Sensing Soil Moisture Using NIR Spectroscopy

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Abstract. *Seven California soils were studied to determine if near infrared (700 to 2500 nm) reflectance spectroscopy could be used to determine soil moisture content. Near infrared absorbance data in the 1400– to 2400–nm region correlated well ($r^2 = 0.97$, SEP = 1.3%, Bias = 0.2%) with soil moisture content when a partial least squares calibration model was used to estimate the moisture content of soil samples of the same soil type and particle size as those in the calibration data set. However, when the model was used to estimate the moisture content of a soil sample with a particle size which differed from those included in the calibration set, the performance was degraded due to large slope and bias errors (Bias = 4.0%, SEP = 2.2%). However, the high coefficient of determination ($r^2 = 0.98$) suggested that predictions for soil samples which differ from those included in the calibration set could be improved if the slope and intercept were corrected for a given site. An example validation of this type was shown where the SEP and bias were reduced from SEP = 2.1% and Bias = 6.0% to SEP = 1.0% and Bias = 0.9% after slope and bias correction.*

Keywords. *Soil, Moisture measurement, NIR spectroscopy, Precision agriculture.*

The measurement of soil moisture content is critical in irrigated agriculture to assist in proper irrigation scheduling. For a given amount of irrigation, water will penetrate to a greater depth in a sandy soil than in a clay soil. For every irrigation, the farmer must estimate the number of inches of water to apply to the field (i.e. irrigation scheduling). Soil variability on a site–specific basis is a major problem for efficient irrigation scheduling (Hoffman et al., 1992). Over–irrigation due to variable soil textures coupled with the non–uniformity built into modern irrigation techniques can become substantial. Due to economic constraints, growers monitor moisture content at the driest location in the field to prevent water stress. This procedure leads to over–irrigation in other areas of the field. The calculation of the exact amount of water needed to bring the entire field precisely to field capacity is complicated by spatial variations in the soil texture.

The excess water that is added to a field by an irrigation event percolates below the root zone. This water eventually percolates into the groundwater carrying water–soluble nitrates along with it, and thereby contaminating the groundwater. Thus proper irrigation scheduling can assist in enhancing irrigation efficiency and reducing groundwater contamination. An inexpensive and reliable moisture sensor is crucial to develop a spatially optimal irrigation management scheme.

Several devices have been developed for the measurement of soil moisture content. A brief discussion of their operation and characteristics follows.

Thermogravimetric Determination

The thermogravimetric method is an old standard. A soil sample is weighed shortly after sampling and then dried in an oven at 105°C for 24 h and then reweighed. This method is accurate and has been used to verify most of the other techniques (Smith and Mullins, 1991). The disadvantage of this method is that it is not rapid.

Electrical Resistance

This technique is very old and simple. It consists of measuring the DC resistance between two electrodes. It is alternatively known as electrical conductivity (EC), which is used to measure the soil salinity of a saturated soil. Unfortunately, this technique is extremely sensitive to the salinity content of the soil and its use is limited to certain regions where the salinity content is low (Whalley and Stafford, 1992).

Soil Water Impedance Technique

A simple, very promising sensor based on the dielectric constant of water in the soil has been developed (Gaskin and Miller, 1996). This device measures the dielectric constant by using a probe that acts as a transmission line that terminates in the soil. The impedance of the transmission line is then modified by the dielectric properties of soil moisture. This principle allows a simple circuit comprised of a 100–MHz oscillator to measure the impedance change that relates to the soil moisture content. The instrument is

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reported to be accurate under simulated field conditions, and as such is still being investigated for *in situ* measurements. It may be some time before this technique is fully developed for real–time dynamic measurement of soil moisture content.

Soil Capacitance Method

A capacitance sensor is similar to the impedance sensor in that it seeks to measure the dielectric constant of the soil water. Whalley et al. (1992) developed a capacitance sensor that was used to measure the soil water content dynamically as a tractor drove through the field. This sensor was found to be sensitive to fluctuations in the soil bulk density. Unfortunately, most fields have non–uniform soil bulk densities and a density correction is needed to overcome this problem.

