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A new spectral index to detect *Poaceae* grass abundance in Mongolian grasslands

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Abstract

The objectives of the present study were to develop a new index based on remotely-sensed data for detecting the abundance of grasses in the family *Poaceae*, which has a high palatability for livestock in Mongolia, and to map the distribution of these grasses in the semi-arid Mongolian steppes. We measured ground-based spectral reflectance of pure plant leaves – including *Poaceae* grasses – and soils, as well as *in-situ* in the Mongolian grasslands. The hyper-spectral data, taken by a spectroradiometer, were converted into four multi-spectral bands (i.e., blue, green, red, and NIR) to simulate satellite-based imagery data. In order to magnify the characteristics of the spectral signal of *Poaceae*, NGBDI (Normalized Green-Blue Difference Index), NGRDI (Normalized Green-Red Difference Index), NDVI (Normalized Difference Vegetation Index), NNBDI (Normalized NIR-Blue Difference Index) were calculated from the four multi-spectral reflectance values. Poaceae Abundance Index (PAI) was derived by combining these four normalized difference indices. PAI was found out to be a good indicator to discriminate *Poaceae* grass from the other plant spectral data.

Keywords: Mongolian grassland; Normalized difference indices; Poaceae abundance index; Spectroradiometer

1. Introduction

A significant loss of livestock – estimated at 8.5–12 million animals (Danker, 2004; Lise et al., 2006; Tachiiri et al., 2008) – was recorded between 1999 and 2002 by severe winter disasters (so-called *dzud*). Most of the damage was occurred in the consecutive *dzud* winters of 2000–2010 (Shimada et al., 2007). Livestock mortality is reported to increase when a harsh winter follows a drought in the previous growing season (Begzsuren et al., 2004) because it is difficult for livestock to survive winter without having enough stock from the previous growing season. The rapid grassland degradation induced by overgrazing in a few decades (Xie and Witting, 2004; Kawamura et al., 2005; Lise et al., 2006; Xie et al., 2009) is assumed to increase vulnerability to these disasters (Shimada et al., 2007). The total number of livestock increased by more than 8 million between 1993 and 1999 in Mongolia. By 2006, after this *dzud* disaster, the number of livestock in Mongolia had recovered increase to reach pre-*dzud* level. The most notable feature of this is the increase in the proportion of goats in the total livestock population (Shimada et al., 2009), as a result of their resilience to cold weather (Saizen et al., in press) and a strong demand for goat's hair (cashmere; Lise et al., 2006). The increased livestock population is still vulnerable to fluctuating grassland yields that are high correlated with precipitation in July (Miyazaki et al., 2004). Real time spatial information on grassland condition is therefore needed for planning to minimize the damage from future *dzud* events through the mapping of *Poaceae* grass abundance in order to inform herders.

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The Mongolian grassland has been grazed by domestic livestock (cattle, camels, goats, sheep and horses) under a nomadic pattern for thousands of years (Begzsuren et al., 2004). Grasslands are highly complex biomes that vary greatly in species (Xie et al., 2009). The number of plant species occurring in Mongolia is reported to be 2023, of which over 550 species are meadow grasses. Livestock grazing preferences are associated with the grasses of ca. 300 species, including the main 6 grass families, i.e., *Poaceae*, *Typhaceae*, *Liliaceae*, *Asteraceae*, *Iridaceae*, and *Chenopodiaceae* (Imaoka, 1988). It is difficult to determine a fixed palatability by examining plant taxonomy or C_3/ C_4 photosynthetic groups. However, *Poaceae* grasses have an obviously high palatability, and herbaceous are preferred over woody plants (Jigjidsurren and Johnson, 2003; Manibazar and Sanchir, 2008). The objectives of this study are to develop a new index for detecting the abundance of *Poaceae* and to map the distribution of the amount of *Poaceae* grasses by remotely sensed spectral data over the semi-arid Mongolian steppes. There have been many studies to assess grassland vegetation condition using remote sensing, mainly focusing on the estimating of aboveground biomass (e.g., Moreau et al., 2003; Gao, 2006; Xie et al., 2009), LAI (e.g., Boegh et al., 2002; He et al., 2007), or vegetation coverage (e.g., Purevdorj et al., 1998). However, there have been few efforts to assess the grazing quality of the grasslands in terms of the livestock palatability focusing on the discriminating of or estimating the abundance of specific grass types, i.e., *Poaceae*, out from the vegetation similar in quantitative aspect, such as biomass, LAI, and coverage among homogenous grassland environment. There have been developed quite a few remote sensing methods to classify vegetation types using the differences in greenness (e.g., Duncan et al., 1993) or structural characteristics (e.g., Chopping et al., 2004) of grass and shrub vegetation, or in phenological characteristics of forest (e.g., Shimada et al., 2006), of cropland vegetation (e.g., Gomez-Casero et al., 2010; Sakamoto et al., 2010), or of

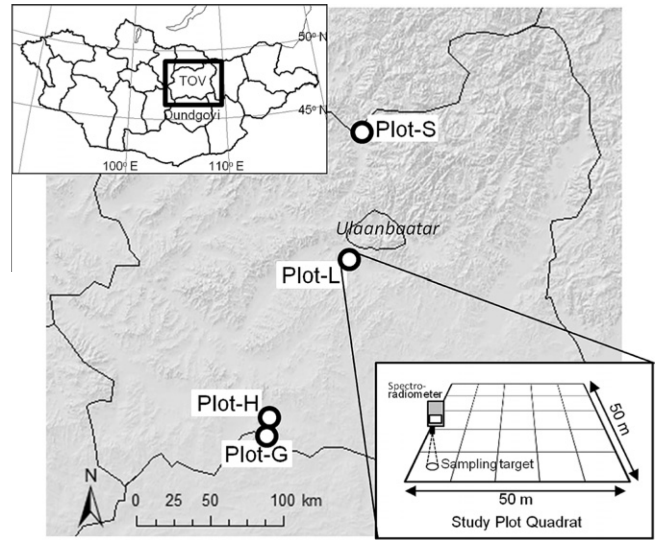

Fig. 1. Locations of Mongolian grassland study site with scheme of study plot quadrat and of *in-situ* data sampling.

