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by Anang Wahyu Sejati

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An object-based image analysis in QGIS for image classification and assessment of coastal spatial planning ☆

Abdurrahman Zaki [a,*], Imam Buchori [b], Anang Wahyu Sejati [b], Yan Liu [c]

[a] Center of Geomatics Application for Sustainable Development, Diponegoro University, Indonesia
[b] Department of Urban and Regional Planning, Diponegoro University, Indonesia
[c] School of Earth and Environmental Sciences, The University of Queensland, Australia

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ABSTRACT

In practice, urban and regional planners often use a pixel-based method for image classification. Unfortunately, it produces lower accuracy than an Object-Based Image Analysis (OBIA) method, especially for the high-resolution images. To assess spatial planning, scholars rarely used the OBIA method in open-source software. This paper aims to develop a method for classifying land cover and assessing coastal spatial planning. We used Sentinel-2A in 2015 and 2020 as the basic data. For image classification, we used the OBIA method in Quantum GIS (QGIS) 3.10.6 and Orfeo ToolBox 7.1.0. Furthermore, we used Artificial Neural Network (ANN) and Cellular Automata (CA) algorithms in QGIS 2.18.20 for projecting future land cover change, and then used the projected land cover map to assess the spatial planning in 2031. The results show that the OBIA method is useful for image classification, achieving 94.50 and 90.98 percent of the overall accuracy for the imageries in 2015 and 2020, respectively. Our coastal spatial planning assessment shows that the plan has not considered adequately the rapid land cover change of the region, especially the increase in waterbodies. We advocate that the local government should consider this issue when evaluating the spatial planning. The methodology using an open-source software such as QGIS in a developing country context also provides a promising exemplar that other local governments can use for assessing their spatial planning.

1. Introduction

Coastal areas are only 10 percent of the mainland of the earth but they are home for 60 percent of the global population (Lakshmi and Rajagopalan, 2000). The agglomeration of population drives the growth of residential and economic activities in coastal cities (Nurhidayah and McIlgorm, 2019; Rudiarto et al., 2018; W. Wang et al., 2014). Consequently, it also drives uncontrolled urban sprawl in the coastal regions, which typically may cause a loss of green open spaces and threaten the sustainability of the environment (Sejati et al., 2019). To minimize the risk of urban sprawl, government should implement effective policies (Belfiore, 2003) such as spatial planning (Buchori et al., 2020; Buchori et al., 2018b). However, spatial planning in developing countries is often unable to effectively control the sprawl of the built-up areas (Al shawabkeh et al., 2019; Buchori et al., 2020; Buchori et al., 2018b). One of the causes of the ineffectiveness of the spatial planning is a lack of consideration for the urban sprawl and the projection of future land cover change (Hakim et al., 2020).

A methodology used in the assessment of spatial planning consists of classifying imageries, projecting future land cover map, and comparing the outcome of the projection with the map of the spatial planning (Amri et al., 2017; Hakim et al., 2020). From the perspective of urban and regional planning practices, a pixel-based image analysis is a commonly used method for image classification (e.g., Al shawabkeh et al., 2019; Amri et al., 2017; Hakim et al., 2020; Sejati et al., 2019; Sejati et al., 2020). However, the pixel-based method has a ''salt-and-pepper effect'' problem creating scattered pixels that are incorrect in their land cover classification (Duro et al., 2012; Kotaridis and Lazaridou, 2020; Yu et al., 2006). This problem can lead to lower accuracy of the classified land cover maps compared to an Object-Based Image Analysis (OBIA) method (An et al., 2007; Chen et al., 2007), especially when applied to

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* Corresponding author.
E-mail addresses: abdurrahman.zaki20@pwk.undip.ac.id (A. Zaki), i.buchori@live.undip.ac.id (I. Buchori), anang@live.undip.ac.id (A.W. Sejati), yan.liu@uq.edu.au (Y. Liu).

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classification of high-resolution imageries (Kong et al., 2006; Lackner and Conway, 2008). The implementation of the OBIA method for spatial planning assessment can improve the quality of urban and regional planning in practice.

Despite its advantages, the OBIA method has several technical challenges. This method requires large amount of computer memory during the process of image segmentation (Whiteside et al., 2011), long processing time of trial-and-error for classifying land cover maps (Johnson and Jozdani, 2021), and optimal parameters for the size of training samples (Ma et al., 2015; Ma et al., 2017). The development of software or tools for applying the OBIA method is needed to solve those technical problems. However, many scholars have been using eCognition/Definiens software for image classification (Blaschke, 2010) and little attention has been given to the use of the OBIA method in open-source software, such as QGIS (Quantum GIS), for assessing a map of spatial planning. Therefore, this paper aims to fill this knowledge gap by contributing an insight into the implementation of the OBIA using an open-source software for assessing regional spatial planning, and for urban and regional planning studies more broadly.

2. Study area and dataset

2.1. Study area

Semarang Metropolitan Region (SMR) has the fourth-largest population in Indonesia and is the capital city of Central Java Province. The region is experiencing rapid land cover change, especially along the national roads within the region (Sejati et al., 2019; Sejati et al., 2020). For example, there are several new clusters of housing and industry in areas surrounding Jakarta-Surabaya road and toll gates in the northern coast of the region in the last five years. To simulate the rapid land cover change in the northern coast of the region, we draw our study area to be within 8 km from the north coast (Fig. 1).

2.2. Dataset

The main dataset used in this study includes three Sentinel-2A imageries with the tile number of T49MCN, taken on October 7th 2015 (02:59:46), September 6th 2019 (02:35:51), and April 23rd 2020 (02:35:51). These imageries were downloaded from the website of European Space Agency (https://www.copernicus.eu/). Given that some part of the 2020 imagery has cloud cover, we used the 2019 classified imagery to replace those areas covered under cloud to produce the final 2020 classified imagery.

