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Spatial Autocorrelation in Growth of Undisturbed Natural Pine Stands Across Georgia

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Abstract. Moran's *I* statistic measures the spatial autocorrelation in a random variable measured at discrete locations in space. Permutation procedures test the null hypothesis that the observed Moran's *I* value is no greater than that expected by chance. The spatial autocorrelation of gross basal area increment is analyzed for undisturbed, naturally regenerated stands in three Georgia forest types: loblolly, shortleaf, and slash pine. The analysis uses 0.4-ha permanent sample plots from a forest inventory that included two remeasurement intervals (1961–1972 and 1972–1982). We present a new statistic for exploratory spatial analyses, and this statistic revealed an anomalous cluster of unusually slow-growing shortleaf pine plots occurred in the mountains 100 km north of Atlanta. A regression model was used to predict gross basal area increment as a function of variables that describe local stand conditions, and no significant spatial autocorrelations existed in the regression residuals. This result suggests that the anomalous cluster of slow-growing plots can be explained by the spatial distribution of local stand conditions rather than spatial patterns of other possible causes such as air pollution, although alternative interpretations are possible. For. Sci. 40(2):314–328.

Bechtold et al. (1991) reported decreases in adjusted mean growth of naturally regenerated undisturbed pine plots in the State of Georgia (150,000 km^2) using forest inventory plots. Between the growth intervals 1961–1972 and 1972–1982, the decreases in pine basal area increment per unit area were 19% for loblolly pine and 28% for slash and shortleaf pine after adjustments for local stand conditions. They were unable to resolve the role of exogenous factors, such as climate or pollution, as possible causes of reduced growth. They suggest that "several factors are contributing to the reductions, probably varying in importance with species, location, and time." However, Hyink (1991) suspects that growth rates computed for 1961–1972 are unusually high, and the observed growth between 1972–1982 represents a return to normal conditions. Lucier and Barnard (1992) conclude that the reduction in growth of certain classes of natural pine stands is "an expected consequence of historical land use patterns, increases in stand age and competition, and other non-pollutant factors," and an abnormal "regional decline of southern pines has not been demonstrated." We conjectured that spatial analyses might reveal nonrandom patterns in the distribution of growth across Georgia that would be consistent or inconsistent with one or more of the many competing hypotheses.

Geographers divide spatial analyses into three categories (Legendre and Fortin 1989). Point pattern analysis (e.g., Penttinen et al. 1992) considers the distribution of discontinuous events over space, such as occurrence of individual trees in a stand or disturbances in a landscape; line pattern analysis considers the network of connections among points; and surface pattern analysis considers spatially continuous phenomena, where measurements are taken only at certain sites within the study area. Point and line pattern analyses use comprehensive maps of a study area, whereas surface pattern analysis is better suited for a sample of sites or plots.

Surface pattern analyses of lattices, such as sample plots, frequently use tests for spatial autocorrelation (Anselin 1992). Spatial autocorrelation exists when a variable has a regular pattern over space, such as clusters (Odland 1988). If there is positive spatial autocorrelation, then plots with large values tend to be surrounded by other plots with large values, and small values are surrounded by other small values (Reed and Burkhart 1985).

Analysis of spatial autocorrelation is a common technique in statistical geography, with examples given in standard textbooks (e.g., Ebdon 1985, Griffith and Amrhein 1991) and specialized texts (e.g., Griffith 1987, Odland 1988). Upton and Fingleton (1985) and the seminal work of Cliff and Ord (1973, 1981) present the mathematical statistics of inference with Moran's I. Examples of spatial autocorrelation analyses in ecology and forestry include Matérn (1960), Sokal and Oden (1978), Greig-Smith (1983), Taylor (1984), Reed and Burkhart (1985), Legendre and Fortin (1989), and Rossi et al. (1992). Matérn (1993) reviews applications of spatial statistics in forestry, which include: Bitterlich's angle-count sampling, estimating precision in systematic sampling, competition indices for growth and yield models, simulating structure of forest stands, and stereology in photo-interpretation.

Spatial autocorrelation is quantified with a scalar statistic that is a function of the value observed at each plot and the values at neighboring plots. There are several such functions, which resemble a correlation, covariance, or difference between values at proximate locations (Anselin 1992). Numerical weights quantify the proximity of all pairs of observed plots. The weight might equal one if a pair of plots are within a specified lag spacing (e.g., 1–18 km, or 36–54 km) and zero otherwise; this is the weighting scheme used in variograms for kriging (Isaaks and Srivastava 1989, p. 146). Or the weights might be a monotonically decreasing function of distance (d) between pairs of plots (e.g., d^{-1}, d^{-2}, or e^{-d}). The null hypothesis is the absence of spatial autocorrelation, where each observation occurs with equal probability at all sample sites. The existence of spatial autocorrelation is accepted if the observed test statistic is extreme compared to the expectation under the null hypothesis. Cliff and Ord (1973, 1981) and Czaplewski and Reich (1993) derive permutation procedures to test such hypotheses.

