Handheld versus Mobile Data Acquisitions for Spatial Analysis of Natural Turfgrass Sports Fields

Chase M. Straw¹, Rebecca A. Grubbs, Kevin A. Tucker, and Gerald M. Henry

Department of Crop and Soil Sciences, University of Georgia, 3111 Miller Plant Science Building, Athens, GA 30602

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Abstract. Research compared handheld and mobile data acquisitions of soil moisture [volumetric water content (VWC)], soil compaction (penetration resistance), and turfgrass vigor [normalized difference vegetative index (NDVI)] of four natural turfgrass sports fields using two sampling grid sizes (4.8 × 4.8 m and 4.8 × 9.6 m). Differences between the two sampling grid sizes were minimal, indicating that sampling with handheld devices using a 4.8 × 9.6 m grid (120–130 samples) would achieve results similar to the smaller grid size. Central tendencies and data distributions varied among the handheld and mobile devices. Moderate to strong correlation coefficients were observed for VWC and NDVI; however, weak to moderate correlation coefficients were observed for penetration resistance at three of the four locations. Kriged maps of VWC and NDVI displayed similar patterns of variability between handheld and mobile devices, but at different magnitudes. Spatial maps of penetration resistance were inconsistent due to device design and user reliability. Consequently, mobile devices may provide the most reliable results for penetration resistance of natural turfgrass sports fields.

Performance testing of natural turfgrass sports fields requires sampling to obtain information on surface properties (e.g., soil moisture, soil compaction, surface hardness, and turfgrass vigor) (Carrow et al., 2010; McAuliffe, 2008). Several researchers have conducted performance testing to evaluate or develop standards for these properties to improve player safety and field playability (Bartlett et al., 2009; Canaway et al., 1990; Holmes and Bell, 1986; Jennings-Temple et al., 2006; McClements and Baker, 1994). Perhaps the most widely adopted testing procedure in the United States is the American Society for Testing and Materials F1936–10, a specification to measure impact attenuation in the field for a variety of sports with a lightweight handheld apparatus (ASTM, 2010). International sport governing bodies, such as the Fédération Internationale de Football Association, also provide a handbook of test methods to assess the performance of surface properties on soccer fields (FIFA, 2012). Previous research and current testing protocols use handheld data acquisition devices to sample at 5–12 locations and use descriptive statistics to analyze the data.

A more detailed approach of performance testing can be accomplished with spatial analysis and the creation of surface maps to detect variability of a given property across a field. Spatial analysis has been used extensively in agronomics to implement precision

agriculture (Emery and González, 2007; James and Godwin, 2003; Taylor et al., 2003). Precision turfgrass management (PTM) is a new, but similar concept that focuses on enhancing input efficiency and management decisions through the application of inputs, such as water, fertilizer, and cultivation, only where, when, and in the amount needed by the plant (Bell and Xiong, 2008; Carrow et al., 2007, 2010; Krum et al., 2010; Stowell and Gelernter, 2008). PTM was developed and based on the premise of site-specific management, which requires detailed site information through intensive sampling (Carrow et al., 2010); therefore, previous sampling methods are likely insufficient.

Minimal research has been conducted on the spatial analysis of sports field surface properties. Three studies have been published using handheld sampling devices in which a GPS was used to obtain geo-referenced field data. Miller (2004) measured surface hardness of two soccer fields with a Clegg Impact Soil Tester (CIST) (Lafayette Instrument Co., Lafayette, IN) at a 10 × 10 m sampling grid (80 samples). Freeland et al. (2008) sampled surface hardness with a CIST on an American football field with a 9.1 × 9.1 m sampling grid (77 samples). Caple et al. (2012) collected data for several surface properties on three soccer fields at the beginning, middle, and end of the season using a sampling grid of unspecified dimensions (135 or 150 samples depending on the field). Maps were created from the data to evaluate the spatial and/or temporal variability of the measured surface properties.

Mobile data acquisition devices equipped with GPS are pertinent for rapid sampling of spatial data in agriculture (Adamchuk et al., 2004; Corwin and Lesch, 2005; Rhoades et al., 1999); however, few mobile devices are currently available for use in turfgrass. Developed in 2005, the Toro Precision Sense 6000 (PS6000) was the first and only mobile multisensor sampling device engineered for turfgrass sites (The Toro Company, Bloomington, MN). The PS6000 was engineered for simultaneous rapid sampling of soil moisture (VWC; %), soil compaction (penetration resistance; MPa), and plant performance (NDVI; unit less with best = 1.0) of complex turfgrass sites. This device has an onboard GPS unit that identifies the latitudinal and longitudinal location of each sample. Carrow et al. (2010), Flitcroft et al. (2010), and Krum et al. (2010) have used the PS6000 for timely data collection and spatial mapping of golf course fairways to develop site-specific management units and protocols to improve irrigation practices and implement site-specific cultivation; however, no research has been published evaluating its use on natural turfgrass sports fields.

