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Land cover classification using LiDAR intensity data and neural network

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Abstract

LiDAR technology is a combination of laser ranging, satellite positioning technology and digital image technology for study and determination with high accuracy of the true earth surface features in 3D. Laser scanning data is typically a points cloud on the ground, including coordinates, altitude and intensity of laser from the object on the ground to the sensor (Wehr & Lohr, 1999). Data from laser scanning can produce products such as digital elevation model (DEM), digital surface model (DSM) and the intensity data.

In Vietnam, the LIDAR technology has been applied since 2005. However, the application of LiDAR in Vietnam is mostly for topological mapping and DEM establishment using point cloud 3D coordinate. In this study, another application of LiDAR data are present. The study use the intensity image combine with some other data sets (elevation data, Panchromatic image, RGB image) in Bacgiang City to perform land cover classification using neural network method. The results show that it is possible to obtain land cover classes from LiDAR data. However, the highest accurate classification can be obtained using LiDAR data with other data set and the neural network classification is more appropriate approach to conventional method such as maximum likelyhood classification.

Keywords : LiDAR, Digital Elevation Model, Digital Surface Model, Neural Network Classification

1. Introduction

Intensity image is often used to create black and white orthogonal image. Given the spectral profile of the ligh LiDAR around the wavelength from near-infrared and infrared, intensity image similar to spectral image of remote sensing image in the thermal band, infrared and near infrared. Orthogonal images that are generated from intensity image is not similar to black and white aerial photographs or panchromatic satellite images. Therefore, using LiDAR intensity images to establish the map should be supplement to this data source to obtain information on the ground. Furthermore, one advantage of the LiDAR intensity is that this ease the problem of the object's shadow as that of optical remote sensing images (Yan & Shaker, 2010).

LiDAR intensity image is also used in other application such as determining the level of flooding. From the intensity image and LiDAR elevation data, it is possible to determine the extent of flooding under the trees in the river basin area (Lang & McCarty, 2009). LiDAR intensity image can also be used to determine the flow and age of lava (Mazzarini *et al.*, 2009). The LiDAR beam, which passes through the canopy to the ground, enable the determination of the routes in the mountainous terrains (White *et al.*, 2010).

Although used in many different applications, intensity image is usually used in the classification and identification of land cover (Antonarakis *et al.*, 2009). In the world, a series of studies were performed to determine the land cover based on intensity image and elevation data (Tymkow & Borkowski, 2008). However in Vietnam, the application of the intensity data has not been much interest. In this paper the possibility of using intensity data for the land cover classification, the most appropriate classificiation methods, and the most usable data sets are defined.

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2. Land cover classification methods using the intensity image

2.1. The LiDAR data and other data sets used in land cover classification

Intensity image was used to classify land cover map in many different studies. Intensity image is used in combination with remote sensing image with equivalent spatial resolution. The intensity images were interpolated from the point cloud for resolution of 0.5m - 1m. Thus, the remote sensing images used in combination with LiDAR intensity data for land cover classification are high-resolution images such as QuickBird, IKONOS, etc. (Barbarella *et al.*, 2004).

In addition remote sensing images, one of the data obtain during the LiDAR point scanning is RGB image with high resolution. This is often used along with the intensity image and elevation data in the land cover classification map (Diez *et al.*, 2008; Tymkow & Borkowski, 2008). Several studies use both panchromatic images and intensity image in combination with elevation data for the land cover classification (Hosomura & Kanazawa, 1998). Even some researchers used the ground image addition to the classification process to improve the accuracy for classification (Hu, 2006)

One problem in using intensity data in determining land cover is the noise of the LiDAR signal. The relative data is often noisy that does not reflect the true nature of the ground reflection (Yan & Shaker, 2010) so it is required that the noise should be removed using the filter techniques before performance the classification process. The noise filter must be performed within the data processing of LiDAR point cloud obtained.

2.2. Methods of land cover classification using LiDAR intensity data

The conventional land cover classification methods such as the maximum likelihood method and the minimum distance, can be used for data combination of LiDAR intensity data and the different elevation data between DSM and DEM. In addition, some secondary data may be used for land cover classification as LiDAR point density, change surface model, etc. (Tymkow & Borkowski, 2008).

