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Hyperspectral Surface Reflectance Data Detect Low Moisture Status of Pecan Orchards during Flood Irrigation

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ABSTRACT. **For large fields, remote sensing might permit plant low moisture status to be detected early, and this may improve drought detection and monitoring. The objective of this study was to determine whether canopy and soil surface reflectance data derived from a handheld spectroradiometer can detect moisture status assessed using midday stem water potential (ψ_{smd}) in pecan (*Carya illinoinensis*) during cyclic flood irrigations. We conducted the study simultaneously on two mature pecan orchards, one in a sandy loam (La Mancha) and the other in a clay loam (Leyendecker) soil. We were particularly interested in detecting moisture status in the -0.90 to -1.5 MPa ψ_{smd} range because our previous studies indicated this was the critical range for irrigating pecan. Midday stem water potential, photosynthesis (*A*) and canopy and soil surface reflectance measurements were taken over the course of irrigation dry-down cycles at ψ_{smd} levels of -0.40 to -0.85 MPa (well watered) and -0.9 to -1.5 MPa (water deficit). The decline in *A* averaged 34% in La Mancha and 25% in Leyendecker orchard when ψ_{smd} ranged from -0.9 to -1.5 MPa. Average canopy surface reflectance of well-watered trees (ψ_{smd} -0.4 to -0.85 MPa) was significantly higher than the same trees experiencing water deficits (ψ_{smd} -0.9 to -1.5 MPa) within the 350- to 2500-nm bands range. Conversely, soil surface reflectance of well-watered trees was lower than water deficit trees over all bands. At both orchards, coefficient of determinations between ψ_{smd} and all soil and canopy bands and surface reflectance indices were less than 0.62. But discriminant analysis models derived from combining soil and canopy reflectance data of well-watered and water-deficit trees had high classification accuracy (overall and cross-validation classification accuracy >80%). A discriminant model that included triangular vegetation index (TVI), photochemical reflectance index (PRI), and normalized soil moisture index (NSMI) had 85% overall accuracy and 82% cross-validation accuracy at La Mancha orchard. At Leyendecker, either a discriminant model weighted with two soil bands (690 and 2430 nm) or a discriminant model that used PRI and soil band 2430 nm had an overall classification and cross-validation accuracy of 99%. In summary, the results presented here suggest that canopy and soil hyperspectral data derived from a handheld spectroradiometer hold promise for discerning the ψ_{smd} of pecan orchards subjected to flood irrigation.**

Pecan is a large deciduous tree that is cultivated primarily for its nuts. With an annual production of 139 million kilograms, the United States is the world's largest producer of pecan. The total area of pecan orchards in the United States is ≈236,000 ha; New Mexico pecan cultivation accounts for ≈7% of that area. In 2012, New Mexico produced 31.3 million kilograms (in-shell basis) of pecan, ≈23% of total U.S. production (U.S. Department of Agriculture, 2012).

New Mexico has an arid to semiarid climate. Much of the pecan cultivation occurs in riparian areas, especially along the Rio Grande River, where water can be diverted for irrigation. However, this supply of surface water often is limited. This means that farmers also must pump groundwater to supplement irrigation, which makes pecan vulnerable to water deficits. Low soil moisture negatively affects several physiological processes in pecan trees, such as photosynthesis (*A*) and gas exchange (Othman et al., 2014a). Water deficit reduced pecan yield 5% to 24% when the applied water was reduced from 5% to 52% relative to control (Garrot et al., 1993).

For the pecan farmer, irrigation must be scheduled to maximize pecan growth and nut production while minimizing costs associated with water appropriation and application. Effective irrigation schedules rely on irrigation application only when an indicator variable reaches a threshold value (Cifre et al., 2005). This indicator variable must be sufficiently sensitive to water status so that the threshold at which irrigation

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starts can be determined with some precision (Jones, 2004). Midday stem water potential has been proposed for detecting moisture status and monitoring irrigation in commercial orchards, including pecan (Jones, 2004; Othman et al., 2014a). However, using ψ_{smd} for irrigation scheduling, especially, on a large scale is labor intensive (therefore, expensive), slow, and unsuitable for automation (Jones, 2004).

Remote sensing applications hold potential for predicting plant water status, growth, and development (Othman et al., 2014a; Rossi et al., 2010). Hyperspectral sensors measure reflectance in a narrow wavelength range (usually 10 nm or less) and contain hundreds of contiguous bands over the electromagnetic spectrum that can be used to estimate the biochemical properties of vegetation (Huber et al., 2008). There has been considerable success in relating hyperspectral reflectance indices to plant physiological properties. For example, the water band index has been shown to be related to surface-atmosphere fluxes of CO_2 and H_2O (Claudio et al., 2006). Hyperspectral reflectance within the 705- to 750-nm spectral range successfully detects water deficit in apple (*Malus domestica*) trees (Kim et al., 2011), and holds promise for doing so in pecan. In grape (*Vitis vinifera*), the reflectance-based water index effectively tracked variation in leaf stomatal conductance (R^2 = 0.81) at a predawn leaf water potential of –0.42 MPa (Serrano et al., 2010). Moisture stress index and vegetation moisture index which incorporate the 850- and 1928-nm spectral bands showed significant strong correlations with equivalent water thickness in 21 *Eucalyptus* sp. subjected to deficit irrigation (Datt, 1999). Sims and Gamon (2003) concluded that the 1150- to 1260-nm and 1520- to 1540-nm wavelength regions can penetrate more deeply into canopies and may be used to accurately detect tree water status. Although the 1944-nm band yielded the best correlation with available soil water, this band is not recommended for practical use because its location in a strong water vapor absorption area makes measurements from space difficult (Weidong et al., 2003). In olive trees (*Olea europaea*), PRI derived from airborne hyperspectral scanner sensor was sensitive to water stress indicators, such as stomatal conductance and ψ_{smd} (Suárez et al., 2008). However, leaf orientation and soil background significantly affected PRI derived from airborne sensor data leading Suárez et al. (2008) to conclude that canopy structure must be considered when PRI is used.

