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Cotton Fiber-Quality Prediction Based on Spatial Variability in Soils

Rui Wang, J. Alex Thomasson, Michael S. Cox, Ruixiu Sui,
and Elizabeth G. Marley Hollingsworth

ABSTRACT

Maximizing cotton fiber quality is crucial for the continued success of the U.S. cotton industry. Previous studies have indicated that spatial variability of fiber-quality properties exists and is a factor in revenue variability across a field. Site-specific fiber-quality prediction potentially could be managed on the farm to optimize fiber quality with respect to profitability, or the harvest could be segregated according to fiber quality to increase a producer's overall crop price. Fiber micronaire was identified as the target property for study because of its moderate variation at the farm-field level and its importance to producers and the textile industry. Two years' cotton and soil data from two fields near Brooksville, MS, were used to investigate the extent to which soil parameters could explain spatial variation in cotton fiber quality. Spatial variability existed in both soil and fiber-quality properties, and as expected from prior research, micronaire was found to have relatively large variability compared to other quality properties. Spatial autocorrelation in the data was considered by using Moran's *I* but found not to be a factor. When simple linear regression was employed, the individual soil-related factors most closely related to overall micronaire variability were clay content, pH, and relative site elevation. Multiple linear regression was also employed, and one soil variable, pH, accounted for 42% of the overall variability in micronaire for the south field in year one; whereas pH, magnesium, and sodium together accounted for more than 41% of the micronaire variability for the north field in year two. Site-specific prediction of micronaire based on soil parameters alone continues to be a challenge according to the results of this study.

Fiber quality is a primary concern in cotton production. High-speed spinning equipment used in modern textile mills requires high-quality cotton fiber to ensure high-quality end products and efficient processing; for example, micronaire in the range of 3.8 to 4.4 (Estur, 2004). Correspondingly, better fiber quality at the farm level enhances price and makes the crop more marketable. It is well known that cotton fiber varies from bale to bale because of genetic variation and environmental factors such as planting date, harvest timing, weather, and soil parameters including fertility, pH, and water availability. Therefore, for maximum profit, it is important for cotton producers to manage both genetics and environmental factors so as to optimize fiber quality and yield. Genetic factors can be managed through variety selection, whereas managing the environmental factors associated with fiber quality presents a greater challenge.

Researchers have reported spatial variability in some fiber-quality factors in agricultural fields (Bradow and Davidonis, 2000; Bradow et al., 1997a, b; Elms and Green, 1998; Johnson et al., 2002), suggesting the potential of site-specific crop management (SSCM) to optimize fiber quality. In SSCM, a field is broken down conceptually into smaller zones, and management decisions are based on the requirements of each zone. Global positioning system (GPS) and geographic information system (GIS) technologies can be combined with variable rate technology (VRT) equipment to apply crop inputs based on the predicted requirements of a particular management zone. As with fiber quality, soil and crop properties vary spatially within a field. If the soil properties affecting micronaire could be determined, they conceivably could be related to fiber quality and enable SSCM to improve it.

Within a given field of a single cotton variety, variation in micronaire generally relates to fiber maturity (Bradow and Davidonis, 2000; Bradow et

R. Wang, 16431 Pasadena Cir., Omaha, NE 68130; J.A. Thomasson* and E. G. Marley Hollingsworth, Department of Biological & Agricultural Engineering, Texas A&M University, 2117 TAMU, College Station, TX 77843-2117; M.S. Cox, Department of Plant and Soil Sciences, Mississippi State University, Box 9555, Mississippi State, MS 39762; and R. Sui, USDA Agricultural Research Service, Crop Production Systems Research Unit. PO Box 350, Stoneville, MS 38776.
*Corresponding author: thomasson@tamu.edu

al., 1997a, b). Factors related to the in-field growth period might greatly influence the maturity of harvested cotton; for example, relatively high micronaire (i.e., mature) fiber results when the supply of carbohydrates is not limited. Disease, water stress, loss of leaf function, potassium deficiency, and cool nighttime temperatures during boll development, among other factors, can decrease micronaire (Kerby, 1994). The premium micronaire range is 3.7 to 4.2, with price penalties for micronaire below 3.5 and above 4.9 (USDA-AMS, 2001).

Typically, significant soil variations occur within a field even under uniform climate, cultural practices, and irrigation schedules (Warrick and Gardner, 1983). Elms and Green (1998) evaluated variability of cotton yield and fiber quality along with soil texture, organic matter (OM), nitrogen (N), phosphorus (P), potassium (K), calcium (Ca), pH, cation exchange capacity (CEC), zinc (Zn), manganese (Mn), iron (Fe), and copper (Cu) within an irrigated cotton field in Texas. They also reported on the relationships between cotton and soil properties, showing that micronaire was positively correlated with soil pH (R = 0.42, $p = 0.001$), and fiber length was negatively correlated with P concentration (R = –0.28, $p = 0.05$).