Decision tree classification method is one of the methods that has the advantage in land cover classification from LiDAR data. Since the LiDAR intensity data is often classified in combination with elevation data, which most of objects are classified based on the difference between the elevation of DEM and DSM (Garcia *et al.*, 2009). However, classification by decision tree method will encounter some difficulties when using the intensity image because the separation of gray scale of multiple objects on the ground in the image is not clear so it can lead to the error.

Because LiDAR data is 3D data so we are able to identify some object on the ground-based blocks such as the buildings, trees, etc. In addition, we may combine with data from other remote sensing data to build more secondary data as texture data to identify objects on the ground (Sasaki *et al.*, 2011). Classification method using feed-forward neural network also can be used for land cover classification, in which the output value of neural in output layer must have value 0 and 1, and the input value is the gray-scale of the bands. All of these methods will be considered and tested in this study to define the most appropriate one for land cover classficiation.

3. Experiment of land cover classification using intensity LiDAR data

3.1. Data and the area of study

The study area is located in Bacgiang City in Vietnam. Experimental area is about 1km x 1km with flat terrain, this area also has a variety of features as residential areas, agricultural areas, the Thuong river, and many lakes, trees. The study area was scanned by LiDAR system with AIC digital camera and LIDAR Harrier56 scanner to build the geographic information database at the scale of 1/2000 together with the DEM and DSM in 2007.

In this study, the input data includes intensity image in Bac Giang city with resolution of 1 meter (Figure 1 (a)), panchromatic World View 1 that was taken at the same time with resolution of 0.5m (Figure 1 (b)), DEM and DSM with resolution of 0.5m (Fig. 1 (c) and (d)) and RGB image with resolution of 0.25m. All of the images were taken on VN2000 coordinate system, zone 30, center meridian 107000. The images were mosaiced into one file and intensity image resolution was increased to 0.5m by using nearest neighbor gray scale

