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Regression-Kriged Soil Organic Carbon Stock Changes in Manured Corn Silage–Alfalfa Production Systems

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Accurate measurement of soil organic C (SOC) stock changes over time is essential to verify management effects on C sequestration. This study quantified spatial and temporal changes in SOC stocks on adjacent 65-ha corn (*Zea mays* L.) silage–alfalfa (*Medicago sativa* L.) fields receiving liquid dairy manure in west central Minnesota. We used regression kriging to interpolate SOC in four soil layers in 2006 and 2015, and calculated stock changes over time. Regression kriging with elevation, topographic wetness index, field (west vs. east), and irrigation (yes vs. no) accurately predicted SOC in the 0 to 15-cm (R^2 = 0.89) and 15 to 30-cm layers (R^2 = 0.51–0.95), where variogram analysis indicated moderate to strong spatial correlation. From 0 to 15 cm, SOC in the west field increased by 7% (+4.5 Mg C ha^{-1}) over the study period caused by gains in irrigated portions of the field. No changes were found in the east field or from 15 to 30 cm in either field. Below 30 cm, a lack of spatial structure and a lack of relationships between SOC and auxiliary variables was found, but simple means indicated SOC gains of 13% (+4.7 Mg C ha^{-1}) in the 30 to 60-cm layer and 24% (+3.9 Mg C ha^{-1}) in the 60 to 90-cm layer across both fields. Regression kriging with easily acquired auxiliary variables offers a highly accurate method of monitoring SOC stock changes over time to 30 cm depth. Current management practices maintain or increase SOC in these fields.

Abbreviations: Dist. tile, distance to the nearest tile line; GHG, greenhouse gas; LiDAR, light detection and ranging; SOC, soil organic C; TWI, topographic wetness index.

Core Ideas

- **Regression kriging with elevation, topographic wetness index, field (west vs. east), and irrigation (yes vs. no) accurately predicted soil organic C (SOC) in the 0 to 15- and 15 to 30-cm layers.**
- **Lack of spatial structure and a lack of relationships between SOC and auxiliary variables precluded the use of regression kriging for the 30 to 60- and 60 to 90-cm layers.**
- **From 0 to 15 cm, SOC in the west field increased by 7% because of gains in irrigated portions of the field, but no changes were found in the east field or from 15 to 30 cm in either field.**
- **Simple means indicated SOC gains of 13% in the 30 to 60-cm layer and 24% in the 60 to 90-cm layer across both fields.**
- **Typical field management practices associated with large, modern dairies can sequester SOC.**

The global C sequestration potential of agricultural soils is estimated to be 31 to 64 Gt, which is only a small fraction (1.9–6.5%) of projected greenhouse gas (GHG) emissions by year 2100 (Lal, 2004; Sommer and Bossio, 2014). Though seemingly small, this potential contribution to GHG mitigation is viewed as an important climate "stabilization wedge" that can provide short-term mitigation until more robust, permanent solutions are developed and put into practice (Pacala and Socolow, 2004; Lassaletta and Aguilera, 2015). Rapidly sequestering C in soils and biomass will help avoid triggering slow climate feedback that could lead to dangerous warming and irreversible climate change (Hansen et al., 2013). Thus widespread application of agronomic management practices that promote rapid C accumulation are vital to climate change mitigation efforts.

The SOC content in agricultural soil is affected by management practices such as crop species and rotation, fertilizer rate, manure application, tillage methods, irrigation, and drainage (Batjes, 1998; Bruce et al., 1999; Lal et al., 1999; Lal, 2002; Liu et al., 2006). These practices directly influence the C input from crop residue and organic amendments, and also the C output through decomposition, leaching, run-off, and erosion (Post and Kwon, 2000). Soil organic C content is also strongly influenced by terrain attributes, such as elevation, slope, aspect, and soil texture, as these factors directly impact the way water moves through and over the landscape (Moore et al., 1993). The combined influence of management factors and terrain

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results in great variability of SOC, even at small spatial scales (Kravchenko et al., 2006; Worsham et al., 2010). This variability presents great challenges in the initial assessment and long-term monitoring of SOC stocks because of the high sampling and analytical costs (Sherpa et al., 2016). Developing reliable and cost-effective ways to quantify variability and verify changes in SOC stocks is of key importance for assessing GHG mitigation strategies for agriculture (de Gruijter et al., 2016). Furthermore, greater precision in SOC maps is important for refining agricultural management practices (McGrath and Zhang, 2003; Liu et al., 2006), such as precision fertilizer application, manure application, and stover harvest technologies.

In this context, regression kriging has emerged as an important tool for quantifying spatial variability in SOC and mapping SOC stocks. Regression kriging is a hybridized geostatistical interpolation approach that combines ordinary kriging with linear regression via spatially explicit auxiliary variables (Hengl et al., 2004). In regression kriging, the target variable is first predicted with a linear regression model, then the residuals of the regression are interpolated using ordinary kriging (Hengl et al., 2007). The final estimate of the target variable is then calculated as the sum of the regression estimate and the ordinary kriging estimate of the residual values at each interpolated location (Ping and Dobermann, 2006). This approach has resulted in increased quality and precision of SOC maps relative to other techniques because of the incorporation of spatial autocorrelation and spatially correlated auxiliary information (Simbahan et al., 2006; Mooney et al., 2007). Incorporation of auxiliary variables cannot only improve prediction accuracy, but by doing so, it can also help optimize sampling designs and reduce the sampling costs associated with SOC inventories (Simbahan and Dobermann, 2006; Simbahan et al., 2006; Omuto and Paron, 2011; Sherpa et al., 2016).

Most regression kriging studies to date have focused on assessing prediction accuracy relative to other interpolation techniques, and generally only report SOC stocks for a single year. Few studies have used regression kriging methods to monitor changes in SOC stocks over time in relation to agronomic management. Furthermore, most studies focus on SOC above 30 cm depth, rarely extending beyond the plow layer to account for C deeper in the soil profile. Here, we employ regression kriging to quantify the spatial and temporal changes in SOC stocks in four soil layers (to 90 cm depth) on adjacent irrigated 65-ha corn silage–alfalfa production fields receiving liquid dairy manure in west central Minnesota. Our objectives were (i) to determine if typical field management practices associated with large, modern dairies can sequester SOC over a 10-yr study period (2006–2015); and (ii) to evaluate the performance of regression kriging with easily acquired terrain and agronomic management data for predicting SOC stocks changes in four soil layers.

