Development and evaluation of low-altitude remote sensing systems for crop production management

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Abstract: Precision agriculture accounts for within-field variability for targeted treatment rather than uniform treatment of an entire field. It is built on agricultural mechanization and state-of-the-art technologies of geographical information systems (GIS), global positioning systems (GPS) and remote sensing, and is used to monitor soil, crop growth, weed infestation, insects, diseases, and water status in farm fields to provide data and information to guide agricultural management practices. Precision agriculture began with mapping of crop fields at different scales to support agricultural planning and decision making. With the development of variable-rate technology, precision agriculture focuses more on tactical actions in controlling variable-rate seeding, fertilizer and pesticide application, and irrigation in real-time or within the crop season instead of mapping a field in one crop season to make decisions for the next crop season. With the development of aerial variable-rate systems, low-altitude airborne systems can provide high-resolution data for prescription variable-rate operations. Airborne systems for multispectral imaging using a number of imaging sensors (cameras) were developed. Unmanned aerial vehicles (UAVs) provide a unique platform for remote sensing of crop fields at slow speeds and low-altitudes, and they are efficient and more flexible than manned agricultural airplanes, which often cannot provide images at both low altitude and low speed for capture of high-quality images. UAVs are also more universal in their applicability than agricultural aircraft since the latter are used only in specific regions. This study presents the low-altitude remote sensing systems developed for detection of crop stress caused by multiple factors. UAVs, as a special platform, were discussed for crop sensing based on the researchers' studies.

Keywords: low-altitude remote sensing, agricultural airplane, unmanned aerial vehicle (UAV), crop production management, precision agriculture

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1 Introduction

In the past two decades, agriculture has been significantly transformed from traditional farming to precision agriculture[1,2]. Traditional farming counts on agricultural mechanization to treat crop fields uniformly, while precision agriculture accounts for within-field variability in soil, crop (pest, water and nutrient) stress, and yield using state-of-the-art information and spatial and spectral sensing technologies. Precision farming realizes site-specific management for crop production from planting, fertilizer and pesticide application, and irrigation to harvesting and it handles in-field variability site-specifically, based on the local requirements within a field.

The key technologies that enable precision agriculture are geographical information systems (GIS), global

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positioning systems (GPS), remote sensing, and their integration with agricultural mechanization[3,4]. With these technologies, management decisions can be made on when, where, what, and how to take actions in variable-rate seeding, and variable-rate application of fertilizers, pesticides, and irrigation.

Remote sensing observes agricultural fields in terms of soil condition, crop growth, weed infestation, insects, plant diseases, and crop water requirements and provides prescription data to guide the operation of precision implements and variable-rate systems on aircraft[5,6]. Modern precision agriculture began with mapping of crop field variability to support agricultural planning and decision making. Realization of the decisions calls for variable-rate technology to implement tactical actions in seeding, fertilizer/chemical application, and irrigation instead of only mapping the field one year for improvements in a subsequent year. Remote sensing in precision agriculture requires observations on a small scale to map within-field variability in a farmed area to acquire high-resolution data for effective prescription of variable-rate equipment. At early stage, for agricultural applications, most airborne imaging systems used either video or single band cameras. The imaging systems were typically built with several still cameras lined up together and each of the cameras with a specific filter lens imaging in a specific band, such as blue band, green band, red band, NIR (Near InfraRed) band, and even thermal band[7-14]. This arrangement typically has the problem of misalignment of images representing the different bands. Although the camera lined up systems are still being developed[15,16], it is preferable for portable single camera systems to line up the images from the different bands with built-in devices and filters to monitor the fields at low altitude so that the composite image can be immediately available for rapid image processing. In precision agriculture, low-altitude remote sensing (LARS) method is effective and versatile to provide timely and accurate data compared to satellite, high-altitude, and ground-based remote sensing[4,17,18]. LARS systems were developed on manned agricultural airplanes and unmanned aerial vehicles (UAVs)[19-21]. UAVs provide a unique platform for continuous remote sensing of crop fields at ultra-low-altitudes[22]. The objective of this research was to introduce the LARS systems we have developed and evaluated for detection of crop stress caused by multiple factors. The applications of the systems were also been presented in the paper. UAVs, as a special platform, were discussed for crop sensing based on our studies.

2 LARS platforms/systems

There are two LARS platforms: manned agricultural airplanes including single-engine fixed-wing airplanes and rotary helicopters and UAVs including fixed-wing, rotary helicopter, and multi-copters which are popular in recent years. To build a LARS system, the imaging system with one or more cameras can be mounted on an airplane to fly over and monitor agricultural fields.

2.1 Imaging systems on manned agricultural aircraft

We designed and built a slide mount that fixes cameras, instrumentation, and any data acquisition systems in the belly of an Air Tractor 402B agricultural aircraft. The mounting system was approved by the FAA (Federal Aviation Administration, Washington, DC). Then, the camera was mounted pointing down (10^{o} back along the vertical line to compensate for the tilt up of the plane head when it flies) so its position was nadir. The camera can be triggered manually by the pilot or an on-board operator of the camera, or controlled by a control system installed on a laptop connected to the camera. Huang et al.[19] developed a multispectral imaging system on a Cessna 210 (Cessna Aircraft Company, Wichita, Kansas) and later built an automated multispectral imaging system on the Air Tractor 402B agricultural aircraft (Air Tractor, Inc., Olney, Texas). On the Cessna 210, the camera can be operated manually by an on-board technician. However, the Air Tractor 402B has no space for the technician to be on board. For the flight at the altitude of 1000-3500 m, the pilot can reliably trigger the camera, but for LARS typically at 200-500 m, it is very difficult for the pilot to trigger the camera accurately over the target field. Therefore, an automated camera triggering scheme was needed for imaging from the plane.