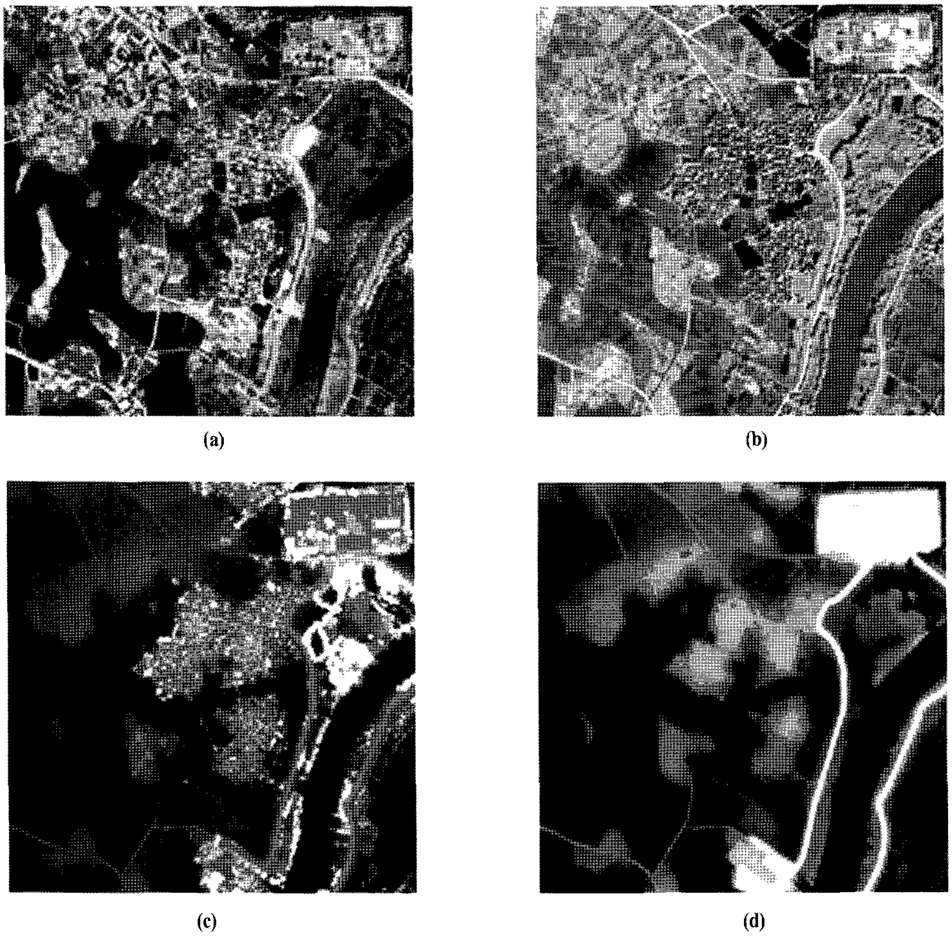


Figure 1. (a) LiDAR intensity image with resolution of 1m, (b) World View panchromatic image with resolution of 0.5m, (c) DSM with resolution of 0.5m (d) DEM with resolution of 0.5m

interpolation and RGB image resolution was reduced to 0.5m by using nearest neighbor interpolation.

In addition, the cadastral map 1:1000 of the study area is used as the reference data for accuracy assessment. It showed that the intensity data still contains a lot of noise values need to study to eliminate for the classification can be achieved with higher accuracy. For example, observe Figure 1(a) we can see that at the location on the water of Thuong river, in accordance with the theory of intensity then the gray-scale value should be very small, aproximate 0. But there are some pixels with very high gray scale values, even up to 255 on 8 bit images. However, the noise filtering of the intensity is beyond the scope of this study, so the usability of intensity image was assessed using existing data.

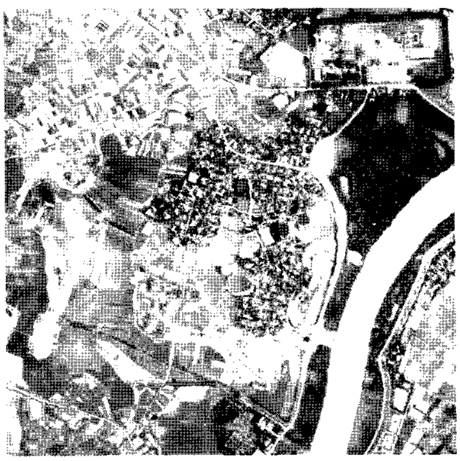


Figure 2. RGB image was taken at the same time LiDAR scaning

3.2. Experiment

After field survey and examination of the properties of reflection and elevation data, there are six types of land covers identified such as houses, asphalt roads, water, grass and low trees, high trees and bare soil. To evaluate the usability of the reflectvie intensity LiDAR images in remote sensing image classification, land cover classification was implemented with the existing data sets as follows:

- Land cover classification only base on intensity image
- Classification base on intensity image and elevation difference image between DSM and DEM
- Classification base on intensity images, elevation difference image between DSM and DEM and panchromatic World View image
- Classification base on all existing data including intensity image, difference elevation image between DSM and DEM, panchromatic World View image, and RGB image

To evaluate of classification algorithm, it is necessary to perform empirical land cover classification using different classification algorithms such as minimum distance, maximum likelihood, neural network classification method. The land cover classification is combined between decision tree classification method and other methods. First, the classification was performed by dividing objects into two groups: high height features (group 1) and low height features (group 2). The high height features include houses, and high trees classes. The low height features include water, grass and low trees, road and bare soil. After field surveys and using RGB image with resolution of 0.25m to evaluate, it is possible to classify that the low height features have height above the ground < 1m. And the features with height > 1 m will belong to group 1. Based on the above criteria we can identify the features of group 1 are the black areas and the features of group 2 are the white areas in the Figure 3.3. Figure 3.3 will be used as a mask for the land cover classification and two groups will be classified separately.

Figure 3. The Objects with low height (white) and the objects with high height (black)

Through the survey properties of gray scale of the group 1, the roof layer consisting of two groups with different spectral profile as tile roof, metal sheet roof and the concrete roof. At some locations of group 1, due to the DSM, manufacturers have used all the measured points of reflective impulse group except the last group to interpolate the DSM. At these locations, even the water class has height values of greater than 1. Therefore, the objects of group 1 will consist of the following land cover: tile roof, concrete roof, water, trees, bare soil. And the land cover of group 2 will consist of river water and lake water, dry bare soil and wet bare soil, and grass (which include the vegetable and crops).

