Machine Learning for Urban Types Classification Using Sentinel-1 And Sentinel-2

Niang Sian Lun[1] **and Sarawut Ninsawat**[1]

[1] Remote Sensing & GIS
Department of Information and Communications Technologies (ICT)
School of Engineering and Technology (SET)
Asian Institute of Technology (AIT)
Email: sianlun10@gmail.com, sarawutn@ait.ac.th

ABSTRACT

The urban various categories characteristics have emphasized the great importance of understanding and creating suitable land evaluations in the future. The overall objective of this study is to classified the urban zone utilizing building height and various satellite-based indexes of Sentinel-2A. First, the building height was estimated from the Sentinel-1A SAR. A new indicator VVH, which can provide a better performance, is produced from the dual-polarization information, VV and VH. Then, the building height model was developed using indicator VVH and the reference building height from NOSTRA building block data. The root mean square error (RMSE) between estimated and reference height is 1.413m. Then the machine learning to classify three urban types which are composed of the residential area, commercial area, and other areas including vegetation, waterbody, car parking, and so on were developed. To classify the urban types, the three-machine learning classifier; support vector machine, random forest, and k-nearest neighbours were developed by using the estimated building height and other satellite-based indices such as NDVI, NDWI, and NDBI. The classification is randomly trained data from eight focus areas and each area is divided into a 100x100m grid. Different parameter components of machine learning models are examined, for example, classification using only building height, and the only spectral indices. There are a total of 16 variables that are the minimum, maximum, mean and standard deviation building height, and the satellite-based indices of NDIV, NDWI, NDBI were used to classify the urban types with the models. Eventually, the Principal Components Analysis (PCA) was used to reduces the variables and get better performance of the models. SVM showed better accuracy than the other two RF and KNN. The accuracy of SVM, RF, and KNN are 0.86, 0.75, and 0.76 respectively.

Keywords*: SAR, building height, urban types classification, machine learning*

1. INTRODUCTION

Urban types identification is carried out for urbanization to comprehend how urban forms evolve and to manage environmental sustainability, congestion, pollution, and natural disasters such as floods and earthquakes (Misra et al., 2018). The utilization of remotely sensed data is becoming more common in distinguishing urban types for their high resolution and availability of information. As optical RS and SAR data are combined, the overall precision of urban classification is higher than when optical remote sensing or Sentinel-1A product is used alone (Corbane et al., 2008), (Bencure et al., 2010).

The objective of the study is to develop a machine learning model to classify urban types. The urban types were classified as (i) residential areas, (ii) commercial areas, (iii) other areas based on the parameters of building height and satellite-based indices. The classification was generated using the 16 variables of minimum, maximum, mean and standard deviation of building heights and the satellite-based indices.

2. STUDY AREA

Nonthaburi province is situated directly northwest of Bangkok on the Chao Phraya River. The population is 259,375 persons in 2019 and the area of Nonthaburi province is 38.90 sq-km which is registered as the second most populous city municipality in Thailand. The Nonthaburi research area is very wide and the process is carried out in the eight study areas in the province. The eight target zones of 500 x 500 meters are selected and each zone is divided into a 100x100m grid as shown in Figure 1, with different forms of the city, which are compact residential, industrial and high-rise buildings.

