Soil physical property estimation from soil strength and apparent electrical conductivity sensor data

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Abstract

Proximal soil sensing is an attractive approach for quantifying soil properties, but many currently available sensors do not respond to a single soil property. For example, soil strength and apparent electrical conductivity (EC_a) sensor measurements are significantly affected by soil texture, bulk density (BD), and water content (WC). The objective of this study was to explore the potential for estimating soil texture, BD, and WC using combinations of sensor-based soil strength and EC_a data obtained from sites with varying soil physical properties. Data collected from three research sites in Missouri included on-the-go horizontal soil strength at five depths up to 0.5 m on a 0.1-m interval, cone index measurements at the same depths, EC_a measured by a Veris 3100, and depth-dependent, laboratory-determined soil properties. An EC_a model inversion approach was used to generate layer EC values corresponding to the depth increments of the other variables. Fits of models using EC to estimate WC were variable ($R^2 = 0.31\text{--}0.79$). Best fitting BD estimation models ($R^2 = 0.11\text{--}0.55$) generally included EC, but soil strength was included in fewer than half of the models. BD model fits were improved considerably by adding lab-measured WC to the model ($R^2 = 0.30\text{--}0.86$), suggesting the need for a WC sensor. Soil clay texture fraction models based on EC and WC fit well ($R^2 = 0.80\text{--}0.93$). This study showed the potential of combining data from multiple mobile proximal sensors to estimate important soil physical properties.

Keywords: precision agriculture; soil sensing; soil strength; cone index; soil electrical conductivity; sensor fusion

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1. Introduction

Precision agriculture, or site-specific management (SSM), where information about within-field variability is used to match inputs to crop needs, has been studied and increasingly adopted in many countries throughout the world. Soil properties provide some of the most important information sources for successful SSM. Soil physical and chemical properties govern the transport of plant-available nutrients and water (Barber, 1984). Soil provides physical support for roots, but soils that are too compacted may exhibit high mechanical resistance impairing seedling emergence or root growth, thereby affecting plant growth (Letey, 1985).

Accurate quantification of soil properties is needed in development and assessment of SSM strategies. Historically, most soil properties have been determined by laboratory testing of collected samples. Some of these include bulk density, water content, texture, porosity, pH, cation exchange capacity (CEC), nutrient status, and organic matter (Tan, 2005). Although laboratory tests may provide useful information for whole-field management, the number of measurements required for SSM makes laboratory tests time-, cost-, and labour-consuming. A sensor-based approach may be one way to alleviate the problems associated with soil sampling and laboratory testing.

Soil strength, an indicator of soil compaction, is affected by various soil physical (e.g., bulk density) and chemical (e.g., organic matter content) properties and provides surrogate information on these properties. Although compaction can be quantified by laboratory determination of related soil properties (e.g., dry bulk density), the common field procedure is to measure soil strength. The main tool used to quantify soil strength by depth and thereby provide information related to soil compaction is the cone penetrometer (Mulqueen, Stafford, Tanner, 1977). The index of soil strength measured by a cone penetrometer, cone index (CI, in MPa), is defined as the force per unit base area required to push the penetrometer through a specified small increment of soil (ASABE, 2011). Soil strength measured as CI is affected by soil properties such as soil water content, bulk density, and texture (Perumpral, 1987; Elbanna & Witney, 1987; Guerif, 1994). Operating depth also affects soil strength due to differences in soil conditions and soil failure mechanisms within the soil profile. Ayers and Perumpral (1982) developed an equation for CI as a function of soil water content and bulk density for five different soil types. They concluded that the specific water content for maximum soil strength depended on the soil type and increased as the percentage of clay increased. Sojka, Busscher, and Lehrs (2001) related CI to water content and bulk density of a silt loam soil. The relationship was poor when derived from full-profile data sets but improved when data were segregated by depth.

Because it is difficult to collect enough penetrometer data to adequately describe within-field compaction variations, several on-the-go, horizontally-operating soil strength sensors have been developed, as reviewed by Hemmat and Adamchuk (2008). In previous research, our team developed the Soil Strength Profile Sensor (SSPS), which measured soil strength to a 0.5-m depth on 0.1-m increments (Chung, Sudduth, Hummel, 2006). Cutting forces of five prismatic tips that extended in front of a main blade were measured by load cells as the tractor-mounted device moved through the soil. Analogous to the CI of a cone penetrometer, the variable quantified by the SSPS was force divided by the base area of the sensing tip, termed prismatic soil strength index (PSSI, MPa). Field research (Chung, Sudduth, Plouffe, Kitchen, 2008) showed that PSSI was affected by WC, BD, and texture. Best results were obtained when depth of operation was included in the model relating soil strength to soil properties ($R^2 = 0.61\text{--}0.66$), or when analysis was conducted within a single depth. If the analysis was conducted across all depths, results were not as good, with R^2 of 0.46 and 0.51 for the two field sites. Andrade-Sanchez, Upadhyaya, and Jenkins (2007) developed a soil cutting-force profile sensor that could measure down to a 0.6 m depth in increments of 0.075 m. In field tests in three different soil types, soil cutting force divided by BD was well-estimated as a function of WC and sensing depth. ($R^2 = 0.85$).