MATERIALS AND METHODS

Site Description

The study was conducted on adjacent 65-ha fields on a privately owned dairy farm in west central Minnesota from September 2006 to October 2015. The study fields had a long history of agricultural production, with a gradual transition from small-scale cropping, grazing, or wildlands to large-scale monocropping (Krueger et al., 2013). Draining depressional areas in these fields began before 1951 and continued in stages, including installation of new drainage tiles in fall 2009 (Fig. 1). These most recent drainage additions primarily impacted the west field, where drainage had been less extensive than in the east field prior to 2009.

The soils were formed in a calcareous loamy glacial till, characteristic of the prairie pothole soils of the Upper Midwest. Soils on higher landscape positions included a well-drained Forman clay loam and a moderately well-drained Aastad clay loam (see Table 1 for the soil series descriptions). The soil on side slopes surrounding the depressions was primarily a somewhat poorly drained Hamerly clay loam, whereas the depressional areas were characterized by poorly drained Parnell silty clay loam, Parnell–

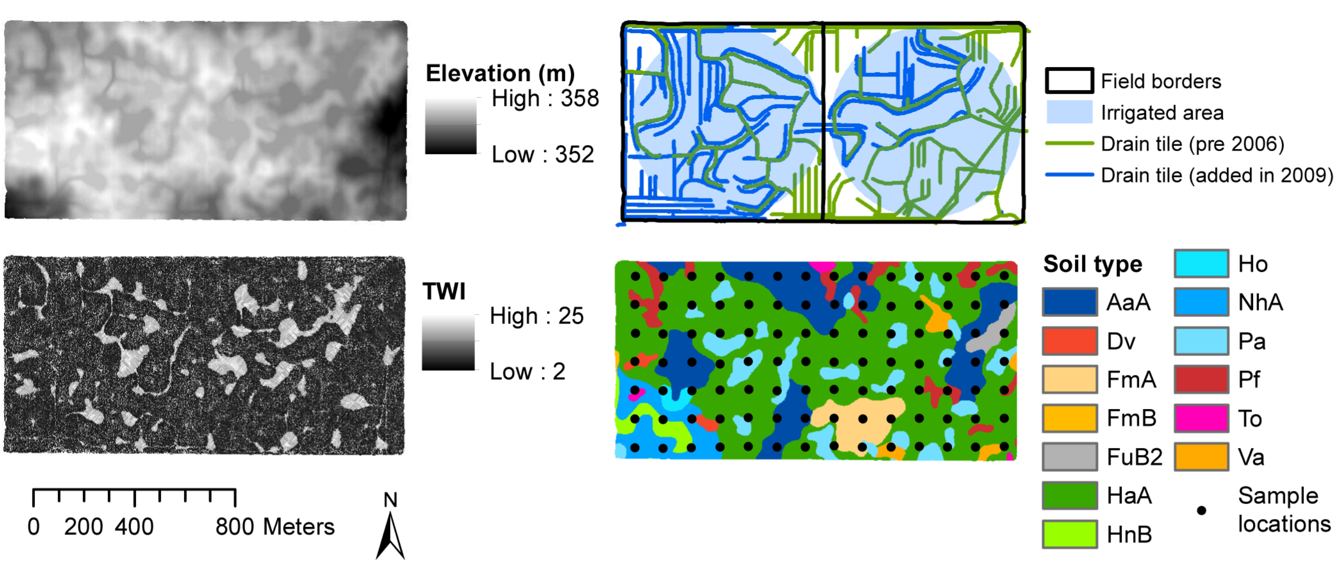

Fig. 1. Maps of research fields, sample locations, and auxiliary variables used for regression kriging of soil organic C (SOC) stocks. Definitions for soil survey map unit symbols are found in Table 1.

Table 1. Summary of soil survey information† for the study site in west central Minnesota

Soil survey map unit symbol	Description	Taxonomic class	Share of study area
			%
AaA	Aastad clay loam, 0–2% slopes	Fine-loamy, mixed, superactive, frigid Pachic Argiudolls	16.2
Dv	Dovray clay, very poorly drained	Fine, smectitic, frigid Cumulic Vertic Epiaquolls	0.7
FmA	Forman clay loam, 0–2% slopes	Fine-loamy, mixed, superactive, frigid Calcic Argiudolls	4.1
FmB	Forman clay loam, 2–6% slopes	Fine-loamy, mixed, superactive, frigid Calcic Argiudolls	0.2
FmB2	Forman clay loam, 2–6% slopes, eroded	Fine-loamy, mixed, superactive, frigid Calcic Argiudolls	1.2
HaA	Hamerly clay loam, 0–3% slopes	Fine-loamy, mixed, superactive, frigid Aeric Calciaquolls	53.1
HnB	Hattie–Nutley clays, 2–6% slopes	Fine, smectitic, frigid Aquic Hapluderts, Fine, smectitic, frigid Chromic Hapluderts	2.1
Ho	Hegne clay	Fine, smectitic, frigid Typic Calciaquerts	0.7
NhA	Nutley–Hattie clays, 0–2% slopes	Fine, smectitic, frigid Chromic Hapluderts, Fine, smectitic, frigid Aquic Hapluderts	5.4
Pa	Parnell silty clay loam	Fine, smectitic, frigid Vertic Argiaquolls	9.7
Pf	Parnell and Flom soils	Fine, smectitic, frigid Vertic Argiaquolls; fine-loamy, mixed, superactive, frigid Typic Endoaquolls	4.5
To	Tonka loam	Fine, smectitic, frigid Argiaquic Argialbolls	0.4
Va	Vallers silty clay loam	Fine-loamy, mixed, superactive, frigid Typic Calciaquolls	1.6

† Source: USDA-NRCS Soil Survey geographic database (Soil Survey Staff, 2016).

Flom silty clay loam, and Nuttie-Hatley clay soils. Mapping of the study site with light detection and ranging (LiDAR) revealed low relief, with elevation varying by approximately 5 m across the 130-ha research site.

