ASSESSMENT OF IMPERVIOUS SURFACE CHANGES FROM MULTI-TEMPORAL LANDSAT DATA AND MACHINE LEARNING TECHNIQUES: A CASE STUDY IN HO CHI MINH CITY

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Abstract

Impervious surface is an artificial surface that prevents water from seeping into the ground. Impervious surface is not only an indicator of the level of urbanization but also a key indicator of the quality of the urban environment. This article presents the results of an impervious surface classification in Ho Chi Minh City area from multi-temporal Landsat image data. Three Landsat image scenes from 2010 - 2020, including Landsat 5 images taken on February 11, 2010, Landsat 8 images taken on February 9, 2015 and February 23, 2020 are used to classify land cover/land use, including impervious surface. Three machine learning algorithms (Random Forest, Support Vector Machine, Classification and Regression Tree) and maximum likelihood method are tested to select the algorithm with the highest accuracy. The results indicate that the Random Forest algorithm achieves the highest accuracy in classifying impervious surfaces, with an overall accuracy exceeding 93% and a Kappa coefficient of 0.915. The results received in the study also show an increase in impervious surface area in Ho Chi Minh City in the period 2010 - 2020. This is important information, helping managers in monitoring and planning urban areas.

Keywords: *Impervious surface; remote sensing; machine learning; Landsat; Ho Chi Minh City.*

1. Introduction

Impervious surfaces are mainly artificial structures such as roads, pavements, roofs,... Impervious surfaces prevent rainwater from naturally seeping into the ground, instead, it accumulates and flows into drainage systems as well as rivers and streams [1]. Due to the above characteristics, impermeable surfaces have a great influence on the environment of urban areas and are considered a main indicator to evaluate the level of urbanization [2]. Most of the rainwater that falls accumulates on the surface, leading to surface flow much larger than underground flow [3, 4]. This greatly affects drainage capacity as well as leads to flooding and water pollution in urban areas [5, 6]. In addition,

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the increase in impervious surface area also leads to the appearance of urban heat islands in large cities [7-9].

Information about impervious surfaces, especially density, location, shape, and spatial distribution, is extremely important for urban management [10]. Impervious surfaces change regularly and continuously with the process of urbanization and socio-economic development. Therefore, the remote sensing method is considered an effective approach for extracting impervious surfaces, supporting monitoring the changes in impervious surfaces in both area and space [11-13].

Since the late twentieth century, many studies have developed methods and techniques for extracting impervious surfaces from remote sensing data based on the image spatial resolution characteristics. Traditional classification methods often encounter many limitations when classifying impervious surfaces from remote sensing data due to the complexity of urban areas' surfaces [14]. Some studies have proposed solutions for classifying impervious surfaces using sub-pixel techniques to overcome the limitations of pixel-based classification methods [15, 16]. In addition, in the case of remote sensing data with high spatial resolution, the object-oriented classification method has higher accuracy compared to the pixel-based classification method [17, 18]. However, this classification method still cannot solve the problems of the influence of shadows and spectral confusion in high spatial resolution remote sensing images, which in turn may cause incorrect classification results [19].

Ridd modeled the urban surface from three components (V-I-S): Vegetation (V - vegetation), impermeable surface (I - impervious surface) and soil (S - soil). Based on the V-I-S model, many spectral indices calculated from multispectral remote sensing images have been proposed to extract impervious surfaces, such as Urban Index - UI [20], Normalized Difference Built-up Index - NDBI [21], Enhanced Built-up and Bareness Index - EBBI [22], Normalized Difference Bareness Index - NDBaI [23], Normalized Difference Bare Land Index - NDLI [24]. In general, the spectral index method allows to improve accuracy of impervious surfaces classification compared to traditional classification methods.

Recently, artificial intelligence techniques have become an important trend in analyzing and identifying objects on remote sensing images, especially with complex objects such as urban land cover [25-30]. Many machine learning algorithms have been proposed to be applied in impervious surface classification such as Random Forest (RF), Support Vector Machine (SVM), Classification and Regression Tree (CART), and Spectral Mixture Analysis (SMA),... Deep learning techniques based on artificial neural networks (Convolution Neural Network - CNN, Cellular Neural Networks, 3D CNN, U-Net_SGD_Bands, U-Net_Adam_Bands) have also been developed to classify impervious surfaces from satellite images in many different studies [31-35]. These studies have demonstrated the effectiveness of machine learning techniques in extracting impervious surfaces from optical satellite images, helping to significantly improve classification accuracy.

