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Small UAS integrated sensing tools for abiotic stress monitoring in irrigated pinto beans

Jianfeng Zhou[1], Lav R. Khot[1], *, Rick A. Boydston[2], Phillip N. Miklas[2], Lyndon Porter[2]

[1] Center for Precision and Automated Agricultural Systems, Department of Biological Systems Engineering, IAREC, Washington State University, Prosser, WA 99350; [2] USDA-ARS, Grain Legume Genetics and Physiology Research Unit, Prosser, WA 99350

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Abstract. *Precision agriculture is a practical approach to maximize crop yield with optimal use of rapidly depleting natural resources. Availability of specific and high resolution crop data at critical growth stages is a key for real-time data driven decision support for precision agriculture management during the production season. The goal of this study was to evaluate the feasibility of using small unmanned aerial system (UAS) integrated remote sensing tools to monitor the abiotic stress of eight irrigated pinto beans (Phaseolus vulgaris L.) with varied irrigation and tillage treatments. A small UAS integrated with a multispectral and an infrared thermal imaging camera was used to collect data of bean field plots on 54, 76 and 98 days after planting (DAP). Indicators such as green normalized vegetation index (GNDVI), canopy cover (CC, ratio of ground covered by crop canopy to the total plot area) and canopy temperature (CT, °C) of crops were extracted from imaging data of the two types of sensor. The statistical difference of the developed indictors in crops with different treatments was analyzed to show their performance in detecting crop stress. The indicators and their combinations of temporal data were also correlated with ground reference yield data to validate the effectiveness in stress monitoring. Results show that the GNDVI, CC and CT were able to differentiate crop grown under full and deficit irrigation treatments at each of the three growth stages. The developed indicators were strongly correlated with crop yield with Pearson correlation coefficients (r) of 0.71 and 0.72 for GNDVI and CC, respectively, in the early growth stage (54 DAP). Canopy temperature also showed high correlation with yield with r of 0.84 at 76 DAP and 0.77 at 98 DAP. Performance of small UAS based indicators in crop yield estimation was improved substantially when temporal data of each indicator were used for correlation. Overall, the small UAS based remote sensing tool has the potential in rapid crop stress monitoring and management.*

Keywords. *Unmanned aerial system; multispectral imagery; thermal imagery; water stress; vegetation indices; canopy temperature.*

Introduction

Global food security is under extreme pressure from a growing population, which requires an increase of 44 million metric tons per year in crop production within the next 35 years (Ray et al. 2013). However, maintaining crop yield is becoming a challenge under adverse environmental conditions, such as shortage of water and rapidly changing climate. For example, about 93% of common bean growing areas are subject to water-deficit stress at some time (Devi et al. 2013), and drought may cause yield losses up to 80% in some regions (Gallegos and Shibata 1989; Cuellar-Ortiz et al. 2008). Precision agriculture with important crop management practices including variable irrigation, variable fertilization, and reduced soil tillage have critically increased crop yield (Barbera et al. 2012; Karlen et al. 2013; Šíp et al. 2013), but site-specific information is needed for improving the use efficiency of natural resources and crop management.

The proper decision making for crop management is facilitated by accurate site-specific crop information, which requires timely and high-resolution data for support. Conventionally, crop response to different field managements was measured using ground-based sensors, such as handheld ceptometer to measure leaf area index (Delalieux et al. 2008) and chlorophyll meter to measure leaf greenness (Gitelson, 2004; Taugourdeau et al. 2014). However, ground-based methods are often time-consuming and not suitable for large acreage, and may not be adequate to acquire sufficient information for crop management.

The potential of using remote sensing technologies to monitor the temporal and spatial variability of crops has been studied for many years (Zhang and Kovacs 2012; Mulla 2013). Common remote sensing platforms include satellites, airplanes, balloons and helicopters, and a variety of sensors such as multispectral / hyperspectral sensors, thermal sensors and light detection and ranging (LiDAR) or radio detection and ranging (Radar) sensors. Such sensors have been integrated with the platforms to gather data at a larger scale. Diagnostic information of crops and soil, such as vegetation indices, leaf area index and water indices, can be derived from data collected using above sensing devices. During the past few years, small unmanned aerial systems (UASs) are attracting the interest of researchers and commercial sectors for high-throughput data collection in precision agriculture and phenomics. Compared to satellite-based remote sensing, small UASs can collect data with higher spatial resolution (up to centimeter) and higher temporal frequency (hourly or daily).

