Journal of Hydrology 516 (2014) 297–303

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Importance of soil organic carbon on surface soil water content variability among agricultural fields

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ARTICLE INFO

Article history:
Available online 21 November 2013

Keywords:
Water content variability
Soil organic carbon
Soil texture
Bulk density
Downscaling soil moisture

SUMMARY

Improvements to the downscaling estimates of soil water content (SWC) from passive microwave retrievals require detailed knowledge of field scale influences on SWC variability. The Soil Moisture Active Passive Validation Experiment (SMAPVEX-12) field campaign provided SWC and physical properties from 50 cropland fields to assess the influence of soil organic carbon (SOC) on SOC variability in a range of SOC, SWC and soil textural class over a 6 week period. Field average SWC over the duration of the experiment was optimally predicted by combination of soil texture and SOC in all soil wetness conditions, although either %Sand or SOC separately also expressed 82% of variance in SWC over all fields covering three soil textural groups. Soil OC explained greater variance in SWC than texture in dry conditions, while texture predominated in moist conditions. The high correlation between SOC and SWC suggests soil OC may contribute to the initiatives to downscale SWC estimates from satellite to field scale where SWC data are sparse or inaccurate.

1. Introduction

The Soil Moisture Active Passive (SMAP) mission scheduled to launch in 2014 will provide frequent global coverage of SWC (Entekhabi et al., 2010) at relatively coarse resolution (9 km in the combined active and passive retrieval). This intensive soil water content (SWC) data will enable strides in weather and climate prediction, agricultural management and improve our understanding of hydrological processes and land-surface interactions (Entekhabi et al., 2010). There are numerous efforts to further downscale these products from the generally coarse resolution of SMAP products (9×9 km) to field scale ($\sim$0.5 km) based on the characterization of vegetation, soil, land surface, topography and rainfall that influence the variability of SWC at the field scale (e.g. Zhu and Lin, 2011). This application requires knowledge of the numerous spatial and temporal controls that affect SWC variability at the field scale including soil physical properties (texture, bulk density), tillage (roughness) and cropping systems (vegetation). While the complexity of soil characteristics relating to texture, organic matter and porosity has been recognized (Crow et al., 2012), to-date, watershed scale studies to validate remote sensing SWC measurement frequently represent soil factors by soil textural class alone (Choi and Jacobs, 2011; Cosh et al., 2004; Famiglietti et al., 2008; Joshi and Mohanty, 2010; Joshi et al., 2011; Ryu and Famiglietti, 2006).

Soil textural classification has been considered the dominant factor affecting the rate of soil water absorption and drainage in initial hydrological models (Saxton et al., 1986) as represented in the moisture characteristic curve (Tuller and Or, 2004). Soil bulk density (SBD) and soil organic carbon (SOC) or organic matter, are considered at times to improve SWC estimation (Rawls et al., 1982, 2003; Saxton and Rawls, 2006). Soil bulk density refers to the ratio of volume to mass of soils and is commonly calculated as:

$$\text{Soil bulk density} = \frac{\text{mass of soil (g)}}{\text{volume of soil (cm}^3)} \tag{1}$$

Porosity refers to the volume of pores that can be filled with either water or air in relation to the total volume of soil and computed as (Brady, 1990):

$$\text{Porosity} = 1 - \left(\frac{\text{soil bulk density}}{\text{particle bulk density}}\right) \tag{2}$$

Particle density is commonly equated to 2.65 g m^{-3}. Porosity is the soil variable frequently applied in hydrological models to accommodate change in the rate of water movement through soils and thus represents SOC, SBD and water infiltration capacity (Pollacco, 2008; Zacharias and Wessolek, 2007). Several studies have included SBD as a measure of soil organic matter (Pollacco, 2008), however, analysis of SOC and SBD data have often been absent from multiple field SWC sampling experiments at remote sensing footprint scale (e.g. $\sim$40 km).

Organic matter [approximated by $1.8 \times$ SOC (Broadbent, 1965)] is considered a state variable in soil affecting aggregate size and

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http://dx.doi.org/10.1016/j.jhydrol.2013.11.018

the aeration and water retention in surface soil (Franzluebbers, 2002). The increase in field capacity from SOC can be attributed to greater macroaggregates and increased porosity for rain infiltration in no-till studies (Franzluebbers, 2002; Shaver et al., 2002). In recent years, the effect of soil organic matter has been studied in the field (Franzluebbers, 2002), through meta data analysis (Hudson, 1994; Rawls et al., 2003) and in models (Pollacco, 2008; Saxton and Rawls, 2006) as a factor that can also affect soil wetting and drying rates. From a compilation of data from the USDA agricultural soil data base over multiple years, soil textural classes and ranges of WC, Rawls et al. (2003) found that including SOC increased the predictive capacity of SWC by 10% over soil textural class alone. This relationship has been explained from the greater effect of organic matter on increasing the field capacity (water holding capacity of soil) compared to the wilting point of soil (Hudson, 1994).

