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Pixel- *vs* Object-based Land Use/Land Cover Classification: a Case Study of the Mendefera Sub-zone, Eritrea

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Abstract

The study compared the performance of the pixel- and object-based land use/land cover (LULC) classifications for the Mendefera sub-zone, Eritrea, using Landsat 8 OLI. The supervised pixel-based image classification was conducted in ArcMap, with the Support Vector Machine (SVM) and segmentation object-based image classification in ArcGIS Pro. Post-classification smoothing and the use of high spatial resolution aerial photos, along with Google Earth images, were employed to improve the accuracy of the exercise. DEM and high spectral resolution satellite images were also used in combination with false composite colours during the creation of the training samples. Overall accuracies of 83.7% and 67% and Kappa coefficients of 76.9% and 49% were obtained for the pixel- and object-based classifications, respectively. Thus, the study concluded that pixel-based LULC classification is the best classification mechanism for the given study area.

***Keywords**: Pixel-based, Object-based, Land use / land cover, Mendefera, Eritrea*

1. Introduction

Having adequate information on the land use / land cover (LULC) of an area/region is essential for various purposes, such as, amongst others, planning activities and resource management (Floody *et al*., 2002). Anthropogenic activities, such as population growth, migration, land use change, agricultural practices, construction, soil erosion, deforestation, etc., and natural processes, such as climate change, have constantly affected the quality, quantity, and attributes of LULC. Generally, land cover can be defined as the surface cover on the ground which might include vegetation, water, bare soil, swamp areas, grasslands, or other (Adam *et al*., 2010), whereas land use is related to the activities of humans or the role played by economic activities in association with a specific piece of land (Puttaswamiogowda et al., 2013). Land use / Land cover (LULC) information is vital for sustainable development and resource management because it provides detailed information on how land has been used and how the landscape changes over time (Kilic *et al*., 2006; Gibas *et al*., 2020). Understanding LULC of an area is crucial for making decisions as to how to manage natural resources, urban growth, agriculture, conservation efforts, and to mitigate, amongst others, climate change. More than 80% of Eritrea's economy is largely dependent on agriculture, with the country facing continuous droughts, soil degradation, and water scarcity (Ghebrezgabher *et al*., 2018). The Mendefera sub-zone, located in the southern part of Eritrea, presents with a diverse mix of land cover types, including urban areas, agricultural land, open areas, forests, and barren lands (Sereke *et al*., 2024). A proper classification of LULC contributes significantly to identifying fertile land and areas prone to desertification, and guides decision-making with respect to crop selection and irrigation projects. Furthermore, it could also help in studies planning for, amongst others, urban growth, infrastructural development, and the allocation of resources.

Image classification is a mechanism whereby pixels of continuous raster are assigned to pre-identified classes − a process of converting raw data to thematic information by measuring certain intervals of electromagnetic energy (Bochenek, 2006).

Different tools, such as pixel-, sub-pixel-, per-field- and object-based techniques, have been used in conjunction with satellite images in the classification of LULCs (Araya *et al.*, 2008**.** Each image classification technique presents its own advantages and disadvantages. The choice of the specific classification technique used depends on many factors, but accuracy is very important; in such cases, the values for overall accuracy and the Kappa coefficient should be high above the threshold (Jovanovic *et al*., 2015).

Pixel-based image classification is a traditional method based entirely on individual pixels (Plat *et al.,* 2008), where spectral − not spatial characteristics − are identified and measured (Hussain *et al*., 2013). This technique is usually applied in coarse resolutions (Araya *et al*., 2008)**.** Pixel-based classifications are marked by an over classification of individual pixels, a lack of aggregations in terms of pixel results, difficulties in processing and Analysing the relevant dataset, and a struggle with higher resolution imagery, thereby resulting in a "salt and pepper" effect (Riggan *et al*., 2009).

Object-based image classification is based on homogeneous images or objects rather than on individual pixels (Bochenek, 2006; Waylen *et al*., 2014). In such cases, pixels are combined into objects, not only in terms of their value, but also in terms of their shape, texture, shade, size, and mutual relations (Rejaur *et al.*, 2008; Manandhar *et al*., 2009), thereby ensuring that they mitigate the problems arising around pixel-based classification. If all the procedures of object-based classification are followed, analysed, and processed wisely, the image objects that we process would then essentially relate closely to objects in the real world. On the contrary, this method of analysis presents with several barriers, and is difficult to employ since it needs advanced techniques such as neural networks, textural measurements, and fuzzy sets (Platt *et al*., 2008).

