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Multispectral satellite imagery to quantify in-field soil moisture variability

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Abstract: As pressure on available water resources increases, the need to exploit technology in order to produce more food with less water becomes crucial. The technological hardware requisite for precise water delivery methods, such as variable rate irrigation, is commercially available. Despite that, techniques to formulate a timely, accurate prescription for those systems are inadequate. Spectral vegetation indices are often used to gauge crop vigor and related parameters (e.g., leaf nitrogen [N] content). However, research heretofore rarely addresses the influence of soil moisture on the indices. The objectives of this study were to determine (1) if vegetation indices derived from multispectral satellite imagery could assist in quantifying soil moisture variability in irrigated maize (*Zea mays* L.) production, and (2) the period of time that a single image is representative of soil moisture. A variable rate irrigation pivot was used to form six water treatment zones. Each was equipped with tensiometers installed in the center of the plots at 20, 45, and 75 cm depths to individually monitor conditions in the water treatment zones. Water was applied for each treatment as a percentage of the estimated evapotranspiration (ET) requirement: 40%, 60%, 80%, 100%, 120%, and 140%. Data collected from tensiometers was paired with the image pixels corresponding to its ground location. Statistical analysis was performed separately to assess whether vegetation indices are representative of soil moisture at several crop growth stages. Findings from this study indicate that Red Edge Normalized Difference Vegetation Index could quantify soil moisture tension variability at V6 (six leaf; $r^2 = 0.850$, $p = 0.009$) and V9 (nine leaf; $r^2 = 0.913$, $p = 0.003$) crop growth stages. Results suggest that satellite-derived vegetation indices may be useful for creating time-sensitive characterizations of soil moisture variability. Further study is necessary to investigate additional crop growth stages, more crops, and other sources of multispectral imagery.

Key words: irrigation—Normalized Difference Vegetation Index (NDVI)—red edge—remote sensing—soil moisture—variable rate irrigation

Agriculture places a heavy burden on available water resources. In the United States, irrigation systems utilize about 80% of the available freshwater (Lea-Cox 2012). Heightened water demand from nonagriculture sectors is expected to increase overall water demand and pressure on water resources. More efficient irrigation systems in the western states have previously contributed to decreases in water application: although irrigated area increased by 850,000 ha between the years 1984 and 2008, agricultural water applications were reduced by over 120 million m^3 (Schaible and Aillery 2012). These efficient irrigation systems, such as center-pivots and linear-move systems, can be exploited to further reduce water usage through precision water management strategies and technology.

One possible solution, which relies on variable rate technology, is precision irrigation. Precision irrigation is site-specific water management: the amount of water applied is spatially explicit, and timing is planned in order to enhance yield, economic gains, and environmental stewardship (Srinivasan 2006). When juxtaposed with traditional irrigation—treating the entire application area equally—precision irrigation may further use variable rate technology to adjust the amount of water applied at every location within the field. These adjustments are meant to reflect the local water requirements within a field in order to optimize water usage.

Evans et al. (1996) identified defining and formulating a prescription for precision water application as the foremost problem for researchers to address. More specifically, the aforementioned authors suggested that "identification and quantification of contributing factors and their interactions that influence a real-time prescription are difficult." Continually changing conditions are likely to make decision algorithms highly temporally dependent, and techniques commonly used today to formulate water prescriptions—such as electrical conductivity—do not directly account for temporal variability. Longchamps et al. (2015) document that spatial and temporal variability in soil moisture content is significant even in precision leveled fields. Sadler et al. (2005) conclude that the inconsistent, highly dynamic nature of actual field circumstances probably necessitates strategically placed sensors to monitor soil moisture and micrometeorological variability in real time. Siegfried et al. (2017) suggest that inexpensive infrared thermometers could be used to gauge in-field soil moisture variability.

For decades, spectral vegetation indices have been employed to remotely monitor crops and other vegetation. While the spectral response of a crop can be used to identify the presence of stress, vegetation indices have the potential to function as surrogate measurements of the severity of that stress at multiple time points.

The red edge, a narrow portion of wavelengths (about 680 to 730 nm) between the red and near-infrared regions of the electromagnetic spectrum, could improve on traditional broadband sensors to enhance the quality of information derived from multispectral satellite imagery because of its greater sensitivity to stress, which manifests as an early decrease in chlorophyll content in the plant canopy (Carter and Miller 1994). The rapid change in leaf reflectance characterized within the red edge makes it particularly useful for early stress detection. One example of a satellite platform mak-

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ing use of the red edge is the RapidEye Satellite Constellation (BlackBridge, Berlin, Germany), which captures the red edge region between 690 to 730 nm. This may be used as a more plant-sensitive replacement for the conventional red band in broadband vegetation index calculations, but few agricultural studies have investigated it.

