Spremljanje sprememb mestnih zelenih površin v Vietnamu z uporabo podatkov Sentinel 2

Monitoring changes in urban green spaces using Sentinel 2 data, a case study from Vietnam

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IZVLEČEK

Mestni zeleni prostor (MZP) ima pomembno vlogo pri izboljšanju urbanega okolja in kakovosti življenja ter prispeva k trajnostnemu urbanemu razvoju. Vendar pa je hitra urbanizacija prinesla pecejšnje spremembe v površini MZP, predvsem njegovo upadanje. Študija se osredotoča na spremljanje MZP v mestu Thanh Hoa v Vietnamu v letih od 2016 do 2024, in sicer v štiriletnem ciklu ter z uporabo slik Sentinel-2 in algoritmov strojnega učenja. Veččasovni podatki Sentinel-2 so bili uporabljeni za izračun spektralnih indeksov NDVI, NDWI, NDBI, BUI in SAVI. V študiji sta bila uporabljena dva algoritma strojnega učenja, Random Forest (RF) in Support Vector Machine (SVM), za razvrstitev treh vrst pokrovnosti tal: vegetacije, nevegetacije in vodnih teles. Med njimi je bil najnatančnejši rezultat razvrstitve uporabljen za prerazvrstitev območja v dve skupini: MZP (vegetacija) in drugo (nevegetacija in voda). Segmentacija je bila izvedena z algoritmom Simple Non-Iterative Clustering (SNIC) za natančnejšo razvrstitev meja. Analiza je razkrila pomembne spremembe v podzemnih zelenih površinah skozi čas, kar poudarja vpliv širitve mest na porazdelitev podzemnih zelenih površin. Te ugotovitve zagotavljajo dragocen vpogled v dinamiko razvoja in degradacije zelenih površin v mestu Thanh Hoa, metoda, predlagana v študiji, pa se za ocenjevanje sprememb mestnih zelenih površin lahko uporabi tudi na drugih urbanih območjih po svetu.

ABSTRACT

Urban green space (UGS) plays an important role in improving the urban environment, enhancing the quality of life and contributing to sustainable urban development. However, rapid urbanization has led to significant changes in land area, especially the decline of UGS. This study is focused on monitoring of UGS in Thanh Hoa city, Vietnam from 2016 to 2024 in a 4-year cycle, using Sentinel-2 images and machine learning algorithms. Sentinel-2 multi-temporal data were used to calculate spectral indices including NDVI, NDWI, NDBI, BUI and SAVI. Next, the study used two machine learning algorithms, Random Forest (RF) and Support Vector Machine (SVM), to classify 3 types of land cover: vegetation, non-vegetation and water bodies. Among these, the most accurate classification result was used to reclassify the area into two groups: UGSs (vegetation) and Others (non-vegetation and water). Segmentation was performed using the Simple Non-Iterative Clustering (SNIC) algorithm to refine the classification boundaries. The analysis revealed significant changes in UGS over time, highlighting the impact of urban expansion on UGS distribution. These findings provide valuable insights into the dynamics of green space development and degradation in Thanh Hoa city and the method proposed in the study can be applied to other urban areas in the world for assessing urban green space changes.

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mestni zeleni prostor, daljinsko zaznavanje, provinca Thanh Hoa, Vietnam

KEY WORDS

urban green space, remote sensing, Thanh Hoa province, Vietnam

1 INTRODUCTION

Amidst the growing pace of urbanization and the increasing severity of climate change, the preservation and development of urban green spaces have become critical challenges for cities worldwide (Mabon and Shih, 2021; Olivadese and Dindo, 2024). Green spaces not only play a crucial role in improving air quality, mitigating urban heat island effects, and enhancing biodiversity but also contribute significantly to public health by providing spaces for recreation and relaxation (Athokpam et al., 2024; Mamajonova et al., 2024; Zhang and Qiuan, 2024). However, rapid urban expansion and industrial growth have led to the shrinking of green spaces, threatening environmental stability and reducing the resilience of urban ecosystems (Semeraro et al., 2021; Azhar et al., 2024; Zhanwen and Islam, 2024).

In Vietnam, urbanization has been progressing at a rapid rate, particularly in large cities such as Hanoi, Ho Chi Minh City, Da Nang, and other neighboring provinces (Kim, 2024; Downes et al., 2024; Huong and Tuan, 2024). Thanh Hoa, located in the North Central region of Vietnam, is no exception to this trend. With a rapidly growing population, urban development, and industrialization, Thanh Hoa faces significant challenges in maintaining and expanding its urban green spaces (Nguyen et al., 2021). The city's green areas are essential not only for enhancing the quality of the living environment but also for the health and well-being of its residents. Yet, as urban and industrial areas expand, the pressure on these spaces continues to mount, threatening their sustainability (Manika and Dhyani, 2024).

While there has been growing awareness among local authorities and the community regarding environmental protection and sustainable development, the monitoring and assessment of changes in urban green spaces in Thanh Hoa remain limited. Traditional monitoring methods are often constrained by high costs, time limitations, and the difficulty of covering large areas. As a result, remote sensing technology and satellite imagery have emerged as invaluable tools for providing accurate, timely, and detailed information about changes in green spaces (Shaikh and Birajdar, 2024; Han et al., 2024). Among these technologies, Sentinel-2, part of the European Space Agency's Copernicus program, offers high-resolution, multi-temporal data that is well-suited for monitoring changes in urban environments (ESA, 2024).

