Estimating Plant-Available Water Capacity for Claypan Landscapes Using Apparent Electrical Conductivity

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Information on plant-available water (PAW) capacity (PAW_c) variation within a field is useful for site-specific management. For claypan soils, established relationships between soil apparent electrical conductivity (EC_a) and topsoil thickness suggested the hypothesis that profile PAW_c could be estimated by assuming a two-layer soil composition, a silt loam topsoil layer and a silty clay sublayer, with known PAW fraction values for each layer. Objectives were (i) to investigate the direct relationships between EC_a and the upper and lower limits of PAW_c, and (ii) to test the previously stated hypothesis. Nineteen and 18 soil profile samples were taken from two Missouri claypan fields in October 2005. The lower limit of PAW_c was determined at −1500 kPa soil water pressure. Samples were taken again from the same locations in March 2006 to determine the upper limit of PAW_c. Calculations were on a 1.2-m basis. The direct relationship between EC_a^{-1} and profile PAW ($PAW_{1.2}$) was significant, with regression r^2 values of 0.67 and 0.87 and RMSEs of 30 and 20 mm for Fields 1 and 2, respectively. The RMSEs for two-layer-estimated $PAW_{1.2}$ were 14 and 16 mm for Fields 1 and 2, respectively, or 7.6 and 8.6% of the respective mean measured $PAW_{1.2}$. With the two-layer approach, some underestimates of $PAW_{1.2}$ resulted from underestimation of topsoil thickness, whereas overestimates were attributed to soil horizons being short of field capacity at sampling due to slow recharge. The resulting field-scale PAW_c information is useful in site-specific decision making for soil and water management.

Abbreviations: C, clay; EC_a, bulk soil apparent electrical conductivity; $LL_{1.2}$, lower limit of plant-available water for a 1.2-m soil profile; PAW, plant-available water; PAW_c, plant-available water capacity; $PAW_{1.2}$, plant-available water for a 1.2-m soil profile; SIC, silty clay; SICL, silty clay loam; SIL, silt loam; $UL_{1.2}$, upper limit of plant-available water for a 1.2-m soil profile.

SOIL & WATER MANAGEMENT & CONSERVATION

The ability of soil to store and supply water to plants is one of its fundamental properties related to crop production. Knowledge about plant-available water (PAW) capacity (PAW_c) is useful for many soil management practices as well as for crop yield modeling applications. Quantitative determination of PAW_c, however, is not an easy task. Determination of PAW involves determining the two limits (i.e., field capacity and permanent wilting point), which can be either monitored from field measurements (Ritchie, 1981) or approximated under laboratory conditions (Jamison and Kroth, 1958). The former requires permanent installation of soil moisture devices and repeated monitoring, while the latter involves destructive sampling and water extraction. Either way, the time-consuming nature prohibits extensive assessment of the spatial variability of this soil property for a given field or watershed. Further difficulties include the limited value of soil survey information (e.g., texture and bulk density) for estimating PAW due to potentially large errors and bias in the estimation (Fortin and Moon, 1999).

A key component of site-specific management is quantification of the spatial variability of soil properties that affect crop yields (Atherton et al., 1999). A map of PAW_c would help advance management decisions such as adjusting fertilizer input and optimizing water management options. This information could also be incorporated in management zone delineation or in crop models. To meet this need, alternative approaches have been proposed (Timlin et al., 2001b; Morgan et al., 2003). Timlin et al. (2001b) used a simple water budget model to simulate yield, and then applied a procedure to match the simulation to observed yield. During the matching procedure, the amount of PAW was varied until the closest match between predicted and observed yield was found. Then available water was estimated at the closest match. By similar principles, Morgan et al. (2003) devised an inverse yield model to create a "look-up" table where corn yields were simulated at a range of PAW levels. Using this correspondence, a map of PAW could be inversely generated based on yield maps. These approaches take advantage of readily available yield data made possible through yield-mapping technologies and assume that

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observed yield is only affected by PAW. Through inherent biophysical relationships between crop yield and water balance, the yield information can be transferred into PAW information.

Apparent profile soil electrical conductivity (EC_a) has become an important tool in site-specific management practices because it relates to a wide range of soil chemical and physical properties that affect crop yield (McNeill, 1992; Lund et al., 2001; Kitchen et al., 2003; Sudduth et al., 2005). Applications of mapped EC_a have included characterizing soil spatial variability (Corwin and Lesch, 2005) and delineating management zones (Kitchen et al., 2005; Jaynes et al., 2005). The direct regression relationships between EC_a and PAW, however, have been examined by only a few (Morgan et al., 2000; Wong et al., 2006), even though high and consistent correlations between EC_a and soil water content on nonsaline soils have been reported by many (Kachanoski et al., 1988, 1990; Sheets and Hendrickx, 1995; Khakural et al., 1998; Sudduth et al., 2001; Reedy and Scanlon, 2003).

