POINT PATTERN ANALYSIS OF FIA DATA

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ABSTRACT.—Point pattern analysis is a branch of spatial statistics that quantifies the spatial distribution of points in two-dimensional space. Point pattern analysis was conducted on stand stem-maps from FIA fixed-radius plots to explore point pattern analysis techniques and to determine the ability of pattern descriptions to describe stand attributes. Results indicate that the Ripley's K(*t*) statistic may be readily calculated for FIA plots, providing an assessment of spatial pattern. Correlation was found between Ripley's K(*t*) and stand disturbance history and forest type. However, spatial pattern assessment may be confounded by stands with few trees per acre. Basal area growth prediction using Ripley's K(*t*) as a predictor variable is seriously limited by past stand disturbances. Although point pattern analysis may be limited by plot buffer creation techniques and the relatively small size of sample plots, extensive FIA sampling across the forests of the United States allows unprecedented spatial analysis of North America's forests.

Information concerning the spatial pattern of individual plants within plant communities may refine understanding of ecological processes (Hasse 1995, Legendre and Fortin 1989). Spatial patterns in plant communities are not only a record of past events, but they may also be a valuable predictor of future processes (Dale 1999). In forest stands, quantifying individual tree spatial patterns may provide information on forest establishment, growth, competition, reproduction, and mortality (Dale 1999). Point pattern analysis, a branch of spatial statistics, can be used to quantify the spatial pattern of plant communities (Cressie 1993). Point pattern analysis using FIA stem-mapping information permits refined analysis of past disturbance events, current forest type, and future stand growth on FIA plots. Such analyses permit the spatial investigation of forests at an unprecedented scale across the United States. A technique and possible benefits of conducting spatial point pattern analysis using FIA data are explored.

STAND-LEVEL POINT PATTERN ANALYSIS

Point pattern investigations may improve the assessment of forest attributes of FIA plots: forest growth, forest type, and disturbance history. The spatial arrangement of individual trees in a stand may explain variations in stand growth patterns previously unexplained by current growth and yield models. Distance-independent diameter growth models do not explicitly account for the spatial aspects of tree data, but they indirectly accounted for spatial effects through inclusion of competition variables such as stand density (Lessard and others 2001). However, the assumption that competitive forces are applied equally throughout a stand is unrealistic for mixed-species, multi-aged forest stands or stands that are patchy due to disturbance (Moeur 1993). Clustering of trees has been found to decrease volume growth by up to 20 percent, compared to regular spatial distributions common to plantations (Miina 1994, Shao and Shugart 1997). Spatial statistics offer alternatives to the traditional broad population density investigations (Weiner 1982) by providing a methodology by which the spatial arrangement of individual plants may be quantified.

Spatial point pattern analysis has been used to investigate stand disturbance histories (Harrod and others 1999, Mast and Veblen 1999, Mateau and others 1998, Moeur 1997). It has commonly been found that as stands age, their tree point pattern shifts from that of a clustered distribution to that of a random distribution (Mast and Veblen 1999, Moeur 1997). Natural gap-disturbance events may increase clustering, while anthropomorphic disturbances, such as timber stand improvement operations, may increase uniformity.

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Spatial point pattern descriptions of stands have been used to describe the competitive interactions between trees in mixed-species forests (Duncan 1991, Szwagrzyk 1992, Ward and others 1996), which may in turn reveal successional pathways. It can be hypothesized that the spatial arrangement of shade-intolerant tree species will be less clustered than that of shade-tolerant tree species, due to species-specific self-thinning behaviors. As forests progress through stand development, from a species composition dominated by shade-intolerant species to those that may be more shade tolerant, one might expect a change in spatial point patterns. In addition to shade tolerance, younger species components of a forest community (more shade tolerant) may tend to be more clustered due to recent regeneration events. Whether as an indicator of stand history, growth, or forest type, spatial point pattern analysis may provide another stand variable of considerable value in ecological analyses.

RIPLEY'S K(*t*)

