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Building classification in Yangon City, Myanmar using Stereo GeoEye images, Landsat image and night-time light data

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ABSTRACT

Yangon, the former capital of Myanmar, is the biggest city in the country with more than five million people and it is also the major country's economic areas. These areas are complex with three classes of residential, commercial and industrial buildings. Understanding building uses in the city with the information of the locations and the quantitative measurement is very important to support urban management and development with various aspects. This research proposed a methodology to classify types of buildings with three classes in Yangon, Myanmar by using remotely sensed data. In this research, stereo GeoEye images, multi-spectral Landsat image and night-time light (NTL) image from Visible Infrared Imaging Radiometer Suite (VIIRS) were employed to extract types of buildings. The Stereo GeoEye images were used to obtain the heights of buildings, the Landsat image was classified to provide land cover areas, and NTL image was applied to separate NTL activities. By using the hierarchy classification with (1) the heights of buildings, (2) land cover areas and (3) NTL consumptions, the buildings were classified into three classes with (1) residential, (2) commercial, and (3) industrial buildings. In the experiments, the estimated building type map by our proposed method was compared with a land use map and surveying building data. The comparing results indicated that our methodology classified types of buildings in efficiency with the accuracy of 76% and the Kappa coefficient of 0.58.

1. Introduction

Yangon, formerly known as Rangoon, is the largest city in Myanmar, formerly known as Burma. Yangon is the major of country's economic areas with more than five million population, and the urban areas look complex with residential, commercial, and industrial buildings (Morley, 2013). The city is located on the terrain mixed with small mountain and flat areas. Yangon has faced many problems causing by flood disasters (mmtimes.com, Accesesed 2015). By knowing the building types with the locations and the quantitative measurement, this information can be employed to contribute to urban management and development to reduce the damages of flooding disasters.

Understanding building information in the city is essential to support urban development and management in several aspects. Many research works relating to the building information for urban management have been introduced in various features. In the ecology perspective, urban planning in term of ecological city has been done by responding to building construction (Liu et al., 2016). In energy aspect, urban management to preserve energy consumptions by using building information has been presented (Ma et al., 2017). In pollution problem, the impact of air pollution by building height information has been introduced (Kuzmichev et al., 2016). In waste management, the estimation of waste construction has been proposed by applying the information on residential buildings (Carpio et al., 2016).

In the past, the building type is provided by surveying method (Kibblewhite et al., 2004). By using surveying method, the deep information of buildings are available with types, designs, materials etc. However, it takes drawbacks from using a number of human workers, long process time including a field trip and high budgets. Furthermore, if the urban areas are very vast and there are various human-built features, it will be required to take the higher resources to collect all the information by surveying method. Hence, this method is suitable for the specific areas or regions more than the entire city or vast areas.

Since Remote Sensing technology provides the observation in large areas, many researchers have widely applied remotely sensed data to detect the building areas and also classify types of buildings in the large areas.

To extract building areas or building boundaries, various research works have been proposed by using spatial and spectral information from remotely sensed data. The aerial photos have been used to extract building extents (Huertas and Nevatia, 1988). Then, Lin and Nevatia

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(1998) introduced the methodology to extract building areas and construct them in 3-D shape by using aerial photos. Next, the researchers employed line extraction as robust algorithm to classify building areas by using aerial images (Kim and Muller, 1999). By using the integration between high-resolution images from IKONOS and LiDAR (light detection and ranging) data, Sohn and Dowman (2007) presented the methodology to automatically extract the building footprints. After that, the research work using the high spatial resolution imagery from QuickBird was proposed (Myint et al., 2011). They applied the object-based classifier to enhance the result of building areas. Then, Grigillo and Fras (2011) introduced the building detection method by using the high-resolution images acquired by GeoEye. They employed the segmentation method to extract the building areas. Next, the building extraction method based on object-based classification was proposed by Turker and Koc-San (2015). They used support vector machine (SVM) method to classify the building areas and then applied Hough transform and perception grouping to extract the building boundaries.