Sentinel-2's MultiSpectral Instrument (MSI) provides vital information on the extent, structure, and condition of urban green cover. By utilizing multi-temporal satellite data, this technology allows for the monitoring of green space dynamics over time, enabling the detection of trends, changes, and the impact of various factors on urban environments (Nguyen et al., 2021). The use of such technology not only offers a cost-effective solution but also enables the monitoring of vast urban areas, such as Thanh Hoa, which are undergoing rapid changes in land use (Phuong et al., 2024).

Studies on green space are common in megacities, but limited in mid-sized cities like Thanh Hoa -highlighting a gap this research addresses, relevant to urban planning in developing regions (Uy and Nakagoshi, 2007; Huang et al., 2017). Therefore, utilizing Sentinel-2 data to assess the dynamics of urban green cover in Thanh Hoa is a crucial research endeavor. This study aims to provide valuable insights into the state of green spaces in the city, offering essential information for urban planners, policymakers, and stakeholders in developing strategies for the preservation and sustainable growth of urban green areas. Understanding the changes in the quantity and quality of green spaces will help decision-makers identify key trends, impacts, and potential risks, allowing for the implementation of effective measures to protect and enhance these spaces in the face of rapid urbanization and climate change (Wang et al., 2019; Sadler et al., 2010).

This paper focuses on using Sentinel-2 MSI satellite data to monitor and assess the changes in urban green spaces in Thanh Hoa City during the period from 2016 to 2024 (4-year cycle). The objective of the study is to analyze the fluctuations in the area and proportion of green spaces, identify key trends in their development and degradation, and provide valuable insights into sustainable urban planning and environmental quality improvement in Thanh Hoa. More broadly, the findings can contribute to global discussions on urban resilience and climate adaptation, particularly in rapidly developing regions.

2 MATERIALS AND METHODOLOGY

2.1 Study area and Materials

Study area. Thanh Hoa city is the administrative, economic, cultural, political and scientific - technical center of Thanh Hoa province (North Central region of Vietnam). After more than 30 years since its establishment, Thanh Hoa city has grown strongly with a high rate of urbanization. Currently, Thanh Hoa city has a natural area of 146,77 km^2 with 20 wards and 17 communes, a population of more than 400 thousand people (Thanh Hoa City People's Committee, 2024). This is one of the cities with large population and area in the Northern region of Vietnam. The location map of the study area is presented in Fig. 1.

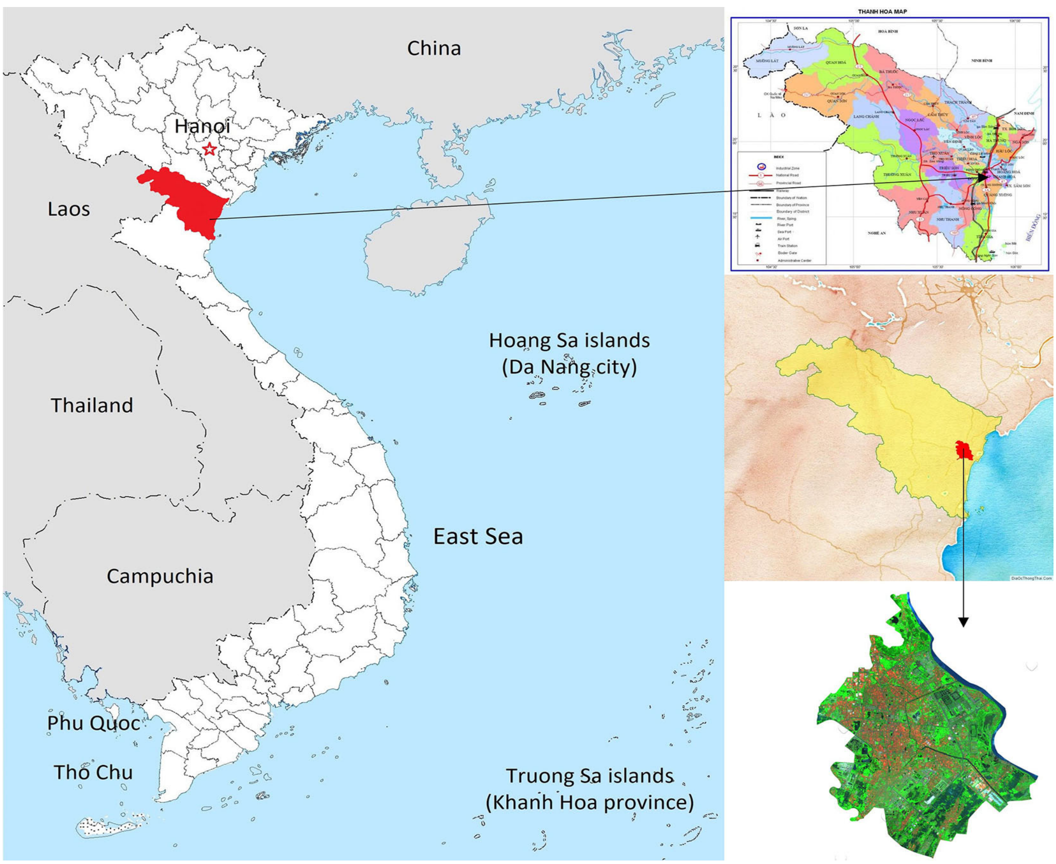

Figure 1: Geographic location of Thanh Hoa city (Thanh Hoa province, Vietnam)

Materials. Sentinel-2 data developed under the Copernicus program of the European Space Agency (ESA), provides high-quality satellite imagery of Earth's surface, supporting various applications in environmental research, agriculture, disaster monitoring, and urban planning (ESA, 2024). The Sentinel-2 constellation consists of two primary satellites: Sentinel-2A and Sentinel-2B, launched in 2015 and 2017, respectively, equipped with the MultiSpectral Instrument (MSI) that collects data from 13 different spectral bands, including blue, red, near-infrared, and shortwave infrared. This allows for detailed analysis of surface features such as land, vegetation, water, and urban areas, with spatial resolution ranging from 10m to 60m, depending on the spectral band (ESA, 2024). With the ability to cover a vast area of 290 km x 290 km per scan and a revisit cycle of approximately 5 days, Sentinel-2 can monitor environmental changes in near real-time. Sentinel-2 data has proven to be valuable in many fields, from monitoring crop growth and plant health to assessing water resources and analyzing land use and urban expansion. Specifically, Sentinel-2 data is an essential tool for monitoring the impacts of climate change and urbanization, enabling policymakers to make informed and timely decisions (ESA, 2013).