In a previous study, we screened several leaf-level physiological measurements to determine which of these leaf-level parameters best represented changes in plant moisture status (Othman et al., 2014a). We concluded that ψ_{smd} was the best performing physiological indicator for detecting moisture status in pecan trees (Othman et al., 2014a). We also found that ψ_{smd} of –0.9 to –1.5 MPa was the critical water status range to prevent significant reduction in *A* and gas exchange (>50%) in pecan (Othman et al., 2014b). It is not known whether vegetation indices derived from advanced sensing technologies can precisely predict water status within this range of ψ_{smd} (–0.9 to –1.5). The objective of this study was to investigate whether hyperspectral remotely sensed data derived from a handheld spectroradiometer could detect pecan low water status as estimated using ψ_{smd}.

Materials and Methods

Site description. The study was conducted in two mature pecan orchards in the Mesilla Valley near Las Cruces, NM, from May 2012 to Nov. 2013. One orchard was at the New Mexico State University Leyendecker Plant Science Research Center [Leyendecker (lat. 32°12′01.14′′N, long. 106°44′30.32′′W) and a privately owned farm in the northern Mesilla Valley [La Mancha (lat. 32°17′06.25′′N, long. 106°50′04.26′′W)]. Trees from La Mancha orchard were grown in sandy loam soil [Brazito very fine sandy loam, thick surface (mixed, thermic Typic Torripsamments)], whereas Leyendecker trees were grown in clay loam soil [Armijo clay loam (fine, montmorillonitic, thermic Typic Torrerts)] (U.S. Department of Agriculture, 1980). Both orchards were composed of rows 'Western' pecan (75%) and pollenizer rows of 'Wichita' pecan (25%). All measurements were made on 'Western'.

Trees from La Mancha orchard were ≈30 years old, 9 to 11 m high, spaced at 6 to 7 m within rows and 8 to 10 m between rows. The total area of the La Mancha orchard was 7 ha. Urea [46% N (250 $kg\cdot ha^{-1}$)] and zinc sulfate (foliar spray, 8 $kg\cdot ha^{-1}$) were applied once in May and July of both years. The field was flood irrigated once every 16 to 24 d from May to October every year. Leyendecker orchard trees were 20 to 30 years old, 7 to 9 m high, spaced at 6 to 7 m within rows and 8 m between rows. The total area of Leyendecker orchard was 4 ha. Urea (225 $kg\cdot ha^{-1}$) and zinc sulfate (7 $kg\cdot ha^{-1}$) were applied once in May of both years. The field was flood irrigated once every 3 to 10 weeks from May to October.

Meteorological data. Meteorological instruments were fixed on a 9.0-m tower above the orchard floor at La Mancha and on a 7.5-m tower at Leyendecker. Instruments were

Table 1. Handheld spectroradiometer, photosynthesis, and midday stem water potential measurements dates for two southern New Mexico pecan orchards subjected to cyclic flood irrigation. Measurements were determined at the middle and near the end of each flood irrigation cycle. Field condition was considered well watered when midday stem water potential ranged from –0.4 to –0.85 MPa and considered water deficit when midday stem water potential was between –0.9 and –1.5 MPa.

Site	Yr	Irrigation	Measurement date	Field condition
La Mancha	2012	4 June	10 June	Well watered
		25 July	31 July	Water deficit
			12 Aug.	Water deficit
		20 Aug.	25 Aug.	Well watered
			31 Aug.	Water deficit
		10 Sept.	16 Sept.	Well watered
			22 Sept	Well watered
	2013	20 May	5 June	Water deficit
		4 June	12 June	Well watered
		16 Aug.	21 Aug.	Well watered
			25 Aug.	Water deficit
Leyendecker	2012	20 May	11 June	Water deficit
		16 June	21 June	Well watered
		3 Aug.	4 Aug.	Well watered
			20 Aug.	Well watered
			30 Aug.	Water deficit
		31 Aug.	7 Sept.	Well watered
	2013	24 May	29 May	Well watered
			11 June	Water deficit
		16 Aug.	25 Aug.	Well watered
			8 Sept.	Water deficit
			29 Sept.	Water deficit

Table 2. Hyperspectral surface reflectance indices that derived from handheld spectroradiometer. Hyperspectral reflectance data were from two pecan orchards, La Mancha and Leyendecker, located in the Mesilla Valley, NM.

Vegetation index	Formula[z]	References
	Canopy vegetation indices	
Water band index	ρ_{900}/ρ_{970}	Claudio et al. (2006)
Normalized difference water index	$(\rho_{860} - \rho_{1240})/(\rho_{860} + \rho_{1240})$	Gao (1996)
Simple ratio water index	ρ_{858}/ρ_{1240}	Zarco-Tejada and Ustin (2001)
Moisture stress index	ρ_{1600}/ρ_{820}	Hunt and Rock (1989)
Normalized multiband drought index	$[\rho_{860} - (\rho_{1640} - \rho_{2130})]/[\rho_{860} + (\rho_{1640} - \rho_{2130})]$	Wang and Qu (2007)
Photochemical reflectance index	$(\rho_{531} - \rho_{570})/(\rho_{531} + \rho_{570})$	Gamon et al. (1997)
Normalized difference vegetation index	$(\rho_{800} - \rho_{680})/(\rho_{800} + \rho_{680})$	Kimura et al. (2004)
Triangular vegetation index	$0.5 \times [120 \times (\rho_{750} - \rho_{550}) - 200 \times (\rho_{670} - \rho_{550})]$	Broge and Leblanc (2001)
Leaf water index	ρ_{1300}/ρ_{1450}	Seelig et al. (2009)
	Soil reflectance indices	
Normalized soil moisture index	$(\rho_{1800} - \rho_{2119})/(\rho_{1800} + \rho_{2119})$	Haubrock et al. (2008)
Soil moisture index	$(\rho_{1450} - \rho_{600})/(\rho_{1450} + \rho_{600})$	Haubrock et al. (2008)
Soil moisture reflectance index	ρ_{1450}/ρ_{1300}	Whalley and Leeds-Harrison (1991)

[z] ρ_{900} = surface reflectance at 900 nm wavelengths; ρ_{970} = surface reflectance at 970 nm wavelengths, etc.

installed 1 m above the trees using metal extension bars attached to the towers. Air temperature and relative humidity (HMP45C; Campbell Scientific, Logan, UT) recorded at 1 min interval using a datalogger (CR206X, Campbell Scientific). Vapor pressure deficit was calculated from air temperature and relative humidity data using the equations of Murray (1967). Precipitation data were obtained from Fabian Garcia Science Center weather station, ≈6 km southeast of La Mancha orchard and Leyendecker Plant Science Research weather station, 90 m north of the Leyendecker orchard.