The study aims to compare pixel- and object-based LULC classifications using Landsat 8 OLI data in the context of the Mendefera sub-zone, Eritrea.

2. Materials and Methods

2.1. Study area

The Mendefera sub-zone, 438 Km^2 in land area, lies in the region of latitudes, $14^{0}48'0''$- $14^{0}57'36''$N, and longitudes, $38^{0}43'12''$- $38^{0}57'36''$E. The sub-zone comprises Mendefera City and 73 farming villages. Subsistence mixed farming, crop and livestock farming are the mainstay of the village households. Teff, maize, sorghum, finger millet, chickpea, cowpea, and lentils are the crops generally grown here under rainfed conditions. Goats, sheep, cattle, donkeys, and camels comprise the livestock reared, with irrigation and dairy farming also common agricultural practices around the city. Mendefera City is also commonly known for the trade and services that it renders in the region. Many dwellers also work in government offices, in the rendering of services, in schools, and in hospitals, etc.

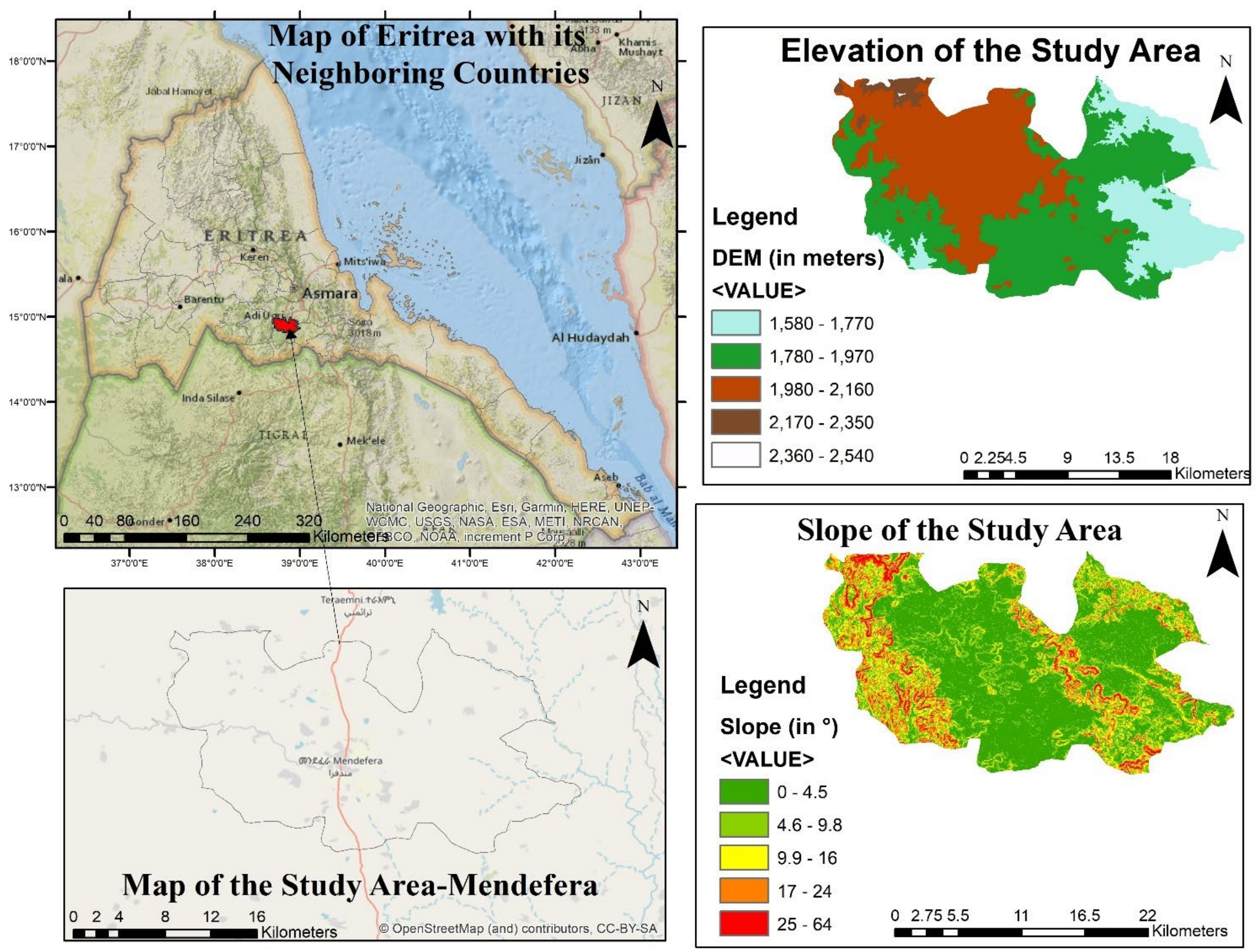

Figure 1. Location, DEM and slope of the study area

2.2. Data and methodologies

Landsat 8 OLI Level I, with WRS path 169, row 50, with a spatial resolution of 30 m and 11 bands, was acquired on 13 February 2022.[1] The vector layer for the study area was extracted from the country's shape file. ASTER DEM was also used. All the spatial data were projected into the global WGS 84 UTM zone 37. ENVI 5.3 was applied for preprocessing, whereas ArcMap 10.5 and ArcGIS Pro 3.0 were used for the pixel-based and object-based image classifications, respectively. The overall methodologies and procedures of image processing and pixel- and object-based LULC classification used in this study are displayed in the flowchart in Fig. 2.

