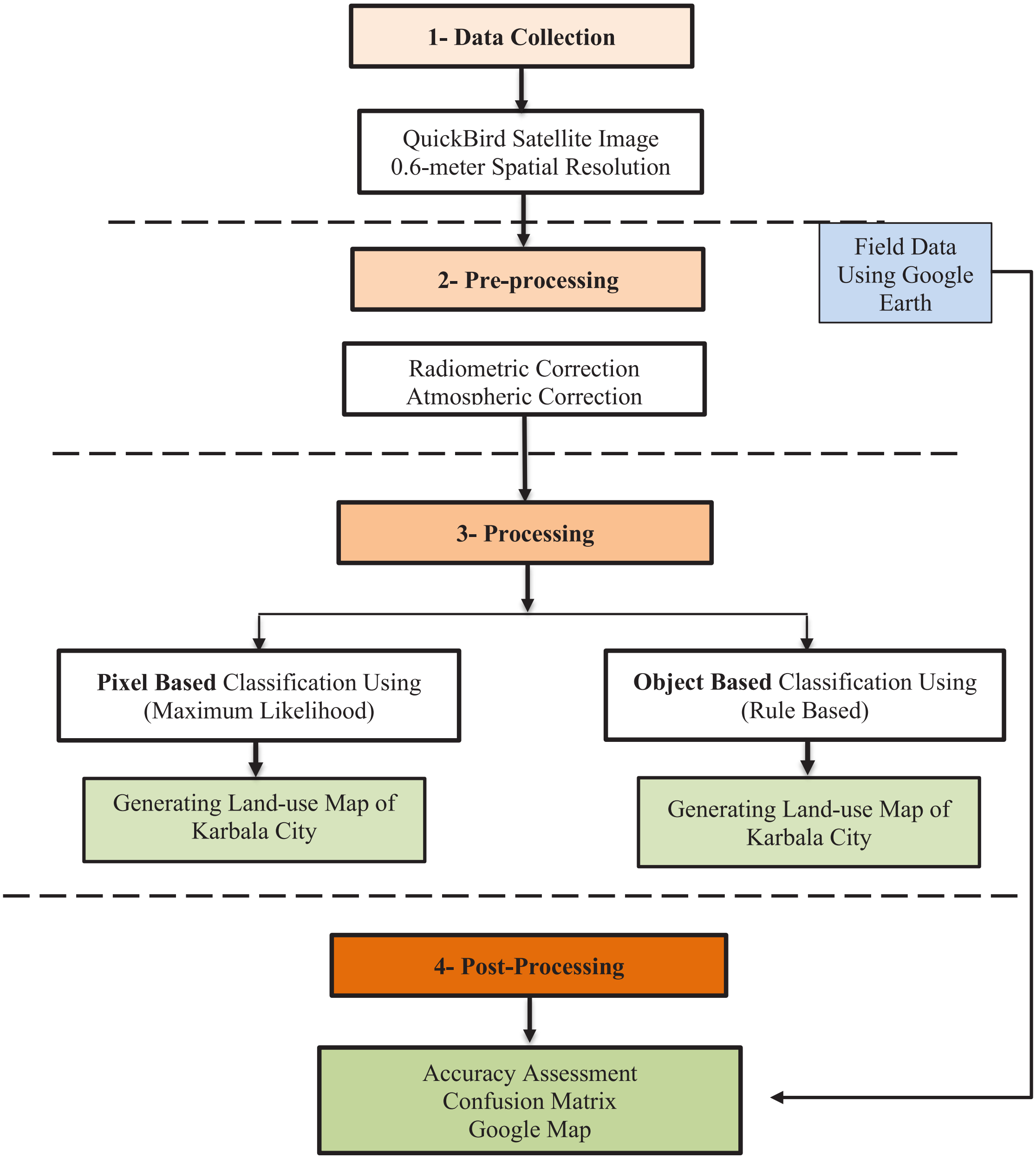

Fig. 3: The overall methodology flow chart.

means that remotely sensed images contain information on the atmosphere and the surface of the Earth. The elimination of the impact of the atmosphere is a crucial pre-processing step for those involved in the quantitative analysis of surface reflectance (Martins et al. 2017). Properties such as water vapor, aerosol delivery, and scene visibility should be understood to account for atmosphere effects. Since these atmospheric properties are seldom calculated directly, some techniques can be used to deduce them from their radiance results. A pixel per pixel can be added to atmospheric correction of this sort since each pixel found on the multi-spectral image includes an individual atmospheric vapor absorption strip measurement.