This article presents the results of applying machine learning techniques in classifying land cover/land use, including impervious surfaces in Ho Chi Minh City from multi-temporal Landsat image data. Landsat images taken on February 11, 2010 (Landsat 5 TM), February 9, 2015 and February 23, 2020 (Landsat 8 OLI_TIRS) were used to classify the impervious surface in the study area. Three machine learning classification algorithms (RF, SVM, CART) and the maximum likelihood method (ML) are used to classify land cover/land use types from Landsat data due to providing highly accurate results in object classification on remote sensing images [11, 13, 36]. Then, the algorithm with the highest accuracy will be selected to classify and evaluate the changes in the impervious surface in Ho Chi Minh City. The Google Earth Engine (GEE) cloud computing platform was used to process multi-temporal Landsat data and image classification. The land cover/land use maps were then exported and further edited using ArcGIS 10 software.

2. Materials and methodology

2.1. Study area and materials

Study area

Ho Chi Minh City - one of the two largest cities in Vietnam, is a major economic, cultural, tourist, educational, scientific, technical, and medical center of the country. The city is located in the transition zone between the Southeast and the Mekong Delta, with geographical coordinates of about 10°10’ - 10°38’ North latitude and 106°22’ - 106°54’ east longitude [37]. The city has diverse and modern infrastructure and is an important transportation hub of the country, including highway systems, seaports, airports, railways... Due to favorable natural and social conditions, the urbanization process in Ho Chi Minh City took place early at a fast pace, deeply impacting the city’s socio-economic development.

Materials

Remote sensing data used in the study are Landsat multispectral satellite images taken of the Ho Chi Minh City area, including 3 image scenes on February 11, 2010 (Landsat 5 TM), February 9, 2015 and February 23, 2010. 2020 (Landsat 8 OLI_TIRS) – Fig. 2. The images data were collected during the dry season (February) and were not affected by weather conditions (not covered by clouds). Images were collected at the L2A processing level, so in this study, only geometric correction and cutting along the boundary of the Ho Chi Minh City area are carried out.