Advances in technology have made remote sensing data vastly more available. Until the beginning of the second millennium, aerial imagery was the prevailing source of remote sensing for agricultural interpretation (Lillesand et al. 2008). However, improvements in both spatial and temporal resolution, along with rapid data availability, have drastically increased the use of satellite imagery for precision agriculture. These benefits could potentially be used to monitor in-field variability of plant water stress at a large scale (e.g., an entire section equipped with sprinkler irrigation), and thus inform precision irrigation systems. Utilizing the information available from remote sensing is an important challenge for irrigated agriculture, as water resource managers rarely take advantage of numerous remote sensing opportunities (Bastiaanssen et al. 2000).

Few studies exist that have addressed the use of multispectral data for monitoring soil water content, and those typically rely on shortwave infrared, microwave, thermal data, or estimate crop coefficients (Clarke 1997; Engman 1991; Li et al. 2001; Neale et al. 2005). Previous researchers were limited by low spatial resolution imagery, which was impractical for field-scale analysis (Adegoke and Carleton 2002). With increasing focus on precision agriculture and the advent of precision variable rate irrigation systems, it is important to investigate whether plant water stress can be characterized at large field scales using readily available, high spatial resolution data. Therefore, the objectives of this study were to determine (1) if vegetation indices derived from multispectral satellite imagery could quantify soil moisture tension variability in an irrigated maize (*Zea mays* L.) production system, and (2) the period of time that a single satellite image is representative of the variability.

Materials and Methods

Study Site. This experiment was conducted over the 2015 maize growing season at a site located north of Fort Collins in northeastern Colorado (40.666° N, 104.998° W). The 12 ha field has been cultivated for many years under a continuous maize cropping system, conventional tillage, and furrow irrigation until 2012, when it was precision leveled and a center-pivot sprinkler system was installed. The soil series is Kim loam, which is characterized as very deep, moderately permeable, and is classified as fine-loamy, mixed, active, calcareous, mesic Ustic Torriorthents (Soil Survey Staff 1980). Slope at this site is between 1% and 3%, and the climate is semiarid with an average annual precipitation of about 40 cm. The field was seeded with east-west rows on May 27, 2015, with DEKALB DKC46-20VT3 at a population of 93,900 plants ha^{-1}.

Experimental Procedure. A Valley variable rate irrigation pivot (Valmont Industries, Valley, Nebraska) was utilized to form six water treatment zones. Each zone was equipped with Hortau tensiometers (Hortau Simplified Irrigation, Lévis, Québec, Canada) installed in the center at 20, 45, and 75 cm depths. Water was applied for each treatment as a percentage of the estimated evapotranspiration (ET) requirement: 40%, 60%, 80%, 100%, 120%, and 140%. The depth of water applied at those rates corresponds to 20, 30, 41, 51, 61, and 71 cm for the entire growing season, respectively. Estimated ETc requirements, or the amount needed to replenish water used by the plants and lost to evaporation, are based on weather conditions, such as solar radiation, wind speed, and humidity. For information on calculating crop water requirements, refer to Allen et al. (1998). The data and more details on the water requirement calculations are available at www.CoAgMET.ColoState.edu. To ensure that each treatment completely surrounded the tensiometers, the treatment zones were created three times larger than the area over which the pivot could accurately adjust the water application depth. Each individual treatment zone was about 325 m^2 in size. To address the possibility of surface runoff, straw wattles were fixed at susceptible locations (figure 1).

The tensiometers were configured to upload data to server storage at 15 minute intervals throughout the growing season. Raw tension data were then downloaded from the web. On multiple occasions during the growing season, the tensiometer water reservoirs became depleted and required rehydration. This process generated data points not representative of actual soil moisture conditions. The date and time were noted for each rehydration event. The period between sensor dehydration and 24 hours after hydration was removed from the data. The return to normal sensor behavior was confirmed by viewing a plot of surrounding data points.