The procedure for the correction of atmospheric effects is used to correct the imagery. To recognize the presence of targets through the reference spectral library, atmospheric correction is necessary for image processing. In this analysis, the atmospheric correction method for Dark Object Subtraction has been used to eliminate a certain atmospheric attenuation.

Radiometric Correction

When the electromagnetic energy released or reflected is detected by a sensor, the energy measured will not correspond with the energy emitted or reflected by the same object observed for a short time. This is because of the sun azimuth and temperature, weather like aerosols, fog, sensor reactions, etc. This is due to the sun. Such radiometric errors must, therefore, be corrected to achieve true irradiance or mprovements are being used to promote vreflection (Vicente-Serrano et al. 2008). Iisual perception and imagery comprehension. Digital imagery has the advantage of allowing us to manipulate digital pixel values in an image.

Processing

Rule-Based Classification (Object-Based)

Because of its greater spatial resolution, conventional digital image processing algorithms are more difficult to obtain thematic facts from this new-fangled image. Given the spatial complexity of urban environments, high-spatial-resolution images (2.5m–0.6 m) in comparatively few adjacent pixels reflect urban cover items.

Using a trial-and-error method to optimize and develop a rule set is time-consuming and optimum rule sets are difficult to identify. The rule sets were automatically generated using a data mining algorithm that denotes to Decision Tree (DT) algorithm and was executed in MATLAB R2015b. The merit of utilizing MATLAB software is that it uses Gini's index as the separation criterion (Hamedianfar & Shafri 2016). Hence, this research applies a data mining algorithm called Decision Tree (DT) and important features to develop the rule sets. The 8 rule sets developed were utilized to distinguish between the classes. The governing Rule-based classification was introduced as a Level 1 hierarchical structure. 4 classes have been described for image classification in this analysis. Although the spatial resolution of QuickBird permits us to go further to level 2 (See Fig. 4).

This city has a homogeneous pattern of land use and the variety of classes was limited. Moreover, identification of the different types of residential areas was difficult because of the lack of ancillary data along with in situ ground control points. The description of classes is shown in Table 1.

In object-oriented analytics, a segmentation of the image is the first step. This process extracts meaningful image objects based on their spectral and textual properties (for example, streets, buildings, and vegetation parts). The segmentation is a half-automated process rule-based, which allows users to identify certain parameters that affect the image segments' size and shape. The artifacts that resulted refer not only to spectrum statistics but also to shape and context information in the surrounding objects and textures factors. The Fuzzy logic supervised approach (FbSP) optimizer was utilized to optimize the parameters of multiresolution segmentation such as scale, shape, and compactness. The optimized parameters contributed to

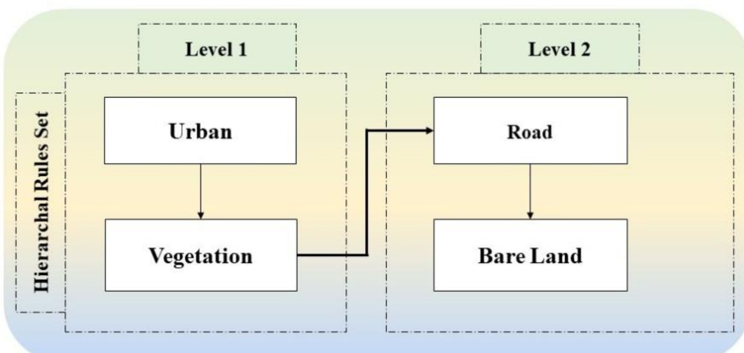

Fig. 4: The flow of hierarchal rule set between the Classes.

Table 1: Descriptions of Land Cover Classes.

