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Fine and Coarse Scale Sampling of Spatial Variability within a *Switchgrass* Field in Oklahoma

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Authors' contributions

This work was carried out in collaboration between all authors. Author AJF designed the study, performed the spatial analysis, and wrote the protocol and first draft of manuscript. Author MG created the two transects on aerial maps prior to sampling. Author KD created the figures, sample collection and analysis. Authors MG, KD, VGK and JM reviewed the manuscript prior and after journal submission. All authors read and approved the final manuscript.

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ABSTRACT

Aim: The objective of this study was to describe the spatial patterns of selected soil properties and biomass yield at fine and coarse scale in a switchgrass field to determine the appropriate sampling approach to enable the calculation of means with minimum variance.
Methodology: Spatial variability of biomass yield and soil properties at fine (2.5 m sampling interval) and coarse (10 m sampling interval) scales were assessed through semivariogram analysis. The site located in Chickasha, Oklahoma, consisted of two soil types a Dale silt loam (fine-silty, mixed, superactive, thermic Pachic Haplustolls) and McLain silty clay loam (fine, mixed, superactive, thermic Pachic Argiustolls). Eighty soil samples were collected along two 100 m transects at 2.5 and 10 m intervals established across each soil type in both 2012 and 2013.
Results: The semivariograms revealed coarse scale organic carbon (OC) to be strongly correlated with range values from 56–78 m for both soils. Normalized difference vegetative index (NDVI) was

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consistently moderately correlated with a distance less than 30 m at the fine scale for both years. Switchgrass yield was strongly correlated at the fine scale for McLain silty clay for both years, while a weak spatial dependence over a range of 36 m in 2012 and a moderate dependence at 5 m in 2013 was observed for the Dale silt loam. Conversely, a reliable spatial dependence could not be identified for total nitrogen (TN).

Conclusion: These results indicate that spatial correlation of coarse scale OC might have been imposed by the cropping system, while spatial correlation of switchgrass yield was influenced by the soil texture, particularly clay content. The use of the NDVI measurement was useful to describe the spatial dependence of switchgrass yield with good precision at the fine scale.

Keywords: Switchgrass; spatial variation; soil type; biomass; semivariogram; fine scale; coarse scale.

1. INTRODUCTION

The challenge for agronomy researchers is to characterize crop yield variation in space and time to provide farmers with useful information to make good management decisions [1]. Several studies have identified a number of reasons for the difficulties in characterizing crop yield variation in space and time. Growing season precipitation, annual temperature, N fertilizer and ecotype are some of the reasons identified for variation in switchgrass yield [2]. In the Ozzano Dell'Emilia valley area in Spain, Di Virgilio et al. [3] conducted a study using GIS and geostatistic methods to produce thematic maps of soil parameters and switchgrass yield to quantify the relationship between biomass yield spatial variation and soil parameters (N,P, soil moisture, soil texture and OM) in a small plot (5 ha) in 2004 and 2005. The maps produced from the study showed significant variability in the relationship between switchgrass yield and nearly all the soil parameters [3].

In the northern U.S., variation in switchgrass population for nine variables (biomass yield, survival, dry matter, lodging, maturity, plant height, holocellulose, lignin, and ash) was partly due to temperature and eco-region defined by soil type [4]. Likewise, switchgrass yield was found to vary across 10 locations in the Great Plains [North Dakota (Munich and Streeter), South Dakota (Bristol, Highmore, Huron and Ehtan) and Nebraska (Crofton, Atkinson, Douglas and Lawrence)] [5]. Kiniry et al. [6] simulating switchgrass yield using the ALMANAC (Agricultural Land Management Alternatives with Numerical Assessment Criteria) model for locations in three southern states [Texas (Dallas, Stephenville, and College Station), Arkansas (Hope) and Louisiana (Clinton)] found that changing the runoff curve number used to determine potential runoff water from the soil by 15% changed the mean annual biomass from 1 to 31% depending on location.