Mobile devices are ideal for intense data sampling for spatial analysis, but handheld devices are more practical due to their greater availability and lesser cost. Increased adoption of spatial analysis of sports field properties along with enhancements in technology will create opportunities for the use of all devices. Therefore, it may be important to compare the two sampling methodologies to determine if they generate similar data. The objective of this study was to compare handheld and mobile data acquisitions of soil moisture (VWC), soil compaction (penetration resistance), and turfgrass vigor (NDVI) on several natural turfgrass sports fields using two sampling grid sizes.

Materials and Methods

Field descriptions. Research was conducted on four natural turfgrass fields selected to represent a wide range of sport, use, management, and soil conditions. Survey dates, field dimensions, turfgrass species, and soil texture characteristics for all fields are presented in Table 1. Texture analysis was derived from a composite sample of 15 soil cores (≈1.3 cm diameter pulled to a 10 cm depth) across each field. Oconee Veterans Park (OVP; Watkinsville, GA) is a recreational field for sporting and non-sporting community events. Flowery Branch (FB; Flowery Branch, GA) is a professional American football practice field. North Oconee High School (NOHS; Bogart, GA) is a high school American football game field. UGA Rec Sports (RS) is a University of Georgia (Athens, GA) field used for a variety of intramural sports and recreational play.

Data collection. The PS6000 mobile sampling device simultaneously measured VWC, penetration resistance, and NDVI on all fields. The PS6000 unit was towed behind a utility vehicle and traversed the field at

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¹Corresponding author. E-mail: cmstra4@uga.edu.

Table 1. Sampling date, field dimensions, turfgrass species, and soil texture characteristics² for all sampled natural turfgrass sports fields.

Field location	Date sampled	Field dimensions (m)	Turfgrass species ³	Sand	Silt	Clay	Soil class
				%			
Oconee Veterans Park	12 June 2014	61 × 98	TifSport	82	10	8	Loamy sand
Flowery Branch	29 Oct. 2014	49 × 110	TifSport	94	6	0	Sand
North Oconee High School	17 Sept. 2015	49 × 110	Tifton 10	94	4	2	Sand
UGA Rec Sports	5 May 2016	58 × 99	Tifway 419	62	18	20	Sandy clay Loam

²Soil texture characteristics were derived from a composite sample of 15 soil cores (≈ 1.3 cm diameter pulled to a 10 cm depth) across each field.

³Hybrid bermudagrasses [*Cynodon dactylon* (L.) Pers. × *C. transvaalensis* Burt Davy].

a speed of 2.7 to 3.3 km·h⁻¹ while taking measurements about every 2.4 m (Krum et al., 2010). Passes downfield were made 4.8 m apart; therefore, measurements were initially collected using a 2.4 × 4.8 m sampling grid (≥ 450 samples per field).

VWC measurements were based on a capacitance sensor (The Toro Company) modified for use on the PS6000 to measure soil moisture at a 0 to 10 cm depth. Two stainless steel probes (9.8 mm diameter, 3.3 cm spacing, and 10 cm length) were installed on the sensor to ensure penetration depth. The sensor was mounted on the end of an actuator arm attached to one end of a shaft on the PS6000. The wheel-driven shaft rotates as the PS6000 unit moves forward, resulting in a circular motion of the arm. As the arm moves, the sensor probes enter the soil and a plate passes a proximity switch that triggers the data loggers to take a measurement. This process is controlled by a clutch switch on the user interface display. The clutch switch is powered on once the PS6000 makes a pass within the test area and switched off between turns outside the test area. Continuous measurements are made without the PS6000 stopping once the clutch is activated.

Penetration resistance was measured with a 1.9 cm diameter stainless steel compression load cell (Omega Engineering Inc., Stamford, CT) located in the soil sampling head of the PS6000. The sensor measured the maximum penetration force transferred to the load cell (top 10 cm of the soil profile) from two probes and was recorded as pounds of force (later converted to MPa). The same probes and methodology used to collect VWC were used to acquire penetration resistance data.

NDVI was collected with a GreenSeeker Model 500 active sensor (Trimble, Sunnyvale, CA). NDVI sensors are equipped with internal light-emitting diodes and a photodiode optical detector that measures the reflectance of red ($R = 656$ nm) and near-infrared ($NIR = 770$ nm) spectra used to calculate a vegetative index ($\{NDVI = [(R770 - R656) / (R770 + R656)]\}$). There were two GreenSeeker Model 500 sensors mounted to the PS6000; however, only NDVI data obtained from the right sensor were analyzed in this study. The sensor emits light pulses every 100 ms and outputs an averaged value every second. Thus, NDVI is measured more frequently than VWC and penetration resistance, but only the measurement made at similar locations was used. In addition, a NovAtel GPS (NovAtel Inc., Alberta, Canada), attached to the PS6000, gathered latitudinal and longitudinal information for all data.

