Precision Agriculture
https://doi.org/10.1007/s11119-018-9593-2

Predicting spatial structure of soil physical and chemical properties of golf course fairways using an apparent electrical conductivity sensor

Rebecca A. Grubbs[1] · Chase M. Straw[1] · William J. Bowling[1] · David E. Radcliffe[1] · Zach Taylor[2] · Gerald M. Henry[1]

Received: 13 September 2017 / Accepted: 9 July 2018

Abstract

Soil apparent electrical conductivity (EC_a) has been used to map spatial variability of soil properties in multiple cropping systems and may have applications in precision turfgrass management (PTM). The objective of this research was to determine whether EC_a data could predict the spatial structure of soil properties relevant to turfgrass management. Research was conducted at the University of Georgia (UGA) and the Georgia Club (GC) golf courses in North GA during the summer of 2016. A mobile Veris Q1000 device was used to collect georeferenced EC_a data from six golf course fairways (three per course). Soil samples were collected from each fairway using a georeferenced grid to determine clay content, soil pH, cation exchange capacity (CEC) and organic matter (OM). To understand the predictive relationship between EC_a and soil properties, correlation coefficients and multiple linear regression models were generated for each fairway. Spatial maps were used to visually demonstrate these relationships. Though some relationships were observed between EC_a and soil properties (primarily clay, soil pH and OM on the UGA course), measured parameters were insufficient to fully explain spatial variability in EC_a. Findings from this study suggest that spatial variability of soil properties in turfgrass can be significant enough to warrant PTM. Though EC_a may be used to partially predict clay content, CEC, OM and soil pH, additional research is required to better understand EC_a variability and its applications for PTM. Future research exploring EC_a for PTM should consider the roles of soil moisture, temporal variability and topography.

Keywords Cation exchange capacity · Clay content · Organic matter · Precision turfgrass management · Soil apparent electrical conductivity · Soil pH

✉ Gerald M. Henry
gmhenry@uga.edu

[1] Department of Crop and Soil Sci, University of Georgia, 3111 Miller Plant Science Building, Athens, GA 30602, USA

[2] Helena Chemical Company, 225 Schilling Blvd., Suite 300, Collierville, TN 38017, USA

Introduction

As of 2010, the number of golf courses worldwide was estimated to be upwards of approximately 32,000, covering between 19,200 and 25,600 km^2 of land (Bartlett and James 2011). Though small compared to many agricultural cropping systems, golf courses tend to be concentrated around urban ecosystems and can have a significant impact on urban air and water quality. Traditional golf course management relies heavily on supplemental fertility to support healthy vegetative growth, since biogeochemical cycling in urban soils is often disrupted by anthropogenic activity that limits nutrient availability (Cheng and Grewal 2009; Milesi et al. 2005; van Delden et al. 2016). Poor understanding of turfgrass nutrient requirements can lead to fertilizer mismanagement and subsequent water and air pollution through leaching, runoff and volatilization of harmful trace gases (Bartlett and James 2011; Milesi et al. 2005; Qian et al. 2003). On the other hand, nutrient deficiencies resulting from low fertility could lead to stunted vegetative growth, tissue chlorosis, as well as eventual necrosis and potential plant death (Carrow et al. 2001; Havlin et al. 2005). Even small nutrient imbalances can have large consequences for turfgrass managers, since they may compromise aesthetic quality, stress tolerance and overall playability.

The implementation of precision agriculture (PA) may optimize nutrient management (Corwin and Lesch 2003; Rhoades et al. 1999). In PA, site-specific management units (SSMUs) are delineated in accordance with the spatial distribution of soil properties that ultimately affect management needs. These same principles are now being applied to turfgrass systems under the name precision turfgrass management (PTM) (Carrow et al. 2010; Ganjegunte et al. 2013; Straw et al. 2016; Straw and Henry 2017). Similar to PA, PTM affords turfgrass managers the opportunity to improve input efficiency, thereby fostering environmental stewardship on large-scale turfgrass production (Carrow et al. 2010). One of the greatest challenges to implementing PA and PTM is that soil sampling procedures are both costly and time-consuming, rendering them impractical when mapping soil spatial heterogeneity (Allred et al. 2008). As such, alternative methods of data collection are employed to provide faster, more efficient methods for predicting spatial distribution of soil properties.

In recent years, quantification of apparent electrical conductivity (EC_a) has been used as a minimally-invasive method for predicting spatial patterns of soil properties important to crop management. It is well-established in the literature that EC_a is effective at producing accurate, large-volume measurements that have practical applications for PA (Cho et al. 2016; Corwin and Lesch 2003; Huang et al. 2016; Pedrera-Parrilla et al. 2016a; Stadler et al. 2015). The EC_a measures conductance through solid soil particles and via exchangeable cations in the solid–liquid interface of clay minerals in addition to the soil solution (Corwin and Lesch 2003; Rhoades et al. 1999).

The presence of exchangeable cations in a given volume of soil is primarily a reflection of soil composition. Specifically, EC_a tends to be positively correlated with soil colloids such as clay particles or organic matter, which will have a greater cation exchange capacity (CEC) (Brady and Weil 2008; Havlin et al. 2005). As a result, in non-saline soils, EC_a has been positively correlated with both clay content (Cho et al. 2016; Fulton et al. 2011; Stadler et al. 2015; Pedrera-Parrilla et al. 2016b) and organic carbon (Gholizadeh et al. 2011). However, in some cases, these relationships are not always consistent (Cho et al. 2016; Stadler et al. 2015). The predominant influence of one property, such as organic matter or soil moisture, may impede the ability to accurately measure another variable such as clay content (Stadler et al. 2015).

The relative concentration and composition of the soil solution, as influenced by soil texture and management practices, can also directly influence conductance by changing the concentration and composition of ions in the soil profile (Corwin and Lesch 2003). As such, EC_a has also been positively correlated to soil moisture (Pedrera-Parrilla et al. 2016b), and saturated hydraulic conductivity (Rezaei et al. 2016). Soil chemical properties, such as pH will further influence conductance by determining the solubility of ionic compounds present.

The applications of EC_a in PTM have centered primarily on salinity management and site-specific leaching (Carrow et al. 2010; Ganjegunte et al. 2013; Krum et al. 2011). There is currently little to no research exploring the relationship between EC_a and other soil properties in turfgrass systems. The continuous surface of vegetation indicative of turfgrass systems presents a unique challenge to precision management, which limits data collection methods to those that are relatively non-invasive. In addition to this, turfgrass management practices contribute to a unique subsurface soil profile. The lack of regular cultivation in turfgrass systems can result in a more pronounced organic matter layer which can inhibit EC_a mapping of subsurface zones in turfgrass systems when compared to agricultural soils without a crop cover (Krum et al. 2011).

The two primary geophysical survey methods employed to measure EC_a are electromagnetic induction (EMI) and electrical resistivity (ER) (Allred et al. 2008). In general, EMI devices are considered non-invasive, because they do not penetrate the soil to collect data, unlike some ER devices which will directly inject electrodes into the surface. Consequently, previous research on EC_a in turfgrass systems has exclusively focused on EMI devices to avoid potential surface damage (Krum et al. 2011). However, in a study comparing the Veris device with an EMI sensor, Serrano et al. (2014) found that Veris devices may be more appropriate than non-invasive EMI devices for measuring soil properties when a vegetative layer is present, as the vegetation may mask soil properties. Veris devices (Veris Technologies, Salina, KS, USA) consist of cart-mounted coulters (discs) that function as four equally-spaced electrodes (referred to as a 4-Wenner array). Several units have been modified to penetrate the soil at a shallower depth of approximately 20 mm and collect measurements for the uppermost 0.3–0.4 m of the soil profile where most turfgrass roots are concentrated. The utilization of this Veris device may make it possible to establish relationships between EC_a and soil properties in turfgrass, expanding its potential applications in PTM beyond measurements of soil salinity. The objective of this research was to determine whether the modified Veris device and EC_a data could be used to accurately predict the spatial structure of soil properties relevant to nutrient management in turfgrass systems (clay content, soil pH, CEC and OM).

Materials and methods

Site descriptions

Research was conducted at the University of Georgia (UGA) golf course in Athens, GA and the Georgia Club (GC) golf course in Statham, GA during the summer of 2016. Six fairways were selected (three per course). Individual fairways ranged from approximately 4000–8000 m^2 in area and were chosen to reflect changes in topography that may impact the spatial distribution of soil physical and chemical properties relevant to soil fertility. Fairways at UGA (F1, F2 and F3) and GC (F4, F5 and F6) were comprised of 'Tifway 419' hybrid bermudagrass [*Cynodon dactylon* L. (Pers.) × *C. transvaalensis* Burtt-Davy] established on native soil.

The UGA golf course was originally developed in 1968 and was extensively renovated in 2006; however, many of the fairways still reflect the original design. Soils for UGA fairways are classified as Pacolet sandy clay loams (severely eroded) with small sections of Cecil sandy loam (moderately eroded). Fairways were irrigated with an automated irrigation system as a supplement to rainfall. Fertility was applied in the spring as a combination of slow-release urea formaldehyde and conventional urea fertilizers at a rate of 48–96 kg N ha^{-1}. Micronutrients (Fe and Mg) were applied as needed.

The GC golf course has 27 holes and was built in two stages. Two fairways (F5 and F6) were constructed and established in 1999–2000, while F4 was established in 2005. Predominant soil classifications at GC were unique to each fairway, and included Pacolet sandy clay loam with moderate to severe erosion (F4), Cartecay and Chewacla soils (F5), and Madison sandy clay loam with moderate erosion (F6). Fairways were irrigated with an automated irrigation system as a supplement to rainfall. Fertility was applied as a slow-release urea–formaldehyde fertilizer (37-0-0) at a rate of 86 kg N ha^{-1}. A plant growth regulator (trinexapac-ethyl) with a liquid iron (Fe) fertilizer was applied intermittently throughout each growing season.