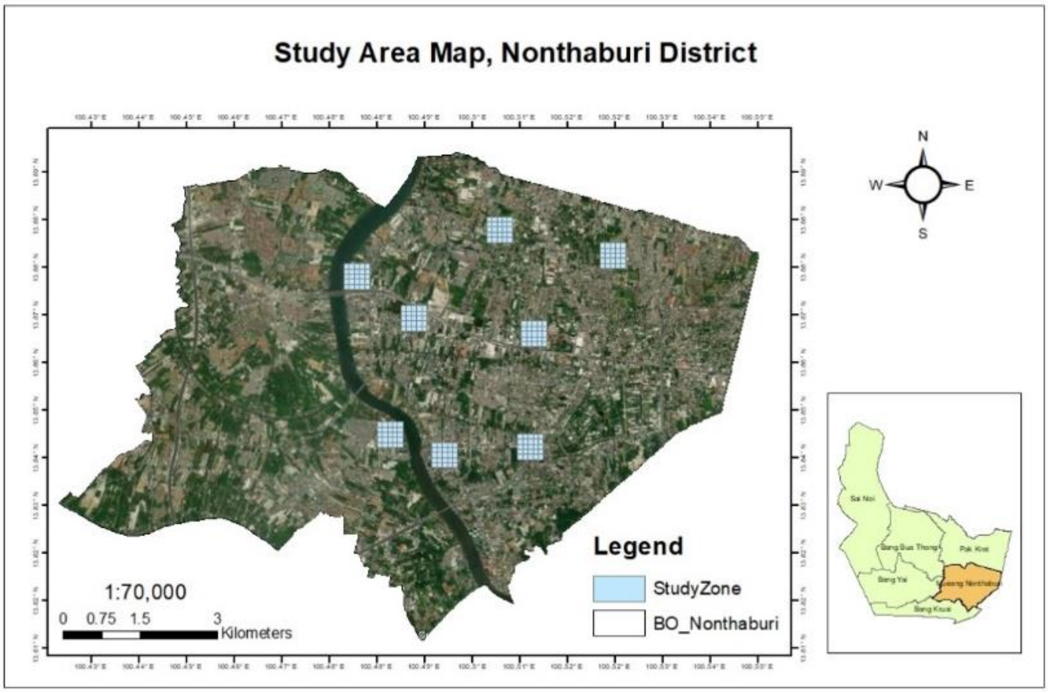

Figure 1 Study Area Map of Nonthaburi Province

3. METHODOLOGY

There are four main parts in the methodology as shown in Figure 2, including data preparation, building height estimation, urban types classification and accuracy assessment. The satellite data used for this research were from Sentinel-1A and Sentinel-2A in the year 2020 and the building block was a GIS shapefile which is developed by NOSTRA company. The data was published in 2012. In the data preparation section, SAR data was preprocessed with noise reduction, calibration, speckle filtering, and terrain correction using SNAP software. Moreover, the preprocessing of Sentinel-2A, multispectral data include atmospheric correction and surface reflectance computation, and the indices such as NDVI, NDWI, and NDBI were calculated. For the reference data, the raw building blocks from 2012 were checked and reorganized the data by adding or deleting the building blocks, calculating building heights from the number of floors.

After preprocessing, VV, and VH polarization were extracted from Sentinel-1A and the mean, minimum, maximum and standard deviation of VV and VH were used to estimate the height of each building. For the classification of urban types, both the estimated building height from Sentinel-1A and satellite-based indices from Sentinel-2A were applied in the 100x100m grid-based zone. There are 100x100m grid zonal statistics of 12 parameters of the three satellite-based indices and 6 parameters from building height including mean, maximum, minimum, and standard deviation. The urban categorization was carried out as a grid-based classification using 194 sample grids in eight zones of the study area. All the minimum, maximum, mean and standard deviations were extracted using zonal statistic table in ArcMap. Three groups of urban types were identified using machine learning algorithms such as random forest, support vector machine, and k-nearest neighbours with the data standardization, principal component analysis, and tuning hyperparameter to reduce the processing time and increase the accuracy. To assesses the performance of urban types classification, the accuracy result was reported by precision, F1-score, recall, and accuracy values.

