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A COMPARATIVE STUDY OF GREEN AREA CLASSIFICATION BY REMOTE SENSING TECHNIQUES IN PHAYAO MUNICIPALITY, THAILAND

Abstract: This research has two primary goals: first, to compare different image classification methods for identifying green areas within the Phayao Municipality, and second, to analyze and compare the resulting proportions of green areas. Using Sentinel 2B satellite imagery, the study classified green areas by applying two methods: Support Vector Machine (SVM) and Maximum Likelihood (ML). A Confusion matrix is used to verify the accuracy of the classification. Finally, the analysis focused on the proportion of green area in relation to the total urban area and the ratio of both total green area and recreational green area to the population count. The results show that both methods were able to classify green areas including community economic green areas, unused green areas, utility green areas, natural green areas, and public green areas. Although differences were found between the areas classified by the SVM and ML methods, the accuracy assessment indicated that the SVM method achieved higher classification accuracy than the ML method. Furthermore, the analysis reveals differences in the estimated proportion of green areas and the ratio of green space per capita between the two classification approaches. The findings suggest that the ratio obtained from the ML method is closer to the value reported by the government reported. Finally, the results can provide useful information for urban green space planning and management.

Keywords: satellite imagery, Support Vector Machine (SVM), Maximum Likelihood (ML), urban planning

Introduction

Nowdays, Thailand places great importance on developing green areas in urban and surrounding regions to maintain ecological balance, especially in major and secondary cities, to achieve sustainable development. According to the World Health Organization (2016), urban green spaces contribute to improving physical and mental health and enhancing environmen-

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tal quality. Phayao Province, located in the upper northern region, has experienced rapid urban development over the past decade due to social growth driven by educational promotion, with the University of Phayao serving as the province's educational hub. In addition, ecotourism and tourist attractions such as Kwan Phayao have contributed to increased economic growth and urban population expansion. Currently, the ratio of green area per capita across the country has been calculated as fundamental data for sustainable green area management. It was found that Phayao Province ranks third among the upper northern provinces in terms of the lowest public green area per capita (square meters per person), with 0.71, following Lamphun Province (0.67) and Phrae Province (0.4) (Office of Natural Resources and Environmental Policy and Planning, 2023).

Urban expansion in Thailand has been increasing rapidly. This growth is driven by population increase as well as technological and economic development. Consequently, the demand for resources and housing has risen, which has led to various problems such as environmental degradation and traffic congestion)Klabsang, 2021). The application of geoinformation technology, such as monitoring urban expansion or using high-accuracy mapping techniques from satellite imagery, has been adopted in urban expansion research)Pattanasak, 2014; Vatseva & Dinkov, 2025). As a complex with a high concentration of resources, environment, population and socio-economy, green space has gradually become the core of building an ecological security system in urban areas (Kang & Cai, 2023). Moreover, Moutet et al. (2026) found that greening interventions targeting car-dedicated space in Paris, such as replacing surplus on-street parking and 20% of street space with vegetation, could reduce all-cause mortality by around 0.8% while promoting more sustainable and resilient cities. Meanwhile, Liu et al. (2026) who reported that prioritizing the expansion of green spaces in labor-dense areas with relatively low vegetation coverage could yield more cost-effective benefits by enhancing heat reduction potential, increasing working hours, and improving average earnings in mega cities. Finally, green areas improve physical and mental health and enhance environmental quality as reported by Ouzir)2003) cited that green infrastructure in the city of Bou-saada can withstand the drought and heat conditions of the area, provide shade and reduce heat, and prevent soil degradation and desertification by stabilizing the soil and mitigating wind erosion. Therefore, geoinformatics by image classification of urban green areas can support organizations in urban planning and management.