EC_a surveys

A 4-disc Veris Q1000 Soil EC Mapping System was used to collect EC_a data (mS m^{-1}) for each fairway. Veris devices measure resistivity (ρ, ω m^{-1}) using an electrode configuration referred to as the Wenner array given by the equation (Burger 1992):

$$\rho = \frac{2\pi a \Delta V}{i} = 2\pi a R \tag{1}$$

where V is the voltage, α is the inter-electrode spacing, i is the electrical current (A) and R is the measured resistance defined as one ohm (ω) of resistance that allows a current of one ampere to flow when a single volt of electromotive force is applied. Since EC_a is simply the inverse of ρ, the equation for EC_a in relation to resistivity can be written as:

$$EC_a = \frac{1}{2\pi a R} \tag{2}$$

The device was towed behind a utility vehicle which traversed each fairway at a speed of approximately 16–25 km h^{-1} and collected measurements at a rate of 1 Hz. The number of data points varied according to fairway size and shape, but ranged from 253–570 for a total of 2493 points across all fairways. Device discs penetrated the ground at a depth of approximately 20 mm and collected EC_a measurements from the uppermost 0.3–0.4 m of the soil profile. For comparison purposes, EC_a is generally expressed by devices such as this at a reference temperature of 25 °C (Corwin and Lesch 2005a). Relative, rather than absolute, EC_a values are what allows for the identification of contrasting soil zones. In order to guarantee relatively uniform soil temperature conditions, EC_a data were collected from all six fairways on the same day. A global positioning system (GPS) receiver (Trimble EZ Guide 250 of Trimble, Sunnyvale, CA, USA) with an upgraded antenna for differential GPS was used in conjunction with the mobile device to simultaneously log EC_a and geographical coordinates. Resulting shapefiles were subsequently imported into ArcGIS (Esri, Redlands, CA, USA) for geospatial analysis.

Soil sampling and analysis

Corresponding soil sampling grids for each fairway were generated in Geospatial Modeling Environment (Spatial Ecology LLC, St. Lucia, QLD, Australia) using a specified grid spacing of 7 m × 7 m. Maps featuring EC_a survey points versus soil sampling grid points for F4 are presented in Fig. 1 as visual examples of each sampling distribution. The total number of soil sample points per fairway varied according to fairway size, but ranged from 80 to 128 points per fairway for a total of 643 samples across all fairways. Each sampling grid was subsequently imported into a GPS receiver (Trimble GPS Geoexplorer 6000) using ArcPad 10 mapping software (Esri, Redlands, CA, USA). Composite samples of 10–15 soil cores (≈ 20 mm in diameter pulled to a 0.1-m depth) were collected within a 0.3-m radius of each georeferenced point. Intact cores were collected in 0.95-l plastic bags and were immediately frozen to preserve core integrity. Individual soil samples were air-dried for 48 h, sieved through a 2-mm mesh and shipped to Waypoint Analytical Labs in Memphis, TN, USA for soil analysis.

Soil samples were analyzed for CEC, pH and OM. Particle-size analysis (% sand, silt and clay) was completed using the hydrometer method to determine soil texture (Bouyoucos 1936; Day 1965). Soil pH was determined using methods outlined by Eckert and Sims (2009). However, deionized water was used in lieu of $CaCl_2$ solution. Determination of OM was completed through loss on ignition (Schulte and Hoskins 2009), with the soil heated at 400 °C instead of 360 °C. Macronutrients (K, Ca and Mg) were extracted using the Mehlich 3 extraction procedure (Mehlich 1984). Cation exchange capacity (meq 100 g^{-1}) was subsequently calculated from the sum of Ca, Mg and K obtained (ppm) using the following equation from Ross and Ketterings (1995):

$$CEC_{sum}\left(\frac{meq}{100g\ or\ cmol_c kg^{-1}}\right) = \left(\frac{ppm\ Ca}{200}\right) + \left(\frac{ppm\ Mg}{120}\right) + \left(\frac{ppm\ K}{390}\right) \tag{3}$$

EC_a semivariogram analysis and kriging

ArcMap 10.3.1 mapping software (Esri), RStudio version 3.2.1 (RStudio, Inc., Boston, MA, USA) and SAS 9.4 (SAS Institute Inc., Cary, NC, USA) were used to develop, display, analyze and interpret the data. All analyses conducted in ArcMap utilized the projected coordinate system NAD 1983 State Plane Georgia East FIPS 1001. Descriptive statistics [mean, min, max, standard deviation and coefficient of variability (CV)] were produced for all sampled fairways to evaluate central tendency and variability of the data for individual soil properties.

Spatial maps were created for both apparent electrical conductivity point data and corresponding soil sampling grids. These maps were used to visualize and compare spatial variability of clay content (%), EC_a (mS m^{-1}), soil OM (%) and CEC (meq 100 g^{-1}). Soil sample and EC_a data collected by the Veris Q1000 were interpolated using ordinary point kriging (Schabenberger and Pierce 2001). Kriging is a geostatistical technique that determines the best combination of weights for interpolation using the spatial parameters (range, nugget and sill) of an experimental semivariogram (Fortin and Dale 2005). Semivariogram parameters were calculated using the VARIOGRAM Procedure in SAS 9.4 to depict the spatial autocorrelation of measured points for each parameter (clay content, OM, CEC, pH and EC_a) on each fairway. Models with Gaussian, spherical or exponential

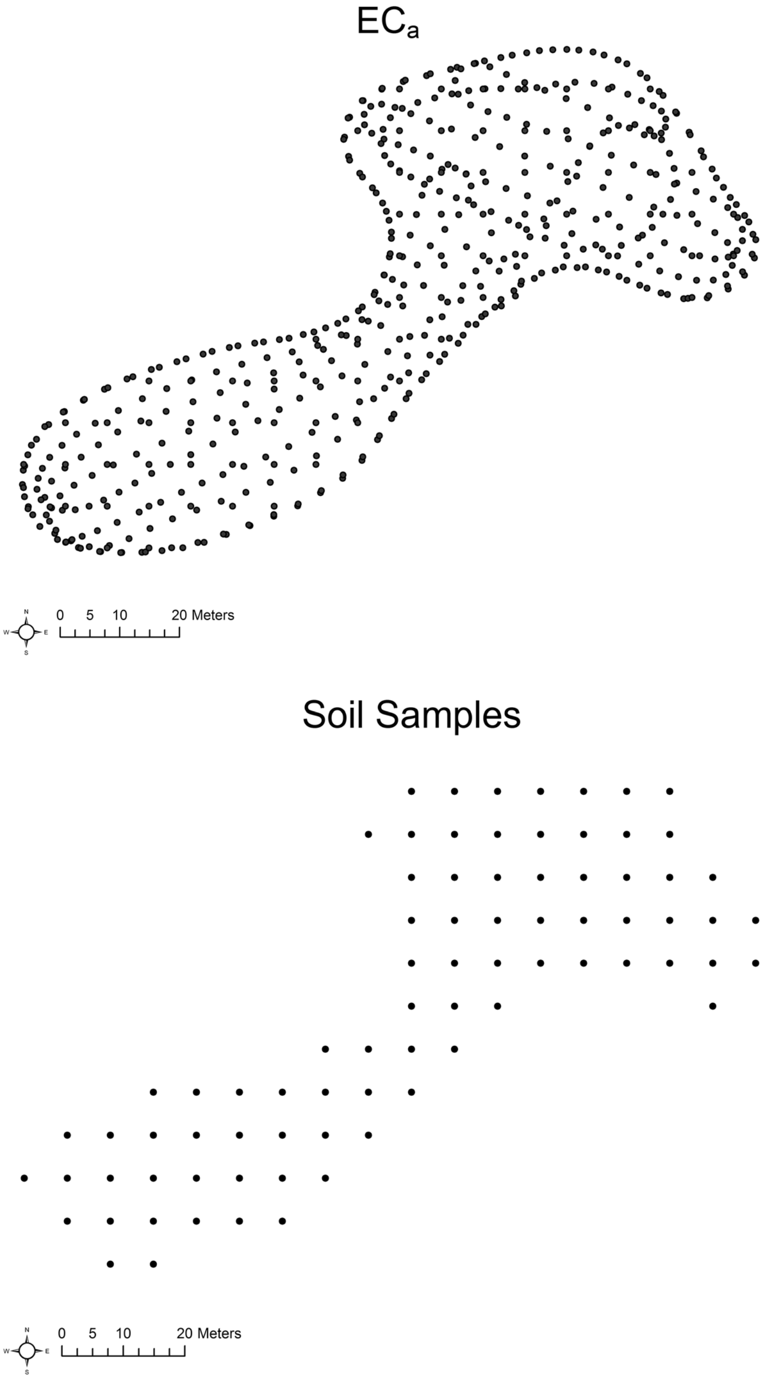

Fig. 1 Geo-referenced sample locations for apparent electrical conductivity (EC_a) data collected by the Veris Q1000 unit, and soil samples collected by hand on Fairway 4 (F4) at the Georgia Club Golf Course in Statham, GA in 2016

structures were selected for all fairways and the best parameters determined according to lowest Akaike information criterion (AIC). Lag sizes were determined either by sample grid spacing when uniform (clay content, pH, CEC and OM) or by calculating the average 'Nearest Neighbor' in ArcMap for more irregular sampling schemes (EC_a data). Semivariograms were subsequently plotted in ArcMap using the Geostatistical Analyst tool when preparing spatial maps.

Because EC_a sample points did not overlap directly with soil sampling points, estimated EC_a values were extracted from each EC_a spatial map to soil sampling points using the 'Extract Values to Points' feature in ArcMap. This made it possible to evaluate the relationship between EC_a and soil physical and chemical properties (clay content, pH, CEC and OM) more directly. The 'modified.ttest' function in the SpatialPack package of RStudio version 3.2.1 was used to calculate a corrected Pearson's r correlation coefficient that accounted for spatial autocorrelation between soil properties (Osorio et al. 2018). When evaluating spatially autocorrelated data, standard statistical tests can show a bias effect where the coefficient is deemed significant more often than it should be (Legendre 1993). The corrected Pearson's r correlation coefficient is more conservative to provide a more accurate declaration of significance. In cases where data distributions were not normal, modified t-tests were conducted on ranked data sets to adjust for skewness.