On the Air Tractor 402B, imaging systems utilizes the following camera systems: Tetracam ADC (Tetracam, Inc., Chatsworth, CA), Electrophysics PV320T thermal camera (Sofradir EC, Inc., Fairfield, NJ), and MS 4100 (formerly Geospatial Systems, Inc., West Henrietta, NY) that have been built, developed and used. Tetracam ADC is a low-cost CMOS (Complementary Metal–Oxide–Semiconductor) multispectral camera. A Tetracam proprietary software package, SensorLink, was used to enable camera triggering with pre-defined waypoints. However, when used with LARS missions, triggering was inaccurate and unreliable[19]. This was caused by mismatch of minimal flight speed and slow GPS updating speed, making it difficult to image the correct field location. The electrophysics thermal camera was used to image and invert the ground surface temperature and was operated to stream continuous digital video to the hard disk of an on-board Toshiba laptop computer. A 35 min running at 10 frames/sec acquisition speed used about 4 GB of hard disk space. Image data could, therefore, be archived on DVD if desired. The MS-4100 camera is a high-performance multispectral 3-CCD (Charge-Coupled Device) color/CIR (Color Infrared) digital camera. This camera is the upgrade of the previously available DuncanTech MS 3100 and 2100 cameras. The imaging system with automated camera triggering function was initially developed and applied on the Air Tractor 402B in 2009[6]. Within the last few years, the MS 4100 has been moved to Optech, Inc. (West Henrietta, NY) and technical support of the control software was discontinued due to the termination of the developer's business. Even so, the system we developed is still been maintained well, upgraded continuously and worked reliably on the Air Tractor 402B to image the crop fields in the research farms of United States Department of Agriculture (USDA), Agricultural Research Service (ARS) in Stoneville, Mississippi.

The MS 4100 camera provides digital images with a 1920 (horizontal)×1080 (vertical) pixel array in each sensor band. We equipped the camera with a Nikon 14 mm, f/2.8 AF-D ED lens (Nikon Corporation, Tokyo, Japan) and 114° wide angle of view. The camera has two spectral configurations: RGB (Red Green Blue) for high quality color imaging and CIR for multispectral applications. The images contain four broad spectral bands between 400 and 1000 nm, i.e. blue band (460 nm with 45 nm bandwidth), green band (540 nm with 40 nm bandwidth), red band (660 nm with 40 nm bandwidth), and NIR band (800 nm with 65 nm bandwidth). These bands approximate corresponding Landsat satellite thematic mapper bands (NASA, Washington, D.C.; USGS, Reston, VA). The MS 4100 can be configured to provide RGB and CIR images concurrently or separately. We adopted the base configuration that supports the three-tap configuration running at 8 bits per color plane (i.e. 24-bit RGB) for running RGB or CIR (green, red and NIR) configuration separately.

The MS 4100 camera was configured for the digital output of image data with CameraLink enclosed in a Magma PCI (Parallel Card Interface) box (Magma, San Diego, CA) to host CameraLink communication with the camera. The CameraLink connected and controlled with the NI IMAQ PCI-1424/1428 frame grabber (National Instruments, Austin, Texas). With the software DTControl-FG (formerly Geospatial Systems, Inc., West Henrietta, NY) and the CameraLink configuration, the camera acquires images from the frame grabber directly from the DTControl program. Dragonfly® (formerly TerraVerde Technologies, Inc., Stillwater, OK) is navigation software with a powerful function to automatically trigger the camera based on the target field shapefile polygon using any submeter-accuracy GPS receiver. Dragonfly configures the camera control based on GPS navigation. As long as GPS coordinates touch the edge of the target field shapefile polygon, the camera automatically acquires images continuously with a preset vertical/horizontal overlay (50% as default) until the aircraft travels through the field polygon under GPS control. This shapefile-based trigger scheme worked especially well with LARS missions as compared with a waypoint trigger scheme. The waypoint triggering scheme may miss the desired location due to the mismatch between the flight speed and GPS updating frequency (they are very sensitive when the airplane flies at low altitude). Figure 1 indicates that the MS 4100 camera is mounted on the belly of the Air Tractor 402B behind with a Magma PCI box for data communication and transferring and a rugged laptop hosting the Dragonfly® software and the target field shapefiles.

Figure 1 MS 4100 camera-based multispectral imaging system on the Air Tractor 402B behind with data-communication Magma PCI box and rugged laptop hosting navigation software

Raw image data from the MS 4100 are digital counts, which must be corrected due to variations of solar illumination and atmospheric conditions. This is essential if images acquired on different dates are to be compared. The correction of MS 4100 images was conducted by radiometric calibration to convert digital numbers of the CIR images to percent reflectance. In the process of radiometric calibration, an IRR 180 irradiance radiometer (formerly TerraVerde Technologies, Inc., Stillwater, OK) was used to record solar irradiance in the field to normalize images. This radiometer was set near the field on the day of field imaging, and the signals were automatically recorded at a preset interval. After imaging, the data were uploaded to the computer. With the uploaded data, the dedicated image correction software, Image Correction Center software (former TerraVerde Technologies, Inc., Stillwater, OK) was used to filter anomalies caused by clouds and normalize the images with radiance data generated from MS 4100 camera calibration data to produce the final reflectance images.