A widely used spatial statistic of point pattern analysis is Ripley's K(*t*), a univariate second-order analysis of point patterns in a two-dimensional space (Dale 1999, Hasse 1995). The term "second order" refers to the analysis of all point-to-point distances, as opposed to first-order analyses such as "nearest neighbor" that use only the mean of inter-point distances (Dale 1999, Hasse 1995). With Ripley's analysis, a circle of radius *t* is centered at each spatial data point and the number of neighbors within the circle is counted (Hasse 1995). The variable *t* is often referred to as the step-size. For *n* individual points in the area A, the density (D=*n*/A) is the mean number of points per unit area (Hasse 1995). The K(*t*) function gives the expected number of points within radius *t* of an arbitrary point under a prescribed distribution (Hasse 1995). If points are randomly distributed (following a Poisson distribution), then the expected value will not exceed a fixed threshold (Hasse 1995). Confidence intervals are calculated for this expected value using Monte Carlo simulations. Simulations entail randomly generating points for plots of the same size as the observed plot, with the lowest and highest values of K(*t*) for each *t* used to estimate the lower and upper bounds of confidence envelopes (Hasse 1995). If the expected value for any size-step exceeds the value established by the confidence envelopes, then the null hypothesis of spatial randomness is rejected for that *t* (Hasse 1995, Mast and Veblen 1999). To achieve a 99 percent confidence interval, 99 simulations must be calculated (Mast and Veblen 1999). Recent research suggests that toroidal edge corrections should be utilized (Boots and Getis 1988, Duncan 1990, Mast and Veblen 1999, Ripley 1977). Toroidal edge correction involves wrapping the plot around a torus such that opposite sides of the plot connect, creating a data set with no boundary (Hasse 1995, Ripley 1977).

OPERATIONAL CONSIDERATIONS OF PATTERN ANALYSIS

Two attributes of the current FIA sampling design confound point pattern analysis. First, the circular subplot shape does not allow for toroidal edge correction. Second, the FIA subplots may be too small to allow for robust spatial analysis. Point pattern analysis is usually conducted on rectangular plots substantially larger than current FIA sub plots. Hence, no literature exists to propose corrections for the confounding factors. Therefore, for this study, the subplots for each FIA plot were truncated to a square shape (excluding all tree locations outside a superimposed square) and all four truncated subplots were combined into one square for each FIA plot. The assumption is that the dispersive and attractive properties of point patterns will be maintained during subsampling and recombination, as long as a minimum scale of sampling is not violated. The toroidal edge correction method (Ripley 1977) replicates the point pattern of rectangular areas eight times and adjoins all eight rectangles for a seamless pattern. The adjoining of all four FIA-subplot point patterns is considered a process analogous to toroidal edge correction whose validity should be elucidated by this and future research.

OBJECTIVES

The study had two major objectives:

1. To examine the relationships between Ripley's K(*t*) and FIA stand stem-map patterns, stand growth, stand disturbance history, and forest type
2. To determine the effect of plot trees per acre (TPA) on Ripley's K(*t*) for individual FIA plots

METHODS

Ripley's K(*t*) is computed using the x,y coordinates of every tree in a rectangular area. Because FIA data are collected using a

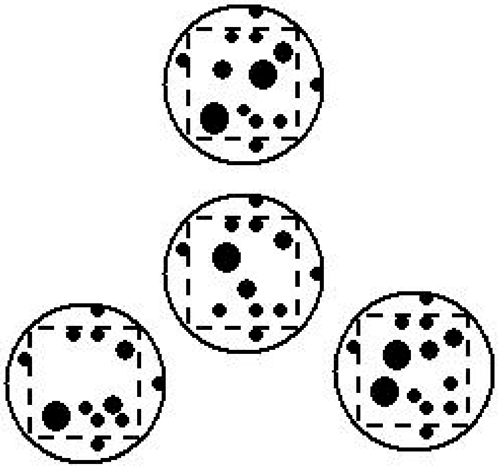

Figure 1a.—*To allow buffer creation, all circular subplots truncated to a square.*

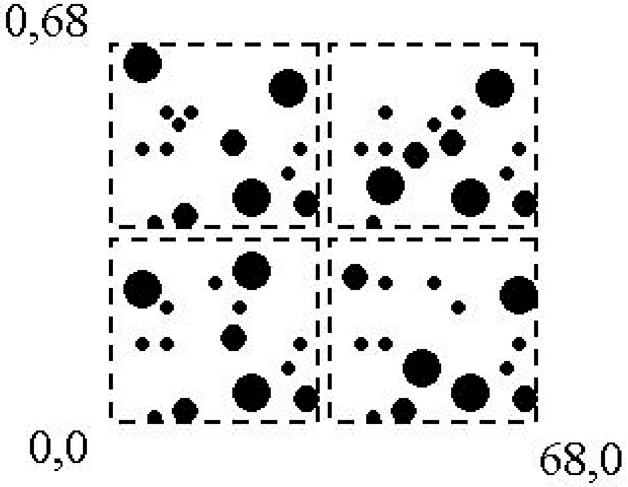

Figure 1b.—*All square subplots combined to one plot square and all bearings and distances transformed to x,y coordinate system (ft).*

four-subplot, fixed-radius sampling design, plot truncation and coordinate transformation are performed. First, the locations (azimuth and distance from subplot center) of trees within a superimposed square are extracted from every subplot (fig. 1a). Next, the distance and azimuth from plot center to each tree 5 inches and greater in d.b.h. are converted to x,y coordinates (using the lower left corner as the origin). Finally, the tree coordinates from each truncated subplot are combined to form a larger square with the lower left corner as the origin and 68-ft sides (fig. 1b). FIA data from Indiana were used (*Time 1:* 1998) (443 plots). To conduct growth analysis, remeasurement information for some of the plots measured in *Time 1* was used (*Time 2:* 1999 and 2000) (69 plots). Ripley's K(*t*) and associated 99 percent confidence intervals were calculated for FIA plots in this study using spatial analysis programs written by Duncan (1990).