Multiple linear regression models were determined for UGA and GC to predict EC_a based on clay content, pH, CEC and OM using the generalized least squares ('gls') function in the 'nlme' package of RStudio (Pinheiro et al. 2015). Several temporary models were first constructed prior to the final model. First, a comparative stepwise forward and backward variable selection procedure was used to determine an initial model for each fairway. Only those parameters that exhibited a relationship with EC_a ($r > |0.1|$) were considered in each model. The stepwise procedure relies upon an AIC, which will penalize the number of explanatory variables to prevent overfitting the model. A temporary semivariogram was fit to the residuals of this model, and the forward–backward selection process was repeated using a fixed spatial autocorrelation structure. Multiple spatial correlation structures (Gaussian, spherical, exponential and linear) were incorporated into the residual patterns. Models with Gaussian or exponential correlation structures were selected for all fairways and parameters according to lowest AIC. The correlation of residuals is determined by the distance between all pairs of data points. After re-fitting the variogram to each mixed model, final models were re-estimated with the final variogram of the residuals. Simple regression models were also determined to predict CEC from OM to demonstrate the importance of OM in determining nutrient availability in turfgrass systems. To visually demonstrate the efficacy of each model, scatter plots showing Predicted EC_a v. Measured EC_a were produced for each fairway with an adjusted R^2 value.

Results

Descriptive statistics and kriged maps Descriptive statistics for soil and sensor data are summarized in Tables 1 and 2. Average soil EC_a was slightly higher at GC ($\bar{x}=6.6$ mS m^{-1}) compared to UGA ($\bar{x}=4.8$ mS m^{-1}). The UGA location exhibited more spatial variability in EC_a with a range of 15.4 mS m^{-1} and a CV of 37.7% compared to a range of 14.2 mS m^{-1} and a CV of 32.5% at GC. Mean clay contents for UGA and GC were 15% and 9%, respectively. Ranges in clay content at each course were comparable (26% at UGA and 24% at GC). However, clay content at GC had a higher coefficient of variation (49.0%) than

Table 1 Descriptive statistics for EC_a^a (mS m^{-1}), clay content (%), soil pH, CEC (meq 100 g^{-1}), and OM (%) at the University of Georgia golf course in Athens, GA in 2016

	Fairway	Sample size	Min	Max	Range	Mean	Standard deviation	CV (%)
			mS m^{-1}					
EC_a	1	253	1.4	8.8	7.4	4.1	1.4	34.4
	2	293	1.3	16.7	15.4	4.4	1.9	43.6
	3	427	1.6	10.5	8.9	5.5	1.7	31.0
	Course[b]	**973**	**1.3**	**16.7**	**15.4**	4.8	**1.8**	**37.7**
Clay			%					
	1	93	2	26	24	14	5.5	39.0
	2	87	4	28	24	14	4.0	28.8
	3	147	6	27	21	16	4.2	25.5
pH	**Course**	**327**	**2**	**28**	**26**	15	**4.7**	**31.1**
	1	93	5.0	6.0	1.0	5.4	0.2	3.1
	2	87	5.1	6.4	1.3	5.5	0.2	4.4
	3	147	5.0	6.2	1.2	5.5	0.2	3.6
	Course	**327**	**5.0**	**6.4**	**1.4**	**5.5**	**0.2**	**3.8**
			meq 100 g^{-1}					
CEC	1	93	3.4	7.2	3.8	4.8	0.9	18.1
	2	87	3.5	9.6	6.1	6.1	1.0	17.2
	3	147	3.4	8.8	5.4	6.0	0.9	15.1
	Course	**327**	**3.4**	**9.6**	**6.2**	**5.7**	**1.1**	**19.2**
			%					
OM	1	93	3.8	8.2	4.4	5.1	0.9	18.3
	2	87	4.1	9.3	5.2	6.0	1.0	16.7
	3	147	3.1	10.3	7.2	5.9	1.2	20.7
	Course	**327**	**3.1**	**10.3**	**7.2**	**5.7**	**1.1**	**20.1**

[a]Abbreviations: EC_a apparent electrical conductivity; *OM* organic matter; *CEC* cation exchange capacity; *CV* coefficient of variation

[b]Descriptive statistics for all three fairways measured at the UGA course

UGA (31.1%) indicating a greater degree of spatial variability in clay content for sampled GC fairways.

Soil pH was acidic for both locations, but more so at UGA ($\bar{x}$=5.5) than at GC ($\bar{x}$=6.3). The optimum pH range for most turfgrasses is between 6 and 7; however, bermudagrass typically tolerates a much wider range (Carrow et al. 2001). Neither location exhibited a high degree of variability with a CV of 3.8% at UGA and 4.1% at GC. Organic matter content was greater at GC ($\bar{x}$=8.1%) compared to UGA ($\bar{x}$=5.7%). Coefficients of variation for OM at UGA and GC were 20.1 and 24%, respectively. Finally, mean CEC was calculated at 5.7 meq 100 g^{-1} at UGA (CV = 19.2%) and 8.3 meq 100 g^{-1} at GC (CV = 14.3%). Semivariograms for EC_a maps for each fairway are presented in Fig. 2, as a visual example of the 30 semivariograms generated to map soil properties. It should be noted that while most EC_a semivariograms demonstrated good spatial structure, the one generated for F2 was almost pure nugget. Additionally, a greater degree of variation was observed for both F2 and F3 (Fig. 2). This is indicted by the larger scale of the y-axis of both graphs, which

Table 2 Descriptive statistics for EC_a^a (mS m^{-1}), clay content (%), soil pH, CEC (meq 100 g^{-1}), and OM (%) at the Georgia Club golf course in Statham, GA in 2016

	Fairway	Sample size	Min	Max	Range	Mean	Standard deviation	CV (%)
			mS m^{-1}					
	4	469	1.6	15.5	13.9	6.7	2.3	34.3
EC_a	5	570	1.3	12.7	11.4	5.6	2.1	37.0
	6	481	2.6	14.7	12.1	7.7	2.1	27.2
	Course[b]	**1520**	**1.3**	**15.5**	**14.2**	**6.6**	**2.1**	**32.5**
			%					
	4	80	2	15	13	7	2.5	34.8
Clay	5	128	4	14	10	8	2.2	29.8
	6	108	4	26	22	12	5.7	47.7
	Course	**316**	**2**	**26**	**24**	**9**	**4.4**	**49.0**
	4	80	6.2	7.2	1	6.6	0.2	3.1
pH	5	128	5.6	6.9	1.3	6.2	0.2	3.6
	6	108	5.7	6.9	1.2	6.3	1.2	3.0
	Course	**316**	**5.6**	**7.2**	**1.6**	**6.3**	**0.3**	**4.1**
			meq 100 g^{-1}					
	4	80	5.3	10.6	5.3	7.8	1.0	12.3
CEC	5	128	5.6	12.1	6.5	8.6	1.2	14.2
	6	108	5.8	13.1	7.3	8.4	1.4	14.3
	Course	**316**	**5.3**	**13.1**	**7.8**	**8.3**	**1.2**	**14.3**
			%					
	4	80	3.7	12.8	9.1	7.5	1.6	21.1
OM	5	128	4.6	18.3	13.7	8.8	2.3	26.0
	6	108	4.9	12.4	7.5	7.7	1.4	18.7
	Course	**316**	**3.7**	**18.3**	**14.6**	**8.1**	**1.9**	**24.0**

[a]Abbreviations: *EC_a* apparent electrical conductivity; *OM* organic matter; *CEC* cation exchange capacity; *CV* coefficient of variation

[b]Descriptive statistics for all three fairways measured at the UGA course

is dictated by the variogram cloud when plotted in ArcMap. Semivariogram parameters for EC_a, clay content, OM, CEC and soil pH for all 6 individual fairways can be found in Tables 3 (UGA) and 4 (GC). A total of 30 maps were generated to visualize spatial distribution of soil physical and chemical properties; however, only select maps will be presented in order to demonstrate specific points for discussion.

Influence of soil physical and chemical properties on spatial variability of EC_a

The relationship between EC_a and soil properties (clay content, pH, OM and CEC) was not consistent across or within locations. Rather, the dominant properties influencing EC_a and the degree of influence varied across fairways. Multiple regression models to show which variables relate to EC_a for each respective fairway are summarized in Table 7.

