SMA for Identification of riparian vegetation using multi-temporal Landsat Imagery

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Introduction

Inland wetlands assimilate pollutants, control floods and serve as breeding, nursery and feeding ground for fish and wildlife(Jensen 2000). Unfortunately riparian wetlands in Korea have been changed to agricultural, residential or commercial land use from 1960s. 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) the Landsat spatial resolution is coarse not to detect vegetated buffer strip of riparian wetlands, 2) didn't consider phenological changes of hydrophytes not to use temporal imagery and 3) 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. Elmore, et al., (2000) validated against the field point measurement of live vegetation cover that linear Simple Mixture Analysis(SMA) can be used to quantify vegetation abundance instead of NDVI saturated at high vegetation abundance.

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.

Study Area and Field Data Collection

The Paldang water catchment area(37°30′ 07″E, 127°17′ 49″N) in Yangpyong County, South Korea, is the main water catchment area for Seoul, sixty kilometers downstream(Fig 1). It lies beside the Han River, one of the largest rivers in Korea and the source of most of Seoul's drinking water. But non-point source pollutions around the Paldang area like livestock farming or agricultural practices threatens Seoul's clean water supply. Recently the importance of the riparian wetlands have been constructed artificial wetlands near several wastewater treatment areas of the Paldang area for natural purification of non-point source pollutants.

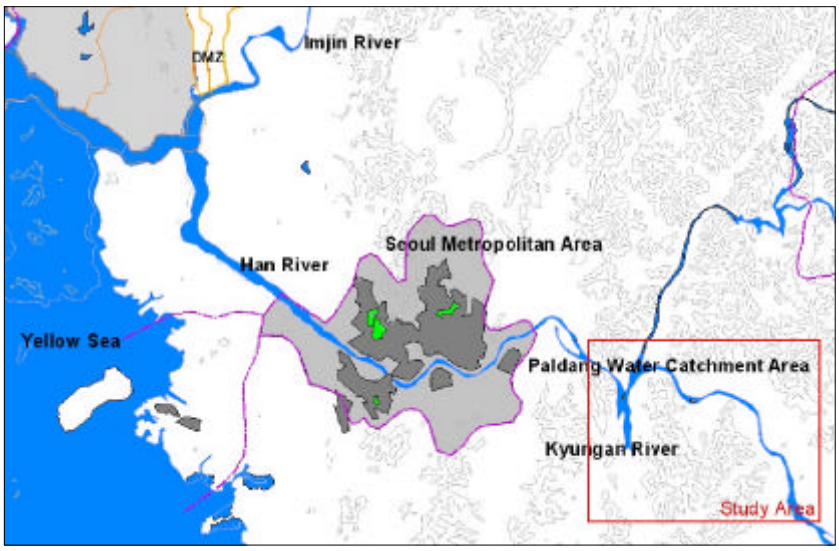

Fig. 1. Paldang Water Catchment Area and Vicinity

Field data were collected from summer of 2002 to 2003. The 'Land Cover Maps' from the MOE and the Digital Topographic Maps(1/5,000) were used as base maps for field survey and GPS (Trimble GeoExplorer) 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 ERDAS Imagine 8.5.

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, Zizania latifolia, Phragmites japonica, Miscanthus sacchariflorus, Potamogeton distinctus, Trapa japonica, Alisma plantago-aquatica, Sagittaria aginashi and *Persicaria hydropiper*. Ecotonal plants are *Populus euramericana, Populus Tomentiglondulosa* 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(Lillesand and Kiefer 2000). The imagery were geometrically rectified based on GCPs taken from digital topographic maps at 1: 25,000 scale (TM BESSEL(middle)). Nearest-Neighborhood resampling was adopted and the RMS error was smaller than 0.5 pixel.

Identification of riparian vegetation using SMA

Riparian identification using remotely sensed imagery

In essence, a wetland is the edge between uplands and adjacent water areas(Lyon 1993). An area is considered a jurisdictional wetland only if all three wetland criterion are met. The evaluation of these criterion includes a determination as to : (1) whether the soils are considered hydric (2) whether the soils show demonstrable evidence of hydrologic conditions associated with flooding of water (3) whether 50% of the dominant plants found growing on the site are those commonly found in wetlands(Lyon, 1993). Among these criteria, vegetation is prior to others(U.S. Army Corps of Engineers 1987). Therefore in this study, we determined riparian wetlands in the Paldang area using main indicator species such as reed or cattail.

Phenological cycle of vegetation is very important when attempting to identify different vegetation types or to extract useful vegetation biophysical information from remotely sensed data(Jensen 2000). The temporal factor is not only the plant's phenological cycle but also soil moisture, biomass and understory materials. We assumed the differences between natural vegetation systems and managed agricultural systems make it easy to identify riparian wetlands to paddy fields. Phenologically in May, Reeds grow to maturity but rice is being transplanted to paddy fields. In September, rice and reed are in maturity but the understory background material of paddy fields is wet soil, while the background of wetlands is saturated soil.

