Assessment of Regional Land Cover Fractions of Mongolian Semiarid and Arid Area based on Multi-channel Radiance Data.

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Keywords: *Land covers fractions, spectral unmixing approach, semiarid, and arid area*

Introduction

In Mongolia, grazing has increased during long time by nomadic herd activities. Therefore, grazing process is main anthropogenic factor that affects land cover fractions (LCFs) in ecosystem. LCFs are more difficult to determine and measure accurately among many parameters of dominant land cover types (photosynthetic vegetation (PV), nonphotosynthetic vegetation (NPV), and bare soil) communities at the field site.

In this context, this study focused on regional LCFs of semiarid area of Kherlen river basin and arid area of Gobi region of Mongolia using multi-channel radiance data, by adopting methods of spectral unmixing approach (Anser and Lobell, 2000), bi-directional distribution function (Rahman et al, 1993) and supervised classification method (SCM). In addition, LCFs calculated by various methods were analyzed and compared with LCFs determined visually in the field, enabling us to propose an effective method for estimating LCFs in semiarid and arid area. In this study, we have included some results of estimated land cover fraction.

Methods

Description of study area

The field observation survey included vegetation type of mountain forest steppe, mountain meadow steppe, dry steppe, and desert steppe zones in semiarid and arid area of Mongolia.

Field observations

The semiarid and arid area of Mongolia (figure 1) was chosen for investigation in the present study and the 'Fieldspec' was used in ground-based observations. We carried out bi-directional reflectance spectrometry over study sites. Additionally, digital camera was used to measure dominant land cover type's community in the field site. The site of each quadrate was 50x50 cm. The digital camera was installed 1 m above the quadrate and images taken vertical to the quadrate, and then resulting images were stored. The spectral data were collected for a full range from 350nm to 2500 nm by a spectrometer with 8 ^{o} sensor fore optic attached. The resolution of wavelength is 10 nm. 8 azimuth view angles (solar direction and every 45^0 from solar direction) were selected. Then a sensor viewing angle was hold at 30^0,50^0 and 70^0 in each diagonal for 8 azimuth angles. The observations were performed during daytime between 9 and 19-hour local time. A series of observation took around 20 minutes, which depend on solar condition.

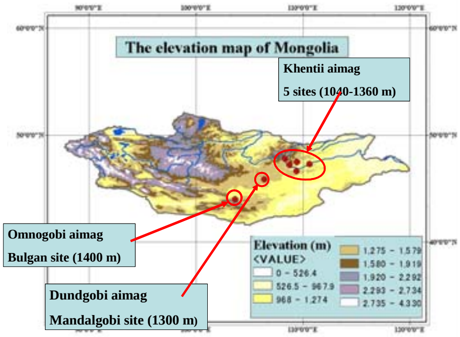

Figure 1. The main observation areas with elevation map of Mongolia.

24 effective series of data were obtained in the intensive observation in 2005 from semiarid area and 26 series of data in 2006 from arid area of Mongolia. Radiance measurements were converted to reflectance using a white panel, which were measured immediately before each canopy or soil measurement.

Bi-directional reflectance function

We prepared spectral dataset using bi-directional distribution function model (BRDF). There have been several models for BRDF. Thus, using this model, we can get vegetation information and generate standard condition for corrected dataset from field spectral database. A standard condition for solar elevation angle was 30^o and measuring evolution angle was nadir position in our study. We used model, developed by Rahman et al (1993), which is shown by following equations.

$$\rho(\theta_s,\theta_v,\phi) = \rho_o \frac{\cos\theta_s^{\kappa-1}\cos\theta_v^{\kappa-1}}{(\cos\theta_s+\cos\theta_v)^{1-\kappa}} F(g)\left[1+R(G)\right] \quad (1)$$

$$F(g) = \frac{1-\Theta^2}{\left[1+\Theta^2-2\Theta\cos(\pi-g)\right]^{1.5}} \quad (2)$$

$$R = \frac{1-\rho_0}{1+\left[\tan^2\theta_s+\tan^2\theta_v-2\tan\theta_s\tan\theta_v\cos\phi\right]^{\frac{1}{2}}} \quad (3)$$

$$g = \cos\theta_s\cos\theta_v+\sin\theta_s\sin\theta_v\cos\phi \quad (4)$$

where ρ is reflectance of solar zenith angle θ_s and viewing zenith θ_v , and viewing azimuth from solar direction clockwise ϕ , and R expresses the hot spot effect, which is extremely high reflectance at round counter side of the sun. Three unknown parameters Θ , ρ_0 , k have to be determine according to observed conditions. In his study, these three parameters were determined by the field spectral data obtained over steppe, desert steppe and bare soils.