For claypan soil landscapes in the U.S. Midwest, the contrasting electrical properties of the claypan and the overlying topsoil have lent EC_a a unique utility of estimating and mapping spatially variable topsoil thickness above the claypan horizon (Doolittle et al., 1994; Sudduth et al., 2003; Sudduth and Kitchen, 2006). Topsoil thickness has been found to highly correlate with crop yield, especially in dry growing seasons (Gantzer and McCarty, 1987; Kitchen et al., 1999), because it serves as a crucial reservoir for PAW and nutrients and provides a suitable rooting environment for plants (Timlin et al., 2001a). Compared with the topsoil, the claypan horizon has a substantially lower PAW_c due to high clay content (usually >50%), low organic matter, and poorly developed structure (Jamison and Kroth, 1958). Yet roots of annual crops, e.g., corn (*Zea mays* L.) and soybean [*Glycine max* (L.) Merr.], can penetrate through the claypan down to a depth of 1.35 m (Grecu et al., 1988; Myers et al., 2007). These characteristics of claypan soils led to the formulation of our study hypothesis: the maximum PAW_c can be approximated with a hypothetical two-layer soil profile comprised of a topsoil layer (usually silt loam in texture) and a sublayer (silty clay or clay in texture) to the bottom of the rooting depth. The proposed procedure, if proven, would provide quick and inexpensive PAW_c estimates at high spatial resolution because topsoil thickness can be estimated by EC_a. The mathematical representation for this hypothesis is given as:

$$\mathrm{PAW}_c = T_{\mathrm{topsoil}}\mathrm{PAW}_{\mathrm{SIL}} + T_{\mathrm{subsoil}}\mathrm{PAW}_{\mathrm{SIC}} \qquad [1]$$

where PAW_c is the profile PAW capacity to the bottom of a presumed rooting depth; $T_{topsoil}$ and $T_{subsoil}$ are thicknesses of the topsoil layer and sublayer, respectively ($T_{subsoil}$ is obtained by subtracting $T_{topsoil}$ [estimated using EC_a] from the rooting depth); and PAW_{SIL} and PAW_{SIC} are PAW fraction values for the two soil textures obtained from the USDA-NRCS soil survey (Young et al., 2001; NRCS staff, personal communication, 2006).

Thus, the specific objectives of this study were to: (i) investigate direct relationships between EC_a and profile PAW and its upper and lower limits, and (ii) test how well the hypothesis expressed in Eq. [1] can approximate profile PAW at a field scale.

MATERIALS AND METHODS

Study Sites

Study sites were two claypan soil fields, Field 1 (39°38′N, 92°20′W) and Field 2 (39°38′N, 92°25′W), located within 2 km of each other near Centralia in central Missouri. Field 1 was 28 ha and Field 2 13 ha in size. Elevation ranged from 262 to 266 m in Field 1 and from 256 to 266 m in Field 2. The primary soil series found in the study fields included Mexico (fine, smectitic, mesic Aeric Vertic Epiaqualfs), Adco (fine, smectitic, mesic Aeric Vertic Albaqualfs), both with 1 to 5% slope, and Leonard (fine, smectitic, mesic Vertic Epiaqualfs), with 2 to 14% slope. All these soil series are somewhat poorly or poorly (i.e., Leonard) drained (Soil Survey Staff, 2006). They are typical claypan soils characterized by an abrupt claypan horizon at varying depths, depending generally on slope and landscape position. The depth to claypan ranged from several centimeters in eroded areas to >1 m in depositional areas. The texture above the claypan ranged from the typical silt loam texture to an occasional silty clay loam texture. Both fields had been managed in a corn–soybean rotation with mulch tillage for about 20 yr. No-till was initiated in 2004 on Field 1 and in 1997 on Field 2. The mean annual temperature in the area is 12°C, and the mean annual precipitation is 96.9 cm (National Climate Data Center, 2002).