However, the information of building boundaries is not sufficient to support in the deep analysis with practical applications for urban management and development. Therefore, many research works about classifying building types have been introduced to contribute to the effective applications. The researchers introduced the methodology to classify building types by using airborne laser scanning data (Belgiu et al., 2014). They applied object-based image analysis to extract the three types of buildings with residential building, apartment building, and industrial Building. Then, Lu et al. (2014) presented the building type classification using LiDAR data. They used LiDAR data to provide the building information such as the height and the shape. Then, the building information was used with machine learning method to categorize building types with three classes of single-family houses, multiple-family houses, and non-residential buildings. After that, the building classification using a high-resolution image and GIS data was introduced by Du et al. (2015). They used the high-resolution image and GIS data as the building information to provide many features of building. They used the random forest method with the features to distinguish building types with seven classes of low-story shantytowns, medium-story apartments, high-rising apartments, commercial buildings, industrial buildings, auxiliary buildings.

In addition, the other aspect of building information by using Remote Sensing technology has been introduced. The damaged building classification by using high-resolution oblique airborne images was proposed (Vetrivel et al., 2015). They detected the damaged building type by using anomaly segmentation of the building extents.

In the building classification, most research works rely on the combination with GIS data that need surveying method that has drawbacks of high used resources. This is one research to aim at using input data from remotely sensed dataset based on pixel-based method to classify types of buildings. Another point is to use nighttime activities from nighttime light data to support the classification of the building types.

In this research, we proposed a methodology to classify the types of buildings with three classes; residential buildings, commercial buildings, and industrial buildings in Yangon, Myanmar by using Stereo GeoEye images, Landsat image and night-time light (NTL) image. A methodology to classify the building type was described in Section 2. In Section 3, the experimental results were compared with validated data and the discussions were explained. Finally, Conclusions of this research were given in Section 4.

2. Methodology

2.1. The relevant factors to indicate the types of buildings

In this research, three types of buildings with (1) commercial buildings, (2) industrial buildings and (3) residential buildings were concentrated. Commonly, commercial buildings, office buildings, and public facilities have the characteristics of the high-rise buildings. Also, at the night, these buildings have high consumptions of light energy due to the various active activities and have crowded people. As a result, the buildings have two characteristics with high-rise buildings and high NTL. In this research, for shortening words, commercial buildings refer to commercial buildings, office buildings, and public facilities. Next, industrial buildings such as factories or plants have the features of high-rise buildings. However, at the night, the industrial buildings take low consumptions of light energy. Therefore, the industrial buildings have two features with high-rise buildings and low NTL. Then, residential buildings have the aspect of low buildings such as houses and take low consumptions of light energy as well. By using two factors with (1) the heights of buildings and (2) NTL activities, our methodology with hierarchy classification is present in Fig. 1. Firstly, the Stereo GeoEye images were used to obtain the height of a building. Then, the Landsat image was classified to provide land cover areas. Next, NTL image was applied to separate NTL activities. After that, we defined the hierarchy classification with (1) the heights of buildings, (2) land cover areas and (3) NTL consumptions to classify the building types with (1) residential buildings, (2) commercial buildings, and (3) industrial buildings. Finally, the improved process was taken an employment to enhance the result of the building classification. The flowchart of our methodology to categorize the building types is depicted in Fig. 1.

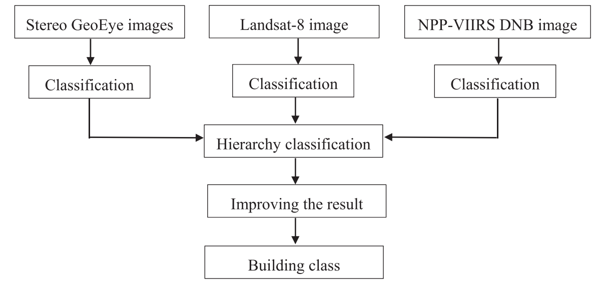

Fig. 1. Flowchart of our methodology to classify the building types.

