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

Time Series Study of Soybean Response Based on Adjusted Green Red Index (AGRI)

Peter Ako Larbi[1,2] and Steven Green[1,2]

[1] Arkansas State University, College of Agriculture and Technology, Jonesboro, AR
[2] University of Arkansas, Division of Agriculture, Fayetteville, AR

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

Abstract. *Four time-lapse cameras, Bushnell Nature View HD Camera (Bushnell, Overland Park, KS) were installed in a soybean field to track the response of soybean plants to solar radiation, air temperature, relative humidity, soil surface temperature, and soil temperature at 5-cm depth. The purpose was to confirm if visible spectroscopy can provide useful data for tracking the condition of crops and, if so, whether game and trail time-lapse cameras can serve as reliable crop sensing and monitoring devices. Using the installed cameras, images were taken between July 22 and August 1, 2015. Color images were obtained for the daytime images captured while nighttime images were monochrome infrared (IR) images. Images at 30-minute intervals were selected for further processing and analysis, however, the nighttime images were not useful due to overexposure to the IR light which rendered the images too bright. The data from the R (red), G (green), and B (blue) bands of the images selected were extracted and exported to Microsoft Excel using the RGBExcel software application developed in-house. For each image, an AGRI (adjusted green red index) image dataset was generated based on the equation* $AGRI = 0.5\ [1-((I_G-I_R)/(I_G+I_R))]$, *where* I_G, *and* I_R *are the signal intensities (or pixel values) respectively in G and R bands. Next, the background (mainly soil) was removed using the Thresholding method and the remaining data averaged. This AGRI average value was plotted against the date and time of image collection, which showed a rise-and-fall trend with daily peaks around 1:00 pm. The AGRI data was regressed on logs of solar radiation, air temperature, relative humidity, soil surface temperature, and soil temperature at 5-cm depth. The following is the decreasing order of correlation: log of solar radiation* ($0.36 < R^2 < 0.65$) *> log of soil surface temperature* ($0.23 < R^2 < 0.38$) *> log of air temperature* ($0.09 < R^2 < 0.29$) *> log of soil temperature at 5-cm depth* ($0.09 < R^2 < 0.20$) *> log of relative humidity* ($0.00 < R^2 < 0.18$)*.*

Keywords. *Visible Spectroscopy, Time Lapse Camera, Soybean, Image Processing, Crop Sensing.*

Introduction

A growing crop responds to the soil and meteorological conditions to which it is subjected (Hollinger and Angel, 2009). Crop health data can be collected alongside soil and meteorological data to establish mathematical relationships (Murthy, 2004) that can be utilized to determine a crop's status at a given point in time. Analysis of meteorological data can provide near real-time information about the status of a crop in terms of quality and/or quantity (Doraiswamy et al., 2003). Such information can serve as an early-warning indicator or decision-support resource for proper planning and timely intervention in order to efficiently manage the crop (Akeh et al., 2000). In fact, crop stress factors such as pest and disease infestations, water and nutrient deficiencies must be detected early enough to allow for early mitigation to prevent massive loss in yield (Nutter et al., 2002).

Satellite and aerial remote sensing (SARS) can generate spectral data from which indices considered to be relevant variables for determining crop status can be derived (Boschetti et al., 2007). SARS deals with imagery of crop at large scales such as whole-farm or much larger scales (Holecz et al., 2013). While SARS can cover large areas, ground based proximal remote sensing (PRS) employing similar image processing and analysis techniques as SARS can also be implemented at much smaller scales such as field or plot scales. Deery et al. (2014) evaluated the potential for using PRS for field-based phenotyping. Such smaller scale implementations can provide representative data for an entire field or can be used to monitor specific locations or networks of locations of interest (Cheng et al., 2016). At any rate, for crop monitoring for precision management, images must be provided on a frequent basis to allow the farmer to respond quickly (Seelan et al., 2003; Toureiro et al., 2016).

Frequent acquisition of images allow for the generation of time series data which can be used to build models describing crop phenology throughout the growth cycle. Crop phenological information from time series data has been employed in multi-sensor mapping of crops by Siachalou et al. (2015).

Two of the limitations to the adoption of crop sensing/monitoring by imagery and image processing for precision farm management are the cost of the instrumentation and image processing software, and the high expertise required (Seelan et al., 2003). For these reasons and a host of others, a high number of the successful advances either still remain at the research level or have had very low adoption by farmers. Some ways to encourage adoption include reducing the cost of the technologies, making the technologies easily accessible, and easy to learn and use. These steps can allow crop consultants, extension agents, and farmers to try small plot applications as proof of concept to encourage the adoption of relevant practices.

Recent efforts to develop low cost image processing and analysis techniques are ongoing in the Precision Application Technology Lab in the College of Agriculture and Technology, Arkansas State University. These efforts have been strengthened by the creation of a software application, RGBExcel (Larbi, 2016a) and the later version RGB2X (Larbi, 2016b). This application extracts and exports image data of digital images (regardless of the camera used for the acquisition and the file format) to Microsoft Excel for further processing and analysis. Studies utilizing this software package include a foundational paper highlighting the implementation of standard image processing techniques using Microsoft Excel (Larbi, 2016c) and another study which compared processed image data from five different cameras representing a range of available commercial color camera options on the market (Vong and Larbi, 2016). Since Excel has over 750 million users worldwide, this innovation will become highly accessible globally as the RGB2X software is made available.