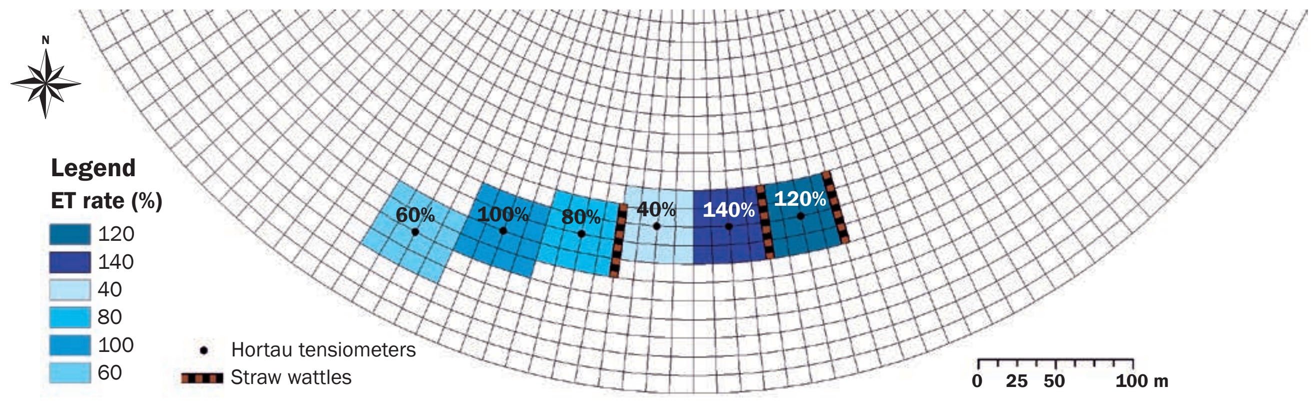
Orthorectified imagery from the RapidEye satellite constellation was provided by FarmLogs (FarmLogs, Ann Arbor, Michigan). The imagery product included radiometric, geometric, and terrain corrections by BlackBridge. The radiometric resolution is 12-bit with spatial resolution of 5 m and a revisit time of 5.5 days. The spectral bands are outlined in table 1. The nine spectral vegetation indices examined were calculated using the formulae defined in table 2.

Data Analysis. An average soil tension was calculated for each irrigation treatment (40% to 140% of estimated ET requirement) over three temporal periods prior to the satellite image acquisition dates: one day (96 soil tension measurements), one week (672 soil tension measurements), and the entire interval between planting and image acquisition (>1,000 soil tension measurements). Those averages were paired with vegetation index values, which were extracted from the satellite images using georeferenced points and geographic information system (GIS) software in order to obtain the pixel values corresponding to the actual ground location of the tensiometers. Points used for this process were acquired with a Trimble Ag114 DGPS receiver (Trimble Navigation Limited, Sunnyvale, California) equipped with OmniSTAR virtual base station (VBS) correction service (OmniSTAR, Houston, Texas).

Ordinary least squares regression of soil tension on vegetation indices was performed using the R software environment (R Core Team 2015). To determine whether vegetation indices derived from multispectral satellite imagery could quantify soil moisture tension, three time intervals prior to each image acquisition were evaluated: average from (1) the previous day, (2) previous week, and (3) from planting to image acquisition date. This was done to assess the sensitivity of the satellite-derived indices to immediate, short-term, and long-term soil moisture variability, respectively. Results presented below are therefore grouped by these time intervals. All combinations of vegetation indices and tension averages were analyzed independently for all the satellite images, which

Figure 1

Variable rate irrigation grid used for the center pivot at Colorado State University Agricultural Research Development and Education Center. Irrigation treatments are represented as filled cells. A different shade designates each zone and includes a point for the tensiometer locations, which are labeled with the percentage of estimated evapotranspiration (ET) used to calculate irrigation requirements for this study in 2015.



were acquired at two leaf, six leaf, nine leaf, and milk (R3) growth stages (table 3 and figure 2). In addition, an image acquired shortly after crop emergence (bare soil) was also analyzed. Statistical significance was determined using the Student's *t*-test.

Results and Discussion

The month of May was especially wet during the 2015 growing season, receiving more than double the historical average precipitation and contributing to above average annual precipitation (Western Regional Climate Center 2015). These conditions delayed planting by several weeks. The beginning of May is conventional timing for planting, but the maize was planted on May 27 for the 2015 season. See figure 3 for daily precipitation and irrigation events.

The relationship between vegetation indices and in-field soil moisture tension was studied at three soil depths where soil moisture tension readings were recorded throughout the growing season. For ease of understanding, the results are presented separately for each time period of soil moisture tension measurement: 24 hours, 1 week, and planting to image acquisition date.

Average Soil Tension from the Previous Day. Regression analysis of soil tension averaged over the day previous to image acquisition on the selected indices produced several noteworthy results (table 4). Red Edge Normalized Difference Vegetation Index (RENDVI) performed best with strong negative linear relationships at both V6 and V9 crop growth stages at 20 cm deep. The strong relationship between satellite imagery and 24-hour average soil tension may potentially be explained by short-term plant physiological response to drought stress, such as erect orientation of leaves, leaf rolling, and graying of tissue that would be detectable by satellite imagery. As shown in figure 4a, functions for both models at this depth were very similar: the slopes were almost identical—less than 2% difference—and the intercept increased almost proportionally from the V6 to V9 growth stage. This indicates that images not only capture immediate soil moisture variability at separate growth stages, but also that a single image could be relatively representative of soil moisture variability between image acquisitions—perhaps up to a couple weeks, as with this study. In other words, an image could be used to help inform variable rate irrigation systems a few weeks after it was initially acquired by the satellite. This is especially important since irrigation water often is not immediately available, and satellite revisit times may not be convenient for management. Additionally, RENDVI was moderately correlated at the R3 growth stage at the 75 cm depth.