2.2. Remotely sensed dataset

The study location of this research was focused on the center areas of Yangon city, Myanmar with the frame from 16.76502° to 16.92635° North (Latitude) and from 96.04246° to 96.27131° East (Longitude).

In this research, remotely sensed dataset were acquired from three sources with GeoEye, Landsat 8, NPP (National Polar-orbiting Partnership) – VIIRS (Visible Infrared Imaging Radiometer Suite). The stereo GeoEye images with a high spatial resolution were employed to provide the heights of buildings. The multispectral Landsat image with a high spectral resolution was classified to obtain land cover areas. The NTL image from NPP-VIIRS, which has the capability to obtain day/night band composite data (DNB), was taken an exploit to observe NTL consuming activities. The radiance of DNB is a number with the magnitude of 10^{-9} and the unit of W/(cm^2-sr). The details of the satellite dataset are displayed in Table 1 and Fig. 2 shows the images of the remotely sensed dataset.

Table 1
Details of the remotely sensed dataset.

Satellite	Resolution	Bands	Acquisition date
GeoEye-1	0.5 m	3	2013/11/08, 2013/11/16
Landsat-8	30 m	11	2015/02/26
NPP-VIIRS (DNB)	460 m	1	2012/04/18–2012/04/26, 2012/10/11–2012/10/23

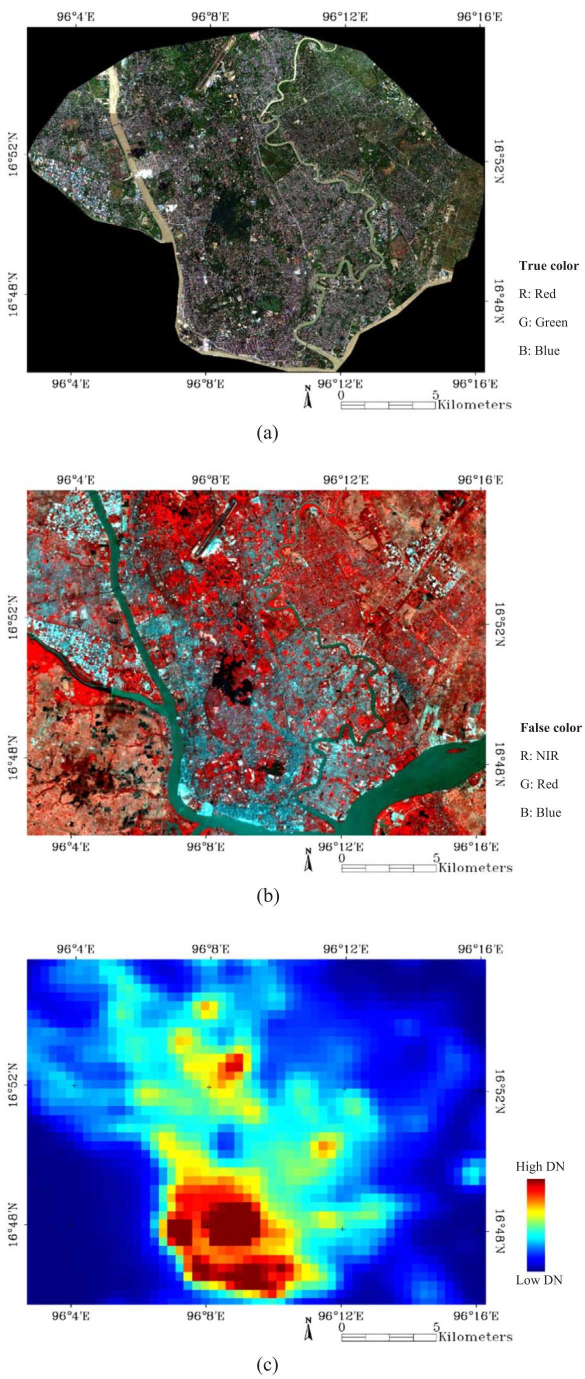

Fig. 2. (a) GeoEye image, (b) Landsat 8 image, (c) NPP-VIIRS DNB image.

