THE INTERNATIONAL SOCIETY OF PRECISION AGRICULTURE PRESENTS THE
13th INTERNATIONAL CONFERENCE ON
PRECISION AGRICULTURE
July 31-August 4, 2016 • St. Louis, Missouri USA

Remote sensing inversion of canopy chlorophyll content and its application in evaluating crop condition and predicting crop mature date

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A paper from the Proceedings of the
13th International Conference on Precision Agriculture
July 31 – August 4, 2016
St. Louis, Missouri, USA

Abstract. *Chlorophyll is one of the most significant biochemical parameters for evaluating crop status. It can be used as an index of photosynthetic potential as well as crop productivity. Crop chlorophyll content has been widely used in identifying crop growth condition, physiological status and health. Crop growth condition monitoring and prediction of crop optimal harvest date are both important to the crop final yield. Crop growth monitoring help farmer take measures in time when the crop is suffering from insect pest, plant diseases or meteorological stress. And yield loss occurs if harvest is implemented either in too earlier or delayed time, both of which are undesirable. In this paper, based on the inversion of crop chlorophyll content, we tested the application of crop chlorophyll content in crop growth monitoring and prediction of crop optimal harvest date, proposing new methods. In crop growth monitoring, we took both the individual and group crop condition into consideration, explored different monitoring indexes of them, including crop chlorophyll content and leaf area index. Then the comprehensive assessment of crop growth condition could be implemented by combining these two indices. In crop optimal harvest date prediction, leaf and stem water content decreasing as crop reached maturity, the color of leaves gradually turning to yellow, a decrease occurs in crop chlorophyll content. Optimal harvest date was predicted by analyzing the change of crop chlorophyll content with temporal variation of harvest yield. Different crop has different characteristics and we used different methods to predict soybean and corn optimal harvest date. The prediction result has been validated to be reliable. The abstract is often the only part of the paper to be read, so include your major findings in a useful and concise manner. Include a problem statement, objectives, brief methods, quantitative results, and the significance of your findings.*

Keywords. *remote sensing; crop chlorophyll content; crop condition monitoring; prediction of optimal harvest date*

Introduction

Agricultural remote sensing has been an important application of earth science. Remote sensing has been applied in precision agriculture since 1970s and has been increased in interest in recent years(Jones and Vaughan, (2010)). The biochemical parameters derived from satellite images has been widely used for many years. Chlorophyll content and LAI are two important indexes in agricultural remote sensing area. The chlorophyll content and LAI could help identify crop status. Both of them can be estimated with many methods including empirical model and physical model(Chunyan et al., 2009; Delegido et al., 2010; Fei et al., 2010; Hasegawa et al., 2010; Jacquemoud et al., 2009; Jie et al., 2009). Empirical model has obvious advantage is its simple rule and calculation. But its robustness is weak. And physical model improves stability with radiative transfer method although with more complexity. So these two models both have each own superiority.

Based on the estimation of chlorophyll content and LAI, these two parameters were applied for crop condition monitoring and prediction of crop optimal harvest date. Real-time monitoring crop condition is beneficial to crop growth because the farm managers could take measures timely according to the monitoring result. Predicting optimal harvest date could reduce unnecessary yield losses as much as possible. So monitoring crop condition during crop growing season and predicting optimal harvest date when approaching the mature date could improve and maximize the final yield. Traditionally, farmers often made these agricultural decisions on the basis of field tour and limited number of sample measurements(Jones and Vaughan, 2010). Thus it is difficult and not practical to acquire the comprehensive information by ground-collecting data because of the large acreage.

In this paper, new methods of monitoring crop condition and predicting optimal harvest date were put forward. In this study, we chose several typical vegetation index to represent chlorophyll and water content and LAI, PROSAIL as the physical model to estimate chlorophyll content. On the basis of the estimation of chlorophyll and LAI respectively as individual and group condition indicators, a more reasonable method was proposed to comprehensively access crop condition. Second, using vegetation indexes and canopy chlorophyll content and water content with different models to predict the optimal harvest date of soybean and corn. And the researches indicated that these new methods could meet the requirement of agricultural management optimization.