Nuclear Magnetic Resonance

Nuclear Magnetic Resonance (NMR) has been used to measure moisture content in corn, peanuts, wheat, and other commodities. NMR signals have also been correlated with the dry weight of avocados (Rollwitz et al., 1983; McCarthy et al., 1989). Possibilities for measuring soil water are still being explored (Smith, 1991). Research is currently in progress to develop an inexpensive NMR sensor (Chen et al., 1989). However, the current cost of NMR instrumentation is prohibitive for a field sensor.

Time Domain Reflectometry

Time Domain Reflectometry (TDR) is best suited for use in permanent installations. Measurements are extremely sensitive to the soil closest to the probe wires, with the breadth of the soil sampled being proportional to wire diameter. Soil insertion is therefore critical for repeatable measurements. Soil electrical conductivity, through saline soil water or surface conduction in clay soils, attenuates the TDR signal that requires additional salinity measurement (Dalton, 1992). TDR is still an area of considerable research and promise. The instrumentation for this technique is also expensive.

Neutron Probe

The neutron probe is an established method for monitoring water content *in situ*; it is reliable, well researched, and can be computerized. Some of the disadvantages for this technique are high equipment cost, required radiological safety procedures, special measures necessary to deal with readings in surface soil, and the care required for the installation of a permanent access tube (Smith, 1991). The technique gives unreliable readings across a wetting front and across discrete soil horizons, such as a plow pan. Neutron probe technology is not suitable for field use without an access tube, which makes it unsuitable for continuous spatial measurements in a field in real–time.

Near Infrared (NIR) Spectroscopy

The use of NIR absorbance spectroscopy has been considered as an attractive technique for measuring water content because it is based upon a fundamental property of water and because there are several prominent water absorption bands in the NIR region (Curcio and Petty, 1951; Norris, 1964). Norris (1964) developed one of the first NIR instruments that were specifically designed to measure the absorbance at 1940 nm of a sample of ground wheat saturated with carbon tetrachloride to determine the moisture content of the wheat. Several researchers (e.g., Hart et al., 1962; Campbell and Martin, 1976) showed that seed moisture could be determined by measuring the NIR absorbance of a water/methanol extract that was centrifuged to remove light scattering particles. Bowers and Smith (1972) used a similar NIR/methanol extraction procedure to measure soil moisture content and reported that the procedure required 1 h to complete. Stermer et al. (1977) observed that a NIR reflectance method based upon a single absorbance band was inadequate in the measuring the moisture of corn and sorghum grain. Using the absorbance at three or four NIR wavelengths they obtained standard error of calibration (SEC) values ranging from 0.8% for corn to 3.4% for sorghum grain. Finney and Norris (1978) used NIR transmittance to measure the absorbance of corn kernels in the 700– to 1100–nm region, and obtained standard error of prediction (SEP) values of about 2%.

Skidmore et al. (1975) developed a portable instrument to measure the NIR reflectance (1950 nm) of the soil surface using an integrating sphere. They observed coefficients of determination ranging from 0.96 to 0.99 when a log–linear relationship was used to calibrate the reflectance at 1950 nm to soil moisture for three soils, but that the log–linear relationships were different for each soil. No attempt was made to develop a global calibration for all three soils.

Kano et al. (1985) developed a hand–held instrument to measure the NIR reflectance of soil at two wavelengths (1800 and 1940 nm). They found that a single calibration model could be used to determine the soil moisture for two soils (clay and loam) with a SEC of 1.9%, however they also observed that a different calibration may be required for sand and sandy loam soils.

In a preliminary study, Upadhyaya et al. (1994) reported that NIR reflectance could be used to determine soil moisture and soil nitrogen rapidly. The study used one soil at three different moisture levels (2, 10, and 15%) and found that soil moisture content could be determined by NIR, SEC = 0.5%, and $r^2 = 0.99$. In a similar study using three clay soils Dalal and Henry (1986) concluded that NIR reflectance could be used to determine soil moisture, organic carbon and nitrogen rapidly using three wavelengths if the soils were within a narrow range of soil color and at moderate levels of organic matter. They also observed that the SEP values were much larger for coarsely ground soils than for finely ground soils.

The potential for using NIR techniques to determine soil moisture content *in situ* is promising. Moreover, the rapid nature of NIR techniques lends itself to the development of a real–time moisture sensor that can be particularly important for automatic irrigation management. The specific objectives of this study were:

1. To study the feasibility of using a global NIR calibration to determine the moisture content of a wide range of California soils, carefully prepared to have a uniform particle size.
2. To determine the feasibility of applying the global NIR soil moisture calibration model developed for objective 1, to a minimally processed soil with a natural particle size distribution representing actual field conditions.
3. To investigate the feasibility of applying the global NIR soil moisture calibration model developed for objective 1, to a minimally processed California soil type not included in the original calibration set.