Fig. 1. Relationship between handheld and mobile data acquisitions for sampling volumetric water content (%) on natural turfgrass sports fields at Oconee Veterans Park (OVP), Flowery Branch (FB), North Oconee High School (NOHS), and UGA Rec Sports (RS) at the evaluated sampling grid sizes. The box-and-whisker plots show the median (bar), the upper and lower quartiles (top and bottom of the box, respectively), the whiskers (maximum and minimum values excluding outliers), and outliers (circles).

The precise location of the first measurement made in each row with the PS6000 and every other measurement until the end of the row was flagged (i.e., a 4.8 × 4.8 m sampling grid). Measurements with handheld devices were obtained at each flagged location immediately following sampling with the PS6000. Measurement locations made with handheld devices coincided with those made with the PS6000 at flagged locations and were geo-referenced using the GPS of the PS6000.

A Field Scout TDR 300 Soil Moisture Meter (Spectrum Technologies, Inc., Plainfield, IL) recorded handheld VWC data through time-domain reflectometry (TDR). The TDR 300 has two stainless steel probes (5 mm diameter, 3.3 cm spacing, and 7.6 cm length) that are inserted into the soil and a measurement is collected by pressing a button on the meter face plate.

A Field Scout SC 900 Soil Compaction Meter (Spectrum Technologies, Inc.), with a 9.8 mm diameter shaft and cone tip (30° angle and 12.8 mm base), measured penetration resistance in the top 10 cm of the soil. The compaction meter has an ultrasonic sensor that determines the penetration depth of the metal shaft once a measurement is initiated. The shaft is manually inserted slowly into the surface to a 10 cm depth and a measurement is obtained in PSI (later converted to MPa). The PS6000 unit records penetration resistance with two probes; therefore, PS6000 data were divided in half for comparison with single penetrometer data recorded with the handheld device (Flitcroft et al., 2010).

A Field Scout CM 1000 NDVI Meter (Spectrum Technologies, Inc.) measured turfgrass vigor. The meter was held ≈ 0.9 m high and aimed at the field surface. A trigger

Table 2. Correlation coefficients² between handheld and mobile data acquisitions for sampling volumetric water content (%), penetration resistance (MPa), and normalized difference vegetative index (NDVI; unit less with best = 1) at Oconee Veterans Park (OVP), Flowery Branch (FB), North Oconee High School (NOHS), and UGA Rec Sports (RS) at the evaluated sampling grids.

	Sampling grid (m)	Sample size	Volumetric water content	Penetration resistance	NDVI ³
			----- Pearson's <i>r</i> -----		
OVP	4.8 × 4.8	259	0.46***	0.30***	0.47***
	4.8 × 9.6	130	0.49***	0.40***	0.49***
FB	4.8 × 4.8	230	0.82***	0.13 NS	0.75***
	4.8 × 9.6	120	0.76***	0.19 NS	0.76***
NOHS	4.8 × 4.8	230	0.85***	0.35**	0.56***
	4.8 × 9.6	120	0.85***	0.31*	0.53***
RS	4.8 × 4.8	241	0.74***	0.63***	0.59***
	4.8 × 9.6	126	0.68***	0.62***	0.59***

²Correlation coefficients were calculated using a modified *t* test to account for the spatial association between handheld and mobile datasets.

³NDVI data were negatively skewed; therefore, correlation coefficients were calculated from the ranks of NDVI for each dataset to adjust for skewness.

NS, *, **, ***Nonsignificant or significant at *P* < 0.05, 0.01, or 0.001, respectively.

Table 3. Semivariogram parameters of volumetric water content (%) at Oconee Veterans Park (OVP), Flowery Branch (FB), North Oconee High School (NOHS), and UGA Rec Sports (RS) for handheld and mobile data acquisitions at the evaluated sampling grid sizes.

