POTENTIAL OF TEMPORAL INFORMATION OF HIGH DENSITY AIRBORNE LIDAR DATA FORINSTREAM FLOW TYPE CLASSIFICATION

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ABSTRACT: Instream habitat mapping is an important task for river management. Remote sensing techniques have been successfully applied to replace the conventional method of habitat mapping due to the disadvantages of conventional method like expansive, labor intensive and time-consuming. Airborne LiDAR (Light Detection And Ranging) combining standard deviation analysis has been proved to be effective for instream habitat mapping in the last research. In this research, we improved the point density of LiDAR data and collected the ground truth data with the aim of GPS for accurate positioning. New methods using temporal information of water surface to discriminate instream flow types are tested and compare to the original method. The result shows that standard deviation of average surface elevation provides the best classification accuracy, and as the LiDAR technique improved, it has a great potential to be a useful tool for instream flow type classification in the future.

1. INTRODUCTION

Remote sensing techniques have been successfully applied to in-stream habitat. For image-based approach, high resolution hyperspectral (HSRH) imagery showed the classification accuracies from 69% to 86% (Marcus et al., 2003). For LiDAR (Light Detection And Ranging) technique, airborne laser scanning (ALS) achieved the classification accuracy of 61.4 % to 86.6% (Lin and Wang, 2011). The use of ALS for in-stream habitat mapping relies on the roughness of the water surface. Milan et al. (2010) showed using not only the information of spatial roughness but also the temporal roughness of the water surface for this task with a very high point density cloud (> 2500 points/m^2) obtained from terrestrial laser scanner (TLS). However, no ALS data was able with sufficient point density and repeated scans to evaluate mapping accuracy of using the temporal roughness derived from ALS data. In this research, we obtained a very high point density ALS data with sufficient repeated scans in one flight to evaluate the mapping accuracy of in-stream habitat using temporal roughness and compared it with the results derived from spatial roughness. River Habitat Survey (RHS) 2003 version was adopted as the guidelines for field reference data collection. Thus, the in-stream habitats are characteristized as flow types, such as broken standing waves (BW), unbroken standing waves (UW), rippled (RP), smooth (SM) and no perceptible flow (NP).

2. MATERIAL AND METHOD

2.1 The study area

The study area is located at Nan-Shih River, northern Taiwan (latitude and longitude of 24°54’11” and 121°33’22”, respectively) (Fig. 1a). The river reach considered in this research was a 2.5 km section that was bracketed between the Shang-Kuai-Shan Bridge and Hsin-Hsia-Kuai-Shan Bridge.

2.1 LiDAR data

The LiDAR data was collected using an Optech ALTM 3070 airborne LiDAR on 7 May 2009 with the altitude at above ground level of 500 m by a local survey service provider. The resultant ALS data achieves the point density of 160 points/m^2 within the study area. Due to safety reasons for flying in a valley landscape, the flightlines are not evenly distributed so is number of repeated scans for the study area (Fig. 1b). Following previous study (Lin and Wang 2011), the ALS point data were gridded by 1 m × 1 m cells. The average of repeated scan for all the cells is 11. The aerial imagery was collected concurrent with the LiDAR data. The orthophoto with a spatial resolution of 5 cm (shown in Fig. 1a) was produced using the aerial imagery and the digital surface model (DSM) generated from the LiDAR point cloud. All the LiDAR point clouds from non-water surfaces were removed with the help of the orthophoto.