Johnson et al. (2002) reported on spatial variability in cotton yield and fiber quality relative to the underlying soil spatial variability in a South Carolina field. Over two years of study, data on the majority of fiber properties were normally distributed. Soil moisture, pH, P, and OM appeared to have the greatest influence on both cotton yield and quality. None of the correlations between soil properties and the length and diameter group of fiber properties exceeded a magnitude of 0.500. However, the positive correlations of soil Ca, magnesium (Mg), and pH with fiber length indicated that site-specific application of lime and, to a lesser extent, K, possibly could have resulted in longer fiber. Furthermore, additional P and OM possibly could have increased fiber diameter and reduced short fiber content. On the basis of simple correlation analyses, the addition of P and/or OM, as well as soil amendments that lower soil pH, appeared to increase fiber maturity and, correspondingly, micronaire. Increased levels of P also were correlated with decreased fiber yellowness and increased fiber whiteness. High levels of K and OM were correlated with improved fiber whiteness as well. The field site highest in pH, Ca, and Mg content produced immature fiber with micronaire in the price penalty range. These studies suggested that integrating site-specific maps of fiber properties with maps of soil properties could allow optimization of cultural inputs and other production practices.

Johnson et al. (1999) studied a field in Louisiana and found lint yield positively correlated to soil OM, boron (B), Cu, Fe, Mn, and Zn. The best predictors of fiber length and short fiber content were Mn, B, and Fe, whereas Na and Mg best predicted fiber diameter. Fiber maturity (described by theta, immature fiber fraction, micronaire, etc.) was most highly related to Mg, K, Cu, and arsenic (As). Although significant correlations between soil and fiber properties were observed, the strength of these correlations was weak. Field maps of yield and fiber-quality parameters showed they were influenced by landscape position and soil nutrient distribution. Soil erosion processes apparently had modified the distribution of soil nutrients in this field. The center of the experimental site, with high elevation, had the lowest yield but appeared to produce the most mature fiber.

Although yield is clearly the most significant variable output in terms of profitability, fiber quality is also a significant factor. Ge et al. (2011) compared the fiber-quality contribution to revenue variability with the yield contribution in two fields. They found that fiber quality was 13% as important as yield in one of the fields and 31% as important in the other. Thus, producers have incentive to manage their crops to maximize fiber quality.

The primary objective of this research was to examine simple linear and multiple linear correlations between cotton fiber-quality properties (micronaire, strength, length, length uniformity, Rd, and +b) and soil fertility properties (pH, Ca, Mg, K, Na, and P), soil texture properties (clay and sand content), and field topography properties (relative elevation and slope). A secondary objective was to account for spatial variability in the process by considering Moran's *I* statistic. If soil properties could explain enough of the variation in fiber quality, SSCM of soil conditions could then possibly be used to optimize fiber quality. Additionally, a fiber-quality prediction model potentially could be used to distinguish regions of similar fiber quality for site-specific harvesting.

MATERIALS AND METHODS

Data Collection. Data from two cotton fields totaling approximately 35 ha (86 acres) near Brooksville, MS, were collected over two cotton production seasons. The fields, referred to as South and North, consist primarily of Brooksville silty clay loam (fine, smectitic, thermic Aquic Chromudert) and are nonirrigated. A GPS receiver with horizontal positioning accuracy of approximately 1.0 m (3.3 ft) was used to locate 0.4-ha (1.0-acre) grid points for soil sampling at 48 sample positions in the North field and 38 in the South field. Ten soil cores of 15-cm (6-in) depth were extracted with a 2.5-cm (1.0-in) diameter probe within a 10-m (33-ft) radius of each measured grid point and mixed to form a 500-g (1.10-lb) composite sample. Each composite sample was air dried at room temperature, ground thoroughly to pass through a 2-mm (0.08-in) sieve, and analyzed for selected chemical and physical properties. Extractable Ca, Mg, K, Na, and P were analyzed according to the Lancaster Soil Test Method (Cox, 2001) and Mehlich 3 Method (Mehlich, 1984). Soil pH in a 1:2 (soil:water) slurry was measured with a pH meter. Soil texture was determined with the hydrometer method (Gee and Bauder, 1986). Elevation above a reference point within the field was mapped with laser-plane elevation survey equipment, and a differential GPS receiver was used for the horizontal field position measurement. Slope values were determined by converting the elevation measurements into cell-based digital elevation models with a spline-function interpolation method (Cox et al., 2005). Because physical properties of soils and topography typically remain stable from year to year, these data were measured during one year and assumed to be the same for both years.

The soil parameters studied were selected based on their ability to be altered at reasonable cost as well as previously established effect on plant growth and development that could affect fiber quality under certain conditions. Although OM and N are important factors, both were deemed unsuitable for determining consistent fiber-soil relationships. Although soil OM is generally stable over the course of a growing season, the scope of this study was limited to determining the relationships between fiber quality and manageable soil factors, and thus OM was not considered a variable of interest. In general, the effect of OM can be reflected in the soil fertility parameters (which are readily manageable). Furthermore, there is no viable soil test N method available to producers in the mid-South, and N fertilizer recommendations generally are made based on yield goals (pre-plant) or on in-season plant-canopy based spectral reflectance (Stewart and McBratney, 2001; Thompson et al., 1999). Hence, N also was determined to be unmanageable based on spatial and temporal variability.

