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Spatial variability of Southeastern U.S. Coastal Plain soil physical properties: Implications for site-specific management

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Abstract

Our objectives were to describe the field-scale horizontal and vertical spatial variability of soil physical properties and their relations to soil map units in typical southeastern USA coastal plain soils, and to identify the soil properties, or clusters of properties, that defined most of the variability within the field. The study was conducted on a 12-ha field in Kinston, NC. A 1:2400 scale soil survey had delineated three soil map units in the field: Norfolk loamy sand, Goldsboro loamy sand, and Lynchburg sandy loam. These are representative of millions of hectares of farmland in the Coastal Plain of the southeastern USA. Sixty soil cores were taken to ~1-m depth, sectioned into five depth increments, and analyzed for: soil texture as percentage sand, silt, and clay; soil water content (SWC) at −33 and −1500 kPa; plant available water (PAW); saturated hydraulic conductivity (Ksat); bulk density (BD); and total porosity. A penetrometer was used to measure cone index (CI) at each sample location. Variography, two mixed-model analyses, and principal components analysis were conducted. Results indicated that soil physical properties could be divided into two categories. The first category described the majority of the within-field variability and included particle size distribution (soil texture), SWC, PAW, and CI. These characteristics showed horizontal spatial structure that was captured by soil map units and especially by the division between sandy loams and finer loam soils. The second class of variables included BD, total porosity, and Ksat. These properties were not spatially correlated in the field and were unrelated to soil map unit. These findings support the hypothesis that coastal plain soil map units that delineate boundaries between sandy loams versus finer loam soils may be useful for developing management zones for site-specific crop management.
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1. Introduction

Site-specific management or precision agriculture seeks to identify, analyze, and manage spatial and temporal variability within fields in order to optimize profitability, sustainability, and environmental protection (Robert et al., 1996). Variability in soil properties can present management challenges to producers. Soil classification and survey have been widely used to characterize this variation (Trangmar et al., 1985). Soil surveys generate maps of soil classes representing soil properties estimated within a defined region or mapping unit (Webster, 1985). Traditional soil surveys may lead to a general understanding of the effects of soil mapping units on crop productivity. However, they were not intended for making within-field recommendations at the same scale used today for site-specific management (Mausbach et al., 1993). Sadler et al. (1998) reported that crop yields in southeastern U.S. coastal plain soils were correlated with soil map unit, but the relationship was weak at best.

Management zones are subdivisions of fields within which uniform management is appropriate (Doerge, 1999). Stafford et al. (1996) reported that management zones might be defined using a soil survey, namely by soil types. However, soil physical properties can vary considerably between sampling sites, not only within a soil map unit but also within a small area of seemingly uniform soil (Bigger, 1978; Tsegaye and Hill, 1998). Spatial heterogeneity of soil properties is caused by a number of factors and processes acting at different spatial and temporal

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scales. Consequently, another approach to defining management zones might be through direct analysis of the spatial distribution of soil physical properties (Boruvka et al., 2002).

Attempts have been made to examine the variability of soil physical properties within a given field using the coefficient of variation (CV). Warrick and Nielsen (1980) reported that bulk density and saturated water content had low CVs of 7 to 11%, particle size distribution and water retention had medium CVs of 12 to 62%, and saturated hydraulic conductivity had high CVs of 86 to 420%. While the CV gives a relative estimate of a property's variability, it provides no information about how that variability is distributed through space. Geostatistical tools such as variogram analysis allow differentiation between spatially structured and unstructured variation (Cressie, 1993). They have been used to estimate spatially variable soil physical properties (Cambardella et al., 1994; Tsegaye and Hill, 1998; Cassel et al., 2000), map soil properties, and guide site-specific management and development of management zones.

We sought to assess quantitatively the horizontal and vertical spatial variability of soil physical properties between, within, and across morphologically defined soil series taxonomic units. Our objectives were to describe the field-scale horizontal and vertical spatial variability of soil physical properties in relation to soil map units in typical southeastern U.S. coastal plain soils, and to identify the important soil variables, or clusters of variables, that define most of the variability within a field. The study aimed to provide a quantitative test of the ability of the classification system to account for the spatial variability of soil physical properties.

2. Materials and methods

2.1. Site description

The study was conducted on a 12-ha field that hosts a long-term experiment on remote sensing-informed N management and water quality at the Lower Coastal Plain Tobacco Research Station, Kinston, NC. An intensive (scale = 1:2400) soil survey (North Carolina Agric. Exp. Stn., 1976) mapped three soil series in three drainage classes in the field: Norfolk (No) loamy sand (fine-loamy, siliceous, thermic, Typic Paleudults), Goldsboro (Go) loamy sand (fine-loamy, siliceous, thermic, Aquic Paleudults), and Lynchburg (Ly) sandy loam (fine-loamy, siliceous, thermic, Aeric Paleaquults). Norfolk loamy sand is well-drained, Goldsboro loamy sand is moderately well drained, and Lynchburg sandy loam is somewhat poorly drained. In the FAO classification system (FAO, 1998), the Norfolk and Goldsboro would likely be classified as Orthic Acrisols and the Lynchburg among the Gleyic Acrisols. These soils are representative of millions of hectares of farmland in the Coastal Plain of North Carolina and the southeastern United States.

2.2. Soil sampling and analyses

Sampling sites corresponded to the locations of time domain reflectometry (TDR) profiling probes that had been installed to monitor soil moisture. Thirty sampling sites were at cell centers within a regular 60-m grid. An additional 30 sites were placed randomly within the constraints of being an adequate distance from the cell center, outside a cell border-harvest buffer area, and inline from plot to plot parallel to crop rows to facilitate field operations. This sampling scheme combined elements commonly associated with designed-based (random sampling) and model-based (geostatistical grid) approaches (De Gruijter and ter Braak, 1990; Lark and Cullis, 2004). Sampling sites were georeferenced using a differential GPS (DGPS) and projected to North Carolina State Plane NAD83 meters using ArcView GIS 3.2 (ESRI, Redlands, CA). Soil map unit polygons were created by scanning and georeferencing soil maps from the research station survey. Fig. 1 is a map of the study area showing locations of soil sampling sites. The grids resulted in the three soil map units being sampled in approximate proportion to their areal extent in the field: Goldsboro, 6.9 ha, $n=40$; Lynchburg, 3.0 ha, $n=14$, and Norfolk, 0.95 ha, $n=6$.

Relatively undisturbed soil core samples were taken to about 1-m depth by inserting a hydraulically driven soil tube (Giddings Machine Co., Windsor, CO). The soil cores were sectioned into depth increments that corresponded to the centers of the TDR probe profiling increments. Segments of 7.6-cm diameter by 7.6-cm length corresponding to depths of 4 to 12, 19 to 27, 34 to 42, 49 to 57, and 64 to 72 cm were cut and placed into soil cans immediately after core extraction, capped using air-tight plastic caps, and stored at 4 °C until they could be processed.

