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LAND COVER MAPPING USING SPECTRAL AND TEMPORAL LINEAR MIXING MODEL AT LAKE BAIKAL REGION

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ABSTRACT: The aim of this study is to map the land cover at Lake Baikal region in Russia by using remote sensing technique and phenological pattern of plants. In this paper, a new linear mixing method, spectral and temporal linear mixing model is proposed, which is developed from both spectral and temporal aspects. In order to estimate the proportion of components in the mixed pixel, the Linear Mixing Model (LMM) is applied to five temporal scenes of LANDSAT-7/ETM satellite data. The proposed LMM has two steps. In the first step as spectral LMM, the area proportions of each endmember (basic land cover class) for all five scenes are estimated. In the second step as temporal LMM, the annual fluctuations of proportion of each endmember are used as new endmembers. Finally, the proportion of several plants in the mixed pixel is estimated which has distinctive phenological pattern. In the proposed model the characteristics of annual fluctuations of each endmember are used to determine land cover classes. It will be expected to improve the accuracy of classification and reliability. In this paper, the method of proposed LMM is introduced and the validation of this LMM will be hold in the following research.

1. INTRODUCTION

Nowadays the demand of exact land cover maps is increasing in order to detect the solution of global issues such as global warming, land degradation and the lack of water supply. And a lot of researches are being attempted to estimate the effect of climate change and anthropologic damage and to monitor the change of land cover. It is considered that the land degradation caused by climate change is sometimes vague and it affects the phenological pattern of plants through the change of temperature and precipitation. Hence the LMM that can estimate the proportion of basic land cover in the mixed pixel is very useful. The analysis of phenology is expected to improve the accuracy of classification comparing with hard classification methods such as maximum likelihood classification and unsupervised or supervised clustering classification.

The study area is central part of Selenga basin, southern Lake Baikal in Russia where the ground data was collected in summer in 1999 and 2000. The study area is illustrated in figure.1. The characteristic of this region is forest-steppe ecosystem among Selenga Mountains. There are three rivers; Selenga, Chikoj and Jida river. They are orienting from Lake Baikal and flow into Mongolia. In this region, cutting trees are widely done and forest fires often occur especially in dried and windy season.

There are many techniques to mapping of land cover using LMMs (Adams and Smith 1986, Bosdogianni *et al*. 1997, Roberts *et al*. 1998, Settle and Drake 1993). Most of LMM bases on spectral aspect of basic land cover class and spectral LMMs are frequently referred to the necessity of temporal analysis (Iverson *et al*. 1994, Mücher *et al*. 2000, Quarmby *et al*. 1992). And several LMM studies are done mainly emphasizing temporal aspect (DeFries *et al*. 1997, 1998, 1999, 2000-a, 2000-b). In the temporal analysis of LMM, definition of phenological information is important. DeFries.*et.al* (1997, 1998, 1999, 2000-a, 2000-b) used mean, maximum, minimum and amplitude of NDVI and band 1 to 5 of NOAA/AVHRR as phenological information. The suspicion, however, occurs that those values really represent the characteristics of phenological information. Hence, in this paper simpler indices for phenological information are proposed to introduce new aspect of temporal analysis.

2. DATASETS

The dataset that is used to analyze the proposed LMM is five temporal LANDSAT-7/ETM, path 132, row 25 with center of coordinate 50°17`N, 106°24`E. The acquisition date of five scenes is 13 April, 19 August, 20 September, 22 October and 23 November 2000. In this research, reflected six bands are used, there are band 1 to 7 except band 6. The study area is center part of Selenga basin that is located at 50°00` - 51°20`N and 105° 00` - 108°00`E, see figure 1.

