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Gully Inventory Mapping Using Object – Based Image Analysis: A case study of Ali Al-Gharbi District, Maysan Governorate, Southern Iraq

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Abstract

Many studies have been carried out to find the best method for classification of remote sensing data. Traditional methods depend only on pixel value without using the spatial and geometric information of object which is consider an important source to classify the satellite imagery. This study compared between pixel-based and object-based classification algorithms using Sentinel-2 imagery. As for object-based image analysis, the image was segmented in to homogeneous groups using appropriate variables such as scale, shape, size and probability. Classification based on segments was done by a nearest neighbor classifier, while the classification based on pixel value was done by manual digitizing by using the principles of visual interpretation. For accuracy assessment, an error matrix was used to assess the classification between two types of classification. The producer's accuracy for gully class using object-based image analysis was 90.7% while the user's accuracy for gully using pixel classification was 84.8%. These classification techniques were subjected to accuracy assessment and the overall accuracy was 89.2% and 0.78 for Kappa coefficient. The results of classification and its accuracy assessment show that the object-based image analysis approach gave more accurate results.

Key words: Gully erosion, OBIA, Error matrix, Maysan , Iraq

Introduction:

Geomorphological changes or land degradation is affected mainly by weathering processes, Fluvial erosion and sediment transportation caused by surface runoff. It is worth mentioning the difficulties that face the interpretations of such data due to the complex nature of hydro geomorphological processes. These data besides climate and lithology are controlling factors on geomorphological evolution of landforms [1].

Gully erosion is one of the most environmental threats in all over the world because it is affects badly on lands and soil functions [2]. There are a lot of evidence refers to the existence of severe gully erosion in a different times and various parts of the world. Gullies are considered as one of the few resources of the morphological events for lands for past phases of severe soil erosion which is reflects the effects of environmental changes especially as a result of interaction between geomorphological features and land use changes - on one hand - and extreme climate events on the other hand [3].

Gully can be defined as eroded channel which is relatively deep consisting of surface runoff accumulation in narrow flow paths which is composed of removing soil parts, and it is probably developed to be deeper than 30 cm in a short time period [4].

The development of remote sensing technique using high resolution satellite images and object-based image analysis (OBIA), shows the possibilities of the determinations of gullies in less effort , short time and acceptable level of accuracy [5], [6], [7].

Previous studies shows that supervised classification technique like maximum likelihood classification (MLC) does not express water erosion features as good as we want due to the spectral similarities with other erosional features [8], [9], [10].

The using of Object-based image analysis (OBIA) is more powerful and realistic than other traditional digital classification technique [11].

Objectives:

1. Extract Gullies using object-based image analysis (OBIA).
2. Create reference data by using manual digitizing for gullies.
3. Accuracy assessment to OBIA compared with reference data.

Description of study area:

The study area is a part of Ali Al-Gharbi district that is located in northern Maysan Governorate (Fig. 1) and covers an area of 1,576 km^2. The considered area is bounded on the northeast by the Iraqi-Iranian border and on the southwest by the Tigris River (outside of the considered area). The surface elevation ranges from 2 m to 144 m. The climate of the study area is generally arid to semiarid and is basically characterized by two distinct seasons, with hot and dry summers and cold and wet winters. The minimum and maximum monthly average temperatures for the period 1995-2015 were 12.75 °C and 38.5 °C, respectively. The average monthly recorded temperature is 26 °C. The monthly average minimum and maximum rainfall totals are 0 mm and 62 mm. The rainy period extends from

October till May. Rainfall in the remaining months of May to October is rather low. Generally, the eastern parts (hills) of the considered area receive greater rainfall than the western parts (plains). The average mean of annual rainfall is 212 mm/year [12].

Geologically, the exposed rocks in the study area belong to the Quaternary sediments (Pleistocene and Holocene Epochs) [13] (Fig. 2). The Quaternary sediments are unconsolidated and usually finer grained than the underlying Mukdadiya and Bai Hassan Formations [14]. The major lithological units of the Quaternary deposits are alluvial fan, flood plain, depression fill, and aeolian [15] (Table 1).

For tectonic point of view, Iraq is divided into three distinct areas: stable shelf, unstable shelf, and Zagros suture [16]. Most of the study area is located within the eastern part of the Mesopotamian zone within the stable shelf and bounded on the northeast by the high folded zone (Himrin Hills). Regarding the geomorphology, the study area is a flat and featureless surface bounded by the foothill zone in the northeast (Iraq-Iran border). The trend of these hills is southeastern and parallel to the Zagros Mountains. Generally, hills are not continuous ridges but a series of ridges with their axes oriented in a northwest–southeast direction [13].

The upper parts of the hills are generally exposed to weathering and the erosion process, and thus a thick soil layer of fine texture has formed over them. The dominant landforms within the study areas are sand dunes, glacis, alluvial fan, floodplains, and depressions (Fig. 3).

3- Object-Based Image Analysis (OBIA)

As for pixel based image classification, it depends only on the value of reflectance per pixel and spectral signature of features. In this case sometimes it may be happening for the same features there are more than one-pixel value, and hence the software which is deals with image classification, classify it in two or more class for the same feature.