Another sensor-based measurement that can provide an indirect indicator of important soil physical properties is EC_a of the soil profile (Sudduth, Kitchen, Myers, Drummond, 2010). Soil salinity, clay content, cation exchange capacity (CEC), clay mineralogy, soil pore size and distribution, and soil water content are some of the factors affecting EC_a (McNeill, 1992). In non-saline soils, EC_a variation is primarily a function of soil texture, water content, bulk density, and CEC (Corwin & Lesch, 2005). One EC_a sensor widely used in North America is the Veris 3100/3150 (Veris Technologies, Salina, KS) that uses six rolling coulters for electrodes and provides two simultaneous EC_a measurements (Lund, Christy, Drummond, 1999). For the shallower of the two measurements, 90% of the response comes from soil depths of 0 to 0.3 m, while for the deeper measurement, 90% of the response comes from soil depths of 0 to 1.0 m (Sudduth et al., 2010). Several approaches have been developed to calculate EC values of discrete soil layers of interest from the integrated EC_a measurement, with varying degrees of success. Recently, a spatially-constrained one-dimensional inversion model has shown promise in estimating the true vertical distribution of soil conductivity (Monteiro Santos, Triantafyllis, Bruzgulis, 2011; Triantafyllis & Monteiro Santos, 2013).

As described above, soil sensor measurements, including soil strength and EC_a , respond to a number of different soil properties. Therefore, it is often difficult to quantify individual soil properties with data from a single

sensor. For improved results, a fusion approach (Adamchuk, Viscarra Rossel, Sudduth, Schulze Lammers, 2011) could be used to combine multiple sensors. For example, multifunction penetrometers have been developed to measure additional soil variables important for interpreting CI, including soil water content (e.g., Hummel, Ahmad, Newman, Sudduth, Drummond, 2004; Sun, Ma, Schulze Lammers, Schmittmann, Rose, 2006) and apparent electrical conductivity (EC_a) as a surrogate indicator for soil texture (e.g., Sudduth, Hummel, Drummond, 2004). Sun, Schulze Lammers, Daokun, Jianhui, Qingmeng (2008) developed a multi-sensor penetrometer for measuring soil WC, mechanical strength and electrical conductivity. Sun, Cheng, Lin, Schellberg, Schulze Lammers (2013) used a similar device to investigate the relationship of the measured soil sensor data (water content and CI by penetrometer and EC_a determined by Geonics EM38) to crop yield. They reported that yield was significantly related to all three sensor readings. Multifunction penetrometers have been commercialised, including the Veris P3000 and P4000 (Veris Technologies, Salina, KS, USA), and their uses in soil investigations have been described (Sudduth, Myers, Kitchen, Drummond, 2013; Wetterlind, Piikki, Stenberg, Söderström, 2015).

Other sensor fusion projects incorporated horizontal soil strength sensors. Mouazen and Ramon (2009) and Quraishi and Mouazen (2013) tested an on-line sensor for the prediction of BD. The sensor consisted of a load cell to measure draft, a visible and near infrared (vis-NIR) reflectance sensor to measure WC, and an operating depth sensor. In field tests over a range of textures ranging from sandy loam to loam, BD was well-estimated ($R^2 = 0.86$) by a previously-developed model (Mouazen & Ramon, 2002) that included draft force and WC, after application of an additional correction factor based on WC (Mouazen & Ramon, 2009). The same sensor and model were also applied in fields with soil types ranging from sand to clay (Quraishi & Mouazen, 2013). A field-specific correction factor based on texture and WC was used, and accuracies varied ($R^2 = 0.51\text{--}0.96$) among the 14 test fields.

These projects showed the potential for combining data from multiple sensors to determine the variation in soil physical properties (e.g., BD, WC, and texture) occurring within a field. The high-resolution data available from sensors may also aid in the spatial interpretation of soil property data and subsequent planning of field management. However, past research reports on soil sensor fusion are few, and more information is needed for a variety of sensor types and soil conditions. Therefore, the objective of this study was to estimate soil WC, BD, and clay texture fraction using soil EC_a data measured by the Veris 3100, and soil strength data measured by a cone penetrometer and the SSPS.

2. Material and methods

2.1. Field Sites

Data were collected at three field sites selected for a high degree of spatial soil variability. Two of these (site 1, 13.5 ha and site 3, 13 ha) were located within 3 km of each other near Centralia (39.230° N, 92.117° W), in central Missouri, USA. Site 1 (S1) had been in a minimum-tillage corn-soybean rotation since 1990, while site 3 (S3) had been in a no-tillage corn-soybean rotation since 1996. Both S1 and S3 were on claypan soils, which are distinguished by a greater than 50% increase in clay from topsoil and subsoil horizons. Measured topsoil depth above the claypan (depth to the first Bt horizon) at S1 and S3 ranged from less than 0.1 m to greater than 1 m (Sudduth, Kitchen, Bollero, Bullock, Wiebold, 2003). On claypan soils, variation in the topsoil depth above the restrictive claypan layer leads to variation in hydrology, profile soil properties, and crop productivity. Surface textures at S1 and S3 ranged from silt loam to silty clay loam. The subsoil claypan horizon(s) were silty clay loam, silty clay or clay, and contained as much as 50 to 60% clay.