MATERIALS AND METHODS

Seven California soils were chosen to assure a diverse group of soil textures and chemical constituents in the development of a NIR calibration model. Yolo loam and Reiff fine sandy loam soil samples were obtained from the UC Davis Agricultural Experiment Station. The remaining five soils, Ahwahnee (loamy sand), Chwanakee (sandy loam), Hurlbut (sandy loam), Los Osos (loam), and Two Log (clay), were obtained from the UC Davis Land, Air, and Water Resources Department (Le Bissonnais and Singer, 1993).

For the main soil data set used in this study, six soils (all but the Reiff fine sandy loam) were coarsely sieved to remove stones and then air dried (5 h in an air oven at 60°C and then allowed to cool overnight at 25°C). The soil samples were then ground to a uniform particle size distribution. Each soil was subdivided into 7 to 9 treatment levels depending upon the maximum moisture capacity of each soil type. The moisture content of each treatment level was carefully adjusted by adding water to each soil sample to achieve a uniform moisture range from air dry to field capacity. The diverse selection of soils in this study had maximum water retention capacities ranging from 21 to 32% moisture content (dry weight basis). Three to four replicate soil samples, depending upon the total number of moisture levels for that soil, at each moisture treatment level were prepared in order to obtain a total of approximately 30 samples for each soil across the range from air dry to field capacity. The result was a total of 196 samples in the main soil data set.

Three types of external model validation were incorporated in the statistical design of the experiment. First, to allow external model evaluation on a set of soils of the same type and preparation method as those used in calibration, the main soil sample set was split randomly into two portions as described by Neter et al. (1990) using one portion for calibration and the other for validation. All replicate soil samples at each of two moisture levels for each soil type were randomly selected from the main soil set to form a validation set (no. 1) consisting of 46 samples. The remaining 150 soil samples were used as the main calibration data set. Second, to evaluate the applicability of a calibration model to soil of the same type but with a particle size distribution differing from that in the calibration, a set (no. 2) of 28 Yolo loam soil samples was prepared by irrigating the soil in situ in an agricultural field to a range of soil moisture

levels from very dry to field capacity and with only a minimum of coarse sieving used to remove any stones. Third, to evaluate the applicability of the calibration model to a soil type not present in the calibration data set, a set (no. 3) of 28 Reiff fine sandy loam soil samples were prepared in situ in an agricultural field in the same manner as the Yolo loam soil of the second validation set. Although field capacity and air dry soil are uncommon moisture levels for an implement–based sensor to encounter in an agricultural field, it is helpful in NIR regression to include the extremes for model development. These extreme levels also allow assessment of the linearity of the system over the whole moisture range.

The optical absorption spectrum from 400 to 2500 nm was measured by placing approximately 30 g of each soil in a sample cup with a 50–mm diameter quartz window. A rapid scanning (1.8 scans/s) spectrophotometer (model 6500, NIRSystems, Silver Spring, Md.) configured for reflectance mode was used to record the absorbance spectrum. The average of 250 individual optical scans for each sample was stored for later use. A sample cup containing a 50–mm diameter ceramic disk was used as the optical reference standard for the system. The optical and soil moisture data were then merged and a partial least squares (PLS) regression analysis (Martens and Naes, 1989) was conducted using the NSAS software package (version 3.18, NSAS, 1990). A trial and error process was used to determine which portion of the electromagnetic region studied would provide the best prediction of soil moisture content using the PLS multivariate calibration technique. The correct number of regression factors for the PLS model was determined by the minimum mean square error of internal cross validation where the calibration data set was split into 10 subsets of equal size. Once the calibration model was developed, it was used to predict the moisture content of each of the soil samples reserved for external validation.

RESULTS AND DISCUSSION

Ideally a real–time soil moisture sensor would be inexpensive. Toward this objective, NIR calibrations for soil moisture were developed which relied solely upon electromagnetic information from the 700– to 1100–nm range as well as the entire 700– to 2500–nm range. The 700– to 1100–nm region was specifically isolated because silicon photodetectors are sensitive to radiation in this region and are less expensive than photodetectors that are sensitive to longer wavelengths.