Legendre and Fortin (1989) list several methods to quantify spatial autocorrelation. The two most common measures are the Moran's I and Geary's c statistics. The correlogram is a special case of Moran's I that uses 0–1 weights for a range of mutually exclusive lag spacings. With similar weights, the variogram equals Geary's c multiplied by a constant (i.e., the variance of the observed response variable). The variogram is used in kriging to model spatial covariance and estimate a continuous spatial response surface. Moran's I provides more powerful tests of hypothesis than Geary's c (Cliff and Ord 1981, p. 15), and Moran's I is more sensitive to extreme values (Legendre and Fortin 1989). Spectral analysis is an alternative to Moran's I or Geary's c; however, spectral analysis requires a large sample size and is insensitive to patterns that are not combinations of repeatable patterns (Legendre and Fortin 1989).

Our first objective is to test the null hypothesis that there is no spatial autocorrelation in the data that Bechtold et al. (1991) used to detect reduced growth of undisturbed naturally regenerated southern pines. Our second objective is to demonstrate that spatial analyses can contribute to the formulation or tests of hypotheses regarding cause-effect relationships. Our third objective is to propose a new exploratory statistic that helps reveal more details regarding nonrandom spatial patterns, such as spatial clusters.

DATA

Our study uses data from Bechtold et al. (1991), which were gathered by the Forest Inventory and Analysis (FIA) Work Unit of the Southeastern Forest Experiment Station, USDA Forest Service. Analyses are conducted for loblolly (*Pinus taeda* L.) and shortleaf (*P. echinata* Mill.) pine stands in the Piedmont and Mountain physiographic regions of Georgia, and slash pine (*P. elliottii* Engelm. var. *elliottii*) stands in the Coastal Plain region. The data were screened to isolate similar sets of timber stands from each of the two remeasurement intervals; all plots were naturally regenerated and undisturbed, meaning there was no evidence of planting or artificial seeding, or visual evidence of serious treatment or disturbance (such as timber cutting or pathogen, disease, or fire damage) within the measurement period for which the plot qualified (Bechtold et al. 1991).

The approximate locations of the sample plots are given in Figure 1. The FIA sampling frame is based on a systematic sample from a regular grid; however, the screening criteria resulted in a small subsample of FIA plots that gives the appearance of a random sample in Figure 1.

Table 1 gives the number of FIA sample plots and the moments of the growth rate distributions. The number of selected plots is smaller in the 1972–1982 interval than the 1961–1972 interval because disturbance rates were higher between 1972 and 1982, and the conversion of natural loblolly stands to planted stands was more prevalent. Also, a change in FIA plot configuration between 1961 and 1972 produced a larger plot that had less chance of being in a homogeneous condition.

The logarithmic transformation of gross pine basal area increment produced approximately symmetric distributions (Figure 1), which increased the power to detect spatial autocorrelation among slow-growing plots. However, the logarithmic transformation is not normally distributed in half the cases (Table 1); therefore, we used the moments of Moran's I that assume random permutations rather than normal distribution of observations (Cliff and Ord 1981, p. 42–46, Reed and Burkhart 1985, p. 577). Growth on undisturbed plots during the two remeasurement intervals (1961–1972 and 1972–1982) was analyzed separately because most plots occurred in only one of these two 10-yr time intervals; it was unlikely that a plot remained undisturbed over the entire 21-yr interval (1961–1982).