Red Edge Chlorophyll Index (RECI) also produced significant models with good relationships for V6 and V9 crop growth stages at 20 cm deep (figure 4b). In this case, the functions between the two differed considerably, and the coefficients of determination, although still very strong, indicated weaker correlations. It appears that RECI is less sensitive to changing soil water content, so the imagery did not show potential for extended postacquisition utility, as was the case with RENDVI, for which the equations over the V6 and V9 growth stages were quite similar.

Table 1

Spectral bands for the RapidEye Satellite Constellation (Planet 2016).

Name	Range (nm)
Blue	440 to 510
Green	520 to 590
Red	630 to 685
Red edge	690 to 730
Near-infrared	760 to 850

All of the green indices—Green Ratio Vegetation Index (GRVI), Green Normalized Difference Vegetation Index (GNDVI), and Green Atmospherically Resistant Index (GARI)—were strongly correlated at the V2 stage at 75 cm and considerably outperformed red indices (table 4). This was expected due to the prevailing soil background during early plant growth and was only observed at V2—the earliest growth stage examined. Our results are quite similar to those of Peterson and Baumgardner (1981), who found a strong linear relationship between soil moisture tension and green reflectance between 520 to 580 nm. Although their study was conducted using an indoor spectroradiometer, the wavelengths discussed are nearly the same as the green waveband of the RapidEye satellites used in this study. The relationships at this depth are quite strong, but unfortunately they are not useful for making decisions on how to irrigate given the shallow rooting depth at this early V2 growth stage.

Except for the Enhanced Vegetation Index (EVI), the model for NDVI exhibited the

Table 2
Formulae for spectral vegetation indices examined in this study (Harris Geospatial Solutions 2015).

Vegetation index	Formula
Red Edge Normalized Difference Vegetation Index (RENDVI)	$RENDVI = \frac{(NIR - Red\ Edge)}{(NIR + Red\ Edge)}$
Red Edge Chlorophyll Index (RECI)	$RECI = \frac{NIR}{(Red\ Edge)} - 1$
Renormalized Difference Vegetation Index (RDVI)	$RDVI = \frac{(NIR - Red)}{\sqrt{(NIR + Red)}}$
Optimized Soil Adjusted Vegetation Index (OSAVI)	$OSAVI = \frac{1.5 \times (NIR - Red)}{(NIR + Red + 0.16)}$
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$
Green Ratio Vegetation Index (GRVI)	$GRVI = \frac{NIR}{Green}$
Green Normalized Difference Vegetation Index (GNDVI)	$GNDVI = \frac{(NIR - Green)}{(NIR + Green)}$
Green Atmospherically Resistant Index (GARI)	$GARI = \frac{\{NIR - [Green - 1.7(Blue - Red)]\}}{\{NIR + [Green - 1.7(Blue - Red)]\}}$
Enhanced Vegetation Index (EVI)	$EVI = 2.5 \times \frac{(NIR - Red)}{(NIR + 6 \times Red - 7.5 \times Blue + 1)}$

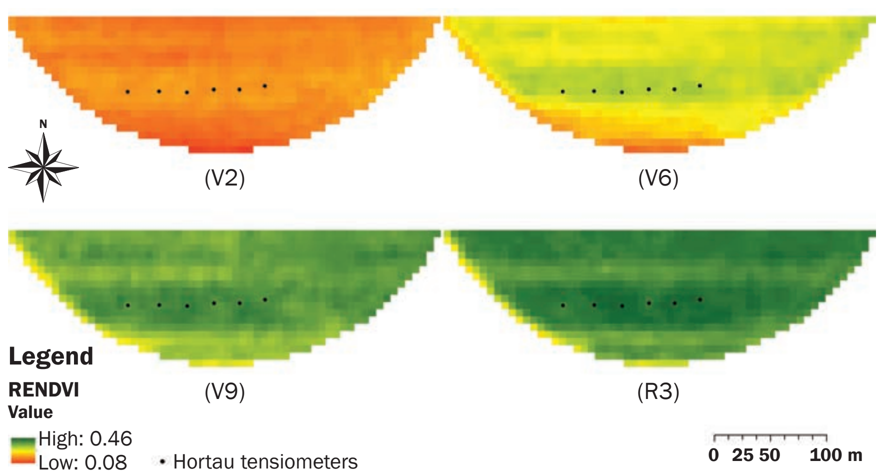
Note: NIR = near-infrared.

Table 3
Satellite image acquisition days and corresponding crop growth stages (Ritchie and Hanway 1989).

DOY*	Growth stage
164	Emergence (bare soil)
178	Two leaf (V2)
192	Six leaf (V6)
204	Nine leaf (V9)
242	Milk (R3)

*DOY = day of year.