A quantitative estimation of spatial variability of soil properties and crop yield can be obtained using semivariogram modeling [3,7-9]. A semivariogram describes the relationship between spatially separated data points as a function of distance [9-11]. The relationship is described for each variable by the semivariogram parameters: Nugget, sill (total semi-variance) and range. Nugget is the variance at distance of zero and represents inherent variability or experimental error; sill is the semi-variance value at which the semivariogram reaches the upper bound after its initial increase; range is the distance at which each variable becomes spatially independent (samples closer to the range are related, samples further apart are not). Traditionally, one of the main reasons for deriving a semivariogram is to use it to predict or estimate values at unsampled locations in kriging interpolation [3,7,12]. However, a semi-variogram can also be used to relate semivariance of spatial separation and provides concise and unbiased description of the scale and pattern of spatial variability [12,13]. For example, spatial distribution of soil properties, erosion and crop yield along a cultivated transect and an adjacent transect in virgin grassland was studied by Moulin et al. [14]. The statistical distribution of soil properties and crop yield in the landscape was found to be affected by erosion that was a result of the interaction between elevation and surface curvature. Likewise, Huang et al. [7] observed a periodic behavior for soil total carbon along a transect that was mainly dependent on field topographic position and not on land use.

Site specific crop management using remote sensing and geographic information systems that make use of semivariogram modeling has been proposed as a means of managing the spatial and temporal variation of soil related, biological, landform and meteorological factors that influence crop yield [15-18]. Remote sensing is the process of acquiring information about an object by a device separate from it by some distance such as ground-based booms, aircraft, or satellite. Barnes et al. [19] outlined three applications for using remote sensing data in site-specific agriculture. In the first application, multispectral images are used for detection of plant stresses (such as pest, water stress and nutrient deficiency). In the second application, variation in spectral responses is correlated to specific variables such as soil properties. Once these site-specific relationships are developed, multispectral images can be translated directly to maps of fertilizer applications and yield variability. In the third application, multispectral data is converted to quantitative units such as vegetative indices (VIs) with physical meaning. Vegetative indices can be integrated into physically based growth models used for assessing crop growth and development. Remotely sensed measurements through various VIs can assess crop yield potential for switchgrass production and can provide reliable and consistent information about spatial and temporal variability at regional production scale.

Characterizing of variation within a field is dependent on the sampling method used. The selection of the appropriate sampling approach is important to enable the calculation of means with the minimum variance. Curran and Williamson [20] reported that systematic, as opposed to random sampling offers the potential to increase the precision. The proportion of nugget to sill or total semivariance in a semivariogram is a strong indicator of whether the precision of a parameter can be increased with systematic, as opposed to random, sampling [20,21]. Furthermore, Curran, [12] suggested that the semivariograms can be used for remote sensed and ground data to aid the choice of sample units and sample numbers. Thus, the objective of this study were to describe the spatial patterns of fine and coarse scale sampling of OC,TN, NDVI and switchgrass yield; and to determine the appropriate sampling approach to enable the calculation of means with minimum variance.

2. MATERIALS AND METHODS

2.1 Experimental Site

This study was conducted on an eight (8 ha) hectare switchgrass (Alamo) field established in 2010 at Chickasha, Oklahoma (35.042°N, -97.917°W). The field is comprised of two soil types, Dale silt loam [fine-silty, mixed, superactive, thermic Pachic Haplustolls] (~60%) and McLain silty clay loam [fine, mixed, superactive, thermic Pachic Argiustolls] (~40%). Soil P and K were maintained at the levels recommended by the Oklahoma State Soil testing laboratory for warm season grasses. Annual N fertilization (82 kg ha^{-1}) was applied in the second year after the establishment of switchgrass and each subsequent year. Table 1 describes the climatic condition of the site for the 2012 and 2013 growing seasons.

Table 1. Precipitation (mm) and temperature (°C) at Chickasha, Oklahoma during 2012 and 2013

Months	Rainfall (mm)		Temperature (°C)	
	2012	2013	2012	2013
Jan	50	38	5	4
Feb	16	73	7	6
Mar	113	27	15	9
Apr	79	269	18	13
May	150	76	22	20
Jun	71	113	26	26
Jul	48	145	30	27
Aug	43	24	28	27
Sep	117	49	24	28
Oct	14	58	16	16
Mean/Total	701	872	19	18

2.2 Yield and Soil Measurements

During 2012 and 2013, the field was sampled at fine and coarse scale to permit spatial modeling of biomass yield and soil properties. For coarse scale sampling, switchgrass biomass and soil samples were collected within a 0.5 m^2 area centered on geo-referenced-grid nodes spaced every 10 m along the two 100m transects. While, fine scale sampling of feedstock biomass and soil samples were collected within a 0.5 m^2 area distributed every 2.5 m along the two 100 m transects (Fig. 1). After randomly assigning transects location in 2012, it was later discovered that majority of transect 1 was located on the Dale silt loam and the entire transect 2 on the McLain silty clay loam. Therefore, in 2013, transects were randomly assigned to each of the soil type (Fig. 1).