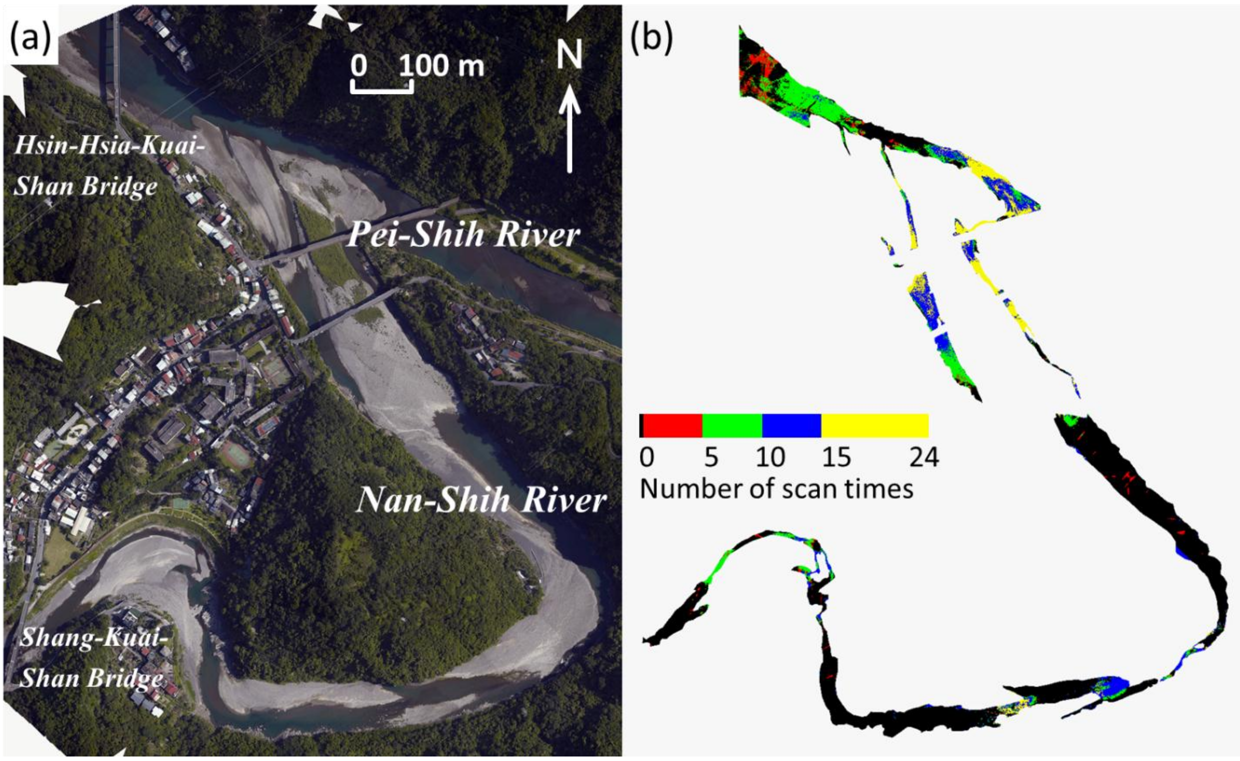

Fig. 1. (a) The study area is located at Nan-Shih River, northern Taiwan (b) The color represents number of repeated scans within 1m × 1m grid. Black color denotes the area that no signal returns to ALS, and these area are SM and NP. The laser beams were reflected away from the ALS system because the mirror-like surface of these areas.

2.2 Ground reference data

The ground reference data were collected by the field team in the river section from the Shang-Kuai-Shan Bridge and to the Hsin-Hsia-Kuai-Shan Bridge (Fig. 1a), on the same day with ALS data collection. We follow the flow type description in River Habitat Survey (RHS) 2003 version, and adapt the RHS form for the flow type mapping in this research. For each reference site, the field team recorded the coordinates using a differential GPS unit with the plane accuracy of 2 cm. The GPS antenna was placed as closely as possible to the reference site without risking the field team and a panoramic photography was created using the field photography as a record for the flow type. A total of 65 reference sites were visited.

2.3 Flow type classification

Standard deviation had been successfully used to describe water surface roughness (Lin and Wang, 2011; Milan et al., 2010). Standard deviation shows the vertical deviations of the water surface, which represents the roughness of the water surface. A low standard deviation indicates the elevations of water surface tend to be very close to the mean value, whereas high standard deviation indicates the elevations are more dispersive. The former situation usually happens in SM and NP, and the latter situation usually happens in high energy flow types like BW and UW. Water surface roughness ρ can be defined as:

$$\rho = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(Z_i - \bar{Z})^2} \quad (1)$$

where Z_i is elevation of ith ALS point data points within the computation cell, $\bar{Z}$ is the mean value of the elevation and n is the number of ALS points. A minimum point density threshold of 40 points/m^2 is adopted for data calculation on 1m × 1m cells in order to assure the classification accuracy (Lin and Wang, 2011).