Each field was chisel plowed followed by disking each spring. Cotton cultivars planted in both fields were Deltapine 33B in year one of the study and Deltapine 458BR in year two. The cultivars were planted in 97-cm (38-in) rows formed by ridge tilling. Weed and insect populations were controlled on an as-needed basis with standard production practices.

Rainfall was similar overall in both growing seasons—taken as 1 April to 30 September for the critical precipitation window—with 49.8 cm (19.6 in) in year one and 42.5 cm (16.8 in) in year two. However, rainfall distribution was not consistent across seasons. Although the year one growing season had a little more overall rainfall than year two, year one had almost 20% less in the 6 wks prior to planting, 26% less in the 25 d after planting, 202% more in the next 35 d of crop development, and approximately 16% less during the next 50 d of midseason fruit development, with no rain for 28 d in late July and early August.

Standard management practices were used for boll opening and defoliation. During harvest, seed cotton was hand harvested in blocks at the soil-core sites to estimate yield. Also, samples for fiber-quality analyses were collected manually at the outlet of a two-row cotton-picker duct from 6 m (20 ft) on either side of the soil-sampling grid points. Approximately 0.6-kg (1-lb) seed cotton samples were ginned on a small roller gin at the Southwestern Cotton Ginning Laboratory (USDA Agricultural Research Service) in Mesilla Park, NM. After ginning, the samples were measured for color, trash content, fiber strength, micronaire, length, and length uniformity with a High Volume Instrument (HVI) cotton classing system at the Cotton Classing Office (USDA Agricultural Marketing Service) in Dumas, AR.

Data Analysis Methods. Analytical procedures within the SAS (SAS Institute, 2017) statistical software package were used to calculate descriptive statistics for and correlations between fiber-quality properties (HVI length, strength, micronaire, uniformity, and the reflectance properties of Rd and +b) and the following sample-site properties: soil texture (clay and sand), certain soil nutrients (extractable Ca, K, P, Mg, and Na), site topography (elevation and slope), and yield. The PROC MEANS procedure was used to produce basic descriptive statistics, and PROC CORR was used to produce the Pearson correlation matrix.

Multiple linear regression (MLR) analysis was used to determine the ability to use soil properties to estimate cotton properties, with a focus on micronaire. The PROC RSQUARE procedure was used in an effort to eliminate the effects of possible additional collinearity. This method assumes that, for a given number of independent variables in a model, the combination with the highest R^2 value is the optimal model. However, the value of R^2 increases with each additional independent variable in the model regardless of the variable's predictive power. Therefore, Mallow's C_p was used in determining the model with the most appropriate number of independent variables. For a subset model in which k is the number of variables used, $C_P > k+1$ indicates a potentially under-specified model, whereas $C_P < k+1$ indicates a potentially over-specified model. When the value of C_p is approximately equal to the number of regressors in the model, a reasonable model is indicated. It should be pointed out that PROC RSQUARE uses the error mean square from the most complete model to estimate variance. If this is not a good estimate, then the bias portion of C_p can be negative, in which case C_p can be less than k (Walpole and Myers, 1993). According to Myers (1990), the lowest value of C_p in a group of regression models generally indicates the most appropriate model.

In addition to the problem of collinearity among measured parameters, spatial autocorrelation can present a problem with linear models. Cliff and Ord (1973) stated that spatial autocorrelation among regression residuals could imply an improper regression model. Spatial autocorrelation, the relationship of a variable to itself across space, exists between two points if the value at one point can give an indication of the value at the other point. Because linear regression assumes independent and identical error distribution, spatial autocorrelation presents a problem for regression models if the error terms show a spatial pattern in which points close together are more similar or different than points farther apart. Positive spatial autocorrelation means that more similar values tend to be near each other, whereas negative spatial autocorrelation means that more different values tend to be near each other.

Spatial error dependence in a linear model commonly is diagnosed with Moran's I statistic (Moran, 1948). Moran's I compares the value of the variable at any one location with the value at all other locations (Anselin and Rey, 1991; Griffith, 1987) and is formally defined as follows:

$$I = N \bullet \frac{\sum_i \sum_j w_{ij}\left(x_i - \bar{X}\right)\left(x_j - \bar{X}\right)}{\left(\sum_i \sum_j w_{ij}\right)\sum_i \left(x_i - \bar{X}\right)^2}$$

where N is the number of cases, x_i is the value of the variable at location i, x_j is the value at location $j(i \neq j)$, $\bar{X}$ is the mean of the variable,and w_{ij}, a distance-based weight, is the inverse distance between locations i and $j(1/d_{ij})$.