Small UAS-based remote sensing technologies have been used for the research of yield prediction (Swain et al. 2010), stress detection (Elarab et al. 2015), field management (Bellvert et al. 2014; Castro et al. 2011; Khot et al., 2016; Tilly et al. 2015) and high-throughput phenotyping in field conditions (Sankaran et al., 2015a; Sankaran et al., 2015b). However, the potential of using small UAS-based remote sensing technologies to detect the effect of irrigation and tillage on crop yield of pinto beans has not been fully studied. Therefore, the objectives of the study were to 1) evaluate feasibility of small UAS-based multispectral and infrared thermal imaging for rapid crop stress monitoring in irrigated pinto beans, and 2) the usefulness of temporal data in improvement of the yield estimation accuracy.

Materials and methods

Establishment of experimental plots

Pinto bean, a market class of common bean (*Phaseolus vulgaris* L.) was planted in 56 cm rows in a sandy loam soil containing 1.3% organic matter at Washington State University research farm near Prosser, WA on May 21, 2015. Four irrigation plots of 80.1 m by 12.2 m in dimension with 4.6 m buffers were scheduled with two irrigation levels, full (100%) irrigation and deficit (50%) irrigation. The plots were irrigated using linear move low energy spray application technique with nozzles spaced 1.5 m and just above the crop canopy. Each irrigation plot was spilt into four tillage plots in dimension of 18.3 m by 12.2 m with 2.3 m buffers and prepared with two tillage treatments, i.e. conventional and strip tillage. A preceding cover crop of fall-planted winter wheat was killed with glyphosate in early April, 2015. Conventional tillage consisted of disking twice and a final pass with Lely power harrow with a packer. Strip tillage consisted of tilling a 30 cm wide strip over each row to be planted using double disk row cleaners, a chisel shank in the crop row, and rolling packer baskets. Final tillage in all plots occurred 15 days before bean planting.

Within each tillage plot, eight subplots of 4.6 m by 6.1 m were used to plant eight cultivars of pinto bean based on randomized complete block design (RCBD). Overall, each pinto bean cultivar was repeated four times on 16 subplots with two irrigation levels and two tillage treatments, resulting in 128 subplots in total. The details of the eight pinto bean cultivars are listed in Table 1. All plots were fully irrigated to replace evapotranspiration (ET) until 30 days after emergence at which time two irrigation treatments were implemented and applied to different plots until senescence (September 11, 2015). ET was estimated and weather data recorded from WSU AgWeathernet (weather.wsu.edu) station located near field plots. Plots were irrigated 2 to 3 times per week with the full irrigation treatments designed to replace 100% ET while deficit irrigation treatments received half as much irrigation during each irrigation event. The full irrigation treatments received 53 cm of irrigation water for the entire growing season, whereas the deficit irrigation treatments received 31 cm. Total rainfall for the months of May, June, July, August, and September were 1.5, 0, 0, 0, and 4.3 cm, respectfully. Plots were harvested September 15, 2015 with a growth period of 117 days.

Table 1 Details of the pinto bean cultivars.

Cultivars	Drought tolerance	Maturity/senescence
C1	Susceptible	Medium season
C2	Susceptible	Full season
C3	Intermediate-susceptible	Medium season
C4	Tolerant	Full season
C5	Tolerant	Full season
C6	Tolerant	Medium season
C7	Tolerant	Full season
C8	Tolerant	Early season

Field data collection

A small UAS was used to collect multispectral and thermal images of the field plots. The small UAS (ARF OktoXL 6S12, HiSystems GmbH, Moormerland, Germany) is a remote controlled platform with a payload lift capability of up to 4 Kg and flight time up to 20 min using a 6500 mAh Lithium-ion polymer battery pack. A radio transmitter (MX20 Hott, Graupner, Stuttgart, Germany) with the range of up to 4 km was used to remotely operate the small UAS. A modified multispectral digital camera (NiteCanon ELPH110 LDP LLC, Carlstadt, NJ, USA) with near infrared (NIR, 670-750 nm), green (G) and blue (B) bands was used for aerial imaging. The camera was mounted onto a gimbal underneath the small UAS that is capable of automatically adjusting the nick and roll shifts to the pre-set orientation during flight. A firmware was used to enable geo-referenced interval shooting to acquire images every 5 s during waypoint navigated flights. The captured 8-bit JPG images with the resolution of 16.1 megapixels (4608 × 3456) were stored to an on-board camera SD card. During above flights, an infrared thermal imaging sensor (Tau 640 uncooled cores, Flir Systems, Goleta, CA, USA) combined with a custom designed ThermalCapture hardware (TeAx Technology UG, Wilnsdorf, Germany) with pre-define sampling interval of 3 s was used in this study. The thermal camera has a resolution of 640×512 with a field of view (FOV) of 32°×26° (19 mm lens). The thermal camera was powered using a portable 5 VDC battery.

