RELEVANCE OF VEGETATION INDICES FROM MULTISPECTRAL IMAGE AND AIRBORNE FULL-WAVEFORM LIDAR IN URBAN AREA

Hsien-Ming Wu[1] and Tee-Ann Teo[2]
[1] PhD Student, Dept. of Civil Engineering, National Chiao Tung University, Hsinchu, Taiwan 30010.
E-mail: cheminwu@gmail.com
[2] Associate Professor, Dept. of Civil Engineering, National Chiao Tung University, Hsinchu, Taiwan 30010.
E-mail: tateo@mail.nctu.edu.tw

KEY WORDS: Multispectral image, Waveform, Lidar, Vegetation indices

ABSTRACT: Vegetation detection in urban area is an important task to understand the greenness of a city. With the development of remote sensing technology, we are able to obtain the multispectral image and full-waveform (FWF) lidar point clouds. The features of multispectral image for vegetation detection include spectrum, texture and 3-D surface information from image matching. Airborne FWF lidar receives one dimensional continuous signal and offers useful information about the spatial structure of the target. Lidar also records the backscattering of laser pulse. As the multispectral image and lidar data can provide both spectrum and geometric information, it is important to understand the relevance of vegetation indices from both sensors. This study compares and analyzes different vegetation indices from active and passive sensors. We verify the detection rate of the vegetation using normalized difference vegetation index (NDVI), greenness index (GI), spectral and surface textures from multispectral image, and canopy height model, echo ratio (ER), echo width, backscattering and surface texture from airborne FWF lidar data. Texture information includes entropy and angular second moment (ASM) based on Gray Likelihood Co-occurrence Matrix (GLCM). These image-derived and lidar-derived features are used to separate vegetation and non-vegetation in an urban area. The test data are WorldView-2 multispectral images and Rigel Q680i lidar point clouds. The experimental results the correlation coefficient of echo ratio from airborne FWF lidar data is higher than 70% with NDVI from multispectral images, followed by the echo width and backscattering coefficient.

1. INTRODUCTION

The greenness of a city is becoming important because of the growing of city. The vegetation indices show the degree of greenness. The normalized difference vegetation index (NDVI) from multispectral images in the plant growth season (e.g. summer or winter) is a useful index to detect vegetation, but it is not easy to detect leaf-off vegetation in deciduous season (e.g. autumn or winter). The new technology of full-waveform (FWF) lidar systems has appeared in the last twenty years. Airborne FWF lidar is a kind of active remote sensing technology, and it can collect the information of ground by direct georeferencing, and it has been used in various applications in urban area like vegetation detection (Höfle and Hollaus, 2010 and Rutzinger et al., 2008).

The feature of FWF lidar includes radiometric properties such as intensity, amplitude, echo width, backscatter cross section, etc. Wagner et al. (2006) extended the radar equation (Jelalian, 1992) to airborne lidar, and they also presented the theoretical considerations for backscatter cross section ([m^2]) estimation and radiometric calibration. Wagner (2010) considered the backscattering coefficient (BS [m^2m^{-2}]) as additional physical quantity for ground surface characterization and to be used for radiometric calibration particularly. Alexander et al. (2010) compared backscatter cross section and backscattering coefficient for the terrain classification accuracy, the backscattering coefficient was better than backscatter cross section.

Guo et al. (2011) proposed various features from multispectral image and FWF lidar for urban scene classification. There are many studies to associate the lidar and vegetation index (Tang et al., 2014 and Beland et al., 2014). Compared to other studies on vegetation detection, this study concentrates on a complex urban area, which have a high structural complexity with multilayer objects. This aim of study is to analyze the multispectral image from passive sensor and lidar from active sensor to understand the vegetation indices in urban areas.