MEASUREMENT TIMING AND IRRIGATION TREATMENT. At both orchards, 10 trees were selected randomly for plant physiological and hyperspectral measurements. Those measurements were made during and after prescribed flood irrigations of the orchards. Midday stem water potential was taken on multiple days during an irrigation cycle. Photosynthesis and canopy surface reflectance data were taken several times (Table 1) during an irrigation dry-down cycle at two levels of ψ_{smd}; well watered (–0.40 to –0.85 MPa) and water deficit (–0.9 to –1.5 MPa). Midday stem water potential and A measurements were taken between 1100 and 1300 HR from fully expanded leaves and synchronized with canopy measurements of the handheld spectroradiometer.

MIDDAY STEM WATER POTENTIAL. Midday stem water potential was determined on two fully equilibrated leaves on the lower shaded part of each tree and close to the trunk (≈2 m from the soil surface) with a pressure chamber (PMS Instrument Co., Corvallis, OR). Leaf position was chosen based on results from other studies with pecan that determined that leaves on the lower shaded portion of the canopy were the most representative of whole plant status (Heerema et al., 2014).

To equilibrate the two leaves with the xylem water potential and prevent overheating by the solar radiation, leaves were enclosed in aluminum foil for 2 h. We then determined ψ_{smd} of the two leaves immediately and used the average ψ_{smd} of the two leaves in the analysis.

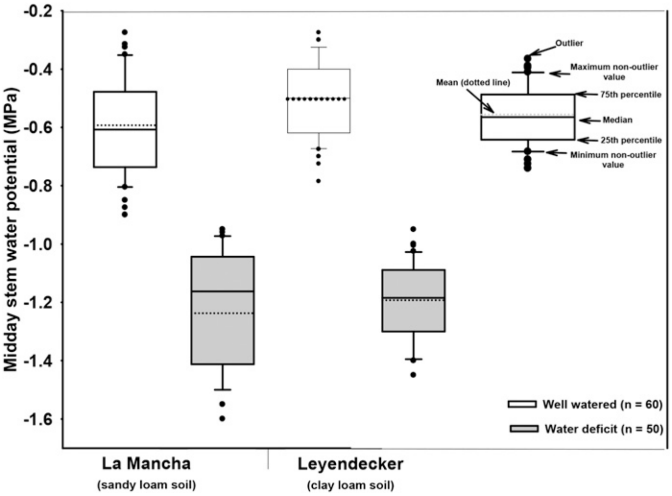

Fig. 1. Midday stem water potential boxplots of La Mancha and Leyendecker pecan orchards (Mesilla Valley, NM) measured in 2012 and 2013. Rectangles represent the 25%, 50% (median), and 75% percentile of the data.

PHOTOSYNTHESIS. Pecan trees have odd-pinnately compound leaves (7 to 17 leaflets). The number of leaflets varies among cultivars. Photosynthesis was determined on one leaflet of the middle pair of leaflets from each of two leaves (≈5 m from the soil surface and fully exposed to sunlight) using a portable photosynthesis system (LI-6400XT; LICOR, Lincoln, NE). Light intensity was set to track ambient photosynthetically active radiation, flow rate to 500 $\mu mol \cdot s^{-1}$, and reference CO_2 to 390 $\mu mol \cdot mol^{-1}$. Leaf temperature ranged from 30 to 33 °C. The average A of the two leaves was then used. Photosynthesis of well-watered trees (ψ_{smd} –0.40 to –0.85 MPa) was compared with the same trees of water deficit (ψ_{smd} –0.9 to –1.5 MPa).

HYPERSPECTRAL MEASUREMENTS. Canopy and soil spectral reflectance within the 350–2500 nm were measured on clear sky days between 1100 and 1300 HR with the handheld spectroradiometer (Fieldspec Pro 2; Analytical Spectral Devices, Boulder, CO). This instrument has a spectral resolution of 3 nm for the 350- to 1000-nm wavelength regions and 10 nm for the 1000- to 2500-nm wavelength regions, a 25° field of view, and 1-m fiber optic cable that feeds directly into the spectrometer. The spectroradiometer sensor was oriented in a nadir position (the measured point on the ground vertically beneath the sensor) and 10 measurements each was taken at

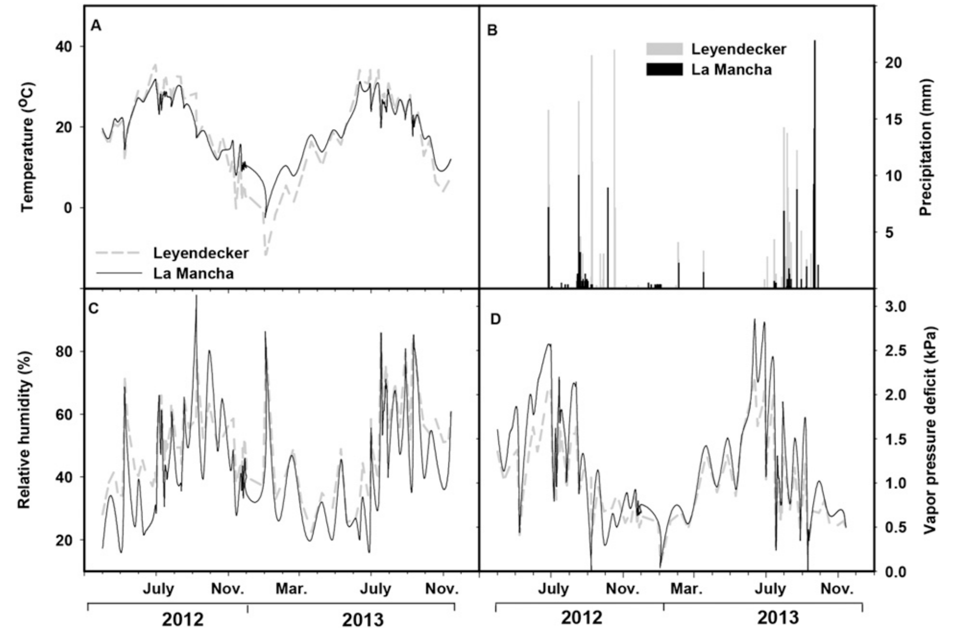

Fig. 2. (**A**) Daily air temperature, (**B**) precipitation, (**C**) relative humidity, and (**D**) vapor pressure deficit of two Mesilla Valley, NM, pecan orchards (La Mancha and Leyendecker) during the experimental period (May 2012 to Nov. 2013).