S/N	Land Cover	Description (s)	Color
1	Urban or built-up areas	This class includes continuous and discontinuous urban fabric, industrial, commercial, and other related built-up areas.	Red
2	Open/bare land	Barren soil is a desert area without plants and unstructured lands.	Yellow
3	Vegetated areas	This comprises green urban areas, non-irrigated arable land, irrigated land, scrubs, and palm cover.	Green
4	Road	Asphalts, unpaved roads, and transportation	Gray

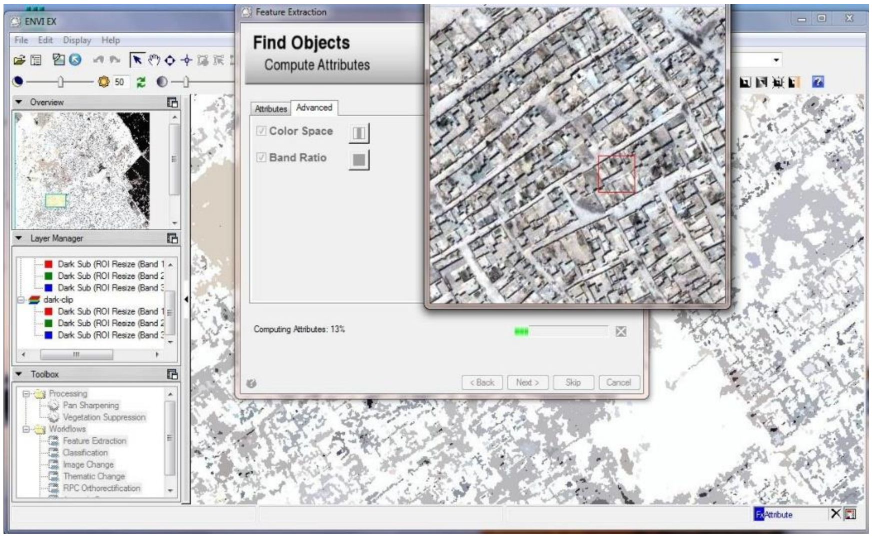

Fig. 5: Segmentation of the rule-based classification.

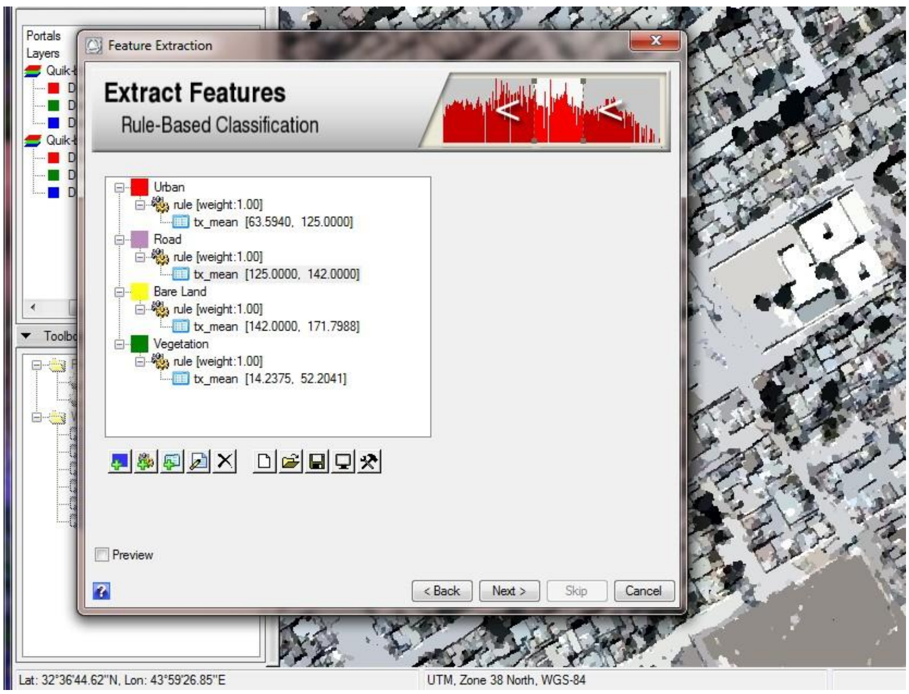

Fig. 6: Extract feature based on the reflectance of textural mean.

distinguishing between the classes. With a 0.6 m spatial resolution, several pixels reflect the typical individual land objects (built-up structures). The segmentation was rendered using the following criteria by measuring all 3 bands equally. Scale Level 50, Merge Level 30, Smoothness 0.4/ Compactness 0.5. Fig. 5. shows the segmentation of Rule-Based classification.