To reduce the influence of light variation and shade on the image quality, all the images were acquired at solar noon time with the least shade of plants in clear sky. A reference reflectance panel (Micasense, Seattle, WA, USA) was placed on the ground in the imaging area to correct the diffuse of reflectance during post-processing of images. The optimal flying altitude was set as approximately 105 m above ground level based on the preliminary tests in previous research (Sankaran et al., 2015a), resulting the spatial resolution of 3.5 and 9.4 cm·pixel^{-1} for multispectral camera and thermal camera respectively. The images taken at the predefined altitude covered the experimental field plots including the reference board. Images were collected at three growth stages, i.e. on July 14, August 5 and August 26, 2015, which were 54, 76 and 98 days after planting (Table 2). These collection dates represented three distinct crop growth stages for measuring crop response. Early stage imaging represented bloom stage and early pod development of the crop nearing canopy row closure. Mid stage imaging represented mid to late pod fill stage and full row closure of the canopy, and late stage imaging represented mature pod stage with pods beginning to yellow (desiccate).

Table 2 Aerial data collection and field management with respect to days after planting (DAP).

Activities/Plant stage	Sensor	Date (2015)	DAP
Planted	--	5/21	--
Irrigation levels initiated	--	6/26	36
Early stage imaging	Multispectral	7/14	54
Mid stage imaging	Multispectral + thermal	8/05	76
Late stage imaging	Multispectral + thermal	8/26	98
Ground reference yield	--	9/15	117

Image processing and data analysis

Pinto beans with different irrigation and tillage treatments may show difference in vegetation indices, visible canopy size and canopy temperature. The selected vegetation index in this study was green normalized difference vegetation index (GNDVI), which has been widely used as a reliable index for indicating the crop canopies vigor (Gitelson et al., 1996; Khot et al., 2016). The average value of GNDVI of each plot was extracted with a customized algorithm developed using Matlab® (2014a, The MathWorks, MA, USA) with the following processing protocol: (1) Separate multispectral images into three bands of NIR, G and B; (2) Adjust the pixels of three bands with the difference between 255 and the maximum pixels of the reference board; and (3) Calculate GNDVI and removing background (soil) with a threshold. Thresholding was based on the assumption that crops reflect more NIR and absorb more G, resulting in substantially higher GNDVI for crops than that for soil. In the end, 128 subplots were segmented from GNDVI images by evenly splitting one tillage plot into eight subplots, and the average GNDVI of each subplot was calculated. Also, the number of pixels with value over zero (visible crop canopy) in each subplot was counted to calculate the *canopy cover* using the following equation (Trout et al. 2008):

$$CC = \frac{N_C}{N_P} \quad (1)$$

where *CC* is canopy cover of a subplot, N_C and N_P are the number of pixels over zero and the overall number of pixels for a subplot, respectively. Canopy cover is considered as an indicator of light interception and was used to relate to crop yield and water use (Grattan et al. 1998; Neale et al. 2005; Trout et al. 2008).

Crop canopy temperature is also closely related to crop stress/water requirement (Jackson et al. 1977; Wang et al. 2016), crop yield (Irmak et al. 2000) and chlorophyll concentration (Elarab et al. 2015). To evaluate the potential of thermal images in the detection of crop stress, crop canopy temperature (CT) was extracted using the similar image processing protocol as that of multispectral images. The crop canopies were segmented by removing the background (soil), which had higher temperature than crops, from thermal images. The average temperature of all plants in each subplot was calculated as a potential parameter to monitor crop stress and estimate crop yield.