Thus, global Moran's I statistics were calculated with the residuals of MLR to validate selected MLR models, given the potential spatial autocorrelation in the soil and cotton data. Crimestat II (Levine, 2002) software was used for this purpose as it calculates Moran's I and related statistics to detect spatial autocorrelation in sample residuals. If no spatial autocorrelation exists, the expected value of I, $E(I)$, is calculated as:

$$E(I) = 1/(1 - N)$$

where N is the sample size of I. The values of I and $E(I)$ are used to calculate a normalized statistical value for I, $Z(I)$ which should have a normal distribution. The null hypothesis of the normality test is the absence of spatial autocorrelation; if $|I, Z(I)| > 1.96$ for a two-tailed test with confidence level p=0.05, the null hypothesis is rejected at this confidence level. The Z statistic was calculated as:

$$Z(I) = [I - \mathrm{E}(I)]/S$$

where S is the standard deviation of I.

Data Mapping Methods. Relationships between soil and cotton properties could be useful in zone delineation for site-specific practices, so it was important to map the parameters measured. Any spatial autocorrelation in a particular parameter must be accounted for when creating interpolated maps of that parameter. Kriging is a method of interpolation that, when calculating values of points that have not been sampled, generally assumes the existence of spatial autocorrelation evident at the sampling distance. According to the cross-validation variance, the Gaussian model fit the data best of the models available.

The Gaussian function is described as follows:

$$\gamma_h = C_0\,(1 - e^{-(-h/L)^2}) + \gamma_0$$

Where h = lag, γ_0 = nugget, C_0 = sill-nugget, and L = length scale.

If spatial autocorrelation is not found at the spatial scale of the data, other interpolation methods can be equally valid. Regardless, kriging maps were developed for all soil and cotton HVI parameters with the Surfer version 14 software package (Golden Software, Golden, CO). The size of the sampling grid, 0.4 ha (1.0 acre), restricted the minimum distance at which the actual ranges of spatial autocorrelation could be calculated to roughly 64 m (209 ft), the shortest distance between two grid points. The existence of spatial autocorrelation at a smaller scale was not detectable with the data set at hand and would not have affected the MLR analyses regardless.

RESULTS

Data Summary. The difference in growing-season rainfall distribution between years one and two was evident in the yield (Table 1), which was 53% higher (on average) in year two than year one. The lesser amount of pre-plant rainfall in year one resulted in less available soil moisture to initiate a good stand, and the lesser amount of rain over the first 25 d after planting added to the problem. Then, the much higher rainfall over the next 35 d of crop development led to rank growth of biomass and delayed onset of fruiting. Finally the lower rainfall in the next 50 d of midseason fruit development, along with a 28-d span with no rainfall in late July and early August, the hottest time of year, further compounded the problem, severely reducing yield in year one. The reduction was particularly acute in South field, which had better soil conditions. Year two yield in South field was 84% higher than in year one, whereas year two yield in North field was 22% higher than in year one. Average elevation (Table 1) in South field was 7.6 m higher than that of North field, but the average slope of South field was 3.3%, whereas North field averaged 5.1%.

Notable differences in soils data are as follows (Table 2). Clay content was 8% higher in South field. A soil constructed of the average clay and sand contents from the two fields would rate as silty clay loam for the South field and silt loam for the North field. Soil pH was higher in North field and slightly higher overall in year two. Levels of K were higher in South field and higher overall in year one. Levels of P were higher in South field. Levels of Mg were higher in North field and higher overall in year two. Levels of Ca were much higher in North field, corresponding to its higher pH. Levels of Na were higher in South field and higher overall in year one. Other than Ca and P, soil properties exhibited normal or nearly normal distributions. There was considerable variability in the soils data for each year and field. Coefficients of variation (CVs) above 50% in soil properties existed for Ca and P in North field year one and Na in North field year two.

Fiber-quality properties (Table 3) were normally distributed and exhibited significant variability in each year and field as well. However, the only fiber property with a CV in excess of 10% was micronaire, with a high of 12.4% in North field year two and a low of 5.3% in South field year two. The higher level of in-field variability of micronaire compared to other fiber-quality properties is consistent with the literature and is the reason why studies of spatial variability of fiber quality have tended to focus on micronaire. The value of micronaire (overall mean of 4.20) tended to be higher in South field, probably because of the better soils in South field and thus the likely greater level of water availability during fiber development. Year-to-year trends had micronaire increasing in South field—as might have been expected because of better rainfall patterns and correspondingly higher yield—but decreasing in North field. The reason for reduced micronaire in North field year two is unknown, but it is likely related to the following: (a) North field had lower clay content and higher average slope than South field, which could have caused the high rainfall in the early part of year one to run off and percolate through more quickly, meaning a lower propensity to be waterlogged and thus more mature plants during the fiber development period; and (b) the lesser amount of rain early in year two could have resulted in a lack of water for adequate plant growth early in the season, meaning that fruiting was delayed. Each field and year included some cotton in the micronaire discount and premium price ranges (Table 4), with North field year one being the best (2.2% low, 0.0 % high, 55.6% premium) and North field year two being the worst (22.9% low, 2.1% high, and 33.3% premium). Strength had an overall mean of 26.8 g/tex. Length (overall mean of 33.4 32/in) and uniformity (overall mean of 81.3%) were slightly higher in year one. The values of Rd and +b were higher in year two, with Rd being slightly higher overall in South field, whereas +b was slightly higher overall in North field.