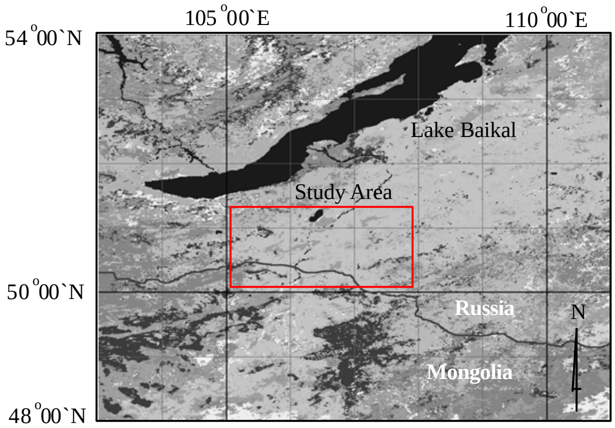

Figure 1 Study area: central part of Selenga basin area

3. METHOD

Several basic land cover classes in the LMM are called endmembers. Endmembers represent the characteristics of the percent reflectance of land cover classes. In the case of LANDSAT/ETM satellite data, three or four endmembers are frequently selected for the LMM, because of the correlation among reflected bands. And if the six reflected bands of LANDSAT/TM data are dealt with, and the fifth and sixth principal components are found, these components contain nothing but noise (Settle and Drake 1993). Therefore, even if the other endmembers are added in order to estimate more land cover classes, it may cause the insufficient accuracy of the result.

There are two kinds of methods to decide endmembers. One is the image endmember method and another is the reference endmember method. The image endmember method means that percent reflectances of endmembers are decided using the digital number (DN) of images and those values are sometimes derived from the classification algorithm such as maximum likelihood classification and principal component analysis. On the other hand, the reflectance endmember method means that percent reflectance of endmembers are decided using the experimental observation of the field. In the case of temporal analysis, it is difficult to measure the percent reflectance of endmembers through all the year. Therefore, in this paper the image endmember method is applied to the decision of endmember based on the classification algorithm and visual interpretation.

There are two steps in proposed LMM, the spectral and temporal linear mixing model. In this research the estimation of proportion of endmembers is based on the Constrained Least-Squares (CLS) method (Shimabukuro and Smith 1991, Holben and Shimabukuro 1993). The CLS method assumes that the proportion values of endmembers must be nonnegative, and they also must add to one. The basic concept of spectral LMM can be expressed as followings.

$$r_i = \sum_{j=1}^{n} (a_{ij} x_j) + e_i \qquad (1)$$

where r_i = observed spectral reflectance for the ith spectral band of a pixel containing one or more components: a_{ij} = spectral reflectance of the jth endmember for the ith spectral band: x_j = proportion value of the jth component in the pixel: e_i = error term for the ith spectral band: j = 1,2,…,n (number of components): i = 1,2,…, m (number of spectral bands). In the CLS method, spectral LMM (1) can be rewritten as:

$$e_i = r_i - \sum_{j=1}^{n} (a_{ij} x_j) \qquad (2)$$

In this case, the function to be minimized is:

$$F = \sum_{i=1}^{m} e_i^2 \qquad (3)$$

where m is 6 spectral bands for the reflected bands of LANDSAT/ETM. Now, supposing that n is 3 for the explanation and considering the first constraint; i.e., $x_1+ x_2+ x_3=1$ or $x_3=1-x_1-x_2$ and substituting x_3 into (3), the function to be minimized as

$$F = \quad A_1 x_1^2 + A_2 x_2^2 + A_3 x_1 x_2 + A_4 x_1 + A_5 x_2 + A_6 \qquad (4)$$

where the coefficients A_1 to A_6 are functions of the reflectance values, a_{ij} (reflectance of endmember) and r_i (pixel reflectance). Considering the function to be minimized, in order to find a minimum, the partial derivatives are calculated and set equal to zero:

$$\partial F / \partial x_1 = 2A_1 x_1 + A_3 x_2 + A_4 = 0 \qquad (5a) \qquad \partial F / \partial x_2 = 2A_2 x_2 + A_3 x_1 + A_5 = 0 \qquad (5b)$$

Solving for x_1 and x_2:

$$x_1 = (A_3 A_5 - 2A_2 A_4) / (4A_1 A_2 - A_3^2) \qquad (6a) \qquad x_2 = (A_3 A_4 - 2A_1 A_5) / (4A_1 A_2 - A_3^2) \qquad (6b)$$

The error for each spectral band and the mean error of the CLS method are estimated as follows:

$$Error = \quad e'_i \; = \; \sqrt{(r_i - \sum a_{ij} x_j)^2} \qquad (7a) \qquad Mean \quad Error = (\sum_{i=1}^{m} e'_i) / m \qquad (7b)$$

3.1 Step1: Spectral Linear Mixing Model

In the first step, the proportion values of each endmember in the mixed pixel are calculated by using spectral LMM as mentioned the CLS method. In this research four endmembers are assumed such as photosynthetic vegetation (green vegetation GV), non-photosynthetic vegetation (NPV), soil and water. Those reflectance values are derived from the classification algorithm and the visual interpretation. Four such spectral signatures are illustrated in figure 2. In the case of part of study area whose ETM data acquired at 13 April 2000, four estimated proportion values of each endmember are illustrated in figure 3. And the proportion values of other four scenes are also estimated by the same method.