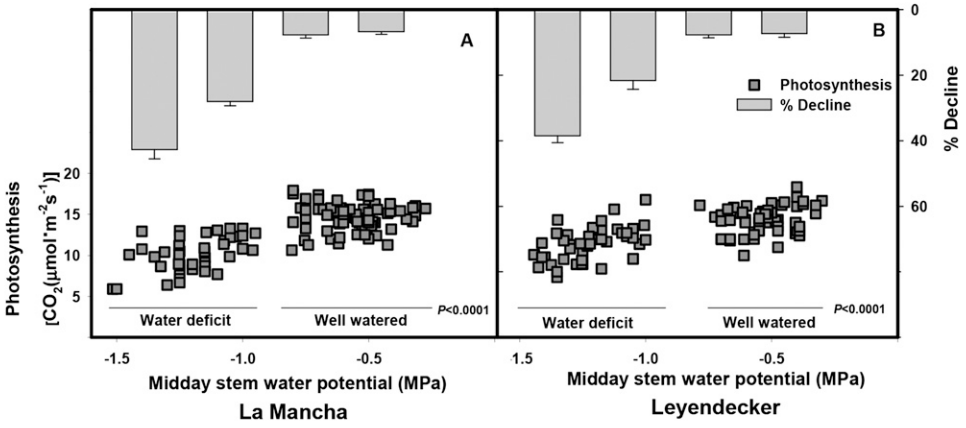

Fig. 3. Photosynthesis and percent decline (vertical bars) in photosynthesis (compared with the same tree at well-watered level) of two Mesilla Valley, NM, pecan orchards, (**A**) La Mancha and (**B**) Leyendecker during the experimental period (May 2012 to Nov. 2013). Groupings for the decline (%) bars are –0.3 to –0.59,–0.6 to –0.89, –0.9 to –1.19, and –1.2 to –1.5 MPa. Mixed model analysis was used to test the significant differences in *A* between well-watered (ψ_{smd} –0.4 to –0.85 MPa) and water-deficit (ψ_{smd} –0.9 to –1.5 MPa) trees. At both orchards, *A* and the decline (%) of well-watered trees and water deficit was significantly different ($P < 0.0001$).

a distance of 1 m above the canopy, and 1 m above the soil surface (fully exposed to sun and close to tree with no or insignificant vegetation cover <10% above it). Three-wheeled, motorized hydraulic manlifts were used to raise the operator and the handheld spectroradiometer above the tree canopy. The average of 10 spectral reflectance measurements per tree was then used to derive specific hyperspectral reflectance indices (Table 2). These indices were selected because they significantly predict water deficit in other crops.

STATISTICAL ANALYSIS. Statistical analyses were performed using SAS (version 9.3; SAS Institute, Cary, NC). Boxplot analysis used to determine whether ψ_{smd} (the moisture status ground reference) clearly separated well-watered individual trees from the same trees showing water deficits in the middle or the end of irrigation cycle. Boxplots display data visually while simultaneously providing information about means, medians, and the distance between extreme values and the central portion (Royeen, 1986). Midday stem water potential of well-watered and water-deficit trees were considered clearly separated when there was no overlap in minimum and maximum nonoutlier values between treatments. All ψ_{smd} measurement dates listed in Table 1 were used in the analysis.

Simple linear regression was conducted to determine which remotely sensed data exhibited the strongest relationship with ψ_{smd}. Regression results were considered sensitive to changes in plant water status when the coefficient of determination was greater than 0.80, moderately sensitive when coefficient of determination was between 0.60 and 0.80, and weak when coefficient of determination was less than 0.6 (Eitel et al., 2006). Analysis of variance procedure (PROC MIXED) in SAS with field condition (well watered and water deficit) as fixed effect was used to test the significant differences in *A* and in wavelength sensitivity of reflectance data between trees water status.

Discriminant analysis using PROC DISCRIM in SAS was performed to determine how precisely hyperspectral surface reflectance indices could separate individual trees that were well watered from those showing water deficits. The selection of canopy and soil bands and the surface reflectance indices that were used in the discriminant analyses was achieved using forward stepwise linear regression (Weidong et al., 2002). Variance inflation factors of included variables were assessed to minimize multicollinearity, and 0.15 was the significance level for entry into the model. Then, the procedure of Wang et al. (2012) was used to derive discriminant function models for remotely sensed data. Several data sets were evaluated using the discriminant analysis. In the first set, we only tested canopy reflectance candidates that were selected from stepwise regression. Soil reflectance data parameters were used in the second set. In the third set, soil and canopy reflectance variables were used together in the discriminant models.

Results

MIDDAY STEM WATER POTENTIAL AND PHOTOSYNTHESIS. We used box-and-whisker plots to examine the overlap of ψ_{smd}

values for different levels of water deficit (Fig. 1). Boxplots of ψ_{smd} revealed a clear separation between well-watered trees and trees experiencing water deficit near the end of a flood irrigation dry-down cycle. At La Mancha orchard (sandy loam soil), ψ_{smd} in well-watered trees remained relatively constant at –0.4 to –0.85 MPa and ranged from –0.9 to –1.5 MPa in water-deficit trees. The Leyendecker ψ_{smd} (clay loam soil) of well-watered trees was between –0.4 and –0.7 MPa whereas water-deficit trees ranged from –0.9 to –1.4 MPa. Although weather conditions were warm and dry at both sites (Fig. 2), high temperature (Fig. 2A) and precipitation (Fig. 2B) at certain times during the growing season caused the irrigation cycle length to vary (Table 1). Photosynthesis was higher in recently irrigated trees (ψ_{smd} –0.4 to –0.85 MPa) than those ψ_{smd} between –0.9 and –1.5 MPa at the later part of the irrigation dry-down cycle. When ψ_{smd} of pecan trees ranged from –0.9 to –1.5 MPa at La Mancha orchard, the average decline in *A* (compared with the same trees in well-watered conditions) was 34% (Fig. 3A). A significant decline in *A* (25%) also was noticed in Leyendecker orchard when ψ_{smd} ranged from –0.9 to –1.5 MPa (Fig. 3B).