The 900– to 1040–nm region was found to provide the best PLS calibration model for soil moisture in the silicon NIR region for the six California soils in the main calibration data set. This range included the dominant water absorption band centered at 960 nm (Williams and Norris, 1987). Internal cross validation indicated that a calibration model using 4 PLS factors was appropriate, $r^2 = 0.89$ and SEC = 2.7%. External validation results were obtained from application of the calibration model to the remaining 46 soil samples. When applied to the validation data this model had a coefficient of determination of $r^2 = 0.81$ and a SEP of 3.2% with a bias of

1.3%. These results indicated that use of 4 PLS factors did not lead to overfitting although the performance of this silicon region calibration model was not satisfactory.

In an attempt to improve the performance of the model, two additional calibration models were identified, one with wavelengths selected from the 1100– to 2500–nm region and the other using wavelengths from the entire 700– to 2500–nm region. A 10 factor PLS calibration using the 1400– to 2400–nm region provided the best results in the 1100– to 2500–nm region. As before, the number of factors was determined by internal cross validation and its performance was $r^2 = 0.98$ and SEC = 1.3% (fig. 1). This range includes the dominant water absorption bands centered at 1410, 1460, and 1910 nm (Curcio and Petty, 1951; Williams and Norris, 1987). A third model was constructed by developing a PLS calibration based upon the 900– to 1040–nm region from the first model and the 1400– to 2400–nm region from the second model. This combined region resulted in a calibration model with 11 PLS factors (internally cross validated) with a $r^2 = 0.98$ and SEC = 1.1%. External validation results were obtained from the application of these two calibration models to the 46 soil samples in the validation data set. When applied to the validation data the 1400– to 2400–nm model had a coefficient of determination of $r^2 = 0.97$, a SEP of 1.3% with a bias of 0.2% (fig. 2), and the 900 to 1040 nm and 1400 to

2400 nm combined model had a coefficient of determination of $r^2 = 0.98$, a SEP of 1.1% with a bias of 0.5%. These results indicated that the number of PLS factors used in each model did not lead to overfitting. The results from these three models indicated that the 1400– to 2400– nm region was superior to the 900– to 1040–nm region when a PLS calibration model was used to estimate the moisture of soil samples of the same soil type and particle size as those in the calibration data set.

The three models were further evaluated using the two external validation soil sets that were irrigated *in situ* and only coarsely sieved (to remove stones) in an attempt to assess their performance under more realistic field conditions. The first of these sets contained 28 Yolo loam soil samples ranging from 4.2 to 23.0% moisture. All three calibration models had high coefficients of determination in predicting the moisture content of the Yolo loam soils, however they also had significant slope and bias errors (table 1). The second soil set contained 28 Reiff fine sandy loam soil samples ranging from 5.1 to 21.2% moisture. The performance of the three calibration models in predicting the moisture of the Reiff fine sandy loam soils was similar to that found for the Yolo loam soils (table 1). The slope and bias errors for the 1400– to 2400–nm model are shown in figures 3 and 4 for the Yolo loam and the Reiff fine sandy loam soils, respectively. Since the performance of the 900 to 1040 nm and 1400 to 2400 nm combined model was not superior to the 1400– to 2400–nm model, the combined model was dropped from further study.

This situation, where the coefficient of determination (upon validation) is high but there are substantial slope and bias errors, was not surprising given the difference in particle size between the soils in the calibration set and those in validation sets no. 2 and 3. Two methods were investigated for mitigating these problems, a slope and bias correction and a second derivative pretreatment.

The slope and bias errors of the calibration models for the Yolo loam external validation set (no. 2) were used to perform a slope and bias adjustment of each model. The performance of the corrected calibration models were then evaluated by predicting the moisture content of the Reiff fine sandy loam soil (set no. 3). This procedure substantially reduced the bias errors of the models, but only the 1400– to 2400–nm model showed improvement in SEP when predicting the moisture content of the Reiff fine sandy loam soil (table 1). The performance of the slope and bias adjusted 1400– to 2400–nm model is shown in figure 4. These results show that the 1400– to 2400–nm raw absorbance model may be applicable to soils not included in the calibration set as long as a slope and bias adjustment is performed.

