Short Paper

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Identification of invasive vegetation using hyperspectral imagery in the shore of the Kinu River, Japan

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Abstract

Weeping love grass (*Eragrostis curvula*) has become a well-established invasive species along the Kinu River, Japan and is now considered a problematic invasive weed species. The aim of this study was to map the probability of the establishment of this invasive grass in the shore of the Kinu River using airborne hyperspectral imagery. Binary logistic regression analysis was used to model the probable presence/absence of weeping love grass. This study tried entering two types of input variables, original reflectance bands and MNF (Minimum Noise Fraction) transformed bands, into the regression model. No available variable of original reflectance data was selected, but two bands of MNF were selected in the regression analysis. The final classification, using the selected MNF bands, has distinguished weeping love grass from pseudo-absence pixels with user's and producer's accuracies of 100% and 66.7% respectively. The kappa coefficient was 0.74. These results indicate that the MNF transformed hyperspectral bands are more suitable than the original reflectance data to estimate the distribution of invasive weeping love grass in the shore of the Kinu River.

Key words: Binary logistic regression, Hyperspectral imagery, Invasive vegetation.

1. Introduction

Weeping love grass is originally a grass from southern Africa that was introduced into Japan in 1959 in order to protect soil on dikes and for greening reasons (Muranaka and Washitani, 2001). However, it is now found along several riverbeds in Japan, such as Kinu Riverbed and Yoshino Riverbed (Washitani *et al*., 2010), and recently the grass has become a problematic plant. This is because it's rapid and widespread expansion has disturbed the riverbed ecosystem. The existence of native plants, such as *Aster kantoensis* Kitam. and *Anaphalis margaritacea* (L.) Benth. et Hook.f. subsp. *yedoensis* (Franch. et Sav.) Kitam., has been threatened since the soil quality, light availability and the riverbed topography has changed due to the invasion of the weeping love grass (Matsumoto *et al*., 2000; Muranaka and Washitani, 2001, 2002). Therefore, monitoring and estimating the distribution of weeping love grass is of great importance for planning its removal. To make clear the expansion dynamics of weeping love grass, spatial information of the distribution of the flowering grass which produces a large number of seeds is the most important. Thus, the objective of this study was to investigate the invasive vegetation of weeping love grass, which were flowering, using hyperspectral remote sensing imagery on the Kinu Riverbed. We used the binary logistic regression model to predict the occurrence of the grass. Two types of input variables (original reflectance data and MNF transformed data) were tried to obtain a reasonable indicator to predict the potential existence of weeping love grass.

Minimum noise fraction (MNF) transformation is used to determine the inherent dimensionality of image data, to segregate noise in the data, and to reduce the computational requirements for subsequent

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processing (Boardman and Kruse, 1994; Green *et al*., 1988). The MNF transformation is essentially two cascaded Principal Components Transformations. The first transformation, based on an estimated noise covariance matrix, decorrelates and rescales the noise in the data. This first step results in transformed data in which the noise has unit variance and no band-to-band correlations. The second step is a standard Principal Components Transformation of the noise-whitened data. For the purposes of further spectral processing, the inherent dimensionality of the data is determined by examination of the final eigenvalues and the associated images. This data space can be divided into two parts: one part is associated with large eigenvalues and coherent eigenimages, and the other is a complementary part with near-unity eigenvalues and noise-dominated images. Noise is separated from the data by using only the coherent portions. This then improves the spectral processing results. The MNF transformation has been demonstrated to be effective for mapping invasive weeds with some hyperspectral data (Underwood *et al*., 2003; Mundt *et al*., 2005; Hestir *et al*., 2008).

2. Materials and Methods

We chose a study site where weeping love grass was spread widely along the shore of the mid and lower reaches of the Kinu River, near Ujiie Ohashi. The center of the study area was around 36°41′ 21″ N, 139°56′ 23″ E. The AISA (Airborne Imaging Spectrometer for Applications) hyperspectral imagery was acquired on 26 May 2004. AISA is a hyperspectral sensor which is manufactured by Spectral Imaging CO., LTD. in Finland. The images that the AISA collected had 68 contiguous spectral bands, sampled at approximately 9 nm intervals in a range from 398 to 984 nm. One pixel size was 1.5×1.5 m. The radiance was calculated as the upwelling radiant energy received at the sensor, and the apparent reflectance was defined as the ratio between the upwelling and downwelling radiant energy. The downwelling radiant energy from the sun was measured by the onboard fiber optic downwelling irradiance sensor (FODIS). Images were recorded as the apparent reflectance measured at the instrument height. Detailed field information on the invasive grass was obtained from the end of May to the middle of June 2004. Thirty five 5×5 m plots were established, and in each plot, three 1×1 m subplots were randomly chosen to measure the coverage of weeping love grass. Means from the three subplots were used to represent each 5×5m plot. The locations of the four corners of each of these plots were recorded on a Trimble Pathfinder ProXR GPS device. This provided us with sub-meter accuracy.

Logistic regression models were used to predict the per-pixel probability of the occurrence of weeping love grass. This study tried entering two types of input variables for the regression models. One was the original reflectance data (68 bands) and the other was the selected bands of the minimum noise fraction (MNF) transformation of hyperspectral data. In selecting the input MNF bands, all of the MNF bands were visually inspected and they were discarded if they exhibited severe flightline effects and contained a lot of noise with eigenvalues that were near 1. The remaining bands (18 bands) were chosen through stepwise entry into the logistic regression model. The regression model was trained and validated using a random sample of pixels with >60% cover from the Kinu Riverbed (n=7), as well as a random sample of pseudo-absence points (n=18). These points were a random sample of pixels selected from the region that was most comprehensively surveyed for weeping love grass.

