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INTEGRATING OBJECT-BASED IMAGE ANALYSIS WITH ONTOLOGY FOR LAND USE LAND COVER CLASSIFICATION

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Abstract. *Object-based image analysis (OBIA) has emerged as a popular method for land use and land cover (LULC) classification from satellite imagery. Integrating ontology with OBIA has shown promise in improving the accuracy and efficiency of LULC classification. This approach involves developing domain knowledge with input from experts, generating classification rules using Semantic Web Rule Language (SWRL), and using ontology for LULC classification reasoning. In this study, we present the potential of OBIA with ontology for LULC classification. We demonstrate that the approach achieves an overall accuracy of over 80% with improved efficiency compared to conventional OBIA methods. The ontological model for image object properties uses OBIA with an ontological structure for further extension, feature extraction, rule generation, and ontology-based classification. The results of this study suggest that OBIA with ontology can be a useful approach for accurate and efficient LULC classification. Further research could explore its application to different regions and compare its performance with other classification techniques.*
Keywords: Object-based image analysis, Ontology, Land use and land cover, Satellite image

1. **Introduction.** Remote sensing technology is commonly employed for land use and land cover (LULC) classification, which involves the analysis of satellite image data. Two primary methods for analyzing image data are pixel based image analysis (PBIA) and object based image analysis (OBIA) [1,2]. The PBIA assigns the individual pixels to different geographic classes solely based on their reflectance values obtained from various spectral bands. This method does not make use of other spatial, geometrical, or contextual characteristics that could be valuable [3]. PBIA operates at the pixel level, which creates the issue of mixed pixels where a single pixel represents multiple types of image objects. As satellite image resolutions improve, the utilization of PBIA reduces because of concerns like the "salt and pepper" effect. In this effect, single pixels are incorrectly classified within a cluster of pixels that represent a specific class [4-6]. The change has occurred over a few years. Most classification method of LULC has been moved from PBIA to OBIA [7]. OBIA is a method used for analyzing satellite imagery that focuses on identifying and classifying image objects based on their spectral, spatial, and contextual features, rather than individual pixels. OBIA allows for more accurate and efficient analysis of satellite imagery, as it can account for mixed pixels and incorporate additional features beyond just spectral reflectance [8]. OBIA uses the feature values of image objects to establish rule sets that can categorize them into diverse classifications. This technique varies from PBIA approaches in that it considers several characteristics, such as spatial, textural,

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and contextual, in addition to spectral features to classify image objects. Object-based methods can be applied at multiple scales, making them more versatile than PBIA methods. One limitation of OBIA is the requirement for manual parameter tuning, which is not only subjective but also time-consuming. OBIA relies on a set of parameters, including scale, shape, and compactness, to determine the segmentation process. However, these parameters can vary depending on the image resolution, study area, and desired level of detail. Thus, users must manually adjust the parameters to achieve the optimal segmentation outcome, which can be a time-consuming and subjective process. To enhance the efficiency of classification, knowledge representation methods were employed to aid in the process, including forest classification, farmland classification, and ocean classification [9-11].

An ontology is a language for presenting knowledge that offers a particular lexicon for a given subject or field. It is a precise and unambiguous explanation of a shared understanding of a field that is established by specialists and intended to encourage interoperation, reuse, and distribution of domain expertise [12]. The Web Ontology Language (OWL) is a machine-readable language that is utilized for expressing and distributing ontologies. It allows ontologies to be exchanged and repurposed across various applications and systems. Description logic, a formal logic employed for knowledge representation, is the foundation for OWL. It offers an extensive array of constructs to establish classes, properties, and connections between them [13]. Reasoning engines can examine and uphold the logical coherence of an ontology by identifying and reporting any discrepancies, paradoxes, or other inaccuracies in the ontology. Commonly used reasoning engines for ontologies include Pellet, HermiT, and FaCT++ [14]. The Semantic Web Rule Language (SWRL) enables the development of conditional rules to supplement the reasoning abilities of semantic web reasoners [15]. These regulations are executed via a semantic reasoner, which uncovers new implications and integrates them into an established ontology.