2.3. Individual classifications

For individual classifications, we had mainly three classification processes. Firstly, the Stereo GeoEye images were used to classify the building classes with low and high buildings. Secondly, the Landsat image was classified to provide land cover classes with three classes of urban, vegetation and water. Thirdly, NTL image was classified NTL activities into three classes of low, medium, and high light energy consumptions. The details of each process are explained as follows.

For the first classification process, the stereo GeoEye images were used by using PCI Geomatica 2015 software to provide Digital Surface Model (DSM). Then, the DSM was filtered by Morphological filter to get Digital Terrain Model (DTM). By subtracting DSM with DTM, Digital Building Model (DBM) was provided. Next, the stereo GeoEye images were also used with the DSM to provide the orthorectified image with RGB bands. After that, the orthorectified image was classified by using Mahalanobis distance method (Maesschalck et al., 2000). Mahalanobis method is a well-known supervised classification that separates each class by corresponding to the mean and covariance matrix of observed data. We separated the orthorectified image into two classes with (1) vegetation and (2) non-vegetation. The training samples per each class were collected more than five hundred samples. After classifying with Mahalanobis method, we got the classification result with two classes of vegetation and non-vegetation. By using non-vegetation areas and the DBM, the heights of buildings without the negative effects of trees or grasses were obtained. The flowchart to extract the heights of buildings without trees and grasses is presented in Fig. 3. Fig. 4 shows the estimated heights of buildings without trees and grasses.

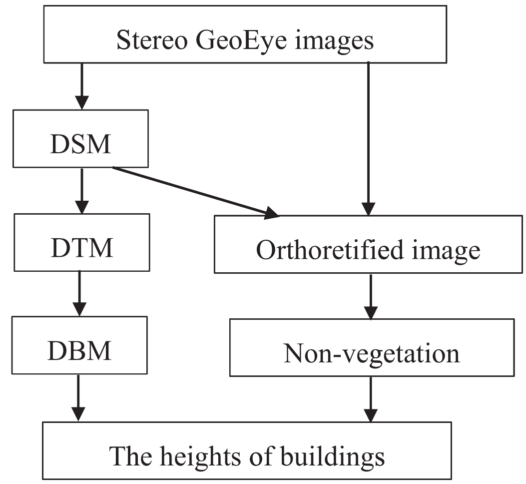

Fig. 3. The flowchart of obtaining the heights of buildings without trees and grasses.

After that, we classified the heights of buildings into two groups by using manual thresholding. There were two classes with (1) low buildings from 2 to 10 m (1–2 floors) and (2) high buildings with more than 10 m (more than 2 floors). In general, one floor of a residential building is 3.1 m and one floor of a commercial building is 3.9 m (heightcalculator.ctbuh.org, assessed 2015). Fig. 5 shows the result of the building classes with low and high buildings.

For the second classification process, the multi-spectral Landsat image was classified by using Mahalanobis distance. Land cover classes were separated into three classes with (1) urban, (2) vegetation, (3) water. The training samples were selected more than five hundred samples per each class. After classifying with Mahalanobis distance method, the land cover result with three classes was provided (see in Fig. 6).

For the third classification process, we separated NTL image into

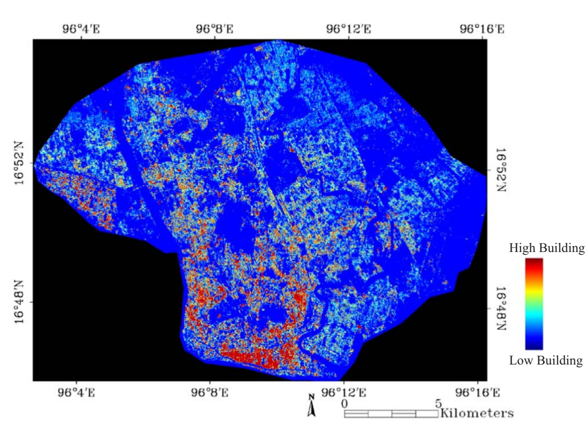

Fig. 4. The heights of buildings without trees and grasses.