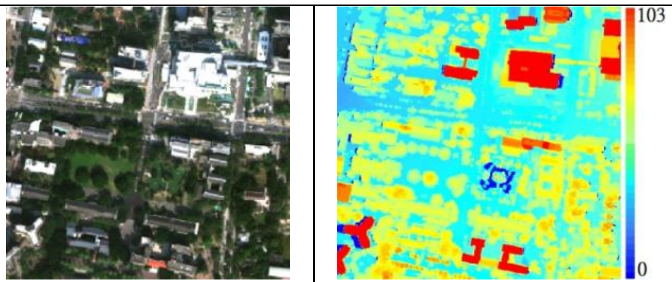
2. MATERIALS

2.1 Study area

The test area is located at Tainan city of Taiwan, and its area is about 240,000 (500*480) square meters (Figure 1). The terrain is flat, no particular topography, and the tallest building is about 70 meters. The study area is characterized by buildings, roads, as well as trees and grass in the park.

2.2 Multispectral image and FWF lidar

The multispectral image data were collected on December 12, 2010 by WorldView-2. The wavelength of satellite image is from 400nm to 900nm, and contains eight multispectral bands, including coastal (400~450nm), blue (450~510nm), green (510~580nm), yellow (585~625nm), red (630~690nm), red edge (705~745nm), NIR-1 (770~895nm) and NIR-2 (860~900nm). This study used multispectral image, and the spatial resolution is about 2 meters. The airborne FWF lidar data were obtained on August 4, 2010 by Rigel Q680i system. The laser pulse of system belong the near-infrared light, and the wavelength is 1550nm. The total number of point clouds in the study area is about 230 million, and convert density is about 9.6pt/m^2 (Table 1).



(a) RGB Image (b) DSM Image

Figure 1. The study area.

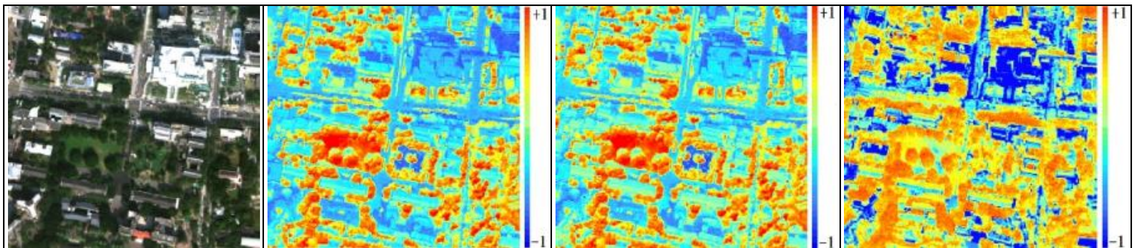
Table 1. Parameters of data.

Multispectral Image		FWF Lidar	
Satellite	WorldView-2	System	Reigl LMS-Q680i
Collection time	2010/12/12	Collection time	2010/8/4
Wavelength	400~900 nm	Wavelength	1550 nm
Spatial Resolution	1.84 m (Nadir)	Point density	9.6 pt/m^2

3. METHODOLOGY

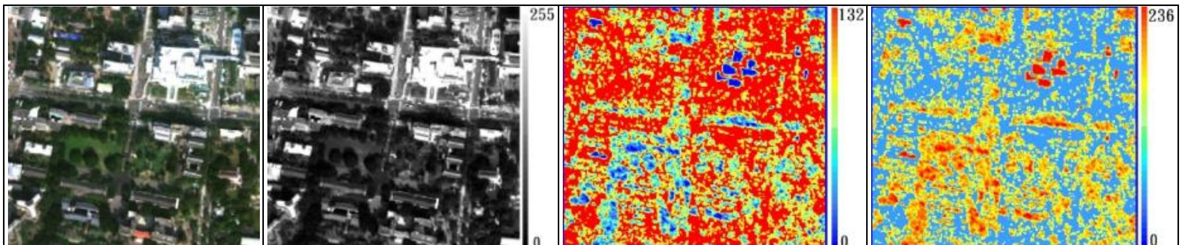
3.1 Vegetation index from multispectral image

