Land use classification based on object and pixel using Landsat 8 OLI in Kendari City, Southeast Sulawesi Province, Indonesia

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Abstract. Current development on method and technique for data processing in remote sensing has received a great importance, since it provides a base for a myriad of applications, including land use monitoring. OBIA- and pixel-based approach are commonly used as classification technique in remote sensing. This present work aimed to compare both approaches in classifying the land use in Kendari, Southeast Sulawesi Province, using Landsat 8 OLI (Operational Land Imager). Digital images were processed using both techniques with the use of support vector machine (SVM) algorithm. The 188 sampling spots in the study site were randomly determined, then classified into 5 groups of land use: water body, follow land, built up land, residential area, and vegetation. Data obtained were then validated according to data from google earth and ground check. The accuracy was assessed by confusion matrix method using Region of Interest (ROI). The results showed that OBIA-based classification coupled with SVM algorithm showed overall accuracy of 81.38%, Kappa coefficient of 78.77%, in which the accuracy was 9.57% higher than pixel-based classification. Based on this finding, OBIA was reported to produce a better performance in identifying land use in urban area.

1. Introduction
Remote sensing technology offers many advantages and plays a significant role in inventory assessment and monitoring of natural resources based on spatial data; thus, adoption of this technology in a variety of sectors is increasing [1]. Remote sensing data are also capable of identifying the land use in urban area [2, 3], which is theoretically tested and economically feasible [4]. Numerous studies on remote sensing for land classification have been made, but newer techniques to produce more appreciable results are still emerging. Current techniques for land identification included pixel-, subpixel- and object-based methods [5].

In the pixel-based method, each imagery pixel was classified into diverse feature classes [6]. Since it frequently involves spectra method [7], the object detail is less effectively interpreted [8]. Some researchers have conducted studies concerning the development of classification method having more desirable accuracy [9, 10, 11, 12, 13]. However, to produce thematic map is limited with some problems that come from land cover complexity, imagery data availability, data processing, and classification approaches, thus remarkably affecting the quality of classification [14].
Currently, object-based approach has been introduced [15]. It classifies the object in segment unit grouped according to shape, scale, color, and object features [8]. This approach was claimed to exert higher accuracy in extracting the land from image satellite and deal with disadvantages of pixel-based method that frequently produces salt and pepper effect [16]. Nevertheless, the advantages of OBIA technique are highly dependent on quality of image segmentation [17]. Image segmentation in remote sensing can be performed using either parametric or non-parametric approach. Maximum likelihood (ML) is more frequently applied. ML refers to a supervised classification capable of grouping pixels based on probability of belonging to a particular class with average value and covariant modelled into normal distribution in a multispectral feature [18], which make it difficult to integrate spectral data and additional data [14].

In non-parametric algorithm, data are not required to fit a normal distribution. Statistical parameters are also not required to classify image according to classification scheme [19]. SVM algorithm is commonly used as parameter in non-parametric approach. It constitutes a supervised classification initially developed by Vapnik and Chervonenkis [20]. Interestingly, SVM algorithm was reported to show a higher accuracy compared to ML [21]. Nevertheless, high resolution image in studies using object-based method was more used for classifying the urban land use [2], while medium resolution image such as Landsat is less applied. On the other hand, the use of medium resolution image in pixel-based technique has been reported in many studies. Therefore, the current study was to compare accuracy of urban land use classification obtained from object-based method and pixel-based method using medium resolution image from Landsat 8 OLI.

2. Methods

2.1 Study area
The study area was Kendari City, in which it geographically located in south of equator line and geographic coordinates of 3°54’30” – 4°3’11” south latitude and 122°23’ – 122°39’ east longitude. Administratively, the city shared borders with sea and several regencies, i.e. Konawe Regency in north, Kendari Sea in east, South Konawe Regency in south, and South Konawe Regency in west (figure 1).

2.2 Materials
The satellite imagery for this study was obtained from Landsat 8 OLI with a spatial resolution of 30m, acquired July 26, 2016, and downloaded from USGS (United States Geological Survey). The characteristics of satellite imagery from Landsat 8 OLI are presented in table 1.