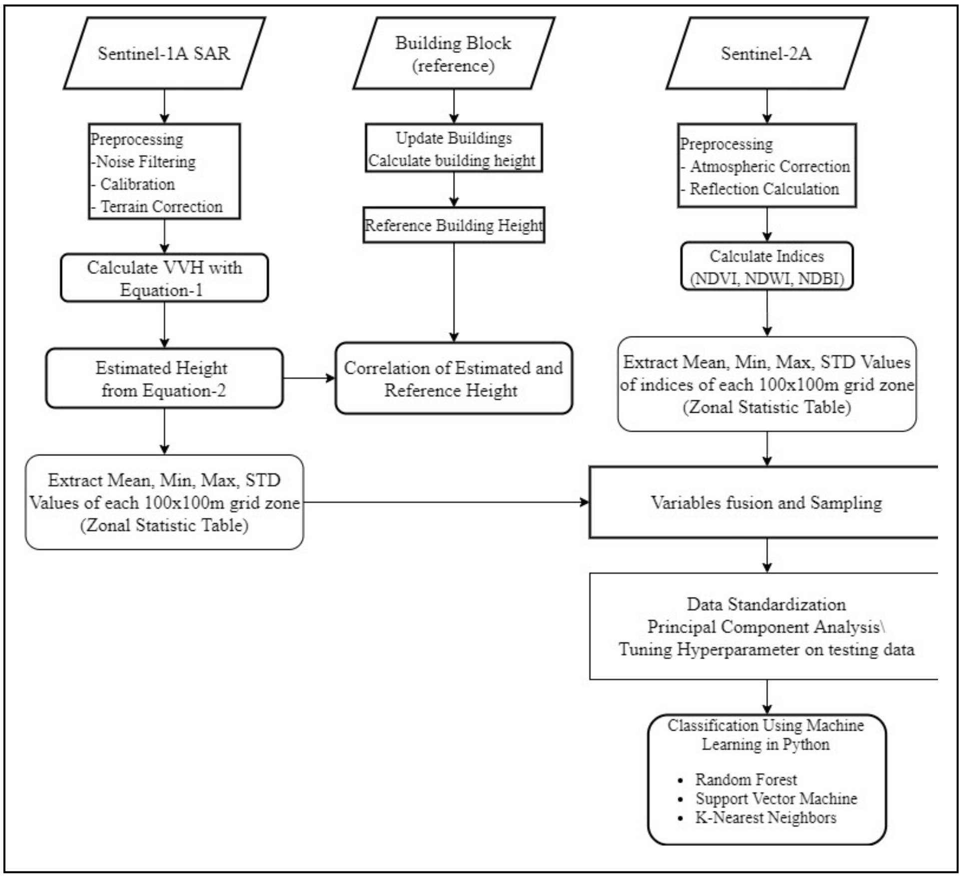

Figure 2 Overall Methodology of the Study

3.1 Building height model

A new indicator was processed for estimating building height in the first step after preprocessing Sentinel-1 GDR data. The mean value of the backscatter coefficient, VV, and VH, was extracted from the image to calculate the VVH indicator, equation 1 (Koppel et al., 2017). The equation for the new indicator of VVH shows better performance and a lower uncertainty range of estimated building heights (Li et al., 2020).

$$VVH = VV * \gamma^{VH} \tag{1}$$

To get the VVH value, the sigma 0 VV and VH value are calculated at different percentile levels that are ranging from 5% to 100% at a step of 5%. After that, VVH is enumerated with Equation (1) using different γ values ranging from 1 to 10 and compared the results. The estimated height is extracted by using equation (2) from the 8 study zones and compare with the reference height.

$$lnH = a * VVH^b + c \quad (2)$$

3.2 Machine learning classification of urban types

The machine learning model for urban types classification was developed by using building heights and satellite-based indices. The zonal statistic of mean, minimum, maximum and standard deviation of satellite-based indices include NDVI, NDWI, and NDBI of each grid were utilized to process the classification of the urban type. The 100m grid-level were generated in 500m eight zones.

In this study, three classifiers including support vector machine (SVM), random forest (RF), and K-nearest neighbours (KNN) were used. As shown in Table 1, a total of 194 sample grids were categorized for each urban type with a test size of 0.3. PCA and standardization which are for scaling and reducing the number of features were used. There are 5 experiments as shown in the Table 2 to distinguish urban types using a different composition of 16 parameters.

Table 1 Training Set Size for Training and Testing

Classes	Training	Testing
Residential Area	89	39
Commercial Area	26	12
Other Area	20	8

4. RESULT AND DISCUSSION

4.1 Building height estimation in the Nonthaburi

The VVH was calculated from VV and VH values which are percentile values, the output values change according to the γ value, gamma values are ranging from 1 to 10. Among them, $\gamma = 1$ produced the best R square value (0.8561). When γ values are higher, the R square of VVH dropped because γ is a parameter to characterize the relative impact of VH, which has negative values and is lower than VV values to the derived VVH. The VVH performs better and has a reduced uncertainty range of predicted building heights.

It should be emphasized that the term "building height" in this study refers to the average height inside the 100 m grid, which includes both buildings and non-building such as roadways and parking lots. To achieve a balance of model performance and spatial details of derived building heights, 100 m is the aggregation resolution with the equation (2) at $\gamma = 1$ of VVH value. The final parameters of a, b, and c are 0.2799, 1, and 5.727 respectively. The building height model using Sentinel-1A image and reference building height data performed well with root mean square error 1.413m and 0.8557 of R square value as shown in figure 3.

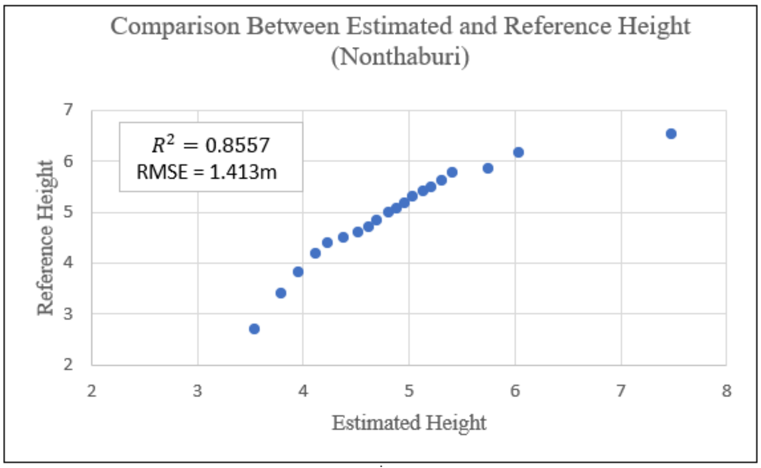

Figure 3 Chart Comparison of Estimated and References Height in Nonthaburi

4.2 Urban types classification

In this research, the classification results were produced and compared by combining different five cases as shown in table 2 to check which composition would provide good accuracy. Overall, the support vector machine worked very well as compared to other models. The results may change according to the variables which are used for classification.