This study integrates OBIA with ontology for LULC classification. The methodology involves constructing a domain ontology using OWL, writing SWRL rules, and using a semantic reasoner for object classification. Section 2 reviews related work, while Section 3 presents a case study of LULC in Phitsanulok, explaining the integration of OBIA with ontology. Section 4 discusses the results, and Section 5 concludes the paper, summarizing the study's implications. This study demonstrates the benefits of integrating OBIA with ontology, including enhanced accuracy, semantic understanding, flexibility, interoperability, and decision support for LULC classification.

2. Related Work.

2.1. **Image interpretation for LULC.** Image interpretation involves the analyzing of satellite or aerial images to identify and classify different types of LULC [16,17]. It can be for monitoring the changes of land use patterns [18] in particular area. In this interpretation, there are several steps including preprocessing the image to correct for distortions or atmospheric effects, segmenting the image into individual objects, extracting features from the objects, and classifying the objects into different land cover or land use categories using machine learning or rule-based approaches. Accuracy depends on various factors such as the spatial resolution, and the effectiveness of the classification algorithm. LULC classification can be applied and deployed as a tool for planning in the geographic area or sector such as environmental monitoring, urban planning, and natural resource management.

2.2. **OBIA with ontology.** OBIA is a technique commonly utilized for analyzing remote sensing imagery [16,19,20], which involves breaking down images into meaningful objects, such as buildings, roads, and fields [21-23]. To improve the accuracy and efficiency of image analysis, ontology has been integrated with OBIA [24]. An example of using the domain-specific ontologies is to verify the result of an image interpretation [25,26]. A domain ontology is created to capture the semantic relationships among the objects in the image. Then this semantic relation also provides an easiness to segment and classify the image. The inclusion of ontology enhances the precision of object classification and minimizes the computational burden associated with image analysis. Another example of OBIA with ontology is the use of ontologies to select features for object classification in remote sensing images [27]. In this approach, ontologies define a set of relevant features likely to be present in the image objects of interest, and these features are used to train machine learning algorithms for object classification. The use of ontology in this technique reduces the dimensionality of the feature space, which can improve the efficiency of machine learning algorithms for object classification. Overall, integrating ontology into OBIA has great potential for improving the accuracy and efficiency of image analysis in remote sensing applications. As technology advances, the use of ontology in OBIA is expected to become more widespread, leading to more precise and informed decision-making in various fields.

3. **Integrating OBIA for LULC Classification: A Case Study of LULC in Phitsanulok.** This section introduces the concept of using OBIA with ontology for LULC classification in satellite images. The workflow will be presented, and case studies conducted for this research will be described. Figure 1 illustrates the methodology for OBIA with ontology, which comprises the following steps.

Step 1: The initial step in the methodology involves preprocessing the image data, which includes tasks like atmospheric correction, noise removal, and georeferencing of satellite imagery. In this study, multi-temporal satellite data from the USGS Earth Explorer platform was utilized, which was captured on December 10, 2020, covering Path 130/Row 48, utilizing the Landsat 8 OLI. The data contained six spectral bands: Band 2 (blue, 0.450-0.51 μm), Band 3 (green, 0.53-0.59 μm), Band 4 (red, 0.64-0.67 μm), Band 5 (near-infrared, 0.85-0.88 μm), Band 6 (short-wave infrared 1, 1.57-1.65 μm), and Band 7 (short-wave infrared 2, 2.11-2.29 μm).