In both years, subsamples of the switchgrass biomass [0.1 m^2 (0.5 m row at 0.20 m row spacing)] were hand-clipped and processed for determining dry matter yield. Soil samples were collected in March of both years from 0-15 cm depth and analyzed for total organic carbon (OC) and total nitrogen (TN). Soil OC and TN concentrations were determined by dry combustion using LECO CN analyzer (LECO Corp., St. Joseph, MI).

2.3 Acquisition of Sensor Reflectance Measurements

Spectral data was collected from aerial photograph taken in August 2012 and 2013. Imagery was converted into reflectance values to compute the normalize difference vegetation index (NDVI).

2.4 Spatial Analysis

Spatial variability of feedstock (NDVI and yield) and soil properties (TN and OC) at fine and coarse-scales were assessed through semivariogram modeling to quantify the spatial variation for each variable [9]. Traditionally, modeled semivariogram are used in kriging interpolation, but the parameters of a semivariogram can also be used to describe the spatial dependence (pattern) of a variable with distance [7]. There are several models to describe semivariogram. However, in this study, spatial variation was characterized using circular and spherical models.

2.5 Calculating Semivariogram

For a transect running across the field of equally spaced samples and measurements of soil properties, NDVI (pixel value) and biomass yield there were *m* pairs of observations separated by the same lag(distance). Thus, the semivariance *γ (h)* was estimated as:

$$\gamma(\mathrm{h}) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2. \qquad (1)$$

Where N(h) is the number of pairs separated by lag distance h; Z(xi) is measured sample value (soil properties, NDVI (pixel) and biomass yield) at point i; and Z(xi + h) is measured sample value at point i+h.

To obtain the best-fitted model, the model data frequency distribution was compared to a normal distribution. The shape of the data distribution is often described by the skewness coefficient. An absolute value greater than 2 indicates that, the distribution is considered as skewed [7]. A significant positive value indicates a long right tail; a negative value indicates a long left tail.

2.6 Statistical Analysis

Data analysis for each transect dataset was performed to determine normality, descriptive statistics (mean, standard deviation, maximum, minimum and CV) and semivarigorams were defined and differences in nugget and total semivariance and range examined for each of the variable. The ArcGIS 10.1 (ESRI, Redlands, California, USA) was used to analyze the spatial structure of the data and to define the semivariograms. Selection of the best fitting semivariogram model was based on the lowest RMSE (root mean square error) and confirmed by visual inspection. The lag-distance used was between 2 and 8 depending on the variable.

Spatial correlation with distance for each variable was assessed quantitatively by dividing the nugget by the sill. The classification classes describe by Cambardella et al. [21] was used to describe the nugget/sill ratio:1)<25%, strong spatial dependence; 2) 25-75% moderate spatial dependence; 3) >75% spatially independent or pure nugget; and 4) random when the slope of semivariogram is close to zero, regardless of nugget ratio.

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistics

The descriptive statistics for TN, OC, NDVI and biomass yield for 2012 and 2013 at fine (2.5 m) and coarse (10 m) scale sampling distance for each transects is presented in Table 2. Mean TN was similar between soils, while higher OC and biomass yield was observed for the McLain silty clay loam for both years. Switchgrass yield increased for each soil from 2012 to 2013, while OC and NDVI value decreased. Distributions of TN, OC, NDVI and biomass yield were normally distributed for the fine scale sampling distance based on the skewness value (skewness coefficient<2).The McLain silty clay loam NDVI was significantly negatively skewed at the coarse scale for both years of the study. Log transformation generally reduced skewness, but skewness values for NDVI increased after the log transformation. The standard deviation and CV were used as estimates of variability (Table 2). In general, greater variation for the soil parameters (OC and TN) were observed in the Dale silt loam, but the McLain silty clay loam reported greater variability for yield parameters (NDVI and switchgrass yield) based on the standard deviation and CV values. Switchgrass yield was highly variable with CV greater than 40% for Dale silt loam and 50% for McLain silty clay loam at fine and coarse scale. The yield ranges from 150–816 g/0.10 m^2 in 2012 and 260–1463 g/0.10 m^2 in 2013 for the Dale silt loam at fine and coarse scale. Yield for the McLain silty clay loam ranges from 35–1655 g/0.10 m^2 and 55–1498 g/0.10 m^2 in 2012 and 360–2670 g/0.10 m^2 and 390–2580 g/0.10 m^2 in 2013 at the fine and coarse scale respectively. The variation observed between the soils for the soil parameters and yield parameters may be attributed to intrinsic characteristics related to each soil and extrinsic sources. Rao and Wagenet, [22] define intrinsic variation as the natural variations within a soil and extrinsic variation as the variations that imposed on a field as part of crop production practices. Same production practice when imposed on the entire field, the variation in soil parameters can be considered to be more intrinsic; whereas variation in yield parameters maybe attributed to a combination of intrinsic and extrinsic sources.