Site 2 (4.5 ha) was located near Hartsburg (38.753° N, 92.384° W), also in central Missouri. Site 2 (S2) was managed in a minimum-tillage corn-soybean rotation. The alluvial soils at S2, located in the Missouri River flood plain, had high spatial variability due to periodic flooding of the nearby Missouri River. Surface textures of the soils found at S2 ranged from clay to sand, while subsoil textures were less variable, ranging from silt loam to sand. At S2 the surface horizons generally had more clay than subsurface horizons, while the opposite was true at S1 and S3. Topsoil depth of the soils found at S2 ranged from 0.2 to 0.4 m, but soil layering was much less pronounced at S2 than in the claypan soils at S1 and S3.

2.2. Data Collection

Penetrometer and on-the-go SSPS data were collected at S1 and S2 in October 2003 as part of a research project to evaluate the performance of the SSPS (Chung et al., 2008). Soil water conditions were relatively dry after corn harvest and prior to fall rains. The SSPS transects were slightly angled (about 5°) with respect to the crop row to minimise effects of possible systematic patterns of soil strength due to past crop and field management practices. The nominal operating speed of the tractor-mounted SSPS (Fig. 1) was 1.5 m s⁻¹. Data collection transects were aligned with the longer dimension of the site on a 30-m spacing for S1, and a 20-m spacing for S2. On a 30-m interval along each SSPS transect, triplicate cone index (CI) profiles were obtained

within a 1-m² area with a hydraulically-powered, recording ASABE-standard (ASABE, 2011) small-cone (30° cone angle, 12.8 mm base diameter) penetrometer. A non-standard penetration rate of 40 mm s⁻¹ was used to speed data collection and because our previous research (Sudduth et al., 2004) showed no significant difference between this rate and the standard 30 mm s⁻¹. For 52 of the CI collection locations at S1 and 25 of the locations at S2 (Fig. 2), 42 mm diameter soil cores were obtained and segmented into five 0.1-m-long depth intervals (i.e., 0.05 to 0.15 m, 0.15 to 0.25 m, 0.25 to 0.35 m, 0.35 to 0.45 m, 0.45 to 0.55 m) for gravimetric determination of dry BD and soil WC. These sampling locations were chosen to balance spatial coverage over the test area with the number of laboratory samples that could be practically analysed. Although some recommendations for core-based BD determination specify larger diameter cores for improved accuracy, others (Allen, Dickey, Wright, Stone, Hunsaker, 1993) reported BD errors of less than 4% in a study using coring equipment and procedures similar to those used here. Although higher accuracy reference methods are always desirable, the 42 mm diameter cores were near the maximum size that was feasible in these soils with the available coring equipment. In future studies, use of larger diameter cores should be considered, perhaps along with an assessment of BD measurement accuracy similar to that described by Allen et al. (1993).

Penetrometer and SSPS data were collected at S3 in October 2005 as part of a project to compare SSPS performance with another on-the-go soil strength sensor (Adamchuk, Ingram, Sudduth, Chung, 2008). Soil water conditions were similar to those during data collection at S1 and S2. Penetrometer and SSPS measurements were obtained in 80 different field locations (a 50 x 50 m grid and 15 directed points established in a previous project, Fig. 2). At each location, CI profiles were obtained using five recording ASABE-standard large-cone (30° cone angle, 20.3 mm base diameter) penetrometers (ASABE, 2011) mounted to a single hydraulically-driven frame. Duplicate measurements with the 5-probe unit provided a total of 10 profiles at each location within a 1 m² area. At each CI collection location, a single soil core was obtained as described above for laboratory determination of dry BD and soil WC. Soil texture (sand, silt, clay) was available by horizon for the 15 directed points at S3 from another study (Sudduth et al., 2003). A depth-weighted averaging procedure translated horizon measurements of texture to the uniform depth increments used in this study. For all field data collection, positional information was obtained using a DGPS receiver with an accuracy of 1 m or better.

Coincident with other data collection, soil EC_a data for S1 and S2 were obtained using a Veris 3100 following data collection procedures described by Sudduth et al. (2003). The Veris 3100 collects two simultaneous EC_a datasets, a shallow reading (EC_{a-vsh}) with 90% of the response from the soil profile to a 0.3 m depth and a deep

reading (EC_{a-Vdp}) with 90% of the response from the soil profile to a 1.0 m depth. Soil EC_a in milliSiemens per meter ($mS\ m^{-1}$) was recorded on a 1-s interval, corresponding to a 4-m to 6-m data spacing, along transects spaced 20 m apart. Veris 3100 data for S3 were obtained using the same procedures but with a 10-m transect spacing in October 2005 coincident in time with other data collection.

2.3. Data Processing and Analysis

Multiple CI measurements were obtained around each soil sampling location within a 1 m x 1m area. Because individual measurements were not georeferenced, we averaged all CI profiles obtained at a location (generally 3 for S1 and S2, and 10 for S3) to a single profile. Next, the CI data were averaged to the same 0.1-m-long depth increments used for these other parameters, centred on the nominal operating depths of the five SSPS tips (i.e., 0.1, 0.2, 0.3, 0.4, and 0.5 m).

Commercial software (invVERIS version 1.1, EmTOMO, Lisbon, Portugal) was used to calculate layer conductivities for the same 0.1-m depth increments. The invVERIS software uses the spatially-constrained one-dimensional inversion modelling approach described by Triantafilis & Monteiro Santos (2013), adapted for use with the technology of the Veris EC_a sensors. Veris 3100 data for each field were input to the invVERIS software and inversion modelling procedures suggested by the developers (EmTOMO, 2015) were followed. The inversion models obtained were of good quality, with lack-of-fit RMSE of $0.6\ mS\ m^{-1}$ or less for each field. Hereafter, the layer output data are by convention referred to as EC rather than EC_a because these are calculated “true” conductivities for the layers rather than the integrated “apparent” conductivities measured by the sensor.