Step 2: Image Segmentation – The next step is to segment the image into meaningful objects using a segmentation algorithm. The multi-resolution segmentation algorithm is often utilized for this purpose and is configured with appropriate parameters [28] such as scale, shape, color, compactness, and smoothness to produce precise outcomes. The research focuses on the Muang District of Phitsanulok Province, Thailand, encompassing an area of 750.8 square kilometers. The district is located primarily in the lower and northern parts of the upper central region of Thailand, with the Nan River flowing through the city's center. The area is known for its diverse LULC, as displayed in Figure 2. The segmentation techniques applied in this study utilized the multi-resolution method and

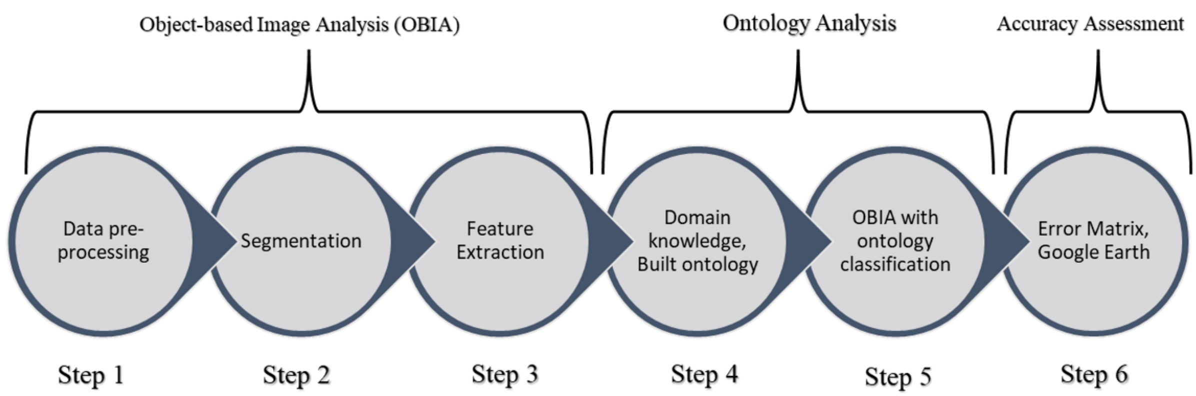


Figure 1. An overall methodological workflow for OBIA with ontology

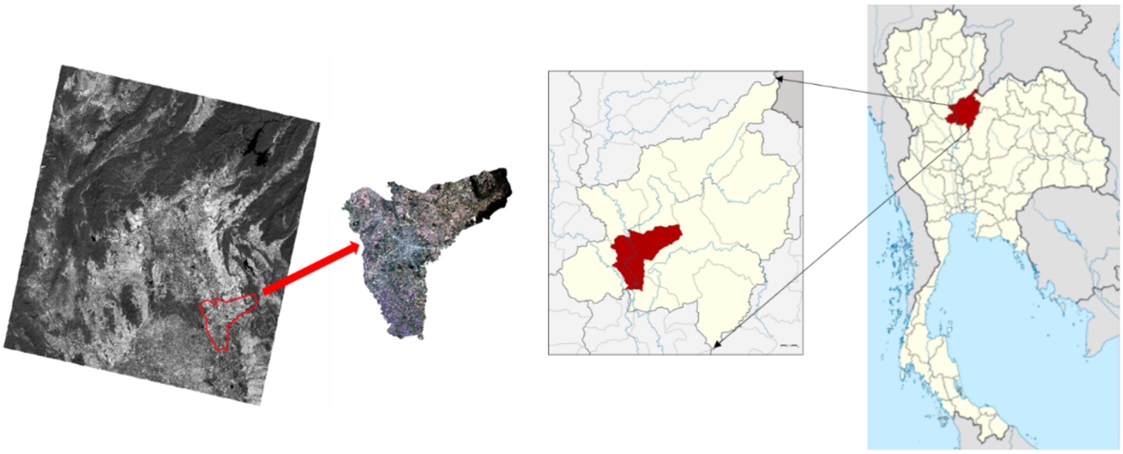
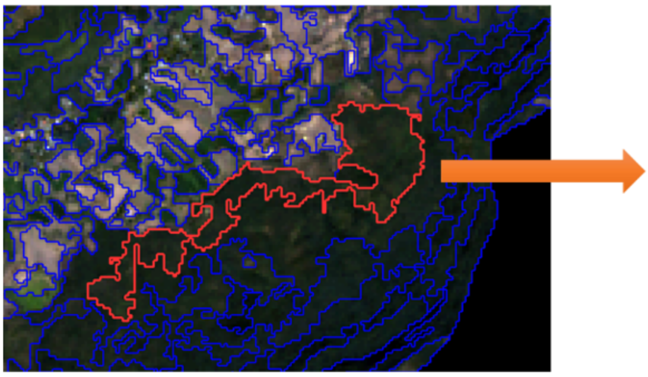