Agronomic Management

The study fields, designated as the "west field" and the "east field", were managed as part of the cooperating dairy, and all management decisions were made by the farm operator. The east field was planted to corn each year of the study; the west field was planted to corn from 2006 to 2012, and alfalfa from 2013 to 2015 (Table 2). Corn was harvested for silage each fall on dates ranging from 28 August to 29 September. A winter rye (*Secale cereal* L. var. 'Rymin') cover crop was established in the west field following the silage harvest in 2007 and then terminated in May 2008 by applying glyphosate [*N*-(phosphomonomethyl) glycine] at a rate of 1.2 kg acid equivalent ha^{-1}. Winter kill of alfalfa occurred in some of the low-lying areas of the west field in the winter of 2014 to 2015. The following spring, the cooperating farmer seeded orchardgrass (*Dactylis glomerata* L.) in these areas to provide additional ground cover. Corn silage yields were generally similar between fields over the study period, though the C removed in harvest was lower in the west field during alfalfa years. Center pivot irrigation was installed in both fields in October 2008, and irrigation began in May 2009 and continued each year throughout the study.

Liquid dairy manure was applied most years, though manure management practices differed between fields and changed over the course of our study. From 2006 to 2008, raw liquid dairy manure was applied to both fields. Beginning in 2009, the manure was processed in an anaerobic digester prior to field application. From 2006 to 2012, manure was applied following the silage harvest in the west field by drag-line injection at depths

Table 2. Summary of agronomic management practices, manure C additions, and crop C removal at the study site in west central Minnesota over the study period.

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
					East field					
Crop	Corn	Corn	Corn	Corn	Corn	Corn	Corn	Corn	Corn	Corn
Manure application	Inj.†	Inj.	Inj.	NA¶	Fert.‡	Fert.	Fert.	Fert.	Fert.	Fert.
Manure C applied, Mg ha^{-1}	2.8	2.2	1.7	0	2.3	0.4	1.0	1.5	0.2	0.1
Crop C removed, Mg ha^{-1}	–§	4.7	7.6	9.4	8.8	7.9	9.0	8.7	7.6	7.4
Irrigation, mm	NA	NA	NA	102	126	52	106	155	30	0
					West field					
Crop	Corn	Corn–rye	Rye–corn	Corn	Corn	Corn	Corn	Alfalfa	Alfalfa	Alfalfa–orchardgrass
Manure application	Inj.	Inj.	Inj.	Inj.	Inj.	Inj.	Inj.	NA	Aer.	Aer.
Manure C applied, Mg ha^{-1}	2.8	2.2	1.7	0.8	0.9	0.9	0.9	0	0.6	0.7
Crop C removed, Mg ha^{-1}	–	4.9	6.5	9.3	9.4	7.5	9.1	2.2	5.7	5.7
Irrigation, mm	NA	NA	NA	62	59	0	130	65	42	10

† Inj., injected; Fert., fertigated; Aer. aerway slurry applicator.

‡ From 2010 to 2015, manure was applied in the east field via center pivot irrigation, except in pivot corners where it was injected.

§ Crop C removal in harvest was not estimated in 2006.

¶ NA, not applicable.

of 16 to 18 cm and rates of 97,000 to 150,000 L ha^{-1}. Rates of manure injection were determined by desired N rates. In 2006, manure was pumped directly from the stirred lagoon, but in all other years, the manure slurry was screened to remove some solids before injection. After manure applications in 2006 and 2007, the field was tilled to a depth of 23 to 30 cm with a disk ripper (Ecolo-Tiger 870, Case IH, Racine, WI); from 2008 to 2012, tillage occurred before manure application. Dates of manure injection ranged from 28 August to 4 November over this period. No manure was applied in 2013 to alfalfa; however, in 2014 and 2015, manure was applied to alfalfa after the first harvest via subsurface deposition slurry applicator (Aerway SSD, Holland Equipment Ltd., Norwich, ON, Canada) at rates of 82,000 and 96,000 L ha^{-1}, respectively, and no tillage was used.

Manure management in the east field was identical to that of the west from 2006 to 2008, but no manure was applied in the east field in 2009. Starting in 2010, manure was applied to the east field via a center-pivot irrigation system (i.e., fertigation) at 53,000 to 150,000 L ha^{-1} on dates ranging from 25 June to 16 July. In 2015, manure was applied to only about one-third of the east field because of an irrigator malfunction. Mineral fertilizer was applied to the remainder of the field through the irrigator. In the pivot corners where fertigation was not possible, manure was injected each year at similar rates as in the west field. Fall tillage in the east field occurred after corn silage harvest, applying similar practices as in the west field.

For injected dairy slurry, grab samples of the manure were obtained from the pump station just prior to or during application. For fertigated dairy slurry, sample containers were placed in the field during fertigation to collect grab samples. Samples were analyzed for dry matter content by a commercial laboratory (Agvise Labs, Benson, MN). In 2006, manure C was determined using an Elementar Variomax C/N analyzer (Elementar, Hanau, Germany). On the basis of the 2006 analysis, the manure C in remaining years was calculated as a constant fraction (442.5 g kg^{-1}) of dry matter content. For both fields, total C applied as manure ranged from 0.1 to 2.3 Mg C ha^{-1} yr^{-1} and generally declined over the study period, corresponding to reduced N application rates and use of anaerobic digestion.

Soil Sampling

Soil samples were collected in fall after the corn silage harvest and before manure application, on 8 Sept. 2006, 25 Aug and 10 Sept. 2015. Samples were collected at 49 locations in each field in a grid pattern with approximately 113 m between sample locations (Fig. 1). Samples were collected to a depth of 90 cm with a hydraulic sampler with a core inner diameter of 6.5 cm. One core was collected for chemical and one for physical analysis, and cores were subdivided into 0 to 15-, 15 to 30-, 30 to 60-, and 60 to 90-cm layers. The uppermost segment of the cores taken for chemical analysis was further subdivided into 0 to 5- and 5 to 15-cm layers. Samples for chemical analysis were dried at 37°C and ground to <0.5 mm, and samples for physical analysis were dried at 105°C and their core dry weights were obtained. Samples were analyzed via dry combustion, and SOC was calculated as total C less inorganic C (Bremner and Mulvaney, 1982; Wagner et al., 1998). Soil organic C stocks at each sampling point were calculated via equivalent soil mass methods (Wendt, 2012; Wendt and Hauser, 2013) for four soil mass layers (0–2000, 2000–4000, 4000–8000, and 8000–12,000 Mg ha^{-1}). The average depth to equivalent soil mass for these layers was 17, 32, 61, and 88 cm, which corresponds closely with our target sampling depths of 15, 30, 60, and 90 cm. To calculate SOC stocks in the 0 to 15-cm layer, a depth-weighted average SOC concentration was calculated with SOC values from the 0 to 5-cm and 5 to 15-cm layers. Soil layer masses were estimated via physical analysis of the core dry weights. Results are reported on the basis of the targeted sampling depth layers.

