Near-real-time Remote Sensing and Yield Monitoring of Biomass Crops

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Abstract

The demand for bioenergy crops production has increased tremendously by the biofuel industry for substitution of traditional fuels due to the economic availability and environmental benefits. Pre-Harvest monitoring of biomass production is necessary to develop optimized instrumentation and data processing systems for crop growth, health and stress monitoring; and to develop algorithms for field operation scheduling. To cope with the problems of missing critical timing of field crop conditions in the traditional remote sensing process (e.g., satellite or aerial imaging systems), an experimental near-real-time remote sensing platform with high spectral resolution, spatial resolution and temporal resolution was proposed, designed and developed for a biomass production field pre-harvesting crop monitoring. The crop monitoring system can scan the crop field within 15 minutes. 91 images are captured daily to cover a 35-acre crop field. The multi-spectral imaginary of a bioenergy crop with spatial resolution of 100 mm/pixel was automatically collected and an intelligent control algorithm, e.g., camera movement such as zoom, focus and robust real-time multi-spectral camera parameters adjustment such as gain and exposure time under varying natural lighting conditions in the field, were developed to automatically capture high quality daily images through the growing season. The Normalized Difference Vegetation Index (NDVI) was calculated for understanding of the temporal vegetation response variations in the crop growth cycle over the growing seasons after imaginary geometrical corrections and geo-referencing. Special algorithms were developed to compile the high-resolution images to form an entire field crop index map. The image processing results from the proposed near-real-time remote sensing system were then compared to the biomass yield data in this paper. With the crop index map as a field condition-monitoring tool, the accurately geo-referenced biomass yield data points (1m x 1m) were generated through manually harvested, dried and weighed Miscanthus plants during the growing season.
A novel "daily canopy reflectance accumulation" algorithm was developed to match the field yield data. To increase data processing accuracy, both GPS readings and (manually identified) image patterns were used to locate the manually harvested data points. Preliminary analysis results show that the crop monitoring system can generate a high-resolution yield map that can explain

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84.96% of the daily (distributed) biomass gain during the growing season. Moreover, the in-field growth variation and the plant growth pattern of the Miscanthus were derived and recognized. The biomass yield was predicted during an earlier growing season and provided decision support for the optimum harvest scheduling and site-specific crop management for the biofuel industry.

KEYWORDS : Remote sensing, Precision agriculture (PA), Site-specific crop management (SSCM), multi-spectral imaging, growth condition monitoring, Normalized Difference Vegetation Index (NDVI), ground reference data, yield prediction, harvest schedule

INTRODUCTION

As concerns over energy security and environmental degradation have increased, ensuring sustainable biomass and biofuel production has become a critical concern. “Biomass feedstock production (BFP) is a critical subsystem within the overall bio-based energy production and utilization system. It provides the necessary materials input to the conversion process of biomass into fuel, power and value-added materials. This subsystem includes the operations of agronomic production of energy crops and physical handling/delivery of the biomass, as well as other enabling logistics” (Ting et al. 2008). Pre-Harvest monitoring of biomass production is necessary to develop optimized instrumentation and data processing systems for crop growth, health and stress monitoring; and to develop algorithms for field operation scheduling (Li et al. 2014). Remote sensing technology has been recognized as the key technology to enable site-specific management of crop production for crops like corn and soybeans. The same methodology has the potential of being applied to the biomass feedstock production to monitor the growth conditions and maximize the efficiency of biomass feedstock production.