The second dataset is the training and testing samples, which we collected through field photographic observations and Google Imagery. We used the training samples to classify the land cover maps in 2015 and 2020, and used the testing samples to assess the accuracy of the image classifications. The accuracy assessment was conducted by comparing the classified images with the testing samples.

The third dataset is a group of spatial variables used as driving factors of land cover change. We adopted six spatial variables as driving factors of land cover change from Kusniawati et al., (2020) – including distance from the river, distance from the built-up area, population density, and distance from the road - and added two spatial variables including land value and slope level (Fig. 2). This dataset was collected from various sources, such as Development Planning Agency of Central Java Province, National

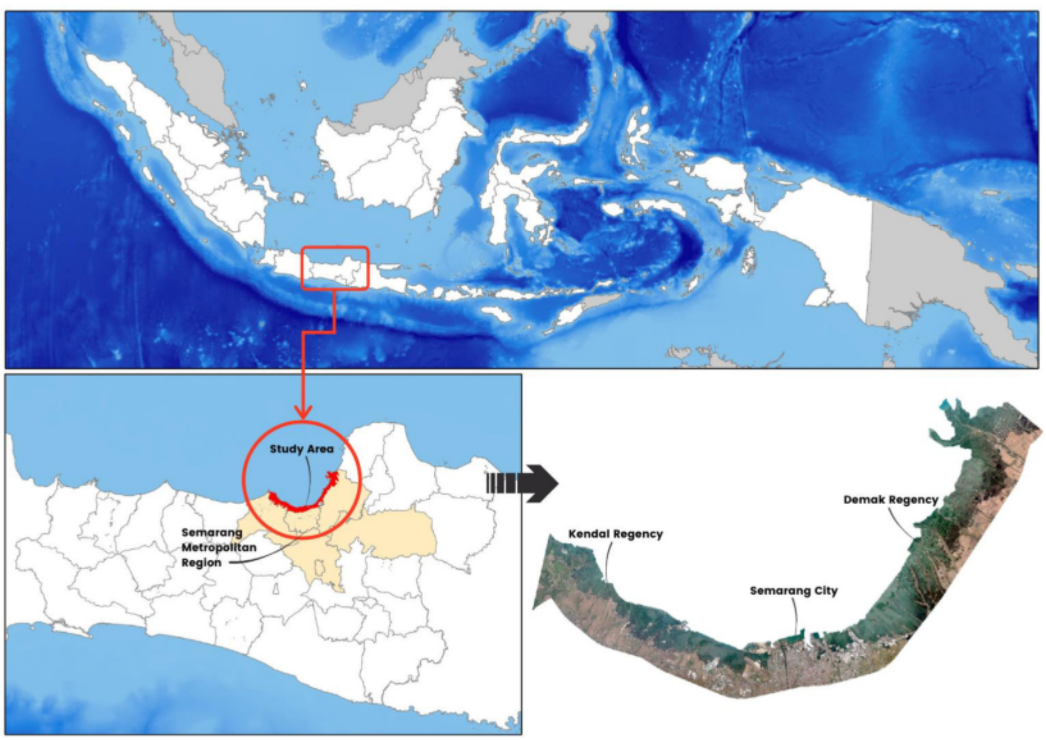

Fig. 1. The study area (Source: diva-gis.org, Central Bureau of Statistics, and Sentinel-2A imagery).

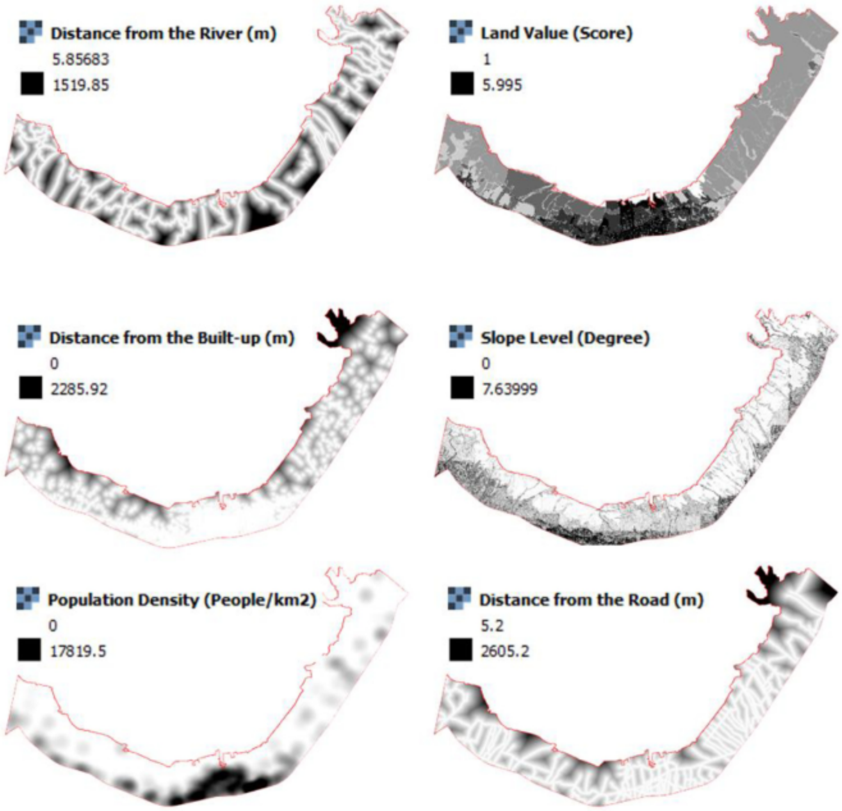

Fig. 2. The spatial variables used for land cover prediction.

Land Agency, Geospatial Information Agency, and Central Bureau of Statistics. All spatial variables were processed using several methods, namely Euclidean distance analysis, unsupervised classification, slope analysis, and kernel density estimation.

The fourth dataset used is a set of maps of the spatial planning of the city and regencies within the study area (Semarang City, Kendal Regency, and Demak Regency) in 2031. The classified land cover maps in 2015 and 2020 were used for the projection of future land cover maps in 2025 and 2030. Thereafter, the projected land cover map in 2030 was compared with the map of spatial planning in 2031 to evaluate concordance between the spatial planning and the projected land cover change scenario.