The soil cores were analyzed in the laboratory for saturated hydraulic conductivity, bulk density, porosity, soil water contents at −33 and −1500 kPa, and particle size distribution. Saturated hydraulic conductivity was measured using a constant head permeameter (Klute and Dirksen, 1986). A hydraulic head difference was imposed on the soil column, and the resulting flux of water was measured. Bulk density was measured on core soil samples by drying in a low-temperature (105 °C) oven for at least 24 h or until the sample was at a constant weight. Soil bulk density was calculated based on the sample dry weight and core section volume. Total soil porosity for each sample was calculated using the measured bulk density of the sample and assuming a particle density of 2.65 g cm^{-3} (Danielson and Sutherland, 1986).

The sample was then ground and sieved through a 2-mm mesh sieve. Soil particle size distribution was determined by the hydrometer method after pretreatment with Na-hexametaphosphate (Gee and Bauder, 1986). Soil water content (SWC) by weight at −33 kPa and −1500 kPa was measured on samples passing a 2 mm sieve, saturated for 24 h, and then equilibrated for 24 h on a pressure-plate apparatus (Klute, 1986). Plant available water (PAW) was calculated as the difference between SWC by weight at soil water tension of −33 kPa and −1500 kPa.

A handheld cone penetrometer was used to measure soil strength (cone index, CI) in the field near each location where the core samples were taken. The penetration resistance was recorded as a function of depth and stored on an index card. Three sets of readings were taken at each location. Cone index values were determined by averaging the readings from the three sets over an interval of ±5 cm from the desired nominal depth. Only the CI values within the depth range of the soil core samples are reported here.

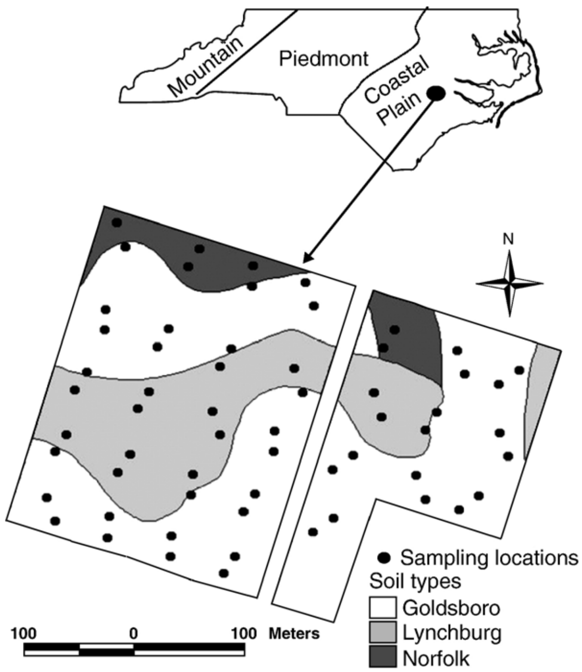

Fig. 1. Map of North Carolina showing the three physiographic regions, location of the study field within the Coastal Plain, and distribution of soil sampling sites within soil map units in the study field.

2.3. Statistical methods

The descriptive statistics mean, maximum, minimum, range, coefficient of variation, and skewness and kurtosis coefficients were calculated for each variable using PROC MEANS in SAS Release 9 (SAS Institute, Cary, NC). Skewness and kurtosis coefficients are used to describe the shape of the data distribution. If an absolute value of either coefficient is greater than two, the distribution is considered either skewed or kurtotic (Huang et al., 2001). Correlations among soil parameters were determined using PROC CORR in SAS Release 9. Regarding the particle size distribution parameters (percentage sand, silt, and clay), we caution that the constant sum constraint (i.e., must sum to 100%) of such closed compositional variables violates correlation theory assumptions of potentially independent variances and covariances and results in a bias towards negative correlations among such variables (Chayes, 1971). The latter is intuitively obvious: as the proportion of one component increases, that of one or more of the others must decrease.

The theory of regionalized variables was used to investigate spatial variability of soil physical properties (Matheron, 1971). The semivariance calculation, semivariogram function model fitting, and kriging were performed using geostatistical software, GS+ version 5.1 for Windows (Gamma Design Software, Plainwell, MI), with consideration restricted to half the maximum lag distance (Journel and Huijbregts, 1978). No anisotropy was evident in the directional semivariograms of any soil properties, thus isotropic semivariogram models were fitted to the data. Spherical, exponential, Gaussian, linear, or linear to sill models were fitted to the empirical semivariogram. Selection of semivariogram models was made based on the regression coefficient of determination (r^2). We caution that there are concerns regarding the behavior of the Gaussian model as it approaches lag zero: it is infinitely differentiable and deterministic (Wackernagel, 2003). We present the best fit among the theoretical semivariogram models available in GS+ solely to describe the form of the empirical semivariogram; we ascribe no practical nor theoretical significance to the best fit model.

The nugget semivariance expressed as a percentage of the total semivariance (i.e., the nugget to sill ratio) enables comparison of the relative magnitude of the nugget effect among soil properties (Trangmar et al., 1985; Cambardella et al., 1994), especially if sampled at similar scales. To define distinct classes of spatial dependence among soil properties with depth, nugget-to-sill ratio ranges similar to those presented by Cambardella et al. (1994) were used. If the nugget-to-sill ratio was <25%, the variable was considered strongly spatially dependent; if the ratio was between 25 and 75%, the variable was considered moderately spatially dependent; and if the ratio was >75%, the variable was considered weakly spatially dependent. Additionally, spatial dependence was defined as weak if the best-fit semivariogram model had an $r^2<0.5$. When the spatial dependence was considered to be moderate or strong, an effective range was also computed. For spherical, exponential, and Gaussian models the effective range was calculated by multiplying the best-fit model's range parameter by 1.0, 3.0, or 1.73 respectively (Gamma Design Software, 2002).

To determine the proportion of soil physical property variability captured by soil map units, the data were analyzed using two mixed model approaches. In the first approach, analyses of variance were calculated at each depth interval using the restricted maximum likelihood (REML) algorithm in PROC MIXED in SAS Release 9 (SAS Institute, Cary, NC) following the procedure outlined by Hong et al. (2005) modified for our case, which did not include a randomized complete block design structure. Three isotropic spatial covariance functions (spherical, Gaussian, and exponential) both with and without nugget effects were considered because of their applicability in describing the spatial covariance structure commonly encountered in agriculture and soil science. It is important to note that the covariances estimated in the PROC MIXED spatial analysis were not the same as those described above in the variography of the original data. The covariances estimated in the mixed model analyses with map unit and depth as fixed effects were similar, but not identical, to estimating the covariances of the residuals of classical (iid) ANOVA models including these fixed effects. They were thus distinctly different from estimating the covariances of the original data. Also, in the variography of the original data, we restricted semivariance estimation to half the maximum lag distance to better estimate the semivariogram within the spatial correlation range and to avoid inaccurate estimates at long lag intervals where few observation pairs were available (Journel and Huijbregts, 1978). In contrast, REML within PROC MIXED uses information similar to the full semivariogram calculated over all lag distances, but in fact does not actually calculate the semivariogram (Littell et al., 1996).