		Sampling grid (m)	Sample size	Nugget	Sill	Range	Lag size ²	Number of bins ³	Model ⁴	RMSE ⁵
OVP	Handheld	4.8 × 4.8	259	18.6	22.3	58.8	4.8	12	Exponential	4.74
		4.8 × 9.6	130	19.4	23.4	59.2	7.4	8	Exponential	4.96
	Mobile	4.8 × 4.8	259	6.5	7.4	58.8	4.8	12	Exponential	2.77
		4.8 × 9.6	130	6.7	8.1	59.2	7.4	8	Exponential	2.94
FB	Handheld	4.8 × 4.8	230	4.8	27.5	19.5	4.8	12	Spherical	3.48
		4.8 × 9.6	120	7.0	26.4	19.9	7.4	8	Spherical	4.09
	Mobile	4.8 × 4.8	230	1.5	14.3	17.1	4.8	12	Spherical	2.54
		4.8 × 9.6	120	4.2	13.2	18.5	7.4	8	Spherical	2.93
NOHS	Handheld	4.8 × 4.8	230	3.1	14.8	58.8	4.8	12	Exponential	2.62
		4.8 × 9.6	120	4.2	15.5	59.2	7.4	8	Exponential	2.97
	Mobile	4.8 × 4.8	230	3.1	13.3	58.8	4.8	12	Exponential	2.44
		4.8 × 9.6	120	4.4	13.4	59.2	7.4	8	Exponential	2.80
RS	Handheld	4.8 × 4.8	241	42.0	59.9	50.0	4.8	12	Spherical	6.87
		4.8 × 9.6	126	38.5	60.0	50.0	7.4	8	Spherical	6.74
	Mobile	4.8 × 4.8	241	16.1	25.6	45.0	4.8	12	Spherical	4.33
		4.8 × 9.6	126	14.0	28.6	59.2	7.4	8	Exponential	4.56

²The lag size is the respective sample grid spacing. The average from the 4.8 × 9.6 m sampling grid was used.

³The number of bins was calculated from half the maximum distance in the data set divided by the respective sampling grid spacing.

⁴The model was selected based on best visual fit from exponential, spherical, or Gaussian model.

⁵RMSE = root mean squared error.

activated the targeting lasers to record a single measurement at each sampling location.

Data analysis. ArcMap 10.3.1 mapping software (ESRI, Redlands, CA) and RStudio 3.2.1 statistical software (RStudio Team, 2015) was used to develop, display, analyze, and interpret the data. The projected coordinate system NAD 1983 State Plane Georgia East FIPS 1001 was used for all spatial analysis in ArcMap. Since the initial PS6000 sampling grid (2.4 × 4.8 m; ≥450 samples) is not practical for handheld devices, PS6000 sample locations that were not flagged were omitted once point data were entered into ArcMap. Therefore, a 4.8 × 4.8 m sampling grid (230–259 samples), consisting of measurements made with handheld and mobile devices, was used for each field in the study. In addition, the 4.8 × 4.8 m sampling grids were manipulated into 4.8 × 9.6 m sampling grids (120–130 samples) for comparisons. Thus, two sampling grid sizes were evaluated (4.8 × 4.8 m and a 4.8 × 9.6 m).

Analyses were conducted through comparisons of central tendency and distribution of each dataset with box-and-whisker plots using the “boxplot” command in RStudio. Correlation coefficients to determine the strength and direction of relationship between each field property measured with

handheld and mobile devices were calculated using the “modified.ttest” function in the SpatialPack package of RStudio (Osorio and Vallejos, 2014). This methodology is based on work by Clifford et al. (1989) and takes into account the spatial association between handheld and mobile datasets to calculate a corrected Pearson's *r* correlation coefficient (Dutilleul, 1993). All NDVI data in this study were negatively skewed. It is typically recommended to calculate Spearman's rho instead of Pearson's *r* for skewed data (Zou et al., 2003). The Spearman correlation is essentially the Pearson correlation calculated from the ranks of the data; therefore, modified *t* tests were conducted on the ranks of the NDVI for each dataset to adjust for skewness. The correlation coefficients were expected to be positive and between 0 and 1. A positive value indicates a positive relationship (i.e., as values for the handheld devices increase, so will values for the mobile device). The closer the coefficient is to 1, the stronger the relationship between sampling devices.

Spatial maps were used to visually compare the variability of each field property. The maps were generated by first plotting the empirical semivariograms (half the squared difference of the value between two points

for all pairs of a dataset on the *y* axis, and the distance between two points for all the pairs on the *x* axis). The number of bins was calculated from half the maximum distance in the data set divided by the respective sampling grid spacing (Schabenberger and Gotway, 2004). All empirical semivariograms were plotted using the “variog” function in the GeoR package of RStudio (Ribeiro and Diggle, 2001). The eyefit command was used to test a variety of model and parameter combinations and select the most appropriate based on best visual fit. The exponential, spherical, or Gaussian models were evaluated. However, the Gaussian model is generally seen as an “artificial” model for spatial dependence and does not command respect among alternatives (Schabenberger and Gotway, 2004); therefore, the Gaussian model was not given consideration when exponential or spherical models fit similarly. Spatial structure of the semivariogram is described by the nugget, range, and sill parameters. The nugget intercepts the *y* axis and is measurement error and/or microscale variations at small spatial scales. The range is the point at which there is no autocorrelation among two points with separation distances beyond it. The sill is the semivariance at the range (Isaaks and Srivastava, 1989).