Materials and methods

Study area

The study area is Hongxing farm, an experimental station for precision agriculture, with an average area of 53.3 hectares. This farm is located in northern Heilongjiang province, Northeast China (48°09′ N, 127°01′ E). The major crops are soybean, corn and spring wheat. The growing season of soybean and corn are respectively from beginning of May to mid-September and October. In this study, we chose soybean plot in 2011 and corn plot in 2014 as experimental data. In 2011, the proportion of soybean planting area was 41%. And in 2014, the proportion of corn planting area was 51%.

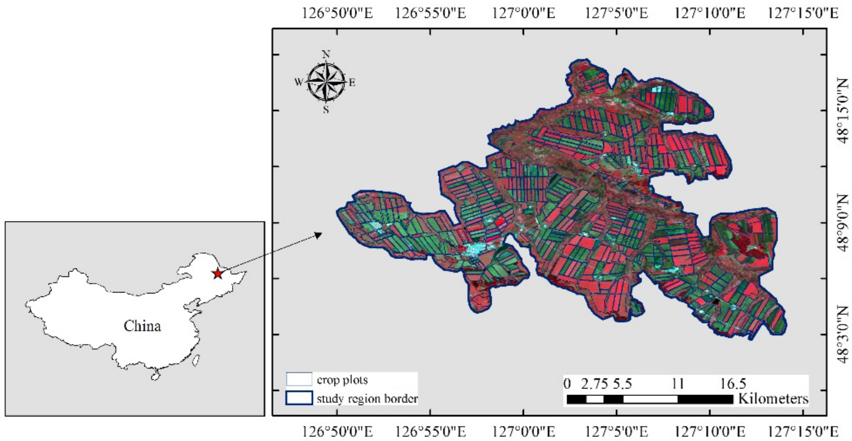


Figure 1. Study area (Hongxing Farm) in view using HJ-1 CCD images

Field observation campaign

The field campaigns were carried out during the maturing stage of soybean from September 11 to October 2 2011 and during the whole growing season from June to October, 2014. In total, 41 soybean sites were selected in 2011 and 40(27+13) corn sites were selected in 2014. And experimental sites were located in relatively homogeneous areas bigger than 200m×200m.

The soybean yield was sampled by measuring the production of 10 plants in each site at a frequency of 3 days between September 11 and October 2, 2011. Each of these 10 sampled plants was randomly selected on alternate rows of all 20 rows. In total, 8 yield observations were acquired from harvest at different stages of maturity. In 2014, chlorophyll content and LAI of 9 corn plots, 27 corn experimental sites were selected. In total, 54 group experimental data of chlorophyll content and LAI were acquired on July 14 and September 7, 2014. And thirteen more corn sample plots were selected during the maturing stage for validation of predicting corn optimal harvest date.

Acquisition of chlorophyll content, LAI, corn kernel moisture

A simple method for acquiring the chlorophyll content is use of the new handheld Field Scout CM1000 Chlorophyll Meter (Spectrum technologies, Plain-field, 1L). LAI was acquired by using WinScanopy (Regent Instruments Inc., Quebec, Canada), which is a canopy analysis system based on colored hemispherical images. WinScanopy is a widely used software designed for canopy hemispherical or rectangular image analysis. The moisture of corn kernel was determined by using LDS-1G Grain Moisture Meter and the measurement of the instrument is ±0.5% with measurement range from 3% to 35%. The geo-coordinates of each site were read from Trimble GPS (GeoExplorer 3000) with a spatial accuracy of >1 m.