As the CI and soil core data were collected within a relatively small area spanning approximately 1m in size, the spatial support for these data, after preprocessing of CI data as described above, was approximated as 1 m x 1 m x 0.1 m depth. The lateral support of the layer EC data would be expected to vary somewhat as a function of depth and the lateral support of the PSSI data would vary somewhat based on sensor operating speed. However, both were of similar magnitude to the support of the CI data and therefore all data were assumed to be on the same support (1 m x 1 m x 0.1 m depth). Data from each of the SSPS tips and each EC layer were block kriged, using a 1-m block size, to locations coincident with the penetrometer and soil core measurements. Point-based semivariograms for block kriging were computed using VESPER (v. 1.6,

University of Sydney, Sydney, Australia). As the semivariograms showed little in the way of isotropy, best-fitting anisotropic models were selected in each case. While several model types were investigated (exponential, spherical, linear-sill, Gaussian, etc.), the EC datasets were generally better fit by Gaussian models, while the SSPS models were better fit by exponential models. Table 1 provides the statistics of the semivariogram models used for kriging each of these data layers. While the semivariogram shapes were slightly different between the EC and SSPS models, the model fits were quite good in all cases, with well-defined nuggets and sills, and relatively small RMSE values. It is recognised that some amount of error was likely introduced in the block kriging process because the semivariograms were calculated from data with a non-point spatial support.

Spatial regression analysis was applied to predict soil WC, BD and clay soil texture fraction at each specific depth at each site as a function of sensor variables (CI, SSPS, EC) at that depth using GeoDa software (Anselin, Syabri, Kho, 2006). Weight matrix files were created for each dataset using Euclidean distance metrics with a minimal threshold distance such that all nodes had at least one neighbour. In each case, a series of standard ordinary least squares (OLS) regressions were performed first, to explore issues with multicollinearity, normality of errors, heteroscedasticity, and spatial dependence. A significance level of 0.05 was required for a variable to be included in all regression models. Where test statistics indicated that spatial dependence was significant, the diagnostic methods provided by Anselin and Rey (2014) were used to determine whether spatial lag models or spatial error models were appropriate, and those spatial regressions were performed and evaluated to determine the most appropriate final model.

Equation (1) is the OLS model, with $\mathbf{y}$ representing an $n \times 1$ vector of dependent observations, $\mathbf{X}$ representing an $n \times k$ matrix of n observations by k independent predictor variables, β representing the $k \times 1$ vector of regression coefficients and $\mathbf{u}$ representing the $n \times 1$ vector of errors.

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{u} \quad (1)$$

The spatial lag model (Ord, 1975; Anselin, 1988) in Eq. (2) adds to the OLS model a term $\rho\mathbf{W}\mathbf{y}$, which is a combination of a spatial autoregressive parameter ρ and the spatial lag term $\mathbf{W}\mathbf{y}$, based upon the defined neighbourhood weight matrix $\mathbf{W}$.

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\beta + \mathbf{u} \quad (2)$$

GeoDa was used to perform spatial lag regressions, where indicated, using the maximum likelihood method. The spatial error model in Eq. (3) differs from the original OLS equation in that the error vector $\mathbf{u}$ follows a

spatial autoregressive process, with λ as the spatial autoregressive parameter and ϵ as the vector of idiosyncratic errors.

$$\mathbf{u} = \lambda \mathbf{W} \mathbf{u} + \epsilon \quad (3)$$

Anselin and Rey (2014) provide more detail on the derivation of this model and the methods available to perform the regression. In the few cases where a spatial error regression was indicated, a maximum likelihood method was used to perform the regression.

Table 1 – Descriptive statistics of semivariogram models used to block kriging EC and SSPS data. Models used for EC were Gaussian, while those for PSSl were exponential.

Site	Sensor	Depth (m)	RMSE ^a	Range (m)	Nugget	Sill
1	EC	0.1	0.17	34.21	1.50	27.01
		0.2	0.46	34.87	1.22	29.75
		0.3	0.95	36.01	1.20	36.85
		0.4	2.27	37.85	1.25	53.05
		0.5	7.70	40.15	1.89	117.89
	PSSl	0.1	0.01	35.02	< 0.00	0.12
		0.2	0.01	73.79	0.01	0.18
		0.3	0.01	36.22	0.01	0.17
		0.4	0.01	3.43	0.01	0.07
		0.5	0.09	8.19	0.01	0.51
2	EC	0.1	3.13	73.74	11.56	91.91
		0.2	2.83	67.65	5.77	103.04
		0.3	4.24	59.70	3.31	126.41
		0.4	5.75	55.54	4.19	163.69
		0.5	9.12	49.80	6.86	221.66
	PSSl	0.1	< 0.00	6.87	0.01	0.06
		0.2	< 0.00	10.95	0.01	0.07
		0.3	0.01	22.36	0.03	0.23
		0.4	0.01	18.46	0.05	0.27
		0.5	0.03	36.82	0.01	0.46
3	EC	0.1	0.23	40.18	0.38	5.15
		0.2	0.68	41.06	0.96	14.85
		0.3	1.41	41.47	1.89	30.39
		0.4	3.23	41.94	3.60	68.73
		0.5	8.80	41.44	8.45	178.55
	PSSl	0.1	< 0.00	15.75	< 0.00	0.06
		0.2	< 0.00	37.35	0.01	0.08
		0.3	< 0.00	48.07	0.02	0.07
		0.4	0.02	12.56	0.01	0.15
		0.5	< 0.00	7.26	0.01	0.12

^a RMSE (root mean squared error) is in units of mS m⁻¹ for EC and MPa for PSSl.