FIGURE 2. The geographical position of study area

were executed using eCognition Developer Version 9 software. Multispectral data (Bands 2-7) was used to perform a multi-resolution segmentation process to extract image objects. The scale parameter was set to 100, while the shape, color, compactness, and smoothness parameters were set to 0.1, 0.9, 0.5, and 0.5, respectively.

Step 3: Feature Extraction – After segmenting the image into objects, the next step is to extract relevant features from each object. The features that can be extracted from the segmented objects include mean wavelength, brightness, standard deviation, maximum difference, reflection values of specific spectral bands (Bands 2-7), as well as vegetation indices such as NDVI, NDWI, and NDBI (Figure 3). As an instance of feature extraction, areas that exhibit NDVI values of 0.3 or higher are potentially indicative of vegetation, while NDWI values greater than 0 may indicate water areas. Similarly, NDBI values greater than a certain threshold may indicate built-up areas, and so on.



Object features	Customized
NDBI	-0.1091
NDVI	0.3058
NDWI	-0.2943
Leyer Values	**Mean**
Brightness	10636.66
Band2	7909.12
Band3	8719.83
Band4	8502.60
Band5	15993.03
Band6	12846.32
Band7	9848.99

FIGURE 3. Examples of objects that can be classified as vegetation

Step 4: Create a domain-specific ontology for capturing LULC class knowledge in the methodology. This ontology is constructed with inputs from experts and research papers and provides a structured and consistent framework for organizing and representing knowledge. The process of ontology analysis involves the identification of concepts and relationships that exist within a particular domain of knowledge. In this study, the domain knowledge was derived from various sources related to LULC classification, such as documents, images, and expert information. The ontology was developed using Protégé 5.6.1, an open-source tool by Stanford University [29]. The ontology model is created by analyzing the structure of the domain using expert knowledge from various sources. In some