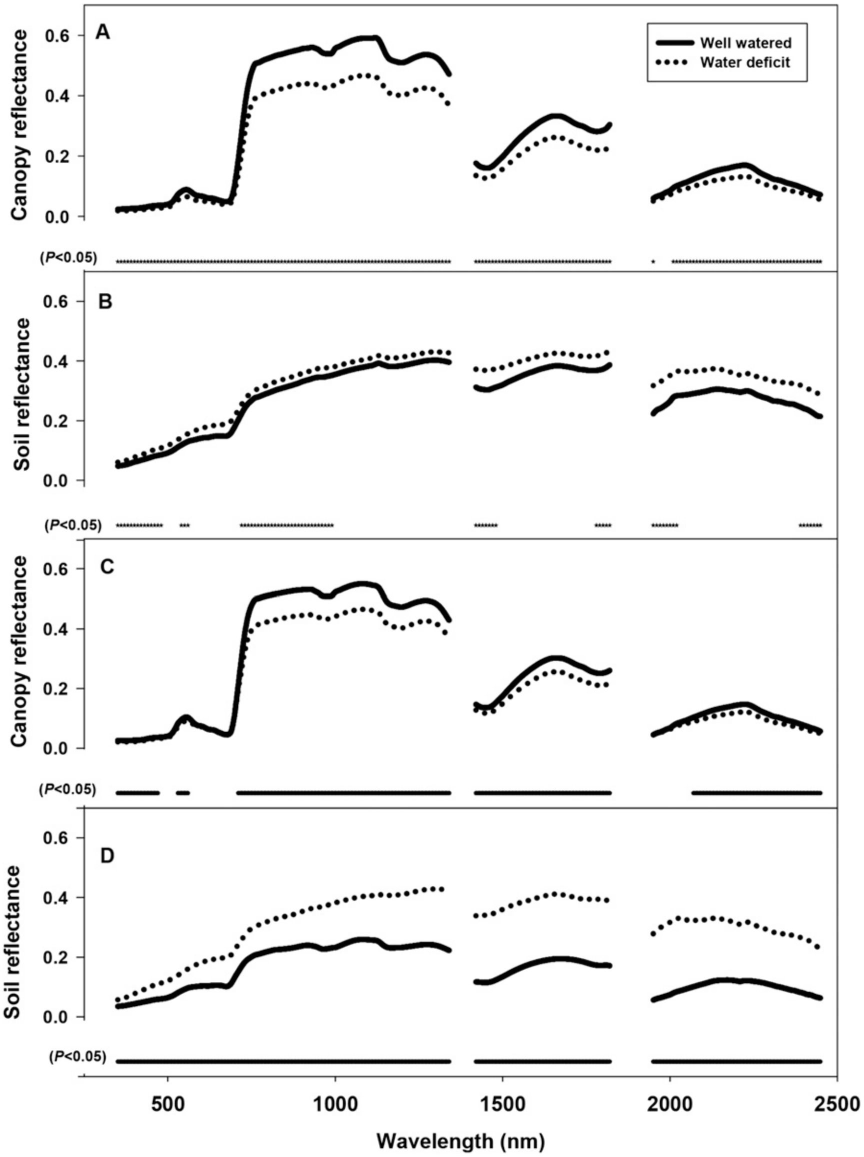

Fig. 4. Mean spectral reflectance of canopy, and soil measured using handheld spectroradiometer of La Mancha (**A** and **B**) and Leyendecker (**C** and **D**) orchards during the experimental period, 2012 and 2013. Pecan orchards are located in the Mesilla Valley, NM. Asterisks at the bottom of each graph indicate a significant difference ($P < 0.05$) between well-watered (ψ_{smd} –0.4 to –0.85 MPa) and water-deficit (ψ_{smd} –0.9 to –1.5 MPa) trees. At both orchards, well-watered curve of canopy and soil band is an average of 60 measurements while water deficit is an average of 50 measurements.

HYPERSPECTRAL SURFACE REFLECTANCE DATA. Mean canopy surface reflectance in visible (500 to 700 nm) near infrared [NIR (700 to 1200 nm)] and shortwave IR [SWIR (1300 to 2500 nm)] of well-watered trees (ψ_{smd} –0.4 to –0.85 MPa) was significantly ($P < 0.05$) higher than the same trees experiencing water deficits (ψ_{smd} –0.9 to –1.5 MPa) at the end of an irrigation dry-down cycle at La Mancha (Fig. 4A). Conversely, soil surface reflectance of well-watered trees at La Mancha was lower than water-deficit soil (Fig. 4B). Soil reflectance bands of well-watered trees within the 350- to 470-, 520- to 560-, 710- to 990-, 1420- to 1480-, 1950- to 2020-, and 2390- to 2500-nm ranges differ significantly from water deficit at La Mancha orchard. Except for the 480- to 520-, 570- to 700-, and 1950- to 2070-nm bands, well-watered trees canopy reflectance bands at Leyendecker (sandy loam soil) were significantly higher than the same trees exhibiting water deficit at the end of irrigation dry-down cycles (Fig. 4C). However, soil reflectance of well-watered trees and water deficit were significantly different over the visible, NIR and SWIR bands (i.e., 350 to 2500 nm) (Fig. 4D).

Canopy reflectance bands provided better regressions than soil bands ($P < 0.0001$) within the 730 to 1340-nm range ($R^2 \approx 0.4$) at La Mancha (Fig. 5A). Conversely, within the 450- to 700-nm and 1300- to 2500-nm ranges, soil bands showed higher relationship ($P < 0.0001$) with ψ_{smd} at Leyendecker orchard (Fig. 5B). Coefficient of determination between ψ_{smd} and soil bands at Leyendecker ranged from 0.4 to 0.57 and 0.52 to 0.77 for the 450- to 700-nm and 1300- to 2500-nm ranges, respectively. However, the coefficient of determination (canopy and soil) never exceeded 0.8 regardless of the reflectance wavelength and the orchard.