Spectral unmixing model

We used model, developed, by Anser and Lobell (2000). They successfully tested spectral unmixing model including Monte Carlo Unmixing approach (MCU) for estimating dominant land cover types such as PV, NPV, and bare soil using spectral reflectance signatures from shortwave-infrared region between 2,000 nm and 2,400 nm. We used the main equation of spectral mixture model by following equation.

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$$\rho_{\text{pixel}}=\sigma[\sum\rho_e\cdot C_e]+\varepsilon=\sigma[\rho_{\text{veg}}\cdot C_{\text{veg}}+\rho_{\text{soil}}\cdot C_{\text{soil}}+\rho_{\text{NPV}}\cdot C_{\text{NPV}}]+\varepsilon \quad \textbf{(5)}$$

where ρ and C are reflectance of and cover fractions of each endmember, and ε is error term of the solution at wavelength .

A schematic of the MCU algorithm and its processing steps are shown in Figure 2. This algorithm is used to correct spectral reflectance data of a pixel, calculated by BRDF, inducing PV, NPV, and bare soils information (top right), and derived endmember's reflectance bundles of PV, NPV, and bare soils are inputs to the model (top left). Indeed, endmember spectra set is randomly selected from each endmember bundle, and the pixel deconvolution is calculated iteratively using Monte Carlo technique.

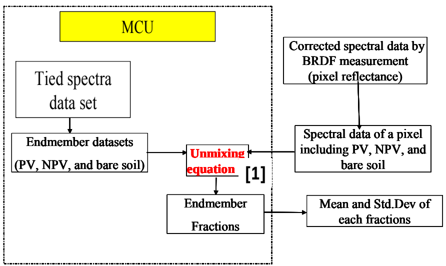

Figure 2 Schematic of calculation algorithm

Supervised classification method

Calculation of land cover fractions using SCM with digital camera images has been used in many studies (Li, 2002). With the support of ERDAS IMAGINE 9.0 image processing software, the representative LCFs training sampling areas are selected on digital color image. There are many ways to express the color space of given color, most of which are applicable to different situations (Healey 1989). However, the image processing systems have three color guns. These correspond to red, green, and blue (RGB), the additive primary colors. However, to reduce of each characteristic component in space the RGB color system, it is usually necessary to change RGB to other color characteristic color space. The IHS color space system is very suitable for the image processing based on human visual features of color reorganization. Therefore, we have to changed RGB image to IHS image using ERDAS IMAGINE 9.0 image processing software. Its processing steps are First, digital color image were converted into RGB space and then to IHS space. Secondly, SCM was applied with the maximum likelihood method to the IHS images.

Results and Discussion

Effects of noise on cover fractions

A field spectral dataset of PV, NPV, and bare soils was complied for 50 semiarid and arid sites in eastern steppe and Gobi steppe of Mongolia, representing wide type of data structure of plant species, vegetation conditions, and soil properties. In the short-wave-infrared (SWIR) region, spectral reflectance of dominant land cover fractions varied widely among the sites. For example, sample nadir reflectance of dominant PV collected at 50 semiarid and arid sites in eastern steppe and Gobi steppe regions of Mongolia are shown in Figure 3.

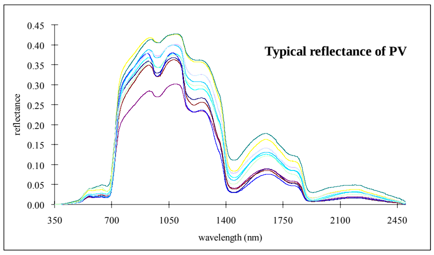

Figure 3. Typical reflectance of the PV in full spectral region.

Generally, reflectance of PV varied differently within full spectral region and the spectral reflectance value varied throughout most of the visible and near-infrared region. However, within the observed sites, there is stable reflectance for PV, NPV, and bare soil in the SWIR region from 2000 nm to 2400 nm in Figure 4.

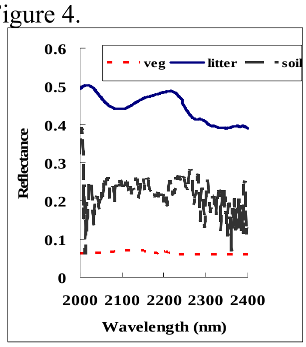

Figure 4. Typical reflectance of PV (dotted), NPV (solid), and bare soil (dashed) in SWIR region

Therefore, we reanalyzed to find which wavelength SWIR region is most appropriate for spectral unmixing model using endmember sets. High frequency filtering and linear transformation to emphasize spectral shape were used and it includes two possibilities for characterizing spectral shapes, i.e., "DERIVATIVE" spectra and "TIED" spectra, with the latter defined as subtracting the value at one wavelength from other wavelengths. This is the tied point.