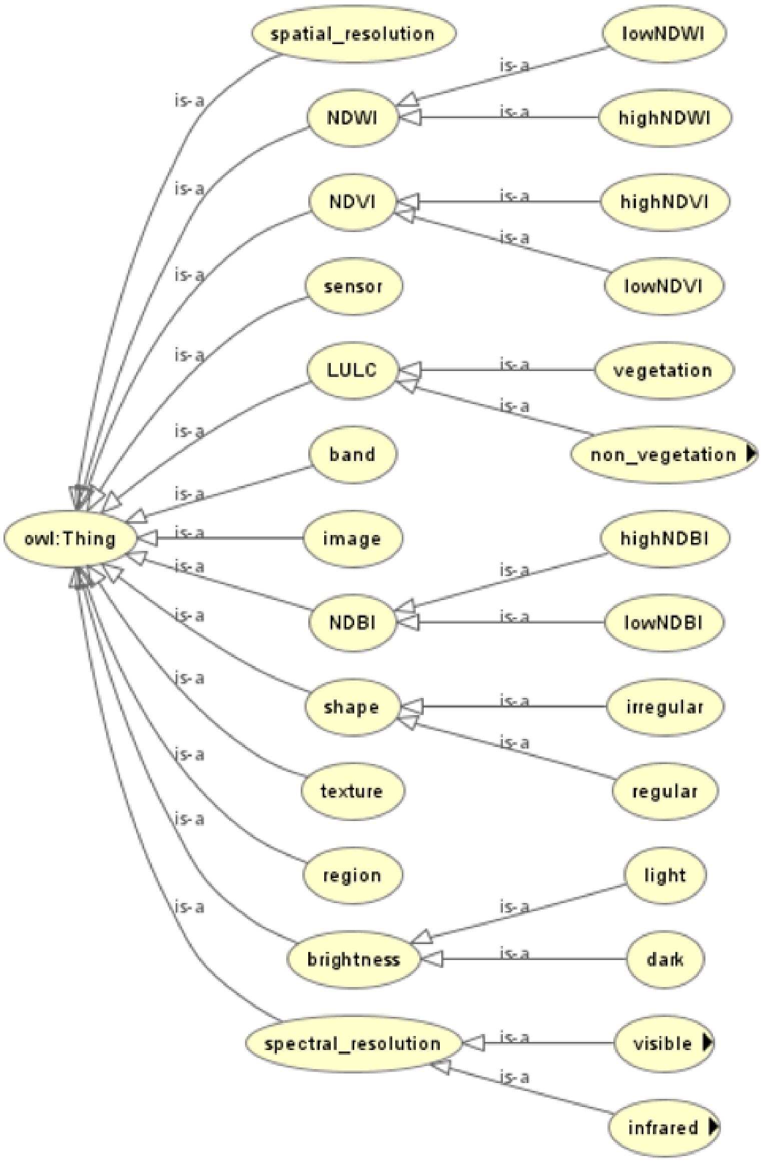


Figure 4. Ontology model for LULC

cases, satellite image data may be used, but it requires selecting or defining concepts and properties to include in the model. These properties, relationships, axioms, and associated instances are transformed into a machine-readable format using OWL and presented in Figure 4.

Step 5: Using OBIA with ontology for classification involves generating classification rules using an SWRL editor, which defines the relationships between features and LULC classes. The SWRL specification is used to create these rules, and a reasoner is utilized to execute them using reasoning tools. An example SWRL rule is presented below:

$$highNDVI\ (?\ x) \wedge dark\ (?\ x) \wedge rough\ (?\ x) \wedge irregular\ (?\ x) \rightarrow vegetation\ (?\ x)$$

In this context, a vegetation can be identified as an image object exhibiting highNDVI, dark, rough, and irregular. Here, C(?x) represents a class, where x is an individual belonging to that class. Taking vegetation as an example, the presence of dark, rough, irregular, and highNDVI characteristics indicates that the object should be classified as vegetation. SWRL can express an instance of the NDVI type as shown below:

$$NDVI\ (?\ x?\ y),\ greaterThanOrEqual\ (?\ y,\ 0.3) \rightarrow highNDVI\ (?\ x)$$

The formula means that when NDVI is greater than or equal to 0.3, the object is high-NDVI.

Step 6: Accuracy assessment: Finally, the reasoner is used to classify the objects based on the rules generated in the previous step. Additionally, we need to convert the OWL format file and SHP format file to obtain image objects in SHP format. The classification results are validated using ground truth data from Google Earth. To evaluate the accuracy of a classification result, a comparison is made between the result and data obtained from Google Earth, and Random Sampling is used. The standard error matrix is used to calculate various metrics, such as the overall accuracy (OA), producer accuracy (PA), user accuracy (UA), and Kappa statistics (K) (Equations (1)-(4)) [30,31].

$$OA = \frac{\textit{The count of pixels that are correctly classified}}{\textit{Total number of pixels}} \tag{1}$$

$$PA = \frac{\textit{Number of correctly identified pixels of a given class in the reference data}}{\textit{Number actually in that reference class}} \tag{2}$$

$$UA = \frac{\textit{Number of correctly identified in a given map class}}{\textit{The number of correctly classified pixels in the reference data for a given class}} \tag{3}$$

$$K = \frac{P_o - P_c}{1 - P_c} \tag{4}$$

where P_o = The proportion of units for which there is agreement, OA; P_c = Proportion of units expected to agree by chance.

