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Application of LiDAR's Multiple Attributes for Wetland Classification

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ABSTRACT

Wetlands have received intensive interdisciplinary attention as a unique ecosystem and valuable resources. As a new technology, the airborne LiDAR system has been applied in wetland research these years. However, most of the studies used only one or two LiDAR observations to extract either terrain or vegetation in wetlands. This research aims at integrating LiDAR's multiple attributes (DSM, DTM, off-ground features, Slop map, multiple pulse returns, and normalized intensity) to improve mapping and classification of wetlands based on a multi-level object-oriented classification method. By using this method, we are able to classify the Yellow River Delta wetland into eight classes with overall classification accuracy of 92.5%

Keywords: wetlands, classification, multiple attributes, LiDAR, accuracy

1. INTRODUCTION

Wetlands are recognized as one of the most valuable natural resources as breeding, rearing, and feeding grounds for many kinds of plants and animals. Remote sensing has become one of the most efficient and popular methods of monitoring wetlands. But misclassification occurs among different objects that have similar spectral information. Airborne LiDAR offers an enhanced potential for discriminating different classes such as canopy estimation, vegetation determination, and wetland detection (Sadro et al., 2007; Trevor et al., 2010; Yao et al., 2012), because it provides spatial attributes. Now, modern LiDAR systems can collect more attributes such as intensity, multiple return and full waveform. Few studies have focused on the application of LiDAR's multiple attributes. Additional inputs of datasets can provide more characteristics and lead to better resource management and behavior modeling.

This study examines the application of LiDAR's multiple attributes for wetland classification using an object-oriented classification method. The Yellow River Delta (YRD) of China was selected as the study area to conduct wetland classification. LiDAR's attributes were exploited for identifying different wetland classes.