The statistical analysis of GNDVI, CC and CT of each subplot was performed using SAS® (9.2, SAS Institute, Cary, NC, USA). The treatment effects were assessed using ANOVA ('PROC GLM') analysis with the least square mean difference ('LSMEANS/PDIFF') option to compare the treatment at 0.05 level of significance. The correlation of the calculated indicators of GNDVI, CC and CT with yield data (ground truth) was performed using 'PROC CORR' procedure with 'Pearson' option. Meanwhile, a linear regression analysis ('PROC REG') was conducted between yield data and a temporal combination of GNDVI, CC and CT at different growth stages to test the potential. The output trends were plotted using SigmaPlot® (11.0, Systat Software, San Jose, CA, USA).

Results and discussion

Crop stress monitoring using multispectral imaging

Pinto bean cultivars under two irrigation levels and two tillage methods had different response in GNDVI, CC and CT. The means of GNDVI of all bean cultivars under different treatments at 54, 76 and 98 DAP are shown in Fig. 1a. Overall, ANOVA analysis showed no significant difference between GNDVI means of two tillage treatments under full irrigation in all three growth stages. However, the pertinent treatments resulted in significantly different vigor (i.e. GNDVI) of crops under deficit irrigation level at 54 DAP. Pinto beans in strip-tilled plots had more vigor than those in conventional-tilled plots under deficit irrigation in the early growth stage, but the effect lessened as the crop approached maturity. The ANOVA suggests that the interaction effect of irrigation and tillage was not significant on GNDVI at any of the three growth stages, with *p*-values of 0.21, 0.09 and 0.85 at 54, 76 and 98 DAP, respectively. The irrigation level had significant effect ($p < 0.0001$) on vigor at three growth stages with the means of GNDVI in fully irrigated crops (0.25 ± 0.05 [mean ± s.d.], 0.29 ± 0.03 and 0.22 ± 0.04 at three growth stages, respectively) were significantly higher than those with deficit irrigation (0.16 ± 0.06, 0.25 ± 0.04 and 0.17 ± 0.03). Overall, the multispectral imaging derived GNDVI had the ability to distinguish crops with full irrigation and deficit irrigation (drought stress) at all three growth stages studied in this research.

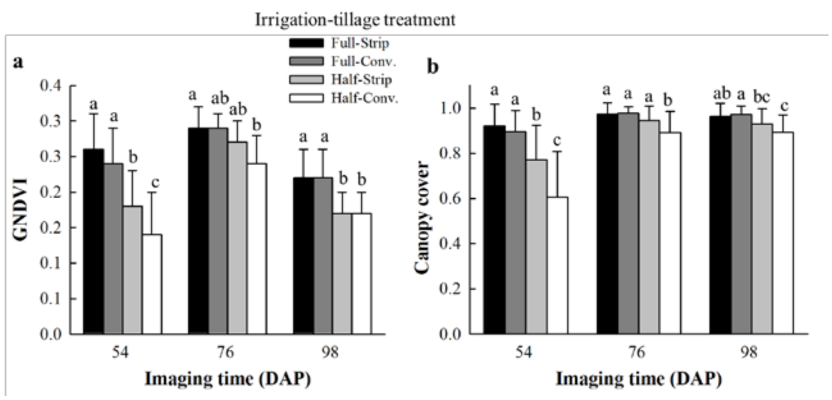

Fig. 1 Mean values of (a) GNDVI and (b) canopy cover of all bean cultivars under four irrigation-tillage treatments at three growth stages specified as days after planting (DAP). The letters signify difference between means of irrigation-tillage treatments associated GNDVI or canopy cover evaluated separately for respective growth stages.

Similar patterns were observed in canopy cover of pinto bean cultivars with different treatments, as shown in Fig. 1b. Canopy cover was not significantly different within different tillage treatments in full irrigation at all three growth stages. However, canopy cover was significantly lower in bean cultivars with deficit irrigation and conventional tillage than that of fully irrigated beans with both tillage methods. Up to 76 DAP, the effect of tillage was significant for the cultivars with deficit irrigation suggesting that tillage method may affect the growth of pinto beans more under the water stress than non-stress condition. In the late season (senescence stage), bean plants were brown. Less chlorophyll content in leaves at senescence resulted in less reflectance in NIR channel, which reduced the GNDVI difference between crops for the two tillage methods. Overall, the canopy cover of the bean plots increased from 0.80 ± 0.19 at early stage (54 DAP) to 0.95 ± 0.72 at mid growth stage (76 DAP) and saturated to 0.94 ± 0.69 at late growth stage (98 DAP). The canopies were not in full row closure in early stage resulting in lower canopy cover than that of fully closed canopies in mid and late growth stages. Thus, canopy cover might be a useful indicator for crop stress monitoring during early growth stage, but inadequate during the late stages.