Fig. 2. Kriged maps of volumetric water content (%) from handheld and mobile data acquisitions on natural turfgrass sports fields at Oconee Veterans Park, Flowery Branch, North Oconee High School, and UGA Rec Sports using two sampling grid sizes.

Fig. 3. Relationship between handheld and mobile data acquisitions for sampling penetration resistance (MPa) on natural turfgrass sports fields at Oconee Veterans Park (OVP), Flowery Branch (FB), North Oconee High School (NOHS), and UGA Rec Sports (RS) at the evaluated sampling grid sizes. The box-and-whisker plots show the median (bar), the upper and lower quartiles (top and bottom of the box, respectively), the whiskers (maximum and minimum values excluding outliers), and outliers (circles).

The semivariogram models, and their parameters determined in R, were input into Geostatistical Analyst of ArcMap to create maps through ordinary kriging. Kriging uses the values at sampled locations to estimate the areas on the field that were not sampled. The equation for the ordinary kriging predictor is:

$$\hat{Z}(s_0) = \hat{\mu} + \sigma' \Sigma^{-1} (\mathbf{Z}(s_i) - 1\hat{\mu})$$

where, $\hat{\mu}$ is the generalized least squares estimator of the average value, $\sigma = \text{Cov}[\mathbf{Z}(s_i), \mathbf{Z}(s_0)]$, and $\Sigma = \text{Var}[\mathbf{Z}(s_i)]$, and $\mathbf{Z}(s_i)$ is the measured value at a given location. The calculation of σ and Σ depends on the type of model. Data do not need to be normally distributed when using kriging as a predictor (ESRI, 2004); therefore, NDVI data were not transformed before kriging. After kriging, root mean square error (RMSE) was recorded as an indicator of how well the predicted values fit the actual measurements.

Results and Discussion

Volumetric water content. The median and distribution of VWC data changed minimally for both handheld and mobile devices when comparing between sampling grid sizes (Fig. 1). At OVP, FB, and RS, the median VWC was higher with the handheld device. At NOHS the median VWC for the handheld device was substantially lower than the mobile device (≈ 13.0 and 23.0% VWC for handheld and mobile devices, respectively).

Correlation coefficients between handheld and mobile sampling devices ranged from 0.68 to 0.85 on FB, NOHS, and RS (Table 2), indicating a strong relationship. OVP had moderate correlation coefficients (0.46 and 0.49 for the 4.8×4.8 m and 4.8×9.6 m sampling grids, respectively); however, all correlations at each field were significant ($P < 0.001$). The strength of the correlations increased (OVP), decreased (FB and RS), or stayed the same (NOHS) between sampling grid sizes, but changes were minimal.

The semivariogram parameters used to generate spatial maps of VWC and the RMSE outputs are presented in Table 3. Exponential or spherical models were used in each instance. The kriged maps of VWC are presented in Fig. 2. Differences in variability were minimal among sampling grid sizes for both handheld and mobile devices at each field. In general, patterns of variability between sampling devices were also comparable, specifically for the sand fields (FB and NOHS). Minor differences in variability were detected at OVP and RS. The substantial difference in the magnitude of VWC at NOHS is evident from the color scale; though, the spatial variability of VWC followed similar patterns between the two sampling devices.

Soil moisture is measured indirectly by determining the dielectric properties of the soil when using capacitance and TDR sensors (Dean et al., 1987). The underlying principles

Table 4. Semivariogram parameters of penetration resistance (MPa) at Oconee Veterans Park (OVP), Flowery Branch (FB), North Oconee High School (NOHS), and UGA Rec Sports (RS) for handheld and mobile data acquisitions at the evaluated sampling grid sizes.