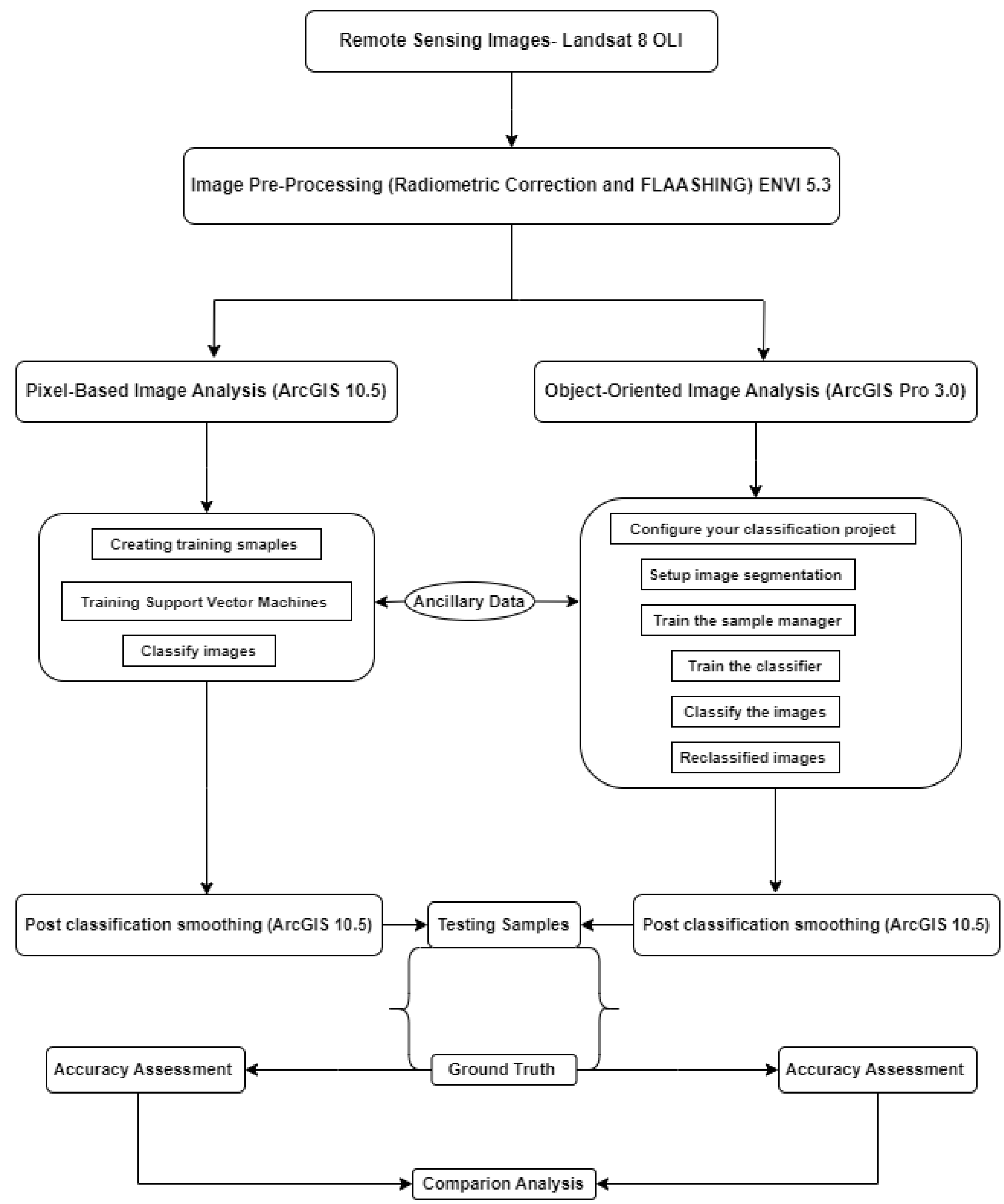

Figure 2. Flowchart: image processing and pixel- and object-based LULC classification.

1 The study area is comparatively free of cloud cover in the month of February.

The pixel-based classification for Landsat 8 OLI data is an efficient, simple, and widely used practice; however, confusion might arise on account of its unambiguous attributes, with mixed pixels and complex boundaries in cases where different land cover types coexist within a single pixel (Adam *et al*., 2010; Hussain *et al*., 2013; Tassi *et al*., 2021). On the other hand, the object-based classification could work well in heterogeneous landscapes in that it incorporates the spatial context, as in the shape, size, and texture of the relevant objects. However, owing to the need for segmentation, the object-based classification tends to be more demanding computationally and is more sensitive to the spatial resolution of the data (Araya *et al*., 2008; Platt *et al*., 2008). On the other hand, pixel-based classification works particularly well for land cover types that exhibit distinct spectral separability attributes.

2.3. Land use / land cover classes

The LULC classification scheme proposed by AfriCover was adopted in the study. It has also already been adopted by the Department of Land and by the Ministry of Land, Water and the Environment (MoLWE-DoL) of Eritrea (MoLWE-DoE, 2005). The general LULC classes in the study area and their simplified explanations, based on the MoLWE-DoL, are presented in **Table 1**.

Table 1: LULC classes and their simplified explanations based on the MoLWE-DoL (MoLWE-DoE, 2005)

S. No.	LULC classes	Simplified Explanation based on the MoLWE-DoL
	Built-up area	Industrial, commercial and public built-up areas; transportation, and others
	Water bodies	Dams and other water bodies
	Agricultural land	Any type of rain-fed agriculture; irrigated land
