VEGEATION PARAMETERS RETRIEVAL USING TM/ETM+ DATA, A CASE STUDY IN THE TYPICAL SEMI-ARID STEPPE IN INNER-MONGOLIA, NORTH CHINA

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1. INTRODUCTION

Remote sensing technology is very useful in getting synoptic estimates of grass bio-parameters which is important for rangeland monitoring [1]. The retrieval of bio-parameters is usually realized by developing empirical regression formula. However, it is less convincing if the regression line is built on limited observations from one growth stage [2]. In this research, three field surveys were carried out at different periods in a growing season in the typical semi-arid steppe in North China. The correlation between bio-parameters (leaf area index, dry weight, canopy water content) and TM spectral data were studied with about 240 observation data. The objective of this research is twofold: to learn the temporal difference of the correlation between bio-parameters and spectral variables, and to find which bio-parameter can be determined most easily from spectral information.

2. METHODS AND MATERIALS

The study sites were located in Xilinhot, North China. It is a typical semi-arid steppe (N44.14°, E116.30°) and the dominant grass is Krylov needlegrass *(Stipa krylovii Roshev).* The study site includes grazed and ungrazed regions. Within the ungrazed region, a patch of grass was harvested last year, and the remaining grass was not harvested so the soil is covered with plant litter.

80 plots (25m╳25m) were established in a 1km╳0.8km area according to the cyclic sampling design proposed by Burrows et al (2002) [3]. Each plot was geo-located to within 0.5m using differential GPS system. 5 subplots (50cm╳50cm) located at the four corners and the center positions were surveyed. First, LAI was estimated using a Li-Cor LAI2000 instrument. Second, the grass in a subplot was harvested and preserved in a bag. Within 2 hours, the fresh grass were weighted and then were oven dried for 24h at 70°, so the dry weight (aboveground biomass) as well as canopy water content (difference between fresh weight and dry weight) can be determined. The measurements from the five subplots were averaged for each plot.

Table 1 Summary statistics of bio-parameters for the 80 plots. The unit of CWC and DW is kg/m^2

	6-10 July			26-30 July			22-27 August		
	mean	*std*	CV	*mean*	*std*	CV	*mean*	*std*	CV
Canopy Water Content (CWC)	0.11	0.04	0.40	0.15	0.04	0.28	0.19	0.08	0.42
Leaf Area Index (LAI)	0.58	0.16	0.27	0.61	0.20	0.33	0.84	0.22	0.27
Dry Weight (DW)	0.07	0.03	0.40	0.15	0.03	0.23	0.14	0.05	0.34

Field surveys were carried out on early growth stage (6-10 July), vegetative stage (26-30 July) and early productive stage (22-27 August). According to the timing of field work, two TM images (124/29) were purchased that were respectively acquired on 8 July and 25 July. One ETM+ image (124/29) acquired on 1 Aug was downloaded from the web (http://glovis.usgs.gov/).

The three Landsat images were geo-referenced and co-registered. RMS errors of the correction were lower than 0.5 pixel. Calibration of DN values to radiance was performed using the coefficients included in the header files. The atmospheric correction of TM data acquired on 8 July was based on 6s modeling because the water vapor and AOD information was available from CE318 observations. To ensure spectral integrity of the multi-temporal series, the atmospheric correction of the other two images utilized stable targets, which were a deep water body with low reflectance and an airport runway with high reflectance.

3. RESULTS AND ANALYSIS

3.1. Statistical analysis of grass bio-parameters

Mean values, standard deviations and coefficients of variation of the three bio-parameters at different growth stages were presented in Table 1. Mean value of LAI was about 0.6 in July and increased to 0.8 in August. CWC showed a linear increase from July to August, whereas DW first increased significantly then decreased slightly. Results for CV indicated that CWC had the highest dispersion except in vegetative stage (26-30 July).

3.2 Correlation analysis between spectral variables and bio-parameters

Table 2 present the Pearson correlation coefficients between bio-parameters and TM spectral variables. In the early growth stage the plant coverage was low, suggesting strong influences of the reflectance from background soil exist. Correlation coefficients between spectral and bio-parameters were low. The highest coefficients were observed for the band5 located in the SWIR. CWC was weakly correlated with band2 (green), band 3 (red), NDVI (Normalized Difference Vegetation Index) and LSWI (Land Surface Water Index) [4]. The correlation

Table 2 Pearson coefficients between bio-parameters and TM spectral variables based on individual dataset. Highest correlation coefficients are typed in bold.