3. Results and Discussion

3.1 Descriptive Statistics

Descriptive statistics of the sensor and soil data are summarised in Table 2. At S1 (silty topsoil and clay subsoil, minimum-tillage to 0.15–0.2-m depth), the maximum mean CI occurred around 0.2 m and decreased slightly afterward. At S3 with similar soils but under no-tillage management, the maximum mean CI was observed at depths closer to the surface, around 0.1 m. These differences were probably due to tillage, with a “plough pan” being created at S1 immediately below the usual tillage depth. Jung, Kitchen, Sudduth, Lee, and Chung (2010) reported similar results on plots adjacent to S1, with depth to maximum CI significantly less for a no-tillage corn-soybean rotation than for a minimum-tillage corn-soybean rotation. At S2, CI increased continuously with depth to around 0.3 m and then remained fairly constant.

The difference between PSSI and CI was higher near the soil surface, while trends were more similar deeper in the soil profile. Similarly, Chung et al. (2006) reported that there was no significant linear relationship between PSSI and CI at 0.1 m, but they were strongly related ($r^2 = 0.60$) at 0.3 m. Hemmat, Khorsandy, Masoumi, and Adamchuk (2009) attributed these differences to the different soil failure mechanisms created by vertical and horizontal penetrometers near the soil surface, and stated that measurements from these two types of sensors were not correlated at depths less than 0.3 m. Values of EC varied less with depth at S2 than at S1 and S3. Soil texture, the primary driver of EC variation in these soils was less variable with depth at S2. On the other hand, EC variation among sampling points was higher at S2, reflecting the greater texture differences between the soil types present at that site.

Bulk density and WC appeared to be inversely related (Table 2) for S1 and S2 on claypan soils. Trends in BD and WC as a function of depth were similar for these sites. Bulk density was lower near the surface (0.1 to 0.2 m depths), and increased deeper in the profile (0.3 to 0.5 m). Water content was higher near the surface (0.1 to 0.3 m) and remained fairly constant or decreased slightly deeper in the profile. At depths of 0.3 to 0.4 m, the mean WC was highest but the mean BD was lowest (Table 2). At alluvial site S2 BD remained nearly constant over the profile, while WC increased with depth. Clay content data were only available at claypan site S3. Here the pattern of clay with depth followed the standard pattern for a claypan soil (Jung, Kitchen, Sudduth, Anderson, 2006). Clay content was lowest in the topsoil and reached a maximum, much higher level at the transition between topsoil and the claypan subsoil layer.

Table 2 – Descriptive statistics for PSSI, CI, EC, bulk density (BD), water content (WC), and clay content data.

Depth	Sensor data	Soil data
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(m)	PSSI (MPa)		CI (MPa)		EC (mS m ⁻¹)		BD (t m ⁻³)		WC (%)		Clay content (%)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
<u>Site 1 (S1)</u>												
0.1	0.73	0.30	1.15	0.36	25.30	6.60	1.47	0.06	24.65	1.10		
0.2	1.05	0.31	1.67	0.50	28.84	7.53	1.41	0.10	28.12	4.78		
0.3	1.44	0.20	1.49	0.44	32.39	8.92	1.30	0.08	32.93	5.09		
0.4	1.72	0.14	1.31	0.22	37.34	11.24	1.34	0.08	32.37	4.07		
0.5	1.42	0.11	1.30	0.17	47.57	17.23	1.39	0.10	30.84	4.31		
All	1.27	0.41	1.39	0.40	34.29	13.44	1.38	0.11	29.78	5.14		
<u>Site 2 (S2)</u>												
0.1	0.84	0.23	0.98	0.43	22.12	14.13	1.44	0.11	20.23	4.40		
0.2	0.96	0.20	1.22	0.52	24.77	16.68	1.44	0.08	20.77	4.90		
0.3	1.62	0.46	1.64	0.85	26.89	19.26	1.43	0.07	23.73	4.42		
0.4	1.54	0.41	1.79	0.65	29.68	21.12	1.48	0.07	23.82	5.96		
0.5	1.33	0.52	1.79	0.64	34.68	22.82	1.47	0.09	23.69	5.99		
All	1.26	0.49	1.48	0.71	27.63	19.54	1.45	0.09	22.45	5.42		
<u>Site 3 (S3)</u>												
0.1	0.74	0.24	1.83	0.35	8.77	3.26	1.51	0.10	22.82	4.53	25.45	7.26
0.2	1.30	0.27	1.81	0.58	13.83	5.34	1.49	0.12	27.03	6.36	30.80	13.01
0.3	1.30	0.19	1.64	0.68	18.90	7.52	1.41	0.14	30.35	6.46	36.92	13.60
0.4	1.71	0.47	1.70	0.75	28.25	11.16	1.42	0.13	30.76	5.83	38.55	14.25
0.5	1.56	0.25	1.92	0.84	48.02	17.80	1.47	0.11	28.37	4.95	38.34	14.37
All	1.32	0.45	1.78	0.67	23.55	17.28	1.46	0.13	27.87	6.36	34.01	13.77

3.2. Estimating Water Content from Sensor Data

Linear regressions estimating WC as a function of layer EC are summarised in Table 3. In about half of the cases, a spatial model was prescribed in the GeoDa software; in the other cases a standard OLS model was appropriate. In particular, all models at S1, with spatial ranges of EC data ≤ 40 m (Table 1) and a mean distance between soil sampling points of 49 m, were specified as OLS.