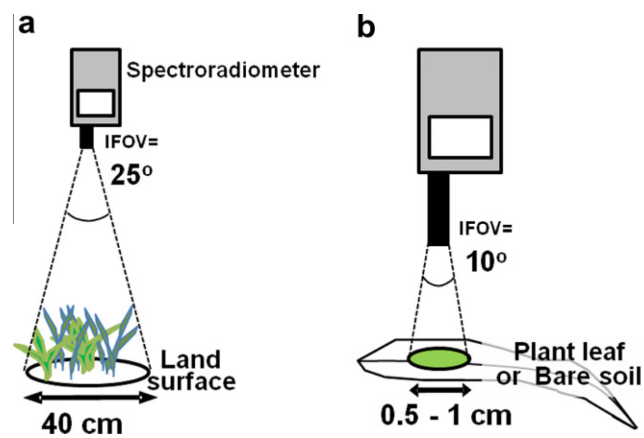

Fig. 2. Schematics of nadir radiometry (a) *in situ* land surface and (b) individual plant leaf or bare soil surface.

Table 1
Location, vegetative condition, date and time of spectral survey plots in Mongolian grassland.

Plot	Latitude (N)	Longitude (E)	Altitude (m)	Dominants	Vetetation Coverage (%)	Poaceae grass Coverage (%)	Above ground dry biomass (g m^{-1})	Survery date/ local time
G	46° 36′ 29″	105° 53′ 57″	1546	*Stipa glareosa*	54.5	6.5	135.8	12 Aug 2006
				Artemisia adamsii				/11:30
H	46° 40′ 39″	105° 54′ 51″	1421	*Caragana phygmaea*	32.3	9.2	180.1	13 Aug 2006
				Artemisia frigida				/11:10
L	47° 40′ 58″	106° 38′ 47″	1307	*Corispermum delimatum*	42.0	15.5	198.5	11 Aug 2006
				Artemisia fridida				/11:30
S	48° 28′ 42″	106° 45′ 58″	1173	*Thalictrum minor*	81.6	29.5	367.8	16 Aug 2006
				Stipa glareosa				/11:45

C4 plant vegetation (Davidson and Csillag, 2003), but no effective method has been developed to spectrally distinguish one type of grass out from grassland vegetation. In most of the cases, up to recent, statistical classification has been considered to be effective to estimate abundance of a target type of vegetation from spectral characteristics (e.g., Wolter and Townsend, 2011; Sanchez-Azofeifa et al., 2011). Radiative transfer models have been successful in predicting the canopy characteristics such as LAI and chlorophyll in croplands (Jacquemoud et al., 1995; Bacour et al., 2002) or grasslands (Darvishzadeh et al., 2008; Vohland and Jarmer, 2008) and are prospective for the grass type separation. Some efforts have been done for the remote determination of forest species using the models in conjunction with Linear Discriminant Analysis (e.g., Féret and Asner, 2011). However, these models deal with many parameters for ground-based measured hyperspectral data and are still in the process of solving the ill-posed inverse problem for the accurate prediction of biophysical and biochemical variables of vegetation canopy. In this study we attempted to develop a simple new spectral index to discriminate *Poaceae* grasses from the other grassland vegetation at the field scale, using ground-based measuring spectral reflectance data and to propose a perspective of application to detect abundance from multi-band satellite-based measurement.

2. Method

2.1. Study area and ground survey

The study area was located in the grassland areas of Tov and Dundgovi Province in Mongolia. Four study plots were established (Plot- G, H, L and S) over the area. Table 1 shows the location, vegetation condition and date of the survey for each plot. At each site we established a 50 m quadrat, which was subdivided into 25 grids of $10\text{ m} \times 10\text{ m}$ sub-quadrat (Fig. 1). Dominant species of the covered vegetation within these quadrats were examined. Above ground dry biomass was estimated after averaging the oven-dried weight values of sampled plants (*in-situ*) from three arbitrarily selected 1 m^2 areas within each quadrat. Nadir spectral reflectance in the wavelength range 350–1050 nm at the center of each grid from all the plots was measured using a spectroradiometer (MS-720, EKO, Inc.), correcting with a diffuse reflector (Spectralon, ASD, Inc.) in the field. Since each target of the spectral reflectance measurement was assumed to be a circle of ca. 40 cm in diameter (i.e., instantaneous field-of-view and distance to surface were set to be 25° and 90 cm, respectively; Fig. 2(a)), vegetation coverage, *Poaceae* grass, forb and *Fabaceae* shrub coverage within the same target area was calculated through image analysis of digital camera images concomitantly taken in the field. Moreover, pure spectral reflectance measurements of individual plant leaves (Table 2) and bare soil were also conducted using the spectroradiometer using an instantaneous field-of-view (IFOV) of 10°. In the individual leaf measurements, leaves were set to be perpendicular to nadir (Fig. 2 (b)). In this study, we categorized the plants into 3 types, i.e., *Poaceae* grass, which palatability for live stock is assumed to be high, *Fabaceae* shrub and forb type.