This study uses multispectral image to calculate the NDVI and GI by spectrum numerical analysis as vegetation indices. These two NDVI were calculated by two NIR bands (Figure 2). Due to the structure of vegetation is complicated than the road surface or roof, so two-dimensional spectral image can also obtains texture information (e.g. entropy and angular second moment (ASM)) based on Gray Likelihood Co-occurrence Matrix (GLCM). The entropy is used to measure the messy degree of texture, the value is greater if the image closer to a random pattern. The ASM is used to measure of the degree of uniformity of the image locally, which is a measurement of the consistency degree of image texture. Figure 3 shows the results of these indices. As the texture feature is visually different from spectral indices, this study only consider NDVI-1, NDVI-2 and GI from multispectral images.



(a) RGB Image (b) NDVI-1 (c) NDVI-2 (d) GI

Figure 2. Spectral indices.



(a) RGB Image (b) Gray Image (c) Entropy Image (d) ASM Image

Figure 3. Lidar indices.

3.2 Vegetation index from FWF lidar

The features of FWF lidar contain the intensity of each return pulse, the amplitude and echo width from the return signals, and the return number from the received time. Those features are useful information about the spatial structure of the target. The canopy height model (CHM) can be calculated through geometric analysis of point clouds, it represented the height of ground objects. The echo ratio can be obtained by statistical analysis (Hofle et al., 2012), it is referred to the structure of the surface coverings and suitable to detect the complex structure of trees. The intensity, amplitude and width of return echo can be calculate by energy analysis. Both intensity and amplitude are based on the energy of pulse. The intensity indicates the magnitude of the reflected pulse, and the amplitude is a ratio of the echo signal and the detection threshold of the instrument (Riegl, 2014). To avoid data errors, we only consider the points within 95% confidence interval (3σ). All these features are interpolated by Kriging interpolation, so the FWF lidar and multispectral image use the same data structure. Figure 4 shows the features of FWF lidar.

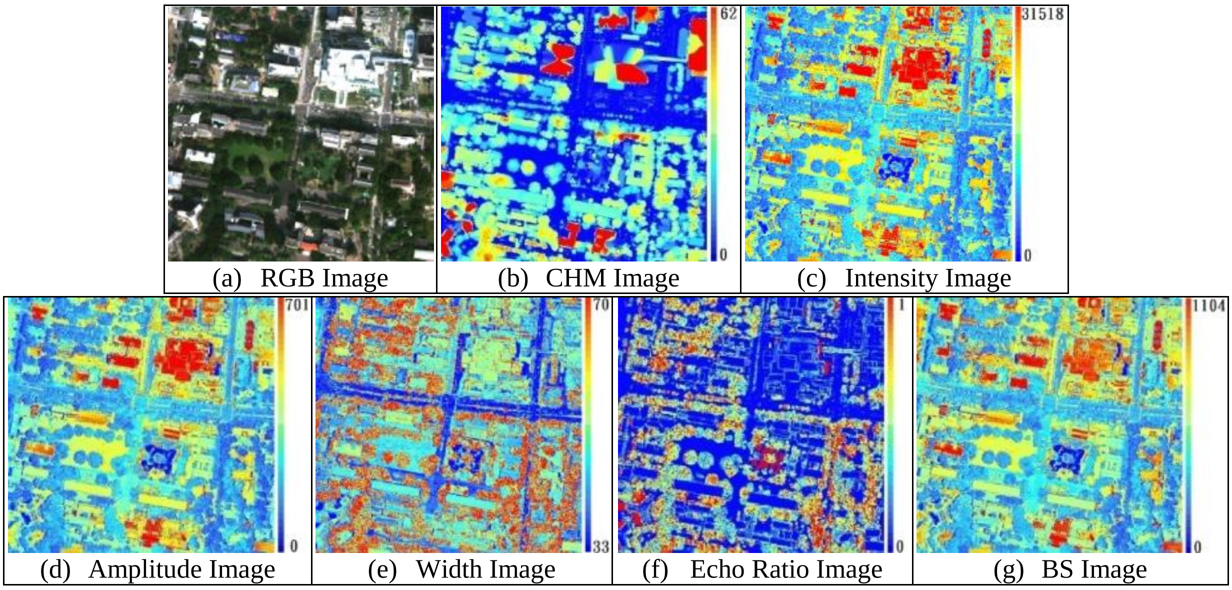


Figure 4. The feature image from FWF lidar.