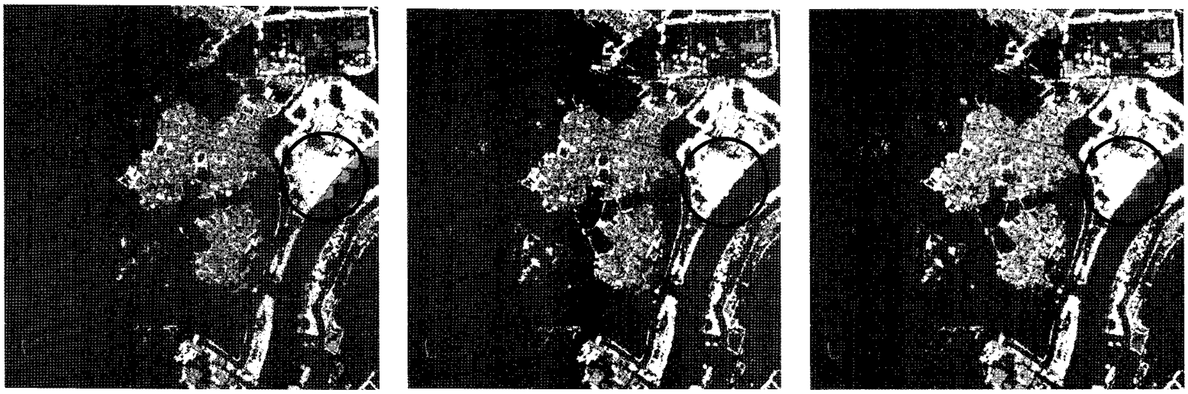
3.3. Results

- **Determination of the appropriate classification method**

To evaluate the appropriate classification method for the LiDAR data, three classification methods were used such as minimum distance, maximum likelihood and neural network. Classification results from these three methods are shown in Figure 4 (a), 4(b) and 4(c). Evaluting the classification result based on a combination of data including intensity image, elevation data, panchromatic image and RGB image, it is showed that the results of classification using minimum distance classification is less accurate than other methods, which there are some areas of Thuong river classified as house class.

The error matrix for each classification method result in Table 1, Table 2 and Table 3 also shows that the neural networks classification method produced land cover classes with the highest accuracy.

Based on these results, evaluation of different data groups such as LiDAR intensity data and elevation data, LiDAR intensity data elevation data, and panchromatic image and LiDAR intensity, data elevation data, panchromatic image and RGB imageare was implemented based on the neural network classification method.



(a) (b) (c)

Figure 4. (a) Classification of group 1 using minimum distance method, (b) Classification of group 1 using maximum likelyhood method, (c) Classification of group 1 using neural network

Table 1. Error matrix of classification using minimum distance method

		Reference					
	Class	**Tree**	**Water**	**Tile roof**	**Concrete roof**	**Bare soil**	**Unclassified**
Classification	Unclassified	0.00	0.00	0.00	0.00	0.00	0.00
	Tree	98.37	18.18	0.00	0.08	0.00	36.89
	Water	1.22	71.53	0.37	1.09	2.33	18.20
	Tile roof	0.00	10.23	89.14	2.26	0.00	19.24
	Concrete roof	0.41	0.00	0.46	84.49	5.06	17.39
	Bare soil	0.00	0.07	10.03	12.07	92.61	8.28
	All	100.00	100.00	100.00	100.00	100.00	100.00

Table 2. Error matrix of classification classes using maximum likelihood method

		Reference					
	Class	**Tree**	**Water**	**Tile roof**	**Concrete roof**	**Bare soil**	**Unclassified**
Classification	Unclassified	0.00	0.00	0.00	0.00	0.00	0.00
	Tree	100.00	0.35	0.00	0.08	0.00	33.09
	Water	0.00	99.65	23.00	1.42	0.00	28.75
	Tile roof	0.00	0.00	70.84	3.10	0.39	13.59
	Concrete roof	0.00	0.00	0.83	93.80	73.93	22.17
	Bare soil	0.00	0.00	5.34	1.59	25.68	2.41
	All	100.00	100.00	100.00	100.00	100.00	100.00