4. Results and Discussion.

4.1. The result. The study area's feature classification using OBIA and OBIA with ontology is demonstrated in the results, as shown in Figure 5 and Figure 6.

Figure 5 illustrates the LULC classification result of the study area employing OBIA. The most extensive area of the study area is covered by vegetation, represented by the green color. The second most dominant category is bare soil, identified by the yellow color. The built-up area is displayed in red, while the water area has the smallest coverage, represented by the blue color. And Table 1 presents the range of user accuracy (UA) and producer accuracy (PA), where UA ranges from 69.57% to 100% and PA ranges from 65.51% to 92.30%. The UA values for specific categories indicate the reliability of the classification for users, with a higher UA indicating a more accurate classification. In particular, the water surface category had a UA of 100%, while the built-up area had a

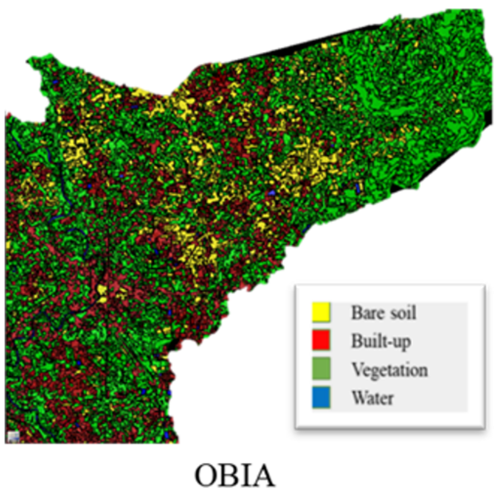


Figure 5. (color online) The result of OBIA classification

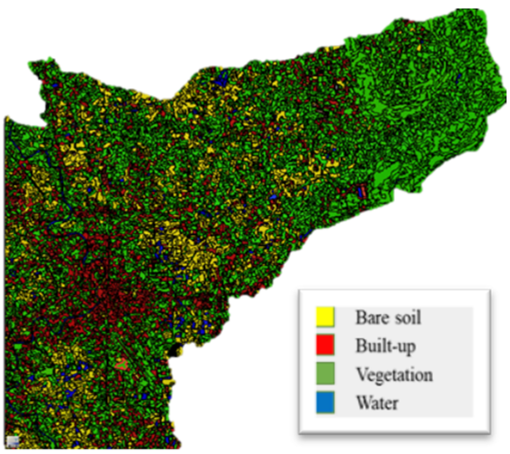
Table 1. Error matrix of LULC classification by OBIA

		Reference data from field						
		Vegetation	Water	Built-up	Bare soil	Total	PA (%)	UA (%)
Classified image	Vegetation	36	2	2	4	44	92.3	81.82
	Water	0	7	0	0	7	70.00	100
	Built-up	1	0	16	6	23	72.72	69.57
	Bare soil	2	1	4	19	26	65.51	73.07
	Total	39	10	22	29	100		
	OA (%)	**78.00**						
	Kappa (%)	**77.55**						

Note that PA refers to producer accuracy, UA refers to user accuracy, OA refers to overall accuracy, and Kappa refers to kappa coefficient.

UA of 69.57%. On the other hand, PA reflects pixels that are classified in a category but do not belong to that category.