Soil particle size affects the amount of NIR light scattered by the soil sample resulting in a baseline shift in the spectra for different particle sizes. Particle size also has a multiplicative effect on the NIR spectra that is proportional to the strength of the absorber. Hruschka (1987) demonstrated the ability of the second derivative pretreatment in reducing the particle size effect in NIR absorbance spectra. Large baseline differences can be observed when the absorbance spectra of three ground Yolo
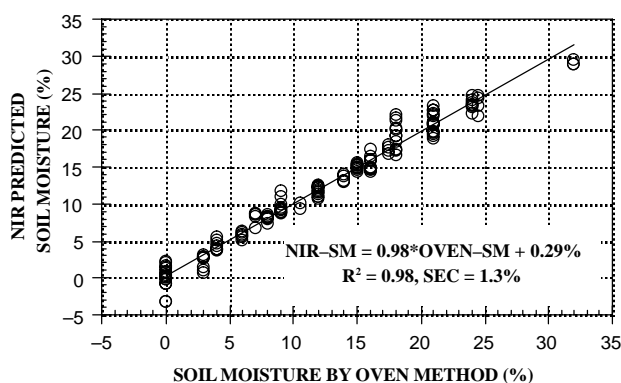

Figure 1. Calibration results for 1400– to 2400–nm model using the six–soil calibration soil set.
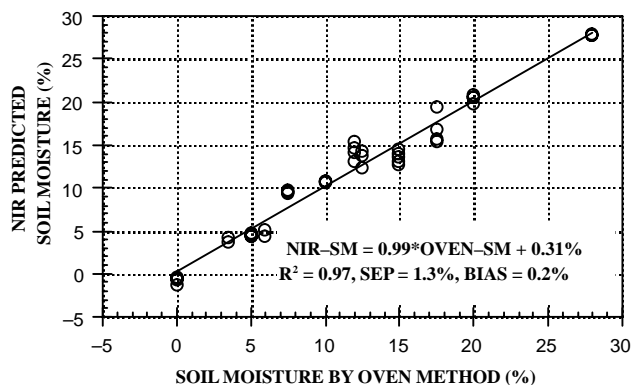

Figure 2. Validation results for 1400– to 2400–nm model using the six–soil validation soil set.

Table 1. Summary of NIR calibration performance for soil moisture determination using NIR absorbance spectra.

Wavelength Range (nm)	Calibration			Validation No. 1[a]			Validation No. 2[b]			Validation No. 3[c]			After Slope and Bias Adjustment	
	No. PLS Factors	R^2	SEC (%DW)	R^2	SEP (%DW)	Bias (%DW)	R^2	SEP (%DW)	Bias (%DW)	R^2	SEP (%DW)	Bias (%DW)	SEP (%DW)	Bias (%DW)
900-1040	4	.89	2.7	.81	3.2	1.3	.82	2.6	4.7	.83	2.4	6.2	2.1	1.0
1400-2400	10	.98	1.3	.97	1.3	0.2	.98	2.2	4.0	.96	2.1	6.0	1.0	0.9
900-1040, 1400-2400	11	.98	1.1	.98	1.1	0.5	.97	2.1	4.5	.90	2.1	5.5	1.6	0.2

[a] Validation no. 1 was conducted on six California soils of the same type and preparation method as in the calibration set.

[b] Validation no. 2 was conducted on the Yolo Loam soil of the calibration set, but irrigated *in situ* in an agricultural field with minimal sample preparation.

[c] Validation no. 3 was conducted on a Reiff loam soil not present in the calibration set, irrigated *in situ* in a agricultural field with minimal sample preparation.
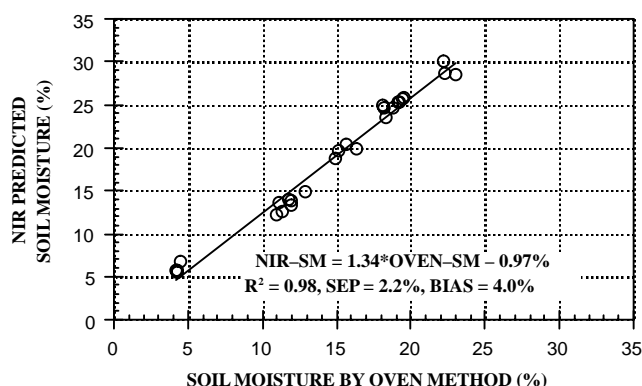

NIR–SM = 1.34*OVEN–SM – 0.97%
R^2 = 0.98, SEP = 2.2%, BIAS = 4.0%

Figure 3. Validation results for the 1400– to 2400–nm model using the Yolo Loam field soil set.