Figure 2
Red Edge Normalized Difference Vegetation Index (RENDVI) derived from satellite imagery is displayed over the four maize growth stages examined in this study: two leaf (V2), six leaf (V6), nine leaf (V9), and Milk (R3).

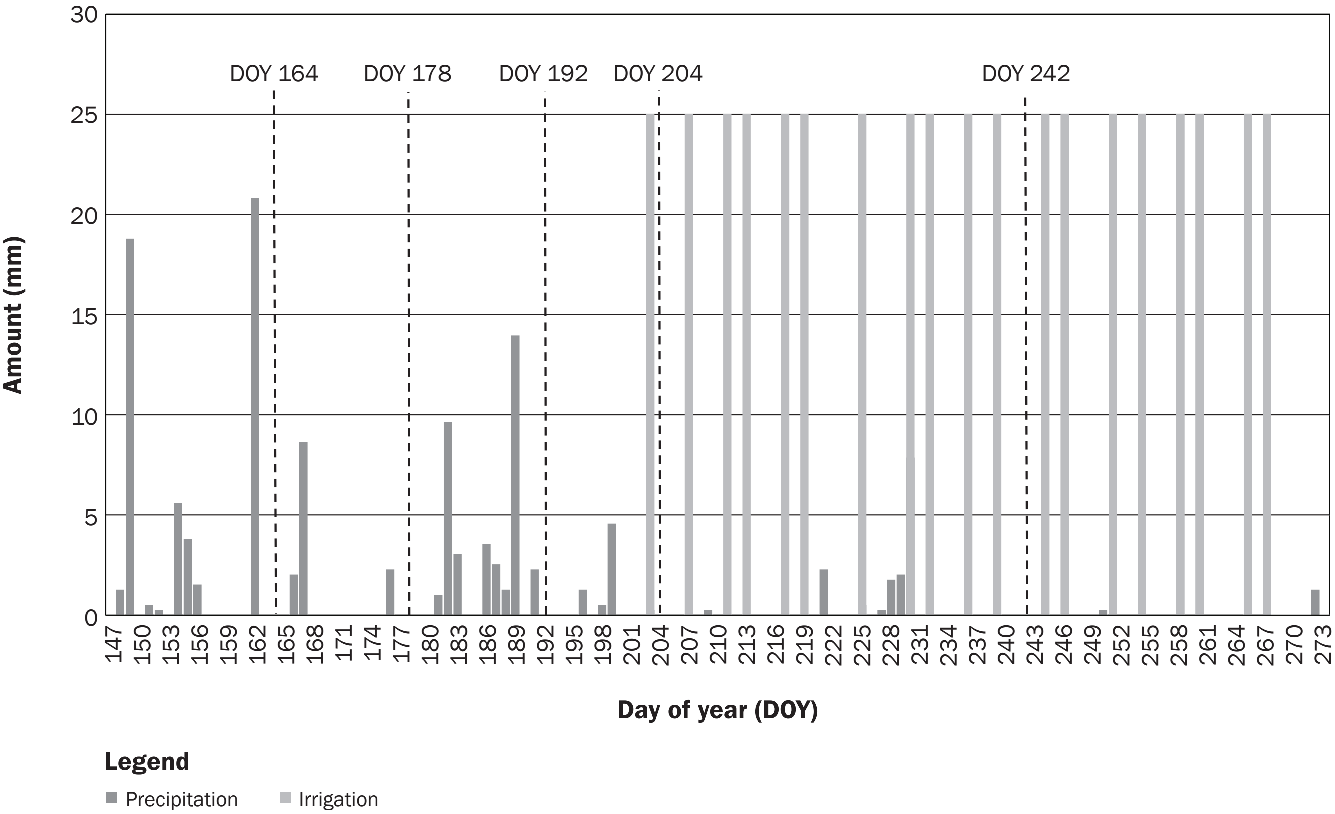


lowest coefficient of determination of all results when considering average tension over the day previous to image acquisition. Consequently, neither NDVI nor EVI seem to be suitable for quantifying immediate variability of soil water content. Our findings agree with Carter and Knapp (2001), who found that the best regression models for chlorophyll concentration occurred within the red edge region, rationalized by the propensity of stressed leaves to exhibit a reduction in chlorophyll. See table 4 for significant results.

Average Soil Tension from Previous Week. Renormalized Difference Vegetation Index and Optimized Soil Adjusted Vegetation Index were moderately correlated with average soil tension from the week previous to image acquisition at V6 growth stage, 20 cm deep (table 5). Frequent precipitation may explain why RENDVI and RECI did not produce significant results as they did with both other tension intervals at 20 cm. Nearly

Figure 3

Daily precipitation at Colorado State University Agricultural Research Development and Education Center and irrigation amounts in millimeters presented by day of year (DOY) during the 2015 growing season. Vertical dashed lines represent satellite image acquisition days.