This study also calculates texture (e.g. entropy and ASM from BS images), echo width image, ER image and CHM image (Figure 5). The boundaries of ground objects can be extracted clearly, but the texture of individual objects are not easy to compare with other features. Hence, this study only discusses BS, width, ER and CHM from FWF lidar.

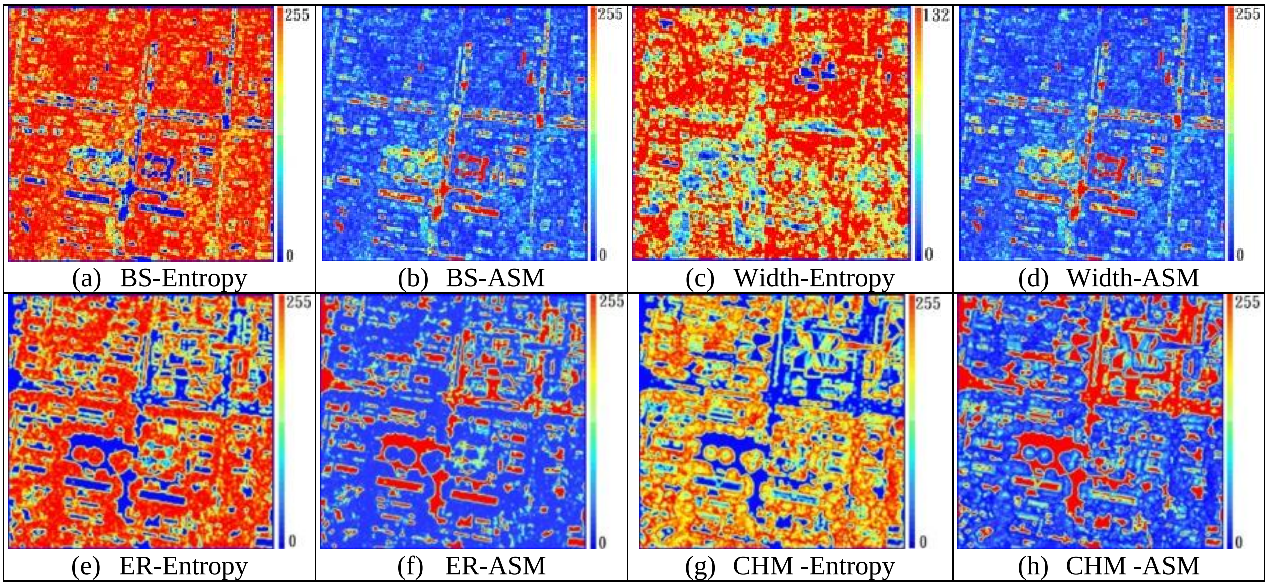


Figure 5. The texture image from the feature of FWF lidar.

3.3 Comparison of various features

The study manually selected 100 blocks which are 25 square (5*5) meters in the study area. The average values were calculated within the block after outlier detection. The land covers for classification are trees, grasses, roads and buildings. Table 2 is the value of different vegetation indices from multispectral image (the values are normalized to 0~255). The value of vegetation is higher than non-vegetation, and distinguish each other easily.

Table 2. The values of various features from multispectral image.