2.2 UAV-based imaging system

Agricultural UAVs are typically low cost, light weight, operated at low flight speed, and have relatively short endurance. Fixed-wing airplanes, rotary helicopters and multi-rotor copters have been developed for LARS over agricultural fields. This research focused on an octocopter LARS platform because in recent years, use of multi-rotor copters has been increased dramatically in research and applications due to their capabilities for precise control and stability.

An RTF X8 octocopter (3D Robotics, Berkeley, CA) was customized to capture images over crop fields. This octocopter was designed to fly 15 min with a payload capacity of 800 grams. It is controlled by the Pixhawk autopilot system (3D Robotics, Berkeley, CA) for ability to fly fully autonomously during take-off, waypoint scanning and landing. A GoPro HERO3+ camera (GoPro Inc., San Mateo, CA) was mounted on the Tarot T-2D brushless gimbal with the octocopter to stabilize the orientation of the camera during flight. The GoPro camera captures digital still photos or video in high-definition through a wide-angle lens and can be triggered automatically through autopilot with mission planning.

To minimize the geometric distortion of the images over the field, the original wide-angle lens of the GoPro camera was replaced with a 2.97 mm f/4.0 low distortion lens. The lens has a 95° of field of view (FOV), which can offer 3 cm/pixel ground spatial resolution of the images at a flight altitude of 50 m. Figure 2 shows the LARS system built on the X8 octocopter with a GoPro HERO3+ camera with the 95° FOV low distortion lens.

Note: The images acquired from the GoPro camera in flight were geo-tagged and processed for the orthomosaic image and point cloud data in 3D coordinate system to represent surface features.

Figure 2 X8 octocopter with a GoPro HERO3+ camera and low distortion lens

3 Systems applications and field evaluation

3.1 Relationship of image data and crop yield

Estimation of crop yield at different scales has been a primary concern in agricultural remote sensing. Field-scale evaluation to relate image data to crop yield is important for estimating crop yield.

3.1.1 Aerial MS 4100 CIR imagery

The MS 4100 multispectral imaging system on the Air Tractor 402B has been used to acquire imagery over crop fields in the growth season for relating image data to crop yield. One of the fields we worked on for the study is in the research farm of USDA, ARS, Crop Production Systems Research Unit in Stoneville, Mississippi (latitude: 33.446485°; longitude: -90.869923°). Figure 3 shows the Google™ Earth map (Google Inc., Mountain View, CA) of the 9.5 hm^2 field. This field contains four subfields from south to north labeled as A, B, C and D. Fields A and B are a mixture of sandy and clay soils, and this variability has shown a commensurate variability in crop growth potential, also depending on rainfall[23]. Fields C and D are in a mix of Tunica and Sharkey clay. At the center of field C, there is a center pivot irrigation system. The three other fields use furrow irrigation.

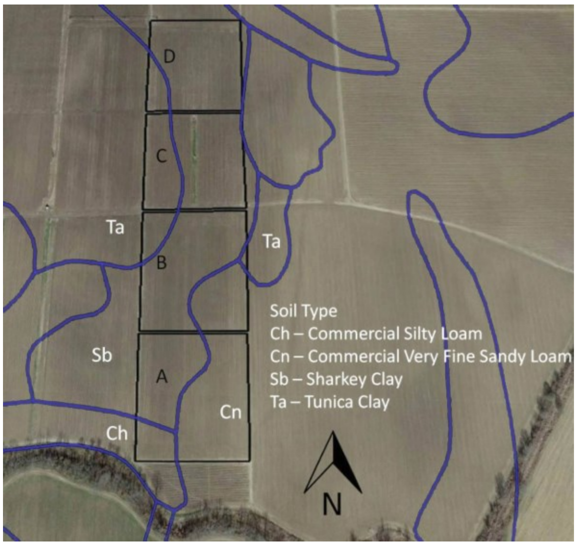


Figure 3 Google map of field A, B, C and D with soil type overlay from SoilWeb (University of California at Davis and USDA Natural Resources Conservation Service)