OBIA enables the interpreter to use pixel value along with some criteria like geometry and knowledge. OBIA classify features into homogeneous groups of the same pixel value, and then convert these pixels into vector domain. In between these processes we can use some functions or filters such as size, probability and threshold to map the target features [5].

4-Data used and Methods

4-1 : Data Used:

The remote sensed images used in this study are the products of Sentinel – 2 taken in 2017. Multispectral Imager (MSI) onboard Sentinel-2 provide 13 spectral sensors in the visible to near infra-red range [17] as shown in figure 4. The spectral, spatial and temporal characteristics of Sentinel-2 are as shown in table 2.

4-2 : Methodology:

Referring to fig (5), the following sequential operations has been carried out to extract the gullies:

4-2-1: Raster pixel processor (RPP):

For this step, pixel based classification was used, the SFP particularly which means single feature probability, and this one was chosen which uses a Bayesian – classifier (Statistic classification). It is suitable for this process taking into account both continuous and discrete variables, learning from training samples, and return a query metric for candidate pixel that matches the training samples (Fig.5 A).

The definition of training samples for gullies as well as background pixels depends upon visual interpretation. During this phase, pixel that are represent individual gullies are chosen by polygon tracing in the imagery to compute pixel cue metrics to use in pixel classifier. For this level, a non-dimensional per pixel calculations were used such as color, tone, site, shape and situation.

4-2-2: Raster object creators (ROC):

The function (threshold and clump) was applied for this step which keeping only pixels with probability greater than threshold value, and then converts the remaining pixels as binary system (0,1). The segmentation of gullies is applied in this step by grouping the continuous and clumped pixels that represent gullies as raster object (Fig. 5B). By using trial and error the most representative and suitable threshold value for gullies is 0.89.

4-2-3: Raster object operators (ROO):

By operating all possible gully raster object, there is a further reduction in the number of non-gully raster object. A size filter was used to remove all tiny object less than 15 m width and 50m length like farms with similar spectral signature. on the other hand, this filter filtered out raster object that are larger than 50m width like sabkha affected area with similar spectral signature fig (5C). Filtering out objects improved efficiency of the model, thus allowing one to restrict the set of raster objects to these of an appropriate size of individual gullies [18] .

4-2-4: Raster to vector conversion RVC:

In this step a polygon tracing was used to vectorised a raster object segments converting object from raster format to vector format. A shape file (.shp) is produced from this step fig(5D).

4-2-5: vector object operators VOO:

In this final step of the procedure, a smooth function was used to reduce the vertices of each polygon because sometimes the polygon may not exactly fit to gully area or being larger than the one that we define in procedure rules fig(5E)

5- Accuracy assessment:

The necessity of assessing the accuracy of spatial data derived from remote sensing technique and used in geographic information system has been regarded as a critical component of many studies [19]. In this study, an error matrix was used to express the accuracy assessment of gully erosion mapping. 100 sample points were created by using GIS environment to compare the true or false observations of any class between two layers: the classified one and referenced satellite image.

Accuracy parameters derived from the error matrix include overall accuracy, producer's accuracy, user's accuracy and the Kappa coefficient. The overall accuracy is computed by dividing the total correct (i.e. the sum of the major diagonal) by the total number of sample units in the error matrix. Traditionally, the division of the total number of correct sample units in a category by the total number of sample units of that category from the reference data (i.e. the column total) is termed the 'producer's accuracy'. This accuracy measure relates to the probability of a reference sample unit being correctly classified, and is really a measure of omission error. On the other hand, if the total number of correct sample units in a category is divided by the total number of sample units that were classified into that category on the map (i.e. the row total), then this result is a measure of commission error. This measure is called 'user's accuracy' or reliability and is indicative to the probability that a sample unit classified on the map actually represents that category on the ground [20].

Producer's accuracy % =100% - error of omission%

User's accuracy % =100% - error of commission% 1

Another measure of map accuracy is the kappa coefficient (K), which is a measure of the proportional (or percentage) improvement by the classifier over a purely random assignment to classes. It shows the extent to which the correct values of an error matrix are due to "true" versus "chance" agreement. Alternatively, it's a measure of agreement that compares the observed agreement to agreement expected by chance if the observer ratings were independent. It also expresses the proportionate reduction in error generated by a classification process, compared with the error of a completely random classification [21]; [22]; [23].

This is computed by the following equations [24]; [25]:

$$\hat{k} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})} \quad 2$$

Where

r = # of rows, columns in error matrix

N = total # of observations in error matrix

Xii = major diagonal element for class i

xi+ = total # of observations in row i (right margin)

x+i = total # of observations in column i (bottom margin)

A possible values range from +1 (perfect agreement) via 0 (no agreement above that expected by chance) to -1 (complete disagreement). With these values as references, [22]and [26] quoted

[27] as developing guidelines for interpreting the kappa as shown in table 3 below.

6- Results:

6-1: Classification results

A map shown in figure (6) illustrate gullies extracted from sentinel-2 image using OBIA. The gully- affected area extracted by this technique was (274) km^2. It is obvious some of small gullies were omitted using size filter because of limitations of satellite image spatial resolution, especially in the middle and middle western parts of study area.