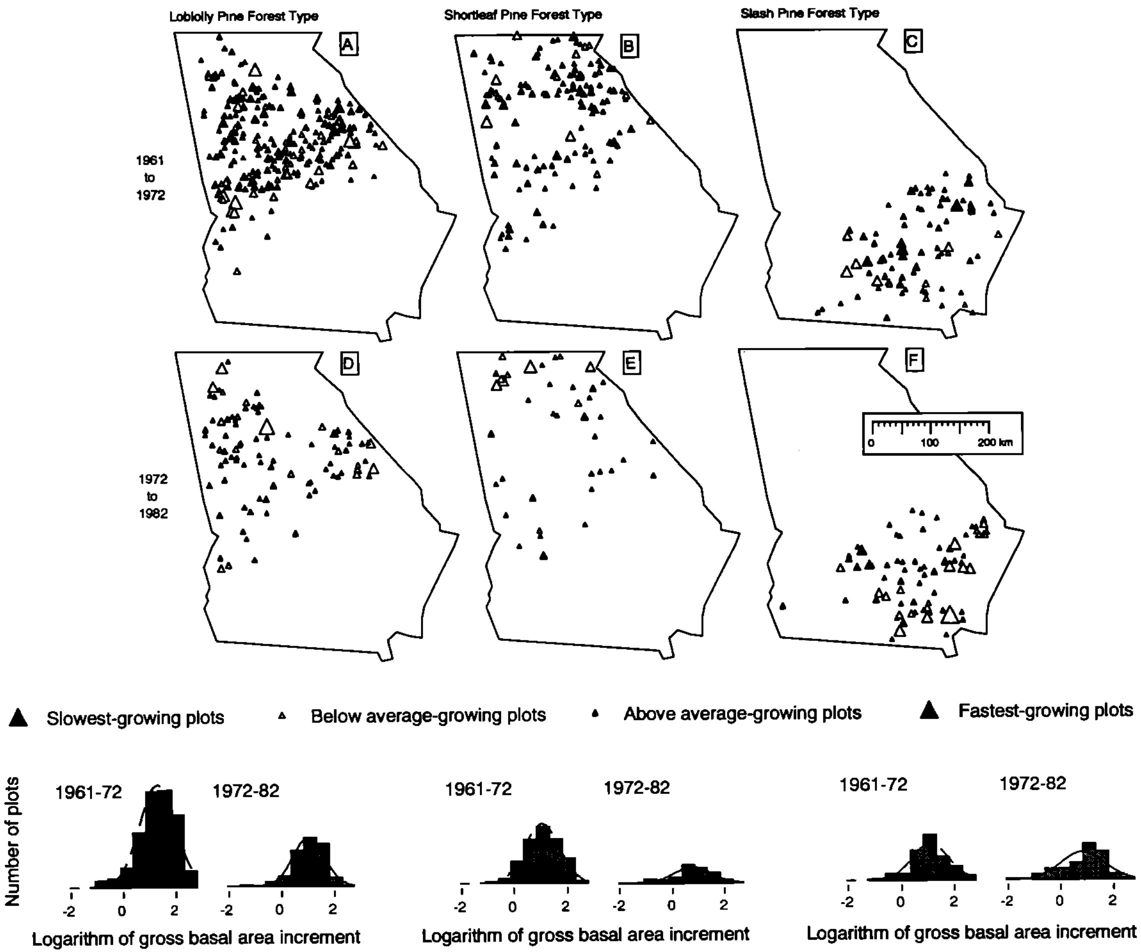

FIGURE 1. Approximate locations of undisturbed natural southern pine sample plots (denoted by triangular symbols) that are used in the analyses of spatial autocorrelation. The boundary represents the State of Georgia, USA (150,000 km^2). Large shaded symbols represent unusually rapid growing plots, small symbols represent plots with approximately average growth, and large unshaded symbols represent unusually slow-growing plots. Histograms give the frequency distribution for each group of plots. Units of growth are logarithm of pine basal area increment in ft^2/ac/yr.

TABLE 1.

Distribution of gross basal area increment.[1]

Forest type	Time interval	Number of plots	Gross increment[2] Mean	Gross increment[2] Standard deviation	Logarithm of increment[3] Mean	Logarithm of increment[3] Standard deviation	Probability of normal distribution[4]
Loblolly	1961–1972	235	4.47	2.72	1.292	0.694	0.0002
pine	1972–1982	97	3.21	1.65	1.015	0.601	0.0002
Shortleaf	1961–1972	127	3.44	2.08	1.045	0.646	0.1628
pine	1972–1982	40	2.72	1.82	0.768	0.742	0.2015
Slash	1961–1972	84	3.74	2.75	1.089	0.697	0.3899
pine	1972–1982	76	3.02	2.09	0.832	0.690	0.0068

[1] See Bechtold et al. (1991, p. 708) for more detailed description.

[2] Units are ft^2/ac/yr basal area increment.

[3] Units are logarithm of ft^2/ac/yr basal area increment. See histograms in Figure 1 for more details on distribution.

[4] D'Agostino et al. (1990).

METHODS

Moran's I is analogous to a weighted correlation coefficient between all possible pairs of the n observations (z_i and z_j, $i \neq j$). This statistic was first proposed by Moran (1950) as:

$$I = \frac{\sum_{\substack{i=1 \\ i \neq j}}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{W \operatorname{Var}(z)}, \tag{1}$$

where w_{ij} is a weight that quantifies the hypothesized spatial association or proximity between observations (z_i and z_j) at sites i and j (e.g., inverse distance between sites), and $w_{ii} = 0$; W is the sum of all n^2 values of w_{ij}; $Var(z)$ is variance of the n observations (z_i); and observations are transformed to center on zero (i.e., sum of all z_i's equals zero). Moran's I is a dimensionless statistic that usually ranges from -1 to 1, although in rare cases it can exceed these extremes depending on the weights (w_{ij}).

Under the null hypothesis, we may consider the set of all $n!$ random permutations, in which each observation is equally likely at any observation site. No assumptions are made regarding the sample distribution that generated the observations (z). Under the null hypothesis, Cliff and Ord (1981, p. 45–51) derive the exact mean and variance of Moran's I for the $n!$ permutations using computations of order n^2, and demonstrate that the permutation distribution of Moran's I is approximately normal for sample sizes $n > 50$ (see also Sen 1976). Therefore, the normal distribution and the exact permutation mean and variance are sufficient to estimate the probability of observing the realized value of Moran's I assuming the null hypothesis is true. Reed and Burkhart (1985) provide more specific details.

Alternative weights w_{ij} are used to test different hypotheses regarding the degree of spatial association (Cliff and Ord 1981, p. 17). An example is a contagious disease, where z_i might be the disease prevalence (centered on zero) in county i, and weight w_{ij} equals 1 if counties i and j are adjacent and 0 otherwise. Or the weights can be more complex, such as: the wavelet transformations described by Bradshaw and Spies (1992) for image pixels; and the tree competition index of Hegyi (1974), where $w_{ij} = (D_j/D_i)/d_{ij}$, D_j is the diameter at breast height of tree j, and d_{ij} is the distance between trees i and j.