Table 3. Error matrix of classification using neural network

		Reference					
	Class	**Tree**	**Water**	**Tile roof**	**Concrete roof**	**Bare soil**	**Unclassified**
Classification	Unclassified	1.01	0.14	0.82	0.17	35.75	2.88
	Tree	98.99	0.00	0.00	0.00	0.00	32.04
	Water	0.00	99.86	0.00	0.00	0.00	23.64
	Tile roof	0.00	0.00	92.88	4.27	0.25	17.48
	Concrete roof	0.00	0.00	0.27	88.54	0.00	17.33
	Bare soil	0.00	0.00	6.02	7.03	64.00	6.63
	All	100.00	100.00	100.00	100.00	100.00	100.00

- **Determination of the best data set for the land cover classification**

After the classification based on neural network classification method for the group 1 and 2, Tables 5, 6 and 7 are the error matrix of the land cover classification classes determined from different data sets include:

Group A: Intensity data and elevation data (Table 4)

Group B: Intensity data and elevation data + Pan image (Table 5)

Group C: Only include RGB image (Table 6)

Group D: Use all types of data to perform classification (Table 3)

For group 2, the classification was also performed as group 1, we use four different data sets include:

Group A: Intensity data and elevation

Group B: Intensity data and elevation + Pan image

Group C: Only include RGB image

Group D: Use all types of the data to perform classification including intensity image, elevation data, RGB image and PAN image.

Figure 6(a), 6(b), 6(c) and 6(d) are classification results from using data sets A, B, C, and D. The error matrix for the four cases are in Table 7, Table 8, Table 9 and Table 10 to evaluate the classification accuracy of the different data types.

4. Analysis and evaluation

The results of the classification will give the highest accuracy when using aggregate data, including intensity image, LiDAR elevation data, panchromatic image and RGB image. With the two groups of the land cover layers (group 1 and 2), the accuracy of classification when using all types of data are reaching very high of 93.7% and 90.3%, respectively. If the intensity and LiDAR elevation data is used only, then the accuracy is relatively low with only 69.2% for the group 1 and 48.2% for the group 2.

(a) (b) (c)

Figure 5. (a) Classification of group 1 using intensity image and LiDAR elevation data, (b) Classification of group 1 using intensity image, elevation data and panchromatic image, (c) Classification of group 1 using RGB image without intensity image and panchromatic image

Table 4. Error matrix of land cover classification using intensity data and elevation LiDAR data

		Reference					
	Class	**Tree**	**Water**	**Tile roof**	**Concrete roof**	**Bare soil**	**Unclassified**
Classification	Unclassified	1.01	0.14	0.82	0.17	35.75	2.88
	Tree	94.55	0.00	15.78	2.68	0.25	33.97
	Water	0.00	99.86	0.00	0.00	0.00	23.64
	Tile roof	4.44	0.00	83.39	97.15	64.00	39.52
	Concrete roof	0.00	0.00	0.00	0.00	0.00	0.00
	Bare soil	0.00	0.00	0.00	0.00	0.00	0.00
	All	100.00	100.00	100.00	100.00	100.00	100.00

Table 5. Error matrix of land cover classification using intensity data, elevation LiDAR data and panchromatic image

		Reference					
	Class	Tree	Water	Tile roof	Concrete roof	Bare soil	Unclassified
Classification	Unclassified	1.01	0.14	0.82	0.17	35.75	2.88
	Tree	95.25	0.00	15.60	3.10	1.25	34.31
	Water	0.00	99.86	0.00	0.00	0.00	23.64
	Tile roof	1.92	0.00	75.36	44.52	0.00	22.81
	Concrete roof	0.00	0.00	0.00	0.00	0.00	0.00
	Bare soil	1.82	0.00	8.21	52.22	63.00	16.37
	All	100.00	100.00	100.00	100.00	100.00	100.00