A map shown in figure (7) illustrate manually digitized gullies using Arc GIS 10.5 software. The gully- affected area was (313) km^2. By using manual digitizing, it is easily to detect small gullies based on the principles of visual interpretation of satellite imagery, therefor, this map can be considered as reference map to use in accuracy assessment.

6.2- Accuracy results:

As shown in table (4), a comparison of classification accuracy statistics was carried out between gullies extracted by using OBIA and the manually digitized map. A user's accuracy of gully area was 84.8% while the producer's was 90.7%. As for non-gully area, the user's accuracy was 92.5% while producer's was 87.7%. The overall accuracy was 89.2% and it is considering high degree of accuracy supported by Kappa accuracy which was 0.78 which according to table (3), the result is substantial agreement between two maps.

7-Discussion:

The overall classification accuracy of 89.2% and the kappa statistic of 0.78 indicate a very good correlation between the gullies extracted by using OBIA and Digitized map. A 90.7% of Producer's accuracy in gully class indicate a good performance of object-based image analysis (OBIA) technique in detecting gullies.

Object-based image analysis accuracy is affected mainly by spectral signature of gully and surrounding area, because some gullies contain vegetation and some other did not. Additionally, gully surrounding areas are varying according to its spectral behavior from moisture content to organic content etc. [28] , [29].

8- Conclusion and recommendations:

Gully erosion mapping by applying object-based image analysis (OBIA) was successfully carried out and the technique is recommended for future studies. The very heterogeneous area of Ali Al-Gharbi district was chosen as study area. The heterogeneity refers to the existing manifold kinds of land use and land cover classes. The classification parameters were developed by using Erdas Imagine 2014, enables the incorporation of knowledge about the target along with pixel value. Although the accuracy assessment of OBIA technique is acceptable, the result can be enhanced by using high resolution imagery to map even small gullies such as Quick bird or Ikonos imagery. The study recommends to use more than threshold, size and probability filters to be tested with the much higher spatial resolution imagery.

References

[1] S. K. Sharma, N. K. Seth, S. Tignath and R. P. Pandey, "Use of GIS in hypsometric analysis of watershed," Indian Journalof Water Resources Society, vol. 31, no. (3-4), pp. 110-123, 2011.

[2] I. E. Luffman, N. Arpita and S. Tim, "Gully morphology, hillslope erosion, and precipitation characteristics in the Appalachian Valley and Ridge province, southeastern USA," Catena, vol. 133, pp. 221-232, 2015.

[3] I. Ionita, M. A. Fullen, W. Ziglobicki and J. Poesen, "Gully erosion as a natural and human-induced hazard," National Hazards, vol. 79, pp. S1-S5, 2015.

[4] A. J. Guerra, M. A. Fullen and J. F. Bezerra, "Gully Erosion and Land Degradation in Brazil: A case study from Sao Luis municipality, Maranhao state," in Ravine Lands: Greening for Livelihood and Environmental Security, Singapore, Springer, 2018, pp. 195-215.

[5] T. Blaschke, "Object based image analysis for remote sensing," ISPRS Journal of photogreametry and remote sensing, vol. 65, pp. 2-16, 2010.

[6] C. Fourie, "A one class object based system for space geographic feature identification, Stellenbosch, South Africa, University of Stellenbosch, MSc. Thesis.," 2011.

[7] S. Oltmanns, I. Marzolf, D. Tiede and T. Blaschke, "Detection of gully-affected areas by applying object-based image analysis (OBIA) in the region of Taroudannt, Morocco," Remote Sensing, vol. 6, pp. 887-893, 2014.

[8] K. Solaimani and A. Hadian, "Application of IRS data in water erosion features detection (case study:Nour Roud catchment ,Iran)," Pakistan Journal of Biological Sciences, vol. 11, no. 15, pp. 1893-1900, 2008.

[9] A. Pirie, "Gully erosion mapping using SPOT 5 satellite imagery, Pretoria, South Africa, University of Pretoria, Honours research report.," 2009.

[10] A. Torkashvand and H. Alipour, "Investigation of the possibility to prepare supervised classification map of gully erosion by remote sensing and GIS," World Academy of Science, Engineering and Technology, vol. 55, pp. 291-293, 2009.

[11] N. Mararakanye and N. Nethengwe, "Gully features extraction using remote sensing technique," South African journal of Geomatics, vol. 1, no. 2, 2012.

[12] "A GIS-based combining of frequency ratio and index of entropy approaches for mapping groundwater availability zones at Badra– Al Al-Gharbi–Teeb areas, Iraq," Sustainable Water Resourses Management , vol. 2, no. 3, pp. 265-283, 2016.

[13] T. Buday and S. Z. Jassim, The regional geology of Iraq: Tectonism, magmatism and metamorphism, vol. 2, Baghdad,Iraq, 352 p.: GEOSURV., 1987.

[14] R. C. Bellen, H. V. Dunnington, R. Wetzel and D. Morton, Lexique Stratigraphique International, Asie. Iraq. Intern Geol Conger Comm Stratigr, 3, Fasc, 10a: 333., 1959.

[15] A. M. Al-Abadi, Hydrological and Hydrogeological Analysis of Northeaster Missan Governorate, South of Iraq Using Geographic Information System. Doctoral Thesis, Baghdad University, 2012.