Figure 5 shows that within the SWIR region, there is most stable reflectance for PV, NPV, and bare soils in from 2075 nm to 2275 nm wavelength region. In case of derivative reflectance, its shape is variable in SWIR region. This result suggests that the MCU procedure should be performed on each simulated spectrum using 100 endmember-database runs in the 2075 - 2275 nm wavelength intervals.

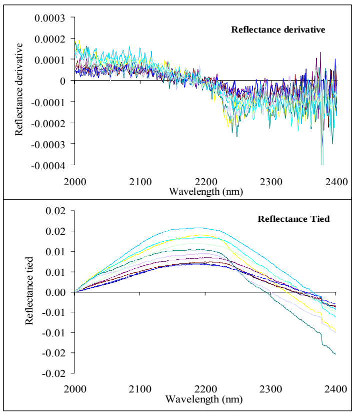

Figure 5. Tied and derivative reflectance value of PV in SWIR region.

Additionally, we tested the effects of varying noise levels on the MCU-derived fractions using both derivatives and tied spectra. Normally distributed noise with mean of zero and standard deviation ranging from 0% to 15% of the signal was added to each of modeled spectra (Table 1).

Table.1. Effects of noise on calculated cover fractions using tied and derivative spectra.

Noise level	PV fraction		NPV fraction		Soil fraction	
%	Tied	Derivative	Tied	Derivative	Tied	Derivative
0	0.40	0.39	0.54	0.54	0.04	0.04
5	0.39	0.38	0.54	0.57	0.05	0.06
10	0.38	0.16	0.53	0.78	0.04	0.04
15	0.39	0.31	0.54	0.53	0.04	0.07
Model fractions	PV=0.4		NPV=0.55		Soil=0.05	

As can be seen in Table 1, in baseline case from 0% noise to 5% noise level, both tied and derivative spectra returned accurate fractions for each modeled true values. However, tied spectra are much less sensitive to noise comparison to the derivative spectra. Indeed, when the modeled true value contained 40% PV, 55% NPV, and 5%, bare soil, calculated PV was 16%, and NPV was 78 % at 10% noise level, and calculated bare soil was 7% at 15 % noise level using derivative spectra. Therefore, the tied spectra were used for spectral unmixing model to determine land cover fractions in study area. Figure 6 shows the calculated mean and standard deviations from MCU performed with varying number of runs on spectrum modeled from different fractions of each endmember. This result suggests that additional runs beyond 40 have little effect on derived fractions. A conservative value of 50 runs was thus chosen for this study.

Bi-directional reflectance correction

We carried out bi-directional reflectance spectrometry

from land cover type's community in the field sites, which were 24 effective series of data from semiarid area in 2005 and 26 series of data in 2006 from arid area of Mongolia. The BRDF technique was used with field bi-directional reflectance data to correct spectral data in semiarid and arid area.

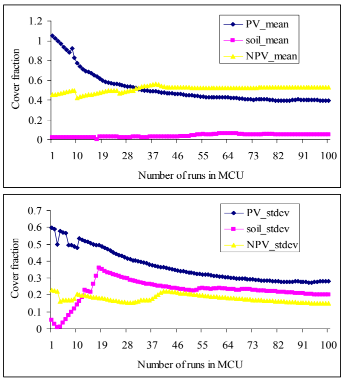

Figure 6. Mean and standard deviation of each endmember fractions number of runs in MCU procedure.

The performance is indicated in Figure 7. Both in semiarid and arid area, quite high agreement between predicted and observed reflectance values on the SWIR spectral region was obtianed.

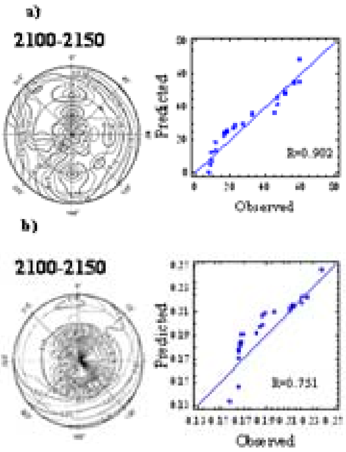

Figure 8. Bi-Directional Reflectance Distribution curve and comparison between predicted and observed reflectance values on the SWIR spectral region.Semiarid (a), and Arid (b)

Therefore, we can be sure that, BRDF can work on SWIR spectral region and corrected reflectance data with BRDF can be used for spectral unmixing approach for land cover fractions.