		Sampling grid (m)	Sample size	Nugget	Sill	Range	Lag size ^z	Number of bins ^y	Model ^x	RMSE ^w
OVP	Handheld	4.8 × 4.8	259	0.43	0.10	58.8	4.8	12	Exponential	0.73
		4.8 × 9.6	130	0.36	0.14	59.2	7.4	8	Exponential	0.71
	Mobile	4.8 × 4.8	259	0.84	0.12	25.9	4.8	12	Spherical	1.00
		4.8 × 9.6	130	0.96	0.13	19.6	7.4	8	Spherical	1.09
FB	Handheld	4.8 × 4.8	230	0.04	0.09	23.2	4.8	12	Spherical	0.27
		4.8 × 9.6	120	0.04	0.09	22.6	7.4	8	Spherical	0.28
	Mobile	4.8 × 4.8	230	0.16	0.20	21.3	4.8	12	Spherical	0.43
		4.8 × 9.6	120	0.17	0.21	19.2	7.4	8	Spherical	0.45
NOHS	Handheld	4.8 × 4.8	230	0.18	0.30	23.6	4.8	12	Spherical	0.48
		4.8 × 9.6	120	0.15	0.21	18.8	7.4	8	Spherical	0.46
	Mobile	4.8 × 4.8	230	0.12	0.45	28.9	4.8	12	Spherical	0.47
		4.8 × 9.6	120	0.09	0.49	34.9	7.4	8	Spherical	0.45
RS	Handheld	4.8 × 4.8	241	1.1	2.2	50.0	4.8	12	Spherical	1.19
		4.8 × 9.6	126	1.1	2.4	50.0	7.4	8	Spherical	1.25
	Mobile	4.8 × 4.8	241	1.5	2.2	50.0	4.8	12	Spherical	1.33
		4.8 × 9.6	126	1.7	2.5	50.0	7.4	8	Spherical	1.46

^zThe lag size is the respective sample grid spacing. The average from the 4.8 × 9.6 m sampling grid was used.

^yThe number of bins was calculated from half the maximum distance in the data set divided by the respective sampling grid spacing.

^xThe model was selected based on best visual fit from exponential, spherical, or Gaussian model.

^wRMSE = root mean squared error.

Fig. 4. Kriged maps of penetration resistance (MPa) from handheld and mobile data acquisitions on natural turfgrass sports fields at Oconee Veterans Park, Flowery Branch, North Oconee High School, and UGA Rec Sports using two sampling grid sizes.

of both methodologies are related; therefore, measurements between the two are expected to be comparable (Gardner et al., 1998). The minor discrepancy of medians and distributions for VWC data between handheld and mobile devices at OVP, FB, and RS may be related to the differences in the length of the probes, since moisture levels can fluctuate at various depths within the soil profile.

Substantially higher VWC values at NOHS for the mobile device may also be

attributed to the additional 2.5 cm length of the probes. The clay layer beneath the sand cap is ≈12.5 cm beneath the surface. As water flows downward through larger pores of the sand profile, movement becomes restricted once it meets the smaller pores of the clay layer. This may result in the formation of a temporary “hanging” water table (Turgeon, 2011). Therefore, soil moisture at a depth of 10 cm (mobile device) may be higher than at 7.5 cm (handheld device). This phenomenon

did not occur at FB, because the field had subsurface drainage and did not have an underlying clay layer.

Penetration resistance. The median and distribution of penetration resistance data changed minimally between sampling grid size for both handheld and mobile devices (Fig. 3). Median handheld values were generally lower than mobile values for all fields except NOHS. Large differences in penetration resistance median (greater than ≈1.6 MPa) were observed on the native soil fields at OVP and RS.

Correlation coefficients differed substantially between fields for penetration resistance measured with handheld and mobile devices (Table 2). The strongest correlations were on RS (0.63 and 0.62 for 4.8 × 4.8 m and 4.8 × 9.6 m sampling grids, respectively; $P < 0.001$ for both). Weak correlations were observed at FB [0.13 ($P = 0.115$) and 0.19 ($P = 0.068$) for 4.8 × 4.8 m and 4.8 × 9.6 m sampling grids, respectively]. OVP and NOHS had moderate, but significant, correlations (0.30 to 0.40; $P < 0.05$). The correlation strength increased (OVP and FB) and decreased (NOHS and RS) between sampling grid sizes; however, the change was minimal.

The semivariogram parameters used to generate the spatial maps of penetration resistance, and the RMSE outputs from each map, are presented in Table 4. Exponential or spherical models were used; however, the spherical was the predominant model. The kriged maps of penetration resistance are displayed in Fig. 4. Sampling grid size had minimal effect on either the handheld or mobile device on any of the fields. Examination of the maps revealed differences in magnitude between the two sampling devices; however, similar patterns of variability were detected on OVP, NOHS, and RS. The largest discrepancy in variability between sampling devices was observed at FB. The field sidelines exhibit higher penetration resistance values when using the handheld device, while the southern and center

portions of the field have the highest values when using the mobile device.

Penetration resistance between mobile and handheld sampling devices had the lowest correlation values and the least comparable spatial maps. Probe characteristics between the two sampling devices may be responsible, because the soil-to-probe friction may differ between various cone angles

and diameters (Vaz et al., 2001). The handheld penetrometer has a 9.8 mm diameter shaft with a cone that has a 30° angle and a 12.8 mm diameter base. The PS6000 shaft is also a 9.8 mm diameter with a 30° cone angle, but the base of the cone's tip is the same diameter of the shaft. It is assumed that higher penetration resistance values would be obtained using the handheld penetrometer

(larger diameter base), but this was not the case at OVP, FB, or RS.