Sampling Procedures and Laboratory Analyses

Profile samples were taken at 19 locations in Field 1 and 18 locations in Field 2 in October 2005 using a hydraulic soil coring probe (38.1-mm diameter). The sampling sites were distributed throughout the fields such that major landscape features were represented. Soil properties and characteristics (e.g., topsoil thickness, horizon designation, and horizon texture) were already available at these sites as they had served as calibration sites for other research projects (e.g., Sudduth et al., 2003, 2005). The texture data indicated that there were four textural classes found at these sites: silt loam (SIL), silty clay loam (SICL), silty clay (SIC), and clay (C). Topsoil was considered as those soil horizons above the claypan whose texture was silt loam or, occasionally, silty clay loam. For sites where the surface texture was silty clay, topsoil thickness was considered zero (i.e., high-erosion areas). During the sampling for this investigation, profile horizons were reexamined guided by the original designation. Horizon lengths were recorded, and then soil profiles were separated by horizon and each horizon sample was collected and sealed in a plastic bag. These horizon samples were air dried for 2 wk before an air-dry weight was obtained. A subsample of about 50 g was oven dried to determine water content for the air-dry horizon samples. Thus, bulk density for each horizon was calculated using air-dry soil mass, water content of the air-dried subsample, and sample volume. Bulk density was used to convert gravimetric water content to volumetric water content. The remaining samples were broken, and small aggregates were used to determine water retention at −33 kPa. Further, sample material passed through a 2-mm sieve was used to determine water retention at −1500 kPa, which was used as the lower limit (LL) of PAW_c. Water retention was determined using pressure chambers (Dane and Hopmans, 2002).

The same sites were resampled on 29 Mar. 2006, following wintertime profile recharge, to determine field capacity, which was used as the upper limit (UL) of PAW_c. An 11-mm rainfall was recorded 2 d before the sampling. Sampling procedures followed those of the October sampling, using the same horizon designations and depths. There was a cumulative 19-cm deficit from normal precipitation during the recharge months (October–March; National Climate Data Center, 2002). To ensure the soil condition was as close to field capacity as possible before sampling, several test samples were taken approximately 2 wk before to compare with historical neutron probe moisture data that had been collected from some of the sampling sites

Table 1. Mean measured topsoil thickness (TT), selected apparent bulk soil electrical conductivity (EC_a) sensor, regression equation, and regression statistics for measured and EC_a–estimated topsoil thickness.

Field	Mean measured TT	Sensor, mode	Regression equation used†	Statistics of fit ($y = \alpha + \beta x$)‡				
				RMSE	β	SE for β	R^2	$P > F$ (β = 1)
	cm			cm				
Field 1	34.8	DUALEM-2S, shallow	$TT = -58.57 + 3913EC^{-1}$	11.5	0.77	0.12	0.71	0.07
Field 2	40.1	DUALEM-2S, shallow	$TT = -88.67 + 5807EC^{-1}$	12.3	0.95	0.09	0.89	0.60

† From Sudduth and Kitchen (2006).

‡ *x* is measured topsoil thickness, *y* is EC_a–estimated topsoil thickness.

at the beginning of June 1997 (seven sites in Field 1) and 1999 (five sites in Field 2) after profile recharge. We judged these neutron data to represent field capacity conditions, especially at deeper depths, because precipitation leading up to the measurement dates was 11 and 18 cm above normal for 1997 and 1999, respectively (from the previous October–May). The average water content measured by the neutron probe on a 1.2-m profile basis was 495 and 483 mm for Fields 1 and 2, respectively. A good comparison was obtained between the neutron-probe field capacity determination and the preliminary sampling in mid-March 2006.

For the actual samples, PAW was determined by the difference between the UL and LL values for each horizon. Profile upper limit ($UL_{1.2}$) and lower limit ($LL_{1.2}$) were obtained as a depth-weighted average of soil horizons to a 1.2-m depth. Profile PAW ($PAW_{1.2}$) was then the difference between the $UL_{1.2}$ and $LL_{1.2}$.

DATA ANALYSIS PROCEDURES

Validation of Estimation Equations for Topsoil Thickness

Our previous research determined regression relationships of soil EC_a to topsoil thickness for the two fields (Sudduth et al., 2003; Sudduth and Kitchen, 2006). Soil EC_a data used to develop these relationships were collected at different times of the year during multiple years using several types of commercial EC_a sensors. The sensors included Geonics EM38 (Geonics Ltd, Mississauga, ON, Canada), Veris 3100 (Veris Technologies, Salina, KS), and DUALEM-2S (Dualem Inc., Milton, ON, Canada). The EM38 had a vertical dipole and a horizontal dipole with respective effective sensing depths of 1.5 and 0.75 m. The Veris 3100 used rolling coulter electrodes to directly sense both shallow (0.3-m effective sensing depth) and deep (1.0-m effective sensing depth) readings of EC_a. The Dualem-2S sensor was designed with a single transmitter and two receivers, allowing simultaneous shallow and deep EC_a readings, with respective effective sensing depths of 1.2 and 3.0 m. Additional details on the sensors and EC_a data collection can be found in Sudduth et al. (2003) and Sudduth and Kitchen (2006). The regression equations of EC_a vs. topsoil thickness were different due to sensor design, effective sensing depth, and variation in field conditions (e.g., moisture and temperature) when EC_a data were acquired. Furthermore, the samples for the current study differed slightly in measured topsoil thickness from the original data used to develop the regression equations because of local variations in topsoil thickness and the subjectivity involved in determining the boundary of the claypan horizon using visual cues in the field. Therefore, a validation of the existing regression equations against the current measured topsoil thickness data was conducted to select the best relationship. All EC_a data sets were kriged to a 5- by 5-m cell size with identical spatial extent. The EC_a values from cells that contained sampling sites were used to develop the regression with measured topsoil thickness. A regression equation for each field was selected based on minimal bias between the measured and estimated topsoil thickness, standard error for the regression coefficient (β), and RMSE. The bias was tested by evaluating the hypothesis of β = 1 in the regression. The validation results showed that the DUALEM-2S sensor used in shallow mode performed the best for Field 1, and the DUALEM-2S sensor used in shallow or deep mode performed equally well for Field 2. For consistency and comparison purposes, we selected the DUALEM-2S sensor in shallow mode to estimate topsoil thickness for further analyses. The selected regression equations and the selection criteria are given in Table 1.