Since little is known about the spatial growth patterns of natural undisturbed southern pines across Georgia, our null hypothesis is that there is no spatial autocorrelation for a broad range of spatial scales. We simply formulated this hypothesis by choosing nine categories of lag spacings, which we defined as 1–18 km, 18–36 km, . . . , and 144–162 km. The weights (w_{ij}) equal 1 if sites i and j are within the same category of lag spacings, and 0 otherwise. Since there is a separate test of hypothesis for each of the nine lag categories, the null hypothesis was rejected only when the p-value for an individual hypothesis was less than $0.05/9 = 0.0055$ according to the Bonferroni method (Legendre and Fortin 1989, p. 112). This test was independently repeated six times, once for each of the three forest types (loblolly, shortleaf, and slash pine) and two growth intervals (1961–1972 and 1972–1982).

We computed the contribution of each sample plot to the overall Moran's I statistic to study the geographic distribution of spatial autocorrelation. We coined the term "partial Moran's I statistic," for this is a new exploratory analysis tool, the mathematics of which are presented in the Appendix. The sum of the n partial Moran's I statistics equals the overall scalar Moran's I statistic. Partial Moran's I statistics are related to the h-scatterplots and local relative variograms which Isaaks and Srivastava (1989, p. 154–166) use to explore spatial continuity. The partial Moran's I can help identify local areas of unusually high spatial autocorrelation, which Haslett et al. (1991) describe as a spatial anomaly. This might mitigate one of the troubling assumptions in classical analyses of spatial autocorrelation, namely that a single dominant spatial structure exists over the entire study area (Legendre and Fortin 1989, p. 112).

Outliers can affect spatial autocorrelation. All permutation tests were checked for individual outliers by deleting one observation at a time, and repeating the test of hypothesis (Cliff and Ord 1981, Christensen et al. 1992). H-scatterplots (Isaaks and Srivastava 1989) were used to informally inspect for multiple outliers.

Growth of natural pine plots is affected by local stand conditions, such as site index, stand age, stem density, and hardwood competition (Zahner et al. 1989, Bechtold et al. 1991, Ruark et al. 1991, VanDeusen 1992). An underlaying spatial pattern in local stand conditions across Georgia could cause spatial autocorrelation in forest growth. To test this hypothesis, we studied the spatial autocorrelation in residuals from the regression model of Bechtold et al. (1991). This model predicts logarithm of gross pine basal area increment as a linear function of several descriptors of local stand conditions: site index; logarithm of stand age; logarithm of stem density; ratio of pine basal area to total basal area, which is used as an index of hardwood competition; and logarithm of basal area mortality per unit area. Like Bechtold et al. (1991), we used separate regression models for each of the three forest types; however, we fit separate regression models to each time interval (1961–1972 and 1972–1982) rather than using an indicator variable for time interval in a single model. Regression coefficients closely resembled those of Bechtold et al. (1991, p. 710). Stem density was the dominant predictor of gross basal area growth; growth increased with density. Site index and stand age were the next most important predictors of growth; growth was positively correlated with site index and negatively correlated with stand age. Mortality was the least important predictor. However, the correlation between mortality and stem density was consistently near 0.50, which was the highest among all predictor variables.

Regression residuals are not mutually independent, even in the absence of spatial autocorrelation. Cliff and Ord (1981, p. 200–203) derive the expected mean and variance of Moran's I that considers the autocorrelation among regression residuals in the absence of any spatial autocorrelation. We used their methods to estimate the probability of obtaining the realized Moran's I statistic under the null hypothesis of no spatial autocorrelation among the regression residuals.

RESULTS

We rejected the null hypothesis of random spatial autocorrelation in the logarithm of pine basal area increment in two of the six analyses (Figure 2). The shortleaf pine forest type exhibited strong positive spatial autocorrelation in the 0–18 km and 36–54 km lag spacings during 1972–1982. There was weak negative spatial autocorrelation for the slash pine forest type in the 72–90 km lag spacing during 1961–1972.

Figure 3 depicts a map of the partial Moran's I statistics [Equation (A4)] for shortleaf pine growth between 1972–1982 in the 0–54 km lag spacing, which includes the greatest overall spatial autocorrelation in Figure 2. The magnitude of spatial autocorrelation is not uniform across Georgia. Rather, there is a local spatial anomaly in the mountains approximately 100 km north of the city of Atlanta (Figure 3), where there is a cluster of plots with large values of the partial Moran's I statistic. These same plots are the slowest growing of the 40 shortleaf pine plots. This cluster is unlikely under the null hypothesis used in the permutation test.

Growth of slash pine sample plots between 1961–1972 exhibited a weak but significant negative spatial autocorrelation in the 72–90 km lag category (Figure 2). A map of the partial Moran's I statistics (similar to Figure 3) indicated a diffuse spatial pattern for slash pine that has no obvious interpretation.

We tested for random spatial autocorrelation in the residual difference between the expected and observed growth on each sample plot using the regression model of Bechtold et al. (1991), which predicts growth as a function of local stand conditions. The null hypothesis of no spatial autocorrelation was accepted for all three forest types, two time intervals, and nine categories of lag spacing. The spatial distribution of different local stand conditions across Georgia might have caused the spatial autocorrelation in growth.

All tests with Moran's I were checked for possible outliers that might affect each test of hypothesis. There are no obvious outliers apparent in the h-scatterplots (Isaaks and Srivastava 1989), and there were no cases in which the deletion of a single observation changed the results of the Moran's I tests.