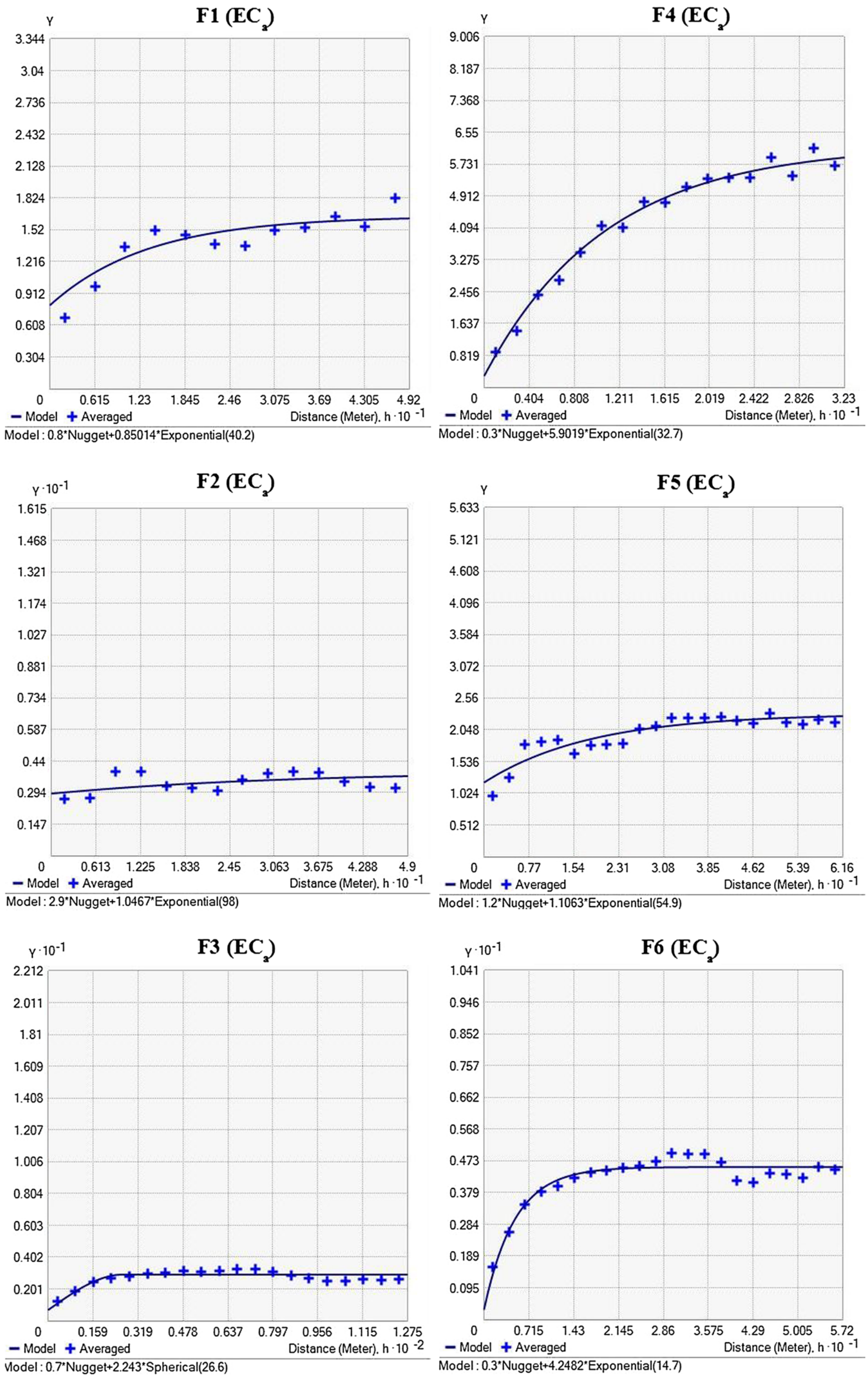

Fig. 2 Semivariograms used to interpolate apparent electrical conductivity (EC_a) data and produce spatial maps for Fairways 1-6 (F1-F6, respectively)

Table 3 Semivariogram parameters of EC_a^a (mS m^{-1}), clay content (%), soil pH, CEC (meq 100 g^{-1}), and OM (%) at the University of Georgia golf course in Athens, GA in 2016

	Sample size	Nugget	Sill	Range (m)	Lag size[b]	Number of bins[c]	Model[d]	RMSE
F1								
EC_a	253	0.8	1.5	40.2	4.1	24	Exponential	1.0
Clay	93	1.2	29.0	98.0	7.0	14	Exponential	3.0
pH	93	0.0	0.0	98.0	7.0	14	Exponential	0.2
CEC	93	0.0	0.7	32.9	7.0	14	Exponential	0.6
OM	93	0.5	0.9	98.0	7.0	14	Exponential	0.9
F2								
EC_a	293	2.9	1.0	98.0	3.5	28	Exponential	1.4
Clay	87	8.8	16.3	44.3	7.0	14	Spherical	3.2
pH	87	0.0	0.1	98.0	7.0	14	Exponential	0.2
CEC	87	0.5	1.1	28.7	7.0	14	Spherical	0.9
OM	87	0.6	1.1	49.6	7.0	14	Exponential	0.9
F3								
EC_a	427	0.7	2.2	26.6	3.7	41	Spherical	1.1
Clay	147	9.6	20.4	98.0	7.0	22	Exponential	3.7
pH	147	0.0	0.0	154.0	7.0	22	Exponential	0.2
CEC	147	49.9	50.7	49.9	7.0	22	Exponential	0.7
OM	147	0.4	1.3	80.4	7.0	22	Exponential	0.9

[a]Abbreviations: EC_a (apparent electrical conductivity); *OM* organic matter; *CEC* cation exchange capacity; *RMSE* root-mean-square error

[b]The lag size is the respective sample grid spacing. If the grid was not symmetrical then the average 'Nearest Neighbor' was used (EC_a data)

[c]The number of bins was calculated from half the maximum distance in the data set divided by the respective sampling grid spacing

[d]Models were selected from spherical, exponential, and Gaussian spatial correlation structures according to lowest Akike information criterion

UGA course

Pearson (r) correlation coefficients served as an exploratory analysis to provide initial insight into which properties relate to EC_a for each fairway (Tables 5 and 6). In this paper, correlations are described as weak ($r<0.35$), moderate ($r=0.36-0.65$), and strong ($r>0.65$) (Taylor 1990). When constructing linear models, negligible ($r<0.1$) relationships with EC_a were not considered.

Correlation coefficients between EC_a and soil properties for F1 were not determined to be statistically significant ($p>0.05$); however, the strength of these relationships and visual comparisons of spatial maps prompted the authors to present them here. The lack of significance is likely due to the more conservative estimation by the corrected Pearson's r method, as influenced by the nature and degree of spatial autocorrelation observed on this fairway (Legendre 1993). It appeared as though EC_a on F1 was weakly related to pH ($r=0.3$), moderately related to CEC and OM ($r=0.39$ and 0.47, respectively), and strongly related to clay content ($r=0.7$). Visual comparison of EC_a and clay content spatial maps (not shown), as well as EC_a and OM spatial maps for F1 (Fig. 3) indicated a clear

Table 4 Semivariogram parameters of EC_a^a (mS m^{-1}), clay content (%), soil pH, CEC (meq 100 g^{-1}), and OM (%) at the Georgia Club golf course in Statham, GA in 2016

	Sample size	Nugget	Sill	Range (m)	Lag Size[b]	Number of Bins[c]	Model[d]	RMSE
F4								
EC_a	469	0.3	5.9	32.7	1.9	35	Exponential	1.3
Clay	80	3.7	6.2	16.0	7.0	9	Spherical	2.5
pH	80	0.0	0.1	63.0	7.0	9	Exponential	0.2
CEC	80	0.6	0.9	13.5	7.0	9	Exponential	1.0
OM	80	2.3	2.7	47.7	7.0	9	Spherical	1.6
F5								
EC_a	570	1.2	1.1	54.9	2.8	44	Exponential	1.1
Clay	128	0.0	0.0	13.5	7.0	18	Gaussian	0.1
pH	128	0.0	0.0	13.5	7.0	18	Spherical	0.2
CEC	128	0.6	1.5	126.0	7.0	18	Exponential	0.9
OM	128	3.0	5.6	82.1	7.0	18	Spherical	1.9
F6								
EC_a	481	0.3	4.3	14.7	2.6	43	Exponential	1.5
Clay	108	6.7	32.9	112.0	7.0	16	Exponential	3.6
pH	108	0.0	0.0	19.2	7.0	16	Spherical	0.2
CEC	108	0.5	1.5	22.3	7.0	16	Spherical	1.1
OM	108	1.5	2.5	112.0	7.0	16	Exponential	1.4

[a]Abbreviations: *EC_a* apparent electrical conductivity; *OM* organic matter; *CEC* cation exchange capacity; *RMSE* root-mean-square error

[b]The lag size is the respective sample grid spacing. If the grid was not symmetrical then the average 'Nearest Neighbor' was used (EC_a data)

[c]The number of bins was calculated from half the maximum distance in the data set divided by the respective sampling grid spacing

[d]Models were selected from spherical, exponential and Gaussian spatial correlation structures according to lowest Akike information criterion

relationship. Visual comparison of EC_a and CEC maps (not shown), as well as EC_a and pH maps (not shown), for F1 did not show a strong spatial relationship. In the stepwise selection of the multiple linear regression model for F1 (null model AIC = − 67.7), pH and CEC were excluded from the final model (Table 7) leaving clay and OM (ΔAIC = 2.8); however, neither parameter was determined to be statistically significant. An exponential model with a range of 18.99 m and a nugget of 0.005 was fitted to the residual spatial autocorrelation. A scatter plot of the predicted versus measured EC_a values for F1 are presented in Fig. 3 ($R^2 = 0.51$).

Results for F2 showed that EC_a was found to be weakly related to clay ($r = 0.14$), CEC ($r = 0.17$) and OM ($r = 0.14$) and moderately related to pH ($r = 0.47$). Maps generated in order to visualize the spatial variability of EC_a and soil pH for F2 are displayed in Fig. 4. Visual comparison of the two maps point to a clear positive relationship with the highest EC_a and soil pH values concentrated on the eastern portion of the fairway and the lowest values concentrated down the center of the fairway. More moderate values for EC_a and soil pH also appear to be directly correlated to one another. In the stepwise selection of the multiple linear regression model for F2 (null model AIC = − 25.3), the final model

Table 5 Multiple linear regression models for Fairways 1, 2, and 3 (F1, F2, and F3, respectively) at the University of Georgia golf course in Athens, GA and Fairways 4, 5, and 6 (F4, F5, and F6) the Georgia Club golf course in Statham, GA to predict EC_a^a (mS m^{-1}) based on clay content (%), pH, CEC (meq 100 g^{-1}), and OM (%) using the generalized least squares method

	University of Georgia (UGA)			*Georgia Club (GC)*		
	F1			F4		
Range (m)	18.99			14.42		
Nugget	0.005			0.208		
Model	Exponential			Gaussian		
	COEFF	**SE**	***p* value**	**COEFF**	**SE**	***p*-value**
Intercept	4.270	0.467	< 0.001***	7.075	5.698	0.218
Clay	0.003	0.007	0.684	–	–	–
pH	–	–	–	– 0.083	0.865	0.924
CEC	–	–	–	–	–	–
OM	0.011	0.024	0.655	–	–	–
	F2			F5		
Range (m)	15.68			21.71		
Nugget	0.009			0.010		
Model	Gaussian			Exponential		
	COEFF	**SE**	***p*-value**	**COEFF**	**SE**	***p*-value**
Intercept	2.358	0.842	0.006**	5.408	0.580	< 0.001***
Clay	–	–	–	0.003	0.009	0.760
pH	0.353	0.135	0.011*	0.036	0.069	0.601
CEC	– 0.012	0.023	0.624	–	–	–
OM	– 0.011	0.026	0.673	–	–	–
	F3			F6		
Range (m)	16.12			17.17		
Nugget	0.005			0.162		
Model	Exponential			Exponential		
	COEFF	**SE**	***p*-value**	**COEFF**	**SE**	***p*-value**
Intercept	0.809	1.180	0.494	− 3.081	4.273	0.473
Clay	0.009	0.010	0.385	− 0.068	0.028	0.018*
pH	0.719	0.187	< 0.001***	1.841	0.687	0.009**
CEC	–	–	–	–	–	–
OM	0.043	0.046	0.348	–	–	–