Table 1. Elevation and slope for South and North fields as well as yield in both fields for years 1 and 2

Field	Mean Elevation (m above field reference)	Mean Slope (%)	Year	Mean Yield (lb./ac.)
South	+10.70	3.28	1	1245
			2	2294
North	+3.15	5.10	1	958
			2	1169

Table 2. Soil properties in South and North fields in years 1 and 2

Field	Clay (%)		Sand (%)		Year	pH		K (ppm)		P (ppm)		Mg (ppm)		Ca (ppm)		Na (ppm)	
	Mean	CV	Mean	CV		Mean	CV	Mean	CV	Mean	CV	Mean	CV	Mean	CV	Mean	CV
South	27.7	11.8	15.7	21.6	1	5.44	11.9	112.7	18.5	31.9	31.5	50.7	24.7	3984	57.9	51.8	27.7
					2	5.93	12.2	72.6	23.7	26.4	30.8	54.8	28.0	4112	162.8	55.9	23.1
North	19.6	34.5	15.1	27.1	1	6.90	11.2	86.4	22.3	7.5	74.2	52.0	27.5	10276	73.2	40.9	38.1
					2	7.25	12.0	63.8	31.3	13.7	35.7	69.4	45.3	10392	94.2	26.3	66.0

Table 3. Cotton fiber properties in South and North fields in years 1 and 2

Field	Year	Mike (units)		Strength (g/tex)		Length (in./32)		Unif. (%)		Rd (units)		+b (units)	
		Mean	CV	Mean	CV	Mean	CV	Mean	CV	Mean	CV	Mean	CV
South	1	4.31	8.6	25.9	5.5	33.6	2.1	81.4	1.1	69.0	2.2	7.00	6.2
	2	4.65	5.3	27.7	6.3	33.0	2.4	81.4	1.0	76.0	1.1	7.84	4.6
North	1	4.06	9.2	27.2	5.9	34.1	2.0	82.0	1.1	69.5	1.4	7.07	3.8
	2	3.88	12.4	26.5	6.3	32.9	2.6	80.5	1.4	73.7	1.7	7.94	3.7

Table 4. Percentage of cotton samples in the low-micronaire and high-micronaire price discount ranges and the premium price range

Field	Year	Low Discount (%)	High Discount (%)	Premium (%)
South	1	2.7	0.0	40.5
	2	0.0	13.2	2.6
North	1	2.2	0.0	55.6
	2	22.9	2.1	33.3

Correlation Analysis. Pearson correlation analysis among all soil properties, site elevation and slope, and fiber properties indicated that numerous properties were correlated across both fields and both years at the 0.05 significance level within and among all variable groups. Yield was positively correlated with micronaire, Rd, and elevation (Table 5). One pair of fiber properties (Rd and +b) and several soil and site parameters were correlated with an R greater than 0.50 in magnitude. The most commonly occurring soil and site properties in this category were clay, pH, and elevation. Soil-clay relationships were expected because clay provides binding sites for soil nutrients and is commonly correlated with elevation due to the size-related dislocation and translocation properties of the soil particles. Crop management practices such as ground work (e.g., tillage, land forming) and fertilizer application can influence correlations among soil nutrients. No fiber properties were as strongly correlated with individual soil and site properties, but micronaire was correlated with elevation, pH, and P at R-magnitude levels above 0.40.

Table5. Individual variables—elevation, slope, yield, soil properties, and fiber properties—correlated with one another at R^2 levels above 0.40

Correlated pairs of properties (|R|>=0.50)	Correlated pairs of properties (0.40<=|R|<0.50)
Rd, +b (0.696)	mike,pH (-0.465)
clay,pH (-0.507)	mike,P (0.405)
clay,Na (0.537)	mike,elev. (0.493)
clay,elev. (0.504)	lngth,unif. (0.417)
pH,Ca (0.695)	lngth,+b (-0.448)
pH,P (-0.533)	clay,P (0.483)
pH,elev. (-0.656)	pH,Na (-0.443)
Ca,Mg (0.577)	Ca,elev. (-0.407)
P,elev. (0.633)	Na,elev. (0.463)
mike, yield (0.683)	elev., yield (0.491)
Rd, yield (0.565)	

MLR Analysis. Based on MLR with Mallow's C_p, the R^2 values for most models were found to be less than 0.5. For the full model with all independent variables (*X*), the dependent variable (*Y*) with the largest R^2 value was micronaire. Collinearity diagnostics (condition index) showed that collinearity existed among the independent variables. The optimal prediction model for micronaire based on Mallow's C_p has an R^2 value of 0.42 (Table 6). Thus, in the best case with an optimal model, soil variability could account for only 42% of the variability in a fiber-quality parameter. It is worth noting that the largest model selected by Mallow's C_p had three regressors. It is also worth noting that Mg was a regressor in three of four optimal models, whereas pH was a regressor in two. For these two fields over the two years of study, pH and Mg had significant explanatory power.

