Identification of riparian vegetation using Spectral Mixture Analysis of multi-temporal Landsat Imagery

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Abstract: To monitor riparian wetlands as one of complex natural ecosystems using remotely sensed data, we need to concurrently consider vegetation, soil and water which constitute complicated wetland ecosystems. To identify riparian distribution we adopted linear Spectral Mixture Analysis in order to improve identification accuracy of riparian areas. This study has indicated that linear SMA adopting tasseled cap endmember selection is an enhanced routine for Identification of riparian wetlands and phenologically autumn imagery is more appropriate to detect riparian vegetation in the Paldang water catchment area.

Ⅰ. Introduction

For a sustainable development of a watershed, building accurate inventories of wetlands at risk and monitoring riparian vegetation are very important. Recently as an inventory for effective management and protection of environment, 'Land Cover Maps' and 'Land Environment Maps' have been constructed by the MOE(Ministry of Environment) of Korea using remotely sensed data. However, the classification accuracy of inland wetlands such as riparian of the Land Cover Maps was rough because 1) conventional classification methods which assigning a class to each pixel of data cube have difficulties to detect a target exactly, 2) the spatial resolution of Landsat imagery is coarse not to detect vegetated buffer strip of riparian wetlands, 3) didn't consider phenological changes of hydrophytes not to use temporal imagery and 4) only focused on the vegetation factor using vegetation indices such as NDVI to classify environmental variables.

Mixture and variation of hydrophytes, soils and water changes make it difficult to classify riparian areas and often produces poor classification accuracy when raw satellite imagery are only used.

Therefore to monitoring riparian wetlands as one of complex natural ecosystems using remotely sensed data, we need to concurrently consider vegetation, soil and water which constitute complicated wetland ecosystems. To identify riparian distribution we adopted linear SMA in order to improve classification accuracy of riparian areas. This case-study documents SMA method is effective or not for riparian identification, and which season is more appropriate to detect riparian vegetation in the Paldang water catchment area using multi-temporal Landsat imagery.

Ⅱ. Study Area and Field Data Collection

Field data were collected from summer of 2002 to 2003. The 'Land Cover Maps' from the MOE and the Digital Topographic Maps(1/25,000) were used as base maps for field survey and GPS (Trimble Pathfinder) device was used to register omitted riparian plots to supplement that maps. And as an ancillary data, SPOT 5, one of the high resolution imagery, was used. Every spatial data were processed and integrated as GIS layers using ArcView v3.2 and ENVI 3.6.

Field survey was focused on main streams of the Paldang area like Han river, and Kyungan River and vicinity(200m Buffers from river channels). Dominant wetland's species in the Paldang area are *Typha latifolia*, *Typha angustata*. Ecotonal plants are *Populus euramericana* and *Salix matsudana*. The Fauna are *Anas poecilorhyncha*, *Fulica atra*, *Egretta intermedia*, and *Ardea cinerea*.

A TM image for May 21, 1999 and an ETM+ image for September 23, 2001 were radiometrically calibrated to reducing path radiance values [3]. The imagery were geometrically rectified based on GCPs taken from digital topographic maps at 1: 25,000 scale (TM BESSEL). Nearest-Neighborhood resampling was adopted and the RMS error was smaller than 0.5 pixel.

Ⅲ. Identification of riparian vegetation using SMA

An area is considered a jurisdictional wetland only if all three wetland criterion, hydrophytes, hydrology and soil, are met. Among these criteria, vegetation is prior to others [5]. Therefore in this study, we determined riparian wetlands in the Paldang area using main indicator species such as reed or cattail.

In a single pixel of Landsat imagery, many categories such as PV (Photosynthetic Vegetation), nPV (non - Photosynthetic Vegetation), wet soil, dry soil, shade and water are included. The radiance values of each pixel are changed by differences in categories and the coverage of each within a pixel.

SMA involves two main steps. The first step is to define a set of pure spectra for selected land-cover material, often referred to as endmembers. Endmembers can be identified using either (a) libraries of known spectra collected with a spectrometer in the field or in a laboratory, (b) libraries of known spectra from previous SMA studies, or (c) spectrally pure or extreme pixels identified within the images being analyzed.

Most applications of SMA will use the third option because libraries of field-collected endmember spectra are rare, and field spectrometers are expensive and not readily available to researchers [4]. Because the Scatterplot of two - dimensional spectral data didn't show a exact triangle, there are several convex models such as PPI, N-FINDER and MESMA to draw an optimum simplex for accurate endmember selections of the data cloud. But ordinarily these models doesn't hold exactly and some observations lie outside of the simplex [6]. Therefore, In this study, main endmembers, ecological factors for wetland identification, were selected not by mentioned convex geometry models but by the 3 vertices of the tasseled cap scatterplots of red and near infrared spectral data.