		NDVI-1				NDVI-2				GI			
Classification		Min	Max	Mean	Std.	Min	Max	Mean	Std.	Min	Max	Mean	Std.
Veg.	Tree	186	206	198.97	4.70	177	200	191.42	5.24	162	171	167.81	1.65
	Grass	198	210	205.47	1.91	189	205	199.45	2.17	157	168	162.43	1.48
Nonveg.	Road	127	137	131.84	1.71	112	125	117.92	2.16	136	154	146.25	2.82
	Building	132	138	135.38	1.01	121	126	123.49	1.30	119	127	123.02	1.73

Table 3 is the value of different vegetation indices from FWF lidar. Among them, the tree can be distinguished from grasses or buildings through BS, but it is easy to be confused with the road. The width of tree is widely, and its standard deviation is higher than grass, road and building. The ER of tree is higher than grass and road because it's complex structure, but is closer to edges of buildings.

Table 3. The values of various features from FWF lidar.

		BS				Width				ER				CHM			
Classification		Min	Max	Mean	Std.	Min	Max	Mean	Std.	Min	Max	Mean	Std.	Min	Max	Mean	Std.
Veg.	Tree	35	226	133.50	34.65	40	65	48.94	3.32	6.89	25.57	16.23	3.50	6.9	26.6	15.15	3.41
	Grass	309	528	366.25	25.72	44	47	45.53	0.57	0.00	0.56	0.02	0.02	0.0	0.3	0.12	0.13
Non-veg.	Road	11	692	166.91	51.87	42	46	43.48	0.68	0.00	1.43	0.07	0.19	0.0	0.1	0.03	0.02
	Building	139	746	586.95	59.07	45	48	46.74	0.73	9.02	61.79	37.41	19.75	6.0	60.0	31.14	17.41

4. RESULTS

All of these indices which contains NDVI-1, NDVI-2, GI, BS, width, ER and CHM were plotted into a scatter diagram (Figure 5). We analysis the correlation coefficient of various indices from point clouds and multispectral image. The results show that ER and NDVI-1/NDVI-2 are highly correlated (i.e. > 0.7). The followings were echo width and backscattering coefficient (Table 4). The study uses pixel-based classification based on minimum distance method. The results of classification through single feature from FWF lidar are not good enough as different land covers contain similar properties (Figure 6). All of the Kappa coefficient are less than 0.6 (Table 5). In which, the grass is similar to roads and roofs. We consider the separation of vegetation and non-vegetation. The detection rate reaches 0.78 kappa coefficient using ER (Table 6).