Best fits to the data were obtained at S2, particularly in the top three layers. Results were also reasonably good in the top three layers at S1 and S3, with the exception of the 0.1 m layer at S1, where there was little variation in WC (Table 2), and no significant model was possible. For the lower two layers at claypan sites S1 and S3, significant models were not possible in several cases perhaps because of the textural discontinuity presented by the claypan horizon. At alluvial site S2 the coefficient of determination was higher than for the other sites, with the best fits occurring in the upper layers.

Table 3 – Fit statistics and model type for estimation of WC as a function of EC for each depth at each site.

Depth (m)	S1			S2			S3		
	R ²	RMSE (%)	Model ^a	R ²	RMSE (%)	Model	R ²	RMSE (%)	Model
0.1	— ^b			0.78	2.05	S _{Lag}	0.42	3.44	S _{Lag}
0.2	0.45	3.62	OLS	0.79	2.22	S _{Lag}	0.69	3.54	S _{Lag}
0.3	0.31	4.30	OLS	0.49	2.37	OLS	0.47	4.68	S _{Err}
0.4	—			0.53	4.28	OLS	—		
0.5	0.38	3.47	OLS	0.45	4.65	OLS	—		

^a Most appropriate model specified by GeoDa software: ordinary least squares (OLS), spatial lag model (S_{Lag}), or spatial error model (S_{Err}).

^b Dash indicates that no significant model was possible at $\alpha = 0.05$.

Overall, it was not possible to obtain consistently good results for estimation of WC using EC. Previous research (e.g., Brevik, Fenton, Lazari, 2006; Sudduth et al., 2005) also found considerable site-to-site variability in the relationship between WC and EC_a. Poor estimation of WC would likely be an impediment to estimating BD from soil strength, as past studies have indicated that WC is an important factor in this relationship (e.g., Ayers & Perumpral, 1982; Sojka et al., 2001). Although several soil WC sensors have been reported (Hummel et al., 2004; Sun et al., 2006) one was not available for this study. Therefore, for estimation of BD and clay as described below, lab-measured WC was used as a candidate variable to investigate the potential improvement that might be seen if a WC sensor had been available.

3.3. Estimating Bulk Density from Sensor Data

Fig. 3 shows the relationship of BD to WC for all depths at each of the three sites. The relationship of BD to WC was much stronger ($r = -0.69$ to -0.86) for claypan soil sites S1 and S3 than for alluvial site S2 ($r = -0.38$). Fig. 4 shows the relationship of BD to layer EC for all depths at each site. The relationship of BD to EC was not significant ($\alpha = 0.05$) at S1, weak but significant at S3 ($r = -0.11$), and somewhat stronger at S2 ($r = -0.23$). In general, BD was inversely related to both EC, which is positively related to clay content (Sudduth et al., 2003), and to WC. This negative relationship between BD and both clay and WC is consistent with previous research. For example, Mouazen and Ramon (2009) and Quraishi and Mouazen (2013) found BD was inversely related to both WC and clay content in field tests over a wide range of textures. Andrade-Sanchez et al. (2007) found a negative relationship between WC and the ratio of soil cutting force divided by BD.

Linear regression models were developed to relate BD to sensor-based soil properties (layer EC and soil strength by CI or PSSI). Additional analyses included WC as an independent variable, using WC data from laboratory measurements. Regressions relating BD to EC and CI are summarised in Table 4, and regressions relating BD to EC and PSSI are summarised in Table 5. For both CI and PSSI, OLS models were appropriate in most instances. The GeoDa diagnostic procedures specified by Anselin and Rey (2014) only indicated the need for a spatial model in fewer than 15% of cases.

Table 4 – Regression statistics, significant variables, and model type for estimation of BD as a function of CI and EC, both with and without WC, for each depth at each site.

Depth (m)	S1						S2						S3					
	Regression without WC			Regression with WC			Regression without WC			Regression with WC			Regression without WC			Regression with WC		
	R^2 (RMSE) ^a	V ^b	M ^c	R^2 (RMSE)	V	M	R^2 (RMSE)	V	M	R^2 (RMSE)	V	M	R^2 (RMSE)	V	M	R^2 (RMSE)	V	M
0.1	— ^d			0.42 (0.05)	WC	S _{Lag}	—			—			—			0.30 (0.08)	WC EC	OLS
0.2	0.33 (0.09)	CI EC	OLS	0.86 (0.04)	WC EC	OLS	—			—			0.30 (0.10)	CI	OLS	0.65 (0.07)	WC EC	OLS
0.3	0.27 (0.07)	CI	OLS	0.80 (0.04)	WC CI EC	OLS	—			0.22 (0.06)	WC	OLS	0.24 (0.12)	CI	S _{Err}	0.65 (0.09)	WC EC	OLS
0.4	0.15 (0.08)	EC	OLS	0.72 (0.04)	WC EC	OLS	0.21 (0.07)	EC	OLS	0.58 (0.05)	WC	OLS	0.38 (0.10)	CI EC	S _{Lag}	0.61 (0.08)	WC EC	OLS
0.5	0.55 (0.07)	EC	OLS	0.77 (0.05)	WC EC	OLS	0.32 (0.08)	EC	OLS	0.70 (0.05)	WC	OLS	0.32 (0.09)	CI EC	OLS	0.54 (0.07)	WC EC	OLS

^a Values in parentheses are root mean squared error (t m^{-3}).