Table 1: Sentinel-2 bands characteristics (Google Earth Engine, 2024)

Bands	Description	Central Wavelength S2A (nm)	Central Wavelength S2B (nm)	Resolution (m)
1	Coastal Aerosol	443.9	442.3	60
2	Blue	496.6	492.1	10
3	Green	560	559	10
4	Red	664.5	665	10
5	Vegetation Red Edge 1	703.9	703.8	20
6	Vegetation Red Edge 2	740.2	739.1	20
7	Vegetation Red Edge 3	782.5	779.7	20
8	NIR	835.1	833	10
9	Narrow NIR	864.8	864	20
10	Water Vapour	945	943.2	60
11	SWIR-Circus	1375.5	1376.9	60
12	SWIR	1613.7	1610.4	20
13	SWIR	2202.4	2185.7	20

2.2 Methodology

The UGS classification chart using Sentinel-2 imagery is presented in Figure 2, outlining a systematic and structured process for identifying and analyzing green spaces in urban areas. Sentinel-2 data processing is performed on the on the Google Earth Engine (GEE) cloud computing platform. The flowchart of medthodology to classify UGSs is shown in Figure 2.

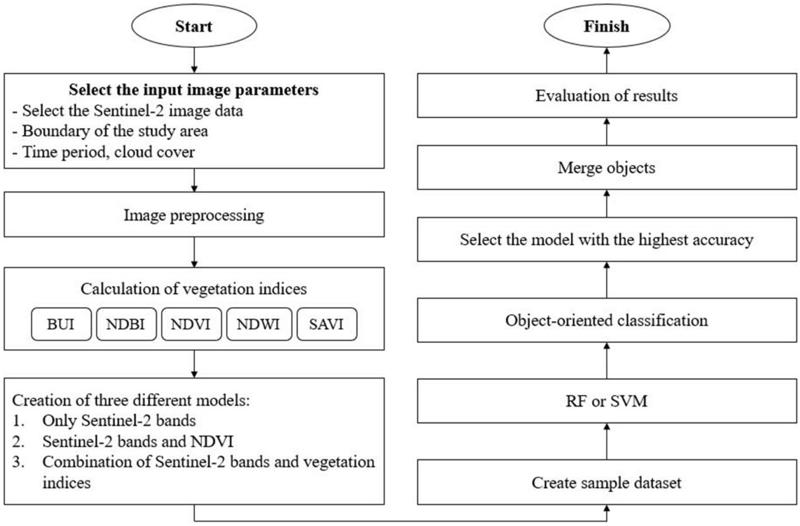

Figure 2: The flowchart of UGSs classification using Sentinel-2 images

Selection of input image parameters:

The first step involves selecting Sentinel-2 image data. This step requires specifying the boundaries of Thanh Hoa city. In addition, analysis period is required. The study utilized Sentinel-2 satellite imagery captured on three distinct dates: May 29, 2016, June 2, 2020, and June 16, 2024. These dates were carefully selected to represent different time points over an eight-year period, providing a comprehensive view of changes in land cover and urban green spaces within the study area. The images were chosen based on their high quality, minimal cloud cover and relevance to the growing season of vegetation, ensuring the accuracy of indices and land classification. The study selected the image acquisition period in May and June because this is the summer season in Thanh Hoa, with little cloud interference.

Image preprocessing:

After selecting the input parameters, the Sentinel-2 images undergo preprocessing to ensure data consistency and accuracy. This includes cloud masking to remove clouds and shadows, atmospheric correction to normalize reflectance values, and resampling of spectral bands to a common spatial resolution. Preprocessing ensures that the images are clean, georeferenced, and ready for further analysis, providing a solid foundation for reliable results. The Sentinel-2 datasets used in this study are available on the GEE platform. These datasets have been preprocessed, ensuring the subsequent spatial analysis (Google Earth Engine, 2024).

Calculation of spectral indices:

Several indices are computed to extract relevant environmental information from the Sentinel-2 imagery. These indices include:

- NDVI (Normalized Difference Vegetation Index): NDVI is a widely used indicator for evaluating vegetation health by analyzing the difference in how plants absorb red light and reflect near-infrared (NIR)

light. NDVI values range from -1 to +1, where positive values indicate vegetation, with higher values representing healthier and denser plant cover. Negative values suggest non-vegetative surfaces such as water, urban areas, or barren land, with values near -1 typically corresponding to water bodies. NDVI is extensively applied in agriculture, forestry, and environmental monitoring to detect thriving vegetation, stressed plants, or barren land, providing critical insights into land cover changes and resource management. NDVI is calculated using the formula (Rouse et al., 1973; Myneni et al., 1995):