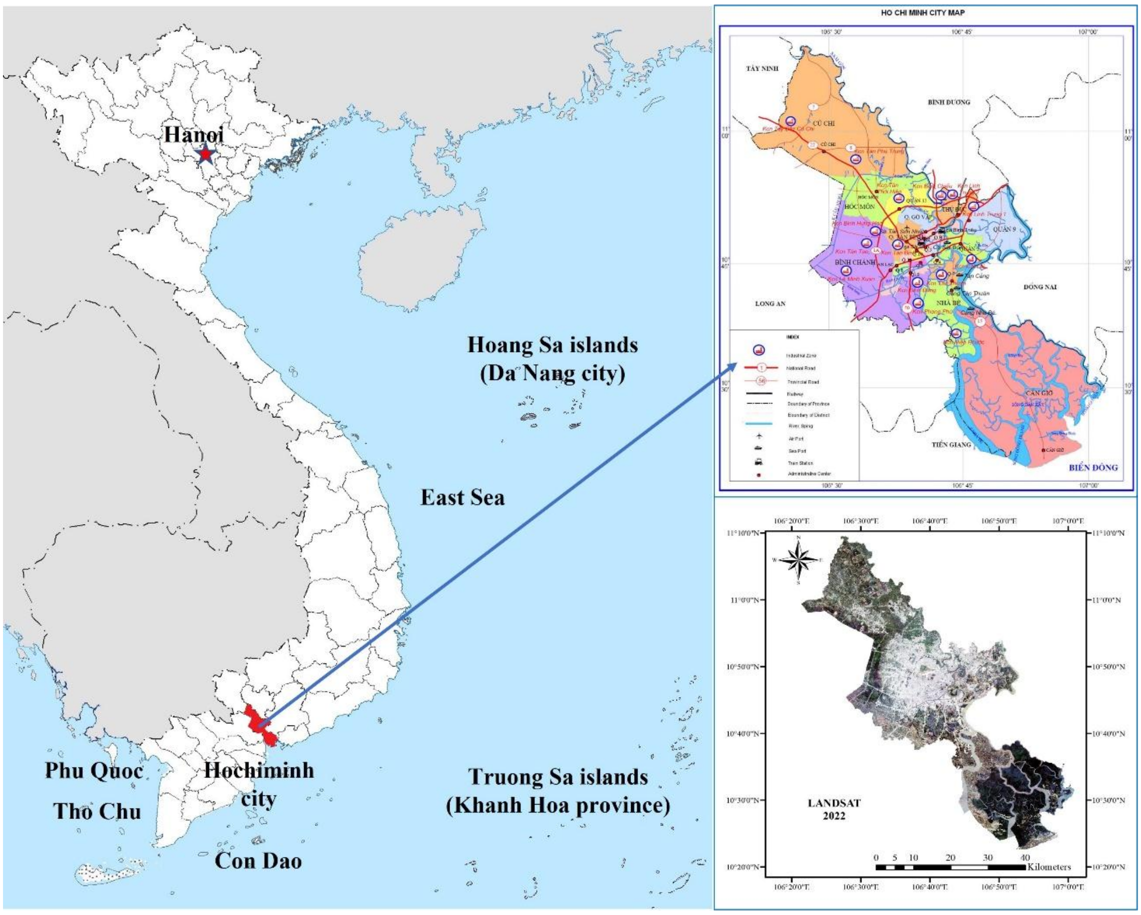

Fig. 1. Geographical location of Ho Chi Minh City.

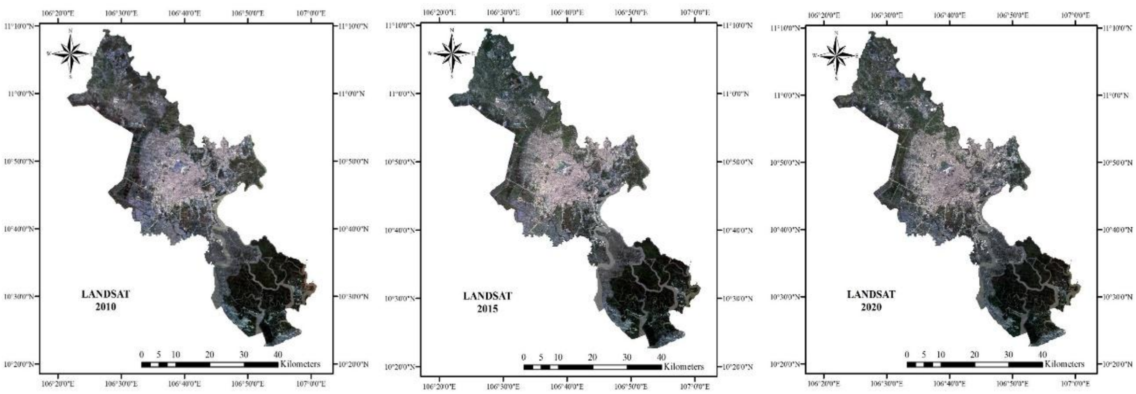

Fig. 2. Landsat image data in Ho Chi Minh City area for the period 2010 - 2020.

2.2. Methodology

Landsat multi-temporal satellite images, after being collected from the USGS database (https://glovis.usgs.gov), are pre-processed to remove spectral and geometric errors and then cropped according to the boundaries of the study area. In this study, three machine learning algorithms, including Random Forest (RF) [38], Support Vector Machine (SVM) [39, 40], Classification and Regression Tree (CART) [41] and and traditional classification method - Maximum Likelihood [42] are tested to classify land cover/land use from Landsat data. In the study, two parameters were used to evaluate the accuracy of classification results, including overall accuracy and the Kappa coefficient (formulas 1 and 2). The classification algorithm with the highest accuracy was selected to build the land cover/land use map and evaluate the changes in impervious surfaces during the study period.