In this present study, the potential utility of a low-cost game and trail time-lapse camera for monitoring crop status is explored. Since the camera can be configured to capture images at a user-defined time interval, very minimal expertise is required for setting it up. The purpose was to emphasize the utility of visible spectroscopy in providing useful data for tracking the condition of crops and determining whether game and trail time-lapse cameras could serve as reliable crop sensing and monitoring devices. The specific objectives were:

1. To test the potential utility of game and trail time lapse cameras for automatic monitoring of soybean plant response to changing environmental condition;
2. To demonstrate the utility of Microsoft Excel for image processing and analysis; and
3. To establish relationships between the processed image data and corresponding weather parameters.

Achieving the above objectives will provide simple tools that can be adopted by crop consultants, extension agents, and farmers as initial steps towards wide scale adoption of precision agriculture practices.

Materials and Methods

In this observational study, four game and trail time-lapse cameras (Fig 1), Bushnell Nature View HD Camera (Bushnell, Overland Park, KS) were installed in an experimental soybean field to capture day and night images of the crop over time. Each camera took images with 8 MP high-quality full color resolution and 1-3 images per trigger, as well as 1280 x 720 pixel high definition video with audio record programmable length from 1 to 60 seconds. A Field Scan time-lapse mode took images at pre-set intervals of 1 to 60 minutes. Each camera had an imbedded temperature sensor with -20 to 60 °C range.

Fig. 1. The four game and trail cameras used in the study.

The experimental field was located at the Arkansas State University Farm (ASU Farm) in Jonesboro, AR. The cameras (referred to as Cam 1, Cam 2, Cam 3, and Cam 4) were installed on a mount as shown in Fig 2 at four corners of a rectangular area. The locations of the cameras are summarized in Table 1. With the cameras overlooking the plants at a height of about 2.4 m (about 8 ft.), each camera captured vertical aerial images.

Fig 2. One of the game and trail time-lapse cameras installed in the soybean field.

Table 1. GPS coordinates and elevation of camera locations.

Camera	GPS Coordinates		Elevation (m)
	Latitude	Longitude	
Cam 1	35.83888	-90.66634	81.5
Cam 2	35.83888	-90.66594	81.8
Cam 3	35.83868	-90.66594	81.6
Cam 4	35.83868	-90.66634	81.4

Using the installed cameras, images were taken between July 22 and August 1, 2015. Color images were obtained for the daytime images captured while nighttime images were monochrome infrared (IR) images. Figure 3 shows images obtained from Cam 1 on July 22 @16:00 (left), July 27 @16:00 (middle), and July 31 @12:00 (right), 2015. Each image was stamped with the camera name, air temperature (both °F and °C), date and time of capture. Due to occasional strong winds, the actual field of view of the cameras at the time of capture shifted slightly within the general area being monitored, but this shift was not considered to affect the results significantly. Some of the images obtained had the shadow of the instrumentation but illumination compensation was accomplished in the image processing to eliminate this illumination defect.

Fig 3. Images of soybean plant canopy captured by Cam 1 on July 22, 27, and 31, 2015.

Images at 30-minute intervals were selected for further processing and analysis. The air temperature stamped on the selected images was plotted over time to track the changing environmental conditions. However, the nighttime images were not useful in the further processing due to overexposure to the IR light which rendered the images too bright. The data from the R (red), G (green), and B (blue) bands of the images selected were extracted and exported to Microsoft Excel for processing and analysis, using the RGBExcel software application (Larbi, 2016). For each image, an AGRI (adjusted green red index) image dataset was generated based on the equation

$$AGRI = 0.5\left[1 - \frac{(I_G - I_R)}{(I_G + I_R)}\right] \tag{1}$$

where, I_G and I_R are the signal intensities (or pixel values) respectively in *G* and *R* bands. Next, the background (mainly soil) was removed using the Thresholding method and the remaining plant data averaged. This plant *AGRI* average values were plotted against the date and time of image collection, which showed a rise-and-fall trends with daily peaks at about 1:00 pm.

As this study was only observational and no treatments were applied to the soybean plants at the different locations, only the plants' response to weather conditions were tracked based on the *AGRI* data. The *AGRI* data was regressed on logs of solar radiation, air temperature, relative humidity, soil surface temperature, and soil temperature at 5-cm depth. The weather data which was obtained from the ASU Farm weather station located roughly at (35.83752, -90.66474) was retrieved from the weather library at www.weather.astate.edu.