3. Methodology

The methodology we use consists of three components: image classification, projection of future land cover patterns, and spatial planning assessment (Fig. 3). Prior to the image classification, we performed calculations using a raster calculator tool in QGIS 3.10.6 (https://www.qgis.org/en/site/forusers/download.html) to convert some band combinations of Sentinel-2A imageries into three indexes: MNDWI (Modified Normalized Difference Water Index), NDTI (Normalized Difference Tillage Index), and NDVIre (Red-Edge-Based Normalized Difference Vegetation Index) using the following equations (Osgouei et al., 2019). We then combined the three indexes to generate a single layer termed MNDWI-NDTI-NDVIre multi-index imagery in 2015 and 2020, respectively. The combination is achieved by assigning MNDWI (representing waterbodies) as band 1, NDTI (representing built-up areas) as band 2, and NDVIre (representing vegetation cover) as band 3.

$$MNDWI = \frac{((Green - SWIR1))}{((Green + SWIR1))}$$

$$NDTI = \frac{((SWIR1 - SWIR2))}{((SWIR1 + SWIR2))}$$

$$NDVIre = \frac{((RedEdge1 - Red))}{((RedEdge1 + Red))}$$

Note: In Sentinel-2A imagery, Green is band 3, SWIR1 (Shortwave Infrared 1) is band 11, SWIR2 (Shortwave Infrared 2) is band 12, Red is band 4, and RedEdge1 is band 5.

The second step in the image classification was image segmentation using Orfeo ToolBox plugin (https://www.orfeo-toolbox.org/download/) and QGIS 3.10.6. This converts pixels with similar characteristics into a polygon (Thomas et al., 2003; Wang et al., 2004). With limited literature discussing about the parameters of image segmentation using Orfeo ToolBox plugin (Kotaridis and Lazaridou, 2020), we made extensive trial-and-error experiments to find the optimal parameters of the image segmentation, which

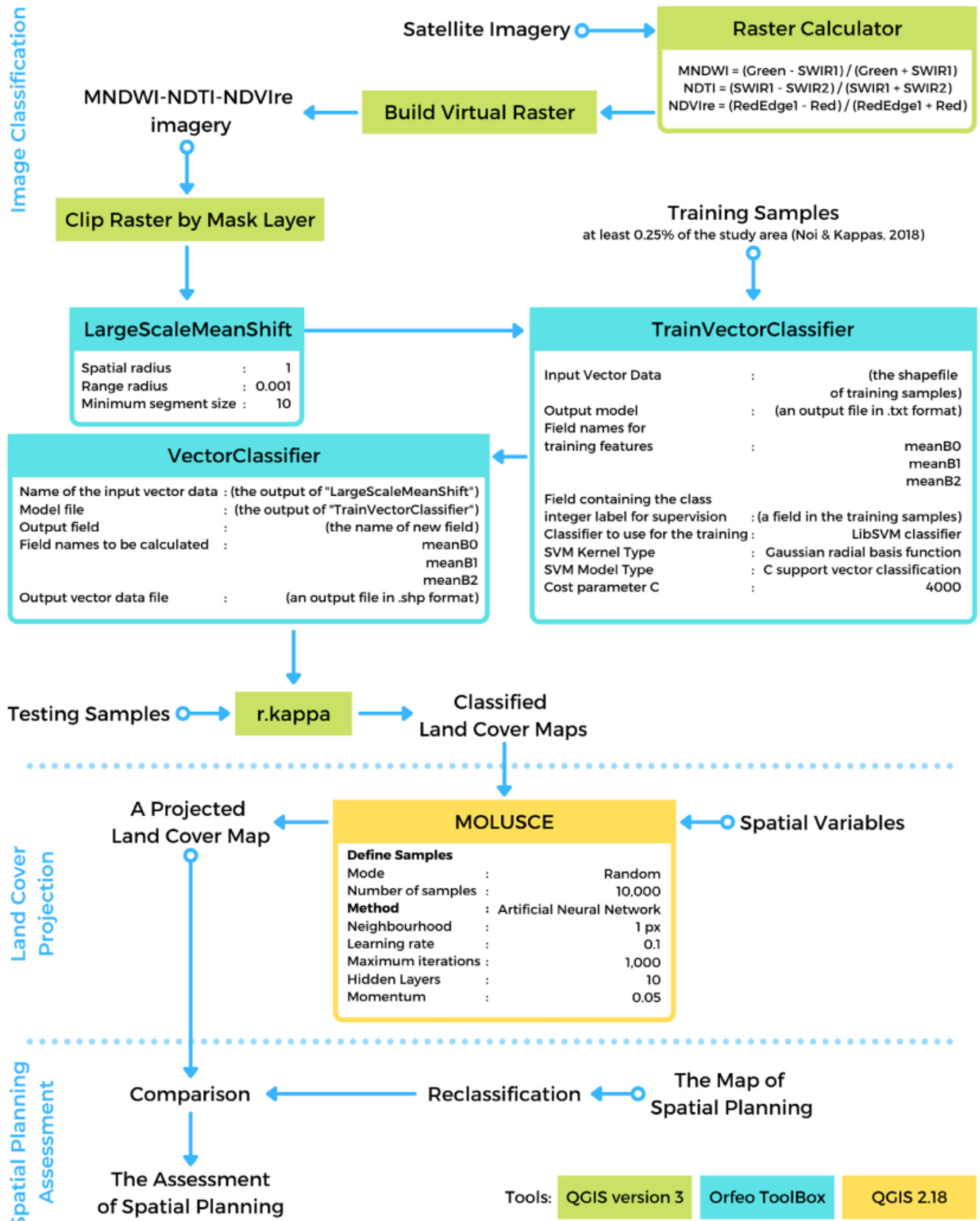

Fig. 3. The workflow of OBIA in QGIS for image classification and assessment of spatial planning.

is time-consuming. The optimal parameter settings we used in the Orfeo ToolBox plugin are: 1 for spatial radius, 0.001 for range radius, and 10 for minimum segment size. This step converted the MNDWI-NDTI-NDVIre imageries in 2015 and 2020 into polygons (Fig. 4).