Remote sensing data processing

The HJ-1 constellation system, which belongs to Environment and Disaster Observing Satellite System of China, consists of two small optical remote sensing satellites (HJ-1A and HJ-1B) and a microwave satellite (HJ-1C satellite). The satellites were planned for use in monitoring environment and natural disasters. HJ-1A/B satellites were launched successfully in September 2008. The onboard imaging systems and infrared cameras provide a global scan every two days. HJ-1 satellites combine two identical CCD cameras that observe a broad coverage of 360 km with a high spatial resolution of 30 m. The CCD cameras have four visible and near-infrared bands, which include B1 (0.43-0.52 mm), B2 (0.52-0.60 mm), B3 (0.63-0.69 mm), and B4 (0.76-0.90 mm). IRS (Infrared Spectro-radiometer) onboard HJ-1B has four bands ranging from near-infrared to thermal infrared, including B1 (0.75-1.10 mm), B2 (1.55-1.75 mm), B3 (3.50-3.90 mm), and B4 (10.5-12.5 mm). The spatial resolution of HJ-1 IRS is 150 m. Both CCD and IRS images are used in this research. Radiometric corrections were implemented using coefficients associated with the image file (gains and offsets). Then MOTRAN 4 model, which is embedded in the ENVI/FLAASH module, was applied for atmosphere correction. The input parameters were set based on the location, sensor type and ground weather conditions observed on the day the image was acquired. Then, the surface reflectance of the HJ-1 image was derived. Accurate geometric correction was done with ground control points derived from 1:50000 topographic maps. A final geo-correction error of less than 0.5 pixel was achieved.

Chlorophyll content and LAI estimation

In this study, PROSAIL physical model and vegetation index were respectively used for estimating chlorophyll content and LAI. Physical model based on stable physical mechanism is found to be a robust model that does not easily change with temporal and spatial variation. In consideration of complexity of PROSAIL model, a global sensitive study was conducted and according to the sensitive index, effective parameters were selected and look-up table method was used to retrieve chlorophyll content. Vegetation index has an advantage of revealing canopy variation. And previous researches also have indicated that vegetation index could estimate LAI with a high accuracy. Accordingly, we chose NDVI, EVI and OSAVI, three vegetation indexes to evaluate LAI.

Crop condition accessment

During the whole growing season, crop condition monitoring method was discussed below. The theoretical basis is the establishment of two-dimensional graph.

Two-Dimensional graph

The new method of monitoring crop condition was based on the two-dimensional graph (Figure 2). First, we divided each indicator into five grades. From A to E grade, each crop condition indicator was ranked in descending order. This research took both crop individual and group characteristics into consideration and a rule was made. If both of these two indicators belong to A-Grade, then the comprehensive grade is A. But if one indicator is graded as A and another is graded as E, then according to two-dimensional graph, the final grade is D. And other types of combination could be figured out in Figure 2. This method integrating chlorophyll content and LAI, two indicators, makes the final results more reasonable.

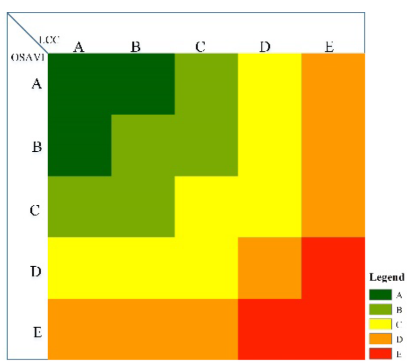


Figure 2. Two-Dimensional graph

Prediction of optimal harvest date of soybean

When soybean is at the stage of near maturation, there are obvious rapid changes in color (de-greening) and water content (dewatering) of soybean plant. Thus 7 widely used remote sensing indices – 6 vegetation indexes and NDWI (normalized difference water index) were selected to test correlation with soybean OHD (optimal harvest date).