[16] S. Z. Jassim and J. C. Goff, Geology of Iraq. Dolin, Prague and Moravian Museum, Brno, Czech Republic, 431p, 2006.

[17] A. Gatti and A. Galoppo, Sentinel-2 products specification document, REF. S2-PDGS-TAS-DI-PSD, Issue 14.5, esa, Thales Alenia space, 510 p., [http://sentinel.esa.int/documents/247904/685211/sentinel-2-products-specification-document], 2018.

[18] G. Alessandra, G. Fabio and C. Domenico, "Identification of death trees in forest area through object and pixel oriented approaches applied to Ikonos images," European journal of remote sensing, vol. 43, no. 1, pp. 3-17, 2011.

[19] T. K. Agyemang, J. Heblinski, K. Shmieder, H. Sajadyan and L. Vardanyan, "Accuracy Assessment of supervised classification of submersed Macrophytes using GIS and error matrices: The case of Lake Sevan, Armenia," Hydrobiologia, vol. 661, no. 85, 2011.

[20] M. Story and R. Congalton, "Accuracy assessment: A User perspective," Photogrametric Engineering and Remote Sensing, vol. 52, no. 3, pp. 397-399, 1986.

[21] J. Cohen, "A Coefficient of Agreement for Nominal Scales," Educational and psychological measurement, vol. 20, no. 1, pp. 37-46, 1960.

[22] S. R. Munoz and Bangdiwala, "Interpretation of Kappa and B statistics measures of agreement," Journal of Applied Statistics, vol. 24, no. 1, pp. 105-111, 1997.

[23] C. Persello and L. Bruzzone, "A novel protocol for accuracy assessment in classification for very high resolution images," IEEE Transactions on Geoscience and Remote Sensing, vol. 48, no. 3, pp. 1232-1244, 2010.

[24] J. Sim and C. C. Wright, "The Kappa Statistic in Reliability studies: Use, Interpretation and sample size requirements," Physical Therapy, vol. 85, no. 3, pp. 257-268, 2005.

[25] J. R. Jensen, "Introductory Digital Image Processing: A Remote Sensing Perspective, Upper Saddle River, New Jersey, Prentice hall.".

[26] A. J. Viera and J. M. Garrett, "Understanding interobserver agreement: The Kappa Statistics," Family Medicine, vol. 37, no. 5, pp. 360-363, 2005.

[27] J. R. Landis and G. Koch, "The measurement of observer agreement for categorial data," Biometrics, vol. 33, pp. 159-174, 1977.

[28] T. Lillesand, R. Kiefer and J. Chipman, Remote Sensing and image interpretation, 6th edition, John wiley and sons, 480 p., 2008.

[29] J. Liu and P. Mason, Image processing and GIS for Remote Sensing, 2nd edition, John wiley and sons, UK, 457 p., 2016.

[30] A. J. Guerra, M. A. Fullen and J. F. Bezerra, "Gully Erosion and Land Degradation in Brazil: A case study from Sao Luis municipality, Maranhao state," in Ravine Lands: Greening for Livelihood and Environmental Security, J. C. Dagar and A. K. Singh, Eds., Singapore, Springer, 2018, pp. 195-215.

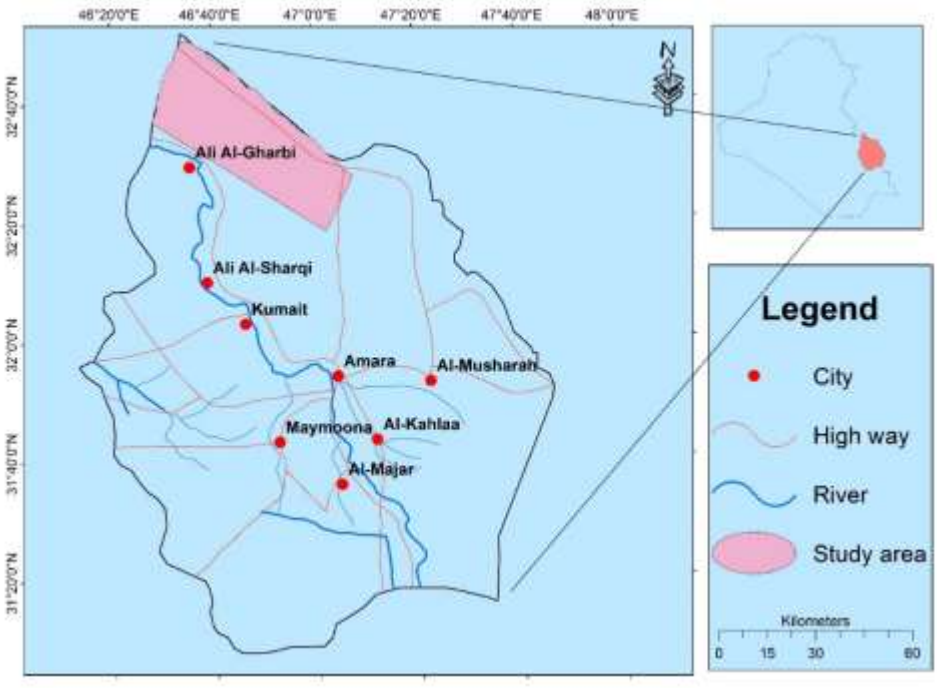

Fig. 1 (Location of study area)