Table 6. Error matrix of land cover classification using RGB image

		Reference					
	Class	Tree	Water	Tile roof	Concrete roof	Bare soil	Unclassified
Classification	Unclassified	1.01	0.14	0.82	0.17	35.75	2.88
	Tree	98.99	0.41	0.00	0.08	0.00	32.15
	Water	0.00	98.48	94.53	0.75	0.00	40.39
	Tile roof	0.00	0.97	4.38	10.71	52.25	6.52
	Concrete roof	0.00	0.00	0.27	88.28	12.00	18.07
	Bare soil	0.00	0.00	0.00	0.00	0.00	0.00
	All	100.00	100.00	100.00	100.00	100.00	100.00

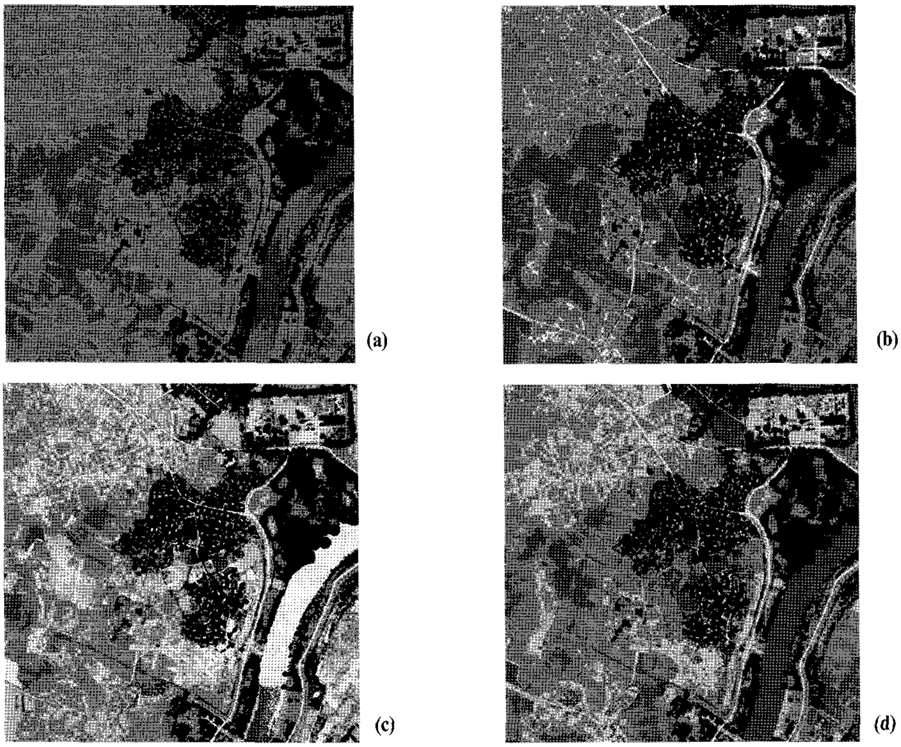


Figure 6. (a) Classification result of group 2 base on reflective image and elevation data, (b) Classification result of group 2 base on intensity image, elevation data and Panchromatic image, (c) Classification result of group 2 base on RGB image, (d) Classification result of group 2 base on intensity image, elevation data, Panchromatic image and RGB image

Table 7. Error matrix of land cover classification of the group 2

	Reference							
	Class	**Road**	**Lake water**	**River water**	**Grass**	**Dry bare soil**	**Wet bare soil**	**Unclassified**
Classification	Unclassified	0.00	14.62	0.00	0.00	0.00	0.00	1.89
	Road	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Lake water	0.00	81.64	43.97	0.00	0.00	2.76	23.16
	River water	0.32	0.50	1.89	1.24	0.00	0.96	1.05
	Grass	99.28	0.56	16.00	89.17	100.00	2.09	40.04
	Dry bare soil	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Wet bare soil	0.40	2.68	38.14	9.59	0.00	94.19	33.86
	All	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table 8. Error matrix of land cover classification of group 2 using intensity and LiDAR elevation and panchromatic image