3.2 Semivariogram Models

The geostatistical parameters describing the soil and yield parameters from the transect datasets were listed in Table 3. Spatial variation was characterized using spherical and circular models. For circular and spherical models, semivariance increases with distance between samples (lag distance) to a constant value (sill or total semivariance) at a given separation distance called the range of influence [21]. Samples separated by range distance are related spatially, and those separated by distance greater than the range are not spatially related. In other words, semivariogram models where the slope is not equal to zero describes samples that are spatially related, while models with slope that is close to zero(where the total variance equals the nugget variance) describes samples that are not related. The semivariogram for the McLain silty clay loam fine and coarse scale TN exhibits a slope close to zero in 2013, suggesting that TN was not related at either the fine or coarse scale sampling distance. Likewise, coarse scale TN and switchgrass yield also reported slope close to zero on the Dale silt loam and the McLain silty clay loam coarse scale NDVI for both 2012 and 2013. Semivariogram slope for OC was positive, except at the 2013 fine scale. A positive slope means that samples within the distance of influence (range) were closely related. Positive slope was also observed for the fine scale NDVI and yield for both soils in 2012.

According to Webster, [23] estimates of range tend to be landscape dependent that may be interpreted to indicate the distance across distinct soil type. However, in this study the estimate of range can be attributed to small landscape changes within a soil type (i.e. wet spots). Range values were considerable variable among the different parameters. There were some similarities in range values for OC, TN and NDVI for the Dale silt loam at the fine scale sampling distance across both years. While, greater variation in range values was observed for the McLain silty clay loam and at the coarse scale sampling distance.

The distinct classification of spatial dependence based on Cambardella et al. [21] that uses a nugget ratio expressed as percentage of the total semivariance was used to determine the spatial dependence of fine and coarse scale TN, OC, NDVI and switchgrass yield of Dale silt loam and McLain silty clay loam soils within the same field for the 2012 and 2013 growing seasons. Semivariograms indicated strong spatial dependence for variables such as coarse scale OC for both soils in 2012 and 2013, McLain silty clay loam fine scale switchgrass yield in 2012 and 2013, and the Dale silt loam coarse scale NDVI in 2013 (Table 3). Strong spatial dependence of OC was also reported for several other studies under different production practices. For example, Cambardella and Karlen [24] reported strong spatial dependence of OC under conventional and organic field in Iowa, Huang et al. [11] for soils under conservation reserve program land for 10 years and partially continuously crop land and Cambardella et al. [3] under tillage and no-till fields. All these studies reported sampling distance greater than 10 m separating each sampling points. Therefore, the strong spatial dependence of the coarse scale OC reported in this study is a strong indication that the coarse scale sampling (10 m) was appropriate for determining the spatial dependence of OC. On the contrary, variations of spatial dependence for the fine scale OC showed strong and close to a weak spatial dependence for the Dale silt loam in 2012 and 2013 respectively, and weak and no spatial dependence for the McLain silty clay loam in 2012 and 2013 respectively. This suggests that the fine scale sampling was not the most appropriate. Considering that the transects location differed each year of the study (Fig. 1),