*,**,***Significant at the 0.05, 0.01, 0.001 probability level, respectively

[a]Abbreviations: EC_a apparent electrical conductivity; *CEC* cation exchange capacity; *OM* organic matter; *COEFF* coefficient; *SE* standard error

[b]Models with Gaussian and exponential spatial correlation structures were selected according to lowest Akaike information criterion

Table 6 Correlation coefficients between EC_a[a] (mS m^{-1}), clay content (%), soil pH, CEC (meq 100 g^{-1}), and OM (%) for fairways F1, F2, and F3 at the University of Georgia golf course in Athens, GA in 2016

	EC_a	Clay	pH	CEC	OM
F1					
EC_a	1				
Clay	0.70	1			
pH	0.30	0.25	1		
CEC	0.39	0.49	0.02	1	
OM	0.47	0.46*	0.05	0.63*	1
F2					
EC_a	1				
Clay	0.14	1			
pH	0.47*	0.01	1		
CEC	0.17	0.17	− 0.07	1	
OM	0.14	0.12	− 0.19	0.24*	1
F3					
EC_a	1				
Clay	0.4*	1			
pH	0.36*	0.25	1		
CEC	0.21*	0.26*	− 0.03	1	
OM	0.21*	0.13*	− 0.13	0.54*	1

Significant correlations (*$p<0.05$)

[a]Abbreviations: *EC_a* apparent electrical conductivity; *CEC* cation exchange capacity; *OM* organic matter

included CEC, pH, and OM (ΔAIC = − 1.8). Of these, only pH was determined to be statistically significant ($p \leq 0.05$). The residual spatial autocorrelation was fitted to a Gaussian model with a range of 15.68 m and a nugget of 0.009. A scatter plot of the predicted versus measured EC_a values for F2 can be found in Fig. 3 ($R^2 = 0.25$).

Correlation coefficients calculated for F3 revealed EC_a was weakly related to CEC ($r = 0.21$) and OM ($r = 0.21$) and moderately related to clay and pH ($r = 0.40$ and 0.36, respectively). In the construction of the multiple linear regression model for F3 (null model AIC: 24.64), CEC was excluded to leave a final model that included clay content, OM and pH (ΔAIC = − 0.8). Similar to the model for F2, only pH was found to be significant ($p \leq 0.001$). An exponential model with a range of 16.12 m and a nugget of 0.005 was fitted to the residual spatial autocorrelation. Measured versus EC_a values predicted by the model yielded an R^2 value of 0.28 (Fig. 3).

GC course

Exploratory analysis for F4 found a weak relationship between EC_a and pH ($r = 0.33$). In the final model predicting EC_a from pH, pH was not determined to be statistically significant ($p = 0.92$). A scatter plot comparing measured versus predicted EC_a value confirmed a weak relationship ($R^2 = 0.13$).

Although both clay content and pH were found to be weakly related to EC_a on F5 ($r = 0.25$ and 0.16, respectively), no strong or significant linear relationship could be established between EC_a and soil physical and chemical properties (Table 7).

Table 7 Correlation coefficients between EC_a[a] (mS m^{-1}), clay content (%), pH, CEC (meq 100 g^{-1}), and OM (%) for fairways F4, F5, and F6 at the Georgia Club golf course in Statham, GA in 2016

	EC_a	Clay	pH	CEC	OM
F4					
EC_a	1				
Clay	0.04	1			
pH	0.33*	0.26*	1		
CEC	− 0.12	− 0.23*	0.07	1	
OM	− 0.10	− 0.48*	− 0.34*	0.35*	1
F5					
EC_a	1				
Clay	− 0.25*	1			
pH	0.16*	− 0.02	1		
CEC	− 0.07	0.23	0.02	1	
OM	− 0.07	0.27	− 0.31	0.57*	1
F6					
EC_a	1				
Clay	− 0.22*	1			
pH	0.27*	0.22	1		
CEC	0.10	0.03	0.25*	1	
OM	0.11	− 0.25	− 0.20	0.44*	1

Significant correlations (*$p<0.05$)

[a]Abbreviations: EC_a, apparent electrical conductivity; CEC, cation exchange capacity; OM, organic matter

On F6 at GC, EC_a was found to be weakly related to all four measured soil properties (Table 6). During the stepwise construction of the linear model to predict EC_a on F6, CEC and OM were excluded. Both clay content and pH were found to be significant ($p=0.018$ and 0.009, respectively); however, the relationship between measured and predicted EC_a values was weak ($R^2=0.12$).

The CEC-OM relationship was significantly positive on all fairways with correlation coefficients ranging from $r=0.24$ (F2) to $r=0.63$ (F1). Parameters for linear regression models used to predict CEC from OM are outlined in Table 7. All models were determined to be significant at the $p<0.001$ level with the exception of F2 ($p=0.164$). This was consistent with correlation coefficients across fairways, since F2 was the only fairway that did not exhibit a strong or significant correlation between CEC and OM. Maps for CEC and OM from F5 are displayed in Fig. 4 to demonstrate the visible relationship between the two soil properties. Areas with higher CEC on the eastern section of the fairway correspond to areas with higher OM, and areas with lower CEC correspond to areas with lower OM on the western portion of the fairway (Figs. 5, 6, 7).

Discussion

The way EC_a related to clay content, pH, CEC and OM varied across fairways. It is important to outline the variability in these relationships, as it may inform future research decisions regarding the way in which EC_a technology should be implemented in PTM.

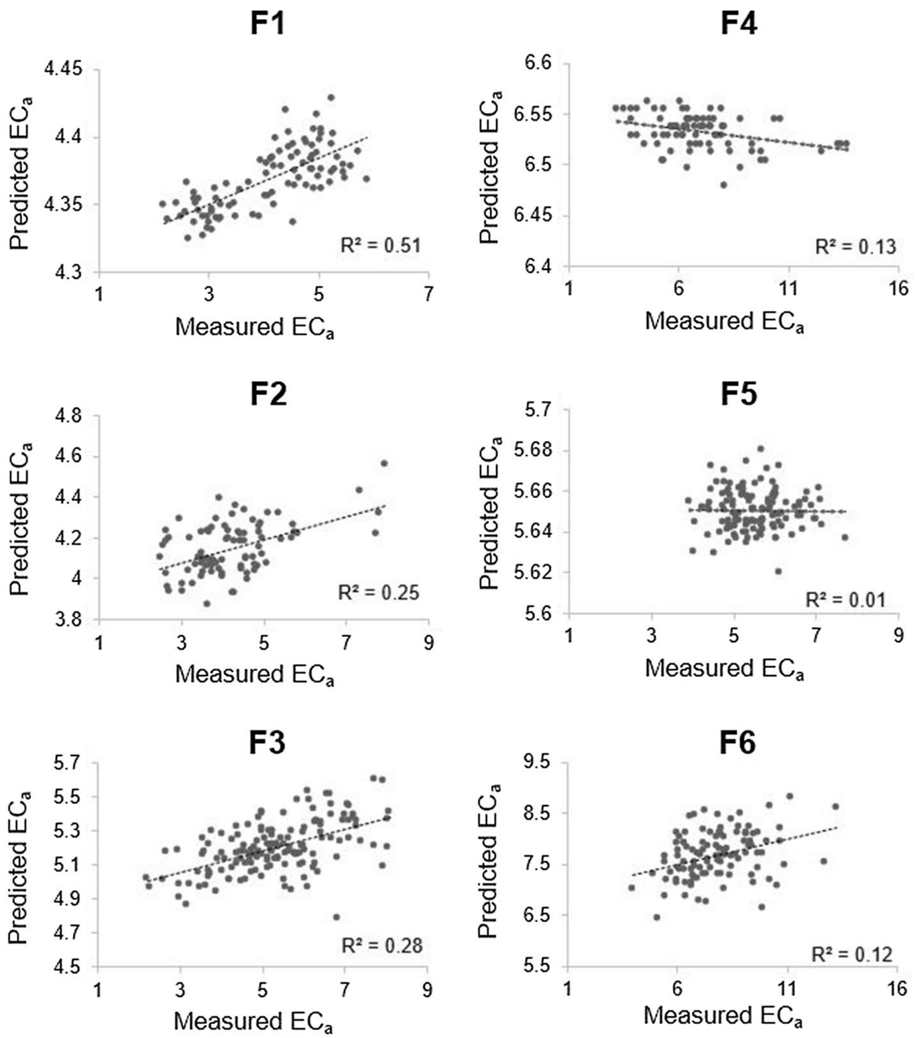

Fig. 3 Scatterplots for measured versus predicted apparent electrical conductivity (EC_a) for Fairways 1–6 (F1–F6, respectively) using linear models generated in Table 7

The positive EC_a-clay content relationships observed on the UGA course are similar to those observed in previous studies (Pedrera-Parrilla et al. 2016b; Stadler et al. 2015). However, even in previous studies, these relationships were not always consistent across locations within the same study (Stadler et al. 2015). In contrast to UGA, relationships between EC_a and clay content at GC were generally weak and negative. These findings indicate that EC_a collected with a Veris device may not be appropriate for predicting spatial structure of clay content at the GC location. The lack of relationship may be attributed to lower mean clay content. Mean clay content at UGA was greater than at GC (15 and 9%, respectively). Previous research with Veris devices reported poor correlation with coarser textured soils compared to non-invasive EMI devices (Corwin and