In addition to the spatial covariance models, the classical model assuming independent and identically distributed errors (iid) was also considered. The best-fit model among iid and spatial covariance models was selected based on the Akaike Information Criterion (Akaike, 1974) for each model, which was used to compare the relative goodness-of-fit among them. The best-fit model was then used to calculate a separation of least square means by soil map unit at each depth. These estimates were then graphed to allow a visual estimation of any potential map unit by depth interaction. The mixed model by definition incorporates both fixed and random effects. Given our mixed sampling design and the sequential analysis strategy described above, our analyses combined elements of both design and model-based approaches (De Gruijter and ter Braak, 1990; Lark and Cullis, 2004; Hong et al., 2005). The mixed model approach accounts for the spatial dependence inherent in the data and therefore is expected to give more robust parameter estimates and p-values for testing hypotheses (Cressie, 1993; Littell et al., 1996; Hong et al., 2005). However, should the covariance structures differ by depth, this approach would not allow a formal test of the significance of the soil map unit by depth interaction.

Therefore, the complete data set combining all observations over all depths was also analyzed by a second mixed model approach. In this analysis, an unstructured covariance model (Littell et al., 1996) was used to examine the potential interaction of soil map units with depth for each soil property. This fixed effects model including the map unit × depth interaction addresses several elements of our objectives by first answering the questions: “Did a parameter’s variation over depth differ depending on map unit?” and “Did a parameter’s central tendancy as captured by map units vary over depth?” The strength of this approach was that it allowed a formal test of the main effects (map unit and depth) and their interaction (map unit × depth). The potential weakness of this approach was that it ignored the spatial dependence inherent in the data.

Principal component (PC) analysis was run on the soil parameters with PROC PRINCOMP in SAS Release 9 (SAS Institute, Cary, NC) using the means of the combined 4- to 12- and the 19- to 27-cm depth intervals (“plow layer” or Ap), and the mean of all depth intervals (“profile”) to investigate which physical properties contributed most to the soil variability. A sample correlation matrix instead of a covariance matrix was used in the PC calculation due to differences in order of magnitude among the soil properties measured. We caution again that the concerns mentioned above regarding the compositional particle size distribution data apply as well to PC analysis. In addition, compositional data frequently, but not always, exhibit marked curvature that a linear technique like PC analysis may characterize inadequately (Aitchison, 1983). Log linear and log ratio contrast methods of PC analysis have been proposed to address these concerns (Aitchison, 1983, 1986), but we did not attempt them.

2.4. Map interpolation

Interpolated maps of soil properties and principle components 1 and 2 averaged over the 4- to 27-cm depth (plow layer) were computed by block kriging in GS+ version 5.1 for Windows (Gamma Design Software, Plainwell, MI). The results were mapped and classified into five classes using the so-called “smart quantile” classification in the Geostatistical Analyst of ArcGIS version 8.3 (ESRI, Redlands, CA). “Smart quantile” classification, known previously in ArcView GIS as “natural breaks,” does not create quantiles in the traditional sense of dividing a distribution into equal and equiprobable subgroups. Instead, it delineates classes based on natural groupings of data values using the Jenks optimization procedure (Jenks, 1967, 1977), an iterative algorithm that minimizes the variance within each class (ArcGIS, version 8.3; ESRI, 2004). Thus, the resulting classes delineated relatively large changes in data values, where samples with similar values were placed in the same class.

3. Results and discussion

3.1. Descriptive statistics and geostatistical parameters

Mean values of soil properties (Table 1) were representative of typical coastal plain soils. In contrast to the soil survey surficial textural classification, our particle size distribution analyses indicated predominantly sandy loam texture (USDA system; Soil Survey Division Staff, 1993) in the two surficial depth intervals (4–12 and 19–27 cm; plow layer), particularly for the Goldsboro and Norfolk soils where this class accounted for over 90% of samples (not shown). The Lynchburg soil was

Table 1
The mean, median, standard deviation (SD), coefficient of variation (CV), minimum, maximum, skewness, and kurtosis of the percentage sand, silt, clay, total porosity, soil water content (SWC) at −33 and −1500 kPa, and plant available water (PAW); saturated hydraulic conductivity (Ksat); bulk density (BD); and cone index (CI), all averaged over the three soil map units and five depth increments (n = 300)

Variable	Mean	Median	S.D.	CV	Minimum	Maximum	Skewness	Kurtosis
Sand (%)	55.5	55.2	8.3	15	25.3	73.7	−0.24	0.27
Silt (%)	25.6	24.6	5.6	22	5.0	52.9	1.51	5.60
Clay (%)	18.9	19.2	7.7	41	6.3	51.9	0.42	0.22
Ksat (cm h^{-1})	5.3	2.9	5.4	102	0.02	22.9	1.05	0.01
BD (kg m^{-3})	1.6	1.6	0.12	8	1.2	1.9	−0.74	0.92
Total porosity	39.0	38.8	0.05	12	29	55.0	0.74	0.92
SWC at −33 kPa (%)	20.1	20.0	5.1	25	9.2	39.1	0.37	−0.35
SWC at −1500 kPa (%)	7.5	7.5	3.3	44	2.3	17.7	0.56	0.38
PAW (%)	12.7	12.2	2.6	21	6.9	24.3	1.14	2.36
Cone index (MPa)	1.5	1.4	0.9	57	0.03	5.8	1.58	2.76

somewhat texturally distinct, with 46% of samples falling in finer classes: loam, silt loam, sandy clay loam. All of these textural classes were within the range in characteristics described for these soil series at these depths (Soil Survey Staff, USDA-NRCS, 2003, 2004).

Based on the skewness and kurtosis, most of the variables were satisfactorily described by the normal distribution (Table 1) and did not require transformation. Three possible exceptions were silt, PAW, and CI. The high skew in these variables was caused by two sample locations that were inside a small

Table 2
Geostatistical parameters for percentage sand, silt, and clay; saturated hydraulic conductivity (Ksat); bulk density (BD); porosity; soil water capacity (SWC) at −33 and −1500 kPa; plant available water (PAW); and cone index (CI) at the five depth intervals examined