Support Vector Machine (SVM) image classification is one classification method in Machine Learning, which is a crucial technology. It works by combining expert knowledge with a computer to classify land use. Therefore, using this technique to analyze green areas from Sentinel 2 satellite imagery, which is provided free of charge and has moderate resolution pixel details, is beneficial for classifying green areas. There are various analytical techniques for analyzing land use patterns and green areas from satellite imagery. For example, Pattanasak (2014) used Object-Based Image Analysis (OBIA) to analyze land use patterns in Mae Rim District, Chiang Mai Province, Thailand. Sukpromsapp (2015) used Geographic Information Systems (GIS) to analyze land use changes around the University of Phayao, Thailand. Meanwhile, Thepwong and Eamchuuen (2019) studied green area classification in an urban area using the Support Vector Machine method in Chiang Mai Municipality, Thailand. Each analysis method found that the method relying on Support Vector Machine classification yields high data classification accuracy.

In this study, therefore, the technique of image data classification using the Support Vector Machine method, which is a type of Machine Learning classification, was used and compared with the pattern recognition classification method using the Maximum Likelihood method. The results of the study can be used to efficiently develop the green area classification method for Phayao Municipality in the future. This research has the objectives: 1) to compare the classification of green areas in the urban area of Phayao Municipality using image classification methods, and 2) to analyze and compare the proportion of green areas from the classification in the Phayao Municipality area.

Materials and Methods

Study Area and Data

1) Phayao Municipality has an area of 9 square kilometers, or 5,625 rai. It is comprised of two sub-districts (Tambon): Tambon Wiang and Tambon Mae Tam in Phayao province, Thailand. (Phayao Municipality Office, 2025).

The population in the Phayao Municipality area is a total of 16,770 people (Office of Natural Resources and Environmental Policy and Planning, 2024).

The boundaries are as follows:

- North: Borders Tambon Tom, Mueang Phayao District.
- South: Borders Tambon Mae Ka, Mueang Phayao District.
- East: Borders Tambon Tha Wang Thong, Mueang Phayao District.
- West: Borders Kwan Phayao and Tambon Mae Sai, Mueang Phayao District.

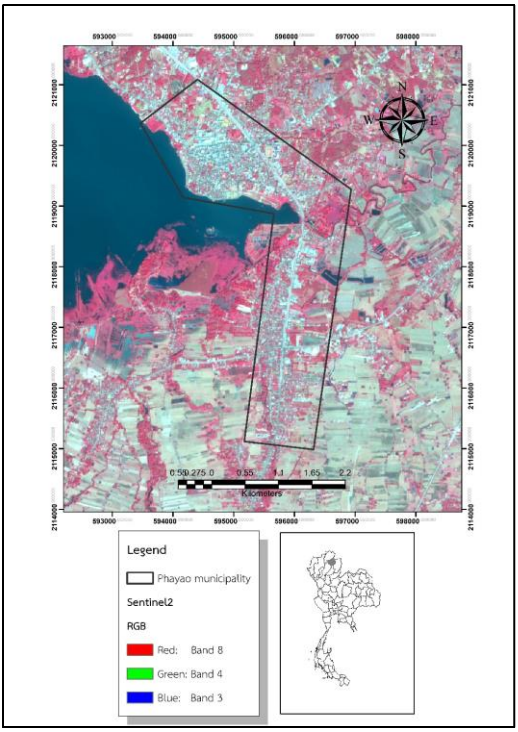

Fig. 1. The boundary of Phayao Municipality from Sentinel-2B satellite image

2) Sentinel 2B satellite imagery was downloaded from the Copernicus website (Copernicus Data Space Ecosystem, 2025). The selected image was dated January 19, 2024, with cloud cover appearing in the image not exceeding 20%. One scene of the image with 13 bands was obtained. Image color composite with false color was used in R-G-B: 8-4-3. The resolution of cell size was 10 meters x 10 meters.