	6-10 July			26-30 July			22-27 August		
	CWC	LAI	DW	CWC	LAI	DW	CWC	LAI	DW
Band2	-0.1967	-0.1917	-0.0718	-0.2789	0.0374	-0.1685	-0.423	-0.5393	-0.3535
Band3	-0.2254	-0.1312	-0.0731	-0.4173	0.0013	-0.2456	-0.5352	**-0.5537**	-0.4578
Band4	0.0012	-0.0695	-0.0320	0.4366	**0.1489**	0.3090	0.5420	0.0705	0.4583
Band5	**-0.2664**	**-0.2699**	**-0.1940**	-0.3071	0.0315	-0.1426	-0.5459	-0.5114	-0.4519
NDVI	0.1950	0.0866	0.0560	**0.5108**	0.0759	**0.3271**	0.6577	0.4463	0.5580
LSWI	0.1506	0.0929	0.0855	0.4806	0.0871	0.2991	**0.6769**	0.3569	**0.5656**

NDVI=(band4-band3)/(band4+band3) LSWI=(band4-band5)/(band4+band5) [4]

Table 3 Pearson coefficients between bio-parameters and spectral variables based on the combined datasets.

	CWC	LAI	DW
Band2	-0.4051	-0.2979	-0.462
Band3	-0.4643	-0.2729	-0.5104
Band4	0.3335	0.1991	0.0375
Band5	-0.5745	-0.4088	**-0.6201**
NDVI	0.5696	0.3452	0.4363
LSWI	**0.6330**	**0.4308**	0.4414

coefficients between Band4 (NIR) and bio-parameters were the lowest, indicating NIR can not reflect vegetation information when plant closure was low, which is consistent with other research results [5].

In late July, plant was in the vegetative stage of growth and the biomass was high. The two spectral indices (NDVI, LSWI) showed the strongest correlation with CWC and DW, indicating the importance of band4 (NIR) for information extraction from vigorous grass. The correlation between LAI and spectral variables were still weak.

In late August, plant was in the early productive stage. The dominant grass (Krylov needlegrass) start to ear and the biomass declined. The two spectral indices (NDVI, LSWI) still showed the strongest correlation with CWC and DW, whereas the performance of LSWI was slightly better and this was different from the former results. LAI was correlated with band2 (green), band3 (red), and band5 (swir1.6um). However, there was no correlation between NIR and LAI.

Table 3 showed the correlation results obtained by analyzing the three datasets together and they were obviously different from the results in Table 2. LSWI showed the strongest correlation with CWC and LAI, and band5 (swir1.6um) showed the strongest correlation with DW.

4. DISCUSSION AND CONCLUSION

The results showed clearly that the correlation was the strongest in late August and CWC can be more easily determined than DW and LAI. The best predictor for CWC changed with time. In the early July when soil exposure was large, SWIR band can provide CWC information. It is probably because SWIR can reflect soil moisture which is related to vegetation status. In late July when grass biomass was large, NDVI showed the highest correlation with CWC, indicating that plant greenness is closely related with plant water content. In late August when the grass starts to ear and senescence took place, LSWI, which directly measure information at water absorption bands, showed the highest correlation with CWC. Since DW and CWC were associated, the spectral variables showing high correlation with CWC also correlated with DW but the correlation magnitude was lower. LAI correlated poorly with spectral variables except in late August when LAI was relatively large. Big uncertainty was found in LAI measurement and further researches are needed.

When the three datasets were analyzed together, band5 (swir1.6um) was the best predictor for DW, and LSWI was the best predictor for CWC and LAI. These results highlighted the importance of SWIR in reflecting the seasonal change of grass bio-parameters.

In our research, the temporal variance of correlation between spectral variables and grass bio-parameters was revealed which is very helpful for rangeland monitoring. However, only observation data from the year 2008 were obtained and analyzed, which is not enough to study the inter-annual variance. In the future, we will continue to carry out filed survey, especially in dry year. More comprehensive results could be derived from samplings collected from multiple years.

5. REFERENCES

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