Statistical Analyses

The mean distances between any two sampling sites were 363 and 244 m for Fields 1 and 2, respectively, and soil properties determined at these sampling sites were assumed spatially independent. Several statistical procedures were used in the data analyses. For each textural class, a two-sample *t*-test was performed between UL and water content at –33 kPa (θ_{-33}), and then a one-sample *t*-test was used to test whether the measured PAW values were equal to the USDA-NRCS PAW values used in Eq. [1]. Both EC_a and the reciprocal function, EC_a^{-1} (Sudduth et al., 2003; Sudduth and Kitchen, 2006) were used to regress against measured $UL_{1.2}$, $LL_{1.2}$, and the difference between the two (i.e., $PAW_{1.2}$). These EC_a values were the same as those used to validate the topsoil thickness. Normal errors were assumed for these simple regression models, and therefore model residuals were tested for normality. For the two-layer profile approach, RMSE calculation and bias tests were performed for measured $PAW_{1.2}$ vs. estimated $PAW_{1.2}$ (Eq. [1]). Furthermore, the estimated $PAW_{1.2}$ (Eq. [1]) and the measured $PAW_{1.2}$ were examined against a 1:1 reference relationship. All statistical procedures were conducted using SAS software (SAS Institute, 2005), and the significance level for all statistical procedures was α = 0.05.

RESULTS AND DISCUSSION

Texture Distributions and Plant-Available Water by Texture

In Field 1, the measured topsoil thickness ranged from 11 to 120 cm with an average of 34.8 cm (Table 1), and all topsoil horizons but one were SIL texture. In Field 2, the measured topsoil thickness ranged from 0 to 120 cm with an average of 40.1 cm. Seven out of the 18 sample profiles had SICL texture for the topsoil horizon, and one profile had no topsoil (i.e., SIC at the surface). The higher clay content in the surface horizons for Field 2 was an indication of more severe erosion having occurred in Field 2 than in Field 1 and a possible result of tillage mixing of the subsoil into the shallow surface horizon. Furthermore, 12 SIL horizons in Field 2 were found in the subsoil (below 40 cm), underlying SIC and SICL textures, while all SIL horizons but one in Field 1 were surface horizons. The SICL horizons were more dispersed across the depth of the profile in Field 2 than in Field 1.

Particle size distributions, UL, LL, calculated PAW, and θ_{-33} for each textural class are given in Table 2. The two-sample *t*-tests indicated that the ULs for the SIL texture in both fields were significantly higher than the corresponding θ_{-33}. The rain event that occurred 2 d before sampling with the somewhat poorly drained

Table 2. Particle size distributions, measured upper limit (UL), lower limit (LL), plant-available water (PAW), and water content at −33 kPa (θ_{-33}) by textural class, and *t*-test results for the UL vs. θ_{-33} and for measured vs. NRCS PAW (numbers in parentheses, except for textural class, are standard deviations).

Textural class (*n*)	Sand	Silt	Clay	UL	θ_{-33}	UL vs. θ_{-33}	LL	PAW (UL − LL)	NRCS PAW†	Measured vs NRCS PAW
	%			$m^3\ m^{-3}$		$P > \|t\|$	$m^3\ m^{-3}$			$P > \|t\|$
					Field 1					
SIL (33)	6.7 (3.3)	73.6 (4.9)	19.8 (3.0)	0.380 (0.051)	0.358 (0.028)	*	0.130 (0.036)	0.250 (0.053)	0.23	*
SICL (32)	2.7 (2.1)	63.6 (2.7)	33.7 (3.2)	0.373 (0.026)	0.415 (0.023)	***	0.252 (0.033)	0.122 (0.036)	0.19	***
SIC (24)	1.7 (1.1)	48.5 (6.4)	49.9 (6.2)	0.420 (0.047)	0.464 (0.031)	***	0.300 (0.046)	0.120 (0.069)	0.12	NS
C (7)	2.9 (2.1)	38.6 (1.1)	60.1 (0.9)	0.454 (0.027)	0.488 (0.028)	*	0.336 (0.024)	0.117 (0.041)	0.11	NS
					Field 2					
SIL (23)	7.1 (3.7)	70.8 (4.9)	22.1 (2.5)	0.369 (0.047)	0.317 (0.029)	***	0.150 (0.025)	0.219 (0.050)	0.23	NS
SICL (39)	6.9 (4.5)	59.9 (4.7)	33.2 (3.7)	0.367 (0.044)	0.366 (0.047)	NS	0.243 (0.049)	0.125 (0.060)	0.19	***
SIC (18)	2.7 (1.9)	50.6 (4.8)	46.7 (5.8)	0.412 (0.066)	0.419 (0.058)	NS	0.293 (0.054)	0.118 (0.044)	0.12	NS
C (2)	1.2 (0.6)	37.1 (2.8)	61.8 (3.3)	0.443 (0.018)	0.503 (0.044)	NS	0.332 (0.007)	0.111 (0.011)	0.11	NS