Soil BD and SOC are also highly correlated in soil (Blanco-Canqui et al., 2006; Blanco-Canqui and Lal, 2007; Franzluebbers, 2002). Soil OC presents a single variable that changes slowly over time compared to SWC. Soil OC has been measured to change by 1% within a single growing season under optimal conditions (Manns et al., 2007, 2009), however, in large scale field trials significant differences are difficult to detect over multiple seasons and crops (Vandenbygaart et al., 2003). Soil OC requires less sampling time and effort than SBD and there are a variety of methods to estimate SOC without physical samples. Soil OC has the potential benefit of being detected by several different methods of multi-spectral remote sensing (Chen et al., 2000; Serbin et al., 2009; Morgan et al., 2009; Ladoni et al., 2010).

The SMAPVEX-12 field sampling campaign was held near Elm Creek Manitoba from June 6 to July 17, 2012. In preparation for the SMAP launch in 2014, the SWC algorithms were validated using remotely derived and ground sampled SWC data, soil and plant sample analysis and surface roughness. This analysis focused on the SWC of ground sample measurements to the soil physical properties of SOC, SBD and soil texture in the top 5 cm of soil at the field scale. The objective was to understand the amount of variability of SWC that can be explained through observations of SOC, as compared to SBD and soil texture, over a large number of agricultural fields.

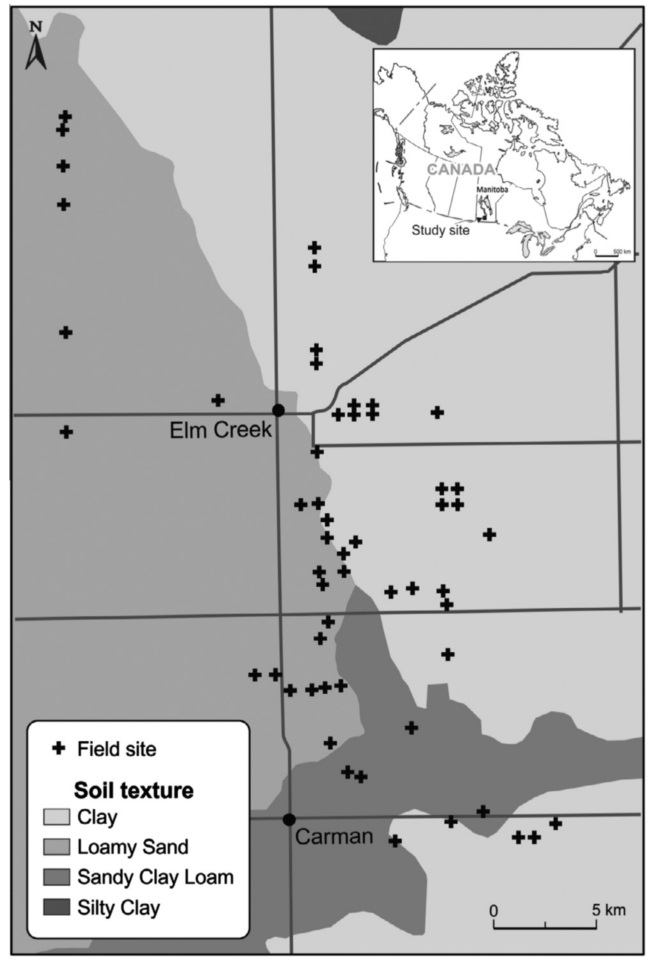

Fig. 1. Location of SMAP field sites in southern Manitoba, Canada in relation to soil texture map. Data from Soil Landscapes of Canada Version 3.2, (Government of Canada, 2011) and National Road Network Version 2.0 (Government of Canada, 2007).

2. Methods

2.1. SMAPVEX-12 field site

Surface SWC was measured in 50 cropland fields around Elm creek, Manitoba (98°23″W, 49°40.48″N) from June 6 to July 17, 2012 for the pre-launch validation experiment of the types of sensors that will be used on the SMAP satellite. The study site included a mix of the common field crops and a range of soil texture from sand to clay (Fig. 1). The topography is relatively level with elevation changing less than 30 m over the study area, characteristic of the Red River valley. The sandy soils to the west were elevated by a moraine dividing them from the heavy clay soils to the east which accounts for most of the elevation change. Loam soils predominated in the south of the study area nearest to Carman. The soils are of the order Chernozem, characteristic of the Canadian prairie, with high organic matter (2–5%), water holding capacity and fertility (Michalyna et al., 1988). Further detail is available from the 1988 survey of the area (Michalyna et al., 1988) or as current digital information in the Soil Landscapes of Canada, (Government of Canada, 2011).

The climate of the region is Continental with long, cold winters and short hot summers with average total rainfall of 398 mm/year. The weather conditions were well suited for the SWC study; the study commenced after a week of dry weather, followed by periods of substantial wetting and drying (Fig. 2). At the beginning of the experiment winter wheat was well established, but most seeded crops were at the early emergence/growth stage (<20 cm). Dominant crops included canola (*Brassica napus*), corn (*Zea mays*), soybean (*Glycine max*) and wheat (*Triticum aestivum*). At the end of the sampling time, winter wheat was ready for harvest, corn was at tassel stage and soybean and canola were at pod filling stage.