	Natural vegetation	Seasonal wetlands, artificial trees, and natural bushes and trees
	Open area	An area left fallow, for grazing, and other purposes
	Barren land	An area neither covered by vegetation nor used for crop production, and covered mainly by hard rock

2.4. Image preprocessing

The area of interest was extracted from the scene, Landsat 8 OLI Level 1, and the bands were stacked and clipped to the study area. The image was preprocessed using ENVI 5.3; it was processed for radiometric calibration and then FLAASHING was applied for atmospheric correction. Preprocessing manages the issues related to image registration, geometrical rectification, and radiometric, atmospheric, and topographic corrections (Hussain *et al*., 2013).

2.5. Image Classification

In this paper, pixel- and object-based image classifications were employed, and their respective performances were compared (Adma *et al*., 2010; Riggan *et al*., 2009). The study employed supervised classification using Support Vector Machines (SVM) as an ensemble-based classifier for both pixel- and object-based classifications. Post-classification smoothing (PCS) was also carried out.

2.5.1. *Pixel-based image classification*

The study employed ArcGIS 10.5 for the SVM algorithm of pixel-based supervised classification. 750 training sites were created by digitizing polygons, and DEM and high spectral resolution satellite images were used for the collection of the training samples. The combination of the ancillary data with the composite band improved the performance of the pixel-based classification. Furthermore, post-classification smoothing was employed (Waylen *et al*., 2014). Finally, the LULC map of the study area with six major classes, namely, built-up area, waterbodies, agricultural areas, natural vegetation, open areas, and barren land, was developed.