* Significant at the 0.05 level; NS, not significant.

*** Significant at the 0.001 level.

† Values were taken from Young et al. (2001).

subsurface was a possible reason for this result. The UL of SICL, SIC, and C textures were all lower than the θ_{-33} in Field 1, but were all the same as the θ_{-33} in Field 2. The UL being lower than θ_{-33} in Field 1 was an indication that, on average at the time of sampling, subsurface soils had not been fully recharged during the fallow period, a result of below-normal precipitation. The fact that our UL compared well with the historical neutron probe data collected in Field 1, however, suggested that the observed UL values represented field conditions normally encountered for this type of soil. A closer agreement between the UL and θ_{-33} may have been found had the field been wet for a longer period of time to allow the subsurface to fully recharge. Between Field 1 and Field 2, PAW values for all texture classes except for the SIL were statistically the same. The PAW for the SIL was higher in Field 1 (0.250 $m^3\ m^{-3}$) than in Field 2 (0. 219 $m^3\ m^{-3}$), with a *P* value of 0.031 (data not shown). This difference stemmed from significantly higher LL for the SIL in Field 2 (0.150 $m^3\ m^{-3}$) than in Field 1 (0.130 $m^3\ m^{-3}$, *P* value = 0.028, data not shown). The higher LL value for the SIL in Field 2 was a result of the SIL horizons distributed deeper in the sample profiles. These deeper SIL horizons had lower organic matter and higher clay content than the SIL horizons found at shallower depths, hence a slightly higher LL.

The PAW fraction values are also included in Table 2. These PAW fraction values were obtained by averaging the two values (a high value and a low value) given by Young et al. (2001) for a given texture. The NRCS PAW values matched well with the measured PAW for SIL in Field 2 and for SIC and C in both fields. The NRCS PAW value was lower than the measured PAW for the SIL in Field 1 and higher on average for the SICL in both fields (Table 2).

Relationships between Apparent Electrical Conductivity and the Upper and Lower Limits of Plant-Available Water Capacity

Simple regression models using EC_a^{-1} yielded better results with all variables ($UL_{1.2}$, $LL_{1.2}$, and $PAW_{1.2}$) than models using EC_a. Thus, the results using EC_a^{-1} are presented and discussed here. The mean and standard deviation for the $UL_{1.2}$, $LL_{1.2}$, and $PAW_{1.2}$ expressed in millimeters of water, as well as for EC_a^{-1}, are given in Table 3. The regression coefficients of EC_a^{-1} were significant for $LL_{1.2}$ for both fields. The r^2 values were 0.66 and 0.75 for Fields 1 and 2, respectively (Fig. 1).

Soil water content is one of the chief factors affecting EC_a. Kachanoski et al. (1988) reported high correlations between volumetric water content measured over a 0.5-m soil depth and EC_a measured over a series of soil depths ranging from 0.5 to 6 m. Good correlations remained between one-time measured EC_a and water content measurements taken over time, provided that the spatial variability of water content was relatively temporally stable (Kachanoski et al., 1990), and that potential temporal correlation among water content measurements was small enough not to impact the estimation equation (Reedy and Scanlon, 2003). The sample $LL_{1.2}$ ranged from about 160 mm (~0.13 $m^3\ m^{-3}$) to 340 mm (~0.28 $m^3\ m^{-3}$, Fig. 1), which was consistent with the water content ranges (<0.30 $m^3\ m^{-3}$) where highly significant relationships were reported in the literature. Because the lower limit water content was obtained at a fixed soil water pressure, however, the variation in $LL_{1.2}$ was mainly caused by soil texture and horizonation, rather than by field conditions such as structure and drainage.