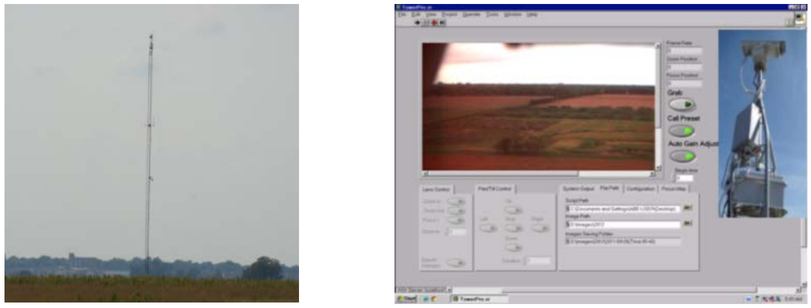
The agronomic production depends on tracking the yield variability over the growing season and utilizing the optimum-harvesting window to meet quantity and quality targets. The measurement of yield variability of biomass is needed for developing and evaluating site-specific crop management practices. In different growth stages, field spectroscopy has the fundamental importance for assessing spectral response of plant canopies and photosynthetically active radiation for biomass conversion. Traditional remote sensing technology (e.g., satellite or aerial imaging systems) has the limitations of missing the critical timing of field crop conditions. Site-specific near-real-time remote sensing systems are desirable and convenient to perform site-specific monitoring of bio-energy crops and data collection. Field spectroscopy involves the study of interrelationships between the spectral characteristics of objects and their biophysical attributes in the field environment (Milton, 1987). The multispectral imagery refers to images that capture data at specific wavelengths across the electromagnetic spectrum. The relationships between crop reflectance in the visible and near infrared wavelengths are closely correlated with the amount of photosynthetically active tissue in the crop (Baret and Guyot, 1991). Currently, both hyper-spectral and multi-spectral images are used for agricultural remote sensing to identify crop stress (JØrgensena et al., 2003, Yao and Tian, 2004, Bajwa and Tian, 2001, Yang et al. 2004). The most widely accepted method for describing vegetative growth using reflectance spectra is band ratios or vegetation index. Vegetation index is spectrally-based values generated through the mathematical manipulation of reflectance measurements from two or more spectral wavelengths (Xiang and Tian, 2007). The vegetation index is used to quantify the concentrations of green leaf vegetation (Thorp and Tian, 2004). Linear combinations from two or more wavebands may be too sensitive and robust to assess the crop status than a single band (Lyon et al., 1998). The Normalized Difference Vegetation Index (NDVI) is the most commonly used vegetation index and usually the annual maximum NDVI is chosen as a proxy of vegetation productivity (Bausch and Duke, 1996). One of the potential biomass crops is Miscanthus, which is a high yielding, perennial crop with good resistance against disease, cold and drought. To ensure proper growth of Miscanthus, it is essential to know the plant timing, physical parameters, and soil environment. It is important to monitor and observe these parameters over the growing season. The traditional field data acquisition methods are limited by the vehicle ground clearance and complicated traffic condition during the growing season.

An experimental near-real-time remote sensing tower platform with high spectral and temporal resolution was developed for a biomass production field pre-harvesting crop monitoring. The multi-spectral imagery of the bioenergy crop with spatial resolution of 100 mm/pixel was automatically collected and processed. A novel "daily canopy reflectance accumulation" algorithm was developed to match the field yield data. The accumulated NDVI value was tested for continuous monitoring of biomass yield. The data was collected over the entire growing season to capture the temporal vegetation response variations in the crop growth cycle. Special algorithms were developed to compile the high-resolution images to form an entire field map. The image processing results from the proposed near-real-time remote sensing system were then compared with manually harvested biomass yield data. A yield prediction model was established based on the accumulated NDVI. Therefore, the in-field growth variation and the plant growth pattern of the Miscanthus were derived and recognized. The biomass yield was predicted during an earlier growing season to provide decision support information for the optimum harvest scheduling and site-specific crop management.

MATERIALS AND METHOD

Near-real-time remote sensing platform

The stand-alone tower remote sensing system was proposed to monitor the bioenergy crop for the first time (Ting et al., 2008, Li et al., 2014, Ahamed et al. 2011, 2012, 2010). The system consists of a motorized high-resolution multi-spectral camera MS4100 3-CCD (Geospatial, NY) which was erected in the center of a field on the Energy Farm of the University of Illinois at Urbana-



(a) Tower remote sensing system (b) Tower camera control interface

Fig. 1 Near-real-time remote sensing system for site-specific monitoring of biomass energy crop

Champaign, Urbana, IL, USA (Ahamed et al. 2011) and is shown in Fig. 1 (a). The tower camera system is able to capture a RGB visible and color-infrared image plane of four spectral bands including red (550-700 nm bandwidth), green (450-580 nm bandwidth), blue (400-470 nm bandwidth), and NIR (650-800nm bandwidth) at the same time. As indicated in Fig. 1 (b), the algorithm is able to control the pan/tilt device to rotate on horizontal and vertical axis to capture the images according to the plot distributions. The camera sensor and multi-spectral imaging system was developed to capture images from the 125 feet (38-meter high tower for Miscanthus, switchgrass, prairie grass, and corn. The average plot size was 35 acre. The spatial resolution of the images is between 20-100 mm.