The rate of probe penetration may also influence measurements (Vaz et al., 2001). The use of the rotating arm and wheel-driven shaft allow the PS6000 probes to enter the soil at a more consistent, steady rate. Penetration rates for handheld penetrometer probes are highly dependent on the user. Twomey et al. (2011) tested individual user reliability of a penetrometer by dropping a 9 kg weight from a height of 0.5 m to push the conical end of the shaft into the surface. Reliability refers to the consistency or repeatability of a measure (Downing, 2004), including when the penetrometer is used by more than one person. The penetrometer produced moderate and strong reliability levels between six testers ($0.55 \leq \text{intraclass correlations} \leq 0.73$). The operator physically pushed the cone of the penetrometer used in our research into the ground without a weight. Two experienced operators obtained penetration resistance data in this study (operator 1 at OVP and FB; operator 2 at NOHS and RS); however, a difference in force applied between operators was possible and could have affected results.

Soil factors, such as water content, bulk density, and structure, also influence penetration resistance. As soil dries below field capacity, penetration resistance substantially increases for a given soil (Henderson et al., 1988), making cone penetration more difficult for an operator using handheld devices. Carrow et al. (2010) reported soil moisture as a factor of spatial variation is minimized when penetration resistance is mapped at field capacity. Therefore, when sampling at field capacity, variations of high penetration resistance are more likely to resemble foot traffic patterns (rather than the effect of soil drying) and could also make cone penetration easier for the operator.

Normalized difference vegetative index. The median and distribution of NDVI data changed minimally between sampling grid size for both handheld and mobile devices

Fig. 5. Relationship between handheld and mobile data acquisitions for sampling normalized difference vegetative index (NDVI; unit less with best = 1) on natural turfgrass sports fields at Oconee Veterans Park (OVP), Flowery Branch (FB), North Oconee High School (NOHS), and UGA Rec Sports (RS) at the evaluated sampling grid sizes. The box-and-whisker plots show the median (bar), the upper and lower quartiles (top and bottom of the box, respectively), the whiskers (maximum and minimum values excluding outliers), and outliers (circles).

Table 5. Semivariogram parameters of normalized difference vegetative index (NDVI; unit less with best = 1) at Oconee Veterans Park (OVP), Flowery Branch (FB), North Oconee High School (NOHS), and UGA Rec Sports (RS) for handheld and mobile data acquisitions at the evaluated sampling grid sizes.

		Sampling grid (m)	Sample size	Nugget	Sill	Range	Lag size ^z	Number of bins ^y	Model ^x	RMSE ^w
OVP	Handheld	4.8 × 4.8	259	0.003	0.007	20.3	4.8	12	Spherical	0.07
		4.8 × 9.6	130	0.003	0.006	21.8	7.4	8	Spherical	0.08
	Mobile	4.8 × 4.8	259	0.006	0.004	34.1	4.8	12	Spherical	0.09
		4.8 × 9.6	130	0.006	0.004	48.0	7.4	8	Spherical	0.09
FB	Handheld	4.8 × 4.8	230	0.0002	0.004	18.2	4.8	12	Spherical	0.034
		4.8 × 9.6	120	0.0006	0.003	19.3	7.4	8	Spherical	0.034
	Mobile	4.8 × 4.8	230	0.0005	0.005	23.0	4.8	12	Spherical	0.026
		4.8 × 9.6	120	0.0002	0.005	21.3	7.4	8	Spherical	0.030
NOHS	Handheld	4.8 × 4.8	230	0.002	0.003	48.0	4.8	12	Spherical	0.051
		4.8 × 9.6	120	0.001	0.001	59.2	7.4	8	Exponential	0.032
	Mobile	4.8 × 4.8	230	0.006	0.009	49.7	4.8	12	Spherical	0.088
		4.8 × 9.6	120	0.004	0.006	58.5	7.4	8	Spherical	0.07
RS	Handheld	4.8 × 4.8	241	0.0007	0.0015	47.3	4.8	12	Spherical	0.03
		4.8 × 9.6	126	0.0007	0.0014	39.0	7.4	8	Spherical	0.03
	Mobile	4.8 × 4.8	241	0.0006	0.0017	47.7	4.8	12	Spherical	0.03
		4.8 × 9.6	126	0.0007	0.0018	44.9	7.4	8	Spherical	0.03

^zThe lag size is the respective sample grid spacing. The average from the 4.8 × 9.6 m sampling grid was used.

^yThe number of bins was calculated from half the maximum distance in the data set divided by the respective sampling grid spacing.

^xThe model was selected based on best visual fit from exponential, spherical, or Gaussian model.