In this study, the rule-based algorithm classification has been applied based on wavelength measures and performs class assignments. The classification of the image as the key layer attribute (helpfulness, line, and max diff), a feature space based on the rule was chosen for this analysis. Various spectral measurements were used to determine textural and land-use classes of various reflections. Fig. 6. shows the extraction feature based on the reflectance of the textural mean

Maximum Likelihood Image Classification (Pixel-Based)

One high-resolution and multispectral scene of QuickBird has been applied for this study. It was acquired in September 2007. First, the scene was sub-sat in a part of Karbala city. Having implemented the preprocessing on the image such as radiometric correction and Atmospheric correction, it was classified into 4 different classes according to the Anderson scheme using the pixel-based Maximum Likelihood method. Somehow the entire region of the analysis is cloudless, allowing for fast processing and exact classification. The same number class was extracted as a Rule-based approach (Urban, Road, Vegetation, and Bare Lands). There was a sufficient number of training sites for each Land/use class which was applied to the image by using ENVI 5.2 software. The class included trees, industrial areas, sports, and administrative buildings and large-scale structures, and bare land and roads (asphalted and primary networks and minor networks).

Accuracy Assessment

The accuracy of the LULC map was evaluated by comparing actual ground data to the classified area. Error matrix or confusion matrix is a common way to directly define and compare the percentage of the map area with reference data. In this analysis, the overall accuracy and kappa value provided by data coverage are compared and tested with the Google map topographical scale as a result of visual interpretation. Accuracy tests were carried out based on confusion matrices and kappa statistics for both classifications. A marginal homogeneity test was used to assess the statistical significance of the difference between the kappa coefficients for the pixel-based, main component, and object-based classification.

Table 2: Land use area using Rule-Based classification.

Land use	Area [m^2]	Area [ha]	Percentage
Bare Land	2507777.8	250.77	22.93
Road	2867484.6	286.75	26.22
Urban	4181496.5	418.15	38.22
Vegetation	998873.82	99.89	9.13
Unclassified	382196.14	38.22	3.49

RESULTS AND DISCUSSION

In this research, Karbala city, Iraq was utilized as a case study to generate and evaluate rules using high spatial resolution (0.6 meters) QuickBird. The segmentation parameters were optimized using the Fuzzy logic supervised approach (FbSP) optimizer approach. A technique developed by Bartels and Wei, 2010 was employed by using 10-fold cross-validation to have a high-accuracy prediction. Applying two methods for classifications have been illustrated different results for feature extractions.

The results of the rule-based classification showed that land use included a total of 1094 hectares. Such land uses have been categorized with high precision compared with other land use in the region of the case study, despite the spectral heterogeneity of urban and road. Table 2. shows land-use areas of Rule-based classification in the study area. Fig. 7. shows the chart of Land-use areas using the Rule-Based classification method.

According to the findings, urban areas of 418.15 hectares have the highest area relative to other uses, and plant ecosystems of almost 100 hectares (agricultural land and green lands) have a minimum area for the study site.

The result of the Maximum Likelihood showed different areas for each land-use class, however, the total area of the entire study is the same almost 1094 hectares. The area of land/uses classified by the Maximum Likelihood classifier

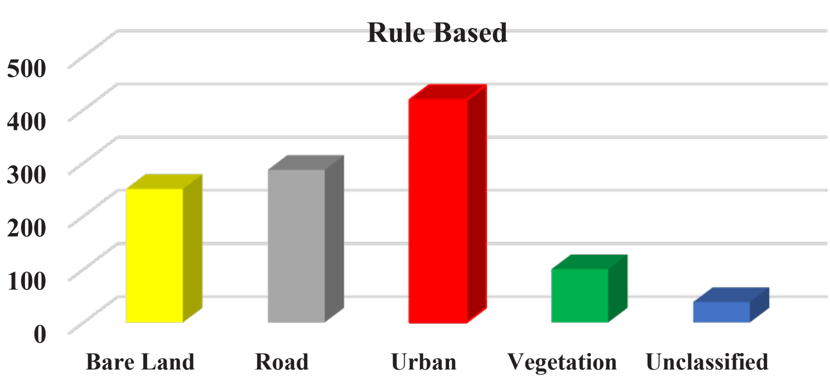

Fig. 7: Chart of Land-use area using rule-based classification method.