Variable	Soil depth [cm]	Best-fit model	R^2	Nugget	Sill	Nugget to sill ratio[a] [%]	Spatial dependence[b]	Effective range[c] [m]
Sand	4 – 12	Sph	0.89	0.1	102	0.1	strong	81
	19 – 27	Sph	0.87	0.1	85	0.1	strong	79
	34 – 42	Sph	0.5	12	27	43	moderate	112
	49 – 57	Gau	0.57	18	37	49	moderate	168
	64 – 72	Sph	0.83	19	38	50	moderate	390
Silt	4 – 12	Sph	0.91	0.1	56	0.2	strong	76
	19 – 27	Sph	0.8	0.1	42	0.2	strong	64
	34 – 42	Linear	0.01	24	25	95	weak	–
	49 – 57	Linear	0.01	24	25	96	weak	–
	64 – 72	Exp	0.07	0.01	16	0.1	weak	–
Clay	4 – 12	Sph	0.86	0.01	10	0.1	strong	86
	19 – 27	Sph	0.78	0.6	23	3	strong	75
	34 – 42	Exp	0.69	0.01	25	0.04	strong	63
	49 – 57	Sph	0.8	19	63	31	moderate	411
	64 – 72	Exp	0.13	21	43	50	weak	–
Ksat	4 – 12	Linear	0.02	24	24	99	weak	–
	19 – 27	Linear	0.03	2	2	98	weak	–
	34 – 42	Linear	0.19	31	31	100	weak	–
	49 – 57	Linear	0.15	30	30	100	weak	–
	64 – 72	Exp	0.1	26	52	50	weak	–
BD	4 – 12	Linear	0.03	0.01	0.011	91	weak	–
	19 – 27	Sph	0.8	0	0.02	0.1	strong	70
	34 – 42	Sph	0.1	0.01	0.02	47	weak	–
	49 – 57	Linear	0.01	0.01	0.012	94	weak	–
	64 – 72	Exp	0.56	0.001	0.01	15	strong	92
Porosity	4 – 12	Linear	0.01	15	16	95	weak	–
	19 – 27	Sph	0.79	0.01	21	0.1	strong	70
	34 – 42	Sph	0.12	13	26	50	weak	–
	49 – 57	Linear	0.02	16	17	94	weak	–
	64 – 72	Exp	0.56	2	14	15	strong	94
SWC at −33 kPa	4 – 12	Sph	0.86	0.01	19	0.1	strong	81
	19 – 27	Sph	0.91	0.01	16	0.1	strong	94
	34 – 42	Sph	0.7	6	22	25	strong	365
	49 – 57	Gau	0.86	8	35	21	strong	496
	64 – 72	Sph	0.27	9	17	49	weak	–
SWC at −1500 kPa	4 – 12	Sph	0.87	0.001	3	0.04	strong	83
	19 – 27	Sph	0.81	0.01	4	0.3	strong	77
	34 – 42	Exp	0.73	0.01	4	0.2	strong	75
	49 – 57	Sph	0.79	3	6	50	moderate	224
	64 – 72	Exp	0.03	5	10	50	weak	–
PAW	4 – 12	Sph	0.82	0.01	9	0.1	strong	73
	19 – 27	Sph	0.81	3	7	26	moderate	110
	34 – 42	Sph	0.66	3	12	26	moderate	354
	49 – 57	Sph	0.55	3	6	39	moderate	356
	64 – 72	Sph	0.63	2	5	37	moderate	352
CI	0 – 15	Sph	0.52	0.1	0.2	47	moderate	342
	15 – 30	Sph	0.61	0.6	1.3	45	moderate	113
	30 – 45	Sph	0.52	0.1	0.2	50	moderate	411
	45 – 60	Sph	0.31	0.1	0.2	50	weak	–

Four semivariogram models (spherical [Sph], Gaussian [Gau], exponential [Exp], and linear) were considered. The best-fit model is indicated.

[a] Nugget to sill ratio (%) = (Nugget semivariance / total semivariance) × 100.

[b] Spatial dependence was defined as strong, moderate, or weak for nugget to sill ratios <25, 25 to 75, or >75, respectively, and weak if the best-fit semivariogram model $r^2 < 0.50$.

[c] The effective range is the model range parameter multiplied by 1.0, 3.0, or 1.73 for spherical, exponential, and Gaussian models, respectively.

Table 3
Unstructured covariance mixed model analysis for the effects of soil map unit (Soil), depth, and their interaction for percentage sand, silt, clay; saturated hydraulic conductivity (Ksat); bulk density (BD); total porosity; soil water content (SWC) at −33 and −1500 kPa; plant available water (PAW); and cone index

	Sand	Silt	Clay	Ksat	BD	Porosity	SWC at −33 kPa	SWC at −1500 kPa	PAW	Cone Index (CI)
Soil	***	*	*	NS	NS	NS	*	*	NS	***
Depth	***	***	***	**	***	***	***	***	***	***
Soil × depth	**	***	**	NS	NS	NS	***	**	***	***

NS = not significant.
*, **, and *** Significant at $p \leq 0.05$, 0.01, and 0.001, respectively.

depression. However, for these soil properties, the mean and median values were similar, with the median either equal to or less than the mean despite skewness of the distribution. This showed that the outliers did not dominate the measure of central tendency. Shukla et al. (2004) also reported a similarity of means and median for several soil physical, chemical, and biological properties.

Coefficients of variation (Table 1) for most of the soil properties exceeded 20%, indicating considerable spatial variability. For many soil properties, the CVs were similar to those previously reported by Warrick and Nielsen (1980) and fell within the same CV ranges that they characterized as low, medium, and high variation. For example, BD had the lowest CV (8%), particle size distribution and SWC had medium CVs (15 to 44%), and Ksat had the highest CV (102%). Kvaerno and Deelstra (2002) also reported high variability of Ksat in a silty clay loam in southeastern Norway, and high CVs for Ksat have also been documented by other investigators (Jury, 1989; Tsegaye and Hill, 1998; Webb et al., 2000; Shukla et al., 2004).

The results of the geostatistical analyses (Table 2) suggested that the soil properties fell into two general categories. The first group consisted of particle size distribution (sand, silt, and clay), SWC, PAW, and CI. These properties had moderate to strong spatial dependence especially between 0 and 27 cm (Table 2). When soil properties show strong spatial dependence, it may indicate that the variability in these properties is controlled by intrinsic variation in soil characteristics (Cambardella et al., 1994). Similar to the findings of Cambardella and Karlen (1999), the degree of spatial dependence for these soil properties decreased with increasing soil depth (Table 2). The effective ranges of spatial correlation generally increased with depth, varying from 63 to 94 m in the plow layer and from 112 to 496 m at deeper depths. The second category consisted of Ksat, BD, and total porosity. These soil properties showed weak to no spatial dependence (nearly horizontal linear semivariograms, i.e., pure nugget effect) over most of the depth intervals examined (Table 2). Babalola (1978) found that large variations in Ksat within a 0.3-ha plot relative to a 92-ha field were caused by local changes in particle size distribution and bulk density. In addition, extrinsic variations, such as tillage, may control the variability of these weakly spatially dependent parameters (Cambardella et al., 1994). The notable exceptions to the weak spatial dependence were BD and total porosity at the second depth interval (19–27 cm), where they were strongly spatially dependent.