2.5.2. *Object-based image classification*

The study used ArcGIS Pro 3.0 for its object-based classification. Image segmentation was conducted (Platt *et al*., 2008), with 750 training samples being created. DEM and high spectral resolution satellite images with false composite colours were used during the collection of the training samples. If insufficient samples were created, training the classifier was employed again. The segmented raster was classified during the image classification step. This was based on the available classifiers in that either SVM or Random Forest classifiers were chosen. In addition, the maximum number of classified segments was specified. A confusion matrix was also generated. Finally, an LULC map of the study area was developed. The six major classes included built-up area, water bodies, agricultural area, natural vegetation, open area, and barren land.

2.6. 2.6. Accuracy assessment

The overall accuracy indicator and kappa coefficient were employed to assess the performance and accuracy of the pixel- and object-based image classification techniques employed using the ground truth mechanism. For the pixel-based classification, 509 randomly created accuracy points in ArcMap were checked, compared, and marked against the true image using Google Earth Pro. After that, the user accuracy, producer accuracy, overall accuracy, and kappa coefficient were calculated manually. In the case of the object-based image classification, 502 random accuracy points were created, with the accuracy assessments calculated in ArcGIS Pro.

3. Results and Discussion

3.1. Land use/land cover classes and maps

Pixel- and object-based land use / land cover classes, namely, water bodies, agricultural land, natural vegetation, open areas, barren land and built-up areas were identified in the study area (**Fig. 3)**.