Table 6. Micronaire prediction model selected based on multiple linear regression with Mallow's C_p for optimal model size

Year	Field	R^2	Model Variables
1	South	0.42	pH
1	North	0.31	Mg
2	South	0.20	Ca, Mg
2	North	0.41	pH, Mg, Na

Spatial Autocorrelation Analysis. The Moran's *I* statistics for each field and year include *Z*(*I*) values between -1.96 and +1.96 (Table 7), so no significant spatial autocorrelation appears to exist in the residuals at the 0.05 significance level. This result indicates that the 64 m (209 ft) sampling distance did not cause autocorrelation problems in the prediction models, and that an interpolation method other than kriging would have been reasonable.

Table 7. Results of Moran's *I* in residuals of regression model

Field and	Year	Sample Size	Moran's I	Expected I	Std of I	Z(I)
South	1	37	-0.008	-0.028	0.036	0.538
North	1	45	-0.037	-0.023	0.030	-0.494
South	2	38	-0.030	-0.027	0.036	-0.074
North	2	48	0.001	-0.021	0.028	0.779

Data Mapping. In the South field, micronaire maps from years one and two (Figs. 1 and 2) indicate that the southwestern part of the field tended to produce higher micronaire fiber, regardless of the year. In the North field, micronaire maps from years one and two (Figs. 3 and 4) indicate that the north-central and southeastern parts of the field grew higher micronaire fiber, regardless of the year. Some level of consistency in the micronaire maps between years suggests that these maps can provide an estimate of future micronaire values, perhaps serving as a starting point for segregated harvesting based on micronaire.

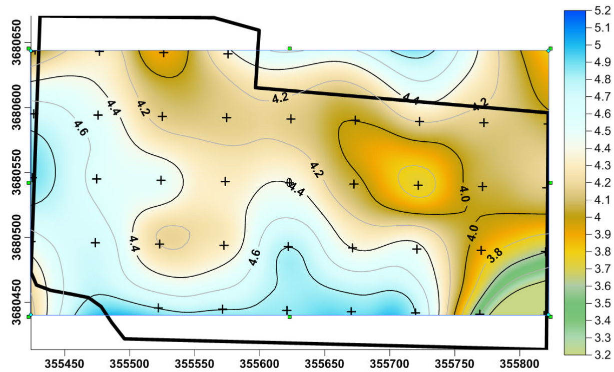

Figure 1. South field micronaire map, year 1.

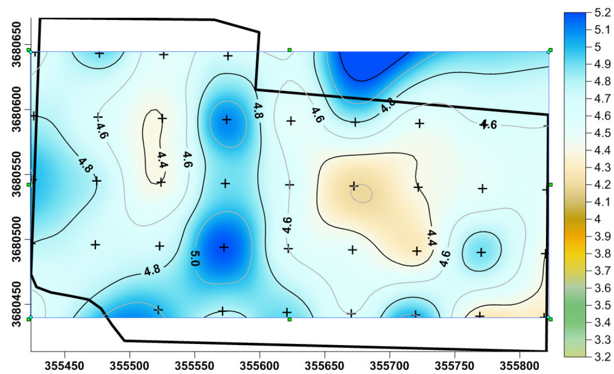

Figure 2. South field micronaire map, year 2.

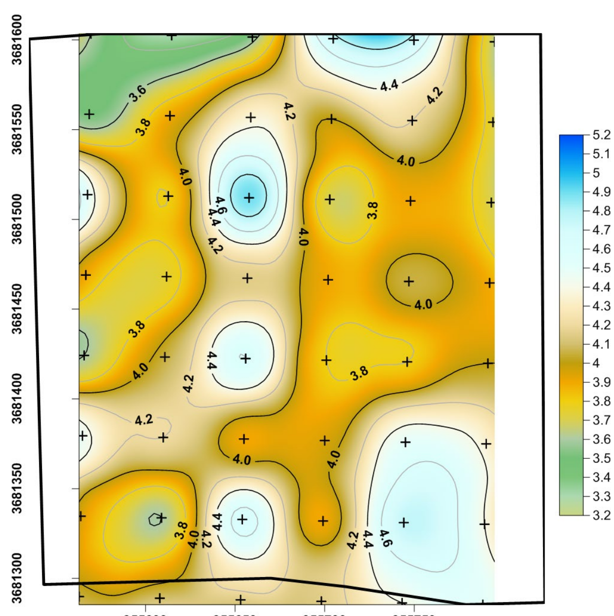

Figure 3. North field micronaire map, year 1.