Regression Kriging

Fine-resolution auxiliary variables available for each field included relative elevation, topographic wetness index (TWI), soil type, latitude, longitude, and distance to the nearest tile line (Dist. tile) for each sampling point. Elevation was derived from a 1-m resolution LiDAR digital elevation model (DEM) of the site obtained from the Minnesota Geospatial Information Office (MnGeo, 2016). Topographic wetness index was calculated for each 1- by 1-m cell in the digital elevation model as $\ln(a \div \tan\beta)$, where a is the local upslope area draining through a certain point per unit of contour length (flow accumulation) and β is the local slope in radians (Sørensen et al., 2006). Flow accumulation was calculated with a D-infinity flow algorithm (Tarboton, 1997). A digital soil map was downloaded from the national Soil Survey Geographic database (Soil Survey Staff, 2016) and was used to classify the study area based on soil type. Latitude and longitude were calculated for each grid location. Distance to the nearest subsurface tile drainage line (in m) was calculated for each grid location by using digital maps of the tile drainage system obtained from the farm operator. This variable was calculated for both 2006 and 2015 to account for differences in drainage patterns as a result of tile line additions in 2009. Additional auxiliary rasters created for regression included irrigation (yes vs. no) and field (west vs. east). All auxiliary variables were resampled to 1-m resolution raster datasets for analysis.

Statistical Analysis

Linear regression models for predicting SOC stocks were developed with elevation, TWI, Dist. tile, soil type, irrigation, latitude, longitude, and field as predictors. Preliminary analysis revealed significant effects of year and depth on SOC stocks; therefore, a unique regression model was fitted for each depth within year. Shapiro–Wilk tests for normality revealed non-normal distributions for SOC stocks in the 30 to 60-cm and 60 to 90-cm layers. These data were square-root or log transformed to ensure normality for regression analysis. Testing for multicollinearity among predictors using the *vif* function in the "usdm" R package (Naimi, 2013) revealed that no predictors exhibited significant variance inflation (>3). Therefore, all predictors were included in the full model. Final regression models for kriging included only variables with $P \leq 0.1$ as determined by post-hoc ANOVA of the full regression model. Variograms were fit with the *autofitvariogram* function and kriging was conducted with the *autokrige* function in the "automap" R package (Hiemstra et al., 2009). All points were used for variogram construction and model fitting. As a result, cross-validation was done by leaving out one point at a time and kriging an estimated value at its location from the remaining samples (Isaaks and Srivastava, 1989; Pebesma, 2004). Cross-validation statistics included the root mean square error (RMSE) for prediction and the R^2 for observed versus predicted SOC stocks. When significant effects of field and irrigation were observed, we used the *extract* function in the "raster" R package to calculate mean SOC stocks for fields and irrigated vs. rain-fed areas by using polygons of the target areas. When no significant regression predictors were identified, mean SOC stocks were compared between years using paired *t*-tests. All analyses were conducted in R 3.3.0 (R Core Team, 2016).

RESULTS AND DISCUSSION

Summary of SOC Stocks and Auxiliary Variables

In 2006, SOC stocks ranged from 0.1 to 101.5 Mg C ha^{-1} across all depths, and mean SOC stocks were 65.4, 50.9, 36.6, and 15.8 Mg C ha^{-1} in the 0 to 15-, 15 to 30-, 30 to 60-, and 60 to 90-cm soil layers, respectively (Table 3). By 2015, SOC stocks ranged from 2.2 to 111.0 Mg C ha^{-1} across all depths, and mean SOC stocks were 67.0, 50.4, 41.4, and 19.8 Mg C ha^{-1} in the 0 to 15-, 15 to 30-, 30 to 60-, and 60 to 90-cm soil layers, respectively. Elevation ranged from 352.6 to 357.5 m across both fields, with a mean value of 355.8 m, and TWI ranged from 2.0 to 25.0 with a mean value of 7.5. In 2006, Dist. tile ranged from 0.9 to 214.2 m, with a mean value of 31.9 m. After the installation of new tile lines in 2009, Dist. tile ranged from less than 1 to 56.3 m, with a mean value of 13.8 m.

Table 3. Descriptive statistics for soil organic C (SOC) stocks and auxiliary variables at the study site in west central Minnesota.

Parameter	Min.	Mean	Med.	Max.	SD
2006 SOC					
0–15 cm, Mg ha^{-1} (n = 98)	28.2	65.4	65.5	101.5	13.0
15–30 cm, Mg ha^{-1} (n = 98)	21.5	50.9	50.1	86.7	14.7
30–60 cm, Mg ha^{-1} (n = 97)	0.1	36.6	37.2	101.8	21.6
60–90 cm, Mg ha^{-1} (n = 94)	0.1	15.8	13.9	70.4	14.2
2015 SOC					
0–15 cm, Mg ha^{-1} (n = 98)	47.3	67.0	66.5	96.0	9.2
15–30 cm, Mg ha^{-1} (n = 98)	18.4	50.4	50.5	81.5	13.7
30–60 cm, Mg ha^{-1} (n = 98)	7.9	41.4	38.8	111.0	18.2
60– 90 cm, Mg ha^{-1} (n = 98)	2.2	19.8	18.3	82.2	10.2
Elevation, m†	352.6	355.8	355.9	357.5	0.8
TWI	2.0	7.5	6.0	25.0	4.2
Dist. tile 2006, m	0.9	31.9	23.0	214.2	36.7
Dist. tile 2015, m	0.0	13.8	11.4	56.3	11.1

† n = 1274403 for elevation, topographic wetness index (TWI), and distance to the nearest tile line (Dist. tile) (797 × 1599 raster).