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

- *NDWI (Normalized Difference Water Index):* NDWI is a vegetation index used to distinguish healthy vegetation from vegetation affected by water or drought. It is highly sensitive to changes in the liquid water content within plant canopies, making it a reliable tool for assessing the impact of water availability on vegetation health. NDWI is particularly effective in identifying areas where vegetation suffers from water shortages, supporting better water resource management and sustainable agricultural practices. This index utilizes the spectral properties of the near-infrared (NIR) and green bands, which are indicative of water content in vegetation. First introduced by Gao in 1996, NDWI has become widely used in agriculture, forestry and environmental monitoring to analyze drought effects and water dynamics (Gao, 1996). NDWI values range from -1 to 1, indicating surface water presence and moisture levels. Negative values (-1 to 0) represent dry land, built-up areas, or healthy vegetation. Positive values (0 to 1) indicate water or wetland areas, with open water bodies typically having NDWI > 0.5. The formula for NDWI is:

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{2}$$

- *NDBI (Normalized Difference Built-Up Index)*: NDBI is a spectral index designed to identify and map built-up or urbanized areas (Zha et al., 2003). NDBI distinguishes urban features such as buildings, roads, and other man-made structures from natural land cover types like vegetation and water. NDBI is particularly useful in urban studies, helping to monitor urban expansion, assess land use changes and analyze the impact of urbanization on the environment. The index leverages the spectral differences between shortwave infrared (SWIR) and near-infrared (NIR) reflectance as urban surfaces typically exhibit higher reflectance in SWIR and lower reflectance in NIR. NDBI is widely applied in land use classification, urban planning, and environmental monitoring. The formula for calculating NDBI is:

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \tag{3}$$

- *BUI (Built-Up Index):* BUI is an important tool in the classification of UGSs as it helps to distinguish urbanized or built-up areas from natural features such as vegetation, water bodies and built-up land. By exploiting the spectral differences between urban surfaces and other land cover types, BUI effectively identifies urban structures such as roads and buildings. This improves the accuracy of UGSs classification by reducing misclassification of green spaces, especially in densely populated or mixed land use areas. BUI also plays an important role in monitoring urban expansion, allowing the detection of land cover changes, such as the conversion of green spaces into built-up areas. The formula for BUI is calculated as follows (He et al., 2010):

$$BUI = NDBI - NDVI \tag{4}$$

where NDBI and NDVI are 2 vegetation indexes described in equations 2 and 3.

- SAVI (Soil-Adjusted Vegetation Index): Vegetation indices can be influenced by factors like soil brightness, moisture, and saturation from dense vegetation. SAVI was developed to reduce soil brightness noise, which can affect indices like NDVI (Huete, 1988). SAVI incorporates a canopy background adjustment factor for more accurate vegetation analysis, especially in areas with significant soil exposure. SAVI is calculated using the red and near-infrared (NIR) bands with the formula:

$$SAVI = \frac{(NIR - Red)*(1+L)}{NIR + Red + L} \quad (5)$$

where L is the adjustment factor, typically set to 0.5 in areas with moderate vegetation cover (Ettehadi Osgouei et al., 2019; Ismayilova and Timpf, 2022).

These indices are calculated from Sentinel-2 spectral bands and provide valuable insights into land cover characteristics and highlight vegetation features.

Creation of three different models:

Based on the input data and calculated indices, three distinct models are created for analysis:

1. A model using only the Sentinel-2 bands.
2. A model combining Sentinel-2 bands and the NDVI index, focusing on vegetation analysis.
3. A comprehensive model combining Sentinel-2 bands and all calculated indices, providing an integrated view of the study area.

These models help in comparing the accuracy and effectiveness of different approaches for classification and analysis.

Creation of sample dataset:

A sample dataset is created by selecting representative training points or regions from the study area. These samples are labeled with ground truth data, which is essential for training and validating classification models. The dataset must be representative of all classes to ensure robust model performance.

The study developed a sample dataset that includes three main land cover classes: vegetation, non-vegetation, and water bodies. These classes are essential to ensure accurate classification of urban green spaces. The dataset includes 1280 samples for training and 440 samples for testing, which are manually selected for each class on the original images, minimizing bias during classification (Cui et al., 2019).

For vegetation, samples were selected from areas with dense and healthy vegetation as well as sparse, isolated vegetation to capture the characteristics in this class. Non-vegetation samples included built-up areas, bare land, and other unvegetated surfaces, ensuring a diverse representation of urban and unnatural land cover classes. For water bodies, samples were taken from rivers, lakes, and other water features to account for spectral differences in aquatic environments.

Select classification algorithm:

During the classification process, the study tested two popular machine learning algorithms, Random Forest (RF) (Luo et al., 2020) and Support Vector Machine (SVM) (Zylshal et al., 2016). The algorithm with the highest accuracy will be used for the target analysis.

Random Forest:

RF algorithm is a machine learning technique based on an ensemble of decision trees (Breiman, 2001). Each tree is constructed using a subset of training data through a process called bootstrap sampling. During training, the algorithm randomly selects features at each node to determine the best split, introducing variability and reducing correlation between the trees. The final prediction is derived by aggregating the outputs of all trees through majority voting for classification tasks or averaging for regression tasks. Mathematically, let $\{h_1(x), h_2(x),..., h_T(x)\}$ represent the predictions of T decision trees, then the RF prediction H(x) is given by:

$$H(x) = \frac{1}{T}\sum_{i=1}^{T} h_i(x) \quad \text{(for regression)} \tag{6}$$

or

$$H(x) = \text{mode}\{h_1(x), h_2(x),..., h_T(x)\} \quad \text{(for classification)} \tag{7}$$

This structure makes RF robust to overfitting and highly effective for handling high-dimensional data and mixed data types.

