Monitoring Barley Growth Condition with Multiscale Remote Sensing Images

Yingying Dong Key laboratory of Digital Earth Science, Aerospace Information Research Institute, Chinese Academy of Sciences Beijing, China dongyy@aircas.ac.cn

Huichun Ye Key laboratory of Digital Earth Science, Aerospace Information Research Institute, Chinese Academy of Sciences Beijing, China yehc@aircas.ac.cn Jihua Wang Beijing Research Center for Agricultural Standards and Testing, Beijing Academy of Agriculture and Forestry Sciences Beijing, China wangjh@brcast.org.cn

Yining Zhu* School of Mathematical Sciences, Capital Normal University Beijing, China ynzhu@cnu.edu.cn Wenjiang Huang* Key laboratory of Digital Earth Science, Aerospace Information Research Institute, Chinese Academy of Sciences Beijing, China huangwj@aircas.ac.cn

Abstract—Crop growth condition monitoring at regional scale with remote sensing data has been widely implemented. The normal method is extracting biophysical and biochemical parameters, and then setting thresholds for these parameters to grade different levels of crop growth. In which, as the parameters inversion has scale effects based on different remote sensing observations with different spatial scales, it is difficult to setting the threshold at multi-spatial scales. To achieve space consistency for multi-scale crop growth monitoring results, we constructed two new vegetation indexes for crop growth monitoring, and then proposed a new crop growth grading system. We constructed two new crop growth indicators, i.e., Crop Growth Monitoring Index 1 (CGMI1), and Crop Growth Monitoring Index 2 (CGMI2), based on Leaf Area Index (LAI) and Canopy Chlorophyll Density (CCD). Compared with the existed crop growth indicators, these two new growth indicators could provide a much more comprehensive description of the characteristics of crop growth status from the aspects of crop structure and biochemical conditions. To achieve the space consistency of crop growth monitoring, we constructed a new crop growth grading system based on multiple spatial resolution satellite images. Firstly, we proposed a spatial adaptive threshold selection method by integrating with data histogram and Gaussian distribution theory for thresholds selection based on the statistical analysis of CGMI1 and CGMI2, then to strengthen robustness of threshold selecting on multi-scale. Moreover, we carried out research on crop growth monitoring and ranking based on the selected thresholds of CGMI1 and CGMI2 from the aspects of crop canopy morphology structure (large, medium, and small) and crop canopy biological activity (strong, middle, and weak). Taking barley as our research object, three multi-source and multi-scale remote sensing images are obtained during the jointing-booting stage of barley, which include Advanced Land Observing Satellite-Advanced Visible and Near Infrared Radiometer type 2 (ALOS-AVNIR2) image, Small Remote Sensing Satellite Constellations A Star-CCD2 (HJ 1A-CCD2) image, and the 8-day composite MODIS Surface Reflectance Product (MOD09A1). Experimental numerical results showed better space consistency for crop growth monitoring based on multiple spatial scale dataset (ALOS, HJ, and MODIS). The new proposed crop growth indicators CGMI1 and CGMI2 based on LAI and CCD to both consider the crop morphology structure and biological activity. And the new growth grading rules provide a spatial adaptive threshold selection algorithm to keep the space consistency when mapping different crop growth grading. Theoretical

analysis and numerical experiments fully confirmed the new system, not only effectively enhance the crop growth evaluation, but also revealing better results on the space consistency with multi-scale data.