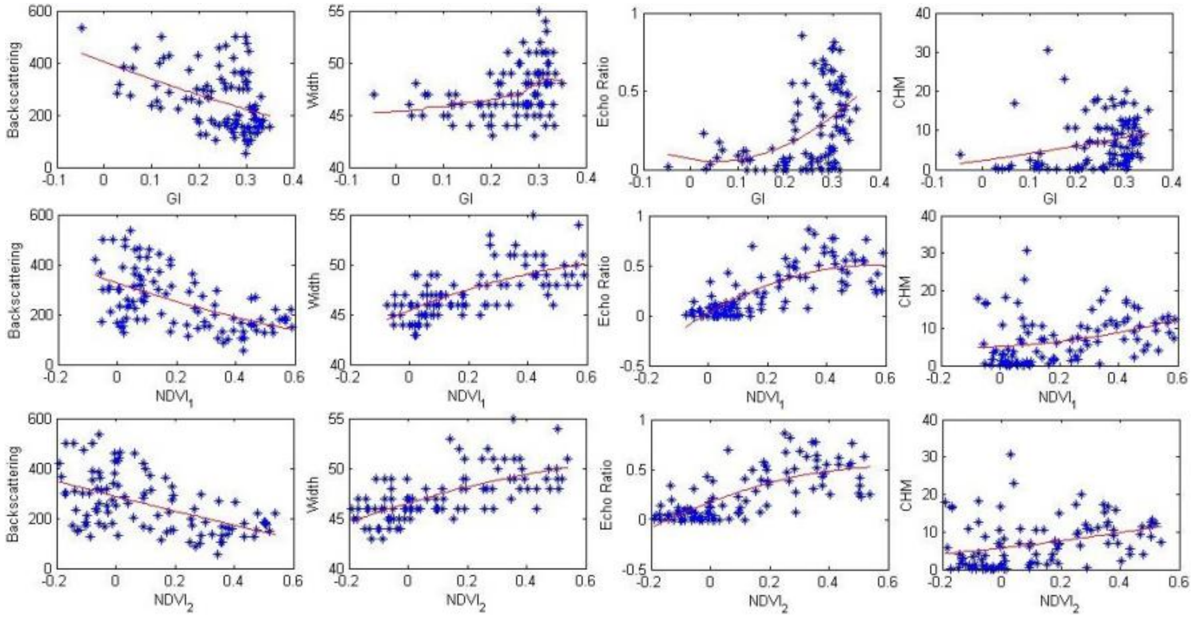


Figure 6. Scatter plot of the various vegetation indices.

Table 4. Correlation Coefficient Matrix.

	NDVI_1	NDVI_2	GI	Int.	Amp.	BS	BS_E	BS_A	Wid.	Wid_E	Wid_A	ER	ER_E	ER_A	CHM	CHM_E	CHM_A
NDVI_1	1	0.992	0.373	-0.431	-0.392	-0.551	0.195	-0.227	0.672	0.439	0.439	0.736	0.583	-0.514	0.326	-0.551	-0.506
NDVI_2	0.992	1	0.338	-0.403	-0.382	-0.530	0.175	-0.209	0.656	0.420	0.420	0.712	0.545	-0.475	0.330	-0.530	-0.486
GI	0.373	0.338	1	-0.316	-0.375	-0.432	0.026	-0.039	0.353	0.191	0.191	0.443	0.346	-0.291	0.268	-0.432	-0.489
Int.	-0.431	-0.403	-0.316	1	0.754	0.766	0.038	-0.034	-0.210	-0.082	-0.082	-0.570	-0.415	0.370	-0.150	0.766	0.329
Amp.	-0.392	-0.382	-0.375	0.754	1	0.727	0.162	-0.140	-0.155	-0.022	-0.022	-0.429	-0.256	0.219	-0.186	0.727	0.300
BS	-0.551	-0.530	-0.432	0.766	0.727	1	0.178	-0.168	-0.285	0.039	0.039	-0.656	-0.380	0.320	-0.194	-0.392	0.373
BS_E	0.195	0.175	0.026	0.038	0.162	0.178	1	-0.987	0.358	0.247	0.247	0.282	0.525	-0.547	0.073	0.178	-0.244
BS_A	-0.227	-0.209	-0.039	-0.034	-0.140	-0.168	-0.987	1	-0.388	-0.275	-0.275	-0.296	-0.523	0.541	-0.118	-0.168	0.231
Wid.	0.672	0.656	0.353	-0.210	-0.155	-0.285	0.358	-0.388	1	0.662	0.662	0.688	0.585	-0.534	0.455	-0.289	-0.455
Wid_E	0.439	0.420	0.191	-0.082	-0.022	0.039	0.247	-0.275	0.662	1	1.000	0.356	0.378	-0.330	0.227	-0.139	-0.215
Wid_A	0.439	0.420	0.191	-0.082	-0.022	0.039	0.247	-0.275	0.662	1.000	1	0.356	0.378	-0.330	0.227	-0.139	-0.215
ER	0.736	0.712	0.443	-0.570	-0.429	-0.656	0.282	-0.296	0.688	0.356	0.356	1	0.665	-0.608	0.391	-0.656	-0.621
ER_E	0.583	0.545	0.346	-0.415	-0.256	-0.380	0.525	-0.523	0.585	0.378	0.378	0.665	1	-0.978	0.263	-0.380	-0.701
ER_A	-0.514	-0.475	-0.291	0.370	0.219	0.320	-0.547	0.541	-0.534	-0.330	-0.330	-0.608	-0.978	1	-0.187	0.320	0.672
CHM	0.326	0.330	0.268	-0.150	-0.186	-0.194	0.073	-0.118	0.455	0.227	0.227	0.391	0.263	-0.187	1	-0.194	-0.400
CHM_E	-0.551	-0.530	-0.432	0.766	0.727	-0.392	0.178	-0.168	-0.289	-0.139	-0.139	-0.656	-0.380	0.320	-0.194	1	0.373
CHM_A	-0.506	-0.486	-0.489	0.329	0.300	0.373	-0.244	0.231	-0.455	-0.215	-0.215	-0.621	-0.701	0.672	-0.400	0.373	1