Regression Analysis

Regression analysis for the 0 to 15-cm layer indicated that elevation, TWI, and field were significant predictors of SOC stocks for both 2006 and 2015 (Table 4), and irrigation was a significant predictor for 2015. This pattern was repeated for 15 to 30-cm SOC stocks, except that field was not significant for 2006. Regression predictors accounted for 58, 55, 5%, and 48% of the variation in SOC stocks for the 2006 0 to 15-, 2015 0 to 15-, 2006 15 to 30-, and 2015 15 to 30-cm layers, respectively. Auxiliary variables had little ability to predict 2006 SOC stocks in the 30 to 60-cm and 60 to 90-cm soil layers. For 2015, soil type was a significant predictor for 30 to 60-cm and 60 to 90-cm SOC stocks, and Dist. tile was significant for 30 to 60-cm stocks only.

Table 4. Tests of fixed effects on soil organic C (SOC) stocks by soil layer and year at the study site in west central Minnesota

Effect†	df	0–15 cm				15–30 cm			
		2006		2015		2006		2015	
		F	*Pr (>F)*	*F*	*Pr (>F)*	*F*	*Pr (>F)*	*F*	*Pr (>F)*
Elevation	1	16.76	<0.001***	21.91	<0.001***	5.64	0.020**	11.96	<0.001***
TWI	1	10.25	0.002***	11.84	<0.001***	4.37	0.040**	5.01	0.028**
Field	1	19.2	<0.001***	4.5	0.022**	1.56	0.214	5.71	0.019**
Soil type	9	1.47	0.170	1.07	0.394	1.11	0.295	1.11	0.365
Irrigation	1	0.32	0.572	2.97	0.088*	0.02	0.883	4.09	0.046**
Dist. tile	1	0.12	0.735	0.05	0.829	0.67	0.416	0.79	0.374
Lat	1	0.03	0.864	0.67	0.413	0.01	0.933	0.04	0.852
Lon	1	0.18	0.669	0.44	0.509	0.56	0.456	0.08	0.777
		30–60 cm				**60–90 cm**			
		2006		**2015**		**2006**		**2015**	
		F	***Pr (>F)***	***F***	***Pr (>F)***	***F***	***Pr (>F)***	***F***	***Pr (>F)***
Elevation	1	0.27	0.612	1.41	0.238	0.00	0.946	0.15	0.698
TWI	1	1.49	0.226	0.45	0.504	0.82	0.367	0.21	0.644
Field	1	0.19	0.660	0.44	0.510	0.16	0.688	0.02	0.881
Soil type	9	1.51	0.158	2.50	0.014**	0.79	0.620	3.82	<0.001***
Irrigation	1	0.01	0.935	1.15	0.286	0.03	0.864	0.11	0.744
Dist. tile	1	0.03	0.861	3.39	0.069*	0.01	0.929	0.40	0.530
Lat	1	1.06	0.307	0.53	0.471	1.01	0.356	0.02	0.876
Lon	1	0.02	0.901	1.20	0.277	0.00	0.98	1.27	0.262

* Significant at the 0.1 probability level.

** Significant at the 0.05 probability level.

*** Significant at the 0.01 probability level.

† TWI, topographic wetness index; Dist. tile, distance to the nearest tile line.

Spatial Autocorrelation and Variogram Estimation

Spatial correlation structures of SOC stocks varied among depth layers and years as indicated by the fitted variogram model, sill, range, and nugget/sill ratio (Table 5). In 2015, the 15 to 30-cm SOC stock had a nugget/sill ratio larger than 0.96, indicating poor spatial correlation and a high degree of unexplained

Table 5. Parameters for omnidirectional semivariograms of soil organic C (SOC) stocks by year and soil layer at the study site in west central Minnesota.

Year	Layer	Fitted model†	Nugget	Sill	Range (m)	Nugget/Sill
2006	0–15 cm	Sph	30.0	108.4	171.6	0.28
	15–30 cm	Ste	0.0	193.6	68.2	0.0
	30–60 cm	Ste	391.1	402.9	605.4	0.97
	60–90 cm	Sph	184.7	185.5	697.8	1.0
2015	0–15 cm	Ste	0.0	60.2	72.2	0.0
	15–30 cm	Sph	123.1	127.8	404.6	0.96
	30–60 cm	Ste	239.9	248.0	100.8	0.97
	60–90 cm	Sph	61.4	67.4	102.4	0.90

† Sph, spherical model; Ste, Matern Stein's parameterization model.

variability (Cambardella et al., 1994). For all other 0 to 15-cm and 15 to 30-cm layer variograms, the nugget/sill ratio was below 0.30, indicating moderate to strong spatial correlation of SOC stocks. Variogram analysis indicated poor or no spatial correlation for SOC stocks in 30 to 60-cm and 60 to 90-cm soil layers.

Reported ranges for spatial correlation of SOC or soil organic matter vary widely depending on soil type, land use, and, as we have found here, also with soil depth. Typical SOC correlation ranges reported for agricultural soils are between 65 and 300 m, with nugget/sill ratios from 0 to 0.37 for samples up to 30 cm depth (Cambardella et al., 1994; Ping and Dobermann, 2006; Simbahan et al., 2006; Worsham et al., 2010; Sherpa et al., 2016). In the present study, the range varied from 68 to 172 m for variograms with well-structured spatial covariance (upper profile) and extended up to 698 m where the spatial structure was weak (below 30 cm). Spatial correlation of topsoil SOC in the present study was comparable to that in literature reports, but correlation declined with soil depth as indicated by increased range and nugget/sill ratio. Thus our sampling distance of 113 m provided adequate parameters for variogram estimation in the upper soil profile (to 30 cm) but was insufficient for the deeper soil layers.

Predicted SOC Stocks and Changes over Time

In the 0 to 15-cm layer, predicted SOC stocks in 2006 ranged from 30.7 to 107.0 Mg C ha^{-1}, with the highest values associated with areas of low elevation and high TWI (Fig. 2a). For instance, the highest SOC value of 107.0 Mg C ha^{-1} was predicted in the east field, where the relative elevation was 355.2 m and TWI was 23, representing the 20th and 99th percentiles for these data, respectively. Conversely, the lowest SOC value of 30.7 Mg C ha^{-1} was predicted in the west field, where the elevation was 356.6 m and TWI was 3, representing the 88th and third percentile, respectively. Mean SOC stocks in the 0 to 15-cm layer were calculated for each field, and stocks were greater in the east (73.3 Mg C ha^{-1}) than in the west field (60.5 Mg C ha^{-1}). According to the landowner, historical management of these two fields was very similar, dating back to the early 1970s. However, estimates of 2006 SOC stocks differed by nearly 13 Mg C ha^{-1}, which suggests either drastic differences in agronomic management prior to initiation of the study or some unimagined presettlement difference between fields.