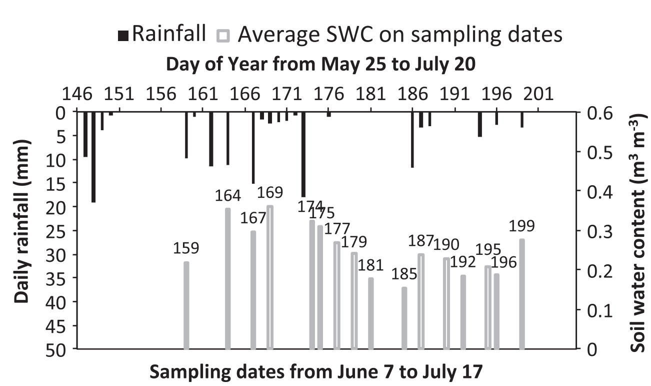

Fig. 2. Rainfall (mm) (dark bars) from May 25 to July 20 and soil water content ($m^3\ m^{-3}$) averaged over all 50 fields at each sampling time during the SMAPVEX-12 field campaign from Jun 7 to July 17, 2012.

2.2. Volumetric moisture

In each agricultural field, SWC was sampled with Stevens Hydraprobes (Stevens Water Monitoring Systems Inc., Portland) in the top 5 cm of soil on 16 sampling dates from June 6 to July 17, 2013 (approximately every second day) (Fig. 2). Field averages are the mean of the 16 points. The hydraprobes detected SWC to an RMSE of less than 0.04 $m^3\ m^{-3}$ over all soils and fields (Rowlandson et al., 2013). Samples were taken at 16 sample points located in 2 transects of 800 m, with 100 m distance between sample points and transects. At each sample point, measurements were taken 3 times; 1st between the plants along the row, 2nd 1/4 way between rows and 3rd at midrow. This analysis focused on the 3rd measure, midway between the rows that would be most representative of the general soil conditions. Particularly in the early growing season (before June 20), the effect of plant roots or shade on SWC midway between the rows would be minimal, allowing for a more accurate determination of the relationship of soil physical parameters to SWC. In order to compare SWC by wetness range in addition to the average over the 16 days, a few dates most representative of the range of SWC were averaged. 'Wet' SWC occurred on day numbers 164, 167 and 169 during or following large rain events, 'dry' conditions represent the lowest average SWC over all fields that occurred on day 181, 185 and 192 and 'drying' conditions represented the centre of an extended drying time (days 175, 177, 179) (Fig. 2).

2.3. Core sample analysis

A soil core, 4.7 cm diameter by 4.6 cm deep, was taken at a single sampling point on each of the 16 SWC sampling days. The sampling point rotated consecutively from sampling point 1 to 16 over the sampling time and was taken at the midrow location. The soil was dried inside the metal core ring for 24–48 h at 105 °C to calculate gravimetric WC (Nelson and Sommers, 1982) from the difference between initial total mass and mass after drying. From the dried soil cores, SBD ($g\ cm^{-3}$) was calculated as Eq. (1) and soil volumetric water content (SWC) ($m^3\ m^{-3}$) was calculated as follows (Parent and Caron, 1993):

$$SWC = \text{Gravimetric SWC} \times \text{SBD} \tag{3}$$

The field average SBD was preferred for the computation of SWC at each point to alleviate site specific variability in SBD measurement (Rowlandson et al, 2013). A selection of oven dried cores was reserved for particle size analysis and cores from all fields on 4 sampling dates (June 7, 17, July 3, 17) were reserved for analysis of soil OC. Particle size analysis was performed at the University of Manitoba by the pipette method following Sheldrick and Wang (1993).

Prior to SOC analysis, the soil core samples were further ground to pass a 2 mm sieve, followed by grinding of a 25 g subsample in a mortar and pestle to 0.5 mm. The subsamples were redried at 105 °C for 24 h to eliminate the possibility that moisture from the air during sample processing was included in the loss of mass during carbon analysis. A 3 g subsample of the finely ground soil was weighed into a ceramic crucible for measurement by loss on ignition in a muffle oven. The samples were heated to 375 °C for 16 h and reweighed to determine loss of mass (Ball, 1964). Oxidation of inorganic carbon can occur at higher temperatures, therefore 375 °C temperature was selected as it has been recommended to prevent loss of inorganic carbon in the mass loss during the heating process (Ball, 1964; Wang et al., 2011). Soil OC was computed following Broadbent (1965):

$$\text{SOC} = \frac{\left[\frac{\text{mass loss after ignition (g)}}{\text{dry mass before ignition}}\right]}{1.8} 100\% \tag{4}$$

Values for SOC were averaged over the 4 sampling dates to obtain a field average. The field averages obtained by (4) were not significantly different by paired *T*-test from a random selection of 20 samples tested for SOC on a LECO by an independent lab.