Support Vector Machine:

SVM algorithm is a supervised learning algorithm that aims to find the optimal hyperplane that separates data points into distinct classes (Cortes and Vapnik, 1995). In the case of linearly separable data, the hyperplane is defined as:

$$w \cdot x + b = 0 \tag{8}$$

where w is the weight vector, x is the input vector, and b is the bias term. The algorithm maximizes the margin between the hyperplane and the nearest data points from each class, known as support vectors. For non-linearly separable data, SVM employs kernel functions $\phi(x)$ to map data into a higher-dimensional space where it becomes linearly separable. The optimization problem is formulated as:

$$f^* = \min_{w,b} \frac{1}{2}\|w\|^2 \quad \text{subject to} \quad y_i(w \cdot x_i + b) \geq 1, \ \forall i, \tag{9}$$

where y_i represents the class label. By solving this, SVM creates a decision boundary that generalizes well to unseen data, making it effective for both linear and non-linear classification tasks (Drucker et al., 1997).

Object-oriented classification:

To enhance accuracy, an object-oriented classification approach is implemented. Instead of analyzing individual pixels, this method groups pixels into objects (segments) based on spectral and spatial characteristics, ensuring that the classification reflects real-world patterns more accurately. This step helps in reducing noise and improving the coherence of classification results. The study employs the SNIC (Simple Non-Iterative Clustering) algorithm (Achanta and Susstrunk, 2017) in GEE for segmentation.

Selection of the best model:

The classification output from the three models combined with the two machine learning algorithms is evaluated based on accuracy metrics including overall accuracy and Kappa coefficient. The model with the highest accuracy is selected for further analysis and final reporting.

Merging objects and evaluation of results:

The classification results from the algorithm with the highest accuracy are grouped into two categories: UGSs and others. In this process, the vegetation class is reclassified as UGSs, while non-vegetation, and water bodies are grouped into Others.

Finally, detailed data on the total area and the percentage of area for UGSs are analyzed to evaluate the changes in green spaces within the study area. This analysis focuses on identifying trends in the expansion or reduction of green spaces over time. By comparing the classified results across different time periods, the study aims to quantify the extent of these changes, providing insights into the dynamics of urban green space development.

3 RESULTS AND DISCUSSION

Various indices were calculated including BUI, NDBI, NDVI, NDWI and SAVI. These indices were derived using the spectral bands of Sentinel-2 imagery, each serving a specific purpose in differentiating land cover types. BUI and NDBI were used to detect urbanized and built-up areas, while NDVI and SAVI highlighted vegetation health and density. NDWI was utilized to identify water bodies and assess vegetation water content. By leveraging these indices, the study gained a comprehensive understanding of the spectral characteristics of the study area, enabling accurate classification and monitoring of changes in urban green spaces over time. Figure 3, Figure 4, and Figure 5 respectively present the original Sentinel-2 imagery and the calculated indices.

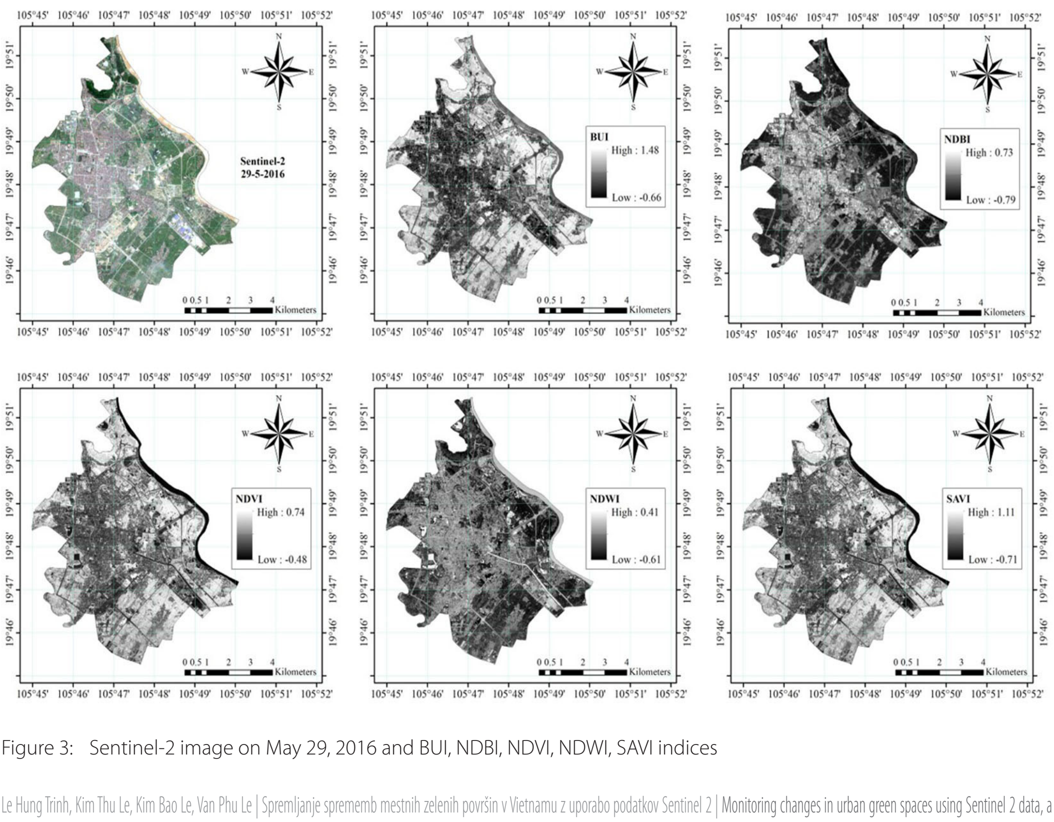

Figure 3: Sentinel-2 image on May 29, 2016 and BUI, NDBI, NDVI, NDWI, SAVI indices