![Figure 1. Study area.](image-url)
Table 1. Characteristics of satellite imagery from Landsat 8 OLI.

| Band       | Range (nm) |
|------------|------------|
| Band 1     | Costal aerosol | 0.43-0.45 |
| Band 2     | Blue        | 0.45-0.51 |
| Band 3     | Green       | 0.53-0.59 |
| Band 4     | Red         | 0.64-0.67 |
| Band 5     | NIR         | 0.85-1.88 |
| Band 6     | SWIR 1      | 1.560-1.660 |
| Band 7     | SWIR 2      | 2.100-2.300 |
| Band 8     | Panchromatic | 0.500-0.680 |
| Band 9     | Cirrus      | 1.360-0.390 |
| Band 10    | TIRS 1      | 10.60-11.20 |
| Band 11    | TIRS 2      | 11.50-12.50 |

Source: www.landsat.usgs.gov

2.3 Pre-processing of satellite images

The pre-processing of the images consisted of geometric correction, radiometric correction, and atmospheric correction. The geometric correction aimed to adjust position of satellite images, ensuring that it is correspondent with original position in earth surface [19]. In this study, the correction was carried out using meta data available in satellite imagery from Landsat 8 OLI. Furthermore, radiometric correction was to provide data having pixel values associated with backscatter reflected by the surface. The radiometric data were calibrated to be backscatter coefficient [22]. Atmospheric correction was performed to enhance data quality and carried out using FLAASH (Fast Line of Sight Atmospheric Analysis of Spectral Hypercube). FLAASH enabled to analyze wide range of spectrum from visible light to low infra-red in multi-spectra and hyper-spectra [23].

2.4 Image processing

The image processing was performed using two methods: object- and pixel-based method.

a. Pixel-based method

This method involved an algorithm that was designed to collect complete information about the object according to pixel values of the images [24]. It used guided classification with SVM algorithm. SVM is a non-parametric classification capable of selecting vector or line as a base to segregate two classes or more through optimizing class border between land uses according to principle of linear classifier [8]. The SVM algorithm was expressed as follows:

\[
D (X^T) = \sum_{i}^{l} y_i \alpha_i X_i X_i^T
\]

Where:
- \(y_i\) Class label from support vector
- \(X_i X_i^T\) Data testing
- \(\alpha_i\) and \(b_0\) Numeric parameters automatically determined through SVM algorithm optimization
- \(l\) number of vector support.

b. Object-based classification (OBIA)

OBIA was capable of identifying each object appearance in the image according to similarity on spectra, which were then grouped into some classes of land use. This technique consisted of segmentation and classification. In both processes, the land identification was obtained from extraction of shape, texture and spectra [25]. The algorithm process in segmentation was multiresolution segmentation (MRS) with scale of 0.5, shape of 0.01 and compactness of 0.03. These values were determined by using try and error test in study area, thus we could directly focus on
them. Additionally, algorithm concept in the classification was SVM, which was a guided classification technique based on linear classifier allowing to search for a proper hyperlane in both classes [26].

2.5 Accuracy test
In this stage, the result of classification was validated, enabling to compare the accuracy between standardized information and unvalidated images [27], and evaluate the accuracy of studied method for classification accuracy test, a total of 188 spots were randomly sampled, widespread throughout research sites. Validation was then performed, by comparing data from google earth and ground check. The accuracy of land use classification was assessed in both techniques using confusion matrix, consisting of overall accuracy (OA), Producer’s accuracy (PA), user’s accuracy (UA), and Kappa statistic [28].

3. Results and discussion
3.1 Classification using OBIA
The classification of images from Landsat 8 OLI using OBIA with SVM algorithm could produce object in multiscale segmentation process. Scale parameters served a key role in determining the number and size of the object. Furthermore, segmentation parameter affected object size according to area characteristics, but the object size might be over segmented and/or under segmented (figure 2). This leads to a significant effect on the result of land use classification. In this work, number and size of segmentation was determined by multiresolution segmentation (MRS) at scale 0.5, shape 0.01, and compactness 0.03. The results suggested that these features seemed to affect the outputs of land use classification.