The equations used to compute the above-mentioned indices are listed below.

$$NDVI = (R_{NIR} – R_{R}) / (R_{NIR} + R_{R}) \quad (1)$$

$$SAVI = (R_{NIR} – R_{R})(1+0.5)/(R_{NIR} + R_{R} + 0.5) \quad (2)$$

$$EVI = (R_{NIR} – R_{R})/ (R_{NIR} + 6R_{R} -7.5R_{B} +1) \quad (3)$$

$$GNDVI = (R_{NIR} – R_{G}) / (R_{NIR} + R_{G}) \quad (4)$$

$$VARI = (R_{G} – R_{R}) / (R_{G} + R_{R} – R_{B}) \quad (5)$$

$$CVI = (R_{NIR} /R_{G})*(R_{R} / R_{G}) \quad (6)$$

$$NDWI = (R_{NIR} – R_{SWIR}) / (R_{NIR} + R_{SWIR}) \quad (7)$$

The 7 spectral indices used in this study can be grouped in 3 categories based on their initial sensitivity to green biomass (NDVI, SAVI, EVI, VARI), leaf chlorophyll (GNDVI, CVI) and vegetation liquid water content (NDWI).

Prediction of optimal harvest date of corn

Monitoring Methodology of corn OHD

The monitoring methodology of corn OHD is based on the estimation of CKM(corn kernel moisture). According to the variation in CCC (canopy chlorophyll content) and CKM, the relationship between CCC and CKM was established. Based on 9 modeled plots and 27 data groups, CCC was retrieved using the look-up table method. Subsequently, owing to the change trend of the CKM, the logarithmic model was selected between CCC and CKM.

Predicting Methodology of corn OHD

One hundred-grain weight and yield is the foundation of the methodology of predicting CKM. The results indicated that linear relationship could be built between the delay in harvesting and average value of CKM. This study made use of the measured CKM of early periods to establish the linear model, and used this model to predict the OHD.

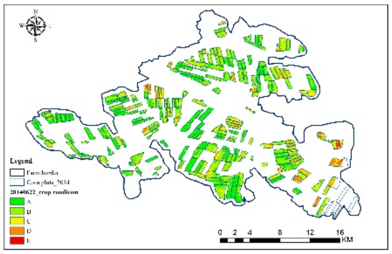
Results and discussion

Chlorophyll content and LAI estimation

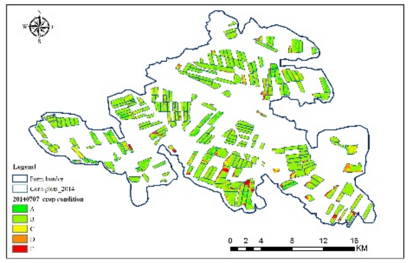
Based on PROSAIL model, using LUT method to retrieve LCC and CCC, the validation results showed that R^2 of 0.82 and 0.51 were reached. Among 3 vegetation indexes-- NDVI, EVI, OSAVI we selected in this study, OSAVI showed better performance. Therefore we chose OSAVI as the indicator to represent LAI. Both of the estimation accuracy of chlorophyll content and LAI indicated that the results could meet the agricultural application requirement and could be applied into crop condition monitoring and prediction of optimal harvest date.

Crop condition assessment

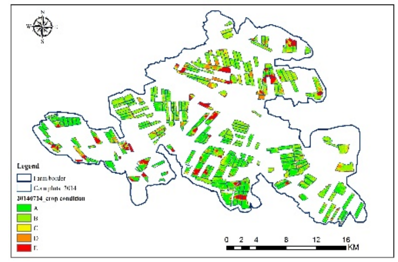
LCC and OSAVI were used as individual and group index for real-time monitoring crop condition. We selected 7 high quality satellite images of 2014 and estimated the LCC and LAI. Then each indicator was divided into 5 grades based on specific nodes of every growing stage. And the nodes were ruled by the historical and empirical data of 2010-2013. According to the established two-dimensional graph, the final grade of corn was showed in Figure 3. The results showed that most corn plots were graded as A and a little part were graded as C. The results were consistent with the actual crop condition of Hongxing farm. In addition, 2 images of July showed that there were parts of plots that graded as E because the satellite images of those plots were covered by clouds and the values were null.