RESULTS/DISCUSSION

Point pattern analysis of FIA data has numerous limitations and caveats. First, the actual area of analysis is reduced due to buffer creation resulting in a substantial loss of data. Second, Ripley's K(*t*) may only be calculated on data from the newly adopted four-plot fixed-radius sampling designs. All the previous surveys using variable-radius sampling designs cannot be used for spatial analysis. Third, Ripley's K(*t*) may only be calculated for trees greater than 5 inches in diameter. The fixed radius for sampling of trees less than 5 inches in d.b.h. is 6.8 ft, a size insufficient for broad deductions about tree spatial distributions. Fourth, because the FIA plots used in this analysis are actually a combination of subplots that are spatially disparate, plots located in ecotonal/multi-use areas may confound tree point pattern analysis; e.g., where one subplot is located on cropland while the other three are on forest land. The number of conditions and the actual ground land use classifications should be considered when calculating the Ripley's K(*t*) statistic. Finally, to ease the data management requirements for spatial analysis of large inventories, a single step-distance (*t*) may need to be selected.

Although numerous limitations exist, for a large proportion of the forest land sampled by FIA, the Ripley's K(*t*) statistic may prove to be an important measure of spatial character. From visual inspection of two FIA plot stem-maps, spatial arrangement differences are obvious (figs. 2 and 3). One distribution qualitatively appears random, while the other appears clustered. The Ripley's K(*t*) statistic quantifies these apparent differences in tree spatial distributions. The stand that is described as clustered is significantly (a=.01) clustered at scales between 12 and 28 ft according to the square-root transformed Ripley's K(*t*) statistic (Busing 1996); i.e., its spatial distribution is significantly different from a random distribution (fig. 4). For the stem-map qualitatively described as random, the Ripley's K(*t*) quantifies its spatial pattern as random across all scales of observation (null hypothesis of spatial randomness is not rejected) (fig. 5). Based on visual observations for over 400 stands, the Ripley's K(*t*) statistic appears to correctly quantify the spatial patterns of FIA plots.

Figure 2.—*Random distribution of individual tree locations*

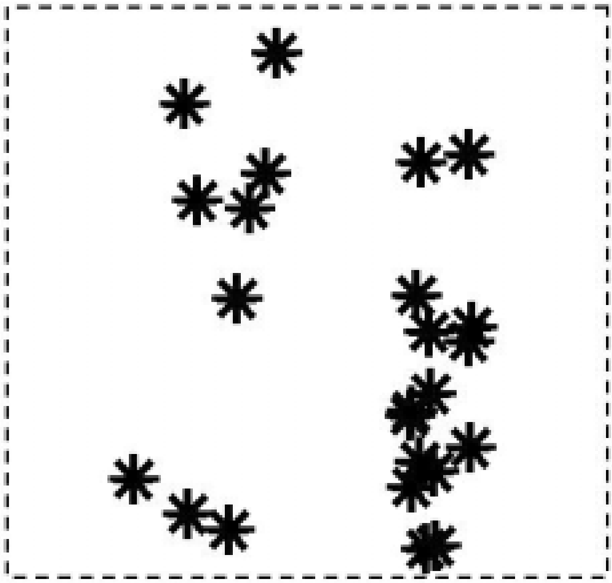

Figure 3.—*Clustered distribution of individual tree locations (Indiana, County 93, Cycle 4, plot 82).*