Keywords—crop growth monitoring, remote sensing, vegetation index, multi-scale

I. INTRODUCTION

Crop growth monitoring is of great importance for field management and plant protection, such as irrigation, fertilization, pest and disease protection [1-3]. Remote sensing as a technology to quickly and regionally achieving observation at large scale is widely used for crop growth monitoring. Normally the crop growth grading is based on crop growth grading system, including crop growth indicators and grading rules. For the crop growth indicators, vegetation indexes, such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Canopy Chlorophyll Density (CCD), biophysical parameters and biochemical parameters, such as Leaf Area Index (LAI) and Leaf Chlorophyll Content (Cab), are widely used [4-8]. For grading rules, the threshold segmentation method is the normal one [9-12]. These existed crop growth grading system perform better in one scale, but for multi-scale dataset, as the extraction and inversion of the crop growth indicators has scale effects, and the thresholding method has the problem of threshold values setting among different spatial scales, then it is difficult to achieve space consistency with the existed grading system.

The key point of crop growth monitoring with multi-scale remote sensing data is the construction of new crop growth grading system. Crop growth condition monitoring includes morphology structure monitoring and biological activity monitoring, thus the normally used growth indicators couldn't meet the actual application needs. And, crop growth grading results based on thresholding methodologies are simple and widely used, these methods show reasonable performances limit to specific image at the exact spatial scale or phenological stages, which restrict their use for growth grading of multi-scale dataset. Moreover, existed crop growth grading system couldn't keep consistency among different spatial scales.

In order to fulfill the needs of quickly mapping crop growth condition using multi-scale remotely sensed data, new crop growth indicators and grading rules are proposed in this study. For this purpose, two new crop growth monitoring indexes are constructed, and a new grading rules based on statistical analysis are introduced to monitor the regional crop growth. This could effectively enhance the space consistency of crop growth monitoring at multi-spatial scales. With the new crop growth grading system, taking barley as the object, numerical experiments based on multi-scale satellite images are selected for crop growth monitoring.

II. MATERIALS AND METHODS

A. Study Area and Data

The study area is situated in Labudalin farm (50° 01' N to 53° 26' N, 119° 07' E to 121° 49' E) of Hailaer Farming Cultivate Bureau in Inner Mongolia, China, which shown in Fig.1. The main crop types in this region are barley. Three multi-source and multi-scale remote sensing images are obtained during the jointing-booting stage of barley, which include Advanced Land Observing Satellite-Advanced Visible and Near Infrared Radiometer type 2 (ALOS-AVNIR2) image obtained in July 8, 2010 with a spatial resolution as 10 m, Small Remote Sensing Satellite Constellations A Star-CCD2 (HJ 1A-CCD2) image obtained in July 8, 2010 with a spatial resolution as 30 m, and the 8-day composite MODIS Surface Reflectance Product (MOD09A1) obtained during July 4 to 11, 2010 with a spatial resolution as 500 m [13-15]. The study area and the satellite image are shown in Fig.1.



Fig.1. Location of the experimental area in Labudalin, Inner Mongolia, China.

B. Crop Growth Indicators

To comprehensively and quantitatively describing crop growth condition both considering the crop morphology structure and biological activity, we constructed two new crop growth indicators, i.e. Crop Growth Monitoring Index 1 (CGMI1), and Crop Growth Monitoring Index 2 (CGMI2), based on LAI and CCD, which shown in (1) and (2). Compared with the existed crop growth indicators, these two new growth indicators could provide a much more comprehensive description of the characteristics of crop growth status from the aspects of crop structure and biochemical conditions.

$$CGMI1=LAI\times CCD$$
(1)

C. Crop Growth Grading Method

To achieve the space consistency of crop growth monitoring, we constructed a new crop growth grading system based on multiple spatial resolution satellite images. Firstly, we proposed a spatial adaptive threshold selection method by integrating with data histogram and Gaussian distribution theory for thresholds selection based on the statistical analysis of CGMI1 and CGMI2, then to strengthen robustness of threshold selecting on multi-scale. Moreover, we carried out researches on crop growth monitoring and ranking based on the selected thresholds of CGMI1 and CGMI2 from the aspects of crop canopy morphology structure (large, medium, and small) and crop canopy biological activity (strong, middle, and weak). The crop growth grades are shown in Fig.2.



Fig.2. Crop growth grades.