Tower remote sensing principle and methodology

As indicated in Fig. 2, an automatic image capture and preprocessing system was proposed to perform near-real-time remote sensing and multi-spectral imaging of the biomass energy crop; the system will boot up at predetermined times to launch the LabVIEW program, which performs the image capturing tasks: system startup, camera startup, pan/tilt system, automatic camera adjustments, and call 91 presets to capture the image. The Matlab program will be immediately run to process the daily image after the images are captured and transferred to the server. The presets according to the field distributions were established using the caller identifications and automatic rotations of the developed pan/tilt device. The lens motorization was developed externally and used two motors to control zoom and focus. The gain of the camera ranged from 0 dB to 36 dB corresponding to 95 to 1023 in 16-bit digital number representation, respectively, and 928 steps in total. The gain is automatically adjusted with an intelligent control algorithm based on the calibration model with a 25% reflectivity calibration panel and 4 Channel light reflectance sensor SKR 1850 (Skye Instruments, Wales, North England) experiment. The maximum frame rate of the camera was 10 frames per second.

The tower-based system captures near-real-time RGB and CIR images of four fields growing four different crops, namely, Miscanthus, switchgrass, mixed prairie, and corn. The layout of the field is depicted in Fig. 3(a). A LabVIEW-based real time algorithm was developed to capture images from the field over the growing season. Initially, 91 preset positions were set to cover each of the fields as indicated in Fig. 3(b). The 50 mm fixed focal length was chosen to capture the images. The NIR, red and green channel were averaged in the image acquisition process. The tower coordinates and the ground reference points were surveyed using an RTK GPS unit. The stand-alone images for the reference points present the crop response and physiological changes. Four different ground reference points for Miscanthus were observed during the growing season and the yield and specific leaf area data was collected from early spring to winter during 2012. In order to accurately calculate the total sampled biomass field, the area of the quad, 75 cm by 75 cm was field sampled four times during June 20, July 11, July 31, and August 30 respectively during the entire season. The leaf, stem, and floral bunches were dried and weighed and added up to get the biomass yield in g/m^2.

However, data acquisition is difficult due to the lack of a high clearance vehicle operating as the on-the-go sensing system for Miscanthus and other biomass feedstock. Furthermore, the pre-harvest monitoring systems need to be able to fulfill data collection in different traffic conditions with high maneuverability, stability and mobility for either high plants and short plants or different bio-energy crop plants in all growing seasons. The two-month-old stand of Miscanthus grows faster, the height of these plants is approximately 50 cm and the 3-year old stand of Miscanthus grows up to 3 meters high as indicated in Fig. 4. However, pre-harvest monitoring of biomass crops has not been widely done. This paper proposes to develop and complete optimized instrumentations for stand-alone remote sensing applications to monitor perennial growth of biomass feedstock, particularly Miscanthus over the growing season. And the reference points for Miscanthus (OM1, OM2, OM 3 and OM4) were remote sensing, field sampling, and correlation for biomass yield monitoring in this paper.

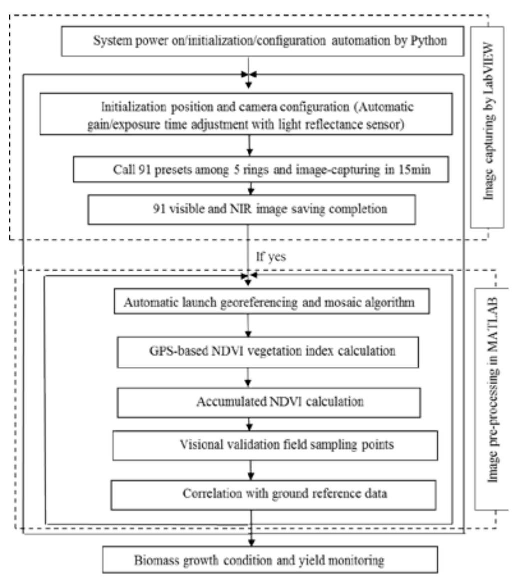
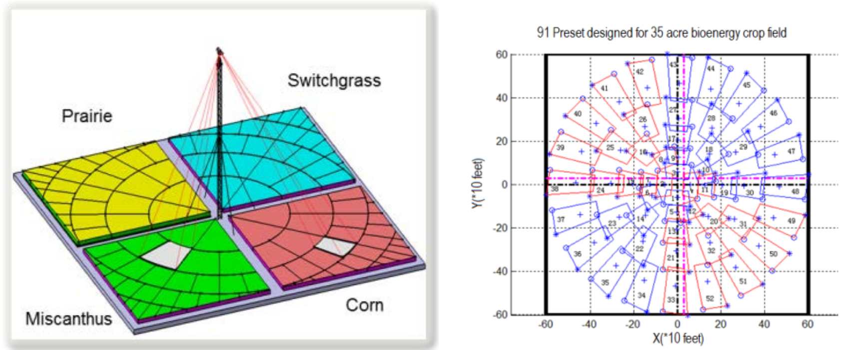