2.2. Indices used in the study

For the purpose of application to satellite-based optical remote sensing (e.g., ALOS, LANDSAT, IKONOS, or Quickbird imagery), four multi-spectral bands of blue (470–501 nm), green (539–580 nm), red (637–668 nm) and near-infrared (NIR: 801–870 nm) were calculated from the measured hyper-spectral reflectance data by averaging each multi-spectral band range. In order to emphasize the

Table 2
Plant species used for individual spectral reflectance measurement with palatability.

Category	Family	Genus/species	Palatability[a]	Observed plot
Poaceae grass	Poaceae	*Agropyron cristatum*	–	L
	Poaceae	*Stipa glareosa*	5	G, H, S
	Poaceae	*Leymus chinensis*	4–5	G, H
	Poaceae	*Elytrigia repens*	5	G, H, S
Forb	Chenopodiaceae	*Chenopodium serotinum*	–	G, L
	Chenopodiaceae	*Chenopodium galucum*	–	G, L, H
	Chenopodiaceae	*Chenopodium delinatum*	–	G, H
	Asteraceae	*Artemisia adamsii*	0	G, L
	Asteraceae	*Artemisia frigida*	5	G, H, L
	Asteraceae	*Saussurea amara*	0–1	G
	Iridaceae	*Iris lactea*	0–4	G
	Lamiaceae	*Phlomis tuberosa*	–	S
	Ranunculaceae	*Thalictrum minus*	3	S
	Fabaceae	*Trifolium lupinaster*	–	S
	Rosaceae	*Potentilla tanacetifolia*	–	S
Shrub	Fabaseae	*Caragana microphylla*	3–4	H, L

[a] Cited from Jigjidsurren and Johnson (2003) and Manibazar and Sanchir (2008).

difference of the characteristics of spectral curve, normalized difference indices (NDIs) between green – blue (Normalized Green-Blue difference index; NGBDI), green – red (Normalized Green-Red Difference Index; NGRDI) (cf. Hunt et al., 2005), NIR – red (Normalized Difference Vegetation Index; NDVI) and NIR – blue (Normalized NIR-Blue Difference Index; NNBDI) of each grass type and soil were calculated, using the following equations.

$$\mathrm{NGBDI} = \frac{R_{\mathrm{Green}} - R_{\mathrm{Blue}}}{R_{\mathrm{Green}} + R_{\mathrm{Blue}}} \quad (1)$$

$$\mathrm{NGRDI} = \frac{R_{\mathrm{Green}} - R_{\mathrm{Red}}}{R_{\mathrm{Green}} + R_{\mathrm{Red}}} \quad (2)$$

$$\mathrm{NDVI} = \frac{R_{\mathrm{NIR}} - R_{\mathrm{Red}}}{R_{\mathrm{NIR}} + R_{\mathrm{Red}}} \quad (3)$$

$$\mathrm{NNBDI} = \frac{R_{\mathrm{NIR}} - R_{\mathrm{Blue}}}{R_{\mathrm{NIR}} + R_{\mathrm{Blue}}} \quad (4)$$

where R_{Blue}, R_{Green}, R_{Red} and R_{NIR} indicate reflectance values in the blue, green, red and near-infrared bands, respectively.

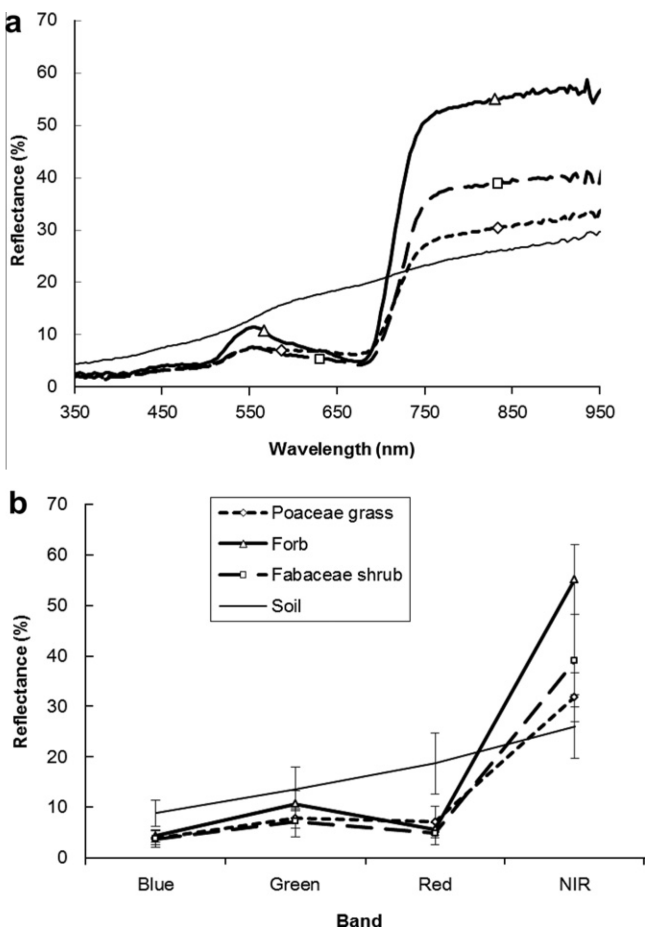

Fig. 3. (a) Curves of mean reflectance vs. hyper-spectral wavelength (350–1050 nm), and (b) mean (±SD) reflectance vs. multi-spectral band (Blue, Green, Red, and Near infra-red) for *Poaceae*, forb and *Fabaceae* shrub leaves and bare soil surface.