Milan et al. (2010) assessed the vertical variation in water surface elevation over time by the analysis of average surface roughness (σ_Z) values of each biotope between 13 repetitive TLS scans. The idea is that high energy flow types like BW not only have large spatial variation over the water surface but also have significant change of surface characteristics (such as spatial roughness and slope) over time. The low energy flow type like SM and NP share the similar appearance of having a steady water surface, and the temporal changes for SM and NP should be marginal. Based on this idea, several methods are tested in order to reveal the temporal difference between flow types. Since the water surface roughness ρ of each flow type may change over time, mean and standard deviation are first adopted, which can be expressed as:

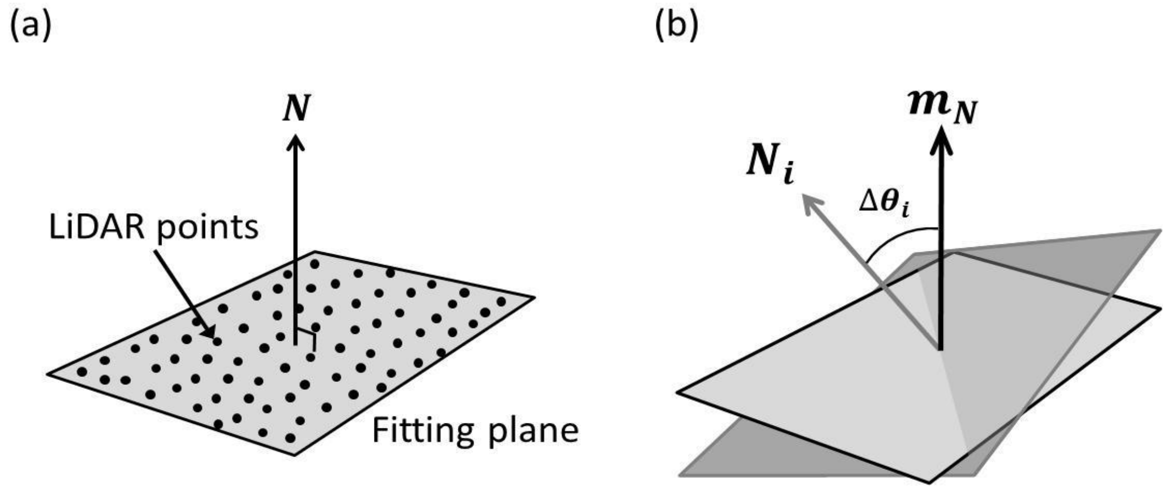

Fig. 2. A schematic figure showing the change of slope of the water surface between different ALS scans. (a) The dots are the ALS points, the grey plane is the fitted plane, and the vector N is the normal vector of that planar surface. (b) N_i is the normal vector of the *i*th ALS scan, m_N is the normal vector for all the ALS points from all repeated scans within this cell, and $\Delta\theta_i$ is the angular difference between the N_i and m_N.

$$m_\rho = \frac{1}{t}\sum_{i=1}^{t}\rho_i \tag{2}$$

and

$$S_\rho = \sqrt{\frac{1}{t-1}\sum_{i=1}^{t}\left(\rho_i - m_\rho\right)^2}, \tag{3}$$

where ρ_i is the water surface roughness for the ith scan, m_ρ is the mean roughness, S_ρ is standard deviation of roughness, and *t* is the number of repeated scan. Considering both mathematical meanings and the completeness of computation results, at least 5 repeated scans are required for all the computations in this research.