Figure 5. Absorbance spectra of ground (___) and unground (– – –) samples of Yolo Loam soil with similar moisture contents.

UNADJUSTED MODEL
NIR_SM=1.34*OVEN_SM+0.36%
R^2=0.96, SEC=2.1%, BIAS=6.0%

SLOPE AND BIAS ADJUSTED MODEL
NIR_SM=0.98*OVEN_SM+1.26%
R^2=0.96, SEP=1.0%, BIAS=0.9%

Figure 4. Validation results for the 1400– to 2400–nm model using the Reiff Loam field soil set.

Figure 6. Second derivative (20–nm gap) absorbance spectra of the ground (___) and unground (– – –) samples of Yolo Loam soil from figure 5.

Loam samples from the calibration set with moisture contents of 16% and three unground Yolo Loam samples from the validation set no. 2 with moisture contents of 15.1, 15.7, and 16.4% are compared (fig. 5). If a second derivative pretreatment is applied to these spectra, the baseline differences are eliminated (fig. 6).

The choice of second derivative segment and gap parameters was investigated using the Norris Regression option of the NSAS software package (NSAS, 1990). Preliminary analysis indicated that a segment of 4 nm and a gap of 4 nm would provide the best results, with larger segment and gap sizes giving nearly identical but slightly inferior results. Two secon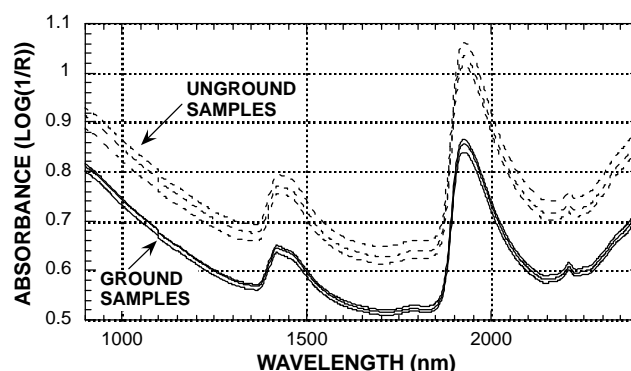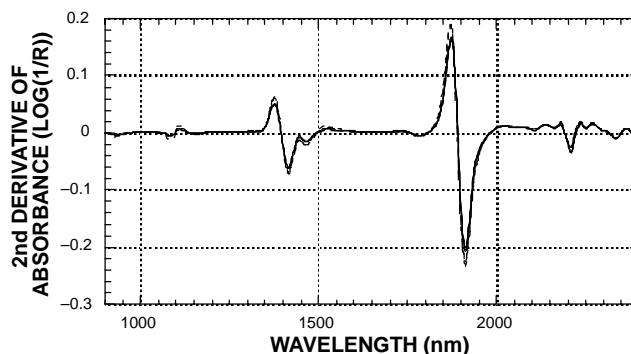d derivative spectral data sets were created for each of the four soil sample sets (calibration and the three validation sets), one with a segment of 4 nm and a gap of 4 nm and a second with a segment of 4 nm and a gap of 20 nm. New PLS calibration models were developed for each of the two wavelength regions previously identified (900–1040 nm and 1400–2400 nm) using the second derivative pretreated data.

A 5 factor PLS calibration using the 4–nm gap second derivative pretreatment in the 900– to 1040–nm region was obtained by internal cross validation and its performance was $r^2 = 0.76$ and SEC = 3.9%. The performance of the 20–nm gap second derivative pretreatment in the 900– to 1040–nm region was similar (table 2). Validation performance of these second derivative PLS models was similar or slightly inferior

Table 2. Summary of NIR calibration performance for soil moisture determination using second derivative spectra.