From the relationships between EC_a^{-1} and topsoil thickness and between EC_a^{-1} and $LL_{1.2}$, a relationship between topsoil thickness and $LL_{1.2}$ could be expected. Correlation analysis showed significant correlation coefficients between topsoil thickness and $LL_{1.2}$ (−0.92 and −0.93 for Fields 1 and 2, respectively; $P < 0.0001$). For a Mexico soil, the amount of water retained at −1500 kPa in an Ap horizon with a SIL texture (~0.12 $m^3\ m^{-3}$) is normally only about one-half of the amount retained in a Bt hori-

Table 3. Basic statistics for measured upper limit ($UL_{1.2}$) and lower limit ($LL_{1.2}$), and calculated plant-available water capacity of a 1.2-m soil profile ($PAW_{1.2} = UL_{1.2} - LL_{1.2}$), along with apparent bulk soil electrical conductivity (EC_a) and EC_a^{-1} statistics.

Field	Statistic	$UL_{1.2}$	$LL_{1.2}$	$PAW_{1.2}$	EC_a	EC_a^{-1}
		mm			mS m^{-1}	(mS $m^{-1})^{-1}$
Field 1	Mean	469	287	181	42.5	0.0244
	SD	29	36	53	8.4	0.0050
Field 2	Mean	454	279	175	48.7	0.0220
	SD	23	57	58	12.8	0.0060

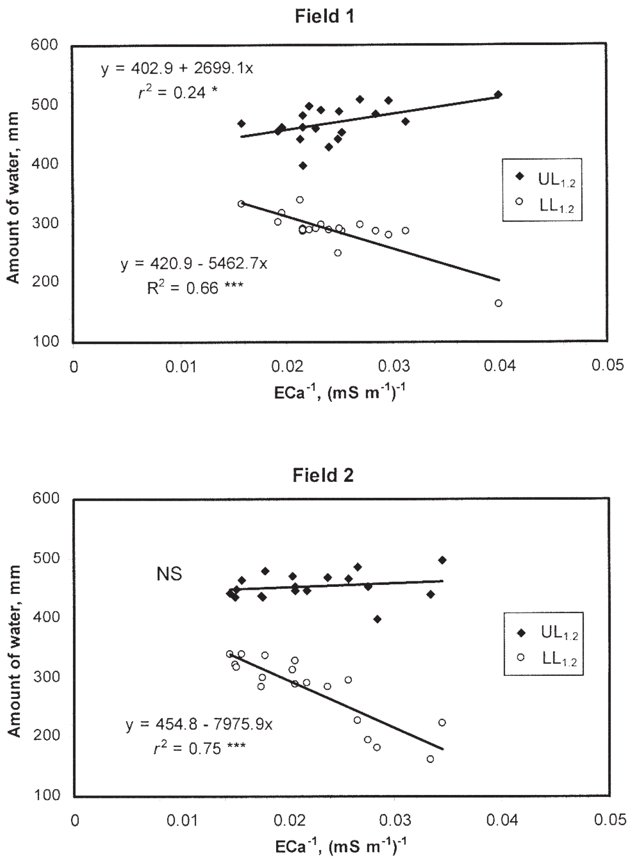

Fig. 1. Plots of the reciprocal of bulk soil apparent electrical conductivity (EC_a^{-1}) vs. the upper limit ($UL_{1.2}$) and lower limit ($LL_{1.2}$) of plant-available water for a 1.2-m soil profile, along with regression equations fit to the data and r^2 values. The EC_a^{-1} values were obtained from the kriged 5- by 5-m cell containing each sampling site. * Significant at the 0.05 level. * Significant at the 0.001 level.**

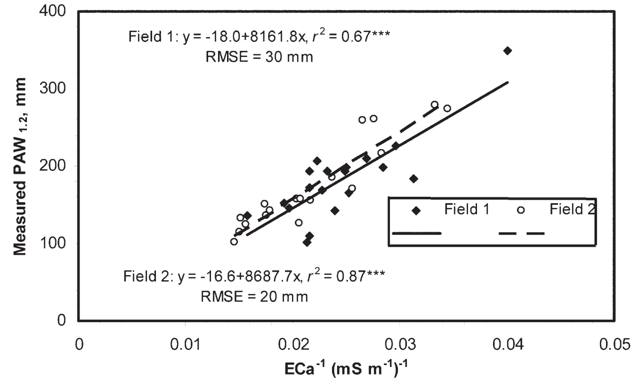

Fig. 2. Plot of the reciprocal of bulk soil apparent electrical conductivity (EC_a^{-1}) vs. measured plant-available water for a 1.2-m soil profile ($PAW_{1.2}$), along with regression equations fit to the data, r^2 values, and RMSEs. The $PAW_{1.2}$ was calculated as the difference between the profile upper limit ($UL_{1.2}$) and lower limit ($LL_{1.2}$). * Significant at the 0.05 level. * Significant at the 0.001 level.**

zon with a SIC texture (~0.24 m^3 m^{-3}; Chung, 1989). Thus, the thicker the topsoil, the more water can be released before the lower limit is reached. This result explained the significant relationship between EC_a^{-1} and $LL_{1.2}$ shown in Fig. 1.