Derived land cover fractions from SCM

The image should be scanned accordingly and the image elements representing true LCFs can be calculated as percentage of total image elements, with the result obtained being the final LCFs. We show a result of the classification is presented in Figure 8 with classified percentage of LCFs at KBU 1 site.

Derived land covers fractions from SUM

Finally, we tried to determine land cover fractions of semiarid and arid area in Mongolia using reflectance signature from SWIR region, calculated by spectral unmixing approach including Monta Carlo analysis. The performance is indicated in Figure 9. Comparison of calculated each endmember's fractions value by SUM and SCM agree with each other but error of the model was too high (figure 9) which is unacceptable.

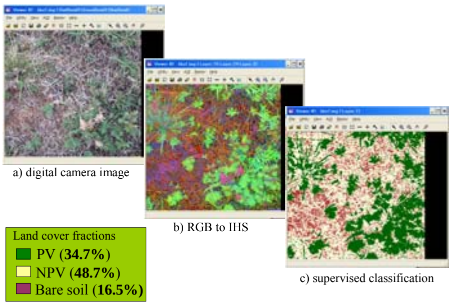

Figure 8 . Derived typical LCFs at KBU site 1.

Indeed, there are some difficulties in estimation of parameters of the model due to fitting 50 numbers of runs in MCU within area. Anyway, with some assumptions we estimated the typical LCFs of Mongolian semiarid and arid area using reflectance data from shortwave-infrared region. Results of the simulation are presented in Figure 9.

Application of the SUM needs further improvement with more data and some additional spectral measurements. However, this analysis will serve as pilot information for further application in Mongolia.

Table 2. Correlation coefficients of estimating LCFs from different methods

PV	Visual	MCU	*SCM*
Visual	1		
MCU	0.98	1	
SCM	0.88	0.80	1

NPV	Visual	MCU	*SCM*
Visual	1		
MCU	0.5	1	
SCM	0.4	0.3	1

Bare soil	Visual	MCU	*SCM*
Visual	1		
MCU	0.93	1	
SCM	0.80	0.75	1

From Table 2, it can be seen that, both MCU and SCM have good relationship with visually determined true values. However, MCU is better than SCM to calculate the LCFs.
Otherwise, the following correlation represents the relationship of the correlation coefficient for the LCFs calculations using visually determined and the results of applied methods for determining the LCFs: MCU (R=0.98) > SCM (R=0.88) in case PV, MCU (R=0.5) > SCM (R=0.4) in case NPV and MCU (R=0.93) > SCM (R=0.80) in case bare soil. These results confirm that the spectral unmixing model including Monte Carlo analysis has the highest accuracy for estimation of LCFs.

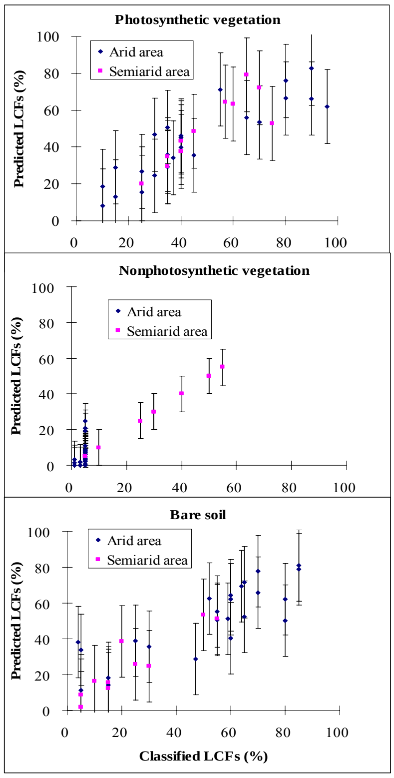

Figure 9. Comparison of predicted LCFs by SCM and those by MCU from semi-arid and arid area.

Summary

We presented estimation of land cover fractions value at study area. We can summarize the results.

- BRDF model can work in SWIR spectral region
- Conservative value of 50 runs number is enough in MCA
- Spectral unmixing model better than supervised classification method to estimate land cover fraction
- This paper tested SUM for land cover fractions in semiarid and arid area in Mongolia, using reflectance data from shortwave-infrared region.
- Application of the SUM needs further improvement and comparison with more data and some additional spectral measurements. However, this analysis will serve as pilot information for further application in Mongolia.

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