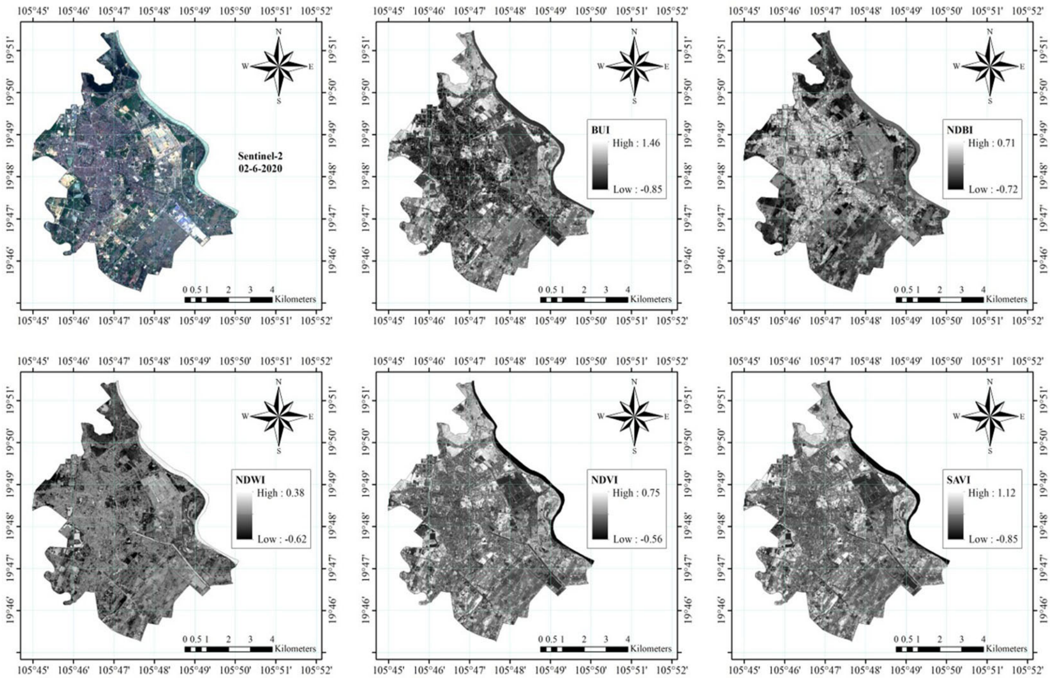

Figure 4: Sentinel-2 image on June 2, 2020 and BUI, NDBI, NDVI, NDWI, SAVI indices

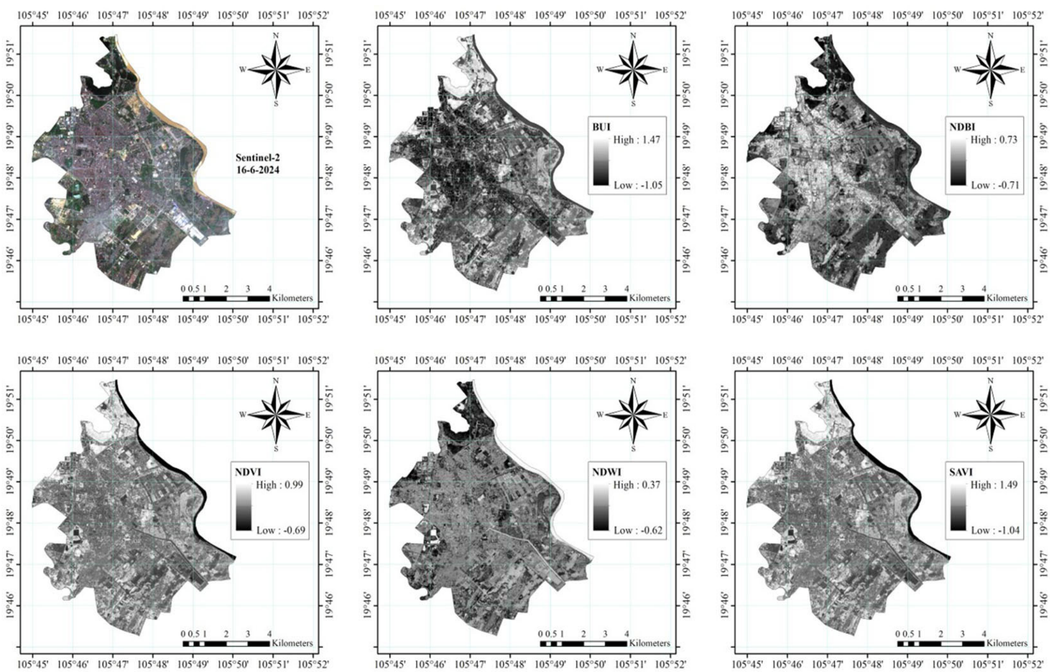

Figure 5: Sentinel-2 image collected on June 16, 2024 and BUI, NDBI, NDVI, NDWI, SAVI indices

Next, the images were classified under three scenarios using two machine learning algorithms. The three scenarios described above were designed to test different combinations of input features for classification. Each scenario was processed using the RF and SVM algorithms to evaluate their performance in distinguishing land cover classes (vegetation, non-vegetation, and waterbody). This comparative approach allowed the study to identify the most effective combination of features and algorithms for accurately classifying urban green spaces and other land cover types. Figure 6 and Figure 7 respectively present the classification results under the three scenarios using the two machine learning algorithms.