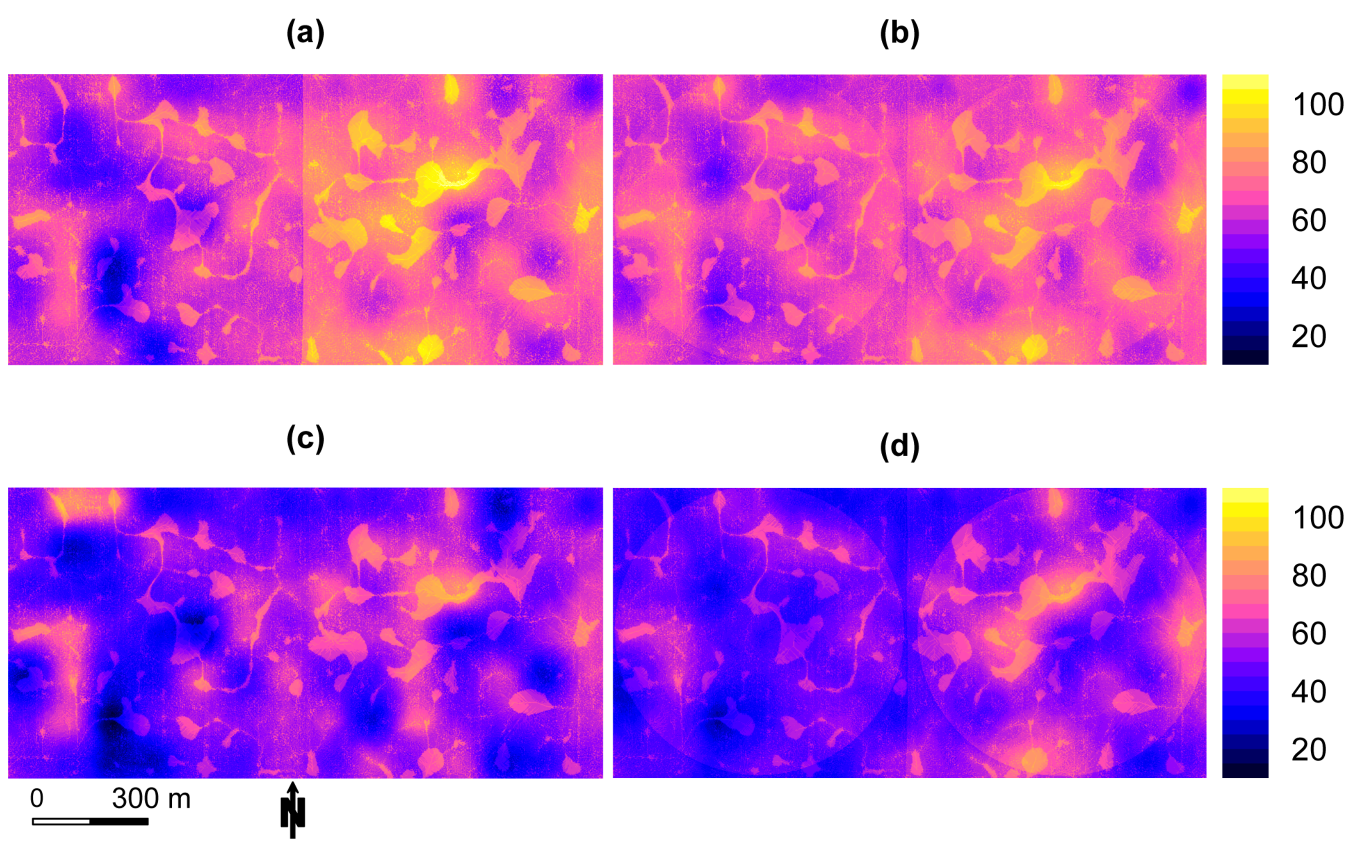

Fig. 2. Maps of regression-kriged soil organic C (SOC) stocks (Mg C ha^{-1}) for the 0 to 15-cm soil layer in (a) 2006 and (b) 2015, and for the 15 to 30-cm soil layer in (c) 2006 and (d) 2015.

Strong relationships between SOC and terrain attributes can be found throughout the literature because of the direct impact of terrain on water flow and soil moisture patterns (e.g., Moore et al., 1993; Sumfleth and Duttmann, 2008; Pei et al., 2010). Soil moisture patterns regulate microbial metabolism and rates of decomposition (Linn and Doran, 1984) and, in doing so, also exert significant influence on SOC dynamics (Parton et al., 1987; Burke et al., 1989). Topographic wetness index quantitatively represents the balance between water accumulation and drainage conditions at the local scale, with increasing values representing greater water accumulation (Pei et al., 2010). As such, it represents long-term soil moisture patterns and therefore closely relates to SOC dynamics, as we and others have found. For example, Moore et al. (1993) found that TWI was positively correlated ($r = 0.57$) with soil organic matter in a northeastern Colorado agroecosystem, which is consistent with our findings here.

By 2015, predicted SOC stocks in the 0 to 15-cm layer ranged from 42.2 to 108.9 Mg ha^{-1}, and mean stocks remained greater in the east (71.3 Mg C ha^{-1}) than in the west field (65.0 Mg C ha^{-1}; (Fig. 2b). However, SOC stocks in the west field have increased since 2006 (+4.5 ± 4.2 Mg C ha^{-1}) but there was no detectable change in the east field (−2.0 ± 3.7 Mg C ha^{-1}) over the study period (Fig. 3a). The increase in the west field was caused by SOC gain in the irrigated portion of the field (+5.3 ± 4.3 Mg C ha^{-1}), whereas no change was observed in the rain-fed pivot corners (+1.6 ± 3.5 Mg C ha^{-1}). In contrast, no effect of irrigation was observed in the east field, where, on average, irrigation rates exceeded those of the west field by 45 mm yr^{-1}. Soil organic C gains in the west field appear to be greatest in locations where SOC was lowest in 2006 (i.e., areas of relatively high elevation and low TWI). Similarly, the areas of highest SOC in the east field appeared to lose SOC over the study period, whereas those low in SOC showed slight gains. Rapid gains in SOC on the top slopes suggest that these areas were previously depleted. These gains may be related to improved soil stabilization and reduced erosional transfer of organic matter to lower slope positions, particularly in the west field, where alfalfa and a rye cover crop were integrated into the rotation.