Results and Discussion

The changing environmental conditions over the period of observation, as portrayed by the changing temperature value stamped on the images, is shown in Fig 4. Throughout this period, temperature at Cam 2, Cam 3, and Cam 4 locations appeared to be similar, while that at Cam 1 location was higher. The diurnal temperature variation (Lillesand et al., 2015) at all four camera locations were similar to the temperature data obtained from the ASU weather station. Overall, temperature values at all four camera locations were higher than that at the ASU weather station during the day and lower during the night. The temperature difference between Cam 1 and the ASU weather station (temperature error) is shown in Fig 5 to better portray this difference.

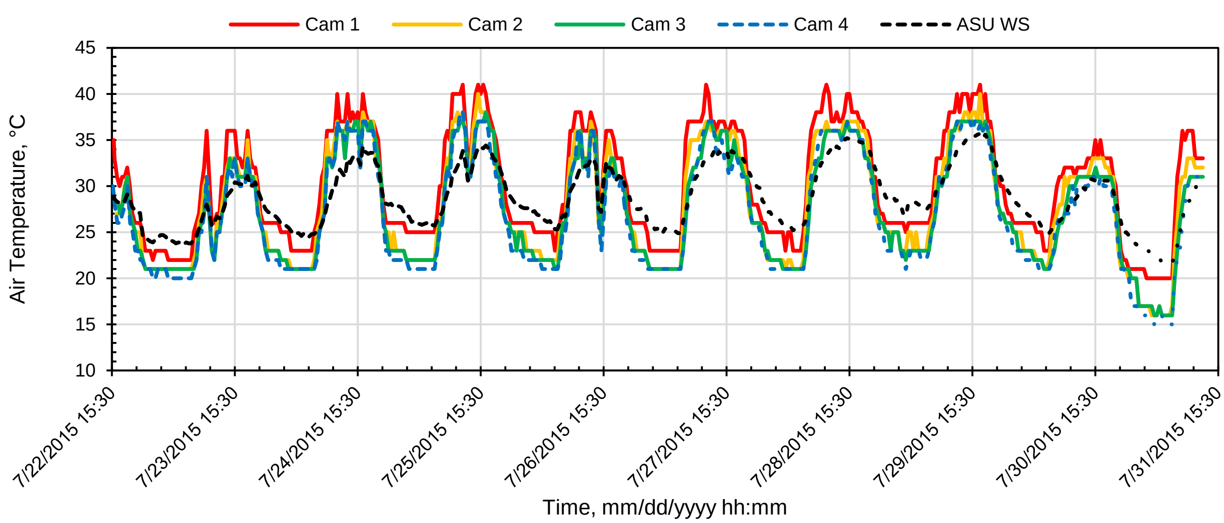

Fig 4. Diurnal temperature variation at the four camera locations and the ASU weather station.

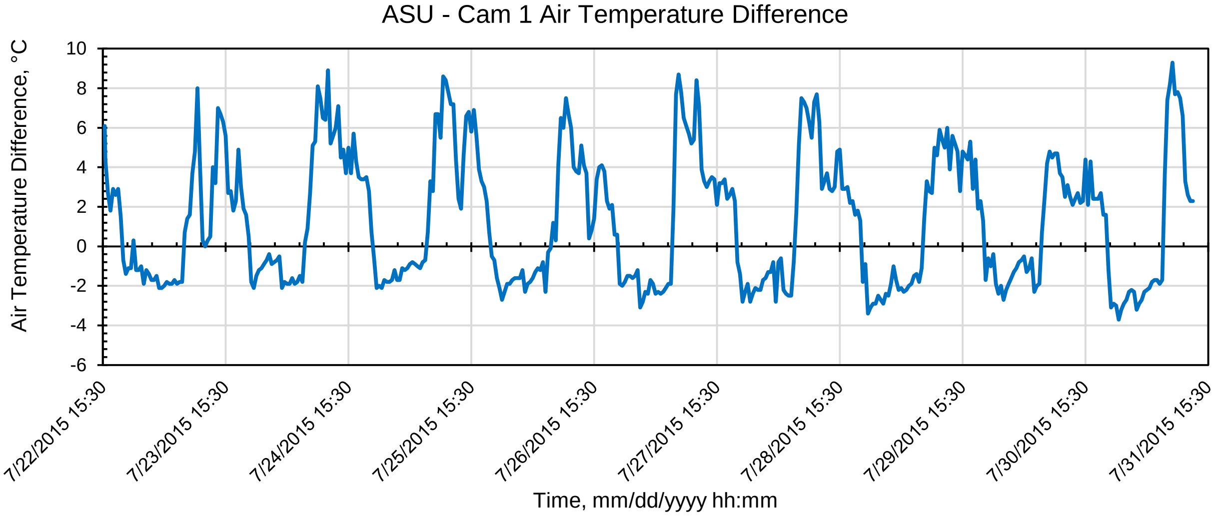

Fig 5. Diurnal temperature difference between the ASU weather station and Cam 1 air temperature.

The raw R and G images were processed to obtain the *AGRI* image data. Fig 6 shows an example of the *AGRI* images obtained from one of the images from Cam 1. The plant pixel values were observed to range from about 0.40 to 0.48, while values outside this range represented the background. Fig 7 shows a further enhanced image of Fig 3 with the background (mainly soil) removed by the Thresholding method. Some plant pixels were falsely cutoff due to high reflection, but the proportion of pixels affected was considered to be insignificant.