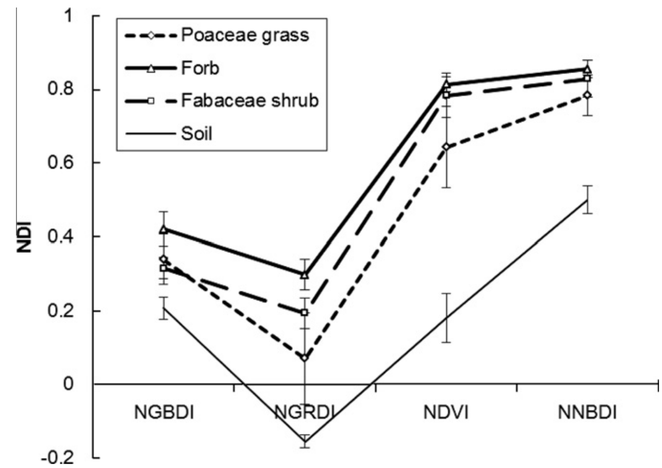

Fig. 4. Curves of mean (±SD) normalized different indices for *Poaceae*, forb and *Fabaceae* shrub leaves and bare soil surface.

Considering the spectral characteristics of *Poaceae* (discussed in Results), we propose the *Poaceae* Abundance Index (PAI) as Eq. (5):

$$\mathrm{PAI} = \frac{1}{\sqrt{2}}(\mathrm{NGBDI} - \mathrm{NGRDI} - \mathrm{NNBDI} - \mathrm{NDVI}) \quad (5)$$

An analysis of variance (ANOVA) test with least significant difference (LSD) post hoc test were conducted in order to evaluate PAI as a distinguisher of *Poaceae* in the individual spectral signal level.

The adequacy of the PAI for isolating *Poaceae* in the *in-situ* data in view of the mixed spectral signal (from various plant types as well as the soil surface; cf. Table 1) was also examined. The 25 mixed spectral data sets collected from

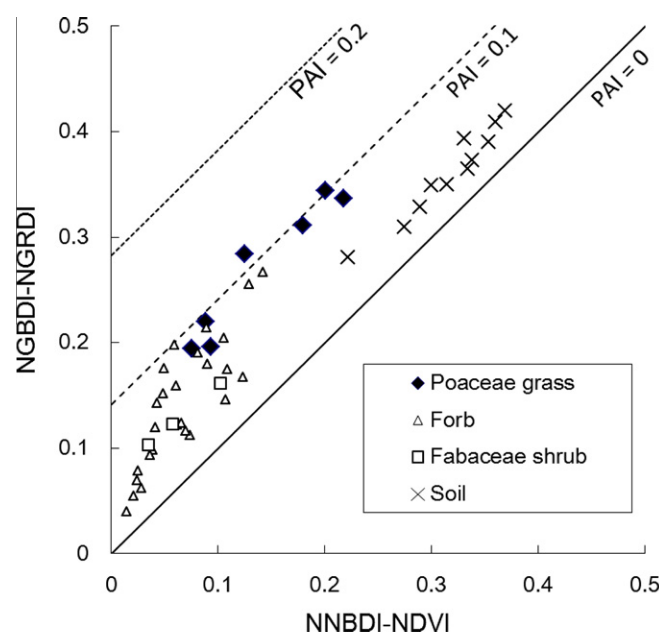

Fig. 5. Image of Poaceae Abundance Index (PAI) in the space of normalized difference indices subtractions (NGBDI – NGRDI vs. NNBDI – NDVI).

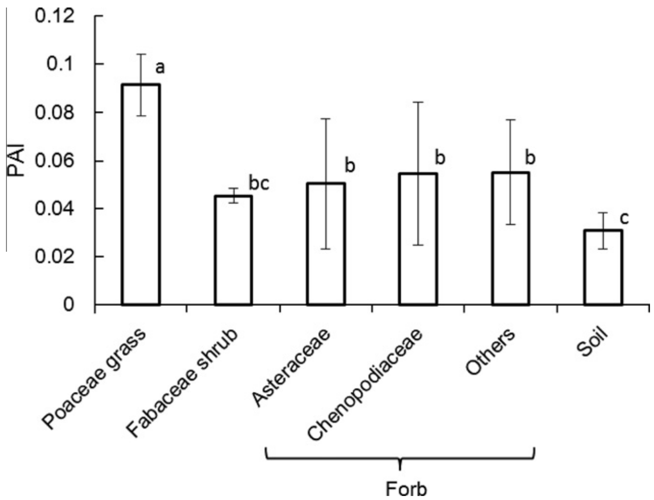

Fig. 6. Mean (±SD) Poaceae Abundance Index (PAI) for each plant type or soil surface. Letters above the box indicate the result of ANOVA with post hoc test. The same letters are not significantly different at the $P < 0.05$ significance level ($a > b > c$).

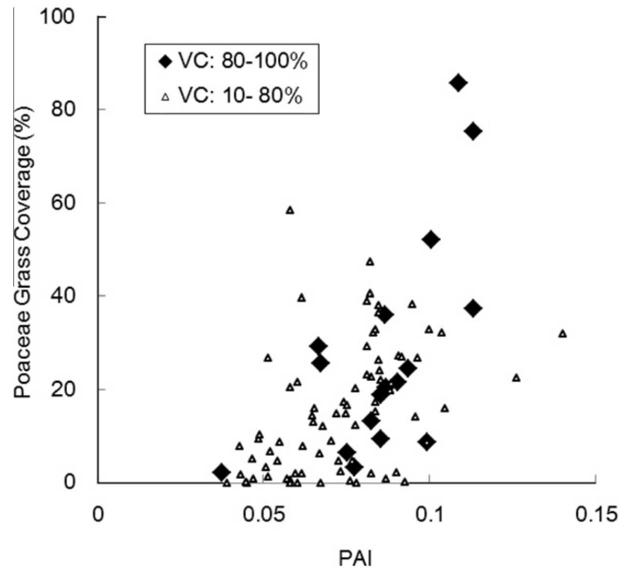

Fig. 7. All the measured *in-situ* data values plotted in data space of *Poaceae* grass coverage vs. Poaceae Abundance Index (PAI) with vegetation coverage (VC) over 80% (solid diamonds) and between 10% and 80% (hollow triangles).