Fig. 2 Near-real-time remote sensing and image capture procedure



(a) Energy farm layout (b) 91 Preset pre-defined for 35 acre field

Fig. 3 Image acquisition scheme proposal for four plots at the energy farm, University of Illinois at Urbana-Champaign using tower-based multi-spectral camera

Fig. 4 Miscanthus growth height variation during different growing seasons

Field sampling and pin-pointing approach for remote sensing

The field biomass yield samples were manually harvested four times during the growing season with the GPS location recorded for further analysis and interpretation. The GPS location of the yield sample point is projected on the compiled field images (Fig. 5). The individual field image resolution is 3930 pixels by 3930 pixels. The entire field compiled image resolution will vary from 20 mm-100 mm with respect to five different rings around the center of the tower, the closer to the tower center, the higher resolution of the image.

In order to increase the accuracy of capturing the actual crop canopy growth conditions, the field sampling points were recorded and verified by manually processing the original raw images. The manually found data points were compared with the GPS projection in the compiled image and visual inspection. The goal is to verify the field sampling point by comparing the images before and after the field sampling so that the field sampling points can be pinpointed within the actual field sampling size around 1 m by 1 m. The pinpoint was exactly projected in the raw images as indicated in Fig. 6.

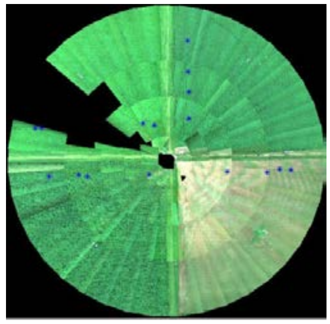


Fig. 5 Ideal projection of GPS field sampling on the mosaic mapping

Fig. 6 Pin-pointing field sampling combined manual tracing back raw image

Due to GPS error and the varying compiled image resolution, as well as the fluctuation of the pixels in the image caused by wind disturbance and the tower derrick vibration, three different resolutions were used for each field experiment, namely 1 m by 1 m, 2 m by 2 m (twice the actual field sampling area), and 3 m by 3 m (three times larger than the actual field sampling area) as indicated in Tab. 1. The biomass yield experiment was carried out using the original (individual) images to calculate the vegetation indices (VIs). With respect to the image resolution, the original image could represent the actual points better because of its higher resolution. With the crop index map as a field condition-monitoring tool, the accurately geo-referenced biomass yield data points (1 m × 1 m) were generated through manually harvested, dried and weighed Miscanthus plants during the growing season. The yield measurement consisted of the analysis of the weight and area of the stem, leaved, and floral bunches.

Tab. 1 Three resolution approaches for compilation and single image analysis

Resolution	Compilation	Original image	pixels
1 m by 1 m	20-100 mm per pixel	10 mm per pixel	100 by 100 pixels
2 m by 2 m	20-100 mm per pixel	10 mm per pixel	200 by 200 pixels
3 m by 3 m	20-100 mm per pixel	10 mm per pixel	300 by 300 pixels

NDVI and daily canopy reflectance accumulation algorithm

The live green plants absorb solar radiation in the photosynthetically active radiation (PAR) spectral region, which they use as a source of energy in the process of photosynthesis as indicated in Fig. 7(a). Leaf cells have also evolved to scatter solar radiation in the near-infrared spectral region (which carries approximately half of the total incoming solar energy). Researchers have noticed that an accurate yield can be calculated if the entire season PAR can be estimated. The process of plant growing can be related to absorbed PAR (aPAR) and harvest index (HI) (Sibley et al., 2014):

$$\textbf{Yield = aPAR x RUE x HI} \qquad (1)$$

Where, RUE is the radiation use efficiency inherent to the crop. Two key steps in this approach are to estimate the fraction of photosynthetically active radiation (PAR) absorbed by the canopy (fPAR) on a given day based on reflectance or VIs and to obtain enough fPAR estimates throughout the growing season to approximate the total season aPAR.