Table 3: Land use Area using Maximum Likelihood Classification.

Land use	Area [m^2]	Area [ha]	Percentage
Bare Land	1853207.68	185.32	16.94
Road	2398698.97	239.87	21.93
Urban	5601570.18	560.16	51.21
Vegetation	1084352.03	108.43	9.914

is shown in Table 3. However, Fig. 8. shows the chart of the land-use area using the Pixel-Based classification method.

These results in urban areas with 560.16 hectares (51.21%) which is the highest area compared to other land uses, while vegetation (farmland and green land) is almost 108.43 (9.914%) hectares which is low in comparison with other land uses. Road and Bare Land have almost (21.93%) and (16.94%) percentages respectively. Fig. 10. shows the map of Maximum Likelihood classification. These results sound reasonable considering the similarity of their spectral signatures.

In this research, Karbala City, Iraq was used as a case study to evaluate the performance of the object and pixel-based approaches in improving various urban land cover classes from High-Resolution QuickBird Imagery. The result illustrated that the rule-based classification enables differentiation between the classes accurately. Although, there was a decline in accuracy because of the differences between the characteristics of the classes and environmental conditions. Moreover, variations in the sensors utilize, illumination conditions, spatial resolutions of images, etc. are some other challenges that could impact the outcome as stated by (Ray et al. 2013).

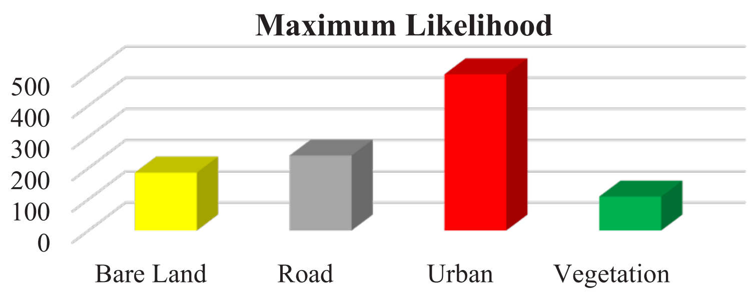

Fig. 8: Chart of Land use area using pixel-based classification method.

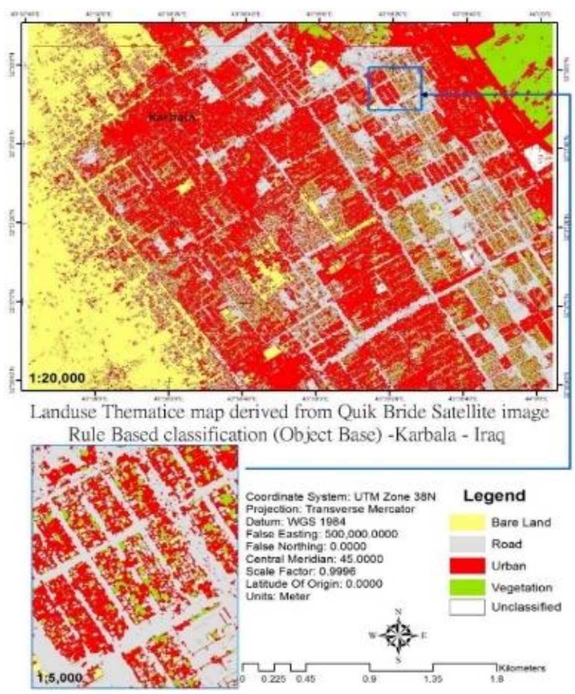

Fig. 9: Object-based classification.