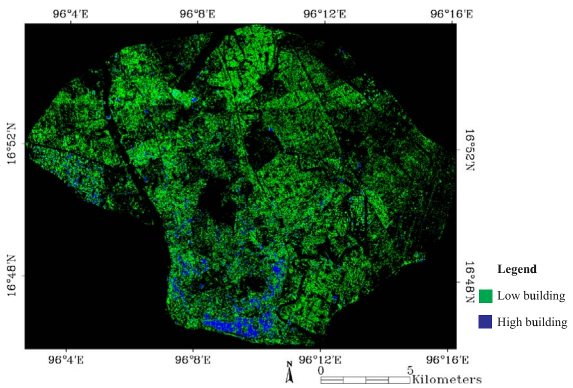

Fig. 5. The result of the building classification with low and high buildings.

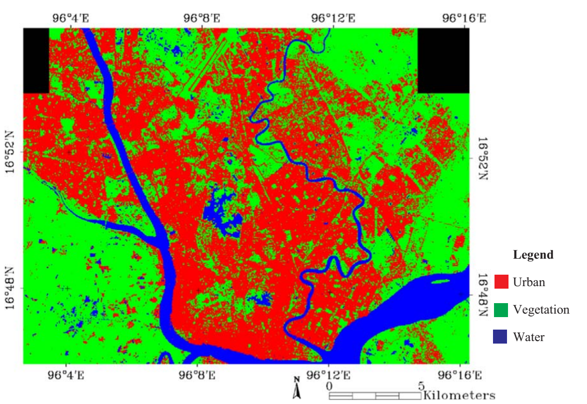

Fig. 6. The result of the land cover classification.

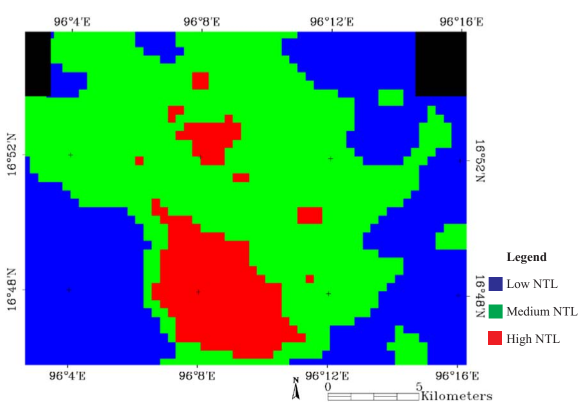

Fig. 7. The result of the night-time light (NLT) classification.

three classes of low, medium and high NTL classes by using K-means (Hartigan et al., 1979). K-means is the unsupervised classification that is popular for automatic clustering in data mining. After using K-means classification, we had three classes of NTL with (1) low NTL class with the mean of 1.83 (Digital number, DN), medium NTL class with the mean of 8.69 (DN) and high NTL class with the mean of 24.13 (DN). Fig. 7 illustrates the NTL result with three classes.

2.4. The hierarchy classification

After obtaining three classification results with (1) the building classes with low and high buildings, (2) the land cover areas, (3) the NTL consuming activities, the hierarchy classification was employed to classify the types of buildings with (1) residential buildings, (2) commercial buildings, (3) industrial buildings.