In addition to the change of water surface roughness over time, another possible use of the temporal information is the change of water surface elevation between repeated ALS scans. The standard deviation of average surface elevation ($S_{\bar{Z}}$) can be adopted for this purpose and is expressed as:

$$m_{\bar{Z}} = \frac{1}{t}\sum_{i=1}^{t}\bar{Z}_i \tag{4-1}$$

$$S_{\bar{Z}} = \sqrt{\frac{1}{t-1}\sum_{i=1}^{t}(\bar{Z}_i - m_{\bar{Z}})^2} \tag{4-2}$$

where $m_{\bar{Z}}$ is the mean of average surface elevation for repeated ALS scans, $\bar{Z}_i$ is the average surface elevation for the *i*th ALS scan, and *t* is the number of repeated scan.

The slope of water surface is another factor that may vary over time. In order to quantify the slope changes, the plane of water surface is fitted with a planar surface, and the normal vector *N* is the vector that is perpendicular to the fitting plane (Fig. 14a). For each repeated ALS scan, a normal vector of the fitted plane was determined (denoted as N_i in Fig. 14b). The normal vector (m_N) of all the ALS points from all repeated scans within that cell was computed as the reference vector for the change of water surface slope. The change of slope for each repeated ALS scan was then computed by the angular difference of the normal vectors between N_i and m_N (denoted by $\Delta\theta_i$ in Fig. 14b). Five statistics, including minimum ($min_{\Delta\theta}$), maximum ($max_{\Delta\theta}$), mean ($m_{\Delta\theta}$), range ($R_{\Delta\theta}$) and standard deviation ($S_{\Delta\theta}$), were employed to evaluate the use of temporal information for in-stream flow type mapping.The 1m × 1m cell was applied for these nine methods discussed in this section, and their classification results were produced by thresholding. Classification results from each method were then compared to ground reference data.

RESULT AND DISCUSSIONS

Fig. 3a is the classification result using Eq. 1, and red, green and blue colors denote BW, UW/RP and SM/NP respectively with the thresholds of 0.057 m and 0.074 m. These thresholds are slightly smaller than previous study (being 0.07 m and 0.09 m). It is postulated that a new strip adjustment method is available to achieve better ALS point accuracy, thus lower the threshold values for instream flow type mapping.

The highest water surface roughness values were obtained from BW, intermediate values were obtained from UW/RP, and no returns were obtained from SM/NP. Milan et al. (2010) discovered that lower energy biotopes like pools, glides or marginal deadwaters return no signal to TLS, and they regarded the no data area as these three biotopes in classification results. In this research, the area with no signal returns and also the area lower than the minimum threshold of point density (40 points/m^2) were assigned to the class of SM/NP. Table 1 shows the