III. ANALYSIS AND RESULTS

The new proposed crop growth indicators and crop growth grading system were tested using multi-scale images, i.e. ALOS, HJ and MODIS. Firstly, calculated the CGMI1 and CGMI2 based on multiple images, in which LAI was estimated with statistical model based on Beer-Lambert Law [16]. And then, the statistics, i.e. average, standard deviation, variance, histogram and thresholds of LAI, CCD, CGMI1 and CGMI2 are calculated and listed in Table I. The thresholds are setting as μ - $\sigma/2$, μ + $\sigma/2$, and μ + $3\times\sigma/2$, while μ is the average value and σ is the standard deviation.

Based on the new proposed crop growth grading system, the crop growth condition is shown in Fig.3. In the figure, we could found that, for CG1, the crop growth monitoring results based on ALOS and HJ are similar, while for MODIS there was difference due to the mixed pixels. The area of CG2 is larger according to the larger spatial resolution of satellite images, because of there are many CG5 around CG2, and CG5 merged with CG2 according to the bigger of spatial scale. In all, CG2 has better space consistency among different spatial scales. In all, our new proposed crop growth grading system are stable and robust.

TABLE I.	TABLE I STATISTICS OF CROP GROWTH INDICATORS BASED
	ON MULTI-SCALE IMAGES

Statistics	ALOS-AVNIR2			
	LAI	CCD	CGMI1	CGMI2
Average	2.2849	5.8276	15.7795	2.4077
Standard deviation	0.7833	3.2521	16.0659	0.3949
Variance	0.6136	10.5762	258.1122	0.1559
Histogram				
Threshold	1.8933 2.6766 3.4599	4.2015 7.4536 10.7057	7.7466 23.8125 39.8783	2.2103 2.6052 3.0001

Statistics	HJ 1A-CCD2			
	LAI	CCD	CGMI1	CGMI2
Average	2.8378	7.9762	25.6462	2.6944
Standard deviation	0.8025	3.9522	21.0829	0.5238
Variance	0.6440	15.6201	444.4907	0.2743
Histogram				
Threshold	2.4365 3.2390 4.0415	6.0001 9.9523 13.9045	15.1047 36.1877 57.2706	2.4325 2.9562 3.4800

Statistics	MOD09A1			
	LAI	CCD	CGMI1	CGMI2
Average	2.6551	6.9548	20.1479	2.5470
Standard deviation	0.6561	2.6532	12.6855	0.3275
Variance	0.4304	7.0396	160.9227	0.1073
Histogram				
Threshold	2.3270 2.9831 3.6392	5.6281 8.2814 10.9346	13.8051 26.4907 39.1762	2.3832 2.7107 3.0382

IV. CONCLUSION AND DISCUSSION

Considering the application needs of crop growth monitoring with multi-scale datasets. We proposed new crop growth indicators CGMI1 and CGMI2 based on LAI and CCD to both consider the crop morphology structure and biological activity. And the new growth grading rules provide a spatial adaptive threshold selection algorithm to keep the space consistency when mapping different crop growth grading. Theoretical analysis and numerical experiments fully confirmed the new system, not only effectively enhance the



ALOS: 10m





Fig.3. Crop growth monitoring based on multi-scale images.

crop growth evaluation, but also revealing better results on the space consistency with multi-scale data compared with the currently existing threshold methods. However, in the future, we should find better index to change CCD as the parameter to characterize biological activity of crop canopies.

ACKNOWLEDGMENT

This study was supported by National Key R&D Program of China (2017YFE0122400), National Natural Science Foundation of China (42071423, 42071320), Beijing Nova Program of Science and Technology (Z191100001119089), and the Youth Innovation Promotion Association CAS (2017085).