2.4. Statistical analysis

Normality of SWC and soil physical parameters was assessed with the Shapiro–Wilk statistic and examination of the plot of residuals of the regression equations that should be evenly distributed over the water content range and between positive and negative deviations. An arcsine transformation was applied to %Sand and %Clay to reduce the skewness that arises from the upper and lower boundary limits of a % distribution (Zar, 1999). Correlation was assessed between soil physical parameters and SWC at all individual sampling times and for the average of the 16 sampling times with the Pearson correlation coefficient. Multiple linear regression was applied to assess the relationship of SWC variability across fields to the soil physical properties including SOC.

All soil variables are inherently correlated and no single predetermined solution to decompose the interaction of soil variables has been presented (Edwards, 1985). Multiple regression was performed for all combinations of soil variables (dependent) to average SWC (independent) using normal least squares regression (Type I sum of squares) (Edwards, 1985). Partial least squares regression (Type II sum of squares) was also computed to determine coefficients using standard deviation (Jaccard et al., 1990). Standardization removes differences in units by expressing all differences in standard deviation (Jaccard et al., 1990) for the determination of coefficients. Residual regression was also applied to the soil variables. This method of sequential least squares regression subtracts the residual of the variable representing the lesser variability from the regression to more dominant variables (Graham, 2003). The resulting regression equation no longer includes correlated variables, while expressing the same sources of variability (Dormann et al., 2012).

Diagnostic commands for variance inflation (VIF) and condition index were included in each regression equation to determine if collinearity was a significant factor in the regression coefficients (SAS Institute Inc., 2008). If the variables are correlated, the linear regression coefficients may be variable from inflated standard error and thus not reliable if the VIF is greater than 5 (Aguinis and Gottfredson, 2010). The multiple regression equations were compared with Akaike Information Criterion (AIC) following McBratney et al. (2002) and Akaike (1973):

$$\text{AIC} = \left[N * \text{Ln}\left(\frac{\text{SSE}}{\text{N}}\right)\right] + (2 * p) \tag{5}$$

where N is the number of fields, p is the number of variables in the equation and SSE is the residual sum of squares from the regression model. The AIC value compares the relative sum of squares error while taking into consideration the number of parameters included in the model. The model with the minimum AIC value is considered the most efficient model according to the criterion (Akaike, 1973).

All combinations of dependent variables were compared by multiple regression to SWC for their values of R^2, p, AIC and VIF over the 50 fields, for all sampling dates and for selected wet, drying and dry periods. Any regression models with variables that did not add significantly to the regression and/or VIF > 5.0 (Aguinis and Gottfredson, 2010) were not preferred over other models expressing the same variability. An F-test was used to test for significant differences in the R^2 values between wet, drying and dry periods for each model.

3. Results/discussion

3.1. Multiple regression predictors of soil water content

Over the 50 fields on 16 sampling dates, covering a range of wetting and drying conditions, the 4 major soil parameters (%Sand, %Clay, SOC and SBD) were highly inter-correlated ($p < 0.001$) and were all significantly correlated to average field SWC (Table 1). The average SWC from all sampling dates was regressed on SOC and formed a significant linear regression over the 50 fields:

$$\text{SWC} = (0.0062 \times \text{SOC}) + 0.062, \quad (R^2 = 0.82, \quad n = 50, \quad p < 0.001) \quad \text{(Figure 3a)}$$

The optimum model to predict field average SWC over all individual ranges of wetness was Arcsine transformed %Sand combined with the residual of SOC from %Sand (AS rOC) with R^2 of 0.88, 0.82 and 0.66 and AIC of −328.5, −310.2 and −317.6 in wet, drying and dry conditions respectively (Table 2). The minimum AIC value was the highest negative number within our data and thus AS rOC was the best model considering the mean square error, the number of parameters and VIF of all combinations of the 4 variables (Sand, Clay, SOC, SBD). A single variable model has a VIF of 1 (no VIF) while a VIF > 10 signifies serious variance inflation due to correlation as observed in the 'Sand Clay' models implying the regression coefficients may not be reliable (Aguinis and Gottfredson, 2010). Where models have the same AIC, the model with the lesser number of variables is shown. The Arcsine transformation was applied to improve the linear model fit and was only beneficial over the untransformed model in the AS rOC model.

The amount of variance explained by each model regression was significantly different between wet/dry periods (Tables 2 and 3) by calculation of an F statistic (49.4) which was greater than F for the corresponding degrees of freedom at $p = 0.001$ of 2.06. The decrease in model accuracy in very dry conditions may relate to increased variability with soil drying observed from many field studies over a wide range of soil and rainfall conditions (Famiglietti et al., 2008). An increase in the amount of variability in SWC explained with increased wetness by soil characteristics was also observed in SGP97 where 67% of SWC variability was explained in wet days and 55% in dry days (Joshi and Mohanty, 2010).