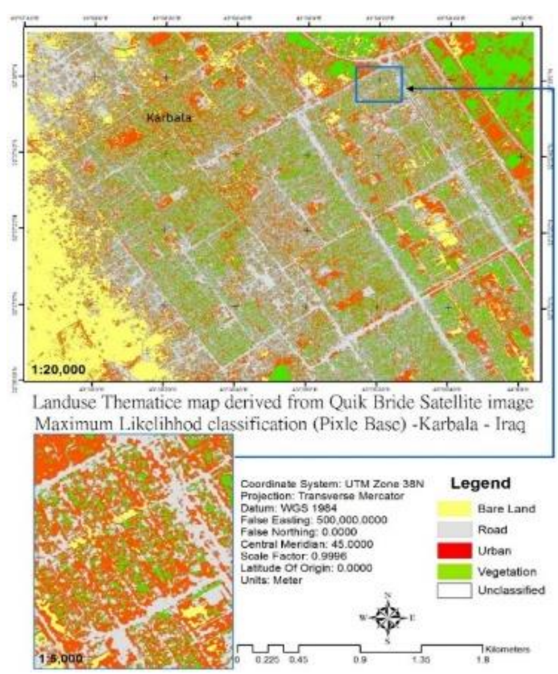

Fig. 10: Maximum likelihood classification.

Table 4: Maximum likelihood Accuracy assessment using a confusion matrix.

Land-use classes	Producer Accuracy %	User Accuracy %	Producer Accuracy pixels	User Accuracy Pixels
Bare Land	77.4	74.26	79117/102213	79117/106535
Road	60.55	84.09	56952/94051	56952/60528
Urban	92.38	26.9	12757/13809	12757/47418
Vegetation	95.68	90.92	99382/103872	99382/99464
Overall Accuracy			(248208/313945)	79.06%
Kappa Coefficient			0.78	

Table 5: Rule-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

Table 6: Comparison of Land use classes derived from the object and pixel-based classification.

Land use	Maximum		Rule-Based	
	Area [ha]	Percentage	Area [ha]	Percentage
Bare Land	185.3	16.9	250.8	22.9
Road	239.9	21.9	286.7	26.2
Urban	560.2	51.2	418.1	38.2
Vegetation	108.4	9.9	99.9	9.1
Unclassified	0.0	0.0	38.20	3.5

Validation of Classifications

Classification accuracy is typically expressed by an error matrix. However, the matrix error is a quadratic sequence of rows and columns and also provides the related classified mage of the reference map. It is recommended and agreed as a common reporting norm that an error matrix is used to represent accuracy.

In this study, overall, the producer's and user's accuracy were considered for investigation of Maximum likelihood by using the confusion matrix while for assessment of Rule-based method 190 sample testing for all land use classes were performed from Google Map as shown in Table 4.

The Kappa coefficient was also measured as one of the most common measures to address the discrepancy between the agreement itself and the change agreement. The Maximum likelihood Accuracy assessment using a confusion matrix is shown in Table 4. and the Rule-Based Accuracy assessment using sampling of Google Earth is shown in Table 5.

The findings of the accuracy evaluation showed that rule-based classification is efficient and reliable for class differentiation. The accuracy of the user and the producer declined in both approaches for road class due to changes in road characteristics such as color changes and abstracted features.

Methods Comparison

Two classification techniques were applied to the same area

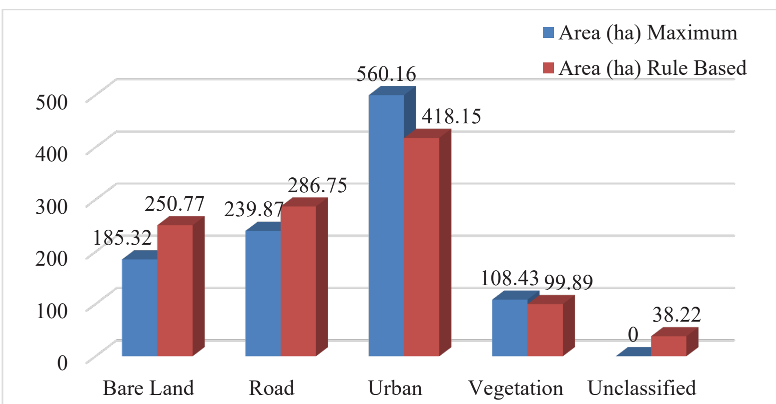

Fig. 11: Comparison ratio of land use classes derived from the object and pixel-based classification.