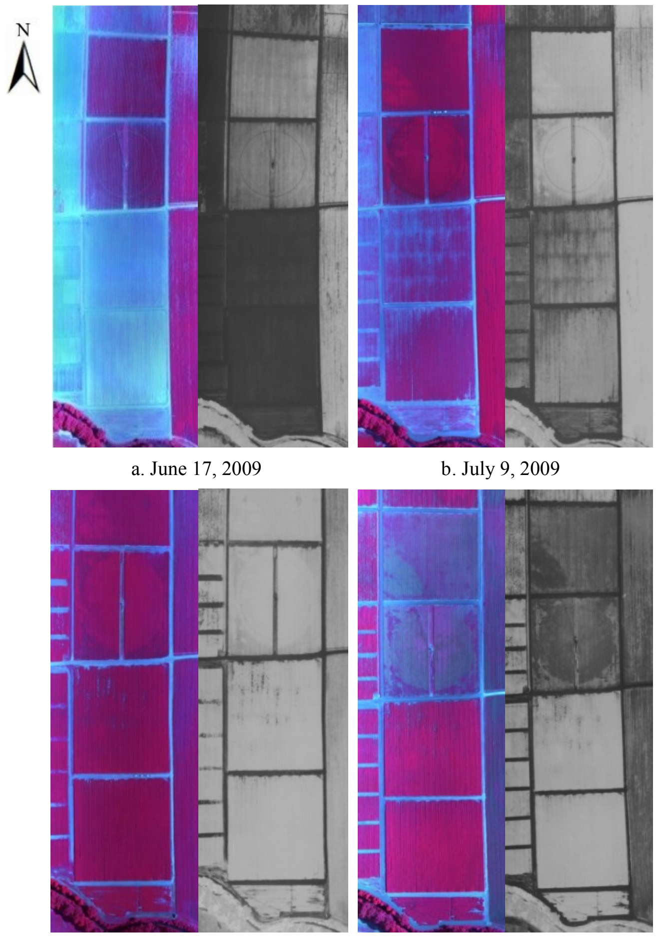
In 2009, the field was imaged with the MS 4100 multispectral imaging system on the Air Tractor 402B from June to September during the crop growth season. During this season, cotton was planted in fields A and B, with soybean planted in fields C and D. Flight altitude was held close to 480 m, resulting in a ground resolution of 77 cm/pixel. Figure 4 illustrates CIR (Color Infrared) and NDVI (Normalized Difference Vegetation Index) images of the field on June 17th, July 9th, August 13th and September 2nd in 2009. NDVI was calculated as (NIR-Red)/(NIR+Red) where NIR were broadband data extracted from the near-infrared region of the spectrum, MS 4100 camera specifies this band center at 800 nm wavelength (65 nm bandwidth); Red signifies broadband data extracted from the red region of the spectrum, MS 4100 camera specifies this band centered at 660 nm (40 nm bandwidth). NDVI is the most popular vegetation index calculated from remotely sensed data to characterize plant vigor[24]. Images indicated that:

(1) On June 17th, the cotton on fields A and B was in seedling stage and the canopy of soybean in fields C and D was about to close;

(2) On July 9th, the canopy of cotton in fields A and B was about to close. The canopy of soybean in fields C and D was closed;

(3) On August 13th, the canopy of cotton and soybean was fully closed and the cotton was maturing;

(4) On September 2nd, the cotton in fields A and B was ready to be defoliated; soybeans in fields C and D were ready for harvest.



a. June 17, 2009 b. July 9, 2009

c. August 13th, 2009 d. September 2nd, 2009

Note: CIR images: reddish color with strong vegetation coverage; NDVI: white color with strong vegetation coverage

Figure 4 MS 4100 CIR and NDVI images

The NDVI image on June 17th showed a bare soil signature in fields A and B, while the CIR image showed the brightness variation of the soil matching with the soil type profile in the field. Both CIR and NDVI in the images on July 9th showed the soil effect on cotton growth matching with the soil type profile in the field. The two images also showed the effects of irrigation in fields C and D, especially the pattern with the center pivot in field C. Figure 5 shows the crop yield overlay of the field on the Google Earth map. Cotton yields in fields A and B were higher in the area of clay soil (Sb) than in the area of sandy soil (Cn and Ch). This variation was clearly characterized by the CIR and NDVI images right before canopy closure (for example July 9th, 2009). However, when the canopy was closed (August and September), NDVI was saturated, and image features were no longer significant. So, the optimal time to estimate cotton yield with MS 4100 imagery could be just before canopy closure. The effect of irrigation on soybean in field C with center pivot was obvious, as shown in Figure 5. The effect of furrow irrigation in field D was indicated in Figure 5 as well, but this field was irrigation limited. This was characterized better in early the images of June and July.

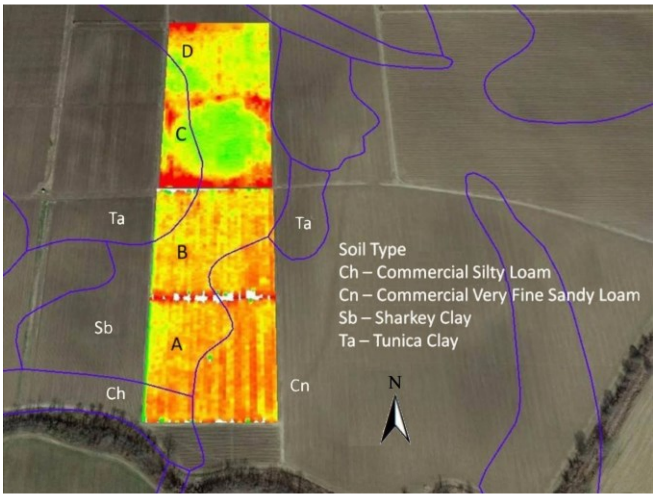
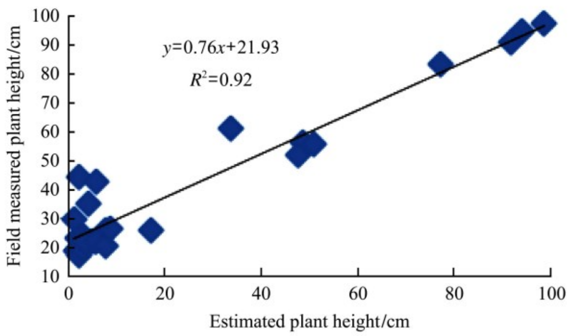