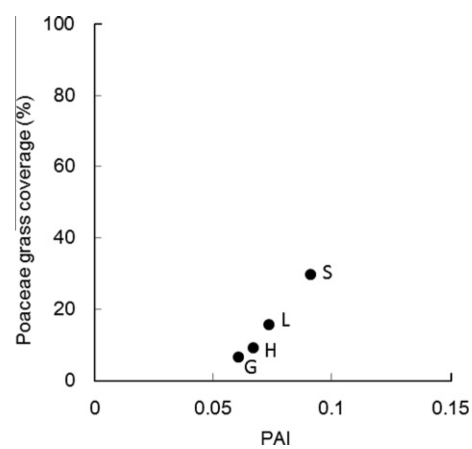

Fig. 8. Averaged *Poaceae* grass coverage vs. Poaceae Abundance Index for each plot with least *Poaceae* coverage in G and maximum in S.

each of the four study plots were converted into PAI, and compared with *Poaceae* grass coverage (areal percentage of *Poaceae* dominant within the target area). We also averaged both PAI and *Poaceae* grass coverage for each plot and examined the relation at the plot scale.

3. Results

3.1. Initial assessment of difference indices

The reflectance curve on both hyper-spectral and multi-spectral band basis for *Poaceae* grass, *Fabaceae* shrub, forb type and soil are shown in Fig. 3(a) and (b), respectively. The reflectance curve for soil type is almost linear with respect to wavelength, as for many soils. Slightly distinctive curve patterns can be seen for each plant type, e.g., relatively lower values in red and NIR for *Poaceae* grass. However, the overlapped SD bars in all the bands imply that it is difficult to discriminate the *Poaceae* grass spectral curve from the other plant spectral curves.

Calculated NDI values for three plant types and soil spectral data are plotted in Fig. 4. Because of the relation of original reflectance values in the green and red bands, NGRDI values for soils are always recorded as negative.

Table 3
Mean (±SD) band reflectances, NDIs, and PII for each plant type.

	Poaceoae grass	Forb	Fabaceae Shrub	Soil
Number of sample	7	26	3	11
Blue	3.9 ± 1.4	5.1 ± 1.8	5.5 ± 1.7	8.7 ± 2.5
Green	7.8 ± 1.9	10.9 ± 2.4	9.2 ± 1.3	13.4 ± 4.2
Red	7.2 ± 3.1	6.7 ± 2.1	7.2 ± 2.6	18.4 ± 5.9
NIR	31.8 ± 4.8	53.2 ± 9.5	41 ± 5.7	25.9 ± 6
NGBDI	0.34 ± 0.07	0.37 ± 0.1	0.27 ± 0.09	0.21 ± 0.03
NGRDI	0.07 ± 0.12	0.25 ± 0.11	0.14 ± 0.12	-0.15 ± 0.02
NDVI	0.64 ± 0.11	0.77 ± 0.09	0.69 ± 0.13	0.18 ± 0.06
NNBDI	0.78 ± 0.05	0.82 ± 0.07	0.76 ± 0.1	0.5 ± 0.04
PII	0.091 ± 0.013	0.051 ± 0.023	0.045 ± 0.003	0.031 ± 0.008

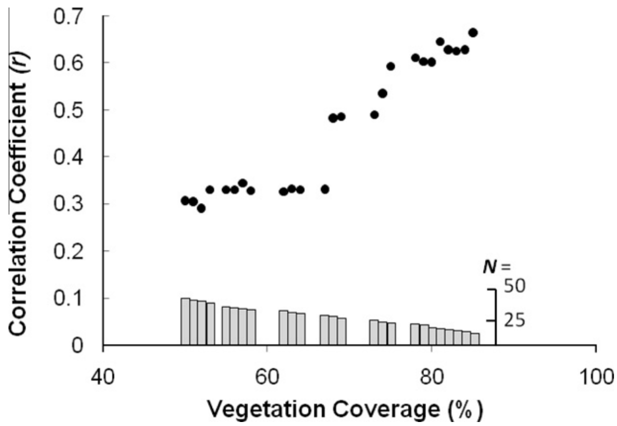

Fig. 9. Changes in correlation coefficient and number of spectral samples of *Poaceae* cover ratio vs. Poaceae Abundance Index relationship as vegetation coverage increases.

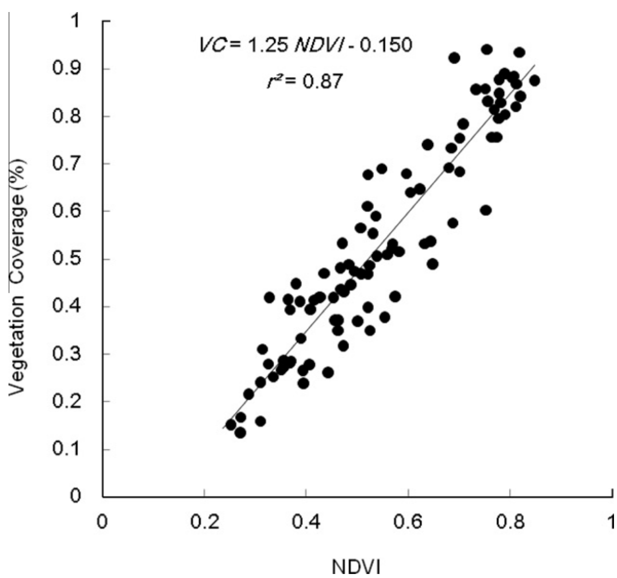

Fig. 10. Correlation between vegetation coverage (VC, %) and Normalized Difference Vegetation Index (NDVI) for all the with the regression equation ($VC = 1.25\ NDVI - 0.150$, $r^2 = 0.87$).