Spectral signatures of each endmember at the same pixel position are altered depending on the each five scene. The estimated proportion in one scene is relative volume only in that scene. It means that the proportion values through a year such as GV are evaluated as relative volume. And it will occur that even if the estimated proportions of GV are the same values through all the year, the actual volumes of GV are not equal. Basically, it is difficult to decide the proportion value of land cover classes in the mixed area by using only one scene because one acquired satellite data could not represent the whole property of the annual fluctuation of GV through a year and it often affected by the observation condition such as cloud, haze and bi-directional reflectance. Therefore, it is not so important to estimate the complete exact proportion of each endmember for five temporal scenes. The most important thing is to obtain the properties of the annual fluctuation of endmember that represent distinct land cover classes and they would enable to estimate more credible proportion value at the second step.

3.2 Step2: Temporal Linear Mixing Model

In the second step, the annual fluctuation of the proportion of each spectral endmember is assumed to the new temporal endmember. In the case of GV, for example, the annual fluctuation of the proportion through five temporal scenes is illustrated in figure 4. It could be considered that distinctive plant has its own phenological pattern and it appears as the fluctuation of the proportion. In the temporal LMM each coefficient of the spectral LMM is converted as equation (1). where r_i = calculated GV proportion for the ith temporal scene of a pixel containing one or more land cover classes: a_{ij} = ideal GV proportion of the jth land cover class for the ith temporal scene: x_j = proportion value of the jth land cover in the pixel: e_i = error term for the ith temporal scene: j = 1,2,…,n (number of land cover classes): i = 1,2,…,m (number of temporal scenes).

The distinctive fluctuation of the GV proportion is assumed such as Plant A to D in figure 4. The properties of fluctuation would depend on the study area where there are distinctive land cover classes. The temporal LMM, however, is expected to improve the accuracy of the estimated proportion in the mixed pixel.

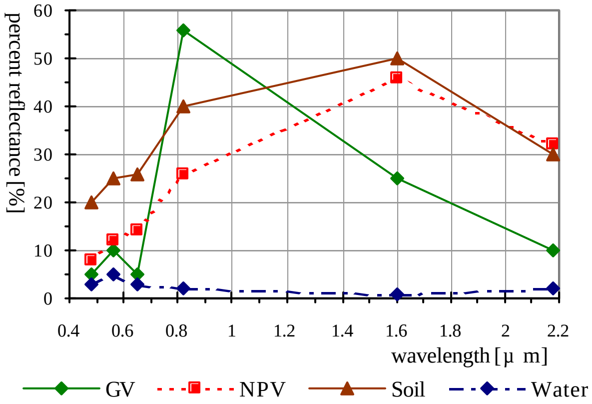

Figure 2 Percent reflectance [imaginary]

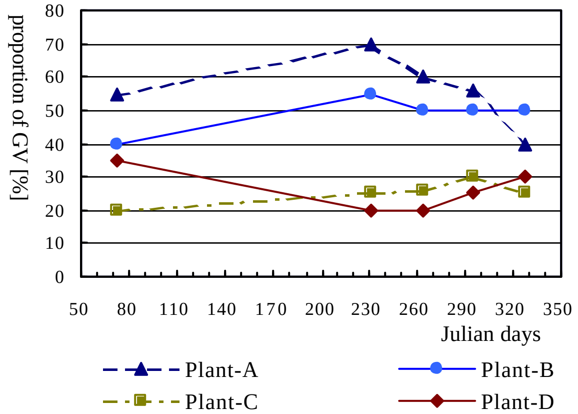

Figure 4 Annual frustration of GV proportion [imaginary]