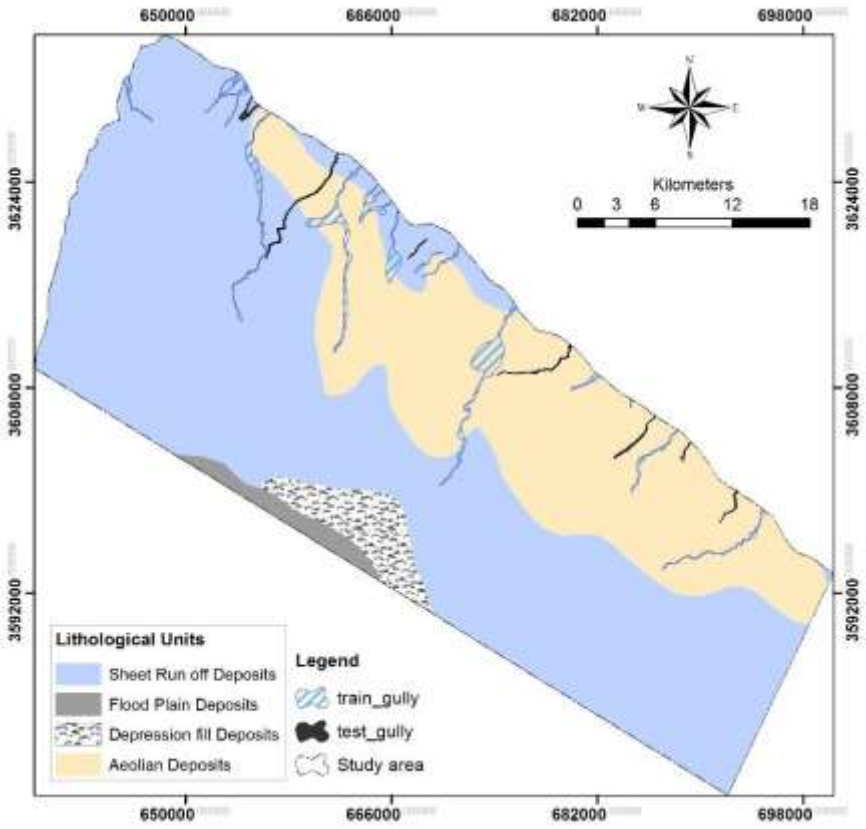

Fig. 2 Exposed lithological units in the study area

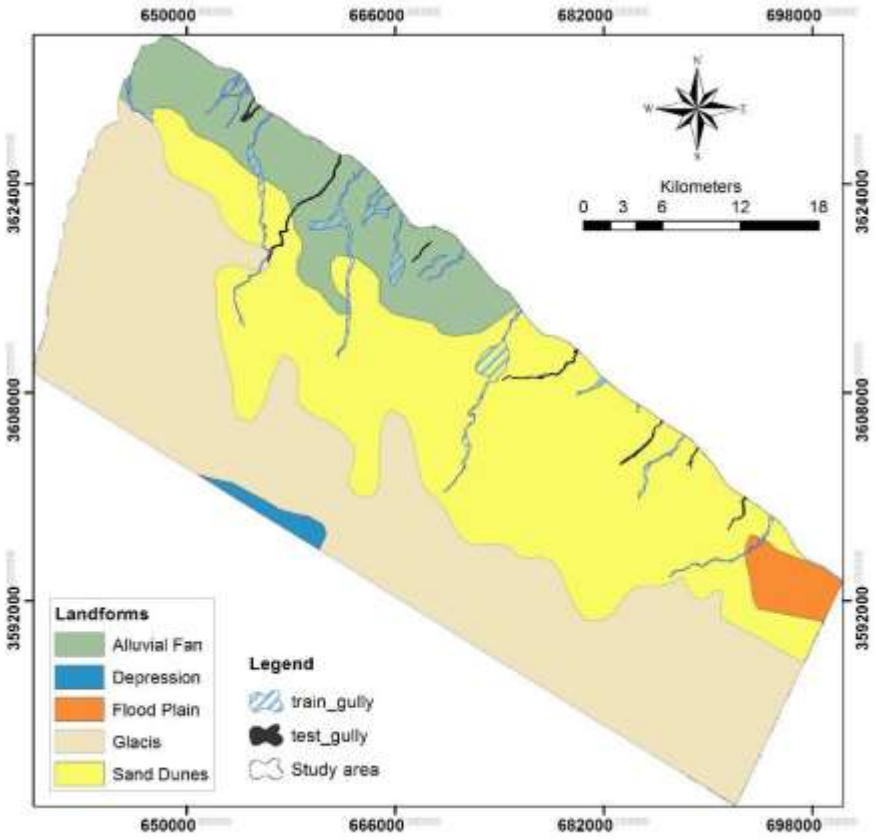

Fig. 3 Major landforms distributed in the study area

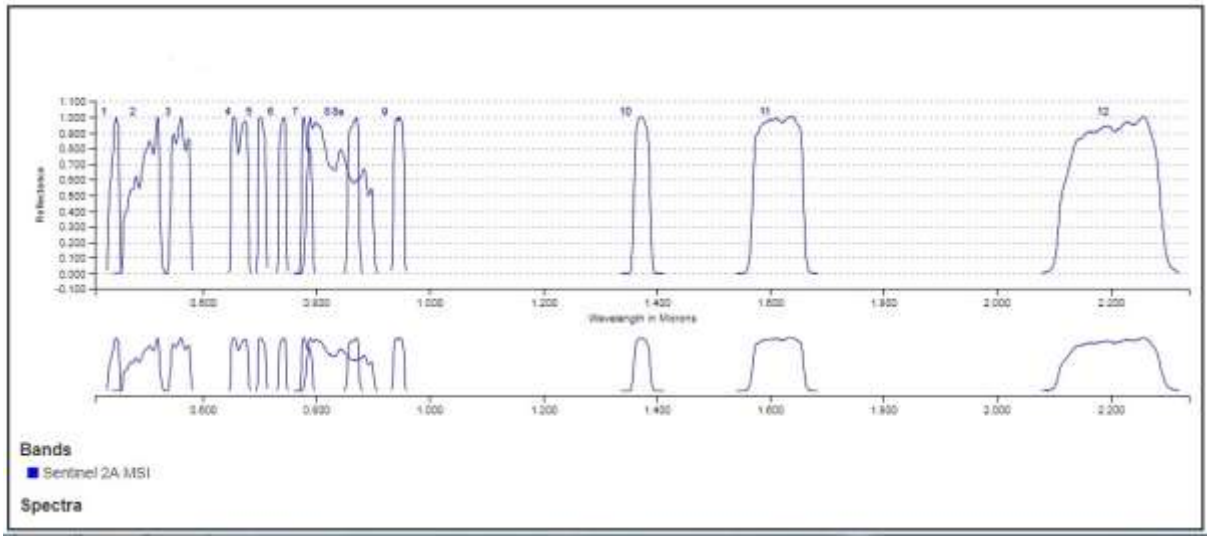

Fig. 4 spectral range of MSI sensor onboard sentinel-2

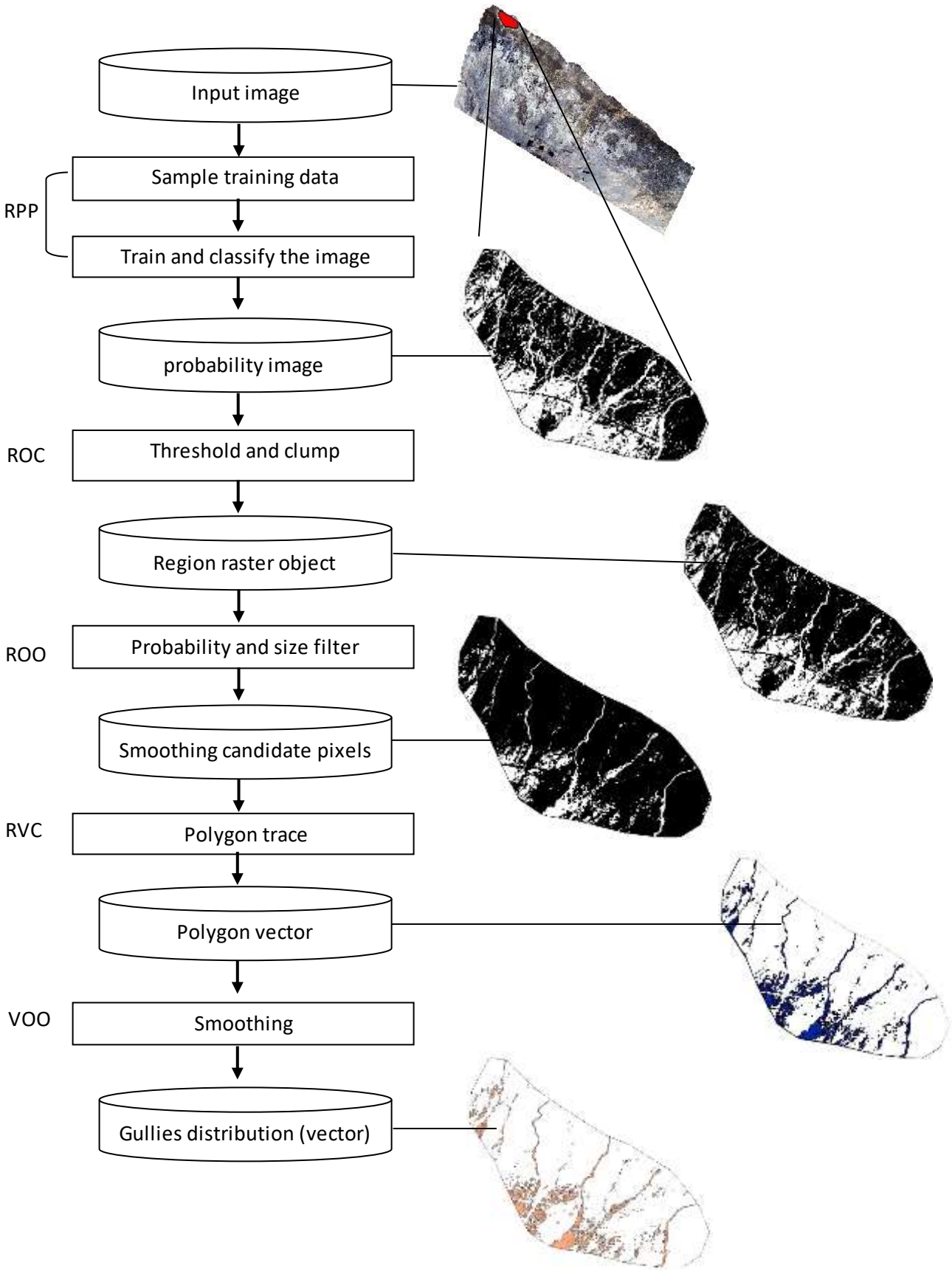

Fig. 5 flow chart

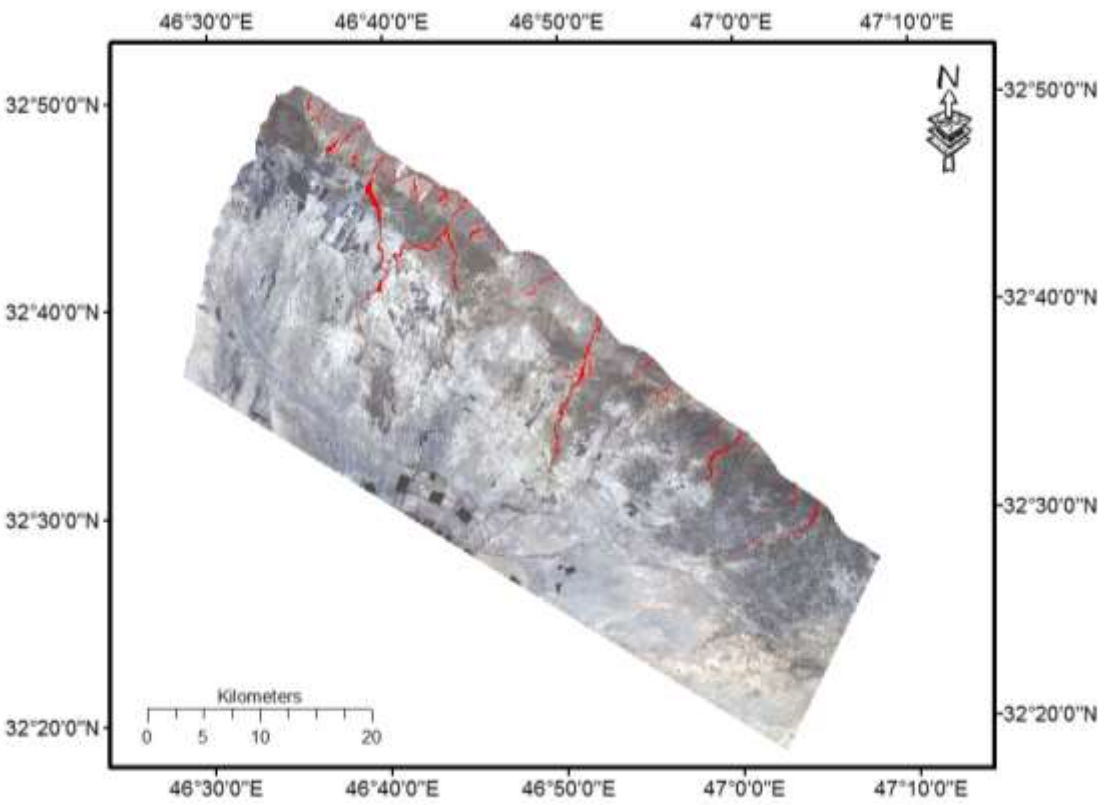

Fig. 6 Gully map using OBIA

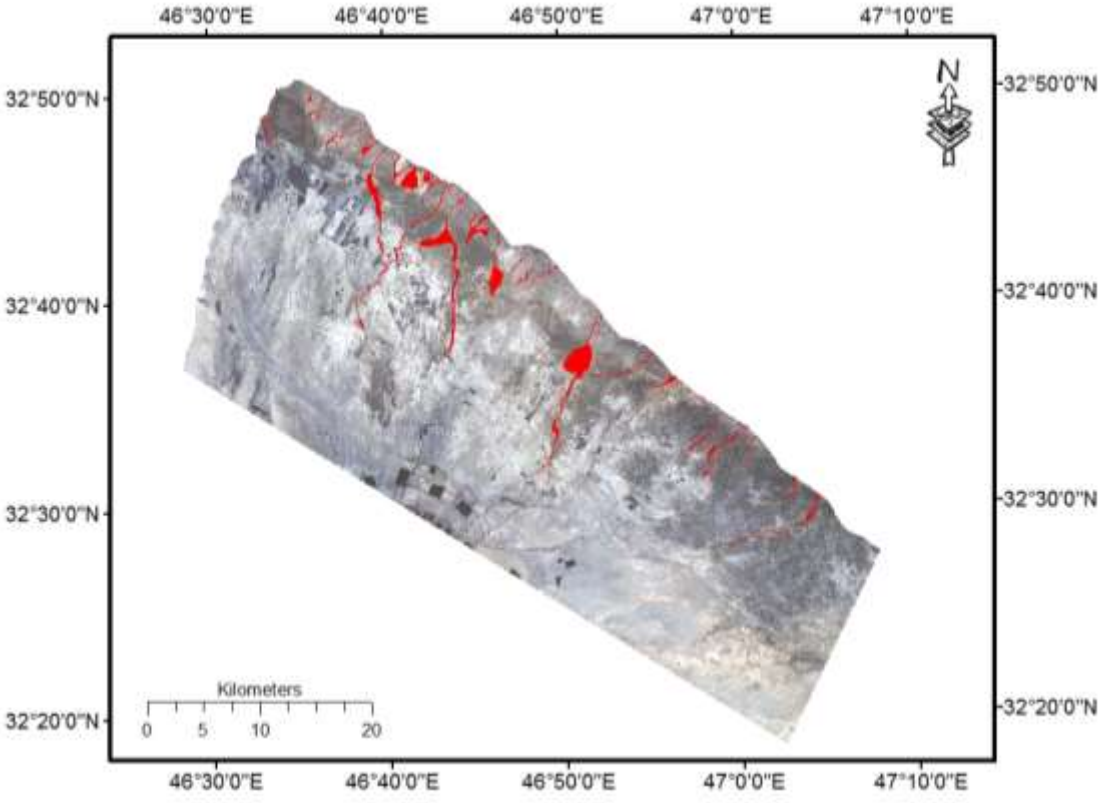

Fig.7 Referenced gully map

Table 1 Lithological units in the study area [15], [13]

Lithological units	Description	Age	Occupied area (km^2)	Area (%)
Alluvial	These deposits mainly comprise gravel, sand, and silty sand with a maximum thickness of 15 m. Poorly sorted cobbles and boulder occur in apical part passing into finer grained better