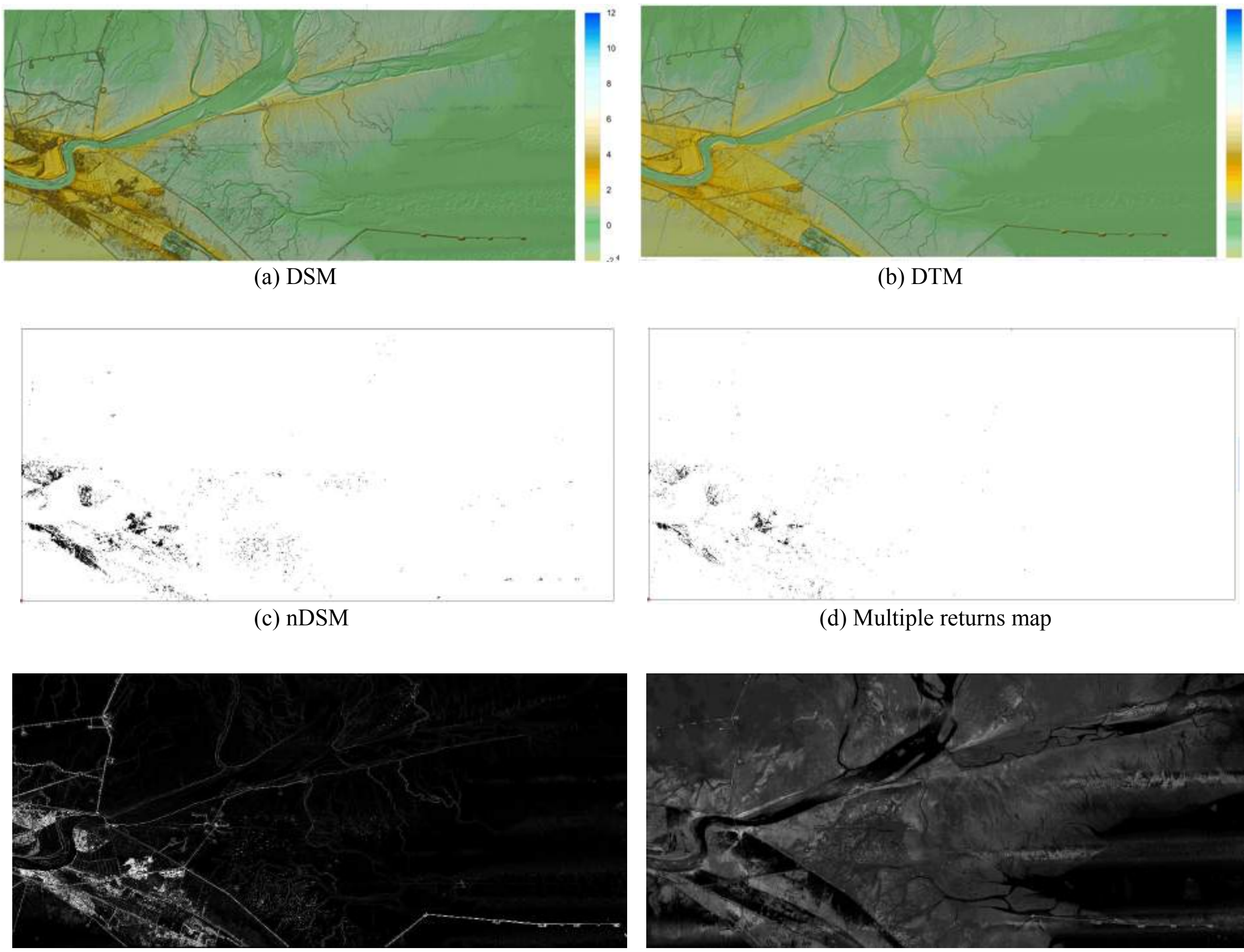
2. STUDY AREA AND DATASETS

2.1 Study area

The study area is located in the estuary of the Yellow River (YR) in Shandong Province of North-Eastern China. It is well known that the YR is the second longest river in China and for its highest sediment concentration in the world. Due to the soil erosion in the middle YR reach, extensive amount of soil and sands are carried turning the river into a yellow hue and resulting in a great amount of suspended sediments in the lower reach. The continual incoming sediments and frequent course changing formed the modern YRD which has experienced complex patterns of erosion and accretion. Area of the newly created wetland enlarges by 32.4km^2 per annum due to deposition of the large amounts of sand and mud transported (Zhao, 1997).

2.2 LiDAR dataset

A discrete-return LiDAR survey was conducted on April 16, 2008 using a Leica ALS50 system at a wavelength of 1064 nm. This system can record at most three returns coming from single pulse. Four strips were acquired from a flight altitude of 2400 m; a pulse repetition frequency of 30.2 KHz; a scanning rate of 14.6Hz; and field of view of 62.5 degrees which resulted in a swath width of 2800 m for each flight line. Six layers were constructed based on LiDAR data for investigating LiDAR's ability in wetland classification. They were regarded as LiDAR's multiple attributes in this study. LiDAR's multiple attributes include: 1) DSM (Digital Surface Model); 2) DTM (Digital elevation model); 3) nDSM (Normalized DSM); 4) Multiple returns; 5) Slope map; 6) Intensity map, shown in Figure 1.



(a) DSM (b) DTM

(c) nDSM (d) Multiple returns map

(e) Slope map (f) Intensity map

Figure 1. LiDAR's multiple attributes

2.3 Wetland classes in YRD

Due to the diversity of wetlands, the YRD wetland is described as both estuarine and coastal wetland systems according to the wetland classification systems (Stewart and Kantrud, 1971). Eight major classes are defined according field surveying and previous studies in this region (Yue et al., 2003). The eight classes include:

1) Wet meadow (WM). It is a semi-wetland meadow which is saturated with water.
2) Forested swamp (FS). It is forest which is inundated with wet meadow permanently or seasonally.
3) Phragmites (PM). It is a large perennial grass found in wetland, which is also called common reed.
4) Lowland (LL). It is an expanse of land with a general low level. It is the landward portion of the upward slope from oceanic depths to continental highlands.
5) Impervious surface (IS). It is artificial objects covered by impenetrable materials, such as roads and parking lots.
6) River (RV). YR is the main river in this region.
7) Sea (SEA). Sea is a large body of saline water. YRD also belongs to coastal wetlands which are surrounded by the Yellow Sea.

8) Intertidal zone (ITZ). It is the area that is above water at low tide and under water at high tide. Due to the fluctuation of tides, Intertidal zones are further classified into three categories: high tidal zone, middle tidal zone, and low tidal zone.

3. WETLANDS CLASSIFICATION EXPERIMENTS

3.1 Classification strategy

The strategy of rule based classification is first to create a four-level scale of segmentation to provide a hierarchy as different classes present different size and priority in classification. Figure 2 is a flow chart describing the classification hierarchy for the method. It describes the four-level segments over the entire area. The level of details increases as the level number increases. Table 1 shows the selected parameters of four-level segmentation.