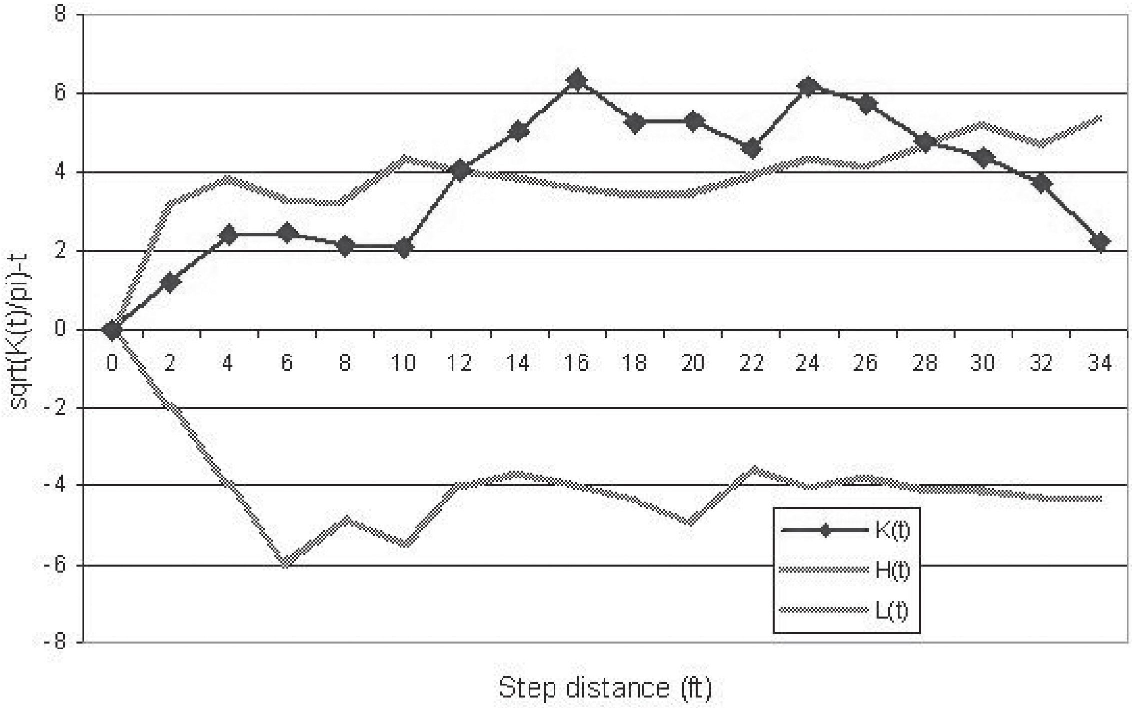

Figure 4.—*Ripley's K(t) and associated 99 percent confidence intervals for one FIA plot (Indiana, County 93, plot 82).*

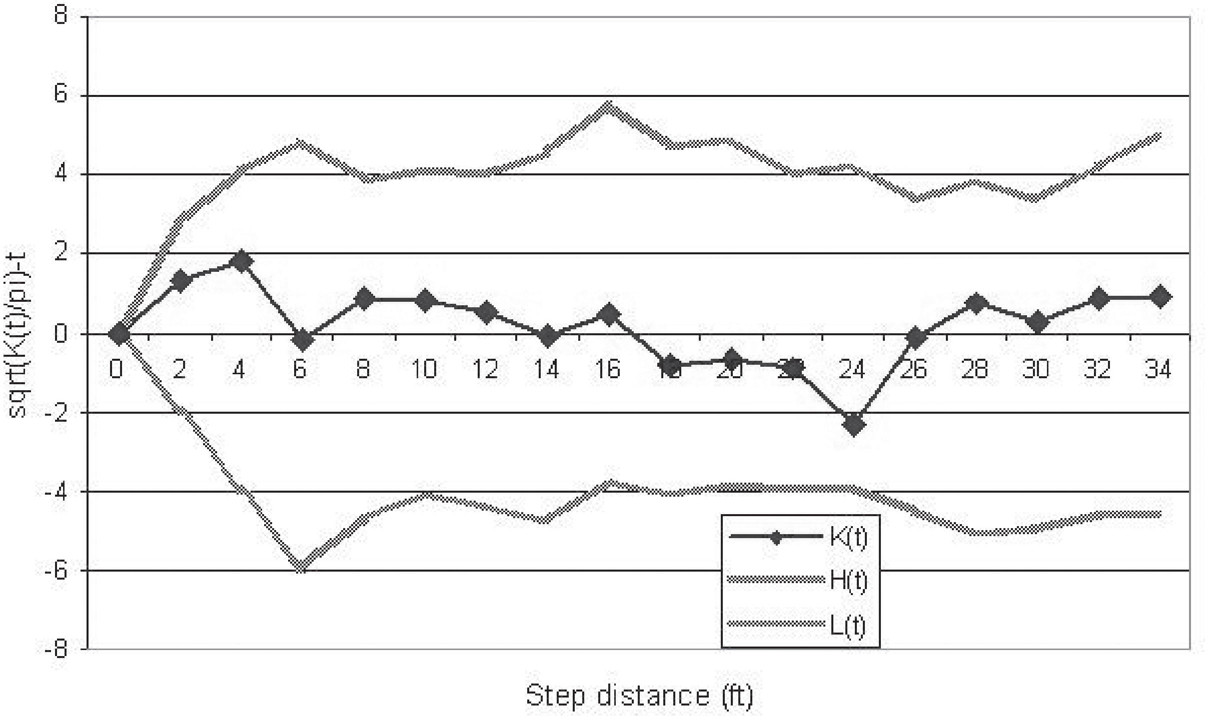

Figure 5.—*Ripley's K(t) and associated 99 percent confidence intervals for one FIA plot (Indiana, County 167, plot 45).*