$$\text{Accuracy} = \frac{\sum_{i=1}^{N} I(C(x_n) = y_n)}{N} \cdot 100 \tag{1}$$

in which n is the number of classes, $I(C(x_n) = y_n)$ is a function that returns a value of 1 if the object y_n is assigned the correct label x_n, and returns a value of 0 otherwise. N is the total number of samples.

$$\kappa = \frac{N\sum_{i=1}^{n} x_{i,i} - \sum_{i=1}^{n}\left(G_i C_i\right)}{N^2 - \sum_{i=1}^{n}\left(G_i C_i\right)} \tag{2}$$

where n is the total number of classes, N is the total number of samples. $x_{i,i}$ represents the number of values that the sample received in class i is correctly classified into class i. In the confusion matrix, this value is equivalent to the value on the diagonal of the matrix. C_i corresponds to the total number of samples predicted to belong to class i, G_i is the total number of collected samples belonging to class i.

The flowchart methodology of this research is available in Fig. 3. In which, multi-temporal Landsat remote sensing image data is collected and pre-processed including Landsat-TM image taken on February 11, 2010, Landsat-8 image taken on February 9, 2015 and Landsat-8 image taken on February 23, 2020. The study experimented by classifying the surface cover of the research area into 6 objects including water bodies, impervious surfaces, grass and shrubs, agricultural land, bare land, and forest by RF, SVM, CART và ML algorithm. Based on the accuracy of the classification results by the above algorithms, select the best classification result for each data set. Finally, the classification results are used to evaluate the change in surface cover of the experimental area during the period 2010 - 2020.