The three variable equations had high R^2 and AIC in each wetness category although they were not considered in model selection due to the high VIF (>10) as well. 'Sand Clay SOC' had the highest AIC of all the 3 variable combinations and is shown to demonstrate the partial least squares values that isolate the amount of variability of SWC explained by each individual variable in addition to the common variance (Steele et al., 1997) (Table 2). Both %Sand and SOC contribute significant individual variability to the regression model 'Sand Clay SOC' in wet and drying conditions (Table 2). However, in very dry conditions, only SOC contributed to significant unique variability ($p = 0.01$). Although the regression model of 'Sand SOC' was not the best selection for determination of SWC due to a VIF of 6.5, the partial least squares details the change in dominant variable from %Sand to SOC. In dry conditions, %Sand explained 1.4% (ns) and SOC 7.8% ($p = 0.03$) of unique variation in SWC explained by the model regression. The reverse was observed in wet conditions, with 7.7% ($p < 0.001$) of additional variance explained by %Sand and 1.61% ($p = 0.03$) attributed to SOC.

Table 1
Pearson correlation coefficients between soil physical variables and average soil water content (SWC) over all sampling times and fields. All values are significant at $p < 0.001$.

	Average SWC	%Sand	%Clay	SOC	SBD
Average SWC ($m^3\,m^{-3}$)	1.00				
Sand (%)	−0.90	1.00			
Clay (%)	0.84	−0.96	1.00		
Organic carbon ($g\,kg^{-1}$)	0.91	−0.92	0.88	1.00	
Soil bulk density	−0.82	0.86	−0.85	−0.87	1.00

3.2. Single predictors; %S and vs. SOC

Percentage sand alone represented more variability in SWC than most two factor models (except for Sand and SOC combinations) without any VIF concerns in wet and drying conditions. Sand also explained the most variability in SWC in other multifield studies considering drainage over larger areas (Kim and Barros, 2002; Kim and Stricker, 1996) and longer time spans (Jawson and Niemann, 2007). Jawson and Niemann (2007) found the most significant empirical orthogonal function that represented a unique factor of variability in SWC, was from sand in ample moisture conditions in pasturelands of the Southern Great Plains (SGP97) analysis. The significance of sand was suggested to relate to the dominant effect of sand on drainage and thus the rate of drying of soil (Jawson and Niemann, 2007).

However, in dry conditions, SOC was a superior model to %Sand, second only to 'AS rOC'. Although %Sand and SOC together expressed the maximum variance in SWC when separated by wetness regime (Table 2), 82% of the variance in SWC could be determined by SOC or %Sand alone when the average SWC over time was considered (Fig. 1a and b). The close similarity between %Sand and SOC in predicting SWC suggests that soil texture, SOC and SWC are all representing the same variability generated by the soil physical structure. This soil characteristic variability has been observed in small scale geostatistical analysis (<100 m) (Kim and Stricker, 1996), but has not been documented in multiple field SWC campaigns. The change in the controlling variable on SWC from %Sand to SOC with drying is consistent with previous research on SOC influence in the water characteristic curve. De Jong et al. (1983) noted that the inflection point in matrix suction where SWC begins to decline was affected by both texture and organic matter at $\sim 0.17\ m^3\,m^{-3}$ for sandy loam soils with 4% SOC.

3.3. Sand vs. clay in SWC variability

In the single model comparison (Table 3), %Clay and SBD explained the least variability at all sampling times. Clay was expected to represent more variability in dry conditions from the physical property of clay on increasing water retention (Brady, 1990; Takagi and Lin, 2012). Clay has been observed as a significant variable in SWC in addition to sand in very dry conditions (Kim and Barros, 2002) and at the local scale (Jawson and Niemann, 2007). However, our fields are also high in SOC, especially with clay soil texture. A possible explanation for the low relationship of %Clay to SWC is the interaction with SOC. High SOC is associated with increased porosity and thus can actually increase the rate of soil drying in clay soils (Hudson, 1994). The 'Sand Clay' model is included in the multiple model predictions for comparison. Although the AIC is higher than for other models, the high VIF disqualifies its use as a model. Clay and sand are representing the same variability in soil (thus the high VIF), but sand represents a greater contribution to SWC ($p < 0.001$) at all times, while clay is not significant. The relationship can be visualized in the regression of %Sand and %Clay to SWC, where Sand has the higher R^2 value (Fig. 3b and c).

3.4. Soil organic carbon vs. bulk density as a predictor of soil porosity

Soil BD did not represent the same amount of variability in SWC as SOC in our study results as would be expected from the frequent application of SBD in favor of SOC in current literature (Pollacco,

Table 2
Summary of optimum model combinations with 2 or 3 variables of sand, clay, SOC and SBD from linear regression to SWC in wet, drying and dry soil wetness conditions. The sum of squares (SS) and R^2 are shown for each model, along with the AIC value and VIF. The partial least squares regression coefficients are given along with the significance of the individual variables in the regression at $p = 0.05$(*), 0.01(**) and 0.001(***) or not significant (ns). The models are sorted within wetness group by AIC, with the optimum model in bold script. A high VIF that disqualifies a model is also in bold script.

