Delineation of Urban Land Cover Changes Using Remote Sensing in the Ninh Kieu District, Can Tho Province, Viet Nam

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ABSTRACT

The study aimed to determine how changes in land cover and surface water are being made using stratified object-oriented analysis based on the interpretation of remote sensing images. It is the first step toward managing the region's annual land-use inventories projects. The study used Sentinel-2 images from 2019 through 2021 to delineate the changing urban land cover in the Ninh Kieu District, Can Tho City, Viet Nam. The study used QGIS software to interpret the images and eCognition software to classify the objects based on the NDBI, NDVI, and NDWI indices. The interpretation results were checked for the accuracy, and the land cover was changed over the years. The results show that urban land cover changes with the increase of urban land and the decrease of vegetation land used for urban land, while water surface area inwards decreased from 2019 to 2020 but increased in 2021. Maps of the current state of the urban land covers in the study area were delineated. The interpretation results contribute to the preliminary method by using satellite images for the annual land use inventory project in the region, even though some difficulties still exist and need to be modified.

Keywords: land cover, water surface, satellite images, sentinel, Ninh Kieu District.

INTRODUCTION

Using land sustainably, economically, and effectively to adapt to climate change has become essential for every country and globally. Like other countries, Vietnam always places the goal of sustainable land management and use first, making land investigation, assessment, land reclamation, and protection a priority task in the development strategy sustainable development. According to MONRE (2014), it explicitly regulates land investigation and assessment activities. Ministries, departments, and localities have implemented several projects and tasks related to the primary investigation of land records at different times. However, according to annual land statistics and a thorough land inventory, the quantity and extent of land remain the main priorities when investing in land surveys. Additionally, the present land use status is mapped every five years. Besides, the People's Committee of Can Tho City (2023) states that information technology and digital transformation in land management should be strengthened. Faster project implementation to create a modern and unified land database and cadastral records system ensure that the land database works well and is managed and used to benefit everyone involved in database management and use.

Technology for remote sensing is improving and being used in more industries and parts of society. Remote sensing technology is used in natural resources and environmental management, which helps to build topographic maps, vegetation cover, and soil types. In addition, it provides parameters for hydrological and hydraulic models, an inventory of changes in land and water resources, as well as monitoring and forecasting natural disasters (drought, flood, landslide,

subsidence, forest fire) and environmental incidents. Linh and Diem (2023) proposed conducting the land inventory and mapping the current land use by integrating traditional and remote sensing approaches to improve the efficiency of information technology applications in land management at the district level.

Zhou et al. (2018) claim that traditional remote sensing image segmentation utilizes a uniform set of parameters universally. The ideal segmentation criteria for an entire image only apply to particular parts, though, as objects differ in size. The concept of spatial dependence states that similar-sized objects of the same kind frequently congregate in one setting to create a scene. Furthermore, various things or geographical phenomena have inherent spatial and temporal scales, making it harder to see complicated high-resolution patterns (De Baan et al., 2013; Zhao et al., 2017). It is necessary to configure the processing scale, also known as the segmentation scale, in a way comparable to object spatial scales to extract or separate objects from their surroundings (De Baan et al., 2013). In object-based image analysis, choosing the correct scale is essential, because choosing the wrong one would result in over- or under-segmentation (Dongping et al., 2012). The efficacy and precision of extracting multiscale information from high-resolution images decline (Ming et al., 2011; Myint et al., 2011).

Ha et al. (2022) developed state-of-the-art models utilizing remote sensing and machine learning to assess the flooding risk of Vietnam's Thua Thien Hue region. Nowadays, the provider can download many satellite images with a resolution of about 30 m for free. According to Chiem (2020), three indicators, NDWI, MNDWI, and WNDWI, were used to distinguish and identify water and non-water areas of Sa Dec city, Dong Thap province. Processing and interpretation are made on the GEE cloud computing platform. Therefore, it significantly affects how long it takes to process and interpret Sentinel-2 images for the study area. The study by Tuan et al. (2018) evaluated the ability to extract urban surface water by enhancing the resolution of short-wave infrared (SWIR) bands. A resolution-enhanced SWIR channel was used to calculate water determination indices, which showed improved water separation. The study also looked at ways to improve image resolution and how to obtain the best image quality and more accurate results when calculating the MNDWI index. A 10-year time series in the Hanoi area was used to test the technique.