The building classes with low and high buildings were provided by considering the effects of trees and grasses. However, some errors from vegetation and water areas still remained since the spectral resolution in the stereo GeoEye image with RGB bands is quite poor when comparing with Landsat 8 image. Hence, integrating between the result of building classification from stereo GeoEye images and the result of land cover classification from multi-spectral Landsat 8 image was applied. By using only urban areas from the land cover result with the result of building classification, the more accurate result of the building classification was provided without any errors from vegetation and water areas. After that, we assigned that the low buildings represent residential buildings, and high buildings represent commercial buildings and industrial buildings.

In order to separate commercial buildings from industrial buildings, the combination between the high building class (commercial and industrial buildings) with the result of NTL classification was applied. We defined that commercial building has high NTL intensity but an industrial building has medium NTL intensity. In this research, we found that low NTL intensity generally indicated non-urban areas. Thus, it did not include in consideration for building classification. The result of the building classification with three classes of (1) residential buildings, (2) commercial buildings, and (3) industrial buildings is depicted in Fig. 8.

2.5. Improving the classification result

Since the spatial resolution of NTL image from NPP-VIIRS DNB is quite low with approximately 460 m. The edge areas among classes in the result of NTL classification had significant errors. In order to solve the problem, the spatial relationship between commercial and industrial areas was employed. Commonly, industrial buildings such as factories and plants probably make loud noises or some pollutions. Therefore, they should be located in isolation from commercial buildings such as shopping malls and hotels or office buildings that have a number of human activities. As a result, the rule of the distance between commercial and industrial buildings was defined that the building that is located near the commercial buildings must be residential or commercial building. In the experiments, we found that the threshold of the ruling distance is 1 km since it gave the high accuracy. Fig. 9a shows the improved result of the building classification.

3. Results and discussions

3.1. Results and validations

In order to validate the result of building classification, we compared the estimated building use image by our methodology (Fig. 9a) with the land use map in 2012 that was provided by International Center for Urban Safety Engineering (ICUS) (Fig. 9b). Since the resultant building use map was represented in term of a building while the land use map was represented in term of an area,

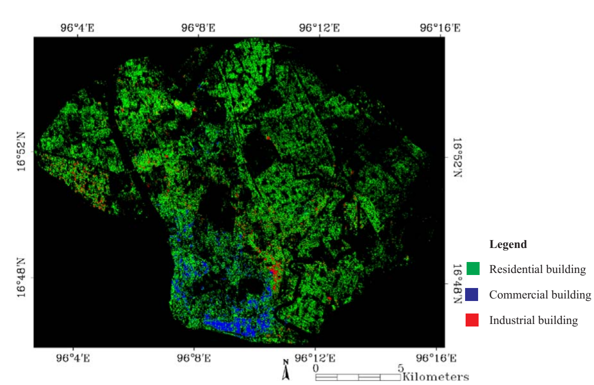

Fig. 8. The result of the building classification with three classes.

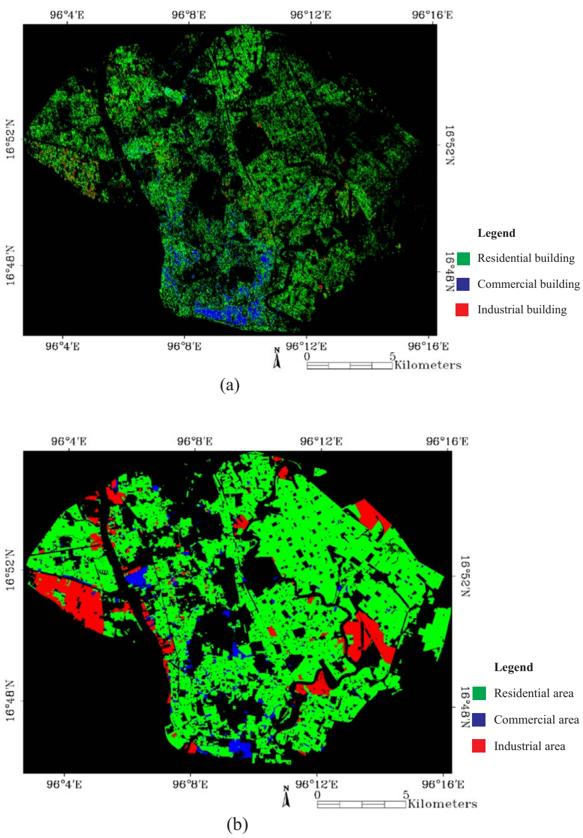

Fig. 9. Comparison between the estimated building type map (a) and the land use map in 2012 (b).