sorted layered fluvial deposits. Gepcrete also developed on the exposed surface of the fan	Pleistocene - Holocene	1018	65.0
Flood plain	Comprise layers of silt clay and clay (10 – 20 cm) and sometimes up to 1 m thick	Holocene	22	1.40
Depression Fill	Comprise reddish – brown fine sand, silt and clayey silt.	Holocene	48	3.10
Aeolian	Comprise silty reddish brown and calcareous sand	Holocene	488	31.0

Table (2) MSI specification [17]

Spatial	spectral	Temporal
10m , 20m , 60m	13 spectral bands in the VNIR and SWIR	5 days

Table 3: Kappa interpretation guidelines of [27]

Kappa statistic	Strength of Agreement
<0	Poor
0.01 – 0.20	Slight
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Substantial
0.81 – 1.00	Almost Perfect

Table 4 : error matrix of gullies

	Referenced data			
Classified data	Gully area	non-Gully area	Total	User's accuracy%
Gully area	**39**	7	46	84.8
non-Gully area	4	**50**	54	92.5
Total observations	43	57	100	
no. of false predicted class	4	7		
False% in class	9.3	12.3		
Producer's accuracy%	90.7	87.7		
Total accuracy%	89.2			
Kappa coefficient	0.78			

اعداد خريطة الاخاديد باستخدام تحليل المرئيات المعتمد على الاجسام: دراسة حالة لمنطقة علي الغربي في محافظة ميسان جنوبي العراق

علي خالد العلي و علاء محسن العبادي

جامعة البصرة–كلية العلوم– قسم علم الارض

المستخلص

تم إجراء العديد من الدراسات لإيجاد أفضل طريقة لتصنيف بيانات الاستشعار عن بُعد. تعتمد الطرق التقليدية فقط على قيمة البكسل دون استخدام المعلومات المكانية والهندسية للجسم المدروس الذي يعتبر مصدرًا مهمًا لتصنيف مرئيات القمر الصناعي. قارنت هذه الدراسة بين خوارزميات التصنيف القائمة على البكسل والجسم باستخدام مرئيات القمر