*_E: Entropy   *_A: ASM

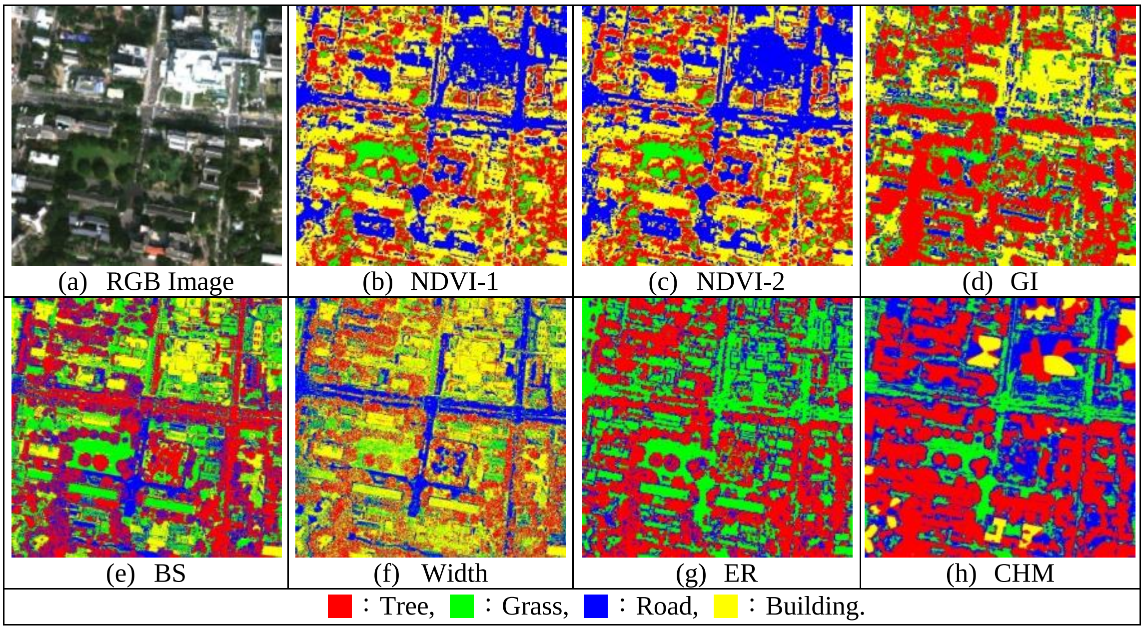


Figure 6. Classification results.

Table 5. Accuracies of classification (4 landcovers)

	Tree				Grass				Overall Accuracy	Kappa
	Commission	Omission	Prod. Acc.	User Acc.	Commission	Omission	Prod. Acc.	User Acc.		
BS	33.21%	33.87%	66.13%	66.79%	55.82%	3.14%	96.86%	44.18%	61.46%	0.4746
Width	7.51%	43.00%	57.00%	92.49%	55.32%	58.41%	41.59%	44.68%	72.64%	0.6120
ER	4.81%	17.31%	82.69%	95.19%	81.48%	2.00%	98.00%	18.52%	41.44%	0.2695
CHM	31.19%	0.46%	99.54%	68.81%	66.68%	6.44%	93.56%	33.32%	61.48%	0.4752