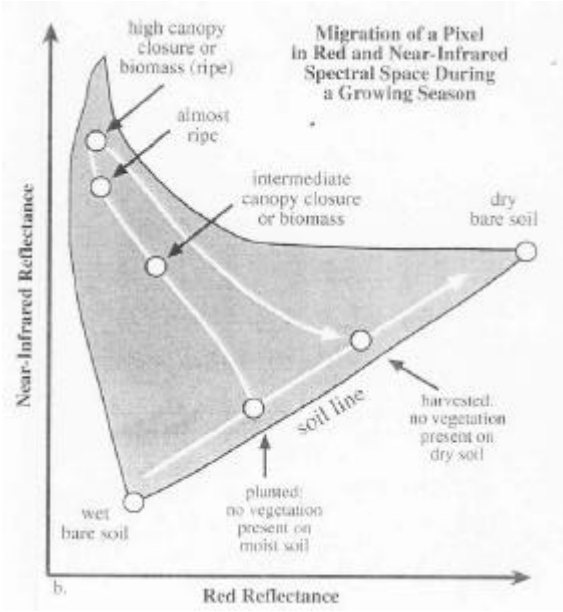

Fig. 2. The migration of a single vegetated agricultural pixel in a scene in red and near-infrared multispectral space (Source : adapted from Jensen 2000, p343).

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. Through the phenological growth cycles of the plant species the portions of categories and radiance values of a pixel changes(Fig. 2) Figure 2 shows the migration of a single vegetated agricultural pixel in red and near-infrared multispectal space during a growing season.

Land cover Classification using linear SMA

Linear Spectral Mixture Analysis is a new technique that "in theory" would allow you to determine the fraction of each surface type in a pixel in order to unmix a pixel. It assumes that the spectrum measured by a sensor is a linear combination of the spectra of all components within the pixel(Roberts et al., 1998; Ustin et al., 1998). For example, in remote sensing a spectral endmember is the spectral signature of a ground component such as green vegetation(Endmember a), soil(Endmember b) and water or shade(Endmember c) from the scattergram of bands i (TM 3) and j (TM 4) as shown in Figure 2 (Fig 3). The spectra of mature paddy field and forest located in the

Endmember *a* but the radiance values of mature riparian vegetations are generally located in inside the simplex between centroid and endmember *a* of the data cloud due to the background effect of ordinary hydrologic conditions in wetlands.

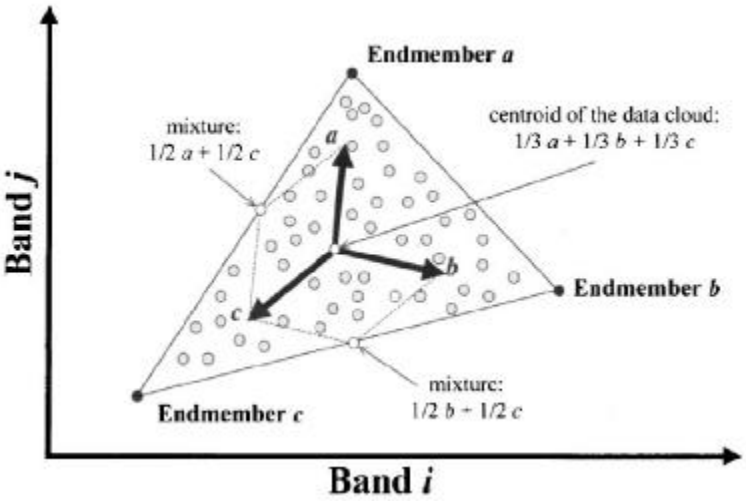

Fig. 3. Scatterplot of two-dimensional spectral data illustrating the physical interpretation of a mixture model based on endmembers. (Source : adapted from Plaza et al., 2002)

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(M. Schweik and G. M. Green 1999). The empirical portion of this article uses this third option. SMA endmembers are selected by testing whether a given pixel's spectra can be described as a mixture of pixel spectra previously analyzed or whether it is itself another end-member (Adams et al., 1993).

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(CSIRO 2003).

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 (Adams et al., 1993; ENVI, 2002). 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_{ij} 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 (Adams et al., 1993; ENVI, 2002).

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 not by the convex geometry models but by the 3 vertices of the tasseled cap scatterplots of band TM (or ETM+) 3, 4 and 5. 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 and 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 method with 4 endmembers on 6-band Spring(May) TM image
2) MRM : MLC using raw 6-band spring(May) TM image
3) MSS : MLC using constrained SMA method with 4 endmembers on 6-band autumn(September) ETM+ image
4) MRS : MLC using raw 6-band autumn(September) ETM+ image

To assess classification accuracy of riparian wetlands, only 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.

