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Case Report

A Case Study Of Predicting Early Season Soybean Populations Using Dual Field-Of-View System For Spectral Data Collection In Changing Atmospheric Conditions.

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Abstract

The use of hyperspectral data for crop management and phenotyping while overcoming the difficulty of fluctuating atmospheric conditions is becoming more and more popular. Using a single spectrometer, the Piccolodual field-of-view device gathers up- and downwelling radiation almost simultaneously. For crop monitoring in extremely fluctuating atmospheric circumstances, such devices hold out a lot of potential. Here, a case study of assessing soybean plant numbers in early vegetative stages was used to illustrate the system's usefulness from a tractor-mounted boom. Two replicas of the same experiment are used to describe the Piccolo system and evaluate its performance under various sky conditions. Partial least squares regression (PLSR) was used to estimate the plant population, and models calibrated and validated under sunny and overcast or cloudy and sunny conditions, respectively, produced stable results. We demonstrate the Piccolo system's operational viability for precision agricultural research and possible commercial applications, and we draw the conclusion that it is efficient for gathering data in a variety of atmospheric circumstances.

Keywords : *hyperspectral; Piccolo dual field-of-view spectrometer; partial least squares regression(PLSR); soybean; site-specific population assessment; replanting*

INTRODUCTION

Precision agricultural research is increasingly using hyperspectral sensors [1,2]. Vegetation indices can be computed using hyperspectral data (hundreds of tiny bands) or the data itself, which simplifies the study but detracts from its depth and richness [3, 4]. It can be difficult to do hyperspectral measurements of plant canopy using the sun as the light source [5], particularly while atmospheric conditions are changing. This necessitates regular reference data collection by the same sensor or another one. In place of the conventional white reference, MacLellan and Malthus [6] proposed the idea of a spectrometer with an adual field-of-view that alternately gets upwelling (radiance) and downwelling (irradiance) data using a cosine response fore optic [7]. The Piccolo, an operational dual field-of-view system invented and presented by MacArthur et al. [8], was installed on a tractor in soybean experimental plots for the current study.The emergence rate of soybean seedlings is frequently slower than the seeding rate. In order to inform decisions about replanting, it is necessary to evaluate plant populations at an early stage of development [9].

In order to extrapolate plants per unit area, the current population assessment methodology typically counts plants within representative quadrats and computes the mean of these samples [10]. Given the variety of existing techniques for estimating soybean populations and the urgency of obtaining this data, automating this process through crop reflectance sensing is an intriguing case study. The density of maize seedlings has been evaluated using hyperspectral imaging [11]. Investigating the performance of a tractor-mounted Piccolo system in the presence of fluctuating atmospheric conditions was the aim of the current investigation. Estimates of the soybean plant population were assessed early in the development process, when decisions about replanting have to be made, as a case study to test the system.Theoretically, the

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Piccolo’s principle of operation dictates that measurements and analyses ought to be uniform irrespective of atmospheric and light circumstances (i.e., a single prediction model that takes into account all light situations).

MATERIALS AND METHODS

Trial Design and Study Area

The University of Wisconsin Arlington Agriculture Research Station (43°1808” N, 89°2008” W) was the site of field tests in 2016.For the two cultivars (AG2433—Monsanto and P28T08R—DuPont Pioneer), tillage and row spacing treatments were used. For each of the primary impacts, 14 seeding rates (3.7 to 51.8 seeds × 104 h−1) were used in order to create population heterogeneity.The plots were 7.6 m long and had either four 0.76 m or six 0.38 m rows. To make room for the tractor-mounted spectral system, driving alleys with soybean plants were dotted around the field (Figure 1a). Four early stages of development were covered by the spectral data collected throughout the trial’s replication (Table 1).The number of plants within 1.5 meters of the middle rows was used to calculate the plant populations (Table 1) for each plot. Depending on the atmospheric conditions, the data collecting days were classified as either sunny or cloudy (Table 1). Clear sky and cloudy, ranging from sporadic to completely covered, were considered sunny.

Gathering Spectral Data

The Piccolo hyperspectral system, which has a Flame (Ocean Optics, Inc., Dunedin, FL, USA) spectrometer with a spectral range of 340 to 1022 nm and an optical resolution of 1.33 nm full-width half-maximum interpolated to 1 nm spacing, was used to collect the canopy spectra of soybean seedlings.A hydraulically operated boom installed the Piccolo system on a tractor (Figure 1a).Protected by optical glass domes (Figure 1b) and equipped with shutters, the upwelling bare fiber saw the target with a 25 view angle, while the downwelling fiber looked up at the sky through a cosine corrected polytetrafluoroethylene fore-optic.Shutter activity and integration times were synchronized via a Raspberry Pi (Raspberry Pi Foundation, Cambridge, UK) single-board computer [8].The Pathfinder software (Trimble Inc., Sunnyvale, CA, USA) differentially adjusted the GPS (Geo 7x) data, and for 99.96% of the corrected positions, the estimated accuracy ranged from 0.05 to 0.15 m. Spectral data were linked to actual plot locations using the GPS data. The field of vision at ground level was approximately 0.13 meters in radius, with the upwelling fiber focused on a soybean row approximately 0.60 meters above the ground. Two passes per plot each collection date permitted data collection from the two center rows, and spectral data were gathered within two hours of solar noon. In order to optimize the unsaturated signal, the integration periods were set at 4–6 ms for downwelling and 13–15 ms for upwelling. Four measurement sequences were used to generate one spectral sample: (1) upwelling dark current; (2) upwelling target measurement;(4) downwelling dark current; (3) downwelling target. Using two fiber optics (400 μm and 600 μm, respectively) that fully covered the 1000 μm long (25 μm wide) spectrometer slit, the spectrometer collected upwelling and downwelling data nearly concurrently (~0.6 s). The air effect on relative reflectance data was reduced by such quick observations from both fore optics using the same spectrometer (Figure 1c–e). Thirteen spectral samples were taken per plot row, with the tractor speed set at 0.22 m s−1 and the actual duration between the starting sites of two consecutive spectral samples being around 2.6 s.