Data Analysis

The operation was conducted according to the objectives, specifically to address Objective 1: to compare the classification of urban green areas in Phayao Municipality using image classification methods. The operational steps included:

Green Area Classification

Green area classification was performed using the SVM method and ML method. Land cover types were classified using geoinformatics software. The Green areas can be classified into six types based on their characteristics and functions. These include **public green areas** such as public parks, botanical gardens, and playgrounds. **Utility green areas** consist of private green spaces in residential areas and private developments, institutional green spaces within educational or government institutions, and green spaces associated with public utility areas such as landfill sites, wastewater treatment facilities, and airport zones. **Linear green areas** refer to vegetated areas along infrastructure, including roadsides, road medians, railway corridors, and waterways. **Community economic green areas** include areas used for agricultural and food production, such as farmland, orchards, and aquaculture areas. **Natural green areas** comprise forests, hillsides, wetlands, and water bodies. Finally, **unused green areas** refer to vacant or abandoned land that has not yet been utilized (Office of Natural Resources and Environmental Policy and Planning, 2024).

The accuracy assessment of green area classification was performed using a confusion matrix, which compares the classified map (from the classification process) with a reference map (based on field surveys and Google Earth imagery). The overall accuracy and Kappa statistic (KHAT: K) were then calculated to evaluate the consistency between the classified data and the reference data. The Kappa statistic measures the level of agreement between the two datasets beyond what would be expected by chance. It can be calculated using the following equation:

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} \cdot x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} \cdot x_{+i})} \tag{1}$$

where:
r = number of rows and columns in the confusion matrix,
Xii = number of points correctly classified (the same in row *i* and column *i*),
Xi+ = total number of points in row *i*,
X+i = total number of points in column *i*, and
N = total number of sample points in the confusion matrix.
(Lillesand et al., 2004)

To address Objective 2, the analysis of the proportion of each type of green areas in Phayao Municipality, Phayao Province, was conducted. The analysis included the percentage of total green areas compared with the total urban area, the ratio of total green areas to population, and the ratio of recreational green areas to population, as shown in the following equations.

$$\text{Percentage of green area} = \frac{\text{Total green area (m}^2\text{)x 100}}{\text{Total urban area (m}^2\text{)}} \tag{2}$$

$$\text{Ratio of total green area to population} = \frac{\text{Total green area (m}^2\text{)}}{\text{Total Population}} \tag{3}$$

$$\text{Ratio of recreational green area to population} = \frac{\text{Total recreational green area (m}^2\text{)}}{\text{Total Population}} \tag{4}$$

Results

The chapter is divided into subheadings. It should offer a short and precise summary of the experimental data, their interpretation, and any experimental conclusions that might be reached.

Green Area Classification

The classification of green areas using the SVM and ML methods was carried out through several steps. First, training areas were selected to represent six types of green areas covering the entire study area. These training areas were then analyzed using the SVM method, which is a non-parametric classification technique. Since SVM does not assume statistical data distribution, it can classify data accurately even with a limited number of training samples. The method is based on a linear model that separates data into two classes, aiming to find a model that avoids overfitting that is, one that does not memorize the training data pattern excessively. The optimal model is the one that maximizes the margin between classes. In addition, a kernel function is used to transform non-linear data into a higher-dimensional space, making it easier to separate the data. In contrast, ML classification is a supervised classification method that uses statistical calculations based on training data. It determines the probability that a given pixel belongs to a particular class, making it particularly useful for classifying overlapping land-use types (Jensen, 2016).

To achieve Objective 1, Sentinel-2B satellite image was downloaded from the Copernicus website. The green areas were classified into six types. The classification results using the SVM method showed that the community economic green areas were the largest, covering 1.93 square kilometers. This was followed by unused green areas at 1.71 square kilometers, utility green areas at 0.71 square kilometers, natural green areas at 0.64 square kilometers, and the smallest were public green areas at 0.42 square kilometers. Meanwhile, the classification results using the ML method showed that the community economic green areas were the largest, covering 2.90 square kilometers. This was followed by unused green areas at 1.41 square kilometers, natural green areas at 0.59 square kilometers, public green areas at 0.56 square kilometers, and the smallest were utility green areas at 0.33 square kilometers.