3.2. Spatial variation and soil map units

The relationship between soil physical properties and soil map units was analyzed using an unstructured mixed model

Table 4
Mixed model analyses testing the significance of soil map units at five depth intervals (4–12, 19–27, 34–42, 49–57, and 64–72 cm) for percentage sand, silt, and clay; saturated hydraulic conductivity (Ksat); bulk density (BD); total porosity; soil water content (SWC) at −33 and −1500 kPa; plant available water (PAW); and cone index

	Soil depth interval									
	4–12 cm		19–27cm		34–42 cm		49–57 cm		64–72 cm	
	Model	*F*-test	Model	*F*-test	Model	*F*-test	Model	*F*-test	Model	*F*-test
Sand	Sph NN	**	Gau NN	**	Exp NN	†	Exp N	NS	Exp NN	NS
Silt	Gau NN	NS	Gau NN	NS	Gau NN	NS	Sph NN	†	Sph NN	NS
Clay	Gau NN	NS	Sph NN	**	Sph NN	NS	iid	*	Gau NN	NS
Ksat	iid	NS	iid	NS	iid	NS	iid	NS	Exp NN	NS
BD	iid	NS	Sph NN	NS	Exp NN	NS	iid	NS	Exp NN	NS
Porosity	iid	NS	Sph NN	NS	Exp NN	NS	iid	NS	Exp NN	NS
SWC at −33 kPa	Exp NN	*	Sph NN	*	Gau N	*	Gau N	NS	Sph N	NS
SWC at −1500 kPa	Gau NN	†	Sph NN	***	Sph NN	*	Exp NN	NS	Gau NN	NS
PAW	Exp NN	NS	Exp NN	NS	Exp NN	NS	Exp NN	NS	Gau N	NS
Cone index	Sph N	NS	iid	***	iid	NS	Exp NN	*	NA	NA

The models that best fit the covariance structure are indicated: no-nugget spherical (Sph NN), no-nugget Gaussian (Gau NN), no-nugget exponential (Exp NN), and the traditional non-spatial model assuming independent and identically distributed errors (iid); $n = 60$.
NS = non-significant.
†,*, **, and *** Significant at $p \leq 0.1$, 0.05, 0.01, and 0.001 respectively.
NA = not available.

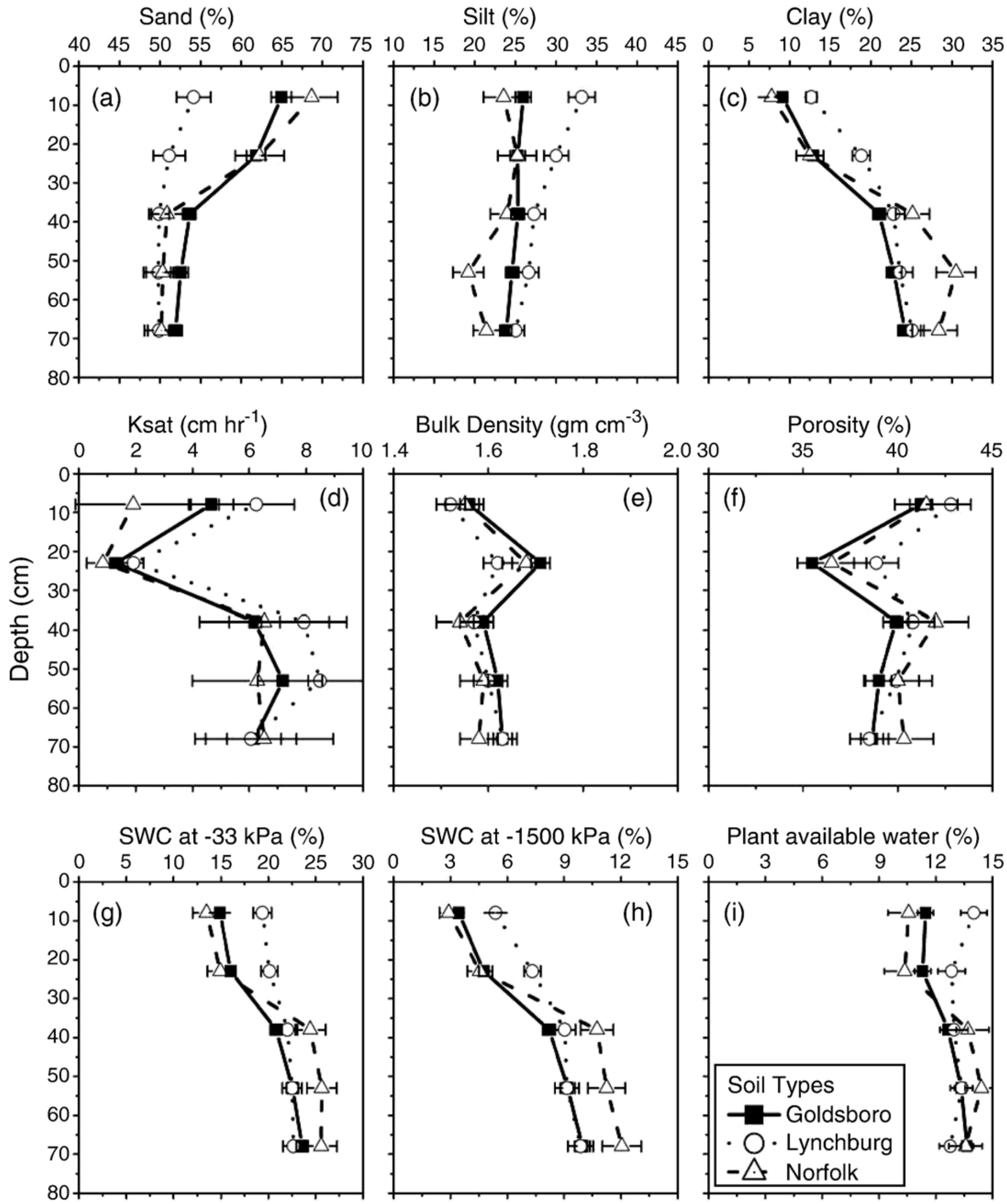

Fig. 2. Variation of soil physical characteristics among the three soil types and the five depth intervals: percentage (a) sand, (b) silt, (c) clay; (d) saturated hydraulic conductivity (Ksat); (e) bulk density; (f) total porosity; soil water content (SWC) at (g) −33 kPa and (h) −1500 kPa; and (i) plant available water. Error bars indicated the standard error of the mean.

approach that ignored the possible presence of spatially correlated errors but allowed for tests of both main and interaction effects. This ANOVA (Table 3) grouped the soil physical properties into the same two categories as the semivariogram analysis (Table 2). For the first category, which consisted of the soil parameters that displayed moderate to strong spatial dependence (particle size distribution, SWC, PAW, and CI; Table 2), soil map units captured a significant proportion of the spatial variability (Table 3). This was indicated by either a significant soil map unit by depth interaction or a significant soil map unit effect. In the second category, which consisted of parameters that had little to no spatial dependence (Ksat, BD, and porosity; Table 2), soil map unit did not capture the variability that existed in these data (Table 3). This ANOVA also indicated that there were significant differences among all the soil characteristics among depths.