![Figure 2. Over Segmentation (left) and under segmentation (right).](image)

Table 2. Classification of land use by object-based approach.

| Types of Land Use | Area (ha) | (%)  |
|-------------------|-----------|------|
| Water Body        | 80        | 2    |
| Follow land       | 487       | 3    |
| Built up land     | 2,635     | 4    |
| Residential area  | 6,417     | 21   |
| Vegetation        | 20,241    | 70   |
| Total             | 26,745    | 100  |

OBIA-based classification in images from Landsat (figure 3 and table 2) showed that vegetation area seemed to dominate the land use, reaching up to 70% (20,241 ha of total area 26,745 ha), followed by 6,417 ha for residential area (21%), 2,635 ha for built up land (4%), 487 ha for follow land (3%), and 80 ha for water body (2%).
3.2 Classification using pixel-based approach

Pixel-oriented classification is performed according to spectra characteristics which were then converted into digital number (DN); however, as previously mentioned, it may show less detail identification in defining an object. On the other hand, OBIA appears to be more powerful since the identification is not only based on spectra features, but also spatial features of the image. In short, OBIA enables to remove the so-called salt and pepper effects that are typical in the pixel-based classification (figure 4). Hence, this may affect the classification result and alter its accuracy of land use mapping. In this research, the algorithm was similar to that used in OBIA, i.e. SVM.

As presented in figure 5 and table 3, the results showed that vegetation dominated the land use up to 70% (19,439 ha of total area 26,745 ha). Meanwhile, housing area accounted for 22% (5,576 ha), followed by 422 ha for flood land (3%), 1,231 ha for built up land (5%) and 77 ha for water body (1%).
Table 3. Classification of land use assessed by pixel-based approach.

| Types of Land Use | Area (ha) | (%)  |
|-------------------|-----------|------|
| Water body        | 77        | 1    |
| Follow land       | 422       | 3    |
| Built up land     | 1,231     | 4    |
| Residential area  | 5,576     | 22   |
| Vegetation        | 19,439    | 70   |
| Total             | 26,745    | 100  |

3.3 Comparison of OBIA and pixel-based approach

We found classification errors present in both OBIA and pixel-based approach (figure 6). In pixel-based approach, the errors occurred in detecting built up land which was then classified as residential area, as well as residential area which was classified as body water.

Figure 5. Land use mapping by using pixel-based.

Figure 6. Comparison of classification errors in both approaches.
The errors may due to presence of atmospheric disturbances, i.e. clouds that contain water (aerosol). This results in salt and pepper effects, leading to a less accuracy in classifying the land use. On the other hand, classification errors from OBIA method were caused by object size that is too small, which may produce misinterpretation. This is a result of under segmentation process.

Based on difference in land use area between OBIA and pixel-based approach (table 4), it suggested that OBIA could perform better result in comparison with pixel-based approach, with the difference ranging from 0.802% to 1.404%. This was also augmented by the result of User’s Accuracy (UA), demonstrating that OBIA showed percentage at ranging from 0.22% (water body) to 0.95% (vegetation), while pixel-based approach showed percentage at ranging from 0.36% (follow land) to 0.85% (vegetation), with a difference from 0.06% (residential area) to 0.37% (follow land).

| Types of Land Use  | OBIA Area (ha) | Pixel Area (ha) | Difference (ha) | OBIA User's Accuracy (%) | Pixel User's Accuracy (%) | Difference |
|-------------------|---------------|----------------|----------------|--------------------------|--------------------------|-----------|
| Water body        | 80            | 77             | 3              | 0.22                     | 0.38                     | 0.16      |
| Follow land       | 487           | 422            | 65             | 0.73                     | 0.36                     | 0.37      |
| Built up land     | 2.635         | 1.231          | 1.404          | 0.64                     | 0.50                     | 0.14      |
| Residential area  | 6.417         | 5.576          | 0.841          | 0.67                     | 0.61                     | 0.06      |
| Vegetation        | 20.241        | 19.439         | 0.802          | 0.95                     | 0.85                     | 0.10      |

3.4 Accuracy test

The classification result was validated using confusion matrix, enabling to determine accuracy of data interpretation of image from Landsat 8 OLI compared with real condition. The result of accuracy test was properly mapped by using OBIA approach (table 5). This is in line with the high accuracy value from User’s Accuracy (US) of 61.11% and Producer Accuracy (PA) of 64.11%, with overall accuracy of 81.38%. These values can be a good indicator that OBIA approach offers a promising alternative for land use mapping, although classification errors still exist.