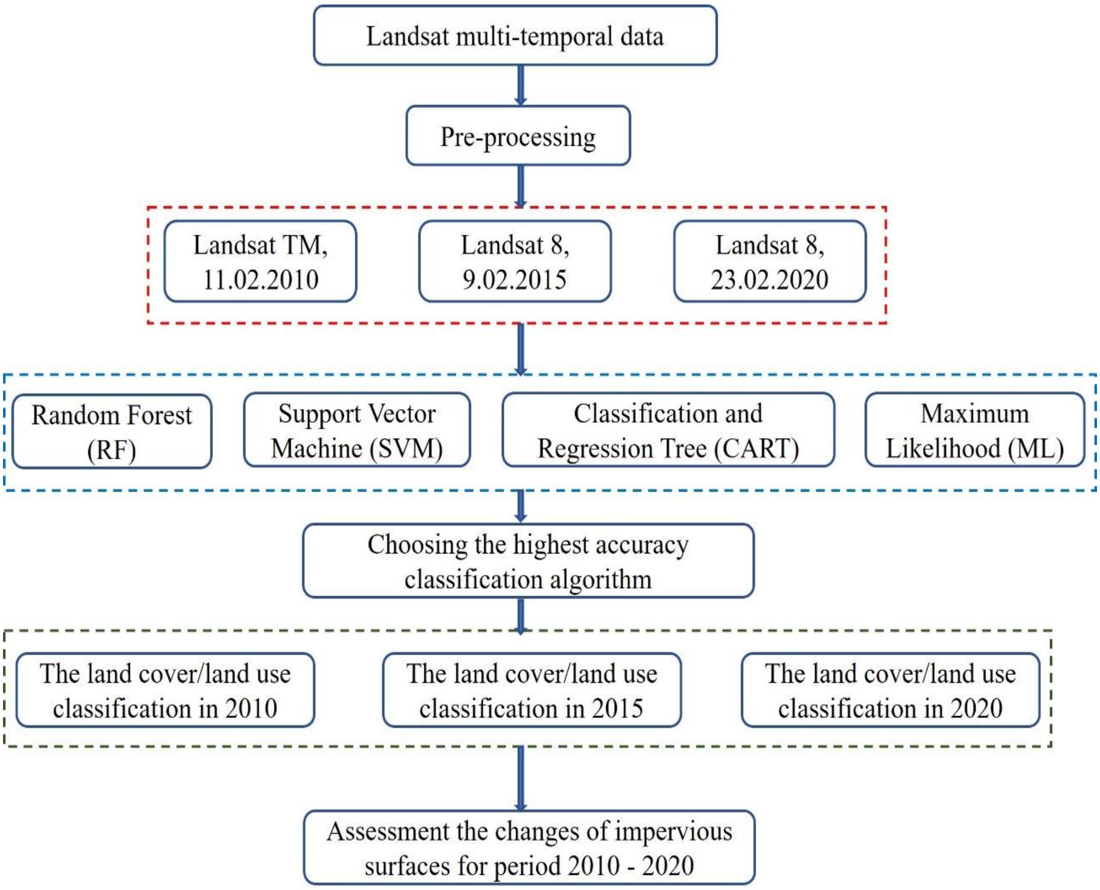

Fig. 3. The flowchart of methodology for impervious classification from Landsat data.

3. Result and discussion

The sample data set includes 4000 samples (pixels) used to classify the land cover/land use of the study area, of which 70% is used to train the model and 30% is used to evaluate the accuracy of the classification results. The classification accuracy was evaluated based on the overall accuracy value and Kappa coefficient (Table 1). For the RF and CART algorithms, the number of trees is a crucial hyperparameter that requires testing to achieve optimal results. Based on consultations with several studies [43, 44], the optimal number of trees was determined to be 250. Besides, the optimal parameter set for the SVM algorithm is kernel Type: RBF, gamma: 1, cost: 10.

Table 1. The comparison of overall accuracy and Kappa coefficient of different classification algorithms

Year	Accuracy	Algorithms			
		SVM	**RF**	**CART**	**ML**
2010	Overall accuracy	86.90%	**93.44%**	90.77%	85.98%
	Kappa coefficient	0.871	**0.919**	0.887	0.829
2015	Overall accuracy	88.72%	**93.54%**	89.81%	87.29%
	Kappa coefficient	0.863	**0.921**	0.876	0.845
2020	Overall accuracy	91.26%	**93.02%**	87.65%	88.10%
	Kappa coefficient	0.892	**0.915**	0.858	0.847

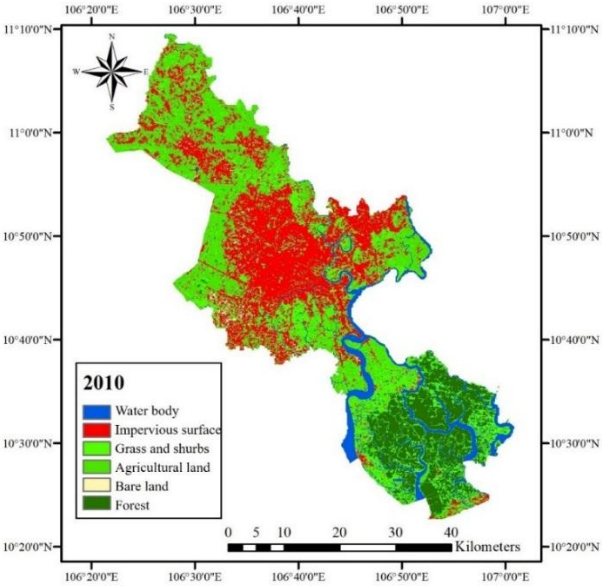

Fig. 4. Results of land cover/land use classification in Ho Chi Minh City area in 2010 using the RF algorithm.

Overall, the RF algorithm gives the highest accuracy results on all three data sets (2010, 2015, 2020) with an Overall accuracy index of over 93% and a Kappa index of 0.915. Meanwhile, the SVM, CART and ML algorithms all have Kappa index values lower than or equal to 0.892 on all three data sets; The highest Overall accuracy index is 93.54% with the RF algorithm, while for the remaining algorithms this value is only 91.26% or less. Besides, the Kappa coefficient obtained in all four methods is greater than 0.82, which shows a good agreement between the observed and predicted classification.

The classification results using the RF algorithm are clearly presented in Fig. 4, Fig. 5 and Fig. 6. It can be seen that the impervious surface area tends to increase over time with the expansion of the impervious surface area to the Northwest.