Because many of these data were spatially dependent, a second mixed model analysis was conducted (Table 4) that specifically allowed for spatially correlated errors within each depth interval sampled. This method was expected to result in better soil map unit mean estimations and separation of those estimates (Fig. 2) (Cressie, 1993; Littell et al., 1996; Hong et al., 2005). Results of this analysis (Table 4) were consistent with those shown in Table 3. The best-fit models differed by depth, indicating that the covariance structure was not consistent across depths or soil physical properties. For example, percentage sand,

Table 5
Correlations between soil physical characteristics: percentage sand, silt, and clay; saturated hydraulic conductivity (Ksat); bulk density (BD); total porosity; soil water content (SWC) at −1500 and −33 kPa; plant available water (PAW); and cone index (CI); $n=300$

Variables	Sand	Silt	Clay	Ksat	BD	Porosity	SWC −33 kPa	SWC −1500 kPa	PAW	CI
Sand	1									
Silt	0.44**	1								
Clay	0.76**	0.25**	1							
Ksat	0.35**	0.03^{ns}	0.36**	1						
Bulk density	0.26**	0.18**	0.16**	0.46**	1					
Porosity	0.26**	0.18**	0.16**	0.46**	1.00**	1				
SWC at −33 kPa	0.77**	0.21**	0.98**	0.38**	0.19**	0.19**	1			
SWC at −1500 kPa	0.81**	0.01^{ns}	0.86**	0.42**	0.36**	0.36**	0.89**	1		
PAW	0.59**	0.27**	0.44**	0.34**	0.46**	0.46**	0.46**	0.82**	1	
Cone index (CI)	0.17*	−0.14	-0.08^{ns}	−0.32**	0.45**	−0.45**	-0.11^{ns}	0.18**	0.2**	1

ns = non-significant.
*, **, and *** Significant at $p=0.05$, 0.01, and 0.001, respectively.

silt, and clay at most soil depths were best fit by no-nugget spherical, Gaussian, or exponential models, while Ksat at most depths showed no spatial covariance and was best fit by the traditional iid model. This was consistent with the variography results (Table 2) that showed particle size distribution to be strongly spatially dependent especially at the shallower depths, and Ksat to be weakly spatially dependent. Results of these two mixed model analyses are described in detail below.

3.2.1. Particle size distribution

Sand content differed by map unit for the two surficial depth intervals, but not for the two deepest intervals (Table 4, Fig. 2a). The results for surficial sand content provide an important example for interpreting the spatial mixed model analyses (Table 4) in the context of the variography results (Table 2). The mixed model F-test indicated that map units captured a significant proportion of the variability of surficial sand content. However, the best-fit was not the iid model but one incorporating a spatial covariance adjustment (Table 4), indicating that map units failed to capture all of the strong spatial dependence of surficial sand content (Table 2). The same conclusions could be drawn for other parameters producing similar results, e.g., SWC to 42-cm depth (Table 4). Such results suggest that improved survey procedures or analyses incorporating appropriate spatial covariates such as remotely sensed data might prove useful in accounting for the spatial variability not captured by current map units.

Silt content was not different among map units, while clay differed among map units at the 19- to 27- and the 49- to 57-cm intervals (Table 4, Fig. 2b and c, respectively). Sand content of the Lynchburg soil remained fairly constant over depth (Fig. 2a), while sand in the Goldsboro and Norfolk soils decreased. At the two shallowest depth increments (<27 cm), Lynchburg had significantly lower sand content and tended to have higher percentage silt and clay than the Goldsboro or Norfolk soil map units (Fig. 2b, c). At deeper depths (>34 cm), all soil map units had similar sand content, but Norfolk tended to have lower percentage silt and higher percentage clay than the other map units. Clay content increased with depth in all soils, but this increase was especially marked in the Norfolk soil. Over all samples, there was a moderate negative correlation between clay and sand, with progressively weaker negative correlations of silt with sand and of silt with clay (Table 5).

The significant relationship between soil particle size distribution and map units at the shallower depth increments (<27 cm) is visualized in the kriged maps (Fig. 4a, b, and c). Areas of low sand content and high clay and silt were predominantly contained within the Lynchburg polygon. One exception to this generalization was along the north-central edge of the field where soil physical properties that appeared to be characteristic of Lynchburg soils were classified primarily as Goldsboro and to a lesser degree as Norfolk. This might be due to a map unit misclassification, or to an area in the field where these physical properties did not correlate well with the defining characteristics of these map units. In either case, this was one

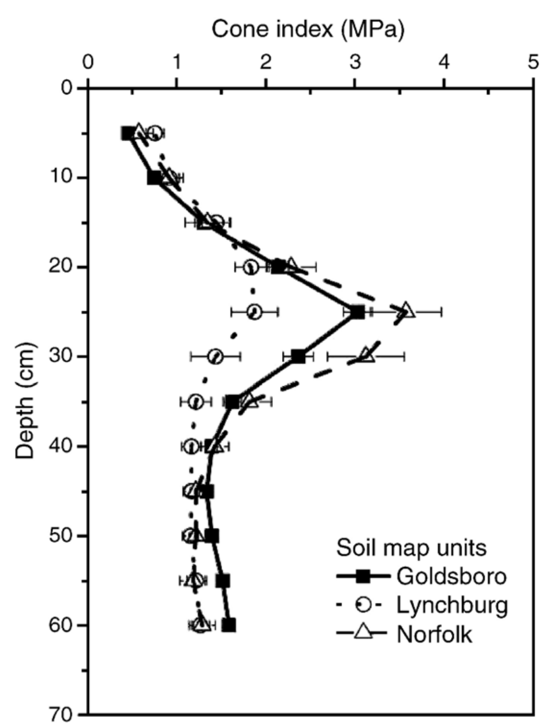

Fig. 3. Cone index for the three soil map units for 12 depth intervals that spanned the core sampled depths. Error bars represent the standard error of the mean.