Because spatial analyses of large forest inventory data sets may encounter a wide range of forest conditions, the effect of TPA on Ripley's K(*t*) values was examined. Because Ripley's K(*t*) was computed for all step-size distance classes from 2 to 38 ft (2-ft step-sizes), one distance class (24 ft) was chosen as a basis of comparison. This step-size appeared to be a distance at which the K(*t*) values stabilized and were usually indicative of clustering or randomness. Using the step-distance of 24 ft, the range of Ripley's K(*t*) values increase with decreases in TPA (fig. 6). Ripley's K(*t*) formulation strictly operates on coordinates, not on the size of individual trees. It would be expected that other measures of tree density such as basal area would have a less robust relationship with Ripley's K(*t*) values. Stands with low TPA may have a greater ability to express clustering tendencies when using only one step-distance as a basis of comparison. Therefore, only FIA plots with at least a fixed minimum number of trees should be used in spatial analysis due to the possibility of extraneous Ripley's K(*t*) values in plots with low TPA.

The relationship between Ripley's K(*t*) values and percentage changes in stand BA for occupied stands (BA > 100 sq ft/ac) was examined. Using a step-distance of 24 ft, the Ripley's K(*t*) value increased for individual stands as the percentage growth in stand BA increased (fig. 7). This result is counterintuitive—as stands became more clustered, stand basal area growth increased. Stands that had spatial distributions that tended toward uniformity (lower K(*t*) values) experienced losses in basal area (fig. 7). Stands with a propensity towards a uniform spatial distribution may have experienced disturbances (mortality or removals) during the remeasurement interval that reduced stand BA. When using spatial pattern information to refine stand growth predictions, past stand disturbances should have a confounding effect. Disturbances may increase individual tree growth, but reduce interim levels of stand growth.

The relationship between stand BA and Ripley's K(*t*) may be more driven by recent disturbance history than density/yield theories. Mean Ripley's K(*t*) values varied according to type of disturbance (fig. 8). Natural disturbances (windthrow, insects, disease, or fire) had the highest mean K(*t*) values, while timber stand improvement (TSI) disturbances had the lowest mean K(*t*) values (fig. 8). Partial stand cuttings and undisturbed