Table 2
The confusion matrix between the estimated building type map and the land use map in 2012.

		Land use map in 2012		
		Residential areas	**Commercial areas**	**Industrial areas**
The estimated building use map	**Residential buildings**	37.588 km^2 (58.63%)	2.189 km^2 (3.41%)	5.240 km^2 (8.17%)
	Commercial buildings	4.153 km^2 (6.48%)	0.994 km^2 (1.55%)	0.173 km^2 (0.27%)
	Industrial buildings	0.668 km^2 (1.04%)	0.042 km^2 (0.06%)	0.976 km^2 (1.52%)

they cannot be compared directly. Therefore, in the comparison, the building areas of our resultant map were selected to compare with land use areas of the land use map. The accuracy of the estimated building type map versus land use map is 76.04% with the Kappa coefficient of 0.57. The confusion matrix is demonstrated in Table 2.

The statistical of the estimated building areas in Yangon is shown in Table 3.

For validating the heights of buildings, we compared the estimated heights of the buildings with surveying building data. In surveying the

Table 3
The statistical of the estimated building areas in Yangon.

The types of the buildings	**Areas**
Residential buildings	55.26 km^2 (86.20%)
Commercial buildings	6.77 km^2 (10.55%)
Industrial buildings	2.08 km^2 (3.24%)
Total buildings	64.11 km^2 (100%)

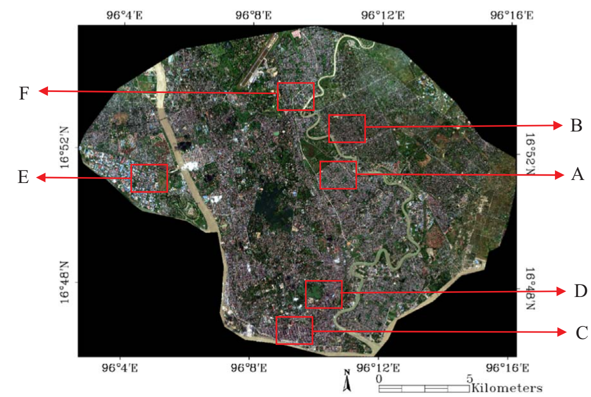

Fig. 10. The six regions of surveying building data from A to F regions.

building data in Yangon, six regions from A to F regions with 59 buildings including 22 residential buildings, 22 commercial buildings, 15 industrial buildings were surveyed in 2015 (Fig. 10). We measured the heights of buildings by using the manual calculation (heightcalculator.ctbuh.org, assessed 2015) and using Smart Measure known as a smartphone application. The comparison of the estimated heights and surveying heights of the buildings is depicted in Table 4.

In addition, since the DTM was employed to calculate the DBM, it needs to be checked to confirm that DBM is reliable to be used. In this work, we compared the estimated DTM with surveying elevation data in 2012 with 98 locations. The surveying elevation data was provided in the Japan International Cooperation Agency (JICA) report that was done by NIHON KOEI Company. The root mean square error (RMSE) between the estimated DTM and the surveying elevation data was 1.62 m.

3.2. Discussions

In the experimental results, our methodology extracted the types of buildings in Yangon, Myanmar with the overall accuracy of 76.04% and the Kappa coefficient of 0.58. It indicated that our methodology has the capability to mainly categorize residential, commercial, and industrial buildings. Firstly, commercial and industrial buildings can clearly separate from residential buildings because of the different heights of the buildings. Secondly, although commercial buildings and industrial buildings are generally high-rise buildings, the activities of commercial buildings and industrial buildings in the nighttime are clearly different. As a result, the commercial buildings can distinguish from industrial buildings by using NTL consumptions.