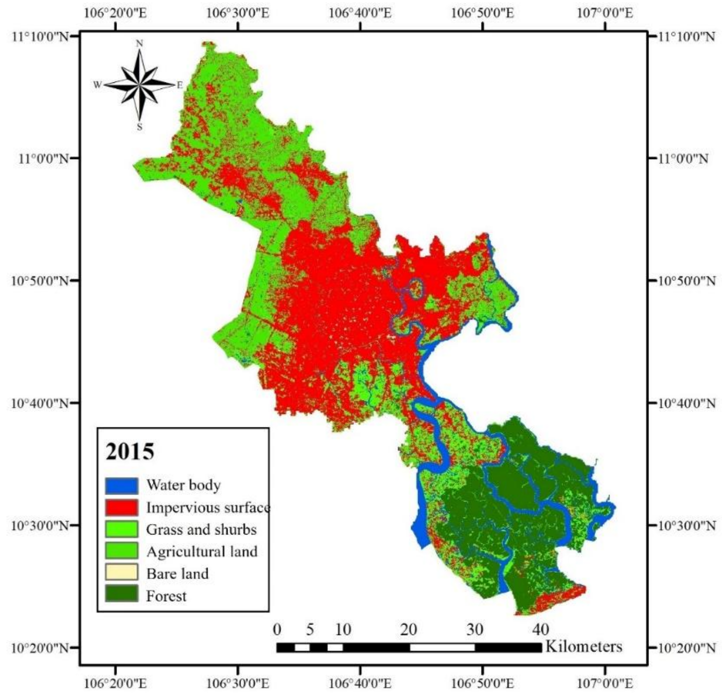

Fig. 5. Results of land cover/land use classification in Ho Chi Minh City area in 2015 using the RF algorithm.

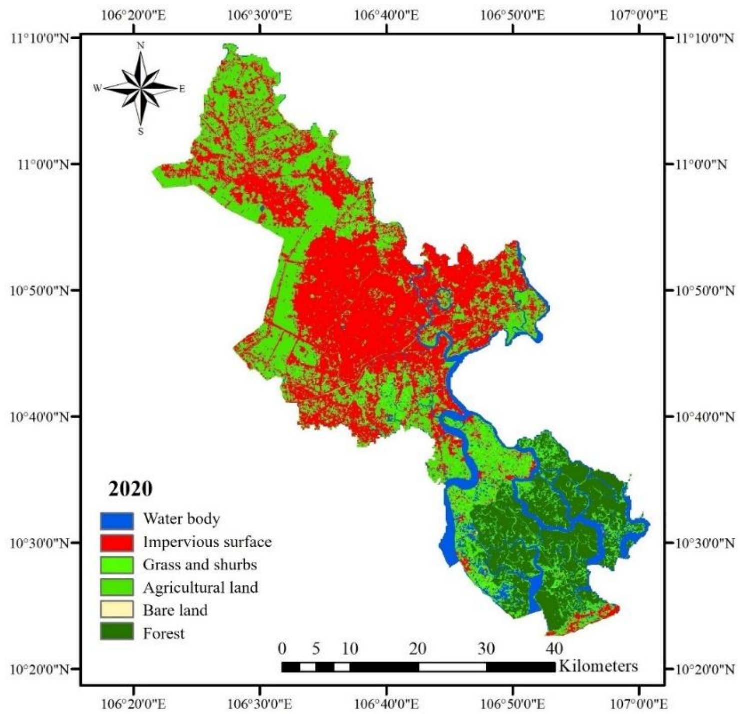

Fig. 6. Results of land cover/land use classification in Ho Chi Minh City area in 2020 using the RF algorithm.

Table 2. The changes in land cover/land use in Ho Chi Minh City area for the period 2010 - 2020

Area (km^2) / Year	2010	2015	2020
Water body	170.149	167.176	161.879
Impervious surface	616.983	786.107	816.806
Grass and shrubs	408.248	268.444	273.423
Agricultural land	551.434	458.123	437.473
Bare land	31.479	19.683	13.706
Forest	263.942	342.702	338.948

Table 2 shows the changes in land cover/land use in study area for the period 2010 - 2020 with the area of the objects of interest extracted by year. Based on Table 2, we can observe the changes in landcover/land use area from the year 2010 to 2020 for six categories:

- The area of the water body has slight fluctuations, from 170.149 km^2 in 2010 to 161.879 km^2 in 2020.