The next steps in the image classification were the classification of land covers using training samples and the assessment of land cover maps using testing samples. Noi and Kappas (2018) suggested that the training samples should be at least 0.25 percent of the study area, randomly distributed, and outside a radius of 15 m from the testing samples. Based on the average spectral value of pixels in each polygon from the image segmentation, the training samples were then used to classify each land cover imagery using a Support Vector Machine and Radial Basis Function

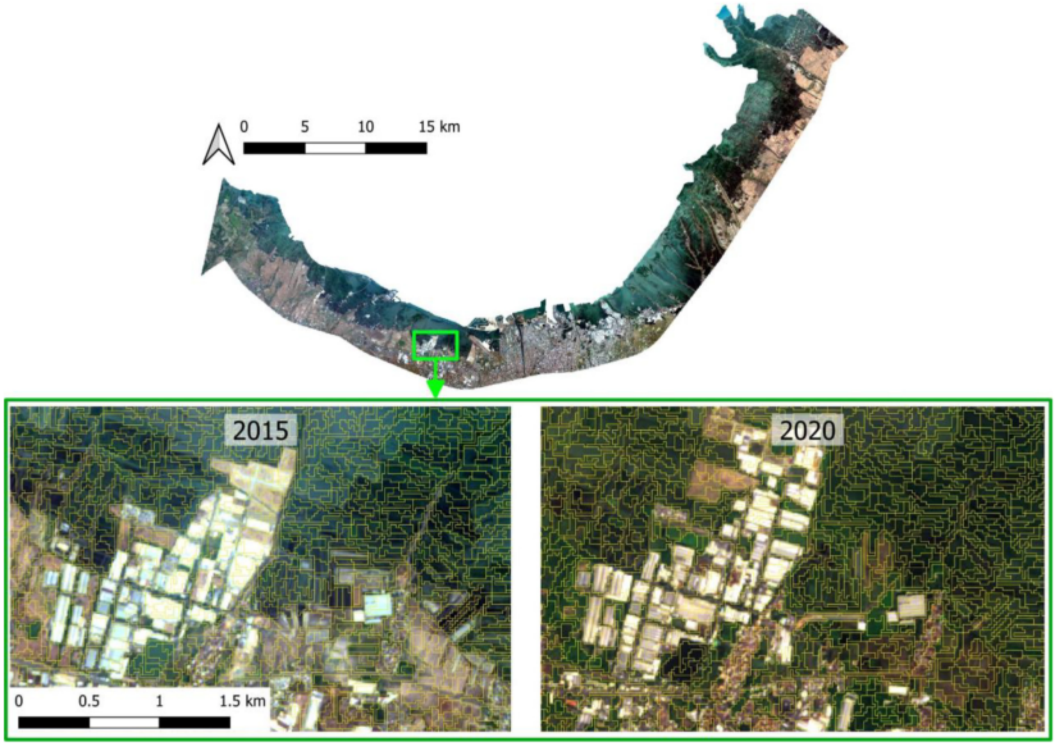

Fig. 4. The outcome of image segmentation in 2015 and 2020.

(SVM-RBF) algorithm in QGIS (Laban et al., 2019; Noi and Kappas, 2018). Thereafter, the overall accuracy and the kappa statistics of land cover maps in 2015 and 2020 were measured using the testing samples.

To project future land cover maps, we used MOLUSCE (Modules for Land Use Change Evaluation) plugin in QGIS 2.18.20. This software plugin has been used by a large number of scholars for projecting future land cover maps (e.g., Issiako et al., 2021; Kusniawati et al., 2020; Rahman et al., 2017; Reddy et al., 2019; Satya et al., 2020). It uses Artificial Neural Network (ANN) for simulating the land cover change from one class to another and cellular automata (CA) for simulating future land cover maps (Kusniawati et al., 2020; Rahman et al., 2017; Satya et al., 2020). Furthermore, it calculates Pearson's correlation between the spatial variables of land cover change and the probability of each land cover changing to other land covers. The final step was the assessment of spatial planning, which was conducted by superimposing the projected land cover map in 2030 and the map of spatial planning in 2031. Thereafter, we compared the two maps based on a pixel-by-pixel based comparison.

4. Results

Using the OBIA method, we achieved an overall accuracy of 94.50 and 90.98 percent for the classification of the land cover maps in 2015 and 2020, respectively (Table 1). The overall accuracy indicates that most of the testing samples have been correctly classified to a land cover type. Table 2 shows the classification accuracy for each land use categories. Overall, waterbodies, paddy fields and bare land, and built-up areas have more than 70 percent agreement (*kappa* > 0.70), indicating substantial agreement between the outcomes of image classification and the testing samples. On the other hand, canopies have a low agreement (*kappa* < 0.30) in both years due to these reasons: (1) most of

Table 1
The accuracy of simulated land cover maps in 2015 and 2020, assessed by comparing the outcomes of image classification to the testing samples.

Year	Land Cover Class	Errors of Comission (%)	Errors of Omission (%)	Estimated Kappa	Kappa	Kappa Variance	Objects Correct	Total Objects	Observed Correct (%)
2015	(1) Waterbodies	0.81	3.52	0.98	0.91	0.00	48,650	51,583	94.50
	(2) Paddy fields and bare land	10.23	7.63	0.86					
	(3) Canopies	70.26	47.29	0.29					
	(4) Built-up areas	9.10	7.35	0.89					
2020	(1) Waterbodies	11.02	1.85	0.77	0.85	0.00	39,310	43,207	90.98
	(2) Paddy fields and bare land	4.71	23.96	0.93					
	(3) Canopies	100	100	0.00					
	(4) Built-up areas	4.06	0.96	0.95					

Table 2
Statistics showing the area of each land cover of the simulated and projected land cover maps in 2015–2030.