The presented study aimed to assess changes to the land cover and surface water area of the Ninh Kieu district in Can Tho City, Viet Nam, using an object-oriented analytic method based on categorizing remote sensing images. Besides, the study also weighed the benefits and drawbacks of using Sentinel-2 images before recommending a technique to determine the land cover changes for the region's annual land use inventory project.

MATERIALS AND METHODS

Study location

According to the government's Decree No. 05/2004/ND-CP (Can Tho Government, 2004), Ninh Kieu is part of Can Tho City and is an urban district in the middle of the city. Most of Can Tho's municipal offices are located here. It borders Binh Minh town and Binh Tan district in Vinh Long province. The west connects the Phong Dien and Cai Rang districts to the south, and the north borders the Binh Thuy district (Figure 1).

Study procedure

The step-by-step procedure for determining the water surface area of Ninh Kieu District is shown in Figure 2.

Data collection

Relevant reference documents for the study area and Sentinel-2 remote sensing image data for 2019, 2020, and 2021 were collected from the USGS site (https://earthexplorer.usgs.gov/).

Image preprocessing

Satellite image bands were combined and the image was cropped based on the Ninh Kieu district's boundary layer to process more data simultaneously. Both steps were performed on QGIS software. Next, the atmosphere of the image was corrected with SNAP software to remove the effects of radiation in the image, which ESA makes specifically for Sentinel satellites. For the SNAP software to work, Sen2Cor and Sen2Three plug-ins are required. Sen2Cor eliminates clouds from the image and accounts for atmospheric factors. A standard reflectivity image from Sentinel-2A was processed using SNAP software at a spatial resolution of 10 meters (Xu et al., 2019).
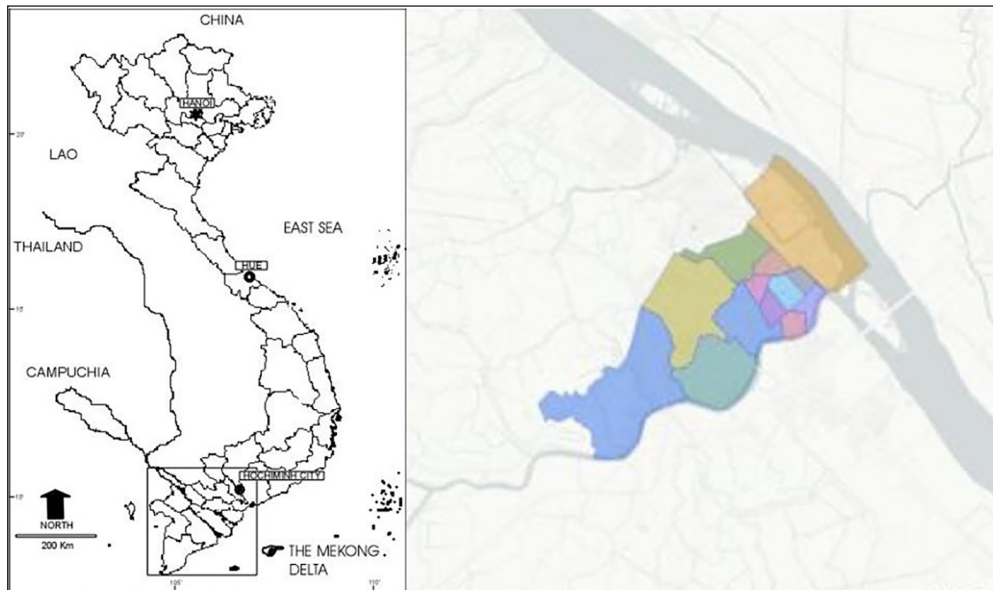
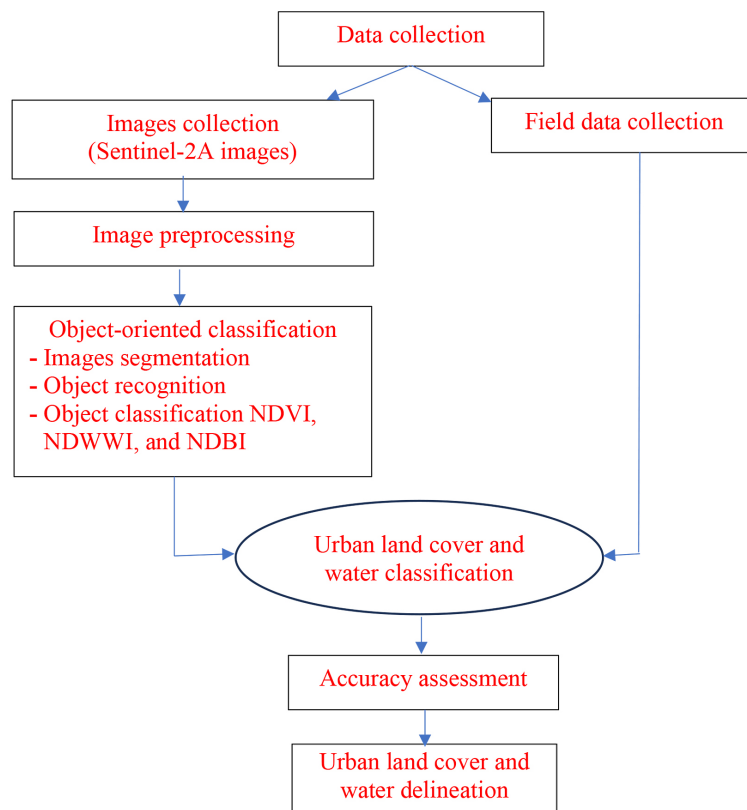**Figure 1.** The District of Ninh Kieu in the Vietnamese Mekong Delta