Overall, remotely sensed derived reflectance indices (canopy and soil) showed no or low relationship with ψ_{smd} (Table 3). While TVI, PRI, NSMI, and soil moisture reflectance index (SMRI) all showed a significant relationship with ψ_{smd} at both orchards, the coefficients of determination for these indices never exceeded 0.62.

Stepwise regression of canopy reflectance data at La Mancha orchard showed that the best wavelengths and vegetation indices set were 760, 860, 950, 990, and 1100 nm, TVI and PRI. Soil reflectance stepwise regression included five bands (480, 680, 690, 1950, and 2430 nm) and two indices (NSMI and SMRI). The Leyendecker canopy reflectance model included

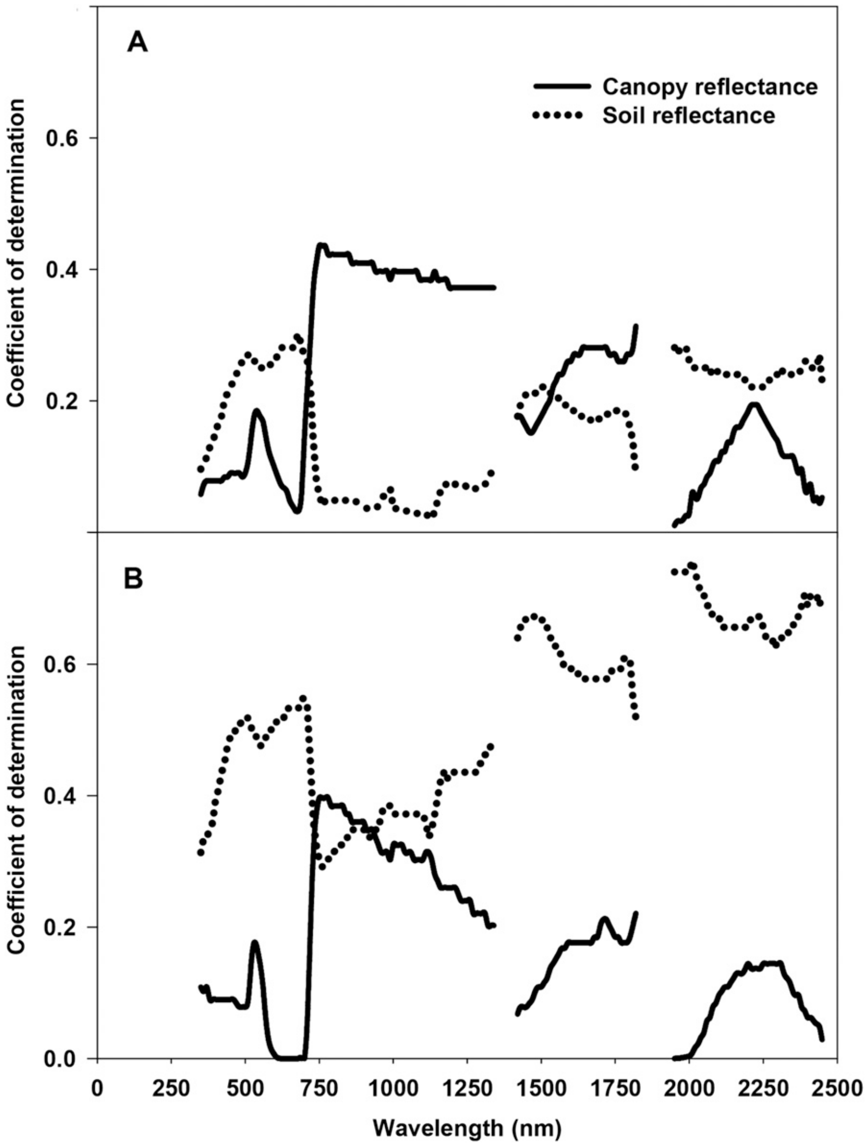

Fig. 5. Coefficient of determination (R^2) between midday stem water potential and canopy and soil surface reflectance at different moisture status levels within the 350 to 2500 nm bands. Data were from two pecan orchards, (**A**) La Mancha and (**B**) Leyendecker, located in the Mesilla Valley, NM. At both orchards, n = 110 (well watered = 60, water deficit = 50).

four wavelengths (350, 520, 690, and 770 nm) and two indices (TVI and PRI). Meanwhile, stepwise regression of soil reflectance data included seven bands (690, 870, 1150, 1340, 1440, 1820, and 2010 nm), and two soil reflectance indices (NSMI and SMRI).

Discriminant analysis of well-watered and water-deficit trees, which weighted with three reflectance indices (TVI, NSMI, and PRI) showed high overall and cross-validation accuracy at La Mancha orchard (Table 4). Overall accuracy was 85% and cross-validation was 82%. For Leyendecker orchard, the highest discrimination with an overall classification and cross-validation accuracy of 99% was achieved using the vegetation index PRI and soil band of 2430 nm (Table 4). The same accuracy result was also achieved using the discriminant model weighted with two soil bands, 690 and 2430 nm. At La Mancha orchard, the classification accuracy of well-watered trees was slightly higher than water deficit (Table 5). For example, accuracy rate was 88% for well watered and 82% for water deficit for TVI-NSMI-PRI discriminant model. Conversely, classification accuracy for water-deficit trees was slightly higher than well-watered trees at Leyendecker orchard (Table 5).

Discussion

Photosynthesis. Water deficits that decreased ψ_{smd} to less than –0.9 MPa decreased A in pecan in both orchards. Small decreases in A could have a large impact on plant productivity even if statistical differences are not apparent between treatments. For example, although euonymus (*Euonymus japonica*) plants had a nonstatistically significant decrease in A when irrigated with wastewater, leaf chlorophyll content and leaf dry weight were statistically higher than plants watered with tap water (Gómez-Bellot et al., 2014). The decline in A, which averaged 34% in La Mancha and 25% in Leyendecker orchard (Fig. 3A and B, respectively), when trees subjected to moderate water deficit (ψ_{smd} –0.9 to –1.5 MPa) exposed the limitation of this study. Although we are able to sense differences between well-watered trees and those exposed to moderate water deficits, remote sensing techniques that can detect very small changes in moisture levels would benefit pecan orchard moisture management. On the other hand, a 50% reduction in A only occurred when ψ_{smd} of pecan trees was less than –1.5 MPa (Othman et al., 2014b) points to a certain amount of resiliency of pecan to water deficits. In contrast, A of peach (*Prunus persica*) trees decreased by 90% (10 to 0.8 $\mu\mathrm{mol{\cdot}m^{-2}{\cdot}s^{-1}}$ $\mathrm{CO_2}$) when ψ_{smd} dropped below –1.8 MPa (Goldhamer et al., 1999).