If the RUE can be accurately measured daily, then the total season aPAR can be calculated instead of being approximated. It is clear that RUE is closely related to the plant growth stage (matured leaves) that can be measured with a remote sensing system. Models have been used to simulate crop growth and yields for multiple combinations of factors such as sowing date, relative growth rate, or soil water holding capacity, and the simulated values of leaf area index (LAI) or fPAR for yield calculation (Clevers, 1997, Dente et al., 2007). With our high-resolution sensing system, we can measure crop growth conditions regularly and monitor the radiation use efficiency inherent to the crop. Once the daily fPAR of the plant was derived, the whole season aPAR would be an accumulative daily aPAR.

In precision agriculture, NDVI is a very useful application of spectral ratio between the visible and near infrared wavelength channel, which is widely used to predict crop leaf area index, crop growth and disease control, biomass productivity, economic yield, etc. (Robert, 1997) .This index relies on the spectral absorption and reflectance characteristics of living (i.e., green) vegetation in primarily the red and NIR wavelength bands. As illustrated in Fig. 7(b), NDVI is calculated as follows:

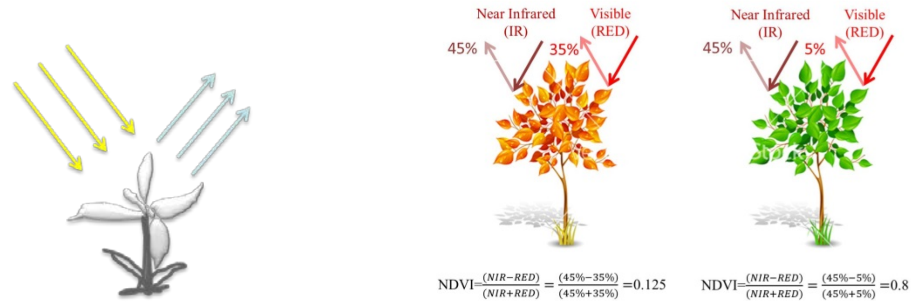
$$\mathbf{NDVI} = \frac{\boldsymbol{\rho(NIR)-\rho(R)}}{\boldsymbol{\rho(NIR)+\rho(R)}} \qquad (2)$$

Where, ρ(NIR)=brightness values (or digital number) of near infrared band, ρ(Red)=Brightness values (or digital number) of red band in a remote sensing dataset.

So we can calculate our yield using the following equation:

$$\mathbf{Y = a_0 P_i + b_0} \qquad (3)$$

Where, Y: Estimated yield (g/m^2), $\mathbf{P_i}$: Accumulated NDVI mean value; i=1-n, $\mathbf{b_0}$: Constant, related to the crop stage during the season from planting to harvesting.



(a) Plant photosynthesis process (b) NDVI conception for plant canopy vivo

Fig. 7 NDVI concept for vigor variations quantification

The accumulated NDVI P_i was the NDVI accumulated from the beginning till the date of biomass field sampled, which will be applied to correlate with the yield harvested as calculated as follows:

$$\mathbf{P_i} = \sum_{k=1}^{n} \boldsymbol{NDVI} \tag{4}$$

RESULTS AND DISCUSSION

The near-real-time remote sensing data from the stand-alone tower remote sensing system are collected, processed and analyzed as well as correlated with the ground reference field sampling data. The details are discussed as follows:

Liner interpolation for seasonal canopy growth monitoring

Due to the poor image quality caused by system error or severe weather conditions, there are portions of the data not available during the season as indicated by the black box in Fig. 8 (a). It can be seen that there existed some missing images or bad images around 158 and 220 days of the year due to system error or weather disturbances. Considering the bioenergy crop canopy continuously evolved and grew, the liner interpolation algorithm was proposed to complete the missing canopy information among the growth season based on the known canopy information before and after that. The result after linear interpolation is indicated in Fig. 8(b). It can be seen that the canopy continuously evolved and converted the solar energy into biomass inside. The proposed linear interpolation based on the data collected before and after the missing data of the canopy information was proposed to provide a complete image of the season. The results show that the linear interpolation is an effective method to interpret the canopy growth condition during the entire season, which is applied in the later correlation analysis with the field sampling yield.