Results and discussion

The fraction images were developed using SMA based on two season's data. Figure 4 is a fraction set for Spring TM image and Figure 5 for autumn ETM+ 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.

Fig. 4. Fraction images from SMA of Spring TM
(GVt, Soil, GVh, Water and RMSE fractions)

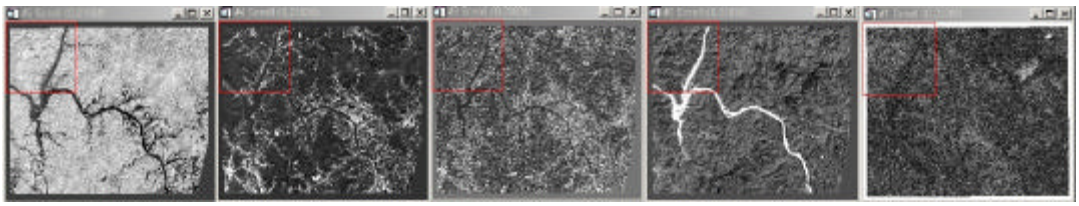

Fig. 5. Fraction images from SMA of Autumn ETM+
(GVt, Soil, GVh, Water and RMSE fractions)

Each riparian class from the MLC results using 4 different data, was segmented and converted to vector layers. Figure 6~9 shows that riparian wetlands from MLC results were overlaid with GIS layers of digital topographic maps and riparian plots(surveyed riparian plots : red points and riparian from topographic maps : pink points). In case of MSM(fig. 6) and MRM(fig. 7), the forest near paddy fields were misclassified into riparian wetlands.

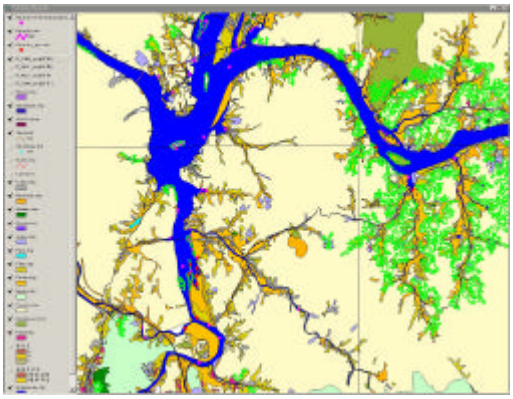

Fig. 6. segmented MSM layer(green)

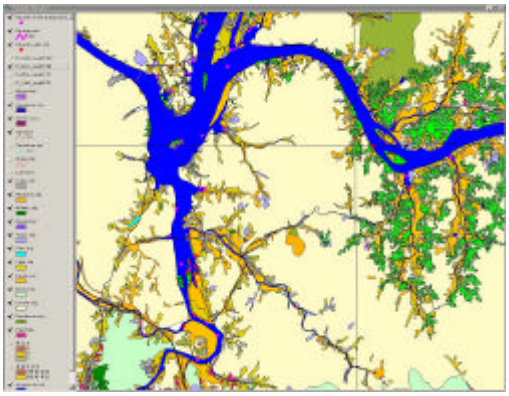

Fig. 7. segmented MRM layer(green)

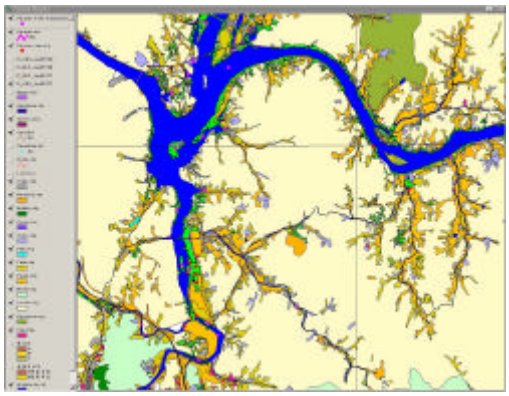

Fig. 8. segmented MSS layer(green)

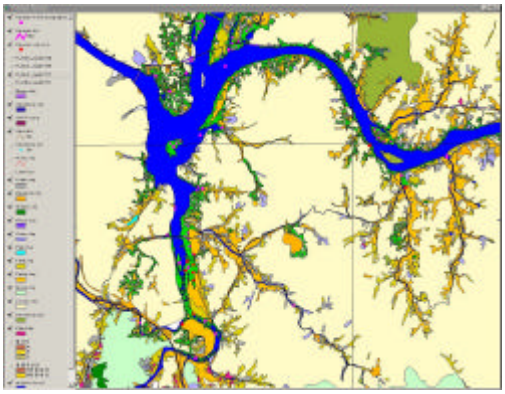

Fig. 9. segmented MRS layer(green)

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(May 21, '99)		Autumn (Sep. 23, '01)	
	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.

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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