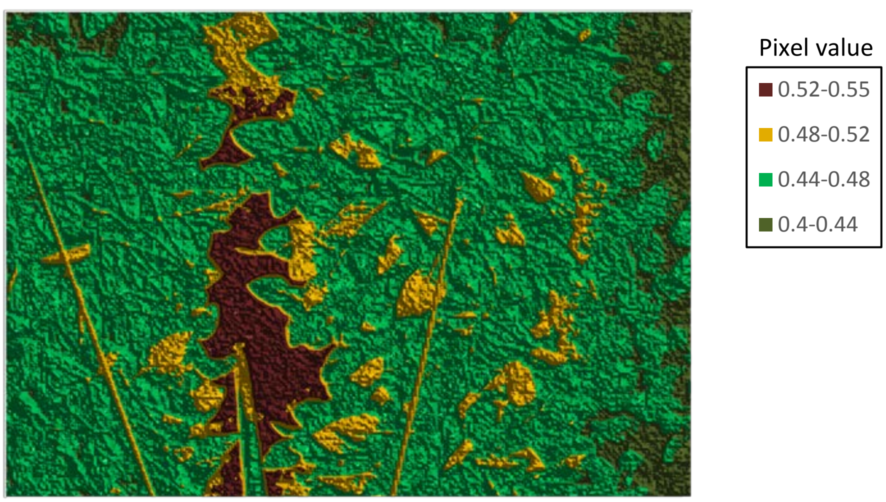

Fig 6. *AGRI* image of one of the images from Cam 1.

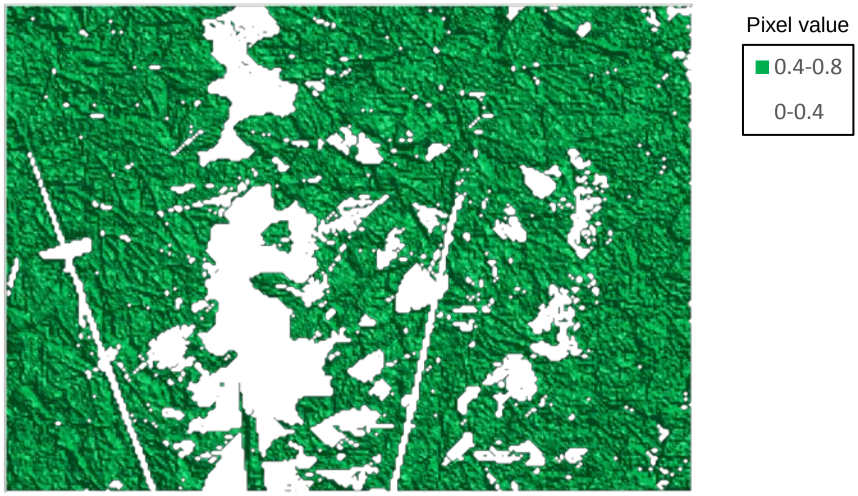

Fig 7. *AGRI* image of one of the images from Cam 1 with background (mainly soil) removed.

The daytime average value of the *AGRI* image data with the background removed was tracked for the period of the observation. Figure 8 shows the time-series data for Cam 1. The *AGRI* plotted data is quite similar to the temperature variation observed in Fig 4 above. The daily peak value was observed to be at about 13:00 each day. The 10-day average *AGRI* data for Cam 1 is shown in Figure 9, while the overall daily average values for all the four cameras are shown in Fig 10. The *AGRI* values from Cam 1 were the highest while those from Cam 2 were the lowest. There was not much difference between the data from Cam 3 and Cam 4, which were located in the interior sections of the soybean field. It is possible that these differences in *AGRI* value at different camera locations represent differences in crop status or even soil conditions. However, this cannot be verified in the current study and was beyond the current objectives.