Classification	2015 (ha)	2020 (ha)	2025 (ha)	2030 (ha)	Δ 2015-2020 (ha)	Δ 2020-2025 (ha)	Δ 2025-2030 (ha)
Waterbodies	15,967.40	18,996.90	19,943.26	20,500.09	3,029.50	946.36	556.83
Paddy fields and bare land	15,282.90	9,737.36	7,816.20	6,803.67	−5,545.54	−1,921.16	−1,012.53
Canopies	630.28	1,428.06	1,459.73	1,468.12	797.78	31.67	8.39
Built-up areas	5,909.65	7,627.92	8,571.04	9,018.35	1,718.27	943.12	447.31

our testing samples of canopies were drawn from trees growing on land; and (2) mangroves at the edge of the coast were correctly classified into "canopies" but trees/forest on land were classified into "paddy fields and bare land". We suggest that future studies involve addressing this issue if they are using MNDWI-NDTI-NDVIre imageries for image classification.

In general, the land cover maps simulated by the OBIA method are relevant to the existing land use based on the knowledge of the authors (Fig. 5). One of the factors driving the rapid land cover change in the study area is the construction of toll road connecting Semarang (in the center of the study area) to Batang (in the western part of the study area). The construction began on June 17th 2016 and finished on December 20th 2018. Other factors driving the land cover change in the study area are tidal flooding, land subsidence, a land reclamation project, and the development of industrial cluster on the northern coastal region in the study area. The tidal flooding (at a rate of 4–14 mm/year) and the land subsidence (at a rate of 60–120 mm/year) are suspected of causing the

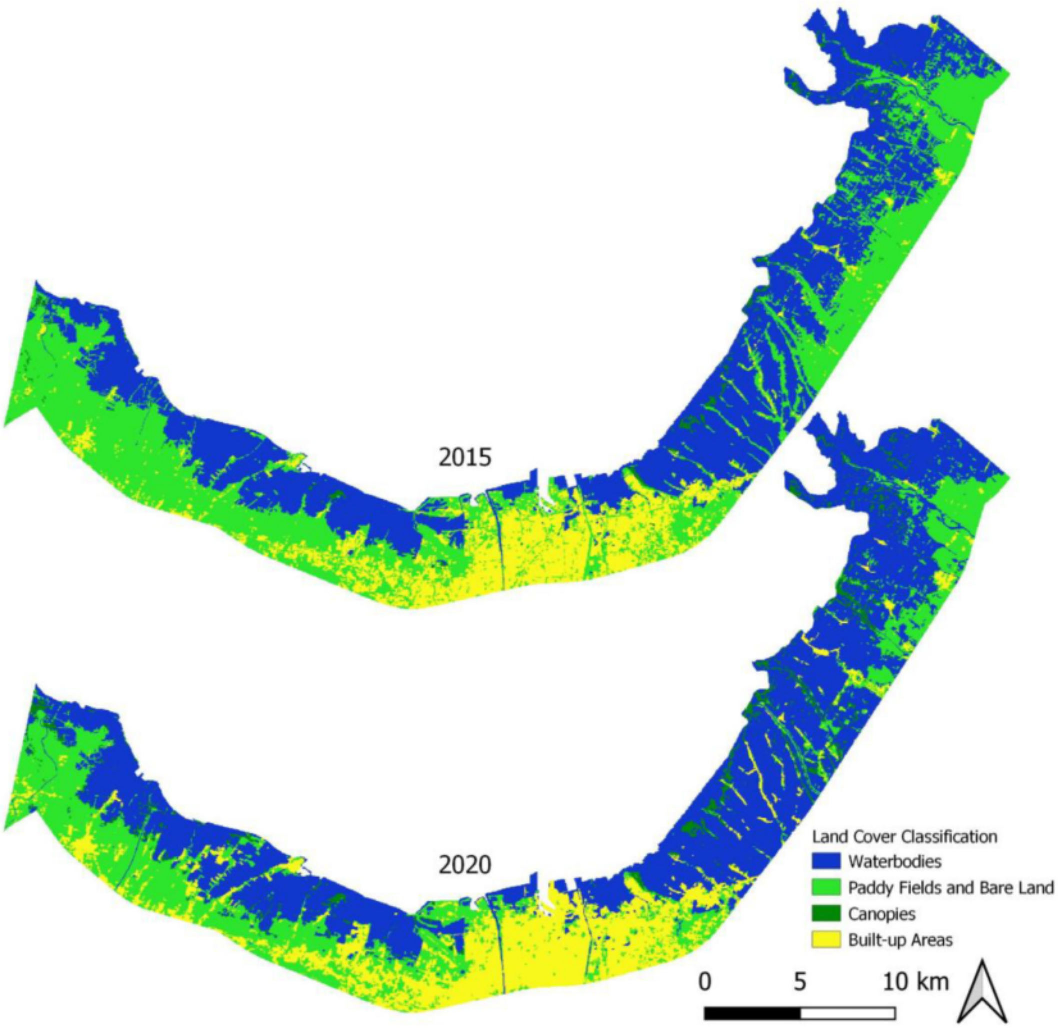

Fig. 5. The outcome of image classification in 2015 and 2020.