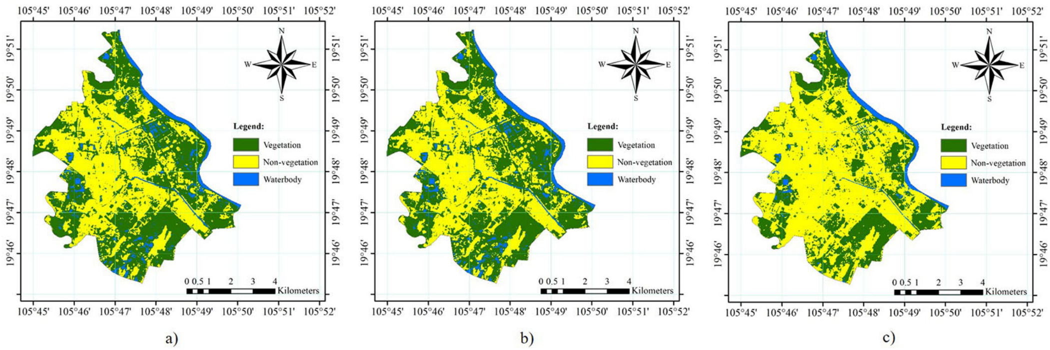

Figure 6: Object classification results according to scenarios with RF algorithm: (a) Only Sentinel-2 bands; (b) Sentinel-2 bands and NDVI; (c) Combination of Sentinel-2 bands and Indices.

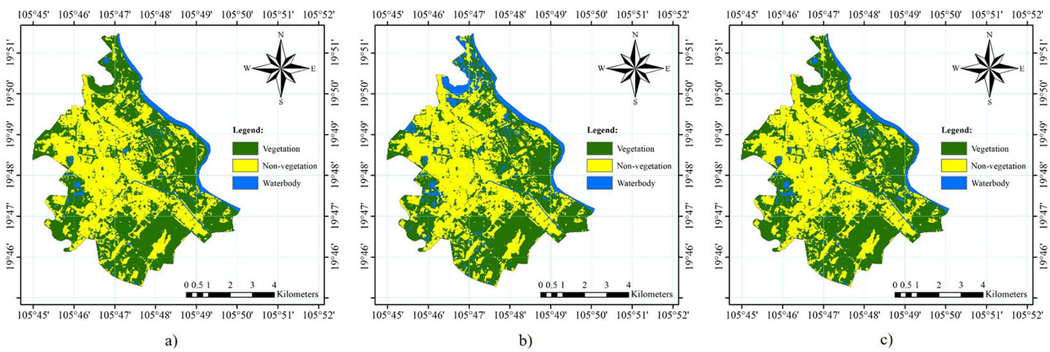

Figure 7: Object classification results according to scenarios with SVM algorithm: (a) Only Sentinel-2 bands; (b) Sentinel-2 bands and NDVI; (c) Combination of Sentinel-2 bands and Indices.

Table 2: Overall accuracy and Kappa index of machine learning algorithms and scenarios

Scenario	SVM		RF	
	Overall accuracy	Kappa index	Overall accuracy	Kappa index
Only Sentinel-2 bands	90.45%	0.735	96.59%	0.895
Sentinel-2 bands and NDVI	90.91%	0.748	97.72%	0.926
Combination of Sentinel-2 bands and indices	92.27%	0.778	98.18%	0.941

Table 2 presents a comparison of the performance of two machine learning algorithms including SVM and RF, evaluated under three distinct scenarios based on input data. These scenarios include the use of Sentinel-2 bands, Sentinel-2 bands combined with NDVI and Sentinel-2 bands combined with indices. The two metrics used for evaluation are overall accuracy and Kappa index, both of which assess the classification performance and agreement of predictions with actual values. In the first scenario, where only Sentinel-2 bands are utilized, the Random Forest algorithm achieves an overall accuracy of 96.59% and a Kappa index of 0.895, significantly outperforming SVM, which attains 90.45% accuracy and a Kappa index of 0.735. This notable difference demonstrates that RF is more capable of handling and accurately classifying data with just spectral band inputs. Moving to the second scenario, the inclusion of NDVI leads to an improvement in both algorithms. SVM achieves 90.91% accuracy and a Kappa index of 0.748, showing a minor improvement, while RF rises to 97.72% accuracy with a Kappa index of 0.926, indicating a stronger enhancement in its ability to distinguish between classes. This trend highlights the significant contribution of NDVI, as it serves as an additional feature that captures vegetation health and density, which improves the classification process.

In the third scenario, the addition of indices alongside Sentinel-2 bands delivers the best overall performance for both algorithms. SVM achieves an overall accuracy of 92.27% and a Kappa index of 0.778, marking its highest performance among the three scenarios. However, the RF algorithm continues to demonstrate superior results, achieving an overall accuracy of 98.18% and a Kappa index of 0.941, which represents the best agreement with ground truth values. This significant increase indicates that the integration of indices provides richer, more relevant information for distinguishing classes, particularly for land cover classification or vegetation-related tasks (Ismayilova and Timpf, 2022). Overall, the Random Forest (RF) algorithm achieved the highest classification accuracy and Kappa values among the tested models. Moreover, the accuracy obtained in this study is higher than that reported in previous studies on similar topics (Huang et al., 2017). Additionally, the incremental improvements seen when NDVI and indices are included suggest that adding derived features can significantly enhance the performance of classification models.