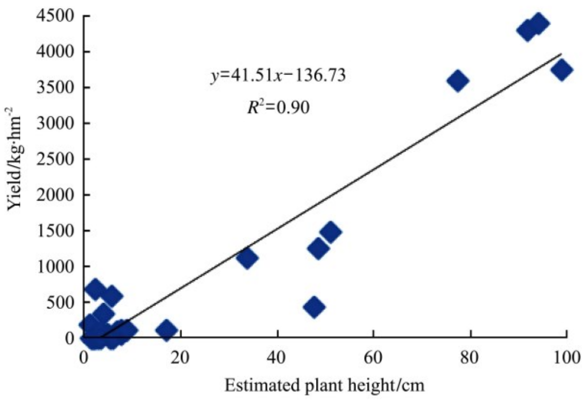
Figure 5 Google Earth map of fields A, B, C and D with crop yield data and soil type overlays

3.1.2 UAV GoPro imagery

Color images acquired by the GoPro camera on the X8 octocopter were geo-tagged and processed using DroneMapper at droneMapper.com for various products, including orthomosaic images, digital surface model (DSM) images, and point cloud data. These products can provide a variety of applications from field vegetation signature identification to field surface feature extraction. In fields A and B (Figure 3), an experiment was conducted for studying soybean injury responding to different doses of dicamba herbicide, in June, 2014. After the experiment, 550 images were acquired by the GoPro camera on the X8 octocopter flying over the field in late July, 2014, with flight altitude of 45 m, resulting in 2.7 cm/pixel ground spatial resolution. Among the 550 images, 60 images were selected, geo-tagged and mosaicked to cover the whole field. With 60 images of the field, the 3D point cloud data were generated, which is in the three-dimensional coordinate system of (X, Y, Z) to represent surface elevation of the field. With the point cloud data around the soybean canopy, the base plane of the field was interpolated. Then, the subtraction of field base plane point data from field surface point data could provide an approximation of plant height, which is an important bio-physical indicator of soybean yield. Figure 6 indicates that the subtraction could approximate the plant height well (R^2=0.92) with a good estimation of soybean yield (R^2=0.90).



a. Soybean plant height estimation vs. field measured values



b. Soybean plant height estimation vs. yield

Figure 6 Estimated soybean plant height and yield from GoPro images on the X8 octocopter

3.2 Characterization of crop herbicide injury with image data

Spray drift of herbicides onto off-target sensitive crops could reduce yield and quality, and this is of great concern to growers and pesticide applicators. Detection of herbicide injury using LARS image data can be a quick and cost effective method of inferring this damage, compared to conventional, tedious method of measuring plant biological responses. Our research determined the effect of herbicide on crop damage related to yield through LARS image analysis.

3.2.1 Aerial MS 4100 CIR imagery

Glyphosate [*N*-(phosphonomethyl) glycine] is the most commonly applied, non-selective herbicide to manage a broad spectrum of broadleaf and grass weeds. With the increased usage of glyphosate due to the adoption of genetically modified (GM) crops, which are resistant to glyphosate (GR), glyphosate drift onto non-target crops from ground or aerial applications is a concern. LARS has been conducted using MS 4100 multispectral imaging system on the Air Tractor 402B to characterize crop injury using remote sensing parameters as a surrogate of plant biological responses.

A field experiment was conducted in 2011 in fields A and B (Figure 3). In the field, cotton, soybean and corn were planted (Figure 7). One of the eight blocks from south to north was divided into four 8-row subplots. Each of the subplots was the smallest unit for experimental treatments. Non-glyphosate-resistant (non-GR) corn was planted on April 19th and non-GR cotton and soybean were planted on May 9th. Glyphosate was applied using a tractor-mounted sprayer with Tee Jet 4003 standard flat-spray nozzles delivering 140 L/hm^2 of water at 193 kPa, four to five weeks after each crop was planted. For corn, application of glyphosate was made on May 17th, when the plant was at the 4-5 leaf stage. Glyphosate rates used were 0.01X, 0.05X, 0.1X, 0.2X, 0.5X and 1.0X [X=0.866 kg ai/hm^2, represents the recommended use rate of the commercial formulation of potassium salt of glyphosate, Roundup WeatherMax® (Monsanto Co., St Louis, MO)]. Completely randomized block design, replicated four times as shown in the figure was used. Similarly, for cotton and soybean, application of glyphosate was made on June 8th, when the cotton was at the 4-5 leaf stage and the soybean was at the 4-5 trifoliolate-leaf stage, at the rates of 0.1X, 0.25X, 0.5X, 1.0X and 2.0X for cotton and 0.1X, 0.2X, 0.4X, 0.5X and 1.0X for soybean.