2.5 cm of rain fell that week with very little difference between irrigation treatments, which probably masked any variability detectable by means of the spectral response of the plants. The 24-hour and planting to image acquisition intervals likely were not affected as strongly because much less precipitation occurred within each of those intervals as a whole. Furthermore, none of the indices were found to be significant over more than one growth stage. Similar to previously discussed results, GARI and other green indices once again had higher coefficients of determination at V2 stage, 75 cm deep when compared to the red indices. The positive correlation between soil tension and GARI is very strong. It is notable that the image for this date is comprised mostly of bare soil, which explains the contrast with otherwise negative correlations in all the imagery with considerably more plant growth. Despite statistical significance, these relationships with the green indices are unlikely to have agronomic value at the V2

Table 4

Results from regression analysis of average soil moisture tension (over the 24 hours previous to satellite image acquisition) on selected indices. Only significant results are presented.

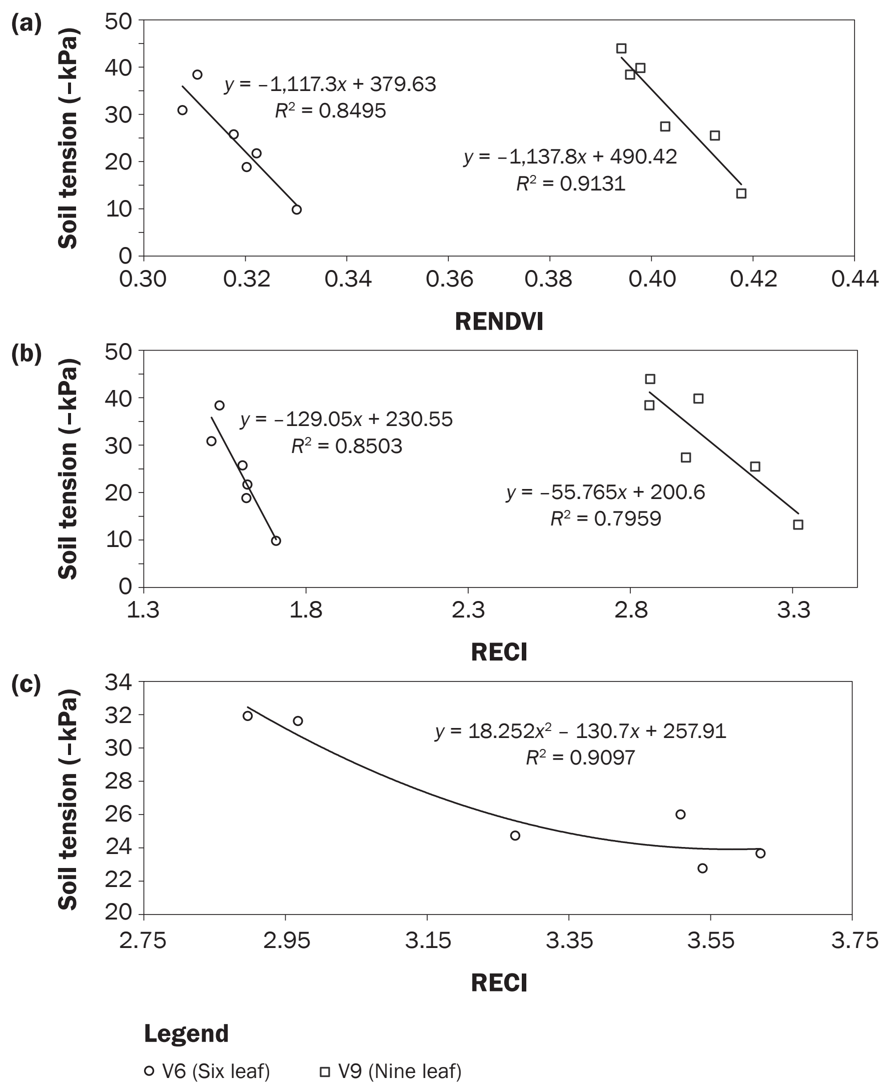
Tensiometer depth (cm)	Index	Growth stage*	r^2	*p*-value	RMSE (–kPa)
20	RENDVI	V6	0.850	0.009	4.291
		V9	0.913	0.003	3.779
	RECI	V6	0.850	0.009	4.280
		V9	0.796	0.017	5.792
75	RENDVI	R3	0.693	0.040	11.850
	NDVI	V2	0.691	0.040	0.698
	GRVI	V2	0.830	0.012	0.517
	GNDVI	V2	0.834	0.011	0.512
	GARI	V2	0.891	0.005	0.415
	EVI	V2	0.669	0.047	0.723

Notes: RENDVI = Red Edge Normalized Difference Vegetation Index. RECI = Red Edge Chlorophyll Index. NDVI = Normalized Difference Vegetation Index. GRVI = Green Ratio Vegetation Index. GNDVI = Green Normalized Difference Vegetation Index. GARI = Green Atmospherically Resistant Index. EVI = Enhanced Vegetation Index.