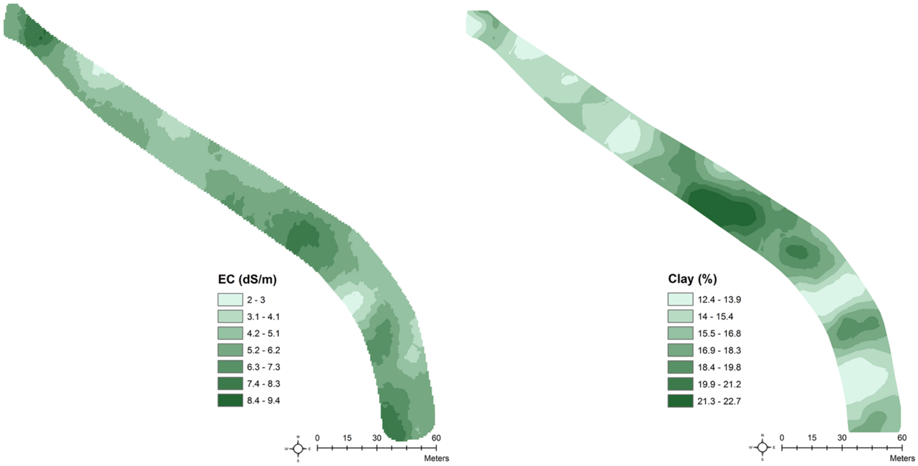

Fig. 4 Kriged maps of apparent electrical conductivity (EC_a) and clay content for Fairway 3 (F3) at the University of Georgia golf course in Athens, GA in 2016 (equal interval legend classifications)

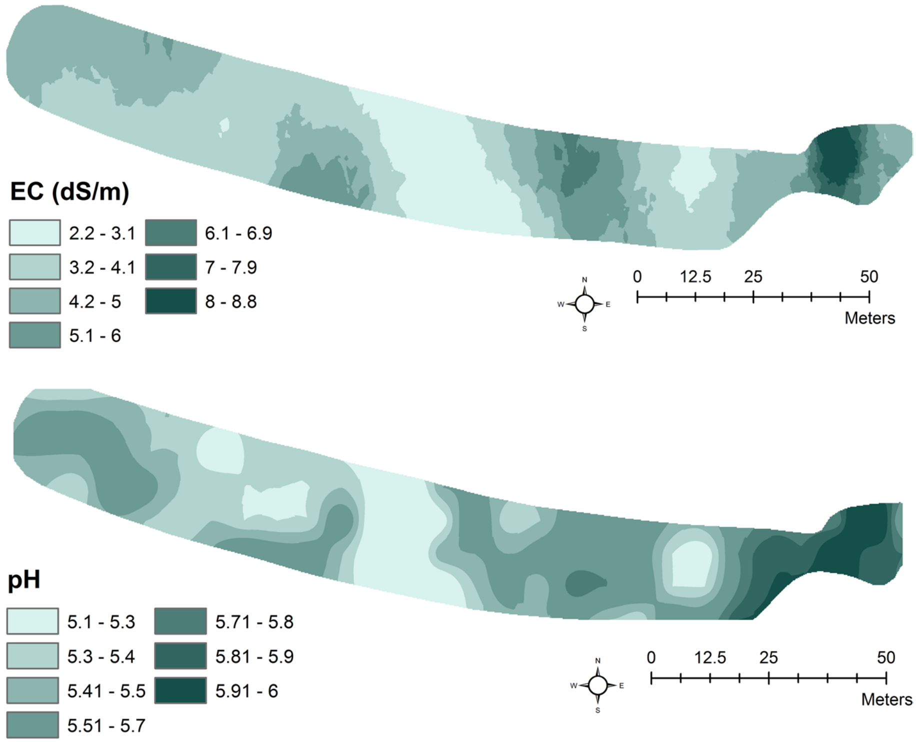

Fig. 5 Kriged maps of apparent electrical conductivity (EC_a) and soil pH for Fairway 2 (F2) at the University of Georgia golf course in Athens, GA in 2016 (equal interval legend classifications)

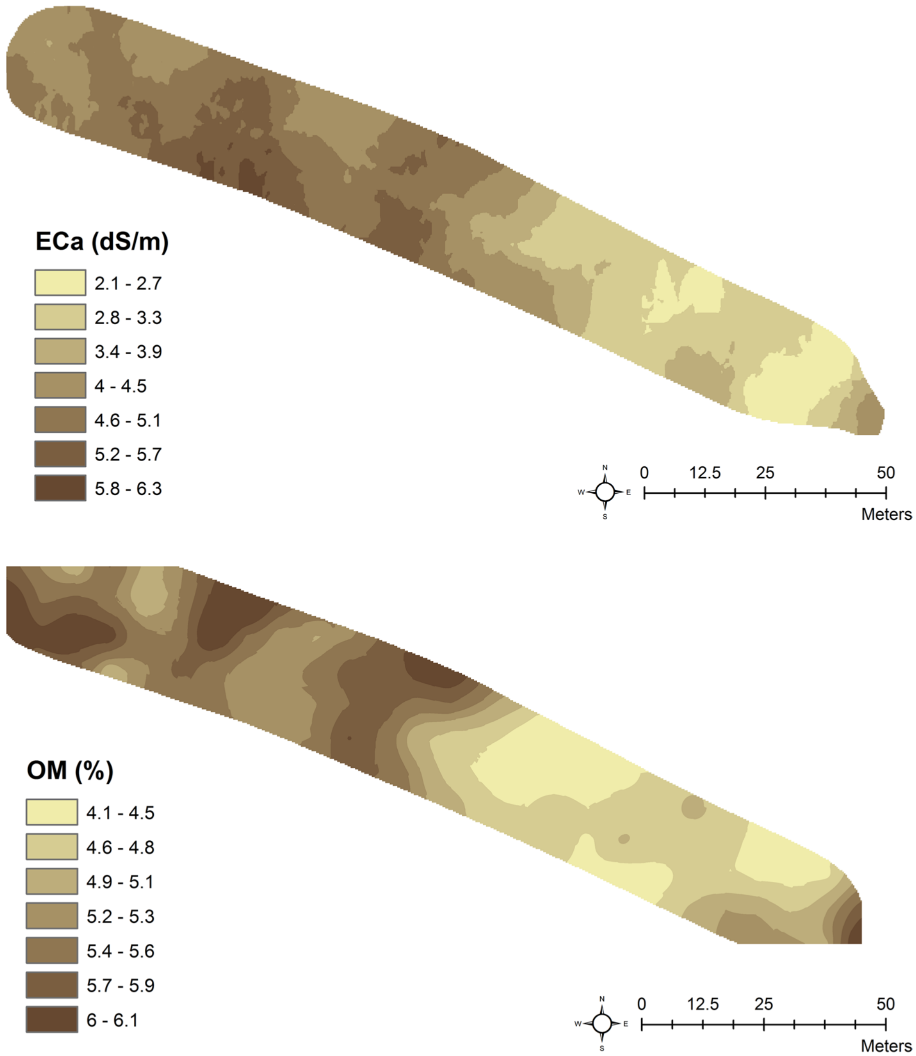

Fig. 6 Kriged maps of apparent electrical conductivity (EC_a) and organic matter (OM) for Fairway 1 (F1) at University of Georgia golf course in Statham, GA in 2016 (equal interval legend classifications)

Lesch 2003, 2005b). Weak or inconsistent relationships between clay content and other soil properties including pH, CEC and OM (Table 6) further supports the hypothesis that clay content is not a dominant property influencing soil physical and chemical processes for the GC location.

Relationships between EC_a and soil pH were more consistent across locations. Though the strength of the relationship varied, positive correlations were observed across all fairways, and pH was included in the predictive models for five out of the six fairways included in this study (Table 7). Minimal research has explored the relationship between EC_a and soil pH. Gholizadeh et al. (2011) observed a significant positive EC_a-soil pH correlation ($r = 0.35$) with shallow EC_a data collected using a Veris device

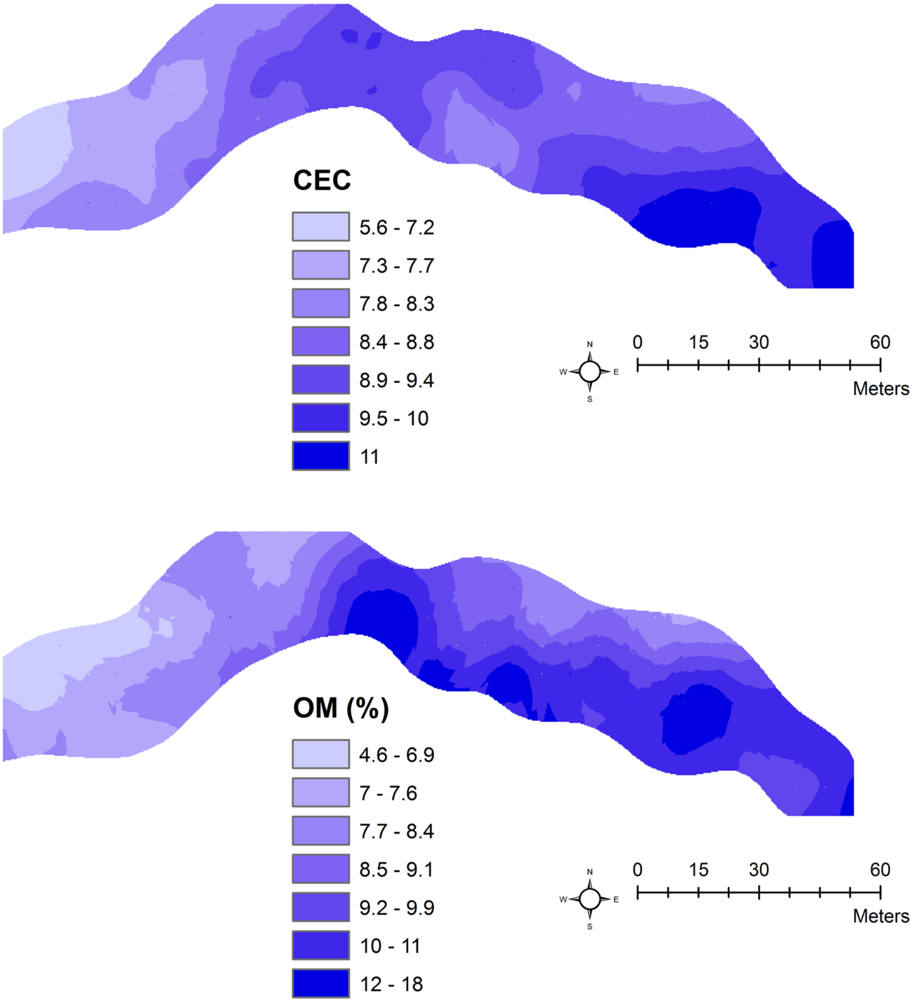

Fig. 7 Kriged maps of cation exchange capacity (CEC) and organic matter (OM) for Fairway 5 (F5) at Georgia Club golf course in Statham, GA in 2016 (equal interval legend classification)

in Malaysian paddy fields with a similar mean pH (5.3). Soil pH influences a number of soil processes and properties that are important for turfgrass management including CEC, soil microbial transformations, lime requirements and nutrient availability (Carrow et al. 2001). The ability to predict spatial structure and identify spatial trends in soil pH may improve precision turf management practices, particularly for applications of soil amendments such as lime.