The results of case 2, using the only average of all index and building height did not appropriate to classify the urban types and also all the classifiers performed poor accuracy ranging from 63 per cent to 71 per cent. Furthermore, cases 3 and 4 were analyzed, using separation of the height and indices show a better performance in some classifiers. RF has the highest result with 0.73 in the case of using only building height, classification with indices has the largest accuracy from the SVM classifier, 0.76.

Table 2 Parameters Used and Accuracy for Classification on Different Cases

Cases	Building Height	NDVI	NDWI	NDBI	RF	SVM	KNN
Case 1	mean, max, min, std	mean, max, min, std	mean, max, min, std	mean, max, min, std	0.75	0.86	0.76
Case 2	mean	mean	mean	mean	0.63	0.63	0.71
Case 3	mean, max, min, std				0.73	0.68	0.66
Case 4		mean, max, min, std	mean, max, min, std	mean, max, min, std	0.72	0.76	0.69
Case 5	mean, max, min, std	mean, max, min, std		mean, max, min, std	0.73	0.81	0.72

Case 5 (exclude NDWI index in this model) produced higher accuracy when compared with cases 2,3 and 4. Since there were numerous numbers of building and vegetated areas and less in the water body, the building height with NDVI, NDBI provided good accuracy for classification. However, the building heights and all satellite-based indices have the highest accuracy among all the combinations. All the variables are considered as mean, minimum, maximum, and standard deviation of each parameter (case1).

Additionally, the Principal Component Analysis (PCA) technique was adopted to minimizes the number of parameters and reduce the redundancy. The number of components in the PCA module was 0.95. After PCA, the new dimensionally reduced components were created. From table 3, the results were different because of high dimensionality with highly linked variables, PCA can increase the classification model's accuracy.

Table 3 The Accuracy Compared With PCA, Without PCA

	PCA			Without PCA		
Cases	**All parameter**	**Heights**	**Indices**	**All Parameter**	**Heights**	**Indices**
RF	0.75	0.73	0.72	0.78	0.68	0.63
SVM	0.86	0.68	0.76	0.78	0.66	0.66
KNN	0.76	0.66	0.69	0.73	0.66	0.66

5. CONCLUSION AND DISCUSSION

Following the objectives, the building heights and classification were generated using Sentinel-1A and Sentinel-2A in the 100 x 100 m grid samples. The research information is beneficial for evaluating urban modelling, assessing changes in population density, energy usage, and so on. The method proposed for building height estimation in this work could be used to provide a global estimate of height. It would be better if more indices, urban layout and more detail classes were applied for the classification of urban types in the future. The number of algorithms will develop and be improved to be more suitable for usage in a variety of urban types.

6. REFERENCES

Bencure, J., Tripathi, N. K., Gallardo, W., Boromthanarat, S., Ebbers, T., & Singhroy, V. (2010). *Integration Of Sar, Optical Remote Sensing Data And Gis For Change Detection And Restoration Of Nipa Palm Plantation In Pak Phanang, Thailand*. *May 2010*.

Corbane, C., Faure, J. F., Baghdadi, N., Villeneuve, N., & Petit, M. (2008). Rapid urban mapping using SAR/optical imagery synergy. *Sensors*, *8*(11), 7125–7143. https://doi.org/10.3390/s8117125

Koppel, K., Zalite, K., Voormansik, K., & Jagdhuber, T. (2017). Sensitivity of Sentinel-1 backscatter to characteristics of buildings. *International Journal of Remote Sensing*, *38*(22), 6298–6318. https://doi.org/10.1080/01431161.2017.1353160

Li, X., Zhou, Y., Gong, P., Seto, K. C., & Clinton, N. (2020). Developing a method to estimate building height from Sentinel-1 data. *Remote Sensing of Environment*, *240*(July 2019), 111705. https://doi.org/10.1016/j.rse.2020.111705

Misra, P., Avtar, R., & Wataru Takeuchi. (2018). *Comparison of Digital Building Height Models and SRTM Digital Surface Models over Yangon City*. https://doi.org/10.3390/rs10122008