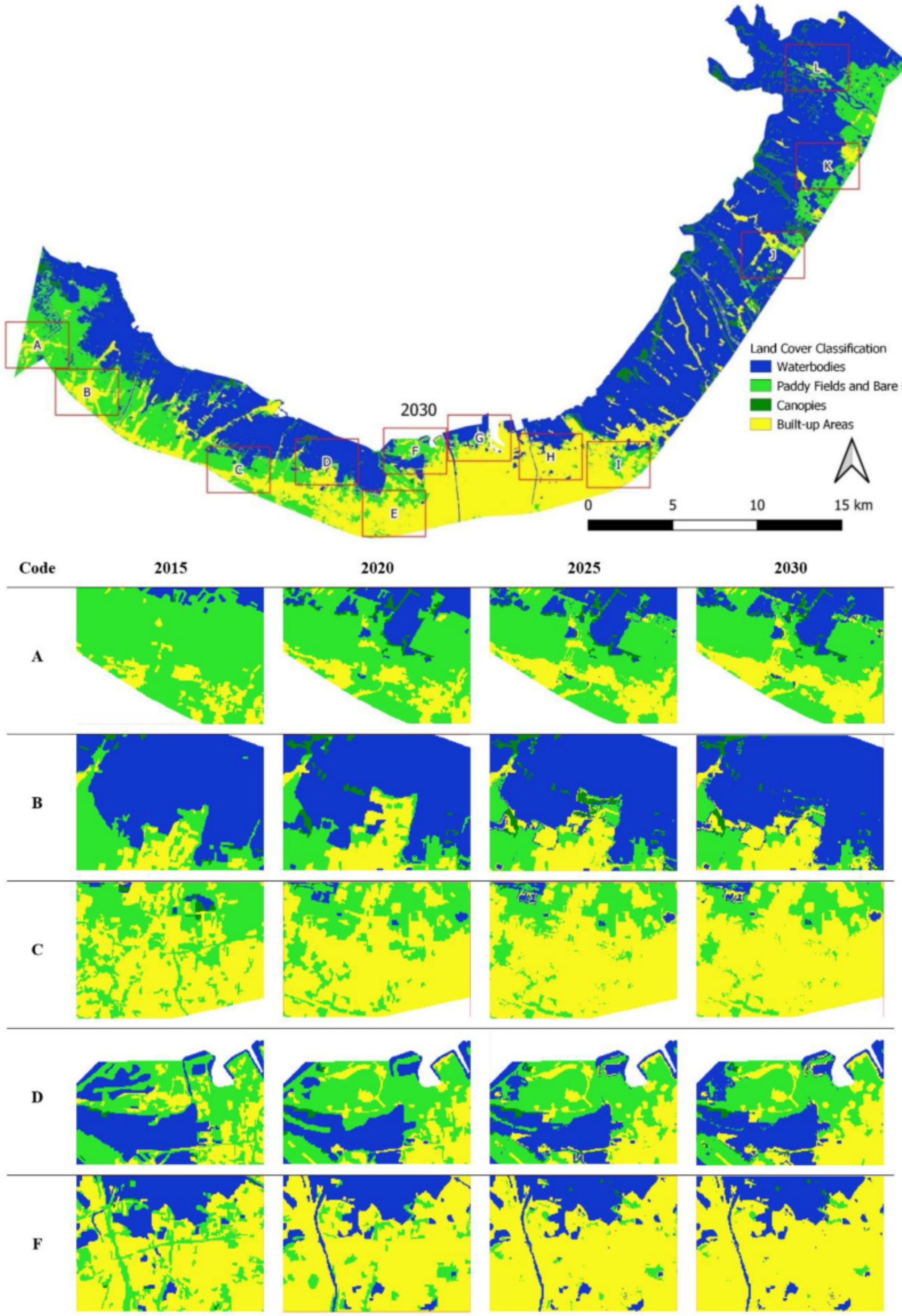

Fig. 6. Land cover changes in areas surrounding the toll gates and the land reclamation project during 2015–2030.

Table 3
Pearson's correlation between spatial variables.

Pearson's Correlation	Distance from the rivers	Land value	Distance from the built-up areas	Slope level (degree)	Population density	Distance from the roads
Distance from the rivers		0.09	−0.14	0.05	0.28	−0.14
Land value			−0.24	0.15	0.45	−0.14
Distance from the built-up areas				−0.17	−0.34	0.75
Slope level (degree)					0.26	−0.12
Population density						−0.26
Distance from the roads						

Table 4
Transition Probability Matrix.

	Land Cover	2020 Waterbodies	Paddy fields and bare land	Canopies	Built-up areas	Total
2015	Waterbodies	0.93	0.03	0.03	0.01	1.00
	Paddy fields and bare land	0.25	0.57	0.04	0.14	1.00
	Canopies	0.40	0.10	0.49	0.02	1.00
	Built-up areas	0.02	0.09	0.00	0.89	1.00