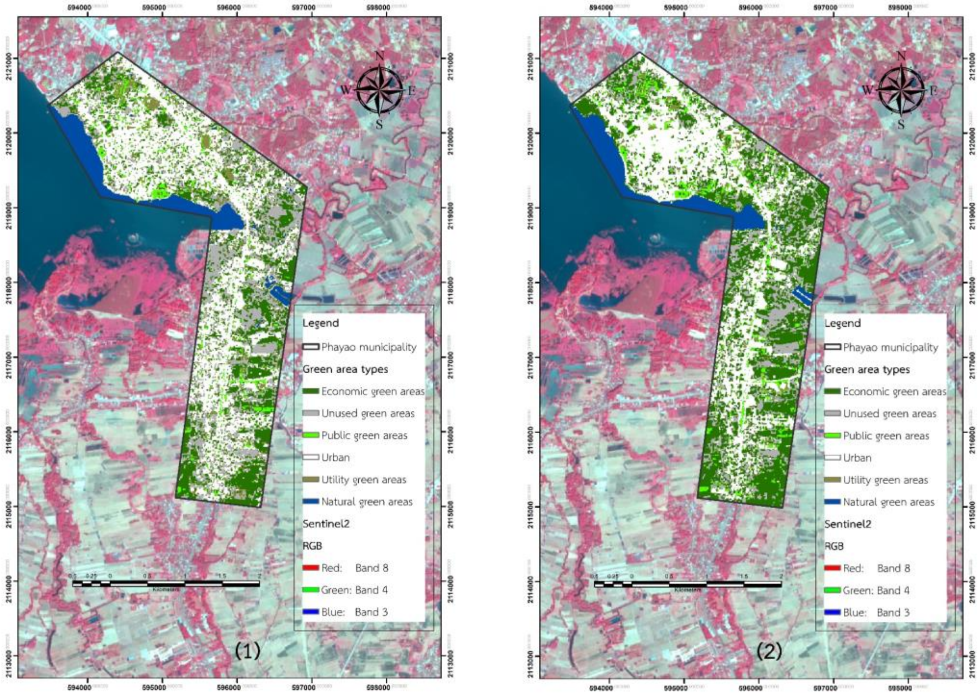

Figure 2. Green area classification: (1) the Support Vector Machine (SVM) method, (2) Maximum Likelihood (ML) method

Table 1. Green area classification

Green area *(Total urban area = 8.75 square kilometers)*	Support Vector Machine (SVM)		Maximum Likelihood (ML)	
	Classified Green Area (m^2)	Percentage of Green Area (%)	Classified Green Area (m^2)	Percentage of Green Area (%)
1. Public green areas	422,400	4.82	564,200	6.44
2. Utility green areas	706,500	8.07	335,600	3.83
3. Linear green areas	0	0.00	0	0.00
4.Community economic green areas	1,928,400	22.03	2,903,400	33.16
5. Natural green areas	636,800	7.27	585,200	6.68
6. Unused green areas	1,717,600	19.62	1,408,700	16.09
Total	3,343,000	38.19	2,957,600	33.78

Accuracy Assessment of Green Area Classification

The accuracy of the green area classification was evaluated by creating a confusion matrix, that compares the classified map (from the classification process) with the reference map (from field surveys and Google Earth imagery). The number of sample points used for comparison was determined based on the following equation.

$$N = \frac{z^2(p)(q)}{E^2} \tag{5}$$

Where:
N = number of sample points
Z = 2 (from the standard deviation value of 1.96 for a 95% two-tailed confidence level)
P = acceptable percentage
q = 100 – P (percent)
E = acceptable error level

The acceptable percentage was set at 85%, with an acceptable error level of 0.05. Therefore, a total of 203 sample points were determined for the accuracy assessment. The results of overall accuracy and Kappa statistic classification are shown in Table 2 and Table 3.