Model predictors	Model				Partial least squares regression coefficients							
	R^2	SS	AIC	VIF	Sand		Clay		OC		BD	
Wet												
AS rOC	0.88	0.514	−**328.5**	1.0	0.509	***			0.005	ns		
Sand OC	0.87	0.509	−324.6	6.5	0.039	***			0.008	*		
Sand clay OC	0.87	0.509	−322.7	**20.0**	0.015	**	0.000	ns	0.008	*		
Sand BD	0.87	0.503	−321.0	4.2	0.092	***					0.003	ns
Sand clay	0.86	0.501	−319.5	**14.5**	0.041	***	0.000	ns				
Drying												
AS rOC	0.82	0.455	−**310.2**	1.0	0.448	****			0.008	ns		
Sand OC	0.85	0.451	−308.1	6.5	0.026	***			0.011	*		
Sand clay OC	0.83	0.453	−307.0	**20.0**	0.016	**	0.002	ns	0.011	*		
Sand clay	0.80	0.442	−303.5	**14.5**	0.047	***	0.002	ns				
Sand BD	0.79	0.440	−302.6	4.2	0.098	***					0.000	ns
Dry												
As rOC	0.66	0.142	−**317.6**	1.2	0.140	***			0.010	*		
Sand OC	0.65	0.140	−315.9	4.0	0.002	ns			0.011	*		
Sand clay OC	0.65	0.141	−315.1	**19.8**	0.004	ns	0.002	ns	0.011	*		
Sand BD	0.61	0.131	−310.6	4.1	0.017	**					0.003	ns
Sand clay	0.60	0.131	−310.1	**14.1**	0.019	**	0.002	ns				

Table 3
Comparison of single variable models (sand, clay, SOC, SBD) in wet, drying and dry wetness categories. Models are sorted by AIC within wetness category. The model R^2 and sum of squares (SS) is also shown. All model regressions are significant at $p < 0.001$.

	Single model comparison		
	R^2	Model SS	AIC
Wet			
Sand	0.86	0.50	−321.30
SOC	0.81	0.47	−304.59
Clay	0.79	0.46	−300.46
SBD	0.71	0.41	−283.87
Drying			
Sand	0.80	0.44	−304.56
SOC	0.77	0.43	−298.08
Clay	0.71	0.39	−287.23
SBD	0.62	0.34	−272.33
Dry			
Sand	0.76	0.21	−316.5
SOC	0.73	0.20	−310.0
Clay	0.68	0.19	−301.8
SBD	0.64	0.18	−296.9

2008; Zacharias and Wessolek, 2007). Soil BD contributed least to the interpretation of field average SWC at all sampling times (Table 3). In our regression analysis, SBD did not add significantly to the regression of SWC from %Sand and SOC in any wetness conditions. Soil OC and texture affect SBD by directly influencing the size, shape and amount of soil pores (Franzluebbers, 2010). A low level of SBD (0.84) in a native North American prairie was characterized by a specific size and shape (cylindrical) of pores that maintained a balance of air and water in soil (Undawatta et al., 2008). Soil BD was highly correlated to SOC in a review of agricultural studies across the southeast USA as well (Franzluebbers, 2010) and in field soil cores in northeastern USA (Blanco-Canqui et al., 2006). Our results are in agreement with the observation by Zacharias and Wessolek (2007) that SWC derived from %Sand and SBD alone, without SOC, would not be the best model in the extremes of dryness. Our estimation of SWC from %Sand and SBD in very dry conditions was 61% of variation ($R^2 = 0.61$) compared to %Sand alone ($R^2 = 0.60$) and SOC alone ($R^2 = 0.64$).

3.5. Soil organic carbon as a sole predictor of soil water content

Our results suggest a distinct linear relationship exists between SOC and SWC in cultivated fields at multiple field sites over all levels of soil wetness and soil textural classes. Soil OC alone could be a realistic indicator of surface soil structure that influences the transmission of soil water over all 3 soil textural classes and in all wetness conditions. While a relationship between SOC and SWC has been documented (Hudson, 1994), SOC has not been investigated previously as a variable affecting inter-field WC variability in multi-field SWC sampling campaigns.

The lack of significance of %Clay and SBD may seem inconsistent with current models. One explanation for the lack of influence of SBD may be the variability measured over the 16 sample points within fields. Another possible explanation for the significance of SOC in SWC is the high levels of SOC for agriculture on our field sites, where otherwise at levels of SOC < 2%, %Clay and SBD would be more influential in SWC. The analysis of particle size distribution based on a single soil sample for each field may not have optimally represented the soil textural classes, although the results were confirmed with the most recent soil map of the area (Rowlandson et al., 2013).