Table 6. Accuracy of classification (tree and non-tree)

	Tree				Non-trees				Overall Accuracy	Kappa
	Commission	Omission	Prod. Acc.	User Acc.	Commission	Omission	Prod. Acc.	User Acc.		
ER	0.05%	19.44%	80.56%	99.95%	21.12%	0.06%	99.94%	78.88%	88.72%	0.7767

5. CONCLUSIONS

The experimental results indicate that the correlation coefficient of echo ratio from airborne FWF lidar data is related to NDVI from multispectral images. Vegetation of urban environment can be detected by NDVI or GI in the lush plant growth season, but the passive spectrum can't analyze correctly when the vegetation lack chlorophyll. Airborne FWF lidar can provide different features such as echo width, ER or BS as vegetation indices in deciduous season. Trees detection can achieve good results through the ER from lidar in urban environment. Echo width from FWF lidar can be roughly distinguish between trees, grass and other ground objects, because of the different roughness of surface. The texture of multispectral image or FWF lidar is still not clear in classification, but it can distinguish the edges of objects for segmentation. The integration of multivariate data will not only can identify more data from spatial information but also improve the correctness of vegetation detection.

ACKNOWLEDGMENTS

This research was partially supported by the Ministry of Science and Technology of Taiwan under project number NSC 101-2628-E-009 -019 -MY3. The authors also like to thank the Strong Engineering Consulting Co., Ltd in Taiwan for providing the test data sets.

REFERENCES

Alexander, C., Tansey, K., Kaduk, J., Holland, D., Tate, N.J., 2010. Backscatter coefficient as an attribute for the classification of full-waveform airborne laser scanning data in urban areas. ISPRS Journal of Photogrammetry and Remote Sensing, 65 (5), pp.423-432.

Beland, M., Widlowski, J.L., Fournier, R.A., 2014. A model for deriving voxel-level tree leaf area density estimates from ground-based LiDAR. Environmental Modelling and Software, 51, pp.184-189.

Guo, L., Chehata, N., Mallet, C., Boukir, S., 2011. Relevance of airborne lidar and multispectral image data for urban scene classification using random forests. ISPRS Journal of Photogrammetry and Remote Sensing, 66, pp.56-66.

Höfle, B., Hollaus, M., 2010. Urban vegetation detection using high density fullwaveform airborne lidar data combination of object-based image and point cloud analysis. International Archives of Photogrammetry. Remote Sensing and Spatial Information Sciences, 38 (Part 7B), pp.281-286.

Höfle, B., Hollaus, M., Hagenauer, J., 2012. Urban vegetation detection using radiometrically calibrated small-footprint full-waveform airborne lidar data. ISPRS Journal of Photogrammetry and Remote Sensing, 67, pp.134-147.

Jelalian, R., 1992. Laser Radar Systems. Artech House, Boston, London.

Rutzinger, M., Hofle, B., Hollaus, M., Pfeifer, N., 2008. Object-based point cloud analysis of full-waveform airborne laser scanning data for urban vegetation classification. Sensors 8 (8), pp.4505-4528.

Tang, H., Brolly, M., Zhao, F., Strahler, A.H., Schaaf, C.L., Ganguly, S., Zhang, G., Dubayah, R., 2014. Deriving and validating Leaf Area Index (LAI) at multiple spatial scales through lidar remote sensing: A case study in Sierra National Forest, CA. Remote Sensing of Environment, 143, pp.131-141.

Wagner, W., Ullrich, A., Ducic, V., Melzer, T., Studnicka, N., 2006. Gaussian decomposition and calibration of a novel small-footprint full-waveform digitising airborne laser scanner. ISPRS Journal of Photogrammetry and Remote Sensing, 60 (2), pp.100-112.