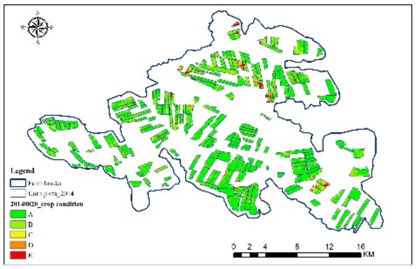
June, 22



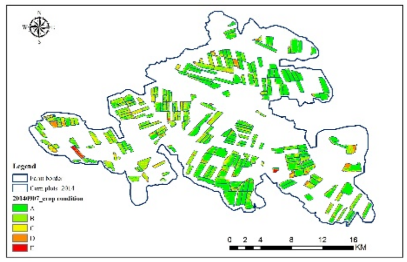
July, 7



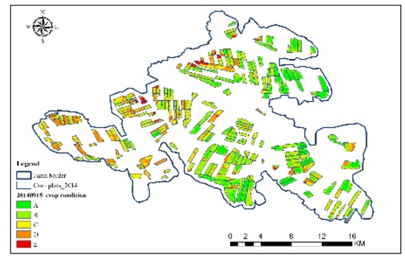
July, 14



Aug, 20



Sep, 7



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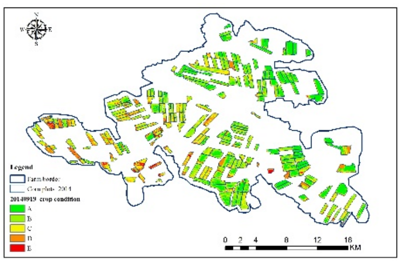

Sep, 19

Figure 3. List of corn growth condition

Prediction of soybean harvest date

Among the 7 vegetation indices, most indices showed the highest correlation coefficient with OHD (optimal harvest date) at August 29, thus indices on that day were selected to develop the OHD prediction model through stepwise regression analysis. Data on 30 sites were used for model development. Through the analysis, three indicators were selected to build the prediction model, which are NDWI, EVI and NDVI. The model is presented in the following formula:

$$OHDpre=22.51+88.50*EVI+23.08*NDWI-48.19*NDVI \quad (8)$$

Where OHDpre is the predicted optimal harvest date, EVI, NDWI and NDVI are images acquired on August 29. And R^2 of 0.753 was reached. The predicted soybean map was showed in Figure 4.

The predicted OHD of soybean in Hongxing Farm in 2011 varied from September 14 to September 25. Distinct differences in OHD were observed between different fields, the difference could be as much as a week even for neighboring fields (see areas labeled with black circles). Usually the within-field OHD variation was less than 3-4 days. For those exceptional fields that have distinct within-field variations (labeled with blue circles), the primary cause was topographic variation which caused inhomogeneity of available sunlight and water resources.

The south area of the farm tends to have an earlier OHD (more red fields in south area), while the north area shows a later OHD (labeled by more blue and cyan colors). This is primarily because it is forested mountain to the north of Hongxing Farm, and the difference in distance of fields to forested areas tends to induce thermal variations between fields. The cooling effect of forest will result in relatively low air temperature to nearby fields, which leads to a later maturity for those fields.

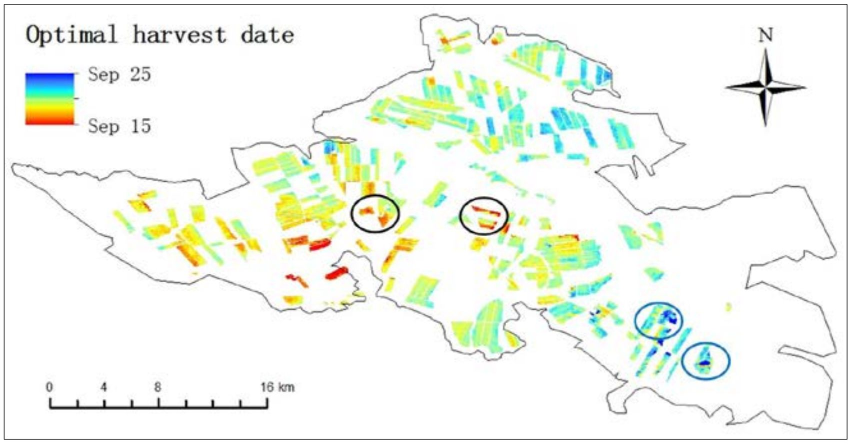

Figure 4. Predicted soybean OHD map for Hongxing Farm, 2011 (non-soybeans are masked)