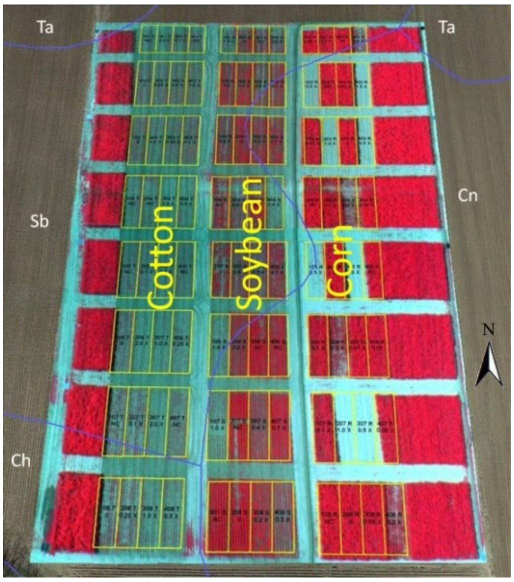
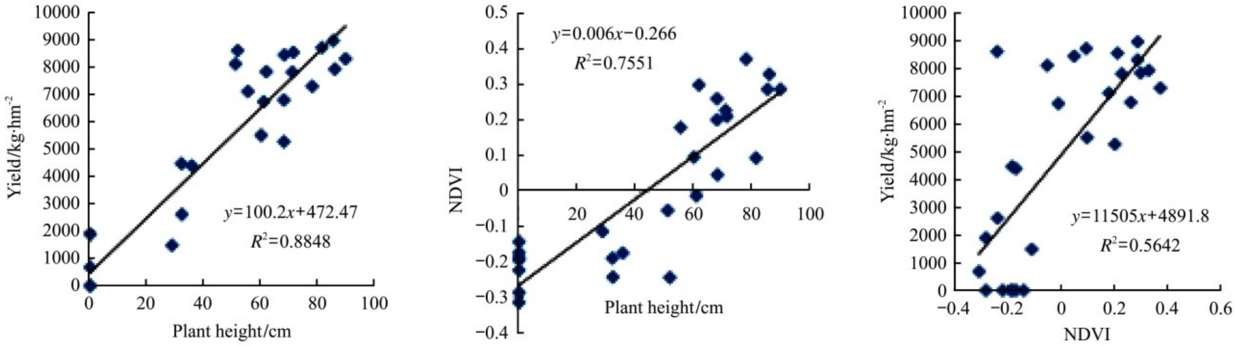
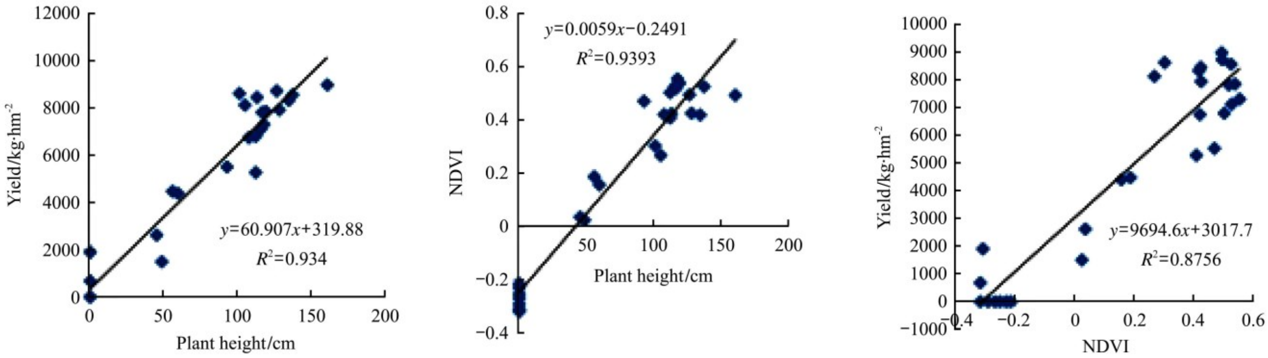


Figure 7 Overlay of MS 4100 CIR image on June 14th, 2011, experimental field layout, and soil type profile on Google Earth map for 2011 crop glyphosate injury study

Plant biological responses of each crop were measured 1, 2 and 3 weeks after treatment (WAT). The measurements were in-situ measured plant height and in-situ sampled leaves for determination of plant dry weight and chlorophyll content in laboratory. Aerial MS 4100 CIR imageries were acquired for corn 1, 2 and 4 WAT, on May 5th, June 1st and June 14th, respectively, and for soybean and cotton 1 and 3 WAT, on June 14th and June 29th, respectively. The flight altitude was held around 380 m in the flights, resulting in a ground resolution of 60 cm/pixel. The CIR images were processed to generate various vegetation indices, including NDVI, SAVI (Soil Adjusted Vegetation Index)[25], RVI (Ratio Vegetation Index) and GNDVI (Green NDVI), to demonstrate the vegetation responses to glyphosate doses at each subplot. SAVI was used to characterize the effect of soil background at the early growth stage of the crops and calculated as $[(\text{NIR-Red})/(\text{NIR+Red}+L)]\cdot(L+1)$ where L is an adjustable factor. When $L=0$, SAVI=NDVI. Typically preset $L=0.5$. RVI=NIR/Red[26]. GNDVI=(NIR-Green)/(NIR+Green)[27] where Green is the broadband data extracted from the green region of the spectrum MS 4100 camera specifies at 540 nm with 40 nm bandwidth. Our study indicated that although the performance of different variables varied, plant height correlated well with plant biological responses and NDVI for characterization of crop injury from glyphosate. Figures 8, 9 and 10 show the correlations between plant height, NDVI and yield of corn, cotton and soybean after treatment and indicate that NDVI is a good surrogate of plant height to characterize crop injury from glyphosate with yield.