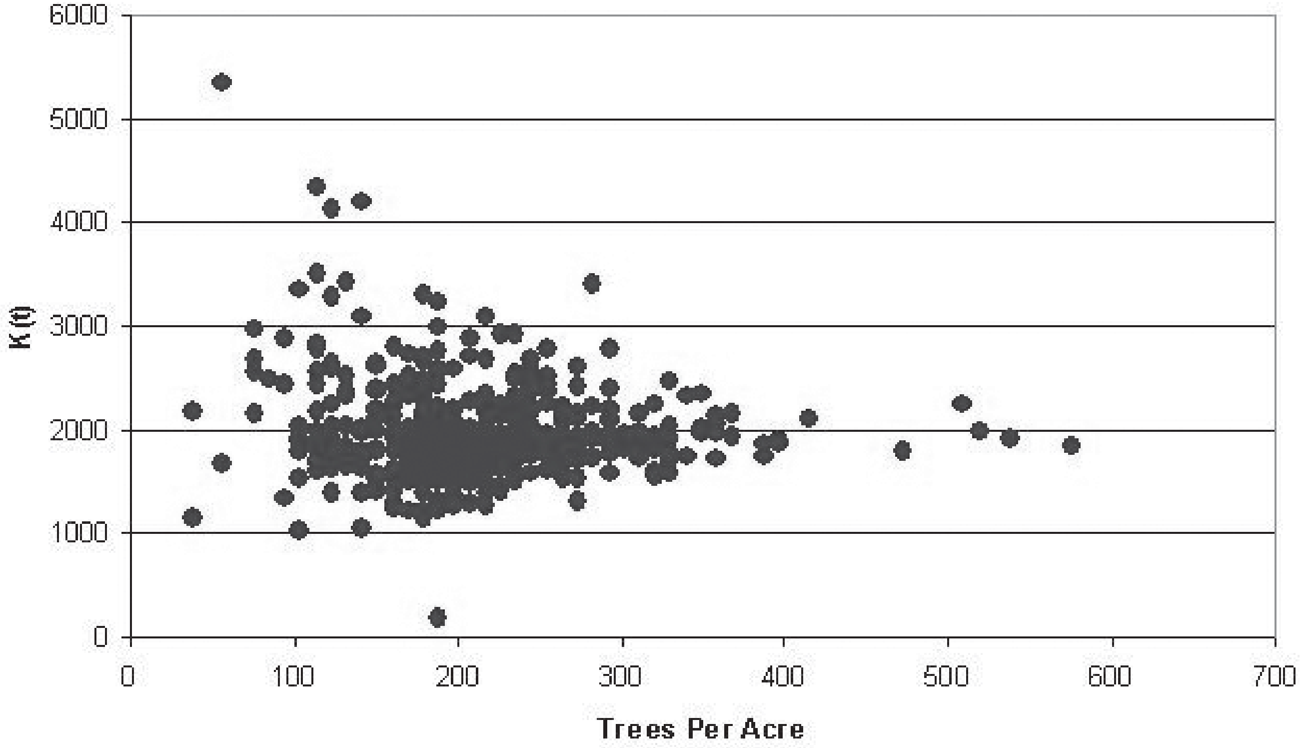

Figure 6.—*K(t) versus Trees Per Acre for FIA plots (Indiana, Cycle 4, t=24 ft).*

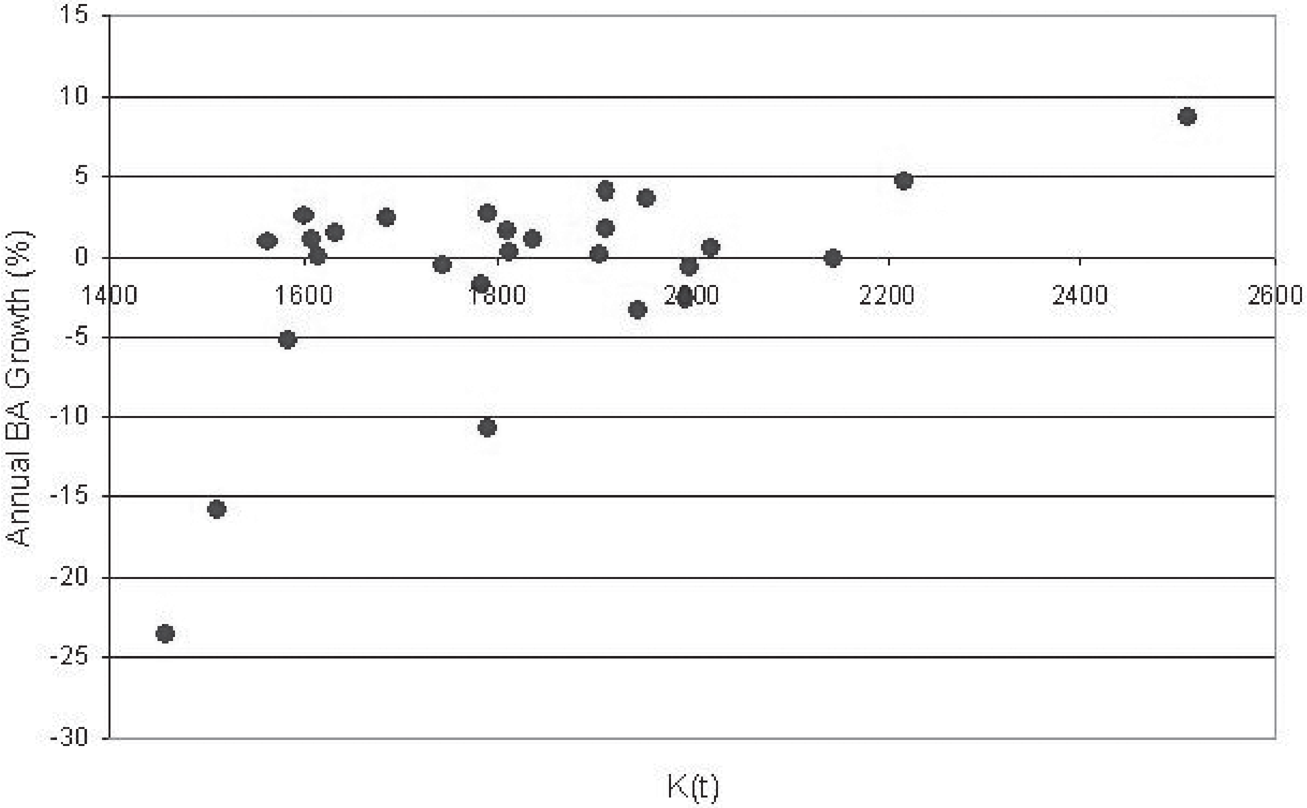

Figure 7.—*Ripley's K(t) versus annual BA stand growth (%), total BA>100 sq ft, Indiana, t=24 ft.*