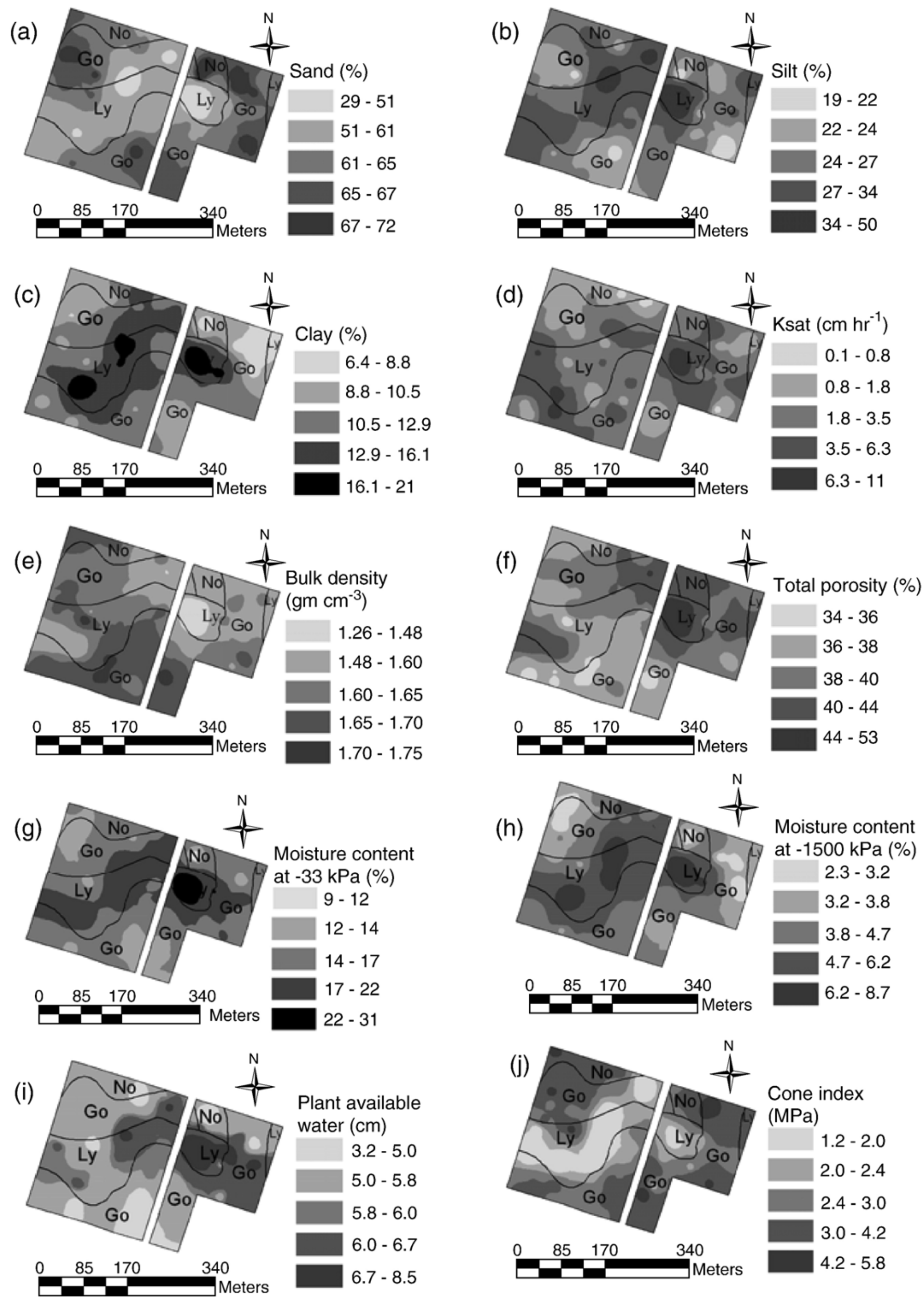

Fig. 4. Spatial distribution of soil physical properties over the two 4- to 27-cm depth intervals (plow layer): (a) sand, (b) silt, (c) clay, (d) saturated hydraulic conductivity (Ksat), (e) bulk density, (f) total porosity, soil water content (SWC) at (g) −33 kPa and (h) −1500 kPa, (i) plant available water, and (j) cone index. Go = Goldsboro, Ly = Lynchburg, and No = Norfolk soil map units. Five "smart quantiles" (ESRI, 2004) are displayed for each variable.

example where the Lynchburg soil map unit did not well capture the combination of lower sand and higher silt and clay content.

3.2.2. Saturated hydraulic conductivity, bulk density, and total porosity

There were no significant differences in Ksat, BD, or total porosity among the three soil map units at any depth (Table 3, Fig. 2d, e, and f). These three physical properties did vary with soil depth. Lower Ksat and total porosity and higher BD were observed at the 19- to 27-cm depth increment across all soil map units. This was likely due to the formation of a tillage pan at that depth, which was consistent with the highest CI values occurring at 25 cm (Fig. 3), and with the spatial correlation in BD and porosity at 19- to 27-cm depth as mentioned above. The

Table 6
Individual and cumulative percentage of total variance explained by each principal component (PC) for soil physical characteristics (percentage sand, silt, and clay; saturated hydraulic conductivity; bulk density; porosity; soil water content at −33 and −1500 kPa; plant available water; and cone index), averaged over two depth intervals: plow layer (Ap: 4 to 27 cm) and full profile (4 to 72 cm)

Principal component	Variance explained (%)	
	Individual	Cumulative
4- to 27-cm depth		
PC 1	61.8	61.8
PC 2	14.7	76.5
PC 4	6.2	90.3
PC 5	5.3	95.6
4– to 72-cm depth		
PC 1	51.1	51.1
PC 2	17.2	68.3
PC 3	12.3	80.6
PC 4	7.6	88.3
PC 5	6.1	94.4

lack of relationships of Ksat, BD, or porosity with soil map units is apparent in the kriged maps (Fig. 4d, e, and f).

3.2.3. Soil water content and plant available water

Consistent with the Lynchburg soil having lower sand but higher silt and clay content at the shallower depth increments (<27 cm), SWC at −33 and −1500 kPa were significantly higher in the Lynchburg soil at these depths than in the other two map units (Fig. 2g and h). Over all samples, the strongest correlations among the soil physical characteristics were positive correlations of SWC at −33 and −1500 kPa with clay and corresponding negative correlations of these with sand (Table 5). The PAW of the Lynchburg soil tended to be higher than the other soils, but no significant differences were found, due probably to the higher inherent variability of PAW calculated as the difference between two measurements, SWC at −33 and −1500 kPa. These soil water relationships were also apparent in the kriged maps of SWC (Fig. 2g, and h), and to a lesser degree in the map of PAW (Fig. 2i). As occurred with soil particle size distribution, the Lynchburg polygon failed to capture the area of higher SWC and PAW along the north-central edge of the field. At the deeper depth increments (>34 cm), the Norfolk soil map unit (which tended to have the highest clay content at those depths) tended to have higher SWC at both −33 and −1500 kPa. However, this did not translate into higher PAW, and at these soil depths all three soil map units had similar PAW (Fig. 2i). Over all samples, PAW exhibited its strongest positive correlation with SWC at −33 kPa, followed by SWC at −1500 kPa, and its strongest negative correlation with sand (Table 5).

3.2.4. Cone index

Cone index measurements provide information that allows comparisons of mechanical impedance or relative hardness of a given soil. Variables known to affect CI are bulk density, soil texture, and soil moisture (Cassel, 1982). Significant differences in CI occurred between soil map units at the 19- to 27- and 49- to 57-cm depths (Table 4, Fig. 3), and among depths (Table 3). The CI results provide a contrasting example to those detailed above for surficial sand content. Cone index exhibited moderate spatial dependence that was accounted for by map units. However, in contrast to the results for surficial sand content, the best-fit for CI was the iid model, indicating that map units accounted well for the spatial variability of CI.

Cone index varied from a low of 0.45 MPa at the shallowest depth for all soils to a high of 3.6 MPa in Norfolk at 25-cm depth. Sojka et al. (1990) studied the relationship between CI and sunflower growth. A soil strength corresponding to a penetrometer resistance of 2 MPa produced some root restriction, and a resistance of 3 MPa created a total barrier to root elongation. Murdock et al. (1995) suggested a penetrometer reading of 2.07 MPa was indicative of severe compaction for Kentucky soils. According to Taylor and Gardner (1963), a CI of >2 MPa can negatively affect crop yields. At a depth of 20 to 30 cm, CI values >2 MPa were recorded for the Goldsboro and Norfolk soil map units (Fig. 3), which is likely to have adverse effects on crop growth. Busscher et al. (2000) observed wheat and soybean yield decreases of 1.5 to 1.7 and 1.1 to 1.8 Mg ha^{-1}, respectively, per MPa increase in mean profile CI for CI ranging from ~0.8 to 2.2 MPa in a Goldsboro soil in South Carolina, USA.