Figure 2. Implementation diagram

Object-oriented classification method using eCognition software

The study presented stratified object-oriented image analysis, which divides scenes into remote-sensing images. This technique can separate a complex image into several scenes with different spatial arrangements. Color value is one

attribute that can separate an image into scenes because like-colored objects have comparable color values. Moreover, as different scenarios may have different levels of visual complexity and organizational structure, the color's texture can be used as a reflection. Scene division and scene image segmentation were carried out using

eCognition multiscale segmentation, the most efficient method (Tan et al., 2007). As a result, the research employed three computed indices. The normal differential vegetation index (NDVI), normal differential water index (NDWI), and urban differential (normal differential building index-NDBI) are included in the dataset, as suggested by Vatandaşlar and Yavuz (2017) (Figure 2). All index images have values ranging from -1 to 1. Also, the values of index images range from > 0 to 1, representing objects spread out and surface conditions like NDVI that make natural objects stand out. For example, NDWI identifies the objects related to water surface distribution, and NDBI identifies the urban land distribution-related objects.

Accuracy assessment

Accuracy is always a concern when using a classification method to understand a remotely sensed image. Field visual evaluation is the simplest and most accurate method of evaluation. Flaws can be identified and their amount roughly calculated by contrasting the image with the interpretation's findings. However, quantitative evaluation methods are necessary to give a trustworthy accuracy rating. Another precision metric is the Kappa coefficient. It compares the categorization results against values that are chosen at random. It takes integers in the range of 0 to 1. There is no agreement between the reference and classified images if the kappa coefficient is 0. The categorized and ground truth images are identical when the kappa coefficient is 1. Consequently, as the classification becomes more accurate, the kappa coefficient increases. After being classified, the image is evaluated for reliability. When applying various algorithms or performing statistical analyses, Cohen's Kappa index (K) is utilized to evaluate and confirm the concordance between various data sources (Tang et al., 2015). The error matrix is used to assess the classification accuracy in addition to the Kappa coefficient (Feizizadeh et al., 2022). This function computes Cohen's kappa (Cohen, 1960), a rating that indicates how much two annotators agree on a classification issue and is defined as:

$$k = (p_0 - p_e)/(1 - p_e) \qquad (1)$$

where: p_0 is the empirical probability of agreement on the label assigned to any sample (the observed agreement ratio), and p_e is the expected agreement when both annotators assign labels randomly, p_e is estimated using a per-annotator empirical prior over the class labels (Artstein and Poesio, 2008).

The accuracy assessment was based on the results of field surveys by collecting coordinates and current status. The study performed checks at 180 locations, and the number of tests was distributed across the study area. The results were evaluated, explained, and described to assist the research in having a more precise and objective view. From there, it was determined whether the result was good or bad, meaningful or not for the research goal.

Mapping the land cover and surface water

After preprocessing, the images are classified, evaluated for reliability, and uploaded to QGIS software to edit the map. This results in a map of the current state of the water surface in the Ninh Kieu district.

RESULTS AND DISCUSSION

Results of image collection

The study collected Sentinel-2 L1C images from 2019, 2020, and 2021. The width and height are 10980, and the image format is ".jpg" with 48 (N) UTM coordinate system, projection WGS84, and resolution of 10 m. Clouds account for about 5–30% of the study area but are not covered, so they are acceptable (Table 1).
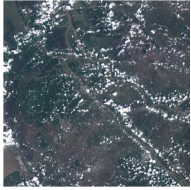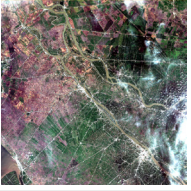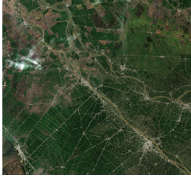
Urban land covers and surface water classification

Because some objects have overlapping classification indices due to color reflection, the classification results must be more accurate, affecting the determination of land covers and water points in the study area.

The NDBI index represents urban objects, ranging from 0.05 to 0.23 in 2019, 0.05 to 0.30 in 2020, and 0.02 to 0.30 in 2021.

NDVI represents vegetation objects, ranging from 0.35 to 0.78 in 2019, 0.50 to 0.70 in 2020, and 0.50 to 0.85 in 2021. The NDWI

Table 1. Example information of some collected images

Image name	Images information	Image
L1C_T48PWS_A013443_20191003T032936	Date: December 17, 2019 Width: 10980 Height: 10980 Ground resolution: 10 m Coordinate system: UTM, WGS84-48N	
L1C_T48PWS_A019735_20201216T033348	Date: December 16, 2020 Width: 10980 Height: 10980 Ground resolution: 10 m Coordinate system: UTM, WGS84-48N	
L2A_T48PWS_A025169_20211231T033256	Date: December 31, 2021 Width: 10980 Height: 10980 Ground resolution: 10 m Coordinate system: UTM, WGS84-48N	

water index represents the object of water ranging from 0.10 to 0.60 in 2019, 0.11 to 0.30 in 2020, and 0.10 to 0.50 in 2021. The indicators above are created by finding the interval of each indicator using the selected tool in eCognition software to produce the results shown in the tables above. This makes it easier to determine the definite value.

Changing of urban land covers and surface water

The image interpretation results show that in 2019, Ninh Kieu District had an area of about 2,911.35 hectares. The largest area is urban land, accounting for 50.01% of the total area, or about 1,456.01 hectares. Vegetation accounts for 34.53% of the total area or about

1,005.23 hectares. Surface water accounts for 9.75% of the total area, or about 283.95 hectares. By 2020, the urban area increased by 3% compared to 2019, accounting for 52.54%, with an area of about 1,529.81 hectares. Vegetation tends to decrease compared to 2019, accounting for 33.00% of an area of about 960.87 hectares. These lands have been converted into urban land. The water surface area tends to decrease compared to 2019, accounting for 8.96% with an area of about 261.06 hectares.