Differing effects of irrigation between fields are likely to be related to differences in the size of the initial C stocks and irrigation rates. Soils with relatively low SOC tend to respond more rapidly to management than those near equilibrium (Sartori and Lal, 2006). For example, after 15 yr of irrigation in Nebraska, Lueking and Schepers (1985) reported an increase of 0.11 Mg C ha^{-1} yr^{-1} for sandy soils with low C content. However, in C-rich soils, Dersch and Böhm (2001) found that 21 yr of irrigation in Austria decreased SOC by between 0.04 and 0.13 Mg C ha^{-1} yr^{-1}, which they attributed to a higher mineralization rate under the wetter soil conditions. Our findings are consistent with the aforementioned studies in that overall SOC gain was only found in the west field where initial SOC was relatively low and irrigation rates were low compared with the east field. In the east field, higher irrigation resulted in a net C balance that was neutral or perhaps slightly negative, similar to the findings of Dersch and Böhm (2001).

In the 15 to 30-cm layer, predicted SOC stocks in 2006 ranged from 11.9 to 96.6 Mg C ha^{-1}, which was generally lower than topsoil SOC stocks but with similar spatial patterns in relation to elevation and TWI (Fig. 2c). Mean SOC stocks were similar in the east and west fields (mean of 52.3 Mg C ha^{-1}). By 2015, predicted SOC stocks ranged from 24.7 to 86.7 Mg C ha^{-1} (Fig. 2d) and mean SOC stocks were greater in the east (55.8 Mg C ha^{-1}) than in the west field (46.8 Mg C ha^{-1}). No change in SOC stocks was observed in the east (+0.27 ± 5.6 Mg C ha^{-1}) or west fields (−2.1 ± 6.3 Mg C ha^{-1}) over the study period (Fig. 3b). However, when averaged across fields, mean SOC stocks were greater in irrigated (52.9 Mg C ha^{-1}) than in the rain-fed areas (46.2 Mg C ha^{-1}) by 2015. Soil organic C gains in the 15 to 30-cm layer occurred where the initial SOC was high, whereas the losses occurred where the initial SOC was low. This is in contrast to the topsoil layer, where gains were found in areas of low initial SOC.

The application of geostatistical techniques requires data that exhibit a spatial structure (Trangmar et al., 1986). Therefore, no spatial interpolation was conducted for SOC stocks in 30 to 60-cm and 60 to 90-cm soil layers because of the lack of spatial correlation among observations and the poor ability of auxiliary variables to predict SOC stocks. Consequently, simple means

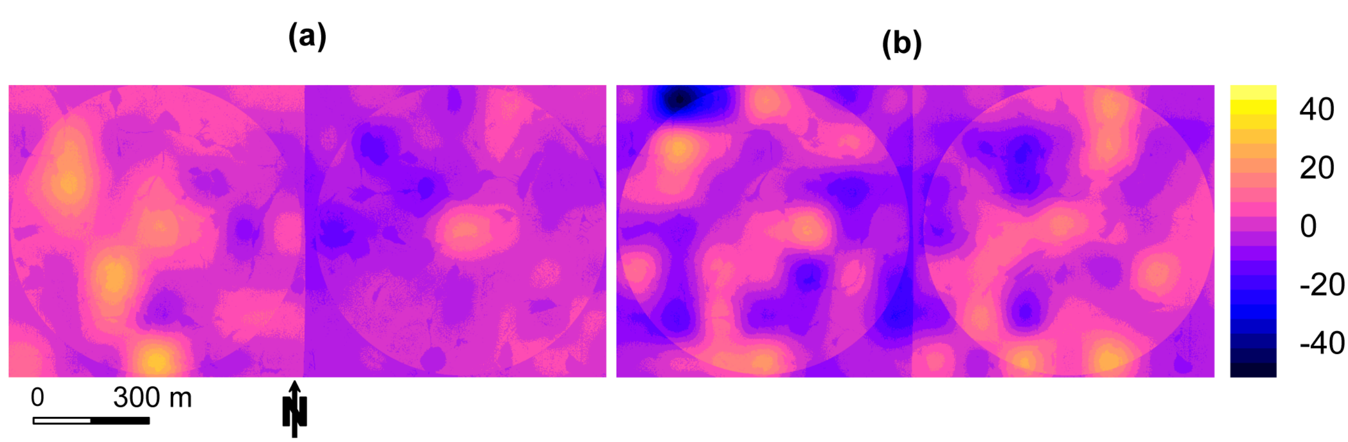

Fig. 3. Maps of changes in regression-kriged soil organic C (SOC) stocks (Mg C ha^{-1}) at the study site from 2006 to 2015 for (a) the 0 to 15-cm soil layer and (b) the 15 to 30-cm soil layer.

were used to calculate SOC stocks in these layers for each year, and differences between years were determined with paired t-tests. Over the entire study area, mean SOC stocks in the 30 to 60-cm layer increased from 36.7 Mg C ha^{-1} in 2006 to 41.4 Mg C ha^{-1} in 2015 ($t = 2.35$, $p = 0.021$), a gain of 4.7 Mg C ha^{-1}. Similarly, SOC stocks in the 60 to 90-cm soil layer increased from 15.9 to 19.8 Mg C ha^{-1} over the study period ($t = 3.14$, $p = 0.002$), a gain of 3.9 Mg C ha^{-1}. Regression models for 2015 SOC stocks in the 30 to 60-cm and 60 to 90-cm soil layers were improved with the inclusion of a term for soil type. However, no significant differences in SOC stocks were observed among soil types.