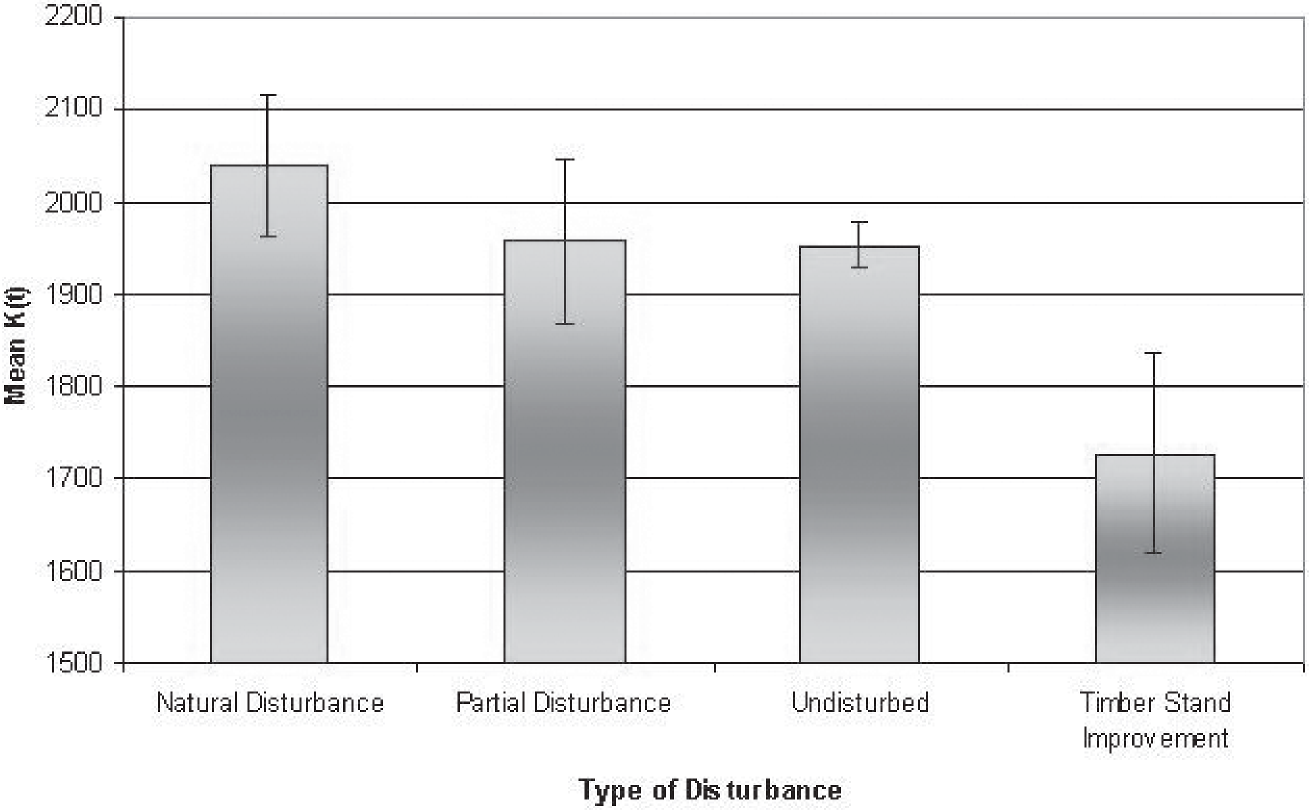

Figure 8.—*Mean K(t) values and associated standard errors for stands by types of identified disturbances (t=24 ft, n > 20).*

stands had nearly the same mean K(*t*) value (fig. 8). Trends in mean Ripley's K(*t*) values across different stand disturbance types may be explained by the inherent spatial attributes of these disturbances. Natural disturbances, such as sub-acre-scale gap disturbances, may increase the clustering nature of tree patterns. Selection thinning, which may remove only certain size or age classes, may only moderately increase the dispersion nature of stands. TSI treatments may actually increase uniformity due to the treatment's objectives of reducing competition experienced by individual trees and removing cull trees.

Mean Ripley's K(*t*) values varied across selected forest types in Indiana (fig. 9). Mean K(*t*) values appeared to increase with the increasing shade tolerance of the constituent tree species of each forest type (fig. 9). The oak and pine forest types collectively had lower K(*t*) values when compared to the more shade tolerant ash, elm, and maple forest types (fig. 9). Shade-intolerant species may resist clustering more than shade-tolerant species that are more adapted for the shading of spatial clustering. Further research should be directed at understanding the spatial dynamics of species through the temporal progression of succession. Eventually, point pattern analyses of FIA data may aid forest typing efforts and predictions about future forest successional trends at large temporal and spatial scales.