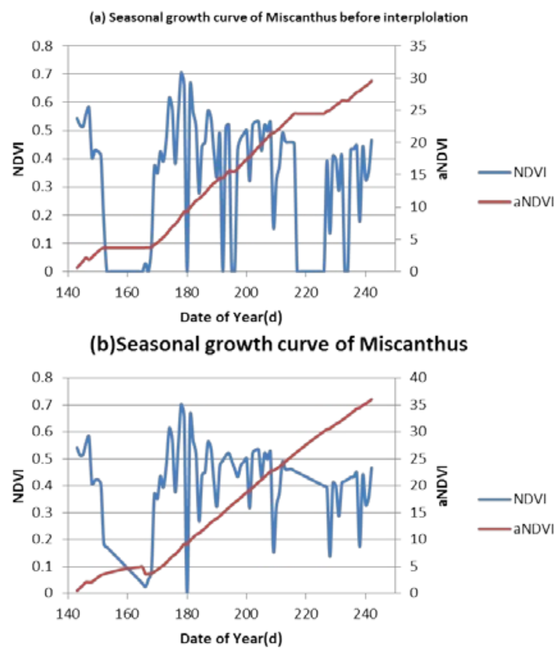


Fig. 8 Miscanthus canopy reflectance evolving before and after linear interpolation

NDVI and accumulated NDVI for crop growth pattern recognition

Once the field sampling points were pinpointed and combined with the GPS projection, and visually verified, the NDVI was calculated for three different resolutions as indicated in Tab.1. The NDVI value was averaged within the field sampling area, or 2×, 3× enlarged area, and then the NDVI value at the beginning of the season to the field sampling data such as June 20, July 11, July 31, and August 30 was accumulated to correlate with the ground reference data from the field sampling. The four field sampling points on August 30 was computed and plotted, which shows that the daily NDVI is changing dramatically due to weather disturbance and the system instability (Fig. 9(a)), whereas the accumulated NDVI curve is much more stable and could be a better representation of the biomass conversion and accumulation of the bioenergy crop (Fig. 9(b)). Based on the daily images from the established biomass energy crop remote sensing system, the daily growth condition of the biomass energy crop can be easily monitored. The daily NDVI value, which represents growth condition, can be calculated, and therefore, the growth pattern of different bio-energy crops in 2012 can be recognized as indicated in Fig. 9(b).

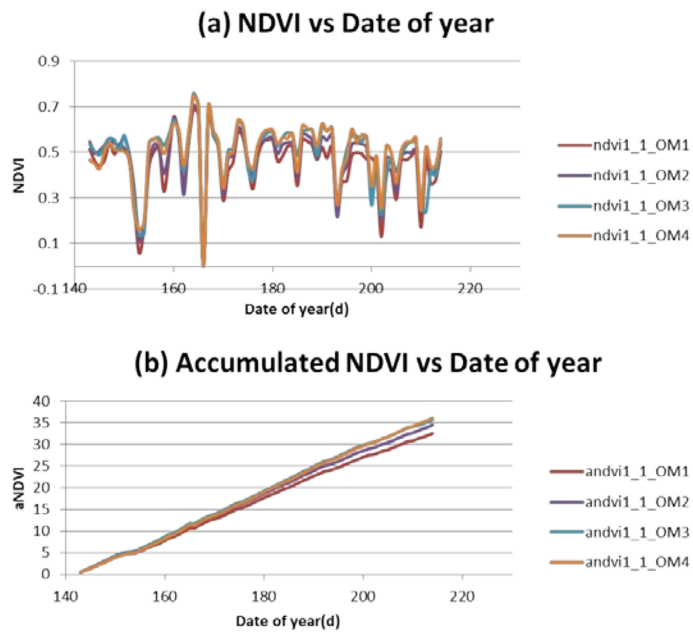


Fig. 9 Miscanthus growth pattern illustration by NDVI and accumulated NDVI

Correlation with field sampling biomass yield

Based on Eq. (3), the accumulated NDVI derived from the remote sensing data was correlated with the biomass yield harvested from the field sampling during the growing season.

The three different resolutions of the field sampling area, namely 1 m by 1 m, 2 m by 2 m, and 3 m by 3 m, were correlated with the ground truth biomass yield data including the dates of June 20, July 11, July 31, and August 30 as indicated in Fig.10. The data of the four dates were plotted in the same figure, so that the overall correlation was considered and the yield prediction model could be established. Additionally, the average accumulated NDVI value of the three different resolutions was tested. It could be seen from above that the resolution of 2 m by 2 m is better for correlation with an accuracy of R^2=80.43% , which means that the 2 m by 2 m resolution could accurately represent the field sampling area as well as compensate for weather disturbance or system instability. Therefore, the resolution of 2 m by 2 m was utilized for interpolations and correlation.