Cliff and Ord (1981, p. 53) found that the permutation distribution of Moran's

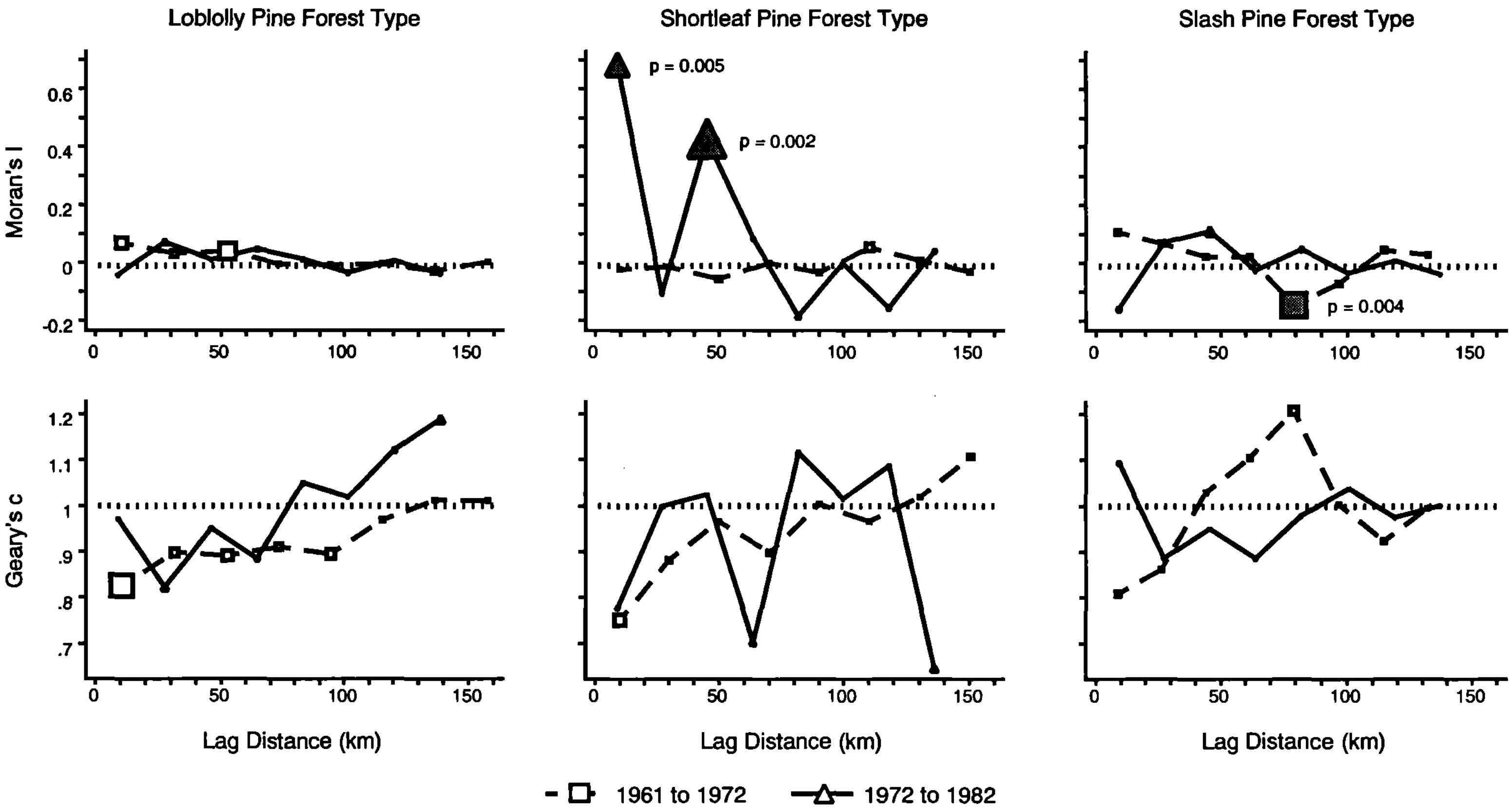

FIGURE 2. Moran's I and Geary's c, which are indicators of spatial autocorrelations, as functions of lag spacing between sample plots. The dashed line is the expected value for a random spatial distribution in logarithm of gross basal area increment. Large symbols represent a low probability that the spatial autocorrelation represents a random spatial distribution; each symbol is inversely proportional to the P-value. There were only three cases in which Moran's I was significant at $P < 0.0055$. Undisturbed, naturally regenerated shortleaf pine growth exhibited positive spatial autocorrelation between 1972–1982 at lag spacings of 0–18 and 36–54 km, and slash pine growth between 1961–1972 had a negative spatial autocorrelation at lag spacings of 72–90 km. In subsequent analyses, regression models were used to predict logarithm of gross basal area increment as a function of local stand conditions, and there was no significant spatial autocorrelation detected in the residuals. We suggest the hypothesis that spatial patterns in local stand conditions caused the patterns in Figures 2 and 3