The absence of discernible trends across fairways indicates that Veris collected EC_a data is not a strong predictor for CEC at either GC or UGA. Although EC_a has been correlated to CEC in previous studies (McBride et al. 1990; Triantafilis et al. 2002), these relationships were attributed to greater variability in soil mineralogy and salinity. Additionally, researchers predominantly used EMI devices, which are non-invasive and less affected by soil moisture and coarse textures (Corwin and Lesch 2003). It is possible that EC_a-CEC correlations could be strengthened with the use of an alternative device, particularly on golf course fairways with lower clay content. Conversely, the continuous surface layer of vegetation characteristic of turfgrass systems may mask soil properties surveyed with an EMI device when compared with other cropping systems (Serrano et al. 2014). Alternative methods for determining CEC may also change EC_a-CEC correlations. Mehlich III and similar extraction methods may overestimate CEC by dissolving precipitate materials in the soil when compared with methods that use different exchange solutions (Dohrmann and Kaufhold 2009). Traditionally, this is not an issue for southeastern soils since they are not calcareous; however, recent lime applications could impact CEC values.

The only fairway that exhibited a significant relationship between EC_a and OM was F3 at UGA ($r=0.21$). Visual comparison of maps (not shown) confirmed a weak relationship. Based on these visual comparisons and a weak correlation value, OM does not appear to be the dominant factor affecting EC_a values for this fairway. Though not significant, F1 had a moderately positive EC_a-OM correlation ($r=0.47$). Visual comparison of spatial maps (Fig. 3) confirms a moderately positive relationship between these two parameters. All remaining fairways (F2, F4, F5 and F6) showed no significant EC_a-OM relationship, and no discernible trends could be established either within or across golf courses. The EC_a-OM relationship varied significantly across previous research (Gholizadeh et al. 2011; Jaynes 1996; Moral et al. 2010). Soil apparent electrical conductivity has been positively correlated to organic carbon in Malaysian paddy fields (Gholizadeh et al. 2011), but exhibited no correlation to OM in Spanish rapeseed fields (Moral et al. 2010).

The relationship between CEC and OM has not been extensively explored in turfgrass systems. Previous researchers have indicated that the role of OM may be unique in turfgrass due to the layered nature of the soil profile, indicative of a continuous perennial surface (Krum et al. 2011). Organic matter influence on root zone CEC may be greater for turfgrass than other cropping systems, because the OM layer is more pronounced and not subjected to cultivation practices that create a more homogeneous soil profile. This is important for nutrient management, since OM content may provide a more definitive indication of nutrient availability in the root zone than soil texture. However, it does not appear that EC_a data collected from a Veris device provides an accurate representation of CEC or OM spatial variability on golf course fairways.

Surface topography can influence the spatial variability of EC_a (Corwin and Lesch 2005b; Fritz et al. 1999). Maps for F1 revealed strong visual trends between soil physical and chemical properties. Interestingly, despite visual evidence of soil spatial relationships between properties, correlation coefficients between EC_a and other soil properties (clay content, pH, CEC, and OM) were not significant (Table 5). Topographical data were not collected, but F1 generally slopes upward from west to east (toward the putting green). For all soil properties, greater values are concentrated on the western section of the fairway, while lower values are concentrated on the eastern portion. This may be an indication of soil moisture and clay colloid accumulation as a function of topographical changes, since smaller particles (clay and OM) are more likely to run off following rainfall and irrigation events (Corwin and Lesch 2005b). Topography has also been found to impact soil aggregation, soil organic carbon and total nitrogen in some systems (Ayoubi et al. 2012). The UGA course is much older than GC, and may be more influenced by topographical changes as a consequence of age. Additional research exploring the role of topography could be important to understand the spatial variability of soil properties, particularly on golf course fairways that were designed with significant changes in elevation. The resulting accumulation at the base of this fairway could lead to an increase in clay content and OM, as well as CEC, pH and EC_a since these properties are positively correlated with one another.

Soil moisture may impact results, because measurements of ER require close contact between the soil and device electrodes (Corwin and Lesch 2005b). Several studies have suggested mapping at field capacity to establish stronger correlations between EC_a and soil physical properties such as clay content (Brevik et al. 2006; Islam et al. 2012; Pedrera-Parrilla et al. 2016b). In one study, Pedrera-Parrilla et al. (2016b) established stronger correlations when EC_a measurements were collected under wet soil conditions, but they did suggest that dry soil does not inhibit the efficacy of EC_a surveys to predict soil texture.

Soil depth may also play a role in EC_a applications for turfgrass systems. Although spatial structure remains intact, previous research in other cropping systems observed shifts in correlations between EC_a and other soil properties (including clay content) with increasing depth. Cho et al. (2016) noted a decline in fit between EC_a and clay content with increasing depth, while Stadler et al. (2015) observed an improvement in fit with increasing depth. Mapping soil properties of the uppermost soil profile is most relevant for fertility management in turfgrass systems, because most rooting occurs there. Current devices may collect data at depths that exceed this region and therefore do not provide the best representation of relevant soil spatial variability.

Future research should explore the EC_a-pH relationship at locations representing a broader range of soil acidity and alkalinity, and should evaluate ways to strengthen or better define this relationship. Soil moisture may significantly influence EC_a, particularly in turfgrass systems with coarser textured soils and minimal OM. Future research should explore not only the relationship between EC_a and soil moisture in turfgrass systems, but the role soil moisture may play in strengthening relationships between EC_a and soil physical and chemical properties. Temporal variability may also have an effect on EC_a-soil relationships. Longitudinal data collected at different time points could provide greater insight into the way these relationships shift over time. Finally, research exploring the role of topography could be important to understand the spatial variability of soil properties, particularly on golf course fairways that were designed with significant changes in elevation. Future research should collect high-resolution topographic data to generate 3-dimensional maps that may better articulate these relationships.

Conclusion

A modified Veris device was utilized to collect EC_a data across six fairways at two golf courses in North Georgia (UGA and GC) to determine whether EC_a could be used to predict the spatial variability of soil physical and chemical properties that are difficult to measure. Golf course fairways exhibited spatial variability of clay content, soil pH, CEC and OM, all of which have an impact on fertility management in turfgrass. Relationships between EC_a and soil properties were determined through a combination of traditional statistical methods and visual comparison of spatial maps. In general, the relationships between measured parameters varied significantly both across and within locations. Although there was evidence of a predictive relationship between EC_a and soil properties (primarily clay content, pH and OM) on some fairways, the parameters measured were insufficient to explain the majority of variability in EC_a. Consequently, more research must be conducted before EC_a data can be used as a tool for mapping soil properties in turfgrass systems.

The Veris device was not determined to have any notable relationship with CEC in this study. Moderate to strong positive relationships were observed between CEC and OM for five out of six fairways. Therefore, CEC in turfgrass root zones may be strongly influenced by OM, which could be important to turfgrass managers when delineating zones for site-specific management. Consistent positive correlations between EC_a and soil pH observed for all fairways indicates that the Veris device is effective at predicting pH trends on golf course fairways at these locations. Accuracy of Veris collected EC_a data in predicting spatial structure of soil physical and chemical properties is location-specific.

Positive relationships between EC_a and pH were observed across all fairways in this study. It is unclear whether the relationship between EC_a and pH would extend to other pH ranges, since existing research has only evaluated acidic soils in the 5.5–6.5 range.

Acknowledgements The authors would like to thank John McMullan, Superintendent, Georgia Club Golf Course and Scott Griffith, Superintendent, University of Georgia Golf Course, for use of their facilities.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Allred, B. J., Daniels, J. J., & Reza Ehsani, M. (2008). *Handbook of agricultural geophysics*. Boca Raton, FL, USA: CRC Press LLC.

Ayoubi, S., Karchegani, P. M., Mosaddeghi, M. R., & Honarjoo, N. (2012). Soil aggregation and organic carbon as affected by topography and land use change in western Iran. *Soil and Tillage Research, 121,* 18–26.

Bartlett, M. D., & James, I. T. (2011). A model of greenhouse gas emissions from the management of turf on two golf courses. *Science of the Total Environment, 409*(8), 1357–1367.

Bouyoucos, G. J. (1936). Directions for making mechanical analyses of soils by the hydrometer method. *Soil Science, 42*(3), 225–229.

Brady, N. C., & Weil, R. R. (2008). *The nature and properties of soils* (14th ed.). Upper Saddle River, NJ, USA: Pearson Education Inc.

Brevik, E. C., Fenton, T. E., & Lazari, A. (2006). Soil electrical conductivity as a function of soil water content and implications for soil mapping. *Precision Agriculture, 7*(6), 393–404.

Burger, H. R. (1992). *Exploration geophysics of the shallow subsurface*. Englewood Cliffs, NJ, USA: Prentice Hall.

Carrow, R. N., Krum, J. M., Flitcroft, I., & Cline, V. (2010). Precision turfgrass management: challenges and field applications for mapping turfgrass soil and stress. *Precision Agriculture, 11*(2), 115–134.