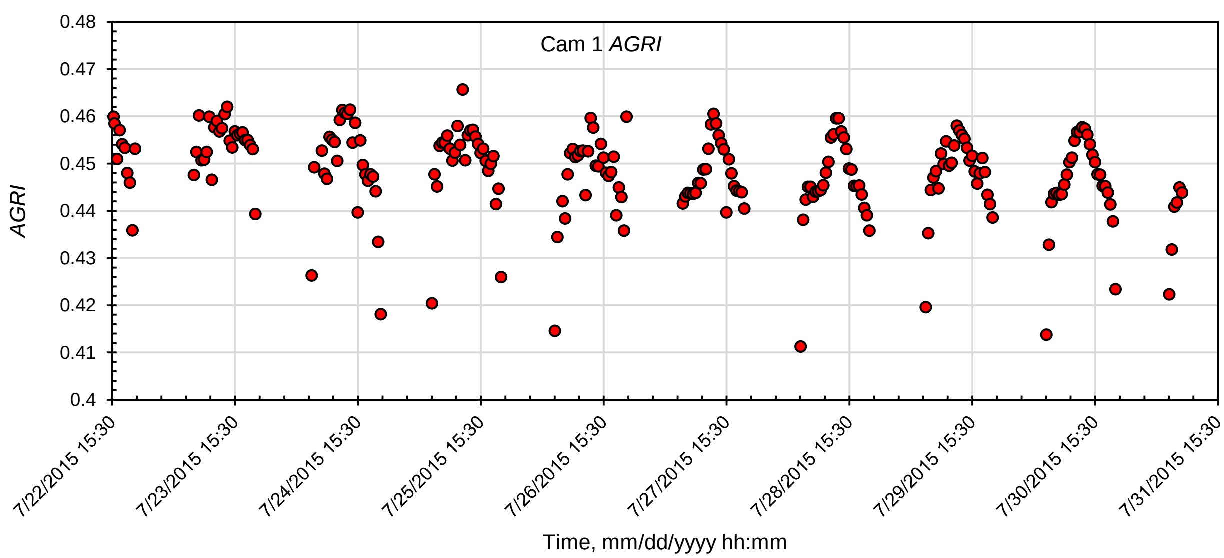

Fig 8. Time-series plot of the average of the *AGRI* image data for Cam 1.

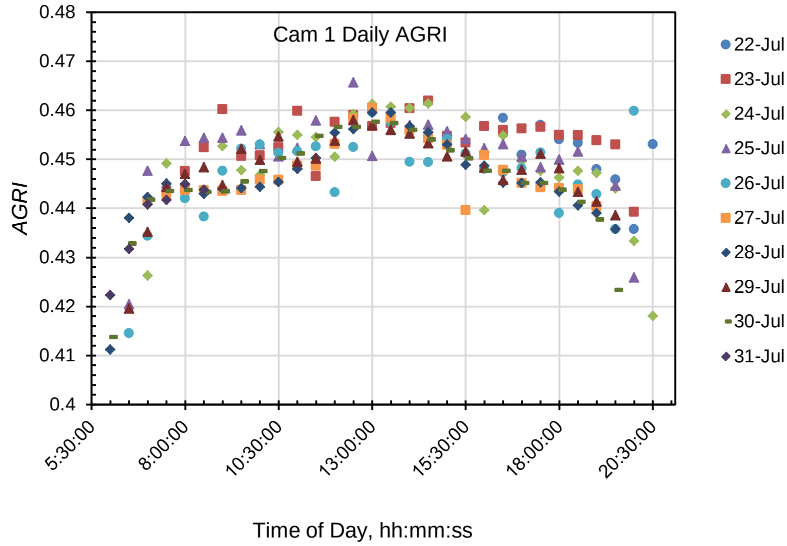

Fig 9. Daily average *AGRI* observed from Cam 1.

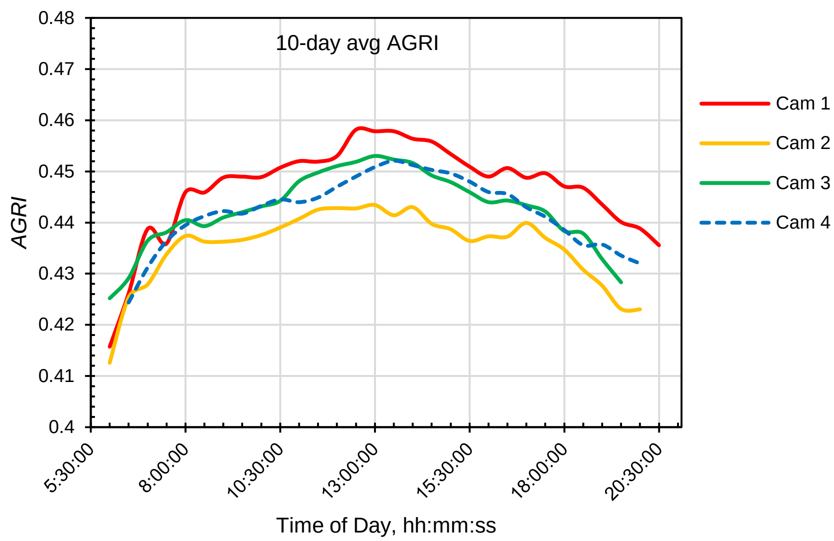

Fig 10. Ten-day average *AGRI* observed from all four cameras.

The regression of *AGRI* values on the logs of selected weather parameters provide some insightful relationships. Figs 11 through 15 show the relationships of average *AGRI* with solar radiation, air temperature, relative humidity, soil surface temperature, and soil temperature at 5-cm depth, respectively, at Cam 1 location (left) and at all four locations (right). Similar trends were observed among all four camera locations, with some variation. Generally, apart from the regression on relative humidity which yielded a negative relationship, all parameters showed positive relationships. The following is the decreasing order of correlation: log of solar radiation ($0.36 < R^2 < 0.65$) > log of soil surface temperature ($0.23 < R^2 < 0.38$) > log of air temperature ($0.09 < R^2 < 0.29$) > log of soil temperature at 5-cm depth ($0.09 < R^2 < 0.20$) > log of relative humidity ($0.00 < R^2 < 0.18$).