CONCLUSIONS

Spatial statistics may refine the assessment and prediction of forest change. Ripley's K(*t*) may be easily calculated for all FIA plots, while affording valuable ecological information. Most of the limitations concerning application of Ripley's K(*t*) involve plot buffer creation and analysis of plots of a relatively small size. Preliminary results using data from the four-plot fixed-radii FIA sampling designs indicate that Ripley's K(*t*) may quantify the spatial point pattern distribution of individual plots. However, plots with relatively low TPA may have extraneous Ripley's K(*t*) values. The ability of Ripley's K(*t*) to refine prediction of stand basal area changes is confounded by past disturbance events, which often determine the spatial pattern of stands in subsequent years. The Ripley's K(*t*) statistic may differentiate between disturbed and undisturbed plots, while also possibly indicating what disturbance may have occurred. Ripley's K(*t*) values may also indicate forest type due

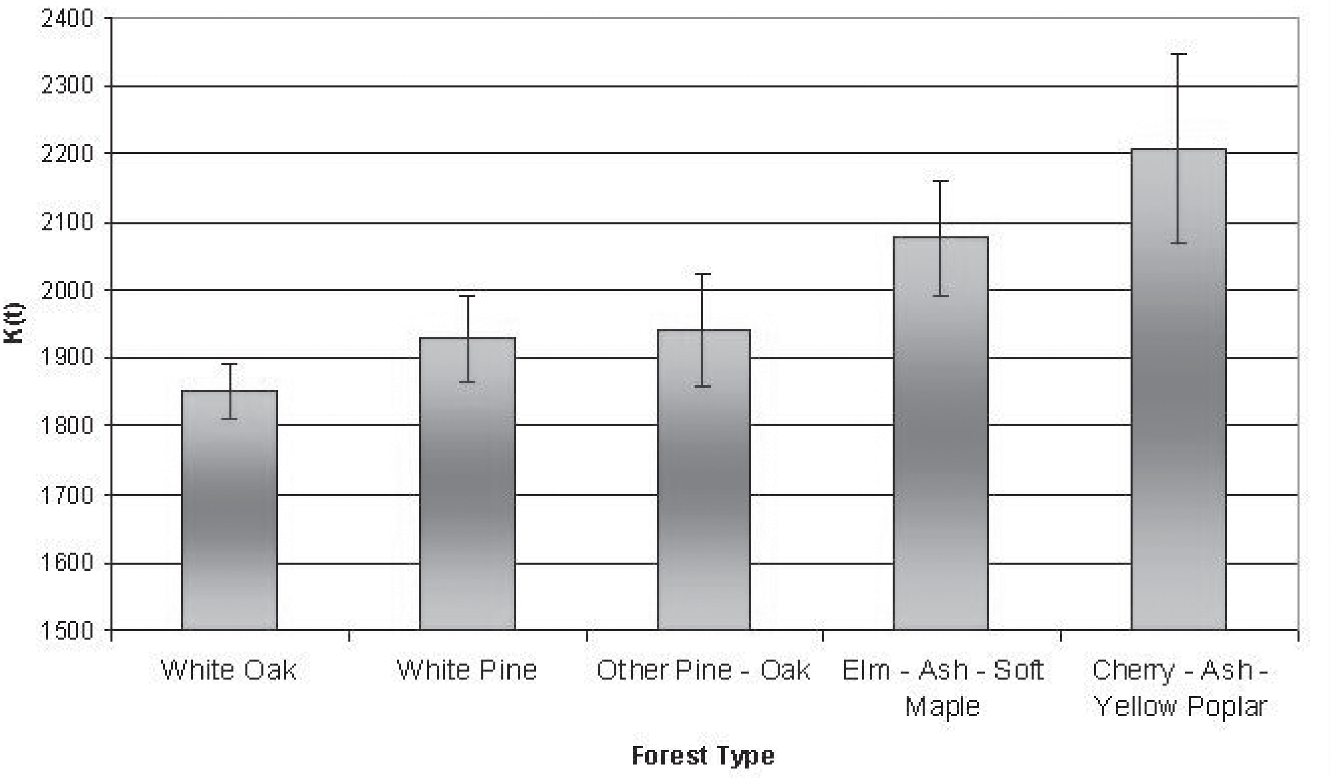

Figure 9.—*Mean K(t) values for various forest types—Indiana.*

to the characteristic shade-tolerance ranges of constituent tree species. Given the small data set of this study and the diverse applications of spatial point pattern analyses using data from the FIA fixed-radius sampling design, numerous research possibilities exist and warrant consideration.

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