| Classification     | Residential Area | Vegetation | Built up land | Follow land | Water Body | Total | UA   |
|--------------------|------------------|------------|---------------|-------------|------------|-------|------|
| Residential Area   | 28               | 2          | 9             | 1           | 2          | 42    | 0.67 |
| Vegetation         | 2                | 106        | 1             | 2           | 1          | 112   | 0.95 |
| Built up land      | 3                | 0          | 9             | 1           | 1          | 14    | 0.64 |
| Follow land        | 2                | 0          | 1             | 8           | 0          | 11    | 0.73 |
| Water Body         | 1                | 2          | 2             | 2           | 2          | 9     | 0.22 |
| Total              | 36               | 110        | 22            | 14          | 6          | 188   |      |

PA: 0.78, UA: 0.96, OA: 0.41, PA: 0.57, OA: 0.33

Average user’s accuracy: 61.11%
Average producer’s accuracy: 64.11%
Overall accuracy: 81.38%
Kappa accuracy: 0.79 or 78.77%

Table 6 demonstrates that pixel-based approach showed percentage of UA and PA at 46.19% and 54.68%, respectively, with overall accuracy of 71.81%. This means that the classification that is oriented to pixel may generate higher number of errors in classifying the land use.
Table 6. Confusion matrix of pixel-based approach.

| Classification | Residential Area | Vegetation | Built up land | Follow land | Water Body | Total |
|----------------|------------------|------------|---------------|-------------|------------|-------|
| Residential Area | 20               | 8          | 3             | 2           | 0          | 33    |
| Vegetation      | 8                | 99         | 2             | 7           | 1          | 117   |
| Built up land   | 2                | 3          | 8             | 2           | 1          | 16    |
| Follow land     | 4                | 2          | 2             | 5           | 1          | 14    |
| Water Body      | 1                | 2          | 1             | 1           | 3          | 8     |
| Total           | 35               | 114        | 16            | 17          | 6          | 188   |
| UA              | 0.57             | 0.87       | 0.5           | 0.29        | 0.5        |

Average user’s accuracy: 46.19%
Average producer’s accuracy: 54.68%
Overall accuracy: 71.81%
Kappa accuracy: 0.69 or 69.16%

Comparison of land use classification obtained from OBIA and pixel-based approach demonstrated a noticeable difference, as presented by Kappa statistic of 78.77% and 69.16%, respectively. The highest classification value was attributed to OBIA; in contrast, the lowest one was attributed to pixel-based classification (table 6). This concluded that OBIA approach could generate a more desirable land use classification than pixel-based approach. As reported in earlier study [24], OBIA approach defines object classes according to spectra and spatial aspects which represent the aggregation of pixels, but pixel-based approach only depends on spectral aspect.

Table 7. Comparison of accuracy assessed by OBIA and pixel-based approach.

| Accuracy test               | OBIA (%) | Pixel (%) |
|-----------------------------|----------|-----------|
| Average user’s accuracy     | 61.11    | 46.19     |
| Average producer’s accuracy | 64.11    | 54.68     |
| Overall accuracy            | 81.38    | 71.81     |
| Kappa statistics            | 78.77    | 69.16     |

4. Conclusion
Based on our experimental data, the classification based on OBIA and pixel was acceptable using Landsat 8 OLI at resolution 30 for identification of land use; yet, classification errors still occurred, resulting in salt and pepper noise present in both techniques. Furthermore, the use of SVM algorithm for segmentation in OBIA-based classification could produce better accuracy in comparison with pixel-based classification, with an increase in accuracy of 9.51%. For this reason, we concluded that OBIA technique using SVM algorithm could serve as a satisfying alternative method for identification of land use in terms of its accuracy, effectivity, and efficiency.

Acknowledgment
Authors would like to express sincere appreciation to Ditjen Sumber Daya IPTEK dan DIKTI and Lembaga Pengelola Dana Pendidikan (LPDP) for financial support under scheme of Beasiswa Unggulan Dosen Indonesia Dalam Negeri (BUDI DN) scholarship given for research and graduate study.
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