	Reference							
	Class	**Road**	**Lake water**	**River water**	**Grass**	**Dry bare soil**	**Wet bare soil**	**Unclassified**
Classification	Unclassified	0.00	14.62	0.00	0.00	0.00	0.00	1.89
	Road	52.68	0.00	1.15	2.17	5.05	0.07	6.50
	Lake water	1.84	73.24	0.00	1.38	0.00	0.42	10.00
	River water	0.24	8.71	82.55	3.73	0.00	10.90	26.76
	Grass	35.01	0.00	1.12	74.46	72.67	20.50	28.45
	Dry bare soil	8.95	0.00	8.10	2.26	21.11	0.00	5.52
	Wet bare soil	1.28	3.42	7.07	16.00	1.18	68.11	20.89
	All	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table 9. Error matrix of land cover classification of the group 2 using RGB image

	Reference							
	Class	**Road**	**Lake water**	**River water**	**Grass**	**Dry bare soil**	**Wet bare soil**	**Unclassified**
Classification	Unclassified	0.00	14.62	0.00	0.00	0.00	0.00	1.89
	Road	93.53	0.00	66.03	0.00	51.64	0.00	32.34
	Lake water	0.00	85.38	0.00	0.00	0.00	0.00	11.04
	River water	3.28	0.00	25.46	0.00	4.04	0.00	7.65
	Grass	0.08	0.00	0.00	90.27	0.84	0.00	15.85
	Dry bare soil	3.04	0.00	8.52	8.90	29.52	0.18	7.04
	Wet bare soil	0.08	0.00	0.00	0.83	13.96	99.82	24.19
	All	100.00	100.00	100.00	100.00	100.00	100.00	100.00

The accuracy of classification is improved with supplement of panchromatic image to LiDAR data. The accuracy of classification increased significantly in group 1 to 72% and the accuracy of group 2 classification by 21% to 69%. The RGB image can also be used to classify land cover with relatively high accuracy up to 73% with the group 1 and to 68% with the group 2. However, if RGB image is used as the only source of data for land cover classification, the classification accuracy of each class is not similar to the others. Some classes have very high precision while other classes are so low. This can be seen clearly in Table 9, while the road surface is classified with an accuracy increased to 93%, the accuracy of classification for dry bare soil is only 25%.

Table 10. Error matrix of land cover classification of the group 2 using RGB image, LiDAR data and panchromatic image

	Reference							
	Class	Road	Lake water	River water	Grass	Dry bare soil	Wet bare soil	Unclassified
Classification	Unclassified	0.00	14.62	0.00	0.00	0.00	0.00	1.89
	Road	55.80	0.00	0.00	0.00	0.00	0.96	5.84
	Lake water	0.08	85.38	0.00	0.14	0.00	7.89	12.87
	River water	5.52	0.00	99.82	0.05	0.00	0.00	27.74
	Grass	0.32	0.00	0.00	94.05	0.50	0.00	16.50
	Dry bare soil	38.29	0.00	0.18	5.49	98.07	0.00	14.25
	Wet bare soil	0.00	0.00	0.00	0.28	1.43	91.15	20.91
	All	100.00	100.00	100.00	100.00	100.00	100.00	100.00

5. Conclusion

The aim of this research is to investigate the possibility of using Vietnamese LiDAR intensity data for land cover classification and the most appropriate classification method for the data. The accuracy assessment showed that the intensity image can be used for land cover classification. However, the remote sensing data and RGB image should be used as supplement to ensure the accuracy of land classification. The reason for that the LiDAR data contain only one spectral band (similar to infra-red spectral band) compared to the remotely sensed imagery, therefore, the information obtained from that may not enough for many land cover classes.

Intensity image enable higher accurate classification, especially for land cover objects which is cannot be detected by classification using optical remote sensing image such as the land cover under the high canopy. The neural networks algorithm prevailed over the conventional classification such as minimum distance, maximum likelihood in classification of land cover using LiDAR intensity. It is possibly due to the variation in the spectral features of the data where the non-parametric machine learning classification work better than the parametric algorithm.

Intensity LiDAR data contains much noise that the accuracy of the classification process is much reduced, So it is necessary to use algorithms to remove noise in the processing of intensity image generation to ensure effec of the data obtained during LiDAR scanning.

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