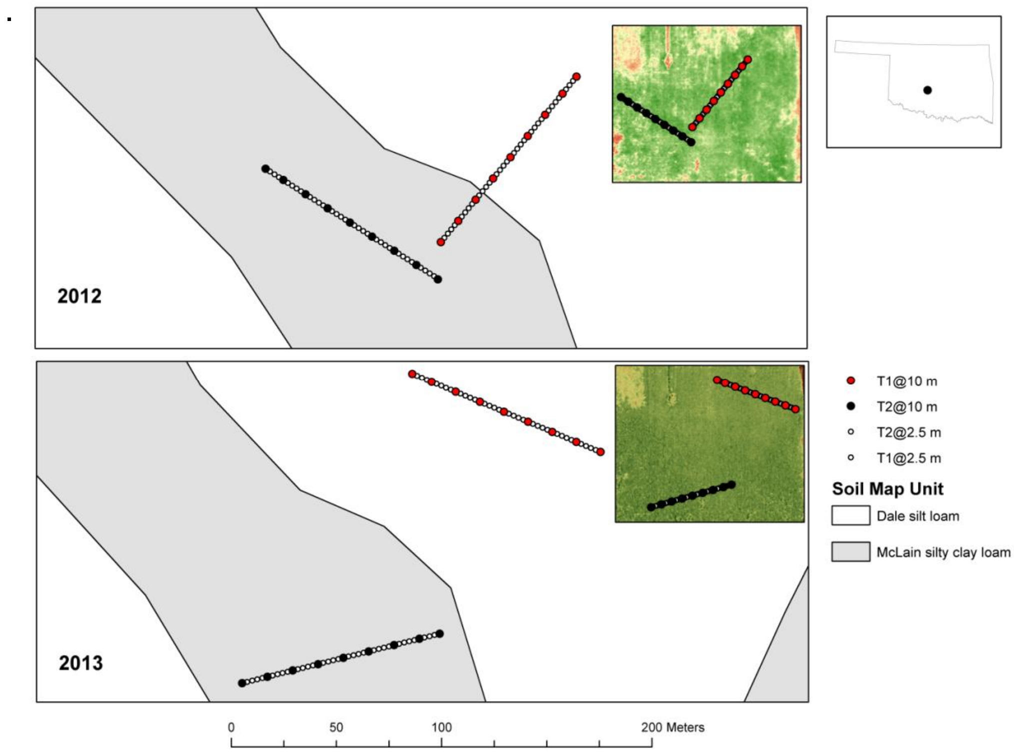

Fig. 1. Site map with location of sampling transects in relation to soil map units for the 2012 and 2013 growing seasons. Transect 1 (T1) was located on a Dale silt loam (fine-silty, mixed, superactive, thermic Pachic Haplustolls) and transect 2 (T2) on a McLain silty clay loam (fine, mixed, superactive, thermic Pachic Argiustolls). Sample data were collected at points 2.5 m apart (fine scale) and 10 m apart (coarse scale). Color inserts display field conditions for 2012 and 2013

the results of this study and others mentioned above are strong indication that spatial distribution of OC can be determined systematically from samples collected at distance greater than 10 m apart.

Spatial dependence of fine scale NDVI did not change from 2012 to 2013, but switchgrass yield spatial dependence did change for the Dale silt loam. In 2012 and 2013 growing seasons, fine scale NDVI was moderately correlated for both soils, but fine scale switchgrass yield was weak and moderately correlated in 2012 and 2013 for the Dale silt loam respectively and strongly correlated for the McLain silty clay loam (Table 3). In contrast, spatial dependence was more variable at the coarse scale. The difference in the range distance was small from year to year. Similar range was observed for switchgrass yield at the fine scale for the McLain silty clay loam for both years, but differed for the Dale silt loam. The range of influence for the McLain silty clay loam was 5mfor both years and the Dale silt loam was 36 and 5m in 2012 and 2013 respectively. The larger range of influence in 2012 for the Dale silt loam could be a result of the inclusion of a few samplings from the McLain silty clay loam (Fig. 1). The small nugget ratio and small range values for the fine scale McLain silty clay loam switchgrass yield for both years (Table 3) is an indication of the high variable in stand density [24] that was observed within the field. Likewise, the small range for the Dale silt loam in 2013 is also an indication of a patchy distribution of switchgrass yield [3]. The McLain silty clay loam high clay content resulted in an extended wet period during the early spring precipitation that impacted the germination and stand establishment. The average number of plants harvested per 0.1 m 2 was 2.3 for the Dale silt loam and 1.4 for the McLain silty clay loam. Therefore, the higher biomass yield observed on the McLain silty clay loam was a result of increased tillering as individual plants took advantage of the available space and less competition (Table 2). In addition, switchgrass stand established at row spacing of 0.2 m have been observed to thin over time resulting in a more patchy distribution. This situation could very be the scenario with the Dale silt loam. Di Virgilio et al. [3] also reported a smaller range in describing the spatial distribution of switchgrass in a field from 2004 to 2005. Spatial dependence at the coarse scale was inconsistent, thus a reliable spatial correlation could not be identified to describe the spatial patterns of NDVI and yield in this field.