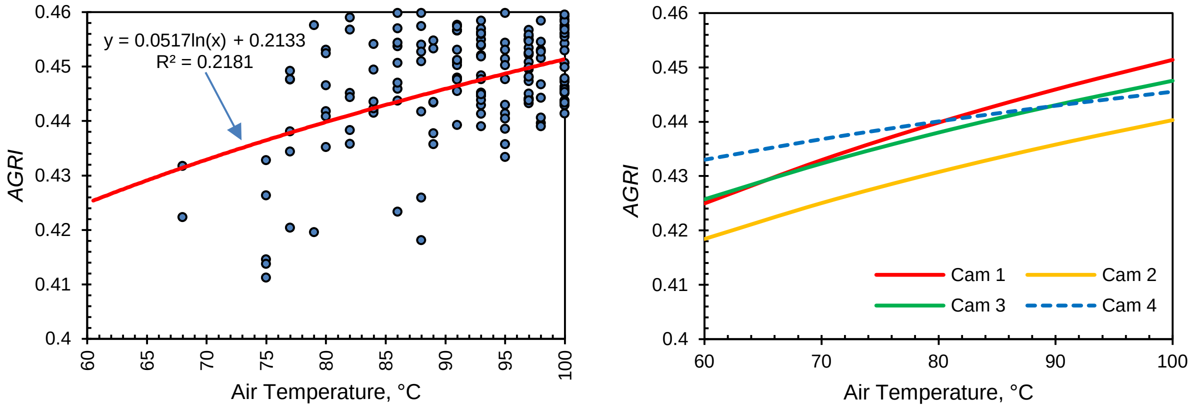

Fig 11. Relationship between *AGRI* and air temperature: Cam 1 location (left) and all four locations (right).

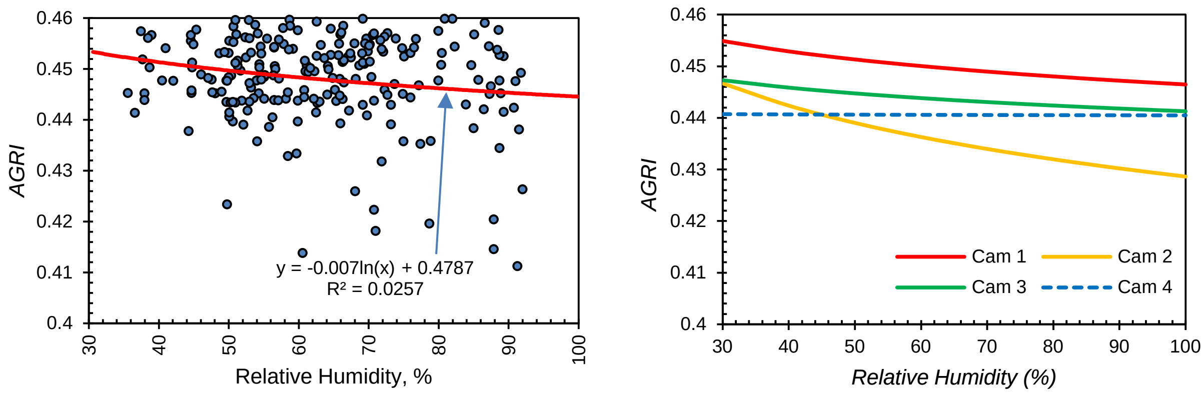

Fig 12. Relationship between *AGRI* and relative humidity: Cam 1 location (left) and all four locations (right).

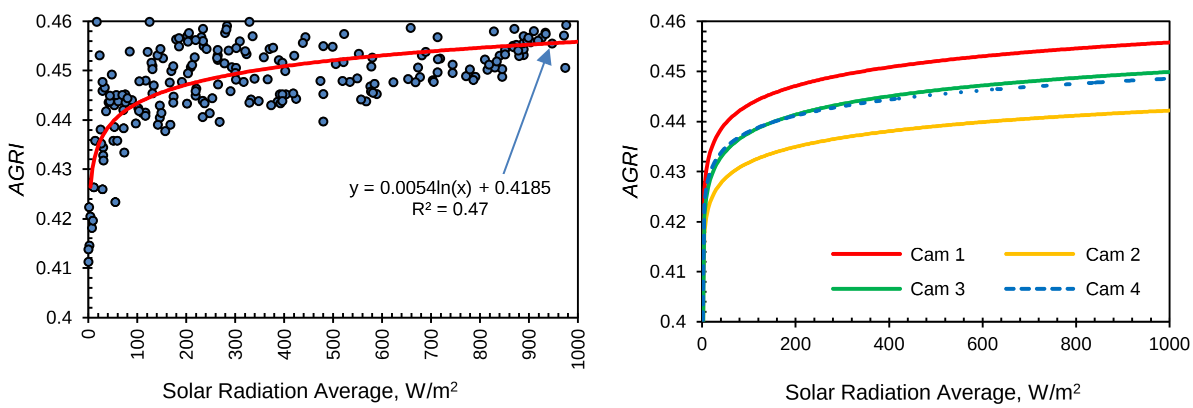

Fig 13. Relationship between *AGRI* and solar radiation: Cam 1 location (left) and all four locations (right).