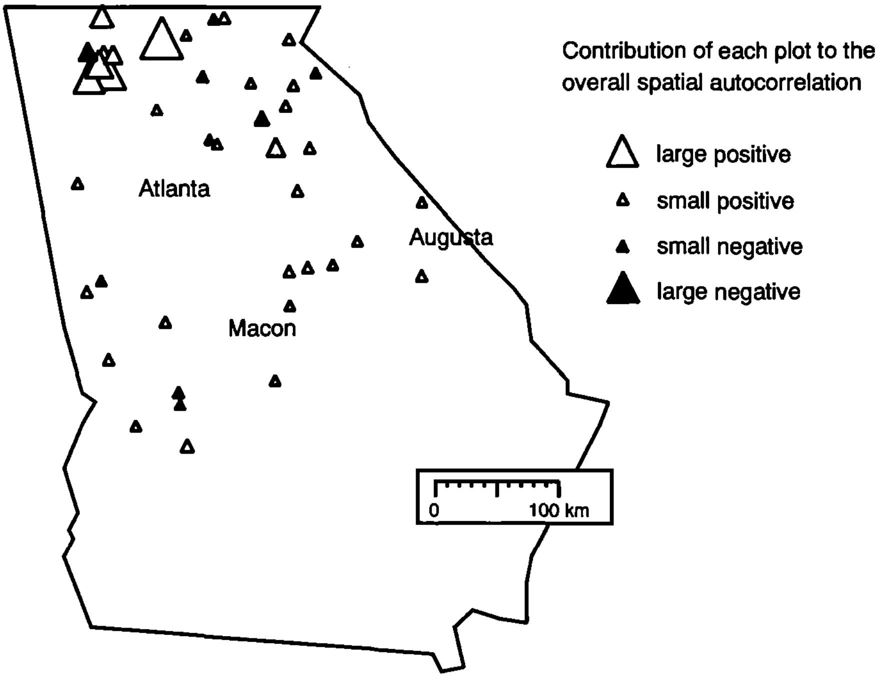

FIGURE 3. Partial Moran's I is a tool to explore the continuity of spatial autocorrelation across Georgia. The location of each selected shortleaf pine sample plot measured in both 1972 and 1982 is denoted by a triangle, corresponding to Figure 1E. The size of the triangle is proportional to the contribution of that plot to the overall Moran's I statistic for the 0–54 km lag spacing [Equation (A4)]. Shaded symbols represent negative partial Moran's I statistics. A localized cluster of 6 slow-growing slash pine sample plots (Figure 1E), located in the mountains 100 km north of Atlanta, provides most of the evidence for spatial autocorrelation in Figure 2; this is likely a nonrandom spatial anomaly. We suggest the hypothesis that spatial patterns in local stand conditions caused this unusual cluster of slow-growing plots.

I is approximately normal under the null hypothesis. We conducted Monte Carlo simulations of each permutation test (Upton and Fingleton 1985, p. 339–340), with 200,000 iterations in each simulation. There was little skewness in any of the simulated permutation distributions, including shortleaf pine during 1972–1982, for which only 40 sample plots were available (Table 1). In all cases, the p-values estimated from the Monte Carlo simulations agreed closely with those computed using the normal distribution with the exact mean and variance for the permutation test.

DISCUSSION

Analysis of spatial autocorrelation can test hypotheses regarding cause and effect relationships. We use the hypothesis that atmospheric pollution has caused a growth reduction as an example. Lucier and Barnard (1992) identify ozone exposure as a justifiable concern regarding the health and productivity of southern pine forests. Pinkerton and Lefohn (1987) and Lefohn and Pinkerton (1988) reported that forested areas in the southeastern portion of the United States had relatively high ozone exposures during 1978–1985. Based on a small set of rural monitoring sites in the southeast, they found lower concentrations in the coastal plains and higher concentrations near larger metropolitan areas and in the Piedmont/Mountain/Ridge-Valley physiographic regions.

Consider the hypothesis that growth rates should be lower near urban areas and at higher elevations because of higher exposure to atmospheric pollutants. We found an anomalous cluster of slow-growing shortleaf pine sample plots in the mountainous region of north Georgia, which is 100 km from the major metropolitan area of Atlanta, and there is only a small probability that the spatial autocorrelation is a chance event. This result is consistent with the pollutant hypothesis. However, the loblolly pine plots do not exhibit a similar spatial autocorrelation in the same geographic region (Figures 1 and 3), and Elsik et al. (1992) found that the effects of ozone were greater for loblolly pine seedlings than shortleaf pine. Also, there was no anomalous cluster of unexpected slow-growing shortleaf pine plots after adjustment for local stand conditions with the regression model. Therefore, our overall results are inconsistent with the atmospheric pollutant hypothesis, although alternative interpretations are given in the next paragraph. Our results are based on observational data alone, which are insufficient to confidently establish cause and effect relationships (Schreuder and Thomas 1992).

Lucier and Barnard (1992) state that abnormal growth reductions, tree mortality, poor site conditions, and insect and pathogen disturbances are associated with abnormal forest decline, although these same symptoms might also be caused by a variety of other natural and man-made factors. In our analysis, plots manifesting pollutant stress might have been eliminated by the screening criteria that were used to select plots, such as visual evidence of serious pathogen or disease disturbance. Or stress caused by atmospheric pollution might affect the spatial pattern of a predictor variable in the regression model, such as mortality, site index, or hardwood competition. Pollutant stress might be uniformly distributed across Georgia, without any resulting spatial pattern in forest decline; however, this hypothesis is difficult to test given the sparse spatial distribution of rural monitoring sites for airborne pollutants. The spatial distribution of loblolly pine plots differs somewhat from the shortleaf pine plots (Figures 1D and 1E), which might explain the differences in spatial autocorrelation and patterns between the two types of plots. Also, the correction in Moran's I for the autocorrelation among regression residuals might decrease the power to reject the null hypothesis when it is false. Birdsey and Schreuder (1992) and Lucier and Barnard (1992) note that some trends in inventory data can be artifacts caused by changes in inventory and sampling design, and Zeide (1992) feels that this is the primary reason for reductions in growth estimates from FIA data.