2nd Derivative Segment, Gap	Wavelength Range (nm)	Calibration No. PLS Factors	R^2	SEC (%DW)	Validation No. 1[a] R^2	SEP (%DW)	Bias (%DW)	Validation No. 2[b] R^2	SEP (%DW)	Bias (%DW)	Validation No. 3[c] R^2	SEP (%DW)	Bias (%DW)	After Slope and Bias Adjustment[d] SEP (%DW)	Bias (%DW)
4 nm, 4 nm	900-1040	5	.76	3.9	.63	4.5	0.8	.86	3.2	-0.2	.84	2.1	-0.2	2.2	-0.6
4 nm, 4 nm	1400-2400	12	.98	1.3	.96	1.4	-0.03	.99	1.3	1.9	.97	1.4	3.0	0.9	0.6
4 nm, 20 nm	900-1040	6	.74	4.1	.63	4.6	1.1	.81	3.7	0.9	.79	2.3	0.6	2.5	-0.8
4 nm, 20 nm	1400-2400	8	.96	1.6	.94	1.8	-.3	.98	0.8	3.7	.96	1.0	3.1	1.0	-0.6

[a] Validation no. 1 was conducted on six California soils of the same type and preparation method as in the calibration set.
[b] Validation no. 2 was conducted on the Yolo Loam soil of the calibration set, but irrigated *in situ* in an agricultural field with minimal sample preparation.
[c] Validation no. 3 was conducted on a Reiff loam soil not present in the calibration set, irrigated *in situ* in a agricultural field with minimal sample preparation.
[d] Only a bias adjustment was necessary for the calibration model based upon the 20-nm gap derivative pretreatment in the 1400- to 2400-nm wavelength region.

to that obtained with the raw absorbance data and was generally not satisfactory.

As with the raw absorbance data the second derivative PLS calibration models in the 1400– to 2400–nm region were superior to those in the silicon region (table 2). It is interesting to note that the number of PLS factors (as determined by internal cross validation) for models in the 1400– to 2400–nm region was 12 for the 4–nm gap derivative pretreatment and 8 for the 20–nm gap derivative pretreatment, while the raw absorbance model used 10 PLS factors. As expected, the performance of the model using the 4–nm gap pretreatment had slightly superior performance in calibration and external validation using data set no. 1. However, when applied to the two unground, *in situ* irrigated validation data sets (no. 2 and 3) the 20–nm gap derivative model had lower SEP values than either the 4–nm gap derivative model or the raw absorbance model. Unfortunately the second derivative pretreatment did not eliminate the need for a slope and bias adjustment when the calibration models were applied to the unground *in situ* irrigated samples. In particular the 4–nm gap derivative model, while better than the raw absorbance model, still required both slope and bias adjustment (using the slope and bias errors from the Yolo loam soil external validation set no. 2) in order to accurately predict the moisture content of the Reiff loam soil (set no. 3). The 20–nm gap derivative model, however, only required a bias correction (using the bias errors from set no. 2) to accurately predict the moisture content of the Reiff loam soil. The fact that the 20–nm gap derivative model used fewer PLS factors and only required a bias adjustment may indicate that it is more robust to changes in soil set than the other models. Since the second derivative pretreatment did not entirely eliminate the need for a calibration adjustment, the results confirm that a PLS calibration model in the 1400– to 2400–nm region may be applicable to soils not included in the calibration set as long as a calibration adjustment is performed.

CONCLUSIONS
- Independent validation performance indicated that a NIR reflectance technique can be successfully used to develop a global calibration to determine the moisture content of soil samples that are similar in soil type and particle size distribution (e.g., from the same site) to those used in calibration.
- The results in predicting the moisture of a Yolo loam soil validation set (prepared with only the stones removed) indicated that: 1) a slope and bias correction to calibration models based on raw absorbance NIR spectra of ground soil samples was necessary to obtain accurate results when the model was used to predict the moisture of samples which were not ground even though ground Yolo loam samples were included in the calibration process, and 2) that only a bias correction was necessary if a second derivative pretreatment of appropriate gap was applied prior to calibration.
- When the Yolo loam soil set (prepared with only the stones removed) was used for slope and bias correction, the 1400– to 2400–nm NIR model accurately predicted the moisture content of a Reiff fine sandy loam soil (also prepared with only the stones removed) that was not included in the calibration data set. The slope and bias correction caused the SEP to drop from 2.1 to 1.0% and the Bias to drop from 6.0 to 0.9% for the raw absorbance based model and the Bias to drop from 3.1 to –0.6% for the second derivative pretreatment based model.

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