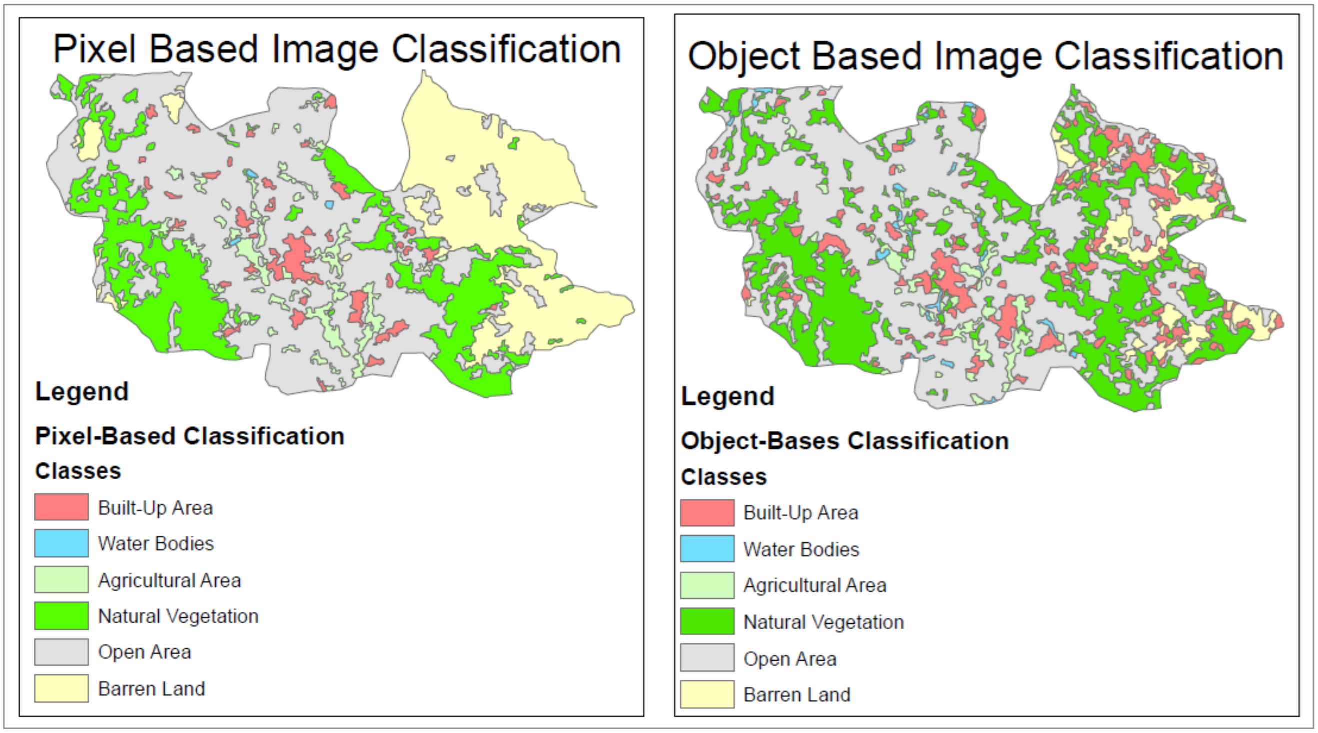

Figure 3. Pixel-based Image Classification (left) and Object-based Image Classification (right), which were both applied to the same geographic location using Landsat 8 satellite imagery. Pixel-based treats pixel individually based solely on its spectral information, while object-based classification groups pixels into meaningful segments before classification

3.2. Accuracy assessment

The statistical measures for producer and user accuracies are presented in Tables 2 and 3

Table 2: Confusion matrix for the pixel-based image classification

i \ j	1	2	3	4	5	6	$\sum_{j=1}^{6} n_{ij}$	UA_i	K
1	10	0		0	0	0	10	100%	
2	0	20	11	0	2	0	33	60.0%	
3	0	0	87	2	13	0	102	85.3%	
4	0	0	13	204	7	2	226	90.3%	
5	0	4	11	3	91	4	113	85.5%	
6	0	0	0	9	2	14	25	56%	
$\sum_{i=1}^{6} n_{ij}$	10	24	122	218	115	20	$\sum n_{ij} = 509$		
PA_j	100%	83.3%	71.3%	93.6%	79.1%	70%		**83.7%**	
K									**77%**

The overall accuracy, user accuracy, producer accuracy and kappa coefficient for the pixel-based classification were calculated manually using the following formulae (Jovanovic *et al*., 2015):

The LULC classes are denoted as: 1 - water bodies, 2 - agricultural land, 3 - natural vegetation, 4 - open land, 5 - barren land, 6 - built-up area, and the matrix $N = \left(n_{ij}\right) -$ is a confusion matrix, where $i,\ j = \overline{1,6}.$

$$N = \begin{pmatrix} 10 & 0 & 0 & 0 & 0 & 0 \\ 0 & 20 & 11 & 0 & 2 & 0 \\ 0 & 0 & 87 & 2 & 13 & 0 \\ 0 & 0 & 13 & 204 & 7 & 2 \\ 0 & 4 & 11 & 3 & 91 & 4 \\ 0 & 0 & 0 & 9 & 2 & 14 \end{pmatrix}.$$

The data contained in the above matrix allowed for the construction of several estimates characterizing the classification efficiency. The most informative proved to be total classification accuracy, producer accuracy, user accuracy, and the Kappa coefficient.

Overall Accuracy (OA) was calculated by means of the formula:

$$\mathrm{OA} = \frac{\sum_{i=1}^{k} n_{ii}}{n} \cdot 100\% = \frac{n_{11} + n_{22} + \ldots + n_{kk}}{n} \cdot 100\%, \qquad [1]$$

Where k = the number of classes considered, $n = \sum n_{ij} = \sum_{j=1}^{k}\left(\sum_{i=1}^{k} n_{ij}\right)$ = the total number of observations (pixels) in the matrix N,

$$\mathrm{OA} = \frac{\sum_{i=1}^{6} n_{ii}}{n} \cdot 100\% \approx 83,7\%.$$

Producer Accuracy (PA) and User Accuracy (UA) were calculated by means of the formulae:

$$PA_j = \frac{n_{jj}}{\sum_{i=1}^{k} n_{ij}} \cdot 100\% = \frac{n_{jj}}{n_{1j} + n_{2j} + \ldots + n_{kj}} \cdot 100\%, \qquad [2]$$

$$UA_i = \frac{n_{ii}}{\sum_{j=1}^{k} n_{ij}} \cdot 100\% = \frac{n_{ii}}{n_{i1} + n_{i2} + \ldots + n_{ik}} \cdot 100\%, \qquad [3]$$

Where k = the number of classes considered, $j = \overline{1,k}.$ and $i = \overline{1,k}.$