^b V = variables included in the regression. Candidate variables were CI, EC, and WC.

^c M = Most appropriate model specified by GeoDa software: ordinary least squares (OLS), spatial lag model (S_{Lag}), or spatial error model (S_{Err}).

^d Dash indicates that no significant model was possible at $\alpha = 0.05$.

Table 5 – Regression statistics, significant variables, and model type for estimation of BD as a function of PSSI and EC, both with and without WC, for each depth at each site.

Depth (m)	S1						S2						S3					
	Regression without WC			Regression with WC			Regression without WC			Regression with WC			Regression without WC			Regression with WC		
	R ² (RMSE) ^a	V ^b	M ^c	R ² (RMSE)	V	M	R ² (RMSE)	V	M	R ² (RMSE)	V	M	R ² (RMSE)	V	M	R ² (RMSE)	V	M
0.1	— ^d			0.42 (0.05)	WC	S _{Lag}	—			—			0.09 (0.09)	PSSI	OLS	0.30 (0.08)	WC	OLS
					EC												EC	
0.2	0.24 (0.09)	EC	OLS	0.86 (0.04)	WC	OLS	—			—			0.29 (0.11)	PSSI	OLS	0.65 (0.07)	WC	OLS
					EC									EC			EC	
0.3	0.11 (0.09)	EC	OLS	0.77 (0.04)	WC	OLS	—			0.39 (0.06)	WC	OLS	0.16 (0.13)	PSSI	S _{Lag}	0.65 (0.09)	WC	OLS
					EC						PSSI						EC	
0.4	0.15 (0.08)	EC	OLS	0.72 (0.04)	WC	OLS	0.21 (0.07)	EC	OLS	0.58 (0.05)	WC	OLS	0.27 (0.11)	EC	S _{Lag}	0.61 (0.08)	WC	OLS
					EC												EC	
0.5	0.55 (0.07)	EC	OLS	0.79 (0.05)	WC	OLS	0.32 (0.08)	EC	OLS	0.76 (0.05)	WC	OLS	0.37 (0.09)	PSSI	OLS	0.54 (0.07)	WC	OLS
					PSSI						PSSI			EC			EC	

^a Values in parentheses are root mean squared error (t m^{-3}).

^b V = variables included in the regression. Candidate variables were PSSI, EC, and WC.

^c M = Most appropriate model specified by GeoDa software: ordinary least squares (OLS), spatial lag model (S_{Lag}), or spatial error model (S_{Err}).

^d Dash indicates that no significant model was possible at $\alpha = 0.05$.

For models without WC, variables entering the model and the goodness of fit varied among sites, depths, and which soil strength variable was used. In most cases results with CI and PSSI were similar, but when there was a difference, CI-based models were generally better. When considering CI-based regressions without WC as a candidate variable, 70% of final regressions included EC, while 30% included CI alone and another 30% included CI along with EC. Similar trends were seen for PSSI-based regressions without WC, where 82% of regressions included EC, while 18% included PSSI alone and another 18% included PSSI along with EC. This suggests that for S1 and S2, BD was primarily affected by soil factors such as variations in clay content that would be reflected in EC rather than the presence or absence of anthropogenic compaction that would be reflected in CI or PSSI. Soil strength variables entered $\geq 80\%$ of the regressions for S3, but rarely at S1 and not at all at S2. The greater presence of PSSI and CI in S3 regressions compared to those at S1, which had similar soil conditions, may have been due to differences in data collection, including an increased PSSI and soil sampling density at S3, and more CI data (10 probes instead of 3) for each location at S3. Although these differences were unavoidable in this case because data from prior studies were used, a standardised procedure should be used in any future investigations.

Models estimating BD as a function of EC and soil strength, either CI or PSSI, were considerably improved by

the addition of WC as a candidate independent variable. Water content was significant in all cases, and model R^2 increased by a minimum of 0.2 (Table 4; Table 5). Based on regression fits, there was no clear trend of one soil strength measurement being better than the other. For S2, 33% of models also included soil strength, while none included EC. These findings are consistent with past research (e.g., Perumpral, 1987; Elbanna & Witney, 1987; Guerif, 1994) which found BD to be related to both WC and soil strength. In contrast, only 10% of S1 and S3 models included soil strength while 90% included EC, suggesting that the variables important for BD estimation may vary with soil type and that clay content or other variables related to EC may be particularly important for BD estimation in high-clay soils.