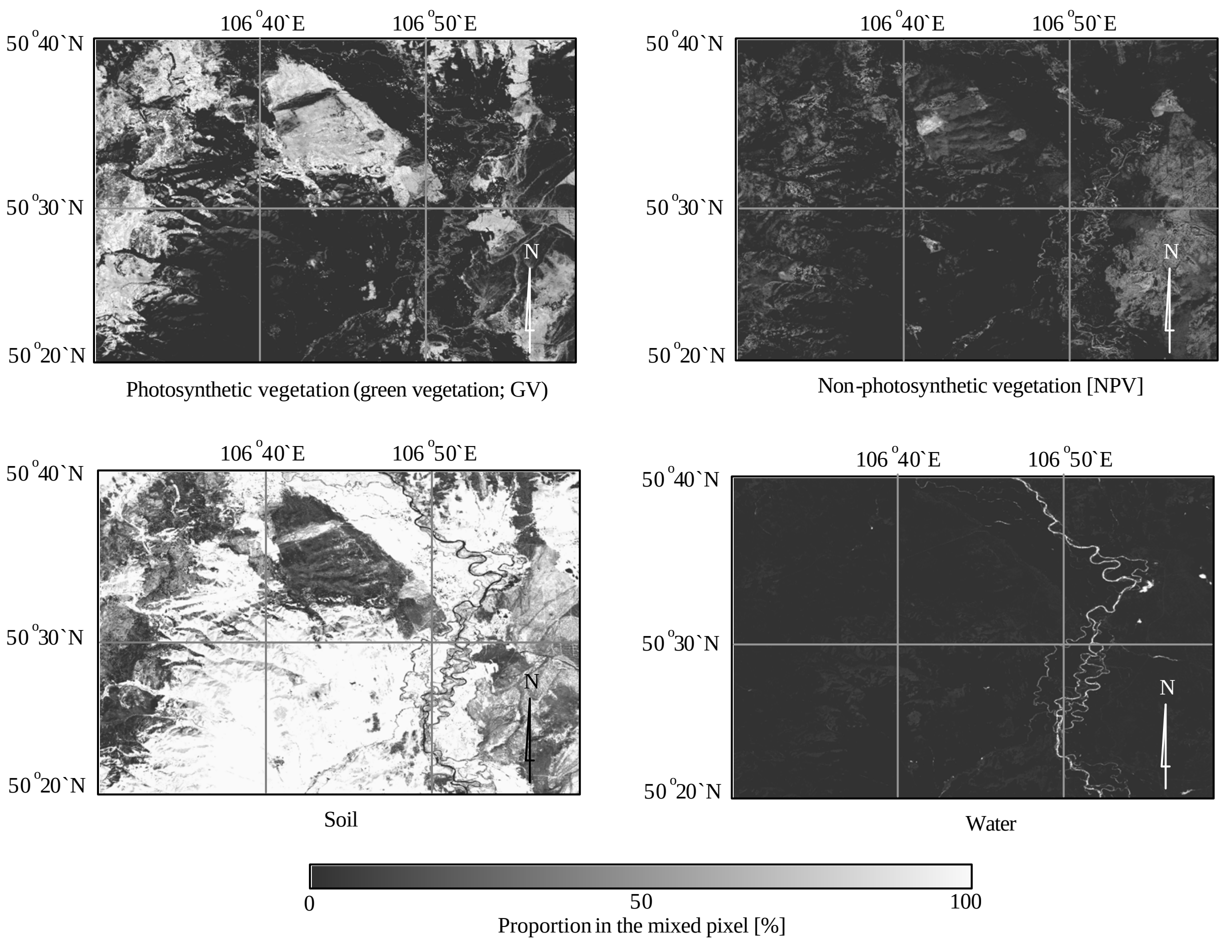

Figure 3 Estimated proportion of each endmember at 13 April 2000 [imaginary]

4. FUTURE VISION

There are several obstacles in the temporal LMM. Firstly, it is difficult to obtain many temporal high-resolution satellite data such as LANDSAT/TM. Clouds often contaminate satellite images and it causes the insufficient estimation and the lack of temporal data. Secondly, obstacle is to gain enough credible percent reflectance for all endmembers. If the filed observed reflectance is used, the observation must be done through all the year. On the other hand, it also has difficulty to decide the reflectance from only satellite image using visual interpretation or classification techniques. In the case of the image reflectance method, of course the decision of endmember must be paid attention, but the temporal LMM has the advantage. Because it emphasizes the relative proportion of endmembers in that scene and it can apply the annual fluctuation of relative proportion of endmembers.

The proposed LMM must be validated at other biosphere not only the Siberian forest. And many could-free satellite data are needed for the temporal LMM. Therefore, it is expected that the temporal LMM be applied to the frequently observable satellite images such as NOAA/AVHRR.

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