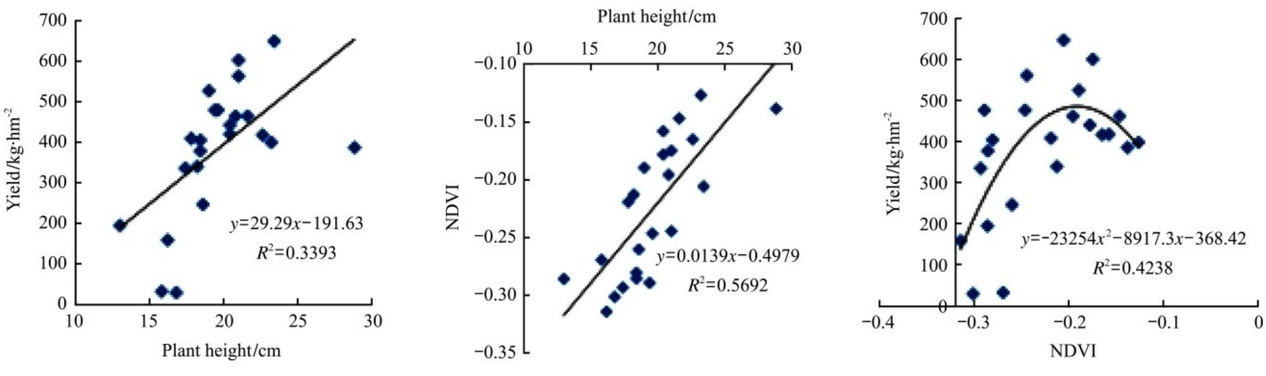


a. June 1st, 2011

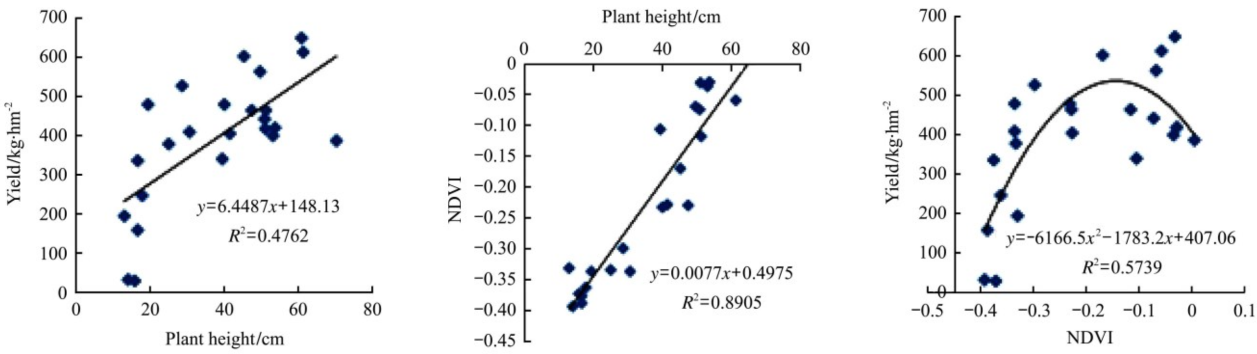


b. June 14th, 2011

Figure 8 Correlations between plant height, NDVI and yield of corn on (a) June 1st, 2011 (b) June 14th, 2011



a. 1 WAT



b. 3 WAT

Figure 9 Correlations between plant height, NDVI and yield of cotton (a) 1 WAT (b) 3 WAT

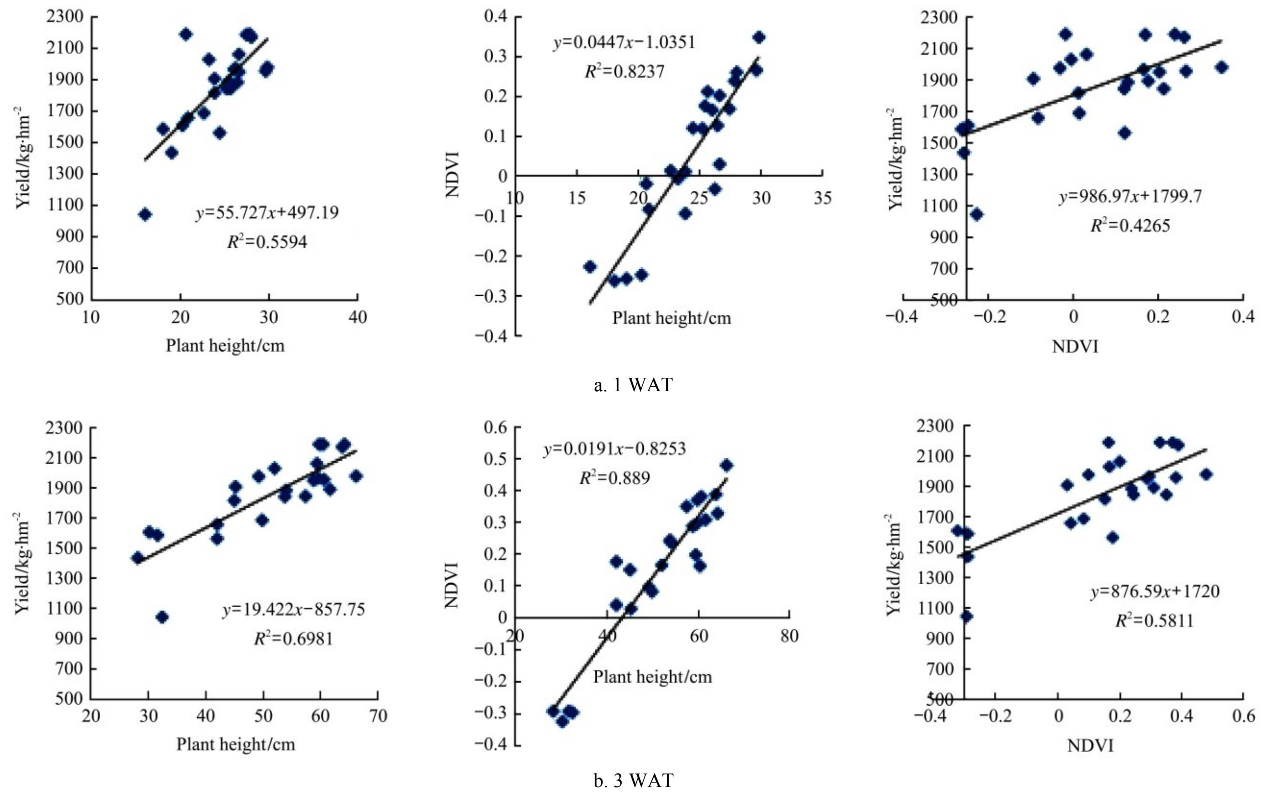


Figure 10 Correlations between plant height, NDVI and yield of soybean on (a) 1 WAT (b) 3 WAT