3. Results and Discussion

No significant original reflectance band was selected by the logistic regression analysis for predicting the presence/absence of the weeping love grass, while a prediction of the formula using the MNF band 13 and 14 optimized the discrimination of weeping love grass from other land cover types. This model was assessed by regressing the estimated probability of weeping love grass occurrence (p) against the percentage coverage estimates from the inventory data. The value of p (p=0.68), corresponding to a 60% cover by weeping love grass with residual errors that were not high, was identified and the pixels were classified as "weeping love grass" if their predicted value exceeded this threshold (Hestir *et al*., 2008).

The predicted p value provided an indicator of the percentage coverage of weeping love grass within a pixel (shown in Table 1). In the training samples, the user's and producer's accuracies for weeping love grass presence were 100% and 71.4% respectively. The total accuracy for all the training samples was 92.0%. The kappa coefficient relative to the weeping love grass was 0.78.

To estimate the prediction accuracy of the model,

Table 1. Confusion matrix and classification accuracy of the weeping love grass logistic regression model training-validation point

			Ground reference				
			Weeping love grass	Pseudo-absence	Total	Producer's accuracy	User's accuracy
Training	Map classes	Weeping love grass	5	0	5	71.4%	100%
		unclassified	2	18	20	100%	90.0%
		Total	7	18	25	92.0%	Kappa=0.78
Validation	Map classes	Weeping love grass	2	0	2	66.7%	100%
		unclassified	1	7	8	100%	87.5%
		Total	3	7	10	90.0%	Kappa=0.74

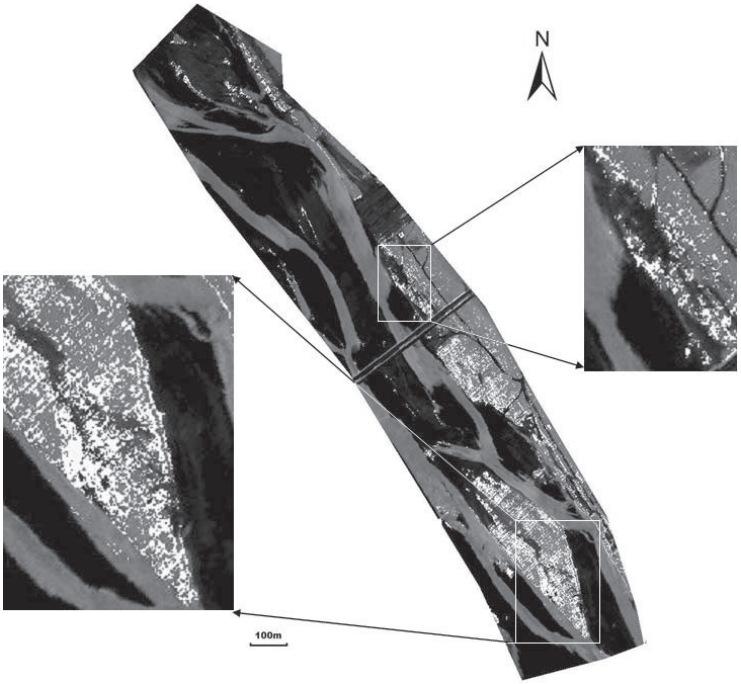

Fig. 1. The potential presence of the weeping love grass (White color) overlaid on the hyperspectral imagery.

the remaining 10 inventory samples were assessed. The final classification distinguished weeping love grass from pseudo-absence pixels with user's and producer's accuracies of 100% and 66.7% respectively. The total accuracy for all the testing samples was 90.0%. The kappa coefficient relative to the weeping love grass was 0.74. The MNF process has reduced the redundancy of the hyperspectral data, and it has also extracted the useful information in the data. The information extraction of the MNF meant it performed well in identifying the invasive weeping love grass (O'Neill and Ustin, 2000).

The potential presence of the weeping love grass was mapped according to the regression model made by logistic regression analysis. Figure 1 shows the potential presence of the weeping love grass overlaid on one band of hyperspectral imagery. To obtain a clear distribution of the invasive weeping love grass, we have masked all the detected weeping love grass pixels which were located in the non-vegetation area by giving a threshold of 0.2 for the NDVI image. The figure shows that most of the weeping love grass occurred along the riverbed where our surveying was conducted to the south of the bridge. Another main area for the distribution of weeping love grass was on the south area of the image, where we saw very

dense weeping love grass growing, but the river had blocked us making any surveys there.

4. Conclusions

We used hyperspectral imagery to detect and map invasive weeping love grass in the shore of the Kinu River, Japan. A binary logistic regression analysis was conducted to model the probable presence/absence of weeping love grass. This study tried to enter two types of input variables, original reflectance data and MNF transformed bands, into the regression model. No reasonable original reflectance band was selected to estimate the presence/absence of the invaded weeping love grass, but two bands of MNF were selected. The final classification using the selected MNF bands distinguished weeping love grass from pseudo-absence pixels with user's and producer's accuracies of 100% and 66.7% respectively. The kappa coefficient was 0.74. These results indicate that the MNF transformed hyperspectral bands were more suitable than that of the original reflectance data to estimate the distribution of the invasive weeping love grass in the shore of the Kinu River. The estimated distribution map of the weeping love grass would be able to help the regional planning of the invaded vegetation removal and protection of native plants.

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