Consistent with the results discussed above, cone index values also indicated the presence of a plow pan spanning ~15- to 35-cm depth and centered at 25-cm in all soil map units, but with greater CI values and thickness in the Goldsboro and

Table 7
Variable loading coefficients for the first two principal components (PC) for percentage sand, silt, and clay; saturated hydraulic conductivity (Ksat); bulk density; porosity; soil water content (SWC) at −33 and −1500 kPa; plant available water (PAW); and cone index (CI)

Soil properties	PC 1	PC2
4- to 27-cm depth		
Sand	−0.38	−0.10
Silt	0.35	−0.07
Clay	0.32	0.38
Ksat	0.20	−0.27
Bulk density	−0.29	0.53
Porosity	0.29	−0.52
SWC at −33 kPa	0.39	0.04
SWC at −1500 kPa	0.35	0.30
PAW	0.30	0.08
CI	−0.25	−0.34
4- to 72-cm depth		
Sand	−0.35	0.34
Silt	0.14	−0.69
Clay	0.34	0.40
Ksat	0.24	0.06
Bulk density	−0.36	0.08
Porosity	0.36	−0.08
SWC at −33 kPa	0.42	0.13
SWC at −1500 kPa	0.34	0.39
PAW	0.32	−0.042
CI	−0.21	0.26

Principle components were calculated for the total variance of all soil physical characteristics for data averaged over two depth intervals: plow layer (Ap: 4 to 27 cm) and full profile (4 to 72 cm).

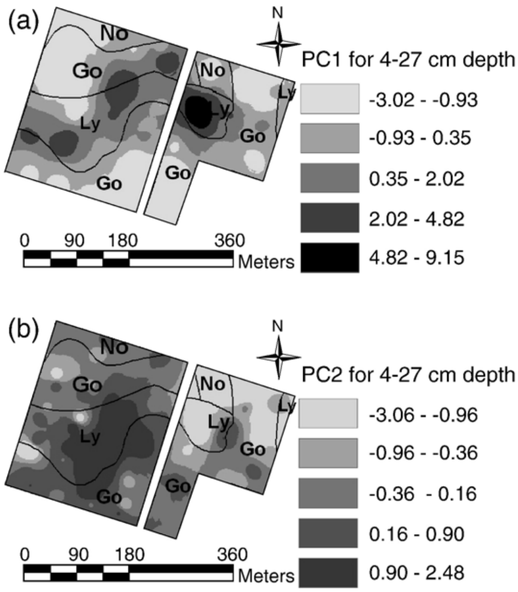

Fig. 5. (a) First and (b) second principal component (PC) maps for the 4- to 27-cm depth interval. Five "smart quantiles" (ESRI, 2004) were displayed.

Norfolk soils (Fig. 3). Cassel (1982) reported a tillage-induced pan at 25-cm depth for Norfolk loamy sand due to its structureless characteristics. The kriged map of CI at 25-cm depth (Fig. 4j) showed the relationship between the lower CI and the Lynchburg soil in this field, and delineated areas especially in the Goldsboro and Norfolk soils where crop growth would likely be adversely affected. As in the particle size distribution, SWC, and PAW maps, an exceptional area where this relationship breaks down can be seen along the north-central field edge.

3.3. Principal component analysis

Soil property data were averaged for the two surficial (4 to 27 cm) depth intervals (plow layer, Ap), and principal components (PC) analysis was used to investigate which soil variables or clusters of variables might explain the majority of spatial variability in this field. Principle component 1 explained 61.8% of the total variance (Table 6) and was dominated by SWC and particle size distribution (Table 7), with a negative loading for sand. Consequently, the kriged map of PC 1 (Fig. 5a) was very similar to the maps of these characteristics and the inverse of sand content (Fig. 4a), and likewise, tended to delineate Lynchburg from the other two soils with the exception of the area in the north-central portion of the field. The second PC explained an additional 14.7% of the total variance (Table 6) and was dominated by BD and total porosity (Table 7). Because BD and porosity were not related to soil map unit (Table 3), the map of PC 2 (Fig. 5b) also showed no correlation with map units.

These findings supported the geostatistical and ANOVA results and indicated that the spatial variability in the upper 27 cm in this field was dominated by two factors. The first factor was driven by soil particle size distribution, showed strong spatial dependency, and was fairly well defined by the distinction between the finer (Lynchburg) and coarser (Goldsboro and Norfolk) soil map units. The second factor, which described considerably less of the variability in this field, was dominated by BD and total porosity. The latter had weak to no spatial dependence and showed no relationship with soil map units, except for the 19- to 27-cm depth interval which showed the strongest expression of the tillage pan.

When the soil physical properties were averaged across all depths (4 to 72 cm), PC 1 explained 51.1% of the total variance (Table 7). This first PC was dominated by SWC at −33 kPa, porosity/BD, sand, clay, and SWC at −1500 kPa. The second PC accounted for 17.2% of the total variance and was dominated by silt, clay, SWC at −1500 kPa, and sand. The spatial distribution of soil particle size distribution, SWC, and PAW differed between the 4- to 27-cm, and 34- to 72-cm depths (Fig. 2). Consequently, it is not surprising that when averaged across all depths, no single physical property or logical cluster of physical properties explained the majority of spatial variability in this field.

With respect to the potential inadequacies of PC analysis for the non-transformed compositional particle size distribution data, for both depth intervals examined, the loadings of PC1 for clay and sand were consistent with the (non-compositional) parameters with which they were most strongly correlated, SWC at −33 kPa and SWC at −1500 kPa, respectively. However, this was not the case for PC2, indicating that a log linear contrast PC analysis might yield a better result.

4. Summary and conclusions

Our objectives were to describe the field-scale spatial variability of soil physical properties in relation to soil map units in a southeastern U.S. coastal plain field, and to identify the important soil variables or clusters of variables that defined most of this spatial variability. The soil physical properties we measured fell into two general categories. Those in the first category (particle size distribution, SWC, PAW, and CI) showed spatial correlation, which was especially strong in the two surface intervals, and spatial variability that was captured by soil map units. However, there was a significant difference in how these physical properties were distributed across soil depths among map units. For example, at shallow soil depths, the Lynchburg soil had lower sand content, higher percentage silt and clay, and consequently a tendency for higher PAW compared to the other two map units. At deeper depths, differences between map units were dominated by the Norfolk soils, which had significantly different silt and clay content compared to the other two soils. However, these differences in particle size distribution at the deeper depths did not result in significant differences in PAW. The second category consisted of Ksat, BD, and porosity, which had no relationship to soil map unit and little to no spatial dependence except for BD and porosity at 19- to 27-cm depth, where strong spatial dependence was likely associated with the tillage pan centered at 25-cm depth.

If soil particle size distribution, PAW in the upper 27 cm, and the degree to which a plow pan has developed are assumed to be important to the development of crop management zones, then our findings support using soil map units to delineate these zones in coastal plain soils of the southeastern USA. This would especially be the case where soil map units delineate differences between loamy sands or sandy loams (Goldsboro and Norfolk) and finer-textured loams (Lynchburg). However, even with an intensive soil survey (1:2400), map units appeared not to classify correctly at least one area of the field (i.e., the north-central edge). This inclusion was greater than 25% of the containing map unit, the U.S. Soil Survey target for dissimilar nonlimiting inclusions (Soil Survey Division Staff, 1993). Principle components analysis (Fig. 5) indicated that the best method for developing management zones might be to map particle size distribution directly, and that this approach could potentially capture about 62% of the variability in the field.

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