Validity of statistical tests of hypothesis, such as the t-test and analysis of variance, require independently distributed errors. Residual errors from regression models must be independent before hypotheses regarding regression coefficients can be validly tested (e.g., Swindel 1991). We found no evidence for nonrandom spatial autocorrelation in residuals from the models that Bechtold et al. (1991) used in their analysis of covariance. However, the assumption of independence for certain t-tests would be suspect because of the spatial autocorrelation among plots (Figure 2).

An analysis of spatial autocorrelation can contribute to geostatistical modeling of a spatial response surface. If we accept the hypothesis that the spatial autocorrelation is no greater than that expected by chance, then the spatial model for the response should be a horizontal plane. Figure 3 suggests a random spatial distribution of growth except for the cluster of slow-growing sample plots north of Atlanta. Ross et al. (1992) suggest that both Moran's *I* and Geary's *c* (Figure 2) be used to help define the scale in models of a spatial surface; however, we found that Moran's *I* yields more interpretable trends and more powerful tests. Distribution of the sample data has more affect on the variance of Geary's *c* than Moran's *I* (Cliff and Ord 1981, p. 15), which explains the higher power of the latter statistic. Our results confirm the observation by Legendre and Fortin (1989) that Moran's *I* is more sensitive to extreme values, such as plots with unusually slow growth.

An analysis of spatial autocorrelation is possible with new FIA data for Georgia, which have been collected since 1982 (Sheffield and Johnson 1993). However, Schreuder and Thomas (1992) recommend that testable hypotheses be specified before any analysis of cause and effect relationships. We chose not to analyze the most recent data until hypotheses regarding the spatial patterns of possible causal agents are more precisely formulated. Between 1982–1988, average net growth of FIA pine plots continued to decrease in public and nonindustrial private ownerships (Sheffield and Johnson 1993, p. 11); however, growth increased on forest industry lands, which is consistent with the results of Cleveland et al. (1992) for the mid-southern United States.

There are numerous hypotheses for the causes of reduced forest growth, including Sheffield et al. (1985), Sheffield and Cost (1985), Hyink and Zedaker (1987), Prinz (1987), Lucier (1988), Zahner et al. (1989), Warren (1990), Bechtold et al. (1991), Ruark et al. (1991), Birdsey and Schreuder (1992), Lucier and Barnard (1992), VanDeusen (1992), and Zeide (1992). The effects of certain causal agents might be more severe in geographic areas that are under chronic ambient stress, such as high elevations, ecotones, or boundaries between broad-scale ecoregions (Gosz 1993, p. 372). Superimposed on these causes is weather, which can be a triggering or synchronizing factor in the short-term manifestation of forest damage (Prinz 1987). And there is regional variability in soil nutrients that affects the spatial expression of changes in forest ecosystems. Moisture stress and numerous abiotic and biotic factors might alter the response of trees to pollutants, such as ozone (Lefohn and Pinkerton 1988).

These confounded factors affect the spatial distribution of regional changes in forest condition. Cumulative effects of multiple causes that have different spatial patterns can produce a response that has a complex spatial pattern, or no apparent spatial pattern relative to the overall variability. Spatial analyses offer the potential to provide evidence that is consistent or inconsistent with one or several hypotheses. However, the results of a spatial analysis might not often permit definitive conclusions regarding specific hypotheses. It is more likely that spatial analyses will provide weak conclusions that contribute to the weight of evidence for or against particular hypotheses. Considerable evidence from observational studies, controlled experiments, and/or process theory are required to confidently infer cause and effect relationships (Schreuder and Thomas 1992).

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APPENDIX

This section provides the computational formulae for a spatial analysis with Moran's I. Matrix notation facilitates implementation with modern matrix languages for personal computers. Czaplewski and Reich (1993) give derivations. Equations (1) and (A1) give the Moran's I statistic:

$$I = \mathbf{1}'[(\mathbf{z}\mathbf{z}')\circledast\mathbf{W}]\mathbf{1}/[W\,\mathrm{Var}(z)] = \mathbf{z}'\mathbf{W}\,\mathbf{z}/[W\,\mathrm{Var}(z)], \qquad \text{(A1)}$$

where $\mathbf{1}$ is a $n \times 1$ vector in which all elements equal 1; $\mathbf{z}$ is a $n \times 1$ vector of the n observations, in which the ith element equals z_i, transformed so that the vector sum is zero (i.e., the mean of z for the n observations is subtracted from each z_i); $\mathbf{z}'$ is the matrix transpose of $\mathbf{z}$; $\mathbf{W}$ is the $n \times n$ matrix in which the ijth element equals w_{ij} [see Equation (1)]; matrix operator $\circledast$ denotes element by element multiplication (i.e., the ijth element of $\mathbf{A} \circledast \mathbf{B}$ is equals $a_{ij}b_{ij}$); $W = \mathbf{1}'\mathbf{W}\mathbf{1}$; and $\mathrm{Var}(z) = (\mathbf{z}'\mathbf{z})/(n - 1)$.