The performance of GNDVI and canopy cover in yield estimation was evaluated by correlating them with ground reference yield data. The average yields of all bean cultivars were 5332.1±722.4, 5712.3±731.9, 2661.3±1330.6 and 3032.0±1292.6 kg·ha^{-1} under the treatments of full irrigation-conventional tillage, full irrigation-strip tillage, deficit irrigation-conventional tillage and deficit irrigation-strip tillage, respectively. ANOVA analysis shows that the overall yield of fully irrigated crops was significantly higher than that of deficit irrigated crops, regardless the tillage method. However, there was no significant difference between yields of crops with different tillage methods in each irrigation level. The correlation coefficients between yield and the developed indictors are reported in Table 3. The overall correlation between crop yield and average GNDVI within the whole field was strong (r = 0.71) at the early growth stage (45 DAP) compared to 76 and 98 DAP where the respective r values were 0.54 and 0.55. Similarly, CC was strongly closely related to crop yield in early growth stage with a higher r (= 0.72) than that of later stages (Table 3). Key reason for the lower correlation might be the saturation of the GNDVI at later growth stages. Also, varied crop yields for different cultivars could have contributed to the above effect as well. Furthermore, the correlation coefficients of GNDVI within each bean cultivar had larger variation with r ranged from 0.50 to 0.92 for 54 DAP, 0.30 to 0.83 for 76 DAP and 0.64 to 0.84 for 98 DAP (Table 3). Similar patterns were also observed in the correlation coefficients of CC. Note that understanding the effect of cultivars on the crop yield is beyond the scope of this study.

Table 3 Pearson correlation coefficients (r) between pinto bean yield and aerial image derived indicators of GNDVI and canopy cover (CC) with respect to three growth stages.

Cultivars	Pearson correlation coefficient (r)							
	GNDVI				CC			
	54 DAP	76 DAP	98 DAP	Combined	54 DAP	76 DAP	98 DAP	Combined
C1	0.86	0.82	0.70	0.94	0.89	0.79	0.63	0.95
C2	0.86	0.64	0.82	0.97	0.82	0.43	0.49	0.95
C3	0.61	0.48	0.64	0.80	0.46	0.49	0.37	0.72
C4	0.81	0.83	0.84	0.88	0.78	0.56	0.77	0.98
C5	0.92	0.51	0.67	0.97	0.89	0.50	0.30	0.95
C6	0.50	0.30	0.70	0.70	0.44	0.18	0.25	0.88
C7	0.84	0.78	0.83	0.91	0.84	0.71	0.60	0.94
C8	0.80	0.75	0.70	0.94	0.80	0.60	0.56	0.93
Overall	0.71	0.54	0.55	0.85	0.72	0.46	0.37	0.82

Performance of the developed indicators towards representation of crop yield was increased substantially when data from different growth stages were combined. Overall, correlation with yield increased to 0.85 and 0.82 using the combined GNDVI and CC, respectively, which were higher than that in individual stages (Table 3). Meanwhile, the correlation of the combined data with yield for each bean cultivar also increased and ranged between 0.70-0.97 and 0.72-0.98 for combined GNDVI and combined CC, respectively. In summary, findings indicate that using temporal data of small UAS-based remote sensing might have higher potential towards crop yield estimation than using individual growth stage data.

Crop stress monitoring using infrared thermal imaging

Fig. 2 shows a false-color thermal image of the pinto bean test plots acquired at 98 DAP and the pertinent effect of irrigation and tillage on the canopy temperature (CT). At either of two growth stages, the CT with deficit irrigation was significantly higher than that of plots with full irrigation in both tillage methods. ANOVA indicated that the interaction of irrigation and tillage was not significantly affecting CT at both mid (p = 0.85 on 76 DAP) and late (p = 0.13 on 98 DAP) growth stages. However, the effect of irrigation was significant with $p < 0.0001$ for both stages, but the tillage effect was not significant (p = 0.56 and 0.25 respectively on 76 and 98 DAP). Thus, CT had the ability to distinguish the crops under different irrigation regimes. Similar to this study, Wang et al. (2016) reported that crop temperature derived from thermal images varied due to different irrigation treatments at different growth stages. However, the data in the early growth stage was not available for analysis and need to be considered to evaluate the earliest potential stage to detect the crop stress. Additionally, the CT may be affected by surrounding micro-climate. The average ground surface temperature measured by the thermal images was 41.6 and 38.1 °C at 78 and 98 DAP respectively, and overall average CT of crops was 28.5 and 29.5 °C at the corresponding days. Resulting temperature differences were 13.1°C and 8.6°C respectively on 76 and 98 DAP, indicating the small difference between crop and soil in the late growth stage. The crops in the late growth stages have less water content and might have higher CT, which could have reduced the difference between crop and soil temperature.