3.2.2 UAV GoPro imagery

Dicamba (3, 6-dichloro-2-methoxybenzoic acid) is an herbicide used to control many broadleaf weeds in corn and sorghum. It could be an option to combat glyphosate-resistant weeds in dicamba-resistant cotton, corn, and soybean when commercialized. Although the release of dicamba-resistant crops is still pending approval, off-target dicamba drift from routine use onto susceptible crops will be a concern. In Mississippi, there has been one dicamba drift complaint in 2012 and 2013 (Source: John Campbell, Bureau of Plant Industry, MS Dept. Agriculture and Commerce). With the adoption of the dicamba-resistant crops in the near future, there will be greater concerns of increased dicamba drift complaints.

Aerial multispectral images were obtained to assess crop injury from different doses of dicamba using aerial MS 4100 CIR imagery for soybean. However, following flight of the Air Tractor 402B at 500 m height (resulting in a ground resolution of about 0.8 m/pixel), it was difficult to differentiate vegetation from soil background to accurately characterize soybean injury, especially at the stage of a few trifoliate leaves. UAVs can be used here to provide lower altitude imagery at slow speeds resulting in imagery of more adequate resolution. If the customized GoPro camera on the X8 octocopter flies over the field at an altitude of 50 m, a 3 cm/pixel ground spatial resolution is achievable. The GoPro images could be used to remove the soil background from vegetation, and allow differentiation of weeds from crop. One disadvantage of GoPro images is that they only have visible bands but no NIR band, so NDVI cannot be generated. A compromise is to use the band data of red, green, and blue to extract plant photosynthetic vigor and pigment features.

Figure 11 shows the soybean plots treated with different dicamba doses: 0 (control), 0.05X, 0.1X, 0.2X, 0.3X, 0.5X and 1.0X (X=0.56 kg ae/hm^2). The entire field was laid out in a completely randomized block design with four replications. The image was processed to convert from RGB (red, green and blue) space into HSV (hue, saturation and value) space to segment out the crop signatures in each plot from weeds and soil background, and then normalized difference photosynthetic vigor ratio (NDPVR) was calculated with the pixels of the crop. The calculated NDPVRs were averaged on each plot for analysis. Figure 12 shows the soybean yield estimation based on NDPVR extracted from the UAV images (same set as 3.1.2) with dicamba treatments in different plots. This figure also shows a monotonically decreasing trend of NDPVR with the increase of dicamba dose. NDPVR is the normalized difference version of PVR (photosynthetic vigor ratio) to use the green band, as a reference band, and the strong chlorophyll absorption red band[28].

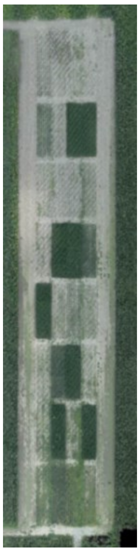
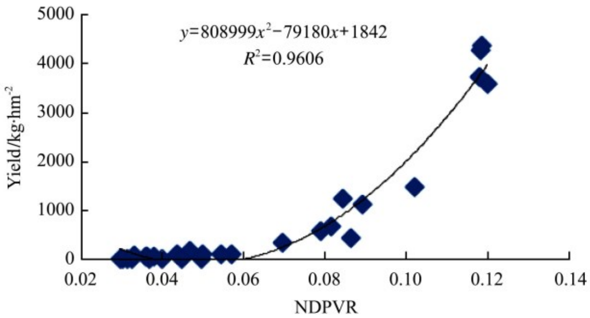
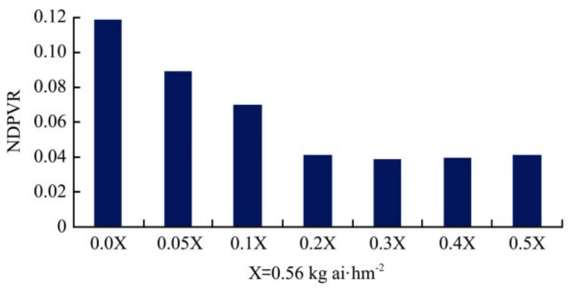


Figure 11 Field layout for soybean injury experiment



a. Soybean yield estimation from NDPVR with different dicamba doses



b. Relationship between NDPVR and dicamba dosage

Figure 12 Soybean yield estimation based on NDPVR extracted from the UAV images with dicamba treatments in different plots

4 Conclusions

Our development and field evaluation indicates that:

1) LARS is a versatile and effective platform for providing guiding data and information for precision agriculture;

2) UAV-based systems can complement use of manned aircraft systems in LARS;

3) UAV-based systems can also be used standalone to provide data for crop management in the level of leaf, canopy, field and even farm.

LARS has great potential to provide high-resolution images of crop fields for improved crop management in precision application of crop production and protection materials.

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