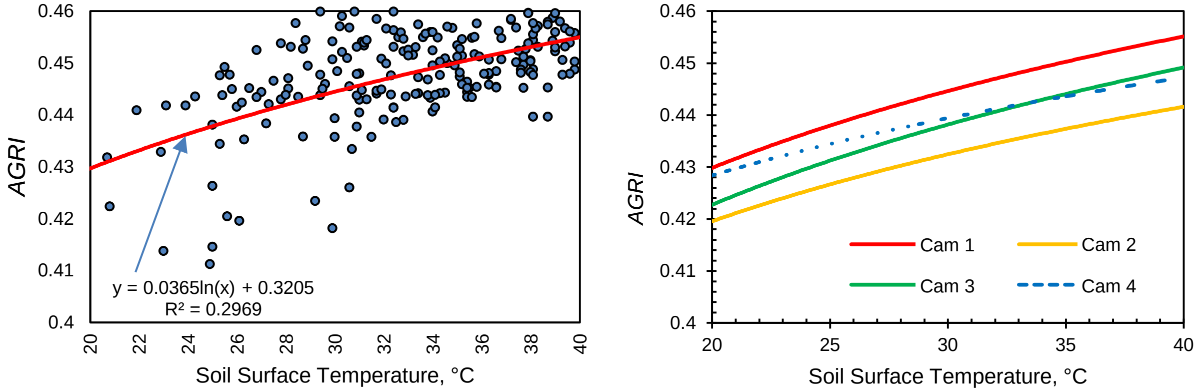

Fig 14. Relationship between *AGRI* and soil surface temperature: Cam 1 location (left) and all four locations (right).

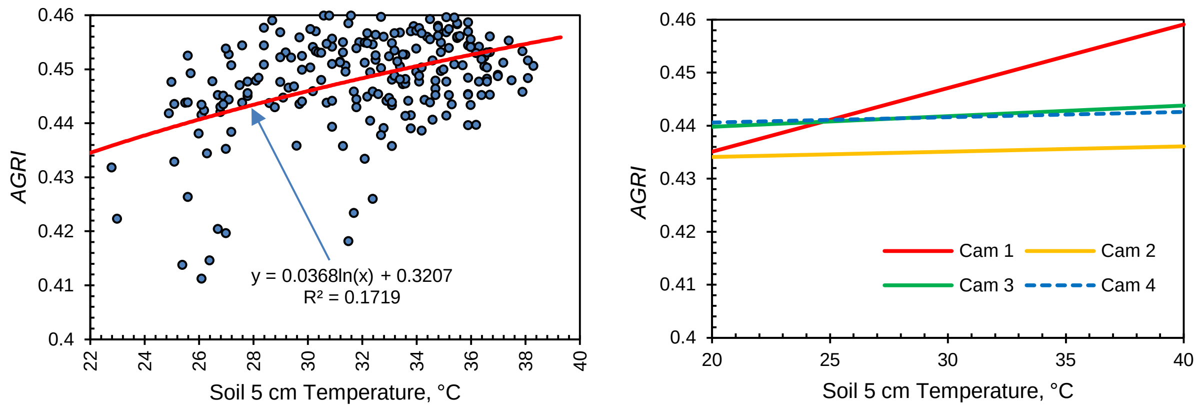

Fig 15. Relationship between *AGRI* and soil 5 cm temperature: Cam 1 location (left) and all four locations (right).

Conclusion

This study has demonstrated the potential of using game and trail time-lapse cameras to provide useful data for monitoring or studying time-series response of crops to changing environmental conditions. The temperature measured by the internal temperature sensor of each camera showed similar trends among the four cameras used and these were similar to the temperature from a nearby weather station. By using the RGBExcel software application to extract RGB image data into Microsoft Excel, images of soybean plants captured by the cameras were successfully processed and analyzed in Excel. The average Adjusted Green Red Index (*AGRI*) which was used to analyze crop response to weather conditions, was regressed on weather data yielding the following decreasing order of correlation: log of solar radiation ($0.36 < R^2 < 0.65$) > log of soil surface temperature ($0.23 < R^2 < 0.38$) > log of air temperature ($0.09 < R^2 < 0.29$) > log of soil temperature at 5-cm depth ($0.09 < R^2 < 0.20$) > log of relative humidity ($0.00 < R^2 < 0.18$).

Future Direction

Similar experimental studies with different treatments applied to the target plants will be accomplished to advance the potential of using game and trail cameras for crop monitoring. Other crops such as a variety of cover crops potentially adoptable in Arkansas will specifically be studied. Additional sensors and experimental treatments will be applied to better understand the applicability and adoptability of this practice by farmers.