The Kappa coefficient was calculated by means of the formula:

$$K = \frac{n \cdot \sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{k}\left(\sum_{p=1}^{k} n_{ip} \cdot \sum_{q=1}^{k} n_{qi}\right)}{n^2 - \sum_{i=1}^{k}\left(\sum_{p=1}^{k} n_{ip} \cdot \sum_{q=1}^{k} n_{qi}\right)} \quad [4]$$

$$K = \frac{140735}{182982} \approx 0.77$$

Table 3: Confusion matrix for the object-based classification

i \ j	1	2	3	4	5	6	$\sum_{j=1}^{6} n_{ij}$	UA_i	K
1	0	4	2	1	2	1	10	0	
2	0	9	5	2	1	0	17	53%	
3	0	7	117	18	7	1	150	78%	
4	0	20	41	181	10	4	256	71%	
5	0	0	4	2	18	1	25	72%	
6	0	0	8	24	3	10	45	22%	
$\sum_{i=1}^{6} n_{ij}$	0	40	177	228	41	17	$\sum n_{ij} = 503$		
PA_j	0	23%	66%	79%	44%	59%		**67%**	
K									**49%**

The confusion matrix for the object-based approach was calculated automatically in ArcGIS Pro after all the parameters had been set correctly.

Overall accuracies of 83.7% and 67% and Kappa coefficients of 77 % and 49% were obtained for the pixel- and object-based classifications, respectively. The results demonstrate that the pixel-based LULC classification technique for the study area performed better than the object-based classification technique. Several pixel- *vs* object-based studies also reported that the pixel-based classification performed better (Adam *et al.,* 2010; Berhane *et al*., 2017), whereas a number of other studies found that the object-based classification technique performed better (Araya *et al*., 2008; Deur *et al*., 2021; Hahn *et al*., 2021; Szabo *et al*., 2020; Tassi *et al*., 2021; Zhai *et al*., 2018).

The object-based classification is particularly effective for very high spatial resolution data sourced from optical satellites such as IKONOS, QuickBird, GeoEye, RapidEye, and EROS A and B, as this method aggregates pixels into meaningful objects based on characteristics such as texture, shape, size, and spatial arrangement (Hussain *et al*., 2013). For example, in their studies, Deur *et al.* (2021) used WorldView, Szabo *et al*. (2020) employed an aerial laser scanner, and Hahn *et al*. (2021) incorporated cameras in their fieldwork. All the datasets for the respective studies mentioned above are considered to be at a high spatial resolution, thereby confirming that object-based classifications outperform pixel-based classifications. Our study employed medium spatial resolution data, namely, 30m Landsat 8 OLI, where the performance of the object-based classification data was at a lower level than that of the pixel-based classification data. In addition, the object-based classification used both spectral information and spatial characteristics (Araya *et al*., 2008; Platt *et al.*, 2008); it also required intensive computational skills and demanded greater effort in defining the optimal parameters for segmentation and object delineation (Platt *et al.*, 2008). On the other hand, the pixel-based classification was found to work with individual pixel values (Hussain et al., 2013) and to have well established techniques which are generally suitable for medium resolution data (Adam *et al*., 2010). Our study found that, with an accuracy of 83.7%, the pixel-based classification outperformed the object-based method with 67 % for the latter approach. This improvement may be related to the fact that the pixel-based classification is sensitive to spectral features. In fact, it is effective when different land cover classes are spectrally distinct (e.g., when water and vegetation, respectively, have distinct values).

4. Conclusion

The study employed GIS and remote sensing techniques with Landsat 8 data to compare the effectiveness of pixel-based and object-based classification methods for the LULC of the Mendefera subzone, Eritrea. Six LULC classes, namely, water bodies, agricultural land, natural vegetation, open areas, barren land, and built-up areas were identified and classified using both methods. The results revealed that the pixel-based LULC classification technique gave better accuracies than the object-based method with overall accuracies of 83.7% and 67% and Kappa coefficients of 76.9% and 49%, respectively. Thus, we concluded that pixel-based LULC classification method with Landsat 8 data is effective for the study area. The developed LULC maps give insights into how the area is being used, and how to develop effective land use planning for the future. Studies with other LULC classification techniques are also advised for further better results.

Conflict of interests: The authors declare that there is no conflict of interest related to this research.

Originality: The authors confirm that this manuscript has not been published elsewhere and is not under consideration for publication by any other journal. No part of this paper has been previously published.

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