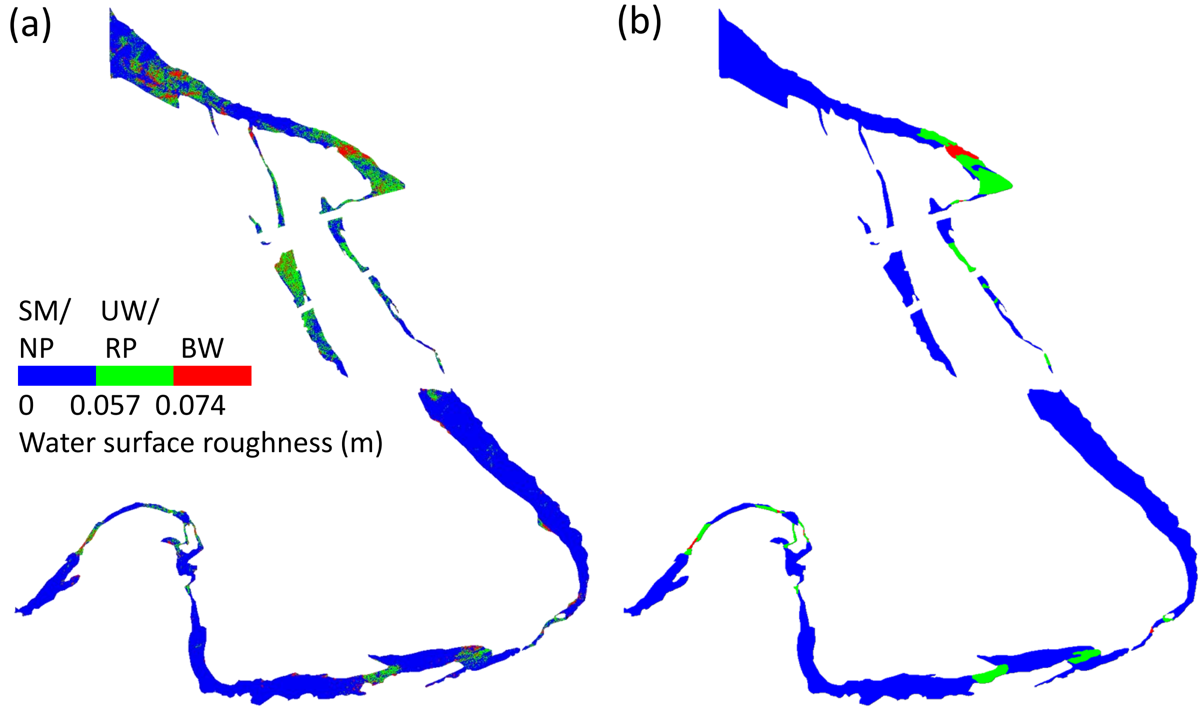

Fig. 3. (a) Classification result of using water surface roughness (b) Ground reference map, which is produce by digitizing in the orthophoto based on knowledge of ground reference data and the field panoramic photography.

classification accuracies of using the nine methods discussed in this research. Fig. 4 shows the eight classification results using the temporal information derived from the ALS data. The boundaries between flow types are usually fuzzy, and removing buffers from edges is used to applied to eliminate the misclassifications at flow type boundaries (Lin and Wang, 2011; Marcus et al., 2003). Three different buffer treatments (no buffer and 1 m and 2 m buffers) were applied for the classification results. The general trend is that a slight increase of classification accuracy coincides with increasing buffers. One example is the classification accuracy of BW, UW/RP, and SM/NP increases from 73.0% to 80.8%, 59.5% to 61.4%, and 82.9% to 83.8%, respectively when using roughness ρ as the classification threshold; the other example is the classification accuracy of BW, UW/RP, and SM/NP increases from 45.2% to 49.8%, 59.0% to 60.0%, and 81.0% to 83.4%, respectively when using maximum normal vector difference $max_{\Delta\theta}$ as the classification threshold. It's worth mentioning that the classification accuracy of BW is especially benefitted by the increase of buffer size because more of the mixed flow type pixels are ignored. To be consistent with previous study (Lin and Wang, 2011), the buffer size of 2 m was adopted.

Among the three classes (BW, UW/RP, and SM/NP), the classification accuracy of SM/NP is the highest (ranging from 77.7% to 90.9 %) for all the nine methods because the water surface is calm and steady during the ALS survey. For BW and UW/RP, they can be mapped by using water surface roughness ρ and mean of roughness m_ρ with the highest classification accuracy among the nine methods, where the classification accuracies of BW are 80.8% and 79.3%, respectively, and of UW/RP are 61.4% and 69.4%, respectively. The result is not surprising because the mathematical definitions of water surface roughness ρ and mean of roughness m_ρ are very similar.

For the rest of the seven methods, which can be regarded as temporal information derived from multiple repeated scans, the std of average surface elevation S_ρ produces better classification accuracies, with BW, UW/RP, and SM/NP being 58.5%, 64.1%, and 83.5%, respectively. The lowest classification accuracy was produced by standard deviation of roughness $S_{\bar{Z}}$, with BW, UW/RP, and SM/NP being 38.6%, 33.3%, and 87.3%, respectively. Among the five classification methods ($min_{\Delta\theta}$, $max_{\Delta\theta}$, $m_{\Delta\theta}$, $R_{\Delta\theta}$, and $S_{\Delta\theta}$) using the temporal information of the change of slope between different repeated scans, the maximum normal vector difference $max_{\Delta\theta}$ produces the highest classification results, with BW, UW/RP, and SM/NP being 49.8%, 60%, and 83.4%, respectively.