There was a small significant increase in the $UL_{1.2}$ with increasing EC_a^{-1} for Field 1 (r^2 = 0.24), but no relationship was found for Field 2 (Fig. 1). Kachanoski et al. (1988) showed that the curvilinear relationship between EC_a and water content, both measured over a 0.5-m soil depth, leveled off at higher water content (>0.30 m^3 m^{-3}), and the slope of the fitted curve changed to negative (which would be positive with ECa^{-1}) when water content increased above 0.36 m^3 m^{-3}. This finding is supported by our result that EC_a^{-1} was insensitive to $UL_{1.2}$, which ranged from about 400 mm (~0.33 m^3 m^{-3}) to 510 mm (~0.43 m^3 m^{-3}) across the two fields.

Having examined how $UL_{1.2}$ and $LL_{1.2}$ were related to EC_a^{-1}, the relationship between the $PAW_{1.2}$ and EC_a^{-1} could be readily examined (Fig. 2). The regression models in Fig. 2 yielded RMSE values of 30 and 20 mm for Fields 1 and 2, respectively. With the two fields combined, the r^2 value was 0.76 and RMSE was 27 mm. These results indicated that soil EC_a^{-1} can be directly used to estimate field-variable profile PAW with certain confidence intervals once a relationship between EC_a and profile PAW to a chosen soil depth is calibrated.

Estimating Plant-Available Water Capacity with a Two-Layer Soil Profile

As presented in Table 1, there was an average RMSE of 12.0 cm for measured vs. EC_a–estimated topsoil thickness for the two fields. To give an insight into how these topsoil thickness errors contribute to estimating $PAW_{1.2}$ with the two-layer approach (Eq. [1]), we applied Eq. [1] to both the measured topsoil thickness and the EC_a–estimated topsoil thickness and obtained two $PAW_{1.2}$ estimates. Then RMSE values were calculated for the measured $PAW_{1.2}$ vs. each of the two $PAW_{1.2}$ estimates. Using the EC_a–estimated topsoil thickness, the RMSE values were 14 and 16 mm as shown in Table 4, which were 7.6 and 8.6% of the mean measured $PAW_{1.2}$ for Fields 1 and 2, respectively. Using the measured topsoil thickness, the respective error percentages were 7.0% (13 mm) and 6.4% (12 mm) of the mean measured $PAW_{1.2}$ (data not shown). The increase in error by using EC_a–estimated topsoil thickness (0.6 and 2.2% for Fields 1 and 2, respectively) was considered relatively minor, confirming our assumption in Eq. [1] that EC_a could be used to estimate topsoil thickness.

Figure 3 plots the regression relationship between the measured $PAW_{1.2}$

Table 4. Regression statistics for measured (upper limit [$UL_{1.2}$] – lower limit [$LL_{1.2}$]) vs. two-layer-estimated (Eq. [1]) plant-available water for a 1.2-m soil profile ($PAW_{1.2}$).

Statistic	Field 1 (*n* = 19)	Field 2 (*n* = 18)	Both fields (*n* = 37)
Measured mean $PAW_{1.2}$ (SD), mm	181 (53)	175 (58)	178 (55)
Estimated mean $PAW_{1.2}$† (SD), mm	185 (23)	187 (38)	186 (31)
Regression equation ($y = \alpha + \beta x$‡)	122 + 0.35*x*	81 + 0.61*x*	100 + 0.48*x*
Regression r^2	0.66	0.83	0.73
SE for β	0.060	0.068	0.050
RMSE§, mm	14	16	16

† Obtained by Eq. [1], where topsoil thickness is estimated by apparent bulk soil electrical conductivity.
‡ *x* is the measured $PAW_{1.2}$, *y* is two-layer-estimated $PAW_{1.2}$.
§ RMSE is the root mean square error of *y* against *x*.