There was a consistent pattern in the spatial correlation between NDVI and switchgrass yield. Moderate spatial correlation for fine scale Dale silt loam NDVI corresponds with a weak and a moderate spatial correlation for yield in 2012 and 2013, respectively. Similarly, a moderate spatial correlation for fine scale McLain silty clay loam NDVI corresponds with a strong spatial correlation for yield in both 2012 and 2013. At the coarse scale, weak spatial dependence for the Dale silt loam NDVI corresponds to a random distribution for the Dale silt loam yield in both years. The McLain silty clay loam coarse scale NDVI and yield were both randomly distributed in 2012, but NDVI was randomly distributed and yield was strongly spatial correlated within a distance of 65 min 2013.

Curran, [20] pointed out that consideration of sample size is of particular importance when remotely sensed data are correlated to ground data or whenever ground data are being estimated from remotely sensed data. The sample size in this study was identical for ground and remotely sensed data. Therefore, the small variation was assumed to be a result of difference in sample area used to compute the NDVI (0.25 m^2) and sampling area (0.1 m^2) for the biomass. The computed NDVI is based on the extraction of a value for the transect point within a pixel in relation to the point location, while the actual sampling collection involve harvesting of a 0.5 m row within the location of each transect point. Based on the sampling approach, the consistency in the spatial pattern observed is a strong indication that remotely sensed data could be used to describe the spatial distribution of switchgrass yield across the two soil types within this field.

In general, remote sensing approach for determining the best sampling approach to enable the calculation of means with minimum variance offers numerous advantages over actual field samples, but should always be support by ground sampling data. For example, in this study a systematic sampling distance 2.5 m was found to be appropriate to describe the spatial distribution of NDVI for both soils. While, actual ground sampling suggests that a random sampling approach might be appropriate for the Dale silt loam and systematic sampling at 2.5 m for the McLain silty clay loam. Sampling at 2.5 m distance is impractical to most producers as it is labor intensive and time consuming. Therefore, the use of remote sensing for the estimation of switchgrass yield can be performed at this fine scale sampling distance inexpensively and with less labor and time. These results indicate that remote sensing measurements could be used to adequately describe the spatial distribution of switchgrass yield at fine scale.

To evaluate temporal variation from year to year, fine scale NDVI was computed for the 2012 and 2013 transect points using the aerial imagery of 2013 and 2012 respectively. The result shows similar spatial correlation for fine scale NDVI using the 2013 NDVI values and 2012 transects points for both soil types (Table 3). When NDVI was computed from the 2013 aerial image for the 2012 transect points the Dale silt loam fine scale NDVI was moderately correlated over a range of 39 m an increase of 10 m and the McLain silty clay loam was moderately correlated over a range of 5m, a decrease of 5 m compared to the 2012 NDVI. Similarly, when 2012 NDVI was computed with the 2013 transects points the Dale silt loam was strongly correlated over a range of 9 m, a decrease of 18 m and the McLain silty clay loam strongly correlated over a range of 23m, a decrease of 1 m compared to the 2013 NDVI. These results further suggest that variation was small from year to year for each of the soil types within the field and also illustrates the benefit of using remote sensed data for describing spatial distribution of switchgrass yield.

Spatial dependence of TN was ranked moderate, weak or random (no spatial dependence). Total N in 2012 was strong and moderate spatial dependence at the coarse scale over a distance of 54 and 66 m for the Dale silt loam and the McLain silty clay loam respectively. In 2013, randomness dominated at the coarse scale for both soil types. At the fine scale, weak spatial dependence was observed for both soils in 2012 and for the Dale silt loam in 2013, but was random for the McLain silty clay loam in 2013

(Table 3). Spatial pattern of OC and biomass yield was, in general, somewhat stable within soil type for both years, but TN varied greatly. The variation of spatial dependence of TN is not surprising. It is well documented that soil nitrogen is influenced by environmental factors such as temperature and moisture. Therefore, the warmer temperature and wetter condition prior to sampling in 2012, opposed to cooler temperature and drier condition prior to sampling in 2013 could have attributed to differences in the spatial patterns observed.