CONCLUSIONS

The use of temporal information of very high point density (and multiple repeated scans) ALS data for instream flow type mapping is evaluated. The ground reference data were obtained by a field team with a differential GPS unit and digital photography. In addition to the roughness-based classification (Lin and Wang, 2011), additional eight methods, namely, the std of average surface elevation S_ρ, mean of roughness m_ρ, std of

Table 1. Classification accuracies of BW, UW/RP and SM/NP for the nine methods.

Method	**Buffer size (m)**	**Classification accuracy (%)**		
		BW	**UW/RP**	**SM/NP**
Roughness ρ	No	73.0	59.5	82.9
	1	80.1	61.0	83.7
	2	80.8	61.4	83.8
Std of Average Surface Elevation S_{ρ}	No	51.8	60.5	81.7
	1	56.2	62.0	82.8
	2	58.5	64.1	83.5
Mean of Roughness m_{ρ}	No	71.4	65.1	86.5
	1	77.1	67.5	87.7
	2	79.3	69.4	88.6
Std of Roughness $S_{\bar{Z}}$	No	34.7	33.2	85.6
	1	34.9	33.5	86.6
	2	38.6	33.3	87.3
Minimum Normal Vector Difference $min_{\Delta\theta}$	No	43.3	47.5	75.6
	1	42.8	48.1	76.9
	2	42.5	48.2	77.7
Maximum Normal Vector Difference $max_{\Delta\theta}$	No	45.2	59.0	81.0
	1	48.3	60.0	82.5
	2	49.8	60.0	83.4
Mean of Normal Vector Difference $m_{\Delta\theta}$	No	41.2	38.0	89.1
	1	45.1	38.5	90.3
	2	48.3	38.8	90.9
Range of Normal Vector Difference $R_{\Delta\theta}$	No	40.5	47.6	84.3
	1	43.1	47.9	85.7
	2	45.1	48.1	86.5
Std of Normal Vector Difference $S_{\Delta\theta}$	No	40.3	42.9	87.0
	1	42.1	43.2	88.2
	2	42.5	42.8	89.0

roughness $S_{\bar{Z}}$, minimum normal vector difference $min_{\Delta\theta}$, maximum normal vector difference $max_{\Delta\theta}$, mean of normal vector difference $m_{\Delta\theta}$, std of normal vector difference $S_{\Delta\theta}$, range of normal vector difference $R_{\Delta\theta}$, were proposed for instream flow type mapping.

It is found that the classification result based on the roughness ρ produced the best classification accuracy with BW, UW/RP, and SM/NP being 80.8%, 61.4%, and 83.8%, respectively. The second best, with the classification accuracy for BW, UW/RP, and SM/NP being 79.3%, 69.4%, and 88.6%, is by mean of roughness m_{ρ}, which in essence is very similar to roughness ρ. The next best classification accuracy was achieved by std of average surface elevation S_{ρ}, with BW, UW/RP, and SM/NP being 58.5%, 64.1%, and 83.5%, respectively, and then by maximum normal vector difference $max_{\Delta\theta}$, with BW, UW/RP, and SM/NP being 49.8%, 60.0%, and 83.4%, respectively. For the four methods, the classification accuracies for UW/RP and SM/NP are similar ranging from 60.0% to 69.4% and 83.4% to 88.6%, which showed the potential of using the multiple repeated scanning ALS data for instream flow type mapping. On the other hand, the classification accuracies for BW showed larger variation, from 49.8% to 80.8%. Among the methods adopted temporal variation, std of average surface elevation gives the best ability of discriminating between flow types, but still not as accurate as the original std-based method due to the limit of repeated scans. As the scan rate of ALS improves with the new generation of LiDAR system, the result can be improved by increasing the number of scan times in the future.

The key factors that determine the successfulness for roughness-based method and the method with multiple repeated scans are both concerned in the scanning strategy. The former needs a high density and evenly distributed LiDAR points to support finer resolution and also provide stable std values for eliminating the classification error. The later need a high temporal coverage data to help evaluating the temporal variation between flow types.