Hyperspectral canopy and soil surface reflectance. Within the range 350 to 2500 nm, canopy surface reflectance from well-watered trees was higher than the same trees experiencing water deficits at the end of an irrigation dry-down cycle at both orchards. Low soil moisture may reduce chlorophyll content, decrease leaf area, and change leaf orientation (Knipling, 1970). As a result, light penetration is higher and reflection is lower in the canopy of a tree that is exposed to water deficits than in one that is well watered. Canopy reflectance in the NIR was higher than those at SWIR. This is because leaf water absorbs radiation in the SWIR (Eitel et al., 2006; Gao, 1996; Pu et al., 2003). Conversely, soil surface reflectance of well-watered trees was lower than those experiencing soil water deficits at both orchards (Fig. 4B and D). Under typical agricultural conditions, wet soil reflects less at all bands in the 350- to 2400-nm wavelengths than dry soil (Weidong et al., 2002). This is because the internal total reflection on the water films that coat wet soil particles cause a portion of the radiation to be reflected back to the soil itself and then absorbed (Ångström, 1925). In addition, wetting the soil changes the medium surrounding the soil particle, increases forward light scattering by soil particles, and increases the probability of light being absorbed before reemerging from soil medium (Twomey et al., 1986). Therefore, soil becomes darker and reflects less energy (Twomey et al., 1986).

In our study, soil spectral data had a red edge which should not be present in typical bare soil spectral reflectance (Fig. 4B and D). This is could be attributed to scattered radiation from adjacent pecan canopy and the aboveground vegetation (<10%), which is mixed with the soil.

Remotely sensed vegetation indices derived from soil and canopy surface reflectance data showed no or weak relationship with ψ_{smd} except for SMRI at Leyendecker orchard ($R^2 = 0.61$) (Table 3). Of all the canopy reflectance indices, only PRI and TVI had a significant relationship with ψ_{smd}. However, coefficient of determination for both indices was less than 0.35 at both orchards. Data from several remote sensing studies showed no or weak correlation with vegetation moisture content (Eitel et al., 2006; Knipling, 1970). One possible explanation is the relatively low differences in reflectance at different levels of water deficit, especially, at moderate levels (Riggs and Running, 1991) combined with large variations in remotely sensed surface reflectance data among leaves at the same level of water deficit (Cohen, 1991). Furthermore, water content and canopy structure affect canopy reflectance data (Zarco-Tejada et al., 2003). Canopy structure and soil background affected the PRI derived from hyperspectral canopy reflectance data (Suárez et al., 2008). Furthermore, canopy orientation can negatively impact the PRI sensitivity to water deficit (Suárez et al., 2008).

HYPERSPECTRAL CANOPY AND SOIL SURFACE REFLECTANCE DISCRIMINANT MODELS. Although the relationship between vegetation indices and ψ_{smd} was not high, a discriminant model derived from combining PRI and TVI classified 83% trees at La Mancha and 76% correctly into their treatment class (Table 4). This result highlights the importance of selecting the proper statistical approach for screening remotely sensed data. The sensitivity of vegetation indices to water deficit depends on their ability to define threshold values between well-watered trees and the same trees exhibiting water deficit symptoms at the end of a dry-down irrigation cycle. Normally, irrigation is applied at moderate water deficit levels and severe water deficits should occur rarely (Dzikiti et al., 2010). Therefore, the capability of vegetation indices to detect moderate water deficit is critical for agricultural crops, including pecan. We used discriminant analysis to identify remotely sensed variables that can precisely classify water deficit levels.

Discriminant models derived from canopy and soil reflectance clearly separated well-watered and moderate treatments at clay loam soil orchard (Leyendecker accuracy = 99%) and at sandy loam soil orchard (La Mancha accuracy = 85%). Higher accuracy at Leyendecker especially that of the soil reflectance data could be attributed to water-holding capacity. Soil water-holding capacity at a depth of 0 to 60 cm is $0.2\ cm^3 \cdot cm^{-3}$ at La Mancha and $0.32\ cm^3 \cdot cm^{-3}$ at Leyendecker (Deb et al., 2013). So, similarly to Streck et al. (2003), we reasoned that soil water decreased soil surface reflectance in all wavelengths within the 350- to 2400-nm spectral range. Because clay soil holds more water than sandy soil, and water absorbs a large portion of the incoming radiation, the difference in soil surface reflectance between well watered and water

Table 3. Coefficients of determination (R^2) of midday stem water potential to remotely sensed derived reflectance indices from handheld spectroradiometer at canopy and soil level. Data were from two pecan orchards, La Mancha (sandy loam soil) and Leyendecker (clay loam soil), located in the Mesilla Valley, NM. At both orchards, $n = 110$.

	Orchard			
	La Mancha		Leyendecker	
Index				
Canopy	R^2	P	R^2	P
Water index	0.03	0.09	0.07	0.008
Normalized difference water index	0.001	0.84	0.02	0.20
Simple ratio water index	0.001	0.97	0.03	0.13
Moisture stress index	0.002	0.70	0.01	0.27
Normalized multiband drought index	0.004	0.57	0.004	0.57
Photochemical reflectance index	0.14	<0.0001	0.21	<0.0001
Normalized difference vegetation index	0.006	0.45	0.06	0.02
Triangular vegetation index	0.27	<0.0001	0.32	<0.0001
Leaf water index	0.004	0.58	0.003	0.56
Soil				
Normalized soil moisture index	0.15	<0.0001	0.38	<0.0001
Soil moisture index	0.003	0.59	0.27	<0.0001
Soil moisture reflectance index	0.13	<0.0001	0.61	<0.0001

Table 4. Overall classification and cross-validation results derived from DISCRIM procedure in SAS (version 9.3; SAS Institute, Cary, NC) for 1) canopy and soil, 2) canopy, and 3) soil surface reflectance data. Data were from two pecan orchards, La Mancha (sandy loam soil) and Leyendecker (clay loam soil), located in the Mesilla Valley, NM. At both orchards, $n = 110$ (well watered = 60, water deficit = 50).