Our data are in agreement with observations from many individual studies and database measures across the US Midwest that indicate significant improvements in estimating SWC by including SOC with soil texture (Hudson, 1994; Rawls et al., 2003). Our results have the benefit of common time, weather, and uniform methods over multiple crop types that may not apply to all metadata studies. The metadata studies of Rawls et al., 2003 in the US and our Canadian data from SMAPVEX-12 support evidence from field studies (Franzluebbers, 2002) and forest studies (Wang et al., 2002) of a significant effect of SOC on water holding capacity of soils.

The strong correlation between SWC and SOC could improve the predictive ability of soil WC models. Soil OC could act as a surrogate for SWC to assist in establishing initial soil water conditions, for interpolation between missing data points (Goovaerts, 1998) and to estimate SWC in areas where measurement is not possible (Champagne et al., 2012). The general rule for deriving pedotransfer functions (PTF) in the soil is to select the variable which is easiest to obtain and from which the other soil

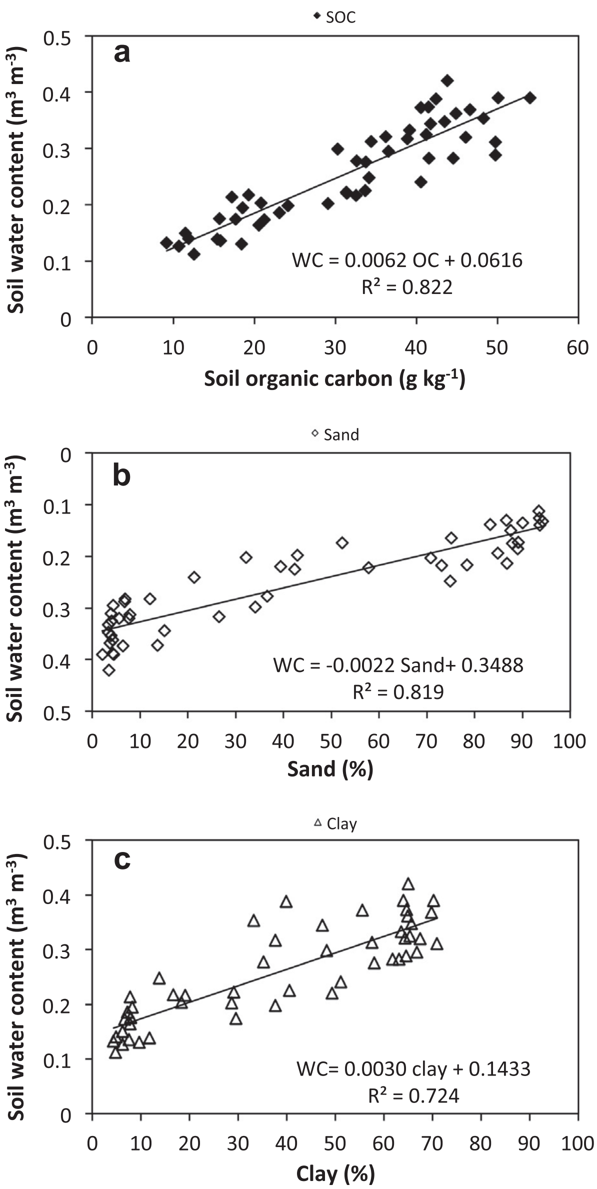

Fig. 3. Average soil water content (SWC) ($m^3\,m^{-3}$) from all sampling times, predicted from (a) SOC, (b) %Sand and (c) %Clay. The regression equation and R^2 are provided on each graph. All the regressions are significant at $p < 0.001$. $n = 50$.

characteristics can be derived (McBratney et al., 2002). Cost is a significant factor in choosing PTF's for predictive ability (Rawls et al., 1982). Soil texture and SOC are thus preferred variables as particle size distribution and SOC are the least expensive and the most stable of soil indices, making them preferable to more expensive and variable indices such as hydraulic conductivity (Rawls et al., 1982). Soil OC presents a unique variable to support SWC variability estimation that is generally applicable to all soil textural classifications, includes the extremes of the SWC range and may be obtainable through direct remote sensing (Chen et al., 2000; Serbin et al., 2009; Stevens et al., 2008).

4. Conclusion

Few studies on agricultural cropland soils with comparatively high organic matter content, have presented highly replicated measurements on both SWC and SOC to assess their relationship over numerous agricultural fields with a large range of soil textures and rainfall events with minimal vegetation and topographical effects. Over the 50 crop fields analyzed, soil texture and SOC combined to optimally represent SWC over the range of wetness, however as a single determinant of SWC, soil texture represented only slightly less variability in average and wet conditions. Similarly, SOC was the superior sole predictor of SWC in very dry soils with almost the same amount of variance explained by the linear regression and AIC values. Our study suggests that SOC was an important predictor of inter-field SWC variability during SMAPVEX-12 and could be used to capture a greater proportion of variability than is commonly associated with parameters such as SBD. The linear relationship between SOC and SWC over all fields may also assist with accuracy in downscaling coarse scale SWC measurements from space based sensors. Further research into approaches for estimating SOC, such as remote sensing techniques, could support and complement the interpretation of SWC spatial variability from passive microwave sensors at coarse scales.