The second step in SMA is to estimate, for each pixel, the abundance of each endmember contained within it by applying a linear mixing equation [1][2]. The general form of this equation, in matrix form, is as follows:

$$p_{ij} = \sum_k e_{ik} c_{kj} + \varepsilon \; , \qquad (1) \qquad\qquad \sum_k c_{kj} = 1 \; . \qquad (2)$$

where

P_j is the i-th band of the j-th pixel,

e_{ik} is the i-th band of the k-th endmember,

c_{kj} is the mixing proportions for the j-th pixel from the k-th endmember,

E is gaussian random error (assumed to be small)

Since the pixel compositions are assumed to be percentages, the mixing proportions are assumed to sum to one.

This SMA equation is used to convert the existing image spectra values for each pixel into endmember fraction matrices. One fraction image is produced for each endmember along with the RMS error matrix. This procedure requires the fraction values produced in matrix X to be positive and sum to unity [1][2]. In this study, 4 endmembers (GVt(trees), GVh(herbaceous), soil and water from spring image(May 21, '99) and autumn image(Sep. 23, '01) were identified. We subdivide GV endmember into GV trees(GVt) and herbaceous plants(GVh) in order to describe the class variety of the vegetation exactly. The abundance of selected land cover materials from 4 endmembers were validated through the field survey and high resolution SPOT 5 image.

To validate SMA is an effective processing routine or not, and which season is appropriate to detect riparian vegetation, 4 different processing methods were tested and their classification results using a maximum likelihood classifier(MLC) were compared. 5 land cover classes - forest, agriculture (paddy, dry field and grass), waterbody, bare land (including urban areas, roads and bare soil) and riparian wetland - were defined of the Paldang area. GPS locations, high resolution image and a general knowledge of the field site were used to select the best ROIs for MLC around the Kyungan river basin.

The following is 4 different methods to compare.

1) MSM : MLC using constrained SMA with 4 endmembers on 6-band May TM
2) MRM : MLC using raw 6-band May TM
3) MSS : MLC using constrained SMA with 4 endmembers on 6- band September ETM+
4) MRS : MLC using raw 6-band September ETM+

To assess the classification accuracy of riparian wetlands, only the riparian class was selected and segmented to vector layers to be overlaid to the GIS dataset of the study site. Riparian segments far from river channel(200m buffer) and something small, were eliminated for effective classification accuracy comparison. Error matrices were calculated by comparing the relationships between the points of riparian (from GPS plots and the digital topographic maps) and classified polygon results.

Ⅳ. Results and discussion

The fraction images were developed using SMA based on two season's data. In the GVt(trees) fraction of spring scene, forest has significantly higher values, while agriculture and riparian have very small fraction values. In the GVt fraction of autumn scene, forest and agriculture have relative higher fraction value than that of riparian wetlands. In the GVh fraction of autumn scene, agriculture(paddy fields and golf links) have the higher fraction values and water and forest have lower fraction values. In the Soil fraction of autumn scene, agriculture has higher value than that of riparian.

Each riparian class from the MLC results using 4 different data, was segmented and converted to vector layers. Riparian wetlands from MLC results were overlaid with GIS layers of digital topographic maps and riparian plots, surveyed riparian plots and riparian from topographic maps. In case of MSM and MRM, the forest near paddy fields were misclassified into riparian wetlands.

Table 1 summarizes the classification accuracy using 4 different methods. Reference plots and classified riparian vectors are compared. In this study we focused on detection of the riparian vegetation and error matrices of riparian classification accuracies from 4 methods were calculated (Table 1).

Table 1. Comparison of Classification Accuracy from 4 different methods

Classification Methods	Classification Accuracy (%)			
	Spring		Autumn	
	MSM	MRM	MSS	MRS
Producer's Accuracy	42.1	44.1	86.5	82.7
User's Accuracy	40.7	42.6	83.3	71.7

In case of MSM and MRM, Producer's and user's accuracy values are very low. That implies, in spring time, wetland's vegetation growing to mature make it hard to identify exact riparian areas themselves and make it difficult to distinguish wetland's species between forest also in the growing to mature. Phenologically Autumn images produced more accurate classification results. Concerning which methods are appropriate to, the MSS (Maximum Likelihood Classification using SMA of 4 endmembers on an Autumn image) is considerably higher than MRS using raw Landsat data. In case of MSS, user's accuracy is little bit lower than that of producer's accuracy. In case of MRS, Producer's accuracy is 82.7 but user's accuracy is 71.7. This means even though 82.7% of the riparian areas have been correctly identified as 'riparian', only 71.7% of the areas identified as 'riparian' within the classification are truly of that category.

Ⅴ. Conclusions

This study has indicated that SMA is an enhanced routine for land cover classification of riparian wetlands and an autumn image is more appropriate to identify riparian vegetation than that of spring. In autumn image, soil and water fractions as well as GV fractions shows the distinctively different values among riparian, paddy fields and forest.

While sub-pixel mapping in this study may appear as a promising technique, limitations to its usefulness undoubtedly exist. When using 2-dimensional scatterplots, at most 3 vertices corresponding to the endmembers can be identified. So to develop high-quality fraction images, relatively unimportant land covers except vegetation, soil and water(or shade) should be masked before the SMA procedure.

This study focused on detection of riparian wetlands. Based on the results of this preliminary study, additional researches adopting finer spatial and spectral resolution imagery would be conducted for delineation of wetland's boundary and hydrophyte classification.

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