and the two-layer-estimated $PAW_{1.2}$, along with a 1:1 line. The regression parameters and test statistics are given in Table 4. The estimated $PAW_{1.2}$ ranged from 146 to 249 mm for Field 1 and from 148 to 274 mm for Field 2, smaller ranges than those for the measured values (Table 4). The regression slopes significantly deviated from the 1:1 line. The estimation procedure tended to overestimate for lower $PAW_{1.2}$ values and underestimate for higher values. The data point of Field 1 indicated by an arrow in Fig. 3 had the largest residual error of 102 mm because there was a 25-cm underestimation in topsoil thickness at this sampling site located in a depositional area of the field. Thus, the estimated $PAW_{1.2}$ was greatly reduced. Deposited topsoil often has higher clay content than in situ topsoil, and this higher clay content detected by the EC sensor may be partially responsible for underestimating topsoil depth. The same reason also applied to the Field 2 data point indicated by an arrow, where there was a 24-cm underestimation in topsoil thickness. The overestimation at the lower end of the regression line, however, was not attributed to topsoil thickness errors because these errors did not correlate with the $PAW_{1.2}$ residual errors (graph not shown). Instead, the overestimation of $PAW_{1.2}$ occurred regardless of whether the residual errors for topsoil thickness were positive or negative. This trend was probably because NRCS PAW values smoothed the variation observed in individual horizons, especially for horizons that were potentially still less than field capacity at sampling. Our soil-sampling field notes confirmed that the greatest overestimation (data points circled at the lower end of the regression line in Fig. 3) occurred at the most eroded sites, where parts of the soil profile may not have reached field capacity.

Overall, the hypothetical two-layered soil body in conjunction with NRCS PAW values and EC_a–estimated topsoil thickness yielded reasonable estimates for the PAW_c over a 1.2-m profile. One key factor in the success of this simplified estimating procedure was that the SIC and SICL textures, dominant textures beneath the topsoil, had similar measured PAW values. Thus, the presence of SICL would not bias the estimation even though this texture was not included in the model (Eq. [1]). The procedure tended to overestimate PAW for soil profiles with higher clay content in one or more horizons (usually eroded areas). With reduced hydraulic conductivity near the soil surface, these profiles may take much more time to recharge to field capacity than what is normally assumed.

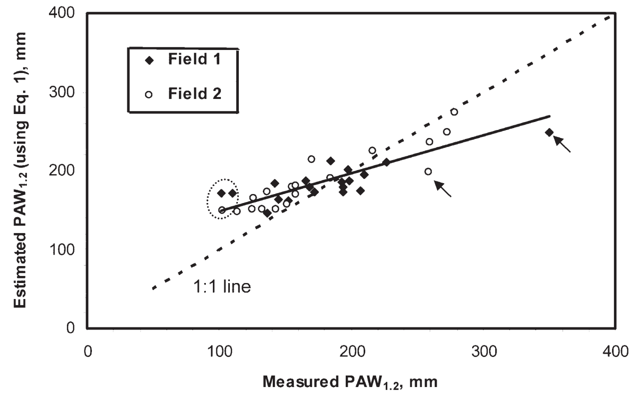

Fig. 3. Plot of measured vs. estimated plant-available water for a 1.2-m soil profile ($PAW_{1.2}$), along with the regression line for the combined data (solid) and a 1:1 reference line (dashed). The measured $PAW_{1.2}$ is the difference between the profile upper limit ($UL_{1.2}$) and lower limit ($LL_{1.2}$), and the estimated $PAW_{1.2}$ was calculated using Eq. [1]. The arrows and circle indicate the data points with the largest underestimating and overestimating residual errors, respectively.

CONCLUSIONS

Our ultimate objective was to quantitatively determine PAW_c at a field scale using soil EC_a information, which can be acquired relatively quickly and inexpensively at high spatial resolutions. Two approaches were examined in this study. The simple regression model showed a significant relationship between EC_a and profile PAW_c. The r^2 values were 0.67 and 0.87 and the RMSE values were 30 and 20 mm for Fields 1 and 2, respectively. These results were derived from the significant relationship of EC_a to the lower limit of the profile PAW_c, which is highly correlated with topsoil thickness.

The second approach further simplified PAW_c estimation by hypothesizing a two-layer soil profile comprised of a SIL topsoil layer and a SIC subsurface layer, whose boundary can be conveniently estimated by EC_a. The RMSE between the measured and two-layer-estimated $PAW_{1.2}$ was 16 mm for the two fields combined. The potential of this approach is that once a good calibration is established between topsoil thickness and EC_a, the map of EC_a can be translated into a PAW_c map. In this case, the chief error source for this method came from sample sites that did not reach field capacity. The NRCS PAW values are given as an average PAW fraction value for a given texture class and do not take into account variability caused by field factors such as recharge and drainage conditions, landscape position, and organic matter content. This, in turn, presents a potential problem in applying this approach for a claypan soil landscape, because soils at certain locations in a claypan field may practically never reach field capacity throughout the whole soil profile even in normal and above-normal precipitation years, due to slow recharge. Another drawback of this approach, due to its deterministic nature, involves the difficulty in assessing estimation errors.

In all, for similar claypan soil types, both approaches can be used as quick and cost-efficient methods to quantify within field profile PAW_c with reasonable accuracy. Being aware of their advantages and disadvantages, the resulting PAW_c maps can be useful for site-specific decision making with regard to soil and water management.

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