Carrow, R. N., Waddington, D. V., & Reike, P. E. (2001). *Turfgrass soil fertility and chemical problems: assessment and management*. Chelsea, MI, USA: Ann Arbor Press.

Cheng, Z. Q., & Grewal, P. S. (2009). Dynamics of the soil nematode food web and nutrient pools under tall fescue lawns established on soil matrices resulting from common urban development activities. *Applied Soil Ecology, 42*(2), 107–117.

Cho, Y., Sudduth, K. A., & Chung, S.-O. (2016). Soil physical property estimation from soil strength and apparent electrical conductivity sensor data. *Biosystems Engineering, 152,* 68–78.

Corwin, D., & Lesch, S. (2003). Application of soil electrical conductivity to precision agriculture. *Agronomy Journal, 95*(3), 455–471.

Corwin, D. L., & Lesch, S. M. (2005a). Apparent soil electrical conductivity measurements in agriculture. *Computers and Electronics in Agriculture, 46*(1–3), 11–43.

Corwin, D., & Lesch, S. (2005b). Characterizing soil spatial variability with apparent soil electrical conductivity: I. Survey protocols. *Computers and Electronics in Agriculture, 46*(1), 103–133.

Day, P. R. (1965). Particle fractionation and particle-size analysis. In C.A. Black (Ed.) *Methods of soil analysis, part 1* (pp. 545–567). Madison, WI, USA: American Society of Agronomy

Dohrmann, R., & Kaufhold, S. (2009). Three new, quick CEC methods for determining the amounts of exchangeable calcium cations in calcareous clays. *Clays and Clay Minerals, 57*(3), 338–352.

Eckert, D., & Sims, J. T. (2009). Recommended soil pH and lime requirement tests. In J.T. Sims & A. Wolf (Ed.), *Recommended soil testing procedures for the northeastern United States. Northeastern regional* *publication no. 493* (pp. 11–16). Newark, DE, USA: The Northeast Coordinating Committee for Soil Testing.

Fortin, M. J., & Dale, M. R. (2005). *Spatial analysis: a guide for ecologists*. Cambridge, NY, USA: Cambridge University Press.

Fritz, R. M., Malo, D. D., Schumacher, T. E., Clay, D. E., Carlson, C. G., Ellsbury, M. M., et al. (1999). Field comparison of two soil electrical conductivity measurement systems. In P. C. Robert, R. H. Rust, & W. E. Larson (Eds.), *Precision agriculture* (pp. 1211–1217). Madison, WI, USA: American Society of Agronomy, Crop Science Society of America, Soil Science Society of America.

Fulton, A., Schwankl, L., Lynn, K., Lampinen, B., Edstrom, J., & Prichard, T. (2011). Using EM and VERIS technology to assess land suitability for orchard and vineyard development. *Irrigation Science, 29*(6), 497–512.

Ganjegunte, G., Leinauer, B., Schiavon, M., & Serena, M. (2013). Using electro-magnetic induction to determine soil salinity and sodicity in turf root zones. *Agronomy Journal, 105*(3), 836–844.

Gholizadeh, A., Amin, M. S. M., Anuar, A. R., & Aimrun, W. (2011). Apparent electrical conductivity in correspondence to soil chemical properties and plant nutrients in soil. *Communications in Soil Science and Plant Analysis, 42*(12), 1447–1461.

Havlin, J. L., Tisdale, S. L., Beaton, J. D., & Nelson, W. L. (2005). *Soil fertility and fertilizers: an introduction to nutrient management* (7th ed.). Upper Saddle River, NJ, USA: Pearson Education Inc.

Huang, J., Scudiero, E., Choo, H., Corwin, D. L., & Triantafilis, J. (2016). Mapping soil moisture across an irrigated field using electromagnetic conductivity imaging. *Agricultural Water Management, 163,* 285–294.

Islam, M. M., Meerschman, E., Saey, T., De Smedt, P., Van De Vijver, E., & Van Meirvenne, M. (2012). Comparing apparent electrical conductivity measurements on a paddy field under flooded and drained conditions. *Precision Agriculture, 13*(3), 384–392.

Jaynes, D. B. (1996). Mapping the areal distribution of soil parameters with geophysical techniques. In D. L. Corwin, & K. Loague (Eds.), *Applications of GIS to the modeling of non-point source pollutants in the vadose zone*, *SSSA Special Publication. 48* (pp. 205–216). Madison, WI, USA: Soil Science Society of America.

Krum, J., Flitcroft, I., Gerber, P., & Carrow, R. (2011). Performance of a mobile salinity monitoring device developed for turfgrass situations. *Agronomy Journal, 103*(1), 23–31.

Legendre, P. (1993). Spatial autocorrelation: trouble or new paradigm? *Ecology, 74*(6), 1659–1673.

McBride, R., Shrive, S., & Gordon, A. (1990). Estimating forest soil quality from terrain measurements of apparent electrical conductivity. *Soil Science Society of America Journal, 54*(1), 290–293.

Mehlich, A. (1984). Mehlich 3 soil test extractant: a modification of Mehlich 2 extractant. *Communications in Soil Science and Plant Analysis, 15*(12), 1409–1416.

Milesi, C., Running, S. W., Elvidge, C. D., Dietz, J. B., Tuttle, B. T., & Nemani, R. R. (2005). Mapping and modeling the biogeochemical cycling of turf grasses in the United States. *Environmental Management, 36*(3), 426–438.

Moral, F., Terrón, J., & Da Silva, J. M. (2010). Delineation of management zones using mobile measurements of soil apparent electrical conductivity and multivariate geostatistical techniques. *Soil and Tillage Research, 106*(2), 335–343.

Osorio, F., Vallejos, R., Cuevas, F., & Diego, M. (2018). SpatialPack: Package for analysis of spatial data. http://cran.r-project.org/web/packages/SpatialPack/SpatialPack.pdf. Accessed 1 September 2018.

Pedrera-Parrilla, A., Brevik, E. C., Giráldez, J. V., & Vanderlinden, K. (2016a). Temporal stability of electrical conductivity in a sandy soil. *International Agrophysics, 30*(3), 349–357.

Pedrera-Parrilla, A., Van De Vijver, E., Van Meirvenne, M., Espejo-Pérez, A., Giráldez, J., & Vanderlinden, K. (2016b). Apparent electrical conductivity measurements in an olive orchard under wet and dry soil conditions: significance for clay and soil water content mapping. *Precision Agriculture, 17*(5), 531–545.

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., & Team, R. C. (2015). nlme: Linear and nonlinear mixed effects models. http://cran.r-project.org/package=nlme. Accessed 25 March. 2017.

Qian, Y. L., Bandaranayake, W., Parton, W. J., Mecham, B., Harivandi, M. A., & Mosier, A. R. (2003). Long-term effects of clipping and nitrogen management in turfgrass on soil organic carbon and nitrogen dynamics: The CENTURY model simulation. *Journal of Environmental Quality, 32*(5), 1694–1700.

Rezaei, M., Saey, T., Seuntjens, P., Joris, I., Boënne, W., Van Meirvenne, M., et al. (2016). Predicting saturated hydraulic conductivity in a sandy grassland using proximally sensed apparent electrical conductivity. *Journal of Applied Geophysics, 126,* 35–41.

Rhoades, J. D., Corwin, D. L., & Lesch, S. M. (1999). Geospatial measurements of soil electrical conductivity to assess soil salinity and diffuse salt loading from irrigation. In L. Corwin, K. Loague, & R.

Ellsworth (Eds.), *Assessment of non-point source pollution in the vadose zone* (pp. 197–215). Washington, D.C., USA: American Geophysical Union.
Ross, D. S., & Ketterings, Q. (1995). Recommended methods for determining soil cation exchange capacity. In J.T. Sims & A. Wolf (Eds.), *Recommended soil testing procedures for the northeastern United States. Northeastern regional publication no. 493* (pp. 75–86). Newark, DE, USA: The Northeast Coordinating Committee for Soil Testing.
Schabenberger, O., & Pierce, F. J. (2001). *Contemporary statistical models for the plant and soil sciences*. Boca Raton, FL, USA: CRC Press LLC.
Schulte, E., & Hoskins, B. (2009). Recommended soil organic matter tests. In J. T. Sims, & A. Wolf (Eds.), *Recommended soil testing procedures for the northeastern United States. Northeastern regional publication no. 493* (pp. 52–60). Newark, DE, USA: The Northeast Coordinating Committee for Soil Testing.
Serrano, J., Shahidian, S., & Silva, J. M. D. (2014). Spatial and temporal patterns of apparent electrical conductivity: Dualem vs. Veris sensors for monitoring soil properties. *Sensors*, *14*(6), 10024–10041.
Stadler, A., Rudolph, S., Kupisch, M., Langensiepen, M., van der Kruk, J., & Ewert, F. (2015). Quantifying the effects of soil variability on crop growth using apparent soil electrical conductivity measurements. *European Journal of Agronomy, 64,* 8–20.
Straw, C. M., Grubbs, R. A., Tucker, K. A., & Henry, G. M. (2016). Handheld versus mobile data acquisitions for spatial analysis of natural turfgrass sports fields. *HortScience, 51*(9), 1176–1183.
Straw, C. M., & Henry, G. M. (2017). Spatiotemporal variation of site-specific management units on natural turfgrass sports fields during dry down. *Precision Agriculture*. https://doi.org/10.2017/s11119-017-9526-5.
Taylor, R. (1990). Interpretation of the correlation coefficient: a basic review. *Journal of Diagnostic Medical Sonography, 6*(1), 35–39.
Triantafilis, J., Ahmed, M., & Odeh, I. (2002). Application of a mobile electromagnetic sensing system (MESS) to assess cause and management of soil salinization in an irrigated cotton-growing field. *Soil Use and Management, 18*(4), 330–339.
van Delden, L., Rowlings, D., Scheer, C., & Grace, P. R. (2016). Urbanisation-related land use change from forest and pasture into turf grass modifies soil nitrogen cycling and increases N_2O emissions. *Biogeosciences, 13*(21), 6095–6106.