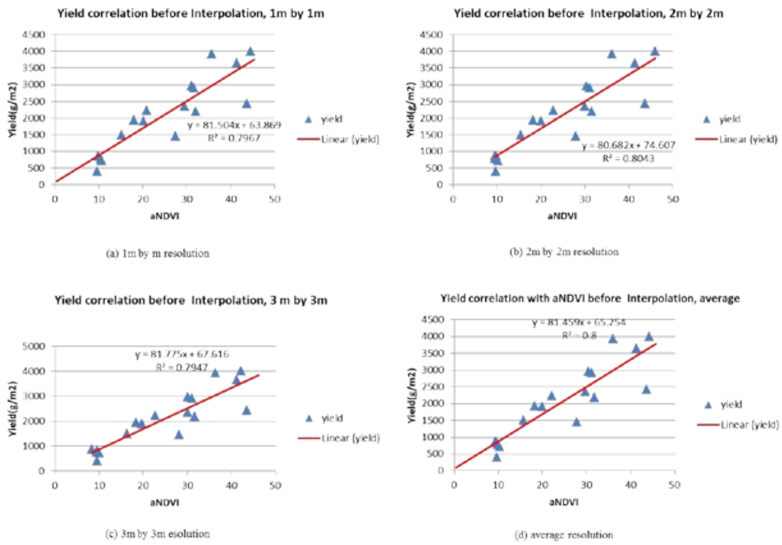


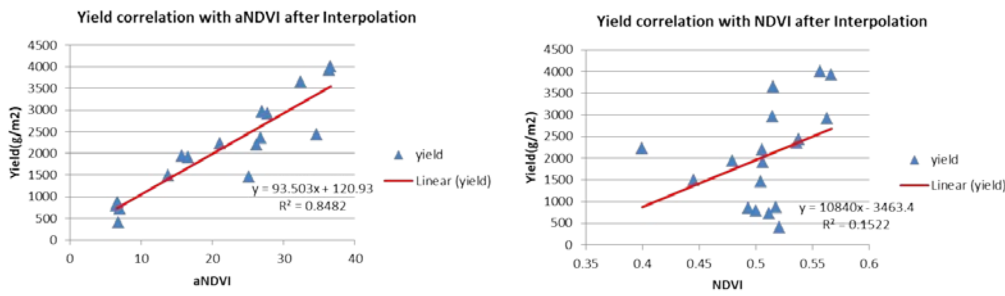
Fig. 10 Different resolution approach for pin-pointing correlation between yield and accumulated NDVI from tower remote sensing data

Yield prediction model based on the accumulated NDVI

To verify the feasibility of biomass yield prediction based on remote sensing data, the NDVI data was linear interpolated and accumulated during the growing season and then correlated with the biomass yield from the ground reference data. The results show that the fitting accuracy (R^2) of the correlation model was 84.82%. Thus, the yield prediction model was established accordingly. The result shows that the correlation between the biomass yield and the accumulated NDVI had improved considerably and stabilized with respect to the near-real-time remote sensing data as indicated in Fig. 10(b) and Fig. 11(a). For comparison, the yield correlation result between one day NDVI of August 30 from the tower remote sensing data based on 2 m by 2 m resolution and the biomass yield is illustrated in Fig. 11(b). It is obvious that the accumulated NDVI model from the proposed near-real-time remote sensing system was more robust and had better accuracy than the satellite image with limited image number and temporal resolution. Therefore, the growth monitoring and yield prediction model based on accumulated NDVI with near-real-time remote sensing could produce a much higher accuracy and better results for site-specific crop management and yield estimation. The daily NDVI value can be accumulated during the entire season for predicting the biomass accumulation in the energy crop.

Yield prediction model verification

The four field sampling points during the entire season were chosen randomly to verify the prediction accuracy of the proposed accumulated NDVI model. The predicted biomass by the model and the biomass harvested by field sampling during the entire season for that of June 20, July 11, July 31, and August 30, 2012 are respectively illustrated in Fig. 12.



a) Yield crrelation with accumulated NDVI from tower remote sensing data (b) Yield correlation wit traditional daily NDVI from tower remote sensing data