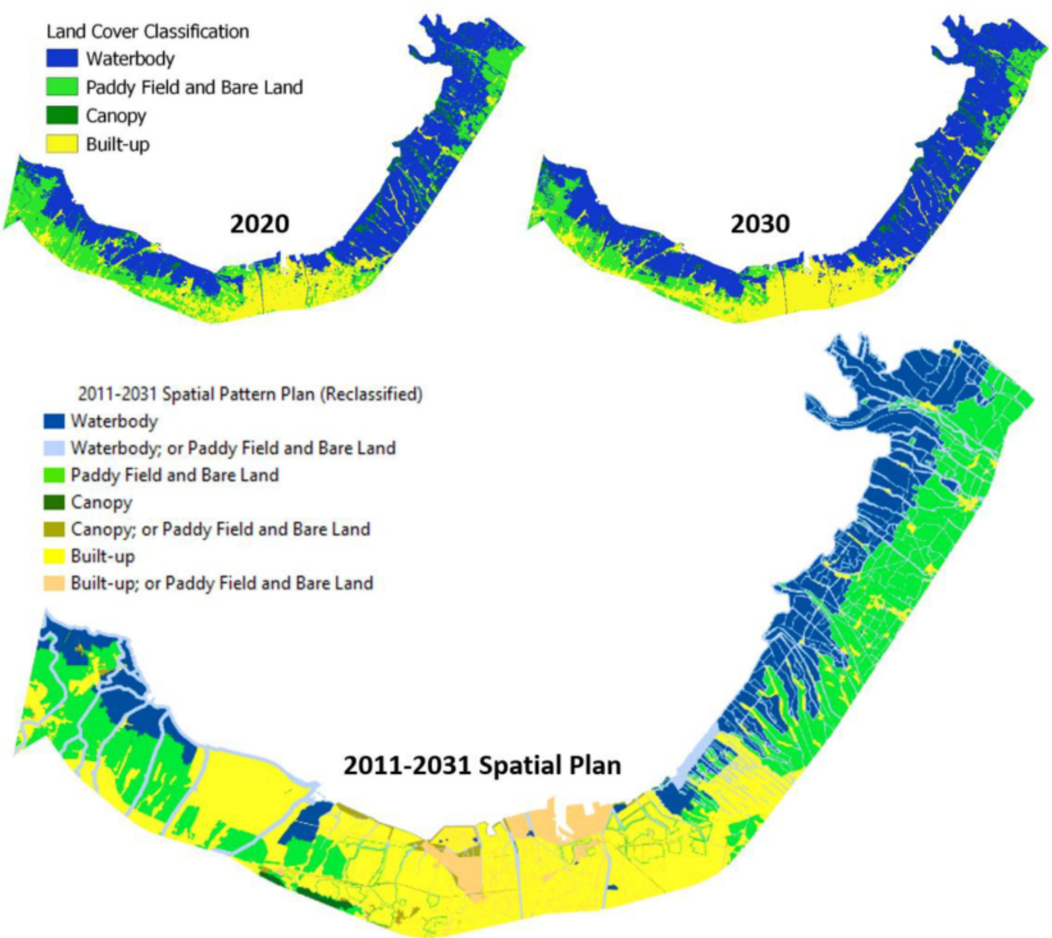

Fig. 7. A visual comparison of the simulated land cover maps in 2020 and 2030 to the spatial planning in 2031.

increase in the area of waterbodies (Bott et al., 2021; Buchori et al., 2018b), especially in Semarang and Demak, the middle and the eastern part of the study area.

The outcome of the projection of land cover map in 2030 (Fig. 6) shows an increase in the density of the built-up areas in Semarang and the development of the built-up areas along the national road connecting Semarang to Demak. There are significant or noticeable land cover changes in several locations coded by the letters A-F. Toll gates (the letters A, C, F) and a land reclamation project (B, D, F) are included in those locations. The projected land cover map in 2030 shows that there will be an expansion of the built-up areas in areas surrounding the toll gates and a threat of coastal erosion due to tidal flooding in areas surrounding the land reclamation project. The statistics of the current and projected land cover changes (Table 5) typically suggest that there is a decrease in green open spaces and an increase in built-up areas.

Most of the variables have negligible correlation (Pearson's correlation = 0.00 to 0.30 or −0.00 to −0.30), but there are three pairs of variables having higher correlation (Table 3). For example, there are a low positive correlation between land value and population density (Pearson's correlation = 0.30 to 0.50), a low negative correlation between distance from the built-up areas and population density (Pearson's correlation = −0.30 to −0.50), and a high positive correlation between distance from the built-up areas and distance from the roads (Pearson's correlation = 0.70 to 0.90). The high correlation between built-up areas and a road network is showed by fact that residential buildings within the study area stretch along the roads. It is also supported by a theory that humans prefer to live in an area with a higher road accessibility (Patarasuk, 2013). Moreover, the transition probability suggests that there are conversions of 25 percent of paddy fields and bare land into waterbodies and 14 percent of paddy fields and bare land into built-up areas in 2015–2020 (Table 4).

This study compares the simulated and projected land cover maps in 2020 and 2030 to the map of spatial planning in 2031 for assessing the relevance of the spatial planning to the current and projected trend of land cover changes (Fig. 7). The comparison then shows the concordant and discordant areas of land covers in