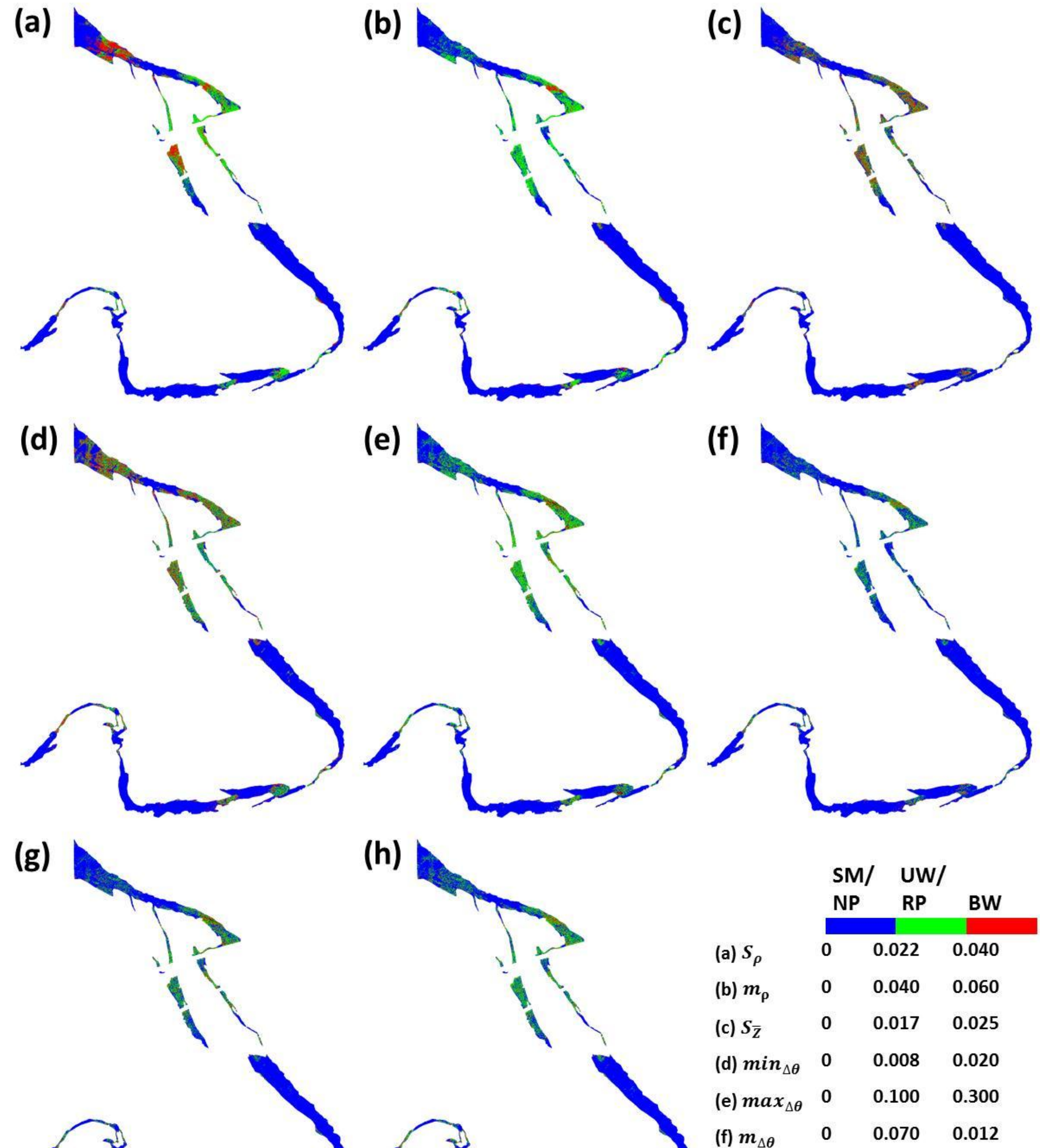

Fig. 4. Classification result of using the temporal information derived from the ALS data. The thresholds values for each method are shown in the legend.

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