Based on the classification results using Sentinel-2 bands combined with indices and Random Forest algorithm with high accuracy and efficiency, the objects based on this result are grouped into 2 classes: USGs and Others. Figure 8 shows the grouping results for each time point of interest.

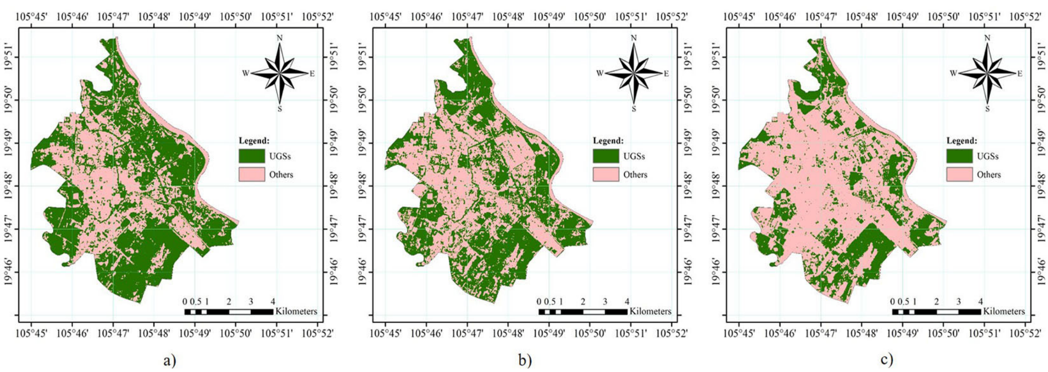

Figure 8: The results of class aggregation at each research time point: (a) May 29, 2016; (b) June 2, 2020; (c) June 16, 2024.

Table 3: The area and percentage of the area of the objects

	May 29, 2016		June 2, 2020		June 16, 2024	
	ha	%	ha	%	ha	%
UGSs	3115.02	58.06	2658.92	49.56	1718.19	32.02
Others	2250.19	41.94	2706.29	50.44	3647.02	67.98

The table provides data on the area (ha) and percentage of two categories of land use: UGSs and Others across three time points: May 29, 2016, June 2, 2020, and June 16, 2024. The data highlights significant changes in land distribution over the years, particularly showing a notable decline in UGSs and a corresponding increase in the Others category.

In 2016, UGSs covered 3115.02 hectares, representing 58.06% of the total area. This figure indicates that urban green spaces initially occupied a dominant share of the land, suggesting a strong presence of vegetation, parks, or similar green areas at this point in time. In contrast, the Others category accounted for 2250.19 hectares, which was 41.94% of the total area. The balance between UGSs and Others in 2016 demonstrates that urban green spaces were prioritized in the landscape.

By June 2, 2020, there was a clear reduction in the area of UGSs to 2658.92 hectares, which now comprised 49.56% of the total area. Meanwhile, the Others category expanded significantly to 2706.29 hectares, making up 50.44%. This shift indicates a turning point where the Others category surpassed UGSs for the first time. The changes could reflect urbanization processes such as infrastructure development, residential or commercial expansion, and a reduction in green spaces. The decline of nearly 456 hectares of UGSs over four years is significant and suggests that urban green spaces were increasingly converted to other land uses, potentially impacting environmental quality, biodiversity, and urban sustainability.

By June 16, 2024, the decline in UGSs became even more pronounced, with the area shrinking to 1718.19 hectares, which accounts for only 32.02% of the total area. In contrast, the Others category continued to expand dramatically to 3647.02 hectares, representing 67.98% of the total. This rapid change highlights a critical trend of diminishing green spaces in favor of other forms of land use. The loss of UGSs between 2016 and 2024 amounts to approximately 1396.83 hectares, illustrating a concerning reduction of green spaces over eight years. This drastic transformation aligns with global findings, particularly in rapidly urbanizing areas (Huang et al., 2017; Ge and Shi, 2025).

Overall, the data reveals a significant and steady decline in Urban Green Spaces (UGSs) over the three different times, with a corresponding increase in the Others category. While UGSs are essential for maintaining ecological balance, enhancing air quality, and providing recreational spaces, the observed trend raises concerns about sustainable urban development. If this pattern continues, cities may face challenges such as increased pollution, reduced quality of life, and adverse impacts on the urban environment. The findings emphasize the urgent need for policies that protect and expand urban green spaces to ensure a more balanced and sustainable approach to land use planning.

4 CONCLUSION

This study uses Sentinel-2 satellite imagery and machine learning algorithms to track and analyze changes, revealing worrying trends in green space loss in Thanh Hoa City. In 2016, UGS covered 3,115.02 ha, accounting for 58.06% of the total area. By 2020, UGS had decreased to 2,658.92 ha (49.56%), reflecting the increasing impact of urban development. The situation worsened in 2024, with UGS shrinking to only 1,718.19 ha, a sharp decline to 32.02% of the total area. Over the eight-year period, UGS lost approximately 1,396.83 ha, a decrease of more than 26% compared to its original area. This decline highlights the increasing pressure of urban sprawl, where green spaces are replaced by infrastructure and housing. By applying indices along with machine learning algorithms such as Random Forests (RF) and Support Vector Machines (SVM), the study effectively classified and analyzed changes in urban green spaces. These findings highlight the urgent need for balanced urban planning to address the environmental and social consequences of green space loss. Policymakers must prioritize strategies to protect, restore, and expand UGS, such as integrating green infrastructure, enforcing stricter land-use regulations, and promoting sustainable urban growth. This study demonstrates the critical role of advanced satellite imagery and machine learning in supporting data-driven decisions to ensure ecological stability, urban resilience, and improved quality of life for future generations.

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