By 2021, the urban area had increased by nearly 40 hectares compared to 2020, with a total area of about 1,566.25 hectares. Vegetation tends to decrease lower than in 2020, accounting for 33.00% of an area of about 641.94 hectares, for the same reason. Water surface

Table 2. Result of image classification index values in 2019, 2020, and 2021

Subject	Year	NDVI	NDWI	NDBI
Water surface	2019	-0.50–0.01	0.10–0.60	-0.45–0.38
	2020	-0.27–0.03	0.11–0.30	-0.28–0.14
	2021	-0.50–0.03	0.10–0.50	-0.5–0.12
Vegetation	2019	0.35–0.78	-0.67– -0.3	-0.38–0.08
	2020	0.50–0.70	-0.59– -0.49	-0.30– -0.21
	2021	0.50–0.85	-0.70– -0.50	-0.46– -0.16
Urban	2019	-0.05–0.05	-0.22–0.04	0.05–0.23
	2020	-0.03–0.02	-0.27–0.05	0.05–0.30
	2021	-0.09– -0.11	-0.38–0.12	0.02–0.30

area tends to increase to about 270.92 hectares. Figure 3 delineates the maps of land covers in 2019 (a), 2020 (b), and 2021 (c), and Figure 4 shows the status of land cover changes.

Accuracy assessment

The study performed checks at 215 locations, with the number of tests distributed across the study area (Figure 5). The estimated reliability of the classification results with an overall accuracy of 3 years is 90.02% (2019), 85.6% (2020), and 87.4% (2021),

and the Kappa coefficient is 0.8 (2019), 0.71 (2020), and 0.75 (2021). It shows that the classification results achieve high reliability (Kappa > 0.71).

Table 3 shows the overall accuracy assessment of image interpretation for land cover and surface water in 2019, 2020, and 2021. In 2019, the water surface object had 32 points observed, with an accuracy of 100%. Because the classified image is not confused with other objects, the water surface object has an accuracy of 100%. Meanwhile, the vegetation objects have 61 points, with an accuracy of 90.2%. However, because 6 points were
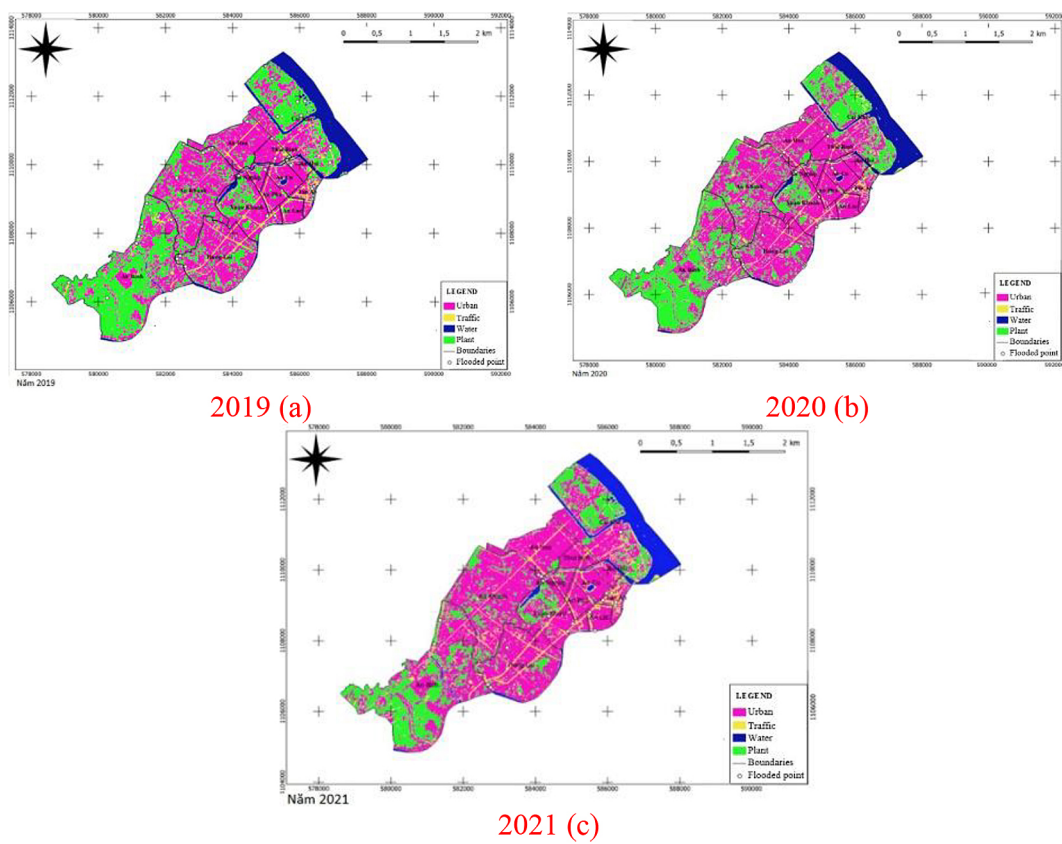