^wRMSE = root mean squared error.

Fig. 6. Kriged maps of normalized difference vegetative index (NDVI; unit less with best = 1) from handheld and mobile data acquisitions on natural turfgrass sports fields at Oconee Veterans Park, Flowery Branch, North Oconee High School, and UGA Rec Sports using two sampling grid sizes.

(Fig. 5). There were, however, noticeable differences among handheld and mobile devices at each location. Furthermore, the handheld devices produced a higher median on all evaluated fields.

All correlation coefficients were significant for NDVI ($P < 0.001$; Table 2). The strongest correlation coefficients for NDVI were at FB (0.75 and 0.76 for 4.8×4.8 and 4.8×9.6 m sampling grids, respectively). OVP, NOHS, and RS had moderate correlations (0.47 to 0.59). Differences in correlation coefficients between sampling grids were minimal.

The semivariogram parameters for NDVI maps and the RMSE outputs are presented in Table 5. Exponential or spherical models were used; however, the spherical model was the predominant model. Kriged maps of NDVI are shown in Fig. 6. Maps of NDVI displayed minimal differences in variability between sampling grid size. Maps between sampling devices showed similar patterns of variability, but the magnitude of the value was different between the sampling devices.

Technically, the NDVI sensors from the handheld and mobile devices are the same. Stationary measurements obtained with the handheld device compared with “on-the-go” data recorded with the mobile device may explain observed discrepancies. Sampling height of the handheld device may have fluctuated during use, whereas the mobile device records NDVI at a constant height. Zhang et al. (2015) reported that NDVI measured from a ground-based imaging spectrometer was not

strongly influenced by shadows. Therefore, shadows cast by the operator or cloud cover had little influence on sampling data.

Sampling time. Sampling for spatial analysis should require minimal effort to achieve a desired level of accuracy (Burgess and Webster, 1980). Oliver and Webster (2014) noted that a minimum of 100 samples are needed to create a reliable semivariogram for kriging. The two sampling grids used in this study met this requirement, but previous research using handheld devices to krig spatial data from natural turfgrass sports fields did not (Freeland et al., 2008; Miller, 2004).

Mobile sampling devices can be used to collect substantial amounts of data in a relatively short amount of time. It took ≈ 1 h to collect the initial sampling grid with the PS6000 (>450 samples). Sampling at that grid interval with handheld devices is much less practical due to time investment; therefore, we deleted half of the samples to generate a more reasonable grid size. It took a team of three people ≈ 1.5 h per field to collect handheld data with the 4.8×4.8 m sampling grid. The 4.8×9.6 m sampling grid detected spatial variability of all measured properties comparable to the 4.8×4.8 m sampling grid; therefore, sampling time and total number of samples would be lower with the increased grid size.

Unfortunately, the GPS on the mobile device was used to geo-reference handheld sample locations. Therefore, additional time would be required to geo-reference data

generated with handheld devices. Handheld sample locations were obtained by flagging PS6000 sample locations. Further preparation and setup would be required to determine handheld sample locations without the aid of the mobile device. Flagging the end lines and side lines of the field to guide sample locations could increase the speed at which handheld samples are obtained.

Mobile sampling devices are the most time efficient sampling method for spatial analysis, but they may be expensive and difficult for managers of natural turfgrass sports fields to obtain. Handheld sampling devices are cheaper and more abundant, but take more time to sample. To improve the efficiency of handheld data acquisition, future research should examine multisensor devices. For example, a combined cone penetrometer-TDR probe, such as the one Vaz et al. (2001) engineered, could simultaneously measure penetration resistance and soil moisture.

Conclusions

This was the first study to compare handheld and mobile data acquisition for spatial analysis of natural turfgrass sports fields. Data collected on 4.8×4.8 m and 4.8×9.6 m sampling grids did not differ greatly throughout the study on any field with both handheld and mobile devices for the measured field properties. Sampling can be conducted as intensively as desired with mobile devices; however, handheld devices can be used on a 4.8×9.6 m grid (120–130 samples) while still achieving the same results as the 4.8×4.8 m grid (230–259 samples). Medians and data distributions varied among handheld and mobile devices; therefore, when sampling over time device consistency is important to reduce fluctuations in test results.

VWC and NDVI had moderate to strong correlations between handheld and mobile sampling devices, but correlations for penetration resistance were weak to moderate at three of the four locations. Maps of VWC and NDVI displayed similar patterns of variability between handheld and mobile devices, but at different magnitudes. Therefore, handheld and mobile devices can produce similar results when detecting variability of VWC and NDVI within a field. Spatial maps of penetration resistance were inconsistent. Mobile devices may provide the most reliable results for penetration resistance on sports fields and the aforementioned considerations should be made when using handheld devices.

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