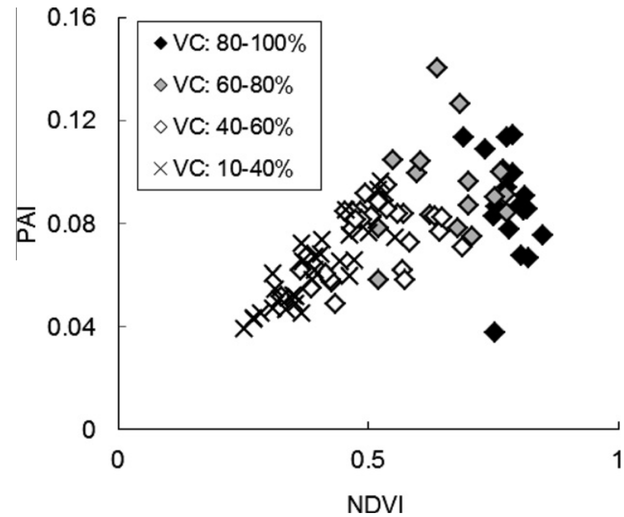

Fig. 11. Relation of Poaceae Abundance Index and Normalized Difference Vegetation Index in relation to the degree of vegetation coverage.

Converting the expression space from reflectance-band to NDI curve seems to magnify the characteristics of the spectral signal of *Poaceae*. *Poaceae* grasses are found to have distinctive characteristics, with lower values in the NGRDI and NDVI compared to the other plant types.

3.2. Development and assessment of a poaceae abundance index

All the associated data values for individually measured targets (plant types and soil) in data space of the NDI subtractions of NGBDI – NGRDI versus NNBDI – NDVI are shown in Fig. 5. The plots from *Poaceae* grass type can be seen around on a regression line ($y = 1.07\ \ x + 0.12$, $r^2 = 0.93$, $P < 0.05$) which is located further from the 1:1 line in this data space. This indicates that *Poaceae* grass is characterized by relatively large values in both NGBDI – NGRDI and NNBDI – NDVI compare to the other plant types, and by larger values in NGBDI – NGRDI than NNBDI – NDVI. It is according to the above characteristics that we proposed the Poaceae Abundance Index (PAI) as the Euclidian distance from the 1:1 line in the data space of NGBDI – NGRDI versus NNBDI – NDVI (Fig. 5), which can be expressed by Eq. (5). The mean (±s.d.) PAI values for *Poaceae* grass, *Fabaceae* shrub, forb (*Asteraceae*, *Chenopodiaceae* and the others) and soil are shown in Fig. 6 and Table 3. According to the results of ANOVA test with LSD post hoc test, *Poaceae* grass is found to have a significantly ($P < 0.05$) greater PAI value. The mean PAI of soil was significantly lower than that of vegetation (Fig. 6), although the difference between that of *Fabaceae* shrub ($N = 3$, Table 3) was insignificant. This result reveals that PAI can be a good indicator for the detection of *Poaceae* grasses from the spectral signals of grassland surfaces.

The 25 mixed (*in-situ*) spectral data sets from each of the four study plots were plotted in data space of *Poaceae* grass coverage versus PAI (Fig. 7). Only a weak correlation ($r = 0.52$, $P < 0.05$) can be found between *Poaceae* grass coverage and PAI. Whilst, confining the domain to plots that have vegetation coverage of more than 80%, we obtained the non-linear regression model ($y = 0.87\ e^{34.9x}$, $r^2 = 0.48$, $P < 0.05$) between PAI and *Poaceae* grass coverage (Fig. 7) and correlation coefficient of 0.60 (linear). The relation of averaged PAI (cf. Table 1) and *Poaceae* grass coverage for each plot with least *Poaceae* coverage in G and maximum in S is shown in Fig. 8. It shows that PAI has a tendency to linearly correspond to the *Poaceae* grass coverage at the plot scale level.

4. Discussion

Poaceae Abundance Index (PAI) was demonstrated to be a good metric for *Poaceae* grass detection from the pure spectral signals. This index magnifies the slight differences in reflectance in the relatively lower blue, green and NIR range, and the higher red band for *Poaceae* grass (Table 3) seen via different combinations of NDI values. Accordingly, leaves of *Poaceae* grasses might have distinct physiological characteristics in the activities of photosynthetic or non-photosynthetic pigments, such as chlorophyll, carotenoid, and phytochrome, whose absorption bands are blue and red, blue to green (Inada, 1980), and , red to NIR (Smith, 2000), respectively.