2019 (a)

2020 (b)

2021 (c)

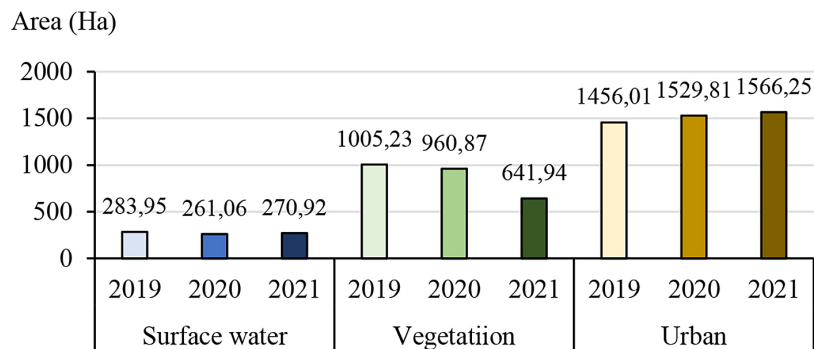**Figure 3.** Maps of land covers in Ninh Kieu

Figure 4. Status of land cover changes in the study area from 2019 to 2021
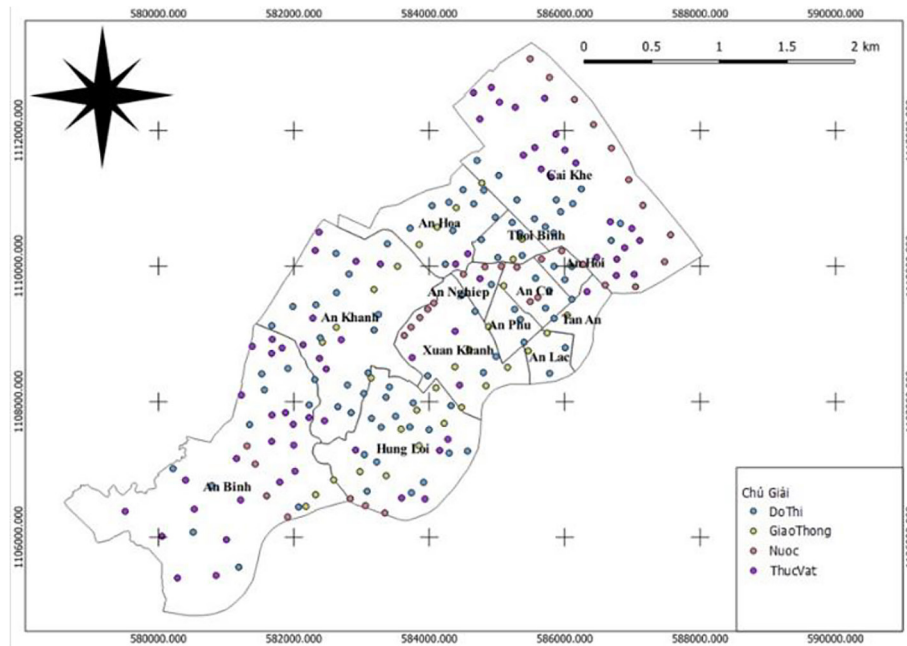
Figure 5. Location of validation sites in 2022