Acknowledgements

This study was carried out under the auspices of the USDA-NIFA Capacity Building Grants for Non-

Land Grant Colleges of Agriculture Program, project no. 2015-70001-23439, and the USDA-NIFA Hatch project no. 1005836. Funding and facility supports were also provided by the College of Agriculture and Technology at Arkansas State University and the Division of Agriculture at the University of Arkansas. The authors also wish to acknowledge the assistance provided by Siddhardha Manne, Kumar Bade, and Anjani Sravanthi Kaikala, graduate students, during the data collection and processing.

References

Akeh, L.E., Nnoli, N., Gbuyiro, S., Ikehua F., & Ogunbo S. (2000). Meteorological early warning systems (EWS) for drought preparedness and drought management in Nigeria. In D.A. Wilhite, M.V.K. Sivakumar & D.A. Wood (Eds.), Proceedings of an Expert Group Meeting on “Early warning systems for drought preparedness and drought management” (pp. 154–167). Lisbon, Portugal: WMO.

Boschetti, M., Stroppiana, D., Giardino, C., Brivio, P. A., Vincini, M., & Frazzi, E. (2007). Proximal and remote sensing observations for precision farming application, the Citimap project: experimental design and preliminary data analysis. New Developments and Challenges in Remote Sensing, Z. Bochenek (ed.). Online access: http://www.earsel.org

Cheng, T., Yang, Z., Inoue, Y., Zhu, Y., & Cao, W. (2016). Preface: recent advances in remote sensing for crop growth monitoring. *Remote Sensing*, 8, 116.

Deery, D., Jimenez-Berni, J., Jones, H., Sirault, X., & Furbank, R. (2014). Proximal remote sensing buggies and potential applications for field-based phenotyping. *Agronomy*, 5:349-379, doi:10.3390/agronomy4030349

Doraiswamy, P.C., Moulin, S., Cook, P.W., and Stern, A. (2003). Crop yield assessment from remote sensing. *Photogrammetric Engineering & Remote Sensing*, 69(6), 665–674.

Holecz, F., Barbieri, M., Collivignarelli, F., Gatti, L., Nelson, A., Setiyono, T.D., Boschetti, M., Manfron, G., Brivio, P.A., Quilang, J.E. & Obico, M.R. (2013). An operational remote sensing based service for rice production estimation at national scale. In Proceedings of the Living Planet Symposium. Edinburgh, United Kingdom: ESA.

Hollinger, S.E. & Angel, J.R. (2009). Weather and crops. In Illinois Agronomy Handbook, 24th edn. (pp. 1–12). Urbana, IL: University of Illinois.

Larbi, P.A. (2016a). RGBExcel: An RGB image data extractor and exporter for Excel processing. *Signal and Image Processing: An International Journal*, 7(1), 1-9.

Larbi, P.A. (2016b). RGB2X: An RGB image data extract-export tool for digital image processing and analysis in Microsoft Excel. ASABE Paper No. 162460787. St. Joseph, MI: ASABE.

Larbi, P.A. (2016c). Advancing Microsoft Excel's potential for low-cost digital image processing and analysis. ASABE Paper No. 162455503. St. Joseph, MI: ASABE.

Lillesand, T.M., R.W. Kiefer, & J.W. Chipman. (2015). *Remote Sensing and Image Interpretation, 7th edn*. Hoboken, NJ: John Wiley & Sons, Inc.

Murthy, V.R.K. (2004). Crop growth modeling and its applications in agricultural meteorology. In M.V.K. Sivakumar, P.S. Roy, K. Harsen, & S.K. Saha (Eds.), Proceedings of the training workshop on Satellite remote sensing and GIS applications in agricultural meteorology (pp. 235-261). Dehra Dun, India; WMO, IMD, CSSTEAP, IIRS, NRSA, SAC.

Nutter, F.W., Tylka, G.L., Guan, J., Moreira, A.J.D., Marett, C.C., Rosburg, T.R., Basart, J.P., & Chong, C.S. (2002). Use of remote sensing to detect soybean cyst nematode-induced plant stress. *Journal of Nematology,* 34(3), 222–231.

Seelan, S.K., Laguette, S., Casady, G.M., Seielstad, G.A. (2003). Remote sensing applications for precision agriculture: A learning community approach. *Remote Sensing of Environment,* 88, 157–169.

Siachalou, S., Mallinis, G., Tsakiri-Strati, M. (2015). A hidden Markov models approach for crop classification: Linking crop phenology to time series of multi-sensor remote sensing data. *Remote Sensing,* 7, 3633–3650.

Toureiro, C., Serralheiro, R., Shahidian, S., & Sousa, A. (2016). Irrigation management with remote sensing: Evaluating irrigation requirement for maize under Mediterranean climate condition. *Agricultural Water Management* (In press), pp. 1–10.

Vong, C.N. and Larbi, P.A. (2016). Comparison of image data obtained with different commercial cameras for use in visible spectroscopy. ASABE Paper No. 162455510. St. Joseph, MI: ASABE.