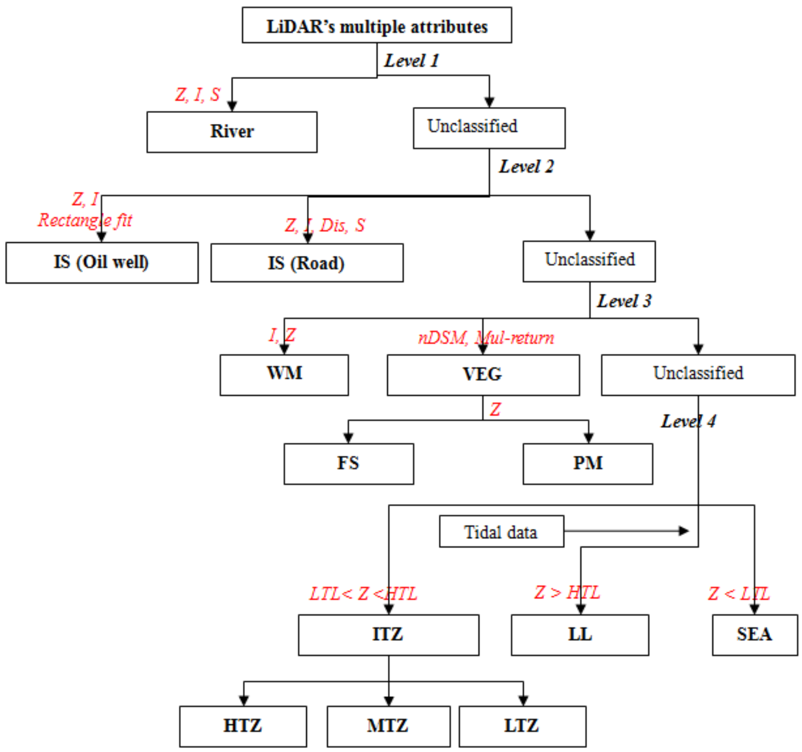


Figure 2. Flow chart of classification

In the classification tree, Z is elevation data from LiDAR derived DTM. I is LiDAR intensity. S is the slope of segments. Rectangle fit is an indicator to identify squares. D is the distance to a defined class. nDSM represents normalized DSM. Multi-return is the number of returns. HTL is high tidal level calculated from tidal data. LTL is the low tidal level.

3.2 Classification result

Figure 3 is the classification map based on LiDAR's multiple attributes. Ground truth data based on field observations with GPS locations and points identified on aerial photos were used. The producer's accuracy (PA) and user's accuracy (UA) have been used for each category (Liu, 2007). PA indicates the probability that a reference pixel being correctly classified, while UA indicates how well the classification performed in the field by row. These measurements are derived from the confusion matrix, which is created on the basis of the comparison between the classification and the verification data.

Table 1. Parameters for four-level segmentation

	Method	Layer for segmentation	Scale	Color	Shape	Smoothness	Compactness
Level 1	Multi-resolution	DTM	200	0.9	0.1	0.9	0.1
Level 2		Slope,	100	0.9	0.1	0.9	0.1
Level 3		Intensity, Slope	50	0.8	0.2	0.8	0.2
Level 4	Chessboard	DTM	5	-	-	-	-