Table 7: Comparison between the pixel and object-based classifications according to user accuracy.

land-cover classes	User Accuracy %	
	Rule-based	Maximum-likelihood
Bare Land	89.85	74.26
Road	70.24	84.09
Urban	80.31	26.9
Vegetation	93.56	90.92

but different results were achieved for every single land/use class. Table 6. shows the comparison of Land-use classes derived from the object and pixel-based classification. Fig. 11. shows the comparison ratio of Land-use classes derived from the object and pixel-based classification.

Precision evaluation is a method used by comparing the classified result with a reference map to determine the accuracy of image classification. This is often known as an integral part of any classification technique of images. The spectral properties of an object in a very urbanized area may be inconsistent to be properly classed. Fig. 12 shows an area built up with a propensity for spectral signatures interfering with unpaved roads due to the reflectance of an old building roof. Table 7. shows the comparison between the pixel and Object-based classifications accuracy assessment. Fig. 12. shows the comparison between the pixel and Object-based classifications according to User Accuracy.

According to this graph user accuracy for extracting the urban area in the rule-based is much more precise than the maximum likelihood method 80% vs 27% almost. Vegetation classes show approximately the same amount of accuracy 91% vs 93% for Rule-based and Maximum respectively. Likewise in bare land class using object base, user accuracy is greater than maximum likelihood. However, Maximum likelihood is shown the better accuracy just in Road detection rather than Rule-based classification (70% versus 84% rule-based and Maximum respectively).

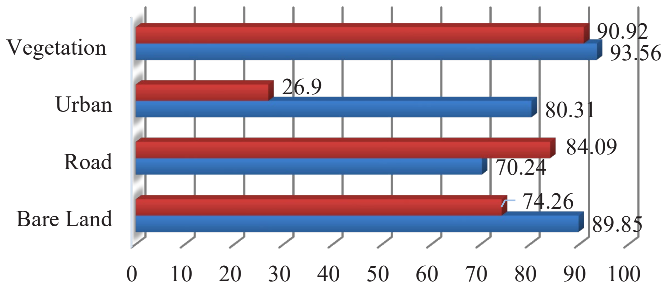

Fig. 12: Comparison between the pixel and object-based classifications according to user accuracy.

Fig. 13: Comprehensive comparisons between methods of classification.

As can be seen from Fig. 13, the urban extraction in the object-based classification method is more accurate and near to the original satellite image of QuickBird rather than pixel-based classification. While it is clear that Roads extracted by the pixel-based approach are near to the original image. Since it has shown a higher accuracy rather than a rule-based classification method.

CONCLUSION

Remote sensing is now an effective method for analyzing and mapping micro-, meso- and macro-level land use/cover. Repetitive coverage is important for remote sensing systems for change detection studies. The preparation of land and ground-cover maps is necessary to ensure planned growth and monitoring of land use patterns. This study shows the usefulness of satellite data to prepare accurate and up-to-date land-use and land cover maps. Classification results indicate consistently positive growth in urban planning and a balanced decrease in urban vegetation. In this study, two types of image classification were applied to a high-resolution satellite image (QuickBird) on a part of Karbala city in Iraq. Two sets of land use with four classes were generated, as a result, an object-based classification using the rule-based approach was not only more accurate in general but also, especially for urban and road classes, which are normally hard to make distinguish, had a great capability to extract features. It is also recommended that guidelines based on high-resolution satellite images such as QuickBird be used for the extraction of residential areas for future studies. It is proposed that the Iraqi Government will facilitate the use of modern GIS and remote sensing technologies to obtain rapid and precise digital information in support of the use of high-resolution satellite images and relegated techniques. As ground surveying methods are not easy and the production of aerial and photographic maps is very costly and time-consuming. A substantial finding from this research is that an improved detailed urban land cover classification based on high-resolution satellite data can be done via the combination of a set of features derived from the visible band and geometric ruleset. Further study is planned to examine the proposed methodology in various regions for land cover classification and informal settlements mapping.

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