Acknowledgements

Sincere appreciation to Rebecca Warren for the preparation and analysis of the soil carbon samples and to Marie Puddister and Adam Bonnycastle for preparing the site map. Many thanks to all the SMAPVEX-12 participants and organizers who made the study possible and in particular Prof. Paul Bullock and lab associates for processing the soil cores. Thanks also to the reviewers for their comments to improve this manuscript. The funding support by NSERC and the Canadian Space Agency is gratefully acknowledged.

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One of the current methods used for soil quality is the wet aggregate stability test (Fig. 4) where a soil sample is placed in a water column to evaluate how rapidly the soil aggregates dissolve. For soils with low aggregate stability, the structure of the aggregates fails under the force of water, and the finer fractioned material that was held within the aggregates begins to clog pore spaces, restricting infiltration and causing runoff conditions to quickly develop during a rainfall event (Hatfield et al., 2017). As the depth of runoff increases, larger soil particles and residue can be mobilized by the flow and transported down the hillslope. This is exaggerated when there is no residue cover to absorb the raindrop energy. Soils with high aggregate stability maintain pore space and infiltration rates during a rainfall event because the aggregates don't change. Producers who have improved their soils will often report being able to "handle a 4-inch rain without any runoff while the neighbor's field is moving into the ditch." We can learn a lot about the quality of the soil by merely observing what occurs during rainfall events.

Fig. 3.

Depiction of changes in aggregate structure when exposed to rainfall for a soil with low and high biological activity.

These same factors that affect the infiltration of water also affect the exchange of gases between the soil and the atmosphere. There are two critical gases for biological activity, oxygen (O_2) and CO_2, and stability of the soil aggregates affect the exchange of both gases. One of the benefits of soil organic matter is enhanced infiltration and reduced bulk density, but we rarely consider these changes in the context of gas exchange. When the aggregate structure is reduced, then gas exchange becomes limited and biological systems below the surface become deprived of oxygen.

What's it worth?

A question that is often asked is what is organic matter worth in soils? It is difficult to place a value on soil organic matter, but we can show the value of what some of the characteristics of soil mean in terms of agricultural production. An analysis by Hudson (1994) revealed the linear relationship between soil organic matter and soil water-holding capacity with a different curve for each soil type (Fig. 5). The role of increased organic matter is to increase the volume of water a soil can hold, and this relationship is only part of the process. Soil can only store water if it is able to enter into the soil, and the role of the stable aggregates at the surface is a vital part of that process in order to be able to infiltrate as much water as possible. The process of infiltration is a necessary step in being able to store soil water. It is not merely the amount of water the soil can hold and make available that affects plant growth, but the impact of that soil water on crop productivity. High production is derived from crops with high water use efficiency, and enhancing soil water availability is one key to enhanced productivity (Hatfield et al., 2001). An example of this impact is shown in Fig. 6 where the results from Fig. 5 are replotted to show the days of available soil water for a corn crop transpiring at the maximum rate during grain filling. As we increase soil organic matter, there are more days of available soil water with four more days in which the corn crop is not water stressed during grain filling at 4% compared with 2%. The effect of the increased availability of soil water could be extremely significant in years with more variable rainfall.

Fig. 4.

Aggregate stability test showing aggregates from (l to r) a no-till system, an intensive tillage system (rototilling 5+ times/year), and a conventional tillage system. Image is a screenshot from a YouTube video from University of Wisconsin Integrated Pest and Crop Management. See https://youtu.be/d1M7EFqqsMM.

The value of enhanced soil water was observed in the results obtained by Egli and Hatfield (2014a and 2014b) where they found a linear relationship between the average county yield for corn and soybean in Iowa and Kentucky and the quality of the soil. Available soil water was the primary factor affecting the ability of a given soil to produce a yield. These same factors determine yield variation within fields, and enhancing the soil organic matter to increase available soil water will pay dividends in terms of being able to stabilize crop yields.

The positive benefits of soil organic matter encompass a range of soil properties; however, the driving force is soil biological activity and the management of the soil microclimate to provide the functional needs for these living organisms. The effect of the increased biological activity on the stability of the soil aggregate affects all of the other positive benefits in terms of increasing infiltration of water and exchange of soil gases. Managing our soils to increase and maintain soil biological activity is the foundation for enhancing them and increasing their capacity to produce crops.

Fig. 5.

Relationship between soil organic matter and available water content for three soils (redrawn from Hudson, 1994).

Acknowledgments

We want to express a sincere thanks to Missouri Rice and Merchandising Council for providing the funding for this project. We also want to express our heartfelt appreciation to Chad Mikeal for assistance with plot management and harvesting, and to Blake Gray of KOCH Agronomic Services, LLC for providing the fertilizer for this study.

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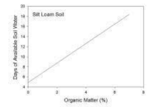

Fig. 6.

Relationship between days of available soil water and soil organic matter content for a silt loam soil using the findings from Hudson (1994).

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Footnotes

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