Previous research also documented the importance of auxiliary variables for improving the BD vs. soil strength relationship. For example, Sojka et al. (2001) found that CI was well-estimated ($R^2 = 0.60$) as a function of WC and BD in the 0.15–0.3 m depth interval, and that WC had a stronger effect than did BD. Another study (Hummel et al., 2004) found that differences in CI between WC levels were strongly related ($R^2 = 0.87$) to WC difference, BD, and clay content. Mouazen, Dumont, Maertens, and Ramon (2003) estimated BD as a function of soil strength measured horizontally, sensor operating depth, and WC. Field maps showed no resemblance between patterns of soil strength and measured BD. However, there was a strong agreement between measured and calculated BD, verifying the importance of WC and operating depth. Quraishi and Mouazen (2013) found that BD could be estimated over a wide range of soil textures through a field-specific correction factor based on texture and WC. Adamchuk, Hempleman, and Jahraus (2009) found that BD was more strongly related to WC ($R^2 = 0.50$) than to soil cutting force ($R^2 = 0.21$). The combination of soil cutting force and WC predicted soil BD with $R^2 = 0.71$. Using another soil sensor, Adamchuk, Hemmat, and Mouazen (2008) found that the R^2 between BD and cutting force was 0.38, while the R^2 between BD and WC was 0.72. Andrade-Sanchez et al. (2007) presented an equation for estimating the ratio of cutting force to BD that depended on both WC and operating depth. Overall, the results of this study, coupled with past research, support the need for combining the outputs of multiple sensors, including at least soil strength, WC, and an estimate of soil clay fraction, for best estimates of BD.

3.4. Estimating Clay Soil Texture Fraction from Sensor Data

Data for estimating clay content from sensor data were only available for 15 locations at S3. However, based on previous research (Sudduth et al., 2003) clay content was generally similar in magnitude between S1 and S3. Variation with depth was slightly greater for S1, where surface clay content was lower, and subsurface clay

content was higher (Fig. 5).

Linear regression models for clay content estimation models were all obtained by OLS as the GeoDa software detected no need for spatial regression. When using only EC as an independent variable, the model provided very good fits in the surface layer, but goodness of the fit decreased with depth (Table 6). Adding WC as a candidate variable allowed the goodness of fit to be maintained throughout the profile. This is consistent with previous research at S1 and S3 where Veris 3100 EC_a was strongly related to both clay and WC variations (Sudduth et al., 2003). Thus, in addition to BD, clay texture fraction is another important soil property where estimation may be improved by combining data from multiple sensors.

Table 6 – Regression statistics for estimation of clay content as a function of EC, both with and without WC, for 15 locations at S3.

Depth (m)	Regression without WC		Regression with WC		
	R ²	RMSE (%)	R ²	RMSE (%)	Variables ^a
0.1	0.84	3.12	0.84	3.12	EC
0.2	0.48	10.58	0.88	5.25	EC, WC
0.3	0.48	10.58	0.88	5.25	EC, WC
0.4	0.23	13.47	0.80	7.16	EC, WC
0.5	— ^b		0.93	4.26	EC, WC

^a V = variables included in the regression. Candidate variables were EC and WC.

^b Dash indicates that no significant model was possible at $\alpha = 0.05$.

4. Conclusion

Analysis of the relationship between sensor measurements (EC_a by Veris 3100 and soil strength as CI and PSSI) and soil physical properties was carried out for three field sites in central Missouri with variations in soil type and tillage practices. Linear regression analysis was used to estimate WC, BD, and clay content at discrete depths from the sensor data.

An EC_a model inversion approach was used to generate layer EC values corresponding to the depth increments of the other variables. By-depth estimates of WC based on layer EC were of variable quality ($R^2 = 0.31$ to 0.79), with the strongest relationships found at alluvial soil site S2. Best results at all sites were generally found around the 0.2 m depth, below surface effects. Bulk density estimates were significant but with relatively poor fits ($R^2 = 0.11$ – 0.55) when using EC_a and soil strength, either CI or PSSI. There was a strong improvement ($R^2 = 0.30$ – 0.86) when adding WC to the model variables, suggesting the need for a mobile soil

water content sensor to complement EC_a and soil strength sensors. In most cases, when WC was included no soil strength variable (CI or PSSI) was significant in the BD model. From a limited dataset at one of three sites, clay fraction estimates based on EC were good near the surface but declined in fit with depth. Adding WC to the model maintained goodness of fit through the 0.5-m depth increment.

Overall, this study showed the potential of fusing data from multiple on-the-go sensors for estimating soil bulk density, water content, and texture. Best results were found for clay content (as a component of texture), although that analysis only included data from one of the three test sites. Sensor-based regression estimates of WC based on EC_a variables were of variable precision. Because of this, BD estimates were improved considerably by adding WC to the model, suggesting the need for a WC sensor. Models for BD that included PSSI and CI generally gave similar results. In the cases where CI models were better, the difference was not large and might be acceptable considering the increased efficiency of an on-the-go soil strength sensor. The relationships developed in this study were specific to each of the five measurement depths at each of the three field sites, which spanned different soil map units and tillage practices. Further analysis should investigate the potential of a more general model relating important soil physical properties to on-the-go sensor data.

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Mention of trade names or commercial products in this paper is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the USDA or its cooperators.

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Fig. 1 – Structure of the SSPS: top view (left), side view of the body plate (centre), and isometric view (right).

Components include: (1) body plate, (2) cover plate, (3) retaining bar, (4) prismatic tip with a 60° apex angle and 1.9 cm × 1.9 cm base area, and (5) load cell. Parts of the body plate include: (A) wiring tunnel, (B) holes for load cells, (C) grooves for prismatic tips, and (D) groove for retaining bar.

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