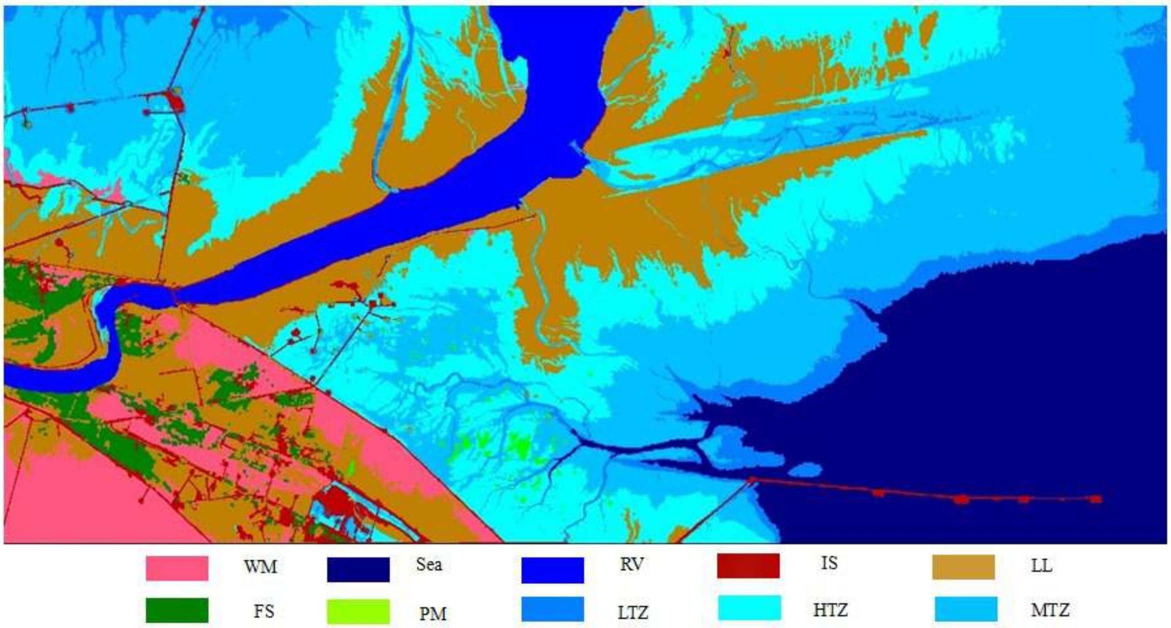


Figure 3. Classification map

Table 2. Accuracy assessment of classification result

Classification data	Reference data								Row Total	UA (%)
	LL	WM	IS	FS	PM	RV	SEA	ITZ		
LL	107	2	0	1	0	3	0	8	121	88.4
WM	4	76	1	3	0	0	0	1	85	89.4
IS	6	4	252	9	0	0	0	0	271	93
FS	1	1	0	189	0	0	0	0	191	98.9
PM	9	0	0	0	76	0	0	21	106	71.7
RV	0	0	0	0	0	40	0	0	40	100
SEA	0	0	0	0	0	0	77	0	77	100
ITZ	0	0	0	0	0	0	0	119	119	100
Column Total	128	83	253	202	64	43	77	150	1010	
PA (%)	84	91.6	99.6	93.6	100	93.0	100	79.3		

Overall accuracy = 92.5%

3.3 Classification result

The classification map offers valuable information about the relationship among various wetland classes. The statistics of classification accuracy are shown in Table 2 with 1010 samples of different classes. In the 1010 samples, 934 points were correctly classified. The overall accuracy of 92.5% justifies the validity of employing LiDAR's multiple attributes for wetland classification.

It is found that the distribution of classified classes reflects the mechanism of YRD where the land is around YR as it is formed by the sediments overrunning the bank. Large vegetation locates in the inland region while low vegetations in the intertidal zone. By examining the contribution of each input LiDAR attribute, it was found that LiDAR's elevation attribute was able to remove all of the confusions among wetland classes which are sensitive to elevation, while those classes are not able to be separated by spectral data. The normalized DSM plays an important part in classifying vegetations. Since the topography of YRD is very flat, an adaptive TIN filter can successfully filter objects above the ground such as vegetation. The multiple return attribute often happens on large vegetations. It represents the distribution of large vegetations. Both of nDSM and multiple returns were utilized in classifying vegetations. The slope map derived from the DTM enhanced significantly segmentation accuracy and integrality of segmented objects, in particular those with great elevation changes at their edges. These topographic features enabled the discrimination of steep classes, such as river, road and oil well. These results showed the contributions of elevation, nDSM and slope in wetland classification. The intensity is sensitive to moisture of objects. Wetland classes with water covered such as river, wet meadow and sea were classified with the help of normalized intensity. Tidal data is useful in separating intertidal zone into three different regions. As different regions will have different impact on species, this kind of classification map will help in ecological studies

4. CONCLUSIONS

This study explored LiDAR's multiple attributes for wetland classification and showed the valuable contributions of LiDAR's multiple attributes in wetland classification. LiDAR's radiometric and spatial data were treated as complementary to each other. The synergy LiDAR's multiple attributes made it possible to discriminate specific wetland classes in YRD. The classification results demonstrated that object-oriented method was suitable for wetland classes, as it provides a hierarchical structure which is similar with ecological system, and contains more meaningful characteristics, such as spectral, shape and contextual information. The overall accuracy of 92.5% justifies the validity of rule based classification method employing LiDAR's multiple attributes for wetland classification and our study provide a trial in combining LiDAR's multiple attributes.

5. ACKNOWLEDGEMENT

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