Orchard	Surface reflectance source	Reflectance indices and band (nm)[z]	Overall classification (%)	Cross-validation (%)
La Mancha	Canopy and soil	TVI, NSMI, PRI	85	82
	Canopy	TVI, PRI	83	83
	Soil	$\rho_{soil\ (680)}$, $\rho_{soil\ (690)}$, $\rho_{soil\ (1950)}$, SMRI	68	66
Leyendecker	Canopy and soil	PRI, $\rho_{soil\ (2430)}$	99	99
	Canopy	TVI, PRI	76	76
	Soil	$\rho_{soil\ (690)}$, $\rho_{soil\ (2430)}$	99	99

[z]TVI = triangular vegetation index; NSMI = normalized soil moisture index; PRI = photochemical reflectance index; SMRI = soil moisture reflectance index: $\rho_{soil\ (680)}$, $\rho_{soil\ (690)}$, $\rho_{soil\ (1950)}$, and $\rho_{soil\ (2430)}$ = soil surface reflectance at 680-, 690-, 1950-, 2430-nm wavelengths, respectively.

Table 5. Classification matrix derived from DISCRIM procedure (count and cross-validation) in SAS (version 9.3; SAS Institute, Cary, NC) for canopy and soil, canopy, and soil surface reflectance data. Data were from two pecan orchards, La Mancha and Leyendecker, located in the Mesilla Valley, NM. At both orchards, n = 110 (well watered = 60, water deficit = 50).

				Field condition^y		
					Predicted	
Orchard	Reflectance source	Reflectance indices and bands (nm)^z	Classification method	Actual	WW (%)	WD (%)
La Mancha	Canopy and soil	TVI, NSMI, PRI	Count	WW	88	12
				WD	18	82
			Cross-validation	WW	87	13
				WD	22	78
	Canopy	TVI, PRI	Count	WW	87	13
				WD	20	80
			Cross-validation	WW	87	13
				WD	20	80
	Soil	$\rho_{soil\ (680)}$, $\rho_{soil\ (690)}$, $\rho_{soil\ (1950)}$, SMRI	Count	WW	75	25
				WD	38	62
			Cross-validation	WW	72	28
				WD	38	62
Leyendecker	Canopy and soil	PRI, $\rho_{soil\ (2430)}$	Count	WW	98	2
				WD	0.0	100
			Cross-validation	WW	98	2
				WD	0.0	100
	Canopy	TVI, PRI	Count	WW	75	25
				WD	22	78
			Cross-validation	WW	75	25
				WD	22	78
	Soil	$\rho_{soil\ (690)}$, $\rho_{soil\ (2430)}$	Count	WW	98	2
				WD	0.0	100
			Cross-validation	WW	98	2
				WD	0.0	100

[z] TVI = triangular vegetation index; NSMI = normalized soil moisture index; PRI = photochemical reflectance index; SMRI = soil moisture reflectance index; $\rho_{soil\ (680)}$, $\rho_{soil\ (690)}$, $\rho_{soil\ (1950)}$, and $\rho_{soil\ (2430)}$ = soil surface reflectance at 680-, 690-, 1950-, and 2430-nm wavelengths, respectively.

[y] WW = well watered; WD = water deficit.

deficit of clay soil is higher than sandy soil. This may have made the discriminant models that included soil reflectance more effective at Leyendecker because of the altered contribution of soil reflectance to the models. In our previous study, we recommended that ψ_{smd} should never exceed –1.5 MPa to prevent significant reduction in *A*, transpiration, and stomatal conductance [>50% (Othman et al., 2014b)]. Therefore, canopy and soil reflectance data hold promise for detecting plant physiological responses that are related to plant water status.

Modeling the relationship between soil reflectance and the soil moisture in a field setting is difficult, as soil color, texture, and organic matter affect remotely sensed data (Muller and Décamps, 2000). Furthermore, the relationship between soil moisture and reflectance is nonlinear (Weidong et al., 2003) and could be reverse after a critical point (i.e., field capacity) (Weidong et al., 2002). We included the soil reflectance data for two reasons. First, in both orchards, soil surface reflectance within the 350- to 2500-nm spectral range of well-watered trees (ψ_{smd} –0.40 to –0.85 MPa) was lower than that of the same trees exhibiting water deficit (ψ_{smd} –0.9 to –1.5 MPa). Second, pecan canopy fractional cover never reached full cover. In fact, canopy fractional cover of 15 pecan orchards (including our orchards) located at Mesilla Valley ranged from 34% to 74% during the growing season (Piñón-Villarreal, 2008). In addition, soil texture, color, and organic matter change slowly with time at a given location, so, surface reflectance will primarily depend on soil surface roughness and moisture (Weidong et al., 2002).

Conclusion

Overall, our results showed that discriminant models derived from a handheld spectroradiometer differentiated between well-watered (ψ_{smd} –0.4 to –0.85 MPa) and moderate water-deficit (ψ_{smd} –0.9 to –1.5 MPa) trees. Canopy PRI–TVI discriminant model classified water status with a moderate error count (accuracy = 83% at La Mancha and 76% at Leyendecker). However, including soil reflectance data improved the classification accuracy by 2% at La Mancha (sandy loam soil) and 23% at Leyendecker orchard (clay loam soil). In addition, remote sensing data from a handheld spectroradiometer detected precisely the moderate reduction in *A* (25% to 35%).

Pecan trees can grow to 30 m. Driving a manlift through orchards to make repeated measurements during cyclic irrigation using a handheld spectroradiometer is quite challenging. However, this procedure is a prerequisite for developing surface reflectance sensors. Our results support the idea of developing remote sensing sensors with specific bands (such as those for chlorophyll content, normalized difference vegetation index) that capture the moisture status of pecan orchards precisely and early. These sensors can be placed permanently on the top of canopy and directly above soil surface and the remotely sensed data on individual trees water status can be upscaled to large areas.

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