On the other hand, the adequacy of PAI for isolating *Poaceae* grasses was lower for *in-situ* spectral data that was contaminated by other spectral signals, compared with the pure spectral data. It is assumed that there are two factors that might explain why PAI was less effective in the mixed/*in-situ* situation: (1) the variation in the proportion of contaminated signals within the mixed spectral reflectance data from the surfaces of the grass, shrub and soil, and (2) the difference in the aboveground physical structure of *Poaceae* grasses, that are erectophile at the *in-situ* level while collimated at the leaf level observations. In order to isolate the effect of the former possible factor and eliminate – or at least reduce – the contribution of the soil surface reflectance, only plots with vegetation coverage (VC) more than 80% were considered (Fig. 7). Indeed, the values of Correlation coefficient rose drastically at VC over 68% from 0.33 to 0.48, and at VC between 73% and 75% from 0.48 to 0.59 (Fig. 9).

PAI was designed to distinguish *Poaceae* without reference to whether the target objects are soil or vegetation (see Figs. 5 and 6). However, under *in-situ* conditions, PAI correlated overall ($r = 0.62$, $P < 0.05$) and under VC less than 80% ($r = 0.73$, $P < 0.05$) with NDVI, which was reported to have a strong correlation with vegetation coverage (Purevdorj et al., 1998) and has also turned out so ($r = 0.93$, $P < 0.01$) in this study (Fig. 10). No significant correlation was found ($r = -0.32$, $P > 0.1$, $N = 18$) between PAI and VC when VC was over 80% (Fig. 11).

These results reveal that the value of PAI is affected by the vegetation coverage, especially under sparse vegetation conditions. Even under dense vegetation conditions, it is still difficult to predict *Poaceae* coverage from PAI ($r^2 = 0.48$, $P < 0.05$; Fig. 7), therefore the confusion may be owing to ignorance of the anisotropy of land surface, which can be eliminated in the collimated pure spectral measuring conditions. Because of the distinctive erectophile architecture of *Poaceae*, shadow effects, a function of the geometry associated with solar angle (sun elevation: 51–53° in this study) and view angle (nadir in this study), might be responsible for the dispersion of PAI values for *in situ* measuring conditions.

5. Conclusions

In order to determine method to isolate *Poaceae* grasses from soil, forbs, and shrubs in Mongolian grasslands, we exploited spectral information content of ground-based measured multi-spectral reflectance data via the development of band ratios/vegetation indices based on field spectroscopy. This study shows the following conclusions:

(1) *Poaceae* grass is characterized by larger values in both the subtractions of normalized difference indices, i.e., (NGBDI - NGRDI) and (NNBDI - NDVI).
(2) Poaceae Abundance Index (PAI) was demonstrated to be a good metric for *Poaceae* grass detection from the pure spectral signals.
(3) The adequacy of PAI for separating *Poaceae* grass was lower for *in-situ* spectral data because of the contaminant of other spectral signals. However, in case that grassland condition is rich (vegetation coverage > 80%) Poaceae abundance can be predicted at 48% of the variability in the value of *Poaceae* grass coverage using satellite-based remote sensing.

The results of this study implied that the pigment composition in the leaf of *Poaceae* grass has unique characteristics compared with the other plant types in Mongolian grasslands. These characteristics are assumed to be extracted in the simple index of the combination of ground-based simulated multi-spectral bands. Although the accuracy became low for *in-situ* level, this simple index is promising to use as an ancillary parameter for the application to predict *Poaceae* abundance by using multi-band satellite-based imagery.

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References

Bacour, C., Jacquemoud, S., Leroy, M., Hautecœur, O., Weiss, M., Prévot, L., Bruguier, N., Chauki, H., Reliability of the estimation of vegetation characteristics by inversion of three canopy reflectance models on airborne POLDER data. Agronomie, 22, 555–565, 2002.

Boegh, E., Soegaard, H., Broge, N., Hasager, C.B., Jensen, N.O., Schelde, K., Thomsen, A. Airborne multispectral data for quantifying leaf area index, nitrogen concentration, and photosynthetic efficiency in agriculture. Remote Sens. Environ., 81, 179–193, 2002.

Begzsuren, S., Ellis, J.E., Ojima, D.S. Coughenour, M.B., Chuluum, T., Livestock responses to droughts and severe winter weather in the Gobi Three Beauty National Park, Mongolia. J. Arid Env. 59, 785–796, 2004.

Chopping, M.J., Su, LH., Rango, A., Maxwell, C. Modelling the reflectance anisotropy of Chihuahuan Desert grass-shrub transition canopy-soil complexes. Int. J. Remote Sens., 25, 2725–2745, 2004.

Danker, M., Hors-Gazar. Cry of a woken bull. Changes in pastoral life and pastureland management in Mongolia. MSc Thesis, Vrije Unisersity, Amsterdam, 2004.

Darvishzadeh, R., Skidmore, A., Schlerf, M. and Atzberger, C., Inversion of a radiative transfer model for estimating vegetation LAI and chlorophyll in a heterogeneous grassland. Remote Sens. Environ., 112, 2592-2604, 2008.

Davidson, A., Csillag, F. A comparison of three approaches for predicting C4 species cover of northern mixed grass prairie. Remote Sens. Environ., 86, 70-82, 2003.

Duncan, J., Stow, D., Franklin, J., Hope, A. assessing the relationship between spectral vegetation indexes and shrub cover in the Jornada Basin, New-Mexico. Int. J. Remote Sens., 14, 3395-3416, 1993.

Féret, J.-B. and Asner, G.P. Spectroscopic classification of tropical forest species using radiative transfer modeling. Remote Sens. Environ., 115, 2415-2422, 2011.

Gao, J. Quantification of grassland properties: how it can benefit from geoinformatic technologies? Int. J. Remote Sens., 27, 1351–1365, 2006.

Gomez-Casero, M.T., Castillejo-Gonzalez, I.L., Garcia-Ferrer, A. Pena-Barragan, J.M., Jurado-Exposito, M., Garcia-Torres, L., Lopez-Granados and F., Spectral discrimination of wild oat and canary grass in wheat fields for less herbicide application. Agronomy for Sustainable Development, 30, 689-699, 2010.