Table 3. Overall accuracy assessment of image interpretation for land cover in the Ninh Kieu district, Can Tho City, Viet Nam

Parameter	Interpreted (points)				
	Year	Water surface	Vegetation	Urban	% Accuracy
Water surface	2019	32	0	0	100
	2020	30	0	0	93.8
	2021	31	0	0	96.9
Vegetation	2019	0	55	5	90.2
	2020	3	52	5	85.2
	2021	3	54	3	88.5
Urban	2019	0	10	77	88.5
	2020	0	9	73	83.9
	2021	0	8	76	87.4
Accuracy (%)	2019	100	84.6	88.5	90.2
	2020	90.9	85.2	86.9	85.6
	2021	88.6	85.7	89.4	87.4
Overall accuracy	2019				85.6
	2020				85.6
	2021				87.4
Kappa's coefficient	2019				0.80
	2020				0.71
	2021				0.75

mixed into urban objects, the vegetation was only correct at 55 points with an accuracy of 84.6%, the urban object has 87 points with an accuracy of 88.5%. Besides, because 10 points were mixed into vegetation, the urban area only had 77 points that were correct with the survey.

In 2020, the water surface object had 32 points with an accuracy of 93.8%. The classification image was mixed with the urban through field testing, while only 30 points were correct for the survey. The vegetation object has 61 points, with an accuracy of 85.2%.

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Because 9 points are mixed into urban objects and water surfaces, vegetation only corrects 52 points with an accuracy of 85.2%, the urban object has 87 points with an accuracy of 83.9%. Due to the confusion of 14 entry points into vegetation, the urban area has only 73 points that match the survey. The water surface objects have 32 points, with an accuracy of 96.9%. Through field testing, the classification image mixed with urban is 1 point, so 31 points are correct compared to the survey. The vegetation object has 61 points, with an accuracy of 88.5%. Due to the confusion of 7 points between urban and water surface objects, the vegetation is only 54 points correct compared to the actual survey; urban objects had 87 points with an accuracy of 87.4%. Because 11 points were mixed into vegetation, the urban area only had 76 points. Generally, the overall accuracy of 2019, 2020, and 2021 is 90.02%, 85.6%, and 87.4%, respectively, with Kappa coefficients of 0.8, 0.71, and 0.75. It is also an accurate and acceptable result of land cover change study for land inventory. Some objects are mistakenly classified as other objects because they occupy a small and insignificant area compared to others, which is the rate of confusion among urban areas. Because the NDVI, NDBI, and NDWI vegetation index threshold levels are relatively similar between subjects, manual correction is required to correct confusion between these subjects.

CONCLUSIONS

The study has delineated the current urban land cover in 2019, 2020, and 2021 by using sentinel satellite images. The maps and the change in the urban land cover and surface water area inwards of Ninh Kieu district were delineated with an overall accuracy of > 85% coefficients > 0.7. The urban land cover changes clearly with the increase of urban land and the decrease of vegetation land used for urban land, while the surface water area inwards decreased from 2019 to 2020 but increased in 2021.

However, clouds have impaired the results. Nevertheless, it contributes to the research for functional agencies to monitor and provide recommendation approaches for annual land-use inventory project for resource management in the regions 168 regions.

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