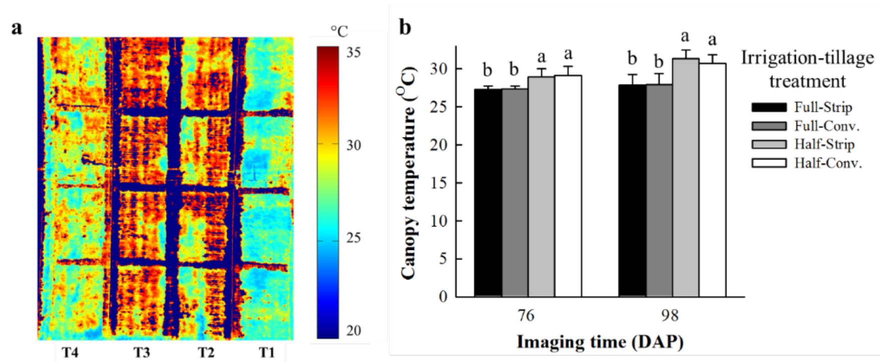

Fig. 2 a False-color infrared thermal image of pinto bean plots acquired at 98 days after planting (DAP). T1 to T4 represent the different irrigation levels of full, deficit, deficit and full irrigation, respectively. b Effect of irrigation-tillage treatment on the canopy temperature (CT). The letters signify difference between means of irrigation-tillage treatments associated CT evaluated separately for respective growth stages.

The performance of the canopy temperature in the representation of crop stress was also evaluated using the correlation between the indicator and ground reference yield data. Table 4 reports such correlation coefficients. It shows that the canopy temperature was strongly correlated with crop yield. The negative correlation signifies that higher the temperature due to higher canopy stress, lower was the crop yield. The overall correlation coefficients were -0.84 and -0.77, with the corresponding variation range of -0.71 to -0.92 and -0.77 to -0.93 among pinto bean cultivars at 76 and 98 DAP, respectively. When the CC data of two stages were combined to correlate with crop yield, the correlation with yield was getting stronger than that of data in individual growth stages. Overall, similar to GNDVI & CC, the temporal canopy temperature data showed better potential in crop yield estimation. Compared to the pertinent GNDVI and CC data, CT had stronger correlation with yield, which might be because former indicators might have saturated in the mid and late growth stages, but temperature was sensitive in all growth stages.

Table 4 Correlation coefficients between pinto bean yield and aerial image derived canopy temperature (CT).

Cultivars	Correlation coefficient (*r*): CT *vs* yield		
	76 DAP	98 DAP	Combined
C1	-0.87	-0.87	-0.88
C2	-0.91	-0.90	-0.93
C3	-0.89	-0.77	-0.93
C4	-0.90	-0.85	-0.96
C5	-0.92	-0.91	-0.96
C6	-0.71	-0.80	-0.81
C7	-0.88	-0.93	-0.95
C8	-0.87	-0.84	-0.88
Overall	-0.84	-0.77	-0.85

Conclusion

This study evaluated the performance of multispectral and infrared thermal imagery from low altitude small UAS for rapid/early crop stress monitoring of pinto beans. The small UAS-based low-altitude remote sensing technologies exhibited great potential for monitoring the crop stress in pinto beans grown under different irrigation and tillage treatments. The results showed GNDVI and canopy cover from multispectral camera might be used as crop stress indicators to monitor crops water stress level at the growth stage as early as 54 days after planting, which was only 24 days after implementing deficit irrigation. Overall, the developed indicators had strong correlation with crop yield in the early stage (54 DAP), and combined data from three stages improved the correlation substantially. Moreover, canopy temperature derived from thermal images at mid and late growth stages had strong correlation with yield in both growth stages, and might be used as a good crop stress/yield indicator. Overall, small UAS-based imagery has the potential to rapidly monitor crop stress of pinto bean and other row crops.

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