- The impervious surface area has also increased over the years, from 616.983 km^2 in 2010 to 786.107 km^2 in 2015 and 816.806 km^2 in 2020.

- Grass and shrubs area has decreased significantly from 408.248 km^2 in 2010 to 273.423 km^2 in 2020. Agricultural land has also decreased over the years, from 551.434 km^2 in 2010 to 437.473 km^2 in 2020. However, agricultural land still accounts for a high proportion of the total area of the city.

- Bare land has fluctuated over the years but has shown a general decrease from 31.479 km^2 in 2010 to 13.706 km^2 in 2020. The forest area has remained relatively stable, with a slight increase from 2010 (263.942 km^2) to 2015 (342.702 km^2), followed by a slight decrease in 2020 (338.948 km^2).

In summary, while the impervious surface areas have increased, the areas of grass and shrubs, agricultural land, and bare land have decreased from 2010 to 2020. However, the water body and forest area have remained relatively stable over the same period.

4. Conclusion

In this study, 3 Landsat multi-temporal satellite images for the period 2010 - 2020 in Ho Chi Minh City were used to classify land cover/land use types, including impervious surfaces based on three common machine learning techniques (RF, SVM, CART) and maximum likelihood method. Analysis of the obtained results shows that the RF algorithm achieved the highest accuracy of impervious surface classification, shown by the overall accuracy value and Kappa coefficient. From the results achieved in this study, the RF algorithm was chosen to classify and evaluate the changes in impermeable surfaces in Ho Chi Minh City.

Analysis of the results shows that the impervious surface area in Ho Chi Minh City has changed significantly in the period 2010 - 2020, from 616.983 km^2 in 2010 to 786.107 km^2 in 2015 and 816.806 km^2 in 2020, equivalent to about 3.24% per year. From the land cover/land use map for the period 2010 - 2020, it also shows that the impervious surface has the strongest change in the north of the study area (Cu Chi and Hoc Mon districts). Meanwhile, in the central area, the impervious surface has little change due to saturation in construction in this area.

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ĐÁNH GIÁ BỀ MẶT KHÔNG THẤM TỪ DỮ LIỆU ẢNH VỆ TINH LANDSAT ĐA THỜI GIAN VÀ CÁC KỸ THUẬT HỌC MÁY: MỘT NGHIÊN CỨU CHO KHU VỰC THÀNH PHỐ HỒ CHÍ MINH

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Tóm tắt: Bề mặt không thấm là các bề mặt nhân tạo, có đặc điểm ngăn nước thấm vào lòng đất. Bề mặt không thấm không chỉ là thước đo mức độ đô thị hóa mà còn là một chỉ số quan trọng đánh giá chất lượng môi trường đô thị. Bài báo này trình bày kết quả phân loại bề mặt không thấm khu vực thành phố Hồ Chí Minh từ dữ liệu ảnh vệ tinh Landsat đa thời gian. Ba cảnh ảnh Landsat giai đoạn 2010 - 2020, bao gồm ảnh Landsat 5 chụp ngày 11/02/2010, ảnh Landsat 8 chụp ngày 09/02/2015 và ngày 23/02/2020 được sử dụng để phân loại lớp phủ/sử dụng đất, bao gồm cả bề mặt không thấm. Ba thuật toán học máy (Random Forest, Support Vector Machine, Classification và Regression Tree) và phương pháp phân loại xác suất cực đại được thử nghiệm để lựa chọn thuật toán có độ chính xác cao nhất. Kết quả nhận được cho thấy, thuật toán Random Forest có độ chính xác cao nhất khi phân loại bề mặt không thấm qua việc so sánh độ chính xác tổng thể và hệ số Kappa với giá trị lần lượt là trên 93% và 0,915. Kết quả nhận được trong nghiên cứu còn cho thấy sự gia tăng diện tích bề mặt không thấm trên địa bàn thành phố Hồ Chí Minh trong giai đoạn 2010 - 2020. Đây là thông tin quan trọng, giúp các nhà quản lý trong việc giám sát và quy hoạch đô thị.

Từ khóa: *Bề mặt không thấm; viễn thám; học máy; Landsat; Thành phố Hồ Chí Minh.*

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