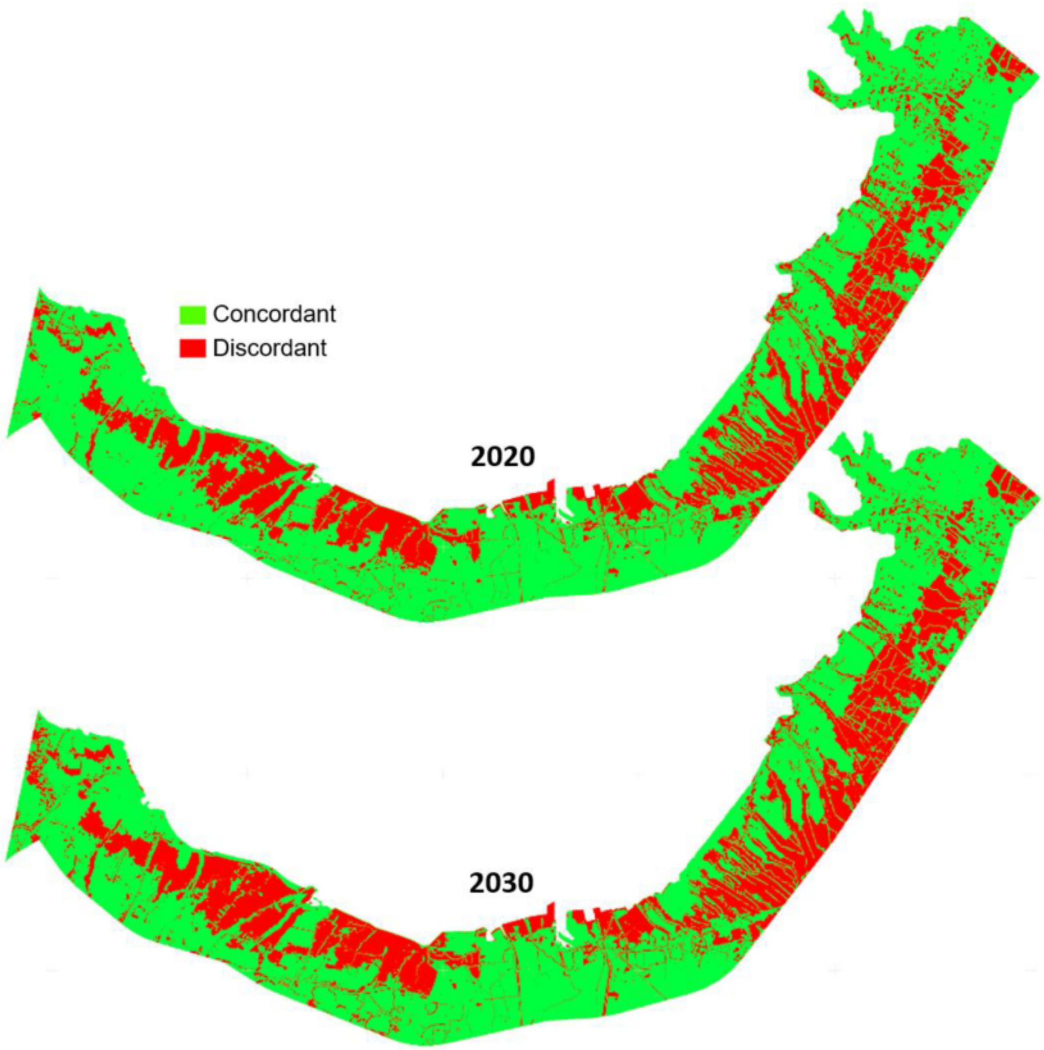

Fig. 8. Concordance between land cover maps in 2020 and 2030 and the spatial planning in 2031.

Table 5
Statistics showing concordance between land cover maps in 2020 and 2030 and the spatial planning in 2031.

	2020 (ha)	2030 (ha)	Δ 2020–2030 (ha)	2020 (%)	2030 (%)	Δ 2020–2030 (%)
Concordant	26,846.39	25,604.58	−1,241.81	71.03	67.75	−3.29
Discordant	10,947.06	12,188.87	1,241.81	28.97	32.25	3.29
	37,795.53	37,795.53		100.00	100.00	

2020 and 2030 with the spatial planning in 2031 (Fig. 8 and Table 5). The discordant areas are projected to increase in 2020–2030, indicating that local government had not considered the worst scenario of land cover changes in future.

5. Discussion

This paper shows that the OBIA method in QGIS gets 94.50 and 90.98 percent of the overall accuracy of classified land cover maps. These percentage of overall accuracy are similar to the overall accuracy of Chen et al. (2007) and An et al. (2007), even when we were using low-resolution imageries. The similarity indicates that the outcomes of image classification using of OBIA method are acceptable, so they can be used further for projecting future land cover maps and assessing spatial planning. In addition to its overall accuracy, the OBIA method is capable to solve the "salt-and-pepper effect" problem in image classification (Blaschke, 2010; Yu et al., 2006). In general, the OBIA method in QGIS can substitute for the OBIA method in eCognition/Definiens software, especially for the purpose of spatial planning assessment. Nevertheless, there are several technical challenges using the OBIA method that scholars need to be fully aware of, including large amount of computer memory during the process of image segmentation (Whiteside et al., 2011), long processing time of trial-and-error for configuring the suitable parameters for image segmentation and classifying land cover maps (Johnson and Jozdani, 2018; Kotaridis and Lazaridou, 2020).

The outcome of the projection of future land cover map shows that there will be a decrease in paddy fields and bare land and an increase in built-up areas and waterbodies. It indicates a typical land cover change as suggested by Sejati et al. (2019). Several factors have been driving the rapid land cover change in the study area, such as an industrialization policy (Fariha et al., 2021; Sejati et al., 2019; Sejati et al., 2020), tidal flooding, and land subsidence (Buchori et al., 2018a; Buchori et al., 2018b; Buchori and Tanjung, 2014).

The local government of Semarang metropolitan region had not considered the worst scenario of land cover changes in future, so the spatial planning of the study area is less relevant to the trend of land cover changes, especially to the increase in waterbodies. Sea level in the study area is rising by 2.1 mm/year and land subsidence at a rate of 60–120 mm/year will only worsen the situation (Bott et al., 2021). In the worst-case scenario, low-lying communities would be threatened due to the drastic increase in waterbodies (Bott et al., 2021; Buchori et al., 2021).

This assessment shows how responsive the spatial planning to land cover changes (Al shawabkeh et al., 2019). It also supports the fact that the spatial planning is unable to control the sprawl of the built-up areas (Al shawabkeh et al., 2019; Buchori et al., 2020; Buchori et al., 2018b). A consideration for the projection of future land cover change is required to make the spatial planning having good response to the current and future land cover change (Al shawabkeh et al., 2019; Hakim et al., 2020).

6. Conclusion

This paper mainly offers an insight into the implementation of an OBIA method in QGIS as one of the open-source software for urban and regional planning studies, especially for assessing regional spatial planning. The OBIA method can substitute for a pixel-based image analysis method in image classification, before its outcomes are used for the projection of future land cover and the assessment of spatial planning. This paper expects to increase the attention of scholars of urban and regional planning to use the OBIA method in QGIS software for developing a methodology of spatial planning assessment.

The assessment of the map of spatial planning in this study indicates that local government in the study area had not considered the worst scenario of land cover changes in future. There is an increase in the discordant areas of land covers in 2020–2030 with the spatial planning in 2031. This study shows that the spatial planning is irrelevant to the current and future pattern of urban growth. The spatial planning can also be ineffective in minimizing the risk of urbanization in coastal cities.

Several recommendations can be made based on this study. We suggest that scholars in urban and regional planning studies use imageries with uniform condition of paddy fields (to avoid inconsistent classification for paddy fields given they may be classified as waterbodies), increase the accuracy of classification for tree canopies growing on land, evaluate the accuracy of the outcomes of land cover projection as suggested by Satya et al. (2020) and Rahman et al. (2017), and analyze social and political aspects driving rapid land cover change. In future, researchers who cannot afford commercial software such as ArcGIS and eCognition/Definiens can develop their spatial planning assessment method using the OBIA in QGIS given it is freely available with user-friendly interface. Furthermore, the methodology using an open-source software such as QGIS in a developing country context also provides a promising exemplar that other local governments can use for assessing their spatial planning.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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