REFERENCES

- Z. P. Fu, J. Jiang, Y. Gao, B. Krienke, M. Wang, K. T. Zhong, Q. Cao, Y. C. Tian, Y. Zhu, W. X. Cao, and X. J. Liu, "Wheat growth monitoring and yield estimation based on multi-rotor unmanned aerial vehicle," Remote Sens., 2020, 508.
- [2] S. H. Shukla, and M. H. Kalubarme, "Winter crop growth monitoring using multi-temporal NDVI profiles in Kapadvanj Taluka, Gujarat State," Int. J. Environ. & Geoinf., 2021, pp. 33-38.
- [3] H. Z. Pan, and Z. X. Chen, "Crop Growth Modeling and Yield Forecasting," Agro-geoinformatics: Theory and Practice, 2021, 205.
- [4] Z. H. Wang, A. K. Skidmore, R. Darvishzadeh, and T. J. Wang, "Mapping forest canopy nitrogen content by inversion of coupled leafcanopy radiative transfer models from airborne hyperspectral imagery," Agric. For. Meteorol., 2018, pp. 247-260.
- [5] A. Verger, I. Filella., F. Baret, and J. Peñuelasab, "Vegetation baseline phenology from kilometric global LAI satellite products," Remote Sens. Environ., 2016, pp.1-14.

- [6] S. Jay, N. Gorretta, J. Morel, F. Maupas, R. Bendoula, G. Rabatel, D. Dutartre, A. Comar, and F. Baret, "Estimating leaf chlorophyll content in sugar beet canopies using millimeter- to centimeter-scale reflectance imagery," Remote Sens. Environ., 2017, pp. 173-186.
- [7] R. Gebbers, D. Ehlert, and R. Adamek, "Rapid mapping of the leaf area index in agricultural crops," Agron. J., 2011, pp. 1532-1541.
- [8] F. Baret, and G. Guyot, "Potentials and limits of vegetation indices for LAI and APAR assessment," Remote Sens. Environ., 1991, pp. 161-173.
- [9] C. C. Li, H. J. Li, J.Z. Li, Y. P. Lei, C. Q. Li, K. Manevski, and Y. J. Shen, "Using NDVI percentiles to monitor real-time crop growth," Comput. Electron. Agric., 2019, pp. 357-363.
- [10] S. Kokhan, and A. Vostokov, "Using vegetative indices to quantify agricultural crop characteristics," J. Ecol. Eng., 2020, pp. 120-127.
- [11] Y. Y. Shi, Y. Zhu, X. C. Wang, X. Sun, Y. F. Ding, W. X. Cao, and Z. C. Hu, "Progress and development on biological information of crop phenotype research applied to real-time variable-rate fertilization," Plant methods, 2020, 11.
- [12] W. R. Raun, J. B. Solie, K. L. Martin, K. W. Freeman, M. L. Stone, G. V. Johnson, and R. W. Mullen, "Growth stage, development, and apatial variability in corn evaluated using optical sensor readings," J. Plant Nutr., 2005, pp. 173-182.
- [13] S. Saunier, P. Goryl, G. Chander, R. Santer, M. Bouvet, B. Collet, A. Mambimba, and S. K. Aksakal, "Radiometric, geometric, and image quality assessment of ALOS AVNIR-2 and PRISM sensors," IEEE Trans. Geosci. Remote Sens., 2010, pp. 3855-3866.
- [14] Q. Wang, C. Q. Wu, Q. Li, and J. S. Li, "Chinese HJ-1A/B satellites and data characteristics," Sci. China Earth Sci., 2010, pp. 51-57.
- [15] Q. J. Du, G. H. Yi, X. B. Zhou, T. B. Zhang, J. J. Li, H. J. Xie, and J. Hu, "Analysis of asymmetry in diurnal warming and its impact on vegetation phenology in the Qinghai-Tibetan Plateau using MODIS remote sensing data," J. Appl. Remote. Sens., 2021, pp. 028502.
- [16] J. M. Chen, and T. A. Black, "Defining leaf area index for non-flat leaves," Plant Cell Environ., 1992, pp. 421-429.