Table 2. Statistical parameters of selected soil properties, NDVI and switchgrass yield along two 100 m transects at two sampling distance over two growing seasons

Parameters	Sample no.	Mean	Stand. Dev	Minimum	Maximum	Skewness	Coeff. Var.
				2012			
TN (g kg^{-1})							
T1@2.5 m	40	1.10	0.20	0.70	1.60	0.29	19
T1@10 m	9	1.10	0.20	0.70	1.40	-1.01	20
T2@2.5 m	40	1.30	0.20	0.90	1.60	-0.01	14
T2@10 m	9	1.30	0.20	1.00	1.40	-1.01	13
OC (g kg^{-1})							
T1@2.5 m	40	11.2	2.60	7.80	20.7	1.26	23
T1@10 m	9	13.0	2.40	8.10	15.30	-0.61	18
T2@2.5 m	40	14.9	1.40	12.20	18.70	0.72	9
T2@10 m	9	14.7	1.50	12.60	16.90	0.45	10
NDVI							
T1@2.5 m	40	0.491	0.03	0.416	0.545	-0.45	7
T1@10 m	9	0.492	0.02	0.464	0.519	-0.68	4
T2@2.5 m	40	0.488	0.08	0.153	0.611	-1.85	16
T2@10 m	9	0.470	0.13	0.150	0.610	-2.10	28
BM (g /0.1 m^2)							
T1@2.5 m	40	403	185	150	816	0.66	46
T1@10 m	9	385	238	150	816	0.94	62
T2@2.5 m	40	619	383	35	1655	0.72	62
T2@10 m	9	720	505	55	1498	0.47	70
				2013			
TN (gkg^{-1})							
T1@2.5 m	40	1.10	0.10	0.90	1.30	-0.15	8
T1@10 m	9	1.10	0.10	1.00	1.20	-0.18	7
T2@2.5 m	40	1.20	0.10	1.10	1.30	-0.07	6
T2@10 m	9	1.20	0.00	1.20	1.30	1.33	0.3
OC (g kg^{-1})							
T1@2.5 m	40	11.0	1.10	9.00	13.7	0.29	10
T1@10 m	9	11.1	1.20	9.50	13.7	0.88	11
T2@2.5 m	40	13.4	0.60	12.4	15.5	0.98	4
T2@10 m	9	13.3	0.20	12.4	14.0	-0.39	5
NDVI							
T1@2.5 m	40	0.358	0.05	0.267	0.455	0.04	13
T1@10 m	9	0.348	0.04	0.267	0.401	-0.72	12
T2@2.5m	40	0.444	0.07	0.267	0.600	-0.24	17
T2@10m	9	0.437	0.01	0.267	0.497	-1.97	2
BM(g/0.1m^2)							
T1@2.5 m	40	538	228	260	1463	1.80	42
T1@10 m	9	712	342	260	1463	1.04	48
T2@2.5 m	40	1051	515	360	2670	1.28	49
T2@10 m	9	1087	681	390	2580	1.20	63

Transects (T1 and T2) were 100 m long with sample points every 2.5 and 10 m apart, T1 was located on a Dale silt loam and T2 on a McLain silty clay loam within the same switchgrass field in Chickasha Oklahoma

Table 3. Semivariogram models and spatial distribution parameters of switchgrass yield, total nitrogen and organic carbon collected across two seasons (2012 and 2013) at different sampling distance (2.5 m and 10 m) along two 100 m transects on different soil types (Dale silt loam and McLain silty clay loam) within the same field