*V2, V6, V9, and R3 are the two leaf, six leaf, nine leaf, and milk stages of maize growth, respectively.

Figure 4

(a) Soil tension (20 cm depth) averaged over the day previous to image acquisition as a function of Red Edge Normalized Difference Vegetation Index (RENDVI) for V6 and V9 maize growth stages. (b) Soil tension (20 cm depth) averaged over the day previous to image acquisition as a function of Red Edge Chlorophyll Index (RECI) for V6 and V9 growth stages. (c) Average soil tension (20 cm depth) from planting to acquisition date as a function of RECI for R3 growth stage.



growth stage at 75 cm deep, since roots are still shallow. See table 5 for significant results.

Average Soil Tension from Planting to Image Acquisition Date. The average tension from planting to image acquisition date represents the sole occasion where traditional red NDVI had the highest coefficient of determination: it was highly correlated with soil tension at 75 cm deep (table 6). Unlike at other crop growth stages, this is once again a positive relationship at V2, which is logical because soil color as affected by water content probably had a stronger influence on reflectance over this larger interval with frequent rainfall than the influence of sparse vegetation. The only significant correlations found at the 45 cm depth were at the R3 stage, probably because moisture conditions closer to the soil surface have a greater effect on immediate plant response, and measurements deeper in the profile are more representative of long-term water infiltration when consistent rainfall is prevalent. RENDVI and RECI were highly correlated at both 20 and 45 cm depths at the R3 stage, suggesting value for quantifying soil tension in both vegetative and reproductive crop growth stages. Although the linear models are well correlated, it is important to note that the shape of the quadratic fit, as depicted in figure 4c, represents an intuitive trend. The curve in this case levels off at the wettest soil tensions. This is characteristic of excessive irrigation, at which point adding more water fails to benefit the crop and will eventually cause stress.

Bare Ground (Emergence) Image. Data from all three tensiometer depths examined in this study (20, 45, and 75 cm) indicate that soil surface albedo provides information deeper into the profile than the light can fundamentally penetrate, although the correlations tend to be slightly weaker. For average tension between planting to the image acquisition, RENDVI and RECI produced coefficients of determination above 0.71 at both 20 and 75 cm depths, while results at 45 cm were just outside the alpha = 0.05 significance level. These observations may arise from the combined influence of soil physical properties (e.g., organic matter content, texture, and color), which affect its spectral response and are concurrently related to the behavior of soil when water is introduced (e.g., infiltration rate and water holding capacity).

It was demonstrated that soil reflectance as influenced by water content could be applied amongst contrasting soils if the water content were expressed as soil moisture tension instead of percentage dry mass (Brady 1985). Our results support those findings and also suggest that this can be accomplished at the field scale. Multispectral satellite imagery could then help inform variable rate irrigation systems by accounting for temporal variability at high spatial resolution. Aerial bare soil imagery has been used at field scale to delineate site specific management zones for variable rate nitrogen (N) management (Khosla 2002), but the literature does not include similar studies for variable rate irrigation. Aside from the number of studies (Bowers and Hanks 1965; Idso et al. 1975; Skidmore et al. 1975), which provide evidence that the optical properties of soil vary with water content, our results indeed agree with the suggestion of Campbell (1988) that visible and near-infrared reflectance must also be related to soil moisture tension.

At depths greater than 20 cm, none of the vegetation indices were found to be well correlated with average tension over 24 hours. However, RENDVI and RECI produce moderate correlations (at alpha = 0.1)

Table 5

Results from regression analysis of average soil moisture tension (over the week previous to satellite image acquisition) on selected indices. Only significant results are presented.

Tensiometer depth (cm)	Index	Growth stage*	r^2	p-value	RMSE (–kPa)
20	RDVI	V6	0.661	0.049	5.361
75	OSAVI	V2	0.717	0.033	0.720
	NDVI	V2	0.766	0.022	0.766
	GRVI	V2	0.781	0.019	0.633
	GNDVI	V2	0.784	0.019	0.628
	GARI	V2	0.908	0.003	0.411
	EVI	V2	0.724	0.032	0.711

Notes: RDVI = Renormalized Difference Vegetation Index. OSAVI = Optimized Soil Adjusted Vegetation Index. NDVI = Normalized Difference Vegetation Index. GRVI = Green Ratio Vegetation Index. GNDVI = Green Normalized Difference Vegetation Index. GARI = Green Atmospherically Resistant Index. EVI = Enhanced Vegetation Index.

*V2 and V6 are the two leaf and six leaf growth stages of maize, respectively.