Prediction of corn harvest date

By using 9 modeled plots, in total 27 data groups of September 30, based on the estimated CCC and measured CKM, with Origin Software to conduct the nonlinear regression analysis, the nonlinear exponential function estimation model was established. And the corn CKM were showed in Figure 5. And if the CKM value was less than 30%, it is indicated that this plot has reached the optimal harvest date and highest yield. From the 2 images results, we could discover that the CKM on October 4 was less than that on September 30.

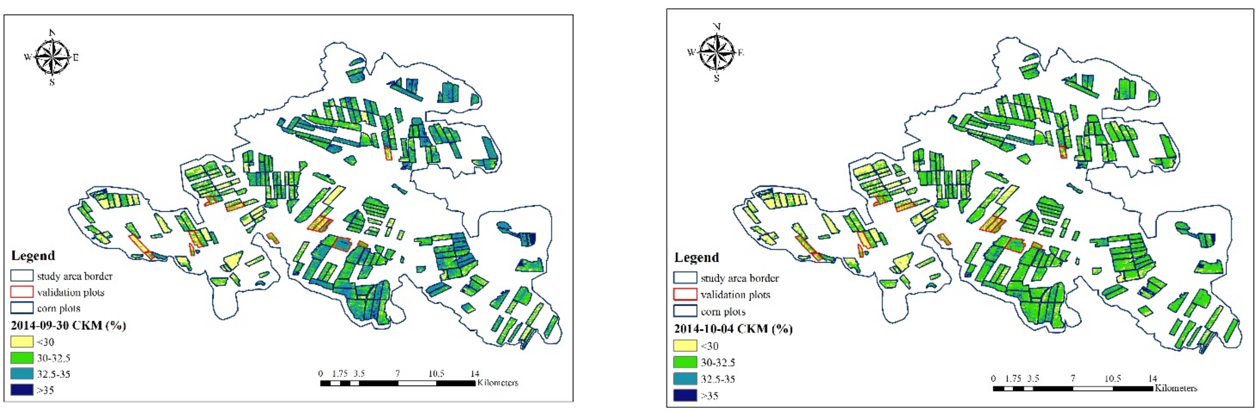

Figure 5. Map of estimated CKM of 2 images

Historical data showed that CKM displayed a linear declining trend and yield displayed a linear increasing trend with temporal variation. Based on the images obtained on September 30 and October 4, and the relationship between the delay in harvesting and average corn kernel moisture, according to the average kernel moisture content of 13 validation plots, a linear relationship was built to predict the kernel moisture on October 13. By using the early kernel moisture of 13 validation plots, the prediction model was established. According to the calculated results, OHD of almost all plots was around October 1 to 10. These results are consistent with those obtained using agronomical methods.

Conclusion or Summary

Using remote sensing technology to monitor crop condition and predict crop harvest date could help increase the yield. And the final goal of every research about them is to improve the yield and the quality. During the crop growing season, based on this more comprehensive method, farmers would be kept well informed of crop condition. Once the disaster happens, measures could be taken as soon as possible. This is more important than estimating the final yield, because the better crop condition is, the higher yield will be reached. And optimal harvest date provides the scientific method for arranging reapers to ensure that every plot could reach its max yield. On the basis of these researches, more experiments need to be conducted for further application and validation. And the accuracy of these models still have potential to be improved.

Acknowledgements

This work was funded by STS (Science and Technology Service Network Initiative) Program of Chinese Academy of Sciences(KFJ-EW-STS-069), the National Natural Science Foundation of China (41171331, 41010118), the 863 Program of China (2013AA12A302, 2012AA12A307).

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