Statistical Analysis and Data Processing

In order to calculate relative reflectance, dark current was first subtracted from upwelling radiance and downwelling irradiance. The radiance was then divided by the irradiance while taking field of view, fiber diameter, and integration times into consideration (Python scripts are available at https://github.com/prabu-github/tracolo); the formula is shown in [13]. After a 2nd order polynomial and a 5 nm filter [14] smoothed the 1 nm spectra, the relative reflectance in the 400–900 nm range was averaged per plot at 5 nm intervals. All potential two-band correlations with the recorded plant population were examined using the normalized difference spectral index (NDSI)[15] analysis. The estimation of soybean plant populations as a function of the hyperspectral readings was done using partial least squares regression (PLSR)[16], a useful forecasting method for spectral reflective data. The datasets underwent independent, cross-validation, and calibration. For 75% of the samples, cross-validation and calibration were performed. For a random sample distribution of calibration (75%) and cross validation (25%), the calibration and cross validation procedure was repeated 100 times, yielding 100 models. These models produced estimated plant population numbers after being independently validated for the samples excluded from the calibration and cross-validation procedures. The mean estimated population was calculated by averaging the estimated values, and the R2 and root mean square error (RMSE) of calibration, cross validation, and validation were obtained by regressing the estimated versus measured plant population values.

RESULTS AND DISCUSSION

PLSR was used to forecast plant populations at the V1 and V3 stages of development. In one trial duplicate, this was done in the sun, while in the other, it was done in the cloud shows that there were no trends in residuals between sunny and cloudy projected vs. observed plant populations, indicating that atmospheric conditions had no effect on the quality of predictions. A reduced RMSE and a higher R2 of independent validation were seen in the later stages of development, as anticipated given the population count time (Table 1). With both sunny and overcast plots overestimating V1 plant populations, the V1 predictions performed worse than the V3 predictions. This was anticipated since smaller V1 seedlings are less likely to be in Piccolo's line of vision. Figure 2b shows some underestimate for V3 plots with more than ~30 plants × 104 h−1(hectare−1).Higher populations are more likely to overlap at this stage of development because seedling foliage overlaps more than that of earlier stage plants. The models based on sunny and cloudy data (V1 and V3) had comparable prediction quality to those based on cloudy alone (V2; Figure 2c), according to the prediction vs. measured plant population for development stage (treatments and replicates pooled together). As well as development stage models (4) and all-data-together (1), Table S1 displays the R2 and root mean square error (RMSE) of all calibration cross validation and validation PLSR models down to treatment level (32). Neither of the two until therapies showed a significant advantage. Different row spacing and tillage treatments were pooled in the development phases and all-data models; this generalization lowers the quality of the models, particularly in the RMSE values.The generic models' RMSE values were over ten times greater than the treatment-specific models' RMSE values.For 15 of the 32 datasets examined, the NDSI identified 565 and 710 nm as the top 10 band combinations.

In maize stand counts, Thorp, Steward, Kaleita, and Batchelor [11] bolster the significance of green- and red-edge bands. Additionally, the spectral system's capacity to deliver high-quality data in both sunny and cloudy settings is supported by the NDSI[565, 710] plant population estimation models. The figures in Figure S1 and Table S2 illustrate all of the NDSI[565, 710] models. The PLSR models outperformed the NDSI in population assessment, demonstrating the benefit of numerous narrow bands over a pair of bands.

By doing away with the requirement for regular reference standard measurements, the Piccolo system offered an effective way to gather plant reflectance. Before the current investigation started, the system's performance was evaluated by measuring a patch of grass close to solar noon in both sunny and cloudy situations. The fore optics were shifted a few centimeters to prevent the target from being shaded by the gadget. As anticipated, sunny conditions resulted in much higher photon counts for both upwelling and downwelling than cloudy ones (Figure 1c–e). With a small variation in the near-infrared regions, the relative reflectance spectra were almost the same in the visible and red-edge wavelengths.

CONCLUSIONS

It was discovered that the Piccolo dual field-of-view spectrometer system worked well for gathering data under dynamic air circumstances. This illustrates how it can be used for precision agriculture research and possible commercial uses. For the plant population assessment case study, (1) V2 and V3 are the best development stages for plant population assessment specifically for treatments (row spacing and tillage; Table S1), while V1, V2, and V3 models are of similar quality for pooling treatments per development stage; and (2) hyperspectral data produced better population assessment than NDSI [565, 710]. It will be necessary to test the device for a variety of applications once devices like the Piccolo are integrated into the typical array of crop monitoring equipment installed on tractors or other agricultural equipment, even though alternative technologies might be appropriate for crop population monitoring.To investigate aerial implementation and more effective data collection, software and hardware changes would be necessary.

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