The lack of spatial interpolation in lower soil layers precludes an analysis of SOC change across depths (0–90 cm); summation of sample point data from deeper layers with interpolated raster data from upper layers would be methodologically unsound. Hence, we cannot provide confidence-bounded estimates of SOC change across the entire sampled profile. However, for the sake of discussion, we consider that SOC stock in the west field increased in all but the 15 to 30-cm layer, gaining 13.1 Mg C ha^{-1} across the other three layers. The east field showed relatively stable SOC in the top two layers, whereas the deeper two layers gained a combined 8.6 Mg C ha^{-1}. These gains suggest that typical field management practices associated with large, modern dairies can indeed sequester SOC. Both manure application (Sommerfeldt et al., 1988; Maillard and Angers, 2014) and irrigation (Lueking and Schepers, 1985; Denef et al., 2008) are commonly shown to increase surface soil SOC under certain conditions. Reports of increased SOC in deeper soil layers in response to these factors are less common. However, Mikha et al. (2017) recently showed that long-term manure applications increased total SOC to 90 cm depth and increased mineral-associated organic matter C up to 30 cm depth relative to mineral fertilizer applications on a cropped very-fine sandy loam soil in Nebraska. The authors also showed that the fraction of total SOC associated with mineral-associated organic matter C increases with soil depth, especially in manured systems. Application of liquid dairy manure can increase dissolved organic C leaching through the soil profile (Royer et al., 2007), as can any activities that stimulate mineralization of organic matter (Kalbitz et al., 2000), such as irrigation. In subsoil horizons with low C contents, dissolved organic C leached from the topsoil may be adsorbed strongly to mineral surfaces (Kalbitz et al., 2000). Thus the changes in deep soil layers observed in the present study may be related to movement of dissolved organic C through the profile as a result of liquid manure application and irrigation.

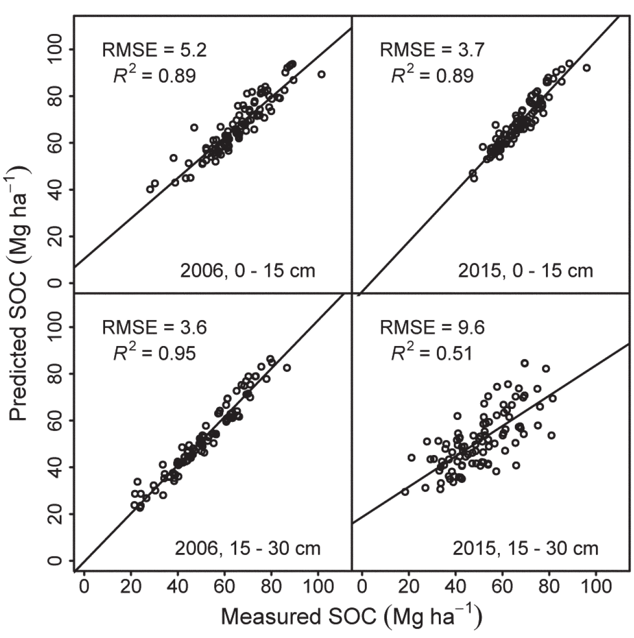

Fig. 4. Comparison of predicted and measured soil organic C (SOC) stocks (Mg C ha^{-1}) by year for 0 to 15-cm (top panels) and 15 to 30-cm (bottom panels) soil layers.

In the upper soil layers, manure application method and cropping differences probably played a role in the observed differences between fields. Manure was digested prior to application in most years (2009–2015). This reduces the amount of readily oxidizable C in the slurry, leaving behind more recalcitrant C compounds (Holly et al., 2017). Undoubtedly, this results in less initial decomposition following manure application and probably expedites the formation of soil organic matter relative to undigested manures. Powlson et al. (2012) found that SOC gain was threefold greater using digested biosolids than raw farm manures in a long-term study in the UK. The authors attributed this to the recalcitrance of C in biosolids, reflecting the greater degree of decomposition that had already occurred during the digestion process. We suggest that injection of manure slurry deeper into the profile may further assist in the physical protection of recalcitrant C compounds; this may be part of the reason why we observed greater SOC gain in the west field. Finally, alfalfa root biomass and rhizodeposition surely contributed to gains in SOC in the west field. In as little as 3 yr, alfalfa can increase soil aggregation and SOC relative to corn cropping (Angers, 1992).

Cross-validation

Leave-one-out cross-validation showed excellent predictive ability for SOC stocks in the 0 to 15-cm layer, with $R^2 = 0.89$ for both 2006 and 2015 (Fig. 4). For the 15 to 30-cm layer, the R^2 between observed and predicted SOC stock was also high in 2006 ($R^2 = 0.95$) but was substantially lower for 2015 ($R^2 = 0.51$). The root mean square error of prediction ranged from 3.6 to 9.2 Mg C ha^{-1}, and was highest for the 15 to 30-cm layer in 2015. Cross-validation was not conducted for 30 to 60-cm and 60 to 90-cm soil layers, since SOC stocks were estimated with simple means.

The prediction performance of regression kriging depends, in part, on the relationship between the target variable and the explanatory co-variables. The closer the dependency and the more systematically the primary variables vary across the landscape, the more the prediction performance of the regression kriging model increases (Sumfleth and Duttmann, 2008). Elevation, TWI, field, and irrigation showed strong systematic variation with SOC at our study site, which contributed to the very high prediction efficiency of the analyses here. However, prediction performance also depends on the degree of spatial correlation. Soil properties with a strong spatial structure can be mapped more accurately than those with a weak structure (Kravchenko, 2003). This was evident for the 2015 15 to 30-cm layer, where poor predictive ability and high error clearly resulted from poor spatial correlation, in spite of the fact that regression predictors accounted for nearly half of the variability in SOC stocks. Sumfleth and Duttmann (2008) note that strong spatial dependences are usually caused by intrinsic factors (e.g., soil type, terrain), but can be weakened by extrinsic factors such as soil management and tillage practices. Management practices, especially irrigation and tile drainage, probably contributed to a homogenization of SOC over the study period, which would, in turn, reduce spatial correlation and prediction performance in this layer.

CONCLUSIONS

Ongoing efforts to mitigate GHG emissions and adapt to shifts in climate require the ability to accurately and cost-effectively verify changes in SOC stocks. Our results show that regression kriging with easily acquired auxiliary variables offers a highly accurate method of monitoring SOC stock changes to 30-cm depth in this agroecosystem, where the spatial distribution of SOC corresponded closely with elevation, TWI, and irrigation. High-resolution LiDAR data are readily available for all of Minnesota and a number of other states, and the relevant variables used here are easily derived. Future research should evaluate the potential of regression kriging with this data for accurately quantifying management-induced SOC changes at a broader variety of sites and spatial scales. For deeper soil increments, a lack of spatial structure and lack of relationships between SOC stocks and auxiliary variables was found, suggesting that high sampling densities or alternative interpolation techniques are required to monitor SOC changes. Finally, after 10 yr of monitoring, SOC stocks to 90 cm depth have been maintained or increased at this farm, suggesting that typical field management practices associated with large, modern dairies can sequester SOC.

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