Fig. 11 The yield correlation with accumulated NDVI and traditional daily NDVI

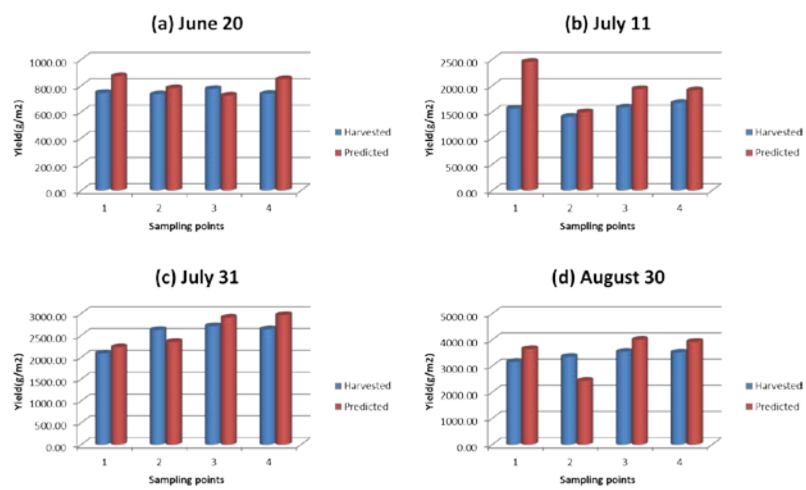
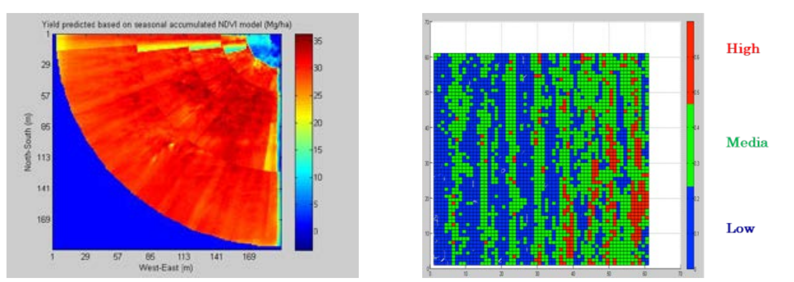


Fig. 12 Yield map generated based on the accumulated NDVI model



(a) Yield prediction map (b) Prescription map for SSCM

Fig. 13 Potential application of the yield model proposal

Application of proposed accumulated NDVI model

The yield prediction model was verified by comparison between the actual harvested biomass yield and the yield predicted based on the model proposed. Moreover, the results show that the predicted accuracy is effective and acceptable, which could be applied to generate the prescription map for the in-field crop site-specific management and yield prediction for harvest scheduling as indicated in Fig. 13(a) and Fig. 13(b). Therefore, large-scale biomass yield prediction based on the near-real-time remote sensing image after re-calibration with the ground reference data becomes possible.

CONCLUSION

To cope with the problems of missing the critical timing of field crop conditions in the traditional remote sensing process (e.g., satellite or aerial imaging systems), a novel experimental stand-alone near-real-time remote sensing platform with high spectral resolution, spatial resolution and temporal resolution was proposed, designed and developed for a biomass production field pre-harvesting crop monitoring. The proposed crop monitoring system was able to scan the crop field within 15 minutes with 91 preset locations to cover a 35-acre crop field on the Energy Farm at University of Illinois at Urbana-Champaign, Urbana, IL, USA. The daily 91 images were captured, geo-referenced, compiled and processed as well as correlated with the ground reference data. The Miscanthus was field sampled during the growing season and the biomass was dried and weighed for a 75 mm by 75 mm quad area. The field sampling points were pinpointed by GPS projection and manually image processed for visual verification. The linear interpolation was performed to complete the canopy evolution based on the before and after known canopy reflectance data. The NDVI and accumulated NDVI of each field sampling points were calculated. Three different resolutions with 1 m by 1 m, 2 m by 2 m, 3 m by 3 m of the field sampling area was calculated and compared. The results show that 2 m by 2 m (twice the actual size) could represent the actual field sampling size and compensate the system disturbance to the model. The accumulated NDVI from the remote sensing data were correlated with the biomass yield from field sampling and accuracy improved with R^2=84.82%, which indicated that the crop monitoring system and the biomass yield model based on the accumulated NDVI can estimate 84.82% of the daily (distributed) biomass gain during the growing season. The results show that the accuracy of the proposed yield model improved considerably when compared to traditional methods. The yield prediction model was verified by comparing the predicted biomass yield with the biomass harvested during the growing season. Thus, a novel "daily canopy reflectance accumulation" algorithm was developed to match the field yield data successfully. Additionally, the yield prediction model could be effectively utilized to predict the yield for optimum harvest scheduling in an earlier growing season and generate the prescription map for site-specific crop management. The model could be improved and verified by the high quality image data from further research during additional seasons so that a bioenergy crop growth and yield database could be established. The system stability and robustness during outdoor conditions for crop in-field variability need to be further improved in the future.

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