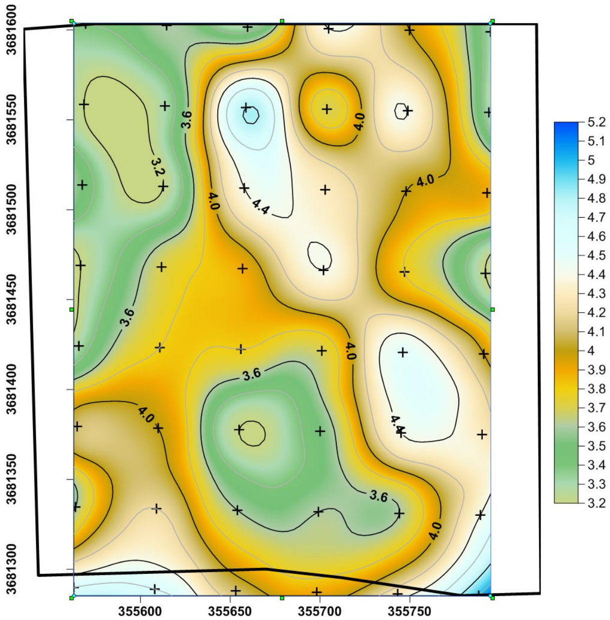

Figure 4. North field micronaire map, year 2.

DISCUSSION

The level of spatial variability in soil and fiber properties, particularly regarding micronaire, followed the literature (Elms and Green, 1998; Johnson et al., 2002; Kerby, 1994; Warrick and Gardner, 1983) and suggested that micronaire is the best candidate for prediction in the field. However, because soil-parameter variation accounted for a maximum of 42% of the variation in micronaire, predicted micronaire maps could not be expected to reflect accurately the actual micronaire maps. Ultimately, predicting cotton micronaire values based on soil parameters alone appears to be impractical, and more factors (such as history of spatial variation, temperature, and precipitation trends during the growing season, cultural practices, planting and harvesting date, and variety) should be considered to be able to delineate field zones for precision management of micronaire. Research on engineering solutions to mapping of classing-office fiber quality data back to the field has been conducted (Ge et al., 2012). Modern harvesters, which produce modules of seed cotton onboard the machine, enable the collection of position data during harvest, so it is now possible to map the boundaries of each harvested module. If fiber quality data from bales originating from each module were averaged and mapped back to the module harvest zone, micronaire maps could be made at the resolution of individual modules. Furthermore, research has been conducted to develop image-based optical sensors for micronaire estimation (Sui et al., 2008), and this capability was ultimately developed for seed cotton so that it could be applied on a harvester (Schielack et al., 2016), potentially enabling high-resolution micronaire maps to be produced. Similarities that existed between micronaire maps of the same field for two different years suggest that historical micronaire maps can help provide an estimate of future micronaire values and perhaps serve as a starting point for segregated harvesting based on micronaire. An intelligent information system that can store and analyze multiyear and multifield data sets might be useful in finding a more effective prediction method for micronaire. Significant percentages of cotton from these fields were in the micronaire discount and premium price ranges, an indication that harvest separation potentially can be economically justifiable.

CONCLUSION

Previous research found that cotton fiber-quality variation exhibits some correlation with soil-property variation. However, there has been no solid evidence that fiber-quality variation could be predicted effectively by soil parameters. Two years' data of soil nutrient content and texture for two fields in Brooksville, MS were studied with respect to their predictive capabilities in regard to fiber quality. Multiple regression analyses were conducted to determine whether fiber-quality factors could be estimated effectively from soil parameters, and spatial autocorrelation was considered by calculating Moran's *I*. Kriging maps were produced for all measured parameters and for predicted micronaire values. The following conclusions were drawn: 1. a notable amount of variation existed in most of the soil parameters and in some cotton fiber-quality factors; 2. cotton fiber micronaire exhibited relatively large variability among fiber-quality parameters; 3. significant percentages of cotton from these fields fell in the micronaire discount and premium price ranges; 4. spatial autocorrelation was shown not to be a factor in the field data, which were collected at a grid distance of approximately 64 m (209 ft); 5. similarities existed between micronaire maps of the same field for two different years; and 6. soil parameters accounted for only a portion of the variation in micronaire, at best approximately 42%.

REFERENCES

Anselin, L., and S. Rey. 1991. Properties of tests for spatial dependence in linear regression models. Geographical Anal. 23(2):112–131.

Bradow, J.M., and G.H. Davidonis. 2000. Quantization of fiber quality and the cotton production-processing interface: a physiologist's perspective. J. Cotton Sci. 4(1):34–64.

Bradow, J.M., P.J. Bauer, O. Hinojosa, and G.F. Sassenrath-Cole. 1997a. Quantization of cotton fibre-quality variations arising from boll and plant growth environments. Eur. J. Agron. 6(3-4):191–204.

Bradow J.M., L.H. Wartelle, P.J. Bauer, and G.F. Sassenrath-Cole. 1997b. Small-sample cotton fiber quality quantization. J. Cotton Sci. 1(1):48–60.