Table 2. Confusion matrix from classification using the SVM method

	Green area types (Reference map)								
	Green area	Public green areas	Urban areas	Utility green areas	Community economic green areas	Natural green areas	Unused green areas	Total	User's accuracy
Green area types (Classified map)	Public green areas	3	4	0	0	2	1	10	0.30
	Urban areas	2	61	0	8	9	1	81	0.75
	Natural green areas	0	2	15	0	0	1	18	0.83
	Utility green areas	0	6	0	38	0	3	47	0.80
	Community economic green areas	0	1	0	1	7	1	10	0.70
	Unused green areas	1	5	1	9	2	19	37	0.51
	Total	6	79	16	56	20	26	203	
Producers' Accuracy		0.73	0.57	0.93	0.68	0.42	0.43		Total (143/203)* 100 = **70.44%**

From Table 2, the overall accuracy was calculated to be 70.44%, and the Kappa statistic was 0.60.

Table 3. Confusion matrix from classification using the Maximum Likelihood (ML) method

		Green area types (Reference map)							
	Green area	Public green areas	Urban areas	Utility green areas	Community economic green areas	Natural green areas	Unused green areas	Total	User's accuracy
Green area types (Classified map)	Public green areas	2	5	0	0	1	2	10	0.20
	Urban areas	11	54	0	11	1	4	81	0.67
	Natural green areas	0	2	14	1	0	1	18	0.78
	Utility green areas	1	1	0	41	0	4	47	0.87
	Community economic green areas	3	0	0	3	3	1	10	0.30
	Unused green areas	1	0	0	19	1	16	37	0.43
	Total	18	62	14	75	6	28		
Producers' Accuracy		0.11	0.87	1.00	0.55	0.50	0.57		Total (120/203)* 100 = **64.04%**

From Table 3, the overall accuracy was calculated to be 64.04%, and the Kappa statistic was 0.52. From Table 2 and Table 3, it was found that the overall accuracy and Kappa statistic of the SVM method are higher than those of the ML method.

Analysis of the Proportion of Each Type of Green Area in Phayao Municipality

SVM method

The analysis of the proportion of each type of green area in Phayao Municipality based on classification using the SVM method is presented in Table 1, and the calculations were performed as follows.

$$\text{Ratio of total green area to population} = \frac{\text{Total green area (m}^2\text{)}}{\text{Population}} \tag{6}$$

Substituting the values:

Ratio of total green area to population = $\frac{3{,}343{,}000}{16{,}770}$

The population of Phayao Municipality in 2024 (B.E. 2567) was 16,770 (Phayao Municipality Office, 2025).

The ratio of total green area to population is 199.34 square meters per person.

When calculating public or recreational green area, it can be calculated as follows:

The ratio of public green area to population = $\frac{422{,}400}{16{,}770}$

The ratio of public green area to population is 25.18 square meters per person.

ML method

The analysis of the proportion of each type of green area in Phayao Municipality based on classification using the ML method is presented as follows.

$$\text{Ratio of total green area to population} = \frac{\text{Total green area (m}^2\text{)}}{\text{Population}} \tag{7}$$

Substituting the values:

Ratio of total green area to population=$\frac{\mathbf{2{,}957{,}000}}{16{,}770}$

The ratio of total green area to population is 176.33 square meters per person.

When calculating public or recreational green area, it can be calculated as:

The ratio of public green area to population = $\frac{564{,}200}{16{,}770}$

The ratio of public green area to population is 33.64 square meters per person.

The analysis of green area proportions in Phayao Municipality found that the ratio of total green area to population was 199.34 m^2/person, and the ratio of public green area to population was 25.18 m^2/person. In comparison, using the ML method, the ratio of total green area to population was 176.33 m^2/person, and the ratio of public green area to population was 33.64 m^2/person.

Comparison of Classified Areas

The comparison of green areas classified using the SVM method and ML method, compared with data from the Office of Natural Resources and Environmental Policy and Planning (2024), is shown in Table 4. It was found that the ML classification produced values for the percentage of total green area relative to urban area and the ratio of total green area to population that were close to the values reported by the Office of Natural Resources and Environmental Policy and Planning (classification method not specified). However, the ratio of public green area to population from both methods still differed from the official data.