Parameters	Model	Range (m)	Nugget ratio†	Class‡	RMSE
		2012			
TN (g kg^{-1})					
T1@2.5 m	Spherical	35	75	W	0.02
T1@10 m		0	100	R	0.02
T2@2.5 m	Spherical	56	80	W	0.02
T2@10 m	Spherical	66	49	M	0.02
OC (g kg^{-1})					
T1@2.5 m	Spherical	90	20	S	0.13
T1@10 m	Spherical	56	22	S	0.17
T2@2.5 m	Spherical	8	80	W	0.15
T2@10 m	Spherical	65	0	S	0.07
NDVI					
T1@2.5 m	Spherical	29	48	M	0.03
T1@10 m	Spherical	56	76	W	0.03
T2@2.5 m	Spherical	10	38	M	0.07
T2@10 m		0	100	R	0.14
T1-NDVI13[1]	Spherical	39	70	M	0.04
T2-NDVI13[2]	Spherical	5	63	M	0.07
BM (g /0.1 m^2)					
T1@2.5 m	Spherical	36	87	W	191
T1@10 m		0	100	R	258
T2@2.5 m	Spherical	5	11	S	366
T2@10 m		0	100	R	524
		2013			
TN (g kg^{-1})					
T1@2.5 m	Spherical	52	75	W	0.01
T1@10 m		0	100	R	0.01
T2@2.5 m		0	100	R	0.01
T2@10 m		0	100	R	0.01
OC (g kg^{-1})					
T1@2.5 m	Circular	5	74	M	0.08
T1@10 m	Spherical	78	5	S	0.08
T2@2.5 m		0	100	R	0.05
T2@10 m	Circular	54	9	S	0.03
NDVI					
T1@2.5 m	Spherical	27	64	M	0.05
T1@10 m	Spherical	65	2	S	0.03
T2@2.5 m	Circular	24	70	M	0.07
T2@10 m		0	100	R	0.08
T1-NDVI12[3]	Spherical	9	0	S	0.03
T2-NDVI12[4]	Spherical	23	25	S	0.04
BM (g /0.1 m^2)					
T1@2.5 m	Spherical	5	60	M	244
T1@10 m		0	100	R	391
T2@2.5 m	Spherical	5	32	S	534
T2@10 m	Spherical	65	6	S	468

*†Nugget ratio = (Nugget semivariance/sill)*100;[1] NDVI computed for T1@2.5 m using 2013 aerial image;[2] NDVI computed for T2@2.5 m using 2013 aerial image;[3] NDVI computed for T1@2.5 m using 2012 aerial image; and [4] NDVI computed for T2@2.5 m using 2012 aerial image. ‡Spatial Class: S= strong spatial dependence (% Nugget ratio <25); M = moderate spatial dependence (% Nugget ratio between 25 and 75); W= weak spatial dependence (% Nugget ratio >75); R = random (slope of semivariogram close to zero, regardless of nugget ratio)*

Some researcher hypothesized that strongly spatially dependent properties may be controlled by intrinsic variations in soil characteristics such as texture and mineralogy and weak spatially dependence properties may be controlled by extrinsic variations such as fertilizer application and cropping practice [21,22]. Therefore, the weak to random spatial correlation observed for TN at the fine and coarse scale could be seen as indicators of the influence of extrinsic variations, such as fertilizer application and cropping practice and the medium spatial dependence of NDVI controlled by the combined effect of the intrinsic and extrinsic factors. On the contrary, the consistent strong spatial dependence of coarse scale OC across the different soil types suggest that it may be controlled by extrinsic factors such as cropping system and residue removal. Whereas, the differences in spatial correlation for switchgrass yield between the two soils further suggest that soil surface texture was the dominant influence. Di Virgilio et al. [3] study evaluated the spatial dependence of numerous soil characteristics (silt content, clay content, sand content, organic matter, soil strength, soil moisture, pH, P and N) based on nugget/ sill ratio [21] in a switchgrass field found only clay content to have strong spatial correlation with distance. The soils used in this study are almost identical with the major difference being that the McLain silty clay loam contains 31% clay to 20 % of the Dale silt loam [25].

4. CONCLUSION

Since most spatial analysis studies of a field involved multiple soil types, this study was preformed to determine the appropriate sampling method and distance to obtain a mean with the minimum amount of variability for OC, TN and biomass yield. The result of this study reports similar spatial pattern of OC across soil type, but greater variation in spatial pattern for yield and TN. Based on these results the best precision (mean with minimum variation) for OC maybe achieved by systematic sampling. While the best precision for switchgrass yield and TN maybe achieved by random sampling.

These results indicate that the coarse scale sampling was appropriate for determining the spatial variation of OC, while fine scale sampling was appropriate for switchgrass yield. Also, the relationship between the spatial dependence of NDVI obtained from aerial imagery and the spatial dependence of switchgrass yield from ground sampling also suggest that aerial imagery could be an appropriate sampling approach for estimating switchgrass yield.

Finally, spatial patterns described for the different parameters indicates that spatial dependence of coarse scale OC was independent of soil type, fine scale switchgrass yield was greatly influenced by the soil type (clay content) and spatial dependence of TN could not consistently be identified from year to year on the same soil type.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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