Cliff, A., and J. K. Ord. 1973. Spatial Autocorrelation. Pion, London, UK.

Cox, M.S. 2001. The Lancaster soil test method as an alternative to the Mehlich 3 soil test method. Soil Sci. 166:481–489.

Cox, M.S., P.D. Gerard, and D.B. Reynolds. 2005. Selected soil property variability and their relationships with cotton yield. Soil Sci. 170:928–937.

Elms, M.K., and C.J. Green. 1998. Cotton yield variability and correlations between yield, previous yield, and soil properties. p. 630–636. *In* Proc. Beltwide Cotton Conf., San Diego, CA. 5-9 Jan. 1998. Natl. Cotton Counc. Am., Memphis, TN.

Estur, G. 2004. Quality requirements on export markets for U.S. cotton. In Proc. 2004 Beltwide Cotton Conf., 2306-2311. Cordova, Tenn.: National Cotton Council of America.Ge, Y., J.A. Thomasson, C.L.S. Morgan, S. Stanislav, and R. Sui. 2011. Cotton revenue apportioned between lint yield and fiber quality: a precision agriculture perspective. J. Cotton Sci. 15:274–281.

Ge, Y., J.A. Thomasson, and R. Sui. 2012. Wireless-and-GPS system for cotton fiber-quality mapping. Precision Agric. 13:90–103.

Gee, G.W., and J.W. Bauder. 1986. Particle size analysis. p. 383–411 *In* A. Klute (Ed.) Methods of Soil Analysis, Part 1—Physical and Mineralogical Methods. SSSA Book Ser. No. 5. Soil Science Society of America, Madison. WI.

Griffith, D.A. 1987. Spatial Autocorrelation: A Primer. Assoc. of American Geographers, Washington, D.C.

Johnson, R.M., J.M. Bradow, P.J. Bauer, and E.J. Sadler. 1999. Influence of soil spatial variability on cotton fiber quality. P. 1319-1320. In Proc. Beltwide Cotton Conf., Orlando, FL. 3-7 Jan. 1999. Natl. Cotton Counc. Am., Memphis, TN.

Johnson, R.M., R.G. Downer, J.M. Bradow, P.J. Bauer, and E.J. Sadler. 2002. Variability in cotton fiber yield, fiber quality, and soil properties in a southeastern coastal plain. Agron. J. 94:1305–1316.

Kerby, T.A. 1994. Early temperature and cotton growth. Cotton Grower. 30(5):40.

Levine, N. 2002. CrimeStat II: A Spatial Statistics Program for the Analysis of Crime Incident Locations (Version 2.0). Ned Levine & Assoc., Houston, TX. Nat. Inst. Just., Washington, D.C.

Mehlich, A. 1984. Mehlich-3 soil test extractant: a modification of Mehlich-2 extractant. Commun. Soil Sci. Plant Anal. 15(12):1409–1416.

Moran, P. 1948. The interpretation of statistical maps. J. Royal Statistical Soc. B. 10(2):243–251.

Myers, R. H. 1990. Classical and Modern Regression with Applications. 2nd ed. Boston, Mass.: PWS-Kent.

SAS Institute. 2017. SAS, Release 9.4. SAS Institute, Cary, NC.

Schielack, V.P., III, J.A. Thomasson, R. Sui, and Y. Ge. 2016. Harvester-based sensing system for cotton fiber quality mapping. J. Cotton Sci. 20:386–393.

Stewart, C.M., and A.B. McBratney. 2001. Development of a methodology for the variable-rate application of fertilizer in irrigated cotton fields. *In* Robert et al. (ed.). Precision Agriculture [CD-ROM]. Proc. Int. Conf., 5th, Minneapolis, MN. 16–19 July 2000, pp.1-13. ASA, CSSA, and SSSA, Madison, WI.

Sui, R., J. A. Thomasson, Y. Ge, and C. Morgan. 2008. Multispectral sensor for in-situ cotton fiber quality measurement. Trans. ASABE 51(6):2201–2208.

Thompson, J.M., J.J. Varco, and M.R. Seal. 1999. Formulating decision support factors for variable-rate nitrogen fertilization. p. 1283–1285 *In* Proc. Beltwide Cotton Prod. Res. Conf. Orlando, FL. 3-7 Jan. 1999. Natl. Cotton Counc. of Am., Memphis, TN.

United States Department of Agriculture Agricultural Marketing Service [USDA-AMS]. 2001. Classification of upland cotton—micronaire. p. 5. *In* The Classification of Cotton. USDA Agric. Marketing Service, Washington, D.C.

Walpole, R. E., and R. H. Myers. 1993. Probability and Statistics for Engineers and Scientists. 5th ed. New York, N.Y.: MacMillan.

Warrick, A.W., and W.R. Gardner. 1983. Crop yield as affected by spatial variations of soil and irrigation. Water Resources Res. 19(1):181–186.