However, when considering in the classification result in each class, our methodology detected the residential buildings with some errors since some residential buildings have the heights of the buildings more than two floors (3–4 floors). Hence, our methodology did not capture those buildings and it made the incorrect result. For commercial or office buildings, our methodology had high errors for this class because some commercial or office buildings have the heights of the buildings less than three floors (1–2 floors). Our methodology failed to detect them properly and it detected them as the residential buildings. Especially, for industrial buildings, since in Yangon city, there were mixed industrial buildings between heavy industrial buildings and medium industrial buildings. Our method could not find some medium industrial buildings (1–2 floors). As well as, in heavy industrial areas, the industrial buildings are combined between high-rise buildings (factories or plants) and low-rise buildings (official buildings for the industries). As a result, it made huge errors for this class since it classified those buildings as residential buildings. In order to solve such problems, the spatial analysis algorithm in profound analysis can be included in the methodology.

For estimating the heights of the buildings, our method to extract

Table 4
The comparison of the estimated heights and surveying heights of the buildings.

Region	Type of buildings	The number of observed buildings	The average of the surveying heights of the buildings	The average of the estimated heights of the buildings
A	Residential buildings	12	5.9 m	7.2 m
B	Residential buildings	10	5.5 m	6.0 m
C	Commercial buildings	11	47.8 m	19.3 m
D	Commercial buildings	11	27.9 m	19.4 m
E	Industrial buildings	12	20.0 m	14.6 m
F	Industrial buildings	3	13.0 m	10.5 m

the heights of the buildings has the limitation that it cannot detect a building that is higher than 25 m. Since some commercial buildings in the skyscraper center are very tall buildings with around 40–80 m, our method estimated these buildings with around 25–40 m. However, this estimated result of the heights of the buildings is good enough to separate commercial or industrial buildings from residential buildings.

In statistical of the building areas, we found that there were 55.26 km^2 (86.20%) for residential buildings, 6.77 km^2 (10.55%) for commercial buildings and 2.08 km^2 (3.24%) for industrial buildings. It means most areas were covered with low-rise buildings (defined as residential buildings) with 86% and some areas were combined with (1) high-rise buildnings and high nighttime activites (defined as commercial buildings) with 11% and (2) high-rise buildnings but low nighttime activites (defined as industrial buildings) with 3%. The ratio among these types of buildings can possibly indicate the economic state or the human problem in the city. As well as, by combination with flood disaster vulnerability, this information can be used in urban planning and management to increase or reduce some types of the buildings and find suitable locations for each building type in order to reduce the damages of the disaster in the future.

4. Conclusions

We proposed a methodology to classify building types using remotely sensed data in Yangon, Myanmar. Stereo GeoEye images were used to provide the heights of buildings. The multi-spectral Landsat-8 image was applied to provide land cover areas. NTL image from VIIRS was employed to separate NTL activities. After that, the hierarchy classification was applied to classify the types of buildings with (1) residential buildings, (2) commercial buildings, (3) industrial buildings. The rule of the distance between commercial and industrial buildings was defined to improve classification result.

To validate the estimated map of the building classification, we compared it with the land use map in 2012. The comparing results indicated that our methodology extracted the types of buildings in efficiency with the accuracy of 76% and the Kappa coefficient of 0.58.

The statistical information of building use can be applied to indicate the current economic state or problem in the city and support to plan urban development with sustainability. By combining with flood vulnerability map, it can be support urban planning and management to reduce flood disasters.

As the current problem by using our methodology, the estimated residential buildings look overestimate. Since some commercial and industrial buildings are low-rise buildings; especially industrial buildings, low-rise buildings of commercial and industrial buildings were classified to be residential buildings that are incorrect. To against this problem, the spatial analysis method in deep analysis can be applied.

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