Figure 6 depicts the results of LULC classification in the study area using OBIA with ontology. The dominant land cover type is vegetation, which is represented by the green color. Bare soil, represented by the yellow color, is the second most dominant category. The built-up area is displayed in red, while the water area has the smallest coverage, represented by the blue color. It should be noted that the number of yellow areas representing bare soil has decreased, while the number of red areas representing built-up areas has increased. Table 2 presents the overall accuracy between the OBIA method and the integration of OBIA with ontology. The findings indicate a significant enhancement in classification accuracy through the integration of ontology with OBIA. Specifically, the overall accuracy value for the generated category improved from 78% to 81%. The UA and PA for the generated classification demonstrated notable performance, reaching as high as 73.91% and 77.27% respectively. Moreover, the classification of bare soil, vegetation, and water areas also exhibited improved accuracy compared to the traditional OBIA method. It is important to note that although misclassifications may occur due to incomplete knowledge of OBIA with ontology, the classification results obtained using this integrated approach are slightly superior to those achieved with the traditional OBIA method, and the difference is not significant.



OBIA with Ontology

Figure 6. (color online) The result of OBIA with ontology classification

Table 2. Error matrix of LULC classification by OBIA with ontology

	Reference data from field							
		Vegetation	Water	Built-up	Bare soil	Total	PA (%)	UA (%)
Classified image	Vegetation	36	2	2	4	44	92.3	81.82
	Water	0	7	0	0	7	77.78	100
	Built-up	1	0	18	5	24	77.27	73.91
	Bare soil	2	0	3	20	25	70.00	80.77
	Total	39	9	23	29	100		
	OA (%)	**81.00**						
	Kappa (%)	**80.61**						

Note that PA refers to producer accuracy, UA refers to user accuracy, OA refers to overall accuracy, and Kappa refers to kappa coefficient.

4.2. **Discussion.** Three issues have arisen, with the first one being related to the marginal improvement in classification accuracy that can be achieved by using ontology with OBIA. Nevertheless, it is essential for human operators and software agents to comprehend the intricate structures involved. Ontological frameworks enable in-depth knowledge analysis and explicit ontologies, which promote the reuse of common ontology frameworks and expand the knowledge domain in other areas. The LULC ontology model caters to the specific requirements of different problem domains based on geographic models and enhances the semantic comprehension of land cover types. Expert image interpretation in geographic domains necessitates parameter fine-tuning based on the problem domain [32]. Ontology-classified OBIAs proficiently identify regional disparities in changing land use and land cover. Integrating building map data into the knowledge domain resulted in improved building-related classification accuracy and overall accuracy exceeding 80%, Table 2 presents the improvements in classification results achieved by using OBIA with ontology for the study area.

The second issue concerns the potential impact of random sampling on the accuracy of LULC classification. Both large and small sampling approaches can be effective, depending on the research question and study objectives. Large sampling provides a broad overview of the study area, while small sampling offers a more detailed and accurate assessment of specific areas or features of interest [33]. The choice of sampling method should consider the research question, study objectives, and data availability and quality.

The last issue concerns the possible future directions for utilizing OBIA with ontology for LULC classification. These include integrating additional data sources, examining alternative ontological frameworks, refining OBIA algorithms, comparing the approach to alternative classification techniques, and extending the methodology to other geographic regions. Exploring these opportunities for further research may enhance our comprehension and capability to accurately classify LULC.

5. **Conclusion.** The objective of this study was to use OBIA and ontological techniques for classifying LULC using Landsat 8 satellite imagery. The OBIA analysis involved using multi-resolution segmentation with specific configuration parameters, allowing for feature extraction based on wavelength reflection properties and establishing a hierarchical structure for data classification. The features were determined using properties such as mean wavelength, brightness, and reflection values of specific bands, along with vegetation difference indices like NDVI, NDWI, and NDBI. Four LULC types were classified: vegetation, water, bare soil, and built-up areas. Domain knowledge and ontology concepts were developed using input from experts and relevant information such as building information. Classification rules were established using SWRL language, leading to improved classification demonstrated in Table 2. The integration of OBIA with ontological

analysis resulted in successful LULC classification with over 80% overall accuracy in the study area. The ontology approach proved to be more efficient in LULC classification than traditional OBIA methods, as indicated by the high kappa coefficient of 80.61, signifying good agreement between the classification results and ground truth data from Google Earth.

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