Table 4. Comparison of proportions from green area classification

Method	Support Vector Machine (SVM)	Maximum Likelihood (ML)	Office of Natural Resources and Environmental Policy and Planning
Percentage of total green area to urban area (%)	38.19	33.78	32.67
Ratio of total green area to population (m^2/person)	199.34 square meters per person	176.33 square meters per person	175.35 square meters per person
Ratio of public green area to population (m^2/person)	25.18 square meters per person	33.64 square meters per person	6.98 square meters per person

Discussion

Green area classification was performed using the SVM and ML methods. Green areas were classified into six types based on their characteristics and functions: community economic green areas, unused green areas, utility green areas, natural green areas, and public green areas. No linear green areas were found in the study area. This classification is consistent with the classification proposed by the Office of Natural Resources and Environmental Policy and Planning (2023), Prachchayakup (2024).

The accuracy assessment of green area classification was conducted using a confusion matrix. Phayao Municipality, with a total area of 8.70 square kilometers, was sampled at 203 random points. The analysis found that the overall accuracy of the SVM method was 70.44 %, with a Kappa statistic of 0.60. The ML method showed the same overall accuracy (64.04 %) and Kappa statistic of 0.52. Comparisons of image classification methods indicate that AI-based extraction methods provide higher classification accuracy than pixel based classification (Van Ninh & Waisurasingha, 2017; Kranjčić et al., 2019; Mondal et al., 2012). These findings are also consistent with Baig et al. (2021), who reported that land-use classification using the SVM method achieves higher accuracy than the ML method. Moreover, applying hyperparameter optimization algorithms to model tuning can improve classification accuracy. As reported by Yan et al. (2023) cited that the application of the Marine Predators Algorithm (MPA) enhanced classification accuracy, and the MPA-RF (Random Forest) model achieved very high overall accuracy in urban green space classification.

The study analyzed the proportion of each type of green area in Phayao Municipality, Phayao Province by examining the percentage of total green area relative to the urban area, the ratio of total green area to the population, and the ratio of recreational green area to the population. The ML method produced values for the percentage of total green area relative to urban area and the ratio of total green area to population that were close to the data from the government report. However, the ratio of public green area to population differed between the two methods. This may be because both the SVM and ML methods used the same training area data, but the algorithms of each method are different. As a result, areas defined based on land cover characteristics may differ from actual green areas in each category. For example, the utility green area around the Phayao Provincial Fisheries Office has land cover that includes water bodies, trees, and grass, which may lead to misclassification and inaccurate interpretation of the green area types. This issue is consistent with the findings of Pal & Mather (2003) noted that insufficient or non-representative training data may lead to misclassification and reduced classification accuracy. Therefore, training samples should adequately represent the spectral variability of each land cover class to improve classification performance.

The analysis of green areas using satellite image classification can be applied in countries experiencing urban expansion and increasing demand for urban green spaces. On the other hand, urban expansion affects the amount of green space. According to the study by Lahcene et al. (2022) noted that the drop-in water leads to the degradation and reduction of green spaces. Therefore, appropriate land use planning is required. The proposed classification framework can be generalized and adapted to medium-sized municipalities across Asia and the Mediterranean region, such as Istanbul, Ankara, Izmir, and Antalya in Turkey, providing a consistent and cost-effective approach for monitoring green spaces (Çoşlu, 2025).

Conclusion

This study classified urban green areas using Sentinel-2B satellite imagery and compared the performance of the Support Vector Machine (SVM) and Maximum Likelihood (ML) methods. Six types of green areas were selected as training areas, and classification accuracy was evaluated using overall accuracy and the Kappa statistic. The results showed that the SVM method achieved higher classification accuracy than the ML method.

The proportions of green area were analyzed using indicators including the percentage of total green area relative to urban area, the ratio of total green area to population, and the ratio of recreational green area to population. The ML method produced values for the percentage of total green area relative to urban area and the ratio of total green area to population that were consistent with government data. However, the ratio of public green area to population differed between the two methods.

Future studies should explore additional machine learning techniques, such as Random Forest (RF) and Artificial Neural Networks (ANN), and incorporate higher-resolution satellite imagery to improve classification accuracy. The findings of this study can support urban green space assessment and provide useful information for urban planning and sustainable city development.

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