Table 6

Results from regression analysis of average soil moisture tension (from planting to satellite image acquisition) on selected indices. Only significant results are presented.

Tensiometer depth (cm)	Index	Growth stage*	r^2	p-value	RMSE (–kPa)
20	RENDVI	R3	0.772	0.021	2.143
	RECI	R3	0.861	0.008	1.672
	Quadratic†	R3	0.910	0.027	1.556
	NDVI	R3	0.699	0.038	2.461
	GRVI	V2	0.664	0.048	1.259
	GNDVI	V2	0.657	0.050	1.271
45	RENDVI	R3	0.827	0.012	4.190
	RECI	R3	0.851	0.009	3.891
	RDVI	R3	0.754	0.025	4.992
	OSAVI	R3	0.799	0.016	4.514
	NDVI	R3	0.767	0.022	4.862
75	RDVI	V2	0.736	0.029	0.771
	OSAVI	V2	0.816	0.014	0.644
	NDVI	V2	0.882	0.005	0.515
	GARI	V2	0.808	0.015	0.658
	EVI	V2	0.729	0.023	0.729

Notes: RENDVI = Red Edge Normalized Difference Vegetation Index. RECI = Red Edge Chlorophyll Index. RDVI = Renormalized Difference Vegetation Index. OSAVI = Optimized Soil Adjusted Vegetation Index. NDVI = Normalized Difference Vegetation Index. GRVI = Green Ratio Vegetation Index. GNDVI = Green Normalized Difference Vegetation Index. GARI = Green Atmospherically Resistant Index. EVI = Enhanced Vegetation Index.

*V2 and R3 are the two leaf and milk stages of maize growth, respectively.

†Quadratic regression is included because it is more intuitive than the linear model.

at all three depths for one week and planting to image acquisition date tension intervals. This suggests that although immediate soil moisture conditions near the surface are strongly correlated with the spectral response of soil, conditions deeper in the soil profile are only related after a considerable lag is allowed—likely for precipitation to infiltrate to that depth.

These results support the use of bare soil multispectral imagery for characterizing heterogeneous soil moisture conditions. It is important to note that the acquisition time for the larger unmasked image is early in the morning, so the image is particularly dark.

General Discussion. Results from regressions of soil tension on RENDVI and RECI indicate that spectral vegetation indices derived from multispectral satellite imagery are capable of characterizing high frequency soil moisture variability at single time points and at large field scales. Simple linear models had high coefficients of determination at more than one vegetative growth stage (both V6 and V9) at the same 20 cm depth. For RENDVI, the slopes were also nearly identical between stages, and the increase in the y-intercept for V9 growth stage was almost proportional. This consistency suggests that a single satellite image acquisition could be reasonably representative of soil moisture variability over time—at least up to a couple weeks after image acquisition—and may help mitigate issues with temporal resolution for variable-rate irrigation management.

Considerable differences between the models at V6 and V9 growth stages suggest that RECI may indeed reflect immediate soil moisture variability, but also that conditions may not be well represented up to a couple weeks as is the case with RENDVI, which is particularly sensitive to slight change. Conversely, models for RECI do appear to be slightly more representative later in the growing season, once reproductive growth is well underway. The shape of the quadratic curves also suggests that the red edge indices are capable of characterizing the stagnant point where applying more water will not benefit the crop. Models from the R3 crop growth stage indicate that long-term (planting to image acquisition date) soil moisture conditions are also well represented up to 45 cm deep.

Although additional data points may improve upon the value of the study, it should be noted that the state-of-the-art variable rate irrigation system was used to create variability (40%, 60%, 80%, 100%, 120%, and 140% ET treatments); adequately measuring the variability required fewer samples. In addition, the variable rate irrigation system application efficiency and accuracy were verified with catch cans. Likewise, to maintain accuracy of water application depth, the treatment zones were three times larger (about 325 m^2) than the area over which the pivot could accurately adjust the water application depth. This was done to ensure that each treatment completely surrounded the tensiometers within it. Furthermore, soil tension is a physical property that is stable and highly correlated with soil moisture content.

Moreover, soil tension measurements were repeated every 15 minutes, thus generating a vast amount of data that allowed confirmation of the stability of the data acquired.

Summary and Conclusions

Multispectral satellite imagery, particularly with a red edge waveband, demonstrates potential for quantifying soil moisture tension variability, and hence could be used for variable rate irrigation management. RENDVI was especially sensitive to soil moisture tension and demonstrated that a single image could be representative of spatial variability up to two weeks after acquisition. However, it is unlikely that multispectral satellite imagery could be used to detect rapid changes in soil moisture. It is necessary to confirm repeatability of these results at more maize growth stages and with other crops. Finally, an economic study to evaluate the monetary and environmental implications of such management at field scale would help transition these findings into industry adoption.

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