الاصطناعي الاوروبي Sentinel–2A. بالنسبة لتحليل الصور المستند إلى الاجسام ، تم تقسيم الصورة إلى مجموعات متجانسة باستخدام متغيرات مناسبة مثل المقياس والشكل والحجم والاحتمال. تم التصنيف بناءً على الأجزاء بواسطة طريقة المجاور الاقرب ، بينما تم التصنيف بناءً على قيمة البكسل عن طريق الرقمنة اليدوية باستخدام مبادئ التفسير البصري. لتقييم الدقة ، تم استخدام مصفوفة خطأ لتقييم التصنيف بين نوعين من التصنيف. بلغت دقة المنتج بالنسبة للفئة gully باستخدام تحليل الصورة المستندة إلى الكائنات 90.7 ٪ ، في حين كانت دقة المستخدم لتصنيف البيكسل84.8 gully ٪ .تعرضت تقنيات التصنيف هذه لتقييم الدقة وكانت الدقة الكلية 89.2٪ و 0.78 لمعامل .Kappa تظهر نتائج التصنيف وتقييم دقتها أن نهج تحليل الصور القائم على الكائنات أعطى نتائج أكثر دقة.

الكلمات المفتاحية: التعرية الاخدودية ، تحليل المرئيات المعتمد على الاجسام ، مصفوفة الخطأ