He, YH., Guo, XL., Wilmshurst, J.F. Comparison of different methods for measuring leaf area index in a mixed grassland. Can. J. Plant Sci. 87, 803-813, 2007.

Hunt Jr., E.R., Cavigelli, M., Daughtry, C.S.T., Mcmurtrey III, J.E., Walthall,C.L. Evaluation of Digital Photography from Model Aircraft for Remote Sensing of Crop Biomass and Nitrogen Status. Precision Agriculture, 6, 359-378, 2005.

Imaoka,R. Characteristics of natural condition on Negdel, the Agro-livestock Cooperative. Mongolian Studies, 11, 2-30, 1988. (In Japanese).

Inada, K. Spectral absorption property of pigments in living leaves and its contribution to photosynthesis. Japan. J. Crop Sci., 49, 286-294, 1980.

Jacquemoud, S., Baret, F., Andrieu, B., Danson, F.N. and Jaggard, K., Extraction of vegetation biophysical parameters by inversion of the PROSPECT + SAIL models on sugar beet canopy reflectance data. Application to TM and AVIRIS sensors. Remote Sens. Environ., 52, 163–172, 1995.

Jigjidsurren S., Johnson, D.A. Forage Plants of Mongolia, in: RIAH (Ulaanbaatar), p. 563, 2003.

Kawamura K., Akiyama T., Yokota H., Tsutsumi M., Yasuda T., Watanabe O. Wang S. Quantifying grazing intensities using geographic information systems and satellite remote sensing in the Xilingol steppe region, Inner Mongolia. China Agriculture, Ecosystems & Environment, 107, 83-93, 2005.

Lise, W., Hess, S., Purev, B. Pastureland degradation and poverty among herders in Mongolia: Data analysis and estimation. Ecological Economics, 58, 350-364, 2006.

Manibazar N., Sanchir C. Flowers of Hustai National Park, Hustai National Park (Ulaanbaaatar). p. 304, 2008.

Miyazaki, S., Yasunari. T., Miyamoto, T., Kaihotsu, I., Davaa, G., Oyunbaatar, D., Natsagdorj, L., Oki, T. Agrometeorological conditions of grassland vegetation in central Mongolia and their impact for leaf area growth. J. Geophysical Res., 109, D22106, 2004.

Moreau, S., Bosseno, R., Gu, X., Baret, F. Assessing the biomass dynamics of Andean bofedal and totora high-protein wetland grasses from NOAA/AVHRR. Remote Sens. Environ., 85, 516–529, 2003.

Purevdorj, T., Tateishi, R., Ishiyama, T., Honda, Y. Relationships between percent vegetation cover and vegetation indices. Int. J. Remote Sens., 19, 3519-3535, 1998.

Saizen, I., Maekawa, A., Yamamura, N. Spatial analysis of time-series changes in livestock distribution by detection of local spatial associations in Mongolia. Appl. Geog., 30, 639–649, 2010.

Sakamoto, T., Wardlow, D.W., Gitelson, A.A., Verma. B.S., Suyker, E.S., Arkebauer, J.T. A Tow-Step Filtering approach for detecting maize and soybean phenology with time-series MODIS data. Remote Sens. Environ. 114, 2146-2159, 2010.

Sanchez-Azofeifa, A. Rivard, B., Wright, J., Feng, JL., Li, PJ., Chong, M.M., Bohlman, S.A. Estimation of the Distribution of Tabebuia guayacan (Bignoniaceae) Using High-Resolution Remote Sensing Imagery. Sensors 11, 3831-3851, 2011.

Shimada, S., Takahashi, H., Limin, S.H. Hydroperiod and phenology prediction in a Central Kalimantan peat swamp forest by using MODIS data. Tropics, 15, 435-440, 2006.

Shimada, S., Sekiyama, A., Yokohama, M., Buhe, A., Tamaki, K. Developing the prediction method of soil moisture and vegetation cover ratio in Mongolian grassland using remote sensing images. J. Arid Land Studies, 17, 77-80, 2007. (In Japanese).

Shimada, S., Yokoyama, H., Toyoda, H., Sekiyama, A., Buhe, A., Yokohama, M. GIS analysis of grazing selection by goats in Tov Province, Mongolia. J. Arid Land Studies, 19, 29-32, 2009.

Smith, H. Phytochromes and light signal perception by plants–an emerging synthesis. Nature, 407, 585-591, 2000.

Tachiiri, K., Shinoda, M., Klinkenberg, B., Morinaga. Y. Assessing Mongolian snow disaster risk using livestock and satellite data. J. Arid Env., 72, 2251-2263, 2008.

Vohland, M. and Jarmer, T., Estimating structural and biochemical parameters for grassland from spectroradiometer data by radiative transfer modeling (PROSPECT + SAIL). Int. J. Remote Sens., 29, 191-209, 2008.

Wolter, P.T., Townsend, P.A. Multi-sensor data fusion for estimating forest species composition and abundance in northern Minnesota. Remote Sens. Environ, 671-691, 2011.

Xie, Y., Witting, R. The impact of grazing abundance on soil characteristics of Stipa grandis and Stipa bungeana steppe in northern China (autonomous region of Ningxia). Acta Oecologica, 25, 197-204, 2004.

Xie, Y., Sha, Z., Yu, M., Bai, Y., Zhang, L. Comparison of two models with Landsat data for estimating above ground biomass in Inner Mongolia, China. Ecological Modelling, 220, 1810-1818, 2009.