Cliff and Ord (1973, p. 32–33, 1981, p. 45–46) derive the exact expected mean, $E[I]$, and variance, $Var(I)$, of the distribution of Moran's I under the null hypothesis over the $n!$ permutations, conditional upon the n observations in space:

$$E[I] = 1/n \tag{A2}$$

$$Var(I) = \frac{\left(\begin{array}{l} \qquad\qquad n\,[3\,W^2 + (n^2 - 3\,n + 3)S_1 - nS^2] \\ - \left(\dfrac{Var(z)}{m_4}\right)[6\,W^2 + (n^2 - n)S_1 - 2nS_2] \end{array} \right)}{(n - 1)\,(n - 2)\,(n - 3)\,W^2} - \frac{1}{(n - 1)^2} \tag{A3}$$

where $m^4 = [(\mathbf{z} \circledast \mathbf{z})'(\mathbf{z} \circledast \mathbf{z})]/n$, $S_1 = \mathbf{1}'(\mathbf{W} \circledast \mathbf{W} + \mathbf{W} \circledast \mathbf{W}')\mathbf{1}$, and $S_2 = \mathbf{1}'(\mathbf{W}'\mathbf{W} + 2\mathbf{W}\mathbf{W} + \mathbf{W}\mathbf{W}')\mathbf{1}$ (Czaplewski and Reich 1993). Reed and Burkhart (1985) give Equations (A1)–(A3), although without the formulations in matrix algebra.

If all elements in the ith row and column of $(\mathbf{z}\mathbf{z}') \circledast \mathbf{W}$ equal zero, then the ith observation is deleted, all matrix dimensions are reduced by 1, and $n - 1$ is used instead of n in Equations (A1)–(A3). This occurs when weights (w_{ij}) are 0–1 values that indicate observations i and j are within the same spatial lag spacing (e.g., 0–18 km), but none of the observations are within this range for the ith observation.

Moran's I can be disaggregated into n values, which we term "partial Moran's I statistics." We propose this set of statistics as useful tools in exploratory analyses of spatial autocorrelation. These statistics are used in Figure 3 to identify local areas that have high spatial autocorrelation (i.e., spatial anomalies). Let $\mathbf{i}$ be the $n \times 1$ vector that contains this set of statistics, where the jth element represents the contribution of the jth observation to the overall Moran's I statistic:

$$\mathbf{i} = \{[(\mathbf{z}\mathbf{z}') \circledast \mathbf{W}]\mathbf{1} + [(\mathbf{z}\mathbf{z}') \circledast \mathbf{W}]'\mathbf{1}\}/[2W\,Var(z)]. \tag{A4}$$

From Equations (A1) and (A4), it can be seen that the sum of the elements in vector $\mathbf{i}$ equals the overall scalar Moran's I. The $n \times n$ matrix $(\mathbf{z}\mathbf{z}') \circledast \mathbf{W}$ in Equation (A4) is transposed and summed a second time because w_{ij} does not necessarily equal w_{ji}.

Spatial weights can be asymmetric, where $w_{ij} \neq w_{ji}$ (e.g., the index of between-tree competition by Hegyi 1974). However, the weights are usually symmetric, where $w_{ij} = w_{ji}$ and $\mathbf{W} = \mathbf{W}'$. In this special case, $S_1 = 2\;\mathbf{1}'(\mathbf{W} \circledast \mathbf{W})\mathbf{1}$ and $S_2 = 4\;\mathbf{1}'(\mathbf{W}\mathbf{W})\mathbf{1}$ in Equation (A3), and Equation (A4) simplifies to $\mathbf{i} = [(\mathbf{z}\mathbf{z}') \circledast \mathbf{W}]\mathbf{1}/[W\,Var(z)]$.

The weight w_{ij} is often a function of Euclidian distance between sites. The $n \times n$ matrix of Euclidian distances ($\mathbf{W}_\mathrm{E}$) between all possible pairs of sample plots was computed using the $n \times n$ matrix $\mathbf{C}_\mathrm{EW}$, in which all elements of the ith row equal the east-west coordinate in kilometers of the site at which the ith observation was made, and the $n \times n$ matrix $\mathbf{C}_\mathrm{NS}$, in which all elements of the ith row equal the north-south coordinate of the ith observation:

$$\mathbf{W}_\mathrm{E} = \sqrt{}[(\mathbf{C}_\mathrm{EW} - \mathbf{C}'_\mathrm{EW}) \circledast (\mathbf{C}_\mathrm{EW} - \mathbf{C}'_\mathrm{EW}) + (\mathbf{C}_\mathrm{NS} - \mathbf{C}'_\mathrm{NS}) \circledast (\mathbf{C}_\mathrm{NS} - \mathbf{C}'_\mathrm{NS})]. \tag{A5}$$

The matrix operator $\sqrt{}$ in Equation (A5) denotes the element by element square root (i.e., if a_{ij} is the ijth element of the $n \times n$ matrix $\mathbf{A}$, then the ijth element of $\sqrt{\mathbf{A}}$ equals the square root of a_{ij}). Using the Pythagorean theorem, the ijth element of $\mathbf{W}_E$ is the Euclidian distance between sites i and j.

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